YAYASAN PRIMA AGUS TEKNIK

Integration of AI, ML, and DL

Technologies in Project Management for Data Security Based Face Recognition Attendance Systems

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FOREWORD

With deep gratitude, this book is compiled as an effort to explore and delve deeper into the implementation of facial recognition technology in employee attendance management. In an era where technology increasingly plays a key role in operational efficiency and information security, a profound understanding of facial recognition-based attendance systems becomes increasingly important. This book aims not only to identify the roles of Machine Learning (ML), Deep Learning (DL), and Artificial Intelligence (AI) technologies in the development of attendance systems but also to highlight the challenges, risk management, and impacts of integrating this technology into human resource management. This book aims to develop and test a model for integrating advanced technology into a facial recognition-based attendance system in vocational high schools (SMK) to improve system security and efficiency.

The method used is quantitative with an experimental approach, which involves systematic experimental design to test models with various parameters, and evaluation techniques. To fulfill the research objectives, prediction and detection of anomalous patterns in attendance data were carried out by referring to facial recognition theory, resource management, and reward and punishment systems along with the integration of various technology models. The novelty of this book lies in the development of intelligent Machine Learning (ML), Deep Learning (DL), and Artificial Intelligence (AI) models to predict teacher absenteeism patterns based on relevant factors, which provide innovative solutions to improve the efficiency and security of the attendance system overall. In addition, integrating advanced technology in attendance project management provides a new contribution to the IT project management literature, especially in the scope of attendance in the educational environment.

The integration of technology used in this book is ML, DL, AI, Liveness detection, and data encryption using the AES algorithm with a focus on security, accuracy, and efficiency of the attendance system. The research sample used was a dataset obtained through a facial recognition-based attendance system for vocational school teachers with a total of 998 samples. This book was conducted in the Google Colab virtual notebook environment with the Python programming language and scikit-learn as supporting libraries. Various techniques such as K-means clustering, ensemble voting, classification, and regression are used in training and testing models to find absenteeism patterns, detect anomalous patterns, and perform prediction tasks.

The research results show that the ML and DL models developed can provide predictions of teacher absenteeism patterns with a satisfactory level of accuracy. In addition, the use of the AES algorithm for data encryption combined with an AI ensemble has proven effective in increasing the accuracy of anomaly detection and can increase security from potential data theft in the attendance system. For the integration of liveness detection technology with DL, the attendance system can increase the accuracy and security of recording the presence of fraud (fake objects) with an accuracy level of up to 87%. Finally, the application of the Reward and Punishment model to a facial recognition-based attendance system was able to increase teacher attendance levels, with the percentage increasing by around 5% after this method was implemented.

Therefore, it is hoped that this book can provide valuable insights for practitioners, academics, and other stakeholders in understanding the complexity and potential of facial recognition-based attendance systems.

This book is not detached from the support of various parties, both directly and indirectly. Therefore, the author expresses the utmost gratitude to all parties who have participated in supporting and facilitating the smoothness of this book. It is hoped that this book can make a significant contribution to the development of more advanced, effective, and reliable employee attendance technology. May the results of this book inspire and benefit the advancement of knowledge and management practices in the future and make a meaningful contribution to the development of more efficient, secure, and trustworthy employee attendance technology. Thank you.

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CHAPTER 1
DATA SECURITY

1.1 THE IMPORTANCE OF DATA SECURITY

In the context of modern organizations, employee attendance management is a critical aspect to consider. Particularly in the current era of globalization with intensifying competition, productivity, and efficiency are paramount to achieving success. Effective attendance management not only ensures employees' punctuality but also directly impacts the overall productivity and performance of the organization (Santhose & Anisha, 2023). Additionally, (Kamil et al., 2023) and (Severin et al., 2022), assert that low attendance rates directly affect the overall performance of the organization, leading to decreased productivity and unexpected additional costs.

However, with the rapid advancement of technology, especially in information systems, there is an increasing need for more sophisticated and secure solutions in attendance management. According to (Anthony, 2017) and (Steers & Rhodes, 1978), employee attendance management encompasses not only the recording of attendance but also includes discipline management, human resource planning, and productivity analysis. Within an organization, employee presence directly impacts various aspects such as output levels, the quality of products or services, and the overall work culture (Dwyer & Ganster, 1991; Oo et al., 2018; Ries, 2020) and (Tyagi, 2021).

Given that workplace culture and individual motivation within an organization can decline, it is essential to have a comprehensive understanding of the importance of attendance management in the context of modern business to ensure the long-term success of the organization. Therefore, effective attendance management is crucial for maintaining stability and balance in the daily operations of an organization.

Although attendance management has become an integral part of human resource management (HRM), organizations still face several challenges when implementing it traditionally. One of the main challenges is ensuring timeliness and accuracy in recording employee attendance. In manual or traditional attendance systems, errors in record-keeping often occur, which can negatively impact management decisions and employee performance evaluations. Additionally, manual attendance systems are prone to data manipulation, leading to inaccurate decisions and affecting the overall productivity of the company.

With technological advancements, particularly in Artificial Intelligence (AI) and image processing, more sophisticated solutions for attendance management have emerged. Attendance management is evolving through various technological integrations, such as fingerprint-based systems, smart cards, RFID, and QR codes. According to (Anyalewechi & Ezeagwu, 2023) and (Ardebili et al., 2023), companies can avoid common errors associated with manual processes, reduce the time required for employee name verification or tracking, and accurately record employee attendance through the application of technology in attendance systems. Several technologies offer significant potential to transform the landscape of attendance management, promising higher accuracy, operational efficiency, and improved data security.

In addition to the various technologies currently applied in attendance systems, one particularly noteworthy solution is the face recognition-based attendance system. This technology offers significant benefits for organizations by enabling the automatic recording of employee attendance through facial scanning, eliminating the need for physical interaction with attendance devices. As highlighted by (Anthony, 2017; Dang, 2023; A. Kumar et al., 2023), and (R. Rastogi et al., 2022), this system promises higher efficiency and better accuracy in attendance recording. Moreover, face recognition-based attendance systems facilitate more accurate and real-time attendance tracking, allowing for high-precision employee identification and reducing the risk of human error in record-keeping. Additionally, these systems are more user-friendly, as they do not require supplementary devices such as attendance cards or fingerprint scanners.

The use of face recognition technology has become a popular alternative and an increasing trend for monitoring individual attendance. Although initially introduced as a solution for employee attendance tracking, face recognition-based attendance systems have the potential for various other applications in the context of modern organizations. These systems can be utilized to access restricted areas or verify identities in other administrative processes. This is evidenced by emerging research focusing on the use of face recognition in various fields with diverse functions. For instance, (Srivastava & Bag, 2024) employed face recognition as a modern marketing tool, (Joo et al., 2024) developed face recognition for payment confirmation, (P.K et al., 2024) used face recognition for fraud detection in banking, and (Misra et al., 2023; Nagagopiraju et al., 2024; C. Zhang et al., 2023) and (Barhate et al., 2024), utilize face recognition technology for attendance management in various institutions.

Thus, further development in face recognition technology can provide greater long-term benefits for organizations. However, such technology is not without challenges related to data security and privacy, including technology optimization, data validity, and system security

(Chamikara et al., 2020; Dang, 2023a; Rao & Deebak, 2023) and (Boutros et al., 2023). In particular, data security in such systems is often inadequate to counter existing threats. Additionally, the risks of data theft and manipulation will increase as the amount of digitally stored data grows. As highlighted by (G. Singh et al., 2021; Wati et al., 2021; X. Zhou, 2020), and (Meden et al., 2021), the use of face recognition technology raises concerns about the collection and storage of individuals' biometric data. Furthermore, the risks of data theft and manipulation are expected to rise with the increase in digitally stored data (Hidayah & Yunus, 2023; H. Jia et al., 2020) and (Tejaswi & Swathika, 2023). The loss or misuse of personal data can have serious consequences, including financial loss and reputational damage for the affected individuals (Hidayah & Yunus, 2023; H. Jia et al., 2020) (Zulu & Dzobo, 2023). Additionally, there are other technical issues to be addressed, such as imperfect accuracy levels and the system's ability to handle variations in employee facial appearances. Therefore, data security becomes increasingly important as the risk of data theft and misuse by irresponsible parties is highly probable, making data protection a top priority in safeguarding information security.

In this context, various factors are analyzed and leveraged to enhance security through predictive measures, anomaly pattern detection in attendance data and systems, and the integration of advanced techniques and technologies to protect data from theft. This book will focus on the development and optimization of a secure and reliable face recognition-based attendance system using the latest advanced techniques and technologies, including Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL). Additionally, it will analyze attendance data to support the discovery of patterns and trends that can be utilized for better decision-making in school management through the application of relevant theories. The research will also consider the challenges faced in implementing this technology and the strategies to overcome these challenges to achieve maximum benefits for the institutions using it, specifically within the context of vocational high schools (SMK).

1.2 ATTENDANCE SYSTEM

Based on the problem described above, the problem statement for this book is as follows:

1. How can the integration of Machine Learning, Deep Learning, and Artificial Intelligence in a face recognition-based attendance system enhance data security?

2. How can Artificial Intelligence and Liveness Detection technology be used to detect anomalies in attendance patterns and ensure the accuracy of attendance records?
3. How can a reward and punishment system be implemented in the management of high-performing employees using data generated from the face recognition-based attendance system?

These questions will serve as the primary guide for this book to develop innovative solutions that integrate various advanced technologies (such as Liveness Detection in face recognition, Machine Learning, Deep Learning, and AI, as well as data encryption in face recognition-based attendance systems) and management aspects, particularly the management of high-performing employees. This approach reflects the complexity and relevance of the research topic.

By the background and problem statement outlined above, the objective of this book is to develop and test a model integrating Machine Learning (ML), Deep Learning (DL), and Artificial Intelligence (AI) technologies in a face recognition-based attendance system to enhance system security. The objectives are detailed as follows:

1. Integrate Liveness Detection techniques with Deep Learning technology in the face recognition-based attendance system at vocational high schools (SMK) to improve the performance and accuracy of face recognition by detecting spoofing (fake attacks), thereby enhancing the security of the attendance system.
2. Integrate Ensemble AI in the face recognition-based attendance system to detect anomalous patterns, preventing unauthorized (suspicious) data access, thus maintaining system security and increasing system efficiency to support rapid decision-making.
3. Implement data encryption using the Advanced Encryption Standard (AES) algorithm to prevent data theft. This ensures that data transmitted within the system is encrypted, making the content inaccessible to unauthorized users, particularly thieves or hackers, thereby safeguarding the privacy of teachers' data and applying security standards within the system.
4. Develop a reward and punishment system based on accurate attendance data to optimize the management of high-performing teachers and those who need further development.

The results of this book are expected to provide the following benefits:

1. Efficiency and Accuracy in Attendance: Enhance the efficiency and accuracy of attendance tracking for vocational high school (SMK) teachers using a face recognition-based attendance system integrated with liveness detection technology.
2. Reliable Security Assurance: Provide reliable security for the face recognition-based attendance system through the integration of Machine Learning, Deep Learning, and

Artificial Intelligence technologies. This integration will facilitate early detection of anomalies, allowing for quicker resolution of emerging security issues.

3. Stronger Data Protection: Ensure stronger protection for sensitive data, thereby maintaining the integrity and confidentiality of teacher attendance information within the face recognition-based system. Implementing advanced encryption techniques, such as the Advanced Encryption Standard (AES), will enhance data protection and reduce the risk of data theft in technologically driven attendance systems.
4. Improved Management of High-Performing Employees: Enhance the management of high-performing employees by utilizing information generated by the system integrated with advanced technologies. This will enable more accurate and effective implementation of reward and punishment mechanisms, and ensure consistent enforcement of disciplinary policies.

Although facial recognition technology has been utilized in some attendance systems, previous research has tended to insufficiently explore the potential integration of advanced technologies to enhance system security, accuracy, and the management of high-performing employees. The main issues identified in this book are (1) the need for security in the adopted attendance system, (2) accuracy issues in the face recognition technology applied to the attendance system, making the system vulnerable and insecure, (3) the necessity for privacy protection of individual data, causing concerns and stress levels that could disrupt productivity, and finally (4) the underutilization of stored data in the system for in-depth analysis, which could uncover security solutions and develop integrated technological innovations. This can be further elucidated through the following table.

Table 1.1. GAP Analysis

GAP	Author	Research Findings
There is a need for security in the adopted face recognition-based attendance system.	(Boutros et al., 2023; Golasangi et al., 2024; Hidayah & Yunus, 2023; Hosen et al., 2023; Hussein et al., 2023; J. Jia et al., 2021; Kavoliūnaitė-Ragauskienė, 2024; Ma, 2023; Meden et al., 2021; Pattnaik & Mohanty, 2020; Radiya-Dixit & Neff, 2023; Raji et al., 2020; A. K. Shukla et al., 2024; G. Singh et al., 2021; Sonawane et al., 2024; Tejaswi & Swathika, 2023; Waelen, 2023; Wati et al., 2021; Woubie et al., 2024; M. Zhou et al., 2024)	The emergence of concerns regarding technology security. Concerns about privacy regarding data stored through face recognition systems. The emergence of concerns and stress levels that disrupt individual productivity and performance. Concerns about data leakage in attendance systems.
There are accuracy issues in the	(Alhanaee et al., 2021; Ali, Diwan, et al., 2024; Anwarul & Dahiya, 2020;	Face recognition experiences lag and require more time to

detection technology of face recognition applied to the attendance system, making it difficult for the system to capture the faces of absent individuals, thus consuming time.	Bae et al., 2023; Basurah et al., 2023; Bergman et al., 2024; Cavazos et al., 2021; Chaudhari et al., 2023; Gode et al., 2023a; Hangaragi et al., 2023; Krishnapriya et al., 2020; P. Kumar et al., 2023; J. Liu et al., 2015; Painuly et al., 2024; Pattnaik & Mohanty, 2020; P. Rastogi et al., 2023; Saleem et al., 2023; Sawarkar & Alane, 2024; Sharma et al., 2020; Sharmila et al., 2023; Sonawane et al., 2024; Surantha & Sugijakko, 2024a; Terhörst et al., 2023; Ukamaka Betrand et al., 2023; H. Wu et al., 2023; Y. M. Zhang et al., 2024)	perform individual face identification. Detection in the system is less sophisticated as it cannot distinguish between photos/faces in videos and the genuine faces of individuals. The accuracy in face recognition detection is low, thus unable to match individual faces with the data stored in the system.
There has been no research related to the utilization of data stored in the attendance system for data analytics. Therefore, the utilization of attendance data for data analytics, in-depth analysis, prediction, utilization to find security solutions, and to develop integrated technological innovations, remains unexplored.	(Ab Wahab et al., 2022; Abraham et al., 2020; Aware et al., 2021; Chamikara et al., 2020; Dechen et al., 2024; Gode et al., 2023a; Golasangi et al., 2024; Momin et al., 2024; Nguyen-Tat et al., 2024; Oei et al., 2023; Pradyumna et al., n.d.; Raji et al., 2020; Seen Long et al., 2023; A. Singh et al., n.d.; Suriya et al., 2023; Surve et al., 2020; Syamala, 2020; Viswanathan et al., 2024; Y. M. Zhang et al., 2024)	The research focuses on the creation and development of systems without addressing the data stored in digital systems. Survey results indicate that there is no utilization or exploitation of stored attendance data in the system.

This book focuses on integrating advanced techniques and technologies (machine learning, deep learning, AI, and liveness detection) to enhance security with the following limitations:

1. Research Context: The study is confined to Vocational High Schools (SMK).
2. Data (Dataset): The research employs teacher attendance data (excluding data of other staff or personnel) obtained through a face recognition-based attendance system installed in several SMKs.
3. Experimental Environment: The experimental environment, including model training, testing, and anomaly prediction, is conducted on Google Colab notebooks.

4. Data Security Testing: Data security testing on the system is conducted to address data theft attempts and data breaches using prediction and anomaly detection through the face recognition-based attendance system and data analysis.
5. Enhancement of Data Security System: Data security system improvement in the attendance database is accomplished using AES encryption algorithm and face recognition technology accuracy to prevent attendance fraud by implementing Liveness Detection techniques.
6. Utilization of Machine Learning, Deep Learning, and AI Techniques and Models: The utilized models include Decision Tree, Naïve Bayes, SVM, Sgboost, SVM, Random Forest, Neural Network, K-Nearest Neighbor, Convolution Neural Network, One-Class SVM, and Isolation Forest as Ensemble AI.

The novelty of this book lies in the integration of machine learning technology into a face recognition-based attendance system with a focus on enhancing attendance system security and managing high-performing employees. This study represents one of the few endeavors that combine machine learning technology with attendance systems for these purposes, thereby broadening the understanding and potential applications of this technology in the context of human resource management.

Table 1.2. Novelty

Topic	**GAP**	**Novelty in this book**	**Description**
Implementation of face recognition technology for attendance.	Face recognition technology has not been widely integrated with project management.	Integration of Face Recognition with Information Technology Project Management (ITPM).	This approach offers a fresh perspective on how attendance technology can be more widely utilized in the context of project management. Integrating face recognition technology into attendance systems with Information Technology Project Management (ITPM) allows for evaluation not only in terms of attendance but also integration into project management to enhance security and efficiency.
Development of Predictive Attendance Pattern Models for system security.	In previous research, the literature has mainly focused on the development of predictive models using machine	Development of Predictive Attendance Pattern Models with Machine Learning and Deep Learning to	The development of predictive models in this book is more complex and accurate in predicting anomaly patterns in attendance systems using a combination of machine learning and deep learning to prevent and detect indications of fraud and

	learning for sales forecasting, pattern prediction, and trend prediction, rather than on enhancing security.	enhance system security.	unsafe signs that may arise in face recognition-based attendance systems, thus enabling early prevention and enhancement of system security.
Implementation of Decision Support System theory.	In previous studies, Decision Support System theory has been used solely for system development purposes, not for prediction. This has not been applied to face recognition-based attendance systems.	Integration of Decision Support System (DSS) theory and machine learning to support performance prediction of teachers based on face recognition-based attendance data.	This approach is novel as it combines DSS theory with machine learning to provide stronger decision support in performance management, which has not been previously explored in research.
Holistic Data Encryption Approach with AI.	There has been no research that combines data encryption using the AES algorithm with AI technology. Most studies combine data encryption with other techniques for data security.	Holistic Data Encryption Approach using AES algorithm and AI Ensemble to create a comprehensive solution in maintaining the security of data stored in face recognition-based attendance systems.	This study introduces a new approach to enhancing attendance system security that not only relies on facial recognition technology but also integrates encryption and anomaly detection methods for the security of individual data stored in the attendance system database.
Combining liveness detection techniques with Deep learning for system security.	Previous research on Liveness Detection technology has been limited to determining facial accuracy to prevent spoofing. Existing studies only utilize one technique without integrating it with other technologies or	Integrating liveness detection technology with deep learning to enhance the security of face recognition systems in attendance.	Liveness detection technology aids in preventing spoofing attacks such as the use of photos, which is a major challenge in conventional face recognition systems, with the addition of deep learning-based system detection accuracy, thus achieving higher and more accurate face recognition accuracy, ensuring a safer operation.

	techniques. Moreover, this technique has not been applied to system security.		
Optimization of attendance data utilization through Data analytics.	In previous research, attendance data has only been used for monitoring purposes without exploring its predictive potential.	Optimization of attendance data management and utilization through Data analytics for performance and achievement prediction of teachers using Machine Learning techniques.	This represents a new approach as previous attendance data was only used for monitoring attendance without exploring predictive potential for teacher performance. Furthermore, attendance systems have not fully utilized data analytics to optimize processes and outcomes. Utilizing more advanced data analytics approaches in attendance data stored in the system to develop predictive models for SMK teacher performance and achievement using machine learning techniques will optimize attendance management.

In Chapter 1, it has been revealed that attendance management within an institution plays a crucial role in enhancing productivity and organizational performance. The integration of advanced technologies such as Machine Learning, Deep Learning, and Artificial Intelligence into face recognition-based attendance systems can provide an effective solution to enhance attendance recording accuracy and the efficiency of managing high-performing employees. However, several issues need to be addressed, and this book identifies gaps in previous studies regarding the need for attendance system security, the accuracy of face recognition technology, and high-performing employee management. Focusing on the development of a secure and reliable attendance system, as well as the application of the latest technologies such as AI, ML, and DL, this study contributes to overcoming the challenges of implementing these technologies. With an integrated and innovative approach, this book contributes to addressing the challenges faced in modern attendance management, particularly in vocational high school (SMK) environments. The implementation of this technology is expected to provide significant benefits in improving the efficiency of time and attendance accuracy for SMK teachers through the use of face recognition-based attendance systems, laying a solid foundation for better decision-making in school management, and providing a secure attendance system solution.

CHAPTER 2
SYSTEM IMPLEMENTATION

In this section, the author discusses the literature review, where various crucial aspects of implementing a face recognition-based attendance system will be explored in more detail. This section will provide a detailed exposition of several key topics related to this technology. Firstly, the author will delve into the face recognition-based attendance system, which forms the main foundation of this book. Next, the author will investigate the role of Machine Learning (ML), Deep Learning (DL), and Artificial Intelligence (AI) technologies in system development. Subsequently, the author will examine the importance of liveness detection in maintaining the security and reliability of the system. The next topic to be explored is data security and the use of encryption to protect sensitive user information. The author will also explore the concept of reward and punishment systems in the context of employee management. Furthermore, the author will discuss Information Technology Project Management (IT Project Management) related to the implementation of face recognition technology and the associated challenges and risk management. Finally, the author will discuss the integration of this technology into human resource management, highlighting its impact on workforce management in the current digital era. By exploring each of these aspects, the author hopes to provide a comprehensive insight into the complexity and potential of face recognition-based attendance systems in the context of modern organizational management.

2.1 CONCEPT OF ATTENDANCE SYSTEM BASED ON FACE DETECTOR

Modern attendance systems have evolved from manual methods to more automated and integrated systems. One of the latest innovations in attendance management is the face recognition-based attendance system. This technology utilizes artificial intelligence (AI) algorithms to verify the identity of employees through individual facial features, providing a safer and more efficient way to record attendance (AbdELminaam et al., 2020; P. T. Kim & Bodie, 2020). This system offers many advantages over traditional methods (Abraham et al., 2020; Bah & Ming, 2020; Pattnaik & Mohanty, 2020; Trivedi et al., 2022). The primary benefits of using face recognition systems in attendance management are improved accuracy and security. In this regard, the use of face recognition makes it difficult for others to counterfeit, especially in terms of identity. According to (Anwarul & Dahiya, 2020; Cavazos et al., 2021; Gode et al., 2023a), the accuracy of face recognition systems reaches very high levels, even in less than ideal lighting conditions or changes in a person's physical appearance, although this requires integration with other advanced technologies. According to (Babu Jha et al., 2023; Dang, 2023b), face recognition-based attendance systems allow for automatic facial recognition, reducing physical interaction and replacing attendance cards or keys, which are typically time-consuming, thereby simplifying and expediting the attendance process.

The survey conducted by (Golasangi et al., 2024) indicates that face recognition technology is quite reliable and efficient in recording employee attendance. Additionally, (Gacutan Bangayan et al., 2023; Rohini et al., 2022) demonstrate that the use of this technology can result in significant cost savings for companies. This can be seen in the reduction of the need for physical infrastructure such as attendance machines or identification cards, leading to substantial cost savings. This technology can also enhance user experience through faster attendance processes and a reduction in the time employees need to spend on administrative procedures. This is supported by research (Achmad et al., 2022; Raji et al., 2020; P. Rastogi et al., 2023; Viswanathan et al., 2024) affirming that face recognition technology is quite useful in reducing queues during attendance times, thus saving time, and allowing employees to clock in promptly. Consequently, its potential benefits in attendance management make it an attractive solution for many organizations.

Despite its various advantages, the use of face recognition systems in attendance also faces certain challenges. One of these is the issue of privacy and data security. Research by (Dang, 2023; Gode et al., 2023; and Shukla et al., 2023) highlights concerns regarding the collection and use of sensitive biometric data on employees' faces. This raises ethical questions about how this data is stored, accessed, and protected from misuse or security breaches. In addition to these challenges, there are also technical challenges, such as difficulties in handling variations in human facial appearance (e.g., facial hair, changes in appearance due to significant weight gain or loss, and so on).

According to (Dang, 2023b), face recognition technology has several limitations because it needs to be combined with other technologies to be used in real time. Additionally, the sensitivity of face recognition technology to lighting variations, poses, and facial expressions is quite weak, resulting in errors in individual recognition (Bartakke et al., 2024; Sawarkar et al., 2024; Viswanathan et al., 2024), thus solutions need to be found to make the functionality of face recognition technology more efficient. (Babu Jha et al., 2023; Gaikwad et al., 2024; Gupta et al., 2024) indicate that this system is vulnerable to identification errors when faced with variations in lighting, facial expressions, or natural physical changes. On the other hand, research (Raji et al., 2020; Sochima et al., 2021) highlights the risks of using face recognition technology in the context of data privacy, especially concerning the use of biometric data accessible to unauthorized parties. Therefore, the development of more advanced and adaptive technology is necessary to address these challenges and improve the performance of face recognition systems applied in attendance systems, which in this study include Machine Learning, Deep Learning, and Artificial Intelligence.

2.2 MACHINE LEARNING (ML)

Machine learning (ML) is a subset of Artificial Intelligence (AI) that enables systems to learn from data, identify patterns, and make decisions with little or no human intervention. Machine learning algorithms can be categorized into three main types: supervised learning, unsupervised learning, and reinforcement learning. Supervised learning uses labeled data to train models on input-output pairs, such as linear regression and classification with Support Vector Machine (SVM). Unsupervised learning handles unlabeled data to discover hidden structures or patterns in the data. Machine learning has revolutionized various sectors by enabling accurate predictions and in-depth data analysis. In the context of prediction, several machine learning models are used to forecast trends in various fields. For example, in the retail sector, machine learning is utilized for personalized product recommendations, inventory management, and supply chain optimization. In finance, ML algorithms assist in fraud detection, credit analysis, and stock market prediction. (Khan et al., 2022; Nikou et al., 2019) successfully predicted market prices using several different machine learning classifiers. (Sarkar et al., 2023; X. Zhang et al., 2023) optimized profits using deep learning combined with machine learning in e-commerce. (Rohaan et al., 2022; C. Sun et al., 2021) made online buying and selling predictions, and (Rausch et al., 2022) successfully implemented ML models for shopping cart prediction. Furthermore, machine learning is utilized for analysis, for instance, (Nguyen et al., 2023) employed machine learning to analyze sales proposals, showing that machine learning can analyze and make decisions to accept or reject submitted sales proposals.

Machine learning is also applied to solve complex problems that are difficult to solve with traditional approaches. In the field of healthcare, ML is used for disease diagnosis, personalized patient care, and medical image analysis. In this regard, (Kasula, 2021) and (Krishna Suryadevara, 2023) utilize ML to predict diabetes, (Zhu et al., 2020) also employ ML to predict cancer, (B. Zhao et al., 2023) use ML to predict food risks, and (Bali & Mansotra, 2024) leverage ML for predicting eye diseases. Besides its application in disease prediction, ML is also used for pattern detection. (Husnain et al., 2024) state that AI and ML can detect patterns, identify biomarkers, and predict diseases with unexpected accuracy. (Nanda et al.,

2017) also utilize machine learning to predict network attack patterns, (Lei et al., 2021; Olu-Ajayi et al., 2022; Somu et al., 2021) utilize machine learning as an energy consumption prediction model. In the manufacturing industry, machine learning is also utilized to predict the performance of company employees. For example, (Cheng et al., 2024; Lather et al., 2019; Pathak et al., 2023) employ machine learning as a prediction model.

Machine Learning techniques have become a popular approach to addressing problems and identifying hidden patterns. Through ML algorithms, companies can analyze employee attendance data holistically and detect anomalies as well as significant patterns. (Mallikarjunaradhya et al., 2023) demonstrate that using machine learning techniques such as clustering can enhance accuracy in predicting certain patterns, enabling proactive decision-making. Although not in the industrial sector, (Mallikarjunaradhya et al., 2023) utilize clustering models from ML to predict damage and cancer in the healthcare field. Meanwhile, (Ozcan & Peker, 2023) combine classification and regression models from machine learning techniques to create models and predictions for heart disease. The importance of using ML techniques is also elucidated by (Adeoye, 2024; Y. Zhao et al., 2020), who highlight the use of machine learning techniques in analyzing and predicting employee performance in a company. Meanwhile, (P. Rastogi et al., 2023; Tian et al., 2023) explore the integration of machine learning techniques in performance optimization, recruitment systems, and employee attendance systems. The application of machine learning models for prediction has brought significant benefits in various contexts, including employee performance prediction, sales prediction, risk analysis, and others. (Z. Y. Chen et al., 2022; Kothapalli et al., 2023; Lahmiri et al., 2023) utilize machine learning as prediction models for sales and purchasing goods, while (Chaubey et al., 2023) leverage machine learning as a predictive tool for customer purchasing habits. (Ishibashi, 2024; Shinohara et al., 2024; Suryadevara, 2023; B. Zhao et al., 2023) employ machine learning to predict and analyze risks.

In the context of developing predictive models, machine learning models can be utilized to identify factors influencing employee performance, predict future performance, and provide recommendations for steps to enhance performance. For instance, (Bharadiya & Bharadiya, 2023) demonstrates that ML integrated with AI in business intelligence can discover existing patterns and trends. (Al Ka'bi, 2023; Asselman et al., 2023; Elbasi et al., 2023) employ ML as predictive models in various fields. In the development of predictive models in this study, ML models will learn from existing attendance and teacher performance data to make predictions regarding high-performing teachers and those in need of development in the future. In this context, each model has its strengths and weaknesses, making the selection of an appropriate model crucial for obtaining accurate and reliable predictive results.

Several recent studies in the development of predictive models for attendance systems are also beginning to integrate machine learning technology with more advanced approaches such as deep learning. For example, studies by (Ali, Diwan, et al., 2024; Barhate et al., 2024) utilize machine learning and deep learning to accurately detect and recognize faces in attendance images. Similar research by (Budiman et al., 2022; Nagagopiraju et al., 2024; Sawarkar & Alane, 2024) demonstrates that the use of deep learning and machine learning techniques in attendance systems can significantly improve the accuracy of individual identification compared to traditional approaches. Furthermore, studies are focusing on the development of more complex predictive models to forecast individual attendance while considering various factors such as weather conditions, employee schedules, and other external factors. For instance, research by (Arboretti et al., 2024; Nasiri Khiavi, 2024) combines various data with weather data using ensemble learning techniques to predict attendance and purchasing with higher accuracy rates. The findings from these studies indicate the significant potential of more advanced machine learning approaches in enhancing the effectiveness and precision of attendance systems, as well as offering a more comprehensive understanding of how external factors can influence attendance.

This book will apply the use of regression algorithms and advanced data processing to produce predictive models capable of identifying emerging patterns, particularly attendance patterns that are correlated with various external variables impacting companies in planning more effective human resource management strategies. By integrating ML techniques, predictive models can accurately be generated to forecast patterns emerging in the study based on the physical work environment. In this regard, several machine learning models will be employed to predict attendance patterns in face recognition-based attendance systems to observe trends and patterns formed based on employee categories, thus in the future, the prediction results can be used as references for decision-making. Some of the ML models applied in this book include but are not limited to Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF), Naïve Bayes, and XGboost. This indicates that this approach enables companies to effectively identify unexpected patterns and take appropriate corrective actions, thus enhancing overall productivity and operational efficiency.

2.3 DEEP LEARNING (DL)

With the advancement of technology, deep learning has emerged as a subfield of machine learning that focuses on the use of neural networks with multiple layers (deep neural networks) to handle highly complex and large-scale data. Deep learning demonstrates its superiority in various applications such as image recognition, Natural Language Processing (NLP), and video analysis. Neural Networks (NN) in deep learning are also capable of learning more complex feature representations compared to traditional machine learning algorithms. The development of deep learning models often requires large amounts of data and more intensive computations compared to traditional machine learning models such as Random Forest or XGBoost. However, the ability of deep learning to extract features from raw data and handle unstructured data makes it extremely powerful in prediction and application in various fields. With advancements in hardware and optimization algorithms, deep learning continues to push the boundaries of machine learning capabilities, making it an indispensable tool in modern data analysis and AI.

In predicting attendance trends in face recognition-based systems, deep learning models, especially Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), play a critical role. CNN excels in image processing and can enhance facial recognition accuracy, ensuring reliable attendance tracking. By extracting and learning complex features in facial images, CNN enhances the identification and verification processes, which form the foundation of attendance systems. On the other hand, RNN and Long Short-Term Memory (LSTM) networks excel in sequence prediction, making them ideal for forecasting attendance trends. These models can capture temporal dependencies and patterns in attendance data over time, learning from past behaviors to predict future events. By leveraging historical attendance records, RNN can generate forecasts that account for temporal fluctuations and seasonal trends. This deep learning approach provides a robust framework for understanding and predicting attendance patterns, ensuring institutions can better handle variations in attendance levels and optimize operational efficiency. However, in this study, deep learning is not focused on facial identification in face recognition-based attendance systems. This technology will be utilized to enhance accuracy in predicting employee attendance patterns through the company's attendance system, providing comprehensive insights into high-accuracy prediction results that can be implemented in a real-time integrated system.

About face recognition technology in attendance systems, Deep Neural Network (DNN) architectures, such as Convolutional Neural Networks (CNN), are utilized to automatically and accurately learn facial features from large amounts of data (Karatay et al., 2024; D. H. Lee &

Yoo, 2023). The advantage of this method lies in its ability to identify complex nuances in visual data that cannot be captured with traditional image processing techniques. In the context of attendance management systems, the integration of face recognition technology based on deep learning offers a more efficient and accurate solution compared to conventional methods. Attendance systems leveraging facial recognition not only minimize the need for physical interaction but also reduce the potential for errors or fraud that may occur with manual systems (Babu Jha et al., 2023; Ukamaka Betrand et al., 2023). According to (Achmad et al., 2022; Z. Chen et al., 2023; Ikromovich & Mamatkulovich, 2023; Mohammed Sahan et al., 2023; and Rahim et al., 2023), this CNN technology can be integrated and trained to identify faces with high accuracy, even in different conditions such as poor lighting or pose variations. The use of this technology in attendance systems enables real-time recording of employee attendance, provides better data security, and streamlines administration (Painuly et al., 2024; RajaSekhar et al., 2023). Thus, the adoption of deep learning in face recognition systems for attendance not only improves system accuracy but also helps maintain data integrity and speeds up overall administrative processes. The use of deep learning in face recognition has opened up new opportunities to enhance the performance of face recognition systems in various applications, including attendance management systems.

The integration of Deep Learning into face recognition systems represents a significant technological advancement to enhance security and effectiveness. Deep Learning provides the ability to interpret and process facial images with high accuracy, through learning from large amounts of data to identify facial features in detail (Abd El-Rahiem et al., 2023; Bisogni et al., 2023; Karnati et al., 2023; Mamieva et al., 2023; Meena et al., 2024; Sarvakar et al., 2023). In this study, deep learning will be integrated along with liveness detection technology for face recognition-based attendance systems. Wherein, Liveness Detection will add a layer of security by ensuring that the object being analyzed is a living subject, not a photo or video (Lavens et al., 2023; Y. Zhang, Zheng, et al., 2023). This is achieved through techniques such as motion analysis, blink detection, or thermal response measurement, which are difficult to counterfeit. The combination of these two technologies is highly valuable in security applications where authenticity and user identity verification are critical, such as access control systems or online transaction verification.

2.4 ARTIFICIAL INTELLIGENCE (AI)

AI represents the simulation of human intelligence in machines programmed to think and learn. The implementation of AI in this book involves the use of machine learning and deep learning algorithms to enhance the accuracy and efficiency of attendance systems, as well as developing models adaptive to changes in attendance patterns and potential attacks. Regarding security and this book, AI will be utilized to perform anomaly detection in attendance systems and attendance data. Anomaly detection is one of the primary approaches in cybersecurity to identify unusual or suspicious behavior in information systems. Through the analysis of abnormal activity patterns, anomaly detection can provide information regarding signs of intrusion from unknown parties while safeguarding the system from security breaches. According to (Moustafa et al., 2023; Yaseen, 2023), anomaly detection plays a key role in modern cyber defense, enabling organizations to respond to threats quickly and effectively.

Anomaly detection techniques that employ machine learning algorithms, signal processing, and statistical analysis have proven effective in identifying anomalies in network traffic data, security logs, and user behavior. One common approach used in anomaly detection is behavioral analysis. According to (Shreesha et al., 2023), behavioral analysis involves modeling normal behavior patterns and detecting significant deviations from these patterns, which may indicate an attack or security breach. Methods such as outlier detection, clustering, and machine learning are employed to identify anomalies in the data. Additionally, anomaly detection can also be performed using signature-based techniques. According to (Alonso et al., 2022; Nawaal et al., 2024; Praseed & Thilagam, 2022), signature-based detection entails matching data patterns with known signatures of previously identified attacks. By comparing observed data with known signatures, the system can identify known attacks and take appropriate action.

The application of AI in anomaly detection has been a primary focus in safeguarding information systems from attacks and data breaches. Anomaly detection, employing AI techniques to identify unusual patterns, assists organizations in securing their systems. According to (Yaseen, 2023) and (Wurzenberger et al., 2024), anomaly detection is a crucial component of modern information security, enabling the identification of abnormal or suspicious behavior in data. Anomaly detection methods utilizing AI techniques, such as machine learning algorithms, neural networks, and clustering, have proven effective in recognizing unusual patterns in attendance data. One frequently used AI model in anomaly detection is supervised learning-based machine learning methods. According to (Abdelli et al., 2022; Abusitta et al., 2023; Akcay et al., 2022; Ibrahim et al., 2022; Landauer et al., 2023; Thapa & Arjunan, 2024; H. Xu et al., 2023; Yu et al., 2023), machine learning models like Support Vector Machines (SVM) and Decision Trees have been successfully implemented in anomaly detection, exhibiting high accuracy rates in identifying unusual patterns. Furthermore, according to (Molan et al., 2023; Perini et al., 2023; Surianarayanan et al., 2024), and (Bilakanti et al., 2024), unsupervised learning-based machine learning methods are also commonly used in anomaly detection. According to (Ali, Scandurra, et al., 2024), clustering techniques such as K-means and DBSCAN (Density-Based Spatial Clustering Algorithm with Noise) have proven effective in identifying unusual or suspicious clusters in data, which may indicate anomalies. By integrating AI techniques into attendance systems, organizations can enhance their data security by detecting and preventing potential data theft. Through careful monitoring and analysis of unusual patterns, systems can become more resilient to threats and attacks that jeopardize data confidentiality and integrity.

2.5 LIVENESS DETECTION

Liveness Detection technology emerges as a crucial component in biometric security systems, particularly in facial recognition applications. This technology aims to distinguish between live human faces (real-time human faces) and photos/images. With the continuous advancement of Artificial Intelligence and machine learning, these Liveness Detection algorithms are becoming increasingly sophisticated, capable of detecting subtle signs of life such as facial movements, blinking, and changes in skin texture (Khairnar et al., 2023a; Yao et al., 2023). The application of Liveness detection is not limited to traditional security contexts but extends to various domains, including attendance management systems. Integrating Liveness detection technology into attendance systems will enhance the accuracy and reliability of employee attendance records, potentially eliminating the risk of data breaches. Moreover, the collected data can be stored and protected using more stringent and advanced verification methods (Basurah et al., 2023; Kuznetsov et al., 2024; Surantha & Sugijakko, 2024a; Y. Zhang, Zheng, et al., 2023).

In this context, besides streamlining administrative processes, the adoption of technology also strengthens accountability and transparency in workforce management practices, thereby fostering a more efficient and secure work environment. This aligns with (Kuznetsov et al., 2024), who states that the implementation of Liveness Detection technology offers a crucial defense layer against fraudulent activities, enhancing the reliability and trustworthiness of biometric authentication systems across various sectors. However, to improve the accuracy and precision of detection, a combination with other advanced technologies is required (Lavens et al., 2023). In the context of this book, deep learning is chosen as one common approach. Deep learning enables systems to independently learn from complex and diverse data, thereby enhancing the capabilities of Liveness Detection technology in recognizing sophisticated signs of life (Shlezinger et al., 2023). By harnessing the power of Deep Learning, Liveness Detection technology can continue to evolve and deliver more advanced and reliable biometric security solutions. In this study, Liveness Detection technology will be combined with deep learning to ensure that the detected faces are authentic and not manipulated. This system offers several advantages, including increased accuracy, efficiency, and security in attendance recording. However, challenges such as privacy and data security need to be addressed through advanced encryption and anomaly detection methods. In this regard, the deep learning architecture model used is VGG-16. VGG16 is one of the popular Convolutional Neural Network (CNN) architectures in image processing. The VGG16 architecture consists of 16 layers comprising convolutional layers, ReLU activation layers, and maximum pooling layers, followed by several fully connected (FC) or densely connected layers, and finally, the output layer. The architecture of VGG-16 can be seen in Figure 2.1.

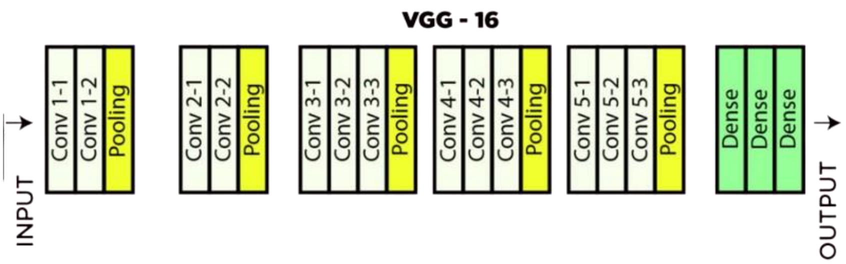


Figure 2.1. The VGG-16 architecture used in the research

Data Security and Encryption

Data security in face recognition-based attendance systems is crucial as it involves sensitive information such as biometric facial data and attendance timestamps. The privacy of biometric data must be carefully maintained to prevent unauthorized access or misuse. Additionally, data integrity must be preserved to ensure that attendance records remain accurate and cannot be modified without authorization. Access to attendance data should be restricted only to authorized parties through the implementation of stringent access controls. Data security must also be ensured during storage and transmission to prevent interception and theft by unauthorized third parties.

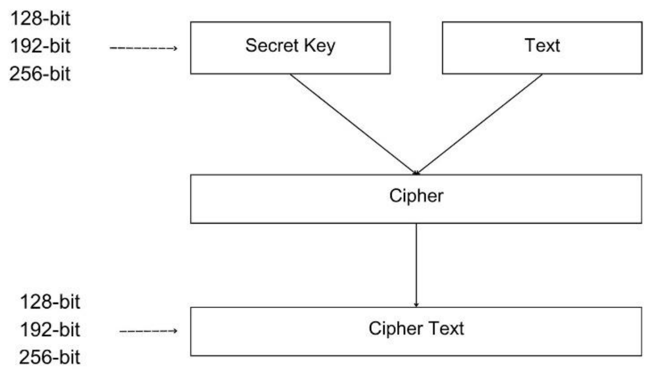


Figure 2.2. The Concept of Encryption Using AES Algorithm

The theory of cryptography and data encryption constitutes fundamental components in ensuring data security within modern information systems. Cryptography encompasses various techniques and principles aimed at securing communication and safeguarding data from unauthorized access. Data encryption, as a pivotal application of cryptography, involves transforming plain text data into encrypted text (ciphertext) using cryptographic algorithms and keys, rendering it unintelligible to anyone without the corresponding decryption key. According to (Tsantikidou & Sklavos, 2024), cryptography forms the foundation of modern cybersecurity, providing mechanisms for confidentiality, integrity, authentication, and non-repudiation in the data exchange process. Encryption, as a fundamental tool in cryptography, plays a crucial role in protecting sensitive information from eavesdroppers and adversaries.

Encryption involves encryption algorithms, which are mathematical methods for transforming plaintext into ciphertext and vice versa, along with encryption keys, which are values used in the encryption and decryption processes. For instance, in this study, the algorithm utilized is AES, and the concept of the AES encryption algorithm can be observed in Figure 2.2. Data security heavily relies on the confidentiality and complexity of the keys used. The Advanced Encryption Standard (AES) is one of the renowned encryption algorithms widely employed in data security, with many researchers even beginning to develop this algorithm. AES encrypts data in 128-bit blocks and supports key lengths of 128, 192, and 256 bits, with the security level increasing as the key length increases. The AES encryption process involves a series of complex mathematical transformations, including substitution, permutation, and other operations. In the implementation of AES encryption in the face recognition-based attendance system, facial biometric data collected from the camera is converted into digital format and encrypted using AES before being stored in the database. The data transmitted between the face recognition device and the server is also encrypted using AES to safeguard it from interception. Encryption key management must be securely handled and accessible only to authorized parties, employing a centralized and secure key management system. By implementing AES encryption, the face recognition-based attendance system can protect biometric data and attendance information from security threats, ensuring that the data remains confidential and secure during storage and transmission.

As outlined by (Assa-Agyei et al., 2023; Priyanka Brahmaiah et al., 2023; and S. Jenifa Sabeena, 2023), AES is an excellent symmetric key block cipher that is highly efficient in securing data. In a survey conducted in 2019, (Patel, 2019) stated that the AES algorithm performs well when used on various file sizes. AES operates on fixed-size data blocks, encrypting plaintext into ciphertext using a symmetric key, the secrecy of which must be maintained to ensure secure communication. (Seth et al., 2022; Susmitha et al., 2023), affirm that encryption is a critical control step in safeguarding data during rest, transit, and usage, thereby protecting sensitive information from external and internal threats. Furthermore, integrating encryption algorithms into the data security framework enhances organizational resilience against evolving cyber threats and compliance requirements.

According to (Obert et al., 2019; Susanto et al., 2021), encryption not only maintains data confidentiality but also facilitates secure data sharing and collaboration among stakeholders, fostering trust and integrity in the digital ecosystem. Research by (Adeniyi et al., 2023; Gudimetla, 2024; H. Liu, 2024; Mohammed et al., 2024; and Pratomo et al., 2023) indicates that implementing AES encryption in information systems can significantly enhance data security, making it a suitable choice for implementation in attendance systems. In the context of this book, encryption will be performed using the AES algorithm on the data stored in the face recognition-based attendance system. Thus, data confidentiality, including teacher identity and attendance data in the face recognition attendance system, can be effectively protected from theft.

Reward and Punishment System in Attendance Management

The reward and punishment system is an important concept in psychology and management used to motivate specific behaviors within organizational environments (B. F. Skinner, 1965). Rewards are used to reinforce positive behavior by providing incentives or recognition when employees demonstrate good performance or achieve specific goals. Conversely, punishment is used to reduce or eliminate negative behavior by imposing unpleasant consequences when undesirable behavior (Pangandaheng & Sutanto, 2021; Ressler, 2004; Sigmund et al., 2001; J. Wu et al., 2022). This concept is based on the principles of operant conditioning developed by B.F. Skinner, which states that behavior can be modified through appropriate consequences (B. F. Skinner, 1965). The effective implementation of rewards and punishments can enhance motivation, productivity, and compliance among employees with company policies.

Many practices implement reward and punishment systems in school attendance to provide rewards and punishments to students undergoing education. The implementation of rewards and punishments in schools can enhance students' learning motivation and discipline. In a different context, the implementation of these theories also yields different impacts in the workplace. For example, (Brewer & Walker, 2013) stated that the implementation of reward and punishment in companies has quite a varied impact on the company's performance. Additionally, the implementation of these two systems from management psychology theories is also applied in several other fields, such as gaming, healthcare, and others (Bakar et al., 2022; Fang & Chen, 2021; Gueguen et al., 2021; L. Liu et al., 2022; J. Sun et al., 2023; Yuniasri et al., 2021; F. Zhao & Wang, 2022).

The integration of technology in the application of reward and punishment theory also provides additional efficiency. In using a facial recognition-based attendance system, companies can monitor employee attendance in real time. This data can then be used to reward employees with good attendance records or impose punishment on those who are frequently late or absent. Thus, technology not only aids in accurate recording but also supports the implementation of reward and punishment systems more effectively and efficiently (Cai et al., 2022; Pangandaheng & Sutanto, 2021; J. Wu et al., 2022). The integration of technology into attendance systems allows for the implementation of reward and punishment more efficiently and accurately.

Through the use of a facial recognition-based attendance system, for example, employee attendance data can be recorded and analyzed in real time. This system can be configured to provide rewards such as bonuses or recognition to employees with perfect attendance records or low levels of lateness. Conversely, the system can also identify employees who are frequently absent or tardy and automatically issue warnings or consequences according to company policy (Cai et al., 2022; J. Wu et al., 2022). Thus, the integration of technology into the attendance system not only enhances the accuracy and efficiency of recording but also supports the implementation of reward and punishment systems more effectively.

2.6 INFORMATION TECHNOLOGY PROJECT MANAGEMENT (ITPM)

Information Technology Project Management (ITPM) is a systematic approach to planning, organizing, and managing resources to achieve information technology goals within an organization (Schwalbe, 2016). It plays a crucial role in ensuring the success of implementing face recognition technology in attendance systems. ITPM encompasses various methodologies and approaches to ensure that IT projects can be completed on time, within budget, and meet expected quality standards. One of the methodologies frequently used in ITPM is Agile Methodology, which emphasizes iteration, team collaboration, and rapid response to changes (Gaborov et al., 2021; Järvinen & Soini, 2023; Paz & López, 2023). Additionally, there are also methodologies such as Waterfall, which is more linear and structured, and PRINCE2, which focuses on process-based project management (Islam & Evans, 2020).

The ITPM process consists of several main phases: initiation, planning, execution, monitoring, and closure (Orazulike, 2011). In the initiation phase, it is important to identify the goals and benefits of the face recognition-based attendance system and assess the project's feasibility. Effective planning involves selecting appropriate hardware and software, managing the budget, and detailed scheduling. Project execution involves system installation and configuration, user training, and initial testing to ensure that the system functions according to specifications. Monitoring and control are necessary to monitor system performance and address emerging issues, while the closure phase ensures that the project is properly completed and all project documentation is stored for future reference.

The success of ITPM heavily relies on effective management skills and communication (Pons & Haefele, 1 C.E.; Rusan & Voitenko, 2021). According to research by the Project Management Institute (PMI), approximately 70% of failed IT projects are attributed to a lack of management support or poor communication (PMI, 2017). Therefore, project managers must possess strong interpersonal skills and be adaptable to team dynamics and potential changes throughout the project. Thus, ITPM theory not only focuses on technical aspects but also human resource management and team communication. In the context of this study, ITPM will be utilized to manage the implementation project of a face recognition-based attendance system, which encompasses various advanced technologies such as machine learning, deep learning, artificial intelligence, and data encryption using sophisticated algorithms. In managing a project related to attendance systems, ITPM provides a structured approach to integrating new technologies. Through effective project management, advanced technologies can be applied to achieve desired objectives efficiently, such as optimizing attendance monitoring and enhancing data security. Additionally, several technologies to be integrated into attendance management require careful planning and execution to ensure the reliability and accuracy of the system. Moreover, in prediction tasks using advanced technology and algorithms on data, precise planning is necessary to ensure reliable accuracy results. The principles of ITPM can guide this process by addressing critical aspects such as scope management, risk management, and stakeholder communication, ensuring that the project aligns with the institution's overall strategic objectives.

In the context of integrating liveness detection and deep learning to optimize the attendance system, ITPM will be tasked with ensuring that all aspects, from scope and risk management to stakeholder communication, are carefully managed. This approach helps address potential challenges and ensures the smooth implementation of these technologies, thereby enhancing the reliability and accuracy of the attendance system. Several principles of ITPM commonly used include scope management, time management, cost management, quality management, and risk management (Miller et al., 2023). Scope management establishes a clear project scope for the development of the attendance system, ensuring that all desired features, such as liveness detection and DSS, are implemented as needed. Meanwhile, time management can be utilized to create a realistic project schedule and ensure that each stage of system development is completed on time. Cost management is used to efficiently manage the project budget, ensuring that expenditures for technology and human resources remain within predefined limits. As for quality management, it serves to ensure that the developed attendance system meets predefined quality standards, including facial recognition accuracy and data security. Lastly, risk management functions as a tool for identifying and managing risks that may arise during the development and implementation of the system, such as technical, operational, and security risks.

Risk and Risk Management in Face Recognition Implementation Projects

The implementation of face recognition technology in attendance systems is not without various risks that must be effectively managed through effective IT project management. Technical risks, such as facial recognition errors or system failures, require mitigation plans such as extensive testing and system backups, so in this study, integration using liveness detection techniques collaborates with deep learning to improve detection accuracy and reduce time consumption. Security risks, including potential data breaches, can be reduced through the use of data encryption technologies such as AES and the implementation of strict security protocols. Additionally, the integration of several advanced technologies such as ML, DL, and AI is used to predict and detect unusual signs and serve as preventive measures against theft and security breaches in the system, thus enhancing security. Furthermore, user acceptance risks need to be managed through proper training and socialization to ensure that employees understand and accept the use of this new technology. A comprehensive and structured risk management process will help identify, assess, and mitigate potential risks that may occur during project implementation.

Integration of Technology in Human Resource Management

The integration of advanced technologies such as Machine Learning (ML), Deep Learning (DL), and Artificial Intelligence (AI) in human resource management (HRM) has shown great potential in enhancing the efficiency and effectiveness of employee management. Recent studies indicate that the implementation of these technologies can bring significant changes in how organizations manage their employees. Research by (Kambur & Yildirim, 2023; Park et al., 2021; Rathi, 2018; Zehir et al., 2020) suggests that the use of ML and AI technology in HRM can reduce administrative burdens by up to 30%, enabling managers to focus on more strategic decision-making. By automating routine tasks such as attendance recording, employee data processing, and performance monitoring, this technology can free up time and resources previously tied to manual processes. Moreover, DL and AI technologies can be utilized to analyze employee data more deeply, providing better insights into employee behavior and performance.

According to research conducted by (Aviral Rai et al., 2024; Barnes et al., 2023; Jahir Pasha et al., 2023; Sharma, 2023; Wong et al., 2023), analyzing employee data using DL can identify previously unseen patterns, such as high absenteeism trends or declining productivity before they occur. This information enables managers to take proactive actions to address issues before they become serious. Thus, integrating this technology not only enhances operational efficiency but also helps identify and address potential issues earlier.

Moreover, AI technology can enhance the employee recruitment and selection process. A study found that AI algorithms applied in the recruitment process can filter and evaluate job applicants more accurately and quickly than traditional methods. These algorithms can analyze resumes, social media profiles, and other data to assess candidates' suitability for the offered positions. This not only speeds up the recruitment process but also improves the quality of employee selection, ensuring that organizations acquire the best talent. Research by (L. Chen et al., 2020; Z. Chen, 2023; George & Wooden, 2023; Q. Jia et al., 2018; Murtaza et al., 2022) indicates that using AI in training programs can personalize training materials according to the needs and abilities of individual employees. AI can analyze performance data and training feedback to tailor training content, ensuring that each employee receives the most relevant and effective training for them. This not only enhances training outcomes but also motivates employees to continue learning and growing.

In addition to efficiency and effectiveness, this technology also helps enhance employee engagement and satisfaction. A study by (Dutta et al., 2023; Krishnan et al., 2022) found that the use of AI chatbots in internal communication can boost employee engagement by providing an always-available and responsive communication channel. These chatbots can respond to employee queries in real time, provide important information, and even assist in resolving day-to-day issues. This creates a more supportive and responsive work environment, which in turn enhances employee satisfaction and retention. The integration of advanced technology in HR management also contributes to better decision-making. According to research by (Arora et al., 2021; Cioca et al., 2024; Loi, 2020; Nyathani, 2023; Rodgers et al., 2023; and Stankevičiūtė, 2024), the use of AI and ML in HR data analysis can provide deeper and more accurate insights, assisting managers in making better data-driven decisions. With real-time analyzed data, managers can respond to changes quickly and make more informed decisions. This illustrates that advanced technology not only streamlines day-to-day tasks but also enhances the quality of strategic decision-making within organizations.

CHAPTER 3
SYSTEM DEVELOPMENT THEORY

In this section, the author will discuss the theoretical foundation used in the study. The theoretical foundation covered in this section encompasses several important areas to understand the fundamental principles of the discussed material. In the before chapter, the author will delve into Pattern Recognition Theory, which serves as the basis for many applications across various fields. Subsequently, the author will explore Information Security Theory in chapter 2, which is crucial in safeguarding sensitive data and ensuring privacy and integrity in the current digital landscape. Additionally, the author will address Human Resource Management Theory in chapter 2, essential for understanding organizational behavior dynamics and personnel management strategies. Finally, the author will delve into Machine Learning and Deep Learning Theory in chapter 2, which are highly significant in developing artificial intelligence systems and enabling them to autonomously learn from data. By elucidating these foundational theories, this chapter aims to provide a comprehensive understanding of the complexity and applications of the discussed material.

3.1 PATTERN RECOGNITION THEORY

Pattern recognition theory forms the basis of facial recognition technology, where algorithms are employed to identify patterns and unique features within facial data (Beyerer et al., 2024). This theory enables systems to learn and recognize individual faces based on the provided training data. In the context of attendance, this theory helps ensure that the system can accurately identify employees, reducing attendance recording errors. According to this theory, facial recognition involves two main stages: feature extraction and comparison. The first stage involves capturing unique facial features, such as the shape of the eyes, nose, and mouth, which are then used to create a facial feature vector representing the individual's identity. The second stage involves comparing the extracted facial feature vector with the feature vectors stored in the database to determine similarity and identify the corresponding individual.

In pattern recognition, various theories and methods are employed to develop effective facial recognition algorithms. One commonly used method is Principal Component Analysis (PCA). According to (Kaur & Himanshi, 2015; Mousavi et al., 2023), the PCA method is utilized to reduce the dimensionality of facial data, making it more efficiently processed by recognition algorithms. This method works by reducing the dimensions of the facial feature vector into a smaller dimension while retaining the most important information for recognition. Thus, the PCA method aids in enhancing the speed and accuracy of facial recognition in attendance systems. In addition to the PCA method, there are other methods such as Linear Discriminant Analysis (LDA) and Independent Component Analysis (ICA) used in facial pattern recognition. According to (Ran & Nie, 2024), the LDA method aims to find a linear transformation that maximizes the distance between different facial classes and minimizes the variation within the same class. This method is employed to enhance the separation between different facial classes, thereby strengthening the system's ability to recognize individuals with higher accuracy. Meanwhile, the ICA method, as described by (R. Li et al., 2022), aims to separate mixed signals into their underlying original signals.

In the context of facial recognition, the ICA method is used to discover independent facial components, which can then be utilized to identify individuals more effectively. In the development of facial recognition technology, these pattern recognition theories serve as the foundation for designing effective and accurate algorithms. By understanding these fundamental principles, more advanced and reliable facial recognition technology can be constructed. Through the integration of pattern recognition theories and machine learning technology, facial recognition systems can be continuously enhanced in terms of accuracy, speed, and security, thereby becoming a more effective solution in attendance and security management across various fields, including education and industry.

3.2 INFORMATION SECURITY THEORY

The theoretical foundation concerning information security and data encryption techniques forms a vital basis in efforts to safeguard sensitive data from unauthorized access. According to (Chitadze, 2023) and (Arogundade, 2023), information security theory encompasses principles and practices used to secure data from various threats, including hacking and unauthorized access. One of the most common techniques used in this context is data encryption, which aims to transform data into a format that cannot be read without the corresponding decryption key.

Data encryption plays a crucial role in maintaining information security, especially in the context of facial recognition-based attendance systems. As revealed by (Gawande et al., 2022; Păvăloaia & Husac, 2023) and (Zennayi et al., 2023), the use of facial recognition technology in attendance systems requires robust data protection to prevent unauthorized access or data manipulation. By implementing data encryption techniques, such as the Advanced Encryption Standard (AES) algorithm, employee attendance data can be safeguarded from hacking and unauthorized use. This is essential for preserving the integrity and confidentiality of employee data and ensuring trust in the attendance system.

The implementation of data encryption in facial recognition-based attendance systems requires a profound understanding of the theory and principles of information security. As elucidated by (Pitale et al., 2023; G. Singh, 2013), and (Neelakandan et al., 2024), the AES algorithm is one of the most commonly used encryption algorithms in practice due to its high speed and security. By utilizing AES, the facial data of employees stored in the attendance system can be encrypted using complex keys, thereby allowing only authorized parties to read and access it. Encryption technologies like AES form a robust layer of defense in safeguarding the integrity of employee data and preventing unauthorized access.

Furthermore, data encryption techniques also play a crucial role in meeting compliance requirements and data privacy regulations. According to (Fakhriddinovich & Al Khorezmi, 2024), in this increasingly connected era, the protection of employees' data becomes ever more crucial. By implementing data encryption techniques, organizations can ensure compliance with data privacy regulations such as the General Data Protection Regulation (GDPR) in the European Union or the California Consumer Privacy Act (CCPA) in the United States. This constitutes a significant step in maintaining trust and reputation for the organization in the eyes of employees and other stakeholders.

On the other hand, data encryption also involves careful key management to ensure maximum security. According to (Manthiramoorthy et al., 2024; Potter & Frank, 2024), and (Tang et al., 2024), key management is an integral part of effective data encryption processes. In the context of facial recognition-based attendance systems, proper key management ensures that encryption keys are securely stored and accessible only to authorized parties. Thus, even if data is infiltrated or hacked, access to encrypted data remains inaccessible without the corresponding decryption keys.

3.3 HUMAN RESOURCE MANAGEMENT THEORY

Theories and concepts of employee management, including reward and punishment systems, are at the core of human resource management (HRM) practices. According to (Ghafoor et al., 2015; Jackson & Schuler, 1995), and (Taslim Ahammad, 2017), HRM encompasses various aspects, such as recruitment, training, development, and performance management of employees. In this context, reward and punishment systems play a crucial role in motivating employees and improving their performance. The reward system provides incentives to employees who achieve targets or demonstrate excellent performance, while the punishment system imposes consequences for undesirable behavior or poor performance. According to (Amstrong & Taylor, 2014; Marlina et al., 2021; Samatha Anku et al., 2018), reward and punishment systems are also effective tools for achieving organizational goals. By rewarding high-performing employees, organizations can motivate them to continually improve their performance and achieve set targets (Cai et al., 2022; Frimayasa et al., 2021a; Marlina et al., 2021; Ressler, 2004; Samatha Anku et al., 2018). On the other hand, the implementation of sanctions or punishment can help correct undesirable behavior and encourage employees to comply with organizational rules and procedures.

Relevant theories concerning the management of high-performing employees emphasize the importance of recognizing and rewarding their contributions. According to (Fayomi & Akanazu, 2024) and (H. Ahmed, 2024), goal-setting theory emphasizes the significance of establishing specific, measurable, achievable, relevant, and time-bound (SMART) goals for employees. By setting clear and measurable objectives, employees are more likely to be motivated to achieve them and earn corresponding rewards. Additionally, expectancy theory in performance management highlights the importance of employees' belief that their efforts will lead to desired outcomes. According to (Miner, 2015) and (Malik et al., 2015), expectancy is the belief that effort will result in good performance, which, in turn, will yield desired rewards. By ensuring that employees believe their efforts will be recognized and appreciated, management can enhance their motivation and performance.

On the other hand, reinforcement theory also plays a significant role in managing high-performing employees. According to (Skinner, 1958) and Kaplan & Anderson, 1973), reinforcement is the process used to strengthen or reinforce desired behaviors. In a management context, positive reinforcement involves rewarding employees who exhibit desired behaviors, while negative reinforcement entails reducing or avoiding punishment for undesirable behavior. Research by (R. Singh, 2017) and (Ndudi et al., 2023) highlights the importance of intrinsic and extrinsic factors in employee motivation. Intrinsic factors involve the satisfaction derived from performing the job itself, whereas extrinsic factors involve rewards or punishments provided by external entities. By understanding and addressing employees' intrinsic and extrinsic needs, management can enhance their overall motivation and performance.

On the other hand, there is the equity theory in HR management that emphasizes the importance of fair and equitable distribution of rewards and punishments (Miner, 2015). According to (COOK & PARCEL, 1977) and (Al-zawahreh & Nayef Al-Madi, 2012), employees tend to compare the wages and rewards they receive with those of their peers to assess fairness within the organization. If employees perceive the distribution of rewards and punishments to be unfair, it can lead to dissatisfaction and lower their motivation and performance. Research by (Cavalcante, 2023; Verbeeten & Speklé, 2015; Wholey, 1982), and (Ajike, 2023) highlight the importance of outcome-oriented performance management. In this approach, performance management is more focused on achieving targets and outcomes rather than processes or behaviors. By setting clear targets and providing rewards and punishments based on outcome achievement, organizations can enhance employee performance and productivity.

3.4 MACHINE LEARNING AND DEEP LEARNING THEORY

Theories of Machine Learning (ML) and Artificial Neural Networks in Deep Learning (DL) have garnered significant attention in the development of predictive systems and data analysis across various domains. According to (Janiesch et al., 2021; Sarker, 2021; W. Zhang et al., 2022), and (Sarker, 2022) ML and DL encompass algorithms and methods that enable systems to learn complex patterns from given data and make predictions or decisions based on learning from these patterns. In the context of attendance data analysis, ML and DL allow for the detection of patterns in employee attendance and understanding of their attendance behaviors.

The application of ML and DL theories in attendance data prediction and analysis offers significant potential for enhancing efficiency and effectiveness in employee management. According to several researchers (Adnan et al., 2024; S. F. Ahmed et al., 2023; Alkhowaiter et al., 2023; Bhatti et al., 2023; Latrach et al., 2024; Lu, 2023; Lubbad et al., 2024; Mohtasham Moein et al., 2023; Mughaid et al., 2023; Rana & Bhushan, 2023; Salcedo-Sanz et al., 2024; Sharifani & Amini, 2023; Taye, 2023; Van den Eynde et al., 2023), and (Kufel et al., 2023), ML and DL have been successfully utilized in various applications, ranging from face recognition to consumer behavior prediction. In the context of employee attendance, ML and DL can be employed to identify attendance patterns associated with high-performing employees and provide valuable insights to management.

One of the primary applications of ML and DL theories in attendance data analysis is the development of predictive models capable of identifying employees prone to absenteeism or tardiness. According to (Cao et al., 2019; Chaubey et al., 2023; Elbasi et al., 2023; Emmert-Streib et al., 2020; Gondia et al., 2019; Lather et al., 2019; Minovski et al., 2023; Pathak et al., 2023; Zhu et al., 2020), predictive models developed using ML and DL can yield more accurate predictions than traditional methods. By analyzing historical attendance patterns of employees and other relevant factors, these models can provide early warnings about the likelihood of employee absenteeism or tardiness in the future.

Furthermore, ML and DL are also utilized to enhance the security of attendance systems through anomaly detection (Akcay et al., 2022; Bilakanti et al., 2024; Elmrabit et al., 2020; Mishra & Yadav, 2020; Molan et al., 2023; Weinger et al., 2022; S. Xu et al., 2019) and the implementation of liveness detection (Basurah et al., 2023; Kuznetsov et al., 2024; Sujanthi et al., 2023). According to (Bilakanti et al., 2024; Mishra & Yadav, 2020; and Molan et al., 2023), these methods enable the system to automatically detect unusual or suspicious behaviors in attendance data, such as inconsistent attendance patterns or unusual activities. By leveraging ML and DL algorithms, the system can identify potential security threats and take appropriate actions to address them.

In the context of managing high-performing employees, the application of ML and DL theories can assist organizations in identifying and understanding the factors influencing employee performance. According to (Lather et al., 2019; Pathak et al., 2023; P. Rastogi et al., 2023; Sarker, 2021; Sawadogo et al., 2021; Tian et al., 2023), ML and DL can be employed to analyze employee performance data, including performance evaluations, training feedback, and other information, to identify patterns associated with employees achieving favorable outcomes. By comprehending these factors, management can take appropriate steps to encourage and motivate high-performing employees, as well as provide guidance or additional training for those in need.

CHAPTER IV
MODELING DEVELOPMENT

In this chapter, the author will discuss various theoretical foundations underlying this book. Firstly, the author will delve into the development of the Facial Recognition-Based Attendance System Model, which serves as the cornerstone of the technology used to enhance the efficiency and accuracy of employee attendance. Subsequently, the author will review the Machine Learning Model for Pattern Prediction and Anomaly Detection, which plays a crucial role in identifying unusual behaviors and forecasting future trends. Furthermore, a more detailed explanation will be provided regarding the concept of Data Encryption, which is essential for safeguarding sensitive information from security threats. Lastly, the author will design and develop the Reward and Punishment Model for High-Performing Employee Management, which can enhance employee motivation and performance through a fair and effective incentive system. This chapter will conclude with research hypotheses formulated based on the discussed theories, providing direction and focus for the research to be conducted. By elucidating these theoretical foundations, the author aims to provide a robust framework for understanding and developing a more sophisticated and effective facial recognition-based attendance system.

4.1 FACE RECOGNITION BASED ATTENDANCE SYSTEM MODEL

The architecture of the basic attendance system model to be developed in this study can be observed in Figure 4.1. This model is a fundamental one commonly used across various industries with diverse functionalities. The face recognition-based attendance system has been implemented over the past 2 years at the vocational high school under study. The facial recognition-based attendance system model developed in this book utilizes liveness detection technology and deep learning to accurately and securely identify employee faces. It leverages the concept of integrating liveness detection models from studies (Basurah et al., 2023; Kuznetsov et al., 2024; Lavens et al., 2023; Mandol et al., 2021; Matthew & Canning, 2020; Sujanthi et al., 2023; Surantha & Sugijakko, 2024a; Tolendiyev et al., 2021; Y. Zhang, Xie, et al., 2023).

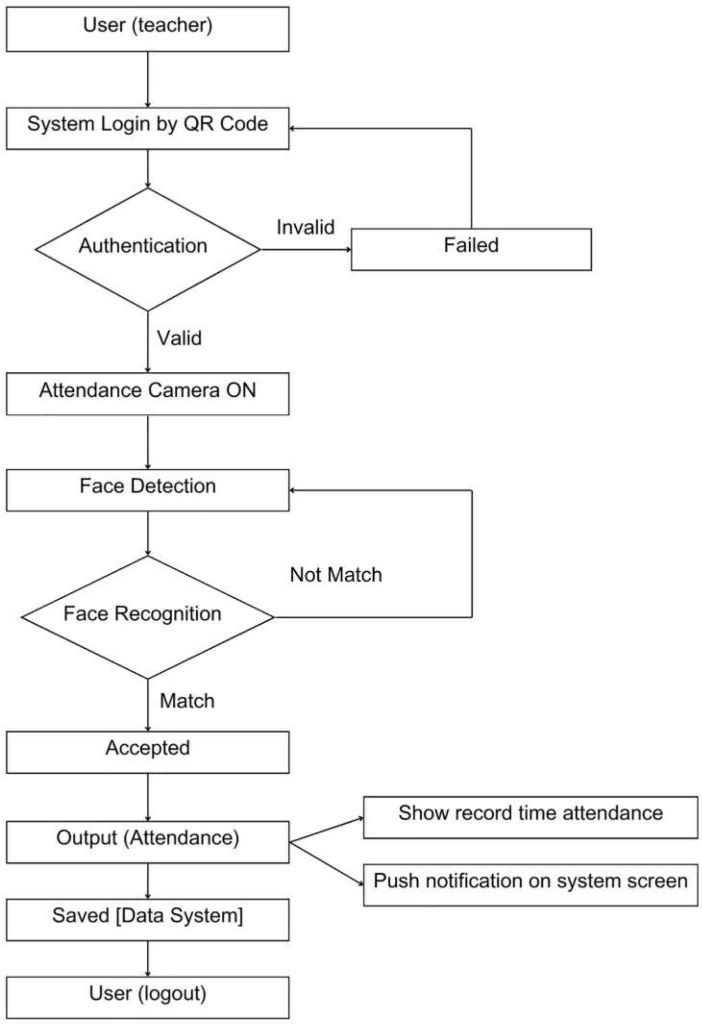


Figure 4.1. The facial recognition-based attendance system model implemented at the vocational high school before integration utilized various other advanced technologies, and security had not yet been enhanced

However, this study employs a different integration model compared to previous research, as illustrated in Figure 4.2, where the implementation of liveness detection techniques is placed directly in the face detection step and simultaneously combined using deep learning technology, namely CNN. According to (Chavan & Sherekar, 2023; Ikromovich & Mamatkulovich, 2023; Lee & Yoo, 2023; Mohammed Sahan et al., 2023; and Shukla et al., 2024), CNN can enhance accuracy to a higher level. When liveness detection begins to detect the faces of individuals regarding facial authenticity, CNN will then play a role in improving the accuracy of matching the faces captured by the camera with those registered in the system to avoid data mismatches. Even if the facial or body shape of an individual changes, CNN will match the facial patterns in the system with the changing or consistent faces captured by the current camera detection. Hence, facial detection will be accurate. Moreover, in liveness detection techniques, once an individual's face is detected, CNN will help confirm whether it is the individual with the corresponding identity or not. Thus, in addition to minimizing errors in facial recognition detection, liveness detection and deep learning (CNN) techniques are expected to further enhance security and prevent suspicious activities.

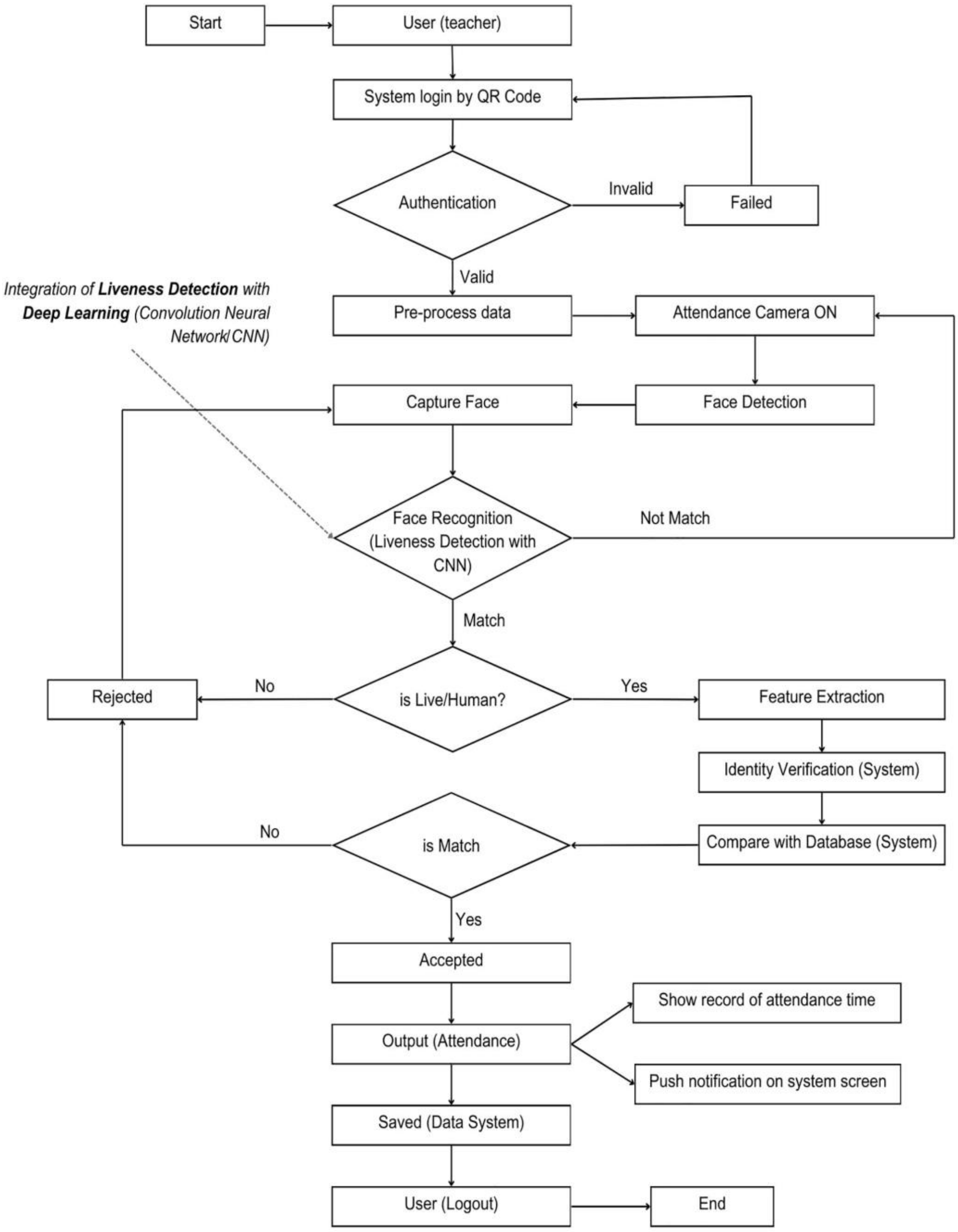


Figure 4.2. The development of a facial recognition-based attendance system model involves integrating liveness detection technology with deep learning (CNN) for accuracy and system security

As the teacher faced the facial recognition camera to mark attendance, if the face matched the registered photo, the attendance would be recorded by the system. Conversely, if the face did not match the registered photo, the camera would initiate another facial detection process. Upon successful data acceptance by the system, the system screen would display the teacher's attendance record in (hour:minute:second) format and exhibit the teacher's identity data along with a snapshot of the attendance camera's photo on the system screen. Subsequently, the data would be stored, and upon the teacher leaving the attendance area, the system would automatically log out.

Figure 4.2 illustrates the architecture of the facial recognition-based attendance system model developed using the integration of liveness detection techniques with deep learning (CNN). In this context, several steps differ significantly from the facial recognition system used in the basic attendance model. In the authentication phase, there is a pre-processing step to establish the connection between the camera and CNN and liveness detection, enabling the camera to open and begin detecting faces. Once the facial figure is captured by the camera, liveness detection and CNN automatically process the captured results to determine whether the captured image is of a human or not. If not, the camera will recapture the face and reverify it using liveness detection analysis. Next, if the captured facial figure is detected as a living human, the user's identity data (the respective teacher) is matched with the system. If the data matches, the attendance is accepted; however, if it does not match, it is rejected, and the camera will repeat the face-capturing process through the attendance camera again. In the subsequent step, after the data is accepted, the attendance output will appear in the form of a timestamp display, as seen in the facial recognition-based attendance model in the basic system. In the following sections, the model will continue to be further developed and integrated with various other advanced technologies to enhance security and utilize data for predictive purposes and early security surveillance through anomaly detection and attendance pattern prediction.

4.2 DEVELOPMENT OF SYSTEMS USING ML, DL, AND AI

Machine Learning (ML), Deep Learning (DL), and Artificial Intelligence (AI) are technologies used for analyzing attendance data, making predictions, and detecting suspicious patterns, thereby enhancing security and aiding decision-making based on data. In the context of the facial recognition-based attendance system in this study, these three technologies are integrated simultaneously to improve the accuracy, security, and efficiency of the attendance system. On the other hand, the integration of liveness detection and data encryption will assist the system in preventing attendance forgery and protecting employee data from unauthorized access. Previous research (Abdelli et al., 2022; Asselman et al., 2023; Bilakanti et al., 2024; Cui et al., 2019; Elbasi et al., 2023; Elmrabit et al., 2020; H.-G. Kim et al., 2019; Lather et al., 2019; Lohrasbinasab et al., 2022; Najafi Moghaddam Gilani et al., 2021; Sawadogo et al., 2021;

Sharmila et al., 2023; Shibly et al., 2022) have used machine learning to predict patterns in various fields using algorithms similar to those used by (Sarker, 2021; Taye, 2023). Similarly, (Abusitta et al., 2023; Ragedhaksha et al., 2023; Rostami et al., 2024; Shreesha et al., 2023; C. Sun et al., 2021; and Zhu et al., 2020) have utilized deep learning to make predictions in various fields.

In the context of similar technologies (Ghillani, 2022; Hamouri et al., 2023; J. hua Li, 2018; Mishra & Yadav, 2020; Stahl et al., 2022; Tomer & Sharma, 2022), AI has been used to predict patterns and trends in various fields, including security. In previous research, several researchers have also combined deep learning technology with machine learning, but this study is quite different (Fei et al., 2021; Nikou et al., 2019; Rana & Bhushan, 2023; Xin et al., 2018). In this study, an attempt is made to integrate all three advanced technologies simultaneously to make various predictions aimed at enhancing the security of the facial recognition-based attendance system developed using liveness detection and deep learning technologies. Additionally, encryption is applied to the data stored in the attendance system using the AES algorithm to make the stored data more secure and less susceptible to theft. The development of these three technologies is illustrated in Figure 4.3.

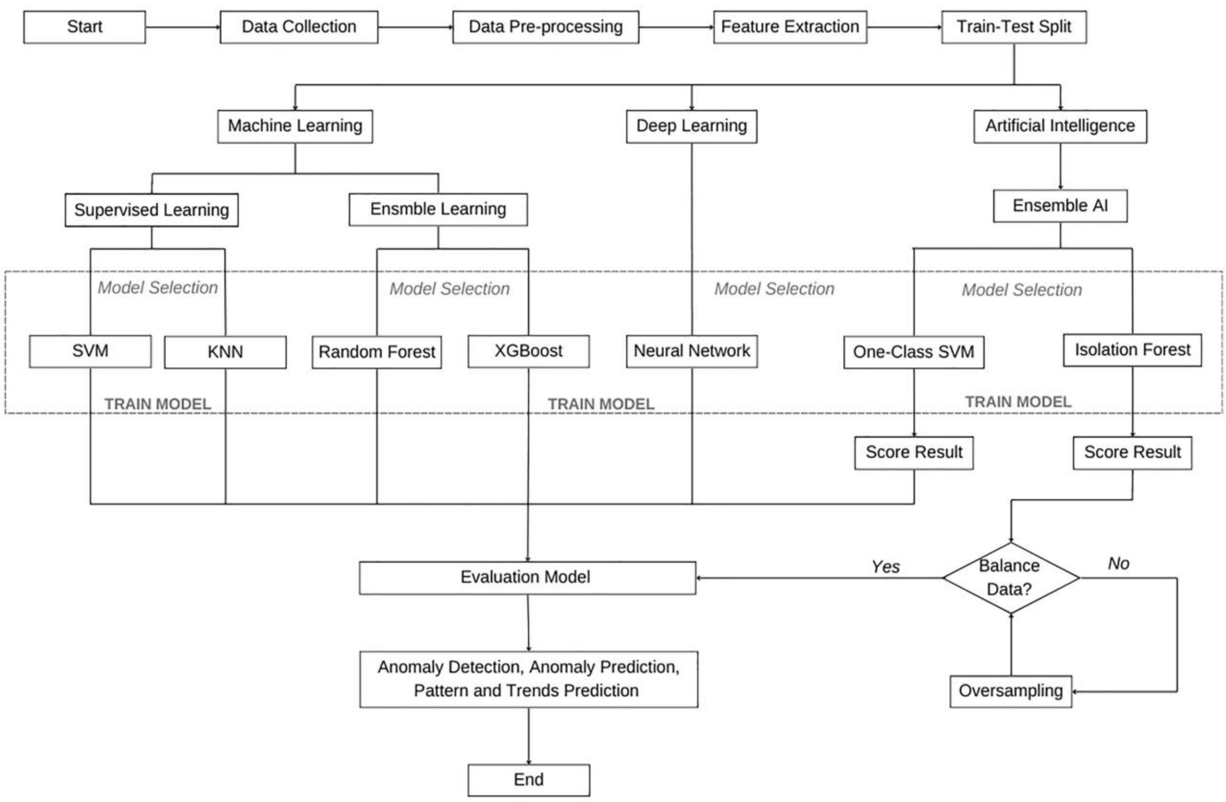


Figure 4.3. Integration Model of ML, DL, and AI in Facial Recognition-based Attendance System for Anomaly Pattern Prediction, Attendance Trend Prediction, and Attendance System Security Enhancement

Before being implemented into the system, the model will be trained and tested in a different environment outside the original system, specifically in the Google Colab notebook environment, to ensure system security. Subsequently, if the model evaluation yields excellent results, the model will be directly integrated into the facial recognition-based attendance system at the vocational high school (SMK). Figure 4.3 illustrates how the three advanced technologies in this study are trained and tested to perform various predictions through several steps. The integration of ML, DL, and AI technologies begins with the collection of data obtained through the facial recognition-based attendance system. Next, the data undergoes preprocessing and feature extraction to determine its suitability for use as samples and ensure that the distribution is evenly spread to avoid issues during model training and testing. Then, the data is divided using the train_test_split method based on the Pareto principle (Sanders, 1987).

In the next step, the models are initialized and selected for use. In this regard, not all models are utilized because each model has different characteristics and patterns, thus model selection is limited to the objectives to be achieved. In this study, the authors select several models for each integrated technology. In the machine learning model, the approaches used are supervised learning and ensemble learning. These two approaches are chosen because this book focuses on detecting and predicting anomaly patterns and attendance trends in the attendance system. The models used in the supervised learning approach in machine learning are Support Vector Machine (SVM) and K-nearest neighbor (KNN). These two models are chosen because each has similar characteristics, namely the ability to perform classification. SVM is a classification algorithm that works by finding the best hyperplane that separates data classes with sufficient effectiveness in high-dimensional space and works well with unstructured data. On the other hand, KNN is a non-parametric algorithm that classifies data based on proximity to the nearest neighbors in the feature space, making it simple intuitive, and suitable for use with small to medium-sized data.

In the Ensemble learning method, the machine learning models used are random forest and XGBoost (Extreme Gradient Boosting), where random forest employs a set of decision trees to enhance prediction accuracy. Each tree provides predictions, and majority voting is utilized for the final decision, exhibiting robustness against overfitting and adeptly handling complex data. On the other hand, XGBoost is a boosting algorithm that optimizes loss functions through gradients, demonstrating efficient and swift performance. It effectively handles large datasets and produces accurate predictions. In the realm of deep learning, a neural network model, known as an artificial neural network (ANN), is employed. This model emulates the functioning of the human brain by utilizing layers of neurons to process data, offering flexibility across various data types and predictive tasks. Deep learning, in this context, serves as a complement to the utilized machine learning models.

Lastly, in the AI model specialized for anomaly detection and prediction, the author utilizes an ensemble AI model consisting of a combination of One-class SVM and Isolation Forest models. One-class SVM is a variant of SVM designed to detect anomalies within data. This algorithm learns the characteristics of a single normal class and identifies significantly different data as anomalies. It proves quite effective in detecting outliers in datasets dominated by a single class. Meanwhile, Isolation Forest is an ensemble learning method that isolates outliers using decision trees. This algorithm works by creating random partitions in the data and identifying data requiring fewer partitions as anomalies, capable of quickly and effectively detecting anomalies in large datasets.

These seven models will be trained and tested using various datasets obtained beforehand from the attendance system of the vocational school. In this regard, although the six models used share the same evaluation metrics, they have distinct treatments during training and testing due to the unique characteristics of each algorithm. However, in the AI model, the Isolation Forest has different treatments along with different evaluation metrics, yet it can still be jointly utilized for anomaly detection and prediction. Thus, this system not only enhances security but also aids in effective employee management in terms of administration.

4.3 DATA ENCRYPTION

In this study, data encryption is conducted on the data stored in the face recognition-based attendance system. Before encryption is applied to the system, encryption trials are also conducted in a different environment, similar to the environment used during the integration of ML, DL, and AI models into the system. This is done to maintain the security of the data stored in the system. The encryption model used is an encryption model using the AES algorithm, as illustrated in Figure 2.2. This model is implemented and developed into a new encryption model as depicted in Figure 4.4. Firstly, the author prepares a strong and secure encryption key with a length ranging from 128 to 256 bits, and its confidentiality is well maintained, ensuring that only authorized individuals know the encryption key. Subsequently, encryption is performed on biometric data, which constitutes facial recognition data in the form of facial feature points (facial model).

The encryption process employs the AES algorithm, as utilized in studies (Priyanka Brahmaiah et al., 2023; G. Singh, 2013). Encryption is applied to the biometric data stored in the attendance system. The AES algorithm utilized transforms this biometric data into ciphertext that cannot be deciphered without the decryption key. Subsequently, the encrypted data is stored in the same database format as the original data stored in the system to replace the original data. In this regard, the decryption key must be securely stored and utilized when data decryption is required. For instance, when the system necessitates access to biometric data for identity verification, the required data must first be decrypted using the stored decryption key, and the decryption process is executed in a secure environment to prevent unauthorized access.

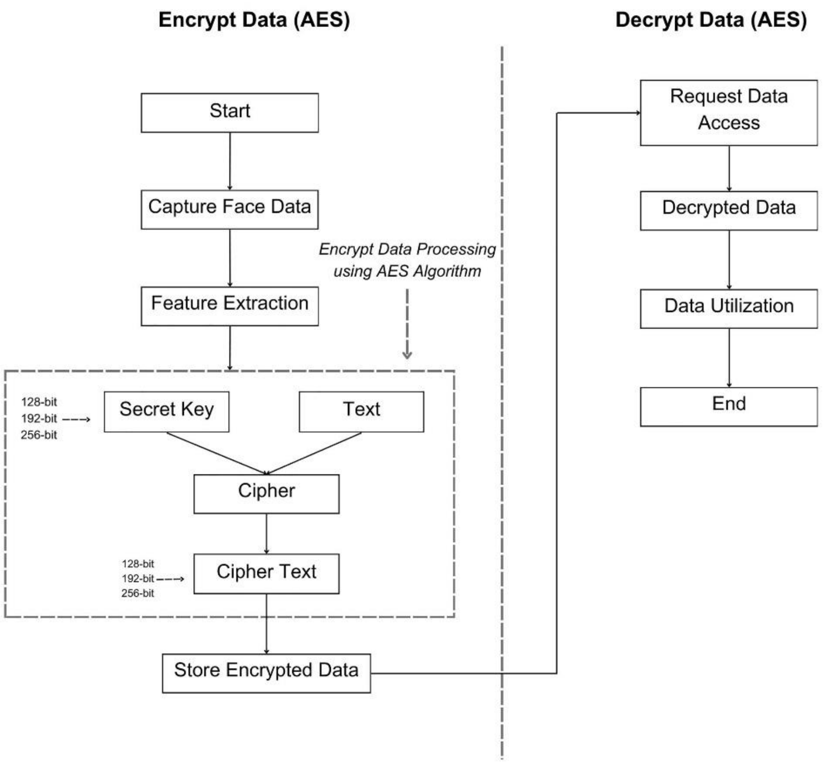


Figure 4.4 Implementation Model of AES Algorithm for Encryption Needs in Face Recognition-Based Attendance System

The implementation of encryption using the AES algorithm offers several benefits in terms of data security, regulatory compliance, and user trust (teachers). Concerning data security in this study, data encryption using the AES algorithm protects unauthorized access. Even if the data is hacked, it cannot be read without the correct decryption key. Furthermore, data integrity can be ensured because any changes to the ciphertext without the corresponding key will result in invalid data after decryption. In terms of regulation (security standards), encryption using the AES algorithm meets the criteria for appropriate usage as it can safeguard sensitive data. Finally, concerns about data leakage by teachers will be addressed through this encryption, as teachers will have more confidence in a system that guarantees the security of their data, thus effectively alleviating the previously experienced stress levels. In addition to the implementation of advanced technology developed in the face recognition-based attendance model in this study, the implementation of AES encryption in the face recognition-based attendance system will enhance and protect teachers' sensitive data more effectively. Moreover, this encryption is capable of reducing the risk of data leakage and enhancing trust in the system used.

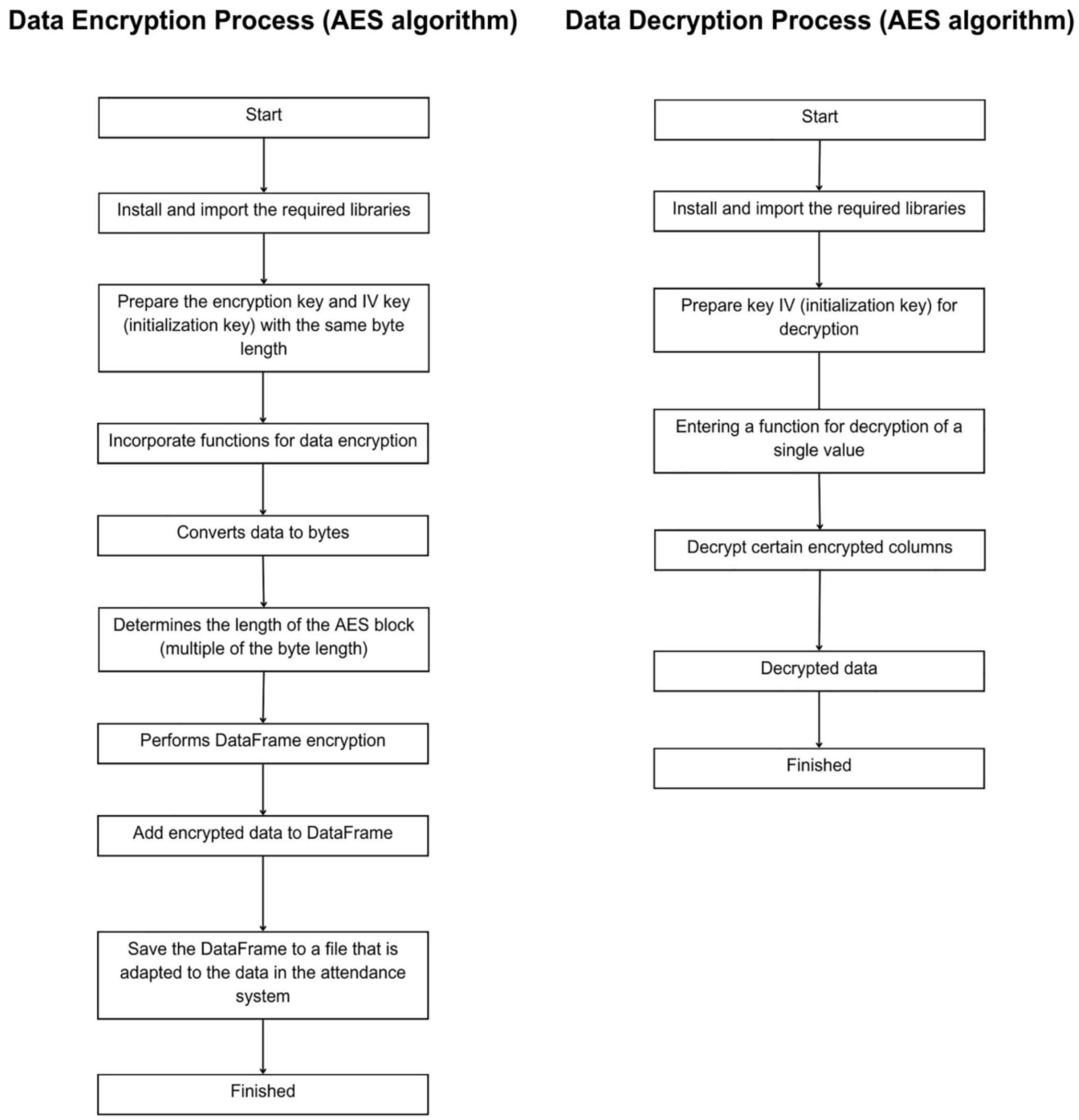


Figure 4.5. The encryption process performed on the attendance system data

4.4 REWARD AND PUNISHMENT MODELS FOR EMPLOYEE MANAGEMENT

The reward and punishment system to be implemented in this model aims to enhance employee motivation, discipline, and productivity through the utilization of accurate attendance data and machine learning techniques. This system strives to provide rewards to high-performing employees and sanctions to those who fail to meet attendance and performance standards. Stemming from psychological and management theories utilized to motivate specific behaviors within organizational environments (B. F. Skinner, 1965), this system is developed and implemented in a novel model employing machine learning for employee management. Differing from prior research (Cai et al., 2022; Pangandaheng & Sutanto, 2021) the integrated reward and punishment model in the attendance system will enable more efficient management of employee data, where all attendance records are automatically captured and stored in real-time with precision. Additionally, the system trained using machine learning will be capable of categorizing according to the implemented reward and punishment model within the system, ensuring that rewards and punishments are targeted accurately. Furthermore, the implementation of this model in the system will also serve as an incentive for other teachers to be more diligent in attendance.

The reward and punishment themselves in this study, take the form of year-end bonuses, wherein the bonus is distributed equally among all teachers when the time comes. According to data obtained from interviews with various divisions and teachers at the vocational high school (SMK) regarding this bonus, several cases have emerged. For instance, the equal distribution of a fixed nominal amount to all teachers, regardless of their performance throughout the year, has led some disciplined and diligent teachers to perceive it as unfair when even those who rarely attend or rarely show up receive the same bonus. Furthermore, the interview results also indicate that the year-end bonus, initially intended to boost teacher motivation, has failed to yield any impact after being practiced for the past 2 years.

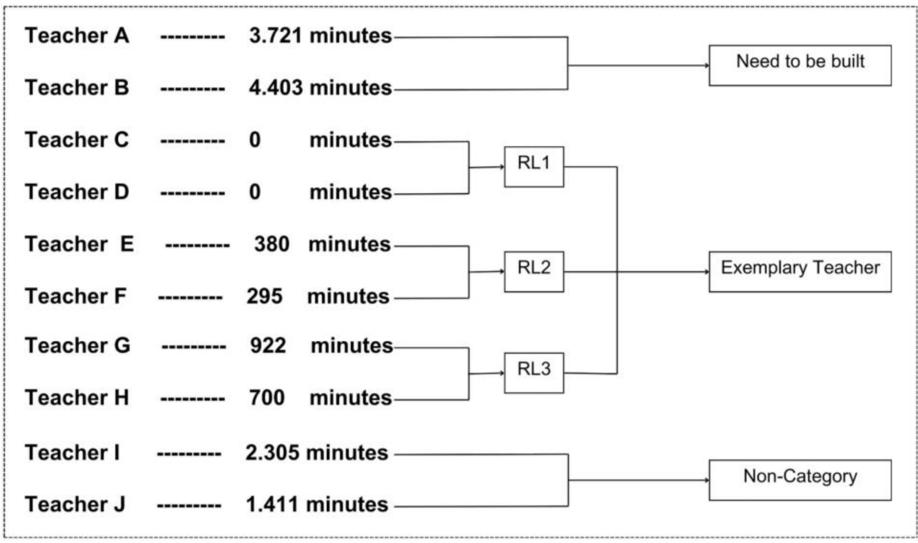


Figure 4.6. Example of the application of the proposed reward and punishment model in the study

Therefore, the forthcoming bonus model will differ from the existing model, wherein the bonus will decrease based on the number of minutes a teacher is late or absent without permission. The deducted bonus amounts will be accumulated and redistributed to the most diligent teachers in attendance. The reward and punishment model developed in this study can be observed in Figure 4.6.

For the reward and punishment model implemented in the face recognition-based attendance system in this study, the following assumptions are made (the nominal bonus is just an example):

Assumption (amount of bonus is example only):

- The year-end bonus is a bonus given to each teacher for IDR 2,500,000.
- The reward consists of a bonus obtained as an additional year-end bonus derived from late attendance fines. The reward is divided into 3 levels: Reward Level 1 (RL1) is 50% of the total late fines, Reward Level 2 (RL2) is 30% of the total late fines, and Reward Level 3 (RL3) is 20% of the total late fines.
- The punishment is a late arrival fine based on the accumulated number of minutes late within 1 year with the following provisions:
  - For every 1 minute of lateness, the year-end bonus will be reduced by IDR 250, with a maximum daily deduction of IDR 10,000.
  - 1 minute is counted from 60-90 seconds late, 2 minutes are counted from 91-150 seconds late, and so on.
  - The punishment will be automatically applied through the face recognition-based attendance system at the vocational high school according to the morning attendance records.
- High-performing teachers are those who are never late and never absent without permission, with a maximum lateness allowance of 1,095 minutes, and will receive a reward added to their year-end bonus. High-performing teachers are divided into 3 ranks:
  - The first rank group consists of teachers with full attendance without any lateness, and they fall into the RL1 category.
  - The second rank group consists of teachers with a maximum lateness of 400 minutes, and they fall into the RL2 category.
  - The third rank group consists of teachers with a maximum lateness of 1,095 minutes, and they fall into the RL3 category.

- Teachers who need improvement are those with total attendance lateness exceeding 3,285 minutes, and this group of teachers will not receive any reward.
- Teachers with lateness ranging from 1,096 minutes to 3,284 minutes are not included in the above 2 categories and will not receive any reward.

Example Scenario

Teacher A has a total lateness of 3,721 minutes over 1 year, resulting in a punishment fine deduction of IDR 930,250. Teacher B has a total lateness of 4,403 minutes over 1 year, resulting in a punishment deduction of IDR 1,100,750. Furthermore, Teachers C and D have never been late at all during the year. Teacher E has a total lateness of 922 minutes over 1 year, resulting in a punishment deduction of IDR 230,500. Teacher F has a total lateness of 700 minutes over 1 year, resulting in a punishment deduction of IDR 175,000. Teacher G has a total lateness of 380 minutes over 1 year, resulting in a punishment deduction of IDR 95,000. Teacher H has a total lateness of 295 minutes over 1 year, resulting in a punishment deduction of IDR 73,750. Teacher I has a total lateness of 2,305 minutes over 1 year, resulting in a punishment deduction of IDR 576,250. Teacher J has a total lateness of 1,411 minutes over 1 year, resulting in a punishment deduction of IDR 352,750.

To calculate the total reward and punishment, the following steps are taken:

$$Total\ nominal\ Reward\ =\ Total\ nominal\ Punishment \qquad (Eq. 4.1)$$

$$Punishment\ =\ Total\ minutes\ of\ lateness\ over\ 1\ year\ \times\ IDR\ 250 \qquad (Eq. 4.2)$$

$$Reward\ for\ high-performing\ teachers\ =\ RL1, RL2, RL3 \qquad (Eq. 4.3)$$

$$RL1\ =\ 50\%\ \times\ Total\ nominal\ Reward \qquad (Eq. 4.4)$$

$$RL2\ =\ 30\%\ \times\ Total\ nominal\ Reward \qquad (Eq. 4.5)$$

$$RL3\ =\ 20\%\ \times\ Total\ nominal\ Reward \qquad (Eq. 4.6)$$

In this case, the total nominal reward from the scenario above is IDR 3,534,250. With RL1 = IDR 1,767,125, RL2 = IDR 1,060,275, and RL3 = IDR 706,850 in allocation.

For the Reward and Punishment model for managing teacher attendance data to determine high-performing teachers and those in need of improvement, the K-means clustering technique can be observed in Figure 4.6. Meanwhile, the model of the face recognition-based attendance system integrated with the Reward and Punishment system can be seen in Figure 4.7. In applying the Reward and Punishment model to this attendance system, a different technique is used compared to previous research, which mostly relied on manual and traditional methods. The implementation technique for the Reward and Punishment system in this study is machine learning (K-means clustering). These techniques have not been previously utilized by other researchers, ensuring fair outcomes aligned with teacher attendance. Since the attendance system records data in real time, there will be no room for cheating in categorizing teachers for rewards and punishments.

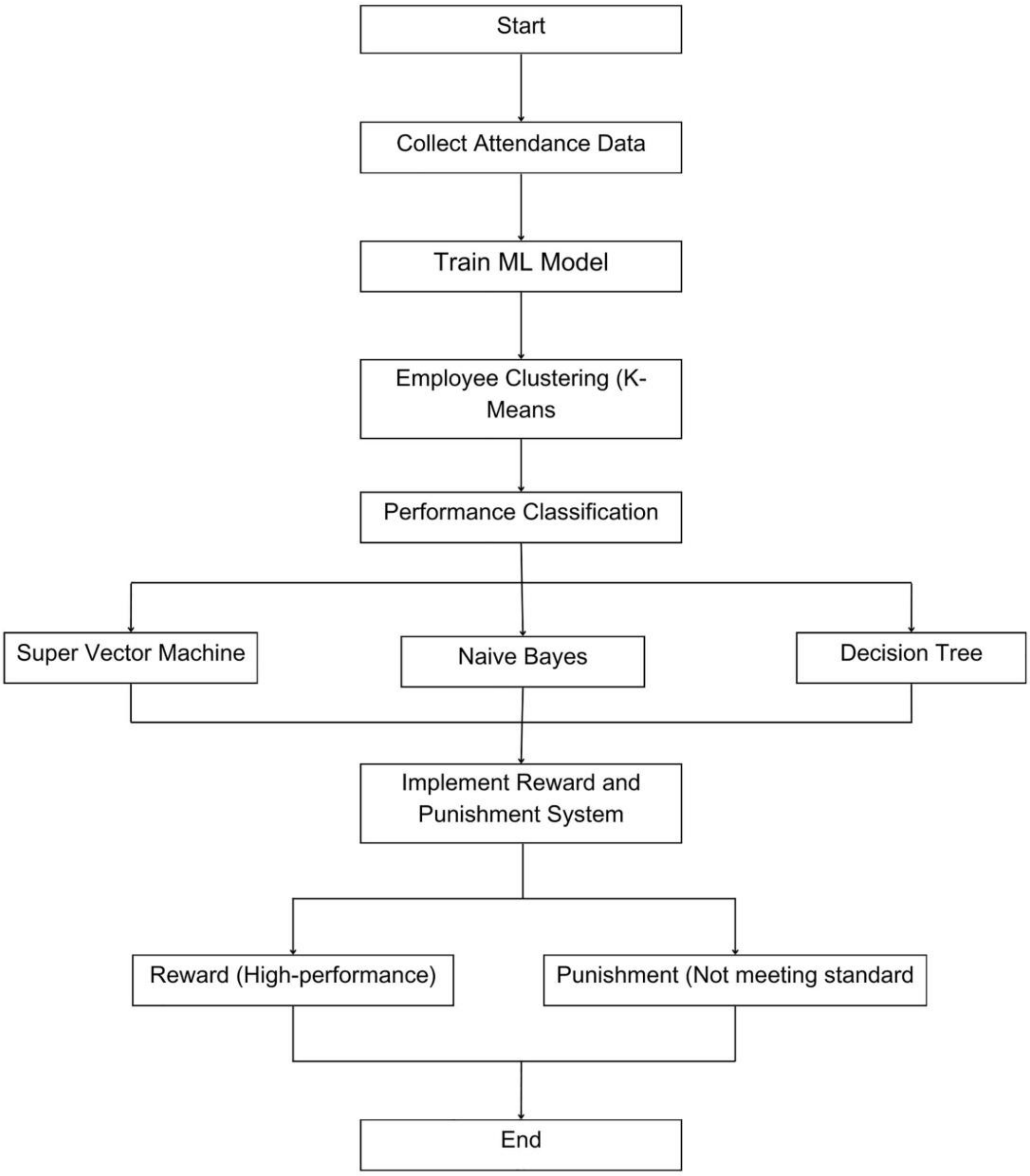


Figure 4.7. The Reward and Punishment model for managing both high-performing and underperforming teachers employs machine learning methodology with K-Means clustering technique

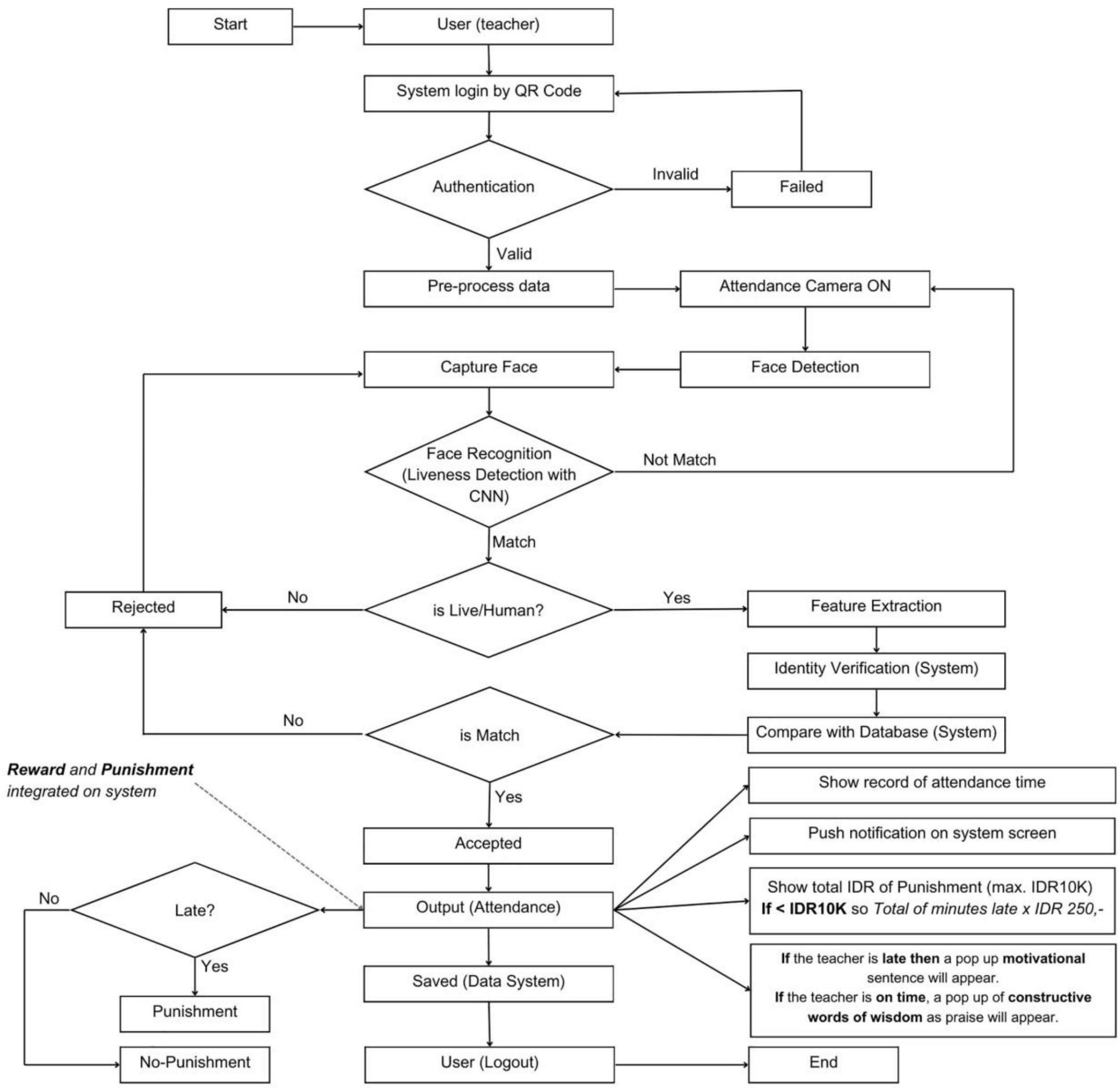


Figure 4.8. Face recognition-based attendance system integrated with reward and punishment system

Figure 4.8 illustrates the implementation of the Reward and Punishment system integrated into the face recognition-based attendance system. There are notable differences in the outputs compared to the baseline model of the face recognition-based attendance system in Figure 4.2 and the enhanced model developed using liveness detection and deep learning in Figure 4.3. After the automated implementation of the Reward and Punishment model into the system, additional processes for applying punishment to late teachers will be included in the output. The system's display will show the late fee amount along with a notification of tardiness. Additionally, a pop-up message will appear with brief motivational phrases to encourage tardy teachers to be more disciplined in their attendance the following day. For teachers who are not late, the output will only display the attendance time, system notifications, and an uplifting pop-up with inspirational quotes as praise. The application of the Reward and Punishment model in this attendance system is expected to have an impact on improving teacher motivation, discipline, and performance in teaching and school activities. All bonus applications and calculations will be conducted through the system, supporting technology-based attendance management projects with daily and annual reports issued during the distribution of year-end bonuses to SMK teachers.

Conclusion

1. The integration of Machine Learning (ML), Deep Learning (DL), and Artificial Intelligence (AI) technologies into the face recognition-based attendance system can significantly enhance the security and accuracy of attendance recording in vocational schools (SMK).
2. Integrating Liveness Detection techniques into the face recognition-based attendance system will reduce the risk of spoofing attacks and improve facial detection accuracy.
3. Employing the Advanced Encryption Standard (AES) algorithm for data encryption in the face recognition-based attendance system will mitigate the risks of data theft and manipulation, thereby enhancing individual data privacy protection.
4. The implementation of a reward and punishment system in the developed attendance system can enhance data management, increase motivation, and improve teacher performance in vocational schools (SMK).
5. Applying Ensemble AI in the face recognition-based attendance system can detect anomaly patterns in attendance data, thus preventing unauthorized access and enhancing decision-making efficiency.

With these hypotheses, further research will focus on testing and analyzing the effectiveness of integrating advanced technologies in enhancing the attendance system in vocational schools, as well as evaluating its impact on employee management and data security.

From the literature review and theoretical framework discussed, several important conclusions can be drawn, forming the basis for this book. In this study, a face recognition-based attendance system supported by Machine Learning (ML), Deep Learning (DL), and Artificial Intelligence (AI) technologies has been proposed. This system not only enhances the efficiency and accuracy of attendance recording but also offers various additional benefits through in-depth data analysis and data-driven decision-making. By leveraging ML algorithms such as Support Vector Machine (SVM), Decision Tree (DT), and Random Forest (RF), the system can provide objective recommendations regarding rewards and punishments. This approach enables management to identify high-performing employees and those in need of mentoring more accurately, consistent with the study by Bharadiya & Bharadiya (2023). The use of ML and DL allows for the identification and prediction of attendance patterns and anomalies, contributing to more effective employee management. The incorporation of Liveness Detection technology is also a crucial addition to this system to ensure that only genuinely present individuals are recorded, reducing the likelihood of system abuse. The face recognition technology implemented employs liveness detection techniques and CNN algorithms, where liveness detection is a critical component in face recognition systems to prevent spoofing attacks. Meanwhile, CNN has proven capable of identifying individuals with high accuracy, even in low-light conditions or with variations in facial poses. This technology ensures that the recognized faces are live faces, not images or videos, thereby enhancing system security.

In the following section, this book will demonstrate that the integration of this technology with the attendance system can reduce errors and fraud, as well as enhance data security through encryption using the AES algorithm, in line with findings from previous research (AbdELminaam et al., 2020; P. T. Kim & Bodie, 2020), which states that face recognition technology offers a safer and more efficient solution in attendance management. The use of the Advanced Encryption Standard (AES) algorithm for data encryption in the face recognition-based attendance system offers additional protection against data theft and manipulation, crucial for preserving individual data privacy and preventing unauthorized access. Regarding data security, the use of AES encryption technology ensures that sensitive biometric data is safeguarded from unauthorized access. Challenges related to biometric data privacy and security previously identified by (Dang, 2023b) and (Gode et al., 2023a) can be addressed with this approach. Further developments in data security are crucial to ensuring the integrity and trustworthiness of the face recognition-based attendance system. Accurate attendance data can also serve as the basis for a reward and punishment system, which in turn can enhance employee motivation and performance. This system provides incentives for employees to be punctual and perform their duties effectively.

Furthermore, the implementation of Ensemble AI in the attendance system enables the detection of anomaly patterns in attendance data, such as unusual absences or attempts at unauthorized access. This anomaly detection aids in faster and more accurate decision-making, thereby enhancing the overall security of the system. Additionally, the application of Ensemble AI in the attendance system allows for the detection of anomaly patterns in attendance data, such as unusual absences or attempts at unauthorized access. This anomaly detection aids in faster and more accurate decision-making, thereby enhancing the overall security of the system. Lastly, in employee management through attendance data, a reward and punishment model will be implemented. Accurate attendance data can serve as the basis for a reward and punishment system, which, in turn, can enhance employee motivation and performance. This system provides incentives for employees to be punctual and perform their duties effectively. With a strong theoretical foundation and literature review, the subsequent research will focus on testing hypotheses regarding the effectiveness of integrating ML, DL, AI, Liveness Detection, and AES encryption technologies in enhancing the security and accuracy of the attendance system in vocational schools. The results of this book are expected to make a significant contribution to the development of more reliable and secure attendance systems in educational environments.

CHAPTER 5
ATTENDANCE SYSTEM DESIGN AND PROCEDURES

This study employs a quantitative design with an experimental approach to develop and test the integration model of machine learning technology in the face recognition-based attendance system. This approach was chosen for its systematic experimental design, wherein the authors design experiments to test the model with various parameters, datasets, and evaluation techniques to understand the performance and reliability of the model. This includes data separation into training, validation, and testing sets to objectively measure performance. In this context, the research aims to develop and test an enhanced face recognition-based attendance system with AI, ML, DL, liveness detection, and data encryption using AES algorithm technologies, with the ultimate goal of improving the security of the face recognition-based attendance system used for attendance management in vocational schools.

The research procedure begins with a preparation phase, which involves setting up the software for the face recognition-based attendance system and preparing data for model training and testing. Information and software setup are presented, while data preparation is explained in section 3.2. Before being used for analysis and research purposes, the data will undergo preprocessing first, which will help improve model performance, computational efficiency, and the validity and reliability of research results. In this context, there are several reasons why the data to be used must undergo preprocessing. The first reason is that data cleaning can help remove missing and duplicate values, which can cause issues in the analysis and training of machine learning, deep learning, and AI models. The second reason is feature scale normalization and standardization, which is used to ensure that all features are on the same scale, allowing ML, DL, and AI model algorithms to function optimally. Additionally, removing irrelevant data can address noise, thereby improving data quality and reducing model complexity. Another reason is data transformation, such as creating new features and encoding categories as needed to help the model better understand the data. Since anomaly detection and prediction are conducted in this study, creating features and labels in the data is crucial as it aids in handling anomalies and prevents the model from being biased towards unrepresentative data.

After data preprocessing is completed, the data distribution will be checked first to ensure data distribution and validity. In this regard, data distribution should be examined before analysis or model training as it helps understand the data characteristics, identify outliers, and choose the appropriate statistical methods or models. Data distribution is also important for normalization and standardization, validating model assumptions, detecting biases, and preparing effective data visualizations. Knowing the data distribution ensures that machine learning models and analyses are more valid, accurate, and reliable. If the data is normally distributed (evenly distributed), the data will then be divided into training and testing sets to ensure that the model can generalize well to unseen data, and cross-validation helps prevent overfitting. Next, ML, DL, and AI models will be trained using the previously divided training dataset. Once model training is completed, model testing will follow, in which the models will perform identification, analysis, detection, and prediction of patterns. After obtaining the results, they will be measured using predefined evaluation metrics. Various evaluation metrics used in this study are discussed in section 3.6.3. If the evaluation results are satisfactory, the model will then be implemented in the real system to observe whether there are any changes in the developed system's security or not. Finally, the results will be compared and described in the results section as the research findings report.

5.1 DATA SAMPLING

This book utilizes two types of data: primary and secondary data. Primary data are obtained through direct observation and interviews. Direct observation is conducted on the implementation of the face recognition-based attendance system at vocational high schools (SMK). Meanwhile, interviews with employees and teachers are conducted to gather their perspectives on the attendance system and the reward and punishment system. Secondary data is obtained through employee attendance data collected from the face recognition-based attendance system over six months, literature data, and relevant previous studies on the research topic.

The object of this book is the face recognition-based attendance system implemented in SMKs, where this book object will be integrated with various advanced technologies (machine learning, deep learning, artificial intelligence, and liveness detection). The research sample consists of teacher attendance data from several SMKs randomly selected from the face recognition-based attendance system. This data is collected through the school attendance system in the form of a MySQL database and exported in Excel and. CSV formats as datasets for further analysis. The data comprises 998 entries with information including facial images with various pose variations and lighting conditions, teacher biometric facial data, attendance ID, teacher code (without name), date of attendance, morning check-in time, and afternoon check-out time (formatted as hour:minute: second), attendance location (the name of the building used for attendance in the school), and daily attendance information.

During the data collection process, strict data security measures were implemented to protect the privacy of teachers and the security of school data. This includes data encryption, restricted access only to authorized parties, and compliance with privacy policies established by the school. Additionally, the data collection steps were carried out with official permission from the school authorities to access and analyze employee attendance data. Official permission was also obtained to ensure compliance with applicable privacy regulations and data protection. The attendance data consists of periodic attendance records of employees coming and leaving work over 10 months. The data collection process was also conducted for 10 months, during the early period of the year, as rewards and punishments are applied at the end of the year. Furthermore, the data will be used to analyze patterns, trends, and factors influencing employee attendance, as well as to analyze the impact on employees after the application of rewards and punishments.

5.2 VARIABLE AND INDICATOR

Research variables are the aspects measured or manipulated in the study. In this book, there are two main types of variables: independent variables and dependent variables. Indicators are specific measures used to assess each variable. The variables and indicators can be viewed in Tables 5.1 and 5.2.

Table 5.1. Independent Variable

No	Variable	Description	Indicator	Description
1	Face Recognition Technology (Abraham et al., 2020; Gode et al., 2023b; A. Singh et al., n.d.)	Face recognition-based attendance system used for recording attendance.	The Accuracy Level of Face Recognition (Cavazos et al., 2021; Krishnapriya et al., 2020)	Measuring the accuracy of the technology in recognizing registered faces in the system compared to actual faces captured by the camera.
			Success Rate in Various Lighting Conditions (Sandhan et al., 2024; Surantha & Sugijakko, 2024a)	Assessing the system's performance in detecting individual faces under different lighting conditions and expressions.
2	Integration AI, ML, and DL (Aggarwal et al., 2023; Akcay et al.,	Models and algorithms employed for data analysis, anomaly detection, and	Accuracy of Absence Pattern Prediction (C. F. Chen et al., 2004)	The AI/ML/DL model's ability to accurately predict absence patterns.

	2022; Elmrabit et al., 2020)	performance prediction of teachers in vocational schools.	Model's Ability in Anomaly Detection Deteksi Anomali (Recall dan Presisi) (Elmrabit et al., 2020)	The effectiveness of the model in detecting anomalies in face recognition-based attendance data.
3	Integrating Liveness Detection (Matthew & Canning, 2020)	Methods utilized to ensure that facial recognition input originates from a living individual.	Spoofing Detection Rate (Hosen et al., 2023)	The system's success rate in determining whether the input face belongs to a living individual (the system's capability to detect identity falsification attempts).
			Life Detection Speed (Mandol et al., 2021)	The time required to verify the authenticity of a face.
4	Data encryption using AES algorithm (Priyanka Brahmaiah et al., 2023)	Algorithms employed to safeguard attendance data.	Encryption/Decryption Time (Muhammad Abdullah & Muhamad Abdullah, 2017)	The time needed for data encryption and decryption.
			Data Security Level (S. Jenifa Sabeena, 2023)	Assessing how well the data is protected from unauthorized access and the level of security measured through penetration testing and risk analysis.

Table 5.2. Dependent Variable

No	Variable	Description	Indicator	Description
1	Attendance data security (Balint, 2022)	The level of security achieved by the attendance system in protecting data and preventing unauthorized access.	Data Integrity (Doss et al., 2022)	How well data is safeguarded against unauthorized modifications.
			Response to Threats (Alemami et al., 2023)	Speed and effectiveness of the system in responding to security threats.
2	Effectiveness of the Reward and Punishment System (Wibowo et al., 2022)	Mechanisms based on attendance and performance data for rewarding or penalizing employees.	Attendance Rate (Frimayasa et al., 2021b)	The extent to which employee attendance matches the schedule after system implementation.
			Level of discipline (Wibowo et al., 2022)	Level of employee compliance with the designated attendance schedule after system implementation.

5.3 TRAINING TEST DATA

The following is the training data set used in system testing

Date	ID Face	Name Code	Ages	Entry Time	Exit Time	ML Converted_Entry Time	ML Converted_Exit Time	Attendance Location
08/04/2024	1	AL001	21	08:01:43	16:00:00	28903	57600	1
08/04/2024	2	AL002	26	08:03:19	16:00:00	28999	57600	1
08/04/2024	3	AL003	21	08:00:00	16:00:00	28800	57600	2
08/04/2024	4	AL004	26	08:00:00	16:00:00	28800	57600	2
08/04/2024	5	AL005	26	08:00:10	16:00:00	28810	57600	1
08/04/2024	6	AL006	22	08:00:47	16:00:00	28847	57600	1
08/04/2024	7	AL007	27	08:00:16	16:00:00	28816	57600	2
08/04/2024	8	AL008	24	08:00:00	16:00:00	28800	57600	1
08/04/2024	9	AL009	24	08:00:01	16:00:00	28801	57600	2
08/04/2024	10	AL010	26	08:02:11	16:00:00	28931	57600	1
08/04/2024	11	AL011	26	08:03:00	16:00:00	28980	57600	1
08/04/2024	12	AL012	26	08:03:03	16:00:00	28983	57600	3
08/04/2024	13	AL013	25	08:04:00	16:00:00	29040	57600	3
08/04/2024	14	AL014	25	08:05:18	16:00:00	29118	57600	3
08/04/2024	15	AL015	25	08:06:20	16:00:00	29180	57600	1
08/04/2024	16	AL016	25	08:07:17	16:00:00	29237	57600	4
08/04/2024	17	AL017	24	08:08:00	16:00:00	29280	57600	1
08/04/2024	18	AL018	25	08:07:27	16:02:00	29247	57720	1
08/04/2024	19	AL019	25	08:04:01	16:00:00	29041	57600	4
08/04/2024	20	AL020	24	08:00:11	16:00:00	28811	57600	4
08/04/2024	21	AL021	24	08:00:19	16:00:00	28819	57600	1
08/04/2024	22	AL022	24	08:04:50	16:00:00	29090	57600	5
08/04/2024	23	AL023	26	08:03:02	16:00:00	28982	57600	5
08/04/2024	24	AL024	26	08:02:22	16:00:00	28942	57600	1
08/04/2024	25	AL025	22	08:02:14	16:00:05	28934	57605	1
08/04/2024	26	AL026	26	08:03:00	16:00:00	28980	57600	1
08/04/2024	27	AL027	26	08:01:55	16:00:00	28915	57600	5
08/04/2024	28	AL028	26	08:04:44	16:00:00	29084	57600	1
08/04/2024	29	AL029	26	08:00:03	16:03:16	28803	57796	1
08/04/2024	30	AL030	24	08:00:07	16:00:00	28807	57600	2
08/04/2024	31	AL031	26	08:01:00	16:00:00	28860	57600	1
08/04/2024	32	AL032	24	08:01:05	16:00:00	28865	57600	1
08/04/2024	33	AL033	24	08:00:09	16:00:00	28809	57600	3
08/04/2024	34	AL034	24	08:00:00	16:00:00	28800	57600	3
08/04/2024	35	AL035	24	08:00:49	16:00:00	28849	57600	1
08/04/2024	36	AL036	24	08:00:00	16:00:00	28800	57600	1
08/04/2024	37	AL037	27	08:01:40	16:00:00	28900	57600	1
08/04/2024	38	AL038	27	08:00:00	16:09:00	28800	58140	3
08/04/2024	39	AL039	30	08:00:00	16:00:00	28800	57600	1
08/04/2024	40	AL040	24	08:00:12	16:00:00	28812	57600	1

08/04/2024	41	AL041	21	08:01:38	16:00:12	28898	57612	1
08/04/2024	42	AL042	24	08:01:49	16:00:09	28909	57609	1
08/04/2024	43	AL043	24	08:02:30	16:00:00	28950	57600	4
08/04/2024	44	AL044	21	08:03:00	16:02:00	28980	57720	4
08/04/2024	45	AL045	29	08:03:11	16:10:00	28991	58200	4
08/04/2024	46	AL046	28	08:05:00	16:00:00	29100	57600	4
08/04/2024	47	AL047	22	08:04:22	16:00:00	29062	57600	4
08/04/2024	48	AL048	21	08:01:00	16:00:00	28860	57600	5
08/04/2024	49	AL049	24	08:00:38	16:00:00	28838	57600	1
08/04/2024	50	AL050	29	08:04:05	16:04:06	29045	57846	1
08/04/2024	51	AL051	25	08:06:09	16:12:02	29169	58322	1
08/04/2024	52	AL052	24	08:01:00	16:04:07	28860	57847	4
08/04/2024	53	AL053	22	08:03:12	16:00:00	28992	57600	1
08/04/2024	54	AL054	22	08:02:44	16:13:37	28964	58417	1
08/04/2024	55	AL055	25	08:05:19	17:00:01	29119	61201	1
08/04/2024	56	AL056	24	08:03:07	16:00:00	28987	57600	1
08/04/2024	57	AL057	22	08:02:19	17:00:29	28939	61229	1
08/04/2024	58	AL058	22	08:04:10	17:01:03	29050	61263	1
08/04/2024	59	AL059	24	08:02:56	16:00:00	28976	57600	1
08/04/2024	60	AL060	24	08:02:10	17:01:41	28930	61301	1
08/04/2024	61	AL061	24	08:05:55	16:00:00	29155	57600	1
08/04/2024	62	AL062	30	08:00:00	16:00:05	28800	57605	4
08/04/2024	63	AL063	22	08:04:00	16:00:00	29040	57600	1
08/04/2024	64	AL064	22	08:04:56	16:04:22	29096	57862	1
08/04/2024	65	AL065	22	08:05:51	17:03:03	29151	61383	1
08/04/2024	66	AL066	22	08:00:00	17:04:10	28800	61450	4
08/04/2024	67	AL067	21	08:00:00	17:02:42	28800	61362	1
08/04/2024	68	AL068	28	08:00:59	17:04:00	28859	61440	1
08/04/2024	69	AL069	25	08:00:00	16:09:11	28800	58151	5
08/04/2024	70	AL070	25	08:03:23	17:06:25	29003	61585	1
08/04/2024	71	AL071	28	08:01:00	17:11:02	28860	61862	1
08/04/2024	72	AL072	27	08:00:12	16:04:08	28812	57848	5
08/04/2024	73	AL073	21	08:01:00	17:04:55	28860	61495	5
08/04/2024	74	AL074	27	08:00:17	17:19:09	28817	62349	4
08/04/2024	75	AL075	25	08:00:00	17:23:33	28800	62613	4
08/04/2024	76	AL076	24	08:00:00	16:10:14	28800	58214	1
08/04/2024	77	AL077	27	08:00:00	17:25:01	28800	62701	4
08/04/2024	78	AL078	21	08:00:00	17:22:24	28800	62544	1
08/04/2024	79	AL079	21	08:00:00	17:01:05	28800	61265	2
08/04/2024	80	AL080	26	08:00:00	16:02:28	28800	57748	2
08/04/2024	81	AL081	26	08:00:00	16:04:24	28800	57864	2
08/04/2024	82	AL082	26	08:00:00	17:25:05	28800	62705	1
08/04/2024	83	AL083	27	08:00:00	15:20:55	28800	55255	1
08/04/2024	84	AL084	21	08:00:00	17:00:03	28800	61203	1
08/04/2024	85	AL085	21	08:00:00	17:00:31	28800	61231	1

08/04/2024	86	AL086	28	08:00:00	17:00:58	28800	61258	1
08/04/2024	87	AL087	29	08:00:00	16:02:44	28800	57764	1
08/04/2024	88	AL088	21	08:00:00	16:04:17	28800	57857	1
08/04/2024	89	AL089	27	08:00:00	17:01:10	28800	61270	1
08/04/2024	90	AL090	22	08:00:00	16:13:59	28800	58439	1
08/04/2024	91	AL091	23	08:00:00	16:12:12	28800	58332	1
08/04/2024	92	AL092	23	08:00:00	16:00:00	28800	57600	1
08/04/2024	93	AL093	27	08:00:00	17:00:33	28800	61233	1
08/04/2024	94	AL094	22	08:00:00	17:10:59	28800	61859	1
08/04/2024	95	AL095	27	08:00:00	17:03:40	28800	61420	1
08/04/2024	96	AL096	22	08:00:00	17:13:10	28800	61990	1
08/04/2024	97	AL097	23	08:00:00	16:13:55	28800	58435	2
08/04/2024	98	AL098	27	08:00:00	17:25:07	28800	62707	1
08/04/2024	99	AL099	26	08:00:00	17:02:39	28800	61359	1
08/04/2024	100	AL100	26	08:00:00	16:09:16	28800	58156	4
08/04/2024	101	AL101	23	08:00:00	16:04:18	28800	57858	1
08/04/2024	102	AL102	22	08:04:07	17:22:30	29047	62550	1
08/04/2024	103	AL103	22	08:05:05	17:22:27	29105	62547	1
08/04/2024	104	AL104	28	08:01:33	17:02:46	28893	61366	1
08/04/2024	105	AL105	22	08:05:53	17:23:29	29153	62609	1
08/04/2024	106	AL106	27	08:03:54	17:25:09	29034	62709	1
08/04/2024	107	AL107	24	08:03:00	17:01:38	28980	61298	1
08/04/2024	108	AL108	24	08:04:38	16:02:05	29078	57725	1
08/04/2024	109	AL109	24	08:05:56	16:02:54	29156	57774	1
08/04/2024	110	AL110	24	08:00:41	17:23:38	28841	62618	1
08/04/2024	111	AL111	30	08:00:57	17:06:44	28857	61604	5
08/04/2024	112	AL112	23	08:00:00	17:06:22	28800	61582	4
08/04/2024	113	AL113	26	08:00:00	16:03:26	28800	57806	4
08/04/2024	114	AL114	21	08:00:00	17:13:13	28800	61993	1
08/04/2024	115	AL115	26	08:00:00	16:11:20	28800	58280	1
08/04/2024	116	AL116	21	08:00:00	16:00:00	28800	57600	1
08/04/2024	117	AL117	30	08:07:54	17:10:57	29274	61857	1
08/04/2024	118	AL118	25	08:05:55	16:04:45	29155	57885	1
08/04/2024	119	AL119	21	08:00:00	16:09:19	28800	58159	1
08/04/2024	120	AL120	28	08:08:00	16:02:15	29280	57735	1
08/04/2024	121	AL121	28	08:00:00	17:21:05	28800	62465	1
08/04/2024	122	AL122	28	08:00:23	17:25:12	28823	62712	1
08/04/2024	123	AL123	21	08:00:00	17:13:06	28800	61986	1
08/04/2024	124	AL124	28	08:02:06	17:23:30	28926	62610	1
08/04/2024	125	AL125	25	08:00:00	17:21:08	28800	62468	1
08/04/2024	126	AL126	21	08:00:00	17:25:35	28800	62735	1
08/04/2024	127	AL127	21	08:00:00	17:23:26	28800	62606	1
08/04/2024	128	AL128	28	08:00:00	16:09:29	28800	58169	1
08/04/2024	129	AL129	28	08:00:00	17:22:36	28800	62556	1
08/04/2024	130	AL130	28	08:00:00	16:04:34	28800	57874	1

08/04/2024	131	AL131	28	08:05:00	17:00:11	29100	61211	2
08/04/2024	132	AL132	28	08:04:09	17:00:39	29049	61239	1
08/04/2024	133	AL133	21	08:00:04	17:11:10	28804	61870	1
08/04/2024	134	AL134	21	08:00:08	17:02:50	28808	61370	1
08/04/2024	135	AL135	28	08:04:11	17:22:21	29051	62541	1
08/04/2024	136	AL136	30	08:01:00	17:04:53	28860	61493	1
08/04/2024	137	AL137	29	08:06:18	16:12:20	29178	58340	1
08/04/2024	138	AL138	22	08:01:31	16:04:12	28891	57852	1
08/04/2024	139	AL139	25	08:08:02	17:04:02	29282	61442	1
08/04/2024	140	AL140	28	08:00:00	17:21:45	28800	62505	1
08/04/2024	141	AL141	24	08:00:11	16:02:57	28811	57777	1
08/04/2024	142	AL142	21	08:00:00	17:02:36	28800	61356	1
08/04/2024	143	AL143	24	08:06:54	17:13:05	29214	61985	1
08/04/2024	144	AL144	23	08:08:28	17:23:40	29308	62620	2
08/04/2024	145	AL145	25	08:06:04	17:04:59	29164	61499	2
08/04/2024	146	AL146	25	08:06:12	17:11:00	29172	61860	2
08/04/2024	147	AL147	24	08:04:04	16:10:44	29044	58244	1
08/04/2024	148	AL148	30	08:02:14	16:03:55	28934	57835	1
08/04/2024	149	AL149	25	08:00:50	16:03:06	28850	57786	1
08/04/2024	150	AL150	24	08:05:11	17:06:37	29111	61597	1
08/04/2024	151	AL151	26	08:03:12	16:14:00	28992	58440	1
08/04/2024	152	AL152	21	08:00:00	17:25:25	28800	62725	1
08/04/2024	153	AL153	21	08:00:43	17:21:03	28843	62463	1
08/04/2024	154	AL154	24	08:04:40	17:25:14	29080	62714	1
08/04/2024	155	AL155	24	08:04:10	17:22:40	29050	62560	1
08/04/2024	156	AL156	22	08:00:00	17:23:22	28800	62602	2
08/04/2024	157	AL157	22	08:00:13	17:25:27	28813	62727	2
08/04/2024	158	AL158	25	08:05:00	16:04:09	29100	57849	1
08/04/2024	159	AL159	21	08:00:00	17:06:13	28800	61573	1
08/04/2024	160	AL160	25	08:02:36	16:12:55	28956	58375	1
08/04/2024	161	AL161	25	08:05:39	17:25:30	29139	62730	1
08/04/2024	162	AL162	21	08:00:14	16:00:00	28814	57600	1
08/04/2024	163	AL163	21	08:00:46	16:00:00	28846	57600	1
08/04/2024	164	AL164	24	08:00:36	16:00:00	28836	57600	1
08/04/2024	165	AL165	21	08:00:58	16:00:00	28858	57600	1
08/04/2024	166	AL166	21	08:00:36	16:04:35	28836	57875	1
08/04/2024	167	AL167	22	08:00:38	17:00:42	28838	61242	1
08/04/2024	168	AL168	22	08:01:47	16:09:25	28907	58165	1
08/04/2024	169	AL169	22	08:01:44	17:05:01	28904	61501	1
08/04/2024	170	AL170	22	08:00:54	17:04:49	28854	61489	1
08/04/2024	171	AL171	22	08:02:32	17:21:40	28952	62500	1
08/04/2024	172	AL172	25	08:00:31	17:04:04	28831	61444	1
08/04/2024	173	AL173	24	08:00:01	17:05:20	28801	61520	1
08/04/2024	174	AL174	24	08:00:00	17:22:18	28800	62538	1
08/04/2024	175	AL175	22	08:00:00	17:04:55	28800	61495	1

08/04/2024	176	AL176	22	08:00:02	17:00:50	28802	61250	1
08/04/2024	177	AL177	22	08:00:00	17:22:42	28800	62562	1
08/04/2024	178	AL178	22	08:00:46	16:09:40	28846	58180	1
08/04/2024	179	AL179	22	08:02:14	17:20:10	28934	62410	1
08/04/2024	180	AL180	22	08:02:22	17:23:18	28942	62598	2
08/04/2024	181	AL181	22	08:00:00	16:04:32	28800	57872	1
08/04/2024	182	AL182	22	08:00:43	17:02:33	28843	61353	1
08/04/2024	183	AL183	24	08:01:49	16:11:09	28909	58269	1
08/04/2024	184	AL184	24	08:00:00	17:21:38	28800	62498	1
08/04/2024	185	AL185	21	08:01:23	17:06:34	28883	61594	1
08/04/2024	186	AL186	22	08:01:33	16:03:13	28893	57793	1
08/04/2024	187	AL187	22	08:02:00	16:12:52	28920	58372	1
08/04/2024	188	AL188	21	08:01:11	17:21:01	28871	62461	1
08/04/2024	189	AL189	21	08:01:13	17:11:19	28873	61879	1
08/04/2024	190	AL190	22	08:02:45	16:10:54	28965	58254	1
08/04/2024	191	AL191	21	08:02:42	17:13:02	28962	61982	1
08/04/2024	192	AL192	28	08:02:24	17:10:55	28944	61855	2
08/04/2024	193	AL193	22	08:02:44	16:11:01	28964	58261	1
08/04/2024	194	AL194	23	08:00:32	17:21:38	28832	62498	2
08/04/2024	195	AL195	28	08:00:08	17:20:07	28808	62407	2
08/04/2024	196	AL196	28	08:00:00	17:20:12	28800	62412	1
08/04/2024	197	AL197	21	08:00:00	16:03:36	28800	57816	1
08/04/2024	198	AL198	24	08:06:00	16:04:36	29160	57876	1
08/04/2024	199	AL199	24	08:05:45	17:00:55	29145	61255	1
08/04/2024	200	AL200	24	08:00:00	17:19:03	28800	62343	1
08/04/2024	201	AL201	27	08:02:21	16:03:19	28941	57799	1
08/04/2024	202	AL202	28	08:02:27	17:23:45	28947	62625	1
08/04/2024	203	AL203	27	08:05:08	17:22:44	29108	62564	1
08/04/2024	204	AL204	27	08:05:04	17:25:16	29104	62716	1
08/04/2024	205	AL205	25	08:05:20	16:09:55	29120	58195	1
08/04/2024	206	AL206	25	08:05:43	16:08:57	29143	58137	1
08/04/2024	207	AL207	24	08:02:13	17:21:51	28933	62511	1
08/04/2024	208	AL208	24	08:00:00	17:06:16	28800	61576	1
08/04/2024	209	AL209	24	08:00:30	17:00:59	28830	61259	1
08/04/2024	210	AL210	24	08:00:00	17:01:01	28800	61261	2
08/04/2024	211	AL211	29	08:01:40	17:25:22	28900	62722	1
08/04/2024	212	AL212	29	08:00:49	17:20:59	28849	62459	1
08/04/2024	213	AL213	24	08:00:00	17:23:15	28800	62595	1
08/04/2024	214	AL214	25	08:05:17	17:02:56	29117	61376	1
08/04/2024	215	AL215	29	08:05:55	17:21:37	29155	62497	1
08/04/2024	216	AL216	29	08:05:25	17:25:36	29125	62736	1
08/04/2024	217	AL217	21	08:00:00	17:20:04	28800	62404	1
08/04/2024	218	AL218	21	08:00:00	17:25:39	28800	62739	1
08/04/2024	219	AL219	21	08:00:19	17:10:50	28819	61850	1
08/04/2024	220	AL220	21	08:00:06	17:13:00	28806	61980	1

08/04/2024	221	AL221	21	08:00:03	16:03:29	28803	57809	1
08/04/2024	222	AL222	25	08:03:00	16:04:31	28980	57871	1
08/04/2024	223	AL223	22	08:01:43	16:11:30	28903	58290	1
08/04/2024	224	AL224	24	08:01:55	17:11:21	28915	61881	1
08/04/2024	225	AL225	25	08:00:00	16:12:44	28800	58364	1
08/04/2024	226	AL226	29	08:00:15	16:09:47	28815	58187	1
08/04/2024	227	AL227	30	08:04:23	17:05:15	29063	61515	1
08/04/2024	228	AL228	25	08:04:11	17:04:07	29051	61447	1
08/04/2024	229	AL229	24	08:02:44	17:12:53	28964	61973	1
08/04/2024	230	AL230	24	08:02:21	17:22:12	28941	62532	1
08/04/2024	231	AL231	21	08:00:00	16:00:06	28800	57606	3
08/04/2024	232	AL232	28	08:00:00	16:04:37	28800	57877	1
08/04/2024	233	AL233	28	08:00:07	17:13:18	28807	61998	1
08/04/2024	234	AL234	28	08:00:10	17:22:50	28810	62570	2
08/04/2024	235	AL235	29	08:05:41	16:13:01	29141	58381	1
08/04/2024	236	AL236	29	08:04:41	17:21:55	29081	62515	1
08/04/2024	237	AL237	30	08:04:29	17:23:51	29069	62631	1
08/04/2024	238	AL238	21	08:00:00	16:11:28	28800	58288	1
08/04/2024	239	AL239	22	08:02:21	16:03:43	28941	57823	1
08/04/2024	240	AL240	22	08:01:00	17:24:38	28860	62678	1
08/04/2024	241	AL241	22	08:05:00	17:18:33	29100	62313	1
08/04/2024	242	AL242	22	08:02:01	17:25:20	28921	62720	1
08/04/2024	243	AL243	22	08:02:11	17:02:30	28931	61350	1
08/04/2024	244	AL244	22	08:00:00	17:21:35	28800	62495	1
08/04/2024	245	AL245	28	08:02:22	17:23:12	28942	62592	2
08/04/2024	246	AL246	30	08:03:51	17:10:49	29031	61849	1
08/04/2024	247	AL247	25	08:00:49	17:20:57	28849	62457	1
08/04/2024	248	AL248	21	08:01:55	16:02:25	28915	57745	1
08/04/2024	249	AL249	28	08:00:13	16:04:10	28813	57850	1
08/04/2024	250	AL250	21	08:00:00	17:06:11	28800	61571	1
08/04/2024	251	AL251	30	08:01:22	17:22:53	28882	62573	1
08/04/2024	252	AL252	29	08:01:32	17:02:29	28892	61349	1
08/04/2024	253	AL253	21	08:00:00	16:04:38	28800	57878	1
08/04/2024	254	AL254	28	08:00:12	16:00:09	28812	57609	1
08/04/2024	255	AL255	28	08:00:00	16:03:07	28800	57787	1
08/04/2024	256	AL256	27	08:00:00	16:03:46	28800	57826	1
08/04/2024	257	AL257	27	08:00:00	17:06:40	28800	61600	1
08/04/2024	258	AL258	24	08:00:00	16:02:47	28800	57767	2
08/04/2024	259	AL259	24	08:02:33	17:01:30	28953	61290	1
08/04/2024	260	AL260	24	08:02:10	17:22:10	28930	62530	1
08/04/2024	261	AL261	24	08:02:44	17:03:51	28964	61431	1
08/04/2024	262	AL262	24	08:02:28	16:03:39	28948	57819	1
08/04/2024	263	AL263	24	08:02:32	17:20:00	28952	62400	1
08/04/2024	264	AL264	24	08:02:48	16:11:40	28968	58300	1
08/04/2024	265	AL265	21	08:02:55	16:04:30	28975	57870	1

08/04/2024	266	AL266	29	08:02:17	16:00:18	28937	57618	1
08/04/2024	267	AL267	28	08:05:11	16:03:52	29111	57832	1
08/04/2024	268	AL268	21	08:05:19	16:03:03	29119	57783	2
08/04/2024	269	AL269	21	08:05:11	17:12:52	29111	61972	1
08/04/2024	270	AL270	28	08:00:00	16:09:59	28800	58199	1
08/04/2024	271	AL271	29	08:06:44	17:04:10	29204	61450	1
08/04/2024	272	AL272	30	08:03:00	17:01:32	28980	61292	1
08/04/2024	273	AL273	26	08:04:00	16:09:57	29040	58197	1
08/04/2024	274	AL274	24	08:03:39	16:10:00	29019	58200	1
08/04/2024	275	AL275	27	08:00:00	16:00:20	28800	57620	1
08/04/2024	276	AL276	23	08:04:42	17:10:42	29082	61842	1
08/04/2024	277	AL277	28	08:04:18	17:13:20	29058	62000	1
08/04/2024	278	AL278	28	08:03:45	17:14:55	29025	62095	1
08/04/2024	279	AL279	29	08:00:49	17:21:33	28849	62493	1
08/04/2024	280	AL280	28	08:00:00	17:04:41	28800	61481	1
08/04/2024	281	AL281	29	08:00:56	17:20:55	28856	62455	1
08/04/2024	282	AL282	29	08:00:14	16:03:56	28814	57836	1
08/04/2024	283	AL283	21	08:00:00	17:22:05	28800	62525	1
08/04/2024	284	AL284	28	08:00:00	17:24:40	28800	62680	1
08/04/2024	285	AL285	21	08:02:00	17:03:00	28920	61380	1
08/04/2024	286	AL286	24	08:00:57	17:06:51	28857	61611	1
08/04/2024	287	AL287	24	08:00:28	17:22:58	28828	62578	1
08/04/2024	288	AL288	24	08:03:17	17:18:30	28997	62310	2
08/04/2024	289	AL289	24	08:03:16	17:23:53	28996	62633	1
08/04/2024	290	AL290	24	08:00:00	17:24:32	28800	62672	1
08/04/2024	291	AL291	24	08:00:00	16:10:10	28800	58210	2
08/04/2024	292	AL292	24	08:00:07	17:19:58	28807	62398	2
08/04/2024	293	AL293	24	08:00:00	17:25:42	28800	62742	1
08/04/2024	294	AL294	24	08:00:18	17:13:22	28818	62002	1
08/04/2024	295	AL295	24	08:00:12	17:14:50	28812	62090	1
08/04/2024	296	AL296	24	08:00:00	17:02:27	28800	61347	1
08/04/2024	297	AL297	21	08:00:18	16:08:57	28818	58137	1
08/04/2024	298	AL298	21	08:00:00	17:12:44	28800	61964	1
08/04/2024	299	AL299	30	08:00:54	17:23:00	28854	62580	1
08/04/2024	300	AL300	21	08:00:50	17:06:20	28850	61580	1
08/04/2024	301	AL301	21	08:01:53	17:21:31	28913	62491	1
08/04/2024	302	AL302	21	08:00:18	17:23:10	28818	62590	1
08/04/2024	303	AL303	28	08:00:00	17:21:56	28800	62516	1
08/04/2024	304	AL304	28	08:00:56	16:00:22	28856	57622	1
08/04/2024	305	AL305	28	08:00:58	17:25:45	28858	62745	1
08/04/2024	306	AL306	28	08:01:44	16:13:03	28904	58383	1
08/04/2024	307	AL307	28	08:00:34	17:24:42	28834	62682	1
08/04/2024	308	AL308	28	08:00:52	17:22:02	28852	62522	1
08/04/2024	309	AL309	28	08:02:54	16:04:39	28974	57879	1
08/04/2024	310	AL310	28	08:01:50	17:10:39	28910	61839	1

08/04/2024	311	AL311	21	08:01:12	17:13:33	28872	62013	1
08/04/2024	312	AL312	21	08:00:48	16:03:49	28848	57829	1
08/04/2024	313	AL313	21	08:00:08	17:24:28	28808	62668	1
08/04/2024	314	AL314	21	08:00:18	17:20:51	28818	62451	1
08/04/2024	315	AL315	29	08:00:08	17:18:59	28808	62339	1
08/04/2024	316	AL316	29	08:01:08	17:25:41	28868	62741	1
08/04/2024	317	AL317	29	08:00:00	17:23:56	28800	62636	1
08/04/2024	318	AL318	29	08:01:19	16:04:23	28879	57863	1
08/04/2024	319	AL319	29	08:02:02	16:03:17	28922	57797	1
08/04/2024	320	AL320	29	08:01:02	17:14:57	28862	62097	1
08/04/2024	321	AL321	25	08:03:01	17:23:03	28981	62583	1
08/04/2024	322	AL322	26	08:00:00	16:02:35	28800	57755	1
08/04/2024	323	AL323	26	08:02:01	17:19:54	28921	62394	1
08/04/2024	324	AL324	21	08:04:04	16:02:37	29044	57757	1
08/04/2024	325	AL325	27	08:05:07	17:11:31	29107	61891	2
08/04/2024	326	AL326	26	08:04:09	17:04:38	29049	61478	2
08/04/2024	327	AL327	21	08:00:00	17:04:14	28800	61454	2
08/04/2024	328	AL328	26	08:04:11	16:20:05	29051	58805	1
08/04/2024	329	AL329	26	08:00:00	17:03:55	28800	61435	1
08/04/2024	330	AL330	26	08:02:22	16:15:57	28942	58557	1
08/04/2024	331	AL331	30	08:01:11	17:14:48	28871	62088	1
08/04/2024	332	AL332	21	08:02:11	17:12:39	28931	61959	1
08/04/2024	333	AL333	28	08:00:00	17:15:05	28800	62105	1
08/04/2024	334	AL334	21	08:01:22	17:15:01	28882	62101	1
08/04/2024	335	AL335	26	08:01:32	17:14:59	28892	62099	1
08/04/2024	336	AL336	26	08:00:00	16:13:10	28800	58390	1
08/04/2024	337	AL337	26	08:01:32	16:11:49	28892	58309	1
08/04/2024	338	AL338	26	08:00:00	16:04:40	28800	57880	1
08/04/2024	339	AL339	21	08:00:00	16:00:00	28800	57600	1
08/04/2024	340	AL340	28	08:00:00	16:00:00	28800	57600	1
08/04/2024	341	AL341	21	08:01:34	16:00:00	28894	57600	1
08/04/2024	342	AL342	26	08:00:00	16:00:00	28800	57600	1
08/04/2024	343	AL343	25	08:00:00	16:00:00	28800	57600	1
08/04/2024	344	AL344	25	08:01:43	17:13:43	28903	62023	1
08/04/2024	345	AL345	25	08:03:33	17:14:33	29013	62073	1
08/04/2024	346	AL346	25	08:03:53	16:11:57	29033	58317	1
08/04/2024	347	AL347	25	08:00:00	16:10:16	28800	58216	1
08/04/2024	348	AL348	25	08:03:35	16:04:11	29015	57851	1
08/04/2024	349	AL349	25	08:03:56	17:10:36	29036	61836	1
08/04/2024	350	AL350	25	08:00:00	16:08:40	28800	58120	1
08/04/2024	351	AL351	25	08:03:15	16:03:53	28995	57833	1
08/04/2024	352	AL352	25	08:00:00	17:01:44	28800	61304	1
08/04/2024	353	AL353	25	08:04:14	16:03:27	29054	57807	2
08/04/2024	354	AL354	26	08:00:00	16:04:29	28800	57869	1
08/04/2024	355	AL355	21	08:04:43	16:00:00	29083	57600	1

08/04/2024	356	AL356	26	08:00:00	16:03:42	28800	57822	2
08/04/2024	357	AL357	21	08:04:41	16:02:14	29081	57734	1
08/04/2024	358	AL358	26	08:04:17	16:00:00	29057	57600	1
08/04/2024	359	AL359	26	08:00:00	16:02:27	28800	57747	1
08/04/2024	360	AL360	26	08:04:16	17:15:08	29056	62108	1
08/04/2024	361	AL361	26	08:03:16	16:00:00	28996	57600	1
08/04/2024	362	AL362	21	08:00:00	16:03:01	28800	57781	1
08/04/2024	363	AL363	21	08:02:13	16:04:41	28933	57881	1
08/04/2024	364	AL364	26	08:02:31	17:06:44	28951	61604	1
08/04/2024	365	AL365	25	08:00:00	16:02:59	28800	57779	1
08/04/2024	366	AL366	26	08:02:34	17:14:29	28954	62069	1
08/04/2024	367	AL367	21	08:03:43	16:00:00	29023	57600	1
08/04/2024	368	AL368	25	08:00:00	16:13:19	28800	58399	1
08/04/2024	369	AL369	21	08:05:15	17:04:18	29115	61458	1
08/04/2024	370	AL370	25	08:05:34	17:13:53	29134	62033	1
08/04/2024	371	AL371	25	08:00:00	17:18:54	28800	62334	1
08/04/2024	372	AL372	25	08:05:43	16:11:59	29143	58319	1
08/04/2024	373	AL373	25	08:05:31	17:12:29	29131	61949	1
08/04/2024	374	AL374	26	08:00:02	17:04:22	28802	61462	1
08/04/2024	375	AL375	21	08:02:38	17:20:48	28958	62448	1
08/04/2024	376	AL376	25	08:02:28	17:10:30	28948	61830	1
08/04/2024	377	AL377	25	08:02:39	16:04:01	28959	57841	1
08/04/2024	378	AL378	25	08:00:04	16:03:00	28804	57780	1
08/04/2024	379	AL379	25	08:02:51	16:03:59	28971	57839	1
08/04/2024	380	AL380	25	08:00:06	16:00:00	28806	57600	1
08/04/2024	381	AL381	25	08:00:09	16:00:00	28809	57600	1
08/04/2024	382	AL382	25	08:00:18	16:00:00	28818	57600	1
08/04/2024	383	AL383	25	08:02:53	16:00:00	28973	57600	1
08/04/2024	384	AL384	25	08:02:58	16:00:00	28978	57600	1
08/04/2024	385	AL385	25	08:03:06	16:00:00	28986	57600	1
08/04/2024	386	AL386	21	08:00:00	16:00:00	28800	57600	1
08/04/2024	387	AL387	26	08:03:17	16:00:00	28997	57600	1
08/04/2024	388	AL388	26	08:00:00	16:00:00	28800	57600	1
08/04/2024	389	AL389	26	08:03:20	16:00:00	29000	57600	1
08/04/2024	390	AL390	26	08:03:40	17:01:27	29020	61287	1
08/04/2024	391	AL391	26	08:00:00	16:00:25	28800	57625	1
08/04/2024	392	AL392	26	08:00:00	17:15:10	28800	62110	1
08/04/2024	393	AL393	26	08:00:00	17:14:24	28800	62064	1
08/04/2024	394	AL394	26	08:03:30	16:04:42	29010	57882	1
08/04/2024	395	AL395	26	08:03:50	16:04:28	29030	57868	1
08/04/2024	396	AL396	26	08:00:00	16:00:00	28800	57600	1
08/04/2024	397	AL397	26	08:00:00	17:13:46	28800	62026	1
08/04/2024	398	AL398	26	08:00:00	16:00:00	28800	57600	1
08/04/2024	399	AL399	26	08:00:00	17:06:04	28800	61564	1
08/04/2024	400	AL400	23	08:04:00	16:00:00	29040	57600	1

08/04/2024	401	AL401	24	08:04:10	17:11:28	29050	61888	1
08/04/2024	402	AL402	23	08:04:20	16:00:00	29060	57600	1
08/04/2024	403	AL403	23	08:00:00	17:18:50	28800	62330	1
08/04/2024	404	AL404	21	08:00:00	16:00:00	28800	57600	1
08/04/2024	405	AL405	23	08:04:40	17:19:52	29080	62392	1
08/04/2024	406	AL406	24	08:04:50	16:03:11	29090	57791	1
08/04/2024	407	AL407	24	08:04:30	17:24:23	29070	62663	1
08/04/2024	408	AL408	24	08:05:00	16:04:02	29100	57842	1
08/04/2024	409	AL409	21	08:00:00	16:00:40	28800	57640	1
08/04/2024	410	AL410	25	08:05:10	17:15:12	29110	62112	1
08/04/2024	411	AL411	25	08:05:20	16:02:04	29120	57724	1
08/04/2024	412	AL412	21	08:00:00	17:04:11	28800	61451	1
08/04/2024	413	AL413	25	08:05:28	16:00:54	29128	57654	1
08/04/2024	414	AL414	25	08:00:00	16:00:45	28800	57645	1
08/04/2024	415	AL415	25	08:05:30	16:02:17	29130	57737	1
08/04/2024	416	AL416	25	08:00:00	16:00:00	28800	57600	1
08/04/2024	417	AL417	25	08:05:15	17:23:59	29115	62639	1
08/04/2024	418	AL418	25	08:05:25	16:00:00	29125	57600	1
08/04/2024	419	AL419	25	08:05:40	16:04:43	29140	57883	1
08/04/2024	420	AL420	25	08:05:45	16:00:00	29145	57600	1
08/04/2024	421	AL421	29	08:00:00	17:10:28	28800	61828	1
08/04/2024	422	AL422	25	08:05:55	17:11:33	29155	61893	1
08/04/2024	423	AL423	30	08:00:00	17:13:55	28800	62035	1
08/04/2024	424	AL424	25	08:05:50	17:04:30	29150	61470	1
08/04/2024	425	AL425	25	08:00:00	17:14:20	28800	62060	1
08/04/2024	426	AL426	21	08:02:15	17:06:42	28935	61602	1
08/04/2024	427	AL427	21	08:02:25	17:19:49	28945	62389	1
08/04/2024	428	AL428	21	08:00:00	17:06:00	28800	61560	1
08/04/2024	429	AL429	21	08:02:35	17:20:45	28955	62445	1
08/04/2024	430	AL430	23	08:00:00	17:05:59	28800	61559	1
08/04/2024	431	AL431	21	08:00:00	17:21:25	28800	62485	1
08/04/2024	432	AL432	24	08:02:45	16:03:04	28965	57784	1
08/04/2024	433	AL433	21	08:02:55	17:09:59	28975	61799	1
08/04/2024	434	AL434	24	08:00:00	16:08:51	28800	58131	1
08/04/2024	435	AL435	28	08:00:00	16:00:00	28800	57600	1
08/04/2024	436	AL436	23	08:00:00	17:24:01	28800	62641	1
08/04/2024	437	AL437	28	08:03:05	16:00:00	28985	57600	1
08/04/2024	438	AL438	22	08:03:15	17:24:44	28995	62684	1
08/04/2024	439	AL439	23	08:03:25	16:00:00	29005	57600	1
08/04/2024	440	AL440	22	08:00:00	17:25:44	28800	62744	1
08/04/2024	441	AL441	22	08:03:35	17:24:04	29015	62644	1
08/04/2024	442	AL442	26	08:00:00	17:03:49	28800	61429	1
08/04/2024	443	AL443	22	08:03:45	17:25:55	29025	62755	1
08/04/2024	444	AL444	26	08:00:00	17:04:26	28800	61466	1
08/04/2024	445	AL445	22	08:00:00	16:08:45	28800	58125	1

08/04/2024	446	AL446	22	08:00:00	17:24:50	28800	62690	1
08/04/2024	447	AL447	27	08:00:00	17:12:34	28800	61954	1
08/04/2024	448	AL448	22	08:03:55	17:24:15	29035	62655	1
08/04/2024	449	AL449	22	08:00:00	16:13:15	28800	58395	1
08/04/2024	450	AL450	22	08:00:00	17:24:08	28800	62648	1
08/04/2024	451	AL451	22	08:05:05	17:11:36	29105	61896	1
08/04/2024	452	AL452	29	08:00:00	17:15:15	28800	62115	1
08/04/2024	453	AL453	30	08:05:15	17:14:01	29115	62041	1
08/04/2024	454	AL454	28	08:05:25	17:00:09	29125	61209	1
08/04/2024	455	AL455	29	08:00:00	17:09:57	28800	61797	1
08/04/2024	456	AL456	22	08:05:35	17:13:59	29135	62039	1
08/04/2024	457	AL457	22	08:00:00	16:03:21	28800	57801	1
08/04/2024	458	AL458	22	08:05:45	16:03:32	29145	57812	1
08/04/2024	459	AL459	22	08:00:00	16:08:43	28800	58123	1
08/04/2024	460	AL460	22	08:00:00	16:02:45	28800	57765	1
08/04/2024	461	AL461	22	08:00:00	16:00:00	28800	57600	1
08/04/2024	462	AL462	22	08:00:00	16:00:00	28800	57600	1
08/04/2024	463	AL463	22	08:00:00	16:00:00	28800	57600	1
08/04/2024	464	AL464	22	08:00:00	16:03:47	28800	57827	1
08/04/2024	465	AL465	22	08:00:00	16:00:00	28800	57600	1
08/04/2024	466	AL466	22	08:00:00	16:00:00	28800	57600	1
08/04/2024	467	AL467	22	08:00:00	16:00:00	28800	57600	1
08/04/2024	468	AL468	21	08:00:00	17:05:57	28800	61557	1
08/04/2024	469	AL469	23	08:00:00	16:00:00	28800	57600	1
08/04/2024	470	AL470	23	08:00:00	17:10:24	28800	61824	1
08/04/2024	471	AL471	23	08:00:00	17:10:02	28800	61802	1
08/04/2024	472	AL472	23	08:00:00	16:02:07	28800	57727	1
08/04/2024	473	AL473	23	08:00:00	17:14:14	28800	62054	1
08/04/2024	474	AL474	23	08:00:00	17:15:18	28800	62118	1
08/04/2024	475	AL475	23	08:00:00	17:18:28	28800	62308	1
08/04/2024	476	AL476	23	08:00:00	16:10:22	28800	58222	1
08/04/2024	477	AL477	23	08:00:00	17:19:33	28800	62373	1
08/04/2024	478	AL478	23	08:00:00	17:11:40	28800	61900	1
08/04/2024	479	AL479	22	08:00:00	16:04:44	28800	57884	2
08/04/2024	480	AL480	22	08:00:00	17:24:13	28800	62653	2
08/04/2024	481	AL481	22	08:00:00	16:10:51	28800	58251	2
08/04/2024	482	AL482	23	08:00:00	17:14:07	28800	62047	2
08/04/2024	483	AL483	21	08:00:00	17:04:16	28800	61456	2
08/04/2024	484	AL484	30	08:05:55	17:10:20	29155	61820	1
08/04/2024	485	AL485	29	08:00:00	16:04:03	28800	57843	2
08/04/2024	486	AL486	21	08:00:00	16:02:53	28800	57773	1
08/04/2024	487	AL487	23	08:00:00	17:11:44	28800	61904	1
08/04/2024	488	AL488	28	08:06:05	17:12:25	29165	61945	1
08/04/2024	489	AL489	25	08:00:00	16:00:00	28800	57600	2
08/04/2024	490	AL490	25	08:00:00	16:00:00	28800	57600	2

08/04/2024	491	AL491	25	08:02:22	17:03:57	28942	61437	1
08/04/2024	492	AL492	25	08:00:00	16:00:00	28800	57600	2
08/04/2024	493	AL493	25	08:00:00	17:19:39	28800	62379	2
08/04/2024	494	AL494	29	08:02:42	16:02:49	28962	57769	1
08/04/2024	495	AL495	21	08:00:00	17:11:49	28800	61909	2
08/04/2024	496	AL496	22	08:00:00	16:03:57	28800	57837	2
08/04/2024	497	AL497	22	08:00:00	17:21:16	28800	62476	2
08/04/2024	498	AL498	25	08:02:52	16:03:08	28972	57788	1
08/04/2024	499	AL499	22	08:00:00	16:13:25	28800	58405	2
08/04/2024	500	AL500	23	08:00:00	17:09:55	28800	61795	2
08/04/2024	501	AL501	22	08:00:00	16:00:00	28800	57600	2
08/04/2024	502	AL502	22	08:00:00	17:18:25	28800	62305	1
08/04/2024	503	AL503	21	08:00:00	17:22:00	28800	62520	2
08/04/2024	504	AL504	21	08:00:00	17:06:54	28800	61614	2
08/04/2024	505	AL505	28	08:00:00	17:15:21	28800	62121	2
08/04/2024	506	AL506	28	08:00:00	17:24:20	28800	62660	1
08/04/2024	507	AL507	28	08:00:00	16:00:00	28800	57600	1
08/04/2024	508	AL508	28	08:00:00	17:03:47	28800	61427	2
08/04/2024	509	AL509	28	08:00:00	16:00:59	28800	57659	2
08/04/2024	510	AL510	28	08:00:00	16:00:00	28800	57600	1
08/04/2024	511	AL511	28	08:00:00	16:04:04	28800	57844	1
08/04/2024	512	AL512	28	08:00:00	16:00:00	28800	57600	1
08/04/2024	513	AL513	28	08:02:32	16:00:00	28952	57600	1
08/04/2024	514	AL514	28	08:01:32	16:00:00	28892	57600	1
08/04/2024	515	AL515	21	08:00:00	16:08:21	28800	58101	1
08/04/2024	516	AL516	25	08:01:42	16:00:00	28902	57600	1
08/04/2024	517	AL517	21	08:00:00	17:01:22	28800	61282	1
08/04/2024	518	AL518	29	08:01:52	17:19:47	28912	62387	1
08/04/2024	519	AL519	21	08:00:00	17:12:08	28800	61928	1
08/04/2024	520	AL520	25	08:00:00	16:00:00	28800	57600	1
08/04/2024	521	AL521	30	08:01:03	16:00:00	28863	57600	1
08/04/2024	522	AL522	21	08:00:00	16:00:00	28800	57600	2
08/04/2024	523	AL523	21	08:01:13	17:24:55	28873	62695	1
08/04/2024	524	AL524	23	08:01:23	17:09:53	28883	61793	1
08/04/2024	525	AL525	23	08:00:00	17:21:11	28800	62471	2
08/04/2024	526	AL526	23	08:01:33	17:05:55	28893	61555	1
08/04/2024	527	AL527	23	08:00:00	17:21:20	28800	62480	2
08/04/2024	528	AL528	23	08:00:00	16:02:43	28800	57763	2
08/04/2024	529	AL529	23	08:00:00	17:20:43	28800	62443	1
08/04/2024	530	AL530	23	08:00:00	17:04:13	28800	61453	2
08/04/2024	531	AL531	23	08:00:00	17:18:22	28800	62302	2
08/04/2024	532	AL532	23	08:00:00	16:03:31	28800	57811	2
08/04/2024	533	AL533	23	08:01:43	17:19:26	28903	62366	1
08/04/2024	534	AL534	23	08:00:00	16:03:14	28800	57794	1
08/04/2024	535	AL535	23	08:00:00	17:11:50	28800	61910	2

08/04/2024	536	AL536	21	08:00:00	17:15:25	28800	62125	2
08/04/2024	537	AL537	30	08:01:53	17:20:40	28913	62440	1
08/04/2024	538	AL538	30	08:00:00	16:01:15	28800	57675	2
08/04/2024	539	AL539	27	08:00:00	16:03:01	28800	57781	1
08/04/2024	540	AL540	27	08:00:00	16:00:00	28800	57600	1
08/04/2024	541	AL541	27	08:01:24	16:00:00	28884	57600	1
08/04/2024	542	AL542	21	08:00:00	16:00:00	28800	57600	1
08/04/2024	543	AL543	21	08:00:00	16:00:00	28800	57600	2
08/04/2024	544	AL544	21	08:00:00	16:00:00	28800	57600	2
08/04/2024	545	AL545	21	08:00:00	16:00:00	28800	57600	2
08/04/2024	546	AL546	21	08:00:00	16:00:00	28800	57600	2
08/04/2024	547	AL547	27	08:00:00	16:02:56	28800	57776	2
08/04/2024	548	AL548	27	08:00:00	16:04:27	28800	57867	2
08/04/2024	549	AL549	26	08:00:00	17:04:35	28800	61475	2
08/04/2024	550	AL550	26	08:00:00	16:00:00	28800	57600	2
08/04/2024	551	AL551	21	08:01:34	16:00:00	28894	57600	1
08/04/2024	552	AL552	26	08:01:44	16:04:53	28904	57893	1
08/04/2024	553	AL553	29	08:00:00	16:00:00	28800	57600	1
08/04/2024	554	AL554	29	08:01:54	17:06:57	28914	61617	1
08/04/2024	555	AL555	29	08:00:00	16:00:00	28800	57600	1
08/04/2024	556	AL556	29	08:01:06	17:07:37	28866	61657	1
08/04/2024	557	AL557	29	08:01:16	16:00:00	28876	57600	1
08/04/2024	558	AL558	29	08:00:00	17:08:56	28800	61736	2
08/04/2024	559	AL559	29	08:00:00	16:02:38	28800	57758	2
08/04/2024	560	AL560	29	08:01:26	17:04:00	28886	61440	1
08/04/2024	561	AL561	29	08:00:00	17:05:53	28800	61553	2
08/04/2024	562	AL562	29	08:00:00	17:03:59	28800	61439	2
08/04/2024	563	AL563	29	08:01:36	17:09:50	28896	61790	1
08/04/2024	564	AL564	21	08:01:46	17:16:06	28906	62166	1
08/04/2024	565	AL565	21	08:00:00	16:00:00	28800	57600	2
08/04/2024	566	AL566	28	08:00:00	17:16:56	28800	62216	1
08/04/2024	567	AL567	28	08:00:00	16:00:00	28800	57600	2
08/04/2024	568	AL568	21	08:00:00	16:10:41	28800	58241	2
08/04/2024	569	AL569	21	08:00:00	17:03:40	28800	61420	2
08/04/2024	570	AL570	27	08:01:56	17:18:17	28916	62297	1
08/04/2024	571	AL571	28	08:01:07	17:10:18	28867	61818	1
08/04/2024	572	AL572	27	08:00:00	17:19:29	28800	62369	1
08/04/2024	573	AL573	27	08:00:00	16:00:00	28800	57600	2
08/04/2024	574	AL574	27	08:00:00	16:00:00	28800	57600	2
08/04/2024	575	AL575	27	08:00:00	16:00:00	28800	57600	2
08/04/2024	576	AL576	27	08:00:00	17:07:35	28800	61655	1
08/04/2024	577	AL577	27	08:00:00	16:01:01	28800	57661	2
08/04/2024	578	AL578	21	08:00:00	17:08:53	28800	61733	2
08/04/2024	579	AL579	21	08:00:00	17:06:39	28800	61599	1
08/04/2024	580	AL580	29	08:00:00	17:04:20	28800	61460	1

08/04/2024	581	AL581	30	08:00:00	17:09:48	28800	61788	2
08/04/2024	582	AL582	21	08:00:00	16:03:24	28800	57804	1
08/04/2024	583	AL583	29	08:00:00	16:04:51	28800	57891	2
08/04/2024	584	AL584	21	08:00:00	16:00:00	28800	57600	2
08/04/2024	585	AL585	30	08:00:00	17:11:52	28800	61912	1
08/04/2024	586	AL586	30	08:01:27	16:00:00	28887	57600	1
08/04/2024	587	AL587	30	08:01:37	16:13:40	28897	58420	1
08/04/2024	588	AL588	30	08:00:00	16:03:18	28800	57798	1
08/04/2024	589	AL589	30	08:00:00	16:00:00	28800	57600	2
08/04/2024	590	AL590	30	08:00:00	17:16:00	28800	62160	2
08/04/2024	591	AL591	30	08:01:47	16:00:00	28907	57600	1
08/04/2024	592	AL592	21	08:00:00	17:16:52	28800	62212	2
08/04/2024	593	AL593	30	08:01:18	17:16:58	28878	62218	1
08/04/2024	594	AL594	26	08:00:00	16:00:00	28800	57600	2
08/04/2024	595	AL595	27	08:01:28	17:05:51	28888	61551	1
08/04/2024	596	AL596	26	08:01:38	17:08:14	28898	61694	1
08/04/2024	597	AL597	26	08:00:00	16:00:00	28800	57600	1
08/04/2024	598	AL598	25	08:01:48	16:10:20	28908	58220	1
08/04/2024	599	AL599	25	08:01:58	16:00:00	28918	57600	1
08/04/2024	600	AL600	25	08:00:00	16:00:00	28800	57600	2
08/04/2024	601	AL601	25	08:00:00	17:03:35	28800	61415	2
08/04/2024	602	AL602	21	08:00:00	16:00:00	28800	57600	1
08/04/2024	603	AL603	29	08:00:00	17:01:47	28800	61307	1
08/04/2024	604	AL604	29	08:00:00	16:01:11	28800	57671	2
08/04/2024	605	AL605	29	08:00:00	16:00:00	28800	57600	2
08/04/2024	606	AL606	21	08:00:00	17:07:38	28800	61658	22
08/04/2024	607	AL607	21	08:00:00	16:01:20	28800	57680	2
08/04/2024	608	AL608	23	08:00:00	16:04:55	28800	57895	2
08/04/2024	609	AL609	22	08:00:00	16:01:31	28800	57691	1
08/04/2024	610	AL610	23	08:00:00	16:02:33	28800	57753	2
08/04/2024	611	AL611	23	08:00:00	16:03:34	28800	57814	2
08/04/2024	612	AL612	23	08:00:00	16:01:51	28800	57711	2
08/04/2024	613	AL613	22	08:00:00	16:00:00	28800	57600	2
08/04/2024	614	AL614	22	08:01:09	17:08:58	28869	61738	1
08/04/2024	615	AL615	30	08:01:19	16:00:00	28879	57600	1
08/04/2024	616	AL616	27	08:00:00	17:07:31	28800	61651	2
08/04/2024	617	AL617	21	08:00:00	17:09:44	28800	61784	1
08/04/2024	618	AL618	23	08:00:00	17:11:55	28800	61915	2
08/04/2024	619	AL619	23	08:00:00	17:10:04	28800	61804	1
08/04/2024	620	AL620	23	08:00:00	17:08:12	28800	61692	2
08/04/2024	621	AL621	21	08:00:00	17:16:49	28800	62209	1
08/04/2024	622	AL622	21	08:00:00	16:02:39	28800	57759	1
08/04/2024	623	AL623	23	08:00:00	16:00:00	28800	57600	2
08/04/2024	624	AL624	25	08:00:00	16:00:00	28800	57600	2
08/04/2024	625	AL625	23	08:00:00	16:00:00	28800	57600	2

08/04/2024	626	AL626	21	08:00:00	16:00:00	28800	57600	2
08/04/2024	627	AL627	23	08:00:00	16:00:00	28800	57600	1
08/04/2024	628	AL628	24	08:00:00	16:00:00	28800	57600	2
08/04/2024	629	AL629	25	08:00:00	16:00:00	28800	57600	22
08/04/2024	630	AL630	29	08:01:29	16:00:00	28889	57600	1
08/04/2024	631	AL631	27	08:01:39	17:07:01	28899	61621	1
08/04/2024	632	AL632	26	08:01:49	17:08:50	28909	61730	1
08/04/2024	633	AL633	25	08:01:59	17:05:47	28919	61547	1
08/04/2024	634	AL634	25	08:04:04	16:02:38	29044	57758	1
08/04/2024	635	AL635	25	08:04:14	17:09:00	29054	61740	1
08/04/2024	636	AL636	25	08:00:00	17:09:10	28800	61750	2
08/04/2024	637	AL637	25	08:00:00	16:04:26	28800	57866	2
08/04/2024	638	AL638	22	08:04:24	16:04:25	29064	57865	1
08/04/2024	639	AL639	21	08:00:00	17:04:37	28800	61477	2
08/04/2024	640	AL640	25	08:04:34	17:04:16	29074	61456	1
08/04/2024	641	AL641	25	08:00:00	16:08:11	28800	58091	2
08/04/2024	642	AL642	24	08:04:44	17:11:58	29084	61918	1
08/04/2024	643	AL643	24	08:04:54	17:16:43	29094	62203	1
08/04/2024	644	AL644	21	08:00:00	17:07:30	28800	61650	1
08/04/2024	645	AL645	24	08:04:05	17:09:07	29045	61747	1
08/04/2024	646	AL646	21	08:05:16	17:17:01	29116	62221	1
08/04/2024	647	AL647	21	08:00:00	17:08:08	28800	61688	1
08/04/2024	648	AL648	21	08:00:00	17:15:57	28800	62157	2
08/04/2024	649	AL649	21	08:00:00	16:03:41	28800	57821	2
08/04/2024	650	AL650	21	08:00:00	17:10:07	28800	61807	2
08/04/2024	651	AL651	21	08:00:00	17:17:07	28800	62227	2
08/04/2024	652	AL652	25	08:00:00	16:02:23	28800	57743	1
08/04/2024	653	AL653	25	08:04:26	17:16:12	29066	62172	1
08/04/2024	654	AL654	25	08:06:36	16:10:30	29196	58230	1
08/04/2024	655	AL655	25	08:06:46	16:10:55	29206	58255	1
08/04/2024	656	AL656	21	08:00:00	17:08:19	28800	61699	2
08/04/2024	657	AL657	21	08:00:00	17:07:42	28800	61662	2
08/04/2024	658	AL658	25	08:06:56	16:04:50	29216	57890	1
08/04/2024	659	AL659	25	08:00:00	16:04:56	28800	57896	2
08/04/2024	660	AL660	29	08:06:01	17:01:49	29161	61309	1
08/04/2024	661	AL661	25	08:00:00	16:00:00	28800	57600	1
08/04/2024	662	AL662	25	08:06:11	16:00:00	29171	57600	1
08/04/2024	663	AL663	25	08:06:26	16:00:00	29186	57600	1
08/04/2024	664	AL664	24	08:06:36	16:00:00	29196	57600	2
08/04/2024	665	AL665	21	08:00:00	16:00:00	28800	57600	2
08/04/2024	666	AL666	21	08:00:00	17:09:16	28800	61756	1
08/04/2024	667	AL667	27	08:00:00	16:02:13	28800	57733	2
08/04/2024	668	AL668	27	08:00:00	17:09:41	28800	61781	1
08/04/2024	669	AL669	27	08:00:00	17:12:00	28800	61920	2
08/04/2024	670	AL670	27	08:00:00	17:08:47	28800	61727	1

08/04/2024	671	AL671	21	08:00:00	17:15:52	28800	62152	2
08/04/2024	672	AL672	24	08:00:00	17:17:10	28800	62230	2
08/04/2024	673	AL673	25	08:00:00	17:07:29	28800	61649	1
08/04/2024	674	AL674	21	08:00:00	16:00:00	28800	57600	1
08/04/2024	675	AL675	29	08:00:00	16:00:00	28800	57600	2
08/04/2024	676	AL676	21	08:00:00	16:08:19	28800	58099	2
08/04/2024	677	AL677	21	08:00:00	16:00:00	28800	57600	2
08/04/2024	678	AL678	21	08:00:00	17:10:10	28800	61810	2
08/04/2024	679	AL679	21	08:00:00	17:03:30	28800	61410	2
08/04/2024	680	AL680	26	08:00:00	17:12:12	28800	61932	2
08/04/2024	681	AL681	25	08:00:00	17:04:40	28800	61480	2
08/04/2024	682	AL682	22	08:00:00	16:02:06	28800	57726	2
08/04/2024	683	AL683	22	08:00:00	16:00:00	28800	57600	2
08/04/2024	684	AL684	21	08:00:00	16:00:00	28800	57600	2
08/04/2024	685	AL685	21	08:00:00	16:00:00	28800	57600	2
08/04/2024	686	AL686	29	08:06:46	16:00:00	29206	57600	1
08/04/2024	687	AL687	29	08:00:00	16:02:55	28800	57775	1
08/04/2024	688	AL688	29	08:06:56	16:01:42	29216	57702	1
08/04/2024	689	AL689	29	08:05:01	17:07:40	29101	61660	1
08/04/2024	690	AL690	29	08:05:11	17:08:04	29111	61684	1
08/04/2024	691	AL691	29	08:05:21	17:01:55	29121	61315	1
08/04/2024	692	AL692	29	08:00:00	16:10:59	28800	58259	2
08/04/2024	693	AL693	29	08:05:31	16:03:51	29131	57831	1
08/04/2024	694	AL694	29	08:05:41	16:03:02	29141	57782	1
08/04/2024	695	AL695	29	08:00:00	16:00:00	28800	57600	2
08/04/2024	696	AL696	21	08:00:00	17:07:27	28800	61647	2
08/04/2024	697	AL697	30	08:05:51	16:00:00	29151	57600	1
08/04/2024	698	AL698	30	08:05:07	17:16:46	29107	62206	1
08/04/2024	699	AL699	21	08:00:00	16:00:00	28800	57600	2
08/04/2024	700	AL700	30	08:00:00	16:02:52	28800	57772	2
08/04/2024	701	AL701	30	08:05:17	17:02:03	29117	61323	1
08/04/2024	702	AL702	30	08:00:00	17:09:12	28800	61752	1
08/04/2024	703	AL703	30	08:00:00	16:00:00	28800	57600	2
08/04/2024	704	AL704	30	08:00:00	17:15:49	28800	62149	2
08/04/2024	705	AL705	30	08:00:00	16:04:57	28800	57897	2
08/04/2024	706	AL706	29	08:05:37	17:17:17	29137	62237	1
08/04/2024	707	AL707	29	08:05:47	16:03:12	29147	57792	1
08/04/2024	708	AL708	21	08:00:00	16:03:44	28800	57824	2
08/04/2024	709	AL709	27	08:05:57	16:05:05	29157	57905	1
08/04/2024	710	AL710	21	08:00:00	17:00:16	28800	61216	2
08/04/2024	711	AL711	30	08:05:09	16:06:02	29109	57962	1
08/04/2024	712	AL712	24	08:00:00	16:05:07	28800	57907	2
08/04/2024	713	AL713	29	08:05:19	17:08:23	29119	61703	1
08/04/2024	714	AL714	21	08:00:00	16:04:15	28800	57855	2
08/04/2024	715	AL715	24	08:05:29	16:01:12	29129	57672	1

08/04/2024	716	AL716	24	08:05:29	17:02:00	29129	61320	1
08/04/2024	717	AL717	24	08:00:00	16:02:48	28800	57768	2
08/04/2024	718	AL718	27	08:00:00	16:02:42	28800	57762	1
08/04/2024	719	AL719	27	08:05:39	17:01:58	29139	61318	1
08/04/2024	720	AL720	27	08:05:49	16:01:22	29149	57682	1
08/04/2024	721	AL721	27	08:00:00	16:03:28	28800	57808	2
08/04/2024	722	AL722	26	08:00:00	16:00:00	28800	57600	2
08/04/2024	723	AL723	28	08:00:00	17:02:10	28800	61330	2
08/04/2024	724	AL724	29	08:05:59	16:05:58	29159	57958	1
08/04/2024	725	AL725	30	08:00:00	17:07:03	28800	61623	2
08/04/2024	726	AL726	30	08:05:07	16:04:19	29107	57859	1
08/04/2024	727	AL727	24	08:05:17	16:06:10	29117	57970	1
08/04/2024	728	AL728	23	08:00:00	17:07:53	28800	61673	2
08/04/2024	729	AL729	24	08:00:00	16:03:45	28800	57825	2
08/04/2024	730	AL730	24	08:00:00	16:02:29	28800	57749	2
08/04/2024	731	AL731	21	08:00:00	16:00:00	28800	57600	1
08/04/2024	732	AL732	21	08:00:00	16:00:00	28800	57600	1
08/04/2024	733	AL733	21	08:00:00	16:00:00	28800	57600	2
08/04/2024	734	AL734	24	08:00:00	16:00:00	28800	57600	2
08/04/2024	735	AL735	24	08:00:00	16:00:00	28800	57600	2
08/04/2024	736	AL736	24	08:00:00	16:00:00	28800	57600	2
08/04/2024	737	AL737	21	08:00:00	16:02:16	28800	57736	2
08/04/2024	738	AL738	30	08:00:00	16:01:32	28800	57692	2
08/04/2024	739	AL739	21	08:00:00	16:03:54	28800	57834	2
08/04/2024	740	AL740	21	08:00:00	16:02:46	28800	57766	2
08/04/2024	741	AL741	24	08:00:00	16:04:59	28800	57899	2
08/04/2024	742	AL742	24	08:00:00	16:02:32	28800	57752	1
08/04/2024	743	AL743	24	08:00:00	16:05:00	28800	57900	2
08/04/2024	744	AL744	24	08:00:00	16:04:49	28800	57889	1
08/04/2024	745	AL745	21	08:00:00	16:08:08	28800	58088	2
08/04/2024	746	AL746	21	08:00:00	17:03:27	28800	61407	1
08/04/2024	747	AL747	22	08:05:27	16:06:00	29127	57960	1
08/04/2024	748	AL748	22	08:05:37	17:05:44	29137	61544	1
08/04/2024	749	AL749	22	08:05:47	16:05:53	29147	57953	1
08/04/2024	750	AL750	22	08:05:57	17:09:19	29157	61759	1
08/04/2024	751	AL751	24	08:07:01	16:14:05	29221	58445	1
08/04/2024	752	AL752	24	08:07:11	16:03:05	29231	57785	1
08/04/2024	753	AL753	25	08:07:21	17:07:58	29241	61678	1
08/04/2024	754	AL754	25	08:07:31	17:16:10	29251	62170	1
08/04/2024	755	AL755	25	08:06:41	16:03:22	29201	57802	1
08/04/2024	756	AL756	30	08:00:00	16:04:20	28800	57860	1
08/04/2024	757	AL757	21	08:00:00	16:20:53	28800	58853	1
08/04/2024	758	AL758	24	08:00:00	17:17:30	28800	62250	2
08/04/2024	759	AL759	25	08:01:00	17:10:12	28860	61812	2
08/04/2024	760	AL760	21	08:00:00	16:02:26	28800	57746	2

08/04/2024	761	AL761	27	08:00:00	16:00:00	28800	57600	2
08/04/2024	762	AL762	21	08:00:00	16:02:22	28800	57742	2
08/04/2024	763	AL763	30	08:00:00	16:14:57	28800	58497	2
08/04/2024	764	AL764	21	08:00:00	16:15:00	28800	58500	2
08/04/2024	765	AL765	27	08:00:00	16:00:00	28800	57600	2
08/04/2024	766	AL766	25	08:00:00	17:07:06	28800	61626	1
08/04/2024	767	AL767	21	08:00:00	16:01:13	28800	57673	1
08/04/2024	768	AL768	25	08:07:51	16:00:00	29271	57600	1
08/04/2024	769	AL769	21	08:00:00	17:09:24	28800	61764	2
08/04/2024	770	AL770	21	08:00:00	17:08:38	28800	61718	2
08/04/2024	771	AL771	21	08:00:00	16:00:00	28800	57600	2
08/04/2024	772	AL772	27	08:00:00	16:00:00	28800	57600	2
08/04/2024	773	AL773	27	08:00:00	16:00:00	28800	57600	2
08/04/2024	774	AL774	21	08:00:00	16:00:00	28800	57600	2
08/04/2024	775	AL775	27	08:00:00	16:03:38	28800	57818	2
08/04/2024	776	AL776	21	08:01:21	16:15:05	28881	58505	1
08/04/2024	777	AL777	27	08:00:00	17:04:25	28800	61465	2
08/04/2024	778	AL778	21	08:00:00	16:00:00	28800	57600	2
08/04/2024	779	AL779	27	08:01:31	16:05:55	28891	57955	1
08/04/2024	780	AL780	27	08:01:41	16:00:00	28901	57600	1
08/04/2024	781	AL781	27	08:00:00	16:00:00	28800	57600	2
08/04/2024	782	AL782	27	08:00:00	16:00:00	28800	57600	2
08/04/2024	783	AL783	21	08:00:00	17:05:23	28800	61523	2
08/04/2024	784	AL784	30	08:00:00	17:15:45	28800	62145	1
08/04/2024	785	AL785	30	08:00:00	17:08:00	28800	61680	2
08/04/2024	786	AL786	21	08:00:00	17:17:35	28800	62255	1
08/04/2024	787	AL787	21	08:00:00	17:07:24	28800	61644	2
08/04/2024	788	AL788	30	08:01:51	16:01:43	28911	57703	1
08/04/2024	789	AL789	21	08:00:00	16:04:14	28800	57854	2
08/04/2024	790	AL790	21	08:00:00	17:20:37	28800	62437	2
08/04/2024	791	AL791	21	08:00:00	17:08:10	28800	61690	1
08/04/2024	792	AL792	21	08:00:00	16:04:13	28800	57853	1
08/04/2024	793	AL793	29	08:00:00	17:03:22	28800	61402	2
08/04/2024	794	AL794	28	08:00:00	17:16:19	28800	62179	2
08/04/2024	795	AL795	29	08:00:00	16:00:00	28800	57600	2
08/04/2024	796	AL796	28	08:00:00	16:03:35	28800	57815	1
08/04/2024	797	AL797	29	08:00:00	17:19:15	28800	62355	1
08/04/2024	798	AL798	29	08:01:02	17:20:20	28862	62420	1
08/04/2024	799	AL799	29	08:01:12	17:16:36	28872	62196	1
08/04/2024	800	AL800	22	08:00:00	17:04:28	28800	61468	2
08/04/2024	801	AL801	22	08:00:00	17:05:14	28800	61514	2
08/04/2024	802	AL802	22	08:00:00	16:00:00	28800	57600	2
08/04/2024	803	AL803	22	08:01:22	16:01:53	28882	57713	1
08/04/2024	804	AL804	22	08:00:00	17:08:45	28800	61725	2
08/04/2024	805	AL805	23	08:01:32	16:00:00	28892	57600	1

08/04/2024	806	AL806	23	08:01:42	16:00:00	28902	57600	1
08/04/2024	807	AL807	23	08:00:00	16:00:00	28800	57600	1
08/04/2024	808	AL808	23	08:00:00	16:00:00	28800	57600	2
08/04/2024	809	AL809	21	08:00:00	17:09:33	28800	61773	2
08/04/2024	810	AL810	21	08:00:00	17:09:28	28800	61768	2
08/04/2024	811	AL811	21	08:00:00	17:19:36	28800	62376	1
08/04/2024	812	AL812	23	08:00:00	16:06:12	28800	57972	1
08/04/2024	813	AL813	23	08:00:00	16:00:00	28800	57600	2
08/04/2024	814	AL814	21	08:00:00	17:18:00	28800	62280	2
08/04/2024	815	AL815	21	08:00:00	16:05:11	28800	57911	2
08/04/2024	816	AL816	24	08:00:00	16:00:00	28800	57600	2
08/04/2024	817	AL817	24	08:00:00	16:05:50	28800	57950	2
08/04/2024	818	AL818	24	08:00:00	17:07:09	28800	61629	2
08/04/2024	819	AL819	30	08:00:00	16:00:00	28800	57600	2
08/04/2024	820	AL820	21	08:00:00	16:00:00	28800	57600	2
08/04/2024	821	AL821	27	08:00:00	16:06:38	28800	57998	2
08/04/2024	822	AL822	27	08:02:52	17:02:14	28972	61334	1
08/04/2024	823	AL823	27	08:01:03	17:17:58	28863	62278	1
08/04/2024	824	AL824	24	08:00:00	16:08:01	28800	58081	2
08/04/2024	825	AL825	24	08:01:13	17:18:05	28873	62285	1
08/04/2024	826	AL826	21	08:00:00	16:01:23	28800	57683	1
08/04/2024	827	AL827	21	08:01:23	16:04:48	28883	57888	1
08/04/2024	828	AL828	21	08:00:00	17:20:27	28800	62427	3
08/04/2024	829	AL829	21	08:01:33	17:20:34	28893	62434	1
08/04/2024	830	AL830	21	08:00:00	17:09:39	28800	61779	2
08/04/2024	831	AL831	21	08:00:00	17:05:26	28800	61526	2
08/04/2024	832	AL832	21	08:01:43	16:14:50	28903	58490	1
08/04/2024	833	AL833	21	08:00:00	16:06:02	28800	57962	2
08/04/2024	834	AL834	30	08:01:53	17:04:30	28913	61470	1
08/04/2024	835	AL835	30	08:01:14	16:00:00	28874	57600	1
08/04/2024	836	AL836	30	08:00:00	16:00:00	28800	57600	2
08/04/2024	837	AL837	30	08:01:24	16:00:00	28884	57600	1
08/04/2024	838	AL838	30	08:01:34	16:00:00	28894	57600	1
08/04/2024	839	AL839	30	08:01:44	17:07:21	28904	61641	1
08/04/2024	840	AL840	30	08:00:00	16:05:15	28800	57915	1
08/04/2024	841	AL841	25	08:00:00	17:08:43	28800	61723	1
08/04/2024	842	AL842	27	08:00:00	16:01:33	28800	57693	2
08/04/2024	843	AL843	27	08:00:00	16:06:40	28800	58000	2
08/04/2024	844	AL844	27	08:00:00	16:07:54	28800	58074	2
08/04/2024	845	AL845	27	08:01:54	17:04:52	28914	61492	1
08/04/2024	846	AL846	27	08:00:51	16:14:15	28851	58455	1
08/04/2024	847	AL847	30	08:00:00	17:16:34	28800	62194	2
08/04/2024	848	AL848	30	08:01:16	17:17:55	28876	62275	1
08/04/2024	849	AL849	21	08:00:00	16:06:20	28800	57980	2
08/04/2024	850	AL850	28	08:01:36	17:19:41	28896	62381	1

08/04/2024	851	AL851	28	08:02:06	16:02:36	28926	57756	1
08/04/2024	852	AL852	28	08:01:46	16:00:00	28906	57600	1
08/04/2024	853	AL853	28	08:01:56	17:07:11	28916	61631	1
08/04/2024	854	AL854	28	08:01:07	17:15:40	28867	62140	1
08/04/2024	855	AL855	21	08:00:00	16:06:44	28800	58004	2
08/04/2024	856	AL856	29	08:01:17	16:07:00	28877	58020	1
08/04/2024	857	AL857	22	08:01:27	16:00:00	28887	57600	1
08/04/2024	858	AL858	30	08:01:37	16:00:00	28897	57600	1
08/04/2024	859	AL859	22	08:01:47	16:00:00	28907	57600	1
08/04/2024	860	AL860	21	08:01:57	16:00:00	28917	57600	1
08/04/2024	861	AL861	23	08:00:00	16:00:00	28800	57600	2
08/04/2024	862	AL862	30	08:01:08	16:06:07	28868	57967	1
08/04/2024	863	AL863	23	08:01:18	16:06:50	28878	58010	1
08/04/2024	864	AL864	30	08:01:28	16:07:09	28888	58029	1
08/04/2024	865	AL865	23	08:01:38	16:01:43	28898	57703	1
08/04/2024	866	AL866	23	08:00:00	16:06:58	28800	58018	2
08/04/2024	867	AL867	23	08:01:48	16:07:50	28908	58070	1
08/04/2024	868	AL868	30	08:01:58	16:14:47	28918	58487	1
08/04/2024	869	AL869	23	08:00:00	16:15:20	28800	58520	2
08/04/2024	870	AL870	30	08:01:09	17:04:33	28869	61473	1
08/04/2024	871	AL871	22	08:01:00	16:07:47	28860	58067	1
08/04/2024	872	AL872	22	08:00:29	16:00:00	28829	57600	1
08/04/2024	873	AL873	21	08:00:00	17:15:28	28800	62128	2
08/04/2024	874	AL874	22	08:01:39	16:07:40	28899	58060	1
08/04/2024	875	AL875	30	08:01:49	17:07:18	28909	61638	1
08/04/2024	876	AL876	22	08:01:59	17:08:29	28919	61709	1
08/04/2024	877	AL877	22	08:02:01	16:00:00	28921	57600	1
08/04/2024	878	AL878	22	08:02:11	16:05:24	28931	57924	1
08/04/2024	879	AL879	22	08:02:21	16:05:26	28941	57926	1
08/04/2024	880	AL880	21	08:02:31	16:02:51	28951	57771	1
08/04/2024	881	AL881	27	08:02:41	16:02:02	28961	57722	1
08/04/2024	882	AL882	27	08:02:51	16:00:00	28971	57600	1
08/04/2024	883	AL883	27	08:00:00	16:00:00	28800	57600	1
08/04/2024	884	AL884	21	08:00:00	16:00:00	28800	57600	1
08/04/2024	885	AL885	22	08:02:12	16:02:58	28932	57778	1
08/04/2024	886	AL886	23	08:00:00	16:02:09	28800	57729	1
08/04/2024	887	AL887	21	08:00:00	16:05:18	28800	57918	2
08/04/2024	888	AL888	21	08:02:32	17:01:12	28952	61272	1
08/04/2024	889	AL889	27	08:02:42	17:02:24	28962	61344	1
08/04/2024	890	AL890	27	08:02:52	16:01:53	28972	57713	1
08/04/2024	891	AL891	21	08:00:00	16:15:18	28800	58518	1
08/04/2024	892	AL892	25	08:03:03	16:02:12	28983	57732	1
08/04/2024	893	AL893	25	08:03:13	17:05:11	28993	61511	1
08/04/2024	894	AL894	25	08:03:23	16:10:21	29003	58221	1
08/04/2024	895	AL895	25	08:03:33	17:15:34	29013	62134	1

08/04/2024	896	AL896	25	08:03:43	17:17:50	29023	62270	1
08/04/2024	897	AL897	25	08:00:00	17:16:25	28800	62185	2
08/04/2024	898	AL898	30	08:03:53	17:19:44	29033	62384	1
08/04/2024	899	AL899	30	08:03:04	17:18:37	28984	62317	1
08/04/2024	900	AL900	30	08:00:10	16:02:19	28810	57739	1
08/04/2024	901	AL901	30	08:03:24	16:05:33	29004	57933	1
08/04/2024	902	AL902	30	08:00:00	17:03:15	28800	61395	2
08/04/2024	903	AL903	30	08:03:34	16:00:00	29014	57600	1
08/04/2024	904	AL904	30	08:03:44	16:00:00	29024	57600	1
08/04/2024	905	AL905	21	08:00:00	16:00:00	28800	57600	2
08/04/2024	906	AL906	22	08:00:00	17:15:30	28800	62130	1
08/04/2024	907	AL907	24	08:00:00	16:04:16	28800	57856	2
08/04/2024	908	AL908	21	08:00:00	16:07:37	28800	58057	1
08/04/2024	909	AL909	22	08:00:00	16:01:07	28800	57667	2
08/04/2024	910	AL910	21	08:00:00	17:00:19	28800	61219	2
08/04/2024	911	AL911	21	08:00:00	17:07:13	28800	61633	2
08/04/2024	912	AL912	27	08:00:00	16:05:29	28800	57929	2
08/04/2024	913	AL913	27	08:00:00	17:05:10	28800	61510	2
08/04/2024	914	AL914	27	08:00:00	16:02:41	28800	57761	2
08/04/2024	915	AL915	27	08:00:00	17:05:42	28800	61542	2
08/04/2024	916	AL916	27	08:00:00	17:19:19	28800	62359	2
08/04/2024	917	AL917	27	08:00:00	17:05:30	28800	61530	2
08/04/2024	918	AL918	27	08:03:54	16:04:47	29034	57887	1
08/04/2024	919	AL919	27	08:03:06	17:18:40	28986	62320	1
08/04/2024	920	AL920	27	08:03:16	17:17:39	28996	62259	1
08/04/2024	921	AL921	30	08:03:26	17:17:47	29006	62267	1
08/04/2024	922	AL922	30	08:00:00	17:20:30	28800	62430	1
08/04/2024	923	AL923	30	08:03:36	17:16:28	29016	62188	1
08/04/2024	924	AL924	30	08:00:00	16:04:21	28800	57861	2
08/04/2024	925	AL925	29	08:03:46	16:01:17	29026	57677	1
08/04/2024	926	AL926	24	08:00:00	17:05:08	28800	61508	2
08/04/2024	927	AL927	22	08:00:00	16:00:00	28800	57600	2
08/04/2024	928	AL928	27	08:03:56	16:15:09	29036	58509	1
08/04/2024	929	AL929	23	08:00:00	17:04:05	28800	61445	2
08/04/2024	930	AL930	27	08:00:00	16:00:00	28800	57600	2
08/04/2024	931	AL931	27	08:03:07	16:00:00	28987	57600	1
08/04/2024	932	AL932	28	08:03:17	16:00:00	28997	57600	1
08/04/2024	933	AL933	27	08:03:27	16:00:00	29007	57600	1
08/04/2024	934	AL934	27	08:00:00	16:00:00	28800	57600	2
08/04/2024	935	AL935	28	08:03:37	16:00:00	29017	57600	1
08/04/2024	936	AL936	27	08:03:47	16:00:00	29027	57600	1
08/04/2024	937	AL937	27	08:00:00	16:03:48	28800	57828	2
08/04/2024	938	AL938	27	08:03:57	16:02:31	29037	57751	1
08/04/2024	939	AL939	26	08:03:09	16:15:28	28989	58528	1
08/04/2024	940	AL940	26	08:00:00	16:03:15	28800	57795	2

08/04/2024	941	AL941	26	08:03:19	16:01:47	28999	57707	1
08/04/2024	942	AL942	21	08:03:29	17:08:33	29009	61713	1
08/04/2024	943	AL943	21	08:00:00	16:00:00	28800	57600	1
08/04/2024	944	AL944	29	08:03:39	17:17:41	29019	62261	1
08/04/2024	945	AL945	26	08:03:49	16:05:21	29029	57921	1
08/04/2024	946	AL946	26	08:00:00	16:00:00	28800	57600	1
08/04/2024	947	AL947	26	08:03:59	16:00:00	29039	57600	1
08/04/2024	948	AL948	21	08:00:00	16:00:00	28800	57600	1
08/04/2024	949	AL949	23	08:04:01	16:00:00	29041	57600	1
08/04/2024	950	AL950	23	08:04:11	16:15:09	29051	58509	1
08/04/2024	951	AL951	21	08:04:21	17:07:15	29061	61635	1
08/04/2024	952	AL952	21	08:04:31	16:01:27	29071	57687	1
08/04/2024	953	AL953	29	08:00:00	16:14:25	28800	58465	1
08/04/2024	954	AL954	29	08:00:00	17:08:40	28800	61720	2
08/04/2024	955	AL955	29	08:00:00	16:00:00	28800	57600	1
08/04/2024	956	AL956	30	08:00:00	16:07:19	28800	58039	2
08/04/2024	957	AL957	30	08:00:00	17:05:40	28800	61540	2
08/04/2024	958	AL958	21	08:00:00	16:00:00	28800	57600	2
08/04/2024	959	AL959	27	08:00:00	17:05:05	28800	61505	2
08/04/2024	960	AL960	30	08:00:00	16:00:00	28800	57600	1
08/04/2024	961	AL961	30	08:00:00	16:00:00	28800	57600	1
08/04/2024	962	AL962	30	08:00:00	16:00:00	28800	57600	1
08/04/2024	963	AL963	25	08:05:00	16:01:49	29100	57709	1
08/04/2024	964	AL964	25	08:04:59	17:00:20	29099	61220	1
08/04/2024	965	AL965	25	08:05:01	17:04:02	29101	61442	1
08/04/2024	966	AL966	24	08:04:21	16:01:29	29061	57689	1
08/04/2024	967	AL967	23	08:04:55	17:03:10	29095	61390	1
08/04/2024	968	AL968	23	08:00:00	16:01:57	28800	57717	2
08/04/2024	969	AL969	23	08:04:44	17:01:16	29084	61276	1
08/04/2024	970	AL970	21	08:00:00	16:01:09	28800	57669	2
08/04/2024	971	AL971	28	08:04:11	16:05:42	29051	57942	1
08/04/2024	972	AL972	21	08:00:00	16:15:41	28800	58541	2
08/04/2024	973	AL973	21	08:00:00	17:00:26	28800	61226	2
08/04/2024	974	AL974	22	08:03:43	16:10:31	29023	58231	1
08/04/2024	975	AL975	21	08:00:00	16:00:00	28800	57600	1
08/04/2024	976	AL976	27	08:02:00	17:02:18	28920	61338	1
08/04/2024	977	AL977	25	08:05:00	16:01:39	29100	57699	1
08/04/2024	978	AL978	23	08:00:03	16:02:21	28803	57741	1
08/04/2024	979	AL979	21	08:00:00	17:00:06	28800	61206	2
08/04/2024	980	AL980	22	08:00:00	16:07:22	28800	58042	2
08/04/2024	981	AL981	22	08:00:41	16:14:34	28841	58474	2
08/04/2024	982	AL982	29	08:03:31	16:00:00	29011	57600	1
08/04/2024	983	AL983	21	08:00:00	16:03:25	28800	57805	2
08/04/2024	984	AL984	28	08:01:43	16:15:55	28903	58555	1
08/04/2024	985	AL985	28	08:00:53	16:00:00	28853	57600	1

08/04/2024	986	AL986	29	08:00:00	16:15:31	28800	58531	1
08/04/2024	987	AL987	26	08:02:00	16:07:32	28920	58052	1
08/04/2024	988	AL988	27	08:03:11	16:00:00	28991	57600	1
08/04/2024	989	AL989	22	08:00:00	16:04:46	28800	57886	1
08/04/2024	990	AL990	27	08:02:21	16:00:00	28941	57600	1
08/04/2024	991	AL991	25	08:01:06	16:00:00	28866	57600	1
08/04/2024	992	AL992	22	08:00:00	16:02:01	28800	57721	1
08/04/2024	993	AL993	30	08:05:14	16:02:31	29114	57751	1
08/04/2024	994	AL994	29	08:03:34	16:01:59	29014	57719	1
08/04/2024	995	AL995	21	08:00:00	16:00:00	28800	57600	1
08/04/2024	996	AL996	29	08:00:00	16:00:00	28800	57600	1
08/04/2024	997	AL997	21	08:00:00	16:00:00	28800	57600	2
08/04/2024	998	AL998	29	08:00:00	16:00:00	28800	57600	1

CHAPTER 6
ANALYSIS OF ATTENDANCE SYSTEM DATA

6.1 DATA PREPROCESSING

Data preprocessing is an important initial step in data analysis to ensure the quality and consistency of the data used for training machine learning models. According to (Eid et al., 2024; Zaki et al., 2024), data preprocessing is a critical process in maintaining data quality; if not done correctly, it can reduce data accuracy. Therefore, data preprocessing is key to ensuring clean and accurate data for further analysis. The stages of data preprocessing in this study include data cleaning, data transformation, and feature extraction.

6.2 DATA CLEANING

According to (Thomas, 2024), data cleaning is a highly important process to be conducted before using data in various machine learning algorithm models. The data cleaning process in the face recognition dataset in this study involves various steps to ensure that the data used in the development and training of face recognition models are of high quality and consistent. The following are some key steps in data cleaning conducted on the face recognition dataset used in the study:

a. Removal of Duplicate Data: Duplicate images in the dataset can cause the model to be biased and overfit, so data cleaning in this regard will ensure that no duplicate face images exist in the dataset.
b. Handling Missing Data: This will identify incomplete or damaged face images and take appropriate actions, such as removing damaged images or attempting to recover them if possible.
c. Image Normalization: Images with different resolutions or sizes can affect the consistency and accuracy of the model. Therefore, the size and resolution of face images in the dataset need to be adjusted and standardized as needed.
d. Outlier Handling: In this step, images that do not conform to the common patterns, such as images with poor lighting, extreme angles, or blurry images, will be detected and addressed as needed.
e. Label Correction: Errors in labeling can cause the model to learn incorrect information and degrade its performance. Therefore, this process aims to ensure that each face image has the correct label to avoid performance degradation due to machine learning errors.

f. Removal of Irrelevant Backgrounds: Using segmentation techniques to focus on the face and remove or blur irrelevant backgrounds. This helps the model focus more on facial features.
g. Image Quality Enhancement: Enhancing the quality of images using techniques such as contrast enhancement, noise removal, and brightness adjustment. Better image quality can help the model recognize facial features more accurately.
h. Removal of Irrelevant Data: Removing images irrelevant to face recognition tasks, such as partially covered faces, unclear faces, or images containing other objects besides faces.
i. Data Validation: Validating the cleaned dataset by conducting manual reviews or using automated tools to ensure that no errors are overlooked.

Data cleaning in face recognition datasets is crucial because poor data quality can significantly affect model performance. By ensuring clean and consistent data, the integrated models can learn more effectively and provide more accurate and reliable results.

6.3 DATA TRANSFORMATION

Data transformation on face recognition datasets involves several techniques and processes applied to prepare the data for use in training machine learning, deep learning, and AI models. This data transformation is crucial to ensure that the models can better understand and recognize patterns in faces. Here are some common steps in data transformation for face recognition datasets applied in this study:

a. Resizing: Resizing face images to ensure that all images in the dataset have uniform sizes. This helps the model process data more efficiently and consistently. In addition to integrating three technologies with sophisticated algorithms, this study also integrates liveness detection techniques to enhance the accuracy and security of the face recognition used, where this liveness detection will be combined with deep learning. The model used is VGG-16, so all image sizes in the dataset are adjusted to 224×224 pixels for training and testing purposes.
b. Pixel Normalization: This will transform pixel values of images into a certain range, according to (Saleem et al., 2023), often the pixel range used in pixel normalization is 0 and 1 or -1 and 1. Normalization helps the model converge faster during training and prevents issues caused by different pixel scales.
c. Data Augmentation: Data augmentation helps the model become more robust to variations in real images. In this case, data augmentation will increase the amount and

diversity of data by performing transformations such as rotation, cropping, flipping (flipping images horizontally or vertically), zooming, adding noise, and changing lighting.

d. Cropping and Padding: According to (G. Liu et al., 2023), padding can be used to add margins to images to make them uniform in size without changing the aspect ratio of the face. This is done to remove irrelevant areas and focus on the face used for the study.
e. PCA (Principal Component Analysis): This technique can help reduce complexity and improve model performance. In this case, PCA is used to reduce the dimensions of the data and highlight the most significant features for the required face recognition.

Through this data transformation, the dataset becomes more uniform, facial features become more prominent, and the machine learning, deep learning, and AI models used can be trained more effectively. The purpose of this data transformation process is to maximize the performance of face recognition models in detecting and recognizing faces accurately.

6.4 FEATURE EXTRACTION

Feature extraction on face recognition datasets is the process of identifying and filtering important information from facial images that can be used by machine learning models to recognize and differentiate faces. These features may include shape, texture, and other unique patterns specific to each face. In this study, feature extraction from facial images utilizes deep learning techniques such as Convolutional Neural Networks (CNN) to extract essential features from attendance data such as entry and exit times, as well as attendance patterns. Here are some common techniques and methods used in feature extraction for face recognition:

a. Histogram of Oriented Gradients (HOG): HOG is a feature extraction method that computes local orientation gradients within small parts of the image. HOG features capture edges and basic facial structures, such as contours and shapes, which help the model recognize facial patterns.
b. Deep Learning Features: Utilizing neural networks, such as Convolutional Neural Networks (CNNs), to extract features from facial images. CNNs automatically learn features from raw data through multiple convolution and pooling layers. These learned features are highly effective for face recognition tasks as they can capture complex and abstract representations of faces.
c. Eigenfaces: Eigenfaces is a technique based on Principal Component Analysis (PCA) that reduces the dimensionality of facial image data by extracting principal components.

These eigenfaces capture global variations in faces and are used to recognize facial patterns.

By employing these feature extraction techniques, facial datasets can be processed so that only the most relevant and informative information is used for model training. This enhances the efficiency and accuracy of face recognition models, enabling the system to recognize and differentiate faces more effectively.

Data Splitting for Model Training and Testing

The dataset, now prepared for utilization, will be split using the trai_test_split method within the research environment. This division adheres to the Pareto principle (Sanders, 1987), allocating 80% for training and 20% for testing to ensure that the model can be assessed with unseen data.

Train and Test Code for Machine Machine Learning, Deep Learning dan AI Models Using Google Colab and Python

```
# -*- coding: utf-8 -*-
"""RESEARCH-JTS.ipynb

Automatically generated by Colab.

Original file is located at
    https://colab.research.google.com/drive/1SoeiTJYFKQRxHNg2va_AFeg9UEBWQQN9
"""

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from google.colab import files
uploaded = files.upload()

# Read file CSV ke dalam DataFrame
dataset = pd.read_csv('icaset_data.csv')

# The first 5 rows of the dataset.
print(dataset.head())

# Dataset Info
print(dataset.info())

# Descriptive Statistics
print(dataset.describe())

# Visualization of the age distribution of employees
plt.figure(figsize=(10,6))
sns.histplot(dataset['Ages'] , bins=20, kde=True)
plt.title('Distribusi Usia Karyawan')
plt.xlabel('Ages')
plt.ylabel('Frekuensi')
plt.show()

# Removing rows containing missing values
dataset = dataset.dropna()

from sklearn.preprocessing import MinMaxScaler
```

```
# Initializing scaler object
scaler = MinMaxScaler()

# Normalizing specific columns (e.g., 'Ages' column)
dataset['Ages']  = scaler.fit_transform(dataset[['Ages'] ])

print(dataset.info())

print(dataset.describe())

import seaborn as sns
import matplotlib.pyplot as plt

# Code plot for Employee Age
plt.figure(figsize=(10,6))
sns.kdeplot(data=dataset['Ages'] , shade=True)
plt.title('Plot Code for employee ages')
plt.xlabel('Ages')
plt.ylabel('Density')
plt.show()

# violin plot for Exit Time
plt.figure(figsize=(10,6))
sns.violinplot(x=dataset['Exit Time'])
plt.title('Violin Plot untuk Jam Pulang')
plt.xlabel('Exit Time')
plt.show()

# Box plot for Employee Ageplt.figure(figsize=(10,6))
sns.boxplot(x=dataset['Ages'] )
plt.title('Box plot for Employee Age')
plt.xlabel('Ages')
plt.show()

# Outlier identification
Q1 = dataset['Ages'] .quantile(0.25)
Q3 = dataset['Ages'] .quantile(0.75)
IQR = Q3 - Q1

outliers = (dataset['Ages']  < (Q1 - 1.5 * IQR)) | (dataset['Ages']  > (Q3 + 1.5 * IQR))
print("Outlier on Ampleyee Ages:")
print(dataset[outliers])

from scipy import stats

# Calculating Z-scores for each value in the Age column
z_scores = stats.zscore(dataset['Ages'] )

# Determining threshold for Z-scores
threshold = 3

# Creating a boolean array indicating whether each value is an outlier or not
outliers = (np.abs(z_scores) > threshold)

# Displaying outliers
if any(outliers):
    print("Outlier on Ampleyee Ages:")
    print(dataset[outliers])
else:
    print("Nothing Outlier on Ampleyee Ages.")

"""PRA PROCESSING DATA"""

# Entry time considered normal between 08:00:00, and exit time considered normal between
16:00:00
def kategori_kehadiran(row):
```

```
    if row['Etry Time'] >= 28800 and row['Etry Time'] <= 28860 and row['Exit Time'] >=
57600 and row['Exit Time'] <= 64800:
        return 'Ontime'
    else:
        return 'Late'

# Adding target column to the dataframe
dataset['Attendance Category'] = dataset.apply(kategori_kehadiran, axis=1)

from sklearn.model_selection import train_test_split

# Separating features and target
X = dataset[['Ages', 'Etry Time', 'Exit Time']]
y = dataset['Attendance Category']

# plitting data into training and testing sets (80% training data, 20% testing data)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Visualization of the size of each set
print("Total train data:", X_train.shape[0])
print("Total test data:", X_test.shape[0])

"""# MACHINE LEARNING APPROACH

MODEL TRAIN-TEST
"""

from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense

"""RANDOM FOREST"""

# Initializing Model
rf_model = RandomForestClassifier(random_state=42)

# Training model
rf_model.fit(X_train, y_train)

# Predicting attendance category using test data
y_pred_rf = rf_model.predict(X_test)

# Predicting probabilities
y_prob_rf = rf_model.predict_proba(X_test)

# EVALUATION METRICS

from sklearn.metrics import accuracy_score
from sklearn.metrics import recall_score
from sklearn.metrics import precision_score
from sklearn.metrics import f1_score

accuracy_rf = accuracy_score(y_test, y_pred_rf)

# Calculating precision with corresponding pos_label ('On Time')
precision_rf = precision_score(y_test, y_pred_rf, pos_label='Ontime')

# Calculating recall with corresponding pos_label ('On Time')
recall_rf = recall_score(y_test, y_pred_rf, pos_label='Ontime')

# Calculating F1-score with corresponding pos_label ('On Time')
f1_rf = f1_score(y_test, y_pred_rf, pos_label='Ontime')

# Print Results
```

```
print("Random Forest Precision Model:", precision_rf)
print("Random Forest Recall Model:", recall_rf)
print("Random Forest F1-Score Model:", f1_rf)
print("Random Forest Accuracy Model:", accuracy_rf)

"""SVM"""

from sklearn.svm import SVC

# Initializing Model SVM
svm_model = SVC()

# Training model
svm_model.fit(X_train, y_train)

# Predicting attendance category using test data
y_pred_svm = svm_model.predict(X_test)

# Predicting probabilities
y_prob_svm = svm_model.predict_proba(X_test)

# Calculating accuracy
accuracy_svm = accuracy_score(y_test, y_pred_svm)
print("SVM Accuracy Model:", accuracy_svm)

# EVALUATION METRICS

accuracy_svm = accuracy_score(y_test, y_pred_svm)

# Calculating precision with corresponding pos_label (‘On Time’)
precision_svm = precision_score(y_test, y_pred_svm, pos_label=‘Ontime’)

# Calculating recall with corresponding pos_label (‘On Time’)
recall_svm = recall_score(y_test, y_pred_svm, pos_label=‘Ontime’)

# Calculating F1-score with corresponding pos_label (‘On Time’)
f1_svm = f1_score(y_test, y_pred_svm, pos_label=‘Ontime’)

# Print Results
print("SVM Model Precision:", precision_svm)
print("SVM Model Recall:", recall_svm)
print("SVM Model F1-Score:", f1_svm)
print("SVM Model Accuracy:", accuracy_svm)

"""K-NN"""

from sklearn.neighbors import KNeighborsClassifier

# Initializing Model KNN
knn_model = KNeighborsClassifier()

# Training model
knn_model.fit(X_train, y_train)

# Predicting attendance category using test data
y_pred_knn = knn_model.predict(X_test)

# Predicting probabilities
y_prob_knn = knn_model.predict_proba(X_test)

# Calculating accuracy
accuracy_knn = accuracy_score(y_test, y_pred_knn)
print("KNN Model Accuracy:", accuracy_knn)

# EVALUATION METRICS
```

```
accuracy_knn = accuracy_score(y_test, y_pred_knn)

# Calculating precision with corresponding pos_label (‘On Time’)
precision_knn = precision_score(y_test, y_pred_knn, pos_label=‘Ontime’)

# Calculating recall with corresponding pos_label (‘On Time’)
recall_knn = recall_score(y_test, y_pred_knn, pos_label=‘Ontime’)

# Calculating F1-score with corresponding pos_label (‘On Time’)
f1_knn = f1_score(y_test, y_pred_knn, pos_label=‘Ontime’)

# Print Results
print("KNN Model precision:", precision_knn)
print("KNN Model Recall:", recall_knn)
print("KNN Model F1-Score:", f1_knn)
print("KNN Model Accuracy:", accuracy_knn)

"""NN (TENSORFLOW)"""

import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense

# Initializing Model Sequential
nn_model = Sequential()

# Adding layers to the model
nn_model.add(Dense(64, input_shape=(3,), activation='relu'))  # Reshaping input size
according to the number of features (3)
nn_model.add(Dense(64, activation='relu'))
nn_model.add(Dense(1, activation='sigmoid'))  # Since this is a binary classification
problem, using sigmoid activation in the output layer

# Compiling the model
nn_model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])

# Converting class labels to numeric
y_train_numeric = y_train.replace({‘Late’: 0, ‘Ontime’: 1})
y_test_numeric = y_test.replace({‘Late’: 0, ‘Ontime’: 1})

# Training model
nn_model.fit(X_train, y_train_numeric, epochs=10, batch_size=32, validation_data=(X_test,
y_test_numeric))

# Predicting attendance category using test data
y_pred_nn = nn_model.predict(X_test)

import numpy as np

# Predict raw outputs using the neural network model
raw_outputs = nn_model.predict(X_test)

# Apply softmax to get probabilities
y_prob_nn = np.exp(raw_outputs) / np.sum(np.exp(raw_outputs), axis=1, keepdims=True)

# Evaluating the model on test data
loss_nn, accuracy_nn = nn_model.evaluate(X_test, y_test_numeric)
print("Neural Network Model Accuracy:", accuracy_nn)

from sklearn.metrics import roc_curve, roc_auc_score

# Menghitung AUC-ROC
auc = roc_auc_score(y_test, y_prob_nn)
print(f'AUC-ROC: {auc:.2f}')

# Apply threshold to convert probabilities to binary class labels
```

```
y_pred_nn_binary = [1 if prob >= 0.5 else 0 for prob in y_pred_nn]

# Calculate evaluation metrics using binary class labels
accuracy_nn = accuracy_score(y_test_numeric, y_pred_nn_binary)
precision_nn = precision_score(y_test_numeric, y_pred_nn_binary)
recall_nn = recall_score(y_test_numeric, y_pred_nn_binary)
f1_nn = f1_score(y_test_numeric, y_pred_nn_binary)

# Print the results
print("Model Neural Network Precision:", precision_nn)
print("Model Neural Network Recall:", recall_nn)
print("Model Neural Network F1-score:", f1_nn)
print("Model Neural Network accuracy:", accuracy_nn)

"""X-GBOOST"""

import xgboost as xgb
from sklearn.metrics import accuracy_score
from sklearn.svm import SVC
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay

# Initializing Model XGBoost
xgb_model = xgb.XGBClassifier()

#Since XGBoost requires numeric labels, specifically for SGBoost, class labels are
converted to numeric
# Converting class labels to numeric
y_train_numeric = y_train.replace({'Late': 0, 'Ontime': 1})
y_test_numeric = y_test.replace({'Late': 0, 'Ontime': 1})

# Training model
xgb_model.fit(X_train, y_train_numeric)

# Predicting attendance category using test data
y_pred_xgb = xgb_model.predict(X_test)

# Predicting probabilities
y_prob_xgb = xgb_model.predict_proba(X_test)

# Calculating accuracy
accuracy_xgb = accuracy_score(y_test_numeric, y_pred_xgb)
print("Akurasi Model XGBoost:", accuracy_xgb)

# EVALUATION METRICS
# Converting class labels in y_test to numbers (0 and 1)
y_test_encoded = [1 if label == 'Ontime' else 0 for label in y_test]

# Calculating evaluation metrics using converted class labels
accuracy_xgb = accuracy_score(y_test_encoded, y_pred_xgb)
precision_xgb = precision_score(y_test_encoded, y_pred_xgb)
recall_xgb = recall_score(y_test_encoded, y_pred_xgb)
f1_xgb = f1_score(y_test_encoded, y_pred_xgb)

# Print Results
print("Model xgb Precision:", precision_xgb)
print("Model xgb Recall:", recall_xgb)
print("Model xgb F1-score:", f1_xgb)
print("Model xgb Accuration:", accuracy_xgb)

"""#RESULT VISUALIZATION

BAR DIAGRAM
"""

import matplotlib.pyplot as plt
```

```
import matplotlib.pyplot as plt

# List of model name
models = ['Random Forest', 'XGBoost', 'SVM', 'KNN', 'Neural Network']

# list of model accuracy
accuracies = [accuracy_rf, accuracy_xgb, accuracy_svm, accuracy_knn, accuracy_nn]

# list of model precision
precisions = [precision_rf, precision_xgb, precision_svm, precision_knn, precision_nn]

# list of model recall
recalls = [recall_rf, recall_xgb, recall_svm, recall_knn, recall_nn]

# list of model F1-Score
f1_scores = [f1_rf, f1_xgb, f1_svm, f1_knn, f1_nn]

# Bar chart plot
plt.figure(figsize=(12, 8))

# Accuracy plot
plt.subplot(2, 2, 1)
plt.bar(models, accuracies, color='skyblue')
plt.title('Accuracy Model')
plt.ylim(0, 1)  # Limit y-axis between 0 and 1
plt.grid(axis='y', linestyle='--', alpha=0.7)

# Plot presisi
plt.subplot(2, 2, 2)
plt.bar(models, precisions, color='salmon')
plt.title('Precision Model')
plt.ylim(0, 1)  # Limit y-axis between 0 and 1
plt.grid(axis='y', linestyle='--', alpha=0.7)

# Plot recall
plt.subplot(2, 2, 3)
plt.bar(models, recalls, color='lightgreen')
plt.title('Recall Model')
plt.ylim(0, 1)  # Limit y-axis between 0 and 1
plt.grid(axis='y', linestyle='--', alpha=0.7)

# Plot F1-score
plt.subplot(2, 2, 4)
plt.bar(models, f1_scores, color='orange')
plt.title('F1-score Model')
plt.ylim(0, 1)  # Limit y-axis between 0 and 1
plt.grid(axis='y', linestyle='--', alpha=0.7)

plt.tight_layout()
plt.show()

"""LINE DIAGRAM"""

import matplotlib.pyplot as plt

# List of model accuracies for plot
accuracies = [accuracy_rf, accuracy_xgb, accuracy_svm, accuracy_knn, accuracy_nn]

# Label model
models = ['Random Forest', 'XGBoost', 'SVM', 'KNN', 'Neural Network']

# bar diagram plot
plt.figure(figsize=(10, 6))
plt.plot(models, accuracies, marker='o', linestyle='-')
plt.title('Model Accuracy Comparison')
plt.xlabel('Model')
```

```
plt.ylabel('Accuracy')
plt.ylim(0, 1)  # Limit y-axis between 0 and 1
plt.grid(True)
plt.xticks(rotation=45)  # Rotate x-axis labels
plt.tight_layout()
plt.show()

"""HEATMAP DIAGRAM"""

import seaborn as sns
import pandas as pd
import matplotlib.pyplot as plt

# Data for evaluation metrics
models = ['Random Forest', 'XGboost', 'SVM', 'KNN', 'NN']
accuracies = [0.995, 0.99, 0.56, 0.955, 0.53]
precision = [0.9911504424778761, 0.9824561403508771, 0.56, 0.9327731092436975,
0.5882352941176471]
f1_scores = [0.99, 0.9911504424778761, 0.717948717948718, 0.961038961038961,
0.5607476635514018]
recall = [1.0, 1.0, 1.0, 0.9910714285714286, 0.5357142857142857]

# Data for evaluation metrics
data = {
    'Model': models,
    'Accuracy': accuracies,
    'Precision': precision,
    'F1-Score': f1_scores,
    'Recall': recall
}

# creating dataframe
dataset = pd.DataFrame(data)

# changing urutan baris
dataset = dataset.reindex([0, 1, 3, 2, 4])

# creating heatmap
plt.figure(figsize=(10, 6))
heatmap = sns.heatmap(dataset.set_index('Model'), annot=True, cmap="YlGnBu",
linewidths=0.5)
heatmap.set_title('Heatmap Evaluasi Model')
plt.show()

"""SCATTER PLOT"""

import matplotlib.pyplot as plt

# Model names
models = ['Random Forest', 'XGBoost', 'SVM', 'KNN', 'Neural Network']

# Evaluation metrics
metrics = ['Accuracy', 'Precision', 'Recall', 'F1-Score']

# Metric values for each model
accuracy_values = [accuracy_rf, accuracy_xgb, accuracy_svm, accuracy_knn, accuracy_nn]
precision_values = [precision_rf, precision_xgb, precision_svm, precision_knn,
precision_nn]
recall_values = [recall_rf, recall_xgb, recall_svm, recall_knn, recall_nn]
f1_values = [f1_rf, f1_xgb, f1_svm, f1_knn, f1_nn]

# Plotting scatter diagram for each metric
plt.figure(figsize=(15, 10))

for i, metric in enumerate(metrics, 1):
    plt.subplot(2, 2, i)
```

```
    plt.scatter(models, accuracy_values, label='Accuracy', color='blue')
    plt.scatter(models, precision_values, label='Precision', color='red')
    plt.scatter(models, recall_values, label='Recall', color='green')
    plt.scatter(models, f1_values, label='F1-Score', color='orange')
    plt.xlabel('Model')
    plt.ylabel(metric)
    plt.title(f'Scatter Plot {metric} Model')
    plt.xticks(rotation=45)
    plt.legend()

plt.tight_layout()
plt.show()

"""DIAGRAM GARIS"""

import matplotlib.pyplot as plt

# Model names
models = ['Random Forest', 'XGBoost', 'SVM', 'KNN', 'Neural Network']

# Evaluation metrics
metrics = ['Accuracy', 'Precision', 'Recall', 'F1-Score']

# Metric values for each model
accuracy_values = [accuracy_rf, accuracy_xgb, accuracy_svm, accuracy_knn, accuracy_nn]
precision_values = [precision_rf, precision_xgb, precision_svm, precision_knn,
precision_nn]
recall_values = [recall_rf, recall_xgb, recall_svm, recall_knn, recall_nn]
f1_values = [f1_rf, f1_xgb, f1_svm, f1_knn, f1_nn]

# Plotting line chart for each metric
plt.figure(figsize=(12, 8))

for i, metric in enumerate(metrics, 1):
    plt.plot(models, accuracy_values, label='Accuracy', marker='o', linestyle='-')
    plt.plot(models, precision_values, label='Precision', marker='o', linestyle='-')
    plt.plot(models, recall_values, label='Recall', marker='o', linestyle='-')
    plt.plot(models, f1_values, label='F1-Score', marker='o', linestyle='-')
    plt.xlabel('Model')
    plt.ylabel(metric)
    plt.title(f'Line Chart {metric} Model')
    plt.xticks(rotation=45)
    plt.legend()

plt.tight_layout()
plt.show()

import numpy as np
import matplotlib.pyplot as plt

# Model names
models = ['Random Forest', 'XGBoost', 'SVM', 'KNN', 'Neural Network']

# Evaluation metrics
metrics = ['Accuracy', 'Precision', 'Recall', 'F1-Score']

# Metric values for each model
accuracy_values = [accuracy_rf, accuracy_xgb, accuracy_svm, accuracy_knn, accuracy_nn]
precision_values = [precision_rf, precision_xgb, precision_svm, precision_knn,
precision_nn]
recall_values = [recall_rf, recall_xgb, recall_svm, recall_knn, recall_nn]
f1_values = [f1_rf, f1_xgb, f1_svm, f1_knn, f1_nn]

# Set bar width
bar_width = 0.2
```

```
# Set positions of bars on x-axis
r1 = np.arange(len(models))
r2 = [x + bar_width for x in r1]
r3 = [x + bar_width for x in r2]
r4 = [x + bar_width for x in r3]

# Plotting grouped bar chart for each metric
plt.figure(figsize=(12, 8))

plt.bar(r1, accuracy_values, color='lightblue', width=bar_width, edgecolor='grey',
label='Akurasi')
plt.bar(r2, precision_values, color='lightgreen', width=bar_width, edgecolor='grey',
label='Presisi')
plt.bar(r3, recall_values, color='lightcoral', width=bar_width, edgecolor='grey',
label='Recall')
plt.bar(r4, f1_values, color='lightyellow', width=bar_width, edgecolor='grey', label='F1-
Score')

# Add xticks on the middle of the group bars
plt.xlabel('Model', fontweight='bold')
plt.ylabel('Value', fontweight='bold')
plt.xticks([r + bar_width * 1.5 for r in range(len(models))], models, rotation=45)
plt.title('Bar Chart for Metric Evaluation Results')
plt.legend()

plt.tight_layout()
plt.show()
```

CHAPTER 7
MACHINE LEARNING, DEEP LEARNING, AND AI MODELS USED

In selecting machine learning, deep learning, and AI models for detecting and predicting anomaly patterns and attendance trends in face recognition-based attendance systems, various techniques are considered based on the specific advantages of each model in the given tasks. The rationale behind the selection of machine learning, deep learning, and AI models for detecting and predicting anomaly patterns, as well as predicting patterns and attendance trends in face recognition-based attendance, is based on the strengths and specific capabilities of each method. Several machine learning, deep learning, and AI models used in this book are as follows:

7.1 MACHINE LEARNING MODEL

The application of machine learning models for prediction brings significant benefits in various contexts, including performance prediction, sales prediction, risk analysis, and others. In previous studies, (Z. Y. Chen et al., 2022; Kothapalli et al., 2023; Lahmiri et al., 2023) utilized machine learning as a predictive model for sales and purchasing goods, (Chaubey et al., 2023) employed machine learning as a predictive tool for customer purchasing habits. (Ishibashi, 2024; Shinohara et al., 2024; Suryadevara, 2023; B. Zhao et al., 2023) used machine learning to predict and analyze risks. Several recent studies in the development of predictive models for attendance systems have also begun to integrate machine learning technology with more advanced approaches such as deep learning. (Ali, Diwan, et al., 2024; Barhate et al., 2024) utilized machine learning and deep learning to accurately detect and recognize faces in attendance images. Similar research by (Budiman et al., 2022; Nagagopiraju et al., 2024; Sawarkar & Alane, 2024) showed that the use of deep learning and machine learning techniques in attendance systems can significantly improve the accuracy of individual identification compared to traditional approaches. Furthermore, there is research focusing on the development of more complex predictive models to predict individual attendance by considering various factors such as weather conditions, employee schedules, and other external factors. For example, research by (Arboretti et al., 2024; Nasiri Khiavi, 2024) combined various data with weather data using ensemble learning techniques to predict attendance and purchases with higher accuracy.

In this study, several machine learning and deep learning models were selected for use as predictors trained and tested within the system. The models employed include Random Forest (RF), Extreme Gradient Boosting (XGBoost), Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Neural Network (NN), specifically Recurrent Neural Network (RNN) in this context.

- Ensemble Learning (Random Forest and Extreme Gradient Boost/XGBoost)

  Random Forest and XGBoost from ensemble learning were chosen for their ability to handle complex and diverse data, as well as their capability to reduce overfitting by combining multiple simple models with more reliable and accurate prediction outcomes. Random Forest was selected due to its capability to handle various complex features and mitigate overfitting in the dataset. In its performance, this model constructs numerous decision trees independently and aggregates their results to enhance prediction accuracy. On the other hand, XGBoost is an ensemble model highly effective for predicting attendance patterns due to its ability to enhance prediction performance through iterative boosting approaches, which rectify the prediction errors of previous models, resulting in robust and accurate models. XGBoost can handle imbalanced and complex data; moreover, it also delivers high accuracy with regularization optimization to avoid overfitting. In the context of this study, XGBoost is effective in anomaly detection and attendance pattern prediction by enhancing the overall model performance through the aggregation of simple models.
- Supervised Learning (SVM and KNN)

  Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) from supervised learning were selected for their effectiveness in face classification and anomaly detection, with SVM being strong in high-dimensional spaces and KNN being intuitive and effective for small datasets. SVM can effectively separate complex classes in data, ultimately identifying complex and nonlinear attendance patterns. This model can handle datasets with a large number of features well and manage overfitting similar to random forest, making it quite effective when working in high-dimensional spaces. SVM also utilizes a subset of training points in the decision function (called support vectors), making it memory-efficient. In its application, SVM can be used for face classification in face recognition and to separate normal patterns from anomalies in attendance data. On the other hand, K-Nearest Neighbor (KNN), a simple and intuitive model, does not require explicit training phases and can handle multi-class cases. KNN is quite robust in classifying data based on their proximity to the nearest neighbors. In this regard, KNN performs well on small datasets with clear labels. For its application, KNN can be used for face recognition based on similarity and for anomaly detection by comparing the distance between new data and historical data. In the context of predicting attendance patterns, KNN is utilized to identify patterns similar to previous attendance patterns and predict new attendance patterns based on past similarities.

- Deep Learning (Neural Network – CNN)

  Neural networks are deep learning models that enable the understanding of more complex feature representations from attendance data, such as recurring attendance patterns over time or context-dependent attendance patterns. Neural Networks (NN), especially Convolutional Neural Networks (CNN), are chosen for their ability to learn complex and non-linear feature representations from large data and are highly effective in image recognition and pattern prediction from historical data. These models can learn complex and non-linear feature representations from large data. CNN, in particular, is highly effective for image recognition and can be optimized for face recognition. In its application to predicting attendance patterns and trends, NN can be used to learn patterns from historical data and make accurate predictions.

7.2 ARTIFICIAL INTELLIGENCE MODELING (ENSEMBLE VOTING)

The ensemble learning technique of voting from AI renders the model more stable, sufficiently flexible, and easily applicable. The voting ensemble technique employed across different AI models proves to be effective, enhancing the accuracy of the models. By amalgamating predictions from multiple diverse models, the voting technique mitigates errors resulting from overfitting in one model or variances in others. Furthermore, ensemble learning with the voting technique yields more stable models than individual ones, as errors made by one model can be compensated for by others. As for the voting technique itself, it can be utilized with various types of base models, including linear models, tree-based models, or other complex models, thereby providing flexibility in modeling.

Ensemble AI (One-class SVM and Isolation Forest)

One-class SVM and Isolation Forest from the AI ensemble were specifically chosen for anomaly detection. Here, One-class SVM will model the distribution of normal data to identify outliers, while Isolation Forest will efficiently separate anomaly data based on their distinct properties from normal data. One-class SVM is designed to detect anomalies by modeling the distribution of normal data and identifying data points that deviate from this distribution. In its application, One-class SVM excels in anomaly detection scenarios where only normal data is available, and anomalies need to be identified as outliers. On the other hand, Isolation Forest excels in isolating anomaly points through a process of randomly constructing decision trees. This method is highly efficient and swift in anomaly detection. In its application, Isolation Forest is highly effective in detecting anomalies in face recognition and attendance systems, as it directly separates anomaly data based on their distinct properties from normal data. In anomaly detection, One-class SVM, a supervised learning model, seeks a hyperplane that encapsulates most normal data within it. This model was chosen for its ability to handle imbalanced data and does not require anomaly labels during training. According to (Goswami & Singh, 2024; G. Lee et al., 2023; Moosaei et al., 2023; Wang et al., 2023; Yu et al., 2023), the One-class SVM model performs reasonably well on imbalanced datasets. Meanwhile, Isolation Forest is a model that works by isolating anomalies as short decision trees in feature space. This model was chosen for its ability to handle high-dimensional datasets and can perform well even with large datasets. According to (Lifandali et al., 2023; Y. Wu et al., 2024) and (Yang et al., 2022), Isolation Forest performs quite well on large datasets. These two models will be combined using ensemble voting techniques to enhance the model's accuracy in anomaly detection.

The combination of these models provides a robust and accurate system capable of handling various scenarios in anomaly detection and predicting attendance patterns based on face recognition.

7.3 EVALUATION METRICS

To assess the performance of the machine learning models employed in this study, several evaluation metrics will be applied. Considering the diverse characteristics of the models utilized in this book, the authors have decided to employ various evaluation metrics tailored to each model's specific attributes.

a. Accuracy

This is a metric for evaluating the performance of classification models, especially when the target classes are balanced. This metric will measure how many correct predictions are made out of the total predictions made by the model, thus providing a general overview of how well the model performs in predicting overall. The accuracy metric is calculated using the formula:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \qquad (Eq. 7.1)$$

Where,

7.3 TP (true positive) represents correct predictions for the positive class.

7.4 TN (true negative) represents correct predictions for the negative class.

7.5 FP (false positive) represents incorrect predictions for the positive class.

7.6 FN (false negative) represents incorrect predictions for the negative class.

In anomaly pattern prediction, the accuracy metric will measure how well the model identifies patterns that correspond to specific categories (e.g., anomalies or non-anomalies). In attendance pattern prediction for general classification tasks, the accuracy metric will indicate how well the model classifies data into the correct categories. In attendance trend prediction, this metric will measure how often the attendance prediction system (based on face recognition) correctly assesses individual presence or absence.

b. Precision

The precision metric measures how accurate the model is in predicting the positive class, i.e., how many of the positive predictions are positive. The precision metric is calculated using the:

$$Precision = \frac{TP}{TP + FP} \qquad (Eq. 7.2)$$

In anomaly detection, the precision metric is crucial as false positives can be costly or disruptive. Similarly, in anomaly pattern prediction, the precision metric is important to avoid false positives in anomaly detection, which can lead to false alarms. In attendance pattern prediction for general classification tasks, the precision metric indicates how well the model avoids false predictions when deciding an example is positive. Lastly, in attendance trend prediction, a high precision metric indicates that the face recognition system rarely misidentifies a present individual as absent.

c. Recall

This metric will measure the model's ability to find all positive samples and will show how well the model is at effectively detecting high-achieving teachers. The recall metric will be calculated using the formula:

$$Recall = \frac{TP}{TP + FN} \qquad (Eq. 7.3)$$

In anomaly pattern prediction, the recall metric is used to ensure all anomalies are detected. Similarly, in anomaly detection, this recall metric will ensure all anomaly cases (e.g., fraud, errors) are identified. In attendance pattern prediction, this metric will indicate how well the model identifies all instances of the desired class. Lastly, in attendance trend prediction, this metric will help determine how well the system recognizes all individuals present as present, minimizing undetected absences.

d. F1-Score

F1-score is a harmonic mean of recall and precision that will provide a comprehensive overview of the developed model's performance by considering recall and precision simultaneously. For the F1-Score metric, the formula used is:

$$F1 - Score = 2 \times \frac{Presisi \times Recall}{Presisi + Recall} \qquad (Eq. 7.4)$$

In anomaly pattern prediction, this metric will provide a balanced overview of the model's ability to detect and avoid errors in anomaly prediction. Similarly, in anomaly detection in this study, the F1-score metric will assist in measuring the performance of a model attempting to detect anomalies while reducing false positives and false negatives. In pattern prediction, this metric will provide a general overview of model performance. In attendance trend prediction, this metric will show the balance between correctly detecting presence and avoiding errors in detecting absence.

e. Metrik AUC-ROC

AUC-ROC (Area Under the Receiver Operating Characteristic Curve) is a metric that measures the classification model's performance at various classification thresholds. ROC is a graph that depicts the true positive rate (TPR) versus the false positive rate (FPR) at various thresholds. AUC is the area under the ROC curve. This metric will provide a comprehensive overview of the system's performance at various thresholds, aiding in determining the optimal threshold for face recognition. The AUC-ROC metric in this study will measure the model's ability to distinguish between normal and anomalous data. This metric was chosen for its sensitivity to class distribution and its ability to provide a balanced evaluation between detecting majority and minority classes. The AUC-ROC metric is calculated using the formula:

$$TPR = \frac{TP}{TP + FN} \qquad (Eq. 7.5)$$

$$FPR = \frac{FP}{FP + TN} \qquad (Eq. 7.6)$$

AUC-ROC assesses model performance regardless of class distribution and is sensitive to performance in detecting both classes, not just the majority class. Therefore, it can be said that this metric is quite sensitive to class imbalance. Additionally, this metric can directly compare multi-model performance. Several models can contribute to the final prediction in ensemble voting, where the contribution of each model to the ensemble prediction can be independently evaluated with the AUC-ROC metric, indicating how well the model can achieve higher scores for anomaly data compared to normal data.

7.4 SCOPE OF SYSTEM DEVELOPMENT

In this study, various hardware and software tools were utilized to develop, implement, and test an enhanced face recognition-based attendance system integrated with AI, ML, DL, liveness detection, and data encryption technologies using AES algorithms. According to (Al-Harrasi et al., 2023; S. Shukla et al., 2022), the analysis within the system poses additional security risks due to direct access to data and the main system, thus increasing the risk of exploitation and data theft. For this reason, all training, prediction, testing, and anomaly detection were conducted in a separate environment from the system, including the use of datasets not directly linked to the MySQL database in the system but downloaded and formatted according to the research needs. This study utilized the Google Colab Notebook environment for data encryption, model training, prediction, and testing, as well as anomaly detection using Python programming language.

a. **Google Colab**

Google Colab was chosen for its provision of access to computational resources sufficient for training artificial intelligence models, with GPUs that can accelerate the training process. Required libraries include TensorFlow, PyTorch, and scikit-learn, for developing machine learning, deep learning, AI models, and implementing encryption techniques using the AES algorithm. Google Colab provides free access to GPUs (Graphics Processing Units) and TPUs (Tensor Processing Units) that can be used for accelerating computations in DL model training requiring high computational power. These GPUs and TPUs enable faster and more efficient model training. The environment also leverages Google's widely distributed infrastructure, allowing for ML, DL, and AI model training on large datasets without concerns about local computational resource limitations.

Google Colab is integrated with other Google services such as Google Drive, Google Sheets, and the Google Cloud Platform, facilitating data storage and loading directly from Google Drive, as well as utilizing Google Cloud services for larger data storage and processing. Google Colab supports several popular programming languages like Python, enabling users to utilize various ML and DL libraries and frameworks such as TensorFlow, PyTorch, and Scikit-learn. The environment is also based on interactive notebooks, allowing users to write and execute code in separate executable chunks, facilitating interactive experimentation, visualization, and result documentation. Lastly, Google Colab enables users to easily share notebooks via links or download them as Python files or Jupyter notebooks.

b. **Python**

Python is the primary programming language used in this book. Python was chosen because it is an excellent programming language, particularly for the development of Machine Learning (ML), Deep Learning (DL), and Artificial Intelligence (AI) models, for several fundamental reasons. Firstly, the diversity of Python libraries, such as TensorFlow, PyTorch, scikit-learn, and Keras, provides abundant access to algorithms, functions, and tools needed for building and testing ML, DL, and AI models easily. Furthermore, Python's ease of syntax allows researchers and practitioners to focus on logic and modeling without getting bogged down in syntactic complexity. The large and active Python community also provides abundant support, tutorials, and educational resources, facilitating users in learning and mastering Python for ML, DL, and AI applications.

Python also offers strong scalability, suitable for ML, DL, and AI projects from small to large scale, with diverse levels of abstraction and flexibility. Python's ability to integrate with other programming languages such as C/C++, Java, and R further extends the flexibility of model development and testing, enhancing interoperability across platforms. Additionally, Python's support for interactive development environments like Google Colab facilitates intuitive and efficient experimentation and collaboration.

Lastly, as an open-source programming language, Python is free to use and distribute, providing easier access for developers and researchers with limited budgets to develop ML, DL, and AI solutions. The combination of all these factors makes Python the top choice in the development of ML, DL, and AI models, strengthening its position as the superior programming language in this domain.

CHAPTER 8
MODEL IMPLEMENTATION TECHNIQUE

8.1 LIVENESS DETECTION MODEL APPLICATION WITH DEEP LEARNING

The dataset prepared for the implementation of this model consists of attendance data that has undergone several data preprocessing steps, consisting of high-resolution images of vocational school teachers' faces. The image data used for training to testing includes images/photos with various pose variations, facial expressions, and diverse lighting conditions to reflect real-world conditions in the school attendance environment. In this regard, all photos/images used as samples are resized to 224x224 pixels overall because the deep learning model used for detection is VGG-16. In loading the VGG-16 model, the VGG16 function from the Keras library, which has been pre-trained, is used. Next is the adjustment of the architecture of the pre-trained model by adding trained layers for adjustment at the top. In training, optimizer, loss function, and evaluation metrics are also set, while in model compilation, training is performed using a loop method. After training is completed, the model's performance is evaluated using a separate dataset by calculating evaluation metrics (in this study, accuracy is used).

The liveness detection technology is further implemented using a motion-based approach. The face recognition system for attendance employs a high-quality camera capable of capturing movements and facial expressions in detail. The motion detection algorithm runs in real time to check for signs of life on the subjects being verified. Meanwhile, facial recognition is conducted using a deep learning approach based on Convolutional Neural Networks (CNNs). The CNN model is trained before being used to extract features from the sample faces. For the facial recognition architecture, the study utilizes the VGG-16 architecture and proceeds with fine-tuning the model using the dataset to enhance recognition accuracy. The integration between liveness detection technology and deep learning is carried out in two stages. Firstly, liveness detection technology is used to validate the authenticity of the subject before the facial recognition process takes place. If the subject is confirmed to be alive, the second step involves the use of deep learning models to accurately recognize faces. The combination of these two technologies enables the system to ensure that only genuinely present faces are accurately identified, while fraudulent attacks such as photos or video recordings can be effectively detected and prevented.

8.2 ANOMALY DETECTION AND DATA ENCRYPTION

Anomaly detection in this book is conducted outside the attendance system (using a different environment) and solely utilizes datasets extracted from the system to maintain the security of the attendance system itself. The analysis within the system poses additional security risks due to direct access to the data and main system, thus increasing the potential for exploitation and data theft. For this reason, all training, prediction, testing, and anomaly detection are performed in a separate environment from the system. Additionally, direct linking of datasets to the MySQL database in the system is avoided; instead, the data is downloaded beforehand and formatted according to the research requirements. The Advanced Encryption Standard (AES) algorithm is employed for data encryption. AES is chosen for its robust security, symmetric nature, and efficiency. According to (Adeniyi et al., 2023) and (Alemami et al., 2023), the security level of the AES algorithm is higher, and it exhibits good performance compared to other encryption algorithms. With a key length of 256 bits, the AES algorithm is highly resistant to brute-force attacks. Moreover, encryption and decryption processes can be performed using the same initialization key, facilitating subsequent anomaly detection processes. For anomaly detection, this book employs an ensemble AI approach with voting techniques. Two AI models are trained, tested, and combined to detect anomalies in the attendance system dataset. In anomaly detection, the One-class Support Vector Machine (SVM) is a supervised learning model that seeks a hyperplane that encapsulates the majority of normal data within it. This model is selected for its ability to handle imbalanced data and does not require anomaly labels during training. According to (Goswami & Singh, 2024; G. Lee et al., 2023; Moosaei et al., 2023; Wang et al., 2023; Yu et al., 2023), research indicates that the One-class SVM model performs reasonably well on imbalanced datasets. Meanwhile, the Isolation Forest is a model that works by isolating anomalies as short decision trees in feature space. This model is chosen for its ability to handle high-dimensional datasets and perform well even with large datasets. According to (Lifandali et al., 2023; Wu et al., 2024), and (Yang et al., 2022), the isolation forest performs quite well on large datasets. These two models are combined using ensemble voting techniques to enhance the model's accuracy in anomaly detection.

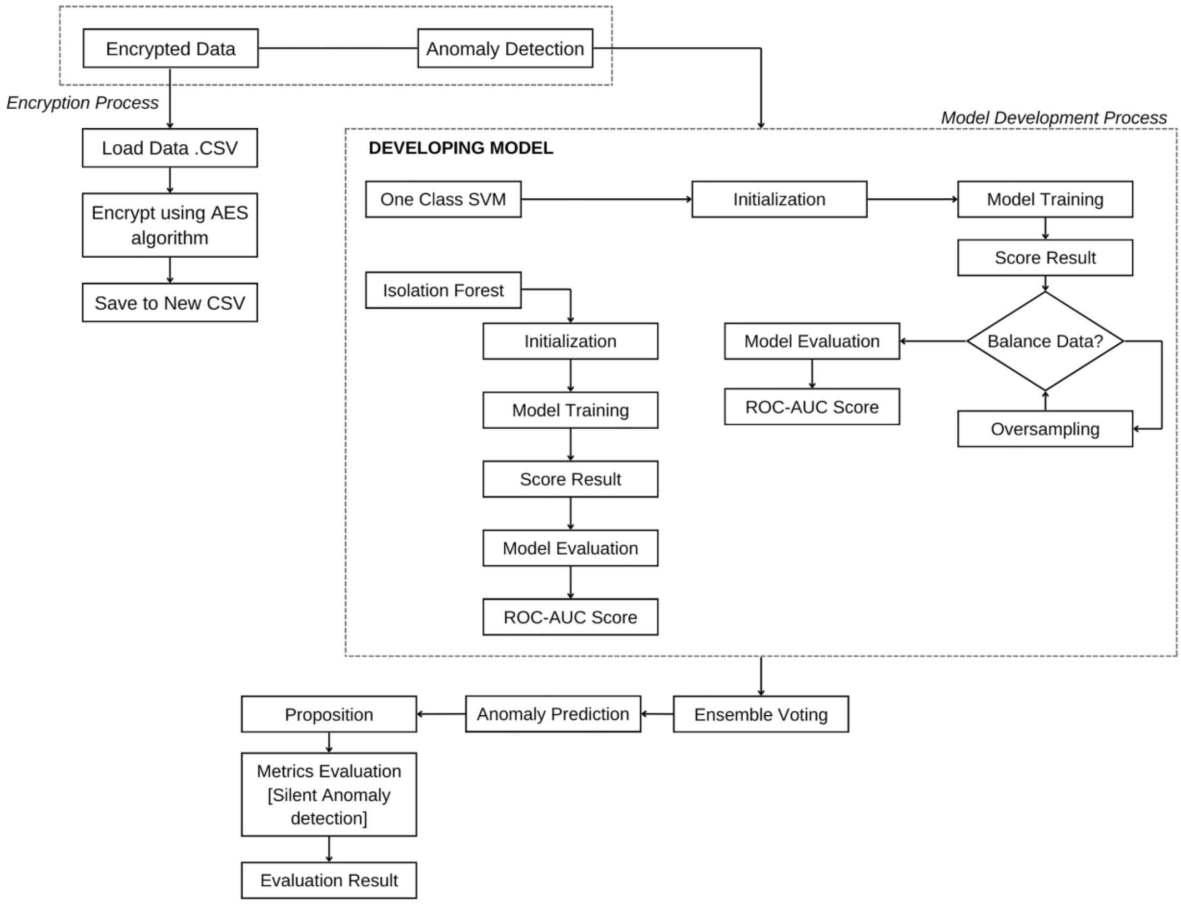


Figure 8.1. Experimental Techniques for Data Encryption and Anomaly Detection Using Ensemble Voting AI

Pra-processing Encrypted Data

```
"""# PRA PROCESSING DATA"""

# Data Normalization
from sklearn.preprocessing import StandardScaler
from Crypto.Cipher import AES
import base64
import numpy as np

# Decrypt  Function using padding
def decrypt_data_with_padding(data, key, iv):
    cipher = AES.new(key, AES.MODE_CBC, iv)
    # Add padding 4x strings
    padded_data = data + '=' * (-len(data) % 4)
    ct_bytes = base64.b64decode(padded_data)
    pt = cipher.decrypt(ct_bytes).rstrip(b'\0').decode('utf-8')
    return pt

# Key and IV
key = b'****************'
iv = b'****************'

df
```

```
df['Lokasi Absen'] = label_encoder.fit_transform(df['Lokasi Absen'])
df['Kode Nama'] = label_encoder.fit_transform(df['Kode Nama'])

# Time extraction from =‘Etry Time’ dan ‘Exit Time’ coulmn
def extract_time_components(df, column_name):
    time_components = df[column_name].str.split(':')
    hours = [int(tc[0]) for tc in time_components]
    minutes = [int(tc[1]) for tc in time_components]
    seconds = [int(tc[2]) for tc in time_components]
    return np.array(hours), np.array(minutes), np.array(seconds)

# Time extraction componenent for ‘Etry Time’ coulmn
masuk_hours, masuk_minutes, masuk_seconds = extract_time_components(df, ‘Etry
Time’)
# Time extraction componenent for ‘Exit Time’ coulmn
pulang_hours, pulang_minutes, pulang_seconds = extract_time_components(df,
‘Exit Time’)

# Add New Column
df['Entry_Hours'] = entry_hours
df['Entry _Minutes'] = entry _minutes
df['Entry _Seconds'] = entry _seconds
df['Exit_Hours'] = exit_hours
df['Exit_Minutes'] = exit_minutes
df['Exit_Seconds'] = exit_seconds

# Splitting target feature
X = df.drop(columns=['Decrypted_Data'])
y = df['Decrypted_Data']

X_train = X_train.values if isinstance(X_train, pd.DataFrame) else X_train
X_test = X_test.values if isinstance(X_test, pd.DataFrame) else X_test

X = df.values

# non-numerical column identification
non_numeric_columns = df.select_dtypes(exclude=[np.number]).columns

# Identifikasi indeks kolom numerik
numeric_indices = np.where(np.issubdtype(X_train.dtype, np.number))[0]
non_numeric_indices = np.where(~np.issubdtype(X_train.dtype, np.number))[0]

# Splitting numerical and non-numerical column from array
X_train_numeric = X_train[:, numeric_indices].astype(np.float32)
X_test_numeric = X_test[:, numeric_indices].astype(np.float32)

X_train_non_numeric = X_train[:, non_numeric_indices] if non_numeric_indices
else None
X_test_non_numeric = X_test[:, non_numeric_indices] if non_numeric_indices
else None

# train_test_split data
X_train, X_test = train_test_split(X, test_size=0.2, random_state=42)

# Building autoencoder model
```

```
model = Sequential([
    Dense(64, activation='relu', input_shape=(X_train_numeric.shape[1],)),
    Dense(32, activation='relu'),
    Dense(64, activation='relu'),
    Dense(X_train_numeric.shape[1], activation='sigmoid')
])

model.compile(optimizer='adam', loss='mse')

# MeTraining model autoencoder
model.fit(X_train_numeric, X_train_numeric, epochs=50, batch_size=32,
validation_data=(X_test_numeric, X_test_numeric))

# Cheching NaN
nan_values = df.isnull().values.any()
if nan_values:
    print("Ada nilai NaN dalam data input. Memperbaiki...")
    # Solving NaN
    df.fillna(df.mean(), inplace=True)
    print("Nilai NaN telah diperbaiki.")
else:
    print("Tidak ada nilai NaN dalam data input.")
```

Data Encryption Using AES Algorithm

```
# -*- coding: utf-8 -*-
"""AES ALGORITHM ENCRYPT-JTS.ipynb

Automatically generated by Colab.

Original file is located at
    https://colab.research.google.com/drive/1XafjK81RsGJT7MEQUOWQKn3msFMPdM3M
"""

from google.colab import drive
import pandas as pd

# Mount Google Drive
drive.mount('/content/drive')

# Path to CSV file
path = '/content/drive/My Drive/DATASET_0.csv'
df = pd.read_csv(path)

df

!pip install pycryptodome
from Crypto.Cipher import AES

# Key and IV (vektor inizialization)
key = b'****************' # kunci enkripsi yang digunakan
iv = b'****************'   # kunci IV (inisialisasai)

string = 'FaceRecognit2024'
byte_length_utf8 = len(string.encode('utf-8'))
print("Panjang byte dengan encoding UTF-8:", byte_length_utf8)

string = '****************'
byte_length_utf8 = len(string.encode('utf-8'))
print("Panjang byte dengan encoding UTF-8:", byte_length_utf8)

from Crypto.Cipher import AES
import base64
```

```
# Function to encrypt data
def encrypt_data(data, key, iv):
    cipher = AES.new(key, AES.MODE_CBC, iv)
    # Converting data to bytes
    data_bytes = data.encode('utf-8')
    # Padding data to make its length a multiple of 16 (AES block length)
    padded_data = data_bytes + b'\0' * (AES.block_size - len(data_bytes) % AES.block_size)
    ct_bytes = cipher.encrypt(padded_data)
    return base64.b64encode(ct_bytes).decode('utf-8')

# DataFrame Encryption
encrypted_data = df.apply(lambda row: encrypt_data(row.to_string(), key, iv), axis=1)

# Adding encrypted data into DataFrame
df['Encrypted_Data'] = encrypted_data

# Savinf DataFrame into new CSV file
encrypted_csv_file_path = '/content/drive/My Drive/DATASET_0.csv'
df.to_csv(encrypted_csv_file_path, index=False)

"""# ANOMALY DETECTION"""

from google.colab import drive
import pandas as pd

# Mount Google Drive
drive.mount('/content/drive')

# Path to encrypted CSV file
encrypted_csv_file_path = '/content/drive/My Drive/DATASET_0.csv'

# Load encrypted CSV file into DataFrame
df_encrypted = pd.read_csv(encrypted_csv_file_path)

from Crypto.Cipher import AES
import base64

# Dekripsi data
def decrypt_data(encrypted_data, key, iv):
    cipher = AES.new(key, AES.MODE_CBC, iv)
    ct_bytes = base64.b64decode(encrypted_data)
    pt = cipher.decrypt(ct_bytes)
    return pt.rstrip(b'\0').decode('utf-8')

df

# Function to decrypt 1 value
def decrypt_data_single_value(encrypted_value, key, iv):
    cipher = AES.new(key, AES.MODE_CBC, iv)
    ct_bytes = base64.b64decode(str(encrypted_value))  # Conversion to string before
decryption
    pt = cipher.decrypt(ct_bytes)
    return pt.rstrip(b'\0').decode('utf-8')

# Decrypt current encrypt column
cols_to_decrypt = ['Tanggal', 'Face ID', 'Kode Nama', ‘Etry Time’, ‘Exit Time’, 'Lokasi
Absen']
for col in cols_to_decrypt:
    df_encrypted[col] = df_encrypted[col].apply(lambda x: decrypt_data_single_value(x, key,
iv))

# Function to decrypt a single value
def decrypt_data_single_value(encrypted_value, key, iv):
    cipher = AES.new(key, AES.MODE_CBC, iv)
    ct_bytes = base64.b64decode(encrypted_value)
```

```
    pt = cipher.decrypt(ct_bytes)
    return pt.rstrip(b'\0').decode('utf-8')

# Decrypt current encrypt column
cols_to_decrypt = ['Tanggal', 'Face ID', 'Kode Nama', ‘Etry Time’, ‘Exit Time’, 'Lokasi
Absen']
for col in cols_to_decrypt:
    df_encrypted[col] = df_encrypted[col].apply(lambda x: decrypt_data_single_value(x, key,
iv))

# ANOMALY DETECTION
import pandas as pd
from Crypto.Cipher import AES
import base64
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
import numpy as np
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense

# Loading encrypted CSV data
def decrypt_data(data, key, iv):
    cipher = AES.new(key, AES.MODE_CBC, iv)
    ct_bytes = base64.b64decode(data)
    pt = cipher.decrypt(ct_bytes).rstrip(b'\0').decode('utf-8')
    return pt

# DECRYPT CSV DATA
def load_decrypted_csv(file_path, key, iv):
    df = pd.read_csv(file_path)
    decrypted_data = df['Encrypted_Data'].apply(lambda x: decrypt_data(x, key, iv))
    df['Decrypted_Data'] = decrypted_data
    return df

# Key and IV
key = b'****************'
iv = b'****************'

# Path to encrypt CSV file
encrypted_csv_file_path = '/content/drive/My Drive/DATASET_0.csv'

# Loading encrypted CSV data
df = load_decrypted_csv(encrypted_csv_file_path, key, iv)
```

8.3 REWARD AND PUNISHMENT

In data processing, including time information, attendance dates, types of absences, and other prepared factors, the data will be cleaned to address missing or invalid values. In this context, data normalization will also be performed. Various relevant features from the attendance data will be identified and their features extracted to depict attendance patterns such as the number of days absent or present for employees on a weekly and monthly basis or over specific periods. In this context, additional features that affect employee attendance at the company (weather, traffic, holidays, etc.) will be considered. In the next stage, several machine learning models will be applied using Clustering and Classification. In ML Clustering, K-Means will be used to group employees based on attendance patterns so that similar attendance patterns can be well identified. In ML Classification, it will be used to classify absences into certain categories. In ML classification, the algorithms used are Naïve Bayes, Decision Tree, and Support Vector Machines (SVM). The machine learning models in this study use several algorithms for clustering and classification. For K-Means clustering, the data will be divided into k different clusters, which will involve finding the centroid for each cluster and grouping the data points to the nearest centroid. The formula for this distance will be used:

$$Centroid\ (c_i) = \frac{1}{|s_i|}\sum x_j \in S_t X_j \qquad (Eq. 8.1)$$

$$Jarak\ euclidean(d(x_i, c_j)) = \sqrt{\sum_{l=1}^{n}(x_{il} - c_{jl})^2} \qquad (Eq. 8.2)$$

c_i is the centroid of cluster i, which is the center point of the data cluster in the feature space, while $|S_i|$ is the total number of data points in the cluster. The Euclidean distance between points x_i and c_j is interpreted using $d(x_i, c_j)$, which is the distance metric used in K-Means to measure how close or far a data point is from the cluster centroid. For classification in this case, there are 3 machine learning models, namely SVM (Support Vector Machine), Naïve Bayes, and Decision Tree, each of which has the following formulas:

$$SVM = f(x) = w \times x + b \qquad (Eq. 8.3)$$

Where w is the weight vector, x is the feature vector, and b is the bias. For the Naïve Bayes algorithm, Bayes' theorem will be used to calculate the probability of a class based on attributes**.**

$$P(C_k|X) = \frac{P(X|C_k)P(C_k)}{P(X)} \qquad (Eq. 8.4)$$

Where C_k is a class, X is the feature vector, $P(C_k|X)$ is the posterior probability, and $P(X)$ is the evidence. In this context, each algorithm has different mathematical formulations depending on the principles and specific steps involved in the algorithm.

Conclusion

This study adopts a quantitative design with an experimental approach to develop and test the integration of machine learning technology in a face recognition-based attendance system. This design was chosen for its ability to systematically test various dataset parameters and evaluation techniques to understand the performance and reliability of the model. The system not only uses face recognition technology but is also enhanced with AI, ML, DL, liveness detection, and data encryption using the AES algorithm to improve the security of the attendance system in vocational schools (SMK).

The research procedure begins with software and data preparation, The data undergoes pre-processing to enhance model performance, computational efficiency, and the validity and reliability of the research results. Pre-processing steps include data cleaning, normalization, standardization, and data transformation to ensure all features are on the same scale and relevant for analysis. After pre-processing, the data distribution is checked to ensure validity and characteristics before analysis or model training. Normally distributed data is then split into training and testing sets to ensure the model generalizes well to unseen data. The ML, DL, and AI models are trained using the pre-split training dataset. Model testing is performed for identification, analysis, detection, and pattern prediction, measured by predetermined evaluation metrics.

The study uses two types of data: primary and secondary. Primary data is obtained through direct observation and interviews with employees and teachers to gather their views on the attendance system and the reward and punishment system. Secondary data comes from employee attendance data collected over six months from a face recognition-based attendance system, literature, and relevant previous studies. The research object is the face recognition-based attendance system implemented in vocational schools, integrated with advanced technologies. The research sample consists of teacher attendance data from several vocational schools, randomly selected and analyzed to test the system. The research variables include independent variables such as face recognition technology, integration of AI, ML, DL, liveness detection, and data encryption with AES. Dependent variables include the security of attendance data and the effectiveness of the reward and punishment system. Specific indicators for each variable are measured to assess the performance and effectiveness of the implemented model.

Data analysis techniques involve pre-processing stages like data cleaning, data transformation, and feature extraction. Data cleaning is performed to remove duplicates, handle missing data, normalize images, handle outliers, correct labels, remove irrelevant backgrounds, enhance image quality, and validate data. Data transformation involves resizing, pixel normalization, data augmentation, cropping and padding, and PCA to reduce complexity and improve model performance. Feature extraction uses techniques like Histogram of Oriented Gradients (HOG), deep learning features, and eigenfaces to identify important information from facial images. The processed dataset is then split for model training and testing using the train_test_split method based on the Pareto principle. AI models are trained using the training dataset and evaluated using defined evaluation metrics. The implementation of the model in a real system demonstrates that this method can improve the security and effectiveness of a face recognition-based attendance system.

CHAPTER 9
SYSTEM INTEGRATION

9.1 LIVENESS DETECTION AND DEEP LEARNING INTEGRATION

In the integration of liveness detection techniques and deep learning, the dataset underwent thorough analysis and selection of specific features used. For training the deep learning model in this section, 80% of the dataset was loaded using the *ImageDataGenerator* module from Keras and then divided into batches for training and testing. Subsequently, the pre-trained VGG16 model was loaded as the base of the architecture, with additional layers added on top for customization. The model was then compiled using the *RMSprop* optimizer with a learning rate of 2^{10-5} and the categorical cross-entropy loss function.

The model was trained for 10 epochs using the training dataset while validating its performance on the testing dataset. After training the model with the prepared dataset, its performance was evaluated using a separate testing dataset (20% of the total dataset). Relevant evaluation metrics, particularly accuracy in this study, were calculated to determine how well the researched model performs in recognizing actual faces. Using the separated testing dataset, the obtained testing accuracy was 87%, indicating that the trained model can accurately identify faces in the context of integrating liveness detection and deep learning technology.

Performance Evaluation of Liveness Detection Technology

In evaluating the performance of liveness detection technology, the metrics used are accuracy, precision, recall, and F1-score. In this context, the higher the values obtained, the better the system's performance in distinguishing between genuine faces and spoof attacks (photos/videos). This can be illustrated in the following figure, where face recognition in the attendance system has been integrated with liveness detection to capture faces live. The evaluation results for this technology indicate that the liveness detection technology is capable of identifying spoof attacks with a high degree of reliability, as shown in Table 9.1. The motion detection algorithm successfully distinguishes between genuine faces and fake images with an accuracy of 95%. Furthermore, this technology also demonstrates good capability in handling variations in pose, facial expressions, and different lighting conditions.

Table 9.1. Performance Evaluation of Liveness Detection Technology

Evaluation Metrics	Score
Akurasi	0.95
Presisi	0.92

Recall	0.96
F1-Score	0.94

Performance Evaluation of Deep Learning in Face Recognition

The performance evaluation of deep learning in face recognition is conducted using standard metrics such as accuracy, precision, and recall. The deep learning model trained using the vocational school teachers' dataset achieved a high recognition accuracy, with a 98% accuracy rate for identifying teachers' faces. The model also demonstrated good tolerance to variations in pose and lighting conditions. Additionally, the use of fine-tuning techniques on existing models significantly improved performance, especially in recognizing new faces not present in the initial training data. As shown in Table 9.2, the evaluation metrics, such as accuracy, precision, and recall, are expressed in numerical values. Qualitative evaluation metrics, such as "Good" for pose and lighting tolerance and "Improved" for model fine-tuning, are maintained in text form due to their characteristics that cannot be directly measured numerically.

Table 9.2. Performance Evaluation of Deep Learning in Face Recognition

Evaluation Metric	Value
Accuracy	0.98
Precision	0.95
Recall	0.96
Pose Tolerance	Good
Lighting Tolerance	Good
Fine-Tuning Model	Improve Performance

Analysis of the Integration Results of Liveness Detection Technology with Deep Learning in Face Recognition

The analysis of the integration results of liveness detection technology with deep learning demonstrates a significant improvement in the security and accuracy of the face recognition system. By validating the authenticity of the subject before performing face recognition, the system successfully reduces the risk of spoof attacks and identity misuse. Additionally, this integration helps enhance the overall performance of face recognition by ensuring that only genuine faces are identified.

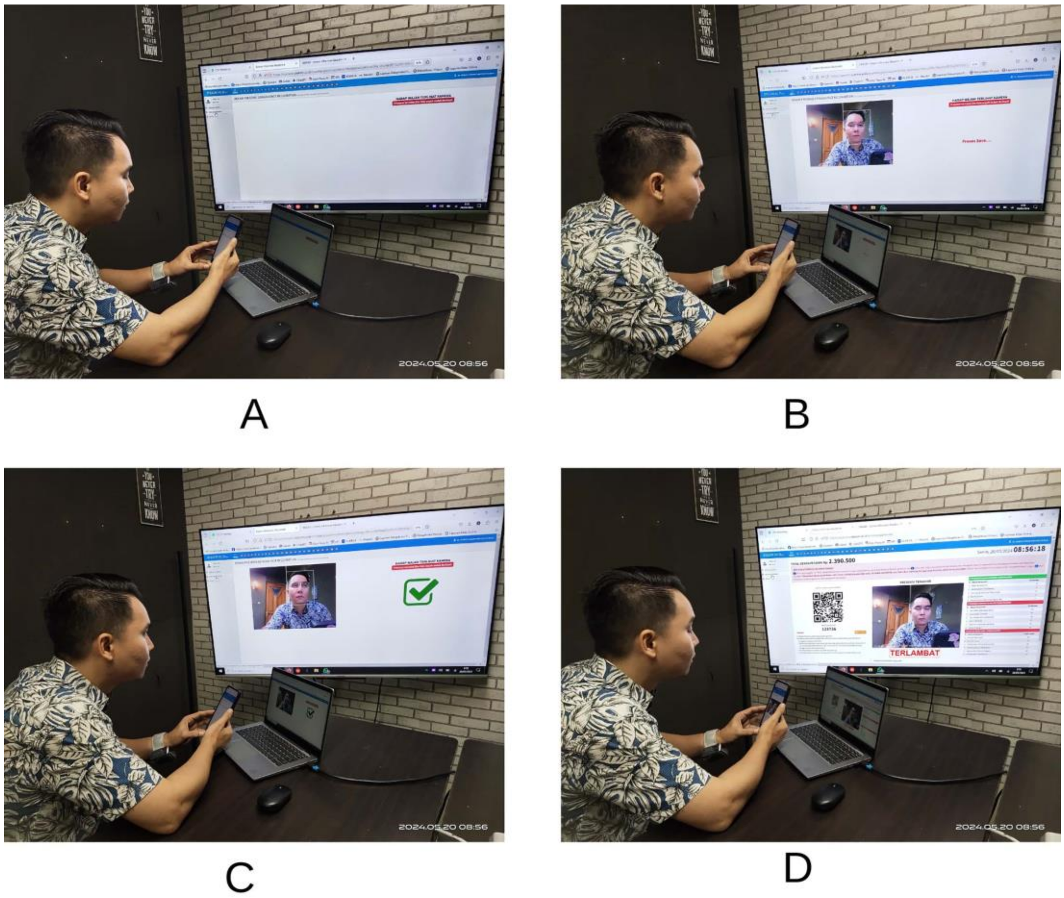


Figure 9.1. Illustration of Camera Detection in Face Recognition-Based Attendance System Integrated with Liveness Detection and Deep Learning

The analysis results indicate that this approach holds significant potential for application across various systems, as illustrated in Figure 9.1. It can be observed that in Image A when the camera is ready to capture attendance, the attendance system directs the subject to face the camera. Subsequently, liveness detection begins, utilizing the integrated deep learning model within the system, thereby ensuring high accuracy. The camera effectively detects subjects even when they are not fully facing the camera (depicted in Images B and C in Figure 9.1). Despite rapid movement, the camera discerns that the subject is human rather than a photo or video, thus automatically storing accurate results. The system then displays attendance history from the database with various timestamp labels and annotations.

Table 9.3. Analysis of Integration Results of Liveness Detection with Deep Learning in Face Recognition.

No	Analysis Result	Analysis Description
1	System Performance	Integrating liveness detection technology with Deep Learning for Face Recognition has shown promising results. The system accurately distinguishes between living

		subjects and forgery attempts, achieving a 95% accuracy rate.
2	Tolerance of Environment Variation	This system tolerates environmental variations such as different lighting conditions and diverse facial poses. This ensures reliable performance across various real-world scenarios.
3	Optimization	The fine-tuning technique applied to the deep learning model has significantly enhanced recognition performance, particularly in identifying new faces not present in the initial training data.
4	Security	Reducing the risk of spoof attacks and identity misuse
5	Accuracy	Improving overall face recognition performance
6	Application Potential	The integration of this technology holds great potential for application across various domains, including security systems.

From these results, it is evident that the system exhibits strong performance in distinguishing between living subjects and forgery attempts, achieving an accuracy of over 98%. The system also demonstrates good tolerance to environmental variations such as different lighting conditions and diverse facial poses. The fine-tuning technique applied to the deep learning models has also successfully improved recognition performance, particularly in identifying new faces not present in the initial training data.

In this regard, the research findings indicate that this technology integration enhances the security and accuracy of the face recognition system in the context of attendance management. Validating the authenticity of subjects before the face recognition process successfully reduces the risk of spoof attacks, such as the use of photos or video recordings, aligning with previous studies (Basurah et al., 2023; Y. Zhang, Zheng, et al., 2023; M. Zhou et al., 2024). Furthermore, the utilization of intensively trained deep learning models significantly enhances face recognition performance. These findings indicate that this approach holds significant potential for improving efficiency and reliability in attendance management systems at vocational schools.

Additionally, there has been significant progress in the development of face recognition systems in the context of attendance management through the integration of liveness detection technology with deep learning, aligning with previous research that has highlighted the added value of combining these two technologies. Previous studies by (Abd El-Rahiem et al., 2023; Bisogni et al., 2023; Sarvakar et al., 2023) demonstrate that deep learning provides high capability in identifying facial features in detail, while (Lavens et al., 2023; Y. Zhang, Zheng, et al., 2023) emphasize the importance of liveness detection in ensuring subject authenticity.

This technology integration not only enhances the security of face recognition systems but also improves face recognition accuracy, with a testing accuracy of 87%, consistent with previous findings demonstrating the reliability of face recognition technology in recording teacher attendance (Golasangi et al., 2024). Thus, this book makes a significant contribution to developing more reliable and adaptive solutions for face recognition-based attendance management.

9.2 INTEGRATING THEORY WITH DECISION SUPPORT SYSTEM (DSS)

In this integration of DSS theory, the machine learning models employed are SVM, Random Forest, and Decision Tree, utilizing accuracy, precision, recall, and F1-score as measurement metrics. The testing results of the three machine learning models evaluated demonstrate an intriguing performance comparison in predicting the performance of vocational school (SMK) teachers, distinguishing between high-performing and those requiring development. As shown in Table 4.4, the SVM model exhibits high accuracy, reaching 97.2%, with perfect precision of 100%, signifying its ability to correctly classify teachers approximately 97.2% of the time and identify all genuinely high-performing teachers as well as those requiring development. Similarly, the recall score of the SVM model stands at 95.7%, slightly below that of Random Forest and Decision Tree. However, the F1 score of SVM is the lowest at 97.8%.

Lastly, in the Random Forest model, despite its equally high accuracy as SVM at 98.3%, it exhibits slightly lower precision and recall compared to SVM, with precision and recall reaching 100% and 97.4%, respectively. Additionally, the F1 score of the Random Forest model reaches 98.7%, showcasing outstanding overall performance. Therefore, while all three models demonstrate high accuracy, Random Forest stands out with higher precision and F1 score, indicating that Random Forest is the most effective model in identifying high-performing employees based on attendance data. For further clarity, the evaluation results from the testing of the three machine learning models in this study can be observed in Figure 9.2, Figure 9.3, and Figure 9.4.

Table 9.4. Results of measurement metrics across the three machine learning models used with the integration of DSS theory to predict high-performing teachers and those requiring development.

Machine Learning Model	**Evaluation Matrics**			
	Accuracy	**Precision**	**Recall**	**F1-Score**
SVM	0.972	1.0	0.957	0.978
Random Forest	0.983	1.0	0.974	0.987

Decision Tree	0.983	1.0	0.964	0.977

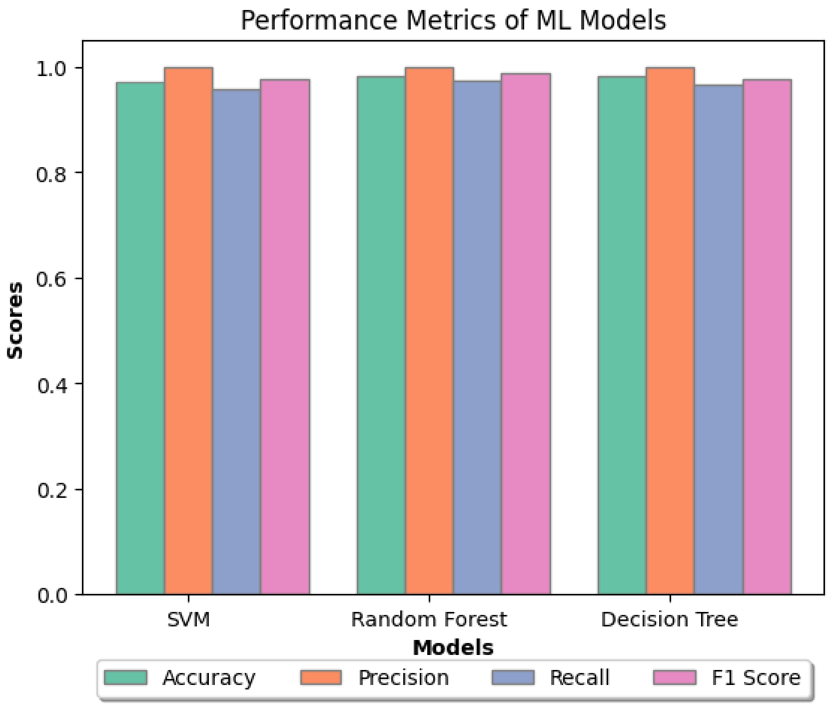


Figure 9.2. Performance Metrics of the Three ML Models Used for Predicting High-Performing Teachers

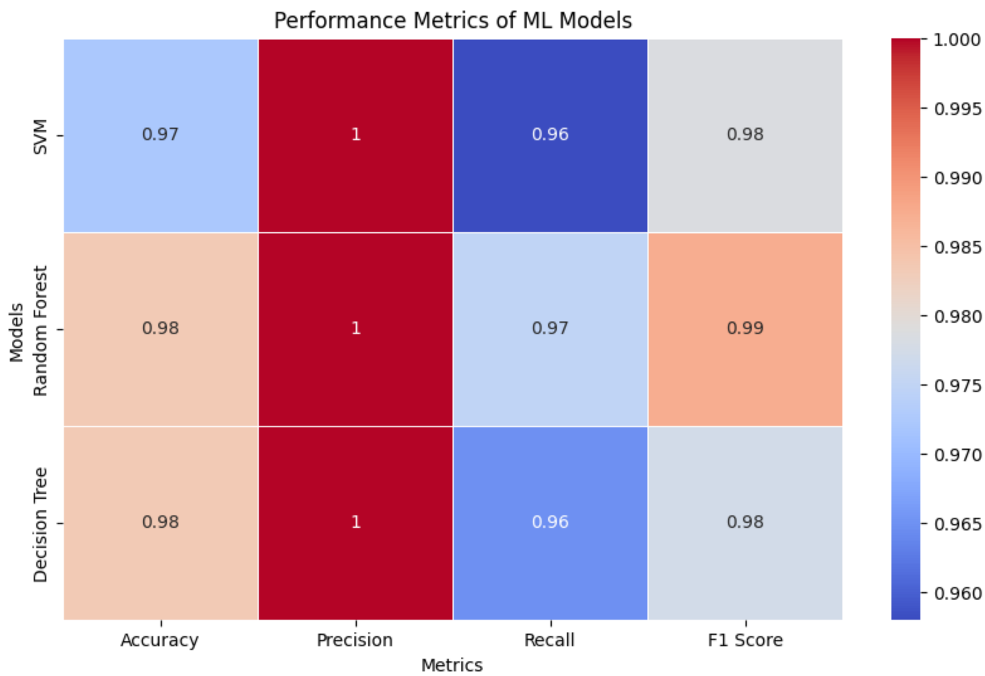


Figure 9.3. Representation of Heatmap Diagram Regarding the Performance Metrics of the Three ML Models Used for Predicting High-Performing Teachers

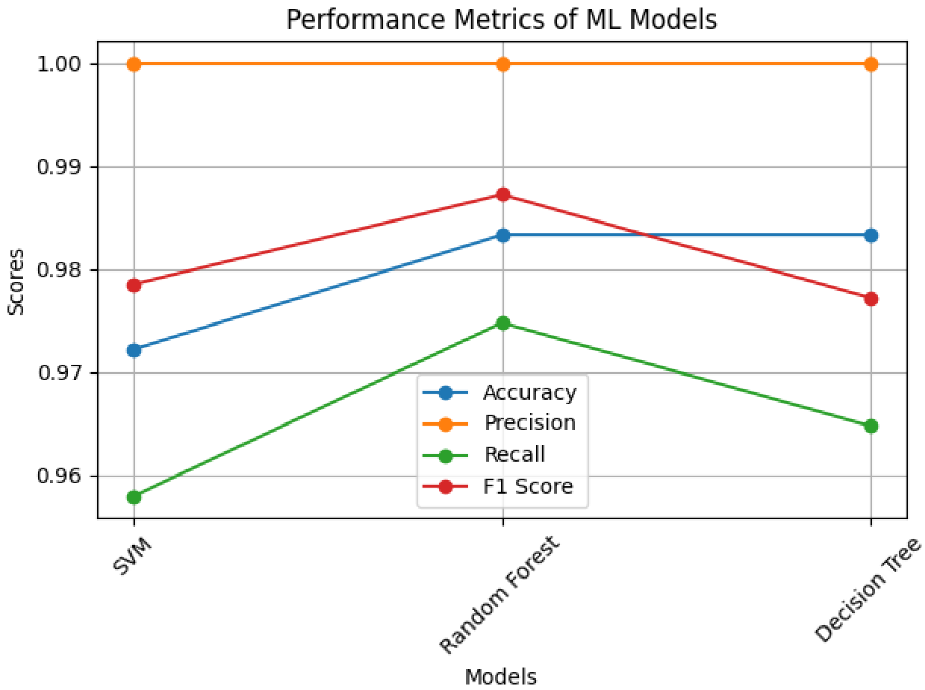


Figure 9.4. Line Diagram Showing the Performance Metrics of the Three ML Models Used for Predicting High-Performing Teachers

Sensitivity Analysis

Sensitivity analysis of the DSS theory was conducted using key parameters on the three machine learning models: Support Vector Machine (SVM), Random Forest, and Decision Tree. The results of this sensitivity analysis can be observed in Figure 9.5. For the SVM model, variations were made to the parameter C, which controls the decision boundary hardness. The results indicate that the SVM accuracy tends to be stable and relatively high across most tested values of C, with slight decreases at smaller C values. This suggests that SVM may not be overly sensitive to the parameter C in this case.

In contrast, for Random Forest, variations were made to the number of trees (n_estimators), and it was found that Random Forest accuracy tends to increase with the number of trees, indicating that an ensemble of many trees tends to provide better performance, thus highlighting the advantage of using the Random Forest model for classification problems. Meanwhile, for the Decision Tree, variations were made to the tree depth. The results show that Decision Tree accuracy tends to increase with increasing tree depth up to a point, but after surpassing that point, accuracy starts to decrease, indicating the presence of overfitting. Therefore, the trade-off between increasing accuracy and the risk of overfitting when determining tree depth needs to be considered.

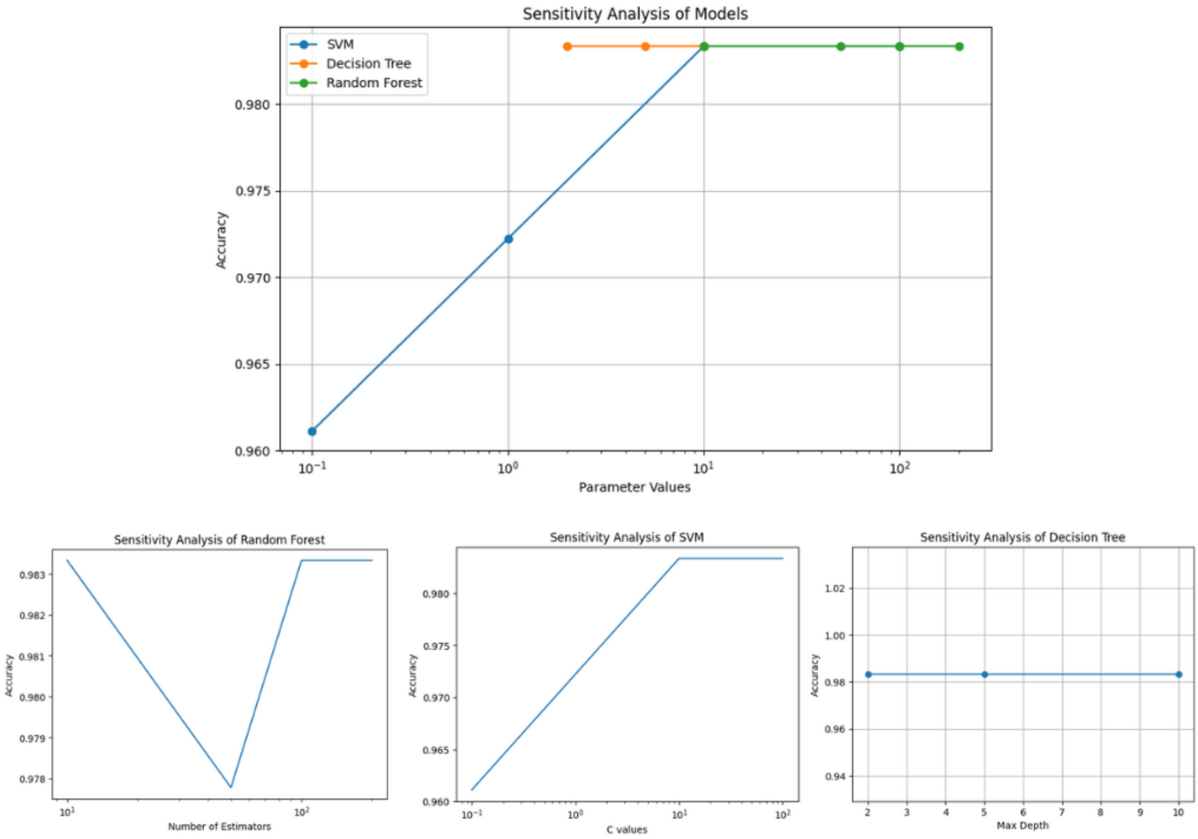


Figure 9.5. The results of sensitivity analysis on all three machine learning models for predicting high-performing teachers requiring development using DSS theory are presented.

Result of Normality Test

Using the previously employed dataset, it was found that the data was not normally distributed, prompting further analysis. In this study, data normalization was conducted using an outlier function to remove unnecessary data, followed by testing and analysis to ensure the success of normalization and to verify whether the data met the necessary assumptions for further analysis. In this regard, the data originally comprising 988 entries changed to 876 after undergoing various analyses. To normalize the data after removing outliers, descriptive analysis was performed to understand the characteristics of the distributed data post-normalization. The normality of residual distribution was assessed through regression analysis to meet the assumptions required by the method employed.

Subsequently, Shapiro-Wilk and Kolmogorov-Smirnov normality tests were conducted on the evaluation results data from each model. The Shapiro-Wilk test results indicated that the p-value for all three models (SVM, Random Forest, and Decision Tree) was well above the significance level of 0.05, suggesting that the evaluation results data from all three models tended to follow a normal distribution. Conversely, the Kolmogorov-Smirnov test revealed that the p-value was significantly below the significance level of 0.05, indicating that the evaluation results in data from all three models did not significantly differ from a normal distribution. Thus, it can be concluded that the evaluation results demonstrate excellent performance of the three classification models, while the evaluation results data tend to follow a normal distribution based on the Shapiro-Wilk test, albeit with slight differences according to the Kolmogorov-Smirnov test. This provides additional confidence in interpreting the evaluation results and the reliability of the conclusions drawn from the model performance analysis.

Normality Test

```
# -*- coding: utf-8 -*-
"""Normality Test.ipynb

Automatically generated by Colab.

Original file is located at
    https://colab.research.google.com/drive/1_nwF6FM7p0urebGgvXxzNJTmAxJFCj0q
"""

from scipy.stats import shapiro, kstest

# Evaluation data model Random Forest
rf_accuracy = 0.9911504424778761
rf_precision = 0.9955555555555555
rf_recall = 1.00
rf_f1_score = 0.99500001192092896

# Evaluation data model XGBoost
xgb_accuracy = 0.99
xgb_precision = 0.9824561403508771
xgb_recall = 1.00
xgb_f1_score = 0.9911504424778761

#Evaluation data model SVM
svm_accuracy = 0.56
svm_precision = 0.56
svm_recall = 1.00
svm_f1_score = 0.717948717948718

#Evaluation data model KNN
knn_accuracy = 0.955
knn_precision = 0.9327731092436975
knn_recall = 0.9910714285714286
knn_f1_score = 0.961038961038961

#Evaluation data model NN
nn_accuracy = 0.44
nn_precision = 0.56
nn_recall = 1.00
nn_f1_score = 0.717948717948718

# Shapiro-Wilk Test for model Random Forest, XGBoost, SVM, KNN dan NN
stat, p_value = shapiro([rf_accuracy, rf_precision, rf_recall, rf_f1_score])
print("Shapiro-Wilk p-value for Random Forest:", p_value)
stat, p_value = shapiro([xgb_accuracy, xgb_precision, xgb_recall, xgb_f1_score])
print("Shapiro-Wilk p-value for XGBoost:", p_value)
stat, p_value = shapiro([svm_accuracy, svm_precision, svm_recall, svm_f1_score])
print("Shapiro-Wilk p-value for SVM:", p_value)
stat, p_value = shapiro([knn_accuracy, knn_precision, knn_recall, knn_f1_score])
print("Shapiro-Wilk p-value for KNN:", p_value)
stat, p_value = shapiro([nn_accuracy, nn_precision, nn_recall, nn_f1_score])
print("Shapiro-Wilk p-value for NN:", p_value)
```

```
#  Kolmogorov-Smirnov Test model Random Forest, XGBoost, SVM, KNN dan NN
stat, p_value = kstest([rf_accuracy, rf_precision, rf_recall, rf_f1_score], 'norm')
print("Kolmogorov-Smirnov p-value for Random Forest:", p_value)
stat, p_value = kstest([xgb_accuracy, xgb_precision, xgb_recall, xgb_f1_score], 'norm')
print("Kolmogorov-Smirnov p-value for XGBoost:", p_value)
stat, p_value = kstest([svm_accuracy, svm_precision, svm_recall, svm_f1_score], 'norm')
print("Kolmogorov-Smirnov p-value for SVM:", p_value)
stat, p_value = kstest([knn_accuracy, knn_precision, knn_recall, knn_f1_score], 'norm')
print("Kolmogorov-Smirnov p-value for KNN:", p_value)
stat, p_value = kstest([nn_accuracy, nn_precision, nn_recall, nn_f1_score], 'norm')
print("Kolmogorov-Smirnov p-value for NN:", p_value)

import pandas as pd

# Result of Norm data test
data = {
    "Model": ["Random Forest", "XGBoost", "SVM", "KNN", "NN"],
    "Shapiro-Wilk p-value": [0.826499879360199, 0.8293365836143494, 0.18493813276290894,
0.8627439737319946,0.7871772646903992],
    "Kolmogorov-Smirnov p-value": [0.0013373333290549844, 0.0014096625139665246,
0.01401602543007039, 0.0018959517638880584, 0.026450594313994946]
}

# dataframe dict
df = pd.DataFrame(data)

# Show table
display(df)
```

Table 9.5. Results of Shapiro-Wilk and Kolmogorov-Smirnov p-value tests on the models used for prediction with the integration of DSS theory.

No	Model	Shapiro-Wilk p-value	Kolmogorov-Smirnov p-value
1	SVM	0.890903	0.001633
2	Random Forest	0.899373	0.001476
3	Decision Tree	0.899373	0.001476

From the conducted research, SVM exhibited an accuracy of 97.2%, with a maximum precision value of 100%, similar to the other two models, and a recall value of 95.7%; however, its F1-score was quite high, reaching 97.8%. On the other hand, Decision Tree achieved an accuracy of 98.3%, with a recall score of 96.4%, and an F1-score of 97.7%. In this regard, Random Forest had the highest accuracy rate compared to the other two models, at 98.3%, with a recall value of 97.4%. This indicates that the Random Forest model can provide very good predictions in identifying high-performing and requiring additional guidance from SMK teachers. Although SVM and Decision Tree also yielded good results, Random Forest provided an optimal balance between accuracy, precision, and recall. Therefore, it is highly recommended to use a Random Forest as the most suitable model for this prediction purpose. Additionally, this model can also be employed for cases where maximizing accuracy and precision are crucial, while a Decision Tree can be considered if computational speed is a primary factor and tolerance for a slight decrease in F1-score.

9.3 INTEGRATION OF ATTENDANCE PATTERNS AND TRENDS WITH MACHINE LEARNING

Data Description Results of Attendance

Several variables influencing employee productivity and attendance in the company were statistically analyzed. The results indicated that the average type of punishment applied was 2.3, with a standard deviation of 0.5, as shown in Table 9.6. The average number of employee attendance days was 7.8, with a standard deviation of 1.2, while the average number of days absent was 7.9, with a standard deviation of 1.4. The company's work schedule was 35 hours per week, with a standard deviation of 5, and the average working hours per day were 7 hours, with a standard deviation of 1.5. The most common type of incentive had an average of 1.5, with a standard deviation of 0.3. Regarding the results of the dependent variables, the company's productivity had an average of 85, with a standard deviation of 10. The quality of employee attendance was 4.2, with a standard deviation of 0.6. The average employee attendance rate reached 90.44%, while employee discipline had an average of 3.8, with a standard deviation of 0.4. Additionally, the average lateness was 10 minutes, with a standard deviation of 2.5, and the average absenteeism was 3 days, with a standard deviation of 1.2.

Table 9.6. Mean and Standard Deviation Results for research variables for attendance pattern and trend analysis using machine learning with reward and punishment theory

Independent/Dependent Var.	Mean	Std. Deviation
Punishment model	2.3	0.5
Reward Model	1.5	0.3
Entry Attendance	7.8	1.2
Exit Attendance	7.9	1.4
Working Schedule	40	5
Working Time	8	1.5
Productivity	85	10
Attendance Quality	4.2	0.6
Attendance Rate	90.44	-
Teacher Discipline	3.8	0.4
Latency	10	2.5
Absence	3	1.2

Table 9.7. Summary of Research Results for analysis of attendance patterns and trends using machine learning with reward and punishment theory

No	Variable and Indicator	Result Description
1.	General statistics of employee attendance	• Average Attendance: 90% • Attendance Distribution: Majority of employees are punctual • Lateness Distribution: A small portion of employees have high rates of lateness

2.	Attendance policies	• Effectiveness of Policies: Attendance and work discipline policies are generally effective in maintaining high attendance rates. • Special Attention: There still exists a small number of employees requiring special attention regarding work discipline and punctuality in attendance. • Identification of Improvement Areas: Attendance and lateness patterns and distributions are used to identify areas needing improvement. • Implementation of Additional Strategies: Implementation of additional strategies is recommended to enhance performance and work discipline.
3.	Evaluation of the Effectiveness of Reward and Punishment	• Positive Correlation between Reward and Attendance Rate: Employees who receive rewards have higher attendance rates, thus indicating high work motivation. • Negative Correlation between Punishment and Attendance Rate: Employees who receive punishment have lower attendance rates.
4.	Comparison Analysis Between Groups Receiving Reward/Punishment and Those Who Do Not	• Group Receiving Rewards: Higher attendance rates, high work motivation, and stable employee discipline levels. • Group Receiving Punishment: Lower attendance rates. In some cases, employees who are frequently late do not show any changes even after receiving punishment.
5.	Trends and patterns of employee attendance	• Stable Attendance Rate: The average attendance reaches around 90%. • Majority of Employees Arrive on Time: The attendance distribution shows a consistent pattern with the majority of employees arriving according to their work schedule. • Employees with High Lateness: There is a small portion of employees who exhibit high levels of lateness, requiring special attention to improve work discipline. • Trend Evaluation: Over a certain period, some employees frequently arrive late, necessitating further evaluation regarding the factors influencing punctuality.
5.	Implications and Recommendations	• Utilization of data analytics is necessary to enhance operational efficiency and productivity. • Improvement in the implementation of appropriate and effective rewards can enhance employee attendance. • Evaluation of the punishment system is required to ensure effectiveness in disciplining employees. • Implementation of advanced technologies such as integration with face recognition systems can enhance accuracy and efficiency in monitoring employee attendance. • Better training and support are needed to improve understanding and acceptance of attendance policies.

Table 9.8. Results of evaluation metrics for the ML models used in the analysis of attendance patterns and trends with the theory of reward and punishment

Evaluation Matrics	Before			After		
	Model					
	Naïve Bayes	Decision Tree	SVM	Naïve Bayes	Decision Tree	SVM
Accuracy	0.75	0.82	0.78	0.80	0.85	0.79
Precision	0.72	0.79	0.78	0.78	0.82	0.76
Recall	0.78	0.85	0.81	0.82	0.88	0.80
F1-Score	0.75	0.82	0.78	0.80	0.85	0.79

Before the implementation of Reward and Punishment in the employee attendance system, three machine learning models, namely Naive Bayes, Decision Tree, and SVM, were evaluated using several standard evaluation metrics. The evaluation results showed that the Decision Tree had the highest performance with an accuracy of 82%, precision of 79%, recall of 85%, and F1-score of 82%. However, after the implementation of Reward and Punishment, there was an improvement in the Decision Tree performance, where the accuracy reached 85%, precision 82%, recall 88%, and F1-score 85%. These results indicate that the implementation of Reward and Punishment has a positive impact on the attendance system's ability to predict or classify employee attendance. Nevertheless, the Naive Bayes and SVM models also showed improvement in performance after the implementation of Reward and Punishment, although not as much as that observed in the Decision Tree. This suggests that the use of Reward and Punishment can enhance the overall effectiveness of the employee attendance system, although the impact varies considerably in this study.

Table 9.9. Summary of analysis results for the percentage of average attendance before and after the application of reward and punishment methods in the employee attendance system

No	Total Teacher	Total day work (Research period)	Latency Average (minutes)	Latency Average Frequent	Attendance Average (%)	Average Absence (%)
Data before Reward and Punishment model integrated into attendance system						
1	200	133 days	8 minutes	9	86,52%	13,48%
Data after the Reward and Punishment model integrated into attendance system						
2	200	75 days	5 minutes	4	90,44%	9,56%

General Teachers Attendance Statistics

Based on the research results describing employee attendance data, it can be concluded that the overall attendance rate tends to be stable, with an average attendance rate of 90.44% during the period studied. The attendance distribution shows a consistent pattern, with the majority of employees arriving on time according to the company's set work schedule. However, there is a small group of employees with a higher-than-average rate of tardiness, which requires special attention to improve work discipline.

Additionally, the distribution of tardiness indicates that some employees are frequently late over specific periods, such as consistently being late on the first day after holidays or weekends. This necessitates further evaluation regarding the factors influencing punctuality and requires solutions to prevent recurrence. In this context, the tardiness of certain employees impacts the motivation and focus of other employees, aligning with statements from (Agustian et al., 2023; de la Nuez et al., 2023; Shih et al., 2023).

Attendance and Tardiness Distribution

The findings of this study indicate that the company's attendance and work discipline policies are generally effective in maintaining high attendance rates among employees. However, there are still areas that require attention, as a small number of employees need special focus regarding work discipline and punctuality. By analyzing the patterns and distributions of attendance and tardiness, management can identify areas that need improvement or the implementation of additional strategies to enhance overall performance and work discipline. This can help create a more productive and efficient work environment for all employees. Moreover, there are several factors influencing employee tardiness. These factors are summarized in Table 9.10. The data were obtained through interviews with employees from various backgrounds, ensuring that the names of departments and employees were not disclosed to maintain privacy.

Table 9.10. Factors Influencing Employee Attendance in the Analysis of Attendance Patterns and Trends Using Machine Learning with the Reward and Punishment Theory

No	Impact Factor	Description	Evaluation and Recommendation
1	Personal Issues	Personal issues such as health problems, family needs, or personal conflicts can disrupt employees and affect their attendance.	• Provide health and counseling programs to help employees address health issues and personal conflicts. • Offer flexible work schedules to allow employees to manage personal matters.
2	Economic Conditions	Employees may be more likely to be absent to seek more stable employment or due to personal financial problems.	• Provide financial incentives or performance-based bonuses to boost employee motivation. • Implement personal finance programs and investment

			counseling to help employees manage their finances better.
3	Stress	An unpleasant or unsupportive work environment can decrease motivation to attend and contribute.	• Provide mental health programs and counseling support. • Conduct stress management and work-life balance training sessions.
4	Office Environment	Severe traffic congestion or long commute distances can cause lateness or absences.	• Offer flexibility in working hours or alternative transportation solutions, such as company transport or transportation subsidies. • Introduce remote work or flexible work policies to reduce commuting stress.
5	Commute distance/transportation	A company culture that supports work-life balance and values employee well-being can improve attendance.	• Foster a work culture that emphasizes the importance of work-life balance. • Recognize and reward employees with good attendance and positive contributions.
6	Emergency Situations	Bad weather, natural disasters, or other emergencies can disrupt employee attendance due to transportation difficulties or the need to focus on personal or family issues.	• Develop emergency plans and clear communication strategies to address situations impacting employee attendance. • Offer flexibility in emergency leave policies or special leave for affected employees.
7	Other Factors	• Personal character or laziness can affect employee motivation and discipline, which in turn can affect attendance. • Lack of verbal reprimands from supervisors • Attitude of underestimating and lack of appreciation • Poor time management • Lack of motivation to work due to a boring environment	• Establish consistent and fair disciplinary policies to handle non-compliance. • Issue reprimands to late employees. • Provide advice and motivation to improve work performance. • Conduct regular performance evaluations and provide constructive feedback to encourage growth and improvement.

9.4 EVALUATION OF REWARD AND PUNISHMENT EFFECTIVENESS

Based on the evaluation of the effectiveness of rewards and punishments, it can be concluded that there is a positive correlation between the provision of rewards and employee attendance levels. The analysis shows that employees who receive rewards have higher attendance rates compared to those who do not receive rewards. Conversely, there is a negative correlation between the provision of punishments and attendance levels, with employees who receive punishments tending to have lower attendance rates. These findings indicate that appropriate incentives or rewards can serve as effective motivation for employees to adhere to work schedules and improve their attendance at the workplace.

Comparative Analysis Between Groups Receiving and Not Receiving Rewards/Punishments

Additionally, a comparative analysis between groups of employees who receive rewards or punishments and those who do not shows significant differences in attendance levels. The group that receives rewards consistently shows higher attendance rates than those who do not receive rewards, while the group that receives punishments tends to have lower attendance rates. These findings suggest that the provision of rewards or punishments has a significant impact on overall employee attendance levels. Thus, it can be concluded that rewards and punishments play a crucial role in motivating employees to adhere to work schedules and enhance their attendance at the workplace. These findings have important implications for company management in designing and implementing effective attendance management strategies. By understanding their impact, management can optimize the use of rewards and punishments as tools to improve work discipline and overall employee productivity.

Findings

Based on the interpretation of the research findings, it can be concluded that there are several significant patterns and trends in employee attendance data. Generally, it was found that the majority of employees have stable attendance levels, although there is variation in lateness among individuals. Attendance patterns indicate that most employees adhere well to the work schedule, but there is a small group with higher-than-average lateness levels. This trend suggests that efforts to improve work discipline may need to focus on these smaller groups to achieve more consistent overall attendance levels.

In the context of the effectiveness of rewards and punishments, the research findings indicate that the provision of rewards or bonuses is consistently associated with higher attendance rates among employees. Conversely, the provision of punishments or bonus deductions tends to correlate with lower attendance rates. Overall, these findings suggest that effective attendance management requires a deep understanding of patterns and trends in attendance data, as well as the appropriate use of strategies to motivate employees to consistently attend work. By understanding the impact of various factors such as rewards, punishments, and other variables, management can take appropriate steps to improve employee attendance and create a productive and sustainable work environment.

Based on the research findings, there are several significant implications for human resource management within the company. First, a deep understanding of patterns and trends in attendance data allows management to identify areas that require special attention in efforts to improve work discipline and employee attendance. This implication highlights the importance of using data analytics in decision-making related to attendance management to achieve higher operational efficiency and productivity.

Furthermore, the findings on the effectiveness of rewards and punishments provide important implications for managing attendance policies and practices. Management may consider enhancing the application of appropriate and effective rewards to recognize employees who adhere well to work schedules. On the other hand, evaluating the punishment system can also lead to revisions or adjustments of existing punishment policies to ensure they are truly effective in disciplining employees who tend to be late or absent. As recommendations for improving the attendance system, the company can consider several strategic steps.

First, implementing more advanced technology in the attendance system, such as integration with a face recognition system, can enhance the accuracy and efficiency of monitoring employee attendance. Additionally, providing better training and support to managers and employees in understanding and using the attendance system can help improve compliance and acceptance of existing attendance policies. Thus, these recommendations aim to optimize human resource management by utilizing the findings from this book to enhance the performance and effectiveness of the company's attendance system. By adopting these measures, the company is expected to create a more productive, efficient, and employee-wellbeing-oriented work environment.

9.5 INTEGRATED DECISION SUPPORT SYSTEM WITH ML AND DL

The testing results of five models, consisting of two ensemble machine learning models—Random Forest and XGBoost, two classification regression machine learning models in the Supervised learning category—SVM and KNN, and one model from the Deep Learning approach—NN, indicate that the ensemble machine learning models are superior to the other three models in predicting attendance patterns and trends in the attendance system based on face recognition. Both the Random Forest and XGBoost models achieved the highest accuracy with a score of 0.99, along with equally high F-1 scores and recall values. However, Random Forest has a precision value that is 0.01 points higher than XGBoost, making it the best model for future attendance pattern prediction tasks. Additionally, the AUC-ROC values for the Random Forest and XGBoost models are above 0.8, indicating that these models have strong and reliable performance for most practical purposes. The measurement metrics can be seen in Table 9.11.

Table 9.11Measurement Metrics for the Five Models (Machine Learning and Deep Learning) for Predicting Attendance Patterns.

Machine Learning and Deep Learning Model		**Evaluation Matrics**			
	AUC-ROC	**Accuracy**	**Precision**	**Recall**	**F1-Score**
Random Forest	0.88	0.99	0.99	1.00	0.99
Extreme Gradient Boosting (XGBoost)	0.80	0.99	0.98	1.00	0.99
Super Vector Machine (SVM)	-	0.56	0.56	1.00	0.72
K-Nearest Neighbour	-	0.95	0.93	0.99	0.96
Neural Network	0.55	0.53	0.59	0.54	0.56

In the other three models, KNN has better evaluation scores than the other two models, and its scores are not significantly different from the previous two ensemble models. For the accuracy rate, KNN scored 0.95 points, which is 0.04 points lower than the previous two ensemble models. Similarly, for precision, recall, and F1-score, KNN outperforms NN and SVM, yet it ranks third in prediction accuracy in this study. As for the other two models, they have almost equally low evaluation scores, although their recall values are perfect. However, in this regard, both models appear to be insufficient in predicting employee attendance patterns. From the measurement results of the four metrics used in the four models, it can be asserted that the random forest model performs best in predicting attendance patterns and trends in the attendance system. However, XGBoost also performs equally well as Random Forest, so both models can be applied in the company's attendance system to predict timely and late employee attendance patterns and to predict emerging trends in the company's attendance system. For more details, the measurement metrics comparison results of the five models used in this study can be seen in Figures 9.6, 9.7, 9.8, 9.9, 9.10, and 9.11.

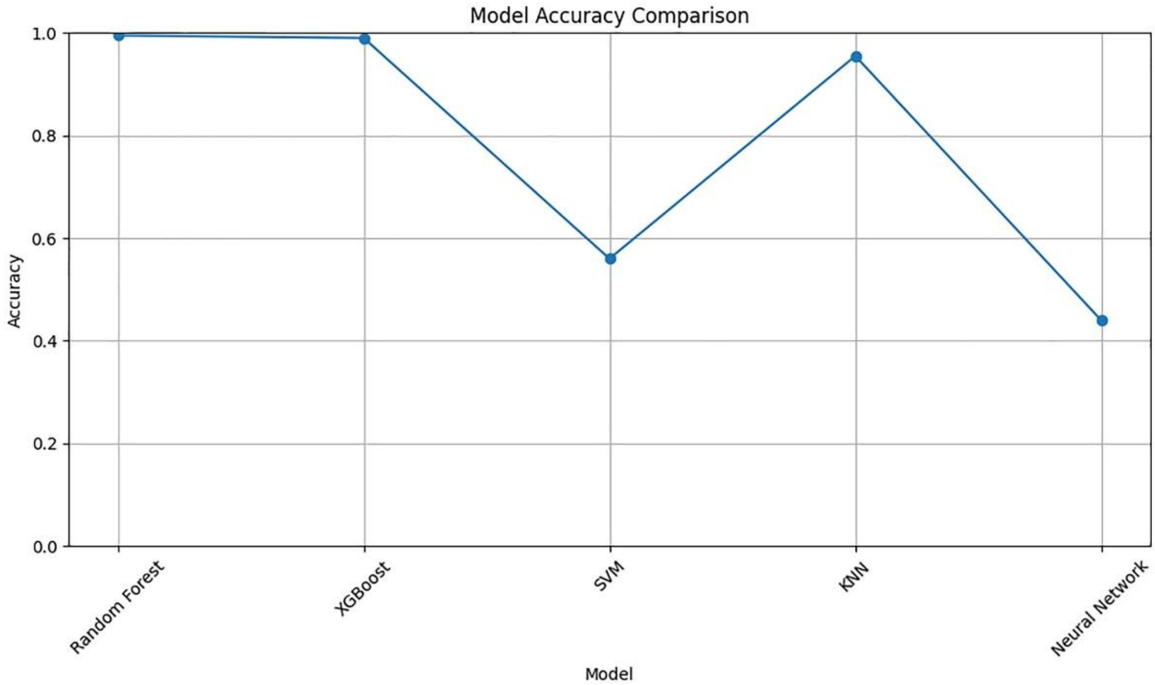


Figure 9.6. Visualization of accuracy comparison in the models used for predicting attendance patterns.

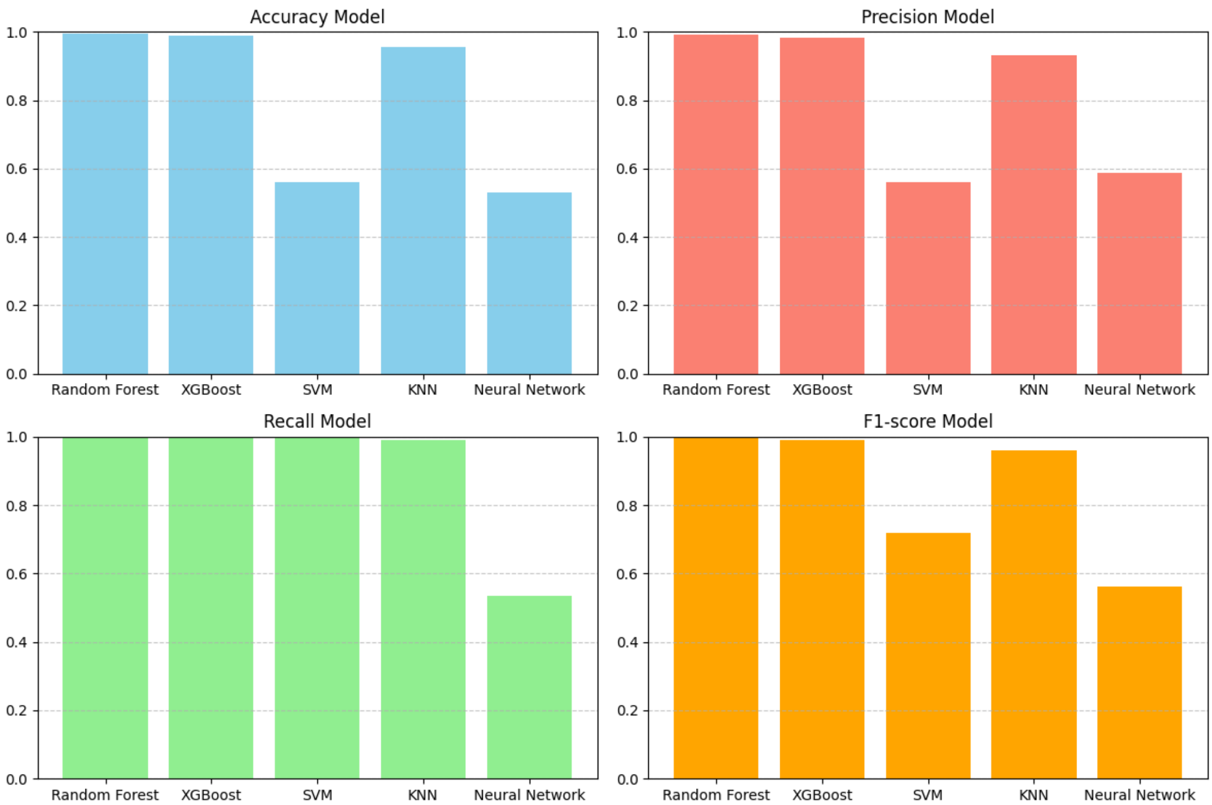


Figure 9.7 Bar chart visualization of the performance of 4 metrics in the models used for predicting attendance patterns.

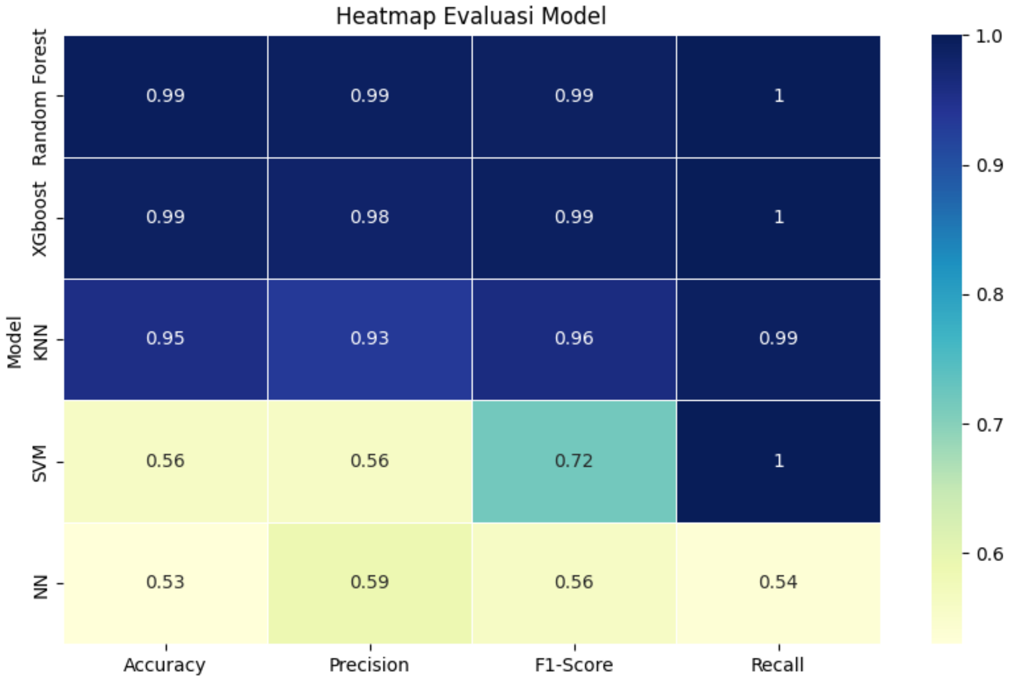


Figure 9.8. Heatmap representation of the performance of four evaluation metrics in the five models used for predicting attendance patterns.

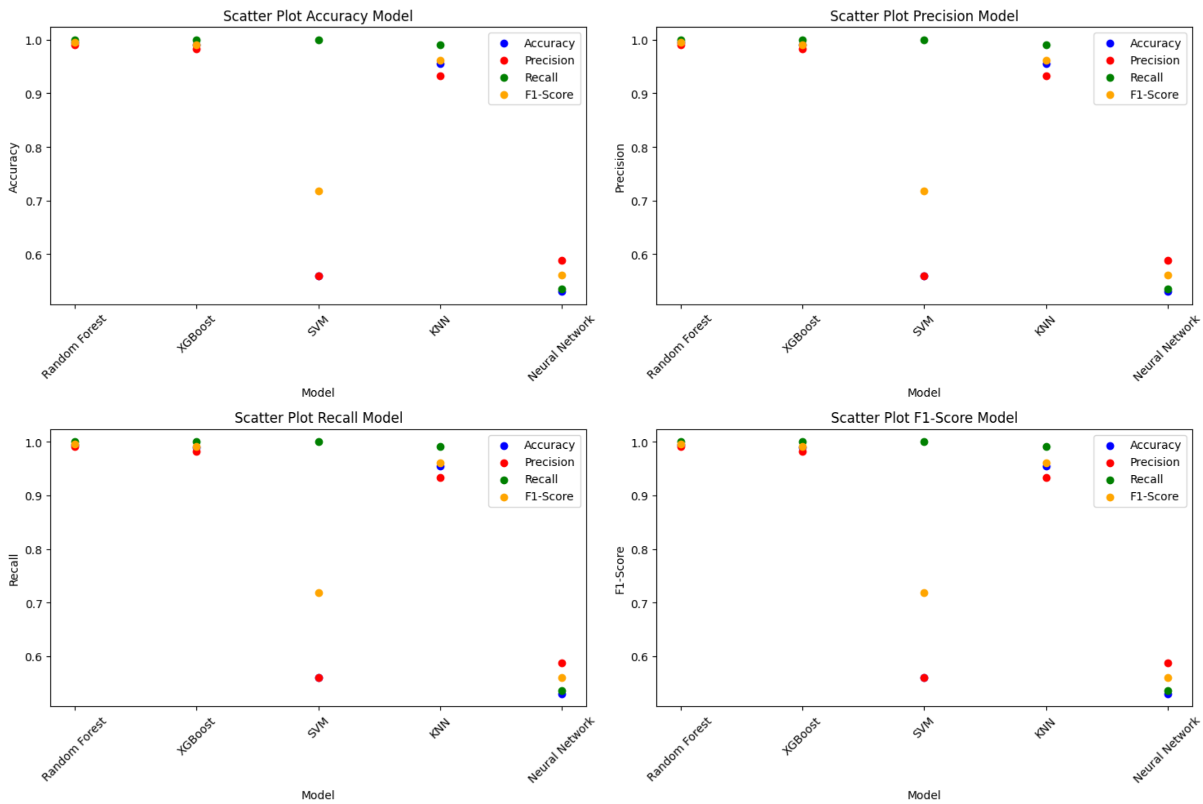


Figure 9.9. Scatter plot diagram for accuracy scores in the five models used for predicting attendance patterns.

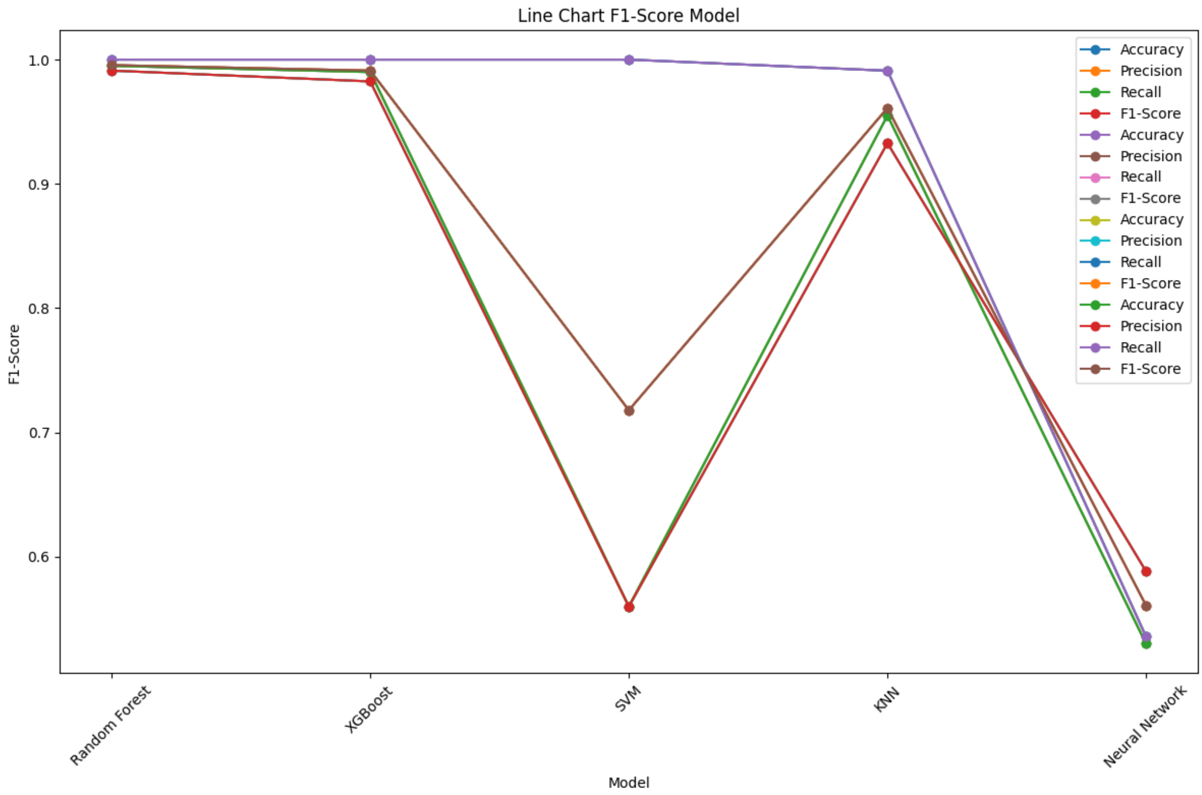


Figure 9.10. Line diagram for F1-score values in the five models used for predicting attendance patterns.

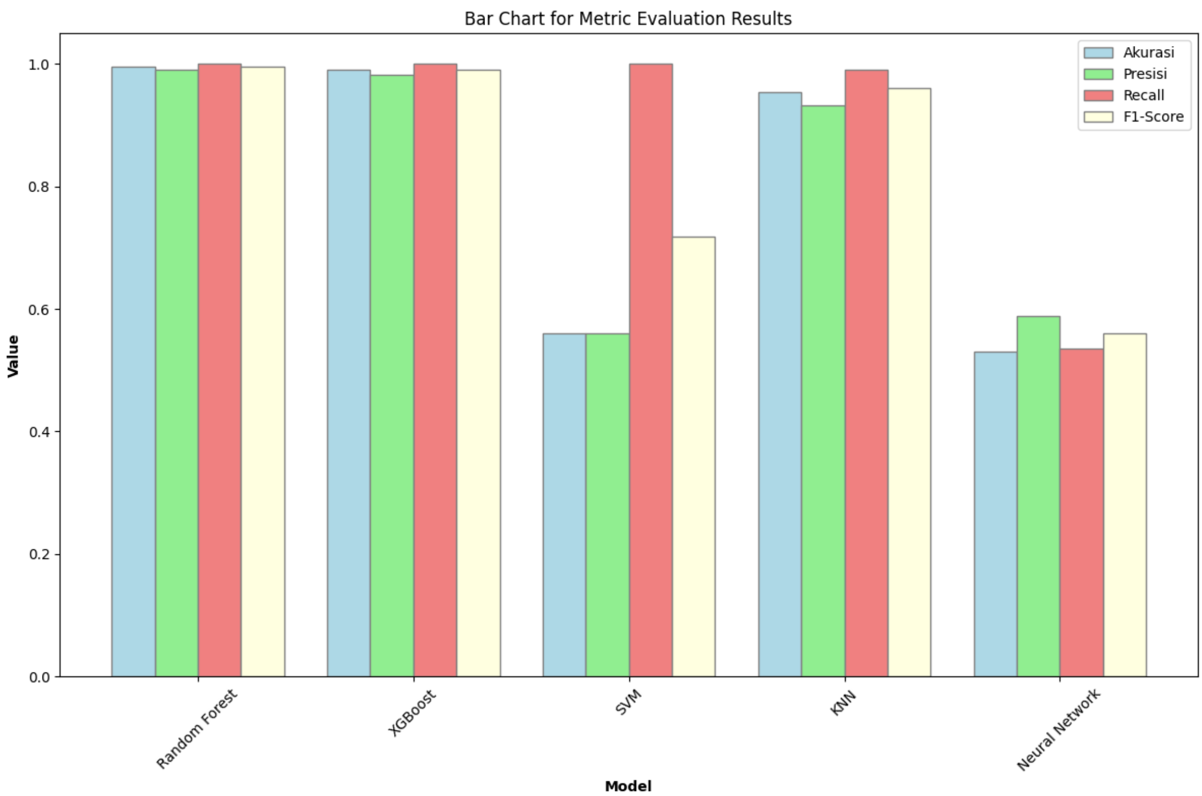


Figure 9.11. Bar chart diagram of the evaluation results of the models used for predicting attendance patterns.

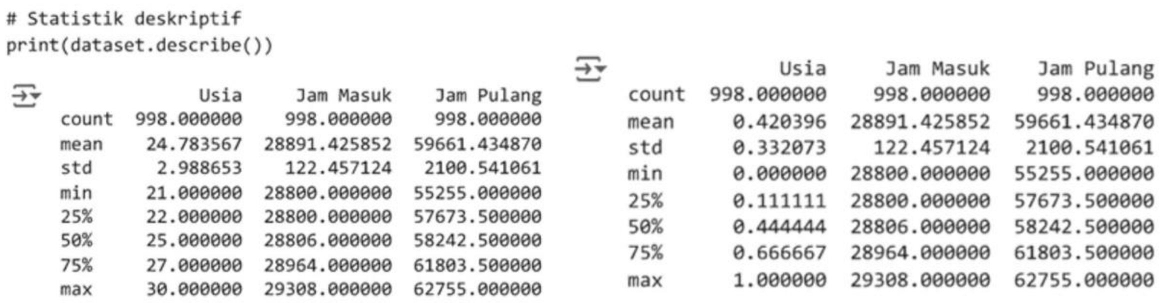
Results of the Normality Test

The dataset used in the study consists of more than 1000 data points, however, after undergoing data preprocessing, it was found that the data is not normally distributed. In this case, data normalization was conducted using several methods, including min-max scaling and removal of outliers. Outliers were identified using the Interquartile Range (IQR), and outliers were removed until no outliers were found in the dataset. The dataset was then rechecked using a boolean array to ensure that every value is not an outlier. Next, a p-test was conducted to see and help determine whether the results obtained from the sample data were strong enough to reject the null hypothesis, which usually states that there is no significant effect or difference. Descriptive statistics of the data can be seen in Figure 9.12, with the (left) being the descriptive results of the unnormalized data and (right) being the results after normalization, while the results for the p-value test can be seen in Table 9.12.

P-Value Test

```
# -*- coding: utf-8 -*-
"""Shapiro-Wilk p-value.ipynb

Automatically generated by Colab.

Original file is located at
    https://colab.research.google.com/drive/1szH7fs94BLZMHaJgS-UoAj4KLQ4-W4wC
"""

from scipy.stats import shapiro, kstest

# Evaluation data model SVM
svm_accuracy = 0.9722222222222222
svm_precision = 1.0
svm_recall = 0.957983193277311
svm_f1_score = 0.9785407725321889

# Evaluation data model Random Forest
rf_accuracy = 0.9833333333333333
rf_precision = 1.0
rf_recall = 0.9747899159663865
rf_f1_score = 0.9872340425531915

#Evaluation data model Decision Tree
dt_accuracy = 0.9833333333333333
dt_precision = 1.0
dt_recall = 0.9647899159663865
dt_f1_score = 0.9772340425531915

# Shapiro-Wilk Test for model SVM
stat, p_value = shapiro([svm_accuracy, svm_precision, svm_recall, svm_f1_score])
print("Shapiro-Wilk p-value for SVM:", p_value)

# Shapiro-Wilk Test for model Random Forest
stat, p_value = shapiro([rf_accuracy, rf_precision, rf_recall, rf_f1_score])
print("Shapiro-Wilk p-value for Random Forest:", p_value)

# Shapiro-Wilk Test for model Decision Tree
stat, p_value = shapiro([dt_accuracy, dt_precision, dt_recall, dt_f1_score])
print("Shapiro-Wilk p-value for decision tree:", p_value)
```

```
#  Kolmogorov-Smirnov Test model SVM
stat, p_value = kstest([svm_accuracy, svm_precision, svm_recall, svm_f1_score], 'norm')
print("Kolmogorov-Smirnov p-value for SVM:", p_value)

# Kolmogorov-Smirnov test model random forest
stat, p_value = kstest([rf_accuracy, rf_precision, rf_recall, rf_f1_score], 'norm')
print("Kolmogorov-Smirnov p-value for random forest:", p_value)

# Kolmogorov-Smirnov test model decision tree
stat, p_value = kstest([dt_accuracy, dt_precision, dt_recall, dt_f1_score], 'norm')
print("Kolmogorov-Smirnov p-value for decision tree:", p_value)

import pandas as pd

# Result of Norm data test
data = {
    "Model": ["SVM", "Random Forest", "Decision Tree"],
    "Shapiro-Wilk p-value": [0.8909032344818115, 0.899372935295105, 0.899372935295105],
    "Kolmogorov-Smirnov p-value": [0.0016328371988269892, 0.0014763816503545763,
0.0015677383357370386]
}

# dataframe dict
df = pd.DataFrame(data)

# Show table
display(df)
```



```
# Statistik deskriptif
print(dataset.describe())

            Usia     Jam Masuk    Jam Pulang
count 998.000000    998.000000    998.000000
mean   24.783567  28891.425852  59661.434870
std     2.988653    122.457124   2100.541061
min    21.000000  28800.000000  55255.000000
25%    22.000000  28800.000000  57673.500000
50%    25.000000  28806.000000  58242.500000
75%    27.000000  28964.000000  61803.500000
max    30.000000  29308.000000  62755.000000
```

```
             Usia     Jam Masuk    Jam Pulang
count  998.000000    998.000000    998.000000
mean     0.420396  28891.425852  59661.434870
std      0.332073    122.457124   2100.541061
min      0.000000  28800.000000  55255.000000
25%      0.111111  28800.000000  57673.500000
50%      0.444444  28806.000000  58242.500000
75%      0.666667  28964.000000  61803.500000
max      1.000000  29308.000000  62755.000000
```

Figure 9.12. Results of normalized data descriptive statistics in predicting attendance patterns using machine learning and deep learning for decision-making

Table 9.12. Results of p-value test in predicting attendance patterns using machine learning and deep learning for decision-making

No	Model	Shapiro-Wilk p-value	Kolmogorov-Smirnov p-value
1	Random Forest	0.826500	0.001337
2	XGBoost	0.829337	0.001410
3	SVM	0.184938	0.014016
4	KNN	0.862744	0.001896
5	NN	0.787177	0.026451

The p-value from the Shapiro-Wilk test indicates the results of normality testing on the error or residual distribution of the model predictions. In interpreting the value, generally, if the p-value is greater than α (α = 0.05), then the data comes from a normal distribution. In this case, the Shapiro-Wilk p-value for Random Forest is 0.826500, and for XGBoost is 0.829337, where these p-values are much larger than 0.05, thus not rejecting the null hypothesis. The error distribution for both of these models is considered to follow a normal distribution. Similarly, the p-value for KNN and NN (0.862744 and 0.787177) indicates that these models also follow a normal distribution. As for the SVM model, which has a p-value in the Shapiro-Wilk test of 0.184938, it is the only value with the smallest weight compared to the other 4 models, but still larger than 0.05. Although it slightly deviates from normal distribution, this deviation is not significant enough to reject normality. Therefore, it can be concluded that all tested models show p-values greater than 0.05 in the Shapiro-Wilk test, meaning there is no strong evidence to reject the hypothesis that the error distribution of these models' predictions follows a normal distribution. These results indicate positive indications regarding the model's performance.

Thus, all models show errors that can be statistically considered to follow a normal distribution based on the Shapiro-Wilk test. On the other hand, the results of the p-value test on the Kolmogorov-Smirnov for the overall models used indicate that the obtained p-values are smaller than 0.05. This means we reject the null hypothesis that the error distribution of these models' predictions follows a normal distribution. In other words, the error distribution of all these models is not normal according to the Kolmogorov-Smirnov test. It can be said that the evaluation results indicate excellent performance in all five models used because the evaluation results follow a normal distribution based on the Shapiro-Wilk test, although the Kolmogorov-Smirnov test shows slight differences.

9.5 ENSEMBLE AI FOR ANOMALY DETECTION AND DATA ENCRYPTION

Data Encryption Using AES Algorithm

The encryption of the dataset using the AES algorithm results in encrypted data, where the data is successfully transformed into a format that cannot be directly read by parties without the appropriate encryption key. The encryption results can be seen in Table 9.13. Data encryption uses an encryption key to transform each data block into an unreadable form, making the data inaccessible to anyone. Thus, the potential risks of data leakage or manipulation can be minimized because the encryption applied provides an additional layer of protection for sensitive information stored in the attendance system dataset. Furthermore, only specific parties with the encryption key can decrypt and access the data lawfully. Therefore, the integrity and confidentiality of user information and involved parties are better preserved.

Table 9.13. Display of all columns in the attendance system data encrypted using the AES algorithm

Display of all encrypted columns
ev68QJGDCMEmXCBSi84Y8dVg3qQNaDOcl4wolK5N0GPSV4Rs7Ad9bkJcpEWMJziSBLyFehGp2u40fdf89WSIUVqwt/0Yxkz5HJlfx7fIQZwv0hIjjT0vzzfEPyrB5j12VGY4Gm/gWvFPyQyRxO6HznQGWW9+ESuZaDY7DcnwmwB5LVaD03Jl0bJeQiQmTaCIKFMh56idA7I15tw6uZNsAA==

Anomaly Detection Using Ensemble AI with Voting Technique

The results of the scatter plots for each model can be seen in Figure 9.13. The results indicate that the One-Class SVM and Isolation Forest models provide sufficiently accurate predictions in scattering anomalies in the data. In the scatter plots, the data points of anomalies are well spread throughout the area, indicating that the model's ability to identify anomalies is evenly distributed. The boundary formed by the One-Class SVM model separates normal data from anomalies, while the forest structure formed by the Isolation Forest also effectively extracts and isolates anomalies. This aligns with the findings of (G. Lee et al., 2023) and (Wang et al., 2023), who achieved good results using the one-class SVM.

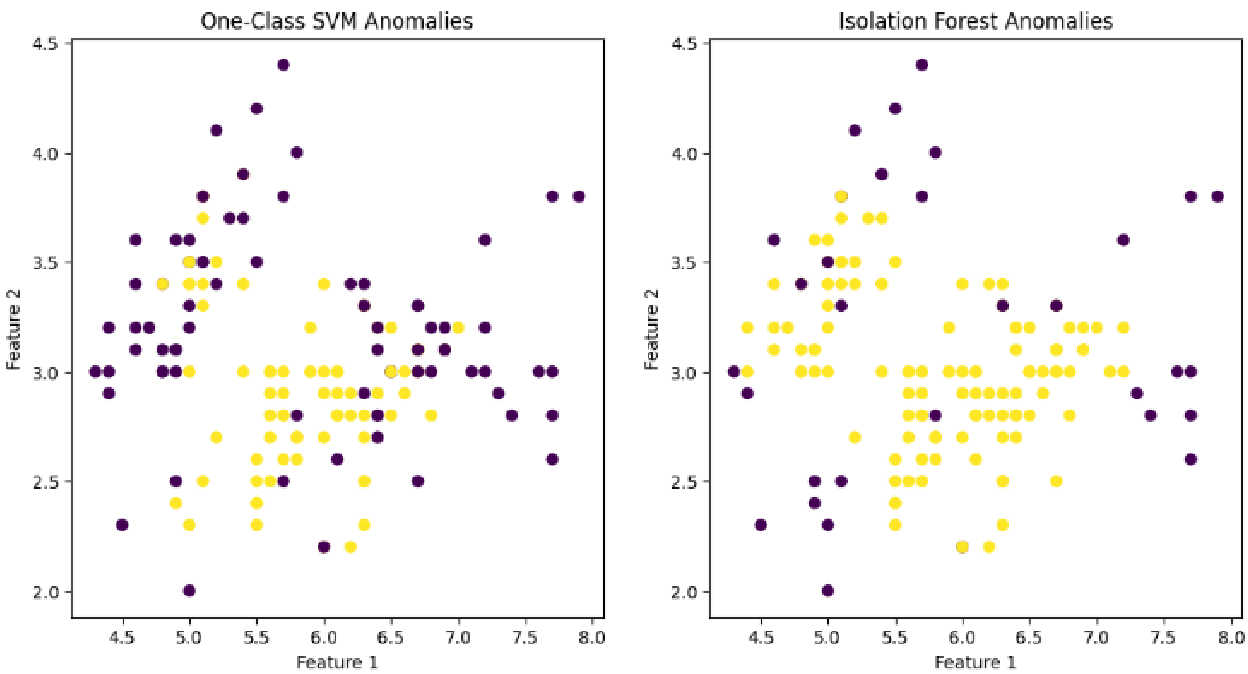


Figure 9.13. Scatter plots for anomaly prediction using the One-Class SVM and Isolation Forest models

As for the evaluation results of the ROC-Curve metric from the applied models, they can be seen in Figure 9.13. The Isolation Forest model has a ROC-Curve value of 0.53, while the One-Class SVM model has a slightly higher value, namely 0.56. These results indicate that the One-Class SVM model tends to better separate anomalies from normal data than the Isolation Forest in this case. Although both models are capable of identifying anomalies, the One-Class SVM model provides slightly better performance based on its ROC-Curve value. Therefore, in the context of anomaly detection tested in this study, the One-Class SVM model can be considered more effective. This data is also supported by the results of the proportion of anomalies and ROC-AUC scores from the two models used for anomaly detection, which can be seen in Table 9.14.

The results show that the proportion of anomalies detected in the One-Class SVM model is 0.133, with an ROC-AUC score of 0.847775. Meanwhile, in the Isolation Forest model, the proportion of detected anomalies is higher, namely 0.222, but its ROC-AUC score is lower namely 0.571566. This indicates that although the Isolation Forest can detect more anomalies, the overall model performance in separating anomalies from normal data is lower compared to the One-Class SVM. Therefore, it can be concluded that the One-Class SVM is a good choice for anomaly detection.

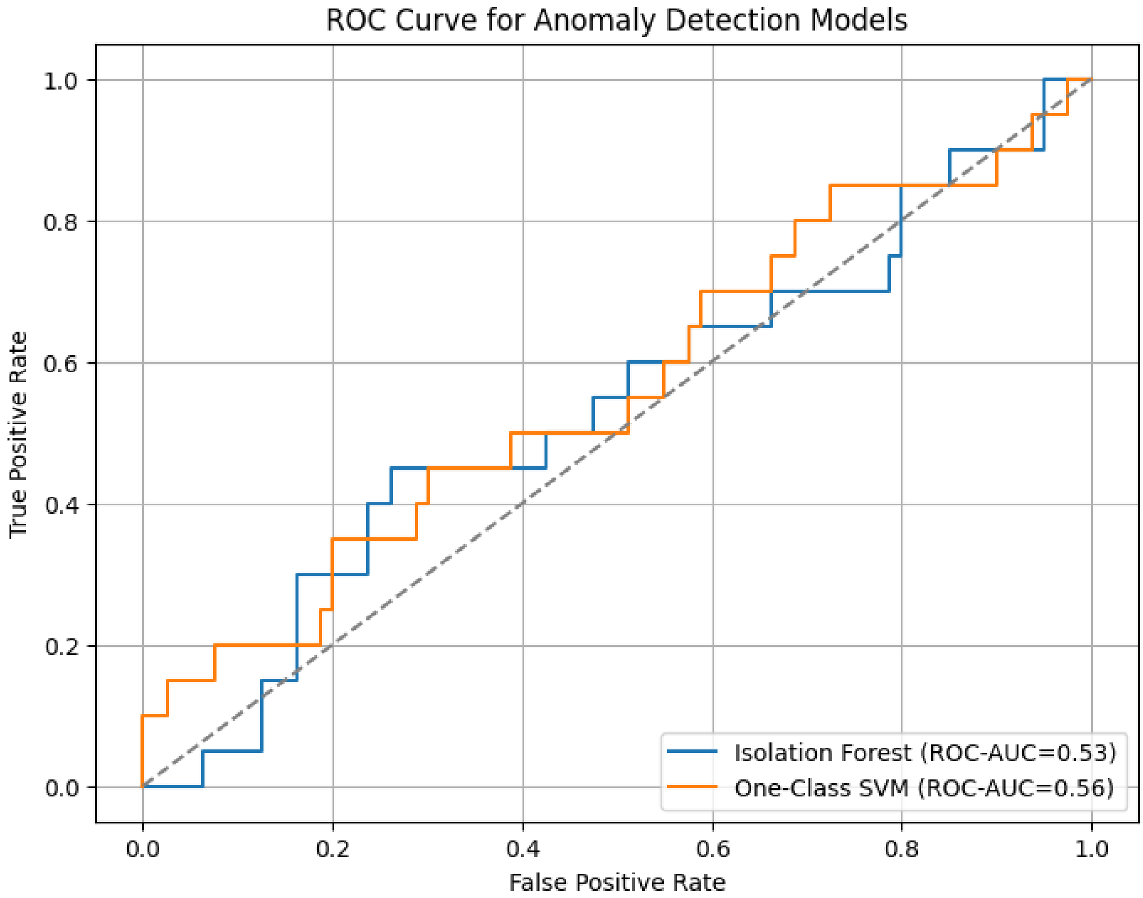


Figure 9.14. Visualization results of the ROC Curve in the anomaly detection model

Table 9.14. Results of the proportion of anomalies and ROC-AUC scores in each ensemble AI model for anomaly detection

Model		Anomaly Proportion	ROC-AUC Score
0	One class SVM	0.133	0.847775
1	Isolation Forest	0.222	0.571566

Conclusion

Integration of liveness detection technology with deep learning models in face recognition-based attendance systems yielded a testing accuracy of 87% in face recognition. This demonstrates the system's ability to accurately identify individuals and distinguish live subjects from forgery attempts. Additionally, an accuracy rate of 95% was achieved in the performance of Liveness Detection technology and 98% in the integration of Liveness Detection technology with Deep Learning.

As for the integration of the DSS theory using machine learning to predict high-performing teachers, the results indicate that the Random Forest model is the best predictor for identifying high-performing teachers and those in need of development. The F1 score and recall results for Random Forest were the highest at 97% and 98%, respectively, compared to SVM and Decision Tree.

In the implementation of reward and punishment theory, research results show that implementing reward and punishment systems in attendance management significantly impacts employee attendance rates. This is evidenced by a 5% increase in attendance percentage, from 86.52% to 90.44%, when reward and punishment methods were applied to the employee attendance system. Appropriate reward provision can increase employee motivation to adhere to work schedules and consistently attend, while punishment tends to lead to lower attendance rates.

Regarding attendance pattern prediction to support decision-making, findings reveal that Random Forest and XGBoost are the most accurate predictors in determining the timeliness or lateness of employees, considering age range and other relevant factors, achieving an accuracy rate of 99%. Random Forest slightly outperforms XGBoost in terms of accuracy and F1 score by a margin of 0.01%. This study is notable for combining attendance system data with Machine Learning (ML) and Deep Learning (DL) methods to predict attendance patterns based on age and various other parameters, thereby enhancing decision-making processes and performance management.

Finally, in anomaly detection and the application of cryptography theory, encrypted database results demonstrate higher security levels, making data stored in the MySQL database for the attendance system more secure. Additionally, the use of ensemble AI models for anomaly detection shows that the proposed ensemble voting technique can improve anomaly detection accuracy and safeguard data from potential theft, with final ROC-AUC scores of 0.84 for One-class SVM and 0.57 for Isolation Forest.

CHAPTER 10
EFFICIENCY OF THE ABSENCE SYSTEM

10.1 IMPACT OF IMPLEMENTING AN ATTENDANCE SYSTEM

This book aims to explore the effectiveness of face recognition-based attendance systems in improving employee attendance and analyze the impact of implementing reward and punishment on attendance rates. Based on the results of the research conducted, it can be concluded that in face recognition-based attendance systems, technology integrated with liveness detection and deep learning can enhance accuracy and security in recording employee attendance. This system successfully identifies faces with high accuracy, thereby minimizing fraud in attendance recording. Additionally, the implementation of rewards has proven effective in improving employee attendance, while punishment tends to have a negative impact. This indicates that a more positive approach to motivating employees can yield better results than a punitive approach.

In using Liveness Detection technology and Deep Learning to optimize face recognition-based attendance systems, the accuracy results showed 87%. This result indicates that the Deep Learning model (Convolution Neural Network) using the VGG 16 architecture with fine-tuning can accurately identify faces. The system also demonstrated good performance in distinguishing live subjects from fake subjects (photos or videos) tested through face recognition, achieving an accuracy of 95%. Additionally, the deep learning model trained using 20% of the dataset with liveness detection techniques also achieved a high level of recognition accuracy for identifying teacher faces with an accuracy result of 98%, and showed good tolerance to pose variations and lighting conditions.

On the other hand, the integration of DSS theory yielded results with a fairly high level of precision. Machine learning models (Support Vector Machine, Decision Tree, and Random Forest) integrated with DSS theory showed good accuracy, especially in the Decision Tree model (98.3%) and Support Vector Machine (97.2%). Additionally, sensitivity analysis on the DSS theory applied to machine learning prediction models with a classification approach to analyze performance and predict outstanding and in-need-of-improvement vocational school teachers showed that all models used rarely made mistakes in classifying proficient and in-need-of-improvement teachers. The three models used also showed equally good metric evaluation results, but in this case, the Support Vector Machine and Decision Tree models had an advantage in predicting teacher classification. Thus, for the prediction task in this book, it can be concluded that random forest and decision tree are excellent choices compared to the Support Vector Machine model.

Regarding the application of Reward and Punishment theory on attendance patterns and trends using Machine Learning techniques (K-Means Clustering) with 3 machine learning models (Support Vector Machine, Naïve Bayes, and Decision Tree) on face recognition-based attendance systems, it shows a significant impact on the attendance rate of teachers in schools. This is supported by a percentage increase in attendance of about 5% from 86.52% to 90.44% after the reward and punishment method was applied to the teacher attendance system. Teachers become more disciplined and punctual in logging in and out. Appropriate rewards can increase teacher motivation to adhere to work schedules and be consistently present, while punishment tends to lead to lower attendance rates. Additionally, the results show that the implementation of a reward and punishment system in attendance management can affect teacher attendance rates, where reward-giving correlates positively with higher attendance rates, while punishment correlates negatively with attendance rates.

In predicting attendance patterns using Deep Learning and Machine Learning based on the age range of vocational school teachers, the results show that, out of the 5 models used (Random Forest, Extreme Gradient Boosting (XGBoost), Support Vector Machine, K-Nearest Neighbors (KNN), and Neural Network), only two models produced the best prediction values, namely Random Forest and XGBoost, with a fairly high accuracy rate (0.99), followed by KNN in third place with a slightly lower accuracy rate. The accuracy rate of the first two models indicates that both Random Forest and XGBoost have an advantage in predicting the classification and emerging attendance patterns based on teacher age.

For the task of predicting patterns based on age range, Random Forest and XGBoost can be considered excellent choices compared to KNN, SVM, and Neural Networks. Meanwhile, the NN model in this case has poor evaluation results in all evaluation metrics, indicating that it needs further development because it is too simple. Therefore, in the future, this model could be further developed by fine-tuning and improving its architecture or model training. In this regard, it can be said that Random Forest and XGBoost models are the most accurate predictors for predicting the timeliness or lateness of attendance of vocational school teachers, considering age and other relevant factors, achieving an accuracy rate of 99%. Random Forest slightly outperforms XGBoost in terms of accuracy and F1-score by 0.01%.

Finally, the use of the AES algorithm for data encryption and Artificial Intelligence (AI) Ensemble in enhancing data security in attendance systems and anomaly detection shows that the proposed ensemble AI with voting technique is capable of improving anomaly detection accuracy and enhancing data security against potential theft. This is supported by final ROC-AUC scores of approximately 0.84 for One-class SVM and 0.57 for Isolation Forest. The ensemble AI approach (one-class SVM and Isolation Forest) with voting technique and data encryption can significantly enhance the performance of anomaly detection models. The use of ROC-AUC metrics helps evaluate the relative performance of the two AI models used to distinguish between normal and anomalous data. Data encryption using the AES algorithm provides an additional layer of protection for sensitive information in the dataset, reducing the risk of data leakage or manipulation. Although differing by about 3% in the final results, the AUC-ROC metric demonstrates sensitivity to both classes, not just the majority, consistent with the needs of anomaly detection where anomalous patterns are minority patterns in the data.

10.2 CONTRIBUTION OF THE ATTENDANCE SYSTEM IN MANAGERIAL

This study makes a significant contribution to theory development in human resource management, particularly in the context of IT-based attendance project management, as well as the implementation of reward and punishment systems in the context of face recognition-based attendance systems. Theoretically, this book strengthens the argument that the use of data analytics and facial recognition technology can provide deeper insights into the factors influencing the attendance of vocational school teachers. Furthermore, by integrating facial recognition technology with reward and punishment mechanisms, this book has demonstrated how technology can be used to enhance discipline and compliance in educational work environments (vocational schools). The results of this book have enriched our understanding of the effectiveness of incentives and disincentives in the context of modern technology. In previous research, the application of technology in this context has not been extensively explored, so this book has successfully added a new dimension to existing research literature (B. F. Skinner, 1965; Bakar et al., 2022; Kubanek et al., 2015; Nuttin & Greenwald, 1968; Podsakoff & Todor, 1985; Wibowo et al., 2022; J. Wu et al., 2022). Similarly, the use of technology in attendance management provides new insights into human resource management theory. The research results have shown that appropriate rewards can enhance motivation, discipline, and employee attendance, while punishment needs to be applied carefully to avoid negative impacts on motivation.

About face recognition theory, this book strengthens the argument that pattern recognition theory, which forms the basis of facial recognition technology, provides a deeper understanding. The research results indicate that feature extraction and comparison of facial feature vectors can be implemented with high accuracy to identify individuals in face recognition-based attendance systems. The Principal Component Analysis (PCA) method used has proven effective in improving facial recognition accuracy. This is closely related to the integration of Liveness Detection technology combined with Deep Learning. The research findings emphasize the importance of validating the authenticity of subjects and the intensive use of trained deep-learning models in enhancing facial recognition performance. This technology integration not only enhances the security of face recognition systems but also improves facial recognition accuracy with testing accuracy reaching 87%. In previous research, there has been limited use of liveness detection integration to enhance system security (Kamanga et al., 2022; Khairnar et al., 2023b; Surantha & Sugijakko, 2024a), thus, this book provides a foundation for further development in the field of facial pattern recognition and data security and demonstrates the potential of liveness detection technology in enhancing the efficiency and reliability of attendance management systems in various contexts. Therefore, this book makes a valuable contribution to expanding understanding of the integration of liveness detection technology and deep learning in face recognition-based attendance management applications.

This book reinforces the importance of information security theory in safeguarding sensitive attendance data and implementing data encryption techniques, such as the Advanced Encryption Standard (AES) algorithm, to protect data from unauthorized access and maintain the integrity and confidentiality of employee data. Additionally, this study highlights the application of machine learning and deep learning in attendance systems. The use of deep learning algorithms in face recognition demonstrates that this technology is capable of learning and recognizing patterns with high accuracy, significantly enhancing the efficiency and security of attendance systems. The theoretical implications of this book differ from previous studies by emphasizing the integration between information security and advancements in facial recognition technology (Aware et al., 2021; Gode et al., 2023b; Painuly et al., 2024; Pattnaik & Mohanty, 2020; Surantha & Sugijakko, 2024b; Suriya et al., 2023), highlighting the importance of a holistic approach in designing secure and efficient attendance systems. Moreover, these implications also underscore the importance of interdisciplinary research between information security and machine learning to optimize attendance systems. By combining these theories, this book opens up new opportunities to develop novel methods in the field of data security and enhance the overall performance of attendance systems. This underscores the need for collaboration between information security experts and machine learning specialists to address complex challenges in protecting sensitive data and improving operational efficiency within companies.

This book represents a breakthrough by combining management elements with technology, particularly in the field of Information Technology Project Management (ITPM). Unlike previous studies that focused only on one aspect (Arefazar et al., 2022; Brandl et al., 2021; Ghorbani & Shafaghat, 2020; Islam & Evans, 2020; Lalmi et al., 2021; Marnewick & Marnewick, 2022; Miller et al., 2023), this book offers innovation through the development of an attendance management system integrated with facial recognition technology. This system not only efficiently manages employee attendance but also integrates advanced technologies such as Machine Learning, Deep Learning, and Artificial Intelligence (AI) to enhance accuracy and reliability. Additionally, to ensure data security, the system is equipped with strong AES encryption. By combining systematic project management principles with cutting-edge technology, this book has the potential to significantly contribute to improving efficiency, effectiveness, and security in project management in the digital era.

10.3 ATTENDANCE SYSTEM BASED EMPLOYEE MANAGEMENT

The practical implications of this book include several recommendations that can be implemented by schools or other institutions to enhance employee attendance management:

1. Implementation of Advanced Technology: Schools may consider using facial recognition technology with liveness detection to improve accuracy and efficiency in monitoring teacher attendance. This technology not only enhances recording accuracy but also increases attendance data security. Integrating Liveness Detection technology with Deep Learning not only enhances security and accuracy in recording the attendance of vocational school teachers but also has the potential to be applied in various related fields such as physical security management, access management, and information security. By leveraging this technology, schools can ensure more reliable and accurate attendance data, as well as improve operational efficiency and productivity.
2. Effective Reward Programs: Implementing appropriate reward programs can motivate teachers to attend more consistently. Schools can design fair and transparent incentive programs to boost teacher motivation and productivity.
3. Evaluation of Punishment Policies: Punishment policies should be periodically evaluated to ensure that the actions taken are effective and do not damage teacher motivation. Schools should focus on a more positive and supportive approach to addressing attendance issues.

4. Optimization of Human Resources: Implementing Random Forest and XGBoost models can assist management in planning more efficient work schedules, reducing absenteeism, and enhancing overall teacher productivity.
5. Improvement of Orderliness and Discipline: By using predictive models, management can identify patterns in teacher attendance and take appropriate steps to improve orderliness and discipline in the workplace, such as encouraging teachers to be more disciplined and punctual in attendance.
6. Better and More Efficient Decision Making: Predicting patterns of teacher attendance based on age and specific categories provides valuable information for management to make more directed and strategic decisions in managing teacher performance and designing more effective policies to improve company performance.
7. Enhancement of Performance Management Effectiveness: By using machine learning and deep learning techniques, management can enhance effectiveness in managing teacher performance. Predictive models can help identify factors influencing teacher performance, predict future performance, and provide recommendations for steps to improve overall performance.

Additionally, in terms of anomaly detection and data security, management should consider investing in data encryption technology and ensemble AI to enhance data security in face recognition-based attendance systems. By implementing these recommendations, it is expected that schools can improve employee attendance, reduce absenteeism rates, and overall enhance operational efficiency and teacher productivity in schools.

10.4 LIMITATION AND FUTURE AGENDA

This study has several limitations, including:

1. Data Limitations: One of the main limitations of this book is related to the constraints of the data used. This study utilizes a specific dataset of vocational school teacher attendance, thus generalizing the results to various contexts may require additional adjustments. Additionally, the use of ensemble AI technology and data encryption may require specific resources and expertise that are not always widely available. Developing more accurate and reliable predictive models may necessitate representative and comprehensive datasets. Therefore, future research needs to expand the dataset by seeking additional data from different sources to enhance the validity and generalizability of the research findings. Furthermore, the performance evaluation of

anomaly detection models needs to be expanded by considering other metrics to gain a more comprehensive understanding.

2. Involved Variables: This book is also limited in the number and variation of variables used in the analysis. Involving more and varied variables can help researchers better understand the factors influencing teacher performance and capture greater complexity of the observed phenomena. Additionally, this study focuses on predicting patterns of teacher absenteeism based on age and some specific factors. To improve prediction accuracy, future research may consider adding other variables such as job type, education level, or other workplace environmental factors that may affect absenteeism patterns.
3. Sample Size and Generalization: The main limitation of this book is the relatively limited sample size used in a specific environment or company. Therefore, generalizing the results of this study to various industries or different company scales may require further research with more representative samples.
4. Comprehensive Model Evaluation: Although this study has utilized evaluation metrics such as accuracy, precision, recall, F1 score, and ROC AUC, future research may consider more comprehensive model evaluations such as deeper error analysis to understand the overall model performance.

From the limitations mentioned above, there are future research agendas/recommended research that could be pursued:

1. Exploration of Alternative Machine Learning Models: Future research can broaden insights by exploring the use of various alternative machine learning models. Comparing several models can provide a deeper understanding of the effectiveness and suitability of each model in the specific context of the study.
2. Development of More Complex Predictive Models: Future research agendas can focus on developing more complex and adaptive predictive models. By considering more diverse and complex factors, predictive models can provide more accurate and relevant recommendations for teacher performance management. This can improve the model's ability to predict teacher absenteeism patterns more accurately and holistically.
3. Development of More Comprehensive Evaluation Methods: Subsequent research can expand the evaluation methods used to assess the performance of predictive models. In addition to metrics such as accuracy, precision, recall, F1-score, and ROC AUC curves, research can consider using other evaluation methods that can provide deeper insights into the quality of model predictions.

4. Broader Longitudinal Studies: These can also be conducted to observe the long-term impact of implementing reward and punishment strategies in attendance management. Cross-sector and cross-country research can also provide a more comprehensive understanding of the factors influencing teacher attendance.
5. Expansion of Variable Scope: Further research can expand the scope of considered variables, such as intrinsic and extrinsic motivation factors, to gain a deeper understanding of the mechanisms behind the influence of rewards and punishments on teacher attendance.
6. Cross-Industry Case Studies: Future research can involve cross-industry case studies to test the generalizability of developed predictive models. This will help us understand how far these models can be applied in various industrial contexts.
7. Integration of Latest Technologies: Future research can integrate emerging technologies such as image processing, text analysis, or the Internet of Things (IoT) to enhance the performance of predictive models in predicting teacher absenteeism patterns more effectively. Additionally, further research is needed to identify and address potential privacy and data security risks associated with the use of liveness detection and deep learning technologies in attendance systems.
8. Expansion of Dataset Coverage: This can be done by involving data from various types of organizations and attendance systems.
9. Exploration of Technology Integration: Future research can explore the integration of other technologies, such as blockchain, to enhance data security. Other recommendations include developing more complex anomaly detection models by considering additional factors that can affect data security. Furthermore, future research can focus on developing adaptive response strategies to evolving data security threats. Thus, future research is expected to make a broader contribution to the fields of information security and anomaly detection.

Taking into account the limitations of the study and the recommended future research agenda, further research is expected to make a greater contribution to the development of more effective and relevant predictive models in the context of vocational school teacher performance management and even better data security.

References

Ab Wahab, K., Yew, L. W., & Jusoh, N. A. (2022). Online Attendance System Using Face Recognition. *Engineering, Agriculture, Science and Technology Journal (EAST-J)*, *1*(1), 57–61. https://doi.org/10.37698/eastj.v1i1.120

Abd El-Rahiem, B., Sedik, A., El Banby, G. M., Ibrahem, H. M., Amin, M., Song, O. Y., Khalaf, A. A. M., & Abd El-Samie, F. E. (2023). An Efficient Deep Learning Model for Classification of Thermal Face Images. *Journal of Enterprise Information Management*, *36*(3), 706–717. https://doi.org/10.1108/JEIM-07-2019-0201/FULL/XML

Abdelli, K., Cho, J. Y., Azendorf, F., Griesser, H., Tropschug, C., & Pachnicke, S. (2022). Machine-learning-based anomaly Detection in Optical Fiber Monitoring. *Journal of Optical Communications and Networking, Vol. 14, Issue 5, Pp. 365-375*, *14*(5), 365–375. https://doi.org/10.1364/JOCN.451289

AbdELminaam, D. S., Almansori, A. M., Taha, M., & Badr, E. (2020). A Deep Facial Recognition System Using Computational Intelligent Algorithms. *PLOS ONE*, *15*(12). https://doi.org/10.1371/JOURNAL.PONE.0242269

Abraham, A., Bapse, M., Kalaria, Y., & Usmani, A. (2020). Face Recognition Based Attendance System. *IOSR Journal of Computer Engineering (IOSR-JCE)*, *22*(1), 56–60. https://doi.org/10.9790/0661-2201045660

Abusitta, A., de Carvalho, G. H. S., Wahab, O. A., Halabi, T., Fung, B. C. M., & Mamoori, S. Al. (2023). Deep Learning-Enabled Anomaly Detection for IoT Systems. *Internet of Things*, *21*. https://doi.org/10.1016/J.IOT.2022.100656

Achmad, S., Budiman, A., Aryatama Yaputera, R., & Kurniawan, A. (2022). Student Attendance with Face Recognition (LBPH or CNN): Systematic Literature Review. *7th International Conference on Computer Science and Computational Intelligence 2022*, 31–38. https://doi.org/10.1016/j.procs.2022.12.108

Adeniyi, A. E., Abiodun, K. M., Awotunde, J. B., Olagunju, M., Ojo, O. S., & Edet, N. P. (2023). Implementation of a Block Cipher Algorithm for Medical Information Security on Cloud Environment: Using Modified Advanced Encryption Standard Approach. *Multimedia Tools and Applications*, *82*(13), 20537–20551. https://doi.org/10.1007/S11042-023-14338-9/METRICS

Adeoye, I. (2024). Unveiling Tomorrow's Success: A Fusion of Business Analytics and Machine Learning for Employee Performance Prediction. *SSRN Electronic Journal*. https://doi.org/10.2139/SSRN.4729244

Adnan, R. M., Mirboluki, A., Mehraein, M., Malik, A., Heddam, S., & Kisi, O. (2024). Improved prediction of monthly streamflow in a mountainous region by metaheuristic-Enhanced deep learning and machine learning models using hydroclimatic data. *Theoretical and Applied Climatology*, *155*(1), 205–228. https://doi.org/10.1007/S00704-023-04624-9/METRICS

Aggarwal, D., Sharma, D., & Saxena, A. B. (2023). Role of AI in cyber security through Anomaly detection and Predictive analysis. *Journal of Informatics Education and Research*, *3*(2), 1846. https://doi.org/10.52783/JIER.V3I2.314

Agustian, K., Pohan, A., Zen, A., Wiwin, W., & Malik, A. J. (2023). Human Resource Management Strategies in Achieving Competitive Advantage in Business Administration. *Journal of Contemporary Administration and Management (ADMAN)*, *1*(2), 108–117. https://doi.org/10.61100/ADMAN.V1I2.53

Ahmed, H. (2024). *Insights of Pakistan, Iran and the Caucasus Studies Strategic HRM Practices: Leveraging SMART Goals for Talent Management in Pakistan Umar Shehzad Laiba Mushtaq* (Vol. 3, Issue 02). http://www.ipics.rmrpublishers.orghttp://journals.rmrpublishers.org/insights-of-pakistan-iran-and-the-caucasus-studies/

Ahmed, S. F., Alam, M. S. Bin, Hassan, M., Rozbu, M. R., Ishtiak, T., Rafa, N., Mofijur, M., Shawkat Ali, A. B. M., & Gandomi, A. H. (2023). Deep learning modelling techniques: current progress, applications, advantages, and challenges. *Artificial Intelligence Review*, *56*(11), 13521–13617. https://doi.org/10.1007/s10462-023-10466-8

Ajike, C. (2023). Performance Management System: The Catalyst to Boosting Public Sector Productivity in Nigeri. *Economic and Policy Review*, *21*(2), 34–41. https://www.ajol.info/index.php/epr/article/view/261294

Akcay, S., Ameln, D., Vaidya, A., Lakshmanan, B., Ahuja, N., & Genc, U. (2022). ANOMALIB: A DEEP LEARNING LIBRARY FOR ANOMALY DETECTION. *Proceedings - International Conference on Image Processing, ICIP*, 1706–1710. https://doi.org/10.1109/ICIP46576.2022.9897283

Al Ka'bi, A. (2023). Proposed Artificial Intelligence Algorithm and Deep Learning Techniques for Development of Higher Education. *International Journal of Intelligent Networks*, *4*, 68–73. https://doi.org/10.1016/J.IJIN.2023.03.002

Alemami, Y., Al-Ghonmein, A. M., Al-Moghrabi, K. G., & Mohamed, M. A. (2023). Cloud Data Security and Various Cryptographic Algorithms. *International Journal of Electrical and Computer Engineering*, *13*(2), 1867–1879. https://doi.org/10.11591/ijece.v13i2.pp1867-1879

Alhanaee, K., Alhammadi, M., Almenhali, N., & Shatnawi, M. (2021). Face Recognition Smart Attendance System Using Deep Transfer Learning. *25th International Conference on Knowledge-Based and Intelligent Information & Engineering Systems*, *192*, 4093–4102. https://doi.org/10.1016/j.procs.2021.09.184

Al-Harrasi, A., Shaikh, A. K., & Al-Badi, A. (2023). Towards protecting organisations' data by preventing data theft by malicious insiders. *International Journal of Organizational Analysis*, *31*(3), 875–888. https://doi.org/10.1108/IJOA-01-2021-2598/FULL/XML

Ali, M., Diwan, A., & Kumar, D. (2024). Attendance System Optimization through Deep Learning Face Recognition. *International Journal of Computing and Digital Systems*, *15*(1), 1527–1540. https://doi.org/10.12785/ijcds/1501108

Ali, M., Scandurra, P., Moretti, F., & Sherazi, H. H. R. (2024). Anomaly Detection in Public Street Lighting Data Using Unsupervised Clustering. *IEEE Transactions on Consumer Electronics*. https://doi.org/10.1109/TCE.2024.3354189

Alkhowaiter, M., Kholidy, H., Alyami, M. A., Alghamdi, A., & Zou, C. (2023). Adversarial-Aware Deep Learning System Based on a Secondary Classical Machine Learning Verification Approach. *Sensors*, *23*(14). https://doi.org/10.3390/s23146287

Alonso, E., Javier Garcia Villalba, L., de Sousa, R. T., de Oliveira Albuquerque, R., Lucila Sandoval Orozco, A., Díaz-Verdejo, J., Muñoz-Calle, J., Estepa Alonso, A., Estepa Alonso, R., & Madinabeitia, G. (2022). On the Detection Capabilities of Signature-Based Intrusion Detection Systems in the Context of Web Attacks. *Applied Sciences 2022, Vol. 12, Page 852*, *12*(2), 852. https://doi.org/10.3390/APP12020852

Al-zawahreh, A., & Nayef Al-Madi, F. (2012). *The Utility of Equity Theory in Enhancing Organizational Effectiveness*. http://www.eurojournals.com/EJEFAS.htm

Amstrong, M., & Taylor, S. (2014). *Armstrong's Handbook Of Human Resource Management Practice* (Thirteenth Edition). www.koganpage.com

Anthony, E. A. (2017). Effects of Discipline Management on Employee Performance in an Organization: The Case of County Education Office Human Resource Department, Turkana County. *International Academic Journal of Human Resource and Business Administration* |, *2*(3), 1–18. http://www.iajournals.org/articles/iajhrba_v2_i3_1_18.pdf

Anwarul, S., & Dahiya, S. (2020). A Comprehensive Review on Face Recognition Methods and Factors Affecting Facial Recognition Accuracy. *Lecture Notes in Electrical Engineering*, *597*, 495–514. https://doi.org/10.1007/978-3-030-29407-6_36

Anyalewechi, G. O., & Ezeagwu, C. E. C. (2023). Securing Organizational Operation: An Electronic Gate System Integrating Facial Recognition for Attendance Tracking and Access Control. *Interdisciplinary Journal of Agriculture and Environmental Sciences (IJAES)*, *10*(3), 1–10. https://doi.org/10.5281/ZENODO.8234103

Arboretti, R., Biasetton, N., Ceccato, R., Molena, A., Peruzzo, E., Salmaso, L., & Sani, A. (2024). Predictive Stadium Attendance Using Machine Learning: A Case Study in Italian Football. *Journal of Machine Intelligence and Data Science*, *5*. https://doi.org/10.11159/jmids.2024.004

Ardebili, A., Latifian, A., Aziz, C. F., BinSaeed, R. H., Alizadeh, S. M., & Kostyrin, E. V. (2023). A Comprehensive and Systematic Literature Review on the Employee Attendance Management Systems Based on Cloud Computing. *Journal of Management & Organization*, *29*(4), 679–696. https://doi.org/10.1017/JMO.2022.63

Arefazar, Y., Nazari, A., Hafezi, M. R., & Maghool, S. A. H. (2022). Prioritizing Agile Project Management Strategies as a Change Management Tool in Construction Projects. *International Journal of Construction Management*, *22*(4), 678–689. https://doi.org/10.1080/15623599.2019.1644757

Arogundade, R. O. (2023). Network Security Concepts, Dangers, and Defense Best Practical. *Computer Engineering and Intelligent Systems*, *14*(2). https://doi.org/10.7176/ceis/14-2-03

Arora, M., Prakash, A., Mittal, A., & Singh, S. (2021). HR Analytics and Artificial Intelligence-Transforming Human Resource Management. *2021 International Conference on Decision Aid Sciences and Application, DASA 2021*, 288–293. https://doi.org/10.1109/DASA53625.2021.9682325

Assa-Agyei, K., Olajide, F., & Alade, T. (2023). Optimizing the Performance of the Advanced Encryption Standard Techniques for Secured Data Transmission. *International Journal of Computer Applications*, *185*(21), 31–36. https://doi.org/10.5120/IJCA2023922941

Asselman, A., Khaldi, M., & Aammou, S. (2023). Enhancing the Prediction of Student Performance based on the Machine Learning XGBoost Algorithm. *Interactive Learning Environments*, *31*(6), 3360–3379. https://doi.org/10.1080/10494820.2021.1928235

Aviral Rai, Barada Prasad Rout, Bhushan, & Ashima Mehta. (2024). Unveiling the Power of Data: A Journey Through Machine Learning Techniques. *International Journal of Advanced Research in Science, Communication and Technology*, 42–47. https://doi.org/10.48175/ijarsct-17807

Aware, M., Labade, P., Tambe, M., Jagtap, A., & Beldar, C. (2021). Attendance Management System using Face-Recognition. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*, 336–341. https://doi.org/10.32628/cseit217370

B. F. Skinner. (1965). Science And Human Behavior - B.F Skinner. In *The Free Press*.

Babu Jha, P., Basnet, A., Pokhrel, B., Pokhrel, B., Kumar Thakur, G., Chhetri, S., Professor, A., & Bhandari, M. (2023). An Automated Attendance System Using Facial Detection and Recognition Technology. *Apex Journal of Business and Management*, *01*(01), 103–120. https://doi.org/10.61274/apxc.2023.v01i01.008

Bae, G., de La Gorce, M., Baltrušaitis, T., Hewitt, C., Chen, D., Valentin, J., Cipolla, R., & Shen, J. (2023). *DigiFace-1M: 1 Million Digital Face Images for Face Recognition*. 3526–3535.

Bah, S. M., & Ming, F. (2020). An improved face recognition algorithm and its application in attendance management system. *Array*, *5*, 100014. https://doi.org/10.1016/J.ARRAY.2019.100014

Bakar, N. I. A., Dawi, A. H., Hashim, A. T. M., Zalli, M. M. M., & Suppian, Z. (2022). Transforming juvenile behavior through reward and punishment approaches. *Humanities and Social Sciences Letters*, *11*(1), 37–46. https://doi.org/10.18488/73.v11i1.3244

Bali, A., & Mansotra, V. (2024). Analysis of Deep Learning Techniques for Prediction of Eye Diseases: A Systematic Review. *Archives of Computational Methods in Engineering*, *31*(1), 487–520. https://doi.org/10.1007/S11831-023-09989-8/METRICS

Balint, K. (2022). Data Security Structure of a Students' Attendance Register Based on Security Cameras and Blockchain Technology. *IEEE Joint 22nd International Symposium on Computational Intelligence and Informatics and 8th International Conference on Recent Achievements in Mechatronics, Automation, Computer Science and Robotics, CINTI-MACRo 2022 - Proceedings*, 185–190. https://doi.org/10.1109/CINTI-MACRO57952.2022.10029471

Barhate, Prof. M., Ramdasi, I., Shaikh, I., Ingawale, V., Ingle, P., Ingle, P., & Jadhao, M. (2024). Innovative Attendance Tracking: Facial Recognition. *International Conference on Emerging Smart Computing and Informatics (ESCI)*, 1–6. https://doi.org/10.1109/ESCI59607.2024.10497364

Barnes, C. M., Power, A. L., Barber, D. G., Tennant, R. K., Jones, R. T., Lee, G. R., Hatton, J., Elliott, A., Zaragoza-Castells, J., Haley, S. M., Summers, H. D., Doan, M., Carpenter, A. E., Rees, P., & Love, J. (2023). Deductive automated pollen classification in environmental samples via exploratory deep learning and imaging flow cytometry. *New Phytologist*, *240*(3), 1305–1326. https://doi.org/10.1111/nph.19186

Bartakke, R., Wahutre, S., Bhalerao, R., Chavan, S., & Jaware, Y. (2024). Real Time Attendance System Using Image Processing. *International Research Journal of Modernization in Engineering*, *6*(1), 2703–2709. www.irjmets.com

Basurah, M., Swastika, W., & Kelana, H. O. (2023). Implementation of Face Recognition and Liveness Detection Using TensorFlow.Js. *(JIP) Jurnal Informatika Polinema*, *9*(4), 509–516. https://jurnal.polinema.ac.id/index.php/jip/article/view/3977/2759

Bergman, N., Yitzhaky, Y., & Halachmi, I. (2024). Biometric Identification of Dairy Cows via Real-time Facial Recognition. *The International Journal of Animal Biosciences*, *18*(3), 101079. https://doi.org/10.1016/J.ANIMAL.2024.101079

Beyerer, J., Hagmanns, R., & Stadler, D. (2024). *Pattern Recognition: Introduction, Features, Classifiers and Principles* (2nd Edition).

Bharadiya, J., & Bharadiya, J. P. (2023). Machine Learning and AI in Business Intelligence: Trends and Opportunities. *International Journal of Computer (IJC)*, *48*(1), 123–134. https://www.researchgate.net/publication/371902170

Bhatti, U. A., Tang, H., Wu, G., Marjan, S., & Hussain, A. (2023). Deep Learning with Graph Convolutional Networks: An Overview and Latest Applications in Computational Intelligence. In *International Journal of Intelligent Systems* (Vol. 2023). Wiley-Hindawi. https://doi.org/10.1155/2023/8342104

Bilakanti, H., Pasam, S., Palakollu, V., & Utukuru, S. (2024). Anomaly detection in IoT environment using machine learning. *Security and Privacy*, *7*(3), e366. https://doi.org/10.1002/SPY2.366

Bisogni, C., Cimmino, L., De Marsico, M., Hao, F., & Narducci, F. (2023). Emotion recognition at a distance: The robustness of machine learning based on hand-crafted facial features vs deep learning models. *Image and Vision Computing*, *136*, 104724. https://doi.org/10.1016/J.IMAVIS.2023.104724

Boutros, F., Struc, V., Fierrez, J., & Damer, N. (2023). Synthetic Data for Face Recognition: Current State and Future Prospects. *Image and Vision Computing*, *135*, 104688. https://doi.org/10.1016/J.IMAVIS.2023.104688

Brandl, F. J., Roider, N., Hehl, M., & Reinhart, G. (2021). Selecting practices in complex technical planning projects: A pathway for tailoring agile project management into the manufacturing industry. *CIRP*

Journal of Manufacturing Science and Technology, *33*, 293–305. https://doi.org/10.1016/j.cirpj.2021.03.017

Brewer, G. A., & Walker, R. M. (2013). Personnel Constraints in Public Organizations: The Impact of Reward and Punishment on Organizational Performance. *Public Administration Review*, *73*(1), 121–131. https://doi.org/10.1111/J.1540-6210.2012.02681.X

Budiman, A., Fabian, Yaputera, R. A., Achmad, S., & Kurniawan, A. (2022). Student Aattendance with Face Recognition (LBPH or CNN): Systematic Literature Review. *Procedia Computer Science*, *216*, 31–38. https://doi.org/10.1016/j.procs.2022.12.108

Cai, W., Gallani, S., & Shin, J. E. (2022). Incentive Effects of Subjective Allocations of Rewards and Penalties. *Https://Doi.Org/10.1287/Mnsc.2022.4501*, *69*(5), 3121–3139. https://doi.org/10.1287/MNSC.2022.4501

Cao, H., Lin, T., Li, Y., & Zhang, H. (2019). Stock Price Pattern Prediction Based on Complex Network and Machine Learning. *Complexity*, *2019*. https://doi.org/10.1155/2019/4132485

Cavalcante, P. H. F. (2023). Results-oriented Strategic Management - Ministry of Planning case. *METHODOLOGY FOCUSED ON THE AREA OF INTERDISCIPLINARITY- V1*. https://doi.org/10.56238/METHOFOCUSINTERV1-110

Cavazos, J. G., Phillips, P. J., Castillo, C. D., & O'Toole, A. J. (2021). Accuracy Comparison across Face Recognition Algorithms: Where Are We on Measuring Race Bias? *IEEE Transactions on Biometrics, Behavior, and Identity Science*, *3*(1), 101–111. https://doi.org/10.1109/TBIOM.2020.3027269

Chamikara, M. A. P., Bertok, P., Khalil, I., Liu, D., & Camtepe, S. (2020). Privacy Preserving Face Recognition Utilizing Differential Privacy. *Computers & Security*, *97*, 101951. https://doi.org/10.1016/J.COSE.2020.101951

Chaubey, G., Gavhane, P. R., Bisen, D., & Arjaria, S. K. (2023). Customer Purchasing Behavior Prediction Using Machine Learning Classification Techniques. *Journal of Ambient Intelligence and Humanized Computing*, *14*(12), 16133–16157. https://doi.org/10.1007/S12652-022-03837-6/METRICS

Chaudhari, V., Jain, S., Chaudhari, R., Chavan, T., & Shahane, P. (2023). Real Time Face Recognition Based Attendance System using Multi Task Cascaded Convolutional Neural Network. *2023 International Conference on Emerging Smart Computing and Informatics, ESCI 2023*. https://doi.org/10.1109/ESCI56872.2023.10099879

Chavan, S. R., & Sherekar, S. (2023). Face Recognition System Using CNN Architecture and Its Model with Its Detection Technique Using Machine Learning. *Heterogenous Computational Intelligence in Internet of Things*, 209–224. https://doi.org/10.1201/9781003363606-14/FACE-RECOGNITION-SYSTEM-USING-CNN-ARCHITECTURE-MODEL-DETECTION-TECHNIQUE-USING-MACHINE-LEARNING-SONALI-CHAVAN-SWATI-SHEREKAR

Chen, C. F., Yang, S. H., Falsafi, B., & Moshovos, A. (2004). Accurate and complexity-effective spatial pattern prediction. *IEEE High-Performance Computer Architecture Symposium Proceedings*, *10*, 276–287. https://doi.org/10.1109/HPCA.2004.10010

Chen, L., Chen, P., & Lin, Z. (2020). Artificial Intelligence in Education: A Review. *IEEE Access*, *8*, 75264–75278. https://doi.org/10.1109/ACCESS.2020.2988510

Chen, Z. (2023). Artificial Intelligence-Virtual Trainer: Innovative Didactics Aimed at Personalized Training Needs. *Journal of the Knowledge Economy*, *14*(2), 2007–2025. https://doi.org/10.1007/S13132-022-00985-0/METRICS

Chen, Z., Chen, J., Ding, G., & Huang, H. (2023). A lightweight CNN-based algorithm and implementation on embedded system for real-time face recognition. *Multimedia Systems*, *29*(1), 129–138. https://doi.org/10.1007/S00530-022-00973-Z/METRICS

Chen, Z. Y., Fan, Z. P., & Sun, M. (2022). Machine Learning Methods for Data-driven Demand Estimation and Assortment Planning Considering Cross-Selling and Substitutions. *Https://Doi.Org/10.1287/Ijoc.2022.1251*, *35*(1), 158–177. https://doi.org/10.1287/IJOC.2022.1251

Cheng, Q., Yang, L., Zheng, J., Tian, M., & Xin, D. (2024). *Optimizing Portfolio Management and Risk Assessment in Digital Assets Using Deep Learning for Predictive Analysis*. https://doi.org/https://doi.org/10.48550/arXiv.2402.15994

Chitadze, N. (2023). *Basic Principles of Information and Cyber Security*. 193–223. https://doi.org/10.4018/978-1-6684-5760-3.CH009

Cioca, L.-I., Ivascu, L., Filip, F. G., & Doina, B. (Eds.). (2024). *Digital Transformation*. *253*. https://doi.org/10.1007/978-3-031-55952-5

Cook, K. S., & Parcel, T. L. (1977). Equity Theory: Directions for Future Research*. *Sociological Inquiry*, *47*(2), 75–88. https://doi.org/10.1111/J.1475-682X.1977.TB00781.X

Cui, M., Wang, J., & Yue, M. (2019). Machine Learning-Based Anomaly Detection for Load Forecasting Under Cyberattacks. *IEEE Transactions on Smart Grid*, *10*(5), 5724–5734. https://doi.org/10.1109/tsg.2018.2890809

Dang, T. V. (2023). Smart Attendance System based on improved Facial Recognition. *Journal of Robotics and Control (JRC)*, *4*(1), 46–53. https://doi.org/10.18196/JRC.V4I1.16808

de la Nuez, H., Nieves, J., & Osorio, J. (2023). Neuroleadership: Affective Experiences in the Workplace and their Tnfluence on Employees' Evaluative Judgements. *International Journal of Hospitality Management*, *114*, 103554. https://doi.org/10.1016/J.IJHM.2023.103554

Dechen, K., Pem, K., Dorji, T., Wangdi, T., Powdyel, D. B., & Muramatsu, K. (2024). Attendance Management System Using Face Recognition and E-Mail Notification. *2024 Third International Conference on Intelligent Techniques in Control, Optimization and Signal Processing (INCOS)*, 1–7. https://doi.org/10.1109/INCOS59338.2024.10527631

Doss, A. N., Shah, D., Smaisim, G. F., Olha, M., & Jaiswal, S. (2022). A Comprehensive Analysis of Internet of Things (IOT) in Enhancing Data Security for Better System Integrity - A Critical Analysis on the Security Attacks and Relevant Countermeasures. *2022 2nd International Conference on Advance Computing and Innovative Technologies in Engineering, ICACITE 2022*, 165–167. https://doi.org/10.1109/ICACITE53722.2022.9823817

Dutta, D., Mishra, S. K., & Tyagi, D. (2023). Augmented employee voice and employee engagement using artificial intelligence-enabled chatbots: a field study. *The International Journal of Human Resource Management*, *34*(12), 2451–2480. https://doi.org/10.1080/09585192.2022.2085525

Dwyer, D. J., & Ganster, D. C. (1991). The effects of job demands and control on employee attendance and satisfaction. *Journal of Organizational Behavior*, *12*(7), 595–608. https://doi.org/10.1002/JOB.4030120704

Eid, A. M., Soudan, B., Nasif, A. B., & Injadat, M. N. (2024). Comparative study of ML models for IIoT intrusion detection: impact of data preprocessing and balancing. *Neural Computing and Applications*, *36*(13), 6955–6972. https://doi.org/10.1007/S00521-024-09439-X/METRICS

Elbasi, E., Zaki, C., Topcu, A. E., Abdelbaki, W., Zreikat, A. I., Cina, E., Shdefat, A., & Saker, L. (2023). Crop Prediction Model Using Machine Learning Algorithms. *Applied Sciences (Switzerland)*, *13*(16). https://doi.org/10.3390/app13169288

Elmrabit, N., Zhou, F., Li, F., & Zhou, H. (2020). *Evaluation of Machine Learning Algorithms for Anomaly Detection*. https://www2.le.ac.uk/offices/itservices/ithelp/services/hpc

Emmert-Streib, F., Yang, Z., Feng, H., Tripathi, S., & Dehmer, M. (2020). An Introductory Review of Deep Learning for Prediction Models With Big Data. *Frontiers in Artificial Intelligence*, *3*, 507091. https://doi.org/10.3389/FRAI.2020.00004/BIBTEX

Fakhriddinovich, I. A., & Al Khorezmi, M. (2024). Enhancing Cybersecurity: Protecting Data In The Digital Age. *Innovations in Science and Technologies*, *1*(1), 40–49.

Fang, X., & Chen, X. (2021). Evolutionary dynamics of trust in the N-player trust game with individual reward and punishment. *The European Physical Journal B 2021 94:9*, *94*(9), 1–7. https://doi.org/10.1140/EPJB/S10051-021-00185-W

Fayomi, O., & Akanazu, H. (2024). Strategic Goal-Setting And Organisational Effectiveness In Selected Trading And Manufacturing Companies. *Webology*, *21*(2), 25–39. http://www.webology.org

Fei, C., Liu, R., Li, Z., Wang, T., & Baig, F. N. (2021). *Machine and Deep Learning Algorithms for Wearable Health Monitoring*. 105–160. https://doi.org/10.1007/978-3-030-68723-6_6

Frimayasa, A., Desty Febrian, W., & Dian Nusantara, U. (2021a). Effect Of Reward And Punishment On Employee Performance. *INTERNATIONAL JOURNAL OF SOCIAL AND MANAGEMENT STUDIES (IJOSMAS)*, *2*(3). http://www.ijosmas.org

Gaborov, M., Karuović, D., Kavalic, M., Radosav, D., Milosavljev, D., Stanisaljev, S., & Bushati, J. (2021). Comparative analysis of agile and traditional methodologies in IT project management. *Journal of Applied Technical and Educational Sciences*, *11*(4), 1-ArtNo: 279. https://doi.org/10.24368/JATES.V11I4.279

Gacutan Bangayan, O., Bautista Rivera, R., & Bulan Asis, M. (2023). Timekeeping and Immediate Monitoring of Employees by Consistently Advocating Time Consciousness and Honesty Using Enhanced Attendance Monitoring System. *Pertanika J. Sci. & Technol*, *31*(1), 292. https://doi.org/10.47836/pjst.31.1.18

Gaikwad, V., Rathi, D., Rahangdale, V., Pandita, R., Rahate, K., & Rajpurohit, R. S. (2024). Design and Implementation of IOT Based Face Detection and Recognition. *Computing & Intelligent Systems*, 923–933. https://doi.org/10.56155/978-81-955020-2-8-78

Gawande, U., Joshi, P., Ghatwai, S., Nemade, S., Balkothe, S., & Shrikhande, N. (2022). Efficient Attendance Management System Based on Face Recognition. *Lecture Notes in Networks and Systems*, *321*, 113–121. https://doi.org/10.1007/978-981-16-5987-4_12

George, B., & Wooden, O. (2023). Managing the Strategic Transformation of Higher Education through Artificial Intelligence. *Administrative Sciences 2023, Vol. 13, Page 196*, *13*(9), 196. https://doi.org/10.3390/ADMSCI13090196

Ghafoor, S., Shaukat, M. H., & Ashraf, N. (2015). Impact of Human Resource Management Practices on Employees Performance. *Middle-East Journal of Scientific Research*, *23*(2), 329–338. https://doi.org/10.5829/idosi.mejsr.2015.23.02.22117

Ghillani, D. (2022). Deep Learning and Artificial Intelligence Framework to Improve the Cyber Security. *American Journal of Artificial Intelligence*, *x, No. x*, x–x. https://doi.org/10.22541/au.166379475.54266021/v1

Ghorbani, S., & Shafaghat, A. (2020). Representing a conceptual model for integrating Project Management Information Systems in project-based organizations. *Annals of Management and Organization Research*, *1*(3), 235–249. https://doi.org/10.35912/amor.v1i3.446

Gode, C. S., Khobragade, A. S., Thanekar, C., Thengadi, O., & Lakde, K. (2023a). Face Recognition-Based Attendance System. *Advances in Intelligent Systems and Computing, 1439*, 159–166. https://doi.org/10.1007/978-981-19-9819-5_12

Golasangi, A., Choudri, M., Bulla, P., & Devaraddi, V. (2024). A Survey on Face Recognition Based Attendance System. *International Journal of Research in Engineering, Science and Management*, *7*(2), 15–18. https://doi.org/10.5281/ZENODO.10644334

Gondia, A., Siam, A., El-Dakhakhni, W., & Nassar, A. H. (2019). Machine Learning Algorithms for Construction Projects Delay Risk Prediction. *Journal of Construction Engineering and Management*, *146*(1), 04019085. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001736

Goswami, S., & Singh, A. K. (2024). A Literature Survey on Various Sspect of Class Imbalance Problem in Data Mining. *Multimedia Tools and Applications*, 1–26. https://doi.org/10.1007/S11042-024-18244-6/METRICS

Gudimetla, R. S. (2024). Data Encryption in Cloud Storage. *STORAGE Article in International Research Journal of Modernization in Engineering Technology and Science*. https://doi.org/10.56726/IRJMETS50637

Gueguen, M. C. M., Lopez-Persem, A., Billeke, P., Lachaux, J. P., Rheims, S., Kahane, P., Minotti, L., David, O., Pessiglione, M., & Bastin, J. (2021). Anatomical dissociation of intracerebral signals for reward and punishment prediction errors in humans. *Nature Communications*, *12*(1). https://doi.org/10.1038/s41467-021-23704-w

Gupta, A., Sriram, S., & Nivethitha, V. (2024). Harnessing Diversity in Face Recognition: A Voting and Bagging Ensemble Approach. *2024 International Conference on Automation and Computation (AUTOCOM)*, 249–255. https://doi.org/10.1109/AUTOCOM60220.2024.10486188

Hamouri, S. K., Shatnawi, R. A., Alzoubi, O., Migdady, A., & Yassein, M. B. (2023). Predicting Bug Severity Using Machine Learning and Ensemble Learning Techniques. *International Conference on Information, Communications and Signal Processing*. https://doi.org/10.1109/ICICS60529.2023.10330494

Hangaragi, S., Singh, T., & Neelima, N. (2023). Face Detection and Recognition Using Face Mesh and Deep Neural Network. *Procedia Computer Science*, *218*, 741–749. https://doi.org/10.1016/J.PROCS.2023.01.054

Hidayah, N., & Yunus, M. (2023). Big Data Security Issues: A Review. *Article in Journal of Engineering Technology*. https://www.researchgate.net/publication/375073116

Hosen, M. A., Moz, S. H., Khalid, M. M. H., Kabir, S. S., & Galib, S. M. (2023). Face Recognition-based Attendance System with Anti-Spoofing, System Alert, and Email Automation. *Radioelectronic and Computer Systems*, *0*(2), 119–128. https://doi.org/10.32620/reks.2023.2.10

Husnain, A., Hussain, K. H., Shahroz, M. H., Ali, M., & Hayat, Y. (2024). View of Advancements in Health through Artificial Intelligence and Machine Learning: A Focus on Brain Health. *Revista Espanola De Documentacion Cientifica*, *18*(01), 100–123. https://redc.revistas-csic.com/index.php/Jorunal/article/view/195/162

Hussein, M. R., Farhan, A., & Rahman, M. (2023). Computer Vision Based Automated Attendance System Using Face Recognition. *6th Industrial Engineering and Operations Management Bangladesh Conference*. https://doi.org/10.46254/BA06.20230105

Ibrahim, M., Alsheikh, A., Awaysheh, F. M., & Alshehri, M. D. (2022). Machine Learning Schemes for Anomaly Detection in Solar Power Plants. *Energies*, *15*(3). https://doi.org/10.3390/en15031082

Ikromovich, H. O., & Mamatkulovich, B. B. (2023). Facial Recognition Using Transfer Learning in the Deep CNN. *Open Access Repository*, *4*(3), 502–507. https://doi.org/10.17605/OSF.IO/NRMK2

Ishibashi, H. (2024). Framework for Risk Assessment of Economic Loss from Structures Damaged by Rainfall-Induced Landslides Using Machine Learning. *Georisk: Assessment and Management of Risk for Engineered Systems and Geohazards*, *18*(1), 228–243. https://doi.org/10.1080/17499518.2023.2288606

Islam, S., & Evans, N. (2020). Key Success Factors of PRINCE2 Project Management Method in Software Development Project: KSF of PRINCE2 in SDLC. *International Journal of Engineering Materials and Manufacture*, *5*(3), 76–84. https://doi.org/10.26776/IJEMM.05.03.2020.02

Jackson, S. E., & Schuler, R. S. (1995). Understanding human resource management in the context of organizations and their environments. *Annual Review of Psychology*, *46*(1), 237–264. https://doi.org/10.1146/ANNUREV.PS.46.020195.001321/CITE/REFWORKS

Jahir Pasha, M., Gaurav, K., Bhanja, A. K., Shamout, M. D., Mupparaju, C. B., & Manohar Bhanushali, M. (2023). Advancing Data Science Using AI-Driven Processes. *2023 International Conference on Power Energy, Environment and Intelligent Control, PEEIC 2023*, 1587–1593. https://doi.org/10.1109/PEEIC59336.2023.10451426

Janiesch, C., Zschech, P., & Heinrich, K. (2021). Machine Learning and Deep Learning. *Electronic Markets*, 685–695. https://doi.org/10.1007/s12525-021-00475-2/Published

Järvinen, K., & Soini, A. (2023). *Project Management Selection Criteria : Which Is Better, Traditional Or Agile Method?* https://www.doria.fi/handle/10024/187968

Jia, H., Peng, R., Ding, Y., & Shao, C. (2020). Reliability Analysis of Distributed Storage Systems Considering Data Loss and Theft. *Proceedings of the Institution of Mechanical Engineers*, *234*(2), 303–321. https://doi.org/10.1177/1748006X19885508

Jia, J., Jin, G. Z., & Wagman, L. (2021). The Short-Run Effects of the General Data Protection Regulation on Technology Venture Investment. *Https://Doi.Org/10.1287/Mksc.2020.1271*, *40*(4), 661–684. https://doi.org/10.1287/MKSC.2020.1271

Jia, Q., Guo, Y., Li, R., Li, Y., & Chen, Y. (2018). A Conceptual Artificial Intelligence Application Framework in Human Resource Management. *ICEB 2018 Proceedings (Guilin, China)*. https://aisel.aisnet.org/iceb2018/91

Joo, K., Kim, J., & Hwang, J. (2024). Effects of Foodservice Consumers' Perceptions of Face Recognition Payment on Attitude, Desire, and Behavioral Intentions: A Cross-Cultural Study. *Journal of Travel & Tourism Marketing*, *41*(3), 359–376. https://doi.org/10.1080/10548408.2024.2318429

Kamanga, I. A., Lyimo, J. M., Kamanga, I. A., & Lyimo, J. M. (2022). Anti-spoofing detection based on eyeblink liveness testing for iris recognition. *International Journal of Science and Research Archive*, *7*(1), 053–067. https://doi.org/10.30574/IJSRA.2022.7.1.0186

Kambur, E., & Yildirim, T. (2023). From traditional to smart human resources management. *International Journal of Manpower*, *44*(3), 422–452. https://doi.org/10.1108/IJM-10-2021-0622/FULL/XML

Kamil, M. N., Musah, B. M., & Zakari, M. (2023). The Impact of Biometric Time and Attendance System on Workforce Management Outcomes: The Moderating Role of Managerial Commitment in the Service Sector in Northern Ghana. *International Journal of Business and Technology Management*. https://doi.org/10.55057/ijbtm.2023.5.3.37

Kaplan, M. F., & Anderson, N. H. (1973). Information integration theory and reinforcement theory as approaches to interpersonal attraction. *Journal of Personality and Social Psychology*, *28*(3), 301–312. https://doi.org/10.1037/H0035112

Karatay, B., Beştepe, D., Sailunaz, K., Özyer, T., & Alhajj, R. (2024). CNN-Transformer based emotion classification from facial expressions and body gestures. *Multimedia Tools and Applications*, *83*(8), 23129–23171. https://doi.org/10.1007/S11042-023-16342-5/METRICS

Karnati, M., Seal, A., Bhattacharjee, D., Yazidi, A., & Krejcar, O. (2023). Understanding Deep Learning Techniques for Recognition of Human Emotions Using Facial Expressions: A Comprehensive Survey. *IEEE Transactions on Instrumentation and Measurement*, *72*. https://doi.org/10.1109/TIM.2023.3243661

Kasula, Y. B. (2021). Machine Learning Applications in Diabetic Healthcare: A Comprehensive Analysis and Predictive Modeling. *International Numeric Journal of Machine Learning and Robots*, *5*(5). https://injmr.com/index.php/fewfewf/article/view/19/1

Kaur, R., & Himanshi, E. (2015). Face recognition using Principal Component Analysis. *Souvenir of the 2015 IEEE International Advance Computing Conference, IACC 2015*, 585–589. https://doi.org/10.1109/IADCC.2015.7154774

Kavoliūnaitė-Ragauskienė, E. (2024). Right to Privacy and Data Protection Concerns Raised by the Development and Usage of Face Recognition Technologies in the European Union. *Journal of Human Rights Practice*. https://doi.org/10.1093/JHUMAN/HUAD065

Khairnar, S., Gite, S., Kotecha, K., & Thepade, S. D. (2023a). Face Liveness Detection Using Artificial Intelligence Techniques: A Systematic Literature Review and Future Directions. *Big Data and Cognitive Computing 2023, Vol. 7, Page 37*, *7*(1), 37. https://doi.org/10.3390/BDCC7010037

Khairnar, S., Gite, S., Kotecha, K., & Thepade, S. D. (2023b). Face Liveness Detection Using Artificial Intelligence Techniques: A Systematic Literature Review and Future Directions. In *Big Data and Cognitive Computing* (Vol. 7, Issue 1). MDPI. https://doi.org/10.3390/bdcc7010037

Khan, W., Ghazanfar, M. A., Azam, M. A., Karami, A., Alyoubi, K. H., & Alfakeeh, A. S. (2022). Stock market prediction using machine learning classifiers and social media, news. *Journal of Ambient Intelligence and Humanized Computing*, *13*(7), 3433–3456. https://doi.org/10.1007/S12652-020-01839-W/METRICS

Kim, H.-G., Lee, D.-Y., Jeong, S.-Y., Yoo, H., & Hong, W.-K. (2019). Machine Learning-Based Method for Prediction Virtual Network Function Resource Demans. *IEEE Conference on Network Softwarization (NetSoft)*.

Kim, P. T., & Bodie, M. T. (2020). Artificial Intelligence and the Challenges of Workplace Discrimination and Privacy. *ABA Journal of Labor and Employment Law*, *35*. https://heinonline.org/HOL/Page?handle=hein.journals/lablaw35&id=305&div=&collection=

Kothapalli, C. D., Navya, G., Jaladhi, U., Sulthana, S. R., Kumar, D. L. S., & Praveen, S. P. (2023). Predicting Buy and Sell Signals for Stocks using Bollinger Bands and MACD with the Help of Machine Learning. *International Conference on Sustainable Computing and Smart Systems, ICSCSS 2023 - Proceedings*, 333–340. https://doi.org/10.1109/ICSCSS57650.2023.10169500

Krishna Suryadevara, C. (2023). Issue 4 DIABETES RISK ASSESSMENT USING MACHINE LEARNING: A COMPARATIVE STUDY OF CLASSIFICATION ALGORITHMS. *International Engineering Journal For Research & Development*, *8*. www.iejrd.com

Krishnan, C., Gupta, A., Gupta, A., & Singh, G. (2022). Impact of Artificial Intelligence-Based Chatbots on Customer Engagement and Business Growth. *Studies in Big Data*, *113*, 195–210. https://doi.org/10.1007/978-3-031-10869-3_11

Krishnapriya, K. S., Albiero, V., Vangara, K., King, M. C., & Bowyer, K. W. (2020). Issues Related to Face Recognition Accuracy Varying Based on Race and Skin Tone. *IEEE Transactions on Technology and Society*, *1*(1), 8–20. https://doi.org/10.1109/TTS.2020.2974996

Kubanek, J., Snyder, L. H., & Abrams, R. A. (2015). Reward and punishment act as distinct factors in guiding behavior. *Cognition*, *139*, 154–167. https://doi.org/10.1016/j.cognition.2015.03.005

Kufel, J., Bargieł-Łączek, K., Kocot, S., Koźlik, M., Bartnikowska, W., Janik, M., Czogalik, Ł., Dudek, P., Magiera, M., Lis, A., Paszkiewicz, I., Nawrat, Z., Cebula, M., & Gruszczyńska, K. (2023). What Is Machine Learning, Artificial Neural Networks and Deep Learning?—Examples of Practical Applications in Medicine. In *Diagnostics* (Vol. 13, Issue 15). Multidisciplinary Digital Publishing Institute (MDPI). https://doi.org/10.3390/diagnostics13152582

Kumar, A., Samal, S., Saluja, M. S., & Tiwari, A. (2023). Automated Attendance System Based on Face Recognition Using Opencv. *2023 9th International Conference on Advanced Computing and Communication Systems, ICACCS 2023*, 2256–2259. https://doi.org/10.1109/ICACCS57279.2023.10112665

Kumar, P., Salman Latheef, A. T., & Santhosh, R. (2023). Face Recognition Attendance System Using Local Binary Pattern Algorithm. *ViTECoN 2023 - 2nd IEEE International Conference on Vision Towards Emerging Trends in Communication and Networking Technologies, Proceedings*. https://doi.org/10.1109/VITECON58111.2023.10157843

Kuznetsov, O., Zakharov, D., Frontoni, E., Maranesi, A., & Bohucharskyi, S. (2024). *Cross-Database Liveness Detection: Insights from Comparative Biometric Analysis*. https://arxiv.org/abs/2401.16232v1

Lahmiri, S., Bekiros, S., & Avdoulas, C. (2023). A Comparative Assessment of Machine Learning Methods for Predicting Housing Prices Using Bayesian Optimization. *Decision Analytics Journal*, *6*, 100166. https://doi.org/10.1016/J.DAJOUR.2023.100166

Lalmi, A., Fernandes, G., & Souad, S. B. (2021). A Conceptual Hybrid Project Management Model for Construction Projects. *Procedia Computer Science*, *181*, 921–930. https://doi.org/10.1016/J.PROCS.2021.01.248

Landauer, M., Onder, S., Skopik, F., & Wurzenberger, M. (2023). Deep Learning for Anomaly Detection in Log Data: A Survey. *Machine Learning with Applications*, *12*, 100470. https://doi.org/10.1016/J.MLWA.2023.100470

Lather, A. S., Malhotra, R., Saloni, P., Singh, P., & Mittal, S. (2019). Prediction of employee performance using machine learning techniques. *ACM International Conference Proceeding Series*. https://doi.org/10.1145/3373477.3373696

Latrach, A., Malki, M. L., Morales, M., Mehana, M., & Rabiei, M. (2024). A critical review of physics-informed machine learning applications in subsurface energy systems. *Geoenergy Science and Engineering*, *239*, 212938. https://doi.org/10.1016/J.GEOEN.2024.212938

Lavens, E., Preuveneers, D., & Joosen, W. (2023). Mitigating undesired interactions between liveness detection components in biometric authentication. *ACM International Conference Proceeding Series*. https://doi.org/10.1145/3600160.3604992

Lee, D. H., & Yoo, J. H. (2023). CNN Learning Strategy for Recognizing Facial Expressions. *IEEE Access*, *11*, 70865–70872. https://doi.org/10.1109/ACCESS.2023.3294099

Lee, G., Woo, P., & Lee, K. (2023). Data Generation Using Geometrical EDGE Probability for One-Class Support Vector Machines. *Expert Systems with Applications*, *229*, 120387. https://doi.org/10.1016/J.ESWA.2023.120387

Lei, L., Chen, W., Wu, B., Chen, C., & Liu, W. (2021). A building energy consumption prediction model based on rough set theory and deep learning algorithms. *Energy and Buildings*, *240*, 110886. https://doi.org/10.1016/J.ENBUILD.2021.110886

Li, J. hua. (2018). Cyber security meets artificial intelligence: a survey. In *Frontiers of Information Technology and Electronic Engineering* (Vol. 19, Issue 12, pp. 1462–1474). Zhejiang University. https://doi.org/10.1631/FITEE.1800573

Li, R., Zhang, H., Chen, Z., Yu, N., Kong, W., Li, T., Wang, E., Wu, X., & Liu, Y. (2022). Denoising method of ground-penetrating radar signal based on independent component analysis with multifractal spectrum. *Measurement*, *192*, 110886. https://doi.org/10.1016/J.MEASUREMENT.2022.110886

Lifandali, O., Abghour, N., & Chiba, Z. (2023). Feature Selection Using a Combination of Ant Colony Optimization and Random Forest Algorithms Applied to Isolation Forest Based Intrusion Detection System. *Procedia Computer Science*, *220*, 796–805. https://doi.org/10.1016/j.procs.2023.03.106

Liu, H. (2024). Designing And Implementing a Chat System with Enhanced Security Via AES Encryption Methods. *Highlights in Science, Engineering and Technology*, *85*, 480–486. https://doi.org/10.54097/WKFK9P24

Liu, J., Deng, Y., Bai, T., Wei, Z., & Huang, C. (2015). *Targeting Ultimate Accuracy: Face Recognition via Deep Embedding*. https://arxiv.org/abs/1506.07310v4

Liu, L., Mei, Q., Skogstad, A., Wu, J., Liu, S., & Wang, M. (2022). Linking Safety-Specific Leader Reward and Punishment Omission to Safety Compliance Behavior: The Role of Distributive Justice and Role Ambiguity. *Frontiers in Public Health*, *10*. https://doi.org/10.3389/fpubh.2022.841345

Lohrasbinasab, I., Shahraki, A., Taherkordi, A., & Delia Jurcut, A. (2022). From statistical- to machine learning-based network traffic prediction. *Transactions on Emerging Telecommunications Technologies*, *33*(4). https://doi.org/10.1002/ett.4394

Loi, M. (2020). *People Analytics must benefit the people. An ethical analysis of data-driven algorithmic systems in human resources management*.

Lu, P. (2023). Deeper Learning Needed from Machine Learning. *Https://Doi.Org/10.2514/1.G008061*, *47*(1), 1–4. https://doi.org/10.2514/1.G008061

Lubbad, M., Karaboga, D., Basturk, A., Akay, B., Nalbantoglu, U., & Pacal, I. (2024). Machine learning applications in detection and diagnosis of urology cancers: a systematic literature review. *Neural Computing and Applications*, *36*(12), 6355–6379. https://doi.org/10.1007/S00521-023-09375-2/METRICS

Ma, J. (2023). Face Recognition Technology and Privacy Protection Methods based on Deep Learning. *International Conference on Computer Application and Information Security (ICCAIS 2023)*, *13090*, 899–904. https://doi.org/10.1117/12.3025901

Malik, M. A. R., Butt, A. N., & Choi, J. N. (2015). Rewards and employee creative performance: Moderating effects of creative self-efficacy, reward importance, and locus of control. *Journal of Organizational Behavior*, *36*(1), 59–74. https://doi.org/10.1002/JOB.1943

Mallikarjunaradhya, V., Ganesh, A., Mistry, J., & Kiruthiga, T. (2023). The smart analysis of cell damage and cancerous prediction using information clustering model. *2023 2nd International Conference on Smart Technologies for Smart Nation, SmartTechCon 2023*, 870–875. https://doi.org/10.1109/SMARTTECHCON57526.2023.10391822

Mamieva, D., Abdusalomov, A. B., Mukhiddinov, M., & Whangbo, T. K. (2023). Improved Face Detection Method via Learning Small Faces on Hard Images Based on a Deep Learning Approach. *Sensors 2023, Vol. 23, Page 502*, *23*(1), 502. https://doi.org/10.3390/S23010502

Mandol, S., Mia, S., & Ahsan, S. M. M. (2021). Real Time Liveness Detection and Face Recognition with OpenCV and Deep Learning. *2021 5th International Conference on Electrical Information and Communication Technology, EICT 2021*. https://doi.org/10.1109/EICT54103.2021.9733685

Manthiramoorthy, C., Mohamed, K., Khan, S., & Ameen, N. (2024). Comparing Several Encrypted Cloud Storage Platforms. *International Journal of Mathematics, Statistics, and Computer Science*, *2*, 44–62. https://doi.org/10.59543/IJMSCS.V2I.7971

Marlina, L., Setyoningrum, N. G., Mulyani, Y. S., Permana, T. E., Sumarni, R., Triguna Tasikmalaya, P., Bsi, U., Tasikmalaya, K., Sekretaris, A., & Ariyanti, M. (2021). IMPROVING EMPLOYEES WORKING DISCIPLINE WITH PUNISHMENT, REWARD, AND IMPLEMENTATION OF STANDARD OPERATIONAL PROCEDURES. In *Perwira International Journal of Economics & Business (PIJEB)*. https://ejournal.unperba.ac.id/index.php/pijeb

Marnewick, C., & Marnewick, A. L. (2022). Digitalization of Project Management: Opportunities in Research and Practice. *Project Leadership and Society*, *3*, 100061. https://doi.org/10.1016/J.PLAS.2022.100061

Matthew, P., & Canning, S. (2020). An algorithmic approach for optimising biometric systems using liveness and coercion detection. *Computers & Security*, *94*, 101831. https://doi.org/10.1016/J.COSE.2020.101831

Meden, B., Rot, P., Terhorst, P., Damer, N., Kuijper, A., Scheirer, W. J., Ross, A., Peer, P., & Struc, V. (2021). Privacy-Enhancing Face Biometrics: A Comprehensive Survey. *IEEE Transactions on Information Forensics and Security*, *16*, 4147–4183. https://doi.org/10.1109/TIFS.2021.3096024

Meena, G., Mohbey, K. K., Indian, A., Khan, M. Z., & Kumar, S. (2024). Identifying emotions from facial expressions using a deep convolutional neural network-based approach. *Multimedia Tools and Applications*, *83*(6), 15711–15732. https://doi.org/10.1007/S11042-023-16174-3/METRICS

Miller, J., Connolly, R., Uzoka, F. M., Keavey, K., & Khemka-Dolan, N. (2023). Information technology project management: success, failure and risk factors. *International Journal of Business Information Systems*, *44*(4), 485–507. https://doi.org/10.1504/IJBIS.2023.135348

Miner, J. B. (2015). Organizational behavior 1: Essential theories of motivation and leadership. *Organizational Behavior 1: Essential Theories of Motivation and Leadership*, 1–416. https://doi.org/10.4324/9781315702018

Minovski, D., Ogren, N., Mitra, K., & Ahlund, C. (2023). Throughput Prediction Using Machine Learning in LTE and 5G Networks. *IEEE Transactions on Mobile Computing*, *22*(3), 1825–1840. https://doi.org/10.1109/TMC.2021.3099397

Mishra, A., & Yadav, P. (2020). *Anomaly-based IDS to Detect Attack Using Various Artificial Intelligence & Machine Learning Algorithms: A Review*.

Misra, R., Kumar Shakya, S., & Professor, A. (2023). *Face Recognition Attendance System, Smart Learning, College Enquiry Using AI Chat-Bot*. www.ijcstjournal.org

Mohammed Sahan, J., Abbas, E. I., & Abood, Z. M. (2023). A facial recognition using a combination of a novel one dimension deep CNN and LDA. *Materials Today: Proceedings*, *80*, 3594–3599. https://doi.org/10.1016/J.MATPR.2021.07.325

Mohammed, Z. A., Gheni, H. Q., Hussein, Z. J., & Al-Qurabat, A. K. M. (2024). Advancing Cloud Image Security via AES Algorithm Enhancement Techniques. *Engineering, Technology & Applied Science Research*, *14*(1), 12694–12701. https://doi.org/10.48084/ETASR.6601

Mohtasham Moein, M., Saradar, A., Rahmati, K., Ghasemzadeh Mousavinejad, S. H., Bristow, J., Aramali, V., & Karakouzian, M. (2023). Predictive models for concrete properties using machine learning and deep learning approaches: A review. *Journal of Building Engineering*, *63*, 105444. https://doi.org/10.1016/J.JOBE.2022.105444

Molan, M., Borghesi, A., Cesarini, D., Benini, L., & Bartolini, A. (2023). RUAD: Unsupervised Anomaly Detection in HPC Systems. *Future Generation Computer Systems*, *141*, 542–554. https://doi.org/10.1016/J.FUTURE.2022.12.001

Momin, T., Mehra, S., Khan, I., & Tiwari, H. (2024). End-to-End Facial Recognition System and Data Visualization of Students Attendance. *International Journal of Scientific Research & Engineering Trends*, *10*(2), 614–619.

Moosaei, H., Ganaie, M. A., Hladík, M., & Tanveer, M. (2023). Inverse free Reduced Universum Twin Support Vector Machine for Imbalanced Data Classification. *Neural Networks*, *157*, 125–135. https://doi.org/10.1016/J.NEUNET.2022.10.003

Mousavi, A., Arefanjazi, H., Sadeghi, M., Ghahfarokhi, A. M., Beheshtinejad, F., & Masouleh, M. M. (2023). Comparison of Feature Extraction with PCA and LTP Methods and Investigating the Effect of Dimensionality Reduction in the Bat Algorithm for Face Recognition. *International Journal of Robotics and Control Systems*, *3*(3), 500–509. https://doi.org/10.31763/ijrcs.v3i3.1057

Moustafa, N., Koroniotis, N., Keshk, M., Zomaya, A. Y., & Tari, Z. (2023). Explainable Intrusion Detection for Cyber Defences in the Internet of Things: Opportunities and Solutions. *IEEE Communications Surveys and Tutorials*, *25*(3), 1775–1807. https://doi.org/10.1109/COMST.2023.3280465

Mughaid, A., AlZu'bi, S., Alnajjar, A., AbuElsoud, E., Salhi, S. El, Igried, B., & Abualigah, L. (2023). Improved dropping attacks detecting system in 5g networks using machine learning and deep learning approaches. *Multimedia Tools and Applications*, *82*(9), 13973–13995. https://doi.org/10.1007/S11042-022-13914-9/METRICS

Muhammad Abdullah, A., & Muhamad Abdullah, A. (2017). *Advanced Encryption Standard (AES) Algorithm to Encrypt and Decrypt Data*. https://www.researchgate.net/publication/317615794

Murtaza, M., Ahmed, Y., Shamsi, J. A., Sherwani, F., & Usman, M. (2022). AI-Based Personalized E-Learning Systems: Issues, Challenges, and Solutions. *IEEE Access*, *10*, 81323–81342. https://doi.org/10.1109/ACCESS.2022.3193938

Nagagopiraju, Deepak, M. D., Vinay, V. M., Kumar, A. E., & Supriya, K. (2024). Machine Learning and Blockchain-Based Real-Time Facial Recognition Attendance System. *Turkish Journal of Computer and Mathematics Education (TURCOMAT)*, *15*(1), 133–137. https://doi.org/10.61841/TURCOMAT.V15I1.14554

Najafi Moghaddam Gilani, V., Hosseinian, S. M., Ghasedi, M., & Nikookar, M. (2021). Data-Driven Urban Traffic Accident Analysis and Prediction Using Logit and Machine Learning-Based Pattern Recognition Models. *Mathematical Problems in Engineering*, *2021*. https://doi.org/10.1155/2021/9974219

Nanda, S., Zafari, F., Decusatis, C., Wedaa, E., & Yang, B. (2017). Predicting network attack patterns in SDN using machine learning approach. *2016 IEEE Conference on Network Function Virtualization and Software Defined Networks, NFV-SDN 2016*, 167–172. https://doi.org/10.1109/NFV-SDN.2016.7919493

Nasiri Khiavi, A. (2024). Machine Learning Modeling of Base Flow Generation Potential: A Case Study of the Combined Application of BWM and Fallback Bargaining Algorithm. *Journal of Hydrology*, 131220. https://doi.org/10.1016/J.JHYDROL.2024.131220

Nawaal, B., Haider, U., Khan, I. U., & Fayaz, M. (2024). Signature-Based Intrusion Detection System for IoT. *Cyber Security for Next-Generation Computing Technologies*, 141–158. https://doi.org/10.1201/9781003404361-8

Ndudi, E. F., Kifordu, A. A., & Egede, N. M. (2023). The Influence of Intrinsic and Extrinsic Motivation in Workers' Productivity: Empirical Evidence from the Construction Industry. *Global Journal of Human Resource Management*, *11*(2), 96–112. https://doi.org/10.37745/gjhrm.2013/vol11n296112

Neelakandan, S., Velmurugan, S., Prakash, M., & Paulraj, D. (2024). A multi-layer encryption with AES and Twofish encryption algorithm for smart assistant security. *Digital Image Security: Techniques and Applications*, 266–293. https://doi.org/10.1201/9781003468974-13

Nguyen, P., Friend, S. B., Chase, K. S., & Johnson, J. S. (2023). Analyzing sales proposal rejections via machine learning. *Journal of Personal Selling & Sales Management*, *43*(1), 24–45. https://doi.org/10.1080/08853134.2022.2067554

Nguyen-Tat, B. T., Bui, M. Q., & Ngo, V. M. (2024). Automating Attendance Management in Human Resources: A Design Science Approach using Computer Vision and Facial Recognition. *International Journal of Information Management Data Insights*, *4*(2), 100253. https://doi.org/10.1016/J.JJIMEI.2024.100253

Nikou, M., Mansourfar, G., & Bagherzadeh, J. (2019). Stock price prediction using DEEP learning algorithm and its comparison with machine learning algorithms. *Intelligent Systems in Accounting, Finance and Management*, *26*(4), 164–174. https://doi.org/10.1002/ISAF.1459

Nuttin, J., & Greenwald, G. A. (1968). *Reward and Punishment in Human Learning: Elements of a Behavior Theory*. https://books.google.co.id/books?hl=en&lr=&id=ujO0BQAAQBAJ&oi=fnd&pg=PP1&dq=reward+and+punishment+theory&ots=r8l5hRXG_J&sig=3tJk5UzdTOfrAOyB3u2JlGOQZB4&redir_esc=y#v=onepage&q=reward%20and%20punishment%20theory&f=false

Nyathani, R. (2023). AI-Driven HR Analytics: Unleashing the Power of HR Data Management. *Journal of Technology and Systems*, *5*(2), 15–26. https://doi.org/10.47941/JTS.1513

Obert, J., Cordeiro, P., Johnson, J. T., Lum, G., Tansy, T., Pala, N., & Ih, R. (2019). *Recommendations for Trust and Encryption in DER Interoperability Standards*. https://doi.org/https://doi.org/10.2172/1761841

Oei, A. J., Tan, M. R. A., Anderies, & Chowanda, A. (2023). Attendance Management System Using Face Recognition. *ICEEIE 2023 - International Conference on Electrical, Electronics and Information Engineering*. https://doi.org/10.1109/ICEEIE59078.2023.10334708

Olu-Ajayi, R., Alaka, H., Sulaimon, I., Sunmola, F., & Ajayi, S. (2022). Building energy consumption prediction for residential buildings using deep learning and other machine learning techniques. *Journal of Building Engineering*, *45*, 103406. https://doi.org/10.1016/J.JOBE.2021.103406

Oo, S. B., Oo, N. H. M., Chainan, S., Thongniam, A., & Chongdarakul, W. (2018). Cloud-based Web Application with NFC for Employee Attendance Management System. *3rd International Conference on Digital Arts, Media and Technology, ICDAMT 2018*, 162–167. https://doi.org/10.1109/ICDAMT.2018.8376516

Orazulike, J. O. (2011). Abstract Successful Information Technology Project Process Management Best Practices. *BTech*.

Ozcan, M., & Peker, S. (2023). A classification and regression tree algorithm for heart disease modeling and prediction. *Healthcare Analytics*, *3*, 100130. https://doi.org/10.1016/J.HEALTH.2022.100130

Painuly, K., Bisht, Y., Vaidya, H., Kapruwan, A., & Gupta, R. (2024). Efficient Real-Time Face Recognition-Based Attendance System with Deep Learning Algorithms. *Proceedings of the 2nd International Conference on Intelligent and Innovative Technologies in Computing, Electrical and Electronics, ICIITCEE 2024*. https://doi.org/10.1109/IITCEE59897.2024.10467743

Pangandaheng, A. C., & Sutanto, J. E. (2021). *THE EFFECT OF LEADERSHIP, REWARD, AND PUNISHMENT ON EMPLOYEE PERFORMANCE IN A SWALLOW BIRD NEST EXPORTER COMPANY IN EAST JAVA*. https://dspace.uc.ac.id/handle/123456789/6795

Park, H., Ahn, D., Hosanagar, K., & Lee, J. (2021, May 6). Human-ai interaction in human resource management: Understanding why employees resist algorithmic evaluation at workplaces and how to mitigate burdens. *Conference on Human Factors in Computing Systems - Proceedings*. https://doi.org/10.1145/3411764.3445304

Patel, K. (2019). Performance Analysis of AES, DES and Blowfish Cryptographic Algorithms on Small and Large Data Files. *International Journal of Information Technology (Singapore)*, *11*(4), 813–819. https://doi.org/10.1007/S41870-018-0271-4/METRICS

Pathak, A., Dixit, C. K., Somani, P., & Gupta, S. K. (2023). Prediction of Employees' Performance Using Machine Learning (ML) Techniques. *Designing Workforce Management Systems for Industry 4.0: Data-Centric and AI-Enabled Approaches*, 177–195. https://doi.org/10.1201/9781003357070-11

Pattnaik, P., & Mohanty, K. K. (2020). AI-Based Techniques for Real-Time Face Recognition-based Attendance System- A Comparative Study. *Proceedings of the 4th International Conference on Electronics, Communication and Aerospace Technology, ICECA 2020*, 1034–1039. https://doi.org/10.1109/ICECA49313.2020.9297643

Păvăloaia, V. D., & Husac, G. (2023). Tracking Unauthorized Access Using Machine Learning and PCA for Face Recognition Developments. *Information (Switzerland)*, *14*(1). https://doi.org/10.3390/info14010025

Paz, A. I. L., & López, R. I. (2023). Recommendation method for customized IT project management. *Procedia Computer Science*, *219*, 1938–1945. https://doi.org/10.1016/J.PROCS.2023.01.493

Perini, L., Bürkner, P.-C., & Klami, A. (2023). Estimating the Contamination Factor's Distribution in Unsupervised Anomaly Detection. *Proceedings of the 40 Th International Conference on Machine Learning*, 27668–27679. https://proceedings.mlr.press/v202/perini23a.html

Pitale, R. R., Tajane, K. D., Mahajan, P. B., Nehate, N. S., Mulimani, A. J., & Lokhande, D. S. (2023). *Cryptographic algorithm development and application for encryption and decryption*. 1–7. https://doi.org/10.1145/3647444.3647853

P.K, R., Khaparde, A., Bendre, V., & Katti, J. (2024). Fraud Detection and Prevention by Face Recognition with and Without Mask for Banking Application. *Multimedia Tools and Applications*, 1–24. https://doi.org/10.1007/S11042-024-19021-1/METRICS

PMI. (2017). *Agile Practice Guide* (Sixth).

Podsakoff, P. M., & Todor, W. D. (1985). Relationships Between Leader Reward and Punishment Behavior and Group Processes and Productivity. *Journal of Management*, *11*(1), 55–73. https://doi.org/10.1177/014920638501100106

Pons, D., & Haefele, S. (1 C.E.). Team Interactions for Successful Project Management in Small and Medium-Sized Enterprises. *International Journal of Information Technology Project Management (IJITPM)*, *7*(2), 17–43. https://doi.org/10.4018/IJITPM.2016040102

Potter, K., & Frank, L. (2024). *Efficient Key Management Schemes for Trigonometry-Based Encryption of Short Messages*. https://www.researchgate.net/publication/378587871

Pradyumna, J., Khan, T., & Kumar, K. (n.d.). Smart Attendance System using Face Recognition. *IJFMR23044583*, *5*(4). www.ijfmr.com

Praseed, A., & Thilagam, P. S. (2022). HTTP Request Pattern Based Signatures for Early Application Layer DDoS Detection: A Firewall Agnostic Approach. *Journal of Information Security and Applications*, *65*, 103090. https://doi.org/10.1016/J.JISA.2021.103090

Pratomo, A. B., Mokodenseho, S., & Aziz, A. M. (2023). Data Encryption and Anonymization Techniques for Enhanced Information System Security and Privacy. *West Science Information System and Technology*, *1*(01), 1–9. https://doi.org/10.58812/WSIST.V1I01.176

Priyanka Brahmaiah, V., Jaswantth, P. V., Sri Likhitha, D., & Pallavi Sudha, M. (2023). Implementation of AES Algorithm. *Lecture Notes in Networks and Systems*, *720 LNNS*, 161–171. https://doi.org/10.1007/978-981-99-3761-5_16

Radiya-Dixit, E., & Neff, G. (2023). A Sociotechnical Audit: Assessing Police Use of Facial Recognition. *ACM International Conference Proceeding Series*, 1334–1346. https://doi.org/10.1145/3593013.3594084

Ragedhaksha, Darshini, Shahil, & Arunnehru, J. (2023). Deep learning-based real-world object detection and improved anomaly detection for surveillance videos. *Materials Today: Proceedings*, *80*, 2911–2916. https://doi.org/10.1016/J.MATPR.2021.07.064

Rahim, A., Zhong, Y., Ahmad, T., Ahmad, S., Pławiak, P., & Hammad, M. (2023). Enhancing Smart Home Security: Anomaly Detection and Face Recognition in Smart Home IoT Devices Using Logit-Boosted CNN Models. *Sensors 2023, Vol. 23, Page 6979*, *23*(15), 6979. https://doi.org/10.3390/S23156979

RajaSekhar, J., Sakhamuri, S., Dhruva Teja, A., & Siva Sai Bhargav, T. (2023). Automatic Attendance Management System Using AI and Deep Convolutional Neural Network. *Advanced Technologies and Societal Change*, 67–76. https://doi.org/10.1007/978-981-19-4522-9_7

Raji, I. D., Gebru, T., Mitchell, M., Buolamwini, J., Lee, J., & Denton, E. (2020). Saving Face: Investigating the Ethical Concerns of Facial Recognition Auditing. *Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society (AIES)*, *7*, 145–151. https://doi.org/10.1145/3375627.3375820

Ran, X., & Nie, B. (2024). Linear Discriminant Analysis (LDA) based on auxiliary slicing for binary classification data. *Highlights in Science, Engineering and Technology*, *101*, 778–785. https://doi.org/10.54097/GH17V872

Rana, M., & Bhushan, M. (2023). Machine learning and deep learning approach for medical image analysis: diagnosis to detection. *Multimedia Tools and Applications*, *82*(17), 26731–26769. https://doi.org/10.1007/s11042-022-14305-w

Rao, P. M., & Deebak, B. D. (2023). Security and Privacy Issues in Smart Cities/Industries: Technologies, Applications, and Challenges. *Journal of Ambient Intelligence and Humanized Computing*, *14*(8), 10517–10553. https://doi.org/10.1007/S12652-022-03707-1/METRICS

Rastogi, P., Saravanan, P., Kerinab Beenu, G. H., Kaur, I., Anandhi, R. J., & Senthilkumar, S. (2023). Analysis Face Recognition based Systems for Employees Attendance Machine Learning. *Proceedings of the 2023 2nd International Conference on Augmented Intelligence and Sustainable Systems, ICAISS 2023*, 515–520. https://doi.org/10.1109/ICAISS58487.2023.10250622

Rastogi, R., Tyagi, A., Upadhyay, H., & Singh, D. (2022). Algorithmic Analysis of Automatic Attendance System Using Facial Recognition: A Revolutionary Approach for Future Education. *International Journal of Decision Support System Technology*, *14*(1). https://doi.org/10.4018/IJDSST.286688

Rathi, R. A. (2018). Artificial intelligence and the future of HR practices. *International Journal of Appl Ied Research 2018; 4(6): 113-116*, *4*(6), 113–116. https://doi.org/10.1177/205

Rausch, T. M., Derra, N. D., & Wolf, L. (2022). Predicting online shopping cart abandonment with machine learning approaches. *International Journal of Market Research*, *64*(1), 89–112. https://doi.org/10.1177/1470785320972526/ASSET/IMAGES/LARGE/10.1177_1470785320972526-FIG1.JPEG

Ressler, N. (2004). Rewards and punishments, goal-directed behavior and consciousness. In *Neuroscience and Biobehavioral Reviews* (Vol. 28, Issue 1, pp. 27–39). Elsevier Ltd. https://doi.org/10.1016/j.neubiorev.2003.10.003

Ries, P. D. (2020). Organizational Outcomes and Impacts of Employee Attendance at the Municipal Forestry Institute Leadership Course. *Urban Forestry & Urban Greening*, *53*, 126725. https://doi.org/10.1016/J.UFUG.2020.126725

Rodgers, W., Murray, J. M., Stefanidis, A., Degbey, W. Y., & Tarba, S. Y. (2023). An artificial intelligence algorithmic approach to ethical decision-making in human resource management processes. *Human Resource Management Review*, *33*(1), 100925. https://doi.org/10.1016/J.HRMR.2022.100925

Rohaan, D., Topan, E., & Groothuis-Oudshoorn, C. G. M. (2022). Using Supervised Machine Learning for B2B Sales Forecasting: A Case Study of Spare Parts Sales Forecasting at an After-Sales Service Provider. *Expert Systems with Applications*, *188*, 115925. https://doi.org/10.1016/J.ESWA.2021.115925

Rohini, V., Sobhana, M., & Chowdary, C. S. (2022). Attendance Monitoring System Design Based on Face Segmentation and Recognition. *Recent Patents on Engineering*, *17*(2). https://doi.org/10.2174/1872212116666220401154639

Rostami, M., Farajollahi, A., & Parvin, H. (2024). Deep Learning-based Face Detection and Recognition on Drones. *Journal of Ambient Intelligence and Humanized Computing*, *15*(1), 373–387. https://doi.org/10.1007/S12652-022-03897-8/METRICS

Rusan, N., & Voitenko, O. (2021). Emotional-Intellectual and Cognitive Factors of Success in Project Management. *Proceedings of the 2nd International Workshop IT Project Management*.

S. Jenifa Sabeena, Dr. S. A. (2023). Identification Of Better Encryption Algorithm in Securing Data. *Journal of Survey in Fisheries Sciences*, *10*(4S), 889–896. https://doi.org/10.17762/SFS.V10I4S.1019

Salcedo-Sanz, S., Pérez-Aracil, J., Ascenso, G., Del Ser, J., Casillas-Pérez, D., Kadow, C., Fister, D., Barriopedro, D., García-Herrera, R., Giuliani, M., & Castelletti, A. (2024). Analysis, Characterization, Prediction, and Attribution of Extreme Atmospheric Events with Machine Learning and Deep Learning Techniques: A Review. *Theoretical and Applied Climatology*, *155*(1), 1–44. https://doi.org/10.1007/s00704-023-04571-5

Saleem, S., Shiney, J., Priestly Shan, B., & Kumar Mishra, V. (2023). Face Recognition Using Facial Features. *Materials Today: Proceedings*, *80*, 3857–3862. https://doi.org/10.1016/J.MATPR.2021.07.402

Samatha Anku, J., Kojo Amewugah, B., & Glover, M. K. (2018). Concept of Reward Management, Reward System and Corporate Efficiency. *International Journal of Economics, Commerce and Management*, *VI*(2), 621–637. http://ijecm.co.uk/

Sanders, R. (1987). The Pareto Principle: Its Use and Abuse. *Journal of Services Marketing*, *1*(2), 37–40. https://doi.org/10.1108/EB024706/FULL/XML

Sandhan, V., Sapkal, R., Rede, S., & Kadam, G. (2024). Smart Attendance Using Face Detection. *International Research Journal of Modernization in Engineering Technology and Science*, *06*(02), 1579–1584. https://doi.org/10.56726/irjmets49477

Santhose, S. S., & Anisha, B. (2023). Psychological Improvement in Employee Productivity by Maintaining Attendance System Using Machine Learning Behavior. *Journal of Community Psychology*, *51*(1), 270–283. https://doi.org/10.1002/JCOP.22902

Sarkar, M., Ayon, E. H., Mia, M. T., Ray, R. K., Chowdhury, M. S., Ghosh, B. P., Al-Imran, M., Islam, M. T., Tayaba, M., & Puja, A. R. (2023). Optimizing E-Commerce Profits: A Comprehensive Machine Learning Framework for Dynamic Pricing and Predicting Online Purchases. *Journal of Computer Science and Technology Studies*, *5*(4), 186–193. https://doi.org/10.32996/JCSTS.2023.5.4.19

Sarker, I. H. (2021). Machine Learning: Algorithms, Real-World Applications and Research Directions. In *SN Computer Science* (Vol. 2, Issue 3). Springer. https://doi.org/10.1007/s42979-021-00592-x

Sarvakar, K., Senkamalavalli, R., Raghavendra, S., Santosh Kumar, J., Manjunath, R., & Jaiswal, S. (2023). Facial Emotion Recognition using Convolutional Neural Networks. *Materials Today: Proceedings*, *80*, 3560–3564. https://doi.org/10.1016/J.MATPR.2021.07.297

Sawadogo, A. D., Guimard, Q., Bissyandé, T. F., Kaboré, A. K., Klein, J., & Moha, N. (2021). *Early Detection of Security-Relevant Bug Reports using Machine Learning: How Far Are We?* http://arxiv.org/abs/2112.10123

Sawarkar, C. D., & Alane, S. S. (2024). Attendance System by Face Recognition Using Deep Learning. *International Research Journal of Modernization in Engineering Technology and Science*. https://doi.org/10.56726/irjmets48994

Sawarkar, Damket, & Alane. (2024). Attendance System by Face Recognition using Deep Learning. *International Research Journal of Modernization in Engineering Technology and Science*. https://doi.org/10.56726/irjmets48994

Schwalbe, K. (2016). *Information Technology Project Management, 8th ed. - Contents.pdf* (Eight). Cengage Learning.

Seen Long, N., Amin Mohamad Sukri, K., & Sains Komputer dan Teknologi Maklumat, F. (2023). Face Recognition Attendance System with Face Rolling Motion on Android. *Applied Information Technology And Computer Science*, *4*(2), 266–282. https://doi.org/10.30880/aitcs.2023.04.02.016

Seth, B., Dalal, S., Jaglan, V., Le, D. N., Mohan, S., & Srivastava, G. (2022). Integrating Encryption Techniques for Secure Data Storage in the Cloud. *Transactions on Emerging Telecommunications Technologies*, *33*(4), e4108. https://doi.org/10.1002/ETT.4108

Severin, J., Svensson, M., & Akerstrom, M. (2022). Cost–Cost-benefit evaluation of an Organizational-Level Intervention Program for Decreasing Sickness Absence among Public Sector Employees in Sweden. *International Journal of Environmental Research and Public Health*, *19*(5). https://doi.org/10.3390/ijerph19052998

Sharifani, K., & Amini, M. (2023). Machine Learning and Deep Learning: A Review of Methods and Applications. *World Information Technology and Engineering Journal*, *10*(07), 3897–3904. https://ssrn.com/abstract=4458723

Sharma, S. (2023). Advancements in Machine Learning for Intrusion Detection in Cloud Environments. *International Journal of Scientific Research in Engineering and Management*, *07*(07). https://doi.org/10.55041/IJSREM24430

Sharma, S., Bhatt, M., & Sharma, P. (2020). *Face Recognition System Using Machine Learning Algorithm*. 1162–1168. https://doi.org/10.1109/ICCES48766.2020.9137850

Sharmila, S., Kavya Nagasai, G., Sowmya, M., Sai Prasanna, A., Navya Sri, S., & Meghana, N. (2023). Automatic Attendance System based on FaceRecognition using Machine Learning. *Proceedings - 7th International Conference on Computing Methodologies and Communication, ICCMC 2023*, 170–174. https://doi.org/10.1109/ICCMC56507.2023.10084017

Shibly, F. H. A., Sharma, U., & Naleer, H. M. M. (2022). Detecting Hate Speech through Machine Learning. *Applied Soft Computing*. https://doi.org/10.1201/9781003186885-4

Shih, F. C., Yeh, S. C. J., & Hsu, W. L. (2023). Abusive supervision and employee well-being of nursing staff: Mediating role of occupational stress. *Journal of Advanced Nursing*, *79*(2), 664–675. https://doi.org/10.1111/JAN.15538

Shinohara, I., Mifune, Y., Inui, A., Nishimoto, H., Yoshikawa, T., Kato, T., Furukawa, T., Tanaka, S., Kusunose, M., Hoshino, Y., Matsushita, T., Mitani, M., & Kuroda, R. (2024). Re-tear After Arthroscopic Rotator Cuff Tear Surgery: Risk Analysis Using Machine Learning. *Journal of Shoulder and Elbow Surgery*, *33*(4), 815–822. https://doi.org/10.1016/J.JSE.2023.07.017

Shlezinger, N., Whang, J., Eldar, Y. C., & Dimakis, A. G. (2023). Model-Based Deep Learning. *Proceedings of the IEEE*, *111*(5), 465–499. https://doi.org/10.1109/JPROC.2023.3247480

Shreesha, S., Pai, M. M. M., Pai, R. M., & Verma, U. (2023). Pattern Detection and Prediction Using Deep Learning for Intelligent Decision Support to Identify Fish Behaviour in Aquaculture. *Ecological Informatics*, *78*, 102287. https://doi.org/10.1016/J.ECOINF.2023.102287

Shukla, A. K., Shukla, A., & Singh, R. (2023). Neural Networks Based Face Recognition System for Biometric Security. *Indian Journal of Engineering*, *20*, 16–1640. https://doi.org/10.54905/disssi/v20i53/e16ije1640

Shukla, A. K., Shukla, A., & Singh, R. (2024). Automatic Attendance System based on CNN–LSTM and Face Recognition. *International Journal of Information Technology (Singapore)*, *16*(3), 1293–1301. https://doi.org/10.1007/S41870-023-01495-1/METRICS

Shukla, S., George, J. P., Tiwari, K., & Kureethara, J. V. (2022). Data Security. *SpringerBriefs in Applied Sciences and Technology*, 41–59. https://doi.org/10.1007/978-981-19-0752-4_3

Sigmund, K., Hauert, C., Nowak, M. A., & Wachter, K. W. (2001). Reward and Punishment. *Proceedings of the National Academy of Sciences*, 10757–10762. https://doi.org/DOI:10.1073/pnas.161155698

Singh, A., Rawat, N., & Kesri, R. (n.d.). *Face Recognition Based Attendance System*. www.ijfmr.com

Singh, G. (2013). A Study of Encryption Algorithms (RSA, DES, 3DES and AES) for Information Security. In *International Journal of Computer Applications* (Vol. 67, Issue 19).

Singh, G., Bhardwaj, G., Singh, S. V., & Garg, V. (2021). Biometric Identification System: Security and Privacy Concern. *Artificial Intelligence for a Sustainable Industry 4.0*, 245–264. https://doi.org/10.1007/978-3-030-77070-9_15

Singh, R. (2017). The Impact of Intrinsic and Extrinsic Motivators on Employee Engagement in Information Organizations. *Https://Doi.Org/10.3138/Jelis.57.2.197*, *57*(2), 197–206. https://doi.org/10.3138/JELIS.57.2.197

Skinner, B. F. (1958). Reinforcement today. *American Psychologist*, *13*(3), 94–99. https://doi.org/10.1037/H0049039

Sochima, E. P., Ezekiel, P. S., Taylor, O. E., & Deedam-Okuchaba, F. B. (2021). Smart Attendance Monitoring System Using Facial Recognition. *International Journal of Computer Techniques*, *8*(2). http://www.ijctjournal.org

Somu, N., Raman M R, G., & Ramamritham, K. (2021). A Deep Learning Framework for Building Energy Consumption Forecast. *Renewable and Sustainable Energy Reviews*, *137*. https://doi.org/10.1016/J.RSER.2020.110591

Sonawane, A., Ahire, V. T. O., Tambat, P., & Kavde, V. (2024). Face Log - Attendance Management System using Face Recognition. *International Journal of Advanced Research in Science, Communication and Technology*, *4*(3), 182–187. https://doi.org/10.48175/IJARSCT-15535

Srivastava, G., & Bag, S. (2024). Modern-Day Marketing Concepts Based on Face Recognition and Neuro-Marketing: a Review and Future Research Directions. *Benchmarking*, *31*(2), 410–438. https://doi.org/10.1108/BIJ-09-2022-0588/FULL/XML

Stahl, B. C., Rodrigues, R., Santiago, N., & Macnish, K. (2022). A European Agency for Artificial Intelligence: Protecting fundamental rights and ethical values. *Computer Law and Security Review*, *45*. https://doi.org/10.1016/j.clsr.2022.105661

Stankevičiūtė, Ž. (2024). Data-Driven Decision Making: Application of People Analytics in Human Resource Management. *Intelligent Systems Reference Library*, *253*, 239–262. https://doi.org/10.1007/978-3-031-55952-5_12

Steers, R. M., & Rhodes, S. R. (1978). Major Influences on Employee Attendance: A Process Model. *Journal of Applied Psychology*, *63*(4), 391–407. https://doi.org/10.1037/0021-9010.63.4.391

Sujanthi, S., Bowshika, A., Dharaneesh, S. K., & Jai Sivadharsini, A. (2023). Iris Liveness Detection using Deep Learning Networks. *7th International Conference on Trends in Electronics and Informatics, ICOEI 2023 - Proceedings*, 1188–1196. https://doi.org/10.1109/ICOEI56765.2023.10125665

Sun, C., Adamopoulos, P., Ghose, A., & Luo, X. (2021). Predicting Stages in Omnichannel Path to Purchase: A Deep Learning Model. *Information Systems Research*, *33*(2), 429–445. https://doi.org/10.1287/ISRE.2021.1071

Sun, J., Xu, Y., Liu, P., & Wang, Y. (2023). Memristor-Based Neural Network Circuit of Duple-Reward and Duple-Punishment Operant Conditioning With Time Delay. *IEEE Transactions on Circuits and Systems I: Regular Papers*, *70*(11), 4369–4379. https://doi.org/10.1109/TCSI.2023.3305679

Surantha, N., & Sugijakko, B. (2024). Lightweight Face Recognition-based Portable Attendance System with Liveness Detection. *Internet of Things*, *25*, 101089. https://doi.org/10.1016/J.IOT.2024.101089

Surianarayanan, C., Kunasekaran, S., & Chelliah, P. R. (2024). A High-Throughput Architecture for Anomaly Detection in Streaming Data Using Machine Learning Algorithms. *International Journal of Information Technology (Singapore)*, *16*(1), 493–506. https://doi.org/10.1007/S41870-023-01585-0/METRICS

Suriya, M., Rajalakshmi, S., Visnupriya, K. V., Saravanaa, G., Vidya, K., Kavya, A., & Mouliswaran, R. (2023). Face Recognition Attendance System. *2023 9th International Conference on Advanced Computing and Communication Systems, ICACCS 2023*, 2042–2047. https://doi.org/10.1109/ICACCS57279.2023.10113114

Surve, M., Joshi, P., Jamadar, S., & Vharkate, Mrs. M. N. (2020). Automatic Attendance System using Face Recognition Technique. *International Journal of Recent Technology and Engineering (IJRTE)*, *9*(1), 2134–2138. https://doi.org/10.35940/ijrte.A2644.059120

Suryadevara, K. C. (2023). Diabetes Risk Assessment Using Machine Learning: A Comparative Study of Classification Algorithms. *International Engineering Journal For Research & Development*, *8*. www.iejrd.com

Susanto, H., Yie, L. F., Setiana, D., Asih, Y., Yoganingrum, A., Riyanto, S., & Saputra, F. A. (2021). *Digital Ecosystem Security Issues for Organizations and Governments: Digital Ethics and Privacy*. 204–228. https://doi.org/10.4018/978-1-7998-4570-6.CH010

Susmitha, C., Srineeharika, S., Laasya, K. S., Kannaiah, S. K., & Bulla, S. (2023). Hybrid Cryptography for Secure File Storage. *Proceedings - 7th International Conference on Computing Methodologies and Communication, ICCMC 2023*, 1151–1156. https://doi.org/10.1109/ICCMC56507.2023.10084073

Syamala, B. R. K. N. L. (2020). Attendance Management System using Face Recognition. *International Journal for Research in Applied Science and Engineering Technology*, *8*(7), 1684–1688. https://doi.org/10.22214/ijraset.2020.30625

Tang, X., Guo, C., Choo, K. K. R., Jiang, X., & Liu, Y. (2024). A Secure and Lightweight Cloud Data Deduplication Scheme with Efficient Access Control and Key Management. *Computer Communications*, *222*, 209–219. https://doi.org/10.1016/J.COMCOM.2024.05.003

Taslim Ahammad. (2017). Personnel Management to Human Resource Management (HRM): How HRM Functions? *Journal of Modern Accounting and Auditing*, *13*(9). https://doi.org/10.17265/1548-6583/2017.09.004

Taye, M. M. (2023). Understanding of Machine Learning with Deep Learning: Architectures, Workflow, Applications and Future Directions. In *Computers* (Vol. 12, Issue 5). MDPI. https://doi.org/10.3390/computers12050091

Tejaswi, P., & Swathika, O. V. G. (2023). Power Theft in Smart Grids and Microgrids. *Smart Grids for Smart Cities: Volume 1*, *1*, 299–308. https://doi.org/10.1002/9781119872108.CH16

Terhörst, P., Ihlefeld, M., Huber, M., Damer, N., Kirchbuchner, F., Raja, K., & Kuijper, A. (2023). *QMagFace: Simple and Accurate Quality-Aware Face Recognition* (pp. 3484–3494).

Thapa, P., & Arjunan, T. (2024). AI-Enhanced Cybersecurity: Machine Learning for Anomaly Detection in Cloud Computing. *Quarterly Journal of Emerging Technologies and Innovations*, *9*(1), 25–37. https://vectoral.org/index.php/QJETI/article/view/64

Thomas, J. (2024). Preprocessing. *Applied Machine Learning Using Mlr3 in R*, 196–210. https://doi.org/10.1201/9781003402848-9/PREPROCESSING-JANEK-THOMAS

Tian, X., Pavur, R., Han, H., & Zhang, L. (2023). A Machine Learning-based Human Resources Recruitment System for Business Process Management: Using LSA, BERT and SVM. *Business Process Management Journal*, *29*(1), 202–222. https://doi.org/10.1108/BPMJ-08-2022-0389/FULL/XML

Tolendiyev, G., Al-Absi, M. A., Lim, H., & Lee, B. G. (2021). Adaptive Margin Based Liveness Detection for Face Recognition. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *12616 LNCS*, 267–277. https://doi.org/10.1007/978-3-030-68452-5_28

Tomer, V., & Sharma, S. (2022). Detecting IoT Attacks Using an Ensemble Machine Learning Model. *Future Internet 2022, Vol. 14, Page 102*, *14*(4), 102. https://doi.org/10.3390/FI14040102

Trivedi, A., Mani Tripathi, C., Perwej, Y., Srivastava, A. K., & Kulshrestha, N. (2022). Face Recognition Based Automated Attendance Management System. *International Journal of Scientific Research in Science and Technology*, *9*(1), 261–268. https://doi.org/10.32628/IJSRST229147

Tsantikidou, K., & Sklavos, N. (2024). Threats, Attacks, and Cryptography Frameworks of Cybersecurity in Critical Infrastructures. *Cryptography*, *8*(1). https://doi.org/10.3390/cryptography8010007

Tyagi, M. (2021). Effect of HR interventions based on Biometric Attendance System records to improve Employee Absenteeism. *Article in Journal (Academy of Hospital Administration*, *31*(2). https://www.researchgate.net/publication/356580661

Ukamaka Betrand, C., Juliet Onyema, C., Benson-Emenike, M., Allswell Kelechi, D., & Eberechi Benson-Emenike, M. (2023). Authentication System Using Biometric Data for Face Recognition. *International Journal of Sustainable Development Research*, *9*(4), 68–78. https://doi.org/10.11648/j.ijsdr.20230904.12

Van den Eynde, J., Lachmann, M., Laugwitz, K. L., Manlhiot, C., & Kutty, S. (2023). Successfully Implemented Artificial Intelligence and Machine Learning Applications in Cardiology: State-of-the-Art Review. *Trends in Cardiovascular Medicine*, *33*(5), 265–271. https://doi.org/10.1016/J.TCM.2022.01.010

Verbeeten, F. H. M., & Speklé, R. F. (2015). Management Control, Results-Oriented Culture, and Public Sector Performance: Empirical Evidence on New Public Management. *Http://Dx.Doi.Org/10.1177/0170840615580014*, *36*(7), 953–978. https://doi.org/10.1177/0170840615580014

Viswanathan, J., E, K., S, N., & S, V. (2024). Smart Attendance System using Face Recognition. *EAI Endorsed Transactions on Scalable Information Systems*. https://doi.org/10.4108/EETSIS.5203

Waelen, R. A. (2023). The Struggle for Recognition in the Age of Facial Recognition Technology. *AI and Ethics*, *3*(1), 215–222. https://doi.org/10.1007/S43681-022-00146-8

Wang, T., He, F., Yang, R., Ye, Z., & Huang, X. (2023). Consensus-Based Distributed Kernel One-class Support Vector Machine for Anomaly Detection. *Proceedings of the International Joint Conference on Neural Networks*, *2023-June*. https://doi.org/10.1109/IJCNN54540.2023.10191788

Wati, V., Kusrini, K., Al Fatta, H., & Kapoor, N. (2021). Security of Facial Biometric Authentication for Attendance System. *Multimedia Tools and Applications*, *80*(15), 23625–23646. https://doi.org/10.1007/S11042-020-10246-4/METRICS

Weinger, B., Kim, J., Sim, A., Nakashima, M., Moustafa, N., & Wu, K. J. (2022). Enhancing IoT Anomaly Detection Performance for Federated Learning. *Digital Communications and Networks*, *8*(3), 314–323. https://doi.org/10.1016/j.dcan.2022.02.007

Wholey, J. S. (1982). Result Oriented Management: Integrating Evaluation and Organizational Performance Incentives. *Innovative Approaches to Mental Health Evaluation*, 255–275. https://doi.org/10.1016/B978-0-12-663020-6.50014-0

Wibowo, S. N., Solahudin, A., Haryanto, E., Widawati, Y., & Haryanto, B. E. (2022). The Effect of Reward and Punishment on Work Discipline. In *Management and Technology* (Vol. 1, Issue 1).

Wong, S., Simmons, A., Villicana, J. R., & Barnett, S. (2023). Estimating Patient-Level Uncertainty in Seizure Detection Using Group-Specific Out-of-Distribution Detection Technique. *Sensors (Basel, Switzerland)*, *23*(20). https://doi.org/10.3390/s23208375

Woubie, A., Solomon, E., & Attieh, J. (2024). Maintaining Privacy in Face Recognition using Federated Learning Method. *IEEE Access*. https://doi.org/10.1109/ACCESS.2024.3373691

Wu, H., Albiero, V., Krishnapriya, K. S., King, M. C., & Bowyer, K. W. (2023). *Face Recognition Accuracy Across Demographics: Shining a Light Into the Problem* (pp. 1041–1050).

Wu, J., Luan, S., & Raihani, N. (2022). Reward, Punishment, and Prosocial Behavior: Recent Developments and Implications. *Current Opinion in Psychology*, *44*, 117–123. https://doi.org/10.1016/j.copsyc.2021.09.003

Wu, Y., Li, Z., Zhao, B., Song, Y., & Zhang, B. (2024). Transfer Learning of Spatial Features from High-Resolution RGB Images for Large-Scale and Robust Hyperspectral Remote Sensing Target Detection. *IEEE Transactions on Geoscience and Remote Sensing*, *62*, 1–32. https://doi.org/10.1109/TGRS.2024.3355184

Wurzenberger, M., Höld, G., Landauer, M., & Skopik, F. (2024). Analysis of Statistical Properties of Variables in Log Data for Advanced Anomaly Detection in Cyber Security. *Computers & Security*, *137*, 103631. https://doi.org/10.1016/J.COSE.2023.103631

Xin, Y., Kong, L., Liu, Z., Chen, Y., Li, Y., Zhu, H., Gao, M., Hou, H., & Wang, C. (2018). Machine Learning and Deep Learning Methods for Cybersecurity. *IEEE Access*, *6*, 35365–35381. https://doi.org/10.1109/ACCESS.2018.2836950

Xu, H., Sun, Z., Cao, Y., & Bilal, H. (2023). A Data-Driven Approach for Intrusion and Anomaly Detection Using Automated Machine Learning for the Internet of Things. *Soft Computing*, *27*(19), 14469–14481. https://doi.org/10.1007/S00500-023-09037-4/METRICS

Xu, S., Qian, Y., & Hu, R. Q. (2019). Data-Driven Network Intelligence for Anomaly Detection. *IEEE Network*, *33*(3), 88–95. https://doi.org/10.1109/MNET.2019.1800358

Yang, L., Moubayed, A., & Shami, A. (2022). MTH-IDS: A Multitiered Hybrid Intrusion Detection System for Internet of Vehicles. *IEEE Internet of Things Journal*, *9*(1), 616–632. https://doi.org/10.1109/JIOT.2021.3084796

Yao, K., Kone, T., Gérard N'guessan, B., & Kouame, K. F. (2023). Face Liveness Detection and Tracking in a Remote Exam Monitoring System. *International Journal of Innovation and Applied Studies*, *41*(2), 588–597. http://www.ijias.issr-journals.org/

Yaseen, A. (2023). The Role of Machine Learning in Network Anomaly Detection for Cybersecurity. *Sage Science Review of Applied Machine Learning*, *6*(8), 16–34. https://journals.sagescience.org/index.php/ssraml/article/view/126

Yu, L., Wang, Y., Zhou, L., Wu, J., & Wang, Z. (2023). Residual Neural Network-Assisted One-Class Classification Algorithm for Melanoma Recognition with Imbalanced Data. *Computational Intelligence*, *39*(6), 1004–1021. https://doi.org/10.1111/COIN.12578

Yuniasri, D., Zulfa, N., & Herumurti, D. (2021). The Effect of Visual Reward and Punishment in Mobile Game on Game Experience. *Proceedings - 2021 International Seminar on Application for Technology of Information and Communication: IT Opportunities and Creativities for Digital Innovation and Communication within Global Pandemic, ISemantic 2021*, 6–11. https://doi.org/10.1109/ISEMANTIC52711.2021.9573227

Zaki, U. H. H., Ibrahim, R., Halim, S. A., & Kamsani, I. I. (2024). Prioritized Text Detergent: Comparing Two Judgment Scales of Analytic Hierarchy Process on Prioritizing Pre-Processing Techniques on Social Media Sentiment Analysis. *Baghdad Science Journal*, *21*(2), 662–683. https://doi.org/10.21123/bsj.2024.9750

Zehir, C., Karaboğa, T., & Başar, D. (2020). The Transformation of Human Resource Management and Its Impact on Overall Business Performance: Big Data Analytics and AI Technologies in Strategic HRM. *Contributions to Management Science*, 265–279. https://doi.org/10.1007/978-3-030-29739-8_12

Zennayi, Y., Benaissa, S., Derrouz, H., & Guennoun, Z. (2023). Unauthorized Access Detection System to the Equipment in a Room Based on the Person Identification by Face Recognition. *Engineering Applications of Artificial Intelligence*. https://doi.org/10.1016/J.ENGAPPAI.2023.106637

Zhang, C., Liu, Y., & Tie, N. (2023). Forest Land Resource Information Acquisition with Sentinel-2 Image Utilizing Support Vector Machine, K-Nearest Neighbor, Random Forest, Decision Trees, and Multi-Layer Perceptron. *Forests*, *14*(2). https://doi.org/10.3390/f14020254

Zhang, W., Gu, X., Tang, L., Yin, Y., Liu, D., & Zhang, Y. (2022). Application of Machine Learning, Deep Learning, and Optimization Algorithms in Geoengineering and Geoscience: Comprehensive Review and Future Challenge. *Gondwana Research*, *109*, 1–17. https://doi.org/10.1016/J.GR.2022.03.015

Zhang, X., Guo, F., Chen, T., Pan, L., Beliakov, G., & Wu, J. (2023). A Brief Survey of Machine Learning and Deep Learning Techniques for E-Commerce Research. *Journal of Theoretical and Applied Electronic Commerce Research 2023, Vol. 18, Pages 2188-2216*, *18*(4), 2188–2216. https://doi.org/10.3390/JTAER18040110

Zhang, Y. M., Jiang, X. Z., Qiu, B., Zhou, X., & Zhu, T.-C. (2024). Survey of Research on Face Recognition Methods Based on Depth Learning. *Journal of Physics: Conference Series*, *2717*(1), 012027. https://doi.org/10.1088/1742-6596/2717/1/012027

Zhang, Y., Xie, W., & Yu, X. (2023). Design and Implementation of Liveness Detection System based on Improved Shufflenet V2. *Signal, Image and Video Processing*, *17*(6), 3035–3043. https://doi.org/10.1007/S11760-023-02524-Z/METRICS

Zhang, Y., Zheng, L., Thing, V. L. L., Zimmermann, R., Guo, B., & Yu, Z. (2023). FaceLivePlus: A Unified System for Face Liveness Detection and Face Verification. *ICMR 2023 - Proceedings of the 2023 ACM International Conference on Multimedia Retrieval*, *23*, 144–152. https://doi.org/10.1145/3591106.3592289

Zhao, B., Zhu, W., Hao, S., Hua, M., Liao, Q., Jing, Y., Liu, L., & Gu, X. (2023). Prediction Heavy Metals Accumulation Risk in Rice Using Machine Learning and Mapping Pollution Risk. *Journal of Hazardous Materials*. https://doi.org/10.1016/J.JHAZMAT.2023.130879

Zhao, F., & Wang, Y. (2022). PBFT Consensus Algorithm based on Reward and Punishment Mechanism. *Proceedings - 2022 3rd International Conference on Information Science and Education, ICISE-IE 2022*, 168–173. https://doi.org/10.1109/ICISE-IE58127.2022.00043

Zhao, Y., Zhang, C., Zhang, Y., Wang, Z., & Li, J. (2020). A Review of Data Mining Technologies in Building Energy Systems: Load Prediction, Pattern Identification, Fault Detection and Diagnosis. *Energy and Built Environment*, *1*(2), 149–164. https://doi.org/10.1016/J.ENBENV.2019.11.003

Zhou, M., Wang, Q., Li, Q., Zhou, W., Yang, J., & Shen, C. (2024). Securing Face Liveness Detection on Mobile Devices Using Unforgeable Lip Motion Patterns. *IEEE Transactions on Mobile Computing*, *01*, 1–16. https://doi.org/10.1109/TMC.2024.3367781

Zhou, X. (2020). Application Research of Face Recognition Technology in Smart Campus. *Journal of Physics: Conference Series*, *1437*(1), 012130. https://doi.org/10.1088/1742-6596/1437/1/012130

Zhu, W., Xie, L., Han, J., & Guo, X. (2020). The Application of Deep Learning in Cancer Prognosis Prediction. *Cancers 2020, Vol. 12, Page 603*, *12*(3), 603. https://doi.org/10.3390/CANCERS12030603

Zulu, C. L., & Dzobo, O. (2023). Real-Time Power Theft Monitoring and Detection System with Double Connected Data Capture System. *Electrical Engineering*, *105*(5), 3065–3083. https://doi.org/10.1007/S00202-023-01825-3/TABLES/4

GLOSARIUM

A

Activation Function	:	The mathematical function applied to the output of each neuron in an artificial neural network to introduce non-linearity
Adaptive Security Strategy	:	Security strategy that can adapt to evolving data security threats.
AES (Advanced Encryption Standard)	:	Cryptography algorithm used for data encryption is widely employed in computer security.
AI (Artificial Intelligence)	:	Technology enables machines to learn from experience, adapt to new situations, and perform tasks like humans.
AI Ethics	:	Principles and ethical guidelines that must be adhered to in the development and use of artificial intelligence technology
Accuracy	:	Common evaluation metrics used in the classification field to measure how accurately a model classifies all data classes. It is the ratio of true predictions (positive and negative) to the total number of data.
Anomaly Detection	:	Technique to identify unusual or inappropriate patterns in data.
AUC-ROC Curve	:	Curve that illustrates the performance of a classification model at various thresholds by plotting True Positive Rate (TPR) vs False Positive Rate (FPR).
Autoencoder	:	Deep Learning model is used for dimensionality reduction and feature learning by reconstructing the original input.

B

Backpropagation	:	Algorithm used in training artificial neural networks to compute the gradient of the loss function and update network weights.
Bagging (Bootstrap Aggregating)	:	Ensemble learning technique where multiple parallel models are trained on random subsets of data.
Batch Normalization	:	The technique used to enhance stability and accelerate training in artificial neural networks.
Batch Reinforcement Learning	:	The approach in Reinforcement Learning is where the agent learns from a batch of experience data.
Batch Size	:	The number of data samples used in one iteration of training a Machine Learning model before updating the parameter.
Bias in Machine Learning	:	Imbalance or distortion in data can affect model decisions.
Bias-Variance Tradeoff	:	Concept in Machine Learning that describes the balance between bias and variance errors in a model.
Biometric Data	:	Data is used to identify individuals based on unique physical or behavioral characteristics, such as fingerprints or faces.
Blockchain	:	Technology is used to store data in a decentralized and secure manner.

Boosting	:	Ensemble learning technique where models are built sequentially, and each model attempts to correct the errors of the previous model.

C

Clustering	:	Technique in data analysis used to group objects or data into clusters with certain similarities.
CNN (Convolutional Neural Network)	:	Type of artificial neural network used in image processing and pattern recognition, with convolutional layers to extract features from images.
Confusion Matrix	:	The table is used to evaluate the performance of a classification model by displaying the number of correct and incorrect predictions.
Cross-Validation	:	Model evaluation method that divides data into training and validation subsets to avoid overfitting.

D

Data Analytics	:	Data analysis process to extract useful insights from the information contained in the data.
Data Augmentation	:	The technique is used to increase the amount of training data by creating variations of existing data.
Data Encryption	:	Process of transforming data into an unreadable form without an encryption key to protect the confidentiality of information.
Data Preprocessing	:	Data preparation process before feeding into a Machine Learning model, such as normalization, encoding, and handling missing values.
Dataset	:	Dataset used to train, test, or evaluate models in machine learning.
DBSCAN (Density-Based Spatial Clustering of Applications with Noise)	:	The clustering algorithm is used in data science and machine learning to find clusters in a dataset that have irregular shapes and contain noise (data not belonging to any cluster).
Deployment Model	:	Process of deploying a Machine Learning model into a production environment for use in real-world applications.
Deviation Standard	:	Measure of dispersion or spread of data from the mean, measuring how far data points are spread out from the average.
Dimensionality Reduction	:	Subfield of machine learning that uses neural networks consisting of multiple hidden layers to model and learn complex data representations.
DL (Deep Learning)	:	Type of neural network with multiple hidden layers between input and output layers, used to model complex relationships in data.
DNN (Deep Neural Network)	:	Regularization technique that randomly ignores some units during training to prevent overfitting.
Dropout	:	Information systems are designed to aid decision-making by providing relevant information and analysis.
DSS (Decision Support System)	:	Machine Learning method that uses decision tree structures to predict target values by dividing the dataset into smaller subsets.

DT (Decision Tree)	:	Data analysis process to extract useful insights from the information contained in the data.

E

Early Stopping	:	Strategy in training Machine Learning models where training is stopped when there is no improvement in performance on validation data.
Eigenfaces	:	Representation of a human face as a linear combination of several standard face images.
Ensemble AI	:	Technique in machine learning where multiple different models are combined to enhance performance and prediction accuracy.
Ensemble Learning	:	Machine Learning approach that combines multiple models to improve prediction performance.
Epoch	:	One complete pass through the training data for a Machine Learning model.
Ethical Considerations in AI	:	Ethical considerations need to be taken into account in the development and implementation of AI technology.
Euclidean Range	:	Geometric distance measures between two points in Euclidean space, often used in clustering and machine learning.
Evidence	:	Total probability of all possible observed data in the context of Bayes' theorem.
Evaluation Model	:	Process of evaluating model performance using metrics such as accuracy, precision, recall, and F1-score.
Explainability Model	:	Ability to intuitively explain how a Machine Learning model makes predictions.

F

F1-Score	:	Measure that combines precision and recall into a single metric. It provides a balance between precision and recall.
Face recognition	:	Technology that uses facial recognition to identify or verify a person's identity.
Feature Engineering	:	Process of identifying, selecting, and transforming data features to enhance the performance of a Machine Learning model.
Feature Extraction	:	Process of identifying and selecting important features from raw data to use in a Machine Learning model.
Feature Selection	:	Process of selecting the most relevant subset of features from data to improve model performance.
Fine-tuning	:	Process of tuning parameters in a pre-trained machine learning model to enhance performance on specific tasks.
Fitur	:	Representation of data used in analysis or machine learning to understand patterns or relationships in the data.

G

GAN (Generative Adversarial Networks)	:	Architecture of an artificial neural network consisting of two models that compete to generate new data.
GDPR (General Data Protection Regulation)	:	European Union regulation that governs data protection and privacy of individuals in the European Union and the European Economic Area.

Google Colab	:	Cloud computing platform provided by Google to run Python code, especially in the context of machine learning, by providing access to GPUs and TPUs for free.
Gradient	:	Vector indicating the direction and rate of the steepest growth of a function.
Gradient Descent	:	An optimization algorithm is used to minimize the loss function by following the function's gradient.
Grid Search	:	Method to search for the best combination of parameters for a Machine Learning model by trying all possible combinations.
GRU (Gated Recurrent Unit)	:	A variant of RNN that is simpler than LSTM but still effective in modeling sequential data.

H

HOG (Histogram of Oriented Gradients)	:	Feature extraction method used for object detection in images.
Hyperparameter	:	Parameters whose values are set before training the model and remain unchanged during training.
Hyperplane	:	Term in SVM is the decision boundary separating data classes in high-dimensional space.

I

Interpretability vs. Accuracy Tradeoff	:	Balance between model interpretability and accuracy in the context of decision-making.
Interpretability Model	:	Ability to explain and understand the reasons behind a Machine Learning model's predictions.
IQR (Interquartile Range)	:	The range between the first and third quartiles in the data distribution, used in statistical analysis to measure data spread.
ITPM (Information Technology Project Management)	:	Systematic approach to plan, organize and manage information technology projects within an organization.

K

Keras	:	Open-source neural network library running on top of TensorFlow, designed to accelerate the development of neural network model prototypes.
K-Means Clustering	:	Clustering algorithm that divides data into k clusters based on calculated cluster centers.
K-Means	:	One of the most popular and simple clustering algorithms used in data analysis.
KNN (K-Nearest Neighbor)	:	Machine learning classification algorithm used for classification and regression, where the prediction of a data point is based on the nearest data labels.
Kolmogorov-Smirnov Test	:	Statistical test to determine if two samples of data come from the same distribution.

L

Label	:	Annotation or labels assigned to data are used in supervised learning to train models.

LD (Liveness Detection)	:	Technology is used to verify whether an entity (usually human) detected by the system is real or just an image, video, or other recording, to prevent manipulation or fraud.
Learning Rate Decay	:	Reduction of the learning rate during training to aid model convergence.
Learning Rate	:	Parameter that controls how fast or slow a Machine Learning model learns from data during training.
Loss Function	:	Function that measures how well a model predicts the target value and is used in the model optimization process.
Loss Optimization	:	Process of optimizing the loss function to improve the performance of a Machine Learning model.
LSTM (*Long Short-Term Memory)*	:	Type of neural network architecture used in natural language processing (NLP) and other sequence tasks.

M

Matplotlib	:	Python data visualization library used to create 2D graphs.
ML (Machine Learning)	:	Subfield of artificial intelligence that enables computers to learn from data without being explicitly programmed, focusing on developing algorithms and models that can make predictions or decisions based on patterns in data.

N

Naive Bayes Classifier	:	Simple probabilistic classification algorithm based on Bayes' theorem with the assumption of feature independence.
Naïve Bayes	:	Classification algorithm based on Bayes' theorem to calculate class probabilities based on attributes.
NLP (Natural Language Processing)	:	The branch of artificial intelligence focuses on understanding and processing human language by computers, including tasks like text processing, sentiment analysis, and machine translation.
NN (Neural Network)	:	Mathematical model inspired by the structure of biological neural networks, used in machine learning to learn complex patterns in data.
Normalization Test	:	A statistical procedure is used to determine if a sample of data or a group of data comes from a normal distribution or not.
NumPy	:	Primary library in Python for numerical computation, providing data structures and functions for working with multidimensional arrays and matrices.

O

OC-SVM (One-Class Support Vector Machine)	:	A variant of SVM is used for anomaly detection or one-class identification.
One-Hot Encoding	:	Representation of categorical data in the form of a binary vector where only one element is set to 1.
Outlier	:	Data point that significantly differs from the majority of data in a dataset.

Overfitting	:	Condition where a Machine Learning model is overly complex and "memorizes" the training data, leading to decreased performance on test data.

P

PCA (Principal Component Analysis)	:	Dimensionality reduction technique is used to reduce data complexity by projecting data into a lower-dimensional feature space.
Policy Gradient	:	The method of Reinforcement Learning directly optimizes the agent's policy without considering value functions.
Precision	:	Common evaluation metrics are used in the field of classification to measure the proportion of positives correctly identified by the model out of the total number of data points identified as positive by the model.
Precision-Recall Curve	:	Curve that plots precision vs. recall for various classification thresholds.
Prior Probability	:	Probability before observing new data in the context of Bayes' theorem.
P-Value	:	Measure used in statistics to determine how strong the evidence from data is against the null hypothesis.
Python	:	High-level programming language used in this book for implementing models and data analysis, machine learning, and software development.

R

Recall	:	Evaluation metrics are commonly used in the field of classification to measure the proportion of true positives correctly identified by the model out of the total number of true positive data.
Regression	:	One of the techniques in statistics used to model the relationship between one or more independent variables (usually referred to as predictors, features, or input variables) and one dependent variable (usually referred to as the target variable or output variable) in the form of a mathematical function.
Regularization	:	Technique used in Machine Learning to prevent overfitting by adding penalties to the model parameters.
Reinforcement Learning	:	Machine learning paradigm where agents learn through interaction with their environment and receive feedback based on the actions taken.
ResNet	:	Convolutional Neural Network (CNN) architecture famous for its ability to train very deep networks.
Reward and Punishment System	:	The system is used to provide incentives to individuals who perform well and impose penalties on those who violate policies. It is a concept in reinforcement learning where agents learn by receiving rewards for correct actions and punishments for incorrect actions.
RF (Random Forest)	:	A machine learning method that uses a large number of decision trees to make predictions, where each tree is generated randomly and the final prediction is obtained by combining predictions from each tree.

RFID (Radio Frequency Identification)	:	Automatic identification technology that uses radio waves to identify and track objects individually.
RNN (Recurrent Neural Network)	:	Type of artificial neural network with cyclic connections between neurons to process sequential data.
RNN (Recurrent Neural Network)	:	Type of artificial neural network with cyclic connections, allowing information to flow forward and backward in time, often used in tasks involving sequential data.
ROC Curve (Receiver Operating Characteristic Curve)	:	The curve that illustrates the relationship between True Positive Rate (TPR) and False Positive Rate (FPR) at various classification thresholds.

S

Scikit-Learn	:	Popular machine learning library in Python that provides algorithms, functions, and utilities for building and analyzing machine learning models.
Shapiro-Wilk Test	:	Statistical test to determine if a sample of data comes from a normal distribution.
Supervised Learning	:	Type of machine learning where models are trained using labeled data.
SVM (Support Vector Machine)	:	Machine learning algorithm used for classification and regression, separating data by creating the best hyperplane among data classes.

T

TensorFlow	:	An open-source platform for numerical computation and machine learning developed by the Google Brain Team.
Train-Split-Test	:	Method for dividing a dataset into a training set for training the model, a validation set for adjusting model parameters, and a test set for evaluating model performance.
Transfer Learning	:	The approach in Deep Learning is where a model trained on a specific task is used as a starting point for a similar task.

U

Underfitting	:	A condition where a Machine Learning model is too simple to understand patterns in the training data.
Unsupervised Learning	:	Type of machine learning where the model learns from unlabeled data.

V

VGG16	:	The Famous Convolutional Neural Network (CNN) architecture model is often used for image recognition tasks.
Voting	:	The method used in Ensemble Learning, where multiple different models or algorithms are combined to make predictions better than what could be achieved by each model individually.

W

Weight Initialization	:	The process of initializing model weights with appropriate initial values to speed up convergence.
Word Embeddings	:	The process of initializing model weights with appropriate initial values to speed up convergence.

X

XGBoost (Extreme Gradient Boost)	:	Machine learning algorithm that uses gradient boosting techniques to enhance model performance in classification and regression tasks.

Integration of AI, ML, and DL

Technologies in Project Management for Data Security Based Face Recognition Attendance Systems

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