Automated Event Attendance Recording Tool Using Facial Recognition

By

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Declaration

I declare that this work has not been previously submitted and approved for the award of a degree by this or any other University. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made in the thesis itself.

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Abstract

Monitoring and measuring participant attendance at events is crucial for several reasons. In addition to offering organizers and sponsors insights into an event's popularity, it is essential for assessing the economic, social, and environmental impacts of the event. Various methods for recording attendance are currently in use, including manual methods such as signing a register which are often inefficient and prone to errors. While electronic attendance systems, such as NFC cards and fingerprint readers, exist, NFC cards are vulnerable to impersonation, and fingerprint readers may raise health concerns due to contact with shared devices. In contrast, facial recognition technology offers a promising solution for improving the accuracy of attendance records at events while mitigating hygiene risks associated with fingerprint readers. However, facial recognition systems tend to be computationally intensive. This research developed an automated event attendance recording tool that integrates Hash-Based Indexing with facial recognition algorithms to enhance the accuracy of attendance records while reducing computational load through record indexing. The study employed agile methodology for developing the automated attendance-recording tool. Testing and evaluation utilized publicly available image databases to train the machine learning image recognition model and assess its performance. The primary evaluation metrics included the accuracy of image identification and the duration of transaction processing. The model achieved 95% accuracy in face recognition, with its performance further analysed using the confusion matrix and classification report. The developed tool provided an interface for event organizers to create events and record attendance offering utilizing the full capabilities of CNN for image recognition. The developed tool offered an interface that allowed event organizers to create events and record attendance, fully utilizing the capabilities of CNN for image recognition and hash-based indexing for faster retrieval of records.

Keywords*: *Attendance, Agile methodology, Electronic attendance systems, Facial recognition, Fingerprint readers, Machine learning, Hash-Based Indexing, Record indexing

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Abbreviations and Acronyms

API	Application Programming Interface
AUC	Area Under the Curve
CNN	Convolutional Neural Networks
FPR	False Positive Rate
HOG	Histogram of Oriented Gradients
LBP	Local Binary Tree
LDA	Linear Discriminant Analysis
ML	Machine Learning
NFC	Near Field Communication
PCA	Principal Component Analysis
RFID	Radio-Frequency Identification
ROC	Receiver Operating Characteristic
SVM	Support Vector Machines
TPR	True Positive Rate

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Chapter 1: Introduction

1.1 Background

Attendance tracking has always been a significant administrative challenge for various organizations hosting events globally. Events are frequently leveraged as strategic tools to boost a region's economic development. Monitoring events is especially valuable in assessing their cultural, social, economic, and environmental impact (Ferrante et al., 2018). Additionally, it provides event managers with essential insights into the location, timing, and execution of activities, along with the satisfaction levels of participants. Thus, tracking participants' space-time behaviour is vital for effective supply management. Traditional methods such as paper-based registers or manual entry systems, though still widely used, are prone to several inefficiencies, including time consumption, human error, and the potential for manipulation (Emmanuel, 2023). These conventional approaches have remained largely unchanged for decades, despite advancements in technology that offer more efficient solutions (Kumar et al., 2022). The increasing number of attendees at events exacerbates the problem, leading to bottlenecks in attendance management, impacting both organizers and participants.

With the rise of digital technology, biometric systems have emerged as a solution for addressing administrative inefficiencies in event attendance. Biometric systems, which include fingerprinting, iris recognition, and facial recognition, offer the potential for more secure, accurate, and efficient systems for identifying individuals (Chowdhury et al., 2020). Facial recognition technology has been explored for various applications beyond security, such as in marketing, retail, and health care (Nguyen et al., 2022). This technology allows for the automatic identification of individuals based on unique facial features, making it a promising solution for attendance tracking at events (Chowdhury et al., 2020). By integrating such technology into event environments, organizations can potentially overcome the traditional challenges of manual attendance recording.

The growing adoption of facial recognition systems in other sectors demonstrates the feasibility and benefits of this technology. In airports, shopping malls, and even smartphones, facial recognition has proven to be reliable in identifying individuals in real-time with a high degree of accuracy (Shukla et al., 2023). Organizations hosting large events could benefit from such innovations. Automated attendance systems using facial recognition provide a non-intrusive, fast, and secure way to record attendance without the need for manual input, reducing the time taken for these administrative tasks (Kumar et al., 2022). Despite the clear advantages, few studies have investigated the practical application of this technology in event management (Akpan & Udo, 2019).

Facial recognition systems, particularly in large-scale event settings, can be computationally intensive due to the need for processing multiple images in real time, identifying unique facial features, and matching them against a database of stored records (Singh & Prasad, 2018). This process involves complex algorithms that analyze facial landmarks and other distinctive attributes. As a result, efficient data management techniques are essential to improve the system's speed and performance. Hash-based indexing offers a solution to these computational challenges by organizing data in a way that enables faster access and retrieval. In essence, hash-based indexing uses a hash function to map data to a fixed-size table known as a hash table, allowing for quick lookups (Ma et al., 2020). When applied to facial recognition, hash-based indexing can significantly reduce the time needed to search and match facial data, as the system can quickly narrow down potential matches instead of scanning the entire database.

Combining facial recognition technology with Hash-Based Indexing offers significant advantages over other biometric systems, particularly in event settings. This approach not only speeds up the recognition process but also minimizes system latency, making it suitable for environments requiring real-time processing. Unlike fingerprint or iris recognition, facial recognition does not require physical contact, providing a more hygienic and practical solution amid global health concerns, such as the COVID-19 pandemic (Chowdhury et al., 2020). Furthermore, advancements in artificial intelligence and machine learning have greatly improved the accuracy and speed of facial recognition algorithms, making it feasible to deploy these systems at large events with minimal lag or error (Sutabri et al., 2019). Integrating Hash-Based Indexing into facial recognition systems enhances the process by enabling real-time data processing, thus providing organizers with valuable insights and streamlining event management.

This research proposes the development of an automated event attendance recording tool that integrates Hash-Based Indexing with facial recognition algorithms to enhance the accuracy of attendance records while reducing computational load through record indexing. The study will employ agile methodology for developing the automated attendance-recording tool. Testing and evaluation will utilize publicly available image databases to train a machine learning image recognition system and assess its performance. The primary evaluation metrics will include the accuracy of image identification and the duration of transaction processing.

1.2 Problem Statement

Organizations face significant challenges in attendance monitoring due to the inefficiencies of conventional log-in systems (Alnuaimi et al., 2023). These systems often fail to ensure accurate tracking, leading to problems such as user manipulation and the obsolescence of biometric devices. Effective attendance monitoring is crucial, particularly for events, as it directly influences participant engagement and overall success. Accurate tracking also provides organizers and sponsors with valuable insights into an event's popularity and plays a key role in assessing its economic, social, and environmental impacts. However, traditional methods, such as manual recording or electronic systems, are often inefficient and prone to human error (Kumar et al., 2021). These methods not only consume valuable time but are also susceptible to manipulation which compromises the integrity of the process (Raman et al., 2020).

Despite the numerous documented challenges present in recording attendance of events, there is little research conducted in the field of attendance recording in events with most scholars focusing on classroom attendance. The focus on class attendance alone leaves a gap in the event attendance literature since events and educational settings have different conditions from environment, number of participants among others. Thus, there is a need for a more reliable, efficient, and secure solution to address these critical issues in event attendance monitoring. Given the rapid advancements in technology, there is a growing need for more efficient, accurate, and secure systems that can address these shortcomings.

Facial recognition technology, which enables the automatic identification of individuals based on distinct facial features, has emerged as a promising solution for streamlining attendance recording (Ahmad et al., 2020). However, facial recognition systems face several challenges, with one of the most significant being the computational load required for efficient identification (Singh & Prasad, 2018). Furthermore, limited research has been conducted on the practical application of facial recognition systems in event management, particularly within the African context (Oluwole &

Akinola, 2021). In Africa, the adoption of such technologies in event management is still in its early stages, with unique barriers such as infrastructural limitations and concerns over data privacy. Notably, there has been no research exploring the combination of facial recognition and Hash-Based Indexing algorithms for automated attendance systems, leaving a gap in the existing body of knowledge on this innovative application.

1.3 Aim

The study aims to develop a facial recognition-based attendance system that can automatically record attendance at events, reducing administrative burdens and increasing accuracy.

1.4 Specific Objectives

i. To analyse challenges faced in implementation of automated attendance recording systems.
ii. To review existing algorithms, models, and frameworks used for attendance recording.
iii. To develop an automated attendance system using facial recognition technology and Hash-Based Indexing.
iv. To test the developed system.

1.5 Research Questions

i. What are the challenges faced in attendance recording?
ii. What are the existing algorithms, models, and frameworks used for attendance recording?
iii. How can an automated attendance tool using facial recognition technology and Hash-Based Indexing be developed?
iv. How can the developed system be tested?

1.6 Study Justification

Attendance monitoring is critical in ensuring participant engagement and overall event success. Automating this process using facial recognition can minimize errors, save time, and improve data security. This study fills a gap in the exploration of facial recognition applications in event management through the integration of NFC card and facial recognition to enhance the accuracy of attendance records while reducing computational load through record indexing. By focusing on the integration of innovative technologies, the research aims to demonstrate how organizations can leverage advanced solutions to solve administrative challenges. Moreover, the growing emphasis on digital transformation across various sectors highlights the need for solutions that improve operational efficiency while maintaining data privacy and security. This system not only benefits organizations by improving administrative accuracy but also enhances participant experiences by minimizing disruptions during events and ensuring fairness in attendance reporting.

1.7 Scope and Limitations

This study focused on the development and testing of an automated attendance tool using facial recognition technology and Hash-Based Indexing within the context of event management. The scope was limited to events and did not extend to other types of institutions or gatherings. The study did not cover other biometric attendance systems such as fingerprint or iris recognition. The generalizability of the developed system was limited by several factors. Environmental conditions like lighting, crowd density, and camera quality could affect system performance in different event settings. Testing was conducted in controlled environments, and further validation is needed to confirm effectiveness in larger, more diverse, and dynamic real-world scenarios. The study also did not consider variations in cultural or regulatory contexts that may influence the acceptance and use of facial recognition technology. These limitations highlight the need for continued research to adapt and evaluate the system for broader applications.

Chapter 2: Literature Review

2.1 Introduction

Research on automated attendance systems has grown significantly in recent years, focusing on the application of biometric recognition technologies, particularly facial recognition, to improve accuracy and reduce administrative burdens in event management. These systems offer a solution to common challenges such as fraudulent attendance reporting (proxy attendance) and inefficient manual recording. This chapter reviews the empirical and theoretical literature surrounding automated attendance systems, highlighting the methodologies, models, frameworks, architectures, and algorithms employed in prior research. Furthermore, this review identifies gaps in the current literature and proposes a conceptual model for examining the impact and effectiveness of automated event attendance systems.

2.2 Empirical Literature

Many researchers and institutions have explored automated attendance systems in educational settings, with fewer studies focusing on their application in event settings. Alnuaimi et al. (2023) proposed a two-factor authentication system based on distance and facial recognition. The system integrated advanced geo-tracking tools and technologies with Web3 features, using double-factor authentication through facial recognition and distance monitoring devices. The system aimed to provide secure, adaptive, and advanced logins for employees while enabling effective attendance monitoring for employers. It was designed to be scalable, with the ability to integrate additional distance-tracking devices without the need for extra support systems. The system was described as smart, user-friendly, and effective, optimizing resource and time allocation for organizations. Compared to other two-factor authentication systems, it was claimed to be faster, more secure, and did not require central devices, offering greater flexibility and user-friendliness. It was presented as a viable solution for maintaining a safe environment and simplifying procedures for both employees and managers. However, while this system introduces innovative integration of geo-tracking and blockchain technology, the added complexity and potential cost of supporting multiple devices could limit practical deployment, especially in resource-constrained event settings. Moreover, the system's performance in environments with large crowds or unstable connectivity remains untested, raising concerns about scalability and reliability in real-time event scenarios.

Alniemi and Mahmood (2023) presented a system that employs face recognition technology to automate class attendance. Their approach involved curating a dataset of 3,900 facial images taken in various positions and lighting conditions. The system's architecture consists of a mobile camera for capturing images, a Haar Cascaded classifier for face detection, and the FaceNet network for face recognition. Once the system detects and recognizes attendees, it cross-references them with a student database to register attendance and automatically sends the results to the teacher. The system achieved an accuracy rate of 97.5%, which demonstrates its efficiency in comparison to traditional attendance systems. However, the study has notable limitations. One significant limitation is its reliance on optimal environmental conditions. The accuracy of the system may decrease in environments with poor lighting or where the camera does not have a clear, direct view of the attendees. Additionally, the system's scalability is uncertain, as it was not tested in larger classroom settings or environments with diverse student demographics. The study also focuses on facial recognition without addressing potential ethical concerns, such as privacy issues related to collecting and storing attendees' biometric data. These factors could limit the system's practical application in real-world educational settings where conditions may vary, and privacy regulations may be more stringent. Future research could explore these aspects by testing the system under more diverse conditions and examining its long-term effectiveness and compliance with data protection standards.

Gomes et al. (2020) proposed a system to improve attendance marking and management using face recognition technology. The main goal was to create a system that is efficient, time-saving, and easy to use. The system consists of four phases: image capturing, segmentation of group images, face detection, and recognition, followed by updating the attendance database. By eliminating the need for manual attendance recording, the system reduces the workload of instructors and administrative staff. However, several limitations are apparent in this study. One significant limitation is the lack of real-time testing in live classroom environments. While the system is designed to work efficiently, its practical performance in settings where lighting, image quality, and student movement vary was not thoroughly explored. Additionally, the system was not tested with attendees wearing accessories like hats or masks, which could affect the accuracy of face recognition algorithms. The study also does not address potential privacy concerns regarding the collection and storage of biometric data, which could pose challenges when implementing such systems in real-world environments. Finally, the researchers did not conduct extensive testing on diverse student populations, potentially limiting the generalizability of their findings.

Muhammad et al. (2023) developed an online system to record attendance using facial recognition technology with an additional feature for detecting face masks. The system was designed to be accessible through a browser, providing ease of use for attendees and teachers alike. The system's core architecture involved training a model using SVM (Support Vector Machine) algorithms to perform face recognition. It also incorporated synthetic data to enable the system to recognize attendees even while wearing face masks, making it particularly relevant in the post-pandemic era. The face recognition model achieved an accuracy of 81.8%, while face mask detection had an accuracy of 80%. The integration of Python and PHP allowed the system to process data on online servers, making it accessible from any terminal. However, the system's limitations are evident. First, the accuracy of the system, particularly for face mask detection, is lower than many other face recognition systems, which could limit its practicality in environments that require high reliability. Additionally, the use of synthetic data for mask detection may not fully capture the complexity of real-world situations, where lighting, face positioning, and mask types may vary. Another limitation is the system's reliance on internet access, which could be problematic in regions with limited or unreliable connectivity. Furthermore, while the system was tested for face recognition with masks, it did not account for other obstructions, such as sunglasses or scarves.

Nguyen et al. (2020) developed a framework that combines machine learning-based face recognition with relational databases to automate student attendance. The system utilized the Histogram of Oriented Gradients (HOG) algorithm for face detection and cosine distance for face recognition, which allows it to work with inputs from webcams, mobile device cameras, and video streams. The key objective was to recognize faces in real-time and register attendance by comparing captured images to those stored in the database. The system was tested in various scenarios, demonstrating its versatility in handling different input methods. However, the study’s limitations need to be considered. The primary limitation is the system’s potential inefficiency in handling large groups of attendees simultaneously. The HOG algorithm, while efficient, may struggle with time delays in detecting and recognizing multiple faces in crowded environments, which could hinder its real-time functionality. Moreover, the system's performance under challenging conditions—such as poor lighting, extreme facial angles, or occlusions—was not thoroughly explored. These factors could negatively impact the accuracy and speed of the system. Additionally, the researchers did not examine the potential ethical implications of using machine learning for facial recognition, such as data security and student privacy. Addressing these concerns is crucial for the system's broader application in educational settings. Improving the system's efficiency in crowded environments and under less-than-ideal conditions, while ensuring compliance with privacy standards, would significantly enhance its practicality.

Sultan et al. (2022) developed a face recognition-based system for marking attendance and generating attendance reports in Excel. The system uses a 1080p HD camera to capture images, followed by noise reduction and the application of the Histogram of Oriented Gradients (HOG) technique for face detection. The Dlib face recognition API was employed to match detected faces with a student database, achieving an impressive recognition accuracy of 97.38%. The system is capable of recognizing attendees from multiple angles and automatically records their attendance, making it a highly efficient tool for classroom use. However, several limitations exist. First, the system's reliance on high-quality camera equipment could be a barrier to widespread adoption, especially in educational institutions with limited resources. Lower-resolution cameras or those affected by lighting issues may reduce the system's accuracy. Additionally, the study does not address the potential challenges posed by environmental factors, such as variations in lighting, student movement, or obstructions like masks or hats, which could compromise the system's effectiveness. The researchers also did not explore the scalability of the system in larger gathering hall environments or its ability to handle more diverse student populations. Lastly, the study did not consider potential privacy concerns related to the use of facial recognition technology in schools, which may limit its implementation. Further research is required to optimize the system for lower-end hardware, improving its robustness against environmental variations, and addressing privacy concerns.

Chowdhury et al. (2020) proposed an automatic student attendance system using Convolutional Neural Networks (CNNs) to detect and recognize faces from video streams. The system was designed to automate daily attendance recording by recognizing multiple faces at once, achieving an average accuracy rate of 92%. The system’s key advantage is its ability to handle video input, making it more versatile in dynamic gathering hall environments. However, the system's limitations are noteworthy. While 92% accuracy is commendable, it falls short compared to some other facial recognition systems, and this gap could be problematic in settings where high accuracy is essential. Moreover, the system’s ability to handle real-time face recognition in crowded or fast-moving environments was not thoroughly tested. Factors such as lighting, camera quality, and student movement were not explored in detail, and these variables could significantly impact the system’s performance. Additionally, the study does not address how the system deals with occlusions like masks or hats, which have become more common in educational settings. Privacy issues related to the use of facial recognition were also not discussed, which could limit the system's adoption in schools with strict privacy regulations.

Bin et al. (2023) developed a web-based attendance system that integrates facial recognition technology with blockchain for secure and efficient attendance tracking. The system works by using a web camera to capture student faces, which are then matched against a database to automatically mark attendance. Lecturers can reject attendance if rules are violated, and attendees can monitor their attendance records. The use of blockchain technology ensures that attendance data is securely stored and managed, reducing the risk of tampering. The system achieved an accuracy rate of 98%, making it one of the most reliable systems available. However, the study has several limitations. First, the integration of blockchain technology, while innovative, may pose scalability challenges when dealing with large datasets, as blockchain systems are typically slower and more resource-intensive than traditional databases. Additionally, the study did not explore the system's performance in environments with poor internet connectivity, which could affect the real-time functionality of the web-based application. Another limitation is the system's reliance on high-quality cameras for facial recognition, which may not be feasible for institutions with limited technological resources. Moreover, the researchers did not address the potential privacy concerns surrounding the use of blockchain for storing personal data, which could present challenges in regions with strict data protection laws.

2.3 Theoretical Literature

The theoretical Literature for this study is built upon the examination of how various attendance technologies work and their practical implementation hurdles. Facial recognition leverages computer vision and machine learning to identify individuals based on their unique facial features. Fingerprint recognition, on the other hand, uses ridge patterns on fingertips for identification, while iris recognition relies on the unique patterns of the eye's iris. Non-biometric approaches like RFID use electromagnetic fields to detect tags associated with individuals, offering speed and convenience but facing security issues. The evaluation of these systems reveals key insights into their suitability for different environments. The limitations and challenges encountered in using each technology motivate the need for a solution that combines efficiency, accuracy, and scalability. This sets the stage for adopting hash-based indexing and facial recognition as the preferred approach for overcoming the drawbacks of traditional attendance systems, offering a contactless, hygienic, and computationally optimized solution for real-time attendance management.

2.3.1 Facial Recognition Technology

Facial recognition technology works by identifying individuals based on their unique facial features, using a multi-step process that includes face detection, feature extraction, and recognition. The system initially captures an image or video stream to detect a face using algorithms such as Haar cascades or deep learning techniques like Convolutional Neural Networks (CNNs), which are adept at locating faces in varied lighting conditions and from different angles (Muhammad et al., 2023). Once detected, the system extracts distinctive features, including the distance between facial landmarks such as the eyes, nose, and mouth. Techniques like FaceNet or Fisherfaces are often used for this feature extraction process (Gomes et al., 2020). These features are then compared with a pre-existing database to identify or verify the individual.

Facial recognition is widely adopted in attendance management due to its non-intrusive nature. Unlike fingerprint or iris scanning, it does not require physical contact, making it suitable for environments where hygiene is critical, such as during the COVID-19 pandemic (Jeong, 2020). Additionally, recent advancements in artificial intelligence have made real-time processing feasible, allowing for immediate feedback on attendance status, which is crucial for large events or educational institutions with many participants (Sutabri et al., 2019). The technology helps reduce administrative workloads by automatically logging attendance and eliminates issues like proxy attendance since only the registered individual can be recognized by the system (Ria, 2020). However, facial recognition does face some challenges, such as lower accuracy in extreme lighting conditions or when individuals have significant changes in appearance (e.g., wearing sunglasses). In addition, Facial recognition systems, especially in large-scale event environments, can demand significant computational resources because they must process numerous images in real time, identify distinct facial features, and compare them against a database of stored records (Singh & Prasad, 2018).

2.3.2 Fingerprint Technology

Fingerprint recognition technology is a biometric method that verifies an individual's identity by analysing the unique patterns of ridges and valleys on their fingertips. The process starts with capturing the fingerprint image using a fingerprint scanner. The system then extracts specific features known as minutiae points, which are distinct characteristics such as ridge endings and bifurcations. These points form a unique pattern that can be compared against a pre-registered fingerprint database for identification or verification purposes (Samet, 2017). Due to its high accuracy, fingerprint recognition is one of the most commonly used biometric methods in various attendance management applications, particularly in controlled environments like offices and schools.

One of the main advantages of fingerprint recognition is its reliability in providing accurate identification for individuals with a consistent fingerprint pattern. The system is also cost-effective, with fingerprint scanners being widely available at reasonable prices (Chowdhury et al., 2020). However, fingerprint recognition has some limitations, including the need for physical contact with the device, which can be a drawback in situations where hygiene is a concern, such as during outbreaks of infectious diseases (Islam, 2017). Additionally, certain conditions, such as cuts, dirt, or moisture on the fingertips, can interfere with the system’s ability to capture a clear image, leading to lower accuracy (Arjun Raj et al., 2020). Another challenge is the risk of spoofing, where artificial fingerprints can be used to trick the system. To counteract this, modern fingerprint systems often incorporate anti-spoofing techniques such as liveness detection, which assesses the characteristics of living skin, like perspiration, to distinguish real fingerprints from fake ones (Ria, 2020).

2.3.3 Iris Recognition Technology

Iris recognition technology uses the distinct patterns in the coloured part of the eye, known as the iris, to identify individuals. The process involves capturing a high-resolution image of the eye using specialized cameras that can detect the intricate details of the iris pattern. The system then processes these details to extract unique features that distinguish one individual from another. Techniques such as Gabor wavelet filtering are often used in the feature extraction process to enhance the quality of the captured image and identify critical iris patterns (Sutabri et al., 2019). The extracted features are then matched with a database of pre-enrolled iris patterns for identification or verification purposes (Chowdhury et al., 2020).

Iris recognition is known for its extremely high accuracy, making it suitable for applications where security is a top priority, such as airport immigration checks and high-security facilities (Jeong, 2020). Unlike fingerprint recognition, iris scanning does not require physical contact, which adds an extra layer of hygiene and convenience. Furthermore, the patterns of the iris are stable throughout a person's life, which reduces the need for frequent re-enrolment in the system (Islam, 2017). Despite that, iris recognition technology has limitations. It requires specialized and expensive equipment, making it less practical for large-scale or budget-conscious applications like specific event tracking (Ria, 2020). Additionally, the technology is sensitive to environmental factors such as lighting conditions, which can affect the quality of the captured image. Users may also find the process intrusive, as it involves close-up scanning of the eye, which can be uncomfortable for some individuals.

2.3.4 RFID-Based Attendance Systems

RFID (Radio-Frequency Identification) technology uses electromagnetic fields to automatically identify, and track tags attached to objects, such as ID cards or key fobs. In an RFID-based attendance system, each user is assigned an RFID tag with a unique identification number. When the user swipes or taps their RFID tag near a reader, the system logs their attendance. This method is popular in workplaces and educational institutions for its simplicity and speed in verifying attendance without the need for manual record-keeping (Chowdhury et al., 2020). The primary advantage of RFID systems is their ability to streamline attendance processes, making them suitable for environments where quick and efficient tracking is required (Bhattacharya et al., 2018).

RFID technology can also be integrated with existing access control systems, allowing organizations to manage attendance and security simultaneously. Nonetheless, RFID-based systems face limitations related to security. Since RFID cards can be easily lost, stolen, or shared, they are susceptible to fraudulent activities like proxy attendance, where someone other than the registered user logs attendance (Ria, 2020). To enhance security, modern RFID systems incorporate encryption and require multi-factor authentication, such as combining card swiping with a PIN or biometric verification (Samet, 2017). Despite these security measures, RFID systems still pose risks if the RFID tag or reader is tampered with. As a result, while RFID provides a practical and fast solution for attendance tracking, it may not be as secure as biometric methods like facial or iris recognition.

2.3.5 NFC Cards

Near Field Communication (NFC) technology enables short-range communication between devices through electromagnetic fields, typically when they are within a few centimeters of each other. NFC cards or tags contain a chip that communicates with an NFC reader to exchange data. In attendance management, NFC cards are used to record attendance by tapping the card near an NFC reader, which logs the individual's presence. This process is quick and convenient, making NFC technology suitable for environments such as schools and workplaces where fast and efficient attendance tracking is required (Chowdhury et al., 2020).

The main advantage of NFC cards lies in their speed and ease of use. Since users only need to tap their card on the reader, the system is straightforward and user-friendly, leading to minimal disruption during check-ins. NFC technology can also be integrated with other systems, such as access control, to streamline operations further. The cards do not require any batteries, which reduces maintenance costs compared to other electronic devices (Samet, 2017). Additionally, the NFC system's contactless nature makes it more hygienic compared to fingerprint-based systems.

However, despite these benefits, NFC cards face some challenges that limit their effectiveness. Security concerns are a significant drawback; NFC cards can be easily lost or stolen, leading to unauthorized access or proxy attendance, where someone else uses the card to log attendance on behalf of the legitimate owner. Although adding multi-factor authentication measures like PIN entry can mitigate this risk, it may reduce the system's convenience. Moreover, NFC technology can be susceptible to data interception or tampering if adequate encryption is not employed (Bhattacharya et al., 2018).

2.3.6 Challenges Faced in Implementation of Automated Attendance System

Implementing automated attendance systems presents a range of challenges depending on the technology used, with each approach having its distinct advantages and limitations. The analysis of these systems, including facial recognition, fingerprint recognition, iris recognition, and RFID-based systems, highlights the merits and shortfalls that influence their suitability for different environments.

i). Facial recognition

Facial recognition technology offers a contactless, hygienic solution for attendance tracking, which is particularly beneficial in settings where health and hygiene are paramount (Singh & Prasad, 2018). Its primary advantage lies in its ability to quickly and accurately identify individuals without the need for physical contact. However, facial recognition systems can struggle in environments with inconsistent lighting, extreme facial angles, or when individuals wear accessories like sunglasses or masks, which may obscure key facial features. These factors can lead to false positives or negatives, particularly in large-scale implementations where lighting conditions vary widely (Sultan et al., 2022). Moreover, the computational requirements for real-time processing of facial data can be intensive, causing delays in environments with large databases. To overcome this, integrating hash-based indexing can reduce computational load by enabling faster searching and matching of facial features across large datasets, thus enhancing the efficiency and scalability of the system (Sutabri et al., 2019).

ii). **Fingerprint Recognition**

Fingerprint recognition is well-known for its high accuracy and cost-effectiveness, making it a popular choice in controlled environments like corporate offices and schools. However, the technology requires direct physical contact, raising hygiene concerns, especially in high-traffic areas or during outbreaks of infectious diseases (Islam, 2017). Additionally, fingerprint systems can face challenges when users have dirty, wet, or damaged fingertips, which can result in errors or difficulties in capturing clear fingerprint images. This contact-based nature of fingerprint systems also limits their scalability in large-scale implementations where contactless verification may be more suitable. While anti-spoofing techniques such as liveness detection have been integrated into some systems, the technology still struggles to achieve the convenience and speed of contactless alternatives like facial recognition (Bhattacharya et al., 2018).

iii). Iris Recognition

Iris recognition technology provides one of the highest levels of accuracy among biometric systems, as the patterns in an individual's iris are unique and remain stable over time. This makes it an attractive option for security-sensitive applications where accuracy is critical. However, the technology is limited by the need for specialized and costly equipment, which may not be feasible for large-scale attendance tracking such as in educational institutions (Sutabri et al., 2019). The process also requires controlled lighting conditions to capture high-quality images, and users may perceive the close-up scanning of their eyes as intrusive, leading to lower user acceptance. While iris recognition offers significant advantages in terms of security and precision, its practical implementation is often hindered by these limitations, making it less appealing for everyday use cases like event or classroom attendance (Chowdhury et al., 2020).

iv). RFID-Based Systems

RFID technology provides a simple and quick solution for attendance tracking by using electromagnetic fields to identify tags attached to ID cards or devices. Its ability to rapidly log attendance makes it ideal for environments where speed is a priority, such as workplaces or busy educational institutions (Bhattacharya et al., 2018). However, RFID-based systems face several drawbacks, primarily related to security risks. RFID cards can be easily lost, stolen, or shared, making the system vulnerable to fraudulent activities such as proxy attendance, where someone logs attendance on behalf of another person. Although encryption and multi-factor authentication can improve security, RFID still lacks the reliability and robustness of biometric methods like facial or iris recognition, which are based on unique physiological traits (Samet, 2017).

Additionally, RFID systems may require regular maintenance to ensure that readers and tags function correctly, adding to the operational costs.

2.4 Models and Frameworks

2.4.1 Models

Several models have been employed in the development of facial recognition-based attendance systems, each utilizing different algorithms and techniques to enhance accuracy and efficiency. These models vary in complexity, from basic statistical methods to advanced deep learning approaches. The following subsections provide detailed descriptions of the most commonly used models in facial recognition, exploring their methodologies, use in attendance systems, and associated limitations.

2.4.1.1 CNN Model

Convolutional Neural Networks (CNNs) are among the most widely used models in image recognition tasks, including facial recognition for attendance systems. CNNs are deep learning models specifically designed to process and analyse visual data. They work by passing input images through multiple layers of convolutional filters that extract features such as edges, textures, and shapes. These hierarchical features are then used to classify or identify images based on patterns learned during training.

The CNN model consists of several types of layers, including convolutional layers, pooling layers, and fully connected layers. Convolutional layers apply filters to the input image to detect features, while pooling layers reduce the spatial dimensions of the data to decrease computational complexity and avoid overfitting. Fully connected layers, located at the end of the network, compile the features extracted from the convolutional layers and make predictions based on them (Zhou et al., 2020). CNNs are highly effective in facial recognition tasks because they can learn complex patterns and features from large amounts of data, making them more accurate than traditional machine learning models.

Zhou et al. (2020) implemented CNNs in their facial recognition-based attendance system and reported high levels of accuracy. The system was able to identify attendees with a high degree of precision due to the deep network's ability to learn distinguishing facial features. However, CNNs require large amounts of labelled data to achieve high accuracy, which can be a limitation in some educational settings where datasets are small or not easily accessible (Sunaryono et al., 2019). Additionally, CNNs are computationally expensive and require significant processing power, making their implementation costly for institutions with limited technical resources (Raghuwanshi & Swami, 2017). Despite these challenges, CNNs remain a preferred model for facial recognition due to their high performance and scalability. However, institutions adopting CNN-based systems must ensure they have the necessary computational infrastructure and access to large, high-quality datasets to train the model effectively.

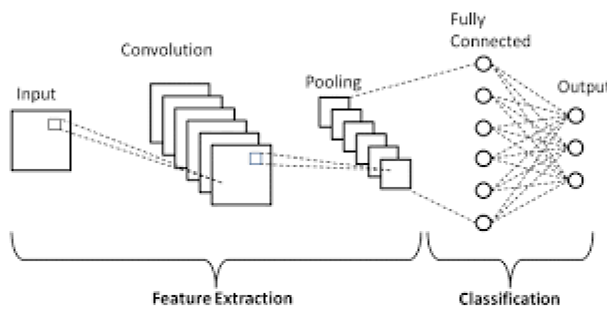

Figure 2.1: CNN Model (Gurucharan, 2020)

2.4.1.2 Principal Component Analysis (PCA)

Principal Component Analysis (PCA) is a statistical technique used in many facial recognition systems to reduce the dimensionality of the data while preserving important features for identification. PCA works by transforming the original data into a set of orthogonal (uncorrelated) variables called principal components, which capture the variance in the data. The first principal component accounts for the largest variance, while each subsequent component captures progressively less variance. By focusing on the most significant components, PCA reduces the complexity of the data, making it easier and faster to process (Chintalapati & Raghunadh, 2013). PCA is often referred to as the Eigenface method in the context of facial recognition. The technique represents faces as linear combinations of eigenfaces, which are the eigenvectors of the covariance matrix of a set of training face images. This method allows the system to reduce a high-dimensional facial image into a lower-dimensional representation that retains the most critical facial features for recognition. PCA-based systems are computationally efficient, making them suitable for environments with limited processing power, such as gathering halls.

Chintalapati and Raghunadh (2013) used PCA in their attendance system and reported an accuracy rate of 78%. However, PCA has several limitations, particularly its sensitivity to variations in facial expressions, lighting, and pose. If the lighting conditions in the classroom change or a student’s facial expression differs from the training data, the system’s accuracy can be significantly reduced (Mehta & Tomar, 2016). Additionally, PCA assumes that the most significant variance in the data is relevant to facial recognition, which may not always be the case, especially in real-world environments where facial features may not follow a linear structure (Chintalapati & Raghunadh, 2013). While PCA offers a computationally inexpensive solution, its limitations in handling complex variations in facial data have led to the development of more advanced models such as CNNs. PCA-based systems may still be useful in smaller, controlled environments where such variations are minimal, but they are generally not recommended for larger, more dynamic settings.

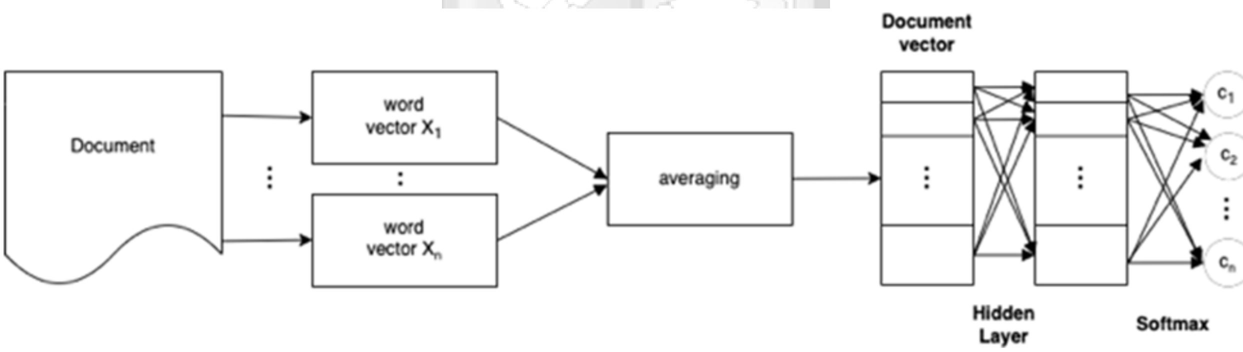

Figure 2.2: Principal Component Analysis (Ayatullah & Suciati, 2023)

2.4.1.3 Local Binary Patterns (LBP)

Local Binary Patterns (LBP) is a texture-based descriptor model that has been widely used in facial recognition due to its simplicity and robustness to changes in lighting. LBP works by comparing each pixel in an image with its neighbouring pixels and encoding the results as a binary number. This binary pattern captures the local structure of the image, which can then be used to describe the texture of a face (Chintalapati & Raghunadh, 2013). LBP is particularly useful in facial recognition because it is invariant to monotonic changes in lighting, making it more resilient to variations in illumination than other models like PCA. LBP is often combined with other models to improve the robustness of facial recognition systems. For example, Chintalapati and Raghunadh (2013) combined LBP with PCA in their attendance system to enhance the system's performance in varying lighting conditions. While LBP improved the system's resilience to lighting changes, it still struggled with variations in facial expressions and occlusions, such as when a student's face is partially obscured by glasses or hair. This limitation is common in texture-based models, which may not capture all the essential features needed for accurate facial recognition (Mehta & Tomar, 2016).

LBP's primary advantage lies in its computational efficiency. It is less resource-intensive than deep learning models like CNNs, making it a suitable choice for institutions with limited technical capabilities. However, LBP's reliance on local texture information can be a disadvantage in more complex environments where facial features may vary significantly from one instance to another. As a result, LBP is often used in conjunction with other models to balance accuracy and computational efficiency (Chintalapati & Raghunadh, 2013; Raghuwanshi & Swami, 2017).

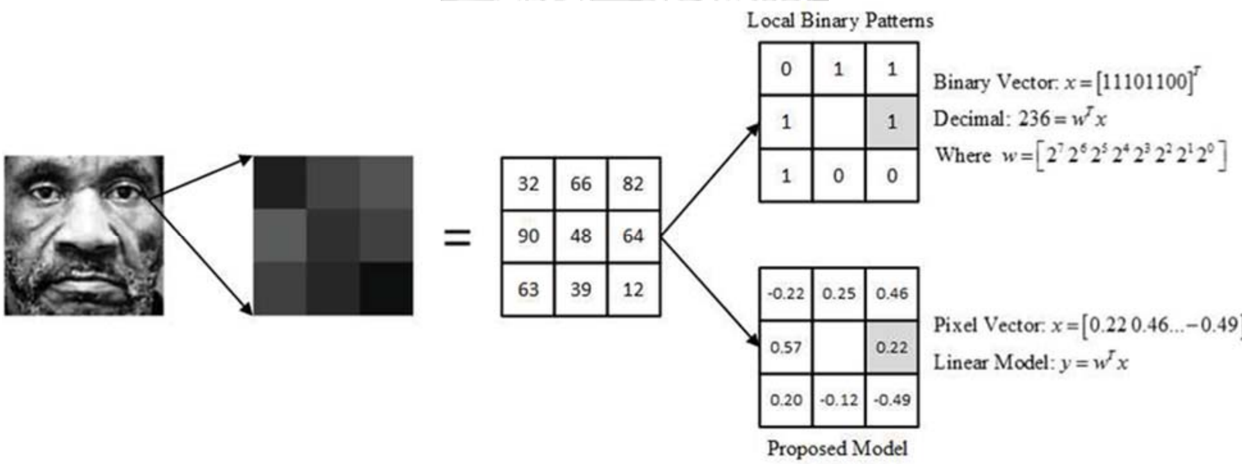

Figure 2.3 Local Binary Patter Model (Gong & Zheng, 2013)

2.4.1.4 Hybrid Models

Hybrid models combine multiple facial recognition techniques to capitalize on the strengths of different approaches while mitigating their individual weaknesses. One common hybrid approach is the combination of PCA and LBP, which leverages PCA's ability to reduce dimensionality with LBP's robustness to lighting variations. Raghuwanshi and Swami (2017) implemented a hybrid model using PCA, LBP, and Linear Discriminant Analysis (LDA), aiming to improve both accuracy and computational efficiency. Their system achieved moderate success, with accuracy rates ranging from 53.33% using PCA to 60% using LDA.

The hybrid approach allows for more flexibility in handling variations in facial data, such as changes in lighting, pose, and expression. However, hybrid models can be more complex to implement and require more computational resources than simpler models like PCA or LBP alone. Additionally, combining models does not always lead to improved performance, as the system may still struggle with edge cases such as occlusions or rapid movements (Sunaryono et al., 2019; Mehta & Tomar, 2016). The success of hybrid models largely depends on the specific context in which they are applied and the balance between computational cost and accuracy. Hybrid models represent an attempt to bridge the gap between traditional statistical methods like PCA and more advanced deep learning techniques like CNNs.

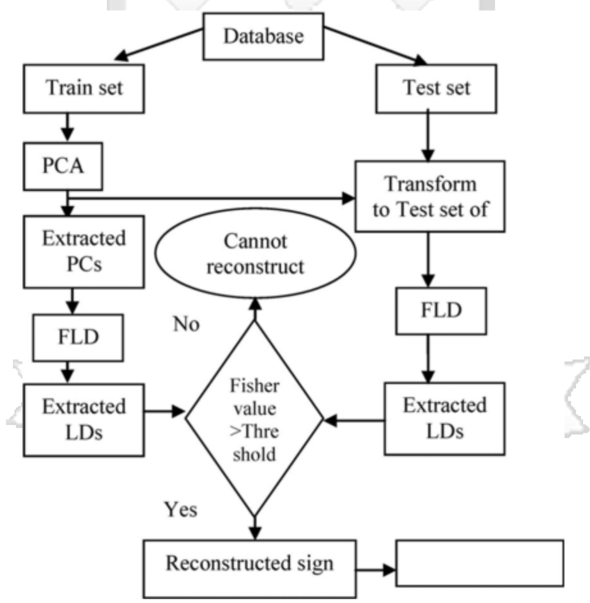

Figure 2.4: Hybrid PCA and LBP models (Hasan & Ahmad, 2015)

2.4.2 Frameworks

The implementation of facial recognition systems for automated attendance tracking often involves the use of machine learning and deep learning frameworks. These frameworks provide the necessary tools for developing, training, and deploying complex models in an efficient and scalable manner.

2.4.2.1 TensorFlow

TensorFlow, developed by Google, is one of the most widely used open-source machine learning frameworks. It is highly regarded for its flexibility, scalability, and ability to handle large datasets, making it a popular choice for building deep learning models, including facial recognition systems. TensorFlow allows developers to create complex neural networks, such as Convolutional Neural Networks (CNNs), which are crucial for tasks involving image recognition (Zhou et al., 2020). TensorFlow provides a wide array of pre-built functions and tools that simplify the process of model training and optimization, while also offering support for both CPU and GPU processing, which enhances computational efficiency (Mehta & Tomar, 2016). One of the key features of TensorFlow is its ability to create computational graphs, where operations are structured as nodes and edges. This approach allows for parallel processing, which is essential when working with large datasets typically required for facial recognition tasks. In facial recognition-based attendance systems, TensorFlow can be used to build CNNs capable of learning complex facial features from a large set of training images. Once trained, these models can accurately identify attendees from their facial images, even in challenging conditions such as poor lighting or occlusions (Zhou et al., 2020).

Zhou et al. (2020) used TensorFlow to implement a CNN-based facial recognition system for attendance tracking. The system was highly accurate in identifying attendees and performed well under various lighting conditions and facial expressions. However, one of the limitations of TensorFlow is its steep learning curve, particularly for developers who are not familiar with deep learning or machine learning concepts. Debugging TensorFlow models can also be challenging due to the complexity of the computational graphs and the low-level operations involved (Sunaryono et al., 2019). Additionally, while TensorFlow provides immense flexibility, this flexibility can sometimes make it harder to build and optimize models, especially for users who prefer a more abstracted framework (Mehta & Tomar, 2016). Another challenge with TensorFlow is the computational resources required to train deep learning models. While TensorFlow does support distributed computing and can be run on cloud-based platforms, these solutions may introduce additional costs, which can be prohibitive for smaller institutions (Raghuwanshi & Swami, 2017).

2.4.2.2 Keras

Keras is another open-source framework that is widely used in the development of machine learning models. Unlike TensorFlow, Keras is designed to be user-friendly and accessible, offering a high-level API for building neural networks. Keras was originally developed to run on top of other deep learning frameworks, including TensorFlow and Theano, but it has since been fully integrated into TensorFlow, allowing users to take advantage of TensorFlow's computational power while enjoying Keras' simpler interface (Mehta & Tomar, 2016).

The primary advantage of Keras is its ease of use. Keras abstracts much of the complexity involved in building and training deep learning models, making it ideal for prototyping and experimentation. Developers can quickly build a model using just a few lines of code, which is especially useful in educational settings where time and technical resources may be limited. Keras also supports the creation of deep learning models such as CNNs, making it a viable option for facial recognition tasks (Raghuwanshi & Swami, 2017).

In the context of automated attendance systems, Keras has been used to build facial recognition models that are both efficient and accurate. Raghuwanshi and Swami (2017) utilized Keras to implement a CNN for their facial recognition-based attendance system. The framework allowed them to quickly prototype the model and fine-tune its parameters with minimal coding effort. However, while Keras simplifies the process of model development, it may not offer the same level of control and optimization as TensorFlow when it comes to fine-tuning models for performance. This can be a limitation in large-scale projects that require precise control over every aspect of the model (Mehta & Tomar, 2016).

Another limitation of Keras is that it is not as well-suited for deployment in production environments compared to TensorFlow. While Keras is excellent for building and training models, it may not provide the same level of support for scaling and deploying models in real-world applications. This limitation is less of a concern in smaller educational institutions where the primary focus is on accuracy rather than large-scale deployment. However, for larger institutions that require robust, scalable solutions, TensorFlow or other frameworks may be more appropriate (Raghuwanshi & Swami, 2017).

In summary, Keras is an excellent choice for developers who need a simple, user-friendly framework for building facial recognition models. Its integration with TensorFlow allows users to take advantage of TensorFlow's computational power while enjoying a more streamlined development process. However, its limitations in terms of scalability and fine-tuning make it less suitable for large-scale or highly complex applications (Mehta & Tomar, 2016; Raghuwanshi & Swami, 2017).

2.4.2.2 PyTorch

PyTorch, developed by Facebook's AI Research lab, is another popular deep learning framework, particularly favoured by researchers for its flexibility and ease of experimentation. PyTorch uses a dynamic computation graph, meaning that the structure of the network can be modified during runtime, making it more intuitive to work with compared to TensorFlow, which uses a static graph. This dynamic nature makes PyTorch particularly useful for research and experimentation, where models may need to be adjusted or iterated on quickly (Sunaryono et al., 2019). One of the strengths of PyTorch is its simplicity in handling data loading and model training, which makes it a good fit for facial recognition tasks where large datasets are involved. In an automated attendance system, PyTorch can be used to implement CNNs or other deep learning models to identify participants from facial images.

Sunaryono et al. (2019) used PyTorch for their attendance system, citing its ability to handle large datasets with minimal coding overhead as one of its main advantages. The system performed well in recognizing attendees and was able to handle real-time processing efficiently. While PyTorch is excellent for research purposes, it may not be as well-suited for production deployment compared to TensorFlow. This is because PyTorch lacks some of the deployment features that TensorFlow offers, such as support for mobile devices and distributed computing. PyTorch models can be more challenging to scale and deploy in production environments, which can be a limitation for institutions that require a robust, scalable attendance system (Zhou et al., 2020; Mehta & Tomar, 2016). PyTorch remains a popular choice among researchers due to its flexibility and ease of use. It is particularly well-suited for smaller-scale projects or educational institutions where the focus is on experimentation and accuracy rather than large-scale deployment (Sunaryono et al., 2019).

2.5 Architectures and Designs

The architecture of a facial recognition-based attendance system plays a crucial role in determining its efficiency, scalability, and robustness. These architectures define how various components such as data collection, image processing, recognition algorithms, and storage interact within the system. This section explores the most commonly used architectures in facial recognition systems for attendance tracking, including client-server architecture, IoT-based architecture, hybrid architecture, and distributed architecture. Each architecture is described in detail, along with its strengths, limitations, and examples of its application in existing systems.

2.5.1 Client-Server Architecture

The client-server architecture is one of the most widely used frameworks for implementing facial recognition-based attendance systems. In this architecture, the client (typically a camera or a mobile device) captures the facial image of the student, which is then sent to a central server for processing and recognition. The server runs the facial recognition algorithm, compares the image to a stored database of student images, and sends the result back to the client. This architecture is simple to implement and provides a clear separation between data collection (client) and data processing (server). The client-server architecture allows for real-time data processing, enabling institutions to quickly track student attendance.

Sunaryono et al. (2019) used a client-server architecture in their facial recognition system, where the client captured the facial images of attendees using a mobile device, and the server processed these images using a Convolutional Neural Network (CNN) to identify the attendees. The system was able to handle multiple attendees simultaneously, making it ideal for large gathering halls. One of the key strengths of the client-server architecture is its scalability. Since the server handles all the processing, the client devices can be relatively simple and inexpensive, making it easy to scale the system by adding more clients (e.g., cameras or mobile devices). However, this architecture also has some limitations. For example, it requires a stable network connection between the client and server, and any disruption in this connection can lead to delays or failures in attendance tracking. Additionally, the central server may become a bottleneck if the number of clients increases significantly, leading to slower processing times (Sunaryono et al., 2019; Zhou et al., 2020).

Another limitation of the client-server architecture is data security. Since the facial images are transmitted over a network, they are vulnerable to interception and unauthorized access. Institutions using this architecture must ensure that the data is encrypted during transmission and that the server is secured against hacking attempts (Mehta & Tomar, 2016). Despite these challenges, the client-server architecture remains a popular choice for automated attendance systems due to its simplicity and scalability.

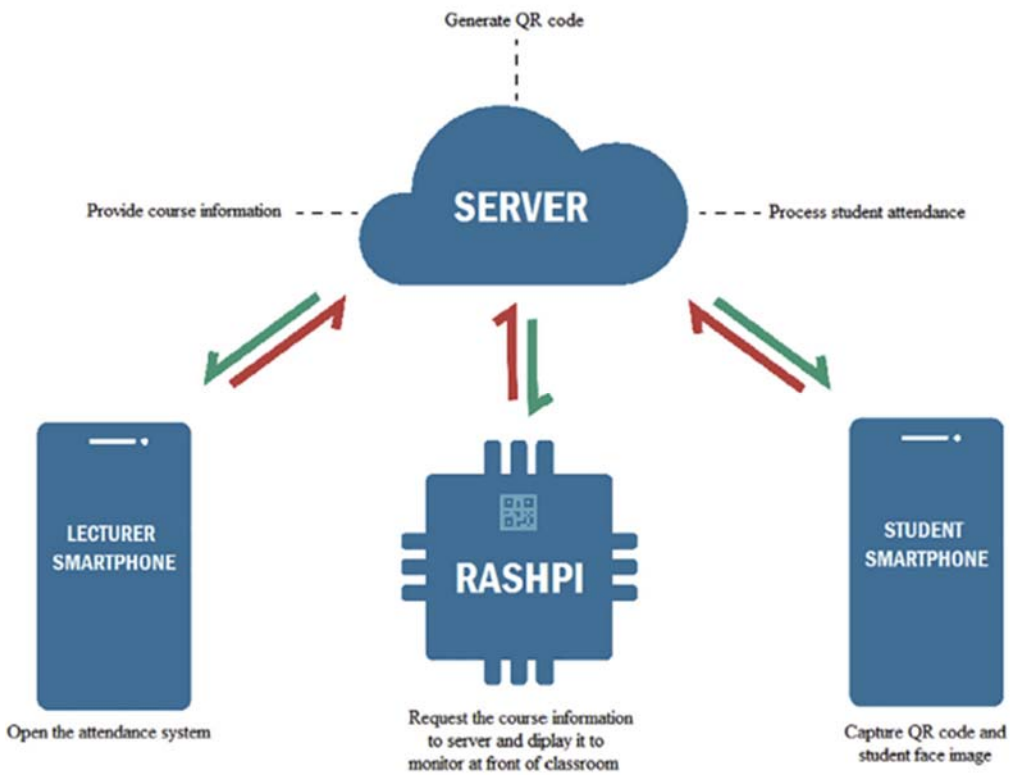

Figure 2.5: Client Server Architecture (Sunaryono et al., 2019)

2.5.2 IoT-Based Architecture

The Internet of Things (IoT) is an emerging technology that connects physical devices to the internet, allowing them to collect and share data. In IoT-based architectures, devices such as cameras, sensors, and mobile devices are connected to the internet, enabling real-time data collection and processing. IoT-based architectures have been increasingly used in facial recognition systems for attendance tracking due to their ability to integrate multiple devices and provide real-time monitoring. In an IoT-based attendance system, cameras and sensors capture facial images of attendees and send them to a central server or cloud-based platform for processing. These systems can be designed to operate autonomously, with minimal human intervention.

Raghuwanshi and Swami (2017) implemented an IoT-based architecture for their facial recognition attendance system, which used networked cameras to capture images and send them to a central server for processing. The system provided real-time feedback to teachers and administrators, allowing them to monitor student attendance remotely. One of the main strengths of IoT-based architectures is their ability to handle large-scale systems with multiple devices. Since the devices are connected via the internet, the system can easily scale by adding more cameras or sensors without significantly increasing the processing load on the central server. IoT architectures also offer flexibility in terms of data storage, as data can be stored locally on the device or in the cloud, depending on the needs of the institution (Mehta & Tomar, 2016).

However, IoT-based architectures also come with several challenges. One major concern is data security, as IoT devices are often vulnerable to hacking and unauthorized access. Securing the network and ensuring that all devices are properly authenticated is essential to prevent data breaches. Additionally, IoT-based systems require a reliable internet connection to function effectively, and any disruption in connectivity can lead to system failures or data loss (Raghuwanshi & Swami, 2017). Despite these challenges, IoT-based architectures are gaining popularity in automated attendance systems due to their scalability and flexibility.

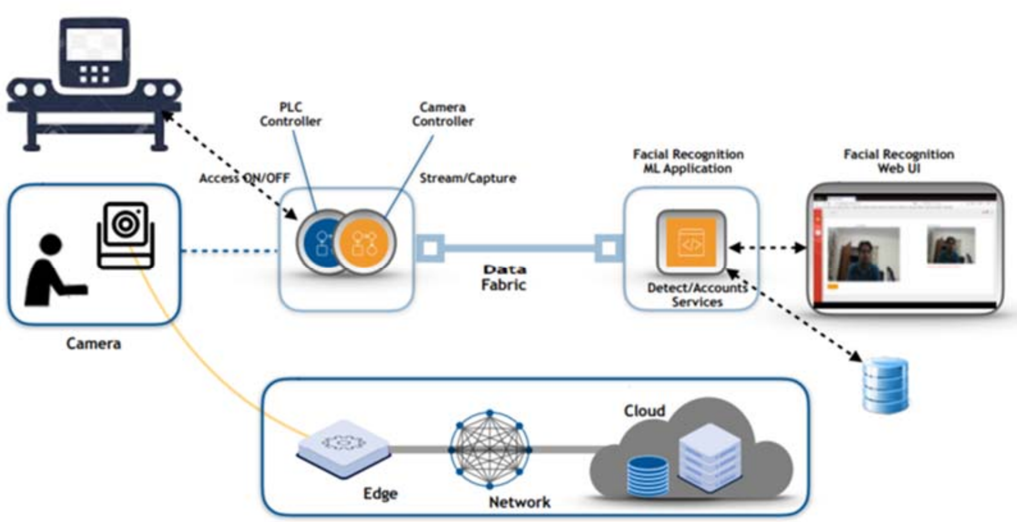

Figure 2.6: IoT Based Architecture (Medapati et al., 2019)

2.5.3 Hybrid Architecture

A hybrid architecture combines elements of both client-server and IoT-based architectures to provide a more robust and flexible solution. In a hybrid architecture, facial images are captured by client devices (such as cameras or mobile devices) and processed either locally on the device or on a central server, depending on the system's configuration. This architecture allows for more efficient processing and reduces the load on the central server by distributing some of the processing tasks to the client devices. J and Suresh (2023) used a hybrid architecture for their facial recognition attendance system, which combined local processing on the client devices with server-based processing for more complex tasks. The system used mobile devices to capture facial images and perform initial recognition tasks, such as detecting the face in the image. The processed data was then sent to a central server for more advanced recognition tasks, such as matching the face to a database of student images. This approach reduced the load on the central server and allowed for faster processing times, especially in large gathering halls.

One of the main advantages of hybrid architectures is their flexibility. By distributing some of the processing tasks to the client devices, the system can handle more clients without overloading the central server. This also allows for more efficient use of resources, as the client devices can perform simple tasks, while the server handles more complex operations. Additionally, hybrid architectures can function even if the network connection between the client and server is temporarily disrupted, as the client devices can continue to process data locally (Mehta & Tomar, 2016). Hybrid architectures also have some limitations. Since the client devices are responsible for some of the processing, they need to be more powerful than in a traditional client-server architecture, which can increase the cost of the system. Additionally, managing the distribution of tasks between the client and server can be complex, and ensuring that the system operates efficiently requires careful planning and optimization (Sunaryono et al., 2019; Zhou et al., 2020).

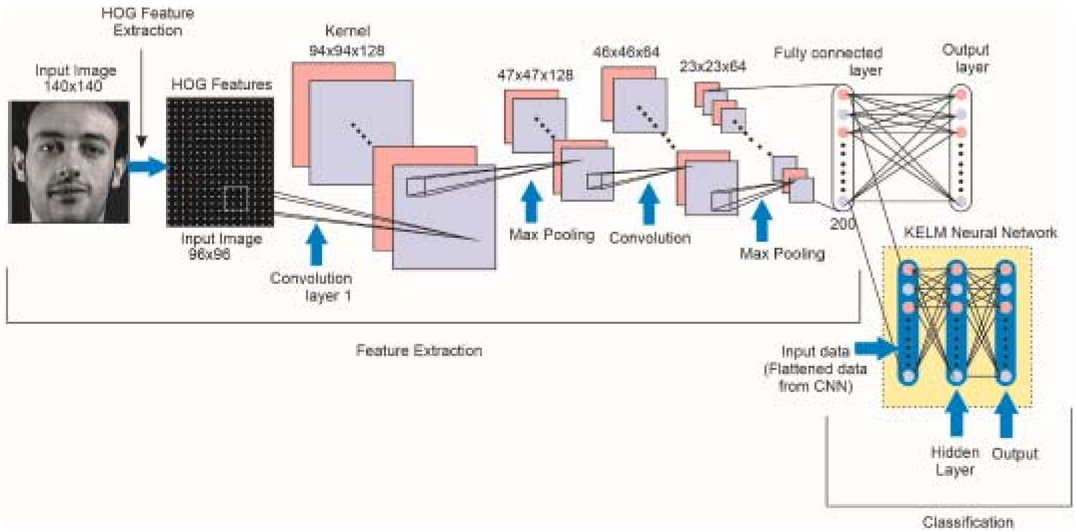

Figure 2.7: Hybrid Model (J & Suresh, 2023)

2.5.4 Distributed Architecture

In a distributed architecture, the processing tasks are spread across multiple servers or devices, allowing for parallel processing and greater scalability. This architecture is ideal for large-scale systems that need to handle a high volume of data, as it can distribute the workload across multiple nodes. In a distributed facial recognition system, images captured by client devices are processed by different servers, and the results are aggregated to provide a final output. Zhou et al. (2024) implemented a distributed architecture for their attendance system, which used multiple servers to process facial images in parallel. This approach allowed the system to handle many attendees simultaneously, making it suitable for large gathering halls or institutions with thousands of attendees. By distributing the processing tasks, the system was able to maintain high performance even under heavy loads.

The main strength of distributed architectures is their scalability. Since the processing tasks are distributed across multiple servers, the system can easily scale to accommodate more clients without significantly increasing processing times. Distributed architectures are also more resilient to failures, as the system can continue to function even if one of the servers goes down (Raghuwanshi & Swami, 2017). However, distributed architectures also have some drawbacks. They require more complex infrastructure, including multiple servers and a robust network to manage the distribution of tasks. This can increase the cost and complexity of the system, especially for smaller institutions. Additionally, distributed systems require careful coordination between the servers to ensure that the data is processed correctly and that the results are aggregated efficiently (Mehta & Tomar, 2016).

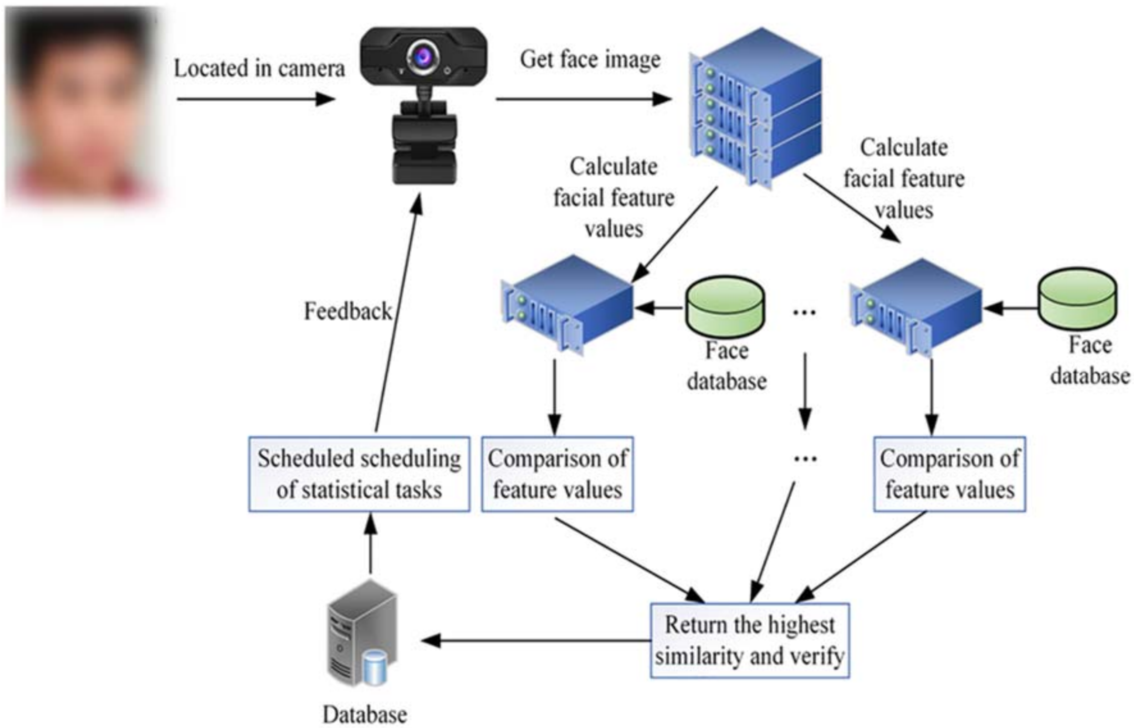

Figure 2.8: Distributed Architecture (Zhou et al., 2024)

2.6 Algorithms

Facial recognition-based attendance systems rely on a variety of algorithms to perform tasks such as face detection, facial feature extraction, and recognition. These algorithms vary in complexity and performance, depending on the dataset, environment, and specific use case. This section reviews the key algorithms used in recent studies for face detection and recognition, along with their strengths and limitations.

2.6.1 DLIB Algorithm

The Dlib Face Recognition API is an open-source toolkit that provides a variety of machine learning algorithms for face detection, facial feature extraction, and recognition. The API uses a deep learning model that generates 128-dimensional face embeddings for each individual, which can then be compared using a distance metric such as Euclidean or Cosine Distance. Sultan et al. (2022) employed the Dlib Face Recognition API in their attendance system, where it was used to detect facial landmarks and extract features for recognition. The Dlib API is known for its accuracy and efficiency, making it suitable for real-time applications. However, one limitation of the Dlib API is that it requires well-aligned and high-quality facial images for accurate feature extraction. In environments where facial images are noisy or poorly captured, the system's performance can degrade (Sultan et al., 2022).

2.6.2 Convolutional Neural Networks

Convolutional Neural Networks (CNNs) are widely used for face detection and recognition due to their ability to learn complex hierarchical features from images. CNNs are particularly well-suited for facial recognition in video streams, where they can process sequential frames to detect and track faces over time. Chowdhury et al. (2020) implemented a CNN-based system for face detection and recognition in video streams. The CNN was trained on a large dataset of facial images and achieved high accuracy in identifying attendees in real-time. One of the main strengths of CNNs is their ability to generalize across different lighting conditions, facial expressions, and poses, making them ideal for dynamic environments such as gathering halls. However, CNNs are computationally expensive and require substantial training data to achieve high performance. Additionally, CNNs are prone to overfitting if not properly regularized, which can lead to reduced performance in new environments (Chowdhury et al., 2020).

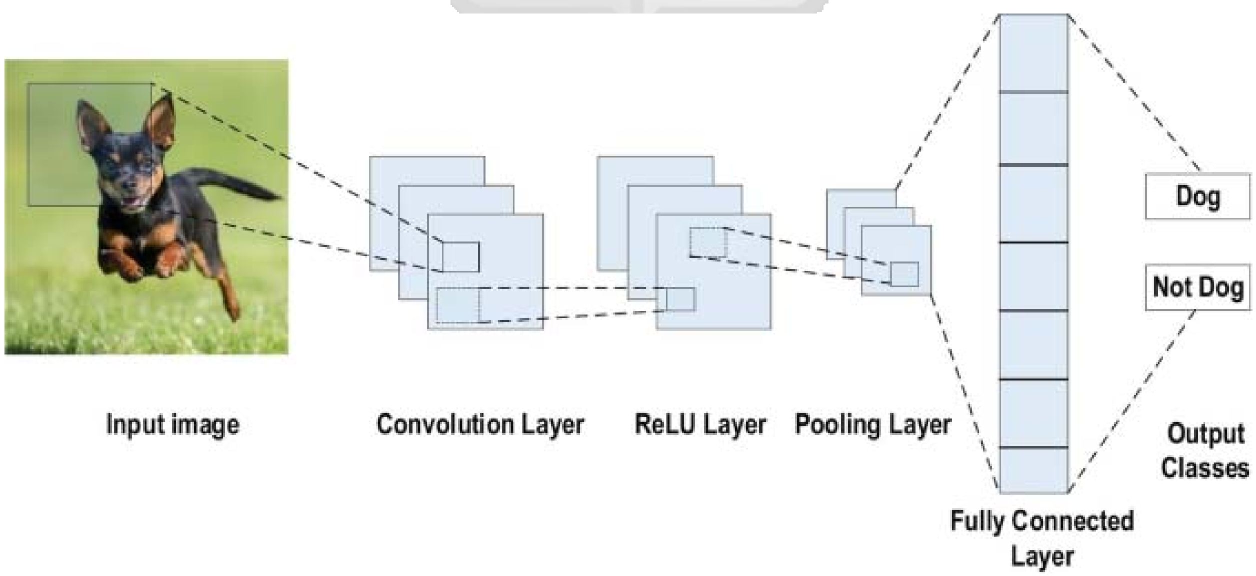

Figure 2.9: CNN Architecture for Image Classification (Alzubaidi et al., 2021)

2.6.3 Cosine Distance

Cosine Distance is a metric used to measure the similarity between two vectors in an embedding space, such as the feature vectors generated by a facial recognition system. It calculates the cosine of the angle between two vectors, with values closer to 1 indicating greater similarity. Cosine Distance is commonly used in facial recognition tasks because it is invariant to the magnitude of the vectors, making it ideal for comparing feature vectors derived from different images. Nguyen et al. (2020) used Cosine Distance in their facial recognition model to compare the feature vectors generated by a deep learning algorithm. The system achieved high accuracy in identifying attendees by measuring the cosine similarity between the extracted features and those stored in the attendance database. One limitation of Cosine Distance is that it assumes the feature vectors are well-normalized and representative of the underlying facial structure. If the features are noisy or poorly extracted, the distance metric may fail to distinguish between individuals accurately (Nguyen et al., 2020).

2.6.4 Histogram of Oriented Gradients (HOG)

Histogram of Oriented Gradients (HOG) is a feature descriptor used to capture the structure or shape of objects within an image. It works by dividing an image into small cells and computing a histogram of gradient directions or edge orientations for each cell. These histograms are then normalized and combined to form a feature vector that describes the object in the image. HOG is particularly useful in facial detection because it captures the local structures of the face, making it more robust to variations in lighting and pose than some other methods. Nguyen et al. (2020) and Sultan et al. (2022) both employed HOG for face detection in their automated attendance systems. HOG was chosen because it is computationally efficient and works well in environments with varying lighting conditions. However, one limitation of HOG is that it relies heavily on the local gradient information, which may not be sufficient to distinguish between individuals with very similar facial structures. Additionally, HOG can struggle with occlusions, such as when a student's face is partially obscured by glasses or hair (Nguyen et al., 2020; Sultan et al., 2022).

2.6.5 Support Vector Machine (SVM)

The Support Vector Machine (SVM) is a supervised learning algorithm used for classification and regression tasks. It works by finding the optimal hyperplane that separates data points from different classes, with the goal of maximizing the margin between these classes. In facial recognition, SVM is often used as the final classifier that distinguishes between different individuals based on features extracted by other algorithms, such as CNNs or HOG (Histogram of Oriented Gradients). Muhammad et al. (2023) employed SVM in their facial recognition model to classify attendees based on the facial features extracted by a deep learning model. SVM was chosen due to its robustness in handling high-dimensional data and its ability to generalize well, even with small training datasets.

One of the main strengths of SVM is its ability to perform well in environments with limited labelled data, which is often a challenge in educational settings. However, SVM's performance depends on the correct selection of hyperparameters, and improper tuning can lead to overfitting or poor generalization to new data (Muhammad et al., 2023). SVM is particularly effective in facial recognition systems that combine it with feature extraction algorithms such as HOG or CNN. However, SVM can be computationally expensive, especially when applied to large datasets, making it less suitable for real-time applications in attendance systems (Nguyen et al., 2020).

2.6.6 FaceNet Network

FaceNet, developed by Schroff et al. (2015), is a deep learning-based facial recognition system that learns a mapping from face images to a compact Euclidean space where distances directly correspond to a measure of facial similarity. In this space, known as the embedding space, the Euclidean distance between two facial images reflects their similarity: smaller distances indicate higher similarity. FaceNet employs a deep Convolutional Neural Network (CNN) architecture that is trained using a triplet loss function, which ensures that the distance between positive pairs (images of the same person) is smaller than the distance between negative pairs (images of different people).

Alniemi and Mahmood (2023) used the FaceNet network in their facial recognition-based attendance system, where it achieved high accuracy in identifying attendees. FaceNet's ability to map faces into a compact feature space allowed the system to handle large datasets efficiently, making it suitable for institutions with large student populations. One of the limitations of FaceNet, however, is its dependency on high-quality facial images for accurate recognition. In environments where facial images are blurry or obstructed, the system's performance can degrade. Additionally, FaceNet requires substantial computational resources, particularly for training the model on large datasets, which can be a limitation for smaller institutions (Alniemi & Mahmood, 2023; Schroff et al., 2015).

2.6.7 Haar Cascaded Classifier

The Haar Cascaded Classifier, a machine learning-based approach for object detection, was first introduced by Viola and Jones (2001). It is widely used for detecting faces in images or video streams. The classifier works by training on a large dataset of positive and negative images, allowing it to detect patterns in facial structures. It uses features called "Haar-like features" that represent the contrast between regions in an image, such as the difference between the brightness of the eyes and the surrounding areas. The algorithm scans the image with these features at multiple scales and locations to detect faces.

In the context of automated attendance systems, Alniemi and Mahmood (2023) employed the Haar Cascaded Classifier for face detection. The system efficiently identified faces in real-time, making it suitable for classroom environments where fast detection is required. However, the Haar Cascaded Classifier has some limitations. It can struggle with complex backgrounds and changes in lighting conditions, leading to false positives or missed detections. Additionally, the classifier is sensitive to pose variations, making it less accurate when attendees are not facing the camera directly (Alniemi & Mahmood, 2023).

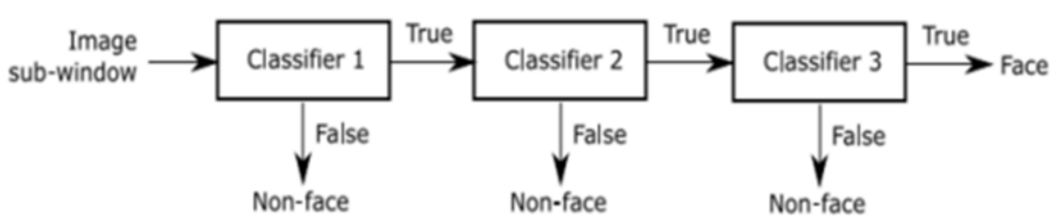

Figure 2.10: Haar Cascaded Classifier

Table 2.2 shows the summary of the algorithms that have been used in automated class attendance systems.

Table 2.2: Summary of Algorithms used in Automating Attendance Systems.

Algorithm	Strengths	Limitations
Haar Cascaded Classifier	-Fast and efficient for real-time face detection	-Sensitive to lighting changes and complex backgrounds
FaceNet	-High accuracy in facial recognition tasks	-Requires high-quality images and substantial computational resources
Support Vector Machine (SVM)	- Robust in handling high-dimensional data	-Computationally expensive and sensitive to hyperparameters
Histogram of Oriented Gradients (HOG)	-Computationally efficient, robust to lighting variations	-Struggles with occlusions and similar facial structures
Cosine Distance	-Invariant to magnitude, ideal for face comparisons	-Relies on high-quality feature extraction for accuracy
Dlib Face Recognition API	- Accurate and efficient, supports real-time applications	- Requires well-aligned, high-quality images for best performance
Convolutional Neural Networks (CNN)	-High accuracy in complex environments	- Computationally expensive, prone to overfitting if not regularized

2.7 Existing Gaps

Research on facial recognition-based attendance systems reveals several significant gaps that limit the effectiveness and applicability of these technologies in real-world event settings. Research in the field of attendance recording for events is relatively limited, with most scholarly work primarily cantered on classroom attendance. This narrow focus on educational settings overlooks the unique challenges and requirements associated with monitoring attendance at events. Unlike gathering halls, events typically involve varying environmental conditions, larger and more diverse crowds, fluctuating participant numbers, and different logistical considerations, such as entry points and security protocols. These distinctions create a gap in the existing literature, highlighting the need for more studies that specifically address the complexities and specificities of event attendance tracking. Expanding research in this area could lead to more effective solutions tailored to the dynamic nature of events, improving accuracy and efficiency in attendance recording.

In addition, most research relies on limited or synthetic datasets that fail to capture the diversity of real-world events. This lack of diversity in testing conditions results in systems that perform well in controlled environments but struggle when faced with variations in lighting, camera angles, or participant demographics. Furthermore, studies often do not consider the effects of occlusions, such as masks, hats, or sunglasses, which have become increasingly relevant in contemporary social environments. As a result, these systems may have reduced accuracy when dealing with real-world complexities. Scalability and performance optimization are notable gaps in the facial recognition literature. While some studies demonstrate high accuracy rates in small-scale environments, they often lack sufficient testing in larger, more complex settings. Systems that perform well in small gatherings or under ideal conditions may face delays or failures when recognizing large numbers of participants simultaneously. Many studies also overlook the practical implications of deploying facial recognition systems in venues with limited technological resources. The reliance on high-resolution cameras or specific hardware setups could limit the broader adoption of these systems in resource-constrained environments.

Privacy and ethical considerations are largely neglected across the reviewed studies. Although biometric systems offer enhanced security and efficiency, the collection, storage, and use of facial data raise significant privacy concerns. Few studies address the secure handling of sensitive biometric information. Ethical issues related to user consent and the long-term impact of using facial recognition in event management are often not explored, which may impede the widespread adoption of these technologies in regions with strict data privacy laws.

Lastly, long-term usability and adaptability of the systems are frequently overlooked. Most studies focus on immediate accuracy without considering how systems might adapt over time as participants' appearances change due to aging, hairstyle variations, or other factors. The lack of longitudinal studies leaves unanswered questions about the systems' ability to remain effective over extended periods. Additionally, the ability of these systems to handle participants' biometric data over time without requiring frequent updates remains a critical gap in the research. Addressing these limitations is at the core of this research, ensuring the creation of robust, scalable, and ethically sound facial recognition-based attendance systems.

2.8 Conceptual Model

The conceptual model of this study is built on the key. These stages include data acquisition, face detection, feature extraction, face recognition, and data storage and reporting. Figure 2.6 illustrates this conceptual model.

The model emphasizes three critical components:

i). **Input and Pre-processing**: This includes the capture of facial images using cameras or mobile devices. The quality of the captured image is crucial for accurate recognition. Pre-processing techniques such as normalization, resizing, and enhancing the image to correct for environmental factors (lighting, background, etc.) are applied at this stage. This process ensures that the facial data is in a consistent format for the subsequent stages.

ii). **Recognition System (Detection, Feature Extraction, and Recognition)**: The core of the facial recognition system involves three sub-processes:

a) **Face Detection**: CNN algorithm will be used to detect the presence of a face in the image. This stage is crucial as the accuracy of detection affects the overall tool's performance.

b) **Feature Extraction**: Once a face is detected, features such as the shape, texture, and orientation are extracted using algorithms CNN. These features are then encoded into a feature vector that represents the unique characteristics of the individual's face.

c) **Face Recognition**: The extracted feature vector is compared against a pre-existing database of participants' faces. The recognition process utilizes distance metrics like Cosine Distance to match the extracted features to the database.

iii). **Output and Post-processing**: Once the recognition system identifies the individual, the system records the attendance in the database and provides real-time feedback to event organizers and administrators. This stage also includes reporting and integrating the attendance data with other management systems for further use, such as generating attendance reports or tracking participant engagement.

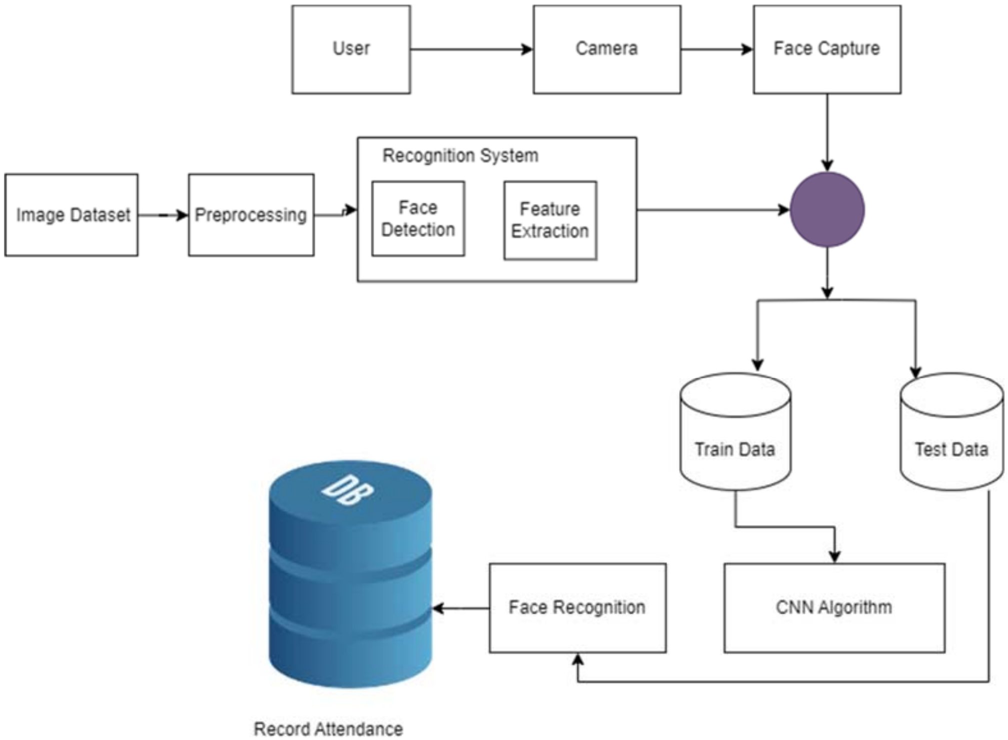

Figure 2.11: Conceptual Model

Chapter 3: Research Methodology

3.1 Introduction

The methodology employed in this research is structured to develop an automated event attendance system using facial recognition technology. This system aims to provide a reliable and efficient solution for real-time tracking of attendance, addressing challenges related to manual or traditional methods. Through the application of quantitative data collection and analysis, this study seeks to evaluate the system's effectiveness in accurately recording attendance. The research design is grounded in a positivist philosophy, ensuring an objective and empirical approach to model development, testing, and validation. The research methodology also incorporates the Agile methodology, allowing for iterative development and continuous improvement based on real-world feedback and system performance.

3.2 Research Design and Philosophy

This research adopts an applied research approach to develop a practical solution for attendance management using facial recognition technology. A quantitative design was chosen because the study focuses on collecting, analysing, and validating data to assess the effectiveness of facial recognition in tracking event attendance. The aim was to implement an automated system capable of accurately recording attendance in real-time. The research is guided by a positivist philosophy, which was selected for its alignment with the scientific approach that emphasizes empirical data and hypothesis testing. This allows for objective analysis and ensures that the results are grounded in observable data. The choice of positivism supports the use of statistical models and algorithms, which are essential for developing and testing the facial recognition system. This empirical approach contributes to creating efficient automated attendance solutions for educational institutions.

3.3 Population and Sampling

3.3.1 Population

In this study, the population comprises attendees and organizers of events where the automated attendance recording tool will be implemented. The system's initial testing will be limited to this group due to the varied nature of event participants and the potential for diverse attendance scenarios, making it easier to implement and evaluate the system's performance.

3.3.2 Sampling

Facial recognition systems rely on sufficient and diverse data for effective training and evaluation. To achieve this, 80% of the collected data will be allocated for training, while the remaining 20% will be used for testing and validation. This division aligns with standard machine learning practices, ensuring the model generalizes well and performs accurately on new, unseen data. The dataset will include images captured in event settings with different lighting conditions and seating arrangements, providing a robust foundation for model training.

3.4 Data Collection Methods and Model Development

3.4.1 Data Collection

This study primarily relied on secondary data obtained from existing facial recognition datasets. Secondary data from publicly available facial datasets, more specifically the Labelled Faces in the Wild (LFW) dataset, provided a foundation for the system's initial training. Multiple images of each attendee was collected to account for various facial expressions, angles, and lighting conditions, improving the robustness of the facial recognition system.

3.4.2 Model Development

The model was built using convolutional neural networks (CNNs), a type of deep learning model particularly suited for image recognition tasks. The CNN was trained to recognize and classify faces by analysing the features of the images captured during event sessions. The data used for training the model included publicly available facial recognition datasets to ensure robustness. The model’s architecture was designed to handle a large volume of data and recognize faces from various angles and lighting conditions.

3.4.2.1 Data Pre-Processing

i). Feature selection

Feature selection focused on identifying the most relevant facial attributes for the recognition process. Facial landmarks such as eyes, nose, mouth, and jawline were used to build a feature map that the model can use to distinguish between individuals.

ii). Feature scaling

Feature scaling was applied to standardize the pixel values of the images. This ensured that the facial recognition model processed images of varying sizes and resolutions without bias. Techniques like normalization and standardization was used to ensure consistency in the input data.

iii). Data Cleaning

Data cleaning involved removing any images that are blurred, improperly lit, or contain incomplete facial information. Outliers and duplicates were eliminated to improve the model's accuracy. The data was annotated to include the correct identity labels for each image to ensure the accuracy of the training set.

3.4.2.2 Model Training

The facial recognition model was trained using the training dataset, which consisted of 80% of the collected facial images. The model employed CNN layers to extract features from the input images and use backpropagation to optimize the model's weights. The Adam optimizer was employed to minimize the loss function and improve accuracy. The training process involved multiple iterations, or epochs, during which the model refined its ability to accurately recognize and classify event attendee faces.

3.4.2.3 Model Testing and Evaluation

The model was tested using the remaining 20% of the dataset. During this phase, the model's ability to correctly identify event attendees and track their attendance was evaluated. Metrics such as accuracy, precision, recall, and F1 score was used to assess the model's performance. Confusion matrices were generated to identify any misclassifications or errors in the model's predictions. The system's overall success depended on achieving high accuracy and low error rates in real-time attendance tracking.

3.4.3 Data Analysis

The collected data was analysed using statistical methods and machine learning evaluation metrics. Confusion matrices were generated to assess the number of correctly and incorrectly identified participants. Additionally, the model's performance was evaluated across different event settings, including varying lighting conditions and seating arrangements, to ensure its robustness.

3.5 Research Quality and Reliability

The study implemented rigorous validation and verification procedures throughout the model training and testing phases to ensure high research quality. Cross-validation methods, including k-fold validation, was used to ensure consistent model performance across various data subsets. Reliability was upheld by thoroughly documenting each step of system development and ensuring that the dataset accurately represents the event attendees. Furthermore, conducting multiple tests in diverse event settings enhanced the model's generalizability and reliability.

3.6 Systems Development Methodology

This research adopted the Agile methodology for the development of the automated event attendance tool. Agile is an iterative, flexible, and customer-focused approach to project management and software development that will enable the team to deliver value incrementally, allowing for quick adjustments based on real-time feedback (Guerrero-Ulloa et al., 2023). The Agile methodology was particularly suitable for this research as it allowed for continuous communication and collaboration between the researcher and the supervisor, ensuring that the system meets user requirements while adapting to any challenges or improvements during the development process.

Agile methodology is centred around four core principles: individuals and interactions over processes and tools, working software over comprehensive documentation, customer collaboration over contract negotiation, and responding to change over following a plan (Agile Manifesto, 2001). These principles guided the system development phases, which was divided into multiple iterations or "sprints." The steps involved in the Agile methodology for this research project included:

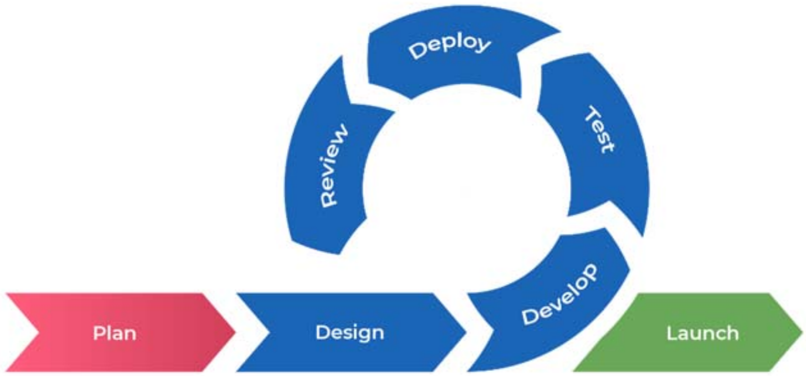

Figure 3.1: Agile Methodology (Martin, 2019)

3.6.1 Plan

In the planning phase, the researcher gathered the system requirements, including the features needed to automate attendance using facial recognition. The project's scope, timeline, and deliverables were defined in collaboration with the supervisor.

3.6.2 Design

The design phase focused on developing the architecture of the attendance system, including the front-end interface for users and the back end for facial recognition processing. Wireframes were created to map out the system's functionalities, while data flow diagrams helped illustrate how data is captured, processed, and stored.

3.6.3 Development

The development phase involves coding the facial recognition system using Python and machine learning frameworks like TensorFlow or Keras. The CNN model was integrated into the system to enable real-time attendance recording.

3.6.4 Testing

Each sprint included a testing phase where the system's functionality and accuracy are evaluated. Unit testing, integration testing, and user acceptance testing (UAT) were conducted to ensure that the system works as expected in real-world event environments.

3.6.5 Deployment

After successful testing, the Automated Event Attendance Recording Tool Using Facial Recognition will be deployed at selected events. The deployment phase will include the installation and configuration of the system, as well as training for event staff to ensure smooth operation and effective use.

3.6.6 Maintenance and Improvement

Post-deployment, the tool will undergo continuous monitoring and updates to ensure it remains effective and reliable. Any bugs or issues identified during use will be addressed in subsequent Agile sprints.

3.7 Utilization of Research Results

The tool developed from this research will be made available for testing and deployment in various event settings. Stakeholders, including event organizers and participants, will have the opportunity to provide feedback on the tool's functionality, which will help refine and improve its design and effectiveness. This collaborative approach ensures that the attendance recording system meets the practical needs of users while enhancing overall event management.

3.8 Dissemination of Research Results

The findings from this research will be shared through academic publications and presentations at conferences, ensuring that the results reach a broad audience within the academic and professional communities. The system's code and data will be made available in an open-source repository, allowing other researchers to build upon this work and contribute to further advancements in the field of event management and attendance tracking. Additionally, the findings will be communicated to policymakers and event organizers to highlight the potential benefits of using automated systems for attendance tracking, promoting more efficient and accurate event management practices.

3.9 Ethical Considerations and Issues

The use of biometric data such as facial images involves several ethical concerns. These include risks to individual privacy, potential misuse of sensitive information, and the challenge of ensuring informed consent. Additionally, facial recognition technologies may exhibit biases that can lead to unfair or discriminatory outcomes for certain groups. Such issues require careful consideration to ensure that biometric systems are deployed responsibly and ethically. Although this study did not involve primary data collection and relied solely on publicly available facial image datasets, these ethical issues were acknowledged. To address them, the research implemented strict data management practices including anonymization and encryption of data both at rest and in transit to prevent unauthorized access. The study protocol was reviewed and approved by Strathmore University's Institutional Review Board, ensuring adherence to ethical standards in biometric data research.

Chapter 4: System Analysis and Design

4.1 Introduction

The design and analysis of the automated attendance recording system aim to establish a robust foundation for implementing facial recognition technology in event settings. This chapter focuses on identifying and specifying the system's requirements, constructing its architecture, and crafting its design elements to meet the functional and operational goals of the system. The emphasis is on ensuring scalability, efficiency, and user-friendliness while leveraging advanced recognition algorithms and database management techniques. Key components of the system, such as the use case diagram, class diagram, sequence diagram, database schema, and wireframes, are systematically developed to ensure the system addresses real-world challenges in attendance management effectively.

4.2 Requirement Specifications

Requirement specifications are critical to defining the functionalities, constraints, and performance criteria of the automated attendance recording system. These requirements guide the development process to ensure that the system meets the needs of event organizers and attendees while addressing operational challenges.

4.2.1 Functional Requirements

The functional requirements describe the specific actions the system must perform. They include:

i). User Registration and Login: Allow event organizers and participants to register and log in to the system.

ii). Event Creation: Enable event organizers to create events, specifying event details such as name, date, and location.

iii). Facial Recognition for Attendance: Automatically record attendance using facial recognition technology.

iv). Real-Time Feedback: Provide event organizers with real-time updates on attendee status.

v). Report Generation: Generate attendance reports that can be exported for further analysis.

vi). Database Management: Maintain a secure database of attendee profiles and attendance records.

4.2.2 Non-Functional Requirements

The non-functional requirements specify system attributes such as:

i). Scalability: The system should handle large numbers of attendees without performance degradation.

ii). Security: Protect sensitive biometric data with encryption during storage and transmission.

iii). Usability: Provide an intuitive user interface for both organizers and participants.

iv). Performance: Ensure real-time attendance recording with minimal latency.

v). Compatibility: Operate seamlessly across devices, including desktops, laptops, and mobile platforms.

4.3 System Architecture

The system architecture is composed of multiple components that work together to enable attendance recording. These components include the Frontend, Camera, CNN Model API, and the Database. During events, the camera captures images and sends them to the CNN model for processing via the API. The model performs facial recognition and returns the recognition results. These results are then displayed to the user for review. Figure 4.1 shows the system architecture.

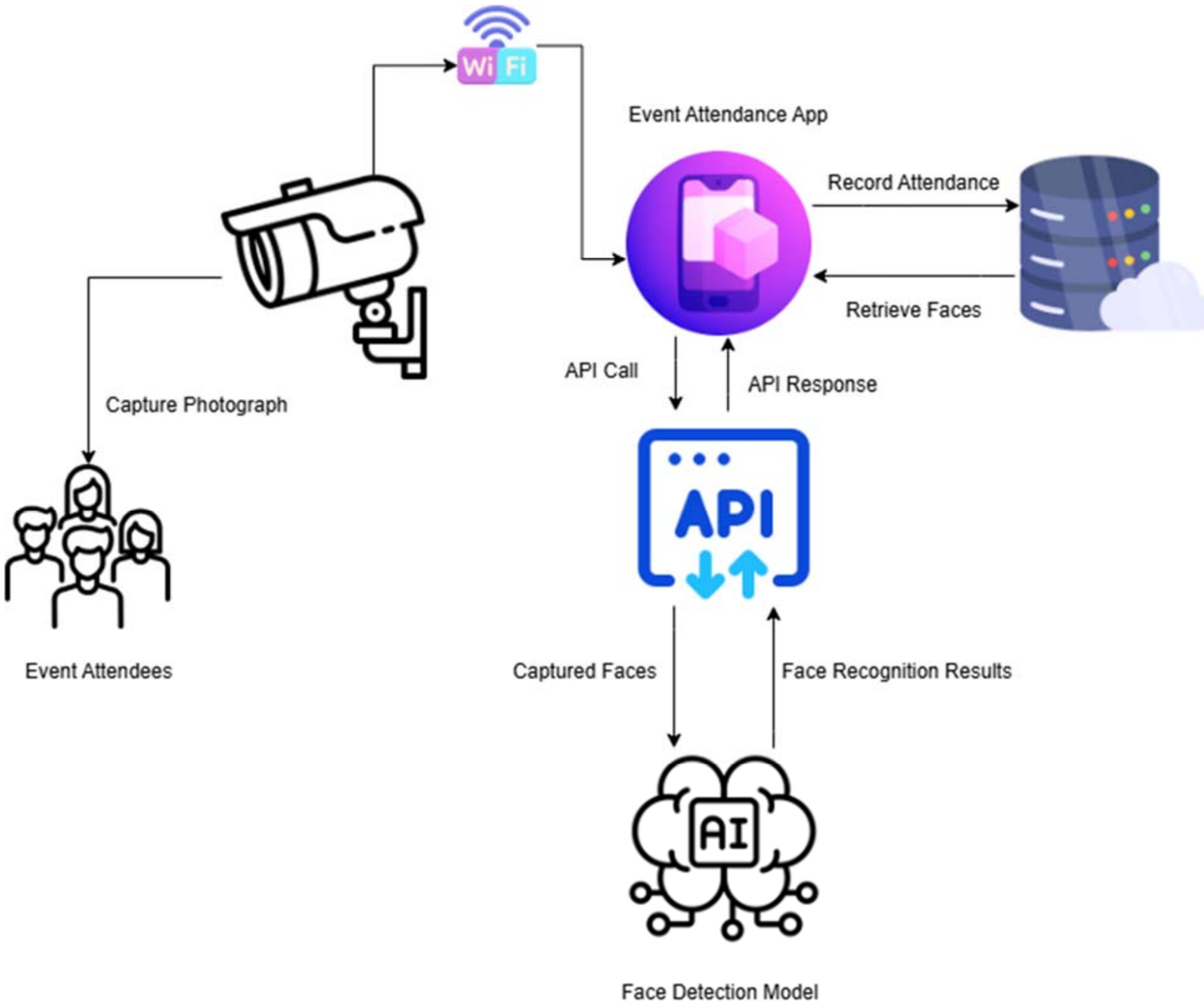

Figure 4.1: System Architecture

4.4 System Design

The design of the automated attendance recording system is based on Object-Oriented Analysis and Design (OOAD) principles, which ensure that the system is modular, scalable, and easy to maintain. OOAD is used to identify and model system components as interacting objects, encapsulating both data and behaviours. This approach allows for a clear representation of real-world entities such as users, events, and attendance records, ensuring that the system is both intuitive and extensible.

4.4.1 Use Case Diagram

The use case diagram represents the interactions between the users (event organizers and participants) and the system. It highlights key functionalities such as registration, event creation, and attendance recording. Each use case is derived from a functional requirement and provides a high-level view of the system's expected behaviour.

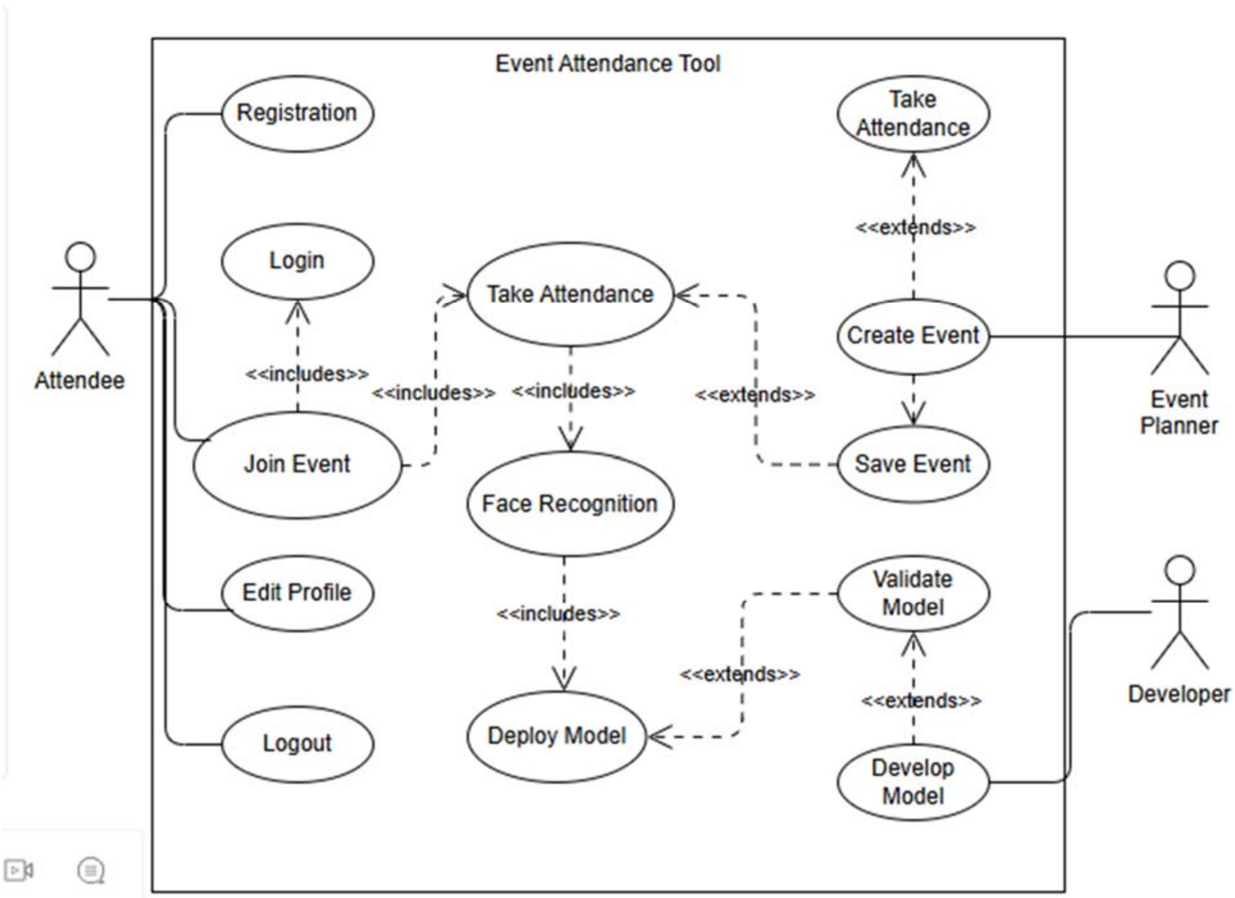

Figure 4.2: Use Case Diagram

3.9.1.1 4.4.1.1 Detailed Use Case Descriptions

Table 4.1 shows the detailed description of use cases in Figure 4.2

Table 4.1: Description of use cases

Use Case	Pre-Conditions	Main Success Scenario	Post Conditions
Register User	None	User provides valid registration details.	User account created.
Login	User is registered.	User enters valid credentials.	User is logged in.
Create Event	User is logged in.	Organizer enters event details.	Event is saved in DB.
Record Attendance	Event exists.	System captures and processes attendee faces.	Attendance is recorded.

4.4.2 Class Diagram

The class diagram captures the static structure of the system, illustrating the relationships between key objects, such as User, Event, Attendance, and Recognition. Each object encapsulates attributes and methods that define its behaviour and interaction with other objects.

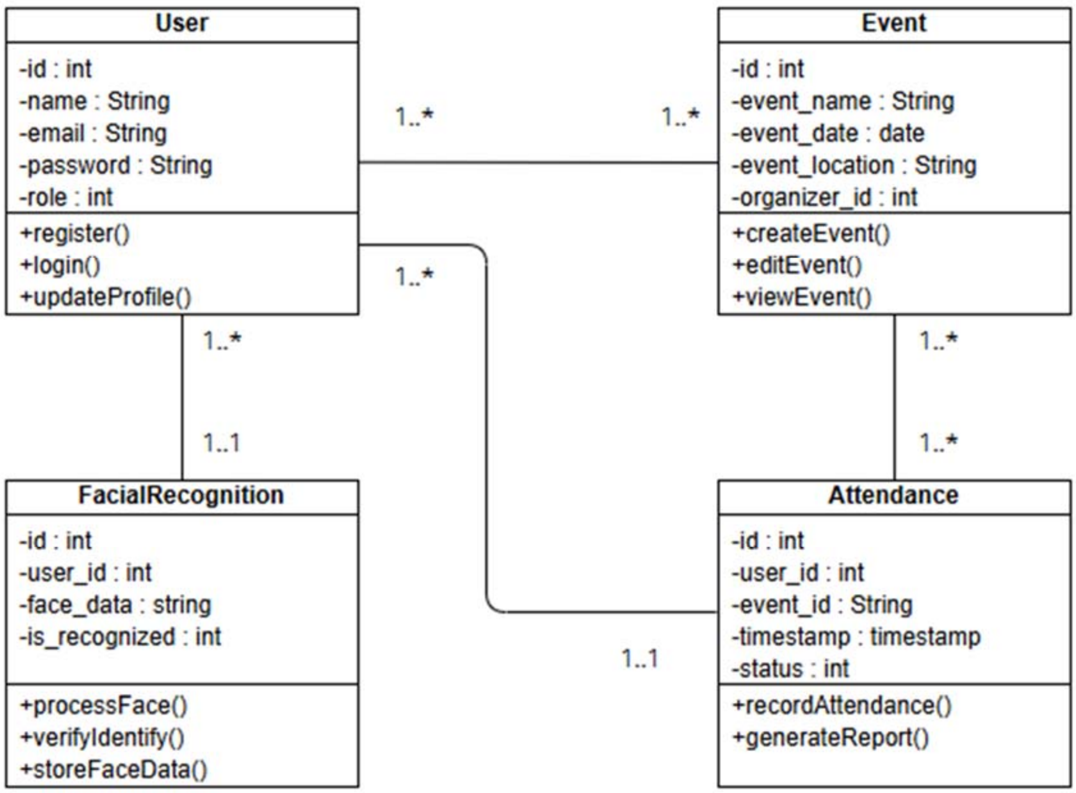

Figure 4.3: Class Diagram

4.4.3 Sequence Diagram

The sequence diagram models the dynamic behaviour of the system by showing the interaction between objects over time. It provides a detailed representation of the flow of actions for key processes, such as logging in and recording attendance.

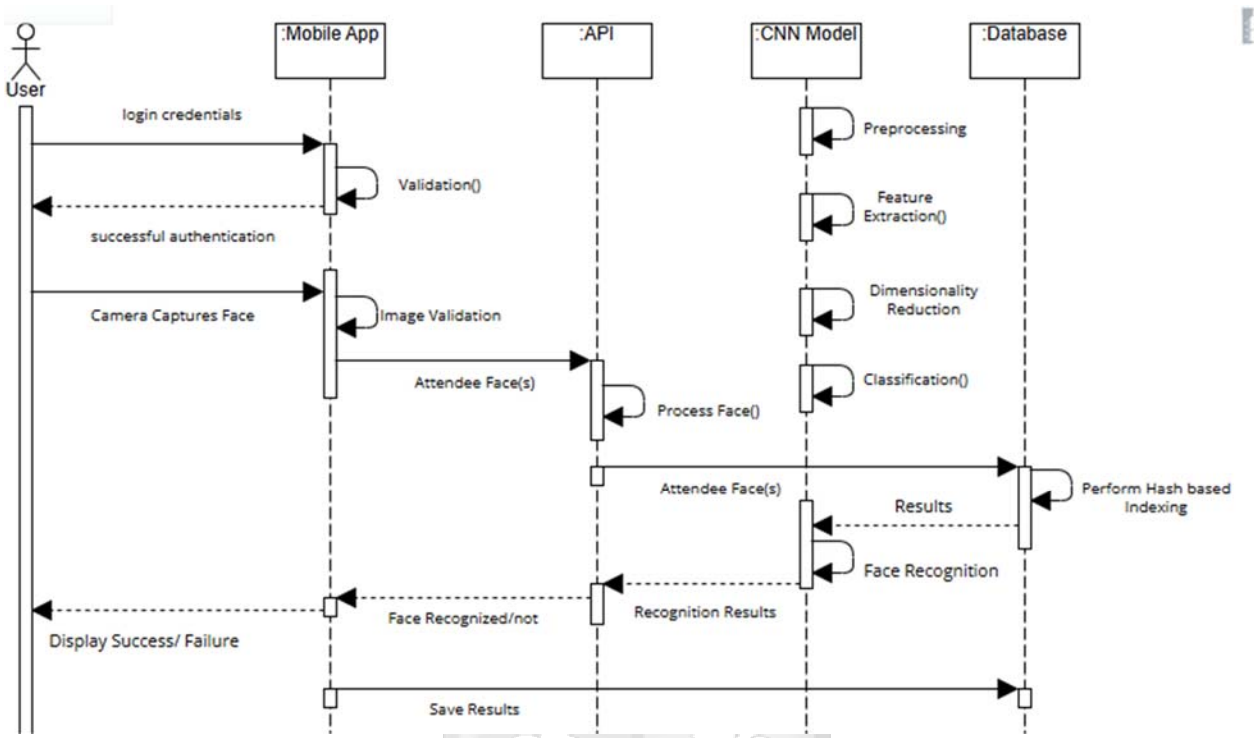

Figure 4.4: Sequence Diagram

4.4.4 Database Schema

The database schema is designed to align with the OOAD principles, with each table corresponding to a system class. For example, the User table maps directly to the User class, while relationships between tables reflect object associations, such as the link between Event and Attendance.

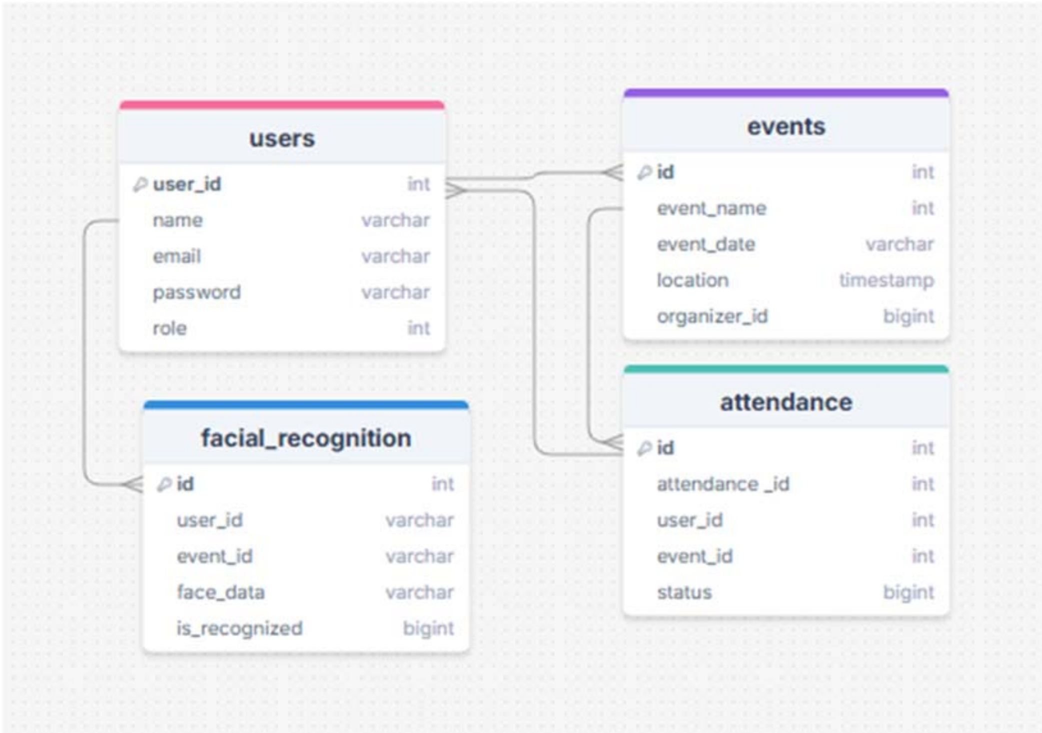

Figure 4.5: Database Schema

4.5 Wireframes

4.5.1 Home Page Wireframe

The home page wireframe provides an overview of the system, including options to log in or register.

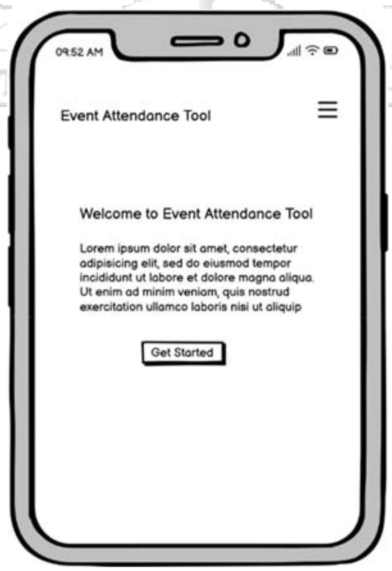

Figure 4.6: Home Page Wireframe

4.5.2 Login Wireframe

The login wireframe shows the interface for users to enter their credentials.

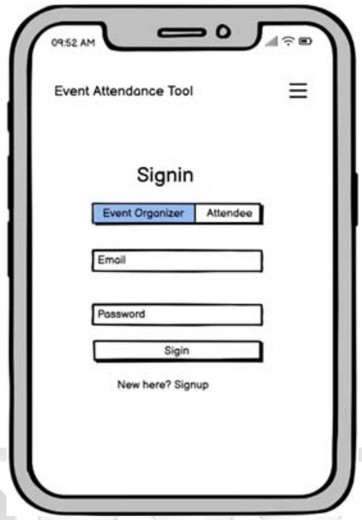

Figure 4.7: Login Wireframe

4.5.3 Register Wireframe

The register wireframe displays the form for new users to create an account.

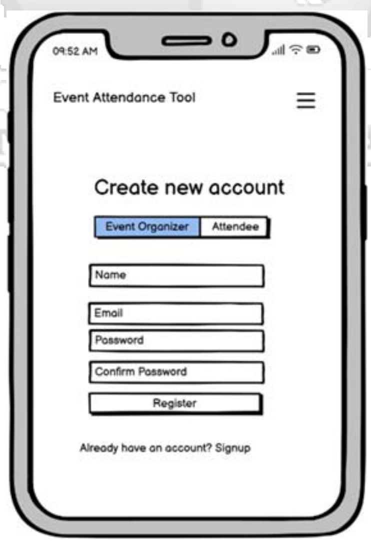

Figure 4.8: Register Wireframe

4.5.4 Attendance Recording Wireframe

The attendance recording wireframe highlights the process of capturing and processing attendee faces.

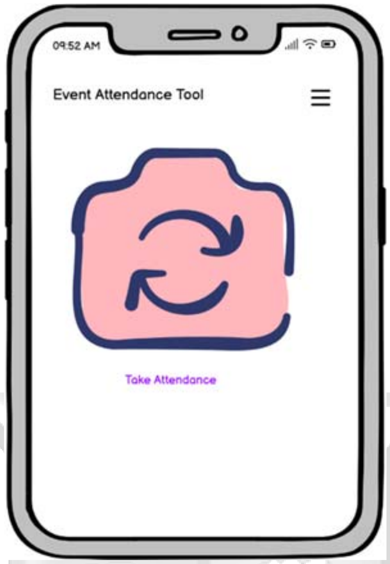

Figure 4.9: *Attendance Recording* Wireframe

4.5.5 Recorded Attendance Wireframe

The recorded attendance recording wireframe highlights the attendees present and absent.

Figure 4.9: *Attendance Recording* Wireframe

4.5.6 Add Event

The add event wireframe shows the interface for organizers to create new events.

Figure 4.10: *Add Event* Wireframe

Chapter 5: System Implementation and Testing

5.1 Introduction

The implementation and testing of the automated attendance recording system were carried out using a structured approach grounded in object-oriented principles and machine learning techniques. The implementation process focused on developing a robust CNN-based facial recognition model, integrating it with a user-friendly interface, and ensuring seamless functionality across the system. The system's key components, including its algorithms, interfaces, and APIs, were designed to provide an efficient solution for real-time attendance tracking. Testing was conducted to evaluate the system's performance, emphasizing accuracy, reliability, and usability. The system was rigorously validated to ensure it meets the functional and non-functional requirements established earlier in this research by leveraging a combination of pre-processed datasets and modern development tools.

5.2 Model Architecture

The Convolutional Neural Network (CNN) architecture was designed to effectively capture the spatial features unique to facial images, balancing model complexity and computational efficiency. The network begins with two convolutional layers, using 36 filters of size 7x7 and 54 filters of size 5x5 respectively, both followed by max pooling layers that reduce spatial dimensions and help extract salient features while controlling overfitting. ReLU activation functions introduce non-linearity, enabling the network to learn complex patterns.

After feature extraction, the model flattens the 2D outputs into a 1D vector, feeding into three fully connected dense layers with 2024, 1024, and 512 neurons respectively. Each dense layer is followed by a dropout layer with a dropout rate of 0.5, which helps prevent overfitting by randomly dropping neurons during training. The final output layer consists of 20 neurons with softmax activation, corresponding to the number of classes in the dataset. This architecture was selected to effectively learn distinguishing facial features while maintaining a manageable computational load, suitable for real-time attendance applications. The relatively large dense layers allow for complex decision boundaries, while dropout regularization addresses the risk of overfitting given the dataset size. The training data was carefully pre-processed to reflect conditions typical of event environments, including variations in lighting and facial poses, helping the model generalize better to real-world scenarios.

```
cnn_model = Sequential([  # Initializes a Sequential model, allowing layers to
    Conv2D(filters=36, kernel_size=7, activation='relu', input_shape=im_shape),
    MaxPooling2D(pool_size=2),  # Adds a max pooling layer to downsample the ir
    Conv2D(filters=54, kernel_size=5, activation='relu', input_shape=im_shape),
    MaxPooling2D(pool_size=2),  # Adds another max pooling layer to further rec
    Flatten(),  # Flattens the 2D output from the previous layer into a 1D vect
    Dense(2024, activation='relu'),  # Adds a fully connected (dense) layer wit
    Dropout(0.5),  # Adds a dropout layer with a 50% dropout rate to prevent ov
    Dense(1024, activation='relu'),  # Adds another dense layer with 1024 neurc
    Dropout(0.5),  # Adds another dropout layer with a 50% dropout rate for fur
    Dense(512, activation='relu'),  # Adds another dense layer with 512 neurons
    Dropout(0.5),  # Adds another dropout layer with a 50% dropout rate to redu
    Dense(20, activation='softmax')  # Adds the output layer with 20 neurons (r
])
```

Figure 5.1: CNN Model Architecture

5.2.1 Convolutional layers

The convolutional layers were responsible for detecting local features in the facial images, such as edges, textures, and shapes. These layers applied a set of learnable filters (also known as kernels) to the input images, performing convolution operations to extract relevant features.

In the model, two convolutional layers were used:

i). **First Convolutional Layer**: This layer had 36 filters with a kernel size of 7x7. It applied the ReLU (Rectified Linear Unit) activation function to introduce non-linearity into the model, allowing it to learn more complex features. The input shape for this layer was defined as (112, 92, 1), which corresponds to the resized grayscale images.

```
Conv2D(filters=36, kernel_size=7, activation='relu', input_shape=im_shape)
```

Figure 5.2: First Convolution Layer

ii). **Second Convolutional Layer**: This layer had 54 filters with a kernel size of 5x5 and also used the ReLU activation function. This layer further refined the feature extraction process by detecting higher-level features from the output of the first convolutional layer.

```
Conv2D(filters=54, kernel_size=5, activation='relu', input_shape=im_shape)
```

Figure 5.3: Second Convolution Layer

Both convolutional layers were followed by max-pooling layers to reduce the spatial dimensions of the feature maps.

5.2.2 Pooling layers

Pooling layers were used to reduce the dimensionality of the feature maps produced by the convolutional layers, while retaining important information. These layers helped to make the model more computationally efficient and less prone to overfitting.

i). **Max-Pooling Layers**: The pooling layers used a pool size of 2x2, meaning they selected the maximum value from a 2x2 region of the feature map. This down sampling operation helped to reduce the spatial size of the feature maps, making the network more efficient.

Each convolutional layer was followed by a max-pooling layer, which progressively reduced the size of the feature maps as the network deepened.

```
MaxPooling2D(pool_size=2)
```

Figure 5.4: Pooling Layer

5.2.3 Fully connected layers

Fully connected layers (also known as dense layers) were used to interpret the high-level features extracted by the convolutional and pooling layers. These layers are where the actual classification decision is made, based on the features that were learned during the convolutional steps.

i). First Fully Connected Layer: This layer had 2024 neurons and used the ReLU activation function to introduce non-linearity. It connected all the neurons from the previous layer (flattened feature maps).

```
Dense(2024, activation='relu')
```

Figure 5.5: First Connected Layer

ii). Second Fully Connected Layer: This layer had 1024 neurons, also using the ReLU activation function, to further process the learned features.

```
Dense(1024, activation='relu')
```

Figure 5.6: Second Connected Layer

iii). Third Fully Connected Layer: This layer had 512 neurons and was followed by another ReLU activation function.

```
Dense(512, activation='relu')
```

Figure 5.7: Third Fully Connected Layer

5.2.4 Output layer

The output layer was responsible for producing the final classification result. Since this model was designed for multi-class classification (recognizing 20 different individuals), the output layer had 20 neurons, each representing a different class. The output layer used the softmax activation function, which converted the raw output scores into probabilities that sum to 1, allowing the model to predict the identity of the individual with the highest probability.

```
Dense(20, activation='softmax')
```

Figure 5.8: Output Layer

5.2.5 Dropout layers

To prevent overfitting and ensure that the model generalized well to new data, dropout layers were added after each fully connected layer. The dropout layers randomly set a fraction (50%) of the input units to zero during training, forcing the model to learn redundant representations and improving its robustness. Each dropout layer had a dropout rate of 0.5, meaning that half of the neurons were randomly ignored during training. This regularization technique was effective in improving the model's ability to generalize and achieve higher accuracy on unseen data.

```
Dropout(0.5)
```

Figure 5.9: Dropout Layer

5.3 Event Attendance Recording Tool

The home interface serves as the main page of the attendance recording system. It provides access to various functionalities, such as adding new events, recording attendance, and exporting attendance reports.

5.3.1 Dashboard Interface

This interface allows event organizers to add attendees, and record attendance. The system automatically links the attendees to the attendance recording system, allowing participants to be marked based on face recognition.

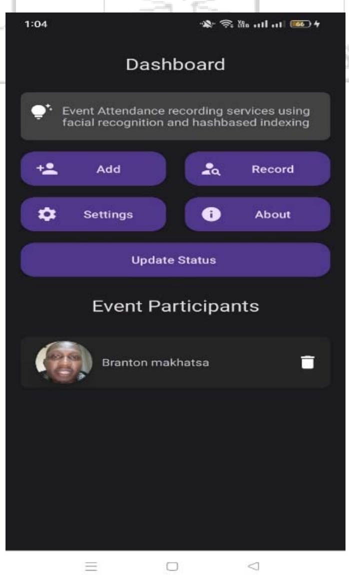

Figure 5.10: Home Page

5.3.2 Record Attendance Interface

This interface is used during the event to capture facial images of participants. The system processes the images using the facial recognition model to identify individuals and record their attendance in real-time.

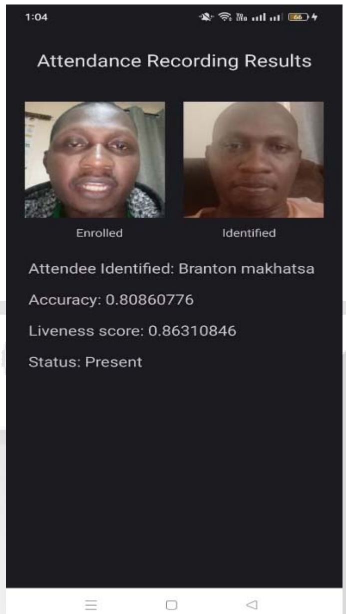

Figure 5.11: Record Attendance

5.3.3 Create Events Interface

This interface allows event organizers to create event prior to adding attendees to the events. It has three input fields for event name, location and date. Figure 5.12 below shows the interface.

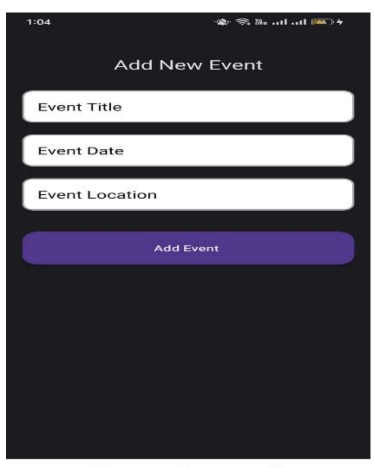

Figure 5.12 Add Event Interface

5.3.4 Event Listing Interface

This interface provides a list of current events. It allows organizers to manage the events by adding, removing, and deleting events. Figure 5.13 depicts event listing interface.

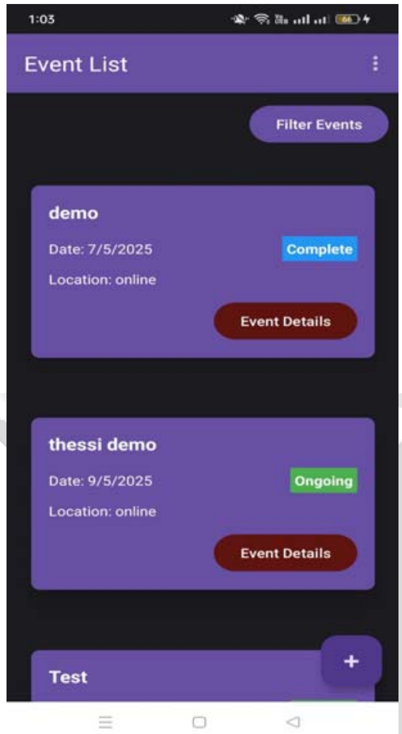

Figure 5.13 Event Listing Interface

5.3.5 Authentication Interfaces

The authentication screens allow users to create new accounts and access the system using the same credentials. Figure 5.14 and 5.15 below shows the authentication screens.

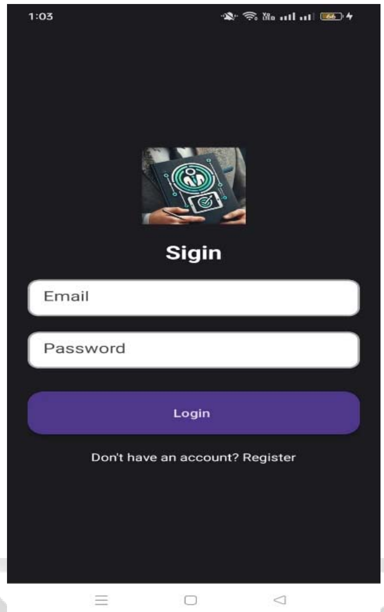

Figure 5.14: Login Interface

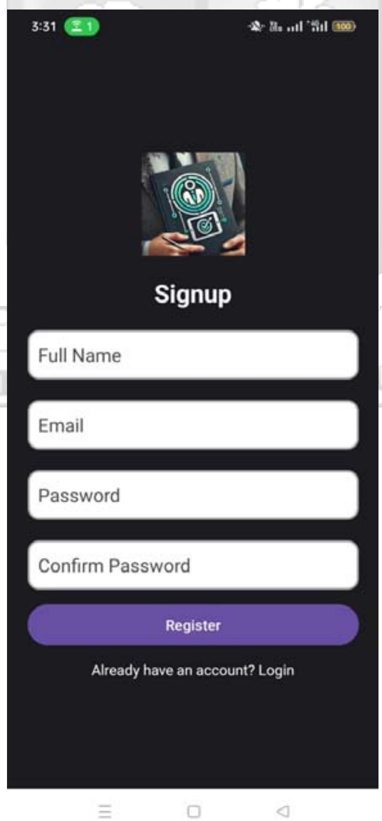

Figure 5.15: Register Interface

5.4 System Implementation

This section describes the development environment and the steps taken to implement the facial recognition model and attendance recording tool.

5.4.1 Development Environment

The system was developed using the following hardware and software components:

i). Python: Used for building the machine learning model and training the facial recognition algorithm.

ii). Windows Operating System: The development environment was set up on a Windows-based machine.

iii). Android Studio: Used for developing the mobile interface for attendance recording.

iv). Google Colab: Used for training the CNN model, leveraging the cloud-based GPU for efficient computation.

v). Flask: Used for API development, enabling communication between the model and the front-end interface.

5.4.2 Face Recognition Dataset Collection

The face recognition model uses the ORL (Oxford Robotics Lab) dataset, which contains facial images of 40 different individuals. Each individual has 10 images with variations in lighting, expression, and angle. The dataset was pre-processed and split into training, testing, and validation datasets.

5.4.3 Data Pre-processing

Data pre-processing played a crucial role in preparing the dataset for training the facial recognition model. This process involved several steps such as normalizing the images, splitting the dataset, and reshaping the data into a format compatible with the Convolutional Neural Network (CNN). Below are the key steps that were followed in pre-processing the dataset:

5.4.3.1 Loading the Dataset

The dataset was loaded from a .npz file, which contained both training and testing images, as well as their respective labels. The dataset included facial images of individuals, and these images needed to be normalized before being fed into the CNN for training. The trainX and testX contained the facial image data, and trainY and testY contained the corresponding labels (identifying each individual).

```
data = np.load(PATH + 'ORL_faces.npz')
x_train = data['trainX']
x_test = data['testX']
y_train = data['trainY']
y_test = data['testY']
```

Figure 5.15: Loading Dataset

5.4.3.2 Normalization of Images

The images in the dataset were originally in uint8 format, representing pixel values in the range [0, 255]. Since CNNs work more efficiently with floating-point numbers in the range [0, 1], the images were normalized by converting the pixel values to floating-point and scaling them by dividing by 255. This normalization step ensured that the input images had consistent intensity values, which improved the model's performance and convergence during training.

```
x_train = np.array(x_train, dtype='float32') / 255
x_test = np.array(x_test, dtype='float32') / 255
```

Figure 5.16: Normalization of Images

5.4.3.3 Splitting the Training Data

To improve the model's generalization and prevent overfitting, the training dataset (x_train and y_train) was further split into training and validation sets. This was done using the train_test_split function, which reserved 5% of the data for validation. The validation set was used to monitor the model's performance during training and helped in early stopping to avoid overfitting.

```
x_train, x_valid, y_train, y_valid= train_test_split(
    x_train, y_train, test_size=.05, random_state=1234,)
```

Figure 5.17: Splitting Data

5.4.3.4 Reshaping the Images

Since the CNN model expected input images to have a consistent size, all images were resized to the target dimensions of 112x92 pixels. Additionally, the images were reshaped to include a single-color channel (grayscale) as input, resulting in a shape of (112, 92, 1) for each image. This reshaping step ensured that the input data was compatible with the expected input format for the CNN architecture.

```
im_rows = 112
im_cols = 92
im_shape = (im_rows, im_cols, 1)

x_train = x_train.reshape(x_train.shape[0], *im_shape)
x_test = x_test.reshape(x_test.shape[0], *im_shape)
x_valid = x_valid.reshape(x_valid.shape[0], *im_shape)
```

Figure 5.18: Reshaping Images

5.4.3.5 Label Preparation

The labels (y_train, y_test, and y_valid) were in integer format, representing the individual identities in the dataset. These labels were used directly during training without any need for one-hot encoding, as the model used sparse categorical cross-entropy as the loss function, which accepts integer labels.


```
y_train = np.array(y_train)
y_test = np.array(y_test)
y_valid = np.array(y_valid)
```

Figure 5.19: Label Preparation

5.4.4 Training Model

The model was trained using the pre-processed dataset consisting of labelled facial images. Training employed the Adam optimizer with a learning rate of 0.0001 and the sparse categorical cross-entropy loss function, suitable for multi-class classification tasks. The process ran for 250 epochs with a batch size of 512, balancing computational efficiency and training stability. Model performance was monitored throughout via training and validation accuracy and loss metrics, allowing for early detection of overfitting or underfitting. Dropout layers with a rate of 0.5 were incorporated to reduce overfitting by randomly disabling neurons during training. The final hyperparameters, including learning rate, batch size, and number of epochs, were chosen based on iterative tuning to optimize model accuracy while maintaining reasonable training times.

```
history = cnn_model.fit(  # Trains the CNN model on the tra
    np.array(x_train),  # Converts the training features (x
    np.array(y_train),  # Converts the training labels (y_t
    batch_size=512,  # Specifies the number of samples per
    epochs=250,  # Defines the total number of training ite
    verbose=2,  # Controls the level of logging during trai
    validation_data=(np.array(x_valid), np.array(y_valid)),
)
```

Figure 5.20: Model Training

5.4.5 Flask API

The Flask API was developed to serve the trained model and integrate it with the front-end interface for attendance recording. The API enables real-time communication between the facial recognition model and the mobile application, ensuring that facial recognition results are processed and recorded efficiently.

```
from flask import Flask, request, jsonify
import numpy as np
from keras.models import load_model
from tensorflow.keras.preprocessing import image
import tensorflow as tf

# Initialize the Flask app
app = Flask(__name__)

# Load the pre-trained model (this assumes your model is saved as 'cnn_model.h5')
model = load_model('cnn_model.h5')
```

```python
# Preprocess the image before passing it to the model
def preprocess_image(img):
    # Resize and normalize the image to match the input shape of the model
    img = img.resize((92, 112))  # Match the input size of (112, 92, 1)
    img = np.array(img)
    img = np.expand_dims(img, axis=-1)  # Adding the channel dimension (grayscale)
    img = img.astype('float32') / 255  # Normalize
    img = np.expand_dims(img, axis=0)  # Add batch dimension
    return img
```

```python
# Endpoint to process the face detection
@app.route('/predict', methods=['POST'])
def predict():
    # Check if an image was provided
    if 'image' not in request.files:
        return jsonify({"error": "No image provided"}), 400

    # Get the image from the request
    img = request.files['image']

    # Convert image to a format that can be passed to the model
    img = image.load_img(img)
    img = preprocess_image(img)
```

```python
    # Make prediction using the model
    predictions = model.predict(img)
    predicted_class = np.argmax(predictions, axis=1)[0]
    predicted_prob = predictions[0][predicted_class]  #

    # Return the result as a JSON object
    return jsonify({
        'predicted_class': int(predicted_class),
        'predicted_prob': float(predicted_prob)
    })

# Run the Flask app
if __name__ == '__main__':
    app.run(debug=True)
```

Figure 5.21: API

5.4.6 Event Attendance Recording Tool

The event attendance recording tool integrates the trained model with the mobile applications. Once an event is created, the tool can automatically recognize participants' faces and record their attendance in real-time.

5.5 System Testing

System testing was conducted to evaluate the performance of the facial recognition model and the overall functionality of the attendance recording tool. The following sections provide details on the testing conducted.

5.5.1 Test on Model Performance

5.2.1.1 Model Accuracy

The model's accuracy was evaluated using the test dataset. The results showed that the model achieved an accuracy of 95% in recognizing faces, with the confusion matrix and classification report used to further analyse the model's performance.

```
test loss 0.2689
test accuracy 0.9563
```

Figure 5.22: Model Evaluation

5.2.1.2 ROC Curve

The Receiver Operating Characteristic (ROC) curve was used to evaluate the classification model’s ability to distinguish between positive (correct face recognition) and negative cases. The ROC curve plots the False Positive Rate (FPR) on the x-axis against the True Positive Rate (TPR) on the y-axis. In Figure 5.23, the orange line represents the ROC curve for the model, which closely follows the top-left corner of the plot. This indicates that the model achieves high sensitivity while maintaining a very low false positive rate. The diagonal dashed line serves as a baseline representing random guessing. The Area Under the Curve (AUC) for this ROC is **1.00**, the best possible score, indicating the model perfectly differentiates between recognized and unrecognized faces. This near-perfect ROC performance reinforces the model’s robustness and accuracy, demonstrating excellent classification capabilities under both test and simulated deployment conditions.

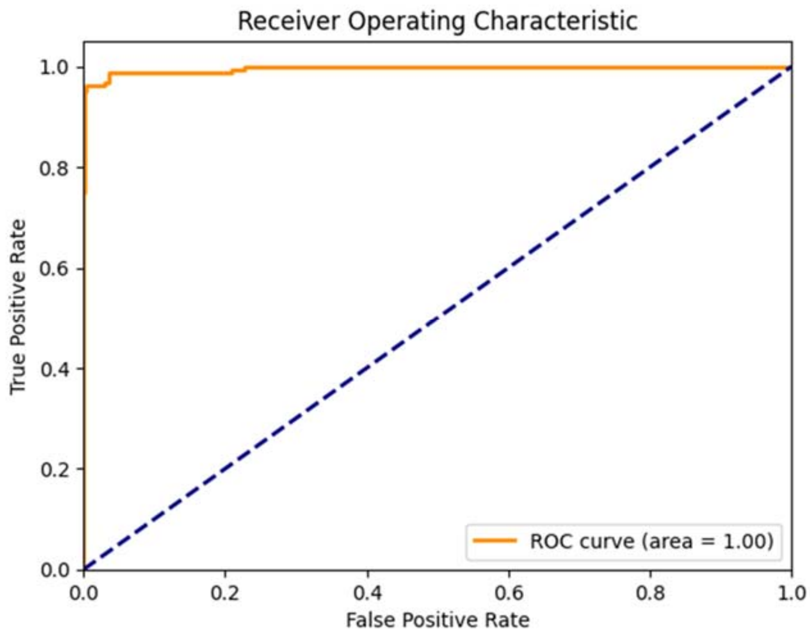

Figure 5.23: ROC Curve

5.5.1.3 Model Loss and Model Accuracy

The model's training progress was monitored using loss and accuracy plots for both training and test datasets over 250 epochs. Both training and test loss values started relatively high and steadily decreased as training progressed. Notably, the test loss declined slightly faster than the training loss during the initial epochs. After about 150 epochs, both losses stabilized and levelled off close to zero. While the training loss curve exhibited some fluctuations, the overall trend was smooth and downward. This pattern indicates that the model is learning effectively without signs of overfitting, as the test loss does not diverge from the training loss but follows a similar decreasing trend.

Training and test accuracy both began near zero and steadily increased throughout the training process. The test accuracy improved more rapidly in the early epochs, reaching 100% accuracy before the training accuracy. The training accuracy then caught up, stabilizing at 100% after approximately 150 epochs. Although the test accuracy showed minor fluctuations during later epochs, it consistently remained at or near 100%. This suggests the model generalizes well to unseen data, maintaining high prediction accuracy outside the training set.

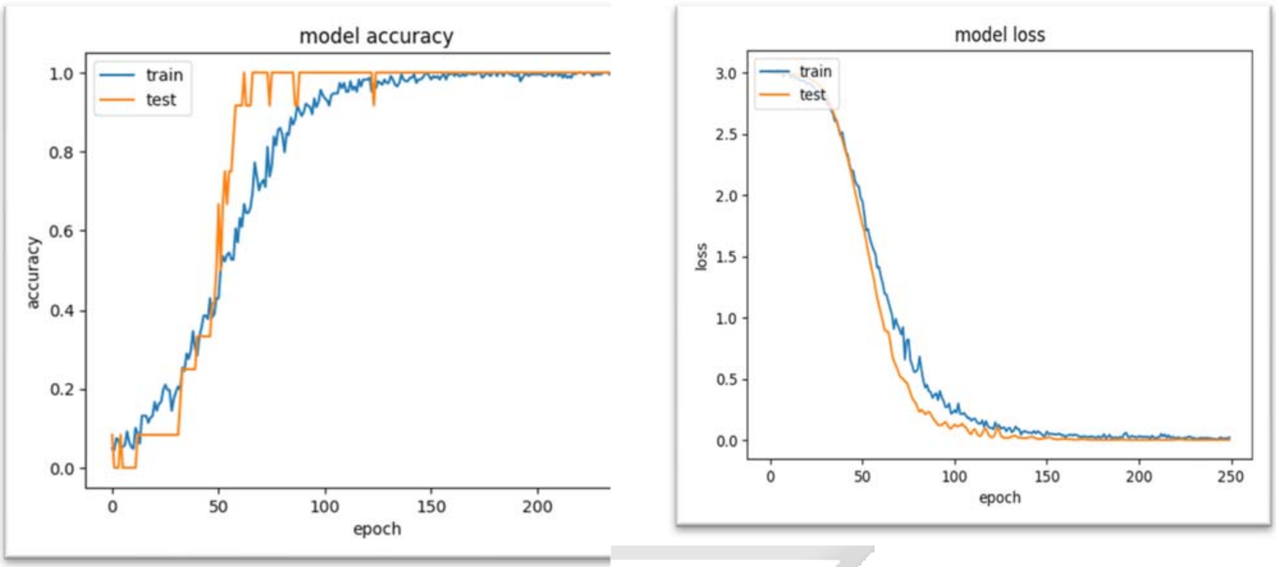

Figure 5.24 Training Accuracy and Loss

Chapter 6: Discussions

6.1 Introduction

The system developed in this study integrates modern computer vision techniques, particularly Convolutional Neural Networks (CNN), to identify individuals and record their attendance with minimal human intervention. Despite the advancements in machine learning and facial recognition, numerous technical and practical challenges arise when implementing such a system in real-world scenarios. This chapter discusses the challenges encountered during the system's implementation, the comparison with existing algorithms, the integration of the attendance recording tool with a mobile app, and the testing phase that ensured the system's functionality and accuracy. By examining these aspects, we gain insight into the limitations and strengths of the proposed system and its potential for future improvements.

6.2 Review of Study Objectives

The research set out to address four objectives within the duration of the research. The research aimed to analyse the challenges faced in the implementation of automated attendance recording systems. It reviewed existing algorithms, models, and frameworks used for attendance recording. The study successfully developed an automated attendance system that utilized facial recognition technology and Hash-Based Indexing. Finally, the developed system was thoroughly tested. All the objectives of the research were successfully achieved, providing valuable insights into the implementation and effectiveness of automated attendance systems.

6.2.1 Challenges Faced in Implementation of Automated Attendance Recording Systems

Implementing automated attendance recording systems, especially those relying on biometric and sensor-based technologies, presents numerous challenges. These challenges are often tied to the technological infrastructure, scalability, environmental factors, and user acceptance. Various methods, including facial recognition, fingerprint scanning, iris recognition, and RFID-based systems, come with inherent limitations that impact their deployment in real-world environments. Facial recognition technology, for example, is widely used for its contactless and hygienic nature, which is particularly advantageous in settings that require health and safety considerations. However, it is not without limitations. Variations in lighting, extreme facial angles, and the presence of accessories like glasses or masks can impede system accuracy (Singh & Prasad, 2018). In large-scale implementations, the computational demands for real-time processing of facial data can lead to delays, affecting the efficiency of attendance recording (Sultan et al., 2022). Moreover, facial recognition systems can struggle in less controlled environments, particularly when dealing with large databases or crowded spaces. Fingerprint recognition systems are another commonly used method, known for their high accuracy and cost-effectiveness in controlled environments. However, they require direct physical contact, which raises hygiene concerns, especially during health crises (Islam, 2017). Additionally, fingerprint systems are prone to failure in cases of damaged, wet, or dirty fingers, leading to errors in identification (Bhattacharya et al., 2018). Furthermore, while effective for small-scale implementations, fingerprint systems lack scalability for large environments where contactless methods may be preferred. Iris recognition, while offering high accuracy, is limited by the need for specialized equipment and controlled conditions, making it impractical for widespread use in settings like educational institutions (Sutabri et al., 2019). Similarly, RFID-based systems, although quick and cost-effective, face security concerns such as proxy attendance and system vulnerability to card theft or sharing (Samet, 2017). The operational costs related to maintaining RFID readers and ensuring functionality further add to the complexity of these systems.

6.2.2 Existing Algorithms, Models, and Frameworks Used for Attendance Recording

The success of automated attendance systems depends heavily on the choice of algorithms and models used for facial recognition or identification. Several approaches are commonly used, each with its own strengths and weaknesses. Convolutional Neural Networks (CNNs) are widely regarded as one of the most effective models for facial recognition. CNNs leverage multiple layers of convolutional filters to detect hierarchical features like edges, textures, and shapes (Zhou et al., 2020). These networks excel in identifying facial features and can achieve high accuracy, particularly in well-lit environments with high-quality data. However, CNNs require large datasets for training and significant computational power, which can pose challenges in resource-constrained environments (Raghuwanshi & Swami, 2017). Another frequently used model is Principal Component Analysis (PCA), a statistical technique that reduces the dimensionality of facial data while preserving the most critical features for identification (Chintalapati & Raghunadh, 2013). PCA is computationally efficient and suitable for systems with limited resources. However, its performance can be negatively affected by variations in lighting, facial expressions, and pose, which are common in real-world scenarios (Mehta & Tomar, 2016). Additionally, PCA assumes that the most significant features in facial data are always relevant for recognition, which is not always the case. Local Binary Patterns (LBP) is another texture-based approach commonly used in facial recognition systems. LBP is particularly effective in environments with varying lighting conditions, as it is robust to monotonic lighting changes (Chintalapati & Raghunadh, 2013). However, LBP's reliance on local textures makes it sensitive to occlusions, such as when a person's face is partially obscured by accessories or hair. In more dynamic or complex environments, LBP may struggle to deliver accurate results on its own and is often combined with other methods, like PCA, to improve performance (Mehta & Tomar, 2016). Hybrid models that combine multiple techniques, such as PCA and LBP, offer a balance between computational efficiency and recognition accuracy. These models aim to address the limitations of individual techniques, but their complexity and computational cost can be a barrier for institutions with limited resources (Hasan & Ahmad, 2015). To implement these models, frameworks like TensorFlow, Keras, and PyTorch are commonly used. TensorFlow, in particular, is popular for its scalability and flexibility, allowing developers to create complex CNN models (Zhou et al., 2020). However, TensorFlow can be difficult to debug, and its computational requirements may make it unsuitable for smaller projects or institutions with limited technical infrastructure. Keras, built on top of TensorFlow, offers a more user-friendly interface for rapid model development but sacrifices some of the advanced control available in TensorFlow (Mehta & Tomar, 2016). PyTorch, on the other hand, is favoured for research due to its dynamic computation graph, making it easier to experiment with different model architectures (Sunaryono et al., 2019). However, PyTorch may not be as well-suited for production environments compared to TensorFlow.

6.2.3 Automated Attendance Recording Tool

The development of an automated attendance recording tool involves the integration of several advanced technologies to ensure high accuracy, reliability, and scalability. The tool developed for this study uses facial recognition technology powered by Convolutional Neural Networks (CNNs) to identify and record individuals' attendance in real time. The process begins with capturing facial images via a camera, which are then processed by the CNN to extract distinguishing facial features. These features are matched against a pre-existing database of registered individuals to determine attendance. To enhance the system's efficiency and performance, the tool employs Hash-Based Indexing. Hash-based indexing is used to speed up the process of facial image retrieval, making it possible to quickly match an individual's features to the stored database without having to compare the input image against every single entry. This technique involves creating a hash value, or a unique digital signature, for each facial feature extracted from the database images. When a new facial image is captured, the system generates a hash of the features and uses the indexing mechanism to quickly locate potential matches, significantly reducing the time spent on facial recognition processing. This combination of CNNs and hash-based indexing offers a highly efficient and scalable solution for automated attendance systems, particularly in environments where large numbers of individuals need to be processed, such as classrooms, corporate offices, or events with high foot traffic. Hash-based indexing minimizes the time required for facial feature matching, allowing the system to handle large datasets without significant delays. Furthermore, the mobile app, which integrates the facial recognition tool, is designed to provide real-time feedback on whether an individual has been recognized. This mobile app is essential for providing a user-friendly interface that allows quick and seamless attendance recording. The system is capable of operating effectively under varying environmental conditions, adjusting image processing algorithms based on the quality of the captured images. This ensures that the system remains reliable even in challenging scenarios, such as low-light environments or crowded spaces. Despite these technological advantages, challenges related to optimizing real-time processing and ensuring that the mobile app can handle the computational load still exist. The inclusion of hash-based indexing, however, significantly improves the system's ability to perform under these demands. The tool was tested extensively to ensure robustness, minimizing false positives and negatives, and ensuring the tool is efficient in a variety of operational settings. Ultimately, this approach provides a scalable, accurate, and efficient solution for automated attendance recording that can be easily implemented in diverse environments.

6.2.4 Model and System Testing

Testing of both the facial recognition model and the automated attendance system is crucial to ensure that the system performs accurately and efficiently in real-world conditions. The model was first trained using a dataset of facial images, ensuring that it could correctly identify individuals under varying conditions, including different facial expressions, lighting scenarios, and angles. During testing, the model was evaluated for accuracy, precision, and recall, with performance metrics such as false positives and false negatives being closely monitored. The system's real-time processing capabilities were also tested under different environmental conditions, including events with varying lighting and crowded areas. Testing was conducted in both controlled to assess the robustness of the system in real-life settings. The mobile app was evaluated for its ability to capture images and process them promptly, ensuring that attendance could be recorded without delays or errors. In addition to accuracy testing, the system was also subjected to stress testing to determine how it handled large databases and high volumes of data. This was particularly important to ensure that the system could scale effectively in environments like large university campuses or corporate offices. Results from these tests indicated that the system could handle up to a certain threshold of simultaneous users without a significant loss in performance. Ultimately, the testing phase highlighted key areas for improvement, particularly in terms of accuracy in low-light conditions and the ability to handle diverse environmental factors. These insights were used to refine the model and optimize the system for better reliability and efficiency. With ongoing testing and refinement, the system is expected to meet the high standards required for large-scale implementation.

Chapter 7: Conclusion and Recommendation

7.1 Conclusion

The development of an automated attendance recording system for events has been successfully implemented, leveraging the power of facial recognition technology to streamline the process. By using Convolutional Neural Networks (CNNs), the system effectively identifies individuals, ensuring accurate and efficient attendance tracking. The integration of Hash Based Indexing has significantly improved the system's scalability, allowing for faster searching and matching of facial data across large datasets. This enhancement reduces computational load, ensuring that the system can handle real-time processing even in high-volume event settings. The facial recognition model, coupled with a user-friendly mobile application interface, provides an efficient tool for organizers, improving the overall event experience. This automated system offers several advantages over traditional methods, including ease of use, speed, and accuracy, while minimizing errors such as proxy attendance. However, challenges such as variable lighting and facial occlusions remain, which may affect the system's performance. Despite these limitations, the system shows great promise for event attendance management and offers a more reliable alternative to manual tracking systems.

7.2 Recommendations

To ensure the effective utilization of the automated attendance recording tool, both users and policymakers must consider the following practical recommendations:

i). Event organizers should prioritize the use of contactless attendance systems, such as facial recognition, to improve efficiency and ensure hygiene during events. These systems eliminate the need for physical interaction, streamline the check-in process, and reduce errors associated with manual methods.

ii). Stakeholders must ensure that robust data encryption, anonymization, and secure storage protocols are in place to protect attendee data. Compliance with data privacy regulations, such as GDPR, is essential to build trust and safeguard personal information collected during events.

iii). Event organizers should select attendance systems capable of scaling to handle large events with diverse attendee profiles. Solutions that incorporate features like hash-based indexing can manage large datasets efficiently and ensure real-time processing under high traffic.

iv). Stakeholders should leverage the system's analytics capabilities to gain actionable insights into attendee behaviour, such as peak attendance times and engagement levels. This data can inform decision-making for future event planning and improve overall event management strategies.

7.3 Future work

While this research has provided valuable insights and contributions, there are several areas for future exploration and improvement in automated event attendance recording systems.

i). Further studies should assess the adaptability of the system in different event environments, from conferences to outdoor gatherings, to determine how the system performs across various lighting and spatial conditions.

ii). Future studies should consider Integrating multi-modal authentication (e.g., facial recognition combined with NFC or QR codes) which would improve the system's security and help prevent proxy attendance.

7.4 Limitations

The current research, while promising, faced several limitations.

i). Lighting Sensitivity: The system's performance may be compromised in environments with poor or fluctuating lighting conditions, which is common in large events.

ii). Hardware Limitations: The requirement for high computational power limits the real-time processing capability of the system, especially in large-scale events with vast databases.

iii). Data Privacy: There are concerns regarding the ethical and legal implications of collecting and storing facial recognition data, especially in public events.

iv). Scalability in High-Traffic Events: While the system performed well in smaller-scale tests, handling extremely high attendee volumes may cause delays in processing, which could hinder its effectiveness in mega-events like concerts or festivals.

7.5 Research Contribution

This research offers several key contributions to the field of automated attendance recording systems, particularly for event-based scenarios. The primary contribution lies in the development of an efficient, scalable system for attendance tracking that uses facial recognition technology. Through the integration of Convolutional Neural Networks (CNNs), the system achieves high accuracy in recognizing individuals and recording their attendance in real time. This approach represents a significant step forward in automating event attendance, reducing the need for manual tracking and mitigating issues such as proxy attendance and human error. A key aspect of this research is the introduction and utilization of Hash-Based Indexing to enhance the performance and scalability of the facial recognition system. Hash-Based Indexing enables rapid searching and matching of facial data across large datasets, which is crucial in environments with high volumes of attendees. By reducing the computational load during the facial recognition process, this technique significantly improves the efficiency of real-time attendance recording, ensuring that the system can function smoothly even in large-scale events. This innovation is particularly valuable for environments where quick processing of data is essential, such as conferences, concerts, and seminars, where large crowds gather and need to be managed efficiently. Additionally, this research contributes to the integration of a mobile application interface that simplifies the attendance recording process for event organizers. The mobile app is designed to be user-friendly, allowing organizers to easily capture images, verify attendees, and manage the event in real time. The app also serves as a powerful tool for tracking attendance, generating reports, and ensuring that the system is accessible to a wider range of users without requiring technical expertise. The combination of a robust back-end system and an intuitive front-end mobile interface makes this tool highly effective in managing attendance at events. Furthermore, the research addresses practical concerns in the implementation of such systems, particularly around lighting conditions and facial occlusions (e.g., sunglasses or masks). While challenges remain, the work provides valuable insights into optimizing system performance under variable conditions and paves the way for further research on improving facial recognition accuracy in real-world settings. The research also makes a significant contribution by presenting a comprehensive framework for system development, testing, and evaluation. The detailed steps taken in model training, data pre-processing, and API development offer a roadmap for future implementations of similar systems.

The integration of real-time facial recognition with event management systems could serve as a foundation for future advancements in automated attendance systems across various domains, such as corporate settings, educational institutions, and public events. Finally, the study emphasizes the practical feasibility of deploying facial recognition systems at scale, offering practical solutions to existing barriers such as computational load, lighting variability, and system integration. As such, this research lays the groundwork for future innovations in automated attendance systems and contributes to the broader field of biometrics and computer vision.

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Appendices

Appendix A: Similarity report

Automated Event Attendance Recording Tool Using Facial Recognition.pdf

ORIGINALITY REPORT

14%	12%	11%	10%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	Submitted to Strathmore University Student Paper	3%
2	eitca.org Internet Source	2%
3	su-plus.strathmore.edu Internet Source	1%
4	Submitted to Swinburne University of Technology Student Paper	<1%
5	Rahaf Adam Alnuaimi, Ranem Khaled Almasalmeh, Sarah Adel Baker, Maryam Nasser Alsaiaari, Moatsum Alawida. "Twajood: Two-Factor Authentication Based on Distance and Face Recognition for Secure and Efficient Employee Attendance Monitoring", 2023 5th International Congress on Human-Computer Interaction, Optimization and Robotic Applications (HORA), 2023 Publication	<1%
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Appendix B: Strathmore University Institutional Ethics Review Clearance Certificate

Strathmore
UNIVERSITY

4th February 2025

Mr Makhatsa Branton,
branton.makhatsa@strathmore.edu

Dear Mr Makhatsa,

<u>RE: Automated Event Attendance Recording Tool Using Facial Recognition</u>

This is to inform you that SU-ISERC has reviewed and **approved** your above **SU-masters** proposal. Your application reference number is **SU-ISERC2607/25.** The approval period is from **4th February 2025 to 3rd February 2026.**

This approval is subject to compliance with the following requirements:

i. Only approved documents including (informed consents, study instruments, MTA) will be used.
ii. All changes including (amendments, deviations, and violations) are submitted for review and approval by SU-ISERC.
iii. Death and life-threatening problems and serious adverse events or unexpected adverse events whether related or unrelated to the study must be reported to SU-ISERC within 72 hours of notification.
iv. Any changes anticipated or otherwise that may increase the risks or affected safety or welfare of study participants and others or affect the integrity of the research must be reported to SU-ISERC within 72 hours.
v. Clearance for the export of biological specimens must be obtained from relevant institutions.
vi. Submission of a request for renewal of approval at least 60 days prior to the expiry of the approval period. Attach a comprehensive progress report to support the renewal.
vii. Submission of an executive summary report within 90 days of completion of the study to SU-ISERC.

Before commencing your study, you will be expected to obtain a research license from National Commission for Science, Technology, and Innovation (NACOSTI) https://research-portal.nacosti.go.ke/ and obtain other clearances needed.

Yours sincerely,

Mr Ambrose Rachier,
Chairperson; SU-ISERC

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