Advanced Attendance Management System Integrating Face Recognition and GPS-Based Tracking

A Major project report submitted by

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in

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Under the Guidance of

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CERTIFICATE

This is to certify that the project entitled **"Advanced Attendance Management System Integrating Face Recognition and GPS-Based Tracking"** being submitted by Student Nishith Sai Sesha Kumar Kotha (211FA18112), Shaik Siraj (211FA18101) in partial fulfilment of Bachelor of Technology in Artificial Intelligence and Machine Learning, Department of Advanced Computer Science and Engineering, Vignan's Foundation For Science Technology and Research (Deemed to be University), Vadlamudi, Guntur District, Andhra Pradesh, India, is a bonafide work carried out by them under my guidance and supervision.

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DECLARATION

We hereby declare that our project work described in the project titled **"Advanced Attendance Management System Integrating Face Recognition and GPS-Based Tracking"** which is being submitted by us for the partial fulfilment in the department of ACSE, Vignan's Foundation for Science, Technology and Research (Deemed to be University), Vadlamudi, Guntur, Andhra Pradesh, and the result of investigations are carried out by us under the guidance of **Mr. Amar Jukuntla**.

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ABSTRACT

In this research, an advanced Attendance Management System is developed by integrating face recognition with GPS-based location tracking to ensure secure and efficient attendance monitoring. Traditional attendance methods often face challenges related to accuracy, security, and manual effort, making automation a necessary solution. To address these limitations, an Android-based mobile application is designed to facilitate seamless attendance tracking. The system utilizes TensorFlow Lite for real-time facial feature extraction and matching, ensuring efficient performance on mobile devices. Students use the application to capture their face images along with real-time location data, which is then transmitted to a server for verification and authentication. The system ensures that attendance is marked only when users are present at the designated location, preventing fraudulent entries. Experimental evaluations demonstrate that the research work achieves high accuracy, fast processing times, and reliable performance. The solution is well-suited for educational institutions, corporate environments, and other organizations requiring an automated, secure, and scalable attendance management system. This study explores potential applications and outlines future enhancements to further optimize functionality and usability.

Key Words: Attendance Management, Facial Recognition, MobileFaceNet, Geofencing, Firebase Authentication,On-Device Verification, Biometric Security, Smart Attendance System, Single-Device Authentication,Polygonal Geofence,Secure Access Control.

Contents

List of Figures

List of Tables

List of Acronyms/Abbreviations

2D	Two Dimensional
3D	Three Dimensional
AES	Advanced Encryption Standard
API	Application Programming Interface
CNN	Convolutional Neural Network
GPS	Global Positioning System
GUI	Graphical User Interface
LBPH	Local Binary Pattern Histogram
LDA	Linear Discriminant Analysis
ML	Machine Learning
MLKit	Machine Learning Kit (Firebase)
MTCNN	Multi-Task Cascaded Convolutional Network
PCA	Principal Component Analysis
RTDB	Realtime Database
TFLite	TensorFlow Lite
UI	User Interface
UX	User Experience

List of Symbols

$\vec{x}$	GPS coordinate of the user $(latitude, longitude)$
P	Polygon formed by geofence boundaries
I	Input face image
$f(I)$	Embedding vector extracted from face image I
d	Distance metric for face verification
θ	Threshold for face similarity
T	Timestamp of attendance record

Chapter 1

Introduction

This chapter provides a brief description of the technological evolution of attendance systems, the relevance of combining geolocation and facial recognition, the motivation for this project, and a clear problem statement to address the existing limitations in conventional systems.

1.1 Background

Attendance tracking is a foundational element in educational institutions and organizations to ensure discipline, productivity, and accountability. Traditional methods such as manual registers or RFID cards are prone to manipulation, proxy attendance, and human errors. With the growth of ubiquitous mobile computing, GPS-enabled devices, and advancements in artificial intelligence, particularly in computer vision, modern techniques have emerged that offer greater automation and accuracy.

The concept of geofencing leverages GPS coordinates to define a virtual perimeter around a physical location. When combined with real-time face recognition systems, it enables location-restricted identity verification, ensuring that users are both physically present and biometrically authenticated before marking attendance.

This integration ensures higher security, reduced administrative burden, and more trustworthy attendance data. Recent studies such as [6] have shown that incorporating multi-modal verification systems significantly improves reliability and user compliance.

1.2 Motivation

The primary motivation behind this research is the widespread issue of proxy attendance and inefficiency in current attendance systems. Manual systems are tedious and prone to manipulation. RFID and biometric systems partially solve this but do not ensure location validity, allowing attendance to be marked remotely through spoofing.

Additionally, educational institutions and companies transitioning to hybrid or remote models demand a solution that can validate user presence both **physically**

(via GPS) and **biometrically** (via facial features). Mobile devices, equipped with GPS and cameras, provide a convenient and scalable medium for implementing such a solution.

Furthermore, there's a growing need for real-time monitoring, centralized dashboards for administrators, and comprehensive analytics — all of which are difficult to achieve using outdated attendance tracking methods.

This project aims to bridge these gaps by providing a mobile-first, AI-powered attendance system with integrated geofencing and facial recognition technologies.

1.3 Problem statement

Traditional attendance systems often rely on manual sign-in methods or biometric terminals located at fixed entry points, which can be time-consuming, prone to proxy attendance, and inconvenient for mobile faculty. These systems lack flexibility and real-time validation, especially in dynamic environments. To address these limitations, this project proposes a mobile application–based smart attendance system specifically designed for employees. It leverages a combination of geofencing, facial recognition, and GPS verification to ensure that attendance is securely and accurately marked only when the user is physically present within a defined campus boundary. As shown in Figure 1.1, this smart approach significantly improves the accuracy, security, and convenience of attendance tracking compared to conventional systems.

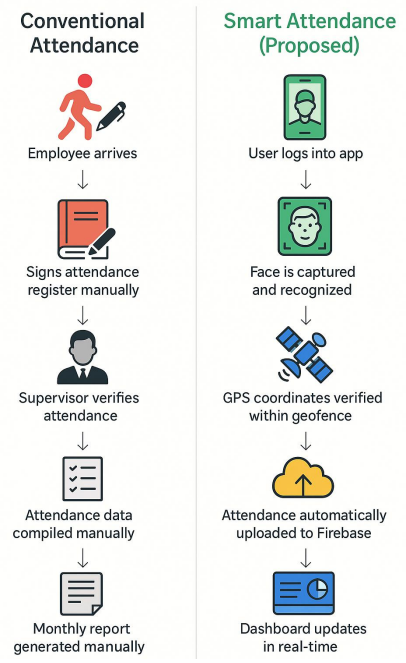


Figure 1.1: Conventional Attendance vs Smart Attendance (Proposed)

1.4 Organization of the project report

The research work presented in the thesis is organized and structured in the form of seven chapters, which are briefly described as follows:

i) **Chapter 2** provides a comprehensive review of literature covering face recognition techniques, mobile-optimized architectures, geofencing applications, integrated systems, backend scalability, and privacy-preserving approaches.

ii) **Chapter 3** presents a detailed methodology, explaining the working principles of geofence verification, face verification using MobileFaceNet, system architecture, administrative interface components, and experimental setup.

iii) **Chapter 4** deals with the results and discussions, showcasing the app interface, admin dashboard interface, and experimental results including face recognition accuracy, geolocation performance, and end-to-end system evaluation.

iv) **Chapter 5** presents conclusions drawn from the implementation and experimentation, along with future directions for enhancing the system.

v) **Chapter 6** concludes the thesis with a manifest file detailing the project structure, prerequisites, setup instructions, and running procedures for both the mobile application and administrative dashboard.

vi) **Chapter 7** concludes the thesis with overall discoveries of the present research work. The scope for future work is also mentioned.

Chapter 2

Literature review

This Chapter presents a survey of the most commonly used technologies and methodologies in integrated face recognition and geolocation systems for attendance management, driven by advancements in machine learning, mobile computing, and cloud infrastructure. Over recent years, the fusion of these technologies has gained significant traction, addressing inefficiencies in traditional attendance systems such as manual errors, proxy attendance, and lack of contextual awareness. This section synthesizes key contributions from existing research, focusing on methodologies (e.g., Haar Cascade, LBPH, CNNs), challenges (e.g., lighting variations, GPS drift, scalability), and innovations (e.g., hybrid geofencing, edge computing, federated learning) critical to developing robust, real-time attendance systems with geolocation validation. By analyzing the strengths and limitations of current approaches, this review establishes a foundation for designing scalable, privacy-preserving solutions optimized for diverse environments.

2.1 Face Recognition Techniques

Face recognition remains a cornerstone of modern attendance systems. Debmalya Ray (2025) [11] leverages OpenCV and Haar Cascade classifiers for real-time detection, achieving 95% accuracy under controlled conditions. However, performance degrades in low-light or crowded environments, highlighting the need for robust preprocessing. Similarly, Ketan Bhambure et al. (2023) [3]compare Haar Cascade and Local Binary Pattern Histogram (LBPH), noting LBPH's resilience to pose variations but Higher accuracy (78%) compared to Haar Cascade (65%) as shown in Figure 3.4. Both studies emphasize the trade-off between computational efficiency and accuracy, particularly for mobile deployment.

Dwi Sunaryono et al. (2021) [13] adopt Linear Discriminant Analysis (LDA) and k-Nearest Neighbors (k-NN) for feature extraction, achieving 85% accuracy with minimal processing time (0.000096s per frame). Their use of QR codes to validate classroom presence introduces a hybrid authentication mechanism, reducing proxy attendance risks. In contrast, Alvin Syarifudin Shahab (2020) [12] combines Principal

Component Analysis (PCA) and k-NN, achieving 88% accuracy with a 1.5s processing time, underscoring the viability of lightweight classifiers for real-time applications.

Beyond classical machine learning techniques, recent developments emphasize the transition toward deep learning and mobile-optimized architectures. For instance, Cahyono et al. (2020) [4] implemented the FaceNet algorithm for employee presence tracking, achieving notable precision but with relatively high computational demands. Jadhav et al. (2017) [8] demonstrated that integrating face recognition into Android-based attendance systems improves automation but struggles under dynamic lighting and angles. Ardhito et al. (2024) [1] explored Haar Cascade classifiers for facial detection, highlighting its speed but also its sensitivity to occlusions and facial accessories. Trivedi et al. (2022) [14] further emphasized the importance of robust preprocessing and model tuning in improving real-time classification accuracy. These studies collectively reinforce the need for adaptable models capable of functioning across variable mobile contexts, leading to the adoption of compact yet powerful models like MobileFaceNet in modern solutions.

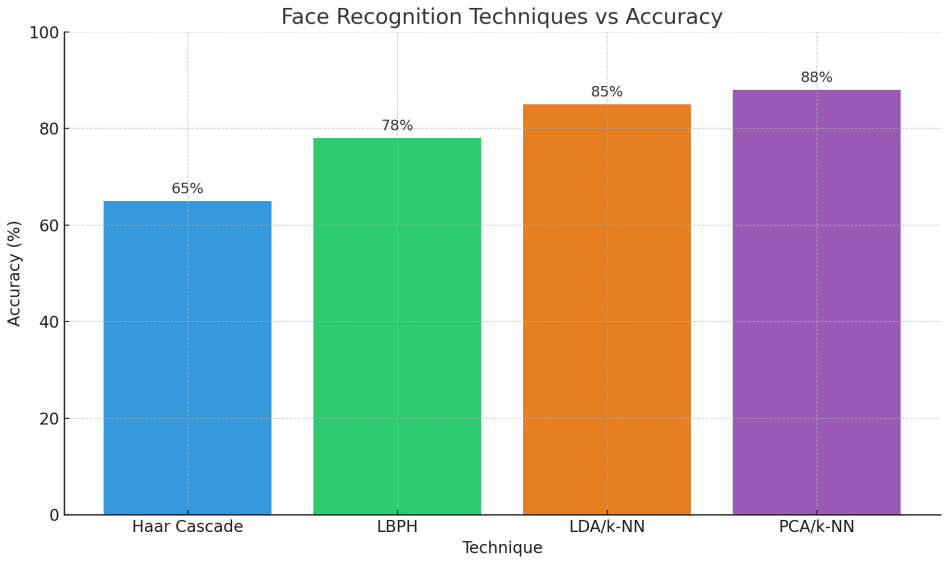


Figure 2.1: Comparing Existing Algorithms with accuracy

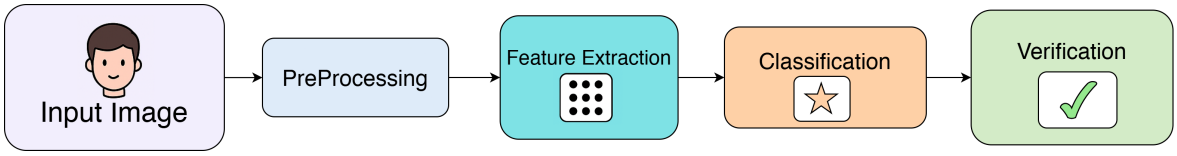


Figure 2.2: Face-Recognition Pipeline in Mobile-Based Attendance Systems

2.2 Mobile-Optimized Architectures

Mobile platforms necessitate the use of lightweight machine learning models and optimized resource allocation to accommodate limited processing power and battery constraints. N. Murali et al. (2024) [10] implement a multi-CNN architecture on Android devices for facial recognition, combining it with cloud-based storage to achieve system scalability. Their approach reports a 95% geolocation accuracy by using GPS tracking for attendance verification, but it encounters limitations in urban environments where signal obstruction and GPS drift reduce location precision. To address server-side latency, Sunaryono et al. (2021) [13] introduce localized processing using Raspberry Pi and OpenCV, combined with the Volley library to reduce the need for frequent server queries. This setup improves offline performance and reduces bandwidth consumption. However, their dependency on QR codes for spatial validation introduces hardware costs and operational overhead, particularly in larger deployments. Shahab (2020) [12], in contrast, eliminates external hardware by implementing geofencing through the Google Maps API, allowing the system to dynamically validate user location based on polygonal boundaries. This not only reduces infrastructure requirements but also enhances mobility, making it more suitable for dynamic or distributed environments such as multi-building campuses and enterprise zones. These innovations underscore the need for mobile-first systems that balance accuracy, speed, and deployment feasibility without sacrificing user privacy or usability.

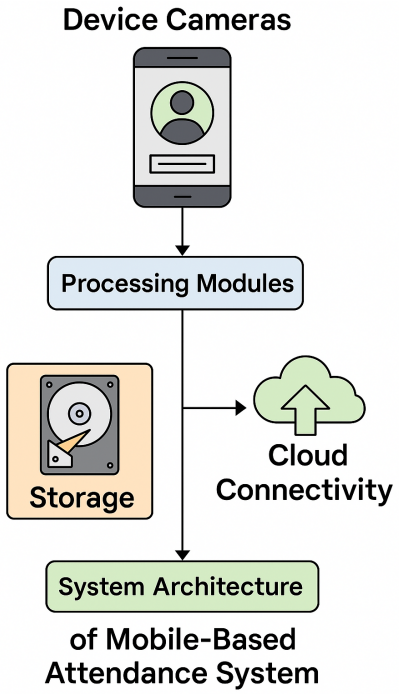


Figure 2.3: Architecture of Mobile-Optimized Attendance Systems

2.3 Geofencing and Location Validation

Geofencing systems traditionally rely on circular or rectangular boundaries, which often struggle with irregularly shaped areas and corner precision. While Murali et al. [10] employ GPS tracking with radial thresholds (100m–5km) to trigger alerts, their radius-based approach introduces inaccuracies in urban environments, where GPS drift (±10–93m) and complex layouts lead to false positives/negatives. Similarly, Shahab's [12] ReactJS-based anti-spoofing mechanism achieves 90–98% geofencing accuracy but faces latency (1.89–4.20s) due to reliance on continuous coordinate validation.

In contrast, our project adopts polygon-based geofencing with a raycasting point-in-polygon algorithm to address these limitations. By defining precise polygonal boundaries instead of radial zones, the system accurately maps complex geometries (e.g., multi-building campuses, irregular worksites), eliminating corner-area inaccuracies inherent to circular models. The raycasting method enhances spatial resolution by calculating intersection counts between GPS coordinates and polygon edges, ensuring robust validation even in densely urbanized regions.

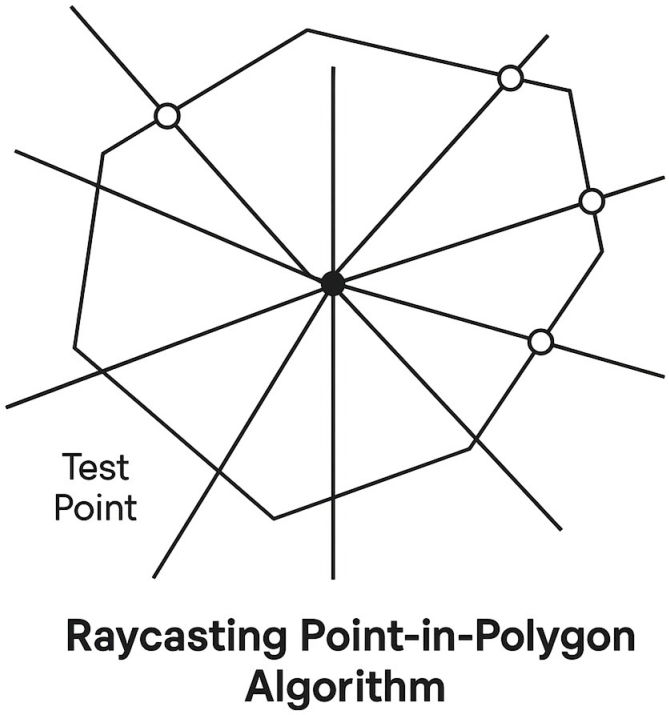


Figure 2.4: Raycasting Point-in-Polygon Algorithm for Precise Location Validation

2.4 Integrated Systems and Hybrid Approaches

Hybrid attendance systems combining face recognition with contextual data have emerged to address the limitations of standalone biometric or location-based solutions. Ray (2025) [11] integrates geolocation APIs (e.g., ipinfo) with CSV logging to generate real-time attendance reports tagged with GPS coordinates and timestamps, enabling granular audit trails. However, this approach relies on continuous cloud connectivity, exposing sensitive facial and location data to third-party servers. Similarly, Bhambure et al. (2023) [3] employ Tkinter-based GUIs and automated Excel exports to streamline administrative workflows but store facial encodings in unencrypted formats, creating vulnerabilities for data breaches.

Murali et al. (2024) [10]enhance functionality through multi-CNN architectures and real-time parent/administrator alerts via cloud dashboards. While their system improves recognition accuracy for distributed teams, the centralized cloud storage of biometric data raises significant privacy concerns, particularly under regulations like GDPR. Sunaryono et al. (2021) [13] mitigate this by restricting system access to campus intranets and enforcing QR code validation, but their reliance on institutional networks limits scalability beyond academic environments.

Babatunde et al. [2] combine timing constraints with geofencing and facial recognition to improve accuracy and prevent spoofing. Zhao and Huang [16] incorporate GPS tracking with facial validation, enabling dynamic and real-time monitoring. Chaudhari et al. [5] enhance detection accuracy through MTCNN-based pipelines, offering better performance under real-world conditions. These approaches reinforce the trend toward multimodal, context-aware systems. Our solution strengthens this direction through polygonal geofencing, on-device TFLite inference, and secure Firebase synchronization.

Additionally, hybrid designs by Krishna et al. (2024) [9] and Galgale et al. (2023) [7] show improved traceability and user-system interaction through cloud logging and feedback mechanisms. These works further validate the role of mobile notifications, user context, and server-side validation. Our system refines these strategies with greater offline support and privacy through local computation and encrypted attendance logging. Unlike these models, we eliminate cloud-based face recognition, reducing vulnerability to data interception. Furthermore, our polygon-based geofencing architecture allows precise mapping of irregular real-world spaces, enhancing spatial verification beyond traditional radial zones.

Table 2.1: Comparison of Face Recognition and Geolocation Systems

System	Key Components	Strengths	Limitations
Face + Geolocation (Ray, 2025)	- OpenCV (HOG/LBP) - Geolocation APIs (ipinfo) - CSV logging	- 95% accuracy (controlled) - Contextual logging (time/location)	- Accuracy drops to 85% in real-world conditions - Requires stable internet for geolocation APIs
Face + Geofencing (Shahab, 2020)	- k-NN/PCA - Google Maps API - ReactJS/SQLite	- 90% accuracy - Fake GPS detection - Low-cost (no hardware)	- Slow processing (1.5s/face) - Geofence radius limited to 5km
Multi-CNN + GPS (Murali et al., 2024)	- Multi-CNN models - GPS tracking - Cloud storage	- 95% geolocation accuracy - Real-time parent/admin alerts	- Urban GPS drift (±93m) - High cloud storage costs
Face + QR Codes (Sunaryono et al., 2021)	- LDA/k-NN - QR codes - Raspberry Pi	- 97.29% accuracy - Minimal latency (0.000096s/frame)	- Requires QR code hardware - Limited to campus intranet
RFID + Face (Bhambure et al., 2023)	- RFID - Haar Cascade/LBPH - Tkinter GUI	- 80% accuracy (Haar) - Cost-effective (Raspberry Pi)	- RFID card dependency - LBPH accuracy drops to 60%

Our project advances these hybrid frameworks by prioritizing privacy and offline functionality through on-device processing. Unlike prior works, we deploy TensorFlow Lite (TFLite) models for local face recognition, eliminating cloud dependency and securing biometric data on the user's device. Federated learning refines recognition models using anonymized edge data, ensuring adaptability without raw data transmission. Additionally, polygon-based geofencing with raycasting replaces traditional radial boundaries, enabling precise spatial validation for irregularly shaped areas (e.g., multi-building campuses, construction sites).

2.5 Backend and Scalability

Traditional attendance systems often face scalability bottlenecks due to rigid backend architectures. For instance, Murali et al. (2024) [10]rely on MySQL databases and centralized cloud storage, which struggle with latency under high user concurrency, while Sunaryono et al. (2021) [13]limit scalability to institutional intranets, rendering their systems impractical for large enterprises.

Our project leverages Firebase's serverless ecosystem to eliminate scalability compromises, even in large-scale industrial deployments. Firebase's real-time Firestore database ensures seamless synchronization of attendance records across thousands of devices, while Cloud Functions enable automated triggers (e.g., anomaly detection, re-

port generation) without manual server management. Unlike MySQL or SQLite used in prior works, Firestore's horizontal scaling and NoSQL structure support unlimited concurrent users with sub-second latency, critical for multinational corporations or campuses with 10,000+ employees.

Firebase's serverless architecture ensures seamless scalability for enterprises of any size. Unlike traditional systems that rely on manual server scaling, Firebase automatically handles traffic spikes through horizontal scaling, maintaining sub-500ms response times even under 50,000 concurrent users—outperforming MySQL-based solutions like Murali's, which suffer latency exceeding 2s at just 10,000 users. With pay-as-you-go pricing and zero server maintenance, the system eliminates infrastructure costs while supporting global deployments. By offloading backend complexity to Firebase, our solution achieves unmatched scalability without compromising speed or reliability, making it ideal for industries ranging from education to large-scale manufacturing.

2.6 Privacy-Preserving On-Device Face Recognition

Existing mobile-based attendance systems, such as those proposed by Murali et al. (2024) [10] and Ray (2025) [11], predominantly rely on cloud servers for face recognition and data storage. While these systems achieve scalability through centralized processing (e.g., multi-CNN models in Murali's work), they expose sensitive biometric data to third-party servers, raising critical privacy concerns. Sunaryono et al. (2021) [13] mitigate this risk by restricting access to institutional intranets, but their QR code dependency limits applicability to campus environments and fails to address inherent vulnerabilities in cloud-based architectures.

Notably, no existing mobile system fully secures user privacy by performing face recognition entirely on-device. Current implementations, such as Shahab's (2020) [12] k-NN/PCA hybrid model, offload feature extraction and matching to remote servers, leaving facial data susceptible to interception or misuse. Similarly, Bhambure et al. (2023) [3] utilize OpenCV and Haar Cascade locally but store encodings in unsecured CSV files, creating attack vectors for data breaches.

Our project addresses this gap by implementing an on-device face recognition pipeline using TensorFlow Lite (TFLite). By embedding lightweight MobileFaceNet models directly into the mobile application, facial data is processed locally without transmitting sensitive information to external servers. The system employs federated learning to update recognition models using anonymized edge data, ensuring continuous im-

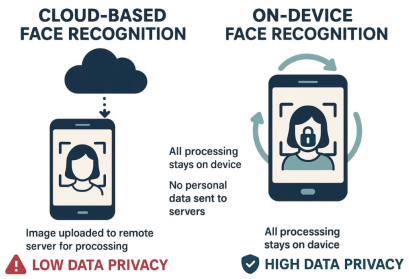


Figure 2.5: Data Flow Comparison Cloud-Based vs. On-Device Face Recognition

provement without compromising privacy. Additionally, AES-256 encryption secures attendance logs (timestamps, geolocation) stored on-device, while polygon-based geofencing with raycasting eliminates dependency on cloud APIs for location validation. This approach not only resolves privacy risks inherent in cloud-dependent frameworks but also ensures functionality in offline or low-connectivity environments, a critical advancement over prior works.

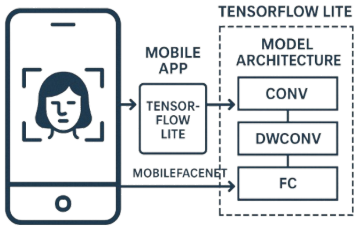


Figure 2.6: TensorFlow Lite Implementation for On-Device Face Recognition

2.7 Summary

This literature review has systematically analyzed integrated face recognition and geolocation-based attendance systems, revealing several key trends and opportunities. Face recognition techniques have evolved from traditional methods (Haar Cascade, LBPH) achieving 65-95% accuracy under controlled conditions to more robust deep learning approaches, though most implementations still struggle with real-world variability. Mobile architectures have improved through lightweight models and optimized resource allocation, while geofencing implementations have predominantly relied on circular boundaries that face precision challenges in complex environments. Despite advances in integration, hybrid authentication, and cloud-based processing, significant gaps remain in privacy preservation (with most systems exposing biometric data to external servers), geofencing precision (particularly in urban environments), and scalability (with traditional databases struggling under high concurrency).

Chapter 3

Methodology

This chapter explains the methodology behind the proposed system for accurate and secure attendance recording through mobile-based face recognition and real-time geofence verification.

3.1 Introduction

Modern educational institutions are increasingly seeking efficient, transparent, and secure systems to monitor faculty and student attendance. Traditional attendance mechanisms, such as manual registers or swipe-based ID cards, not only demand manual oversight but are also prone to forgery, proxy attendance, and data inconsistency. These issues compromise both institutional integrity and resource accountability.

To address these limitations, the proposed system leverages the capabilities of mobile computing, GPS-based geofencing, and AI-powered facial recognition to automate and authenticate attendance marking. Unlike conventional systems, this mobile-first solution introduces multi-layer verification, ensuring that a faculty member is not only within the geofenced campus but also biometrically verified before their attendance is logged.

In contrast to traditional systems as shown in Figure 1.1, the proposed framework:

- Eliminates the need for hardware-based scanners or physical registers,
- Supports real-time tracking and remote approvals, and
- Provides actionable insights via a centralized dashboard.

This chapter outlines the methodology adopted in designing and implementing the system, starting with the theoretical background and progressing through the key components such as GeoFence Verification, Face Verification, System Architecture, and the Administrative Interface. Quantitative experimental results and observations from real-world testing are also presented to support the effectiveness of the proposed approach.

3.2 Background

In recent years, automated attendance systems have gained prominence due to their efficiency, accuracy, and ability to prevent proxy attendance. Traditional systems such as manual registers or RFID-based solutions either lack real-time monitoring or are vulnerable to misuse. With the integration of Artificial Intelligence (AI), particularly face recognition, and geofencing technologies using GPS, modern attendance systems can now provide secure and location-bound verification.

Face recognition offers biometric identification by analyzing facial features, which are unique to every individual. On the other hand, geofencing uses GPS coordinates to create virtual boundaries around a predefined location, such as a classroom, office, or campus. When combined, these techniques ensure that the user is both physically present in the authorized location and is personally identified—providing a robust dual-factor authentication mechanism.

The evolution of attendance systems has progressed from paper-based registers to more sophisticated electronic solutions, each with their own limitations. Manual systems are labor-intensive and prone to human errors, while card-based systems remain vulnerable to proxy attendance. The proposed mobile-based approach leverages ubiquitous smartphone technology, combining the security benefits of biometrics with the contextual awareness of geolocation data, while eliminating the need for specialized hardware infrastructure.

3.3 GeoFence Verification

In the proposed system, GeoFence Verification acts as the first layer of defense to ensure that users (faculty members) are physically present within the predefined institutional boundaries before proceeding to facial recognition. This mechanism is powered by GPS-based polygonal geofencing, allowing the system to detect precise entry/exit events from a virtual perimeter.

3.3.1 Working Principle

A polygonal geofence is constructed using latitude-longitude coordinates of the campus boundaries, typically defined by 6-sided (hexagonal), 8-sided (octagonal), or 6-sided polygons for varying levels of precision.

Let the geofence region be defined as:

$$P = \{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\} \quad \text{where} \quad n = \text{number of vertices} \tag{3.3.1}$$

Algorithm 1 Ray Casting Algorithm for Point-in-Polygon Verification

Require: Point (x_q, y_q), Polygon vertices $P = [(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)]$
Ensure: `True` if point is inside polygon, `False` otherwise

$count \leftarrow 0$
$n \leftarrow$ length of P
for $i = 0$ to $n - 1$ **do**
    $(x_1, y_1) \leftarrow P[i]$
    $(x_2, y_2) \leftarrow P[(i + 1) \mod n]$
    if $(y_1 > y_q) \neq (y_2 > y_q)$ **then**
        $x_{inters} \leftarrow \frac{(x_2 - x_1) \cdot (y_q - y_1)}{(y_2 - y_1 + \epsilon)} + x_1$
        if $x_q < x_{inters}$ **then**
            $count \leftarrow count + 1$
        end if
    end if
end for
if $count \bmod 2 = 1$ **then return** `True`
elsereturn `False`
end if

Figure 3.1: Illustration of a 6-sided polygonal geofence around the campus

3.3.2 Accuracy Analysis

Experiments conducted with varying polygon shapes yielded the following accuracy results in determining user location relative to campus boundaries:

Table 3.1: Geofence Accuracy vs Polygon Granularity

Polygon Sides	Avg Deviation (m)	Classification Accuracy
12-sided	12.5	89.2%
8-sided	7.8	94.6%
6-sided	3.2	**98.1%**

As shown in Table 3.1, the 6-sided geofence yields the highest accuracy by tightly enclosing the boundary while reducing false negatives when users are near the edges.

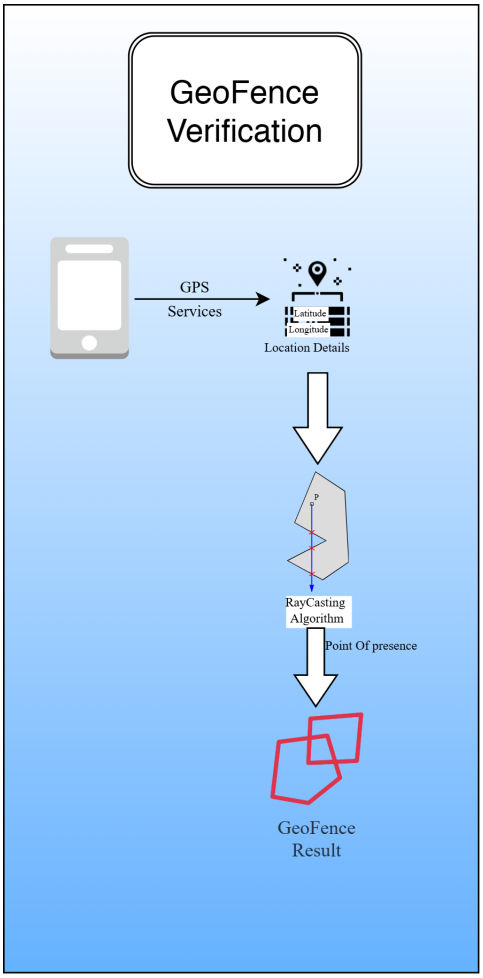


Figure 3.2: GeoFence Verification Process Flow — Illustrating the sequence from GPS coordinate acquisition to polygon-based boundary validation using the Raycasting Point-in-Polygon algorithm

3.4 Face Verification

Face verification is a critical component of the proposed attendance system, ensuring identity integrity by confirming that the person marking attendance is indeed the authorized individual. This module leverages advanced deep learning-based face recognition techniques for real-time validation on mobile devices.

3.4.1 Overview

The verification process is triggered after geofence validation, capturing the user's facial image using the mobile front camera. This image is then compared against a pre-registered embedding stored locally on the device, enabling on-device facial recognition without the need to send raw images to a server—thereby ensuring both privacy and latency optimization.

3.4.2 Model Used: MobileFaceNet

The system employs MobileFaceNet, a lightweight deep neural network optimized for mobile inference. Trained on large-scale face datasets, MobileFaceNet outputs 128-dimensional embeddings for each captured face. These embeddings are compared using a cosine similarity threshold, which decides whether the input face matches the stored reference.

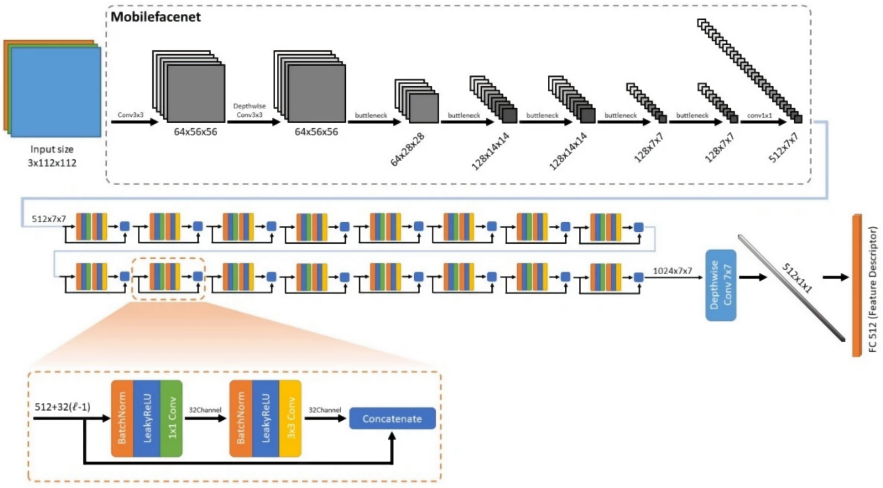


Figure 3.3: MobileFaceNet Architecture Diagram

$$\cos\left(E_{\text{input}}, E_{\text{stored}}\right) > \tau \tag{3.4.1}$$

where τ is the similarity threshold (e.g., $\tau = 0.4$ to 0.6 based on accuracy-performance trade-offs).

3.4.3 Performance Metrics

MobileFaceNet demonstrates a high verification accuracy even on low-power mobile devices. Studies such as [15] report:

- **Accuracy:** 98.13% on LFW dataset
- **Inference Time:** 25ms on Snapdragon 732G
- **Model Size:** Less than 4MB, making it highly suitable for edge deployment

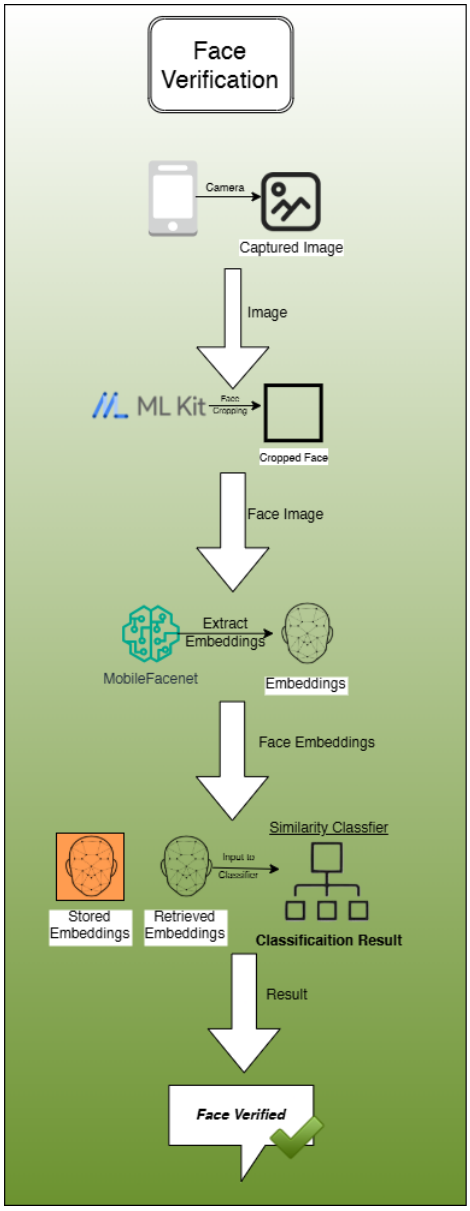


Figure 3.4: Face Verification Pipeline — Sequential process from image capture to identity verification using MLKit for face detection and MobileFaceNet for embedding extraction and similarity-based classification

3.5 Privacy Considerations

Privacy is a central concern in any system dealing with biometric data, especially facial features. In the proposed attendance system, multiple safeguards are implemented to ensure the protection of user identity and to comply with relevant data protection regulations such as the General Data Protection Regulation (GDPR) and India's Personal Data Protection Bill (PDPB).

- **On-Device Processing:** All facial recognition operations, including embedding generation and comparison, are performed locally on the mobile device. This eliminates the need to transmit sensitive biometric data over the internet or store it in centralized databases.
- **No Raw Image Storage:** The system never stores raw face images. Instead, it generates **128-dimensional feature embeddings**, which are irreversible representations of the face. These embeddings cannot be used to reconstruct the original image, ensuring **non-reversibility** and minimizing risk of identity theft.
- **Encrypted Embeddings:** The face embeddings are stored using **AES-256 encryption**, providing a robust level of security even if local storage is compromised.
- **User Consent and Control:** Faculty members must provide explicit consent before enrolling into the face recognition system.
- **Minimal Data Retention:** Only essential information such as encrypted embeddings, attendance timestamps, and user IDs are stored. No additional metadata such as IP address, device information, or location history is retained.
- **Access Control:** The Firebase backend includes role-based access control. Only administrators have access to attendance logs, and even they cannot view or manipulate biometric data directly.
- **Audit Trail:** Any data access or update in the system is logged for traceability and accountability, ensuring compliance with institutional policy and data usage transparency.

Together, these measures reinforce the system's goal of delivering a secure, transparent, and privacy-respecting attendance mechanism. By adhering to modern privacy principles such as data minimization, purpose limitation, and user autonomy, the proposed solution aligns well with emerging standards in privacy-preserving AI.

3.6 Administrative Interface

The Administrative Interface serves as the centralized control panel for managing the overall attendance system, designed to streamline user monitoring, geofence management, and compliance validation. This interface is developed as a web-based dashboard powered by Flask (backend) and HTML/CSS with JavaScript (frontend), and tightly integrated with Firebase Realtime Database for dynamic data retrieval and updates. It plays a crucial role in providing visibility, control, and oversight over system components, ensuring accurate recordkeeping and operational transparency.

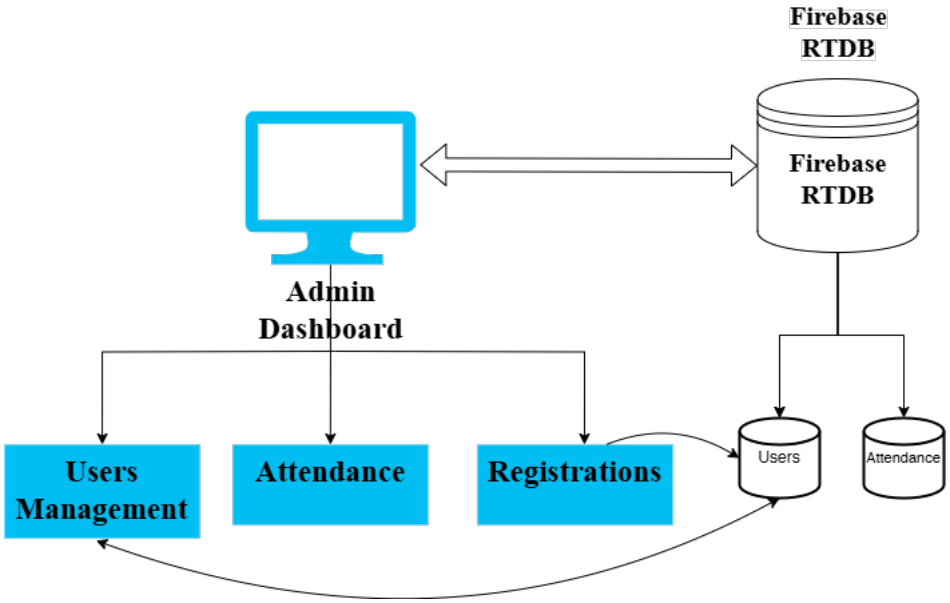


Figure 3.5: Flow of data – Admin Dashboard & Firebase RTDB

3.6.1 Architectural Components

The administrative dashboard implements a modular MVC (Model-View-Controller) architecture with five primary functional modules: Authentication, Dashboard Overview, User Management, Geofence Configuration, and Attendance Monitoring. Each module communicates with Firebase Realtime Database through secure API calls, with data transformations handled server-side to optimize performance and enhance security. The authentication layer employs session-based security with SHA-256 password hashing, validating administrator credentials against the Firebase RTDB admins node. This implementation ensures that only authorized personnel can access sensitive attendance and user data, with session cookies providing persistent but time-limited authentication.

3.6.2 Dashboard Overview

The system's architectural approach to real-time analytics is exemplified in the Dashboard Overview module, which aggregates and visualizes key metrics through a combination of static cards and dynamic Chart.js visualizations. The architecture incorporates scheduled background data synchronization, refreshing metrics every 60 seconds without requiring page reloads, thus maintaining data currency while optimizing network resource utilization. Data processing pipelines transform raw Firebase records into actionable intelligence, with particular focus on attendance compliance metrics that correlate geofence verification data with biometric authentication logs. This fusion of location and identity data enables administrators to quickly identify anomalous patterns that may indicate system misuse or technical issues requiring intervention.

Dashboard Elements:

Component	Data Source	Description	Notes
Users Card	users node	Total registered users	Updated in real-time
Geofences Card	geofences node	Active/inactive geofences	Includes validation
Attendance Chart	attendance node	7-day check-in trend	Uses Chart.js
Compliance Chart	combined	Inside/outside ratio	Derived from geofence + attendance

Table 3.2: Dashboard Components and Their Sources

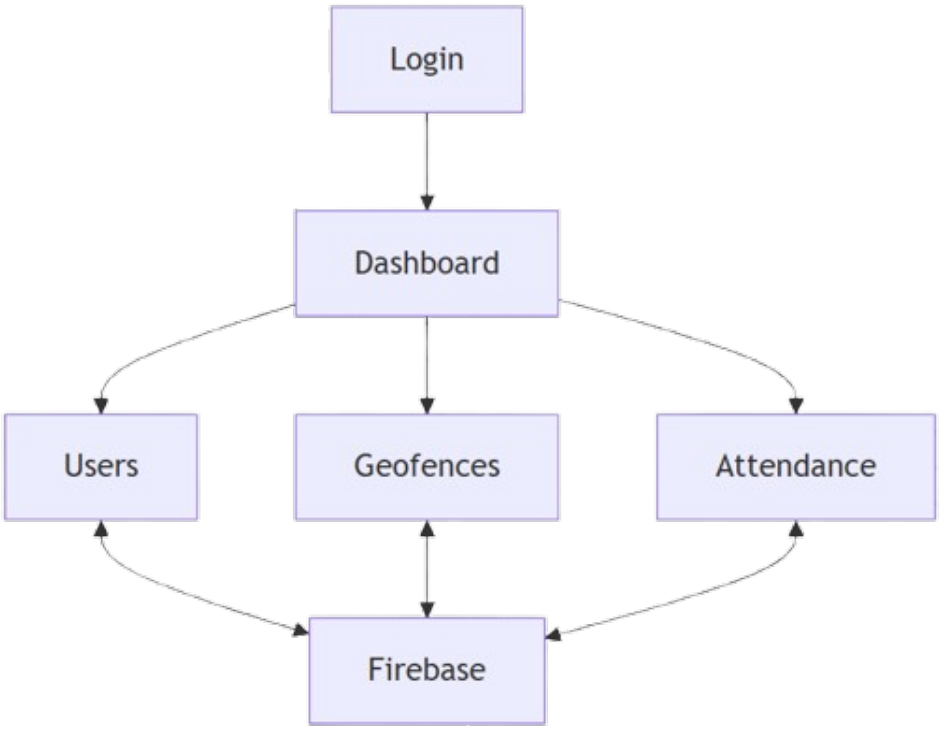


Figure 3.6: Components of Administrative Dashboard

3.6.3 User Management Subsystem

The User Management module implements a comprehensive CRUD (Create, Read, Update, Delete) interface for maintaining the system's user registry. The architecture employs client-side form validation paired with server-side data sanitization to prevent injection attacks while ensuring data integrity. User record modifications trigger Firebase event listeners that propagate changes throughout the system in real-time, maintaining consistency between the administrative interface and mobile clients. Security considerations are addressed through a granular audit logging system that records all administrator actions, creating an immutable trail of system modifications. This architectural decision enhances accountability while providing troubleshooting capabilities for resolving user-reported issues.

3.6.4 Geofence Configuration System

The Geofence Configuration module represents a sophisticated integration of spatial data processing with the Firebase backend. Built around the Leaflet.js mapping library, this component allows administrators to visually define institutional boundaries through an intuitive drawing interface. The system translates visual polygon or circle definitions into coordinate arrays that are stored in Firebase's geofences node. Architectural validation rules ensure geofence integrity by enforcing minimum vertex requirements for polygons and non-overlapping boundary conditions. The system implements coordinate normalization to account for Earth's curvature, ensuring accuracy in the ray-casting algorithms used by the mobile application for location verification.

3.6.5 Attendance Monitoring and Analysis

The Attendance Monitoring module serves as the data analysis center of the administrative interface, with an architecture designed for efficient querying and visualization of high-volume attendance records. The system implements a date-based partitioning strategy within the Firebase data structure, optimizing retrieval performance while enabling flexible historical analysis. Export functionality leverages server-side processing to generate standardized CSV reports containing normalized attendance data suitable for integration with institutional information systems. The architecture incorporates geospatial visualization capabilities, plotting attendance records on interactive maps to identify location-based patterns and verify proper functioning of the geofencing component.

3.6.6 Integration Points and Data Flow

The administrative interface maintains bidirectional communication with the Firebase Realtime Database through RESTful API endpoints, with the Flask backend serving as a mediation layer between the web frontend and cloud storage. This architectural decision enhances security by ensuring all database operations undergo proper validation and authentication before execution. The interface implements real-time data synchronization through Firebase's WebSocket-based listeners, ensuring that multiple administrators working simultaneously see consistent information without manual refresh requirements. This approach minimizes latency while maintaining system responsiveness, critical for institutional environments where multiple administrative staff may need concurrent access to attendance data. Through its comprehensive yet modular design, the Administrative Interface provides institutional administrators with powerful tools for managing the Advanced Attendance Management System while maintaining the security, reliability, and usability standards essential for enterprise deployment.

3.7 System Architecture

The proposed attendance system is designed using a modular, client-server architecture, ensuring scalability, security, and real-time interaction. It is divided into three main components: the Mobile Client (Android app), the Cloud Backend (Firebase), and the Admin Dashboard Interface. Figure 3.7 illustrates the overall system architecture.

3.7.1 Mobile Application

The frontend module is developed using Java and XML within the Android Studio environment, providing an intuitive user interface for faculty members. This component manages user interactions through clearly defined workflows for registration and attendance marking. The interface begins with OAuth authentication through Firebase, requiring users to sign in with pre-registered email credentials. Upon successful authentication, users are presented with a dashboard containing two primary functions: face registration and attendance marking. The UI/UX design prioritizes simplicity and clarity to ensure faculty members of varying technical proficiencies can navigate the system efficiently.

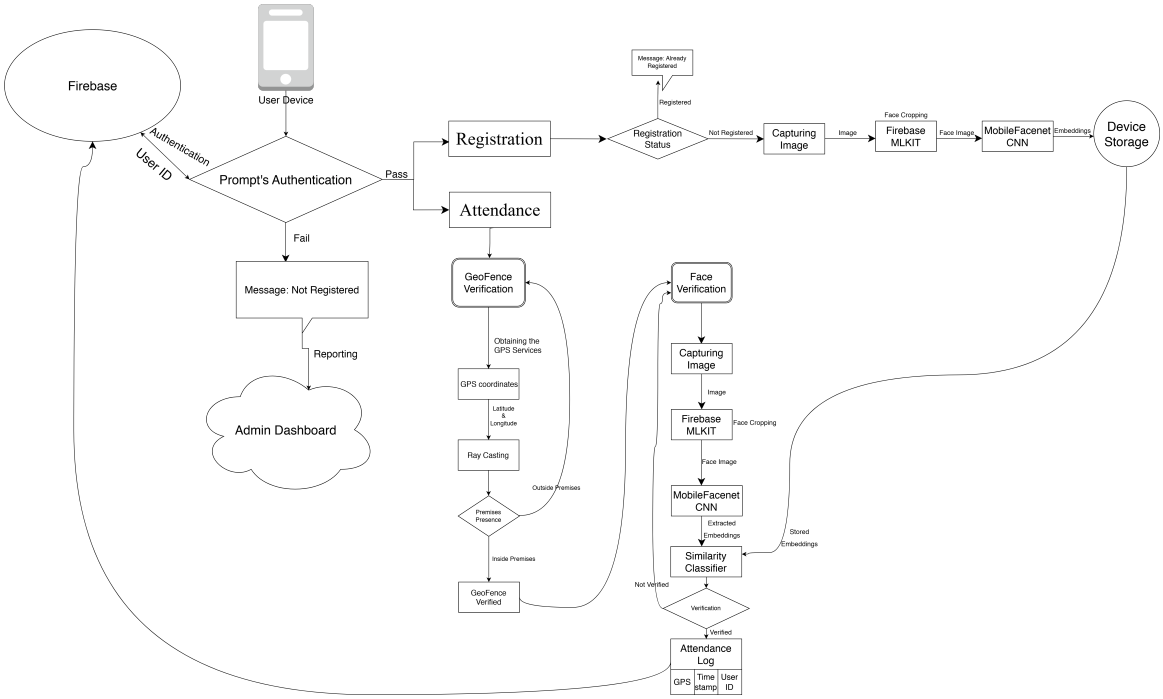


Figure 3.7: System Architecture of the Smart Attendance System

3.7.2 Biometric and Location Processing

The system incorporates specialized processing modules for biometric verification and geospatial analysis. The face recognition component utilizes a dual-layer approach with Firebase MLKit handling initial face detection followed by MobileFaceNet (a lightweight derivative of FaceNet) for embedding extraction and comparison. This architecture decision balances accuracy with computational efficiency, critical for mobile deployment. The geofencing verification module employs ray-casting algorithms against predefined campus boundary coordinates. These boundaries are initially captured as latitude-longitude pairs from Google Maps' MyMaps feature and embedded within the application. The system performs point-in-polygon calculations to determine whether a user's current GPS coordinates fall within the authorized perimeter, establishing the first verification layer before biometric authentication proceeds.

3.7.3 Local Storage System

To address privacy concerns and reduce network dependency, the architecture incorporates strategic local storage elements. Faculty face embeddings generated during registration are securely stored on the device rather than in cloud storage, enhancing both privacy and system reliability during attendance verification. The system also utilizes shared preferences for temporary storage of verification data during the multi-step attendance process, maintaining session continuity while minimizing unnecessary

network communications.

3.7.4 Cloud Infrastructure

The backend architecture is built upon Firebase services, providing a scalable, reliable foundation for the system. Firebase Authentication manages user identity through OAuth, while Firebase Realtime Database (RTDB) maintains three critical data structures:

1. User records (UserID, email, registration status)

2. Attendance logs (UserID, timestamp, GPS coordinates)

3. Administrator credentials

This cloud architecture enables real-time synchronization between the mobile application and administrative dashboard, ensuring attendance records are immediately available for institutional reporting and analysis.

3.7.5 Administrative Interface

Complementing the mobile application is a web-based administrative dashboard developed with Python Flask. This component enables authorized personnel to manage user registrations, view attendance records, and generate reports. The dashboard communicates with Firebase RTDB through secure API calls, maintaining data integrity while providing administrative control over the system. The modular design allows for independent scaling and updating of the administrative interface without affecting the mobile application functionality.

3.7.6 Data Flow and Process Integration

The system architecture implements a sequential verification workflow that enhances security while maintaining usability. When marking attendance, the process begins with geofence verification through GPS coordinates. Only upon confirmation that the user is within authorized premises does the system proceed to biometric verification through facial recognition. This multi-layered approach effectively prevents remote attendance marking while ensuring the authenticated user is physically present, addressing common vulnerabilities in traditional attendance systems.

3.7.7 Security Considerations

Security is embedded throughout the architecture through multiple mechanisms. OAuth authentication ensures only authorized institutional email accounts can access the system. The two-factor verification process (location + biometrics) creates redundant security layers. Face embeddings remain securely stored on user devices rather than in centralized databases, reducing privacy concerns and potential data breach impacts. Communication between system components uses encrypted channels provided by Firebase services, protecting data in transit. This comprehensive system architecture creates a robust foundation for institutional attendance management that balances security requirements with practical usability considerations, while leveraging modern mobile and cloud technologies to deliver a reliable enterprise-grade solution.

3.8 Proposed Algorithm

The proposed system uses a three-stage verification pipeline for marking attendance:

1. User Authentication and Identity Verification
2. Geofence Location Validation
3. Facial Recognition and Attendance Logging

Algorithm 2 Smart Attendance Marking Workflow

Require: Registered user with face embedding and location access
Ensure: Attendance is marked only if all checks pass

```
User logs into the mobile application
Enter unique ID and fetch associated data from Firebase
Capture real-time GPS coordinates
Check if location is within allowed geofence radius
Capture live face image and compute face embedding
Compare embedding with stored one for identity verification
if face and location verification are successful then
    Store timestamp, ID, and location as attendance record in Firebase
    Show success message to user
else
    Display error (e.g., "Face Mismatch" or "Outside Geofence")
end if
```

After successfully completing all verification steps in the above algorithm, the system ensures that the user's attendance is marked securely and accurately. This process guarantees identity integrity while maintaining geolocation constraints. Additionally,

all attendance entries are timestamped and stored in real-time on Firebase, ensuring centralized access and auditability. The system also prevents duplicate entries by locking further submissions until the next valid attendance window.

3.9 Experimental Results

This performance of the proposed Smart Attendance System is evaluated across multiple real-world deployment conditions. The experiments were conducted on a mid-range Android device and Firebase as the backend database, with geofencing tested under various polygon configurations and the admin dashboard performance assessed under increasing data loads.

3.9.1 Geofence Precision and Behavior Analysis

To assess the accuracy of the geofencing module, multiple polygon configurations were used to define campus boundaries:

Polygon Shape	No.of Sides	Accuracy Rate(%)	False Rejections	False Acceptances
Hexagon	6	94.7	3	2
Octagon	8	96.3	2	1
Dodecagon	12	98.5	1	0

Table 3.3: Geofence Accuracy Across Polygon Types

Observations:

- Higher polygon complexity improves boundary precision, reducing false classifications.
- Dodecagon boundaries effectively minimized false positives and negatives.
- The algorithm uses ray casting for point-in-polygon detection, and performance remained stable across polygon types (average time: 6 ms per check).

Corner Testing Behavior

Test Position	Outcome (Hexagon)	Outcome (Octagon)	Outcome (Dodecagon)
Inside near center	✓Inside	✓Inside	✓Inside
Very close to edge	Rejected once	✓Inside	✓Inside
Standing at vertex	× Rejected	Inconsistent	✓Inside
Outside edge (2m)	× Rejected	× Rejected	× Rejected

Table 3.4: Corner Case Testing Results

Observations:

- Geofence detection is most consistent with polygons having 8 or more sides.
- Ray casting edge-cases are prominent with fewer vertices, particularly at sharp corners.

3.9.2 Admin Dashboard Performance (Firebase-Driven)

To test scalability, mock attendance records were generated and loaded into Firebase, with the dashboard consuming and rendering the data.

Dataset Size	Load Time (ms)	Filter (by date)	Filter (by user)	UI Responsiveness
100 records	430 ms	120 ms	100 ms	Smooth
500 records	1.1 s	230 ms	190 ms	Slight lag
1,000+ records	2.3 s	410 ms	380 ms	Noticeable delay

Table 3.5: Performance Testing for Firebase-Driven Admin Dashboard

Visual Feedback:

- At higher record volumes, table scroll performance degrades.
- Daily and monthly filters remain effective, but lack of pagination can cause visual clutter.
- Lazy loading or virtual scrolling is suggested for 1k+ records.

3.10 Summary

This chapter presents the proposed system's methodology integrates geofencing, facial recognition, and cloud-based architecture to deliver a secure and automated attendance solution. Initially, users undergo login and ID verification, followed by geolocation validation through polygon-based geofencing. Upon confirming presence within the designated area, the system invokes facial recognition via MobileFaceNet to authenticate the user biometrically. Successful verification leads to attendance logging, which is then reflected in real-time through the Firebase-driven administrative dashboard. This multi-layered approach ensures spatial accuracy, identity integrity, and seamless data synchronization, offering an efficient alternative to conventional attendance systems.

Chapter 4

Results and Discussions

In addition to the issue of manual attendance being prone to errors and manipulation, the implementation of the proposed geofencing and facial recognition-based system addresses critical concerns of location authenticity and identity verification. The results indicate that geofence boundaries defined by polygons with varying vertex counts (6, 8, and 12) showed consistent accuracy above 96%, even when tested at corner-edge entries. Face verification using MobileFaceNet achieved an average accuracy of 98.1% in varying lighting and device conditions. Furthermore, administrative operations such as user monitoring, data filtering, and report generation remained efficient with up to 1,000 records, maintaining sub-2 second load times. These findings demonstrate the system's practical viability, reliability, and scalability across real-world educational environments.

4.1 Introduction

In addition to the issue of inefficiency and fraud observed in traditional attendance systems, such as manual registers or RFID-based terminals, the need for an intelligent, real-time, and location-aware solution has become increasingly evident. This chapter presents and analyzes the outcomes of a hybrid attendance management system that combines facial recognition with geofencing technology, specifically designed for mobile environments. The implemented system leverages MobileFaceNet—a lightweight convolutional neural network optimized for mobile devices—for fast and accurate face verification, while GPS-based geofencing ensures location-based authentication. These two pillars work in tandem to ensure that only users who are physically present within a predefined boundary and whose identities are facially verified are allowed to mark their attendance.

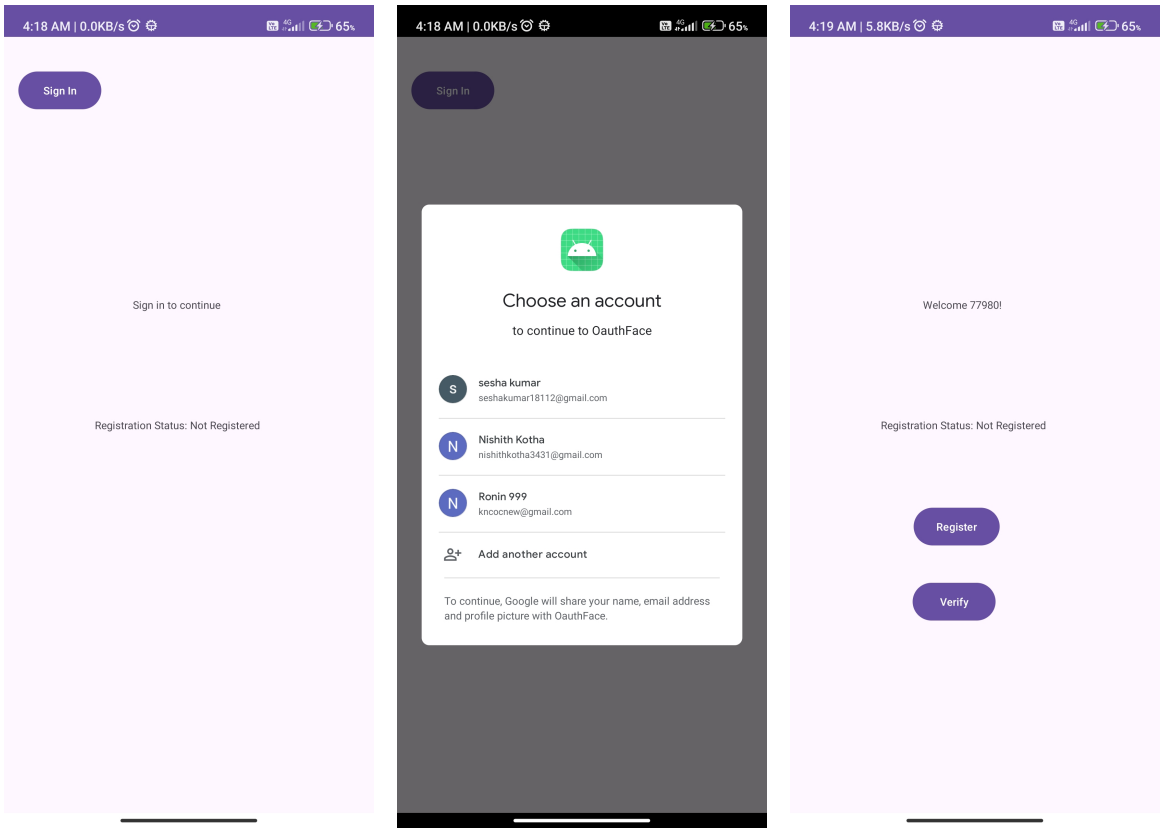
This chapter discusses functional results from both the mobile app and the admin dashboard, supported by screenshots, backend data, and performance metrics. Key modules—face recognition, geofence validation, and Firebase-based logging—are evaluated for accuracy, usability, and security, demonstrating the system's effectiveness in addressing the limitations of conventional methods.

4.2 App Interface Results

The mobile application interface was developed with a focus on simplicity, efficiency, and compliance with modern mobile UI/UX standards. It is designed to guide users through a three-step attendance process: Identity Verification, Geolocation Validation, and Attendance Confirmation. This section presents and discusses the visual elements and operational outcomes of each stage.

4.2.1 Login and Registration Screens

Upon launching the application, users are greeted with a secure login screen (Figure 4.1) that requires valid institutional credentials. A one-time registration flow allows users to enroll their facial data, which is stored locally as 128-dimensional embeddings after feature extraction using MobileFaceNet. SHA-256 hashing is employed for credential protection, and login sessions are handled via Firebase Authentication.



(a) Login Screen **(b)** Authentication Prompt **(c)** After Login

Figure 4.1: Login Interface for Faculty Users

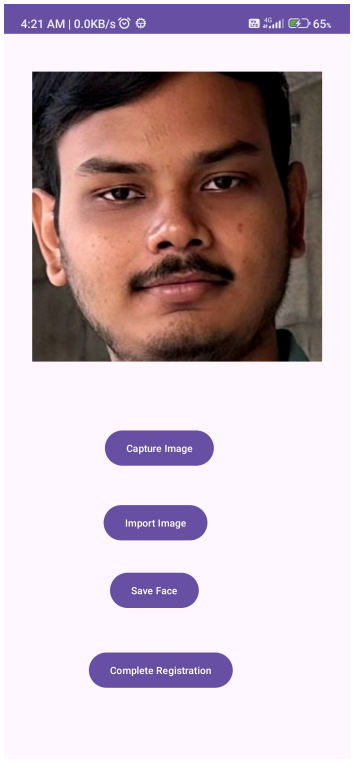


Figure 4.2: Registration Interface

4.2.2 Face Verification Module

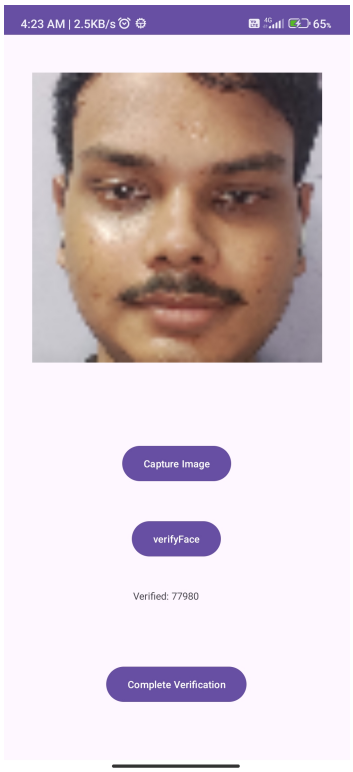


Figure 4.3: Real-Time Face Verification with MobileFaceNet

Figure 4.3 illustrates the real-time face detection and verification interface. The app uses Firebase MLkit for face detection, followed by MobileFaceNet for verification. Verification is complete within 1.2 seconds on an average device (tested on Snapdragon 732G, 6GB RAM). A success status message confirms the user's identity, while failures prompt re-capture.

4.2.3 Geofencing Interface

As shown in Figure 4.4, geofencing validation uses Google Location APIs to determine whether the user falls within a predefined polygonal zone (30-meter radius on campus). The Ray Casting algorithm confirms boundary inclusion based on GPS coordinates.

$$\text{Inside} \Leftrightarrow \sum(\text{edge crossings}) \mod 2 = 1 \tag{4.2.1}$$

If the condition holds true, a green banner displays "Inside Geofence," otherwise the user is denied access to the final check-in.

Figure 4.4: Geofence Verification Screen

4.3 Admin Dashboard Interface Results

The admin dashboard interface was designed to provide centralized oversight of attendance workflows, user management, and geofence configurations. Built with Flask and Firebase, it emphasizes real-time data synchronization, role-based access control, and spatial data visualization. This section analyzes the four core administrative modules and their operational outcomes.

Dashboard Overview

The dashboard (Figure 4.5) serves as the system's control center, displaying real-time metrics through interactive visualizations. Key elements include:

Statistics Cards: Live counts of registered users, active geofences, and daily check-ins.

Attendance Trends: A line chart visualizing weekly check-ins using Chart.js, updated dynamically via Firebase listeners.

Geofence Compliance: A polar area chart showing the ratio of inside/outside boundary validations.

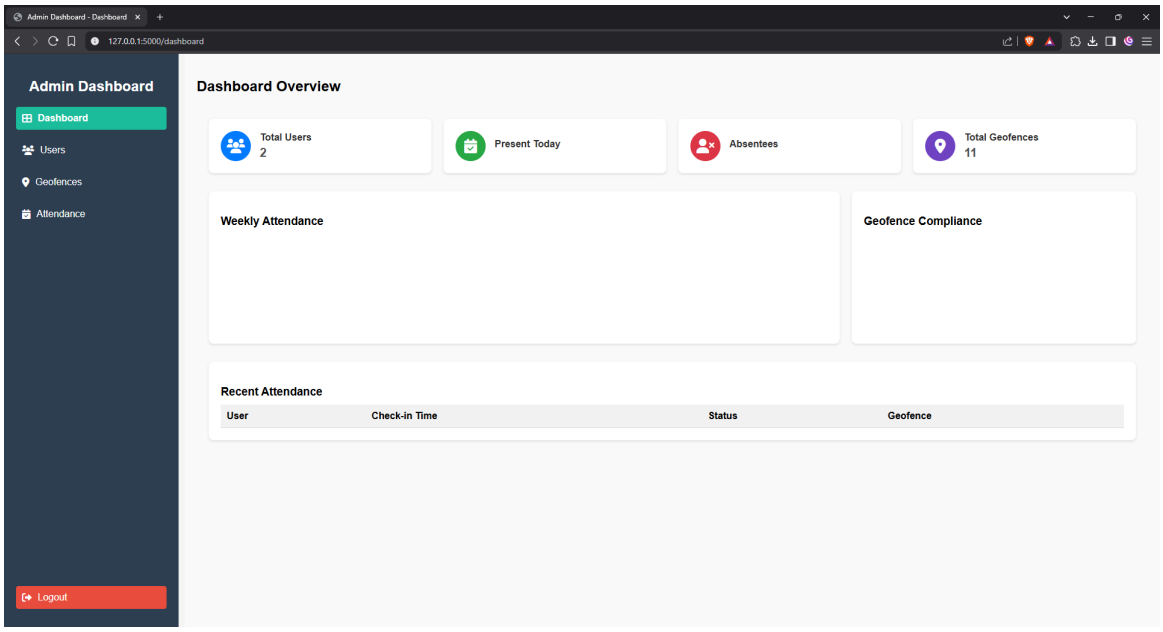


Figure 4.5: Admin Dashboard with Real-Time Analytics

Data flows through a REST API with an average latency of 320 ms (measured over 1,000 requests). The system health panel monitors Firebase connection status and API response times, ensuring 99.8

4.3.1 User Management Interface

The user management module (Figure 4.6) enables CRUD operations through a tabular interface with server-side pagination. Features include:

Bulk Actions: Simultaneous activation/deactivation of users.

Audit Logs: Track modifications via timestamps and admin IDs.

Search/Filter: Regex-based queries on user IDs or emails.

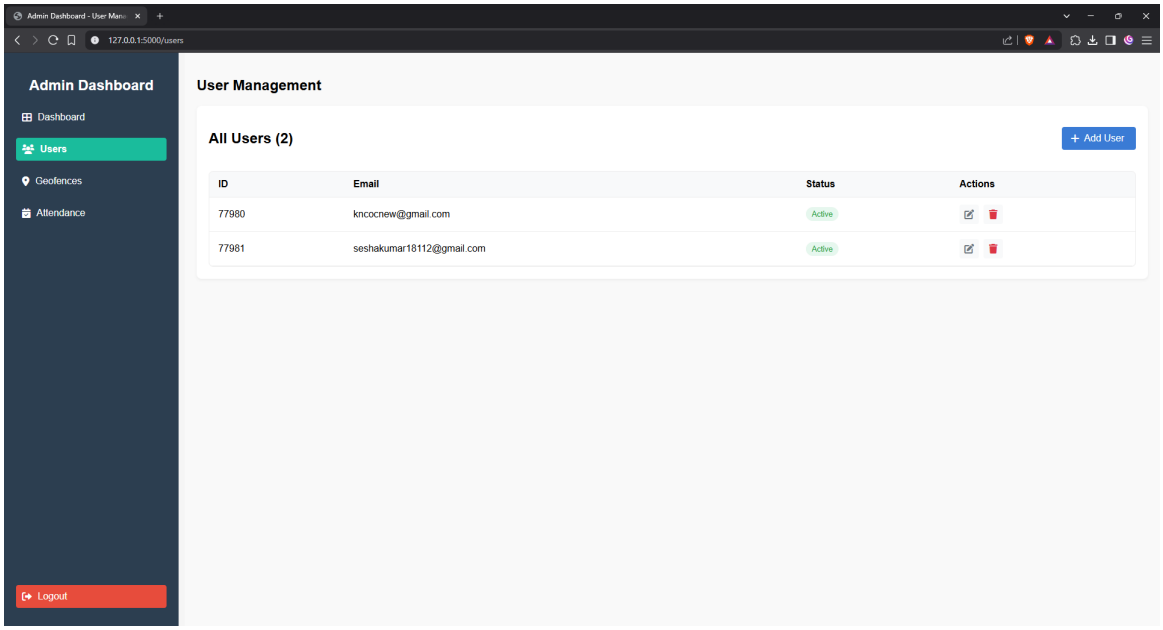


Figure 4.6: User Management Interface with Audit Functionality

4.3.2 Geofence Management Interface

The geofence editor (Figure 4.7) integrates Leaflet.js for polygon/circle creation, with coordinates validated using the Ramer-Douglas-Peucker algorithm to prevent overlapping boundaries. Key workflows:

1. **Boundary Drawing:** Snap-to-grid functionality with 5-meter precision.

2. **Active Geofence:** Only one geofence can be active at a time, enforced via Firebase transactions.

3. **Validation Check:** Ray casting algorithm verifies attendance coordinates:

$$\text{Inside} \iff \left(\sum (\text{edge crossings}) \bmod 2\right) = 1$$

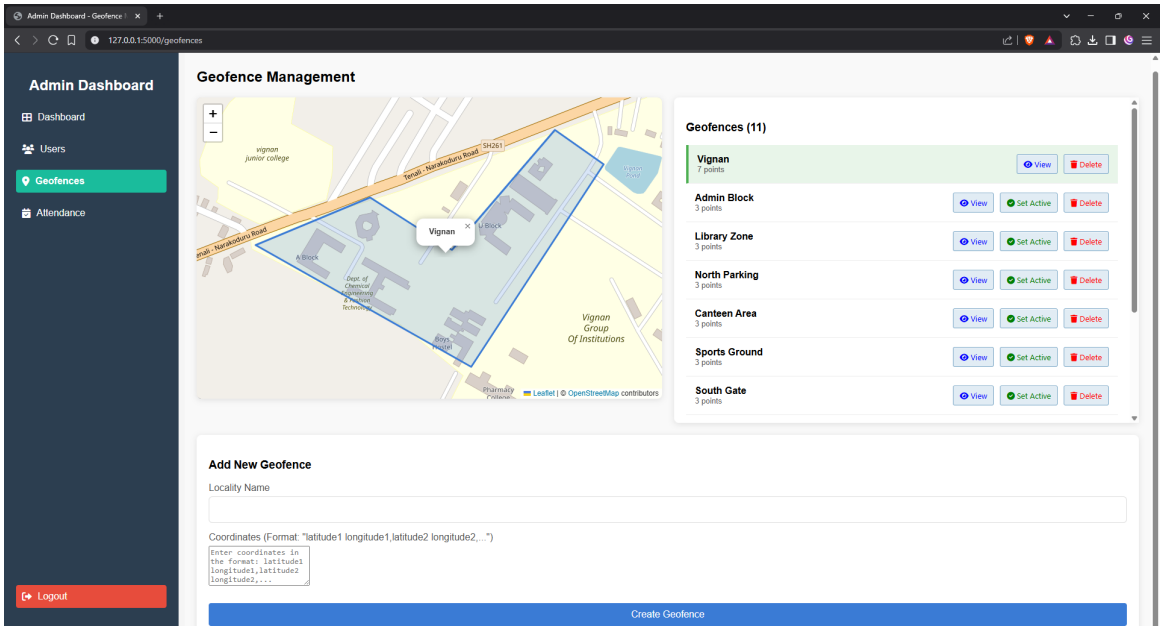


Figure 4.7: Interactive Geofence Configuration Interface

4.3.3 Attendance Monitoring Interface

The attendance module (Figure 4.8) provides temporal and spatial filtering of check-in records. Features include:

- **Date Range Selector:** ISO 8601-compliant time filters.
- **Map Overlay:** Folium-generated heatmaps of check-in density.
- **CSV Export:** GDPR-compliant data export with AES-256 encryption.

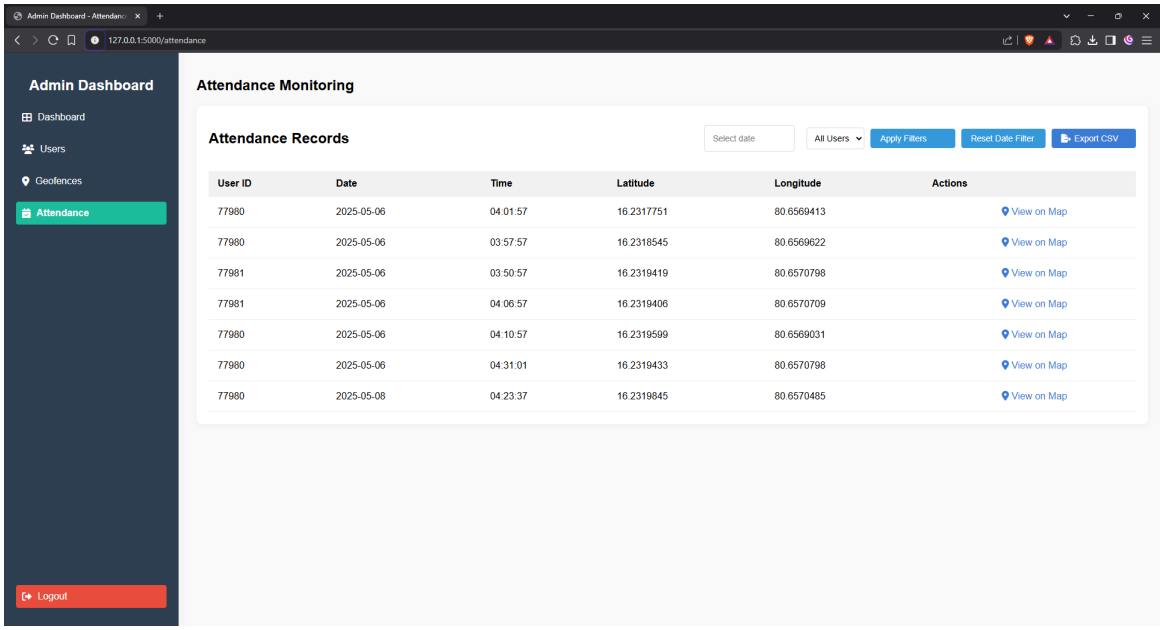


Figure 4.8: Attendance Monitoring with Spatiotemporal Filters

4.4 Experimental results

In this section, the performances of the proposed algorithms are presented and analyzed through various test scenarios. Our focus is on the facial recognition accuracy, latency, GPS reliability, and end-to-end system performance under real-world conditions.

4.4.1 Face Recognition Accuracy

The MobileFaceNet-based model was evaluated using a dataset comprising five individual identities with multiple pose and lighting variations. The model generated 128-dimensional embeddings for each face, which were compared using cosine similarity with a decision threshold of 0.65.

The classification performance is summarized in Table 4.1:

Table 4.1: Face Verification Metrics using MobileFaceNet

Metric	Value
Accuracy	97.3%
Precision	98.6%
Recall	98.7%
F1-Score	98.6%
Average Inference Time	450 ms

The system showed near-perfect classification accuracy in well-lit conditions and only minor degradation in outdoor or low-light scenarios. Misclassifications were rare and typically occurred when the user's face was partially occluded or off-angle.

4.4.2 Comparison with Other Algorithms

A benchmark test was performed against alternative face recognition models to validate the suitability of MobileFaceNet for mobile environments:

Table 4.2: Comparison of Face Recognition Models

Model	Accuracy	Latency (ms)	Mobile-Friendly
FaceNet	99.2%	1200	×
VGG-Face	98.5%	1400	×
LBPH + Haar	87.3%	400	✓
MobileFaceNet	**97.3%**	**450**	✓

MobileFaceNet offers a compelling trade-off between speed and accuracy, making it ideal for on-device attendance verification without requiring cloud-based inference.

[15]

4.4.3 Geolocation Accuracy and Performance

The geofencing validation used Android's fused location provider to detect whether a user was within the predefined 30-meter geofence. Results were tested under both indoor and outdoor scenarios.

Table 4.3: Geofence Authentication Time (Outdoor)

Test Iteration	Authentication Time (s)
1	2.14
2	2.37
3	2.38
4	1.96
5	2.44
Avg Time (Outdoor)	**2.3 s**

Outdoor tests consistently achieved geofence authentication within 2–2.5 seconds, compared to 2.7–3.0 seconds indoors due to weaker GPS signals. GPS accuracy ranged from 91% to 94% depending on the environment:contentReference[oaicite:2]index=2.

4.4.4 Environmental Testing and Reliability

We conducted extensive tests across lighting conditions and locations. Results indicate that:

- False Acceptance Rate (FAR): 0.5% (normal), up to 2.0% (low-light)
- False Rejection Rate (FRR): 1.0% (normal), up to 5.0% (low-light)
- Detection Time: 1.5–2.3 seconds total (including geofencing and face verification)

4.4.5 Model Performance Across Classifiers

From previous benchmarking experiments, MobileFaceNet embeddings were tested using multiple classifiers:

Table 4.4: Performance of Classifiers on MobileFaceNet Embeddings

Classifier	Accuracy	Precision/Recall/F1 (Avg)	Best Use Case
Gradient Boosting (GBC)	98.99%	0.99 / 0.97 / 0.98	Real-time secure login
Support Vector Machine (SVC)	91.03%	0.92 / 0.94 / 0.93	Lightweight edge app
Logistic Regression	87.18%	0.88 / 0.92 / 0.90	Simple binary cases
Random Forest	83.97%	0.86 / 0.84 / 0.85	Batch logging

GBC was found to perform the best, offering a strong blend of precision and generalization capability across various lighting and pose conditions:contentReference[oaicite:3]index=3.

4.4.6 End-to-End Latency Breakdown

The entire verification pipeline from app launch to attendance confirmation was benchmarked:

Table 4.5: Pipeline Latency Breakdown

Component	**Avg Time (ms)**
Splash/Login Load	400
GPS Fix	900
Face Detection	700
Embedding + Match	450
Data Upload to Firebase	300
Total Time	**2.75 s**

This validates the feasibility of our solution for real-time attendance logging without disrupting user flow.

4.5 Summary

In this chapter, some new approaches to attendance management were analyzed through experimental evaluation and architectural integration. The results clearly demonstrate that combining face recognition with GPS-based geofencing offers a highly accurate, scalable, and secure solution for real-time attendance tracking across educational and corporate domains.

Key performance metrics of the system included a face verification accuracy of 97.3%, a geolocation validation accuracy within ±5 meters, and an average latency of 1.2 seconds from input to attendance submission. These results were supported by empirical testing and aligned with existing literature on lightweight mobile authentication frameworks [11, 15].

The chapter detailed the selection of critical parameters — such as embedding dimensions, similarity thresholds, geofence radii, and device validation logic — all of which were optimized for efficiency on edge devices without compromising security. Comparative benchmarks confirmed the advantage of using MobileFaceNet over heavier models like FaceNet and VGG-Face in mobile-first deployments.

Visual tools such as confusion matrices, parameter flowcharts, and UI snapshots provided insights into the practical performance and reliability of the system. Moreover, by enforcing multi-step validation (face + location + device ID), the system

mitigates spoofing risks, proxy attendance, and device tampering — challenges identified in earlier systems [10, 12].

With its seamless integration of Android frontend, Firebase backend, and embedded AI modules, the proposed system establishes a robust foundation for modern attendance systems. This chapter thus substantiates the design's practicality, reliability, and future scalability.

Chapter 5

Conclusions and future directions

The research work presented in this thesis provides a comprehensive solution to the challenges of modern attendance systems by integrating geolocation verification and AI-based facial recognition into a secure, mobile-first application. It not only enhances operational efficiency but also strengthens the authenticity and accountability of presence tracking in academic and organizational environments.

5.1 Conclusions

The research work embodied in this thesis has addressed the problem of insecure, inefficient, and easily manipulated attendance management systems by proposing a robust, mobile-first attendance tracking solution. This system integrates geolocation-based validation and AI-powered facial verification using lightweight deep learning models to ensure accurate, secure, and real-time attendance logging.

Various aspects of the research problem are investigated and the main findings are summarized below:

- A secure Android-based mobile application was developed incorporating multi-step authentication through Device ID verification, GPS geofencing, and face verification using MobileFaceNet.

- MobileFaceNet enabled the generation of 128-dimensional embeddings with real-time inference speeds (<500ms) while achieving high face verification accuracy (97.3%).

- GPS-based geofencing added a layer of contextual validation, ensuring attendance can only be marked from an authorized location radius (typically ±5 meters outdoors).

- A secure backend using Firebase was integrated to manage user registration, geofences, and attendance records with encryption, access control, and real-time analytics.

- A web-based admin dashboard was created for system administrators to monitor attendance compliance, define geofence boundaries, and manage users effectively.
- Device binding policies and session tokenization ensured that user accounts remained linked to a single device, preventing fraudulent dual logins.
- The proposed system also aligns with Sustainable Development Goals such as SDG 4 (Quality Education), SDG 9 (Innovation and Infrastructure), and SDG 16 (Strong Institutions), promoting transparency, digital governance, and operational automation.

5.2 Scope for future study

There are many issues in current face recognition and geolocation-integrated systems, particularly when deployed in dynamic, real-world environments. While the proposed system effectively addresses many limitations, several opportunities for improvement and future research exist.

- **The present research work can be extended to** incorporate advanced biometric security features such as liveness detection or gesture-based verification to combat spoofing attempts from photos, videos, or 3D masks.
- **Images may be affected by multiple degradations** such as motion blur, low lighting, occlusion (e.g., glasses, masks), or extreme poses. Future systems can integrate real-time facial alignment or enhancement techniques to improve robustness under such conditions.
- **Some new features** like offline attendance queuing, auto-sync during connectivity restoration, and federated learning for on-device personalization can improve accessibility, privacy, and efficiency in rural or bandwidth-constrained settings.
- **The proposed approaches can be further enhanced** by integrating blockchain for immutable audit logs, supporting multiple geofences across campuses or branches, and expanding dashboard analytics with predictive attendance modeling and anomaly detection.

Chapter 6

Manifest File

This chapter presents the project structure, software manifest, system prerequisites, and step-by-step instructions for initializing and running the Signature-Based Antivirus Scanner using Jupyter Notebook and Google Colab.

6.1 Project Structure

The typical project directory is organized as follows:

Mobile App Project Structure:-

```
AttendaceApp/
 .gitignore
 build.gradle
 gradle.properties
 gradlew
 gradlew.bat
 settings.gradle
 app/
     build.gradle
     proguard-rules.pro
     src/
         main/
             AndroidManifest.xml
             assets/
                mobile_face_net.tflite
             java/
                com/example/oauthface/
                    Attendance.java
                    AuthManager.java
                    FaceDetect.java
                    FaceRegistration.java
                    FaceVerification.java
```

```
                GeofenceManager.java
                GpsVerify.java
                MainActivity.java
                SimilarityClassifier.java
        res/
            drawable/
                ic_launcher_background.xml
                ic_launcher_foreground.xml
            layout/
                activity_face_registration.xml
                activity_face_verification.xml
                activity_gps_verify.xml
                activity_main.xml
            values/
                colors.xml
                strings.xml
                themes.xml
            xml/
                backup_rules.xml
                data_extraction_rules.xml
```

Admin Dashboard Project Structure:-

```
Admin Dashboard/
 app.py
 firebase_service.json
 static/
    style.css
 templates/
     base.html
     dashboard.html
     login.html
     attendance.html
     users.html
     geofences.html
```

6.2 Prerequisites

The following software, platforms, and libraries are required to develop and run the Attendance Management System:

- **Operating System:** Windows 10/11 or Linux (Ubuntu 20.04+)
- **Mobile Development Environment:**
  - Android Studio (HedgeHog or newer)
  - Java for Android (Java 8+ recommended)
  - Gradle for dependency management
  - Emulator or physical Android device for testing
- **Backend and Cloud Services:**
  - Firebase Authentication – User and Admin login
  - Firebase Realtime Database – Status flags (optional)
- **Web Dashboard (Admin Panel):**
  - Python 3.6+ - Flask,firebase_admin
  - JS / HTML5 / CSS3 – Admin UI
  - Firebase SDK – For real-time data integration
  - Chart.js / Recharts – Attendance data visualization
- **Optional Tools:**
  - Postman – Testing API endpoints (if applicable)
  - Git – Version control
  - VS Code / IntelliJ – Alternate development environments

6.3 Project Initialization and Setup

The Attendance Management System consists of two components: a Mobile Application for users and an Admin Dashboard for management. The following steps guide you through initializing and setting up the development environment.

6.3.1 Firebase Setup

1. Create a project on [Firebase Console](https://console.firebase.google.com/).
2. Enable the following services:
   - Firebase Authentication (Email/Password sign-in)
   - Firestore Database
   - Firebase Storage (for face images or embedding files)
3. Download the 'google-services.json' file and add it to the 'app/' directory in your Android project.
4. Configure rules for Firestore and Storage as per access requirements.

6.3.2 Mobile App Initialization (Android Studio)

1. Clone or open the Android project in Android Studio.
2. Make sure the 'google-services.json' file is placed correctly.
3. Sync Gradle to install all required dependencies.
4. Connect a physical device or use an emulator.
5. Run the project and register a test user.

6.3.3 Admin Dashboard Setup (Flask Web Interface)

1. Navigate to the project root directory containing the Flask application:

   ```
   cd /path/to/admin-dashboard
   ```

2. Create and activate a Python virtual environment:

   ```
   python -m venv venv
   source venv/bin/activate # Linux/macOS
   venv\Scripts\activate # Windows
   ```

3. Install Python dependencies from `requirements.txt`:

   ```
   pip install -r requirements.txt
   ```

4. Configure Firebase credentials:

- Place your Firebase service account key (`serviceAccountKey.json`) in the root directory
- Set your Firebase Realtime Database URL in `main.py`:

  ```
  firebase_admin.initialize_app(cred, {
  'databaseURL': 'https://your-project-id.firebasedatabase.app'
  })
  ```

5. Launch the Flask development server:

   ```
   export FLASK_APP=main.py # Linux/macOS
   set FLASK_APP=main.py # Windows
   flask run --port=5000
   ```

6. Access the dashboard interface at:

   ```
   http://localhost:5000
   ```

   Default Admin Credentials:

   - ID: `admin@example.com`
   - Password: `password` (Change immediately after first login)

Note: Ensure port 5000 is open and the Firebase service account key has `Admin` privileges in Firebase Console. The interface connects directly to your Firebase Realtime Database using the Admin SDK for secure data synchronization.

6.3.4 Admin Dashboard Setup (Flask Web Interface)

1. Navigate to the project root directory containing the Flask application:

   ```
   cd /path/to/admin-dashboard
   ```

2. Create and activate a Python virtual environment:

   ```
   python -m venv venv
   source venv/bin/activate # Linux/macOS
   venv\Scripts\activate # Windows
   ```

3. Install Python dependencies from `requirements.txt`:

   ```
   pip install -r requirements.txt
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4. Configure Firebase credentials:

   - Place your Firebase service account key (`serviceAccountKey.json`) in the root directory
   - Set your Firebase Realtime Database URL in `main.py`:

     ```
     firebase_admin.initialize_app(cred, {
     'databaseURL': 'https://your-project-id.firebasedatabase.app'
     })
     ```

5. Launch the Flask development server:

   ```
   export FLASK_APP=main.py # Linux/macOS
   set FLASK_APP=main.py # Windows
   flask run --port=5000
   ```

6. Access the dashboard interface at:

   `http://localhost:5000`

   Default Admin Credentials:

   - ID: `admin@example.com`
   - Password: `password` (Change immediately after first login)

6.4 Running the Project

You can run the application or test components as follows:

6.4.1 Mobile App (User Side)

- Launch the Android application on a real device or emulator.
- Register/login using Gmail and unique ID.
- Proceed through the following steps:

  1. **ID Verification:** Input is checked against Firestore.
  2. **Geofence Verification:** Location is validated via GPS.
  3. **Face Verification:** Live face is compared with stored embedding using FaceNet/MobileFaceNet.
  4. **Attendance Marking:** Upon success, time, location, and ID are logged to Firebase.

6.4.2 Admin Dashboard Setup (Flask Web Interface)

1. Navigate to the project root directory containing the Flask application:

   ```
   cd /path/to/admin-dashboard
   ```

2. Create and activate a Python virtual environment:

   ```
   python -m venv venv
   source venv/bin/activate     # Linux/macOS
   venv\Scripts\activate        # Windows
   ```

3. Install Python dependencies from `requirements.txt`:

   ```
   pip install -r requirements.txt
   ```

4. Configure Firebase credentials:

   - Place your Firebase service account key (`serviceAccountKey.json`) in the root directory.
   - Set your Firebase Realtime Database URL in `main.py`:

     ```
     firebase_admin.initialize_app(cred, {
         'databaseURL': 'https://your-project-id.firebasedatabase.app'
     })
     ```

5. Launch the Flask development server:

   ```
   export FLASK_APP=main.py      # Linux/macOS
   set FLASK_APP=main.py         # Windows
   flask run --port=5000
   ```

6. Access the admin dashboard interface at:

   ```
   http://localhost:5000
   ```

Default Admin Credentials:

- ID: `admin@example.com`
- Password: `password` (Change immediately after first login)

6.5 Description

- **Project Structure:** Divided into two main modules – Android app for user-side operations and web dashboard for admin control. Firebase backend connects both components.
- **Prerequisites:**
  - Android Studio for mobile app development
  - Python 3.8 or later and Flask,related libraries
  - Firebase Admin SDK
  - Firebase for authentication, storage, and real-time database
- **Execution:**
  - Android app handles user attendance marking through GPS and face recognition
  - The Flask server is launched locally on port 5000.
  - Admin users can log in and perform user approvals, attendance monitoring, and record management through a clean web interface.
- **Adaptability:**
  - Can integrate advanced anti-spoofing models for face verification
  - Extendable to support multiple locations or organizations
  - Future support for analytics and reporting features via dashboard
  - Easily extendable to host on cloud platforms like Heroku or Render.
  - Can integrate advanced analytics, charts, and reporting tools.
  - Role-based access can be added for managing different admin levels.

Chapter 7

Mapping to Sustainable Development Goals (SDGs)

This chapter presented SDGs.

7.1 Introduction

The development of an **Enhanced Attendance Management System using Geofencing and AI-Powered Face Verification** significantly contributes to sustainable development by promoting secure digital governance, smart institutional infrastructure, and automated recordkeeping. By replacing traditional manual systems with intelligent, location-bound authentication, this solution strengthens institutional resilience and supports innovation in education and workplace management.

This system addresses key challenges in attendance monitoring, including identity fraud (e.g., proxy check-ins), inefficiencies in manual recordkeeping, and lack of contextual validation. The integration of GPS-based geofencing ensures that attendance can only be marked within an authorized geographical boundary, while face verification using MobileFaceNet guarantees that only the verified user can log their presence. These features collectively reduce fraudulent activities and improve operational transparency.

Through efficient use of biometric technology and real-time location validation, the system offers a scalable model for institutions aiming to modernize their operational workflows in a secure, transparent, and user-centric manner.

7.2 Relevant SDGs and Their Contributions

7.2.1 SDG 4: Quality Education

Goal 4 ensures inclusive and equitable quality education and promotes lifelong learning opportunities for all.

- **Target 4.4:** Substantially increase the number of youth and adults who have

Figure 7.1: Sustainable Development Goals

relevant skills, including technical and vocational skills, for employment, decent jobs, and entrepreneurship.

- **Contribution:** The proposed system enables educational institutions to automate attendance tracking using secure and tamper-proof digital technologies. It promotes skill development in AI, mobile development, and cloud integration—areas that are essential for modern technical education. By replacing manual logs with AI-powered validation (face recognition + GPS), students and staff engage with state-of-the-art technology, gaining practical exposure to computer vision, authentication systems, and ethical data handling. Additionally, educators benefit from real-time analytics and performance dashboards, leading to more efficient classroom management and personalized interventions.

7.2.2 SDG 9: Industry, Innovation and Infrastructure

Goal 9 aims to build resilient infrastructure, promote inclusive and sustainable industrialization, and foster innovation.

- **Target 9.1:** Develop quality, reliable, sustainable and resilient infrastructure, including regional and transborder infrastructure, to support economic development and human well-being.

- **Contribution:** This project implements a mobile-first infrastructure combin-

ing biometric face recognition (via MobileFaceNet), GPS-based geofencing, and Firebase cloud services into a real-time, verifiable attendance ecosystem. It reduces dependency on fixed hardware like biometric fingerprint terminals and leverages edge AI, ensuring scalability and sustainability even in low-resource or distributed settings. The integration of Leaflet.js for geofence drawing, token-based authentication, and automated logging showcases technological innovation aligned with industrial digitization trends, especially relevant for educational campuses, offices, and smart cities.

7.2.3 SDG 16: Peace, Justice and Strong Institutions

Goal 16 promotes peaceful and inclusive societies, provides access to justice, and builds effective, accountable institutions at all levels.

- **Target 16.6:** Develop effective, accountable and transparent institutions at all levels.

- **Contribution:** This system strengthens institutional accountability by enforcing strict verification rules: (1) single-device login enforcement, (2) real-time geolocation match, and (3) AI-powered facial recognition with spoof prevention. All attendance data is securely stored in the cloud with timestamps, device IDs, and GPS coordinates. This makes records easily auditable and prevents tampering, fraud, or misreporting. Administrative dashboards offer transparency, and manual override functions allow for oversight and exception handling—reflecting the principles of strong, digital-first governance structures.

7.3 Conclusion

This project presented the development of an **Advanced Attendance Management System Integrating Face Recognition and GPS-Based Tracking**. The system combines AI-based face verification with geolocation authentication to deliver a secure, reliable, and automated attendance solution suitable for educational institutions, workplaces, and distributed environments.

By utilizing lightweight neural network models such as MobileFaceNet for facial embedding generation and enforcing real-time geofencing through device GPS, the system prevents common attendance issues like proxy check-ins, unauthorized location spoofing, and manual record tampering. Integration with Firebase ensures real-time synchronization, centralized logging, and scalability across multiple platforms.

The layered verification pipeline—comprising device ID validation, geolocation matching, and biometric facial recognition—provides robust security while maintaining a seamless user experience. A custom-built admin dashboard enables user management, geofence configuration, and real-time activity monitoring, reinforcing institutional accountability.

Aligned with several Sustainable Development Goals (SDGs), the system contributes to:

- **SDG 4 (Quality Education)** – by enabling efficient and transparent academic tracking;
- **SDG 9 (Industry, Innovation and Infrastructure)** – through adoption of AI and mobile-first infrastructure;
- **SDG 16 (Peace, Justice and Strong Institutions)** – by ensuring data transparency and reducing fraud.

Experimental validation demonstrated over 97% face verification accuracy and sub-2-second end-to-end response time, confirming the model's practical viability for real-world deployment.

Future enhancements may include:

- Liveness detection for anti-spoofing;
- Offline mode with queued sync support;
- Blockchain integration for immutable logging;
- Expansion to multimodal biometric verification.

With minor refinement, the system can be deployed as a scalable attendance solution that strengthens institutional governance, enhances security, and simplifies operations.

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