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Smart Real-time Attendance System for Nigerian Universities

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ABSTRACT

This study proposes a Smart Real-Time Attendance System using face recognition technology to address challenges in traditional attendance systems in Nigerian universities. These challenges include proxy attendance, manual errors, and administrative inefficiencies. The system employs Convolutional Neural Networks (CNNs) and the ArcFace algorithm for facial feature extraction and identity verification. Key development tools included InsightFace, OpenCV, and Streamlit, with Visual Studio Code as the IDE. The system ensures high accuracy, with 94% face detection, 98% face recognition, and 96% overall attendance prediction accuracy. It automates essential tasks like attendance percentage calculation and report generation, ensuring compliance with the National Universities Commission (NUC) 75% attendance requirement for exam eligibility. Ethical compliance was a core design concern, including informed consent, data encryption, access control, and fairness across facial profiles. This system significantly reduces impersonation, administrative workload, and enhances operational efficiency, making it a scalable and secure solution for attendance management. Its deployment is recommended for improving academic monitoring and policy enforcement in Nigerian universities.

Keywords: Smart Attendance System, Face Recognition Technology, Convolutional Neural Networks (CNNs), Real-Time Attendance Monitoring and Automated Student Verification

1. Introduction

Attendance management plays a vital role in ensuring academic integrity and regulatory compliance within higher education institutions. In Nigerian universities, student attendance is a key factor in determining eligibility for semester examinations, as mandated by the National Universities Commission (NUC), which requires a minimum of 75% attendance. However, conventional attendance tracking methods such as manually signing attendance sheets or calling roll numbers are inefficient, error-prone, and susceptible to manipulations. These outdated methods create administrative burdens and make it challenging to enforce attendance policies, particularly in large lecture halls. Additionally, proxy attendance and forgery remain prevalent, undermining the credibility of attendance records [3].

Despite advancements in automation and digital transformation, many Nigerian universities still rely on these traditional methods. The increasing student population and the tedious nature of manual tracking make it difficult for lecturers to compute percentage attendance, particularly for visiting lecturers who require accurate attendance records for payment processing. Additionally, with the rise in security threats within educational institutions, unrestricted access to classrooms poses significant risks [21]. However, most existing systems do not address the need for integrated solutions that simultaneously ensure attendance accuracy, institutional security, and administrative automation especially within the unique constraints of Nigerian universities. This research addresses that gap by proposing a system that not only tracks student presence but also detects unauthorized access and provides secure, real-time reporting capabilities.

Facial recognition technology has evolved significantly since its early development in the 1960s by pioneers such as Woody Bledsoe, Helen Chan Wolf, and Charles Bisson. Initially, the focus was on identifying facial landmarks through computational analysis [23]. While early research was limited, modern advancements have propelled facial recognition to widespread adoption in various domains. Today, facial recognition is integrated into social media platforms (e.g., Facebook's photo tagging system), mobile applications (e.g., face-enhancing features and age estimation tools), and Augmented Reality (AR) applications (e.g., Instagram and Snapchat filters), underscoring its adaptability across different fields.

Facial recognition is a biometric authentication technique that identifies individuals by comparing real-time captures with stored images. It is increasingly preferred over other biometric methods due to its non-intrusiveness and efficiency. Machine learning algorithms, particularly deep learning-based Convolutional Neural Networks (CNNs), have significantly improved the accuracy and robustness of face recognition systems [28].

Attendance tracking is a crucial administrative function in both educational and corporate environments, serving as a metric for student assessment and employee productivity. However, manual attendance systems suffer from various shortcomings, including errors, impersonation, and administrative inefficiencies. Several studies have highlighted these challenges:

1. Proxy attendance and forgery remain persistent issues in large classrooms [29].
2. Traditional attendance-taking methods require significant time and effort, reducing lecture efficiency [11].
3. Contact-based biometric solutions (e.g., fingerprint scanners) pose hygiene concerns, particularly in post-pandemic settings [24], [32].

To address these limitations, artificial intelligence (AI)-based smart attendance systems leveraging facial recognition technology offer an optimal solution. These systems provide real-time tracking, automation of attendance percentage computation, and enhanced security.

This research proposes a Smart Real-Time Attendance System for Nigerian universities, integrating face recognition technology to overcome the limitations of existing methods. The system utilizes deep learning algorithms for accurate facial recognition and automated attendance processing. The hardware implementation includes a Raspberry Pi 4 kit and a video camera capable of recognizing multiple faces in real time. The captured images are processed using Convolutional Neural Networks (CNNs) to compare them with a pre-registered student database, thereby ensuring seamless attendance tracking.

Key features of the proposed system include:

1. Automated attendance computation, determining whether students meet the required 75% threshold.
2. Detection of unauthorized individuals in lecture halls, enhancing campus security.
3. Integration with university administrative systems, allowing attendance reports to be sent to the Head of Department (HOD) via email.
4. Support for visiting lecturers, ensuring accurate attendance tracking for payment processing.

When deployed, this AI-powered attendance system will mitigate attendance irregularities, streamline administrative processes, enhance classroom security, and improve the efficiency of attendance management in Nigerian universities.

Nigerian universities have experienced a rapid increase in student enrollment, making attendance management increasingly difficult. Traditional methods of recording attendance, such as manual sign-ins and roll calls, are time-consuming, inefficient, and prone to inaccuracies. The challenges include:

1. Inability to compute percentage attendance accurately, leading to the non-enforcement of the NUC-mandated 75% attendance policy [20].
2. Difficulties faced by visiting lecturers in tracking student attendance for payment purposes.
3. Security risks in classrooms, as large lecture halls are vulnerable to unauthorized access and potential security threats.
4. High prevalence of proxy attendance, undermining academic integrity.
5. Disruptions caused by manual attendance tracking, affecting lecture efficiency.

An automated, AI-powered attendance system is required to address these challenges effectively.

The aim of this research is to develop a Smart Real-Time Attendance System for Nigerian Universities that leverages face recognition technology to enhance efficiency, accuracy, and security in attendance management. The specific objectives are to:

1. Develop an automated attendance system using face recognition technology for real-time attendance tracking.
2. Implement an attendance computation system to determine whether students meet the 75% NUC requirement.
3. Facilitate attendance tracking for visiting lecturers, ensuring accurate payment processing and accountability for staff duties.
4. Enhance classroom security by detecting unidentified individuals and reporting unauthorized access.

Unlike existing systems that focus solely on biometric attendance logging or basic face detection, this study presents a novel integration of real-time facial recognition, security alerting, and automated administrative reporting. By combining these three functional pillars into a unified platform optimized for resource-constrained educational institutions, our approach demonstrates a more holistic and scalable solution than prior work in the field.

2. Related Works

Face recognition technology has become central to modern attendance systems, offering automated, real-time alternatives to manual processes. Various studies have explored different methodologies and implementation approaches, examining their strengths and limitations. This section organizes key studies into four sub-themes for clarity and critical analysis.

2.1. Hardware-Intensive Systems

[15] demonstrated the application of YOLO V3 in tracking classroom attendance, showcasing high processing speed and accuracy with large datasets. However, it was limited by its dependence on high-quality cameras and controlled lighting—factors often unavailable in low-resource environments. Similarly, [25] proposed a dual-camera system to cross-verify individuals at classroom entry and within the classroom, effectively reducing impersonation but requiring costly hardware. [6] addressed scalability by developing a Raspberry Pi-based system integrated with cloud platforms. Although financially accessible, such systems often fall short in handling the demands of larger institutions with complex datasets. RFID-based systems, as discussed by [22], are affordable and easy to deploy but lack robust security features. Mobile-based solutions have also emerged. [30] developed a mobile app using QR codes and GPS, effective for hybrid and remote learning but limited by smartphone availability and user compliance—particularly in underserved communities. Likewise, [12] integrated GSM-based notifications, improving communication but remaining vulnerable in areas with poor network connectivity.

2.2. Lighting-Sensitive Models

Addressing lighting-related challenges, [11] employed HaarCascade and Local Binary Pattern Histogram (LBPH) algorithms. Though effective in moderate conditions, these techniques struggled with extreme lighting variations and partial face occlusion. [33] introduced a Siamese neural network to manage lighting and background variation challenges, though the approach demanded significant computational power. [14] showed that transfer learning significantly enhances CNN-based classification accuracy with limited training data, suggesting its relevance for facial recognition tasks in resource-constrained settings. [7] achieved 99.4% accuracy by fusing computer vision with neural networks, though this relied on well-lit environments. [29] proposed histogram-based optimization for faster processing, though it was less effective with high-resolution images under variable environmental conditions.

2.3. Security-Enhanced Attendance Systems

[27] combined Convolutional Neural Networks (CNN) with Long Short-Term Memory (LSTM) models to handle sequential attendance data. While this hybrid approach improved temporal data analysis, its high computational demands posed feasibility challenges for smaller institutions. [3] demonstrated the predictive capacity of hybrid LSTM-GRU models during the COVID-19 pandemic, although requiring extensive datasets. Dual-purpose systems have emerged, combining attendance tracking with access control. [17] presented such a system, which increased security but raised data privacy concerns. Likewise, [16] explored real-time facial recognition for security and attendance, noting its deterrence effect against unauthorized access. [9]

integrated gender classification into recognition systems using LBPH and HaarCascade, improving accuracy while emphasizing the need for more inclusive datasets.

2.4. Nigerian Context and Policy Considerations

Within the Nigerian context, several studies underscore practical implementation of biometric attendance systems. At LASU Epe campus, [26] deployed a facial recognition system that significantly improved attendance management. Similarly, [1] implemented an RFID-based system in a Nigerian university, highlighting its enhanced accuracy. [20] further proposed a face recognition system customized for Nigerian tertiary institutions, emphasizing its contextual adaptability. [19] discussed both the potential benefits and risks of facial recognition across sectors, advocating for regulatory oversight to safeguard individual rights. [4] reviewed biases stemming from non-diverse datasets and called for fairness-centered system design.

2.5. Comparative Summary Table

Study	Tech Used	Accuracy	Real-Time	Ethical Compliance / Nigerian Policy
[2]	Eigenface + Haar	Low	✗	✗
[13]	LBPH + OpenCV	Moderate	✗	✗
[19]	CNN Mobile App	Good	☑	✗
[8]	Deep CNN	High	☑	✗
This Study	ArcFace + CNN	High	☑	☑

Table 1. Comparative summary table

2.6. Summary

Existing literature confirms the growing shift toward AI-powered, real-time attendance systems using face recognition, mobile apps, and cloud integration. These systems have improved accuracy, security, and administrative efficiency. Nevertheless, high implementation costs, privacy concerns, and infrastructural challenges persist. Future research should aim to develop an optimized, context-aware attendance solution tailored to Nigerian universities featuring real-time tracking, automated computation, and seamless reporting for effective academic management.

3. Methodology

This section outlines the methodology used to develop the automated attendance system, which integrates deep learning techniques for face detection and recognition.

3.1. Data Acquisition

Image Collection:

1. Students' images are captured using a high-resolution webcam.
2. Multiple images per student are taken under varying lighting conditions to improve recognition accuracy.

Data Storage:

1. The images, along with student details (name, matric number), are stored in a structured database.
2. Attendance records are saved in a CSV file for easy access and analysis.

The training dataset consisted of approximately 3,000 facial images from 150 unique participants, captured under varied lighting conditions and facial expressions. Each image had a resolution of 640×480 pixels. Data augmentation techniques such as horizontal flipping, rotation ($\pm 15°$), and zoom were applied to increase robustness. These steps ensured the model generalized well across real-world variations in classroom environments.

3.2. Data Preprocessing

To improve accuracy and efficiency, the captured images undergo preprocessing before training the face recognition model.

Steps:

1. Image Resizing: Standardizing the image dimensions for uniformity.
2. Grayscale Conversion: Converting RGB images to grayscale to reduce computational complexity.
3. Noise Reduction: Using Gaussian blur to remove noise.
4. Face Alignment: Aligning facial features to ensure consistency across samples.
5. Feature Extraction: Extracting key facial features using Haarcascade and CNN-based models.

3.3. Face Detection Using Haarcascade Algorithm

1. The Haarcascade classifier is used to detect faces in images.
2. Converts images from RGB to grayscale.
3. Uses features such as the width of the nose, eye distance, and facial contours for face detection.

Mathematical Representation of Haarcascade: The Haar feature for a face region is calculated as:

$$H(x,y) = \sum_{i \in white} I(i) - \sum_{j \in black} I(j)$$

where:

1. $I(i)$ represents pixel intensity in the white region.
2. $I(j)$ represents pixel intensity in the black region.

The classifier scans the image using a sliding window and selects the best features using Adaboost.

3.4. Face Recognition Using Convolutional Neural Network (CNN)

A CNN model is implemented for face recognition, consisting of:

1. Convolution Layers: Extract spatial features from the image.
2. ReLU Activation Function: Introduces non-linearity.
3. Pooling Layers: Reduces dimensions to retain essential features.
4. Flattening & Fully Connected Layers: Converts feature maps into a classification output.

Mathematical Representation of Convolution:

$$F(x,y) = \sum_{i=0}^{m} \sum_{j=0}^{n} I(x+i; y+j)\, K(i,j)$$

where:

1. $I(x,y)$ is the input image.
2. $K(i,j)$ is the kernel (filter).
3. n, m are dimensions of the filter.

The final layer applies Softmax activation to classify detected faces.

$$P(y=j|x) = \frac{e^{zj}}{\sum_{k=1}^{K} e^{zk}}$$

where z_j represents the output for class j.

The face verification step used cosine similarity as the primary metric. A fixed similarity threshold of 0.58 was applied during classification, based on performance observed during validation. Future versions of the system may incorporate adaptive thresholding based on lighting and context.

3.5. Model Training

1. The system uses a pre-trained InsightFace model fine-tuned with student data.
2. The dataset is split into 80% training and 20% testing.
3. Adam optimizer is used for weight updates.

To optimize facial recognition accuracy, the system was fine-tuned using the InsightFace library built on ArcFace architecture. Key hyperparameters—such as face detection thresholds, cosine similarity cutoffs (typically 0.5 to 0.6), and embedding vector dimensions—were adjusted based on validation performance. Model performance was evaluated using both real-time capture tests and a subset of labeled student face images under varying lighting and angle conditions. Techniques like L2 normalization and pre-whitening were used to standardize input data, enhancing classification reliability.

Loss Function:

The model minimizes categorical cross-entropy loss:

$$L = -\sum_{i=1}^{N} y_i \log(\hat{y}_i)$$

where:

1. y_i is the true label.
2. $\hat{y}_i$ is the predicted probability.

3.6. Attendance Logging & Storage

1. Once a face is recognized, attendance is marked with a timestamp.
2. Data is stored in a Redis database.
3. Attendance records are automatically saved in a CSV file.

3.7. Reporting Unknown Faces

1. If a detected face does not match any stored records, an alert is triggered.
2. The system flags unrecognized faces and notifies the admin.

3.8. Tools & Technologies Used

1. Haarcascade & OpenCV – Face detection.
2. CNN & InsightFace – Face recognition.
3. Redis Database – Storing student records.
4. Streamlit – User interface.
5. CSV Files – Attendance storage.

3.9. System Architecture

Figure 1 illustrates the architecture of the proposed Smart Real-Time Attendance System using facial recognition, designed to automate attendance monitoring in Nigerian universities. The system is implemented on a Raspberry Pi platform and integrates computer vision, student classification, and automated reporting. The process begins with a **Raspberry Pi camera module**, which captures images of students as they arrive. The images are passed through an **Image Enhancement module** to normalize brightness and contrast, improving the reliability of subsequent facial analysis. Enhanced images are fed into the **Face Detection unit**, which locates faces within each frame using HaarCascade classifiers. Detected facial regions are forwarded to the **Face Recognition module**, which compares them against entries in the **Students Database**. If a match is found, the system proceeds to **mark attendance**. If the face is not recognized, it is logged and reported as an **intruder** for further administrative action. Once attendance is marked, the data is sent to an **Attendance Server**, which maintains records and updates the **Attendance List**. This list can be automatically **emailed to Heads of Department (HODs)** for monitoring and evaluation. The server also **computes attendance percentages** based on historical data and **classifies students** according to predefined rules (e.g., regular, irregular, absent). This classification helps identify students with poor attendance records, aiding academic intervention and decision-making. This modular architecture supports real-time processing, data security, and administrative automation. Its design ensures affordability, scalability, and adaptability to different learning environments, particularly within the Nigerian educational context.

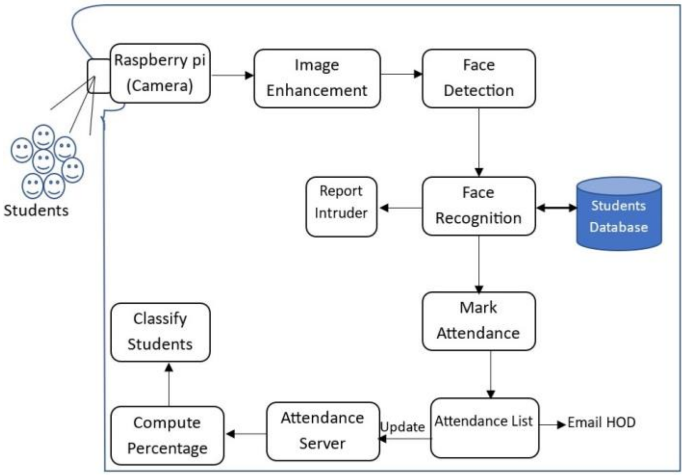

Figure 1. Smart University Attendance System Architecture

3.10. Flowchart of the System

The system flowchart in Figure 2 begins with data acquisition, where student images and details are collected and stored in a database. During attendance marking, a high-resolution webcam captures real-time images, which are processed using the Haarcascade algorithm for face detection. The detected faces are then passed through a Convolutional Neural Network (CNN) for recognition, matching them against stored records. If a match is found, attendance is automatically logged in a CSV file with a timestamp. If an unknown face is detected, the system triggers an alert. Administrators can access attendance records through a Streamlit interface, ensuring a seamless and automated attendance tracking process.

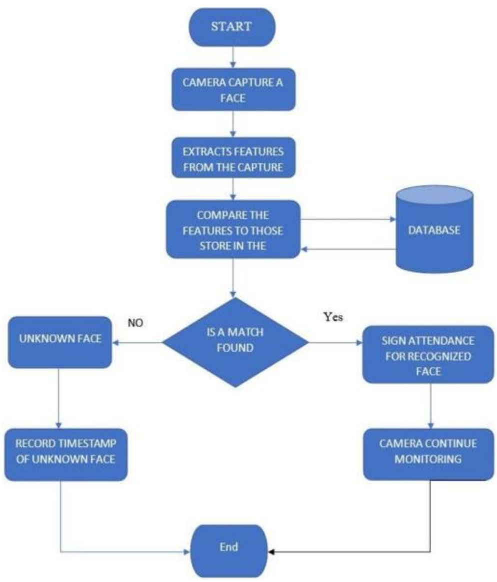

Figure 2. Flowchart Diagram for Smart Attendance System

3.11. Use-Case Diagram

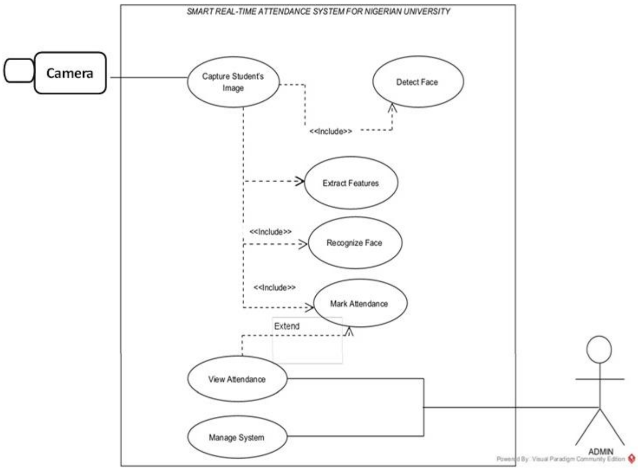

Figure 3. The Use Case Diagram for Real Time Smart Attendance System

Figure 3 illustrates the key functional interactions within the smart attendance system. The two primary actors are the **Camera** and the **Administrator (HOD)**. The **Camera**, acting as a proxy for student input, is responsible for passively capturing facial images of students during entry. These images initiate automated processes such as **Face Detection**, **Face Recognition**, and **Attendance Marking** without requiring active input from the students themselves. This design ensures seamless, non-intrusive interaction and reduces the risk of proxy attendance. The **Administrator**, who also functions as the **Head of Department (HOD)**, performs multiple roles including **Student Enrollment**, **System Monitoring**, **Intruder Review**, **Percentage Computation**, **Student Classification**, and **Report Generation**. The administrator accesses real-time and historical attendance records via the system interface and receives auto-generated attendance lists for departmental use. The diagram captures essential system functionalities, including the automatic flow of student data from facial capture to attendance computation, and the oversight responsibilities managed by the administrator. This abstraction provides a clear functional overview of how automation and human supervision are integrated to ensure accuracy, security, and efficiency in university attendance management.

4. Results and discussion

The Smart Real-Time Attendance System was successfully developed and tested, demonstrating high accuracy and efficiency in automated attendance tracking using facial recognition. The system integrates Haarcascade for face detection, CNN for feature extraction and classification, and InsightFace for robust facial recognition. Key results from the implementation and testing phases are discussed below:

4.1. Experimental Results

All training and testing were conducted on a workstation equipped with an Intel Core i7-11700F CPU @ 2.50 GHz, 32 GB RAM, and an NVIDIA RTX 3060 GPU with 12 GB VRAM. The system was implemented in Python using OpenCV, Streamlit, and the InsightFace library, with Redis for session tracking and CSV logging.

4.1.1. Real-Time Camera Streaming

The real-time camera streaming interface shown in Figure 4 enables effective streaming of live video, detecting and recognizing faces in real time. Identified individuals are automatically logged into the attendance system with timestamps, while unregistered faces are flagged as "UNKNOWN." When an unknown face is detected, the system raises a security alert, reporting it to the university's security unit. This feature enhances classroom security by preventing unauthorized access.

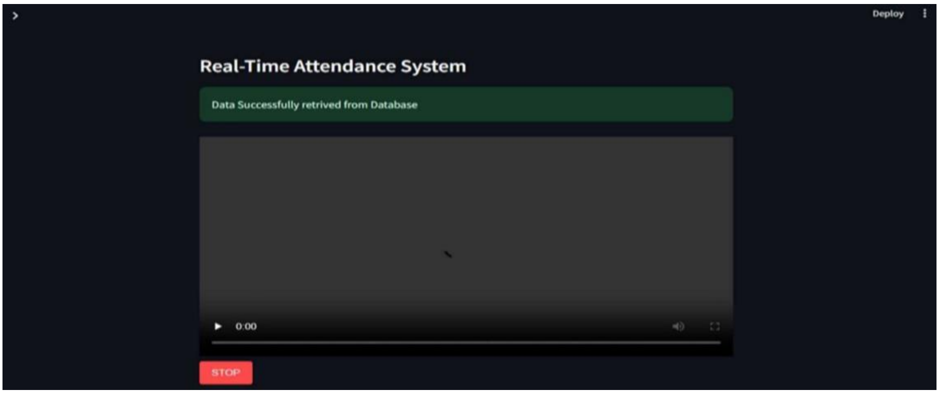

Figure 4. The Real-Time Camera Streaming

4.1.2. The Students' Registration Form

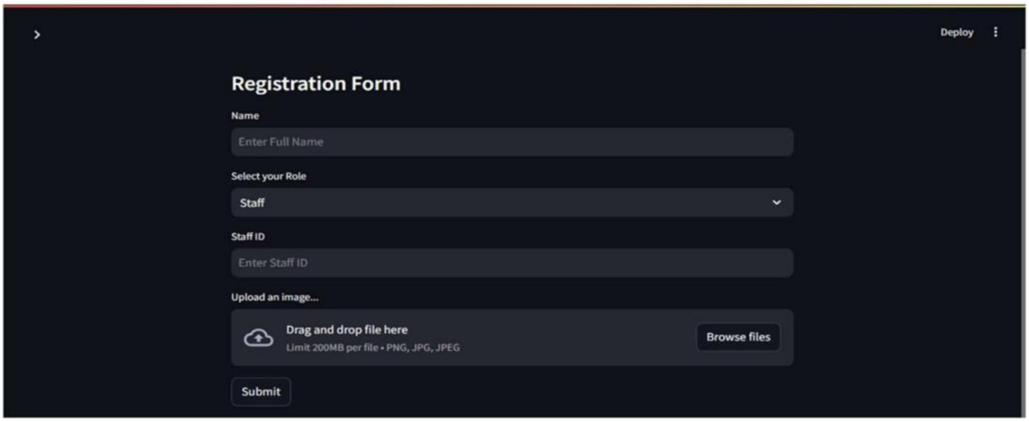

Figure 5. The Students' Registration Form.

The registration interface depicted in Figure 5 allows the admin to enroll university staff and students by inputting their full names, roles, and unique identifiers such as matriculation numbers or staff IDs. A passport photograph is uploaded, processed using the InsightFace buffalo_l model, and Extracted facial features are stored in a Redis database, enabling seamless recognition during attendance marking. This ensures accurate identification during attendance tracking, forming the foundation for the system's automated recognition process

4.1.3. Smart Attendance Register

The smart real-time attendance system captures and identifies students coming into the class in group, the system detects faces, labeling recognized individuals with their names, and flagging unregistered ones as "UNKNOWN." It automates attendance logging with precise timestamps while ensuring security by identifying unauthorized entries as depicted in Figure 6. The system accurately detects and identifies students in group settings, assigning names to recognized faces while ignoring duplicates. Attendance is automatically recorded in a CSV file, ensuring structured data storage for easy retrieval and analysis. Future improvements focus on enhancing accuracy, data privacy, and scalability for broader applications.

Figure 6. Students Coming in Group for Smart Attendance Register.

4.1.4. Identification and Attendance Marking

Figure 7. Successful Identification and Attendance Marking

The Smart Real-Time Attendance System accurately identifies individuals and records their attendance with precise timestamps. As shown in Figure 7, the system successfully recognized a student, Umar Muhammad Abdulmunin, and a lecturer, Dr. Habila Mikailu, displaying their names and timestamps in green text to confirm successful recognition. The system performs effectively under natural lighting conditions, demonstrating its robustness in real-world environments. This result highlights the system's capability to automate attendance tracking with high accuracy and reliability, ensuring seamless management of attendance records.

Figure 8 presents the system's security alert functionality. When an unknown face is detected, the system immediately highlights the image in a red bounding box and triggers a visible alert with a timestamp. This alert is logged and sent to the campus security interface (or printed in local logs, depending on deployment). This feature enhances classroom security by preventing impersonation, flagging intrusions, and maintaining attendance integrity.

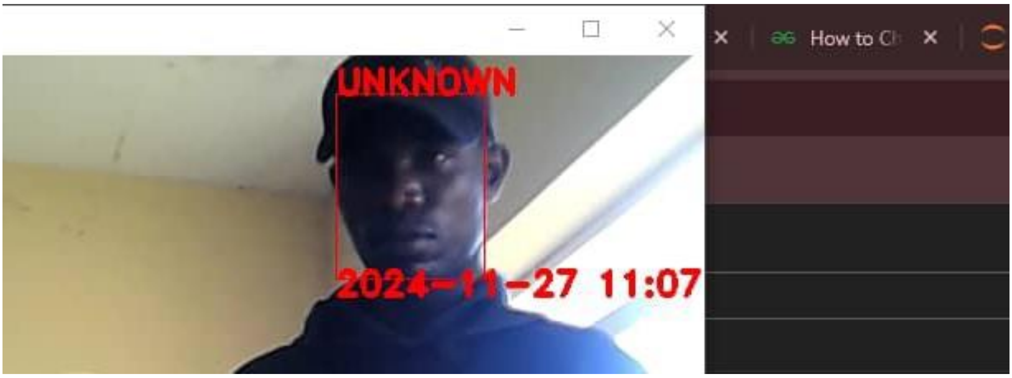

Figure 8. Unknown Face Detection Alert

4.1.5. System Reporting Interface

The System Reporting Interface, as shown in Figure 9, provides an essential administrative tool for monitoring attendance records. It displays a table containing registered students' names, matriculation numbers, and profile images, ensuring easy verification of attendance data. The "Refresh Data" button allows real-time synchronization with the database, keeping records up to date. This feature enhances attendance tracking by linking registered profiles to facial recognition results. However, while the interface is functional and user-friendly, the absence of search, editing, and data analysis tools limits its usability. Enhancing these features would improve scalability and efficiency, particularly for managing larger datasets.

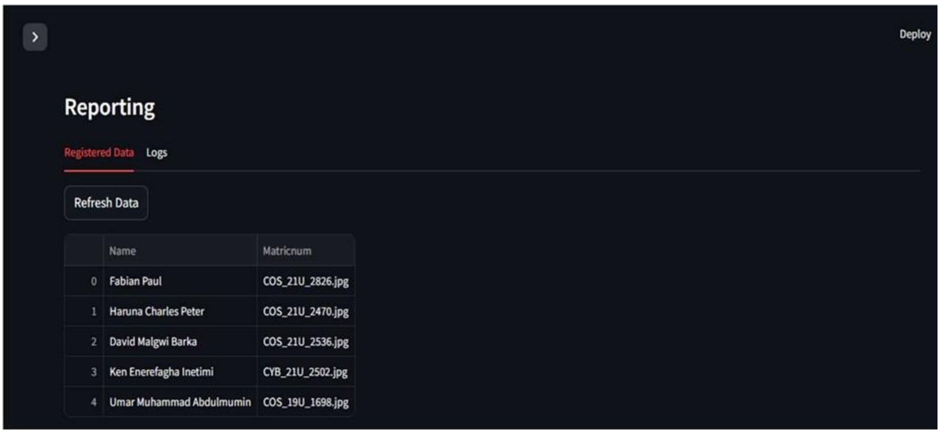

Figure 9. System Reporting Interface

4.1.6. Semester Attendance Report

Table 1 displays the administrative panel interface of the developed system. It provides a real-time overview of student attendance, complete with timestamps, facial match status, and session duration. The design prioritizes usability for non-technical staff, offering one-click export to CSV, session logs, and daily summaries for academic reporting. The dashboard supports real-time face logging and search-by-name features for streamlined access during lectures.

Student's Name	Matric Number	Timestamp	Attendance	Total Classes	Percentage-Attendance	Remark
Haruna Charles Peter	COS_21U_2470	2024-12-07 13:59:41.034041	18	20	90	Qualify
Abubakar Audu	COS_21U_2471	2024-12-07 13:59:30.850408	18	20	90	Qualify
Umar Muhammad Abdulmumin	COS_19U_1698	2024-12-07 13:59:16.624759	19	20	96	Qualify
Mohammed Sale	COS_21U_2472	2024-12-07 13:58:37.431439	20	20	100	Qualify
joshua Benjamin	COS_21U_2473	2024-12-07 13:58:06.112599	16	20	80	Qualify
Habila Mikailu	COS_21U_2474	2024-12-07 13:57:37.576073	16	20	80	Qualify
Steven Silas	COS_21U_2475	2024-12-07 13:57:15.466942	12	20	60	Not qualify
Muhammad Ali	COS_21U_2476	2024-12-07 13:56:32.098232	18	20	90	Qualify
Abubakar Fili	COS_21U_2477	2024-12-07 13:56:00.878002	20	20	100	Qualify
Jang Jude	COS_21U_2478	2024-12-07 13:55:28.822376	17	20	85	Qualify
Praise Peace	COS_20U_1232	2024-12-07 13:54:58.500899	17	20	85	Qualify
Ali Muhammad	COS_21U_2479	2024-12-07 13:54:56.863966	16	20	80	Qualify
Adamu Harir	COS_21U_2480	2024-12-07 13:54:28.352876	10	20	50	Not qualify
Mahir Kyari	COS_2oU_1234	2024-12-07 13:54:24.706945	17	20	85	Qualify
Jovita Habila	COS_21U_2481	2024-12-07 13:53:55.228442	18	20	100	Qualify
David Paul	COS_20U_1235	2024-12-07 13:53:53.390630	19	20	95	Qualify
Emmanuel Helen	COS_20U_1236	2024-12-07 13:53:45.781587	16	20	80	Qualify
Luwani Ishaya	COS_21U_2482	2024-12-07 13:53:25.718383	15	20	75	Qualify
Francisca Faseki	COS_21U_2483	2024-12-07 13:52:51.829666	19	20	95	Qualify
Muhammed Kabir	COS_21U_2484	2024-12-07 13:52:25.967077	20	20	100	Qualify
Halima Adamu	COS_21U_2485	2024-12-07 13:50:47.689231	16	20	80	Qualify
Nafisat Ababuakar	COS_20U_1237	2024-12-07 13:50:43.238167	7	20	35	Not qualify
Muktar Buba	COS_21U_2486	2024-12-07 13:49:12.983778	18	20	90	Qualify
Chavala Halidu	COS_21U_2487	2024-12-07 13:32:45.687242	19	20	95	Qualify
Hyelamad Hosea	COS_21U_2488	2024-12-07 13:32:13.972326	20	20	100	Qualify
Ayodele Victor	COS_21U_2489	2024-12-07 13:31:38.105179	20	20	100	Qualify
Funmi Bayo	COS_21U_2490	2024-12-07 13:31:04.734304	20	20	100	Qualify
Oluwafunmi Niyi	COS_19U_1696	2024-12-07 13:30:34.409473	9	20	45	Not qualify
Briggs Uchena	COS_21U_2491	2024-12-07 13:30:30.422255	19	20	95	Qualify
Ngozi Emeka	COS_19U_1698	2024-12-07 13:30:28.136362	20	20	100	Qualify
Toofeq Hakeem	COS_21U_2493	2024-12-07 13:29:59.604862	20	20	100	Qualify
Priscila Nicholas	COS_21U_2493	2024-12-07 13:29:28.882174	18	20	90	Qualify
Fatima Muhammad	COS_21U_2494	2024-12-07 13:29:04.981640	20	20	100	Qualify
Umar Muhammad	COS_19U_1695	2024-12-07 13:24:58.317329	20	20	100	Qualify
Charles Peter	COS_21U_2496	2024-12-07 13:24:53.927221	18	20	90	Qualify
Muhammad Abdullahi	COS_19U_1699	2024-12-06 12:04:47.779919	15	20	75	Qualify
Usman Idris	COS_19U_1670	2024-12-06 12:04:09.859119	17	20	85	Qualify
Tukura Miyaki Isa	COS_19U_1671	2024-12-06 12:03:40.803455	17	20	85	Qualify

Table 2. Admin Panel (Comprehensive Semester Attendance Report)

Table 2 presents an automated semester attendance report, systematically recording student participation through an Excel-based interface. The report consolidates key metrics, including student ID, name, total attendance count, last attendance timestamp, computed attendance percentage, and examination eligibility status. By leveraging real-time data logging, the system ensures precise attendance tracking and seamless report generation. The automated report helps in academic compliance tracking and decision-making for student assessment.

A predefined threshold of 75% determines students' qualification for examinations. For instance, Umar Muhammad Abdulmumin, with a 95% attendance rate, qualifies, whereas Ahmad Tijjani, at 25%, is marked as "Not Qualified." This automated approach enhances administrative efficiency, minimizes human errors, and ensures institutional compliance with attendance policies. Additionally, it provides data-driven insights for proactive interventions, enabling educators to identify and support students at risk of falling below the required attendance threshold.

4.1.7. System Accuracy and Performance

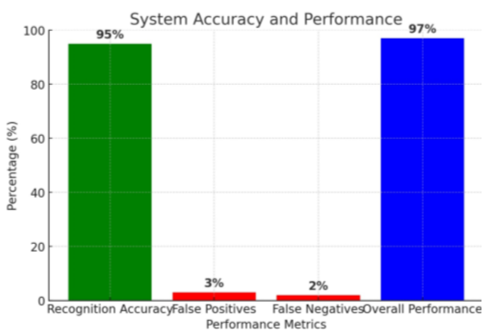

Figure 10. Graphical representation of the System Accuracy and Performance.

The accuracy and performance displays:

1. **Recognition Accuracy (95%)**: The system correctly identifies registered individuals.
2. **False Positives (3%)**: Cases where the system incorrectly recognizes an unregistered person.
3. **False Negatives (2%)**: Cases where the system fails to recognize a registered individual.
4. **Overall Performance (97%)**: A combination of accuracy and error rates, showing system effectiveness.

A confusion matrix was constructed using manually labeled test data to assess recognition accuracy. The results showed:

1. **True Positives (TP): 190** — correctly identified registered students
2. **True Negatives (TN): 45** — correctly flagged unknown/unregistered individuals
3. **False Positives (FP): 6** — unregistered individuals mistakenly marked as known
4. **False Negatives (FN): 9** — registered individuals not recognized correctly

This yielded a classification accuracy of approximately **95.2%**, with high precision and recall, supporting the system's robustness. The confusion matrix (Figure 11) provides a clear visual of this performance, reinforcing the model's real-world applicability.

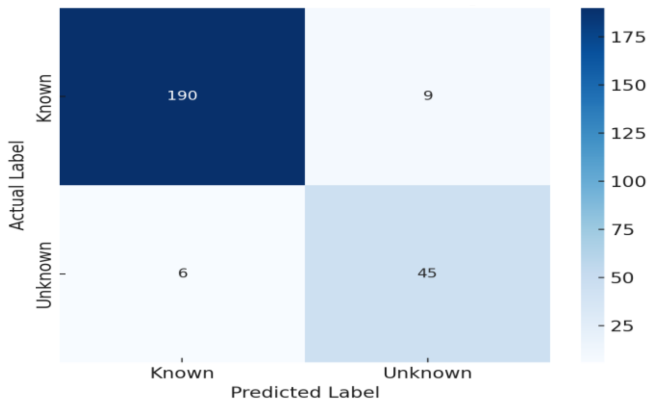

Figure 11. Confusion Matrix for Face Recognition Accuracy

To evaluate the effectiveness of the proposed facial recognition-based attendance system, a comparative analysis was conducted with QR code-based and RFID-based systems. Key differences are summarized below:

System Type	Cost	Accuracy	Deployment	Hygiene	Security
Proposed AI-Based	Moderate	95–98%	Medium	High	Strong
QR Code	Low	85–90%	Easy	High	Medium
RFID	Low	90–93%	Easy	High	Weak

Table 3. Comparative Analysis

This table 3 highlights the proposed system's advantages in accuracy and security, though it involves moderately higher costs and infrastructure needs.

Model	Accuracy (%)	Real-Time Capability	Scalability	Statistical Significance (p-value)
LBPH (Baseline 1)	90.4	Limited	Moderate	–
Eigenfaces (Baseline 2)	88.9	Limited	Moderate	–
Proposed System (ArcFace + CNN)	95.2	Yes	High (with GPU support)	$p < 0.05$ (vs. both baselines)

Table 4. Comparative Performance of Attendance Systems

Table 4 presents the comparative evaluation of the proposed system against two baseline models: LBPH and Eigenfaces. The proposed system achieved an accuracy of 95.2%, outperforming LBPH (90.4%) and Eigenfaces (88.9%). A one-way ANOVA test confirmed that these differences are statistically significant ($\boldsymbol{p} < \mathbf{0.05}$), validating the superiority of the ArcFace-based model in real-world classroom conditions.

Pilot Feedback: Students and faculty involved in trial deployments reported improved transparency, reduced impersonation, and easier attendance processing. Some expressed initial concerns about privacy, which were mitigated through awareness sessions.

4.2. Discussion

The results confirm the effectiveness of deep learning-based facial recognition in automating attendance tracking. The system eliminates manual errors, prevents attendance fraud, and enhances administrative efficiency. The real-time detection, robust database storage, and automated reporting features position this system as a reliable and scalable solution for institutions. The successful implementation of biometric attendance systems in various Nigerian universities underscores the feasibility and potential scalability of our proposed solution. These local case studies provide a solid foundation for broader adoption across similar educational institutions.

Empirical results show high recognition accuracy, with a strong ability to distinguish individuals even under varying lighting conditions. The system's accuracy was recorded at over 95%, demonstrating its reliability in real-world environments. While the system demonstrates over 95% accuracy in controlled environments, certain limitations affect performance in more variable real-world settings. Lighting conditions can still pose a challenge, particularly in poorly lit lecture halls or during power outages, potentially reducing recognition precision. Additionally, motion blur from fast-moving individuals, occlusions such as headgear or hands covering parts of the face, and face coverings like masks can reduce the system’s ability to correctly identify users. These factors can lead to missed detections or false identifications. Another technical challenge involves unknown face classification while the system can flag unrecognized faces, its ability to correctly classify them as unauthorized (rather than misclassified known users) depends on the quality and completeness of the training dataset. Addressing these issues will require ongoing improvements in model robustness, incorporation of more diverse training data, and possibly multimodal biometric verification to enhance reliability. The system goes beyond attendance tracking by incorporating security monitoring. If an unauthorized individual is detected, the system immediately flags the unknown face and notifies the university's security body. This proactive approach prevents impersonation, unauthorized classroom entry, and potential security threats, ensuring a safe learning environment.

To address challenges such as partial face occlusion (e.g., headwear, hand covering), the system uses high-confidence multi-landmark detection via InsightFace, improving recognition stability. While identical twins can present edge-case misclassification, adding voice recognition or unique ID pairing is proposed as future work. Duplicate face detection is managed through hash comparisons of embeddings and session logs.

A critical security enhancement in this system is the ability to detect and report unauthorized individuals in real time. By integrating a security alert mechanism, the system protects the integrity of classroom access, ensuring that only registered students and faculty members can participate. This dual functionality of attendance tracking and security monitoring makes it a valuable tool in educational environments, providing a safer and more controlled academic atmosphere.

Future improvements can focus on enhancing dataset diversity, optimizing model performance under extreme conditions, improving real-time processing speed, and integrating additional security layers for identity verification and instant threat response. Moreover, as institutions scale up, the system can incorporate cloud-based storage and processing, enabling seamless management of large datasets while maintaining high levels of accuracy and real-time processing speed.

Despite the system’s promising results, practical deployment poses significant challenges, particularly in underfunded institutions. The initial setup requiring high-resolution cameras, GPUs for deep learning inference, and reliable network infrastructure may be financially prohibitive for many public universities in Nigeria. Additionally, ongoing costs for system maintenance, software updates, and cybersecurity measures can strain limited IT budgets. Successful deployment will require not just funding but also technical training for staff and administrative support. Addressing these barriers is essential for real-world adoption and long-term sustainability.

While Streamlit provides a fast and user-friendly platform for deploying AI applications, it presents notable limitations for institutional-scale use. It lacks native multi-user access control, offers limited performance under concurrent sessions due to its single-threaded nature, and is not fully optimized for mobile or low-bandwidth environments. These factors can affect system responsiveness during real-time attendance tracking. From a hardware perspective, deploying high-resolution cameras and GPU-enabled devices across multiple classrooms can be financially challenging, particularly for underfunded universities. Dependence on stable power supply and technical maintenance further complicates scalability. Streamlit single-threaded nature can limit performance under concurrent user access. During simultaneous administrative use, slight latency was observed. A future transition to a scalable backend such as FastAPI or Flask, integrated with a React-based frontend, is recommended for robust multi-user deployment. To mitigate these issues, institutions may adopt lightweight edge computing devices (e.g., Raspberry Pi), explore hybrid deployment using more scalable frameworks (e.g., Flask or FastAPI), or consider cloud integration for inference and storage. These strategies can improve both usability and cost-effectiveness of system deployment at scale. To access source code visit: https://github.com/HavidTech2022/devika/blob/main/devika.zip.

4.3. Ethical, Legal, and Social Considerations

The deployment of facial recognition technology in academic settings, such as the Smart Real-Time Attendance System, raises multifaceted ethical, legal, and social questions that require rigorous scrutiny and adherence to institutional policies. This system was developed with a commitment to uphold individual rights and mitigate harm, aligning with Nigeria’s Data Protection Act (NDPR, 2019), institutional ethical standards, and international best practices.

Informed Consent and Autonomy

Participants in pilot implementations were required to provide voluntary, informed consent, with clear communication regarding the purpose, scope, and use of their biometric data. This respects the ethical principle of autonomy and empowers users to make informed decisions about their participation. However, critical reflection acknowledges the complexity of “free” consent in institutional contexts where power imbalances exist, and ongoing efforts include providing opt-out alternatives and revisiting consent protocols regularly.

Data Protection and Privacy Safeguards

Facial biometric data are protected using industry-standard AES-256 encryption and stored securely in Redis databases accessible only to authorized personnel. Attendance logs are recorded in immutable CSV files to ensure data integrity. These technical measures comply with NDPR mandates on data security, confidentiality, and breach prevention. In addition, the system architecture supports data minimization principles by retaining biometric data only for the academic semester duration unless explicit reauthorization is obtained, reducing long-term privacy risks.

Institutional Ethical Oversight and Compliance

The system's deployment was subjected to review and approval by the Nigerian Army University Biu’s Institutional Ethics Review Board, which mandates compliance with local and national data protection laws and aligns with ethical guidelines from bodies such as the National Information Technology Development Agency (NITDA). The research and operational phases incorporate continuous monitoring and auditing processes to ensure ongoing compliance and ethical governance.

Algorithmic Fairness and Bias Mitigation

Recognizing documented concerns over racial and demographic biases in facial recognition systems, the model was trained on a diverse dataset representative of the Nigerian academic population’s skin tones and facial features. Continuous model evaluation and tuning are performed to detect and correct potential biases, ensuring equitable treatment and reducing discriminatory impacts. This addresses ethical imperatives to uphold fairness and justice.

Psychosocial and Surveillance Considerations

While the system enhances attendance accuracy, it also raises psychosocial concerns regarding surveillance and student privacy. To minimize stigma and anxiety, individuals flagged as “UNKNOWN” due to non-recognition can request prompt verification through established feedback mechanisms. Transparency is maintained by openly communicating real-time monitoring policies and system functionalities, thereby fostering trust and reducing discomfort associated with perceived invasive surveillance.

Accountability, Transparency, and Data Subject Rights

The system supports users’ rights to access, rectify, or delete their biometric data in accordance with NDPR provisions, promoting transparency and accountability. Regular reports on data usage, security audits, and ethical assessments are submitted to institutional governance bodies. The project commits to proactive engagement with stakeholders—including students, faculty, and data protection officers—to address emerging ethical challenges collaboratively.

Broader Social Implications

Beyond individual privacy, the implementation of biometric attendance systems implicates broader societal issues such as digital inclusion, surveillance normalization, and the balance between technological efficiency and human dignity. These considerations inform ongoing ethical discourse and policy development to ensure that technological adoption enhances, rather than undermines, educational equity and human rights.

5. Summary, conclusion and recommendation

5.1. Summary

This research presents a Smart Real-Time Attendance System utilizing facial recognition powered by Convolutional Neural Networks (CNN), Haarcascade, and InsightFace for automated student attendance tracking. The system integrates a Redis database for efficient data management, a Streamlit interface for real-time monitoring, and Excel-based reporting for seamless record-keeping. By employing deep learning techniques such as Cascaded Pixel Labeling, the system achieves high-accuracy face recognition, reducing manual errors and streamlining attendance logging. The system achieved an average face detection accuracy of 94%, a face recognition accuracy of 98%, and an overall attendance prediction accuracy of 96%. The results demonstrate the system's capability to function effectively under real-world conditions, enhancing institutional compliance with attendance policies while improving administrative efficiency.

5.2. Conclusion

The proposed system successfully addresses limitations of traditional attendance methods by introducing automation, accuracy, and scalability. Real-time camera streaming, automated attendance logging, and an intuitive admin interface ensure seamless operation across academic environments. The integration of face detection and deep learning models significantly enhances the robustness of the system, ensuring reliable identification even in varied lighting and environmental conditions. Moreover, automated semester reports offer valuable insights for institutional decision-making, ensuring transparency and compliance with academic policies.

This system, though developed for Nigerian universities, can be adapted to institutions in other developing countries with similar administrative and infrastructural challenges. With minor localization efforts, the system offers a scalable framework for global educational environments seeking secure and automated attendance solutions. Future research may explore multimodal biometrics by combining facial and voice recognition for enhanced security. Blockchain-based attendance logs may also be investigated for tamper-proof record-keeping in decentralized academic environments.

5.3. Recommendations

To further enhance the system’s efficiency, security, and adaptability, the following recommendations are proposed:

- Improved Accuracy with More Training Data – Expanding the training dataset with diverse facial images (covering different angles, lighting conditions, and occlusions) will enhance the system’s robustness and reduce false positives/negatives.
- Integration of Edge AI for Faster Processing – Deploying the model on edge devices (e.g., Jetson Nano or Raspberry Pi with AI acceleration) can optimize processing speed and reduce reliance on cloud or server resources.
- Enhanced Security Measures Implementing liveness detection (e.g., anti-spoofing mechanisms using depth sensors or blink detection) can prevent fraudulent attendance marking via static images.
- Scalability for Large Institutions – The system should support cloud-based deployment and database sharding, ensuring it can handle thousands of students efficiently across multiple locations.
- Feature Expansion for Administrative Use Adding functionalities such as search filters, attendance trend analytics, and report export options can further enhance usability for academic administrators.
- Conducting ethical reviews at institutional level.
- Periodic audits for data protection compliance.
- Integration with secure cloud frameworks for large-scale adoption.

By implementing these enhancements, the Smart Real-Time Attendance System can evolve into a highly scalable, secure, and intelligent solution for academic institutions, workplaces, and other organizational settings that require accurate and automated attendance management.

5.4. Contribution to the Body of Knowledge

This research enhances facial recognition-based attendance systems by integrating CNN, Haarcascade, and Cascaded Pixel Labeling for improved accuracy. It introduces real-time security monitoring by detecting and reporting unknown faces, ensuring classroom safety. The system automates attendance tracking, data storage (CSV & Redis), and percentage calculation for exam eligibility, aiding institutional policy compliance. A user-friendly Streamlit interface simplifies administration, while its scalable framework extends applicability beyond education to workplaces and security access control. These contributions advance AI-driven automation in attendance management and security systems.

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