Improving Student Attendance using a Smart Biometric System with Facial Recognition using Insight Face and Cosine Similarity Algorithm

Tousif Mohaimen[1], Nuzulha Khilwani Ibrahim[1*], Norzihani Yusof[1], Zuraini Othman[1], Mohd Hakimi Aiman Ibrahim[2]

[1]Fakulti Technology Maklumat dan Komunikasi, University Technical Malaysia Melaka (UTeM), 76100, Malacca, Malaysia

[2]Fakulti Sains Data dan Komputeran, University Malaysia Kelantan (UMK), Malaysia

*** Corresponding Author**

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ABSTRACT

Student attendance is a critical factor influencing academic performance and success in higher education institutions. However, the rising trend of absenteeism among university students poses a significant challenge to academic integrity and administrative efficiency. In response to this issue, the present study proposes a smart classroom attendance system that leverages facial recognition technology as the primary biometric modality. The system incorporates a high-definition (HD) camera for real-time image acquisition, a deep learning-based facial detection algorithm, and a local server for data processing and storage. Upon successful facial verification, attendance is automatically recorded, eliminating the need for traditional manual sign-ins. The system is engineered to function reliably under varying classroom lighting conditions and offers seamless integration with institutional databases for efficient record management. To enhance recognition performance, various optimization techniques were applied, including parameter tuning and adjustment of the similarity threshold. The cosine similarity algorithm was employed to effectively match facial embeddings, contributing to high recognition accuracy. Additionally, the system features a user-friendly interface that enables educators to monitor student attendance, annotate records, and generate detailed reports with ease. Experimental results confirm the system's effectiveness in minimizing attendance fraud and ultimately streamlining administrative tasks in higher education environments.

Keywords- Class Absenteeism; Student Attendance; Biometric Smart System; Facial Recognition; Cosine Similarity Algorithm

INTRODUCTION

Class attendance serves not only as a formal academic requirement but also as an indicator of student engagement, responsibility, and commitment to the learning process. Although higher education provides students with greater autonomy, absenteeism without legitimate justification can undermine both academic performance and the overall integrity of the educational environment. Numerous studies have established a strong positive correlation between consistent class attendance and academic achievement [1].

Despite its importance, traditional methods of tracking attendance—such as manual sign-in sheets, attendance cards, and barcode scanning—have long been associated with inefficiencies, human error, and vulnerability to fraudulent practices. To address these limitations, this study proposes a student attendance monitoring system based on facial recognition technology, leveraging recent advancements in computer vision and machine learning. By automating the attendance-taking process, the system aims to improve accuracy, reduce administrative workload, and prevent attendance fraud.

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The primary objective of this research is to develop a system that minimizes the time and effort required for physical attendance tracking while enhancing the reliability of student attendance records. The system employs facial recognition algorithms as a robust and non-intrusive biometric solution. The overall architecture and workflow of the proposed system are illustrated in Fig. 1.

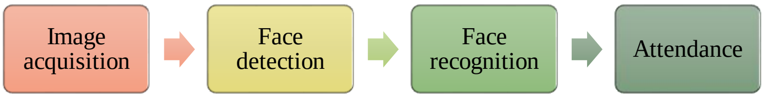

Fig. 1 Workflow of the proposed system

The Process Workflow: The attendance system begins by capturing facial images of all enrolled students during the registration phase. Following image acquisition, the system extracts unique facial features (embeddings) from each image and stores the resulting data in a Redis in-memory database for efficient retrieval. During the attendance-taking phase, the system captures a real-time image of the student, performs feature extraction, and compares the extracted embeddings against the stored dataset using the cosine similarity algorithm. Based on the highest similarity score, the system identifies the best match and retrieves the corresponding student information for attendance recording. This automated approach significantly reduces manual errors, ensures accurate student identification, and enhances the reliability of attendance records.

Related Work

This section reviews relevant literature on student absenteeism as well as the techniques used for facial recognition.

Student Absenteeism: Factors, Impact and Recommendations to Improve

Factors of Student Absenteeism: there are factors identified as the basis of class absenteeism:

- Low Interest in Subject or Lecturer - Students who lack interest in the subject matter or teaching style of the lecturer are more likely to skip classes [2].
- Academic Pressure and Overlapping Assignments - Many students report being overwhelmed by heavy workloads and examination preparation, leading them to prioritize assignments over class attendance [3].
- Unbalanced Lifestyle and Poor Time Management - Irregular lifestyles—including late nights, part-time jobs, and excessive social activities—frequently disrupt students' ability to attend classes consistently [4].
- Mental Health Issues - Conditions such as depression and social anxiety have also been identified as significant contributors to student absenteeism [5].
- Lack of Monitoring and Lenient Attendance Policies - Institutions that do not enforce attendance or implement follow-up measures tend to inadvertently encourage students to neglect class participation [6].

Impacts of Student Absenteeism: recent studies also discuss the impacts of student absenteeism:

- Decline in Academic Performance - Studies show that students who frequently miss classes score significantly lower in examinations compared to regular attendees [1], [7].
- Impact on Professional Values - Absenteeism reflects a lack of discipline and professionalism - qualities that are essential in post-graduate careers [8].
- Disruption to Lecturers and Classmates - Widespread absenteeism can negatively affect class interactivity and teaching motivation [9].

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- Failure to Meet Academic Requirements - Many universities enforce a minimum attendance rate of 80%. Failure to meet this requirement can result in students being barred from examinations [6].

Recommendations to Improve: current researchers have outlined possible recommendations to improve the students' absenteeism:

- Implementation of Early Alert Systems - Automated digital systems that track attendance in real time can help lecturers identify at-risk students early [10].
- Interactive and Relevant Teaching Approaches - Active learning strategies, such as group work, problem-based learning (PBL), and gamification, can improve student engagement and attendance [11].
- Counselling and Psychosocial Support - Universities should offer systematic psychological support to students facing emotional or mental health challenges [12].

Adoption of Biometric and Smart Applications –

- Kakepoto et al. [13] highlights the efficiency and accuracy of biometric attendance systems in universities compared to manual methods.
- Recent research [14] also presented that smart systems based on the Internet of Things (IoT), using RFID and facial recognition, can automatically detect attendance, lateness, and class substitutions with minimal error rates.
- While Alghamdi [15] recommends using mobile apps with biometric fingerprint or QR-code scanning to record attendance without disrupting class time.
- In a study for a university in Malaysia [16], the biometric fingerprint attendance system developed by Universiti Teknologi MARA (UiTM) with IoT integration has received positive feedback for its ease of use and effectiveness.

Biometric and Smart Application for Students' Attendance

Facial recognition technology represents a modern and automated approach to student attendance systems, replacing manual sign-ins and name-calling. This system utilizes cameras and artificial intelligence (AI) algorithms to identify student faces and record attendance in real time. Some previous studies are listed as the following:

- Zhao et al. [17] developed a smart classroom attendance system using IoT that incorporates facial recognition and RFID cards. The system records attendance automatically with a very low error rate in real time.
- Bhagat et al. [18] found that facial recognition enhances security and significantly reduces the time needed for rollcalls.
- Arulogun et al. [19] showed in their study conducted in Nigeria that facial recognition attendance systems were well received by both students and lecturers and were highly effective, especially in crowded classrooms.

From previous research, the attendance system normally consists of a prototype of a smart classroom attendance system for university settings, employing facial recognition as the primary biometric modality. The system architecture comprises three core components: a high-definition (HD) camera for real-time image acquisition, a deep learning–based face detection and feature extraction module, and a backend server for data processing and management. The existing attendance system comprises three key components which are also included in Fig.2

- Hardware module (image acquisition and processing)
- Software module (face recognition and identity matching)
- Integration module (data synchronization and reporting)

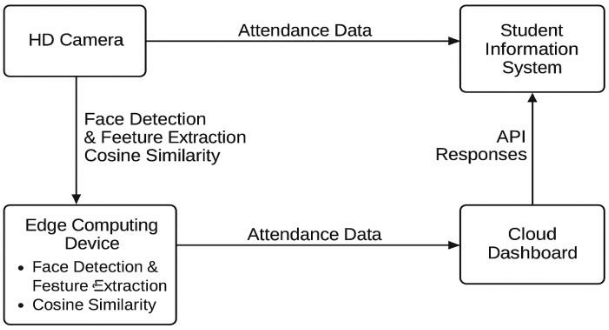

Fig. 2 Existing attendance system and its components

Face Recognition as a Biometric Modality

Biometric identification systems are essential tools in security and authentication due to their ability to verify individuals based on distinct physiological or behavioral characteristics. Among the various biometric modalities, face recognition has emerged as one of the most prominent in both research and commercial applications.

As a physiological biometric technique—alongside fingerprint, iris, and retina recognition—facial recognition involves detecting, extracting, and analyzing facial features to authenticate identity. These features include the distance between the eyes, cheekbone structure, and jaw contour, forming a unique facial signature for everyone [20].

Compared to other biometric modalities, face recognition offers several benefits: it is contactless, non-invasive, and can operate at a distance, making it ideal for real-time surveillance and access control systems [21]. Its application spans mobile authentication, attendance systems, border security, and smart city frameworks.

Privacy and Data Security

In detail, advantages of Face Recognition Technology are listed as the following:

- Automated & Contactless - Requires no physical interaction (unlike fingerprint scanners), making it safer in post-pandemic contexts.
- High Accuracy and Efficiency - Can identify individuals in less than one second with high precision [17].
- Prevention of Attendance Fraud - Effectively eliminates “proxy attendance” where a student attends on behalf of another [18].
- Integration with IoT and Real-Time Attendance Monitoring - Some systems provide instant reporting to lecturers and academic management via cloud-based or mobile applications [19].

Thus, the classification of facial recognition as biometric modality is well-supported in academic literature and technological standards. It continues to play a crucial role in modern identity verification systems, with expanding applications in education and beyond.

Despite these advantages, face recognition may be less reliable than fingerprint or iris recognition in certain scenarios due to lighting variations, facial expressions, occlusion, or aging effects [22-24]. Nonetheless, advancements in machine learning and deep neural networks have considerably enhanced the performance and reliability of face recognition systems [25].

The implementation challenges of face recognition presented by the previous researchers are outlined in brief as the following:

- Privacy and Data Security Concerns - Biometric data is sensitive, and mishandling can pose significant data breach risks [26].

- Limited Accuracy in Certain Conditions - Low lighting, facial expression changes, or face coverings can reduce recognition accuracy [25].
- High Initial Costs - Implementation requires HD cameras, dedicated servers, and facial recognition software.

Feature Extraction using InsightFace Model

The InsightFace framework is a state-of-the-art deep learning model for facial recognition tasks that utilizes deep convolutional neural networks to extract highly discriminative facial embeddings. These embeddings are typically high-dimensional vectors (e.g., 512-dimensional) that encapsulate the unique structural features of a person's face.

The extracted embeddings are designed such that facial images belonging to the same identity lie in proximity within a learned feature space, whereas embeddings from different identities are significantly separated.

To quantify the similarity between two face embeddings, the cosine similarity algorithm is widely employed. Cosine similarity measures the cosine of the angle between two non-zero vectors, producing a score ranging from –1 to 1, where values closer to 1 indicate high similarity.

In the context of face verification or recognition, cosine similarity is applied to compare two embeddings generated by InsightFace; a higher similarity score suggests a higher likelihood that the images belong to the same individual.

Thus, InsightFace acts as the feature extractor, while cosine similarity functions as the decision metric, together forming an effective and efficient pipeline for deep face recognition systems. Fig. 3 shows briefly the comparison between HaarCascade and InsightFace extraction.

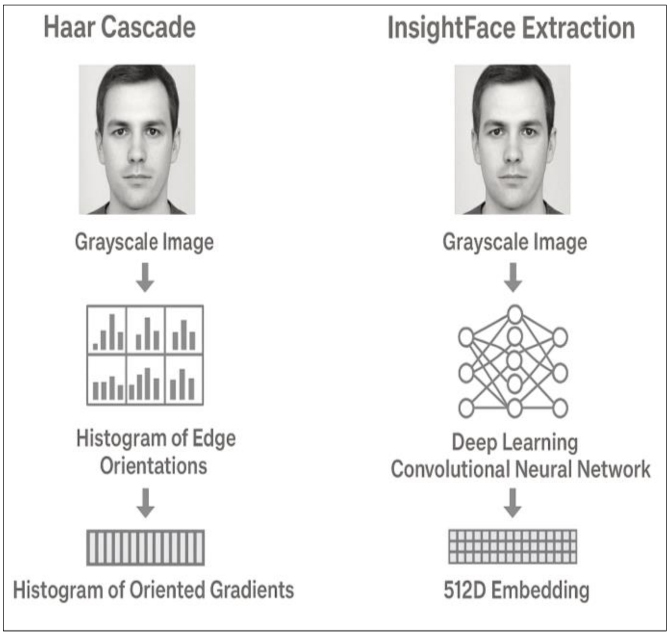

Fig. 3 Comparison between Haar Cascade and InsightFace extraction.

Cosine Similarity for Facial Recognition

Cosine Similarity is a mathematical measure used to compare the direction (not magnitude) of two vectors. In face recognition, it's used to compare the similarity between two face embeddings. For example:

- Input: Two (2) face images.
- InsightFace model will process both images → generates two feature vectors (eg: 512D).
- Cosine similarity is applied to both vectors.

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- If similarity ≈ 1, then they are the same person.
- If similarity ≈ 0, then they are different people.

There are several face recognition models available from CNN, such as VGG-Face, FaceNet, OpenFace, DeepFace, DeepID2, and Dlib. These models take face images as input and return vectors that reflect the image in different ways.

Then, for the verification stage, the representation module gives the verification module two vectors with the same number of dimensions. In this layer, the similarities between these vectors are considered. To figure out how far apart two vectors are, you can use different measures, such as the cosine similarity, the Euclidean distance, or its L2 form.

Table I shows the comparison of input output data for several face recognition models presented in [27], where their study proves that, using Facenet model they got 98.21 %, the highest accuracy among the other models.

TABLE I Threshold And Output Values Using Cosine Similarity From Previous Study [27]

Using Cosine Similarity	**FaceNet**	**VGGFace**	**OpenFace**	**DeepFace**
Threshold	0.40	0.31	0.11	0.13
Accuracy	98.21	89.28	57.85	54.64
Precision	100	97.41	95.83	100
Recall	96.42	80.71	16.42	9.28
F1-score	98.18	88.28	28.04	16.99

Algorithms Relationship

The InsightFace model and the cosine similarity algorithm are closely related in face recognition systems, especially in deep learning–based facial embedding frameworks.

InsightFace is the feature extractor, and cosine similarity is the comparator. They work together to enable face verification or recognition by turning facial images into vectors and then checking how similar those vectors are. Table II shows a clear explanation of the relationship and how they work together.

TABLE II Relationship Between Insight face And Cosine Similarity

Model/ Algorithm	**InsightFace**	**Cosine Similarity**
Purpose	Extracts face embeddings (vectors) from images	Measures similarity between two (2) embeddings
Return value	Embedding is usually 512D	Return similarity score between -1 and 1
How it works	Learns to space same-person embeddings close together	Verifies identity or matched faces based on vector angle

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In comparison, the three (3) algorithms work together to complete facial recognition. Fig. 4 shows the flow sequence of the algorithms, and how they work together, from an input image in the beginning, until an identity output is produced at the end of the process.

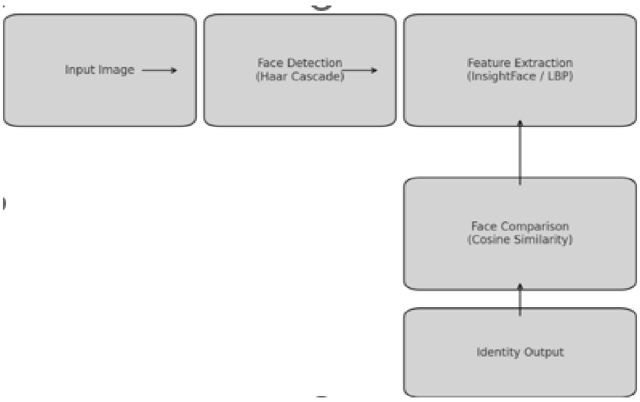

Fig. 4 Flow of process for the three algorithms, Haar Cascade, Insight Face, and Cosine Similarity.

METHODOLOGY

System Configuration

Hardware Configuration: The hardware setup includes

- An HD camera (1080p) for continuous image capture at the classroom entrance.
- An edge computing device (e.g., NVIDIA Jetson Nano or Raspberry Pi 4 with Coral USB accelerator) to support real-time face detection and feature extraction.
- A network-attached storage (NAS) unit for secure storage of biometric templates and attendance logs.
- The system is deployed at the entrance of the classroom to automatically detect and verify students as they enter.

Software and IoT Integration: The integration includes

- The backend server is developed using Python and Flask to handle API requests and data routing.
- Attendance logs are automatically synced with the university's Student Information System (SIS) through a secure RESTful API.
- This allows lecturers and administrators to access attendance records directly from the existing academic portal.
- Furthermore, the system supports IoT connectivity, transmitting attendance data in real time to a cloud dashboard for monitoring and analytics.
- Alerts can be triggered for students with repeated absenteeism, and summary reports can be exported periodically for administrative use.

System Design

This study adopts a design and development approach to construct a prototype smart attendance system for university classrooms utilizing facial recognition as a biometric modality. The software working principles are:

- **Step 1:** Start
- **Step 2:** Registration of (user)teacher for authentication
- **Step 3:** Install a webcam.
- **Step 4:** Face detection and face registration
- **Step 5:** Face recognition
- **Step 6:** Procced, if the face already registered in database
- **Step 7:** If faces are matched the system will mark the attendance.

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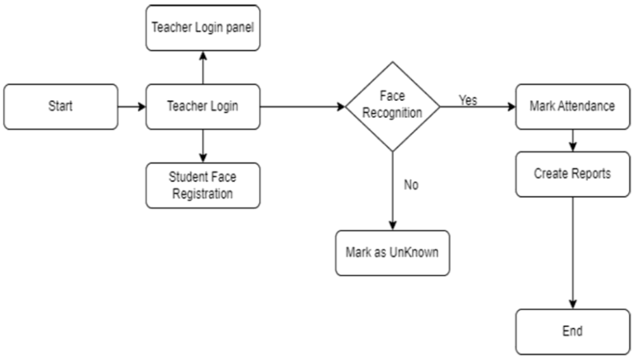

Fig. 5 Shows the overall process flow, as it has been adapted from previous study [28], the researcher has developed software for attendance using facial recognition system.

The strategy comprises of two (2) major steps which are outlined below:

- **Step A** - Feature collection: data collection, feature extraction by way of the InsightFace API.
- **Step B** - Inference: the use of cosine similarity for the purpose of matching various face traits.

Activities in each step:

Data Collection:

- The facial images of enrolled students are captured during this phase.
- Both the training of the facial recognition model and the construction of the attendance database relies on images as their foundation.

Data Pre-processing:

- This task is all about getting the collected data ready for the feature extraction step.
- It may include jobs like resizing, cropping, and normalization to make sure that all facial images are the same size and shape.

Feature extraction:

- During this step, the important facial features from the already-processed images are pulled out using the InsightFace API.
- Then, these traits are turned into feature vectors, which give each person a unique identifier.

Database storage:

- During the inference stage, the extracted feature vectors are saved in a Redis database so that they can be quickly retrieved and matched.
- Sample data stored in the database is presented in Fig. 6.

```
In [21]:   embed_test

Out[21]: array([ 0.12991045, -1.4456009 ,  0.33450627, -0.7121366 ,  1.3419212 ,
                -0.678954  ,  0.03161745,  0.75478154, -0.597753  ,  1.0735943 ,
                -0.36211342,  0.6129742 ,  0.49698702, -1.3452051 ,  0.16735506,
                -0.8574494 ,  1.1986948 ,  1.1829195 ,  0.36729425,  0.8688977 ,
                 0.60346603, -1.781585  , -0.40202004,  0.44984567, -0.28907943,
                -0.03198136, -0.85039264,  0.24502364,  0.66630197,  1.8045151 ,
                 1.5619118 ,  0.4332955 ,  0.7651546 ,  0.75427777, -1.9641825 ,
                -0.21910323, -1.5026369 ,  0.28470385,  2.6117265 ,  1.1120732 ,
                 1.1006424 , -0.24544336, -0.6430967 ,  0.25075692,  0.68334746,
                -0.17270082,  0.6625372 ,  0.35245866,  0.40602964, -2.245058  ,
                -0.12702243, -0.5731243 , -0.66463125, -0.28628096,  0.8638146 ,
```

Fig. 6 Sample data stored in the database

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Inference:

- During this step, new pictures of the face are taken and pre-processed.
- The process of feature extraction is then used to get feature vectors that can be compared.
- Cosine similarity is used to figure out how close the features that were extracted and those that were already in the Redis database are.
- The best fit is found, and the student's name is predicted so that attendance can be kept track of.
- The details of the steps are presented in Fig. 7.

Feature Extraction and Face Recognition

The method used in this study considers the highest accuracy model from previous study [28] is most face identification models are Convolutional Neural Networks (CNN) that have been trained to tell people apart. These models get raw face representation feature vectors that can be used to check faces that haven't been seen.

There are several face recognition models available, such as VGG-Face, FaceNet, OpenFace, DeepFace, DeepID2, and Dlib. These models take face images as input and return vectors that reflect the image in different ways. Our study opted for FaceNet as its accuracy is the best in the previous study [28].

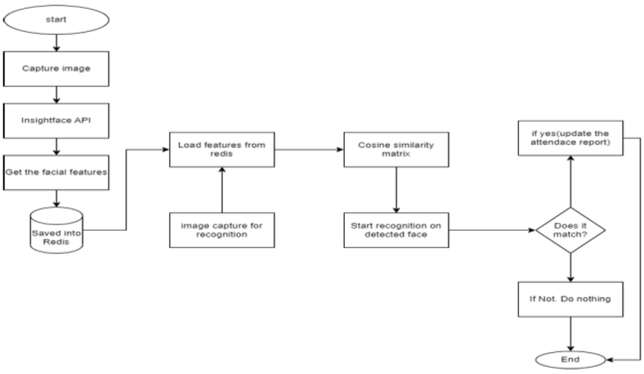

Fig. 7 Face recognition and evaluation

For facial recognition, the system employs a pretrained Convolutional Neural Network (CNN) model (FaceNet) to generate 128-dimensional face embeddings for each student.

To verify identity, the cosine similarity algorithm is used to compute the angular distance between the new embedding and registered embeddings stored in the database. Eq. 1 shows the formula for cosine similarity, where A and B face vectors, the expected and actual output.

$$\text{Cosine similarity} = \frac{A \,.\, B}{||A||\ ||B||} \qquad ..(\text{Eq. } 1)$$

A threshold (e.g., 0.5) is set such that if the similarity score exceeds this threshold, the identity is considered a match. This method is computationally efficient and robust against minor changes in facial expression or lighting conditions.

FINDINGS & ANALYSIS

Result Part 1- Face Recognition based on Different Distances

Facial recognition system's performance evaluation shows its different performance at different distances. With 100% recognition across 20 people at 40 cm, the system is highly accurate. This shows that the system can accurately capture and identify facial features in near-field conditions. The system's performance remains 75% at 70 cm, demonstrating its ability to recognize even at a moderate distance.

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The system performs well, but performance is lower than at closer distances. However, performance drops to 15% at 100 cm. Table III shows facial recognition values based on distance.

Table 3 Accuracy For Facial Recognition from Different Distances

FACIAL DISTANCE (cm)	**Test 1 (40)**	**Test 2 (70)**	**Test 3(100)**
No. of Test data	20	20	20
No. of Pass	20 test data	15 test data	3 test data
No. of Fail	0 test data	5 test data	17 test data
% of Pass (Performance)	100 %	75 %	15 %

The performance drop is expected due to the difficulties of capturing facial features from further away. Reductions in image resolution and feature clarity lower recognition performance.

The results show that the system's facial recognition works best at closer distances. Understanding the system's performance under different conditions helps improve its capabilities and address real-world limitations. Fig. 8 shows the performance for different distances.

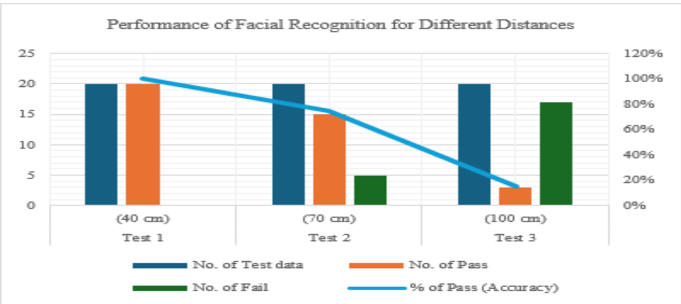

Fig. 8 Performance of Recognition for Different Distances

Result Part 2 - Face Recognition based on Different Face Orientation

Facial recognition system's performance evaluation shows its different performance at different face orientations. At frontal orientation (0 degrees), the system is 100% accurate. This means the system recognizes facial features best when people face the camera. The system achieves 70% performance at 45 degrees face orientation.

The system makes use of moderate face angle variations well despite a reduction from the frontal view. At a side profile orientation of 90 degrees, accuracy drops to 0% due to a larger challenge. Table IV shows facial recognition performance based on distance.

Table 4 Accuracy For Facial Recognition From Different Orientation

FACIAL-ANGLE	**Test 1 (0°)**	**Test 2 (45°)**	**Test 3 (90°)**
No. of Test data	20	20	20

No. of Pass	20 test data	14 test data	0 test data
No. of Fail	0 test data	6 test data	20 test data
% of Pass (Performance)	**100 %**	**70 %**	**0 %**

Face recognition in profile is difficult due to reduced visibility of key facial features. These findings show that the system is sensitive to face orientation variations and performs best when faces face the camera.

Understanding the system's face angle limitations helps improve algorithms and performance in various real-world scenarios. Fig. 9 shows the performance for different distances.

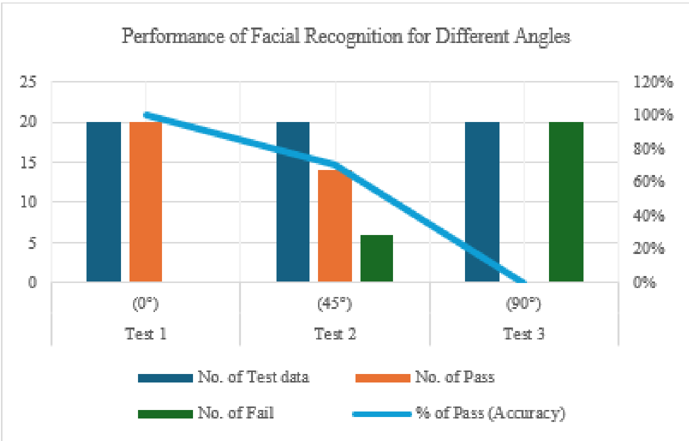

Fig. 9 Performance of Recognition for Different Angles

Taken together, these results highlight two critical weaknesses of the current system: (i) high sensitivity to pose variation, and (ii) performance degradation at greater distances. Addressing these limitations requires methods that are robust to such variations. Potential strategies include pose normalization, multi-angle training datasets, and 3D face modeling to mitigate orientation sensitivity, while super-resolution reconstruction, adaptive camera calibration, or multi-camera capture systems may enhance recognition robustness at longer distances.

CONCLUSION, SIGNIFICANCE AND FUTURE WORK

In terms of facial recognition, the result of performance across different facial orientations (0°, 45°, 90°) and distances (40 cm, 70 cm, 100 cm) shows that the system performs optimally with frontal faces at close range, while accuracy decreases significantly with larger pose deviations and increased distances.

In the wider effort to reduce school absenteeism, this study provides evidence that facial recognition has high potential for specific educational significance. The system also can be upgraded with another higher level of cutting-edge computer vision and machine learning algorithms to improve operations and create creative teaching solutions. Among the important significances of the study are:

- The study gives schools an automated and dependable attendance management solution. It automates attendance tracking, eliminates errors, and minimizes administrative costs.
- Accurate attendance records benefit students. Facial recognition technology reliably tracks pupils' classroom attendance, increasing accountability and transparency.

- This approach considerably decreases the administrative burden on teachers and administrators. It automates attendance, eliminating data entry and verification. Teachers and administrators can spend more time on lesson planning and student support.
- Facial recognition-based attendance is more accurate than manual techniques. Advanced computer vision and machine learning reduce errors and provide real-time attendance tracking.
- Students are held accountable by recording only valid attendance. Educational institutions can ensure attendance integrity by avoiding proxy attendance and unauthorized practices.
- The outcome of the study can save schools time and money. Institutions can distribute resources more efficiently and reduce administrative costs by automating attendance tracking and administrative processes.

We also recommend mitigation plans to overcome the security challenges arises from the biometric and facial recognition issues in future, from each of the following factors:

Privacy

- **Unauthorized surveillance** – Enforce strict legal frameworks, transparency policies, and require explicit consent.
- **Collection of sensitive data (lifetime risk)** – Apply data minimization, anonymization, and limit retention periods.
- **Use without explicit consent** – Adopt clear opt-in consent models and visible public notices.
- **Algorithmic bias & discrimination** – Train AI on diverse datasets, conduct third-party audits, set fairness benchmarks.

Security:

- **Biometric data cannot be changed if leaked** – Store data in encrypted form, use on-device storage instead of centralized databases.
- **Vulnerability to spoofing attacks** – Implement liveness detection (eye movement, pulse, 3D depth checks).
- **Storage infrastructure as cyberattack target** – Storage infrastructure as cyberattack target.
- **Risk of forced access (coercion)** – Provide fallback options: PIN/password override, emergency lock, dual-factor verification.

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