Jurnal Kejuruteraan 38(2) 2026: 985-993
https://doi.org/10.17576/jkukm-2026-38(2)-39

Development of an Automated Student Attendance System Based on Real-Time Facial Recognition Technology

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Received 14 May 2025, Received in revised form 4 November 2025
Accepted 4 December 2025, Available online 30 March 2026

ABSTRACT

Class attendance is vital in education, closely linked to student engagement and academic performance. However, traditional attendance-tracking methods such as roll calls and sign-in sheets are inefficient and error-prone. Modern alternatives such as RFID and QR code scanning improve efficiency but require specialized infrastructures and remain susceptible to proxy attendance. This paper presents a student attendance system that utilizes facial recognition to automate attendance-tracking and enhance accuracy. It identifies students in real-time and automatically updates attendance records. The system employs a low-power single-board computer with a webcam and ultrasonic sensor to detect student presence and capture facial images. These are processed on a consumer-grade workstation. The system first detects faces using a HOG-based detector and then a deep neural network extracts unique facial features for identification. A web-based user interface was also developed to enable instructors to schedule their classes. The system was tested with 20 students, equally divided into two groups: one with their facial images pre-registered in the system, and another without, simulating unregistered users. Each student completed five trials, totalling 100 tests. The system achieved 92% accuracy, with a True Positive Rate of 100% and False Negative Rate of 0%, effectively identifying all registered students. Precision was 86%, while False Positive Rate was 16%, attributed to rare instances of unregistered users being misidentified as registered students. True Negative Rate was 84%, indicating capability to reject most unregistered users. The results demonstrate the system's feasibility for automated, real-time attendance-tracking using facial recognition in classroom settings.

Keywords: Artificial intelligence; computer vision; facial recognition; machine learning; student attendance

INTRODUCTION

Class attendance play a pivotal role in education, influencing students' learning outcomes and academic success. Studies show that students who attend classes consistently are more likely to achieve better academic outcomes, while frequent absenteeism negatively affects skill development and knowledge acquisition (Ha et al. 2024; Fadelelmoula, 2018; Oghuvbu, 2010). Given its importance, education institutions often implement attendance-tracking as a routine component of academic administration (Lu & Cutumisu 2022; Golding 2011).

Traditionally, class attendance is manually recorded using roll calls and attendance sheets. These conventional approaches, however, have well-known limitations. Roll calls are time-consuming and can reduce instructional time, particularly in large classes. Attendance sheets, on the other hand, are prone to proxy attendance, where students mark presence on behalf of absent peers (Sultana et al. 2015). Modern attendance-tracking solutions, including radio-frequency identification (RFID) systems, biometric technologies, and Quick Response (QR) code systems offer enhanced accuracy and can reduce the reliance on paper-based records. However, each of these technologies presents distinct limitations that affect their overall feasibility.

Although RFID systems eliminate manual attendance-tracking efforts, they require extensive infrastructures, including the installation of RFID readers and the issuance of unique RFID tags to all students (Abdul Razak & Wen 2017; Pampapati 2015). Yet, RFID systems remain vulnerable to proxy attendance, where students can exchange their tags to falsify attendance (Kaur et al. 2011). QR code systems offer a convenient alternative by allowing students to scan QR codes using their smartphones to register attendance (Liew & Tan 2021). However, QR-based systems require students to have a reliable internet connection, and they remain vulnerable to fraud as students can exchange login credentials or scan the QR codes remotely to falsify attendance (Chang 2014). Fingerprint scanning can help prevent proxy attendance by uniquely verifying individual biometrics; however, biometric sensors are often susceptible to degradation from dirt or moisture, requiring regular maintenance (Jaiswal 2011). Given these limitations, facial recognition has emerged as a promising alternative for attendance-tracking. It minimizes proxy attendance through unique facial features identification (Kumar et al. 2019; Wirdiani et al. 2019; Gorijavaram et al. 2019), and eliminates the need for manual input, special tokens, or extensive infrastructures.

With the increasing use of artificial intelligence (AI) in numerous aspects of daily life (Athriyah et al. 2022; Stafie et al. 2023; Rodrigues et al. 2023; Bukhori et al. 2024), including in education settings (Lareyre 2020; Mishra, 2023), recent studies have explored the feasibility of facial recognition-based attendance systems, demonstrating their potential while highlighting key challenges. Trivedi et al. (2022) developed an attendance system that detects faces using the Viola-Jones technique and processes them with the Local Binary Patterns Histogram (LBPH) algorithm. Nguyen-Tat et al. (2024) proposed a cost-effective implementation using the Haar cascade algorithm on the Nvidia Jetson Nano embedded computing platform. However, the system's reliance on the Haar cascade algorithm may limit its accuracy compared to more advanced deep learning approaches. Rao (2022) introduced AttenFace, an attendance system that captures snapshots from live camera feeds at regular intervals to reduce computational load. Salac (2019) reported an Android-based application for class attendance monitoring using face recognition, which was highly rated for its portability. Irbaz et al. (2021) presented a face recognition system for remote employee tracking which utilized the FaceNet model (Champandard 2015) and achieved 97.8% accuracy, though its performance remained sensitive to environmental variability.

Building on these advancements, this paper presents the development of a cost-efficient student attendance system based on facial recognition technology. The system automatically identifies students and updates attendance records in real-time, thereby streamlining the attendance-tracking process. It implements facial recognition algorithms using a pre-trained convolutional neural network (CNN) by OpenFace (Amos et al. 2016). CNNs are particularly effective for image feature extraction while requiring relatively fewer parameters compared to fully connected neural networks (Albawi et al. 2017). This makes CNNs computationally efficient and well-suited for real-time applications. To enhance the system's usability, a web-based user interface was also developed to allow instructors to register and schedule their classes conveniently.

The key contributions of this work are threefold. First, we propose a hybrid and cost-effective system architecture that combines a low-power single-board computer as an edge device for presence detection and image capture, while offloading the computationally intensive facial recognition tasks to a central workstation. This hybrid approach ensures scalability and real-time performance without requiring expensive hardware at every attendance point. Second, we integrate the facial recognition engine with a web-based class scheduling database. Our system is not just a facial recognition tool but a complete attendance management solution featuring a web-based interface for instructors to manage class schedules, which in turn automatically triggers the attendance-taking process at the scheduled times. Third, we conduct a comprehensive performance evaluation with both registered and unregistered users to rigorously validate the system's accuracy, precision, and reliability in a simulated real-world condition. This evaluation offers a transparent demonstration of the system's feasibility and reliability for classroom deployment.

METHODOLOGY

The framework for this study is structured into three primary stages: system design, operational implementation, and performance evaluation. The first stage involved designing the system architecture, which integrates edge computing hardware with a central processing server for real-time facial recognition. The second stage focused on the operational workflow, detailing the sequence of events from student detection and image capture to facial feature extraction and identity verification. The final stage was dedicated to a quantitative performance evaluation, where the system's accuracy, precision, and error rates were systematically tested using a controlled experimental setup with both registered and unregistered participants. The following sections detail the system architecture, operations, and the results of this performance evaluation.

SYSTEM ARCHITECTURE AND OPERATIONS

The overall system architecture is shown in Figure 1. It consists of a Raspberry Pi 3 single-board computer (Raspberry Pi 2025) equipped with an 8 MP webcam and an HC-SR04 ultrasonic distance sensor. The system's central processing is handled by a workstation server configured with an 11 GB Nvidia GTX 1080 graphics processing unit (Nvidia, 2025) and a monitor display. All components communicate over a secure local area network to ensure reliable and real-time operation.

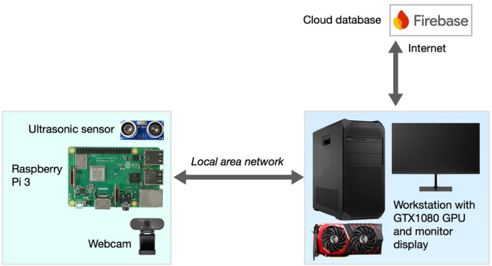

FIGURE 1. System architecture of the student attendance system, illustrating the integration of a Raspberry Pi, webcam, ultrasonic sensor, server, and a cloud-hosted database of class schedules.

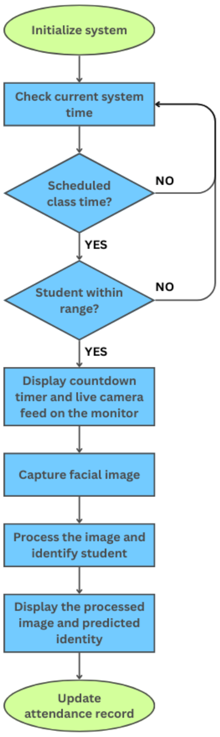

FIGURE 2. Operational flowchart of the automated attendance-tracking system, illustrating the sequence from class schedule monitoring to facial image capture, recognition, and attendance recording.

The Raspberry Pi functions as an edge device responsible for capturing facial images. It also continuously monitors the system clock and compares the current time against a database of scheduled class sessions. When a scheduled class time is detected, the Raspberry Pi automatically activates its camera module. Subsequently, if the ultrasonic sensor also detects a student within range, the system initiates a three-second countdown, which is displayed on the workstation monitor alongside the live camera feed. Upon completion of the countdown, the camera automatically captures a facial image of the student and sends it to the server. Facial recognition algorithms are then applied to the image to determine the student's identity. Finally, the student's image and predicted identity are displayed on the monitor, and the attendance record is automatically updated. A flowchart of the system's operation is presented in Figure 2.

The backbone of the attendance system is the server, which performs two critical functions. First, it executes facial recognition tasks on images received from the Raspberry Pi. These are the face detection, feature extraction, and identification algorithms. Second, the server also maintains a class schedule database accessible via a web-based interface, which enables class instructors to register and manage their class schedules.

FACE DETECTION, FEATURE EXTRACTION, AND IDENTIFICATION

The development of the recognition algorithm is centered on a multi-stage AI pipeline designed to process images received from the Raspberry Pi. Each stage leverages a specific machine learning or deep learning model to perform its task, with the output of one stage serving as the input for the next. First, a face detection algorithm isolates the face region in the image. Second, key facial landmarks are extracted and encoded into numerical representations known as facial embeddings. Finally, in the identification stage, these embeddings are compared against a pre-registered database to verify the individual's identity.

In the first step, a face detection algorithm is employed to isolate the face region in the image. For this task, the computationally efficient Histogram of Oriented Gradients (HOG) method (Dalal & Triggs 2005) is utilized in conjunction with Dlib's pre-trained linear SVM classifier (Dlib 2022). This combination returns the bounding box coordinates of any detected face. This HOG-based approach was specifically chosen for the face detection stage due to its balance of speed and accuracy, making it highly suitable for real-time processing. Then, the detected face undergoes pose alignment, a process that standardizes the orientation of the face, which is important for improving recognition accuracy. This alignment is achieved by detecting and mapping 68 facial landmarks (Kazemi & Sullivan 2014)—such as the eyes, nose, and mouth—onto the image. These landmarks serve as reference points for aligning the face to a standardized position.

In the second step, the aligned face image is passed to a pre-trained face recognition model for feature extraction. One commonly used model is OpenFace (Amos et al. 2016), which is based on a modified version of the ResNet architecture and trained using a triplet loss function. The model transforms a 96 × 96 pixel RGB input facial image into a 128-dimensional numerical vector known as a face embedding. In this embedding space, facial representations of the same individual are located close to each other, while embeddings of different individuals are well-separated. This compact representation captures the discriminative features of the face with high precision, enabling effective face comparison and recognition (Amos et al. 2016; Champandard 2015). Figure 3 shows an example of an image passing through the steps of face detection, landmark detection, pose alignment, and feature extraction to generate the 128-dimensional face embedding.

In the final step, the system compares the unknown student's face embedding against a database of pre-encoded embeddings representing enrolled individuals. This comparison is performed by calculating the Euclidean distance between the input embedding and each stored embedding. The identity associated with the minimum Euclidean distance is returned as the recognized student, but only if this distance is below a pre-defined similarity threshold. If the minimum distance exceeds this threshold, the student is classified as "Unknown". This threshold is a critical parameter that balances the trade-off between the True Positive (TP) and the False Positive (FP) classification outcomes. For this work, the similarity threshold was empirically determined to be 0.45.

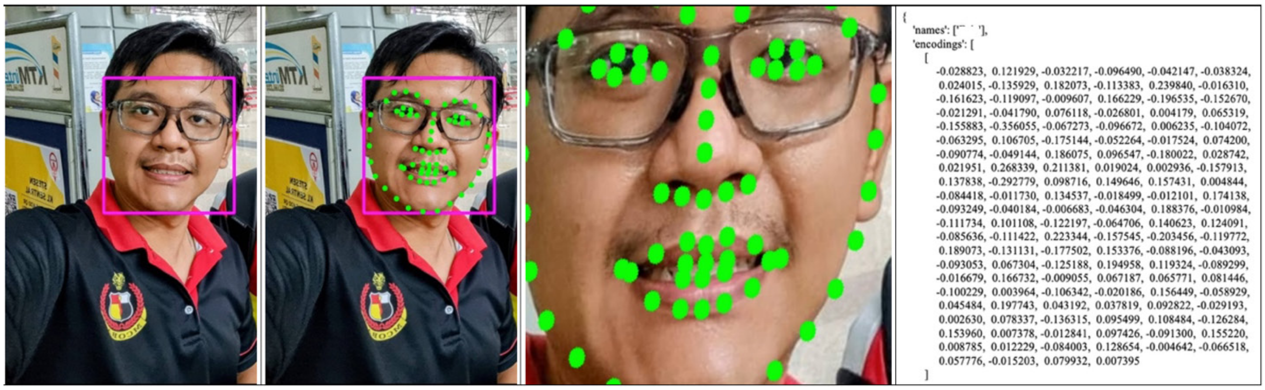

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FIGURE 3. Example of an image passing through the facial recognition pipeline, showing the sequence (from left to right) of 1) face region detection, 2) face landmark detection, 3) pose alignment, and 4) feature extraction, which generates a 128-dimensional facial embedding for identification. Note the slight tilt of the face was corrected by the pose alignment process.

PERFORMANCE EVALUATION PROCEDURE

To evaluate the system's performance, 20 students were randomly selected and evenly divided into two groups: Group A and Group B. Group A consisted of students whose facial images were pre-registered in the system—each student contributed three images, which were encoded and stored in the system's facial embeddings database prior to testing. These students were expected to be correctly recognized by the system. In contrast, Group B served as a control group; their facial images were *not* registered and thus were not expected to be recognized. Effectively, Group B students simulated external or unregistered users, representing the real-world scenario of students attempting to register for a class in which they are not enrolled.

To create the facial embeddings database for registered students, each of the 10 students in Group A provided three facial images captured under controlled indoor lighting conditions. They were instructed to maintain a neutral facial expression and look directly at the camera, with minor variations in head pose permitted to simulate realistic conditions. Each captured image was manually inspected to ensure it was free from significant motion blur, poor lighting, or occlusions. Images that met the quality criteria were then used to generate the 128-dimensional facial embeddings, which were subsequently stored in the system's database. This validated dataset formed the ground truth for evaluating the recognition performance for registered users.

During testing, each student individually approached the workstation monitor. When the system's ultrasonic sensor detected their presence, a three-second countdown was initiated and displayed on the monitor alongside the live camera feed. The students were instructed to position their faces within the camera's field of view during this interval. At the end of the countdown, the system automatically captured a facial image, performed identification, and then displayed both the predicted name and the captured image on the monitor. Each student was then asked to verify whether the system's identification was accurate. This procedure was repeated five times per student to enable quantitative performance assessment. Table 1 summarizes key details of the performance evaluation setup.

TABLE 1. Summary of experimental setup for system evaluation

Aspect	Description
Total Participants	20 students, equally divided into two groups: Group A and Group B
Group A	10 students – each contributed 3 facial images pre-registered in the system
Group B	10 students – no facial images registered in the system: control group simulating unregistered users
System Output	Predicted identity and processed facial image shown on the monitor
Output Verification	Each student verified the accuracy of the system's identification
Total Trials	100 (20 students × 5 trials)

RESULTS AND DISCUSSION

In this section, we present the user interface and class schedule database that were developed for the system, followed by an analysis of the system performance.

USER INTERFACE

Figure 4 shows the user interface developed for the attendance system, implemented as a web-based application with an embedded live video feed. To register attendance, a student aligns their face within the video frame and waits for a three-second countdown. The system then captures the facial image and transmits it to the server for identification. The server processes the image and returns the predicted identity along with a bounding box highlighting the detected face. The student can then confirm their identity and complete the attendance registration by clicking the "Register Student" button.

CLASS SCHEDULE DATABASE

The system maintains a class schedule database that allows instructors to manage their class sessions. This database also enables the system to automatically initiate the attendance-tracking operations at scheduled times. It is implemented using Firebase (Firebase 2025), a cloud-hosted platform that supports real-time data synchronization across clients. Instructors access the database via a dedicated interface developed for the system, shown in Figure 5, which includes three main pages: a login page, a timetable page, and an edit schedule page. Upon accessing the system, instructors first encounter the login page. After successful authentication, they are redirected to the timetable view, which displays their current schedule and features two main controls: an Edit button and a Logout button. Clicking the Edit button opens the schedule editing interface, where instructors can define the class day, time, and duration using specified input fields. Once changes are made, the Submit button refreshes the timetable view and a local copy is saved on the system's server.

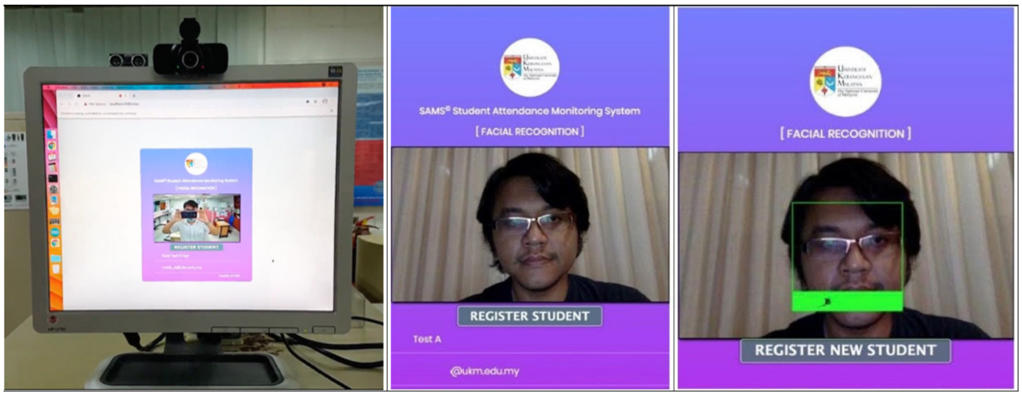
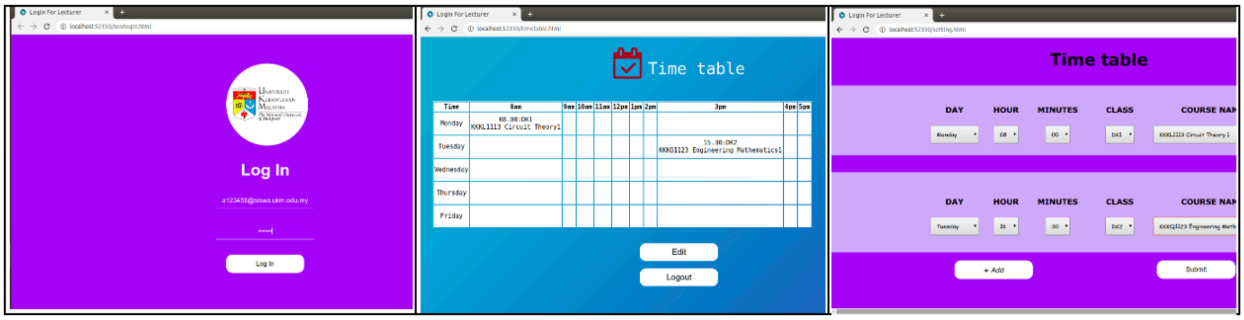


FIGURE 4. Left: The user interface of the attendance system displayed on a monitor with an embedded live video frame. Middle: A screenshot showing a user aligning his face within the frame before image capture. Right: The system returning the processed image with a bounding box around the detected face and a label indicating the predicted identity.



Time	8am	9am	10am	11am	12pm	1pm	2pm	3pm	4pm	5pm
Monday	08.00:DK1 KKKL1113 Circuit Theory1									
Tuesday								15.30:DK2 KKKQ1123 Engineering Mathematics1		
Wednesday										
Thursday										
Friday										

DAY	HOUR	MINUTES	CLASS	COURSE NA
Monday	08	00	DK1	KKKL1113 Circuit Theory 1
Tuesday	15	30	DK2	KKKQ1123 Engineering Math

FIGURE 5. Left: The user interface for the system's class schedule database. Middle: The timetable view is where instructors can view their current schedule, with options to edit or log out. Right: The schedule editing interface is where instructors can specify class day, time, and duration.

SYSTEM'S PERFORMANCE ANALYSIS

The system's performance was quantitatively evaluated using standard classification metrics: True Positive (TP), False Negative (FN), False Positive (FP), and True Negative (TN). A True Positive (TP) was recorded when a Group A student—whose facial image was pre-registered in the system—was correctly identified. Conversely, a False Negative (FN) occurred when a Group A student was not recognized at all, indicating a failure to recognize a known individual. A False Positive (FP) was recorded in two cases: when an unregistered user (Group B) was incorrectly recognized as a registered student, or when a registered student was misidentified as another registered user. A True Negative (TN) occurred when a Group B student was correctly not recognized (i.e., rejected) by the system. A total of 100 recognition trials were conducted, with each student performing five trials. The outcomes of these trials are summarized in Table 2.

From the classification outcomes, the system's standard performance metrics were calculated as follows:

$$\textit{True Positive Rate} = \frac{TP}{(TP + FN)} \tag{1}$$

$$\textit{False Negative Rate} = \frac{FN}{(TP + FN)} \tag{2}$$

$$\textit{True Negative Rate} = \frac{TN}{(TN + FP)} \tag{3}$$

$$\textit{False Positive Rate} = \frac{FP}{(TN + FP)} \tag{4}$$

$$\textit{Accuracy} = \frac{(TP + TN)}{(TP + TN + FP + FN)} \tag{5}$$

$$\textit{Precision} = \frac{TP}{(TP + FP)} \tag{6}$$

A perfect True Positive Rate (TPR) of 100% was attained, meaning all registered students were correctly recognized. Also notably, the system's False Negative Rate (FNR) was 0%, indicating that no registered students failed to be recognized. This indicates the system's ability at ensuring that no legitimate students were incorrectly marked absent.

The system's True Negative Rate (TNR) was 84%, indicating the system was reasonably effective at correctly rejecting most unregistered users. The False Positive Rate (FPR) was 16%, attributed to rare instances where unregistered users were incorrectly identified as registered students. Reducing the FPR would enhance the system's reliability and minimize misidentification.

Overall, the system achieved an accuracy of 92%, reflecting strong capability in correctly identifying both registered and unregistered students. A precision of 86.2% shows that 86.2% of the students that the system classified as registered were correctly recognized. The system's precision could be improved by reducing false positives, i.e., instances where unregistered users were misclassified as registered students. Table 3 summarizes the overall system performance.

TABLE 2. Classification outcomes of the system’s performance test

Recognition Outcome	Classification	Count	Description
Correctly Recognized	True Positive (TP)	50	Registered students correctly identified
Incorrectly Not Recognized	False Negative (FN)	0	Registered students not recognized at all
Correctly Not Recognized	True Negative (TN)	42	Unregistered users correctly rejected
Incorrectly Recognized	False Positive (FP)	8	Unregistered users misidentified as registered students, or misidentification among registered students
		100	

TABLE 3. Overall system performance

Metric	Value	Description
Accuracy	92.0%	Rate of correct identifications among all trials
Precision	86.2%	Rate of correct identifications among those the system classified as registered students
True Positive Rate (TPR)	100.0%	Ability to correctly recognize registered students
False Negative Rate (FNR)	0.0%	Rate of registered students not recognized
True Negative Rate (TNR)	84.0%	Ability to reject unregistered users
False Positive Rate (FPR)	16.0%	Rate of unregistered or registered users misidentified as another person

Figure 6 presents a sample of the test results for Group A students, all of whom were correctly identified by the system. In each image, the system successfully detected the students’ face regions and overlaid a green bounding box around them. Below each bounding box, the system displayed the predicted identity of the student. Also notably, the images exhibit slight variations in facial pose and distance from the camera; yet the system was able to recognize the students and authenticate their attendance. This highlights the system’s robustness in handling moderate variations in real-world conditions.

Figure 7 shows a sample of test results for Group B students, whose facial images were *not* pre-registered in the system’s facial embeddings database and were therefore not expected to be recognized. As shown, four students were correctly rejected, with their identities displayed as “Unknown”. However, two students were incorrectly identified as registered Group A members, resulting in false positive outcomes. These errors could potentially be mitigated by enhancing the quality of facial image captures—for example, by using higher-resolution cameras or ensuring consistent lighting conditions. Another possible approach is to increase the number of facial image samples in the system’s database to improve recognition robustness under varied conditions.

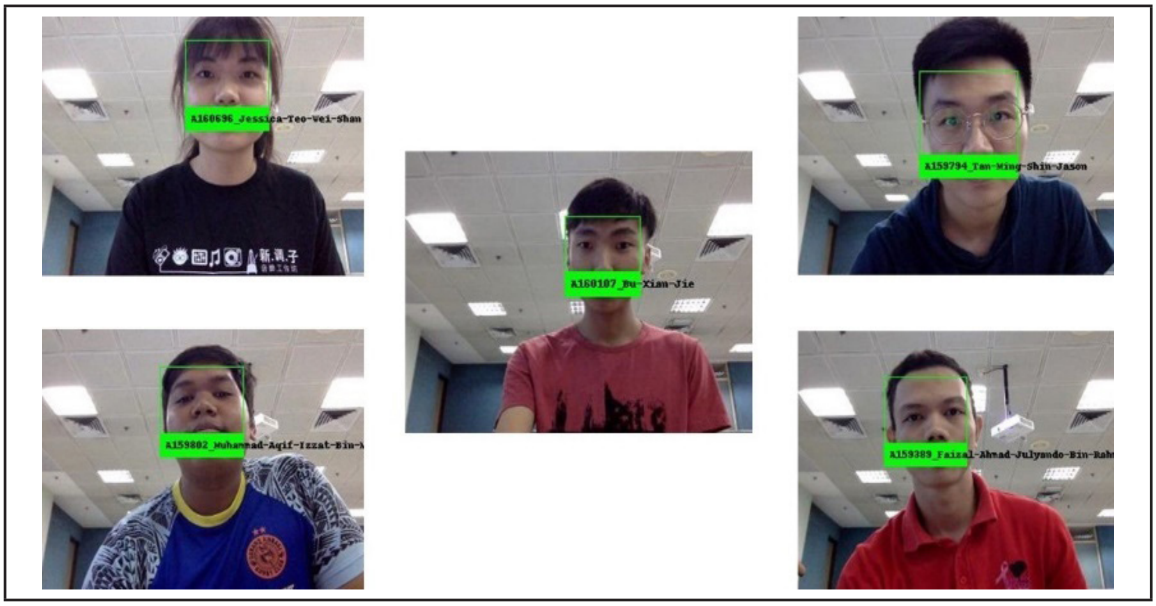


FIGURE 6. Sample test results for Group A students. These students had their facial images pre-encoded and stored in the system’s database. The system successfully recognized and identified each student, demonstrating its effectiveness in recognizing registered individuals.

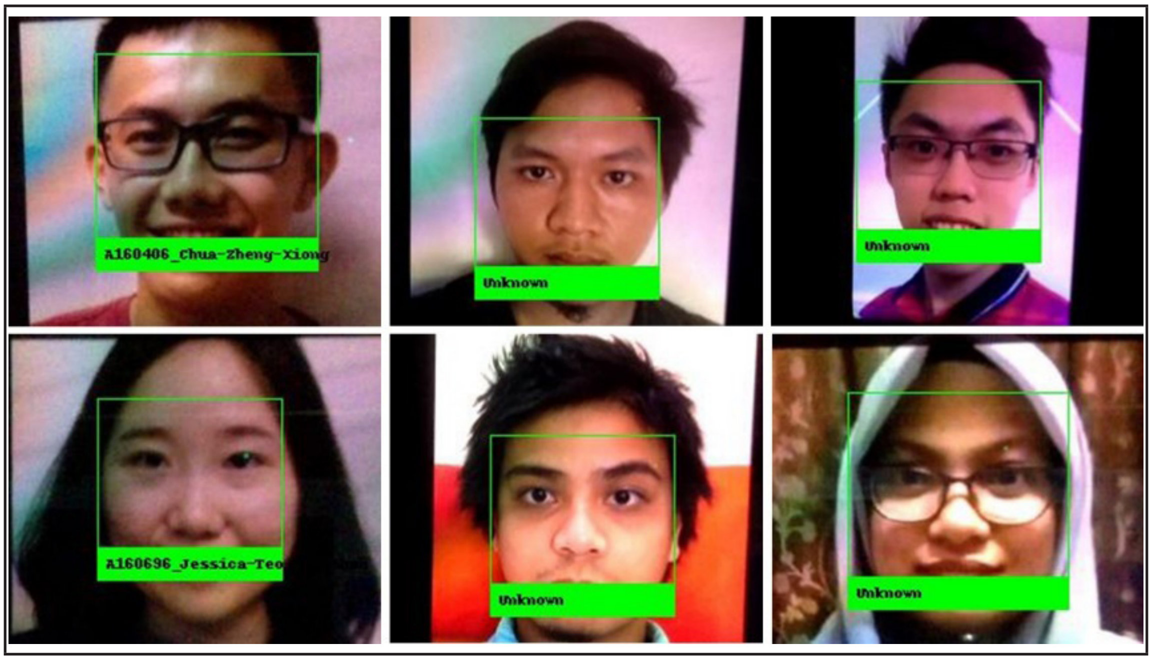


FIGURE 7. Sample test results for Group B students, whose facial images were *not* pre-registered in the system, simulating unregistered users. Four students were correctly rejected, with their identities displayed as "Unknown," while two students were incorrectly identified as registered Group A members, resulting in false positives.

CONCLUSION

We have presented a student attendance system based on real-time facial recognition technology. The system was designed to automate attendance tracking, incorporating face detection and identification using a pre-trained deep neural network. A web interface was also developed to support class scheduling functions. Performance test was conducted with 100 trials performed in total. The system demonstrated high reliability in recognizing registered students, achieving a 100% True Positive Rate (TPR) and 0% False Negative Rate (FNR). The overall accuracy was 92%, and the precision was 86.2%, indicating that most positive identifications were correct. However, the system showed a False Positive Rate (FPR) of 16%, where a few unregistered students were incorrectly identified as registered.

Overall, the results suggest that the proposed system is effective for real-time attendance tracking in academic settings. However, we acknowledge that a key limitation of this study is the constrained sample size of 20 participants. While sufficient for a preliminary study and proof-of-concept, it represents a limitation for validating the system's robustness against a more diverse input variations (e.g., ethnicities, facial accessories, lighting conditions). Additionally, a more in-depth performance analysis could be conducted to evaluate the trade-off between the true positive and false positive rates at various similarity thresholds.

ACKNOWLEDGEMENT

This work was supported by Ministry of Higher Education (MOHE), Malaysia, via the Fundamental Research Grant Scheme (FRGS/1/2023/TK07/UKM/02/10).

DECLARATION OF COMPETING INTEREST

None.

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