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# Effortless Student Attendance: A Smart Human-Computer Interactive System Using Real Time Facial Recognition

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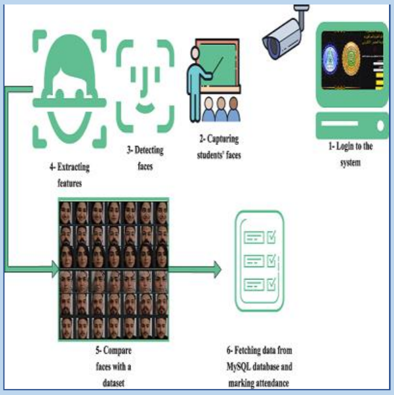
**Abstract**: **Objective:** Recording attendance is a critical process in academic institutions due to its significant impact on student performance and engagement. Current methods for recording attendance are often time-consuming and labour-intensive for lecturers and administrative staff, necessitating the development of more efficient and flexible solutions. While various automated attendance systems have been proposed, they often encounter challenges related to cost, implementation complexity, or reliability, hindering widespread adoption in educational settings. **Method:** This paper introduces a novel approach to automating attendance registration using face recognition technology. Our method integrates multiple feature extraction algorithms within a user-friendly graphical interface, specifically designed in English to enhance usability. By using existing security cameras commonly found in academic institutions, our approach addresses both cost and time inefficiencies. The attendance registration process involves capturing a video of the classroom, which is then processed to identify and log student attendance in a CSV file. A significant aspect of our study is using a comprehensive dataset comprising 2,170 images collected from 31 students at Mustansiriyah University. This extensive dataset enhances the robustness and reliability of our system, providing a diverse range of facial expressions, angles, and lighting conditions that improve the accuracy and generalizability of our model. **Result:** The system demonstrated accuracy of up to 100%, with deep learning algorithms outperforming machine learning methods. **Conclusion:** These promising results suggest that face recognition technology can effectively streamline and automate attendance tracking, offering a viable solution for educational institutions seeking to improve operational efficiency and accuracy.




**Keywords**: Attendance Management, Deep Learning, Face Detection, Face Recognition, MySQL, Yolov7

## Introduction

Locating human faces in images and differentiating them from the background (and differentiating each human face from the others) by enclosing them within bounding boxes is known as face recognition (FR). It involves extracting pixel values representing human faces, converting them from the BGR colour space (the default format for readable images in the OpenCV Library) to grayscale, transforming them into vectors, and comparing them with vectors stored in the database to identify the existing face in the image (1-4). Rapidly advancing in computer vision and artificial intelligence (AI), FR aims to identify and verify individuals based on their facial features, with applications ranging from security systems to social media tagging and personal identification (5).

Two primary applications of this technique exist: the first verifies a person's face within the camera's view by comparing it to faces in the database, yielding a true or false result (6, 7), denoted as a $1 \times N$ comparison. The second type distinguishes faces by comparing people's faces in front of the camera to those stored in the database, resulting in an $N \times N$ comparison, with the identity of the person in front of the camera as the outcome. If the system cannot identify the person, the result is 'Unknown (8, 9).' As traditional attendance tracking methods prove inaccurate, time-consuming, or costly, and some faculty members eschew paper and pen, the need for innovative approaches arises (10, 11).

The contributions of this paper lie in the development of an innovative bilingual system designed to automate student attendance recording. By leveraging advanced feature extraction algorithms and integrating them with various classifiers, the system's real-time performance was rigorously evaluated during a lecture. Impressively, the system successfully managed a dataset comprising 31 students and the lecturer- a participant count surpassing those of previous studies. Despite the professor's exclusion from the database, the system accurately identified all attendees and documented their presence in a CSV file. Moreover, it recognized the professor as an unidentified individual due to the absence of his data in the database. This system is underpinned by a MySQL database, which is seamlessly connected to a bilingual graphical user interface, enhancing user interaction by allowing the easy input and retrieval of student data during both the database design phase and live lectures.

This paper comprehensively investigates the latest advancements in FR technology for attendance registration,

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including performance evaluation, limitations, and challenges. It analyzes the results of applying seven computer vision methods to a novel dataset collected from surveillance cameras in a college setting to develop an automated attendance registration system. This system, tested on 31 students with data stored in a MySQL database, achieved 100% accuracy, showcasing its potential to streamline attendance tracking. Subsequent sections delve into the related works, methods, results, and discussions, concluding with the research findings in this paper's fifth and final section.

## Related Works

One of the two methods must be utilized to record attendance. Using the traditional system, which relies on lists of individuals whose attendance must be registered, the administrative staff provides these lists to the person responsible for attendance registration to complete this process (12, 13). Vehement complaints from attendance officials accompany this process. Regarding errors that may occur due to impersonation or the like, as well as the massive number of archives obtained after a certain period of attendance registration, it is more challenging to return to these lists and search for the presence of a specific individual on a specific date. Due to these factors, researchers devised alternative methods of attendance recording (14-16).

Due to the shortcomings of the traditional method of attendance registration, alternative methods for automating the process have been developed (17, 18). Among these methods was a radio frequency identification card (RFID), in which an individual uses a card containing his information to record attendance by scanning it with a device that can read these cards (19). This method requires a significant amount of time for students to complete registering their attendance, in addition to the expense of such a project, which exacerbates the difficulty of using such a project to automate the attendance registration process as opposed to traditional methods (20, 21). Therefore, research is focused on automating this process with the biometric system, which identifies a person based on their biometric prints (22, 23). Based on the biometric system of the human body, two systems were utilized, namely, the identification of a person through his fingerprints and eyeprints (24). However, both systems are plagued by the same issues, requiring a considerable time to register attendance. It is impossible to simultaneously record multiple students' eyeprints or fingerprints unless multiple systems are constructed (25). In addition, both require a high cost to configure the system. These issues prompted the development of a face-recognition-based automatic attendance system, which can be implemented in various ways.

Recently, FR technology has significantly advanced. However, before we discuss the work accomplished with this technology, we must discuss FR technology in detail. Initially, a picture of the faces to be distinguished is taken. After that, a face detection (FD) algorithm is applied to the image. FD algorithms map the faces' locations in an image to boxes (26). Then, machine learning (ML) or deep learning (DL) algorithms extract the features of the face-representing regions within the boxes and then send the obtained results to the classifiers to compare them with those stored in a previously prepared database (27, 28). ML and DL were used to make a system that recognized faces. There are several methods for detecting and recognizing faces, some of which rely on machine learning and others on DL. Paul Viola and Michael Jones used the Haar Cascade classifier method to detect faces in their Viola-Jones algorithm (29-32). The Haar Cascade classifier is one of the most well-known methods for developing an FD system because of its speed and compatibility with all FR algorithms. An ML method that uses the Haar Cascade classifier is illustrated in (33-37). These methods employ the Haar Cascade classifier for FD and utilize the local binary pattern histogram (LBPH) algorithm to extract facial features. However, they differ in how images are collected for the database and how it is utilized.

Additionally, (38) used LBPH for FR with 97% accuracy. This work is notable for having a speech output function. The students' names are read aloud when the system finishes taking attendance. The Haar Cascade classifier is distinguished by its rapid FD, but this speed comes at the expense of precision. This classifier cannot detect oblique faces (even if their angle of inclination is low) and identify faces far from the camera. In other words, accurate FD requires optimal conditions, which led to the development of alternative FD methods. Other methods were discovered because the Haar cascade was not a perfect FD technique. The backpropagation neural network was one of them, which passes through the entire image once and detects every object, then passes through the image again to eliminate objects that do not face (39). It is a perfect technique, but it takes a long time. As a result, a single-stage detector method was developed. The method scans the image once to detect faces, but it is inaccurate. As a result, other methods, such as you only look once (YOLO), histogram of oriented gradients (HOG), and Multi cascade convolutional neural network (MTCNN), were developed to balance speed and accuracy (40-42). (43) compared three versions of YOLO for FD, employing a lightened convolutional neural network (CNN)and VGGnet for feature extraction. The authors trained the algorithm on the CFR and FDDB datasets from scratch but tested it on their dataset. The accuracy of the FDDB dataset was approximately 93%, and on the tailored dataset, it was 99%. In (44), a single-stage detector was used for FD and DL algorithms for feature extraction and classification. This method of transfer learning makes use of the MobileNet and ResNet-34-like architecture. The information from the students was entered into a MongoDB database, and images were taken to create the dataset. The accuracy, recall, and precision were then calculated. In (45), the HOG algorithm was used for feature extraction and KNN classification to develop a mobile phone-based automated attendance system. The achieved accuracy was 97%, and a comparative study was conducted with other methods. HOG is used to recognize faces in (46). The features were extracted using MobileNetv2 and VGG-16 transfer learning, and the results were sent to either a support vector machine (SVM) or Softmax for classification. (47) describes an additional DL method using AlexNet or ResNet-50 for feature extraction and SVM for classification. This study employed seven datasets whose precision ranged from 94% to 100%. In addition to determining the accuracy, the F-score, precision, and recall were also calculated. Another method employs a principal component analysis (PCA) algorithm with a Self-Organizing Map (an unsupervised neural network) (48). The method's accuracy reached 94%. This method used the ORL dataset as a training and testing dataset, which means it did not use real-time testing, which could be considered a flaw in the algorithm's performance. Eigenfaces (49) were utilized in (50) to build an absence information system dependent on a private dataset. The Eigenfaces algorithm was used for feature extraction, and SVM was used for classification. When tested on individuals, the obtained accuracy was approximately 91%. A texture feature extraction method could generate robust FR models, such as the Gabor algorithm for feature extraction (51). (52) implemented an attendance system with the Gabor algorithm and Fisherfaces; both are methods for extracting ML features and MySQL as a student information database. The Gabor feature is an essential technique in image processing. It was also used with the Haar classifier to build a security system (37). The quality of the study was then determined by comparing the number of students to the model's accuracy. CNN or HOG was used to construct the meeting room's attendance system (53). Six individuals were used to test the system, which required a minimum distance of two meters to function correctly. It was performed to each attendee individually. Microsoft Azure has a robust API for FR, which was used with YOLOv3 in (54) to build a real-time automatic attendance system. The students' information was entered into the SQLite database, and a private dataset was created with near-perfect precision in most instances. This technology has advanced to the point where studies on recognizing masked faces are currently being conducted.

This research addresses the limitations of traditional attendance recording methods by automating the process through security cameras installed in educational institutions. This approach minimizes costs, as the system does not require additional physical components. Furthermore, it enhances efficiency by eliminating the need for manual attendance calls; instead of calling out names and waiting for student responses, attendance is recorded in real time with a generated CSV file containing attendance data. Consequently, this system outperforms traditional attendance recording methods in terms of cost and time efficiency.

## Materials and Methods

### Study Design

This research utilizes a quasi-experimental study design to evaluate the effectiveness of automated attendance registration using the FR technique in an educational setting. The study was conducted at Mustansiriyah University, involving 31 students as participants. This design was chosen due to practical considerations and the need to assess the impact of the developed system in a real-world classroom environment. The developed system, equipped with a graphical user interface, was installed in a classroom setting with an IP camera for real-time monitoring. The system processed live feeds using the Real-Time Streaming Protocol (RTSP) to simulate practical usage.

To address the privacy concerns associated with the use of facial recognition technology, we have implemented several key measures to ensure data protection and user privacy. We have taken steps to anonymize personal data wherever possible, thereby minimizing the risk of identifying individuals without explicit consent. Additionally, informed consent is obtained from all participants prior to any data collection, ensuring transparency and voluntariness in the process. Strict access control protocols are in place, allowing only authorized personnel to access the data, with regular monitoring to safeguard against unauthorized access. Furthermore, the use of facial recognition technology in our system is strictly limited to automating student attendance recording, and the data is not used for any other purposes without obtaining explicit consent from the users. By implementing these measures, we aim to uphold the highest standards of privacy and data protection for all users of our system.

### The Implemented Algorithms

Seven methods were used to develop this system. Each method consists of two algorithms, the first to detect faces and the second to extract and classify the features of the detected faces. These methods included the use of various ML and DL algorithms.

In the first method (Method A), two ML algorithms were used; the Viola-Jones algorithm was used to detect faces, and the Eigenfaces algorithm was used to classify them. While the second method (Method B) included the same algorithm for detecting faces, FR was done using the Fisherfaces algorithm, an advanced version of the Eigenfaces algorithm. As for the third method (Method C), the Viola-Jones algorithm was retained to detect faces, and the LBPH algorithm was used to classify them.

In the fourth method (Method D), an ML algorithm was used to detect faces, and a DL algorithm was used to classify them. The HOG algorithm was used to detect faces and face embeddings from the Dlib library for face classification.

The remaining three methods used DL algorithms to detect and classify human faces. The fifth method (Method F) involved using the MTCNN algorithm to detect faces and the VGG-Face2 algorithm to classify them. The same algorithm used to detect faces remained in Method 6 (Method G), except that FR was done using the Facenet algorithm. As for the seventh method (Method H), the Yolov7 algorithm was used to detect and classify faces.

Finally, this study balanced the use of algorithms, as it used three ML methods and three DL methods, in addition to an integrated method that combines both ML and DL.

### Interaction with the System

Upon activation of the system, the login window becomes visible, featuring two input boxes, one for entering the username and the other for the password. This interface incorporates four buttons: one for login, another for password reset in case of forgetfulness, and the third for registering new users by the relevant department, and the last button to switch between Arabic and English languages, as illustrated by Figure 1. This window serves to fortify the system's security, safeguarding against unauthorized access and potential data tampering. Unauthorized attempts trigger message boxes to notify the user of unauthorized access.

A

B

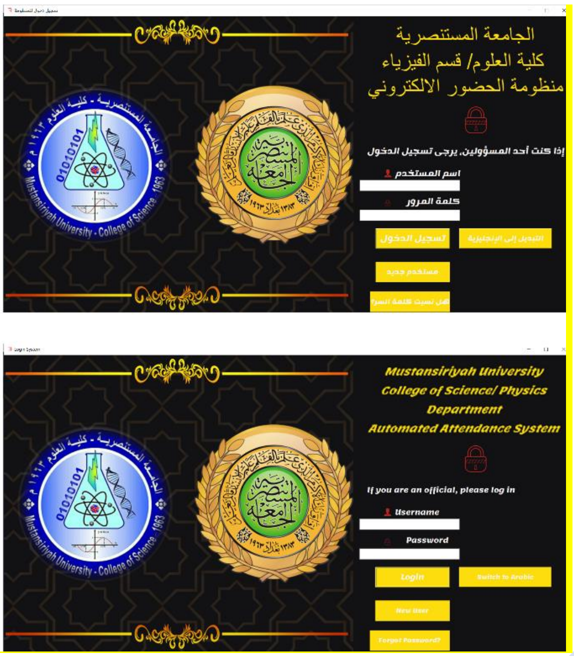


**Figure 1:** The login window: A: Before clicking the “switch to English Button. B: After clicking the “switch to English” Button.

Upon successful login using the credentials of an authorized user, the main system window emerges, as illustrated in Figure 2. It comprises numerous buttons, each leading to windows performing specific functions and facilitating system operation. Subsequent sub-sections will expound on the functionalities of these buttons.


**Figure 2:** The main window of the system.

## 1. Student Information Window

This window collects student data and photos, contributing to database creation. It features multiple fields for student information, as depicted in Figure 3, along with several buttons. The "Edit" button facilitates correction of entered data, allowing modification if necessary. Users can delete a student's data by clicking the "Delete" button. The window also houses "Add Pics." and "Edit Pics." buttons to include or modify images of the current student.


**Figure 3:** Student Enrollment Window.

## 2. Training Data Window

Exclusively featuring the "System Training" button, this window extracts facial features from training images, generating file including these features. This file enables the algorithms to discern faces during testing.

## 3. Attendance Registration Window

Incorporating two list boxes for selecting stage and subject, this window facilitates the preparation of attendance reports with stage and subject titles and time and date parameters for attendance records. Notably, the subject list box displays the phrase "study stage first," emphasizing the correlation between subject selection and study stage, as depicted in Figure 4.

This window represents the final step in the attendance registration process. Additional auxiliary windows include the attendance files window, which imports, edits, and uploads attendance reports as needed. There are also two windows, one for system developers and another for seeking assistance from the relevant department's responsible person.


**Figure 4**: Attendance Registration Window.

## Dataset Creation

The dataset utilized in this study was gathered with the active participation of 31 students from Mustansiriyah University. To initiate the data collection process, the operator clicks on the "Student Information" button located on the main window of the system, as illustrated in Figure 2. This action reveals the database creation window, where all necessary fields are filled. Subsequently, the "Take Pics." button is activated to display the picture-taking interface.

Students are instructed to display various facial expressions during the image acquisition process. Additionally, they are guided to approach and move away from the camera, capturing 70 images. This variety is crucial as students occupy seats at varying distances from the camera in distinct lecture settings. Consequently, amassing images that simulate the diverse distances encountered during lectures becomes imperative for the training of the system.

Each image is stored in a dedicated folder linked to the individual's data. The folder's title corresponds to the person's identity from the data collected. A keyboard button is pressed for each image to facilitate image capture, saving it into the designated folder. The comprehensive dataset amassed for this study comprises 2170 images, averaging 70 images per student.

### Attendance Tracking Process

This method encompasses three key stages of attendance tracking, as depicted in Figure 6. The initial stage involves dataset creation by individually bringing students into the classroom or the designated area for building the student database. Subsequently, a live feed is initiated from the IP camera positioned at the center of the classroom. The frames from this feed are processed sequentially using digital image processing techniques. The processed frames are then directed to an FD algorithm that isolates the student's face from the rest of the frame. The resulting images are saved within a folder labeled with the student's identity, which becomes crucial in the third stage of the attendance tracking process. Notably, using the FD algorithm in this stage serves the purpose of selectively saving only the student's face, thereby reducing the database size and expediting the algorithm training process. The algorithms streamline their processing efforts by focusing solely on the facial region.

Once the images of students' faces are captured and stored in the dataset, the second stage of the attendance tracking process commences algorithm training. In this phase, the previously stored images are introduced to the algorithms to facilitate face differentiation. This training process mirrors the human FR operation, acknowledging that individuals and algorithms require exposure to many images to extract features and train in distinguishing each face. After this stage, the algorithms generate embeddings for these faces, encompassing the identity of each face and the extracted features, which ensures that the algorithm can effectively recognize these faces during attendance registration.

The third phase of the attendance tracking process entails processing the broadcast received from the IP camera and directing it to the FD algorithm. In turn, the algorithm detects the students' faces within the class and transmits the corresponding locations representing these faces to the FR algorithm. Subsequently, the FR algorithm engages in the extraction of features from the detected faces. It then compares these features with those previously extracted during the algorithm training process. Should the confidence value surpass or equal the user-specified threshold, the student information is retrieved from the MySQL database and documented in the comma-separated values file (CSV). Conversely, faces with confidence values below the specified threshold will display the label "unknown." Once all attending students' names are recorded, the system renames the attendance report in the format: [stage] [subject] date@time.csv, as shown in Figure 5 and Algorithm 1.

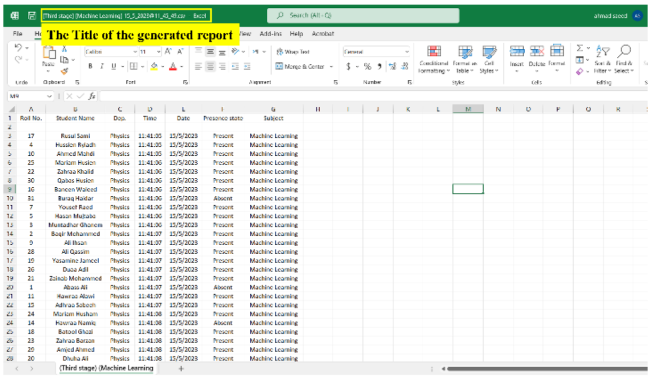


**Figure 5:** The Generated Attendance Report.

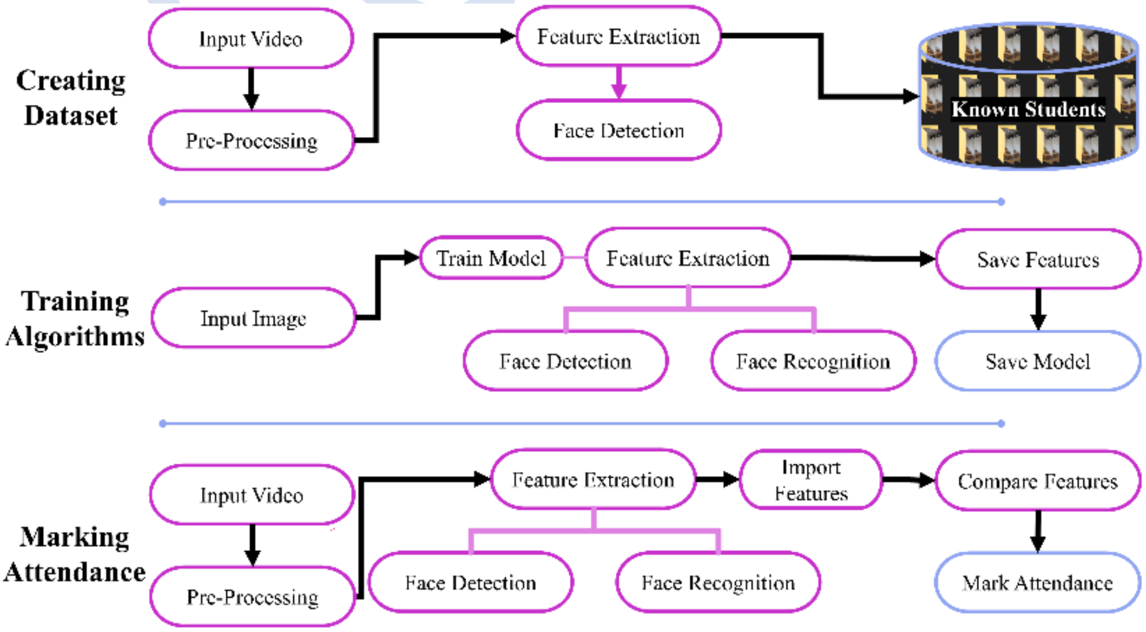


**Figure 6:** Block Diagram of the Developed System.

**Algorithm 1.** *Attendance Tracking Algorithm*

```
Require: A live video from an IP camera
Ensure: CSV file with the details of the attendees
Begin
X, Y the horizontal and vertical coordinates of the bounding box
W, H width and height of the bounding box
EF the extracted features
SF the stored features of faces in the database
while there is a face in the video:
    | predict X, Y, W, H using one of the face detection algorithms
    | extract features of the detected faces
    | compare EF with SF
    | if the features match any of the SFs:
    |     | return the ID of the face
    |     | fetch the ID's information from the MySQL database
    |     | mark attendance of the specific ID in a csv file
    | else:
    |     | either store the face in the database or show "unknown" on the bounding box
    | endif
if (q) key is pressed:
    break
Rename the CSV file with the date and time and the subject name
Store the CSV file in a specific folder
End
```

## Performance Evaluation

There are four terms in this system based on which statistical measures of performance will be calculated, which are as follows:

True positive: These are the students whose faces the FD algorithm was able to detect correctly and whose faces the FR algorithm was also able to classify correctly. It is denoted by (TP).

True negative: They are students who are not registered in the database and whose faces the FD algorithm was able to detect correctly, and the FR algorithm was also able to show the phrase 'unknown' on their faces because they are not registered in the database. It is denoted by (TN).

False positive: These are the students whose faces the FD algorithm was able to identify correctly, but the FR algorithm misclassified them as it gave them identities different from their real identities. It is denoted by (FP).

False negative: There are two types: Either they are students, and the FD algorithm was unable to detect their faces, or it was able to detect their faces, but the FR algorithm showed them the phrase ``unknown,'' even though they were registered in the database. It is denoted by (FN) (55-57).

$$Accuracy = \frac{True\ Positive + True\ Negative}{Total\ Observations} \quad (1)$$

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative} \quad (2)$$

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \quad (3)$$

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

## Results and Discussion

### Method A: Viola-Jones for FD and Eigenfaces for FR

This method represents a quintessential ML paradigm within the system's repertoire. It incorporates the Viola-Jones algorithm for FD and employs the Eigenfaces algorithm for feature extraction and face classification. Figure 7 provides visual insights, revealing the limitations of the FD algorithm, notably in its inability to detect the face of the student situated at the front of the right column, an issue emphasized by the yellow arrow.

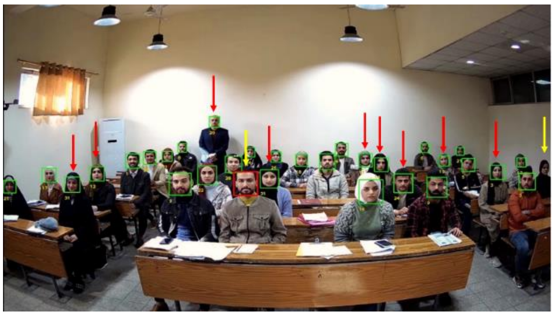

**Figure 7:** Method A Performance in a Real-Time Lecture.

Furthermore, the FR algorithm falls short of accurately identifying eight students, assigning them erroneous identities, as highlighted by the red arrows. Notably, it needs to recognize the face of the student marked by the yellow arrow despite the successful detection by the FD algorithm. The algorithm also mistakenly assigns an identity to a lecturer absent from the database, an instance where it ought to mark the face with a red box and an "unknown" label. Regrettably, the FR algorithm does not demonstrate this capability. Consequently, the accuracy achieved with this method stands at 66%, signalling a need for more reliability in automating the attendance registration process using this FR algorithm.

### Method B: Viola-Jones for FD and Fisherfaces for FR

This method closely aligns with the first to employ the Viola-Jones algorithm for FD. However, a pivotal deviation lies in substituting the FR algorithm, wherein the Fisherfaces algorithm takes precedence, an advancement over the Eigenfaces algorithm. Examining Figure 8 reveals a persistent challenge in detecting the face of the student indicated by the yellow arrow.

**Figure 8:** Method B Performance in a Real-Time Lecture.

Notably, the FR algorithm exhibits marginal enhancement. While unable to discern the faces of six students identified by red arrows, the algorithm also erroneously attributes identity to a professor not registered in the database. This method attains up to 75% accuracy, as detailed in Table 1.

### Method C: Viola-Jones for FD and LBPH for FR

Representing the latest advancement in ML within this system, this method integrates the Viola-Jones algorithm for FD and the LBPH algorithm for FR. The FD algorithm's accuracy remains consistent, as there were no alterations in its implementation. However, significant strides are evident in FR, attributed to the LBPH algorithm, acknowledged as a highly efficient feature extraction algorithm in ML. Remarkably, this method attains a commendable accuracy rate of 91%.

While largely successful, a couple of inaccuracies are notable. The algorithm failed to detect the face of the student positioned at the front of the right column. Additionally, misidentification occurred for a lecturer and a student in the left column, denoted by the red arrow in Figure 9. The algorithm erroneously assigned ID 12 to the student, whereas her ID is 23. Despite these isolated errors, the overall accuracy of this method underscores its efficacy at 91%.

**Figure 9:** Method C Performance in a Real-Time Lecture.

### Method D: Fusion of ML and DL Algorithms

This approach harnesses a synergistic blend of ML and DL algorithms. The HOG algorithm, recognized as an object detection algorithm in ML, takes the lead in FD. Subsequently, the detected faces are forwarded to the face embeddings of the Dlib library for classification. These face embeddings rely on convolutional neural networks, positioning them within DL methods.

The results of this method showcase remarkable accuracy, with the sole exception of detecting the faces of two students seated at the end of the right column, a detail indicated by yellow arrows in Figure 10. However, the method accurately categorizes all detected faces in face classification. Notably, the algorithm identifies the lecturer's absence in the database, prompting the display of the phrase "unknown," as illustrated in Figure 10. Consequently, this method attains an impressive accuracy rate of 94%, signifying a substantial improvement compared to the preceding methods in this study.

**Figure 10:** Method D Performance in a Real-Time Lecture.

This study strategically balances the utilization of ML and DL algorithms. Three methodologies leverage pure ML; one integrates both ML and DL, while the subsequent three methods exclusively employ DL techniques, solidifying their categorization as such.

### Method E: MTCNN and Facenet Integration

The MTCNN algorithm took charge of FD in this method, while the Facenet algorithm handled the classification process. Remarkably, this approach attained an optimal accuracy level, successfully recognizing all faces within the class, including accurately identifying the lecturer's absence in the database, prompting the display of the term 'unknown' on the lecturer's face. Figure 11 visually confirms the outstanding performance of this method, achieving a flawless accuracy rate of 100%.

**Figure 11:** Method E Performance in a Real-Time Lecture.

### Method F: Integration of MTCNN and VGG-Face2 with Multiple Classifiers

FD employed the MTCNN algorithm in this method, while feature extraction was done using the VGG-Face2 model. The classification phase utilized three distinct classifiers: decision tree (DT), random forest (RF), and SVM classifiers. The results of this method exhibited variability contingent on the classifier employed, with the most favourable outcomes achieved using the support vector machine classifier. The overall accuracy for this method reached 94%, demonstrating adept FD; however, misclassifications occurred during face classification. Notably, an error surfaced in classifying the student seated beside the lecturer, denoted by the red arrow, as the algorithm assigned an identity different from the student's actual one. Additionally, the algorithm struggled to classify the student marked with the yellow arrow, leading to the display of the term "unknown," as depicted in Figure 12.

**Figure 12:** Method F Performance in a Real-Time Lecture.

This method represents a contemporary approach within automated attendance recording systems and deserves a thorough examination. To evaluate its performance, the data was divided into training and testing sets, with 80% allocated for training (56 out of 70 images) per class and the remaining 20% used for testing. The results demonstrated 100% accuracy for the RF and SVM classifiers, as illustrated in Figure 13 and Figure 14, respectively. However, the decision tree classifier exhibited a slightly lower accuracy, as depicted in Figure 15. To enhance reliability, we also plan to incorporate standard validation methods such as holdout and cross-validation in future evaluations.

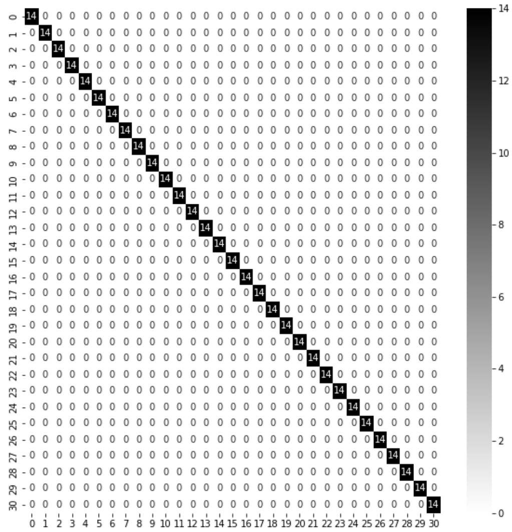

**Figure 13:** Confusion Matrix of RF Classifier.

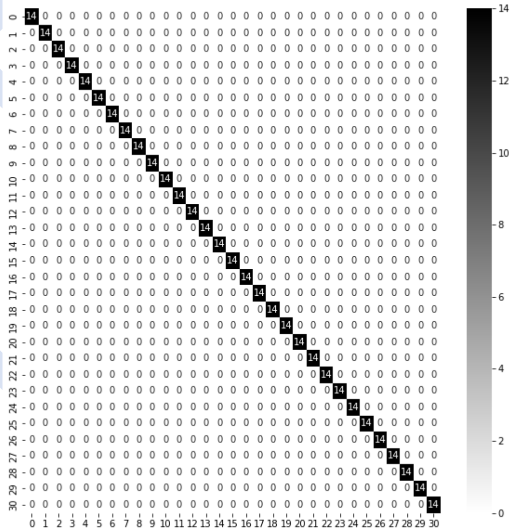

**Figure 14:** Confusion Matrix of SVM Classifier.

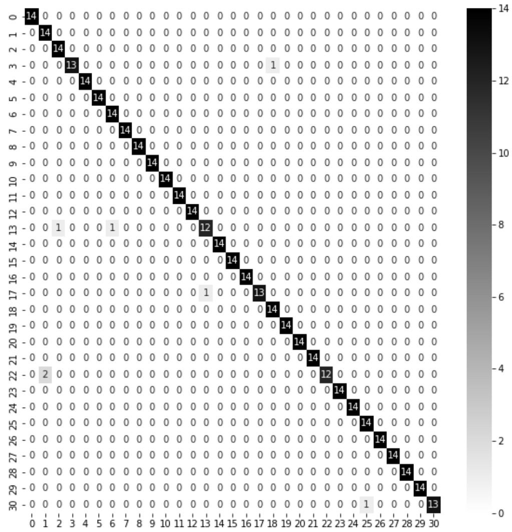

**Figure 15:** Confusion Matrix of DT Classifier.

### Method G: YOLOv7 Integration for FD and Recognition

In this method, the YOLO algorithm, specifically YOLOv7, was employed for FD and recognition of concurrent tasks. YOLOv7, as implemented in this study, comprises 415 layers and 37,358,376 FD and classification parameters. The algorithm's performance aligned with that of the fifth method, achieving an impeccable accuracy of 100% by effectively detecting and accurately recognizing all faces within the classroom. Notably, it proficiently identified the absence of the lecturer in the database, resulting in the display of the term 'unknown' on the lecturer's face.

To ensure optimal performance, the algorithm underwent training on the database utilized in this study for 100 epochs, utilizing three anchor boxes. Figure 16 provides a visual representation of the evolution of different metrics throughout the training process. Subsequently, the algorithm operates in real-time, detecting faces in video streams from the classroom-installed camera and enclosing them within bounding boxes. Non-maximum suppression is then applied to remove boxes with lower confidence.

Figure 16 illustrates ten graphs, each conveying distinct performance metrics:

1. The Box, Objectness, and Classification graphs depict loss values for bounding box regression, objectness score, and class prediction. These components of the YOLO loss function evaluate the model's proficiency in predicting object location, size, confidence, and class.
2. The Precision and Recall graphs present precision and recall values for FD, serving as metrics for evaluating the accuracy of classifiers.
3. The val Box, val Objectness, and val Classification graphs showcase loss values for the validation set, offering insights into the model's generalization ability.
4. The mAP@0.5 and mAP@0.5:0.95 graphs portray mean average precision values at various IoU thresholds, emphasizing the model's accuracy.

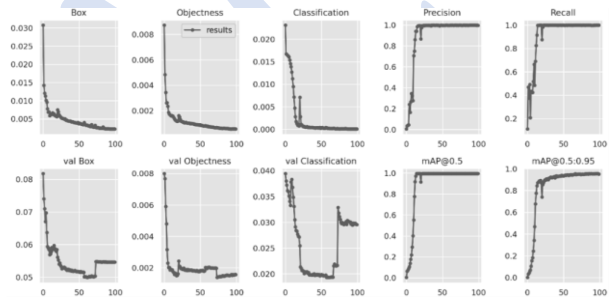

**Figure 16:** Training Metrics.

Figure 17 illustrates a precision vs. confidence curve detailing the model's performance across all classes. Figure 18 depicts the precision-recall curve, highlighting the trade-off between precision and recall. Finally, Figure 19 presents the F1-curve, indicating the model's performance in all classes combined.

Table 1 reveals the challenges ML-based methods face in real-time attendance tracking, a demanding task in computer vision (58). The initial method encountered misclassifications due to the Eigenfaces algorithm's reliance on PCA, leading to the elimination of crucial facial features during training and subsequent accuracy reduction in testing (51). Contrastingly, the second method, employing the Fisherfaces algorithm, an advanced version of Eigenfaces (59), showcased improved results. Adopting the LBPH algorithm, a robust feature extraction method in ML, outperformed prior ML approaches.

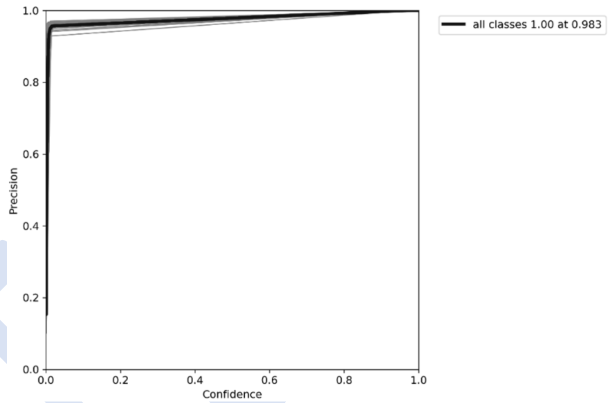

**Figure 17:** Precision-Confidence Curve.

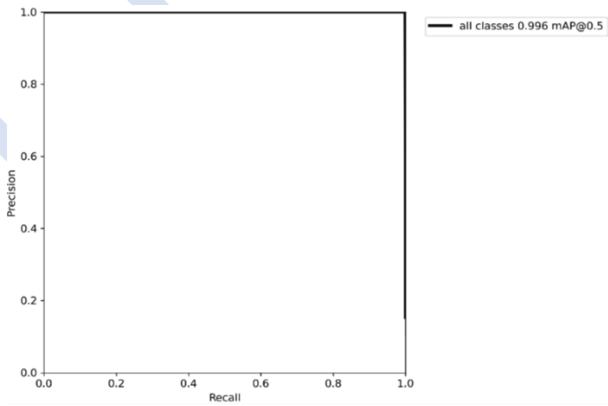

**Figure 18:** Precision-Recall Curve.

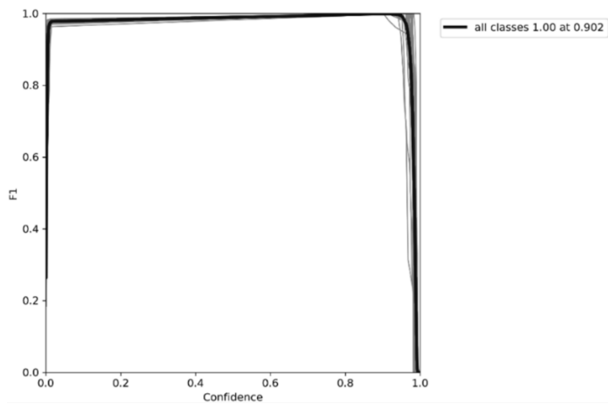

**Figure 19:** F1-Score Confidence Curve.

**Table 1:** Results of each Method.

| Method | TP | TN | FP | FN | Accuracy (%) | Precision (%) | Recall (%) | F1 - Score (%) |
|---|---|---|---|---|---|---|---|---|
| A | 29 | 1 | 0 | 2 | 94 | 94 | 100 | 97 |
| B | 31 | 1 | 0 | 0 | 100 | 100 | 100 | 100 |
| C | 29 | 1 | 1 | 1 | 94 | 97 | 97 | 97 |
| D | 21 | 0 | 9 | 2 | 66 | 91 | 70 | 79 |
| E | 24 | 0 | 7 | 1 | 75 | 96 | 77 | 85 |
| F | 29 | 0 | 2 | 1 | 91 | 97 | 94 | 96 |
| G | 31 | 1 | 0 | 0 | 100 | 100 | 100 | 100 |

The fourth method illustrated the disparity between ML and DL. Utilizing the HOG algorithm for FD and Dlib's facial embedding model for classification, it excelled in classification accuracy while facing challenges in FD. In contrast, the fifth and seventh methods, centred on DL, achieved flawless 100% accuracy. The sixth method, integrating MTCNN for FD and VGG-Face2 for feature extraction, encountered classification errors attributed to using the PCA algorithm, impacting feature removal for expedited training. Classification results varied among classifiers, with the decision tree classifier exhibiting the least favourable outcomes, while the Random Forest and support vector machine classifiers achieved optimal accuracy.

Table 2 highlights the distinctions between the present study and previous research endeavours. This investigation innovatively employs diverse computer vision algorithms to develop an attendance tracking system featuring a user-friendly graphical interface in English. This interface enhances accessibility, facilitating interaction with the system for users across diverse geographical locations. The study showcases the noteworthy accuracy achieved by the implemented methods, presenting promising results that can be relied upon to automate the attendance registration process.

**Table 2:** Comparison with Similar Studies.

| Ref. | Method | Year | No. of Examined Faces | Accuracy (%) |
|---|---|---|---|---|
| **(53)** | Viola-Jones + Dlib | 2020 | 3 | 88 |
| **(60)** | Viola-Jones + LBPH | 2020 | 6 | 100 |
| **(38)** | Viola-Jones + LBPH | 2020 | Just one person in real-time and 11 people in non-real-time | 96 |
| **(61)** | HOG + CNN | 2023 | - | 99 |
| **(48)** | PCA + SOM | 2022 | - | 94 |
| **(62)** | Viola-Jones + LBPH | 2023 | 1 | 94 |
| The Proposed Methods | HOG + Dlib | 2024 | 31 | 94 |
| | MTCNN + Facenet | | | 100 |
| | MTCNN + VGG-Face2 | | | 97 |
| | Viola-Jones + Eigenfaces | | | 91 |
| | Viola-Jones + Fisherfaces | | | 96 |
| | Viola-Jones + LBPH | | | 97 |
| | YOLOv7 | | | 100 |

In contrast to earlier studies, which often involved a limited number of subjects positioned at fixed distances from the camera (63, 64), our study successfully recorded the attendance of 31 students situated at varying distances in real time. Moreover, the system demonstrated its efficacy in the dynamic classroom environment, accommodating individuals not pre-registered in the database. This scenario was intentionally designed to rigorously test the system's ability to register attendance accurately under challenging conditions.

Although the methods employed to develop an attendance registration system utilizing face recognition technology demonstrated promising results, this study has several limitations. Foremost among these is the dataset size, which was constrained by the limited availability of images due to students' busy schedules during lectures. Additionally, factors such as students wearing obstructive accessories like scarves and glasses pose challenges to accurate face detection. While the system was tested successfully on students wearing prescription glasses, experiments involving students wearing sunglasses were not conducted, as university regulations prohibit their use during lectures. Furthermore, the system's effectiveness was evaluated within a limited distance of up to 33 feet, corresponding to the typical distances observed within university classrooms. Future research endeavours could address these limitations by conducting more comprehensive experiments, thereby facilitating the development of an optimal automated attendance registration system based on face recognition technology.

The proposed system demonstrates superior performance over prior studies by achieving 100% accuracy on the dataset in real time, even under varying conditions. Additionally, it includes a graphical user interface (GUI) built using the Tkinter library, enhancing its applicability for use in educational and governmental institutions to automate attendance recording. Notably, student privacy is carefully protected: only authorized users with the system's login credentials can access the database, view student data, or review images, as the system leverages MySQL for secure data storage. Unauthorized access is further prevented through a login portal integrated within the GUI, as illustrated in Figure 1. This design ensures that the system maintains high standards of student privacy.

## Conclusion

This research paper developed a specialized system to streamline the classroom attendance recording process, employing face recognition technology to distinguish the faces of 31 students. The study incorporated over seven machine learning and deep learning algorithms for object detection and identification, yielding accuracy rates ranging from 66% to 100%. The system featured a graphical user interface to enhance user interaction, designed in English for broader global accessibility. A dataset comprising 31 students was created, averaging 70 images per student, totaling 2170. These images were utilized to train the algorithms. The examination process involved capturing a live feed from the IP camera in the classroom, allowing the algorithms to detect and identify student faces, display their identities, retrieve information from the MySQL database, and record it in a CSV file. The CSV file was then renamed with the lecture's name and date for easy reference.

In future work, the integration of situation estimation technology alongside face recognition will be explored to identify and monitor students during exams. A notification system will also be developed to alert the relevant department in cases of suspicious cheating movements or similar behaviour.

## Ethics approval and consent to participate

Not applicable

## Consent for publication

Not applicable

## Availability of data and materials

The dataset generated for this study can be found on the Kaggle datasets with doi: 10.34740/KAGGLE/DSV/4925762.

The codes used in this study can be found on the first author's GitHub under the link: https://github.com/ahd-sd/Automatic-Management-of-Student-Attendance-in-Classrooms-via-Face-Recognition.

## Author's contribution

All authors contributed to the study's conception and design. Material preparation, data collection and analysis were performed by Ahmad S. Lateef and Mohammed Y. Kamil. The first draft of the manuscript was written by Ahmad S. Lateef and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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## Conflicts of interest

The authors declare that there is no conflict of interest regarding the publication of this article

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