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Implementing an attendance system based on facial recognition technology using artificial intelligence technology

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Abstract

In light of recent advances in artificial intelligence, the adoption of deep learning technologies in educational environments has become increasingly important, particularly in Middle Eastern universities, where technological infrastructure remains limited. To address this challenge, this study develops an AI-based attendance system that employs deep learning techniques for face detection and recognition, enabling automatic attendance recording and the generation of daily, weekly, and monthly reports. The system evaluates two face recognition pipelines: MTCNN combined with FaceNet and RetinaFace combined with ArcFace. Experimental results demonstrate that the RetinaFace–ArcFace pipeline achieved an overall recognition accuracy of 98.69%, outperforming the MTCNN–FaceNet approach under challenging classroom conditions, including variations in illumination, facial pose, and occlusion. Finally it was merged RetinaFace for face detection and MTCNN for facial feature alignment and enhancement, followed by ArcFace for accurate facial recognition. The hybrid combination of these three algorithms proved the accuracy and efficiency of the second algorithm, RetinaFace, with the ArcFace algorithm, because the system gave the same results when applied alone or when combined. Thus, when comparing the results of the three operations, the RetinaFace algorithm with ArcFace proved its superiority over the rest of the proposed algorithms. The system was also designed to work under different environmental conditions and in educational institutions with limited technological infrastructure.

Keywords: artificial intelligence, attendance system, educational Technology, technology, face detection, face recognition.

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1. Introduction

In recent years, artificial intelligence has become one of the most important modern technologies contributing to the development of various scientific and practical fields. It has been widely applied in education, healthcare, and security due to its high accuracy and efficiency. One of these technologies is facial recognition based on deep learning, which has received significant attention due to its ability to recognize faces with high accuracy, speed, and security (Choung et al., 2024) . Many universities still rely on traditional attendance systems that depend on manual records, which are time-consuming, require significant human effort, and are prone to errors, in addition to the possibility of proxy attendance. Therefore, many educational institutions are seeking to adopt more efficient and accurate systems that provide automated attendance monitoring. Despite significant technological advancements, many universities in the Middle East still lack smart management systems. The proposed system applies and integrates several previously known algorithms for detecting and recognizing faces within a unified framework to create an integrated attendance system that serves educational institutions, especially those with limited capabilities, meaning that the contribution represents building an integrated system based on these algorithms.

Through a review of previous studies, it was found that artificial intelligence has achieved effective results in the field of facial recognition; however, there are still some challenges related to camera angles and lighting conditions. In this context, the study by (Afroogh et al., 2024) addressed the importance of trust and security management in artificial intelligence systems. The study emphasized the necessity of developing reliable and secure AI systems for sensitive fields such as healthcare, financial, and defense applications. Attendance recognition in Studies (Chen, 2025) and

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(Nehanjali Bangaru et al., 2026) relied on facial recognition techniques using deep learning and real-time recognition using the face-api.js framework, which improved work accuracy, the efficiency of attendance recording, and reduced errors compared to traditional student attendance recording methods. (Nguyen-Tat et al., 2024) examined the development of an intelligent system for managing student attendance using facial recognition technology based on the Haar Cascade algorithm and OpenCV2 techniques. The study aimed to improve attendance recording accuracy and reduce manual intervention and errors associated with traditional methods. The system also relied on the NVIDIA Jetson Nano platform to enhance processing efficiency, and the results showed that it provided a low-cost and effective solution for managing attendance in educational institutions and various work environments. (DD et al., 2025) confirm that the facial recognition attendance system is a better alternative to traditional methods because it is faster, more accurate, and more secure and solves the problems of manual attendance. The study by (Wirdiani et al., 2023) aims to improve the reliability of the system using deep learning techniques and compares its performance with the SVM method. The system consists of two main stages: the registration stage and the recognition stage. In the registration stage, images are captured and processed, while in the recognition stage, YOLOv5 and a Siamese Network are used to extract facial features and compare them with the stored database. The results showed that the model achieved an accuracy of 94%. (Ismail et al., 2022) aim to build an intelligent security monitoring system for real-time face recognition using deep learning techniques, specifically the MTCNN model for face detection and the FaceNet model for face recognition, in order to improve security accuracy in university housing. Study (Susanto et al., 2024) examined the design of an e-learning platform based on facial recognition technology to verify students' identities during attendance registration. This study used the FaceNet identity recognition model and Haar Cascade to detect and identify facial features.The results showed that the system achieved good accuracy in facial recognition, but there were factors that affected performance, such as lighting, wearing hats, or other obstacles that affected the face.

2. Methodology and method

2.1. Face detection algorithms

Detecting faces and pinpointing facial landmarks are difficult tasks given variations in facial positions, lighting conditions, and obstructions like glasses, masks, and hair. These factors increase the difficulty of accurately detecting faces in real-world images. To address these challenges, several face detection algorithms have been developed, each differing in architecture, implementation, and performance.

2.1.1. MTCNN

Face detection and determining facial features is considered a difficult matter due to the variations in facial poses and the different lighting. The presence of occlusions such as glasses, masks or hair. All of these conditions make detecting the face more difficult. However, there are algorithms that work according to these conditions and with different features depending on the performance of this algorithm and the way it is implemented. Among these algorithms is MTCNN, which works according to three sequential neural networks. The first is P-Net (Proposal Network), which quickly searches for possible locations on the face and gives preliminary results. As for R-Net (Refine Network), it refines the results and removes false detections and the network. The latter O-Net (Output Network) confirms the final face and extracts facial landmarks accurately (Zhang et al., 2016), (Malah et al., 2023). After explaining how MTCNN works, it is important to highlight its advantages and limitations. Although MTCNN has proven effective performance in face detection and facial landmark identification, its cascading architecture requires multiple processing stages, which may increase execution time compared to newer face detection algorithms. Furthermore, its performance may decrease when very small faces or faces with extreme side positions are detected. These limitations and drawbacks have motivated researchers to develop more advanced face detection algorithms, among which RetinaFace has emerged as one of the most excellent, effective, and widely adopted algorithms. The structure shown Figure 1.

2.1.2. RetinaFace

RetinaFace is an advanced algorithm that outperforms MTCNN in complex face detection. It differs from MTCNN in that it relies on a single model to detect faces and identify facial features within a single, integrated network, which contributes to increased accuracy and reduced execution time. RetinaFace is also distinguished by its high ability to detect small faces, side faces, and partially obscured faces, in addition to its outstanding performance in group photos and real environments. For this reason, it has become one of the most widely used algorithms in modern facial recognition systems, and is often used with advanced recognition models such as ArcFace to achieve high levels of accuracy and reliability. RetinaFace consists of four interconnected modules: Backbone Network. This module represents the first stage of the model, where it receives the original image and extracts features from it. The function of this stage is to detect edges and basic features. The second stage is the Feature Pyramid Network. The function of this stage is to improve the detection of small faces, maintain the accuracy of detecting large faces, and increase the stability of performance in realistic images. After the Feature Pyramid Network, the attributes are passed to the Context Module. The basic idea from this stage is when looking at a human face, we do not rely only on the face itself, but also take advantage of its surrounding environment. Therefore, the Context Module expands the field of view (Receptive Field) and collects additional information from the areas adjacent to the face as well as enhancing important attributes (Deng, Guo, Zhou, et al., 2019). This module is responsible for a large part of RetinaFace's superiority over many previous algorithms. In the final stage, Prediction Heads, the final results are produced (Deng et al., 2020). Finally, the Prediction Heads generate the detection results by simultaneously performing face classification, bounding-box regression, and facial landmark localization, As shown in Figure 2.

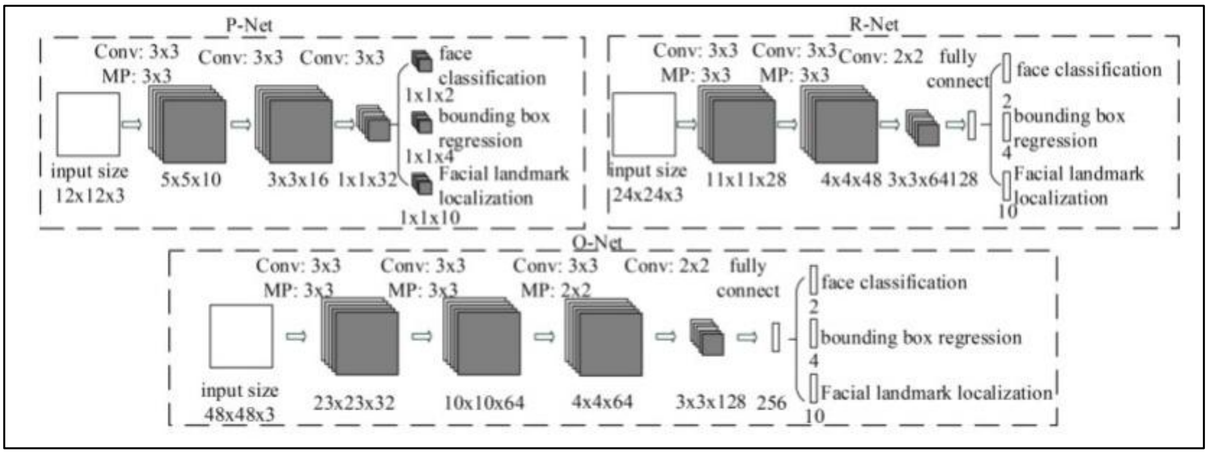

Figure 1. The structure of the MTCNN algorithm and the mechanism of action of its three sequential networks in facial detection and facial landmark identification

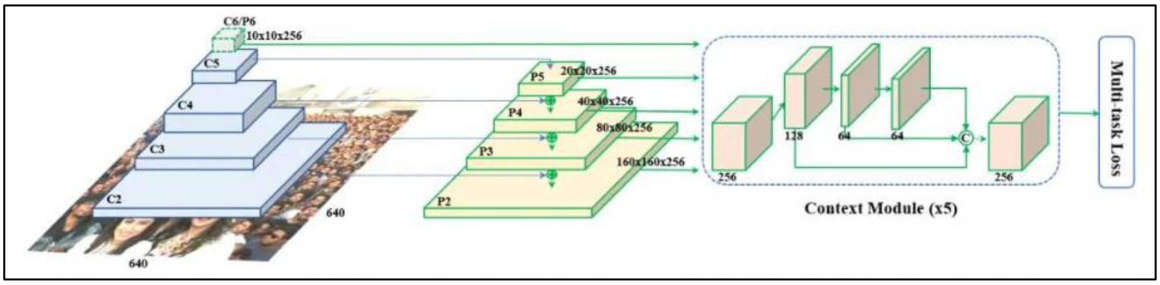

Figure 2. Architecture of the RetinaFace Algorithm

2.2. Face recognition algorithms

After a face has been detected and localized using MTCNN or RetinaFace, face recognition algorithms are employed to extract distinctive facial features and compare them with previously stored feature representations. In this study, FaceNet and ArcFace were utilized, as they are among the most widely adopted face recognition models due to their high accuracy and effectiveness in generating discriminative facial embeddings.

2.2.1. FaceNet

FaceNet is one of the most widely used face recognition models, as it employs deep neural networks to transform a facial image into a numerical vector (embedding vector) that captures the unique characteristics of the face. Rather than directly classifying individuals, FaceNet learns a feature space in which the distance between vectors belonging to the same person is minimized, while the distance between vectors of different individuals is maximized (Schroff et al., 2015),(Liu et al., 2018).

2.2.2. ArcFace

ArcFace represents a developed model of facial recognition, and its work relies on the concept of additional angular margin loss to distinguish between different faces. Instead of relying on distance only. The algorithm also focuses on angular separation between vectors representing faces. Which leads to reducing the contrast between images of the same person. This improves the accuracy of the work in the most difficult conditions, such as low lighting and different angles at which the shooting took place. This algorithm achieved advanced results, which led to its widespread use in facial recognition applications (Deng, Guo, Xue, et al., 2019), (Zhalgas et al., 2025).

The integration is designed to enhance the coverage and full exposure of faces.To improve face detection performance, a hybrid detection strategy was adopted by integrating RetinaFace and MTCNN in the face detection stage, while ArcFace was employed in the face recognition stage. RetinaFace was selected as the primary face detector due to its high detection accuracy, computational efficiency, and ability to provide facial feature representations. Subsequently, MTCNN was applied to detect any faces that might have been missed by RetinaFace. To eliminate duplicate detections, an overlap analysis based on the Intersection over Union (IoU) metric was performed between the bounding boxes generated by both detectors. Faces with an overlap ratio greater than 50% were considered duplicates and excluded, whereas newly detected faces were added to the final detection set. After the face detection stage, ArcFace was utilized to extract facial embeddings and perform identity recognition by computing cosine similarity against the stored facial database. This hybrid framework improved face detection coverage while maintaining a high level of recognition accuracy and system reliability.

2.3. Dataset

The experimental dataset consisted of 400 facial images. Initially, 200 images were stored in the system database as reference images for user enrollment, while the remaining 200 images were used to evaluate the recognition performance of the proposed attendance system. A folder was created to save the person's name and inside it the five images of this person. The system was designed using Python, specifically OpenCV. Experiments were conducted in Google Colab. It can also be deployed on a local laptop with standard specifications, as shown in Table 1.

Table 1. Device Specifications.

Devices	Specifications
Processor	Intel Core i7
Installed Physical Memory (RAM)	8.00 GB
System Type	Windows 11 operating system, X64

4. Results

This section shows the results obtained from the system and the algorithms that were tested on different images. These images were under different conditions and at different angles as well, to prove the effectiveness of the algorithms that were tried. Some images were collected from the Internet and public face image databases, such as LFW (Labeled Faces in the Wild), which contains images of well-known individuals.

When applying the MTCNN algorithm with FaceNet, the results showed that some faces in the tested images were not detected or recognized due to factors related to image size, lighting conditions, and possibly different face angles. Figure 3 shows the face detection results using the MTCNN algorithm.

Figure 4 shows the results of face recognition using RetinaFace, in which all faces were detected under the same conditions, such as the appearance of part of the face or low lighting.

After that, the MTCNN models were tested with FaceNet together, and the results were completed in Figure 5, where part of the faces were identified, while the rest of the faces were identified by the MTCNN model in detecting them and then determining the identity of the shape. The image to which the algorithms were applied was collected from several images with low illumination and different angles, and it was noted that all the people were identified except for one image represented by the person wearing glasses.

In Figure 6, RetinaFace models were applied using ArcFace. This model has proven its accuracy in operation and in various conditions. All characters in the images were discovered and identified under different circumstances, even if the images were sometimes unclear. This indicates the superiority of this model over MTCNN and FaceNet.

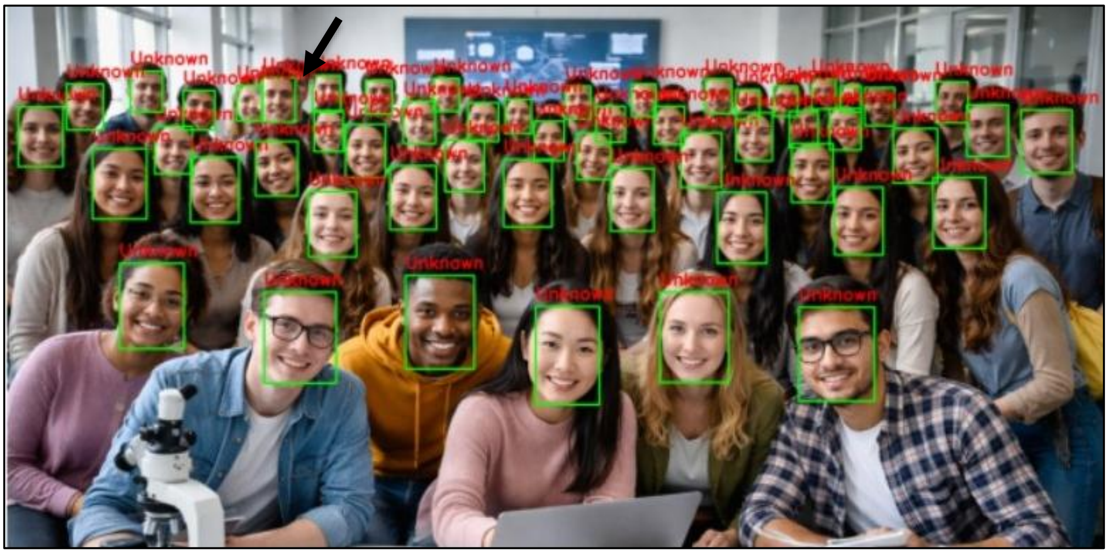

Figure 3. Face detection by MTCNN

Figure 4. Face detection by RetinaFace

Figure 5. MTCNN with FaceNet

Figure 6. RetinaFace with ArcFace

After that, a hybrid framework combining RetinaFace and MTCNN was implemented, followed by the ArcFace algorithm for facial recognition. The experimental results showed that the integration provided only a marginal improvement over using RetinaFace alone, which did not justify the additional computational complexity. Therefore, RetinaFace was selected as the face detection model for the proposed attendance system. Finally, the performance of the three approaches was compared in terms of accuracy under different face angles and lighting conditions, as illustrated in Figure 7.

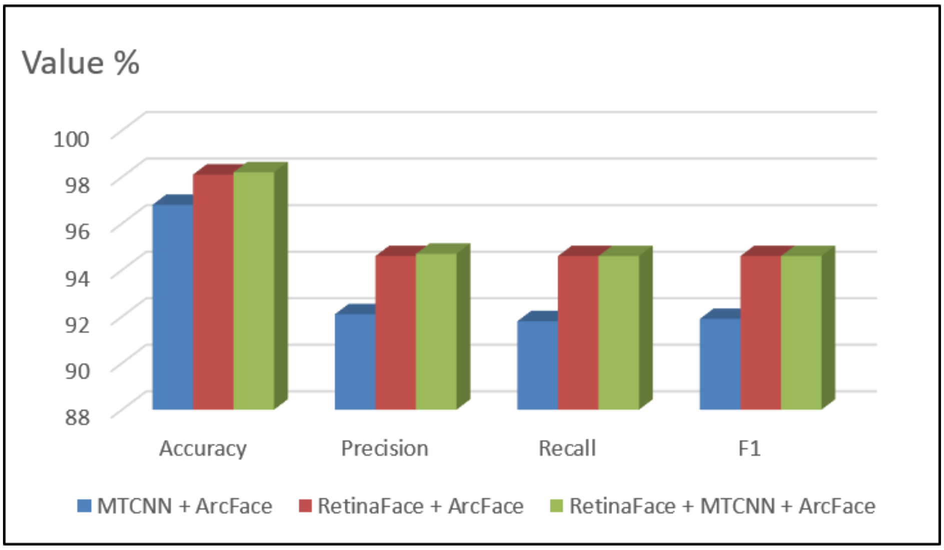

Figure 7. A chart for comparing the results of the three models

Table 2 shows the obtained values of Accuracy, Precision, Recall, F1-score, FAR, and FRR. The FAR and FRR values were calculated using 50 additional facial images that were not previously included in the system database.

Table 2. Standard metrics

Metric	Value (%)
Accuracy	98.69
Precision	94.59
Recall	94.59
F1-score	94.59
FAR	1.87
FRR	0.00

Attendance registration reports are then stored in a file called attendance.csv. The system provides a mechanism for withdrawing daily, weekly or monthly reports as needed. Figure 8 shows a sample of the report and its contents.

1	Name	Date	Time
2	sharir	2026-02-11	19:03:29
3	sharier	2026-02-11	19:41:55
4	vahid	2026-02-11	19:41:56
5	sharier	2026-02-12	7:36:29
6	vahid	2026-02-12	7:36:30
7	ali	2026-02-12	15:45:26
8	menoo	2026-02-12	18:48:41
9	menoo	2026-02-13	9:12:34
10	ali	2026-02-13	9:21:05

Figure 8. Attendance report at attendance.csv

5. Discussion

In recent years, Iraqi universities have witnessed a remarkable development in digital systems, and there has been a strong interest in digital transformation and the importance of digitizing data in various fields. It has become necessary to completely shift to electronic systems and smart systems to confront and keep pace with developments in the world. The study looked at (Bah & Ming, 2020) facial recognition system using the LBP algorithm, but the system is not compatible with poorly lit images. (Duta et al., 2020) dealt with the development of the structure of convolutional neural networks (ResNet), and the study aimed to improve the accuracy of deep learning and training, and these improvements are of great importance in the field of facial recognition. (Farouk et al., 2022) Prove the importance and accuracy of biometric identification in the field of identification, whether iris or face, depending on the application and data availability. Study (Hosen et al., 2023) dealt with an alarm system that relies on sending messages also to e-mail to alert about a specific problem. The system used the Haar Cascade algorithm to detect faces and the LBPH algorithm to identify them, but the results achieved reached 87%. In (Feta, 2023), the study aimed to apply and compare the SVM and KNN algorithms in face recognition and using the Haar Wavelet algorithm to extract image properties. The results showed that the SVM algorithm had an accuracy of 98.8%, while the KNN algorithm had an accuracy of 96.6%. (Generosi et al., 2023) Propose a security system based on facial recognition in factories, improve safety and develop the work environment using Industry 4.0. In (Ejaz et al., 2023) cases, researchers developed a security system that enhances university housing for students in universities. The MTCNN algorithm was used to detect faces and the FaceNet model was used to distinguish faces, but the conditions for the images were suitable and at fixed angles. Other researchers have used many techniques and compared algorithms. The most prominent and latest of these algorithms was MTCNN with FaceNet. This was done using the Python language and images were entered via live video to recognize faces inside a classroom (Lateef & Kamil, 2023) . In Study (P. Raj, 2024), researchers focused on implementing a facial recognition system in light of Covid-19 and wearing a mask. The system proved effective in facial recognition despite the presence of a mask and using the MTCNN algorithm. In (Naser et al., 2025) and (Putra Pratama & Ningrum, 2025), the researchers used MTCNN face recognition algorithms to detect faces and identify basic characteristics, and the accuracy of the results reached 92.9%, which confirms the accuracy of deep learning techniques in face recognition systems and getting rid of old traditional systems. In (Yu, 2026), the study dealt with an intelligent system that combines improving images and improving their lighting, and then introducing them to the object detection system using YOLOv11, which led to improving the accuracy of work and images, but this system will take more time and resources during implementation. The aforementioned studies demonstrate the diversity of applications of artificial intelligence-based systems in solving various problems, starting with facial recognition systems, attendance management, and improving the accuracy of these systems in difficult and diverse environments, all the way to administrative systems such as the management of educational clinics in the College of Dentistry at the University of Iraq (Shaalan Abdulmuneem et al., 2026). This confirms the extent of the increasing interest in electronic automation in various educational fields in Iraq to improve efficiency and accuracy.

6. Ethical Considerations

The system contains a login mechanism that prevents unauthorized persons from accessing sensitive facial data. Access to the system is limited to authorized persons. It is also recommended to encrypt data when implementing the system in educational institutions and to adhere to the approved data protection.

7. Conclusion

The research presented an intelligent system for detecting presence and preparing the necessary reports for that. The system was tested on a group of images chosen under different conditions to prove the accuracy of the system and its ability to detect faces through images, and the accuracy of the (RetinaFace with ArcFace) algorithm reached 98.69%, meaning that it can be relied upon as an ideal algorithm to work in such systems. In the future, additional details can be added to the database of people whose presence needs to be detected or identified, and daily reports can be stored in a database system such as SQL Server. It is also preferable to apply the system to a group of students affiliated with a specific college, so that the system can be examined on very large data of up to 900 students or more.

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