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ORIGINAL

Mobile app for real-time academic attendance registration based on MobileFaceNet Convolutional neural network

Aplicación móvil para el registro de asistencia académica en tiempo real basada en la red neuronal convolucional MobileFaceNet

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ABSTRACT

The attendance record monitors the student's participation in university academic activities, reflecting the commitment to their professional training. However, traditional systems require moderate time to perform this activity and can be susceptible to fraud and errors. In today's technological landscape, facial recognition has become an effective solution to problems in various fields. Currently, all university professors own smartphones. Considering this advantage, this article proposes to develop a mobile application for the registration of academic attendance using advanced artificial intelligence technologies such as Multitasking Cascade Convolutional Networks (MTCNN) in facial detection, MobileFaceNet in facial feature extraction (facial vector) and the Euclidean distance function in the calculation of similarity between obtained vectors. MobileFaceNet was evaluated in Python, using a personalized dataset of top-level students of the Software career of the Universidad Técnica del Norte, achieving an accuracy of 98,9 % and 99,4 % in LWF. The models were then integrated into a mobile app developed with Android Studio. Finally, the time required to register attendance was compared using the university academic platform (SIIU) and the facial recognition mobile application. The benchmarking showed a 24-second reduction of 33 % in attendance registration time.

Keywords: Artificial Intelligence; Facial Recognition; Student Attendance Registration; Mobile App; Convolutional Neural Networks; MTCNN; MobileFaceNet.

RESUMEN

El registro de asistencia controla la participación del estudiante en las actividades académicas universitarias, reflejando el compromiso con su formación profesional. Sin embargo, los sistemas tradicionales requieren un tiempo moderado para realizar esta actividad y pueden ser susceptibles de fraude y errores. En el panorama tecnológico actual, el reconocimiento facial se ha convertido en una solución eficaz a problemas en diversos campos. Actualmente, todos los profesores universitarios poseen smartphones. Considerando esta ventaja, este artículo propone desarrollar una aplicación móvil para el registro de asistencia académica utilizando tecnologías avanzadas de inteligencia artificial como Multitasking Cascade Convolutional Networks (MTCNN) en la detección facial, MobileFaceNet en la extracción de rasgos faciales (vector facial) y la función de distancia euclidiana en el cálculo de similitud entre los vectores obtenidos. MobileFaceNet fue evaluado en Python, utilizando un conjunto de datos personalizado de estudiantes de nivel superior de la carrera de Software de la Universidad Técnica del Norte, logrando una precisión del 98,9 % y del 99,4 % en LWF. Posteriormente, los modelos fueron integrados en una aplicación móvil desarrollada con Android Studio.

Finalmente, se comparó el tiempo requerido para registrar la asistencia utilizando la plataforma académica de la universidad (SIIU) y la aplicación móvil de reconocimiento facial. El benchmarking mostró una reducción de 24 segundos del 33 % en el tiempo de registro de asistencia.

Palabras clave: Inteligencia Artificial; Reconocimiento Facial; Registro De Asistencia De Estudiantes; App Móvil; Redes Neuronales Convolucionales; MTCNN; MobileFaceNet.

INTRODUCTION

Artificial intelligence (AI) and deep learning have been a growing interest and research topic in several fields.[1,2,3,4,5,6,7,8] With the rapid advancement of this technology, new opportunities arise to revolutionize traditional administrative processes.[9] Inefficiencies, inaccuracies, and time-consuming manual processes have often plagued conventional methods of recording attendance in educational settings. Academic institutions now have the opportunity to apply innovative solutions that optimize, improve, and mitigate potential problems related to routine activities,[10] offering an alternative to conventional methods.

High-education institutions' Proper attendance management faces significant challenges that demand an urgent solution. The traditional method, where teachers manually take roll calls, consumes valuable time that could be dedicated to training tasks.[11] An average of 5,01 seconds per student is estimated for the traditional attendance record, which can increase distractions or repetitions of the name.[12] Also, cases have been identified where teachers do not visually verify students, increasing the risk of identity theft and compromising academic integrity.[13] These issues and the potential for human error underscore the need for a more efficient, accurate, and secure system. Integrating facial recognition technology is a promising solution to address these challenges and modernize attendance management in higher education.

The current study recognizes the importance of addressing traditional methods' drawbacks and using facial recognition technology's potential to transform attendance tracking in educational establishments. First, it is intended to streamline the academic process, minimizing administrative expenses and maximizing instructional time. By automating attendance tracking, teachers can spend more time and resources on core educational activities, improving the overall learning experience for students. Second, the study is focused on improving accuracy and completeness in student attendance monitoring. Facial recognition technology eliminates the possibility of attendance by proxy or spoofing, ensuring that attendance registration is accurately reflected. By automating the process, institutions can improve interoperability and consistent and reliable data collection, which is useful for timely academic decision-making.[14]

By exploring the shortcomings of traditional methods and highlighting the benefits of adopting facial recognition technology, this article presents a modernized approach to attendance tracking at Universidad Técnica del Norte (Ibarra-Ecuador). This study aims to develop a mobile application that uses facial recognition technology for real-time recording of student attendance, focusing on improving the limitations of traditional methods and applying the benefits of artificial intelligence. Taking advantage of this technology is intended to enhance the process of controlling attendance, offering an efficient and secure solution, and managing to generate a report in Excel, which is used to record the attendance of students in the academic system of the University.

The facial recognition attendance registration mobile application is based on a robust architecture that integrates facial detection and feature extraction using convolutional neural networks (CNNs). The model selected for its balance between performance and efficiency in mobile devices was MobileFaceNet, which achieved an accuracy of 99,4 %, evaluated in the Labeled Faces in the Wild (LFW) database.[15]

The study used a previously trained model to improve the attendance registration procedure. An already-trained model was assessed for effectiveness in the extraction of facial features. This enabled the work to focus on reducing the time required for attendance registration through facial recognition. The previously trained MobileFaceNet model showed very good performance metrics, making it a viable solution without great effort. MobileNetV2 was recognised for its lightweight architecture and high speed,[16] and FaceNet,[17] a model widely used in facial recognition tasks. However, adopting the latter requires good computational resources, so implementing it on mobile devices was not a viable alternative. It is here that MobileFaceNet[18] proved ideal for the system requirements.

The custom dataset was crafted using video recordings. These videos are then processed using a facial detection algorithm (MTCNN) to extract the facial characteristics of the students. This algorithm captures various variations of facial features and expressions of a face, constituting a dataset for the evaluation of the facial recognition model. Necessary adjustments were made to the model to obtain detailed metrics of the learning process.[18] Consequently, a model retraining protocol is implemented, meticulously monitoring the training history. These data are important to validate the robustness of the model and its generalizability in the specific context of attendance registration using facial recognition.

The development involves two main environments: Google Colab with Python for model evaluation, taking advantage of its processing and collaboration capabilities, and Android Studio with Java for mobile app development because it offers a solid framework for UI and model integration. This combination of technologies and platforms creates efficient and easy-to-use applications, optimizing performance without compromising accuracy and adapting to the limitations of mobile devices.[19]

The contribution of this work lies in integrating facial recognition technology with a highly scalable and adaptable attendance management system. This study provides new knowledge, through a comparative time analysis, between the traditional method of attendance registration and our mobile application based on facial recognition. A solid foundation is laid for future research in this field by measuring and evaluating the time required for both methods. The results of this comparison can significantly influence decision-making processes within academic institutions. This study provides practical guidance for institutions considering modernizing their classroom attendance management systems.

Related Jobs

A lightweight convolutional neural network model has proven very efficient in extracting facial features in facial recognition systems. For children, these systems play a vital role in ensuring safety and facilitating activities within schools. MobileFaceNet,[20] trained with the ArcFace Loss feature, has demonstrated exceptional accuracy on children's datasets. The loss function optimizes feature diversity for samples between classes and similarity for samples within classes, resulting in highly discriminative features. The Dlib library handles the preprocessing tasks, while the classification has been performed using the K-Nearest Neighbors (KNN) algorithm. Experimental results have shown that MobileFaceNet achieves a remarkable accuracy of 96 % in children's personalized datasets. The proposed system offers high accuracy and works efficiently in real time, making it ideal for mobile and embedded devices.

An intelligent attendance management system (SAMS),[21] is proposed for universities to address the challenges of traditional attendance management systems that are time-consuming and vulnerable to tampering. SAMS allows university students to use intelligent assistance, which identifies them individually based on fingerprints or facial identification. The system uses real-time facial verification by applying MobileFaceNet and fingerprint scanning to mark attendance, providing high accuracy and security. The proposed system architecture includes a mobile application for students and instructors connected to a server containing all students' databases. The system is designed to be accessible and easy to use, with a home screen for students to select their classes and check their attendance performance. The system also generates attendance reports. Using biometrics and location identification provides a safer, more efficient, and more accurate way to manage attendance.

In,[22] a real-time facial recognition system called FaceON was proposed for mobile applications. Traditional support mechanisms are prone to fraud and errors, making businesses need to adopt digital assistance solutions. The proposed system uses a convolutional neural network (CNN) with MobileNetV2 architecture to identify employees' faces in real-time. MobileNetV2 is advantageous because it efficiently uses mobile device resources without compromising the accuracy of the CNN model. The system extracts landmarks from the eyes and lips using the BlazeFace model built into the Dart programming language within the Flutter framework. In addition, the mobile application helps prevent possible fraud by implementing anti-spoofing techniques. These techniques mainly strengthen security in applications such as biometric authentication. A new user registers with the name and face image for its operation. The results are stored in a JSON file on the same device. A cloud server processes the images and compares them. If the comparison of the face exceeds the threshold of 80 % concerning the stored records, the system determines whether they correspond to the same person or not.

In,[23] an automatic class attendance system using facial recognition based on convolutional neural networks (CNN) is proposed. The methodology consists of four main stages: data entry, dataset formation, facial recognition, and attendance input. The system captures students' facial data and stores it with the appropriate tags at the data entry stage. The dataset is then trained using a CNN model to recognize faces. The system connects to a video source that captures students' faces in real time, and the detected faces are compared to the dataset trained for recognition. The data of the recognized students is saved in an Excel sheet, marking their attendance. The system achieves an average recognition accuracy of around 92 %, proving its effectiveness in accurately recognizing students' faces.

In,[24] a system was developed that records attendance automatically by recognizing students' faces in a video feed. The Haar cascade classifier is used to detect the location of the face in the image. In contrast, the FaceNet network extracts facial features from images and renders them in a digital vector. The system is trained on a dataset of 3900 face images belonging to 130 students, with 30 face images for each student, achieving an accuracy of 97,5 %. The system can send attendance status to the teacher and student via email and store and retrieve attendance records. The system can be accessed via a mobile phone or a computer, as SQLite3 files are collected and uploaded to the cloud server. The proposed system has several advantages, such as reduced cost compared to other systems, reduced limitations related to camera blind spots, and poor shooting angles. However, the system has some limitations, such as the need for high-resolution cameras and algorithms that may be less sensitive to light to overcome lighting issues.

METHOD

Preparation of the Dataset.

There are multiple approaches to generating a custom dataset; however, this work consisted of capturing individual video sequences of 25 seconds in length for each student. These recordings were made under controlled lighting conditions, including different facial expressions (neutral and smiling), using a Canon EOS T5 professional camera with a resolution of 18mxp with a lens of 18-55+75-300. Later, with Python, individual frames were obtained from the video sequences. Facial detection was then performed on the frames to identify and isolate the regions of interest corresponding to the participants' faces, using MTCNN. The resulting dataset was made up of faces extracted from the videos of the 16 students. Figure 1 details some examples of the personalized dataset of the first-level students of the CSFOT-UTN career.

Figure 1. Personalized student dataset

Neural Networks.

MTCNN: Multi-task cascaded convolutional networks (MTCNN) is an algorithm that performs the facial detection task in a cascaded structure, consisting of three main components: Proposal Network (P-Net), Refinement Network (R-Net), and Output Network (O-Net). P-Net generates candidate bounding boxes around their faces in the input image. It uses a shallow convolutional neural network fed into R-Net. R-Net refines the bounding boxes generated by P-Net and performs face detection by classifying each bounding box as face or non-face. O-Net further refines the bounding boxes generated by R-Net, resulting in the location where it has predicted a face.[25] MTCNN is excellent for face detection because it is more resistant to changes in lighting, movement, and facial expression; it predicts the face's location and landmarks with great accuracy.[26] Its high accuracy and real-time performance justify MTCNN's selection for face detection. Figure 2 details the facial detection process of the three networks that make up MTCNN. P-Net generates candidate regions, R-Net refines those regions, and O-Net accurately detects and adjusts facial features.

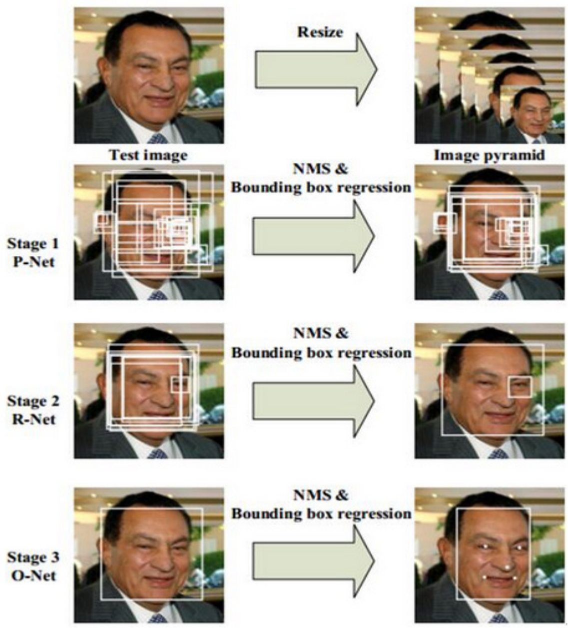

Figure 2. Precision adjustment of facial features[26]

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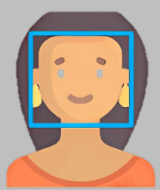
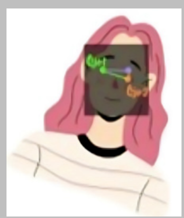
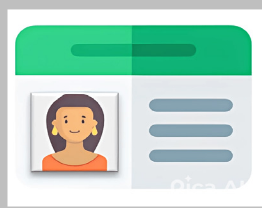
MobileFaceNet is a lightweight and efficient convolutional neural network based on deep learning designed for facial recognition tasks on mobile and embedded devices. It is a compact version of the FaceNet algorithm,[15] achieving impressive results in terms of accuracy and speed.[12] MobileFaceNet, with about 1 million parameters, uses a collection of bottleneck layers based on the deep-separable convolutions architecture found in MobileNetV2.[20] Depth-separable convolution breaks down the conventional convolution into two parts: a depth convolution followed by a 1×1 convolution and a 1×1 point-for-point convolution.[27] This step is essential because significantly superior results are obtained by mapping the channels and spaces of the convolutional layers separately. Each input channel is convoluted independently with a different filter.[28] MobileFaceNet processes face images resized to 112 x 112 pixels with normalized pixel values. The result of this model is a set of 192-byte output channels in a Euclidean space. MobileFaceNet extracts information from specific areas, such as eyes, nose, mouth, eyebrows, cheeks, and chin, among others, also known as embeddings, which describe the location of a face.[12]

MobileFaceNet[18] was used as the basis for the development of the facial recognition system. Various tests were carried out to validate its effectiveness. These tests included evaluating its accuracy and performance on mobile devices to ensure that the model meets the standards of an efficient system capable of operating in real-time.

Implementation of the System

This section presents the facial recognition system's design, implementation, and evaluation, developed in Android Studio using Java 17. To achieve effective facial recognition, a system follows four key phases: (i) detection, (ii) preprocessing, (iii) feature extraction, and (iv) comparison, culminating in a precise decision about the identity of the individual [12]. The phases are presented in figure 3.

Figure 3. Phases of a facial recognition system

Detection	Pre-processed	Feature extraction	Comparison and decision
		$\begin{pmatrix} 8.3921 \\ 2.3031 \\ 2.2928 \\ 0.9053 \\ -0.7635 \\ \vdots \\ -0.4070 \\ -0.4820 \\ -0.1885 \\ 0.7783 \\ -3.7142 \end{pmatrix}$	

The mobile app's facial recognition begins with real-time frame capture using the device's main camera. The phone camera used has the following specifications: Main: 200 megapixels, f/1,9; Wide: 12-megapixel, f/2,2; Depth: 2 megapixels, f/2,4. Each captured frame (image) is converted to a bitmap format (Bitmap.bmp). To isolate the area of interest (facial detection), the MTCNN algorithm is implemented, which is recognized for its effectiveness in detecting faces in various lighting conditions.[25]

Once a face is detected, the next phase is preprocessing. This phase includes image adjustment actions such as cropping (112 x 112) pixels according to the model's requirements and aligning and normalizing pixel values, thus optimizing input for the next phase.

Facial embedding is performed using the MobileFaceNet model, which generates a vector of 192 values. This embedding is a compact and discriminating representation of the individual's facial features. The predicted embedding is compared between a set of embeds pre-stored in a JSON file on the same device to determine the student's identity. A similarity analysis is performed using the Euclidean distance function, which allows measuring the similarity between two vectors in a feature space. This comparison process uses a threshold of 0,80 to determine the student's identity.

Finally, the system generates an Excel report about the identified students. The teacher can integrate this report into the university's academic system, thus facilitating automated attendance registration. Figure 4 details the process followed by the facial recognition application.

MobileFaceNet Evaluation

The facial recognition model was evaluated using the following metrics: a personalized dataset of 12400 images from 16 students of the Software career of the Universidad Técnica del Norte with diversity in facial features. This helps the model generalize better in real-world situations.

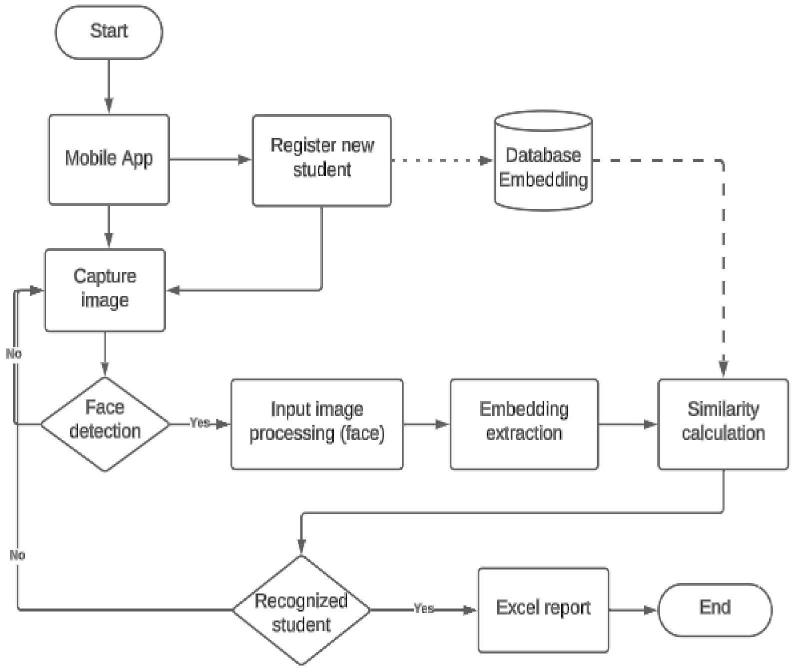


Figure 4. Flowchart of the facial recognition system

Accuracy: Measures the ratio of correct predictions (both positive and negative) to the total number of cases examined, according to equation (1).

$$accurracy=(TP+TN)/(TP+FN+FP+TN) \quad (1)$$

Specificity: Calculates the model's efficiency in identifying all the negative instances detected, according to equation (2).

$$specifity=TN/(TN+FP) \quad (2)$$

Recall: This task assesses the model's ability to correctly identify all positive cases, according to equation (3).

$$recall=TP/(TP+FN) \quad (3)$$

Error Rate: The error rate is an indicator that measures the proportion of incorrect predictions, evaluating false positives and false negatives within a dataset (4).

$$error\ rate=(FP+FN)/(TP+TN+FP+FN) \quad (4)$$

RESULTS AND DISCUSSION

Developing an efficient facial recognition mobile app presents multiple challenges, especially when balancing recognition accuracy with device capabilities. The app developed using the combination of MTCNN for face detection and MobileFaceNet for facial recognition proved to be highly effective and efficient, as stated below.

Model performance.

The evaluation was done by applying a set of metrics widely recognized in machine and deep learning. The metrics considered included accuracy, recall, specificity, and error rate.

Table 1. Model performance in the LWF database and custom database

BBDD/Metrics	Accuracy	Error rate	Recall	Specificity
Students (own)	98,9 %	0,1 %	98,2 %	99,4 %
LFW	99,4 %	0,52 %	99,5 %	99,4 %

When evaluated on the dataset of UTN University students, the system achieved an accuracy of 98,9 %. These results highlight the system's robustness, pointing out that it can generalize in different contexts and suggesting that it is reliable for use in real-world environments.

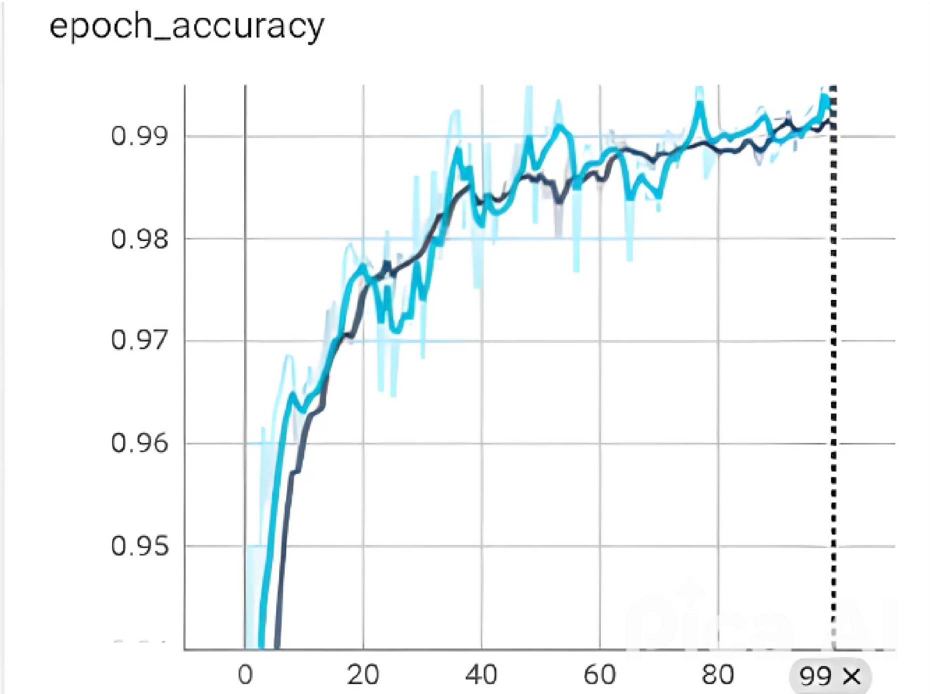


Figure 5. Graph of model accuracy in 100 epochs, where the strong blue color refers to the training data and the soft blue to the validation data in the custom dataset

System performance

The system's overall performance was maintained optimally during tests conducted on 16 students. The group comprised one woman and fifteen men of various ethnicities, including mestizos, indigenous people and people of African descent aged between 18 and 20 years. The app demonstrated its ability to process images in real-time, reaching an average processing time of 0,3 seconds per frame, ensuring a smooth experience. On average, the system took 3,49 seconds to recognize and verify each student's identity. It is important to note that these times can vary depending on the circumstances, although the results obtained serve as a valuable reference for decision-making. The comparison of the times obtained in the attendance record using the mobile application and the traditional method is described in table 2.

Table 2. Comparison of times between attendance recording methods

Method	Average time spent in the academic portfolio	Average time to register attendance	Total average time	Percentage reduction in time
Record attendance using the academic portfolio	1,28 min	1,38 min (List by faculty)	3,06 min	0 %
Attendance registration using the mobile app	1,28 min	1,14 min (Until the report is generated)	2,42 min	33 %

Operation

To register a new individual in the application, information data and a photograph of the student are required. The process begins with the detection and alignment of the face, followed by the normalization of the image. Then, the MobileFaceNet model extracts facial features, generating a vector, which is stored along with the informational data in the JSON file to be later used to compare the student's identity. Figure 6 shows the registration screen for a new student.

The test involved the person responsible for recording attendance, in this case, the teacher or assistant, touring the students' locations and using their mobile phone's camera to capture their faces. On average, it took 3,49 seconds to identify each student due to the time spent walking in front of them. Figure 7 shows the real-time recognition of one student, Figure 7a, and Figure 7b recognizes two students.

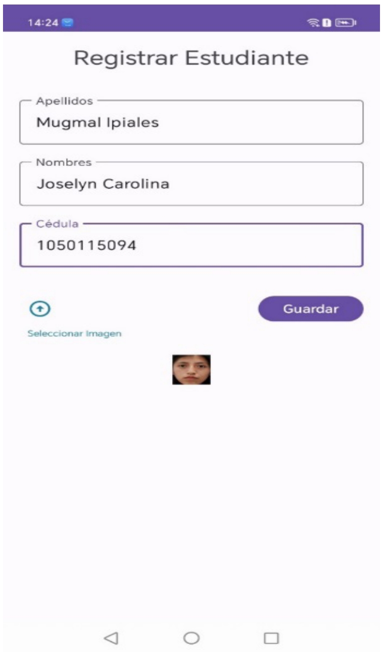
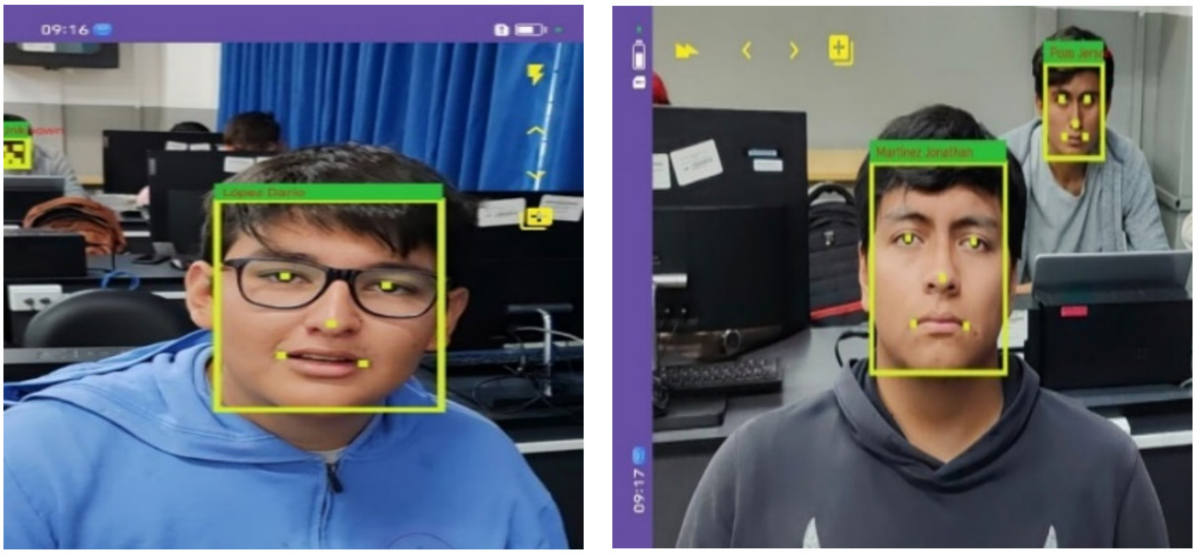


Figure 6. Registering a new student



(a) (b)

Figure 7. Real-time application operation

Comparison with existing studies

Schools are demanding an innovative approach to attendance registration. In,[20] they tackled this challenge using MobileFaceNet and Dlib, achieving 96 % accuracy in children's facial recognition. Our proposal advances along these lines but is implemented in a university with a mobile application, where the model reached an accuracy of 98,9 %. However, when implementing it, we faced computational limitations as we sought a balance between the accuracy and efficiency of the system in real time.

The attendance management system proposed in[21] features a multimodal approach that maximizes accuracy by integrating facial recognition, fingerprints, and GPS location. Its architecture is based on a server hosted in the cloud, which requires a constant internet connection. In contrast, our system focuses exclusively on real-time facial recognition of students.

MobileNetV2 is another pretty satisfying approach to facial recognition on mobile devices.[22] Its ability to extract facial landmarks and employ anti-spoofing techniques stands out. Instead, our system employs MTCNN for accurate face detection and MobileFaceNet for identification, prioritizing speed and accuracy. Similarly, the individual's results are stored in a JSON file in the phone's memory.

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It is possible to record people's attendance from a video stream.[23] The video is uploaded to the application in Python and processed by the CNN model, resulting in the identified individuals. On the contrary, our app captures real-time images from the phone's camera.

The system analyzes video footage in real-time and implements facial recognition to automate the student attendance registration process.[24] This approach integrates the Haar Cascade classifier and FaceNet for facial feature extraction, achieving 97,5 % accuracy in a dataset of 3,900 images (130 students). On the other hand, we have evaluated the model on a dataset of 12,400 images from 16 students, achieving an accuracy of 98,9 %.

The mobile application for attendance registration represents a significant innovation in automating this task, integrating advanced facial recognition algorithms. Its impact is evidenced in a remarkable optimization of time and resources, considerably reducing the duration of the registration process and minimizing the margin of human error. Implementing the system in a mobile application highlights its innovation by leveraging the accessibility and portability of smartphones to offer a flexible and scalable solution that adapts to the demands of the modern work environment.

It is important to recognize the limitations of the current study. The assessment was conducted in a controlled environment with a limited number of 16 students for a particular course. Figure 8 highlights the need to optimize recognition accuracy in low-light conditions and situations where facial expressions vary significantly.

The limitations of tests on 16 students reflect more than methodological deficiency; they reflect a temporal restriction in the research development. Despite its small size, the model was evaluated, which can be greatly increased in future iterations. The initial sample of 16 students acted as a demonstration prototype, confirming the robustness of the CNN architecture and laying the groundwork for a larger-scale implementation. This incremental development strategy is common in technological research, starting with a small sample to ensure feasibility before growth.

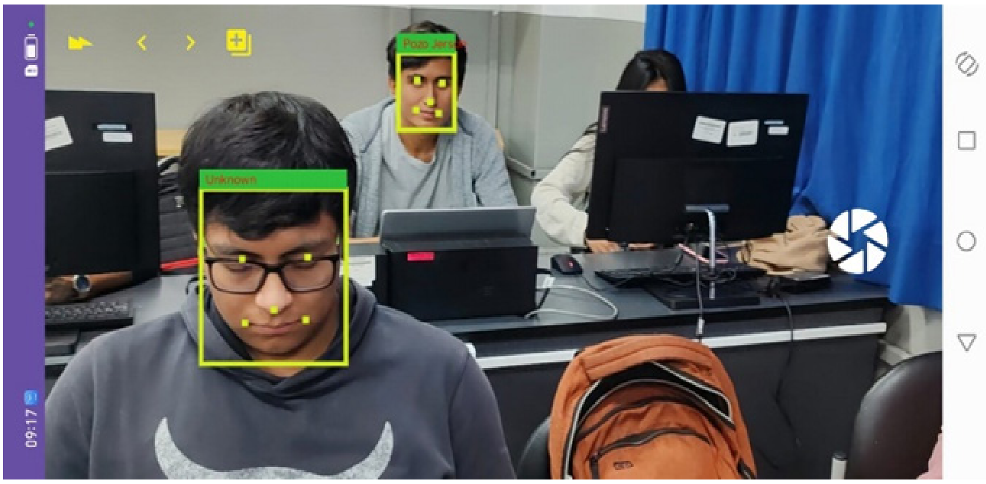

Figure 8. System Limitations

CONCLUSIONS

This research has demonstrated the advantage of automating attendance registration in academic environments by implementing facial recognition and integrating technologies such as MobileFaceNet and MTCNN. MobileFaceNet, when evaluated with our student dataset, achieved an accuracy of 98,9 %, which indicates a high degree of reliability in identification. In addition, the average registration time per student was 3,49 seconds, including the time of login to the academic system. This significantly improves efficiency compared to the traditional method, which was 6,12 seconds (table 2). The system achieves high accuracy in facial recognition without affecting the mobile device's performance, optimizing the time compared to the traditional method of 24 seconds. This approach makes it easier for teachers to automatically generate reports that can be integrated into academic management systems.

This research presents the basis for transforming attendance registration processes in educational institutions. The results validate the proposed approach's effectiveness and pave the way for future research and improvements in facial recognition in academic settings.

Despite the achievements made with the facial recognition mobile app using MobileFaceNet and MTCNN, there are still areas that could be explored and improved in future work. For example, to further refine the speed of face detection, the dataset must contain images with more varied position movements and lighting changes. This will allow the results to be more accurate.

The implemented prototype lays the foundation for future research to enhance and optimize the proposed methodology. The study opens new opportunities for developing advanced facial recognition applications in academic and business contexts, considering scenarios with more participants. This research ensures data protection through informed consent for data collection and the anonymity of facial information. Strict principles of professional ethics and responsibility are used to collect, process, and store facial data.

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