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Automated Classroom Attendance using a Machine Learning-Based Recognition System

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***Abstract*—Manually tracking classroom attendance, an entrenched traditional method, presents significant challenges due to its susceptibility to errors and inefficiencies. These limitations not only consume valuable faculty time but also compromise the accuracy of academic records, affecting the evaluation of student engagement and performance. In response to this problem, we present an approach for automated classroom attendance using an embedded machine learning-based recognition system. This research strives to improve the accuracy, efficiency, and reliability of attendance tracking in educational settings. The heart of our research lies in the design and implementation of the system, clarifying the architecture, data flow, and integration into the classroom environment. The results of our analysis show the system's ability to track attendance while providing accurate information on its performance metrics. We also delve into the ethical and practical considerations of implementing such technology in the classroom. By automating the process using machine learning-based recognition, educational institutions can improve their operational efficiency, reduce errors, and ultimately provide a more productive learning environment. Our study opens the door to future avenues of research and technological advances in education.**

***keywords*— Automated Attendance, Attendance Tracking, Face recognition, Machine Learning, Classroom Technology**

I. Introduction

In education, the task of monitoring classroom attendance [1] has persisted as a necessary but often laborious administrative duty. From primary schools to universities, educational institutions routinely face the challenges associated with traditional methods of manual attendance tracking. These methods are time-consuming and susceptible to inaccuracies resulting from various factors, including human error and spoofing attempts.

Recognizing the need for more accurate, efficient, and reliable attendance tracking, this research presents a transformative solution: automating classroom attendance through a machine learning-based recognition system.

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This study aims to alleviate the burden of attendance tracking while improving its accuracy and reliability within the educational context.

This introduction paves the way for the forthcoming analysis. It highlights the significance of attendance tracking in educational systems, not only for confirming student attendance but also for supporting essential decisions regarding student participation and performance metrics.

The research problem becomes evident in this context: the need for a simplified and effective approach to attendance control. To address this challenge, our study embarks on a multifaceted journey encompassing literature review, methodological development, system implementation, empirical analysis, and reflective discussion.

In the following sections of this article, we delve into a literature review, elucidating the shortcomings of conventional attendance tracking methods and the technological advancements that have paved the way for our machine learning-based recognition system. We describe our methodology, algorithms, data collection processes, and ethical considerations. Furthermore, we present the architecture and implementation of our recognition system, accompanied by an in-depth analysis of the results it has produced.

The discussion section addresses the broader implications of our findings, addressing the increased efficiency and accuracy of attendance tracking and the ethical considerations surrounding the deployment of recognition technology within the classroom.

In summary, this project aims to close the gap between conventional attendance tracking and cutting-edge technology, offering a practical solution for attendance tracking in educational environments. We aspire that this exploration contributes to educational technology and inspires future innovations in the search for more effective and efficient educational practices.

II. Literature Review

The educational technology landscape has witnessed notable transformations in recent years, reshaping traditional classroom practices and administrative procedures. The process of tracking class attendance, a critical but often cumbersome task in educational institutions, has been subject to reevaluation and innovation. This section reviews existing literature, focusing on the challenges associated with conventional attendance tracking methods and the emergence of cutting-edge technologies, specifically machine learning-based recognition systems, as a promising solution.

A. Importance of taking attendance in the classroom

Tracking class attendance is often considered a routine and cumbersome administrative task, with limited perceived contributions to the educational process. However, from [2]–[4] several dimensions are highlighted in which the attendance record plays an important role:

- **Academic accountability:** Tracking attendance helps ensure students are present in class and engaged in learning. It holds students accountable for their academic commitments and encourages regular attendance, which often correlates with better academic performance.
- **Resource allocation:** Educational institutions allocate resources, such as teacher time and classroom facilities, based on expected attendance. Accurate attendance data is crucial to optimizing resource allocation and effectively scheduling classes.
- **Legal and regulatory compliance:** In many jurisdictions, educational institutions are required by law to maintain accurate student attendance records. Compliance with these rules is necessary to avoid legal and financing problems.
- **Financial aid and grants:** Some students rely on financial aid, scholarships, or grants that depend on maintaining a certain level of attendance. Accurate assistance tracking is essential to determining financial assistance eligibility and disbursement.
- **Identification of at-risk students:** Regular attendance tracking allows educators to identify students who are frequently absent. These students may face challenges that impact their ability to attend classes regularly, and early intervention can help address these issues and prevent academic difficulties.
- **Pedagogical considerations:** For instructors, knowing which students are present allows them to adapt their teaching methods and interact with the class effectively. Helps instructors adapt their approach to meet the needs of the students present.
- **Assessment and grading:** Many educational institutions incorporate attendance as a component of a student's overall grade or evaluation. Consistent attendance can contribute positively to a student's academic record.
- **Classroom dynamics:** Active student participation and interaction can improve the overall classroom experience. Attendance tracking supports the creation of an inclusive and engaging learning environment.
- **Parent involvement:** For students at lower educational levels, attendance tracking is essential to involve parents and guardians in their child's education. Parents can be notified of irregular attendance patterns and collaborate with educators to address concerns.
- **Student success and retention:** Regular attendance is often associated with student success and retention rates. Attendance tracking allows institutions to monitor and improve these critical metrics.

B. Conventional attendance tracking methods

Traditional attendance tracking methods have long relied on manual processes, where instructors take roll calls, mark time sheets, or rely on students to sign in [5], [6]. While these methods have served their purpose, they have several limitations, including time inefficiency, susceptibility to human error, and the possibility of proxy assistance (spoofing). These deficiencies have stimulated the exploration of more efficient and precise alternatives.

C. Technological advances in attendance tracking

Recent years have seen an increase in technology adoption in educational contexts, and attendance tracking is no exception. Innovative solutions have emerged that use biometrics, RFID (Radio Frequency Identification) [7], and QR code-based to automate attendance tracking processes. However, these technologies present their challenges, including privacy concerns and logistical complexities.

D. Recognition systems based on Machine Learning

Within the scope of technological advances, recognition systems based on Machine Learning have attracted great attention as a promising way to automate class attendance. These systems use Computer Vision and Machine Learning (ML) algorithms to identify and verify the presence of students in a non-intrusive manner [8], [9]. Potential benefits include increased accuracy, real-time tracking, and reduced administrative burden.

In particular, Convolutional Neural Networks (CNN) and Machine Learning (ML) models have emerged as fundamental pillars in solving complex problems in many areas, including education. CNNs have demonstrated potential and usefulness in identifying and classifying visual objects. Its ability to learn visual patterns and features in large data sets has found innovative applications in student attendance tracking and many other educational fields. ML models, on the other hand, have made it possible to address large-scale problems through the application of machine learning algorithms. These models can analyze complex data, identify trends and patterns, and generate accurate predictions, which is essential for improving efficiency and informed decision-making in the educational environment.

Next, the analysis of different proposals based on using ML models for Assistance in the classroom is presented.

Reference [8] uses the ResNet architecture to investigate a deep learning classification method that identifies student attendance. To do this, facial photographs of students were used to train the ResNet-18 and ResNet-50 models. These models were educated to distinguish between regular and irregular student attendance. The study relies on the FER2013 dataset to label students' faces and images in real-time. The researchers indicate that this deep learning approach demonstrates the reliability and repeatability of students' image analysis.

In [10], a facial recognition system is proposed for the automated management of student attendance in university environments. Implemented in Python using OpenCV, Numpy, and Tkinter, the system uses facial recognition algorithms, such as LBPH (Local Binary Pattern Histogram) and KNN (K-Nearest Neighbor). The proposal seeks to improve the efficiency of the traditional assistance process, avoiding the misuse of resources and time.

Reference [11] proposes an automatic attendance system based on facial recognition using Deep Convolutional Neural Networks (DCNN). SeetaFace, a DCNN-based face detection system, is implemented to identify faces in real-time captured videos. The VIPLFaceNet (an open-source deep face recognition SDK) model is used for facial classification, involving the preparation and training of the model with a dataset of facial images. The article highlights the relevance of facial recognition in automated assistance systems, addressing limitations present in existing systems, such as capturing images in real-time, obstacles in front of faces, and low lighting conditions, which are overcome through the precise use of DCNN.

The Deep Learning Assisted Attendance System (DPAAS) [12] keeps track of students attending a particular class with the help of a continuous stream of images captured from a video streaming device located within a classroom connected to a server remote. The goal of DPAAS is to robustly detect faces under different conditions. There are two key steps in the proposed DPAAS method. The first is to detect whether a face is present in a given region of the image, and the second is to recognize the tag of the person detected in the image using the detection algorithms. It uses a Neural Network called Single Shot Multi-Box Detector for facial detection and a VGG network for multi-class facial recognition. The experimental results show that the proposed DPAAS method provides an accuracy of 94.66%, better than other existing methods.

Virtual teaching, driven by technological advances and accentuated by the pandemic experience, has revolutionized education worldwide. However, this shift towards virtuality has posed new challenges, including managing student attendance. In an environment where students participate in classes remotely or online, attendance management remains a crucial issue that requires attention and appropriate solutions.

In the context of increasing digitalization and the transition to online education, attendance taking and identity validation have become significant challenges. The pandemic has accelerated the adoption of digital educational environments, but concerns have been raised about the accuracy and security of current attendance recording methods, such as QR codes. In the case of virtuality, [2] proposes a Facial Recognition Assistance System with timestamp records based on HOG+SVM (Histogram-Oriented Gradients and Support Vector Machines).

In addition to their primary function of recording student attendance, attendance tracking systems also have the potential to play an integral role in communication between the educational institution and parents [4]. These systems can be leveraged to generate attendance reports that give parents a clear view of their children's attendance, allowing for more active monitoring of their participation in education. Additionally, implementing automated alerts, such as notifications of unexcused absences or tardiness, can help keep parents informed and encourage collaboration between school and home. The expansion of these functionalities not only strengthens transparency in attendance management but also promotes more effective communication and greater involvement of parents in their children's educational process.

E. *Ethical considerations*

As recognition technology integration into the classroom becomes more prevalent, ethical considerations regarding data privacy, consent, and security have become paramount. The literature also explores the ethical implications of using such systems in educational settings and the importance of balancing technological innovation and safeguarding student rights.

Regarding data security and the consequent privacy of those involved, integrating Blockchain technology [13] opens new possibilities to improve student attendance management. This technology could provide significant benefits by ensuring data security through cryptography and promoting transparency and trust through immutable records accessible to all stakeholders. Additionally, it eliminates the need for intermediaries and offers the ability to automate processes, which could transform how student attendance is managed and monitored, ensuring efficiency and reliability in attendance tracking.

F. *Research gaps and future directions*

While the literature highlights the promise of machine learning-based recognition systems for attendance tracking, it also highlights the need for more research to address gaps in knowledge and practical implementation challenges. This section sets the stage for our research, emphasizing the importance of contributing to this evolving field and exploring possible solutions to the identified limitations.

III. Solution Description

In this project's development, four specialized facial recognition methods were used. This process involves taking an image, processing it, and generating it with identifying data of the detected faces [3]. Below is the detail for each of them:

A. *Artificial Intelligence Methods*

Four approaches were used in this project for facial recognition. Multi-task Cascade Convolutional Networks (MTCNN) [14]–[16] and RetinaFace [17], [18], both based on convolutional neural networks; Google's MediaPipe [19]–[21]; and specialized Deep Learning algorithms such as YOLO-Face [16], [22], [23]. Each method is described to provide a comprehensive understanding of its operation and applicability in the context of this project.

1) Multi-task Cascade Convolutional Networks (MTCNN): MTCNN is defined as a set of algorithms based on convolutional neural networks. These algorithms include input layers, convolutional layers for feature extraction, concentration pooling layers, fully connected layers, and Softmax layers. This approach allows the identification of patterns and features in images for facial recognition.

2) RetinaFace: RetinaFace, also based on convolutional networks, uses deep learning algorithms to learn essential features from images. Image preprocessing involves extracting meaningful features and telling the AI the crucial points to identify. This information generates a model to compare with other processed images.

3) MediaPipe: Developed by Google, MediaPipe, based on BlazeFace, uses Python technology and is designed for mobile GPUs. Its architecture focuses on expanding receptive fields, feature extraction, and post-processing. Improvements in inference speed and prediction quality are some of the notable advantages. This model employs depth-separable convolutions and an anchoring scheme to adjust the bounding rectangle in feature identification.

4) YOLO-Face: YOLO-Face, trained with Deep Learning, focuses on facial recognition in images. It uses a neural network-like structure with three scales involving feature extraction and prediction boxes. Combining pre-computations and detailed features enables effective face recognition at different scales.

B. Additional Libraries and Technologies

Implementing these algorithms would not be possible without the support of key libraries. Dlib [24]–[26], an open-source C++ library, excels at feature processing and data comparison. In addition, other relevant technologies not related to AI are explored, such as Telegram Bots, which play an essential role in user interaction and the remote activation of the embedded system.

1) Dlib: Dlib is an open-source software library written in C++. It is used for the development of machine learning software in Python. Provides linear algebra tools and algorithms for inference, classification, clustering, anomaly detection, and feature classification.

2) Telegram Bots: Telegram bots are used as part of user interaction. Telegram provides a cloud-based platform that makes executing tasks through chat messages easy. This eliminates the need for a direct connection to the embedded system, allowing users to perform actions through commands sent to the bot.

C. Analysis of solutions and final selection

The choice to implement the solution in an embedded system responds to the consideration of the end user's specific needs. The versatility and mobility of the embedded system allow the device to be used in various educational and professional environments, where the presence of cameras may be limited, or conditions do not favor complete coverage of the space. The system adapts to practical scenarios where real-time image capture is essential for attendance control by providing a self-contained and compact solution. Furthermore, this strategic choice facilitates testing and experimentation in various environments, allowing a detailed analysis of the technical requirements necessary to optimize image capture. Contrary to cloud-based solutions or mobile devices, this embedded approach guarantees the independence of the device from external infrastructures, thus providing an autonomous and efficient solution.

In the analysis of alternatives for the development of the embedded system, various options were evaluated considering the gap between the technical and scientific knowledge necessary to implement Artificial Intelligence technologies (it must be remembered that the use is oriented in the educational context, where knowledge in technologies could be limited to the average user experience in terms of mobile and WEB applications). Initially, an embedded system design was considered with an ESP32 as a controller and a Raspberry Pi camera for image capture. Although this proposal offered advantages in size and cost, the need for a server to run the AI mechanisms and the associated complexity led to this option being discarded.

The second proposal involved using a Raspberry Pi 4, which can run AI on the device itself. However, the lack of a dedicated GPU and its size proved limiting, so it was discarded. The third option, the Jetson Nano, stood out by having a dedicated GPU and low power consumption. Despite its size and lack of wireless connectivity, it was selected as the most suitable solution.

The resulting architecture of the system (Fig. 1) involves user interaction through the Telegram platform, where a Bot connects to the Jetson Nano. The latter controls the camera and the Artificial Intelligence scripts and can store data in the database.

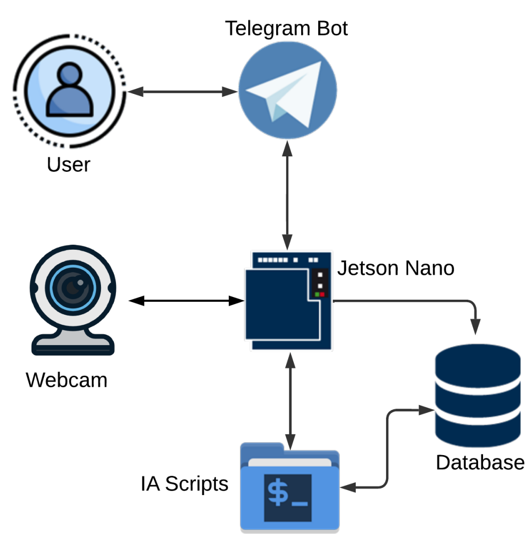

Fig. 1 Architecture of the proposed system

D. Hardware Description

For the embedded system (Fig. 2), a Jetson Nano, an Nvidia development board, is used. Its specifications include a 128-core Nvidia Maxwell™ GPU, a quad-core ARM Cortex-A57 processor, 4 GB of LPDDR4 RAM, 128 GB microSD storage, and Gigabit Ethernet connectivity, among other features. It is complemented by a TARGUS PLUS 1080P webcam for image capture.

Fig. 2 Embedded System Implementation

The design and manufacturing of a casing to house the hardware stands out, contributing to integrating the embedded system.

Due to its embedded nature, the system concentrates costs on hardware components, without depending on payment cloud services or other licenses associated with the software, which is free to use.

The total hardware investment for this project is therefore estimated between $275 and $395 (USD):

- NVIDIA Jetson Nano Development Board: Its price is estimated between $200 and $250 (USD).
- 128 GB microSD card: costs approximately between $15 and $25 (USD).
- TARGUS PLUS 1080P Webcam: This webcam, as well as others in the same range of features, are priced from $50 to $100 (USD).
- Encapsulation Box: It has an estimated additional cost of between $10 and $20 (USD).

E. Software Description

The software is divided into three main parts: the image capture script, the Telegram Bot, and the AI scripts. The capture script, run on the Jetson Nano, takes images at defined intervals and sends them to the Telegram chat. The Bot facilitates user interaction, allowing the capture to be activated or stopped and to execute AI.

The AI software includes MediaPipe, RetinaFace, MTCNN, and YOLO-Face, each with its functions for processing images and recognizing faces. The Bot displays the processed images in the Telegram chat, allowing the user to save or discard the images and providing additional information such as date, time, and recognized people.

F. System Operation and Interaction

The operation of the designed system involves a simple interaction between the user and the embedded system, focusing on the Telegram platform as the main interface (Fig. 3). This interactive and command-based approach aims to facilitate the operation of the integrated system, giving the user precise control over image capture, user registration, and selection of AI processing techniques.

Although the current focus is on education, combining an "embedded system" with "interaction through commands" can be explored in various areas, such as commerce, industry, entrepreneurship, or other contexts. This is especially relevant in situations requiring identifying people and presenting specific environmental and operational variables characteristics.

Fig. 3 Detail of results after processing with RetinaFace

The workflow and key interactions are described below:

1) App Start
   - The user initiates the interaction with the system through the Telegram bot.
   - Sending the "/start" command initializes the bot and presents the available options.
2) Image Capture
   - The user can activate image capture using the "/enable_capture" command.

- Options are provided to set capture intervals, such as 2, 3, 5, or 10 seconds, depending on user preference.
- The captured images are sent in real-time to the Telegram chat, allowing them to be viewed and processed.

3) User Registration
   - In scenarios where the image strictly contains a single individual, users have the option to register a new student in the database.
   - If the student is not previously registered, the name is requested, and facial characteristics are stored in the database.
   - Cases of no person or more than one person in the capture are handled with informative messages.
4) AI Processing Technique Selection
   - To check student attendance, the user can select processing with one of the four available AI image processing techniques("/retina_face", "/media_pipe", "/yolo", or "/mtcnn").
   - The captured image is processed, marking faces, eyes, nose, and mouth and assigning names to identified people.
   - Messages with the date, time, and names of the people identified in the image are sent to the Telegram chat.
5) Post-Processing Options
   - After processing, the user can choose to save the processed image to the system's internal memory ("save") or discard it ("discard").
   - The captured and processed images are recorded in the Telegram chat.
6) Help and Completion
   - At any time, the user can access help information with the "help" command, which provides details about the system's operation.
   - At the end of the session, the user can perform other interactions or end the system execution.

IV. Evaluation and Discussion

This section details the implementation and the conducted **proof-of-concept tests** to evaluate the system's performance. It highlights key considerations, results, and the overarching conclusions drawn from these tests.

Despite variations in processing times among different algorithms, the primary focus of the tests was on assessing the system's overall utility, with a particular emphasis on its ability to identify individuals relevant for Attendance Control.

In every test scenario, the System was tasked with recognizing 7 previously registered individuals. During the development phase, an image configuration process was executed to evaluate the effectiveness of the algorithms, understood as the accuracy in the recognition of correct faces from the total number of faces detected.

It was observed that while high-quality images facilitate the identification of individuals at greater distances, they also lead to longer processing times. This balance between image resolution and processing speed is crucial, highlighting the need for optimizing image quality in alignment with processing efficiency, considering the intended context of use. To ensure the system's performance remains optimal and to prevent any potential overload, a processing time limit of 2 minutes was established for each algorithm.

The quality of the images, for its part, directly affects the ability of AI techniques to identify people. Like humans, they can have difficulty recognizing distinctive features when image quality is poor. In low-quality images, problems could arise in identifying facial features, such as lack of sharpness in contours and difficulty discerning details. This phenomenon highlights the importance of optimizing imaging conditions to ensure accurate results.

The facial angle concerning the camera's position is critical for accurate identification. It was found that the employed techniques face challenges in recognizing faces that are slightly tilted either to the right or left. Establishing a ´tolerance' parameter is vital in this regard. However, care must be taken when setting this parameter, as excessively low values can result in false positives or negatives.

In the project's initial stages, an added challenge emerged when applying AI to individuals wearing glasses. In certain cases, reflections on the lenses hindered accurate person identification. This issue was prevalent across all four identification techniques, underscoring the necessity of accommodating specific usage conditions.

The tests were designed to assess the performance of the four algorithms in various scenarios. These included 'people nearby,' within a 2-meter range, and 'people far away,' located 2 to 6 meters from the device. Tests also included scenarios where individuals were not directly facing the device (Fig. 4) or had their faces partially hidden (Fig. 5), as well as those wearing glasses. Scenarios combining proximity, distance, and glasses were also explored to mimic real-life situations, such as small group classes or work sessions with individuals close to the device and larger group settings where the distance from the device increases. The efficacy of recognition, however, was observed to decrease beyond 7 meters, reflecting the technical constraints of the equipment and establishing this as the maximum testing range.

In the different scenarios, ten tests were conducted to ascertain the System's success rate using the algorithms and to determine the number of people identified in cases of detection failure.

In the ideal test scenario (Table I), with individuals close to the System not wearing glasses and facing the device, effectiveness reached 100%. Each algorithm successfully identified all seven participants in these tests.

However, in a test variant with individuals close to the System, 2 of whom wore glasses (Table II), no algorithm consistently identified every participant. The average number of faces recognized for each algorithm was 5 per case in the tests carried out. Although the average varies between the

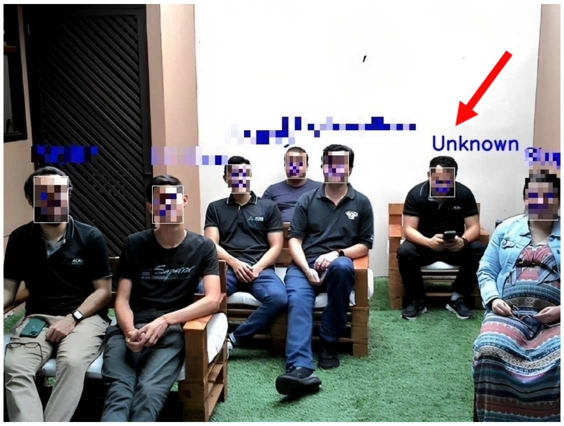

Fig. 4 Test with the presence of a person far from the device and looking away

Fig. 5 Test detail with a person whose face is partially hidden

different test scenarios, the algorithms offered similar results in this section.

The effectiveness, on the other hand, based on the faces that the system found in situations in which it was expected to work correctly, presented variations between the algorithms. In the case of YOLO-Face, it was 77.05%, being the highest. MediaPipe was similar in effectiveness to YOLO-Face. However, it should be considered that both tended to detect fewer faces in some of the test cases (YOLO-Face found 6 people in 3 cases and MediaPipe 6 people in 2 of the test cases). RetinaFace detected seven people in each of the 10 test cases. While MTCNN was less effective and reported the presence of 8 people in 2 of the test cases.

The results were similar in another variant where the individuals were close, but 2 of them looked away (Table III). None of the algorithms could identify all individuals in any of the 10 tests. The average identification rate was 5 for each of the four algorithms. In the case of effectiveness, YOLO-Face again had the highest. However, it must be considered that it reported the presence of 6 individuals in 9 of the tests carried out and 5 in another. RetinaFace, for its part, reported 7 individuals in all tests, MTCNN reported 8 in 2 of the tests,

TABLE I
IDEAL SCENARIO: ALL INDIVIDUALS NEARBY, WITHOUT GLASSES AND LOOKING AT THE DEVICE

Algorithm	**Average recognized faces**	**Effectiveness**
MediaPipe	7	**100.00%**
MTCNN	7	**100.00%**
RetinaFace	7	**100.00%**
YOLO-Face	7	**100.00%**

TABLE II
ALL INDIVIDUALS NEARBY AND TWO OF THEM WEARING GLASSES

Algorithm	**Average recognized faces**	**Effectiveness**
MediaPipe	5	77.05%
MTCNN	5	72.22%
RetinaFace	5	74.29%
YOLO-Face	5	**77.61%**

and MediaPipe 6 in 2 of the tests.

When comparing scenarios where people wore glasses with those in which they looked away, the algorithms performed slightly better in the latter case. However, both wearing glasses and looking away posed challenges to effective identification.

TABLE III
ALL INDIVIDUALS NEARBY AND TWO OF THEM LOOKING AWAY

Algorithm	**Average recognized faces**	**Effectiveness**
MediaPipe	5	80.88%
MTCNN	5	76.39%
RetinaFace	5	78.57%
YOLO-Face	5	**93.22/%**

When individuals were positioned further from the device (Table IV), the success rate of complete identification by the algorithms was 10% for MediaPipe, RetinaFace, and YOLO-Face. MTCNN encountered failures in all 10 tests, inaccurately reporting 8 faces (1 more than the actual participant number) in 6 cases. Similarly, RetinaFace initially detected 8 faces in 4 out of the 10 tests, and YOLO-Face detected 6 faces in 3 out of the tests. These results indicate the challenges that emerge as the distance from the subjects increases. In the average number of people recognized by the four algorithms was 6.

For scenarios where individuals were far away, both wearing glasses (Table V) and looking away (Table VI), the algorithms consistently failed in all tests. They were not able to identify all participants during the test cases. Regarding the average number of individuals identified in scenarios involving glasses,

TABLE IV
INDIVIDUALS LOCATED FAR FROM THE DEVICE

Algorithm	Average recognized faces	Effectiveness
MediaPipe	6	87.76%
MTCNN	6	84.21%
RetinaFace	6	81.13%
YOLO-Face	6	**93.48**%

they reached an average of 4. In scenarios with people facing away, the algorithms had an average success rate of 3. Despite the similarity in the results, MTCNN again showed peculiarities in the faces initially detected; during the tests with glasses, it reported 9 individuals in 5 of the 10 cases, and in the remaining 5 cases, it indicated 8 faces. In the variant with participants looking away, MTCNN reported 8 faces in 9 of the cases. MediaPipe was more effective than YOLO-Face and RetinaFace for the test with participants looking away, but reported the presence of 6 individuals on 4 occasions. In the case of participants wearing glasses, YOLO-Face and MediaPipe had similar effectiveness, considering that YOLO-Face reported the presence of 6 faces in 9 of the cases and 5 faces in another. MediPipe reported the presence of 6 faces in all cases. In the case of RetinaFace, it reported 7 faces in all cases.

TABLE V
INDIVIDUALS LOCATED FAR FROM THE DEVICE AND TWO OF THEM WEARING GLASSES

Algorithm	Average recognized faces	Effectiveness
MediaPipe	4	**74.58**%
MTCNN	4	55.29%
RetinaFace	4	67.14%
YOLO-Face	4	67.14%

TABLE VI
INDIVIDUALS LOCATED FAR FROM THE DEVICE AND TWO OF THEM LOOKING AWAY

Algorithm	Average recognized faces	Effectiveness
MediaPipe	3	61.67%
MTCNN	3	46.84%
RetinaFace	3	52,86%
YOLO-Face	3	**62.71**%

The last test scenario considered people with glasses near and far from the device (Table VII). The average number of faces recognized was 4. In terms of effectiveness, the percentage was also similar between the algorithms, with MediaPipe slightly higher but reporting the presence of 6 individuals on 2 occasions.

TABLE VII
INDIVIDUALS LOCATED FAR FROM THE DEVICE, LOOKING AWAY AND WEARING GLASSES

Algorithm	Average recognized faces	Effectiveness
MediaPipe	4	**67.74**%
MTCNN	4	66.67%
RetinaFace	4	66.67%
YOLO-Face	4	66.67%

The average number of faces recognized remained constant across the different test scenarios, suggesting that the algorithms have a consistent face detection ability regardless of variations in imaging conditions. However, it was observed that the algorithms' effectiveness fluctuated, directly affected by the proportion of faces correctly identified in the total number of detections. This phenomenon highlights the relevance of having a diversified and representative training data set that contemplates a wide range of situations to increase the robustness and precision of facial identification in real and varied scenarios.

V. Conclusions and Recommendations

Testing of the Embedded System for Image Processing and Person Recognition using AI in the context of Student Attendance Control reveals:

A. *Conclusions*

- **System development.** The embedded person recognition system, which integrates specialized hardware and software based on Artificial Intelligence, has achieved an effective implementation, allowing the identification of people in real-time. Significant advances in identification using various AI techniques and implementing an intuitive user interface for algorithm parameterization are highlighted.
- **Effectiveness in different scenarios.** The algorithms' average face detection remained stable across various test conditions, reflecting the consistent capability of facial recognition systems. However, the effectiveness of these systems, defined as the accuracy in recognizing correct faces out of the total number of faces found, presents variations. These differences in effectiveness suggest that, while face detection is a task generally well performed by current algorithms, accurate recognition in challenging circumstances, such as in the presence of glasses, increased distances, or indirect viewing angles, may be susceptible to errors.

B. *Recommendations*

- **Optimizing image conditions and use of high-resolution cameras.** It's recommended to improve image

quality by adjusting factors such as lighting and angle and explore the use of higher-resolution cameras to facilitate identification at longer distances. Specifically, advanced image processing techniques could be explored to compensate for current limitations.
- **Detailed analysis of application contexts.** Analyzing the application context deeply is crucial to adapt the system effectively. This includes incorporating business rules and continuous monitoring mechanisms that ensure the system's usefulness in several scenarios.
- **Adjustments to tolerance parameters and technologies to reduce lens impact.** Careful adjustment of tolerance parameters for tilted faces and exploration of technologies to minimize lens flare are suggested to improve identification accuracy.
- **Data set enrichment.** Expand the training data to include greater variability in glasses use, distance, and face orientation.
- **Data Augmentation.** Evaluate the implementation of image transformation techniques to generate varied conditions in the training set.
- **Multimodal evaluation.** Incorporate data from different modalities that can complement visual information in situations where it is limited.
- **Continuous evaluation and cloud alternatives.** Continuous evaluation at different distances is essential to understand and adjust the limitations of the algorithms. Given the computational power limitation of the embedded device, it's recommended to consider cloud-based solutions or server architectures for real-time image processing.
- **Legal Compliance and Ethical Practices.** In addition to the proposed technical and methodological improvements, it's crucial to consider the following legal and regulatory aspects to ensure a successful and ethical implementation of the facial recognition system in educational environments:
  - **Adherence to data protection legislation:** It's imperative to research and comply with applicable local and international data protection laws. This includes ensuring that all data collected through the facial recognition system are handled transparently and securely, and that explicit consent is obtained from students or their guardians before processing.
  - **Privacy impact assessment:** Before implementation, a privacy impact assessment should be conducted to identify and mitigate potential privacy risks associated with the use of student and faculty data.
  - **Development of clear policies:** Developing and clearly communicating policies on the use of facial recognition technologies is essential to maintain user trust and ensure operational transparency.
  - **Training and awareness:** Educating staff and students about the functionality, benefits, and limitations of the system can help alleviate ethical concerns and enhance system acceptance.

  These recommendations will not only help mitigate legal and ethical risks but will also strengthen the legitimacy and acceptance of the proposed system among all relevant stakeholders.

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