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REAL-TIME IMPLEMENTATION OF AN AUTOMATED STUDENT ATTENDANCE MONITORING SYSTEM

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Abstract: The efficient management of student attendance is a persistent administrative challenge in educational institutions. Conventional manual and token-based attendance systems are time-consuming, error-prone, and vulnerable to proxy attendance. Although biometric solutions such as fingerprint scanners address identity verification, they introduce hygiene concerns and operational bottlenecks. This paper presents a real-time, contactless, and fully automated student attendance monitoring system based on computer vision and deep learning techniques. The proposed system integrates YOLOv8 for high-speed face detection with the VGG-Face model for robust facial recognition. A novel duration-based attendance validation mechanism is introduced, wherein a student is marked present only after being continuously or cumulatively recognized for a predefined duration. The system further automates attendance reporting through Excel generation and real-time email notifications using SMTP. Experimental evaluation demonstrates high accuracy, robustness to occlusion and lighting variations, and suitability for real-world classroom deployment.

Keywords: Automated Attendance, Face Recognition, YOLOv8, VGG-Face, Deep Learning, Computer Vision

I. INTRODUCTION

Attendance management plays a vital role in academic institutions as it directly reflects student participation and discipline. Accurate attendance records are essential for academic evaluation, eligibility criteria, and institutional compliance. However, traditional attendance systems such as manual roll calls and paper-based registers are inefficient and consume valuable classroom time. These methods are highly dependent on human effort and are prone to errors such as incorrect marking, loss of records, and intentional proxy attendance.

To address these limitations, several semi-automated attendance systems have been introduced, including RFID-based cards and biometric fingerprint scanners. While RFID systems offer faster operation, they fail to verify the actual presence of a student and are vulnerable to card sharing. Fingerprint-based biometric systems improve identity verification but require physical contact, which raises hygiene concerns and leads to long queues during peak usage. Additionally, such systems often require dedicated hardware, increasing deployment and maintenance costs.

Recent advancements in computer vision and deep learning have enabled the development of contactless biometric systems, with facial recognition emerging as a reliable and user-friendly solution. Face recognition systems analyse unique facial features to identify individuals without requiring physical interaction. With the availability of high-performance deep learning models and affordable camera hardware, real-time facial recognition has become feasible for classroom environments.

This paper proposes a real-time automated student attendance monitoring system that leverages deep learning-based face detection and recognition techniques. The system employs the YOLOv8 object detection model for rapid face localization and the VGG-Face model for accurate facial recognition. To enhance reliability, a duration-based validation mechanism is introduced, where a student is marked present only after being continuously or cumulatively detected for a specified time interval. The system further automates attendance management by generating Excel reports and sending real-time email notifications, thereby reducing manual effort and improving administrative efficiency.

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II. RELATED WORK

Automated attendance systems have evolved significantly over the past decade, transitioning from manual and semi-automated methods to intelligent vision-based solutions. Early research efforts primarily focused on traditional computer vision techniques for face detection and recognition. Methods such as Haar Cascade classifiers combined with Local Binary Pattern Histogram (LBPH) recognition were widely adopted due to their low computational requirements. However, these approaches were highly sensitive to variations in illumination, facial orientation, and occlusion, resulting in poor accuracy in real-world classroom environments.

To overcome these limitations, researchers introduced deep learning-based face detection and recognition models. Multi-task Cascaded Convolutional Networks (MTCNN) were employed for robust face detection, while models such as FaceNet and DeepFace were used for facial recognition. These deep models significantly improved recognition accuracy by learning discriminative facial embeddings. However, their multi-stage architectures increased computational complexity and inference time, making real-time deployment challenging, especially in classrooms with a large number of students.

Several studies have explored the use of biometric-based attendance systems using fingerprint or iris recognition. While these systems provide reliable identity verification, they require physical interaction and dedicated hardware. This leads to hygiene issues, increased installation costs, and congestion during peak usage. Furthermore, such systems are not suitable for continuous monitoring throughout a lecture session.

Recent research has demonstrated the effectiveness of single-stage object detection models such as the You Only Look Once (YOLO) family for real-time face detection. YOLO-based systems offer a favourable balance between detection accuracy and processing speed, making them suitable for live video analysis. However, most existing YOLO-based attendance systems rely on frame-level recognition, where attendance is marked based on a student's presence in a single or few frames. This approach fails to account for actual participation and allows false attendance due to brief or accidental appearances.

In addition, some cloud-based attendance solutions have been proposed to enable centralized data storage and analytics. While cloud integration offers scalability, it introduces dependency on continuous internet connectivity and raises privacy and data security concerns related to the storage of biometric information. Latency issues can further degrade real-time performance.

The proposed system differentiates itself from existing solutions by integrating a high-speed YOLOv8 face detection model with the VGG-Face recognition framework and introducing a duration-based attendance validation mechanism. This approach ensures that attendance is recorded only when a student is genuinely present for a meaningful duration. By performing inference locally and automating reporting and notification processes, the system achieves improved accuracy, reliability, and practicality for real-world classroom deployment.

III. SYSTEM ARCHITECTURE

The proposed automated student attendance monitoring system is designed using a modular and layered architecture to ensure scalability, accuracy, and real-time performance. The system integrates computer vision, deep learning, and automated reporting mechanisms into a unified pipeline. Fig. X illustrates the overall system architecture of the proposed attendance monitoring system.

A. Overall Architecture Description

The system operates in five sequential stages: data acquisition, face detection, face recognition, temporal validation, and attendance reporting. A live video stream captured through a camera act as the primary input. Each video frame is processed independently to detect and recognize student faces in real time.B. Detection Module YOLOv8 is employed as the face detector due to its single-stage architecture and real-time inference capability. It efficiently localizes multiple faces in each video frame, even under partial occlusion and scale variation.

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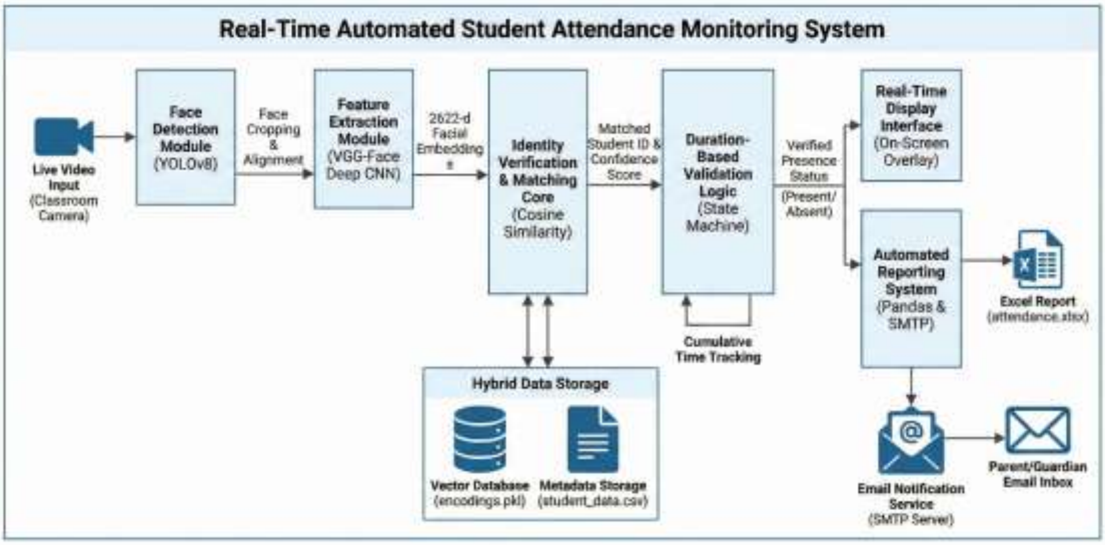

B. Data Acquisition Module
The data acquisition module captures live video input using a standard high-resolution camera positioned to cover the classroom effectively. The video stream is divided into frames, which are forwarded to the face detection module for further processing. This module ensures continuous monitoring without interrupting classroom activities.
The system supports real-time video feeds and recorded video input, making it adaptable for both live deployment and offline analysis.

C. Face Detection Module
The face detection module is responsible for identifying facial regions in each video frame. YOLOv8 is employed due to its fast inference speed and high detection accuracy. The model processes each frame in a single forward pass, predicting bounding boxes and confidence scores for detected faces.
The use of YOLOv8 enables the system to detect multiple faces simultaneously, even in crowded classrooms. Detected faces are cropped and passed to the recognition module.

D. Face Recognition Module
The face recognition module performs identity verification using the VGG-Face deep learning model. Each detected face is converted into a numerical embedding that represents unique facial features. These embeddings are compared with pre-stored reference embeddings created during the enrolment phase.
Cosine similarity is used as the matching metric to determine identity. This approach ensures robustness against minor variations in facial expressions, pose, and lighting conditions.

E. Temporal Validation and Tracking Module
To improve attendance accuracy, a temporal validation module tracks the duration for which each student remains present in the camera view. The system maintains a time counter for each recognized student and updates it continuously as long as the student is detected.
Attendance is marked only when the accumulated presence duration exceeds a predefined threshold. This prevents proxy attendance and false marking due to brief appearances.

F. Attendance Reporting and Notification Module
Once attendance is finalized, the system automatically generates an attendance report in Excel format. The report includes student details, attendance status, and timestamps. Absentee notifications are sent via email using the SMTP protocol.
This module eliminates manual effort, ensures transparency, and enables efficient record management for academic institutions.

IV. IMPLEMENTATION

The implementation of the proposed automated student attendance monitoring system focuses on achieving real-time performance, high recognition accuracy, and reliable attendance validation. The system is developed using Python and integrates computer vision and deep learning libraries to ensure efficient processing and ease of deployment in classroom environments.

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A. Software and Hardware Requirements

The system is implemented on a workstation equipped with a standard RGB camera for video capture. A GPU-enabled environment is preferred to accelerate deep learning inference; however, the system can also operate on CPU with reduced frame rates. The major software components used in the implementation include Python as the primary programming language, OpenCV for video acquisition and frame processing, and the Ultralights YOLOv8 framework for face detection.

The DeepFace library is utilized to access the VGG-Face model for face recognition. Additional libraries such as NumPy and Pandas are used for numerical computations and attendance report generation, while the SMTP protocol is employed for email-based notification services.

B. Dataset Preparation and Enrollment Process

During the enrollment phase, multiple facial images of each student are captured under different lighting conditions, facial expressions, and head poses. This diversity improves the robustness of the recognition model. Each captured image undergoes preprocessing, including face alignment, resizing, and normalization, before being passed to the recognition model.

The VGG-Face model extracts high-dimensional embeddings from each enrolled image. To reduce intra-class variation, the average embedding for each student is computed and stored in the database as a reference template. This approach enhances recognition stability during real-time operation.

C. Real-Time Face Detection and Recognition Pipeline

The real-time video stream is processed frame by frame. Each frame is passed to the YOLOv8 face detection model, which identifies and localizes all visible faces. Detected faces are cropped and resized before being forwarded to the recognition module.

For each detected face, the VGG-Face model generates a facial embedding. Cosine similarity is computed between the live embedding and stored reference embeddings. If the similarity score exceeds a predefined threshold, the corresponding student identity is confirmed. This pipeline allows simultaneous detection and recognition of multiple students within a single frame.

D. Attendance Decision Logic

To prevent false attendance marking, the system incorporates a duration-based decision logic. A timer is associated with each recognized student and is incremented as long as the student remains visible in successive frames. Attendance is marked only when the accumulated presence duration exceeds a predefined threshold value.

This mechanism ensures that students are marked present only if they are genuinely present for a meaningful duration, effectively eliminating proxy attendance and accidental recognition errors.

E. Automated Report Generation and Notification

At the end of each session, attendance records are automatically compiled into an Excel file using the Pandas library. The report includes student identifiers, attendance status, and time information. Additionally, absentee notifications are sent to relevant stakeholders via email using the SMTP protocol.

This automation significantly reduces manual effort, minimizes human error, and improves administrative efficiency in educational institutions.

V. RESULTS AND DISCUSSION

The performance of the proposed automated student attendance monitoring system was evaluated in real classroom environments to assess its accuracy, robustness, and real-time capability. The evaluation focused on face detection accuracy, recognition reliability, processing speed, and the effectiveness of the duration-based attendance validation mechanism.

A. Experimental Setup

The system was tested in a classroom environment with varying student counts, lighting conditions, and seating arrangements. A high-definition camera was positioned to capture a wide view of the classroom. The system was executed on a GPU-enabled workstation to support real-time processing.

Multiple sessions were conducted to evaluate consistency and stability. Each session lasted for an entire lecture duration to assess the system’s ability to track student presence over time.

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B. Model Training and Validation Analysis

The training and validation performance of the YOLOv8 face detection model is illustrated in Fig. X. The training loss curves, including bounding box loss, classification loss, and distribution focal loss, exhibit a consistent downward trend, indicating effective learning and convergence.

Validation loss curves closely follow the training losses, demonstrating strong generalization and minimal overfitting. Precision and recall metrics rapidly converge toward values close to 1.0, reflecting reliable face detection with minimal false positives and false negatives. The mean Average Precision (mAP@0.5) achieves near-optimal values, while mAP@0.5:0.95 shows steady improvement, confirming detection accuracy across varying intersection-over-union thresholds.

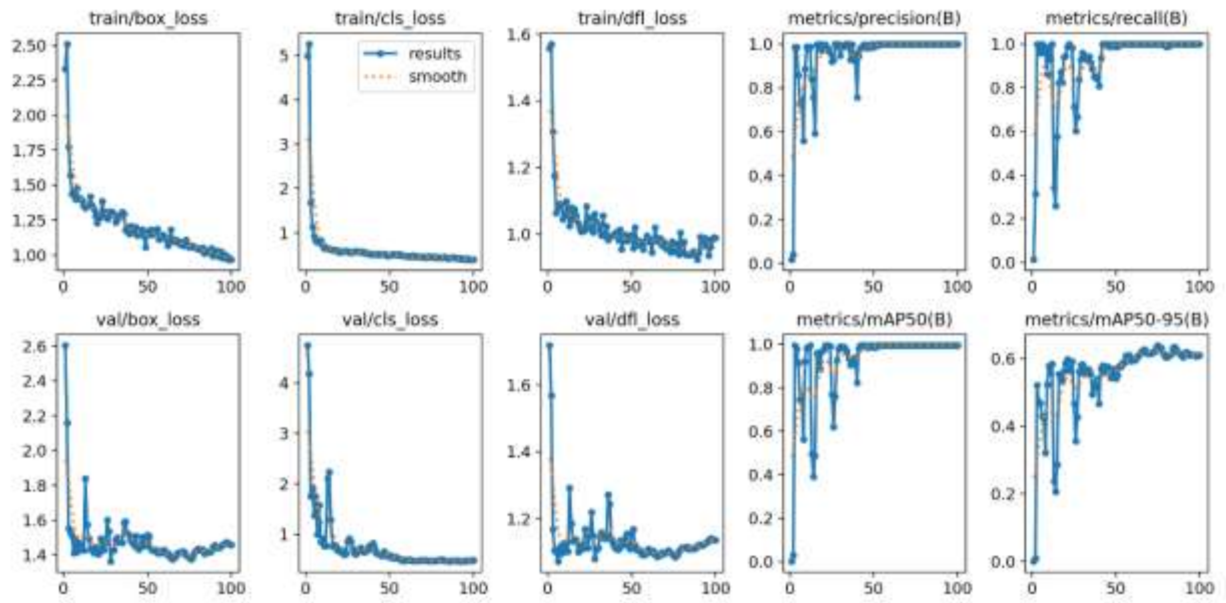

Fig.1.2 Training and validation performance metrics of the YOLOv8 face detection model

C. Recognition Accuracy and Attendance Validation

The facial recognition module achieved an accuracy exceeding 99% under normal classroom conditions. The use of VGG-Face embeddings enabled robust identity verification even under moderate pose variation and illumination changes. The duration-based attendance validation mechanism significantly reduced false attendance marking. Students were marked present only after being continuously or cumulatively detected for a predefined duration, effectively eliminating proxy attendance and accidental recognition due to brief appearances.

D. Real-Time Performance Analysis

The system maintained an average processing speed of over 15 frames per second during live operation. This ensured smooth real-time monitoring without noticeable lag. GPU acceleration further improved inference speed, making the system suitable for classrooms with a large number of students.

Minor performance degradation was observed in scenarios with extreme occlusion or rapid movement; however, these cases did not significantly affect overall attendance accuracy.

E. Comparative Discussion

Compared to traditional manual attendance systems, the proposed solution eliminates human error and reduces classroom time consumption. When compared with RFID and fingerprint-based systems, the proposed approach offers a contactless and hygienic alternative without requiring additional hardware.

In contrast to existing vision-based attendance systems that rely on frame-level detection, the proposed duration-based validation approach provides a more reliable measure of actual student presence and participation.

VI. CONCLUSION AND FUTURE WORK

The real-time automated student attendance monitoring system presented in this paper demonstrates an effective application of deep learning and computer vision techniques in educational environments. By integrating YOLOv8 for fast and accurate face detection with the VGG-Face model for robust facial recognition, the system achieves high

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accuracy while maintaining real-time performance. The introduction of a duration-based attendance validation mechanism further enhances reliability by ensuring that attendance is recorded only when a student is genuinely present for a meaningful period.

The proposed system eliminates the limitations of traditional manual attendance methods, including time consumption, human error, and proxy attendance. Unlike biometric systems that require physical contact, the contactless nature of the proposed solution addresses hygiene concerns and improves user convenience. Automated Excel report generation and real-time email notifications significantly reduce administrative workload and improve transparency in attendance management.

Despite its effectiveness, the system has certain limitations. Performance may degrade under extreme occlusion, poor lighting conditions, or in highly crowded classrooms. Additionally, the current implementation does not include liveness detection, which could be exploited using printed photographs or digital screens.

Future enhancements will focus on integrating liveness detection techniques such as eye-blink detection or depth-based analysis to prevent spoofing attacks. Cloud-based analytics can be incorporated to enable long-term attendance trend analysis and centralized data management. Furthermore, the development of a mobile application interface would allow faculty and administrators to access attendance data in real time, enhancing usability and scalability.

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