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Real-Time Face Recognition Attendance System Using Deep Learning

[1]Dr. Suresh L [2]Sowmyashree S [3]Akarsh Mahesh [4]Chirag L Maney
[5]G A Lakshya Nagdeep [6]Hrishikesh Simpi

[1]*Department of Information Science and Engineering, RNS Institute of Technology,* Bengaluru, India, hod.ise@rnsit.ac.in
[2]*Department of Computer Science – Cyber Security, RNS Institute of Technology,* Bengaluru, India
sowmyashree532@gmail.com
[3]*Department of Information Science and Engineering, RNS Institute of Technology,* Bengaluru, India
1rn23is012.akarshmahesh@gmail.com
[4]*Department of Information Science and Engineering, RNS Institute of Technology,* Bengaluru, India
1rn23is059.chiraglmaney@gmail.com
[5]*Department of Information Science and Engineering, RNS Institute of Technology,* Bengaluru, India
1rn23is075.galakshyanagdeep@gmail.com
[6]*Department of Information Science and Engineering, RNS Institute of Technology,* Bengaluru, India
1rn23is075.galakshyanagdeep@gmail.com
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ABSTRACT

Conventional attendance-management practices in educational institutions — manual paper registers, proxy-vulnerable radio-frequency identification (RFID) cards, and contact-based biometric scanners — remain inefficient, labour-intensive, and susceptible to administrative error. This paper presents a Real-Time Face Recognition Attendance System that leverages computer vision and deep learning to deliver an automated, contactless, and secure alternative. Facial regions are localised from standard classroom video using OpenCV and Dlib and encoded into 128-dimensional facial embedding vectors for identity matching via Euclidean distance. To counter spoofing attempts using printed photographs or digital-display replays, the system incorporates a liveness-verification stage based on Eye Aspect Ratio (EAR) blink detection. A supplementary Facial Expression Recognition (FER) module further provides real-time engagement and mood analytics (e.g., happy, neutral, tired) at the point of attendance capture. Verified attendance records — comprising student identity, timestamp, date, and affective state — are persisted to an SQLite database and exposed through a Flask-based web dashboard with automated Excel report generation. Comparative analysis against traditional registers, RFID readers, and fingerprint biometrics indicates that the proposed system achieves sub-second per-person processing while eliminating physical contact and substantially reducing proxy attendance.

Keywords: *Face Recognition; Deep Learning; Liveness Verification; Eye Aspect Ratio; Attendance Automation*

1. INTRODUCTION

Accurate attendance tracking is central to maintaining academic discipline and administrative compliance in educational institutions. Manual procedures — roll calls or paper-register sign-ins — consume significant instructional time and remain prone to proxy attendance and transcription error. Contact-based biometric systems, such as fingerprint scanners, reduce proxy entries but introduce hygiene concerns, physical queuing delays, and recurring maintenance costs, limitations that became particularly salient following heightened awareness of contact-transmitted illness.

Recent advances in computer vision (CV) and deep learning (DL) enable non-intrusive biometric authentication as a viable alternative. This paper proposes an automated attendance system built on deep facial embeddings, augmented with an active anti-spoofing mechanism based on Eye Aspect Ratio (EAR) blink detection to resist static-photograph and video-replay attacks. An integrated Facial Expression Recognition (FER) module additionally tracks classroom sentiment and engagement, extending the system's utility beyond attendance logging alone. Built on a modular Python stack comprising OpenCV, Dlib, Flask, and SQLite, the resulting architecture offers a scalable, contactless solution for automated attendance management, and is evaluated qualitatively against existing manual, RFID, and fingerprint-based approaches.

2. REVIEW OF LITERATURE

Automated attendance tracking using computer vision has evolved from classical feature-extraction techniques to

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deep convolutional architectures. Table 1 summarises the principal approaches reported in the literature, together with their characteristic strengths and limitations.

Table 1. Summary of Related Approaches in Vision-Based Attendance Systems

Approach	Key Characteristics	Limitation
Local Binary Patterns Histograms (LBPH)	Classical, low computational cost, effective in constrained settings	Degrades under illumination change and non-frontal pose
ResNet-based CNNs	High accuracy across lighting/expression variation via deep feature hierarchies	High computational cost
Custom deep CNNs (classroom-trained)	High recognition rates on institution-specific video streams	Degrades under fast motion or low light without preprocessing
Ensemble models (VGG-Face, FaceNet)	Robust to occlusion and pose via merged embedding spaces	Increased inference latency
Surveillance-style multi-face tracking	Simultaneous multi-face detection in crowded halls	Pose variation and density hinder per-subject resolution
Dynamic thresholding models	Adaptive decision thresholds reduce false positives	Sensitive to threshold-tuning quality
Transfer learning (VGGFace / ImageNet pre-training)	High accuracy with small, institution-specific datasets	Performance bounded by source-domain similarity

Collectively, this body of work motivates a design that combines the accuracy of deep embedding-based recognition with lightweight, real-time inference suitable for classroom deployment — the direction adopted in the present system, which additionally incorporates liveness verification and affective-state analytics not jointly addressed in prior approaches.

3. SYSTEM ARCHITECTURE AND RESEARCH METHODOLOGY

The proposed system operates as an end-to-end processing pipeline spanning video capture, face detection, deep feature extraction, identity matching, liveness verification, and attendance logging, as illustrated in Figure 1.

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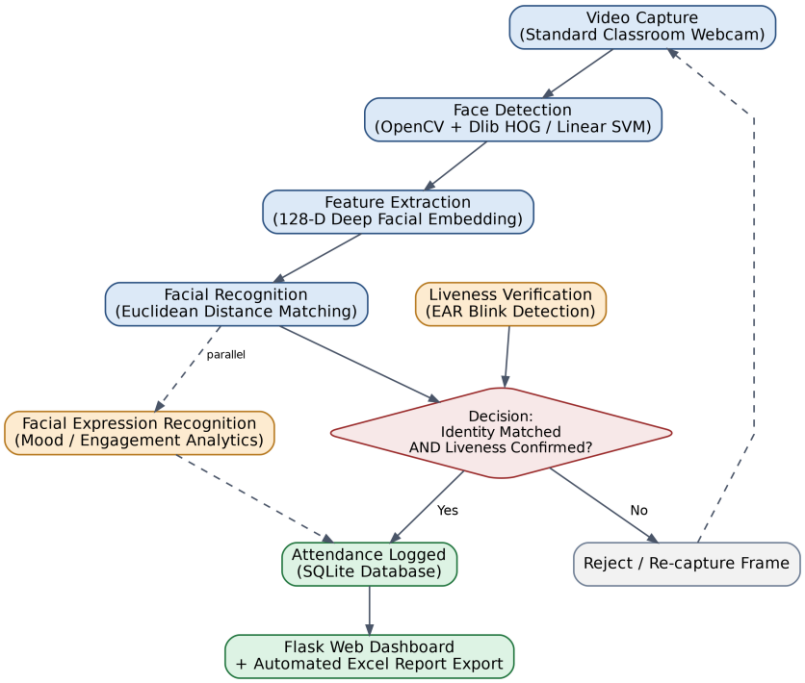


Figure 1. End-to-End Pipeline of the Real-Time Face Recognition Attendance System with Liveness Verification and Emotion Analytics

3.1 Image Capture and Preprocessing

A standard webcam captures video frames at a fixed frame rate. Each frame is resized, converted from BGR to RGB colour space, and preprocessed prior to face detection to normalise input scale and colour representation across varying lighting conditions.

3.2 Face Detection and Feature Extraction

Face localisation is performed using Dlib's Histogram of Oriented Gradients (HOG) detector combined with a linear support vector machine (SVM) classifier. Once a face region is localised, 68 facial landmarks are identified, and a deep neural network maps the aligned facial region into a 128-dimensional embedding space in which facial identity is represented as a high-dimensional feature vector.

3.3 Facial Recognition

The 128-dimensional embedding extracted from the live camera frame (Vlive) is compared against pre-computed template embeddings (Vdb) stored in the enrolment database. Identity is determined via the Euclidean distance between the two vectors:

$$d(Vlive, Vdb) = \sqrt{\Sigma_{i=1}^{128} (Vlive,i - Vdb,i)^2}$$

A candidate identity is accepted as matched when the computed distance falls below a defined threshold, typically d ≤ 0.6.

3.4 Liveness Verification via Blink Detection

To prevent spoofing via static images or replayed video, liveness is verified by computing the Eye Aspect Ratio (EAR) across consecutive frames, using six structural landmark coordinates localised per eye:

$$EAR = (\|p2 - p6\| + \|p3 - p5\|) / (2\|p1 - p4\|)$$

where p1 through p6 denote two-dimensional eye-landmark coordinates. During a blink, the vertical distances ‖p2 − p6‖ and ‖p3 − p5‖ approach zero, producing a measurable drop in EAR below a predefined threshold. Attendance is confirmed only after a valid blink cycle is detected, ensuring that a live subject — rather than a static photograph or screen replay — is present at the point of capture.

3.5 Emotion Detection

An integrated Facial Expression Recognition (FER) module processes the detected facial region of interest (ROI) using

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a lightweight convolutional neural network (CNN) to classify expression into categories such as happy, neutral, or tired, supporting subsequent engagement analytics.

3.6 Data Logging and Management

Following successful recognition and liveness confirmation, the student's identifier, name, date, time, and detected emotional state are logged to an SQLite database. Administrators access records in real time through a Flask-based web dashboard or export them as Excel reports for institutional record-keeping.

4. SYSTEM IMPLEMENTATION AND SPECIFICATIONS

Table 2 summarises the minimum hardware and software specifications required to deploy the proposed system in a classroom environment.

Table 2. Minimum System Requirements

Category	Component	Minimum Requirement
Hardware	Processor	Intel Core i3 / i5 (10th Gen or above)
Hardware	Clock Speed	3.0 GHz or above
Hardware	System RAM	8 GB (16 GB recommended)
Hardware	Storage	256 GB Solid-State Drive (SSD)
Hardware	Input Device	High-Definition USB Webcam
Software	Operating System	Windows 10 / 11 (64-bit)
Software	Programming Language	Python 3.8+
Software	Computer Vision / DL Libraries	OpenCV, Dlib, face_recognition, FER
Software	Web Framework	Flask (HTML5, CSS3, JavaScript)
Software	Database Engine	SQLite3

5. RESULTS AND DISCUSSION

The proposed system was implemented and evaluated on a live classroom video feed, with recognition, liveness verification, and emotion detection running end-to-end. Verified attendance events were persisted to the SQLite database and surfaced to administrators through both an automated Excel reporting module and a desktop control panel, confirming the practical operability of the pipeline described in Section 3.

5.1 Automated Excel Attendance and Mood Reporting

On completion of a session, the system auto-generates a daily Excel report summarising verified attendance and detected affective state. Figure 2 shows the Attendance Log sheet, in which each row records the recognised student's name, enrolment ID, capture timestamp, and detected mood, with conditional formatting flagging non-neutral states (e.g., "Tired") for quick visual review.

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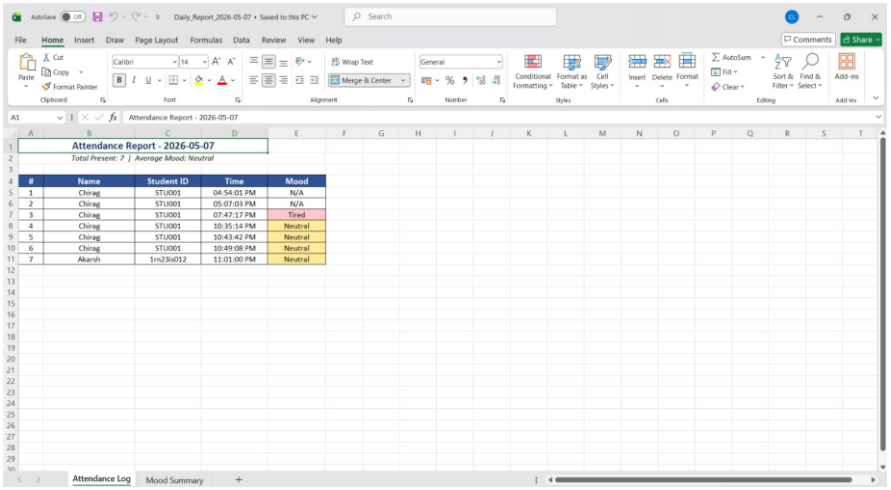


Figure 2. Auto-Generated Attendance Log Sheet Showing Student ID, Timestamp, and Detected Mood

A companion Mood Summary sheet, shown in Figure 3, aggregates these per-event records into class-level engagement statistics, tabulating the count and percentage share of each detected mood category. In the illustrated session, 80% of logged states were classified as Neutral and 20% as Tired, demonstrating the FER module's ability to surface aggregate engagement trends alongside routine attendance data without any additional manual effort.

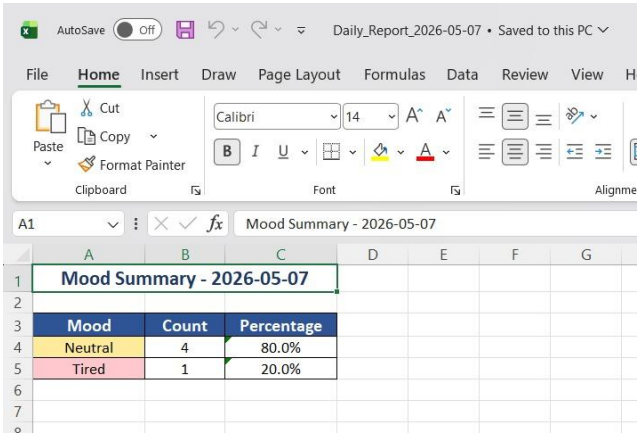


Figure 3. Mood Summary Sheet Reporting Aggregate Mood Distribution for the Session

5.2 Application Control Panel

Administrators interact with the system through a lightweight desktop control panel, shown in Figure 4. A "Start System" control launches the live attendance engine, which drives the webcam feed, EAR-based blink detection, and FER-based emotion analysis described in Sections 3.3–3.5, while separate controls open the web dashboard and trigger on-demand Excel report generation. A dedicated enrolment panel allows a new student to be registered by capturing their name, institutional ID, and a reference facial image, populating the template embeddings used for subsequent identity matching.

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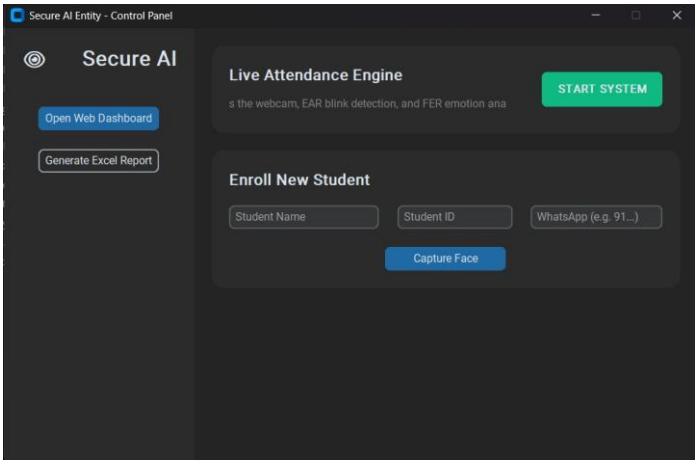


Figure 4. Desktop Control Panel for Launching the Live Attendance Engine, Report Generation, and Student Enrolment

6. COMPARATIVE ANALYSIS AND CONCLUSION

6.1 Comparison with Traditional Biometric Methods

Table 3 compares the proposed system against traditional paper registers, RFID card readers, and fingerprint biometrics across processing speed, proxy-prevention capability, contact requirement, and availability of supplementary analytics.

Table 3. Comparative Analysis of Attendance Methods

Metric	Traditional Registers	RFID Cards	Fingerprint Biometrics	Proposed DL System
Processing Speed	Slow (~10 min/class)	Moderate (~2 min/class)	Moderate (~3 min/class)	Fast (<1 s/person)
Proxy Prevention	Low (easy sign-in)	Low (card sharing)	High	High (liveness-verified)
Contact Requirement	High (pen/paper)	Low (tap card)	High (physical sensor)	None (fully contactless)
Additional Analytics	None	None	None	Student mood / engagement log

6.2 Conclusion

The proposed Real-Time Face Recognition Attendance System provides a contactless, automated solution for classroom attendance management. By integrating 128-dimensional deep facial embeddings with EAR-based liveness detection, the system mitigates both proxy attendance and photo/video-spoofing attacks, while automated logging to SQLite, expression analytics, and a Flask-based dashboard together form a scalable administrative pipeline suited to modern educational institutions.

6.3 Future Work

- Cloud Storage Integration: Migrating local SQLite storage to cloud environments (e.g., AWS, Azure, or Firebase) to enable multi-classroom scalability.
- Mobile and Messaging APIs: Developing mobile administrative interfaces and integrating WhatsApp/SMS APIs for automated notifications to parents and faculty.
- Multi-Camera Feeds: Extending the pipeline to handle parallel multi-stream video for wide-area monitoring in large lecture halls.

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