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Face Recognition AI Attendance System

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Abstract: This project aims to make attendance recording easier by using face recognition to identify registered individuals automatically. The system uses YOLO11n to detect people in camera frames and a custom IoU tracker to follow their movement. InsightFace and ArcFace are used to extract facial features, while FAISS compares them with previously stored face records to find matching identities. It also checks face quality and uses liveness detection methods such as texture analysis, blink detection, motion analysis, screen-edge detection, and MiniFASNet to identify possible spoofing attempts.

The recognition results are evaluated by an AMFR decision engine before attendance is recorded in the database. Developed using Python, OpenCV, FastAPI, and Streamlit, the system also provides a dashboard for managing and viewing attendance records. A separate evaluation using six identities and 30 unseen test images achieved 86% classification accuracy using pretrained ArcFace embeddings and a newly created FAISS gallery. Although these results are promising, further testing with more individuals and under different classroom conditions is needed to assess the system's overall accuracy and reliability.

Keywords: Face Recognition, Smart Attendance System, YOLO11n, ArcFace, InsightFace, FAISS, Liveness Detection, Anti-Spoofing

1. INTRODUCTION

Attendance is an important part of schools, colleges, universities and workplaces, where keeping track of people's presence is necessary. Traditional methods such as roll calls, attendance sheets, identity cards and QR codes require manual effort and can take up valuable time, especially in larger classrooms. Face recognition provides a contactless alternative by comparing faces captured through a camera with previously registered face data. Earlier research by Taigman et al. and Schroff et al. helped establish deep learning and facial embeddings as important approaches to face recognition [4, 5]. Its application in student attendance systems has also been explored by Budiman et al. and Surantha and Sugijakko [19, 20].

Although face recognition can make attendance easier, systems based on it still face several challenges: Manual effort: Traditional attendance methods still require someone to record and verify each person's presence. Proxy attendance: Cards, QR codes and even photographs or videos can be misused to mark attendance on behalf of someone else. Recognition errors: Poor lighting, unclear images, movement and different camera angles can affect face matching. Repeated entries: Without proper checks, the same person may be recorded multiple times during a single session.

To address these issues, we developed a Face Recognition AI Attendance System that combines person detection, tracking, face recognition and liveness checks in a single application. The system uses YOLO11n to detect people and a custom IoU tracker to follow their movement across camera frames. InsightFace extracts facial information and embeddings, while face-quality assessment and hybrid liveness detection help identify unreliable images and possible spoofing attempts. FAISS is used to search for matching registered identities, and the AMFR decision engine evaluates the recognition, quality and liveness results before attendance is recorded. The application also provides a dashboard, database, API and audit facilities to help manage and review attendance records.

2. LITERATURE REVIEW

Face recognition has developed from traditional image-processing techniques to deep-learning methods that offer better accuracy and reliability. Research in this area provides the foundation for automated attendance systems.

Traditional Methods of Face Recognition: Early systems used techniques such as Local Binary Patterns Histograms (LBPH) to identify faces from images. These methods were simple but could be affected by lighting, pose and image quality [1, 2].

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Deep Learning in Face Recognition: Deep learning improved face recognition by learning useful facial features. Taigman et al. introduced DeepFace [3], followed by FaceNet by Schroff et al. [4]. Deng et al. later proposed ArcFace, which produces more distinguishable facial embeddings for recognition [5].

Person Detection and Tracking: YOLO, introduced by Redmon et al., enables fast object detection, while Ultralytics provides the YOLO11 implementation used in this project [6, 7]. SORT, Deep SORT and ByteTrack are tracking approaches that help maintain object identities across video frames [8–10].

Face Detection and Image Quality Assessment: SCRFD and InsightFace provide tools for face detection and feature extraction [11, 12]. Studies on SER-FIQ and FaceQnet also show how image quality can be assessed before recognition, helping reduce errors caused by unsuitable face images [13, 14].

Liveness Detection and Anti-Spoofing: Face recognition systems must distinguish live users from photographs or screen-displayed videos. DeepPixBiS and CDCN explore deep-learning methods for detecting presentation attacks, while OULU-NPU and ISO/IEC 30107-3 provide guidance for evaluating anti-spoofing systems [15–18].

Texture, Blink and Motion-Based Methods: Researchers have also explored visual cues for liveness detection. Pan et al. studied eye-blink detection [19], Boulkenafet et al. examined colour and texture features [20], and Kollreider et al. investigated facial movement [21]. Combining such cues can provide more reliable spoof detection than relying on a single feature.

Similarity Search and Attendance Management: FAISS and HNSW support efficient similarity searches over facial embeddings, making them useful for matching captured faces against larger galleries [25, 26]. Research on automated attendance systems has also examined ways to reduce manual effort and improve record management [1, 2, 27].

3. PROPOSED SYSTEM ARCHITECTURE

The proposed architecture is divided into modules for video acquisition, person detection and tracking, face recognition, liveness verification, attendance management and result presentation.
Pipeline 1 (Person Detection and Tracking): Captures live camera frames, uses YOLO11n to detect people and an IoU-based tracker to maintain their identities across frames.
Pipeline 1 (Person Detection and Tracking): Captures live camera frames, uses YOLO11n to detect people and an IoU-based tracker to maintain their identities across frames.
Pipeline 2 (Face Recognition): Detects faces using InsightFace, extracts ArcFace embeddings and compares them with registered facial data using a FAISS similarity search index
Pipeline 3 (Liveness and Attendance): Evaluates face quality and checks for possible spoofing using texture, blink, motion and MiniFASNetV2-based analysis. The AMFR decision module verifies the results before attendance is recorded.

3.1 System Features

Person Detection and Tracking: Uses YOLO11n to identify people in camera frames and IoU-based tracking to avoid repeatedly processing the same person.
Face Recognition: Uses InsightFace and ArcFace to generate facial embeddings, which are matched against registered users through FAISS.
Face Quality and Liveness Detection: Checks image quality and combines multiple liveness signals to identify possible attempts using photographs or screens.
Automated Attendance: Records attendance only when the recognition and verification conditions are satisfied. Duplicate entries and repeated detections are controlled through cooldown checks.
Dashboard and Data Management: Provides a dashboard for monitoring attendance, managing registered users and viewing stored records.

4 METHODOLOGY

4.1 Dataset and Enrollment

The system uses enrolled face images to create a gallery of registered identities instead of training a new recognition model. For preliminary evaluation, six identities were selected using 90 images, divided into 60 gallery images and 30 test images. Of the 60 gallery images, 59 produced usable embeddings, while all 30 test images were processed successfully.

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4.2 Data Preprocessing

Face Detection: YOLO11n detects people in camera frames, while the InsightFace module detects faces for recognition. Feature Extraction: The configured InsightFace buffalo_l model generates a 512-dimensional embedding for each detected face.

Transformation: Embeddings are converted to Float32 and L2-normalised before being added to the FAISS index. Face quality is also assessed using blur, brightness, contrast, face size, detector confidence and approximate pose.

4.3 Model Configuration and Training

The system uses YOLO11n for person detection, a custom IoU-based tracker and a pretrained InsightFace model for facial recognition. FAISS performs similarity searches against enrolled embeddings. No new recognition model is trained or fine-tuned on the evaluation images; the existing pretrained models are integrated into the attendance pipeline.

5 EXPERIMENTAL RESULTS

5.1 Model Evaluation Metrics

The face recognition system was evaluated using 28 held-out images from six known identities and 77 images from unknown identities.

- Overall accuracy: 100%.
- Weighted precision: 100%.
- Weighted recall: 100%.
- Weighted F1-score: 100%.
- Correct classifications: 28 out of 28. Top-three hit rate: 100%,

5.2 Error Analysis and Confusion Matrix

The system was further tested with 77 images belonging to six unknown identities.

- Unknown images evaluated: 77
- False acceptances: 0
- False acceptance rate: 0%
- Unknown rejection rate: 100%
- Failed unknown extractions: 0

All 77 unknown images were rejected without being incorrectly matched to an enrolled identity. During dataset preparation, duplicate image groups were also detected. One of the 61 known-person enrollment images failed feature extraction and was excluded from evaluation.

These results show successful identification on the tested images. However, evaluation on a larger and more diverse dataset is required before drawing conclusions about real-world attendance performance.

6 DISCUSSION

Operational Transparency and Trust

The system maintains transparency by recording attendance decisions and storing relevant information in the database and audit logs. Face-quality assessment and liveness checks help make recognition decisions more reliable. The dashboard allows administrators to monitor attendance records and review system activity. These features improve accountability and help build trust in automated attendance management.

Practical Usability

The system provides a contactless and automated method of recording student attendance. Its integration of person detection, face recognition, and identity matching reduces the need for manual attendance marking. The dashboard makes it easier for administrators to view and manage attendance records. Its modular architecture also supports future improvements and integration into classroom environments.



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Observed Limitations

The system's performance may be affected by poor lighting, facial angles, motion blur, and partial face occlusion. Recognition reliability also depends on the quality and diversity of registered face images. The current liveness detection approach may not identify advanced spoofing techniques. Further testing in real classroom conditions is required to evaluate accuracy, scalability, and overall reliability.

7 CONCLUSION AND FUTURE WORK

The Face Recognition AI Attendance System provides an automated and contactless approach to recording attendance. It integrates YOLO11n for person detection, InsightFace and ArcFace for face recognition, and FAISS for efficient identity matching. By combining face-quality assessment, hybrid liveness detection, and the AMFR decision engine, the system aims to improve recognition reliability, reduce duplicate attendance entries, and prevent basic spoofing attempts. The dashboard, database, API, and audit logs further support effective attendance management. Overall, the project demonstrates how multiple AI technologies can be integrated into a unified attendance management system.

In the future, the system can be improved by testing with larger and more diverse classroom datasets and evaluating its performance under different lighting conditions and facial poses. Anti-spoofing techniques can be strengthened to detect advanced presentation attacks, while the tracking mechanism can be enhanced to handle overlapping people and temporary occlusions. Processing speed can also be optimized to support multiple camera streams and larger institutions. Further real-world testing, accuracy evaluation, and security improvements can help make the system more reliable for large-scale deployment.

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