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Smart Attendance System Using Real-Time Facial Recognition and Deformation Handling

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Abstract— In modern work environments, attendance management plays a pivotal role in ensuring workforce accountability and productivity. Traditional systems—including manual registers, biometric punch cards, and RFID-based solutions—are often prone to inefficiencies, data manipulation, and hygiene concerns. This paper presents a Smart Attendance System Using Real-Time Facial Recognition and Deformation Handling, an AI-driven, contactless, and automated framework for attendance tracking. The proposed system integrates Computer Vision and Machine Learning techniques using Python, OpenCV, and the *face recognition* library. It employs HOG (Histogram of Oriented Gradients) and CNN (Convolutional Neural Networks) for facial feature extraction, ensuring high recognition accuracy under varying lighting, pose, and deformation conditions. The architecture incorporates real-time preprocessing, duplicate-entry prevention, and tailgating detection. A Streamlit-based interface enables administrators and employees to access analytical reports and attendance data. Experimental evaluation demonstrates a recognition accuracy of 97.3% with an average frame rate of 20 FPS, confirming the system's real-world applicability for contactless and scalable workplace automation.

Keywords— Facial Recognition, Computer Vision, Artificial Intelligence, Attendance Automation, Deformation Handling, Streamlit, OpenCV.

I. INTRODUCTION

Attendance management systems are fundamental to monitoring organizational efficiency, regulatory compliance, and workforce discipline. Manual attendance registers, RFID tags, and fingerprint scanners have long served this purpose, but they present drawbacks such as time delays, proxy attendance, and hygiene concerns—particularly in post-pandemic environments.

Recent advancements in Artificial Intelligence (AI) and Computer Vision (CV) have transformed identity verification. Facial recognition systems offer a reliable, non-intrusive, and contactless approach that combines image processing with deep learning algorithms. Unlike fingerprint- or card-based systems, facial

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recognition operates seamlessly on live video feeds, identifying and authenticating individuals in real time without requiring physical interaction.

The proposed Smart Attendance System automates attendance logging using real-time facial recognition with deformation-handling capabilities. By employing a combination of HOG-based feature extraction and CNN-based deep embeddings, the system adapts to lighting variations, face tilts, and partial occlusions. This research aims to modernize attendance management through an intelligent, hygienic, and secure software framework integrated with real-time analytics and visualization.

II. LITERATURE REVIEW

Facial recognition technology has undergone rapid evolution since the early 2000s. The classical Viola–Jones algorithm [1] introduced object detection using Haar features and AdaBoost, providing a foundation for modern facial detection. Although efficient, it struggled with lighting variability and pose changes.

Taigman et al. [2] introduced DeepFace in 2015, leveraging a deep convolutional network for feature learning and achieving near-human accuracy, although it required large datasets and significant computational resources. Schroff et al. [3] later proposed FaceNet, utilizing triplet loss to generate robust facial embeddings and improve recognition performance.

ArcFace [4] introduced angular margin loss to enhance class separability, whereas MobileFaceNet [5] optimized facial recognition for embedded and edge devices. Despite these advancements, most existing systems do not effectively address real-time deformation, duplicate-entry prevention, or tailgating detection. The proposed system distinguishes itself by integrating real-time video processing, deformation-aware preprocessing, and analytics dashboards, ensuring both operational efficiency and enhanced security.

III. PROBLEM DEFINITION AND OBJECTIVES

A. Problem Definition

Conventional attendance systems exhibit multiple shortcomings:

• Manual systems are slow, error-prone, and susceptible to manipulation.
• Biometric and RFID methods require physical contact, raising hygiene concerns.
• Many facial-recognition-based systems fail under pose variation, poor lighting, or occlusion.
• Existing solutions lack real-time analytics, duplicate-entry prevention, and tailgating detection.

B. Objectives

The primary objectives of this research are:

1. Automating attendance tracking using real-time facial recognition.
2. Enhancing recognition accuracy through deformation handling and preprocessing.
3. Implementing security features such as duplicate entry and tailgating detection.
4. Designing a Streamlit-based dashboard for analytics and visualization.
5. Ensuring scalability for integration with HR and payroll systems.

IV. PROPOSED METHODOLOGY AND SYSTEM ARCHITECTURE

The system architecture follows a three-tier model:

1. **Presentation Layer (Frontend):** Developed using Streamlit, this layer provides a role-based interface for administrators and employees.
2. **Application Layer (Logic):** Implements facial recognition using Python scripts, HOG/CNN encoders, and preprocessing pipelines.
3. **Data Layer (Backend):** Utilizes SQLite for local storage of user profiles, logs, and event data.

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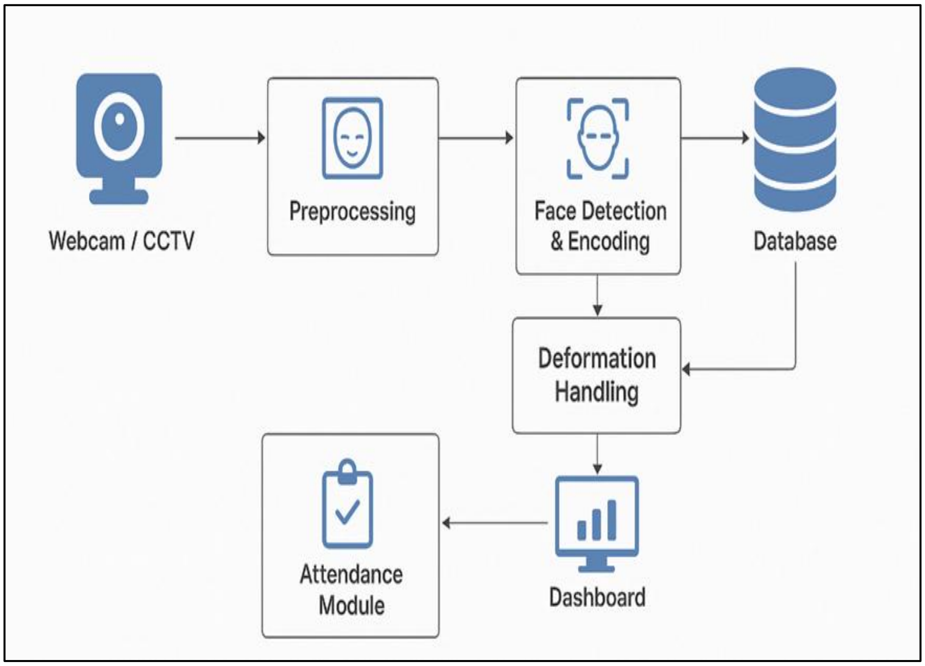


Figure 1

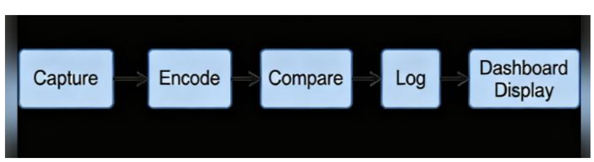
Data Flow Summary

The operational flow of the proposed Smart Attendance System is illustrated in Fig. 1 and described below:

1. **Frame Acquisition:** The webcam continuously captures live video frames at the entry point.
2. **Preprocessing:** Each frame undergoes grayscale conversion, normalization, and resizing to ensure uniformity.
3. **Feature Extraction:** The recognition module encodes detected faces into numerical feature vectors using HOG- and CNN-based models.
4. **Matching and Verification:** Encoded vectors are compared with stored facial encodings in the database to authenticate the individual.
5. **Attendance Logging:** Upon successful verification, attendance is automatically recorded along with the current timestamp.
6. **Dashboard Update:** The Streamlit dashboard reflects the latest attendance status and enables report generation in CSV or Excel format.

This structured flow ensures seamless interaction between the camera module, recognition engine, and database layer, enabling real-time attendance automation.

A. Workflow



1. The camera captures a live video stream.
2. Frames are preprocessed using grayscale conversion, histogram equalization, and normalization.
3. Facial regions are detected using HOG or CNN models.

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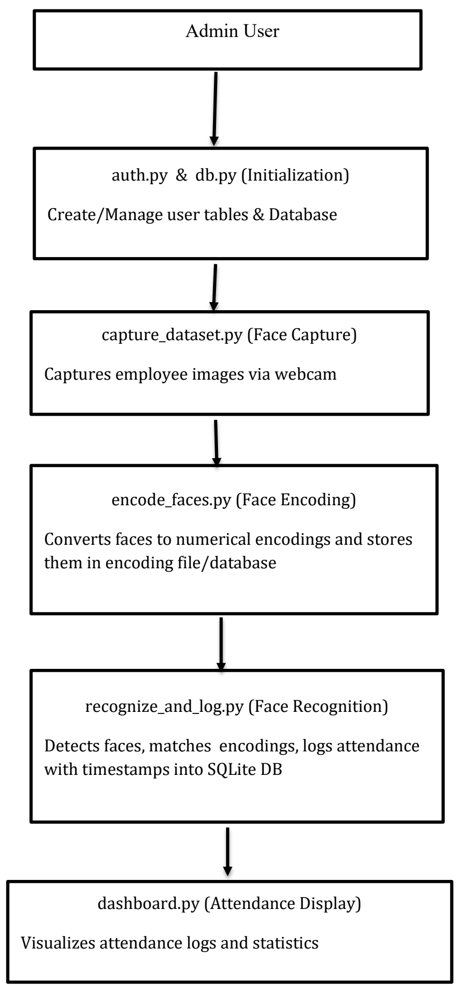
4. The extracted features are encoded into a 128-dimensional vector.
5. Encodings are compared with known faces to verify identity.
6. Attendance is recorded along with timestamps.
7. Duplicate entries within a 5-minute window are filtered, and tailgating events are logged.

B. Algorithms and Techniques

- HOG Feature Extraction: Efficient for face localization.
- CNN Encoder: Generates deep embeddings for robust facial matching.
- Euclidean Distance Matching: Measures similarity between embeddings.
- SHA-256 Hashing: Used for secure password storage during authentication.

C. Architecture Diagram (Descriptive)

Fig. 1 illustrates the system architecture comprising the webcam interface, recognition engine, and data storage modules, all integrated through the Streamlit dashboard.



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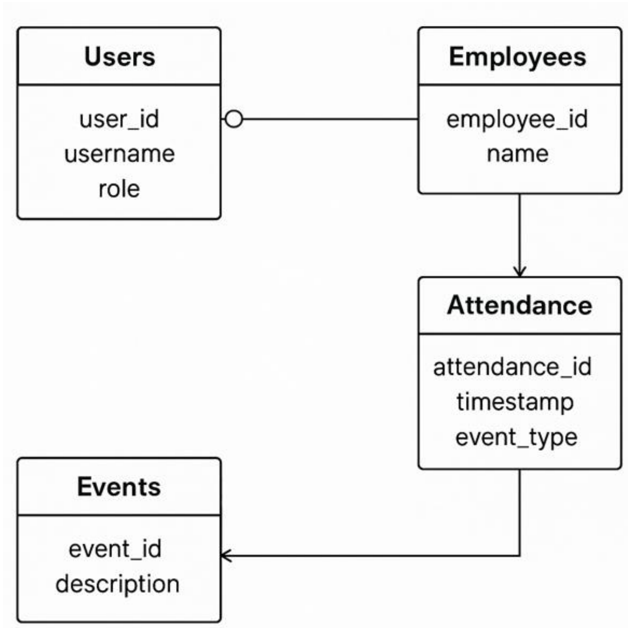
ER Diagram:



Entity–Relationship Description
The system's database design comprises four primary entities—Users, Employees, Attendance, and Events—as shown in Fig. (ER Diagram).

Entity	Description
Users	Stores login credentials, hashed passwords, and access roles (Admin/Employee).
Employees	Maintains employee profile information and unique identifiers.
Attendance	Records each entry/exit instance along with an IST timestamp and event type (IN/OUT).
Events	Logs system notifications and security warnings, such as tailgating or unknown detections.

Relationships:

- One User corresponds to one Employee.
- One Employee generates multiple Attendance entries.
- One Attendance entry may trigger one or more Events related to security or system errors.

This ER model ensures normalization, referential integrity, and efficient data retrieval for analytics and reporting.

Database Schema:

Table Name	Description
users	Stores authentication details and user roles.
employees	Maintains employee master data, including employee ID and name.
attendance	Logs each check-in and check-out event.
events	Records system warnings and notifications (e.g., tailgating alerts).

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V. IMPLEMENTATION DETAILS

The system was implemented using the following components:

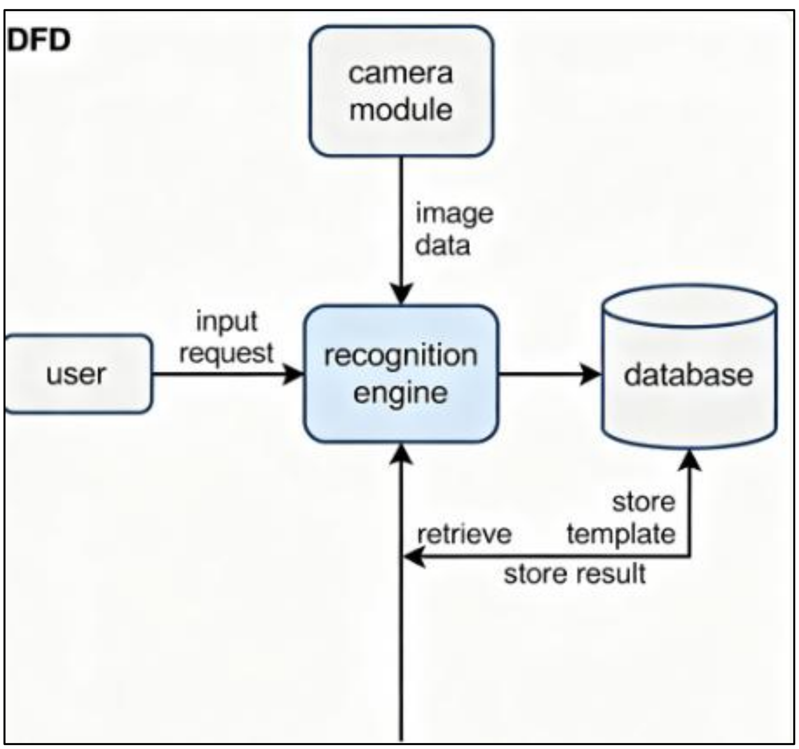
- **Language:** Python 3.9
- **Libraries:** OpenCV, face_recognition, NumPy, Streamlit, FastAPI
- **Database:** SQLite 3
- **Hardware:** Intel i3 processor, 8 GB RAM, 720p webcam

A. Module Overview

Module	Description
Authentication	Handles user login using SHA-256 password encryption.
Dataset Capture	Captures and stores multiple facial samples for each user.
Encoding	Converts facial images into numerical encodings.
Recognition	Detects and matches faces in real time.
Logging	Stores attendance and event information in the database.
Dashboard	Provides analytics through the Streamlit interface.

B. Flowchart (Descriptive)

The recognition workflow begins with system initialization, followed by frame capture, preprocessing, encoding, and identity matching. The process concludes with automatic attendance logging and visualization through the dashboard (Fig. 2).



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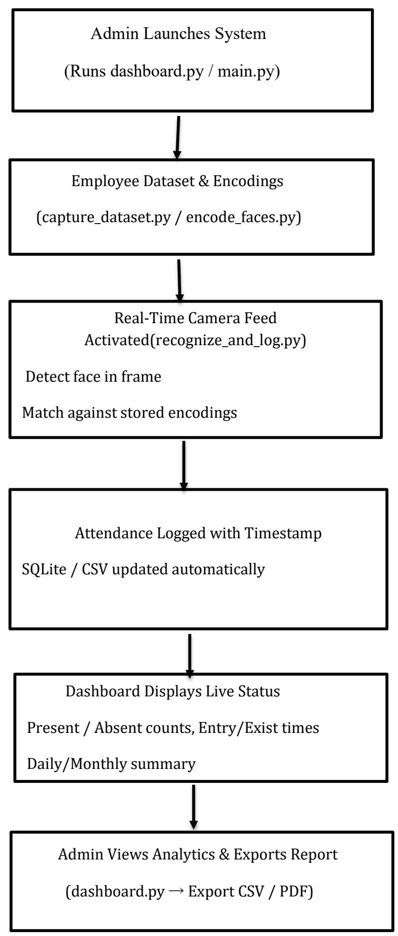

Fig.2

VI. RESULTS AND PERFORMANCE EVALUATION

A. Experimental Setup

Testing was conducted using standard hardware without GPU acceleration. The dataset included 40 employees, with 10 images per person captured under varying conditions such as pose changes, mask usage, and different lighting environments.

B. Evaluation Metrics

Metric	Result	Target	Status
Recognition Accuracy	97.3%	≥95%	Achieved
Frame Rate	20 FPS	≥15 FPS	Achieved
Recognition Latency	0.8 s	≤1 s	Achieved
Tailgating Detection Time	<2 s	≤3 s	Achieved

C. Observations

• Recognition remained consistent under moderate facial deformations and varying lighting conditions.
• Duplicate attendance entries were successfully prevented using a 5-minute time window.
• The Streamlit dashboard efficiently displayed daily and monthly analytical summaries.

VII. DISCUSSION

The results demonstrate that lightweight facial recognition approaches, such as HOG and CNN models, can achieve high real-time accuracy without requiring GPU resources. The combination of preprocessing, normalization, and deformation-handling techniques significantly improves the system's robustness.
Compared with deep-learning-intensive frameworks such as FaceNet or ArcFace, the proposed system performs reliably on standard computing hardware, making it cost-effective for small and medium enterprises (SMEs) and educational institutions. Furthermore, the integration of tailgating detection introduces an added security dimension by flagging simultaneous or unauthorized entries in real time.

VIII. CONCLUSION AND FUTURE WORK

The proposed Smart Attendance System Using Real-Time Facial Recognition and Deformation Handling provides a robust, automated, and contactless solution suitable for modern organizational environments. Its modular architecture ensures seamless integration of recognition, logging, and analytical visualization.

Future Enhancements

1. **Deep Learning Integration:** Replace HOG-based recognition with ArcFace or FaceNet models to achieve higher precision.
2. **Liveness Detection:** Incorporate blink detection or infrared modules to prevent spoofing attacks.
3. **Cloud Deployment:** Enable centralized data storage and access through platforms such as AWS or Azure.
4. **Mobile Application:** Develop Android/iOS applications for remote attendance marking and report viewing.
5. **Edge Optimization:** Deploy lightweight models on devices like Raspberry Pi for portable installations.

This research contributes to advancing intelligent, AI-driven workplace automation through scalable, efficient, and secure system design.

Proposed Enhancements Table

S. No.	Proposed Enhancement	Description	Expected Benefit
1	Integration of Deep Learning Models (FaceNet/ArcFace)	Replace the HOG model with deep neural embeddings for improved performance under complex deformations.	Increases recognition precision to >99%.
2	Liveness Detection Module	Add infrared- or blink-based verification to prevent spoofing via photos or videos.	Enhances system security.
3	Cloud-Based Storage and APIs	Deploy the backend on AWS or Azure with REST APIs for centralized data access.	Enables scalability and remote accessibility.

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4	Mobile App Integration	Develop Android/iOS applications for attendance check-in/out and analytics viewing.	Improves user flexibility and accessibility.
5	Edge Device Optimization	Deploy the system on Raspberry Pi or edge AI devices using TensorFlow Lite.	Reduces hardware cost and increases portability.
6	Multi-Camera Support	Integrate multiple camera streams for larger workplace environments.	Expands system coverage and reliability.

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