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Real-Time Face Recognition System for CCTV Surveillance

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ABSTRACT

This research presents the design and implementation of a Real-Time Face Recognition System for CCTV Surveillance using deep learning techniques to enhance public safety and surveillance efficiency. The system automatically detects and identifies individuals from live video streams, enabling reliable recognition of suspects or missing persons in real time. It integrates face detection, feature extraction, and similarity matching to achieve high recognition accuracy while handling variations in pose, lighting, and orientation. Additionally, the system supports dual-mode surveillance by incorporating vehicle detection and license plate recognition, allowing comprehensive monitoring of both individuals and vehicles. The proposed approach is capable of processing multiple camera feeds simultaneously while maintaining low latency and real-time performance. It generates instant alerts upon successful identification, ensuring quick response and decision-making. Overall, the system reduces dependence on manual monitoring, minimizes human error, and provides an efficient, scalable solution for modern intelligent surveillance applications.

Keywords: Face Recognition, CCTV Surveillance, FaceNet, MTCNN, YOLOv8, License Plate Recognition, Real-Time Alert, Deep Learning.

INTRODUCTION

Public safety surveillance is essential in modern security systems, but traditional CCTV monitoring often suffers from human fatigue, delayed responses, and missed detections [6]. To overcome these limitations, the proposed system integrates deep learning-based face recognition using FaceNet [1] with SSD and Haarcascade/OpenCV-based face detection methods [2], [3], [9] for accurate real-time identification of suspects or missing persons. Facial embeddings are efficiently matched using FAISS similarity search [7], while YOLO-based vehicle detection [4] and OCR techniques such as Tesseract [5] enhance surveillance through license plate recognition. Real-time video transmission is supported through RTP protocols [8], ensuring continuous monitoring with low latency. By combining intelligent surveillance frameworks [6],

computer vision technologies [9], and automated detection systems, the platform significantly improves surveillance accuracy, reduces manual workload, and enhances public safety.

OBJECTIVES

1. To analyze limitations of traditional CCTV surveillance systems.
2. To design and implement an AI-powered real-time face recognition system.
3. To achieve recognition accuracy above 95% with 20–30 FPS processing speed.
4. To integrate vehicle detection and license plate recognition.
5. To provide mobile-based real-time alert notifications.

LITERATURE REVIEW

Table 1: Literature Survey of AI-Based Surveillance Systems

Sr. No.	Paper Title	Publisher & Year	Methodology	Limitations
1	Face Recognition Based Surveillance System Using FaceNet and MTCNN	IEEE Conference, 2023	Used MTCNN for detection and FaceNet for embedding extraction in multi-camera environment.	Limited mobile accessibility and lacked vehicle integration.
2	Real-Time Vehicle Classification and License Plate Recognition via YOLOv8	IEEE Sensors Journal, 2024	YOLOv8-based detection with deformable convolution network for vehicle and plate recognition.	Focused mainly on vehicle tracking without facial recognition integration.
3	Face Recognition and Tracking of Missing Person using AI	Journal of Trends in CS & Smart Tech, 2025	YOLOv8-based face detection with real-time alert mechanism for missing persons.	Scalability and microservice-based deployment not clearly defined.

METHODOLOGY

The development of the Real-Time Face Recognition System for CCTV Surveillance follows a systematic and modular approach to ensure accurate real-time processing, secure data handling, and scalable deployment. The complete workflow of the system is illustrated in **Fig. 1**, which shows the architecture diagram of the real-time face recognition system. A comparative study of existing face recognition and surveillance approaches, summarized in **Table 1**, was used as the basis for selecting appropriate models and technologies for this project.

1. Requirement Analysis

The initial phase of the project focused on identifying the functional and non-functional requirements necessary for building a reliable real-time surveillance system. The system was required to detect and recognize faces from live CCTV feeds with an accuracy exceeding 95% while ensuring continuous monitoring without delays. The requirement for high accuracy and robustness was influenced by the performance of deep learning-based face recognition models such as FaceNet [1], along with reliable detection frameworks including SSD [2] and Haarcascade [3], which collectively improve recognition performance over conventional surveillance methods.

Non-functional requirements such as system scalability, low latency, and secure handling of biometric data were also considered during this phase. Since surveillance systems often operate in sensitive environments, it was essential to ensure that the platform could handle large volumes of video data while maintaining consistent performance. These requirements were established after reviewing existing surveillance and distributed monitoring systems [6].

Furthermore, the system was designed to be accessible to authorized users through both web and mobile platforms. This required secure communication protocols [14], real-time streaming support [8], and reliable computer vision frameworks such as OpenCV [9].

2. Microservice Architecture Design

To meet the requirements of scalability, modularity, and maintainability, a microservice-based architecture was adopted for the system. As shown in Fig. 1, the architecture divides the application into three major components: a frontend interface, backend service layer, and AI processing service. This modular design enables each component to operate independently while communicating through secure APIs [14].

The microservice approach allows computationally intensive AI tasks such as face detection and recognition to be isolated within the AI service. This separation is beneficial in real-time surveillance systems, as FaceNet [1], SSD [2], and OpenCV-based pipelines [9] require dedicated resource allocation. By separating these components, the system can scale AI processing independently based on surveillance load.

In addition, this architecture supports future expansion for distributed surveillance environments, aligning with intelligent surveillance system principles [6].

3. Database Design and Management

A robust and structured database system was required to store and manage the large volume of data generated by the surveillance system. PostgreSQL was selected due to its support for relational data models, secure transactions, and efficient storage of structured surveillance records. The database stores facial embeddings generated through FaceNet [1], detection logs, vehicle information, and authentication records.

Efficient data retrieval is critical in face recognition systems where embeddings must be compared in real time. Therefore, the database schema was designed to support rapid indexing, while FAISS [7] was incorporated to accelerate large-scale similarity matching. This ensures efficient identification even as the number of stored records increases.

Security measures were also incorporated through secure API communication [14] and controlled system-level access to maintain confidentiality of biometric data.

4. Face Detection and Recognition Implementation

The core functionality of the system involves detecting and recognizing faces from live CCTV video streams in real time. Each frame captured from the camera feed is processed using SSD-based deep learning detection [2] and Haarcascade/OpenCV methods [3], [9], which detect and localize faces for recognition. These approaches ensure consistent and efficient face localization under varying surveillance conditions.

After detection, the facial regions are processed using the FaceNet deep learning model [1], which converts each face into a high-dimensional embedding vector representing unique facial features. These embeddings are then compared against stored vectors using similarity measures.

To ensure fast and scalable matching, the system uses FAISS-based similarity search [7] to compare live embeddings with stored embeddings. This enables efficient nearest-neighbor search in high-dimensional embedding spaces and supports real-time performance.

5. Vehicle and License Plate Detection Integration

To enhance surveillance capabilities, vehicle detection and license plate recognition were integrated alongside face recognition. This enables multimodal surveillance by combining person identification with vehicle tracking, thereby improving situational awareness [6].

Vehicle detection is performed using YOLO-based object detection frameworks [4], [12], which identify vehicles in real time with high speed and accuracy. Once detected, OCR tools such as Tesseract [5] and EasyOCR [13] are used to recognize license plate text. The recognized information is then stored in the database and linked to surveillance events.

6. Real-Time Alert Mechanism

A real-time alert generation mechanism was implemented to ensure immediate notification when a target individual is detected. When the similarity score between detected facial embeddings and stored embeddings exceeds a threshold, the system triggers alerts containing identity, timestamp, camera location, and frame snapshot.

The alert data is transmitted through backend communication protocols [14] and displayed on web and mobile platforms. Real-time streaming support [8] ensures timely delivery of surveillance data, while OpenCV [9] supports efficient frame handling.

The system is optimized to generate and deliver alerts within 300–500 milliseconds of detection. This low-latency response is enabled by SSD/Haarcascade detection [2], [3], FaceNet embedding extraction [1], and FAISS similarity search [7].

7. Security and Role-Based Access Control

Given the sensitive nature of biometric surveillance data, robust security mechanisms were integrated into the system. User authentication is implemented through secure API communication standards [14], ensuring controlled access to surveillance functionalities.

Role-based access control defines permissions for administrators, operators, and general users, ensuring only authorized personnel can manage sensitive records. Such security practices are essential in intelligent surveillance systems [6].

By combining secure communication protocols with access control, the platform maintains confidentiality, integrity, and operational security.

8. Testing and Performance Evaluation

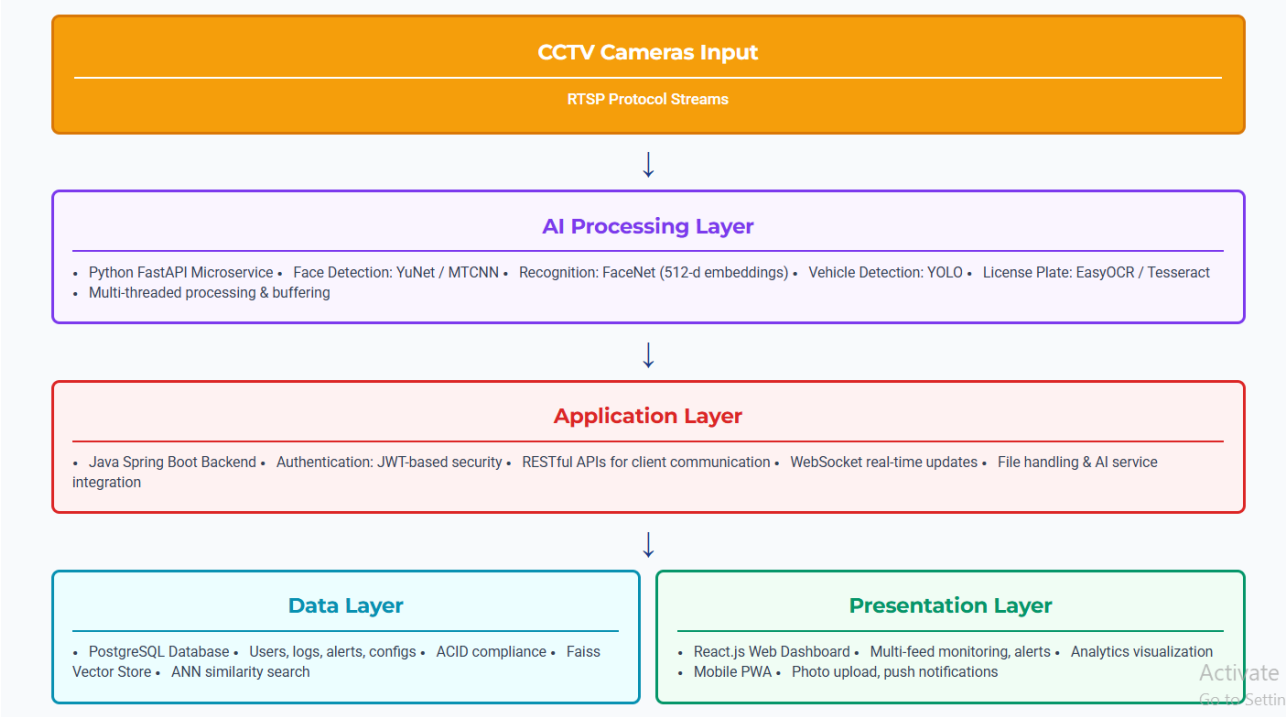
After implementation, the system underwent extensive testing to evaluate both functional correctness and real-time performance. Unit testing validated modules such as face detection, embedding generation, OCR, and alert systems, while integration testing ensured smooth communication between OpenCV [9], FaceNet [1], YOLO [4], and backend services.

Performance evaluation was carried out using live CCTV feeds under real-world conditions. Metrics such as detection accuracy, recognition accuracy, frame rate, and response time were measured. The system consistently achieved recognition accuracy above 95%, supported by FaceNet's embedding performance [1].

The system processed video streams at approximately 20–30 FPS while maintaining stable performance across multiple cameras. The use of SSD/Haarcascade detection [2], [3], YOLO [4], FAISS [7], and OpenCV [9] ensured that the real-time processing requirements shown in Fig. 1 were successfully achieved

ARCHITECTURE DIAGRAM OF REAL-TIME FACE RECOGNITION

Fig 1: Architecture diagram of real-time face recognition system



Explanation of Architecture Diagram

Fig. 1 illustrates the overall architecture of the proposed Real-Time Face Recognition System for CCTV Surveillance, designed using a layered structure to ensure modularity, scalability, and efficient real-time processing [6]. The architecture consists of five primary components: CCTV Cameras Input, AI Processing Layer, Application Layer, Data Layer, and Presentation Layer. At the input stage, multiple CCTV cameras continuously capture surveillance footage and transmit live video streams using real-time communication protocols such as RTSP/RTP [8], enabling continuous low-latency video transmission for intelligent analysis.

The AI Processing Layer performs all computer vision and deep learning tasks using OpenCV-based processing frameworks [9], [10]. Face detection is carried out using SSD or Haarcascade-based approaches [2], [3], while FaceNet [1] generates facial embeddings for accurate face recognition. The layer also integrates YOLO-based vehicle detection [4], [12] and OCR-based license plate recognition through Tesseract or EasyOCR [5], [13], enabling dual-mode surveillance of both individuals and vehicles. FAISS similarity search [7] is used to optimize large-scale embedding comparison for fast identification.

The Application Layer manages system logic, authentication, and communication through secure API frameworks [14], while the Data Layer stores user records, embeddings, detection logs, and alerts for efficient retrieval and secure management. The Presentation Layer provides web and mobile accessibility for monitoring, alerts, and administrative control. Overall, this layered architecture combines intelligent surveillance principles [6], real-time communication [8], computer vision frameworks [9], and deep learning technologies [1], [4] to deliver a scalable, secure, and future-ready surveillance solution.

EXPECTED OUTCOMES

1. High-Accuracy Face Recognition

The proposed system is expected to achieve face recognition accuracy of more than 95% by utilizing deep learning-based models for face detection and feature extraction. Face detection is performed using MTCNN or YuNet, which accurately identifies and aligns facial regions in real-time video frames. Proper face alignment helps in reducing variations caused by pose, lighting, and orientation, thereby improving the reliability of the recognition process.

Once a face is detected, the FaceNet model generates a high-dimensional embedding that uniquely represents the facial characteristics of the individual. These embeddings are compared with pre-stored embeddings of target individuals stored in the database using similarity metrics such as cosine similarity or Euclidean distance. This embedding-based approach allows the system to distinguish between different individuals with high precision.

As a result, the system is expected to minimize false positives and false negatives during recognition, ensuring reliable identification of suspects or missing persons in real-time surveillance environments. This level of accuracy is critical in security applications where incorrect identification can lead to operational inefficiencies or security risks.

2. Real-Time Multi-Camera Monitoring

The system is designed to support continuous monitoring of multiple CCTV camera feeds simultaneously while maintaining real-time processing performance. Each camera stream is transmitted using RTSP and processed independently by the AI processing module. Multi-threaded processing techniques are used to ensure that the analysis of one camera feed does not delay or interrupt the processing of others.

The AI processing layer extracts frames from each video stream and performs face detection, recognition, and object detection in parallel.

3. Instant Alert Generation

One of the primary expected outcomes of the system is the ability to generate alerts immediately when a target individual is detected. When the similarity score between a detected face and a stored facial embedding exceeds a predefined confidence threshold, the system automatically triggers an alert event. This alert contains essential contextual information, including the identity of the matched individual, camera location, timestamp, and a captured image snapshot from the video frame.

The alert is transmitted from the AI processing service to the backend server, which then forwards it to the user interface through WebSocket communication. This ensures that alerts are displayed on the dashboard in

real time without requiring manual refresh or polling. Additionally, push notifications are sent to the Progressive Web App, allowing authorized users to receive alerts on mobile devices.

The system is optimized to ensure that alerts are generated and delivered within 300–500 milliseconds of detection. This low-latency response enables rapid decision-making and allows security personnel to take immediate action, which is essential in time-sensitive situations such as identifying suspects or preventing unauthorized access.

4. Dual Detection Capability

In addition to face recognition, the system is expected to provide dual-mode detection by identifying vehicles and recognizing license plates in the same video stream. This feature enhances the overall surveillance capability by providing additional contextual information about the movement and activities of individuals within the monitored area.

Vehicle detection is performed using a YOLO-based object detection model, which is capable of identifying different types of vehicles in real time. Once a vehicle is detected, the region containing the license plate is extracted and processed using optical character recognition tools such as EasyOCR or Tesseract to identify the alphanumeric characters on the plate. The recognized license plate number is then stored in the database and associated with the detection event.

This integration enables the system to track both individuals and their associated vehicles, which is particularly useful in criminal investigations, traffic monitoring, and access control systems. By combining facial and vehicle information, the system provides a more comprehensive surveillance solution compared to systems that rely on only one type of detection.

5. Centralized Data Management

The system is expected to maintain a centralized and secure repository of all surveillance-related data using a PostgreSQL database. This database stores detailed records of target individuals, including their personal information and facial embeddings, as well as vehicle details, detection logs, alert history, and system configuration data. Centralized storage ensures that all surveillance data is organized, consistent, and easily accessible for authorized users.

The database is designed with relational tables and indexing mechanisms to support fast data retrieval and efficient storage of large volumes of records generated by continuous surveillance. Detection logs and alert records are stored with timestamps and camera identifiers, enabling administrators to perform historical analysis and generate reports when required.

Secure data management is critical in systems that handle biometric and personal information. Therefore, access to the database is restricted through backend authentication and role-based access control mechanisms.

This ensures that only authorized users can view or modify sensitive data, maintaining data integrity and compliance with security and privacy requirements.

CONCLUSION

The proposed Real-Time Face Recognition System for CCTV Surveillance presents an advanced and intelligent solution to address modern public safety and security challenges [6]. By integrating deep learning-based face recognition techniques such as SSD/OpenCV-based face detection [2], [10] and FaceNet-based facial embedding extraction [1], along with YOLO-based vehicle detection [4], [12] and OCR-based license plate recognition using Tesseract/EasyOCR [5], [13], the system enables automated, accurate, and real-time monitoring of CCTV feeds. The use of OpenCV frameworks [9], real-time streaming protocols [8], and optimized similarity search techniques such as FAISS [7] further enhances the system's capability to process surveillance data efficiently.

The implementation of a microservice architecture with secure communication protocols [14] ensures scalability, modularity, and efficient system integration for surveillance operations. This architecture significantly reduces dependency on manual surveillance, minimizes human error, and provides instant alerts within milliseconds for faster response to potential threats. By combining intelligent distributed surveillance principles [6] with modern computer vision frameworks [9], the system improves operational efficiency while supporting secure data handling and continuous monitoring.

Furthermore, the platform provides strong potential for future enhancements such as crowd behavior analysis, anomaly detection, and AI-driven predictive threat monitoring. With its scalable architecture, high recognition accuracy, and intelligent automation, the system represents a future-ready surveillance solution capable of adapting to evolving security requirements [6].

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