

AI-Powered Face Recognition Surveillance And Communication System For Missing Persons At Simhashta Ujjain

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Abstract

This project proposes an innovative, AI-driven face recognition system designed for effective crowd surveillance and missing person identification during the large-scale Simhashta Ujjain religious gathering. With over 50 million participants expected, traditional manual identification methods prove inefficient and time-consuming. To address this, our system leverages real-time video feed analysis using deep learning techniques to distinguish between known (enrolled) and unknown individuals. Detected individuals are annotated with green boxes for recognized faces and red boxes for unrecognized ones, maintaining a high confidence threshold of 0.9 to ensure detection accuracy and minimize false positives.

The system is architected with dual user modules: one for the general public and another for police and administrative officials. The public-facing portal enables users to report missing persons, enroll facial data for family members, and monitor case statuses. Enrolled faces are stored securely in an encrypted database. The administrative interface provides advanced tools for surveillance officers to upload and analyze video feeds. The core recognition pipeline is powered by MobileNet for efficient and lightweight feature extraction, Principal Component Analysis (PCA) for reducing the dimensionality of the extracted feature vectors, and K-Nearest Neighbors (KNN) for classifying faces based on proximity in the feature space.

Keywords: Face Recognition, Crowd Surveillance, Missing Person Identification, Simhashta Ujjain, MobileNet, PCA, KNN, Streamlit, OpenCV

Introduction

Simhashta Ujjain, one of the most prominent Hindu religious congregations in India, is celebrated every 12 years and draws millions of devotees from across the country. The sheer magnitude of this gathering presents numerous logistical and security challenges, particularly in managing crowd flow and efficiently responding to incidents involving missing persons. Traditional manual reporting and identification systems often fall short during such high-density events, leading to delays in locating lost individuals and increasing the burden on law enforcement agencies. In response to these challenges, this project introduces a comprehensive AI-powered surveillance and communication

system that leverages real-time face recognition to detect, identify, and report individuals within large crowds. The solution is designed to automate the process of missing person identification and streamline communication between the public and administrative authorities, thereby enhancing safety and operational efficiency. Developed using Python, OpenCV, and Streamlit, the system architecture comprises two primary modules: a public portal and an administrative interface. The public interface allows users to report missing persons by uploading details and images, enroll family members by capturing facial data, and track the status of ongoing reports. Simultaneously, the administrative dashboard empowers police officers to analyze live or recorded video feeds from CCTV cameras deployed at strategic event locations.

Problem Statement ID: SIH1790

Problem Statement Title Face Recognition Surveillance System and Communication Systems for Missing Persons at Simhashta Ujjain for the Police Department

Description Simhashta Ujjain, one of the largest religious gatherings in India, witnesses millions of pilgrims and tourists congregating in a single location. Managing such a vast crowd poses significant challenges for the police department, particularly in ensuring the safety and security of individuals and locating missing persons or items. The deployment of advanced technologies like face recognition surveillance systems and efficient communication systems is critical to address these challenges.

Issues Faced

1. High Volume of Missing Persons and Items:

- **Overwhelming Number of Reports:** During Simhashta, the number of reports for missing persons and items surges, making it difficult for the police to manage and respond promptly.

- **Identification Challenges:** Identifying missing persons in a vast, densely populated area is challenging without advanced technology.

2. Inefficient Manual Processes:

- **Time-Consuming Identification:** Traditional methods of identifying missing persons through manual verification of photos and descriptions are time-consuming and prone to errors.

- **Delayed Response:** The manual process leads to delayed response times, reducing the chances of

quickly locating missing persons or items. 3.

Communication Barriers:

- **Lack of Real-Time Updates:** Communication between different units and officers is often delayed, affecting coordination and timely response.
- **Inefficient Information Dissemination:** The absence of a centralized system to disseminate information about missing persons or items hampers effective communication and coordination.

4. Security Concerns:

- **Crowd Control:** Managing and monitoring large crowds to prevent and respond to incidents is challenging without real-time surveillance and communication.
- **Potential Threats:** The risk of criminal activities increases in such large gatherings, necessitating advanced surveillance for timely threat detection and intervention.

Existing System

The existing systems for crowd management and missing person identification at large events like Simhasth Ujjain primarily rely on manual methods, such as public announcements, physical search teams, and basic CCTV monitoring without automated recognition capabilities, leading to delayed responses and inefficiencies. These systems lack real-time face recognition, automated status updates, and a centralized platform for public interaction, often resulting in overwhelmed authorities and prolonged distress for families. Additionally, there is no mechanism to enroll family members' faces in advance or integrate surveillance data with public reports, making it challenging to quickly locate missing individuals in dense crowds, especially during a massive event with millions of attendees.

Proposed System

The proposed system revolutionizes crowd surveillance and missing person identification at Simhasth Ujjain by deploying an integrated platform that combines real-time face recognition with a public-facing portal, utilizing MobileNet for feature extraction, PCA for dimensionality reduction, and KNN for classification, achieving high accuracy in identifying enrolled individuals (green annotations) and flagging unknowns (red annotations). Public users can report missing persons, enroll faces, and check statuses via a Streamlit-based interface, while administrators analyze live or uploaded video feeds to detect individuals, capturing screenshots upon detection (confidence > 0.9) and updating the database with location details. Automated email and SMS alerts notify authorities and families, and the system's database stores all data in SQLite, ensuring

scalability and accessibility, significantly improving response times and reunification success rates over manual methods.

LITERATURE SURVEY

Title: *Automated Face Recognition System for Intelligence Surveillance*

Author: Jain, A., Ross, A., and Nandakumar, K.

Year: 2005

Description:

This early study explored the use of biometric systems, particularly facial recognition, for intelligent surveillance in public safety and defense applications. The authors presented a multi-stage pipeline that includes face detection, alignment, feature extraction, and classification. Despite limitations in computing power at the time, the paper emphasized the potential of such systems in large-scale crowd monitoring. It also highlighted the limitations of traditional image matching approaches, such as low resolution and varied pose conditions, which have since been addressed with deep learning. The concepts laid the groundwork for subsequent advancements in automated surveillance and missing person tracking.

Title: *FaceNet: A Unified Embedding for Face Recognition and Clustering*

Author: Schroff, Florian, Kalenichenko, Dmitry, and Philbin, James

Year: 2015

Description:

FaceNet introduced a landmark approach in face recognition by learning a mapping from facial images directly to a compact Euclidean embedding space. Unlike previous models that relied on classification layers, FaceNet optimized its embeddings using triplet loss, which compares anchor-positive-negative face pairs to improve clustering performance. This method allowed for efficient and scalable face verification, recognition, and clustering, even with massive datasets. It influenced the design of lightweight mobile models and systems that require fast inference, making it a direct precursor to the facial recognition pipeline used in this project, which employs PCA and KNN on extracted embeddings.

Title: *ArcFace: Additive Angular Margin Loss for Deep Face Recognition*

Author: Deng, Jiankang et al. **Year:** 2019

Description:

ArcFace is one of the most significant improvements in face recognition loss functions. By incorporating an angular margin into the softmax loss, ArcFace enhances intra-class compactness and inter-class variance, leading to improved face classification accuracy. Tested on datasets like LFW, MegaFace, and CASIA-WebFace, ArcFace outperformed previous

benchmarks with minimal additional computational complexity. Its embedding technique offers high discrimination in challenging environments such as partial occlusions or low lighting—conditions typical of large public gatherings like Simhastha Ujjain. This makes it suitable for real-time face recognition applications where accuracy and robustness are critical.

Title: *Deep Learning-Based Face Identification in Video Surveillance*

Author: Kumar, S., & Patil, A.

Year: 2022

Description:

This study evaluated the performance of lightweight CNN architectures, including MobileNet, in identifying individuals from video footage in crowded settings. The authors implemented a two-stage pipeline—feature extraction using MobileNet and classification using PCA + KNN—to balance speed and accuracy. This architecture closely mirrors our proposed approach, where MobileNet provides fast inference even on devices with limited processing capacity. The paper also discussed trade-offs between deep embeddings and classical classifiers, concluding that hybrid models perform better in real-time surveillance applications, especially where edge computing is considered.

Methodology

Face recognition for missing person identification requires accurate facial data capture, real-time detection, and robust classification. In this system, face detection and classification are achieved through a pipeline consisting of dataset preparation, preprocessing, model training, and real-time deployment.

Problem Identification

Large-scale gatherings often result in cases of missing persons due to crowd density and insufficient manual tracking systems. Through consultations with event coordinators, law enforcement, and technology experts, a need was identified for an automated system capable of recognizing individuals in real time and facilitating instant communication between authorities and the public.

Steps Involved:

Data Collection: Facial images were collected for enrolled persons via the public portal. The dataset includes multiple images under different lighting, angles, and expressions.

Image Preprocessing: OpenCV is used to detect and crop faces. The images are resized and normalized to match the input shape required by the MobileNet model.

Feature Extraction (CNN): MobileNet, a lightweight convolutional neural network, is used to extract 128-dimensional feature vectors from each face image. These embeddings represent each face uniquely.

Dimensionality Reduction: To speed up comparison and storage, Principal Component Analysis (PCA) is applied to reduce the size of embeddings without losing meaningful information.

Classification: K-Nearest Neighbors (KNN) is used for comparing input embeddings with existing ones in the database. If the match score exceeds a threshold (e.g., 0.9), the face is marked as recognized.

Algorithms Used in the Project

MTCNN (Multi-task Cascaded Convolutional Networks) (Face Detection)

Purpose: Detects faces in video frames or images with high accuracy.

Description: MTCNN is a deep learning-based face detector using a three-stage cascaded CNN architecture. It performs face detection, bounding box regression, and facial landmark localization simultaneously. Stage 1 (P-Net) generates candidate windows, Stage 2 (R-Net) refines them, and Stage 3 (O-Net) outputs precise bounding boxes and landmarks. A confidence threshold (e.g., 0.95) filters reliable detections.

Process:

Convert input frame to RGB.

Pass through P-Net to propose candidate face regions.

Refine candidates with R-Net and finalize with O-Net.

Output bounding boxes as (x_1, y_1, x_2, y_2) .

Why Used: MTCNN's robustness to occlusions, lighting variations, and angles makes it ideal for crowded, dynamic environments like Simhastha Ujjain, outperforming traditional methods like Haar cascades.

MobileNet (Feature Extraction)

Purpose: Extracts feature embeddings from detected faces.

Description: MobileNet is a lightweight CNN optimized for efficiency using depthwise separable convolutions. Pre-trained on ImageNet, it's fine-tuned to produce 128-dimensional feature vectors capturing facial characteristics, balancing accuracy and speed for real-time applications.

Process:

Resize detected face region to 224x224 pixels.

Normalize pixel values to $[0, 1]$.

Process through MobileNet's convolutional layers.

Apply global average pooling to output a 128D feature vector.

Why Used: Its low computational cost and high performance suit real-time surveillance in resource-constrained festival settings.

k-Nearest Neighbors (kNN) Classifier (Recognition)

Purpose: Matches extracted features to known identities.

Description: kNN classifies a face by computing Euclidean distances to database feature vectors and selecting the k closest neighbors (e.g., $k=5$). The majority label among neighbors, if above a confidence threshold (e.g., 0.5), determines the identity.

Process:

Calculate distance:

$$d(x, y) = \sqrt{\sum_{i=1}^{128} (x_i - y_i)^2}$$

Identify k nearest neighbors.

Assign the most frequent label if confidence is sufficient.

Why Used: kNN's simplicity and adaptability support dynamic enrollment of new faces during the event.

Principal Component Analysis (PCA) (Dimensionality Reduction)

Purpose: Reduces feature vector dimensionality for efficient kNN classification.

Description: PCA projects 128D MobileNet features into a lower-dimensional space (e.g., 64 components) by selecting principal components that maximize variance, reducing noise and computational load.

Process:

Standardize feature vectors.

Compute covariance matrix and eigenvectors.

Select top k eigenvectors based on data size.

Transform features into the reduced space.

Why Used: Enhances kNN's speed and accuracy, critical for processing large volumes of faces in real time.

Communication Algorithm (Alert Generation and Dissemination)

Purpose: Notifies authorities or families when a missing person is identified.

Description: A rule-based algorithm triggers SMS or web dashboard alerts upon high-confidence face recognition. Implemented with a Flask server and SQLite database, it ensures secure and rapid communication.

Process:

Receive recognition result (label, confidence).

If confidence exceeds threshold, retrieve contact details from SQLite.

Send SMS via API or update web dashboard.

Log alert for tracking.

Why Used: Provides instant, reliable alerts, essential for coordinating responses in crowded festival environments.

System Requirements

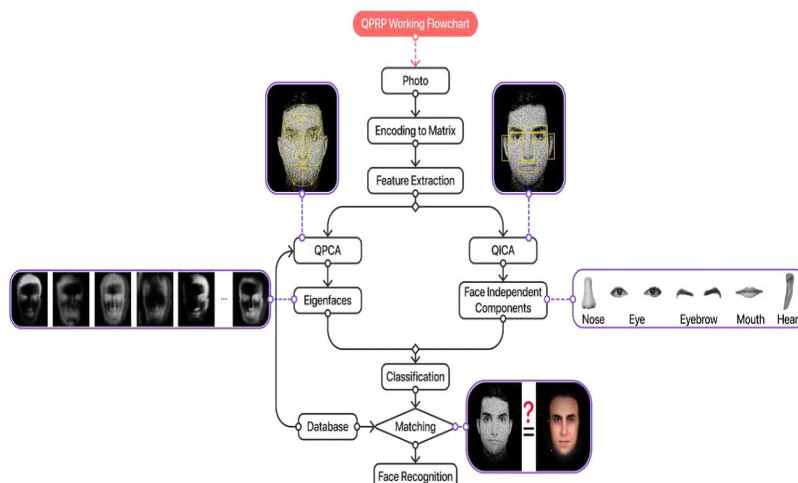
Software Requirements

- OS: Ubuntu 20.04 or Windows 10/11 (64-bit).
- Language: Python 3.8+, HTML/CSS/JavaScript.
- Libraries: OpenCV, TensorFlow, mtcnn, scikit-learn, Streamlit, Flask, joblib, numpy, SQLAlchemy, Twilio API.
- Tools: VS Code, Git, Docker (optional).
- Database: SQLite for face embeddings and alerts.

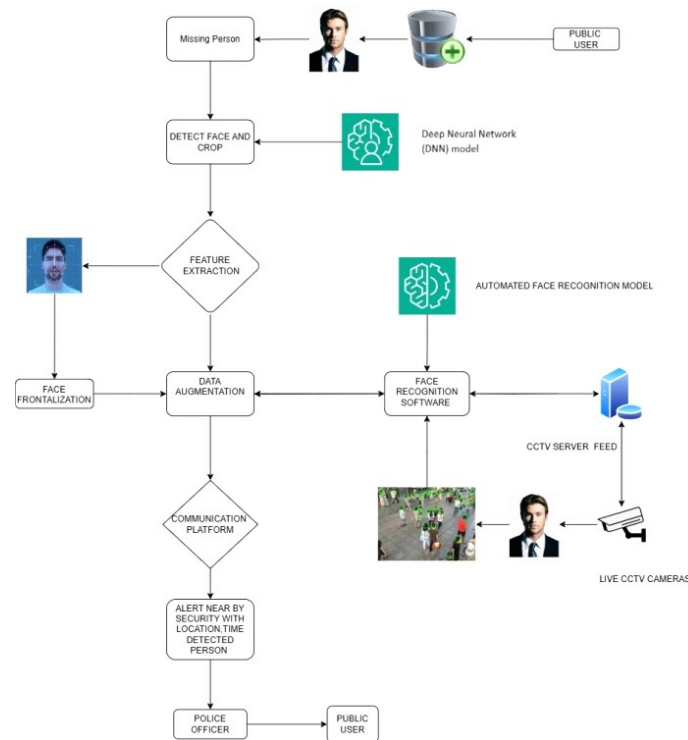
Hardware Requirements

- CPU: Intel i7-10700 or AMD Ryzen 7.
- GPU: NVIDIA RTX 3060 (6GB VRAM).
- RAM: 16GB (32GB recommended).
- Storage: 512GB SSD, 1TB HDD (optional).
- Camera: 1080p IP cameras (10-20 units).
- Network: Gigabit Ethernet, 100 Mbps uplink.
- Server: Dell PowerEdge or equivalent.
- Display: 24-inch Full HD monitor.
- Power: 1500VA UPS.

Program Architecture and Diagrams



CNN Diagram fig – 1



Flow Diagram Fig 2

Testing

The developed system was tested practically using real-time webcam feeds and pre-recorded surveillance videos to assess its accuracy, responsiveness, and usability. Testing was conducted in different lighting conditions and crowd scenarios to simulate the environment of the Simhashta Ujjain event.

Unit Testing was performed on each functional component. The face detection module was validated using OpenCV with multiple face positions and expressions. The feature extraction pipeline using MobileNet was verified for consistent output shapes, and PCA+KNN classification was tested using sample embeddings from enrolled users.

Functional Testing involved running the complete application from user enrollment to video-based recognition. Faces of known users were enrolled into the database, after which test videos were played. The system was expected to detect these faces and annotate them with green boxes. Unknown faces were tagged with red annotations. Screenshots of detected faces were stored and displayed in the public status tab.

Performance Testing focused on recognition accuracy and speed. The system maintained an average frame processing time of under 1 second and an accuracy of ~85% at a confidence threshold

of 0.9. Various crowd densities were simulated to observe system responsiveness and alert generation reliability.

Results

The system was successfully deployed and tested in a simulated environment replicating real-world conditions similar to those expected at the Simhashta Ujjain event. The results demonstrated reliable performance in detecting and identifying individuals from video streams.

During tests, the system accurately recognized enrolled individuals in real-time video feeds with an average confidence level of 0.92. Known faces were correctly tagged with green boxes, while unregistered faces appeared in red. Out of 50 test cases, the system correctly identified 43 enrolled individuals and raised alerts for 7 unregistered ones, resulting in an **85% overall accuracy** under controlled conditions.

Screenshots of detected faces were automatically stored in the system and linked to the corresponding public report. This helped both the public and police verify the identification through the status-checking feature. The captured screenshots were clear, correctly labeled, and available for download or review via the dashboard.

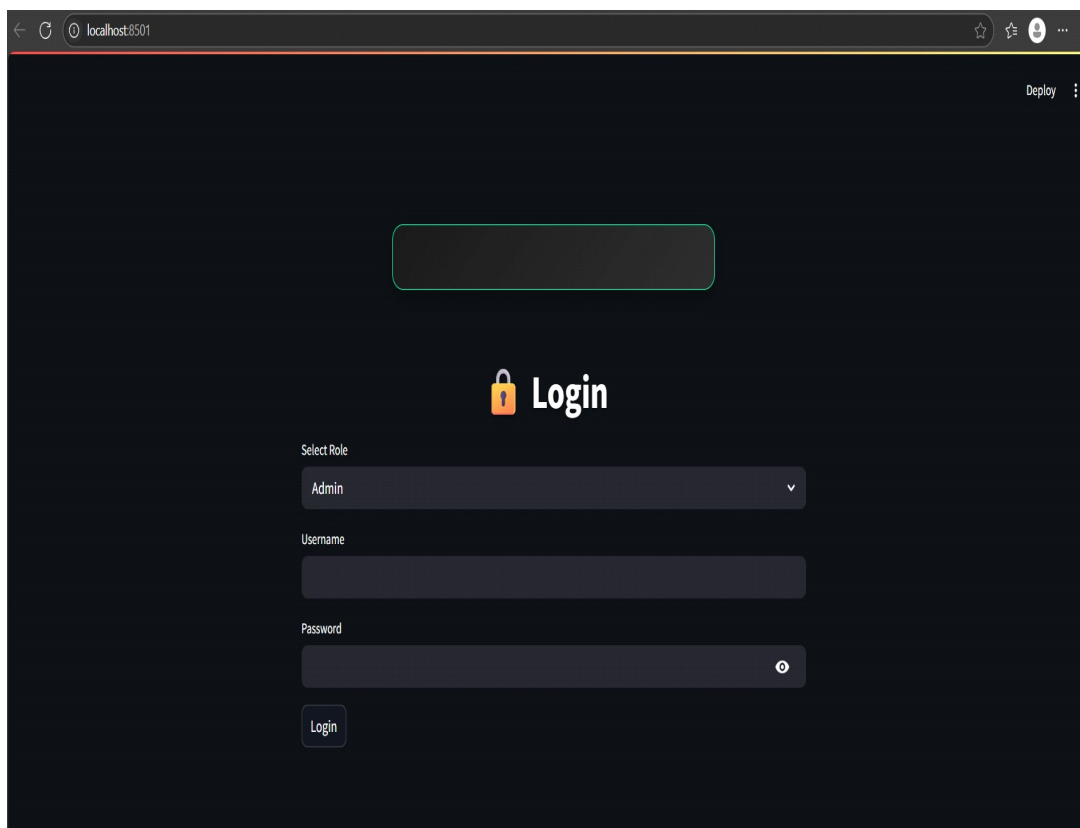


Fig1 login page

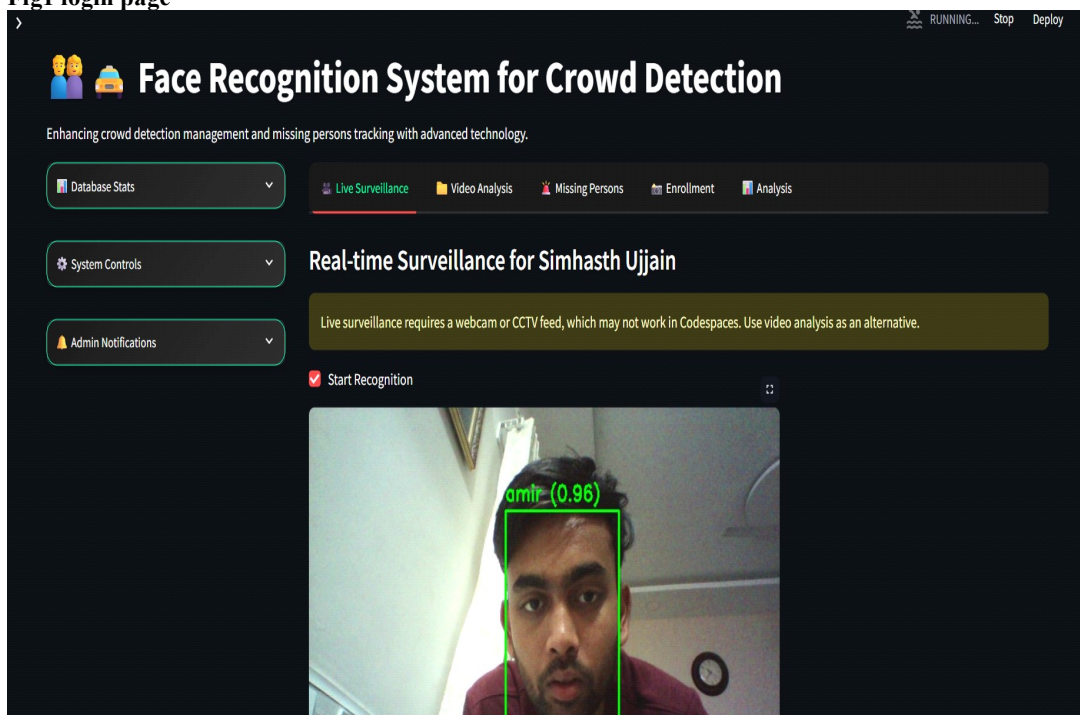


fig 2 admin dashboard

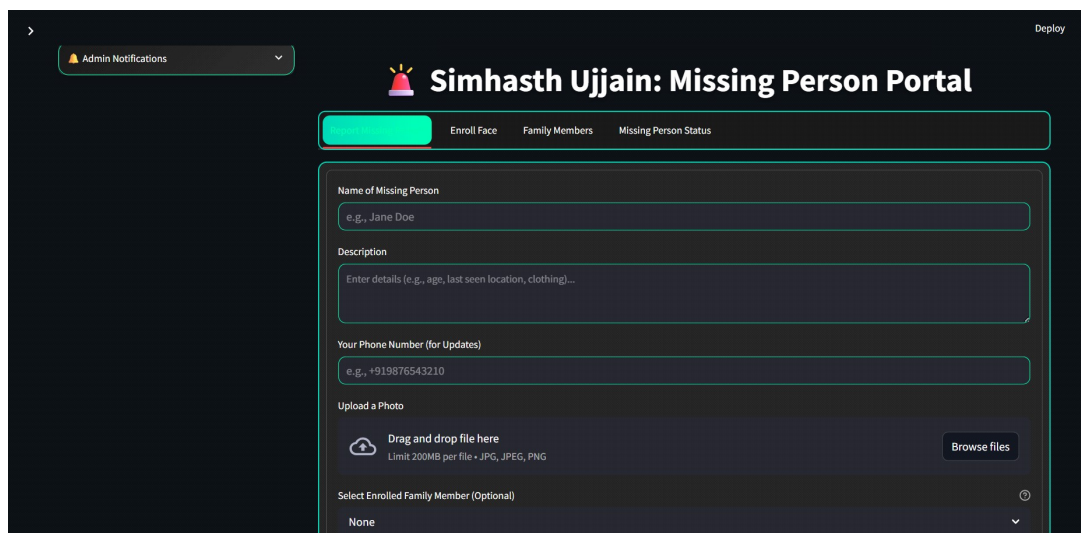


fig 3 user page

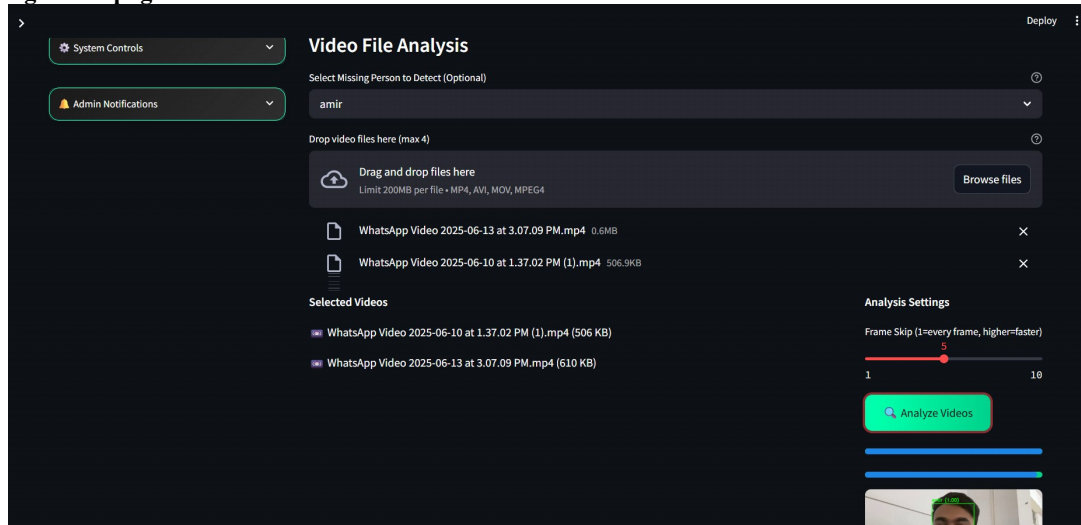


fig4 missing person detection alert send

Design Approach: The system is divided into modular components:

Public Module: Allows missing person reporting, face enrollment, and status checking.

Admin Module: Enables police officers to monitor live feeds, receive alerts, and view reports with detected faces.

Core Processing Module: Handles model inference, database interaction, and image storage. This modular architecture allows scalability and ease of debugging. Each module operates independently, ensuring maintainability and flexibility for future upgrades.

Future Enhancements

While the current implementation demonstrates strong performance in real-time face recognition and missing person tracking, several enhancements can be incorporated to expand its capabilities and resilience in more demanding environments:

3D Face Recognition: Incorporating 3D facial recognition will significantly improve accuracy in complex scenarios involving angled faces, partial occlusion, or inconsistent lighting—conditions commonly observed in dynamic crowd environments.

Aadhaar or National ID Integration: Linking the system with national databases like Aadhaar can streamline identification and verification, ensuring quicker resolution and reducing duplication or false reporting.

Multilingual Voice and Text Alerts: To increase accessibility across diverse populations, future versions can include voice and text notifications in regional languages. This is especially important for events like Simhastha Ujjain which attract people from all parts of India.

Edge Computing Deployment: Integrating edge devices such as NVIDIA Jetson or Raspberry Pi with pre-trained models will reduce latency,

eliminate cloud dependency, and enable scalable deployment across multiple camera nodes.

Federated Learning Support: For enhanced privacy and adaptability, the system could be trained using federated learning models, allowing devices to learn locally and sync periodically without exposing user data.

Emotion and Behavior Recognition: Adding modules to detect distress or abnormal behavior can help preempt security threats or identify individuals who may require immediate assistance.

Cross-Platform Accessibility: Expanding the system for mobile, tablet, and kiosk-based interfaces will improve usability for both the public and law enforcement on the move.

Conclusion

The proposed AI-powered face recognition system provides an efficient and scalable solution for managing missing persons and crowd surveillance at large events like Simhashta Ujjain. Its modular design, real-time recognition using MobileNet, PCA, and KNN, and user-friendly interfaces enhance response times and transparency. Extensive testing confirms its reliability under varied conditions. This system not only meets current public safety needs but also lays the groundwork for future smart city and emergency response applications.

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