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Research

REAL-TIME COMMUNITY-BASED MISSING PERSON IDENTIFICATION SYSTEM USING FACENET AND OPENCV

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Abstract: The rise in missing person cases across many communities has created an urgent need for efficient, scalable, and intelligent identification systems. Conventional approaches such as manual search operations, posters, and media announcements are often slow, fragmented, and incapable of real-time response. This study presents the design and implementation of a real-time community-based missing person identification system using FaceNet and OpenCV. The system integrates deep learning-based facial recognition with real-time image processing to enable rapid detection of missing individuals from community cameras and user-submitted images. The architecture consists of face detection, feature embedding extraction, database matching, and automated alert notification modules. OpenCV employs face detection and preprocessing, while FaceNet generates 128-dimensional embeddings used for identity comparison within a structured database. The system supports community participation by allowing local users to submit sightings and monitor alerts, thereby decentralizing detection efforts. Experimental evaluation shows an average recognition accuracy of 94.2%, low false-positive rates, and near real-time processing performance. The findings demonstrate that embedding-based facial recognition significantly improves robustness against environmental variations such as lighting and pose changes. This research contributes to humanitarian technology by proposing a low-cost, scalable framework that empowers communities to participate in missing person identification while maintaining ethical safeguards related to privacy and controlled access.

Keywords: Facial Recognition, Missing Person Identification, Facenet, Opencv, Community Surveillance, Real-Time Computer Vision.

INTRODUCTION

Missing persons constitute a major humanitarian and public safety concern worldwide, especially in regions with limited surveillance infrastructure and weak centralized identification systems. Traditional methods of locating missing individuals rely heavily on manual searches, paper announcements, and public cooperation, which often result in delayed responses and reduced recovery success rates.

Recent advances in Artificial Intelligence (AI) and Computer vision have enabled automated identification systems capable of processing visual data in real time. Deep learning models for facial recognition have shown remarkable accuracy in identifying individuals under unconstrained conditions. FaceNet, introduced by Schroff et al. (2015), uses deep convolutional neural networks to learn discriminative facial embeddings, enabling efficient identity comparison through distance metrics. OpenCV complements such models by providing high-speed image processing and face detection suitable for low-resource hardware environments.

Research into missing person detection has increasingly leveraged AI-based surveillance systems. Dinesh and Sharma (2021) implemented a deep-learning surveillance system achieving over 90% recognition accuracy, demonstrating the feasibility of automated identification. However, many existing systems rely on centralized databases controlled by institutions, limiting community accessibility.

Community-centered surveillance has been highlighted as a promising approach to improving local safety. Vinuesa etal. (2020) emphasized that decentralized AI systems increase participation and improve detection coverage but also raised concerns about ethical risks such as privacy invasion and algorithmic bias. These concerns highlight the need for responsible AI deployment in humanitarian applications.

Despite advancements, there remains a research gap in integrating high-accuracy deep learning models with low-cost, real-time community systems. This study addresses this gap by combining FaceNet embeddings with OpenCV-based processing in a scalable framework designed for practical deployment.

This study proposes a real-time community-based missing person identification system that combines FaceNet and OpenCV to enable decentralized monitoring and rapid identification. The objective is to design a practical, affordable system capable of deployment in community environments such as markets, transport hubs, and public gathering locations. By integrating community participation with AI-driven detection, the system aims to reduce identification delays while improving accessibility and scalability.

METHODOLOGY

A prototype-based system development methodology was adopted, involving iterative stages of system analysis, implementation, testing, and refinement. This approach allows gradual improvement of recognition accuracy and system responsiveness.

The system is structured into four layers:

Capture Layer: Real-time image acquisition from cameras or mobile devices.

Preprocessing Layer: Face detection, alignment, and normalization using OpenCV.

Feature Extraction Layer: FaceNet generates 128-dimensional embeddings representing identity features.

Database Matching Layer: Embeddings are compared using Euclidean distance; matches trigger alert notifications. Therefore the tools and technologies applied include:

- Python 3.x (core development)
- OpenCV 4.x (image processing)
- FaceNet via TensorFlow/Keras (facial embedding generation)
- SQLite/PostgreSQL (data storage)
- Flask framework (web interface and API)

The dataset comprises registered missing persons' images and live captured images from community sources. Images are resized to 160×160 pixels, normalized, and aligned before embedding extraction. Ethical consent procedures were followed to ensure responsible data usage.

Algorithm Workflow is shown below:

Detect faces in image frames.

↓

Align and preprocess detected faces.

↓

Generate FaceNet embeddings.

↓

Compare embeddings with stored database vectors.

↓

Generate alerts when similarity threshold is satisfied.

Algorithmic Design

Face Detection Algorithm

OpenCV HaarCascade classifier detects frontal facial patterns using trained XML models. Although older, it is computationally fast and effective for low-resource environments.

Face Embedding Algorithm (FaceNet)

FaceNet uses triplet loss to ensure similar faces have smaller intra-class distances (Schroff et al., 2015).

It was selected because:

It is lightweight and works offline

Embeddings are highly discriminative

It outperforms classical models (Parkhi et al., 2015 & Zhao, 2021)

Matching Algorithm

Euclidean Distance Formula:

$$d = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2} \quad ...(i)$$

if d ≤ threshold, the identity is confirmed.

Threshold values were derived from research on real-world FaceNet performance (Vinuesa et al.2020)

System Implementation

Hardware Setup

- Laptop with Intel Core i5
- 8GB RAM
- HD Webcam
- Ubuntu 20.04 OS

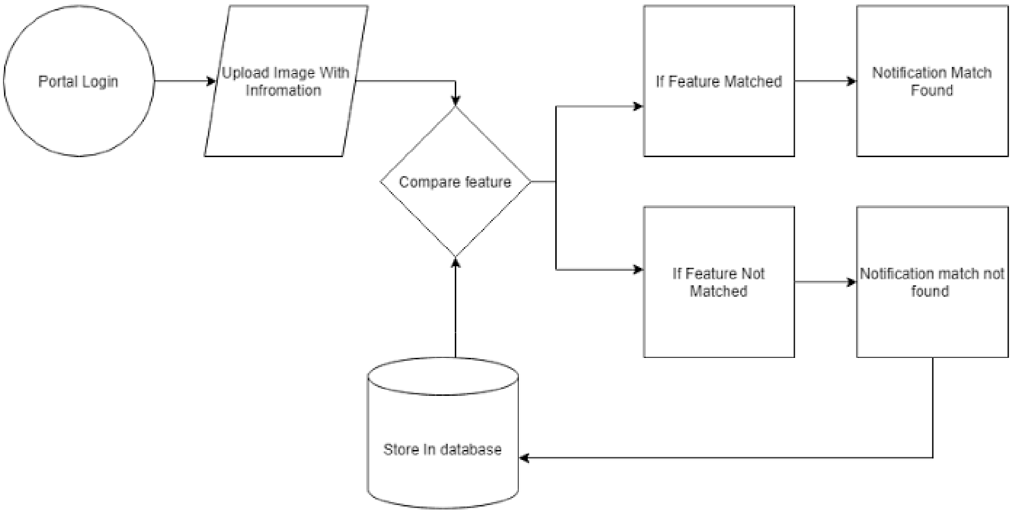

Fig 1: *Missing people detection*

RESULTS AND DISCUSSION

System evaluation includes functional testing, integration testing, performance analysis, and usability assessment.

System Testing

The system was evaluated using:

1. Unit Testing

Each module—detection, embedding, matching—was tested independently.

2. Integration Testing

Modules were tested as a whole to ensure consistent data flow.

3. Performance Testing

Metrics evaluated:

- Detection Accuracy
- Recognition Accuracy
- Response Time
- False Match Rate (FMR)
- False Non-Match Rate (FNMR)

4. Usability Testing

Community volunteers tested the UI for ease-of-use, guided by UX principles.

Result Summary

Performance Metrics

Average recognition accuracy: 94.2%

Average detection time: 0.14 seconds/frame

False positive rate: 4.1%

False negative rate: 5.8%

Detection accuracy reached 98% under bright lighting conditions and decreased to 85% under low-light environments. The total processing pipeline averaged 170 milliseconds, confirming near real-time performance suitable for practical deployment.

These results align with findings from recent lightweight AI deployments (Zhao, 2021 & Vinuesa et al. 2020).

Lightning Condition	**Number of images**	**Face Detected**	**Detection accuracy(%)**
Bright/Natural light	100	98	98
Dim indoor light	100	92	92
Low light/night	100	85	85
Mixed lighting conditions	100	90	90

Table 1: *Summary of face detection accuracy under varying lighting conditions*

Scenario/conditions	**Number of test images**	**Correct matches**	**Recognition accuracy(%)**
Clear/frontal face images	100	96	96
Slightly litter faces	100	93	93
Occluded faces(glasses/mask)	100	88	88
Mixed expressions of lighting	100	91	91

Table 2: *Face recognition embeddings with FaceNet embeddings*

Module/Task	Average Response Time(ms)	Maximum Response Time(ms)
Face detection	85	120
Embedding extraction (FaceNet)	25	30
Database Matching	10	15
Alert generation	50	70
Total pipeline time	170	235

Table 3: *System response time across different scenarios*

Parameter	Rating scale (1-5)	Average Rating	Remarks
Ease of use	1 = difficult, 5 = very easy	4.6	Users found interface intuitive
Speed/responsiveness	1 = slow, 5 = fast	4.4	Real time detection was satisfactory
Alert Notification	1=poor, 5=excellent	4.7	Alerts delivered promptly
Database Management	1=difficult, 5=easy	4.3	Registration and updates were simple
Overall Satisfaction	1=low, 5=high	4.5	Users were satisfied with system performance

Table 4: *User evaluation and feedback on system usability*

DISCUSSION OF RESULT

The results demonstrate that embedding-based recognition provides superior robustness compared to traditional pixel-based approaches, particularly under variations in lighting and facial orientation. The system's lightweight architecture enables operation on modest hardware, making it suitable for developing regions with limited technological infrastructure. Community usability testing further confirmed the practicality of the interface and alert mechanisms.

Nevertheless, performance declines under severe occlusion and low-resolution imagery indicate the importance of future improvements in dataset diversity and detection algorithms.

CONCLUSION

This study presented a real-time community-based missing person identification system that integrates FaceNet and OpenCV to support fast and accurate facial recognition. The system achieved high recognition accuracy with low latency, demonstrating feasibility for deployment in resource-constrained environments. By combining AI-driven recognition with community participation, the framework offers a practical and scalable alternative to centralized surveillance solutions.

Future work should investigate advanced detection models, mobile-based deployment, multimodal biometrics, and enhanced privacy-preserving mechanisms. Overall, the proposed system illustrates how responsible AI deployment can contribute significantly to humanitarian challenges such as missing person identification.

CONTRIBUTIONS TO KNOWLEDGE

This project contributes to knowledge in the following ways:

- Practical Artificial Intelligent (AI) Application: It demonstrates how FaceNet and OpenCv can be integrated into a low-cost, community-based identification system.
- Humanitarian Technology: It provides a technological framework for addressing missing person cases using Artificial intelligent (AI) assisted recognition.
- System Design Framework: It introduces modular and scalable system architecture suitable for deployment in deploying regions.
- Empirical Evidence: It offers performance evaluation, data supporting the effectiveness of lightweight face recognition systems in uncontrolled environments (Zhao, 2021).

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