



FaceTrace: An AI-Based Facial Recognition Framework for Efficient Missing Person Identification

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Abstract: Proliferation of cases of missing persons around the world with grave humanitarian considerations are at times made worse by the impotence of old ways of searching, hard work being put into rummaging through documents, public announcements, and putting posters up. Our approach using AI involves deep-learning face recognition for rapid and improved identification of missing persons. The framework integrates OpenCV and dlib-ResNet algorithms to achieve highly accurate near-real-time face matching using Euclidean distance of 128-dimensional face embeddings. The front end of the user interface is designed in React.js while the back end uses Node.js and Express.js, and the underlying scalable data management is supported by MongoDB. The system uses the WhatsApp Business API for sending real-time alerts, magnifying citizen-family-government collaboration. Performance evaluation based on accuracy, precision, recall, and F1 score was conducted using benchmark datasets. FaceTrace ensures scalability, quick delivery, and data security through cloud-based hosting, enabling an expedited community-driven intelligent missing persons recovery process.

Index Terms: Facial Recognition, Deep Learning, Missing Person Identification, OpenCV, dlib-ResNet, MongoDB, WhatsApp API, Artificial Intelligence.

I. INTRODUCTION

The conditions that make or unmake a life for persons declared missing have become a major humanitarian challenge across the globe. Accepted customs for identifying missing persons — manual checks, poster distribution, and public announcement systems — are slow, inefficient, and emotionally burdensome to families [20], [32], [33]. In contrast, based on fast developments in Artificial Intelligence (AI) and Deep Learning (DL), an automatic face recognition process offers a promising alternative to speed up recovery and enhance identification accuracy [1],[2],[3].

Earlier face recognition methods based on statistical models such as Eigenfaces [19] and Fisherfaces performed well in controlled environments but generalize poorly under illumination, pose, and age variations [16]. The advent of deep convolutional neural networks revolutionized this field, enabling end-to-end feature extraction and representation generation [12][13]. Key architectures such as DeepFace [2], FaceNet [1], VGGFace [4], and ArcFace [3] set high standards by mapping facial images into discriminative feature spaces with near-human-level accuracy. Their embeddings allow clustering, verification, and retrieval even in unconstrained environments [8][9][25].

Further advances through multi-task networks such as MTCNN [5] and RetinaFace [6] combine face detection and alignment for enhanced preprocessing. Improvements like CosFace [11], SphereFace [10], and InsightFace [25] refine loss functions and feature normalization to provide intra-class compactness while maximizing inter-class separation — especially important for missing persons detection across age and expression variation [16],[17],[31].

Ethical and legal considerations regarding facial recognition are also prominent in the literature. Issues of privacy, dataset bias, and fairness have been raised [18],[27]-[30], with frameworks emphasizing transparency, consent, and explainability — especially when facial data are used for humanitarian or law enforcement purposes [29],[30]. FaceTrace builds upon these advances to deliver AI into social good through fast, accurate, and transparent identification of missing persons.

II. LITERATURE REVIEW

Over the past three decades, facial recognition technology has evolved from hand-constructed algorithms into modern deep learning models that allow large-scale real-time identification. This section summarizes prior work across five areas: classical face recognition, deep learning advances, pre-processing and detection frameworks, robustness and re-identification studies, and ethical debates.

A. Classical Techniques of Face Recognition

Earlier recognition systems used statistical techniques such as Eigenfaces [19] and Fisherfaces [21] to reduce data dimensionality and extract distinguishing facial features via principal component analysis. While rapid, these methods were not robust under uncontrolled pose, illumination, or expression changes, and could not scale for real identification tasks due to reliance on handcrafted, noise-sensitive features [23].

B. Face Recognition Using Deep Learning

CNNs changed the face recognition paradigm by learning high-level visual features directly from raw pixels [12][13]. Architectures such as DeepFace [2] and FaceNet [1] integrated triplet loss functions for near-human-level accuracy. VGGFace [4], VGGFace2 [14], and ArcFace [3] further pushed limits through margin-based loss optimization. SphereFace [10] and CosFace [11] introduced angular-margin-based classification, enhancing generalization over large-scale datasets like LFW, MegaFace, and VGGFace2 [8][9][14], forming the basis of real-time systems for law enforcement and humanitarian applications [20][32].

C. Pre-Processing, Detection, and Dataset Fusion

Exact preprocessing and accurate facial alignment are crucial for recognition performance. MTCNN [5] and RetinaFace [6] treat face detection and landmark localization as a joint task, enabling standardized cropping and alignment. Dlib-ResNet [7], an open-source toolkit, became standard for generating robust 128-dimensional embedding vectors resilient to lighting and viewpoint variation. Large-scale benchmark datasets including LFW [9], MegaFace [8], and VGGFace2 [14] enable training and evaluation under unconstrained conditions, while InsightFace [25] provides a scalable 2D and 3D recognition toolkit.

D. Robustness, Re-Identification, and Applications for Missing Persons

Recent research demonstrated robustness under occlusion, low resolution, and cross-age conditions [16],[17]. Zeng et al. [16] improved occlusion handling through attention-based augmentation, while Deb et al. [31] addressed age-progressive identification for missing children. Deep Siamese and transformer-based networks have shown superior performance in person re-identification across cameras [22],[33],[34]. Practical implementations, such as the AI-based missing person system by Monga and Sharma [20] and the mobile reporting platform by Magendiran et al. [32], demonstrate how deep learning can serve humanitarian goals.

E. Ethical, Privacy, and Social Issues

Privacy, bias, and ethics remain prominent research areas amid the proliferation of biometric technologies. Researchers have raised issues around model inversion, data misuse, and algorithmic bias against different demographic groups [27],[28]. Schröder et al. [29] addressed transparency and explainability requirements for face recognition systems, while the Pew Research Center [30] documented public concerns about surveillance misuse. Modern systems must incorporate fairness-aware learning, consent-tracked data management, and strong encryption to maintain ethical integrity in sensitive applications such as missing persons searches.

III. PROBLEM DEFINITION

Historic methods for locating and recovering missing persons — including poster distribution, police record examination, and manual face matching — remain slow, error-prone, and disconnected [20],[32],[33]. These processes fail to coordinate real-time support among law enforcement agencies, the general public, and other bodies, meaning delays can eliminate chances of recovery [31],[35]. The absence of a centralized, automated framework leads to duplication of efforts, loss of relevant data, and lack of reporting uniformity across jurisdictions.

Even existing digital tools face significant technical limitations. Image-based searches fail under poor illumination, occlusions, pose variation, and other conditions known to impair recognition performance [16],[17]. Demographic bias, aging effects, and photographic data variability further impede reliable identification [18],[29]. Without large datasets, strong deep learning models, and adaptive computer vision pipelines, existing systems cannot perform reliably in real-life scenarios.

Ethical, privacy, and security concerns related to biometric data remain important impediments to widespread adoption of facial recognition systems [27]-[30]. Most existing alternatives lack secure storage arrangements or transparent consent frameworks, engendering distrust. There is therefore an urgent need for an intelligent, unified, and ethically governed platform that integrates deep learning-based face recognition with cloud data management and real-time alert systems to enhance both detection accuracy and operational efficiency.

IV. RESEARCH OBJECTIVE

The objective of this research is to define an intelligent and ethically accountable framework using deep learning facial recognition to effectively improve accuracy and reliability of missing persons identification. The research proposes to close existing gaps by embedding computer vision techniques, AI automation, and cloud-based data management into one scalable integrated platform for real-time applicability.

The algorithm will use facial recognition architectures such as FaceNet, ArcFace, and Dlib-ResNet to generate discriminative 128-dimensional facial embeddings that allow accurate similarity comparisons even under occlusion, aging variation, or illumination change [1,3,6,16]. The research particularly aims to:

- (1) Develop a common secure database holding personal information, case details, and facial embeddings for speedy retrieval and comparison.
- (2) Develop a deep learning-based face recognition engine using CNN architectures like Dlib-ResNet and ArcFace for feature extraction and matching.
- (3) Create a user-friendly web and mobile interface through React.js, Node.js, and MongoDB for citizens and authorities to report cases, provide sighting information, and track case status.
- (4) Integrate real-time communication using the WhatsApp Business API for alerts and notifications on potential matches.
- (5) Address ethical considerations including data protection, consented data collection, and transparency following responsible AI principles [27]-[30].
- (6) Validate system performance in terms of accuracy, precision, recall, F1 score, and latency to confirm real-time response.

FaceTrace is intended to serve as a paradigm for AI as an agent of empathy and equity — revising technology in important social applications to support humanity.

V. PROPOSED METHODOLOGY

The FaceTrace system is designed to mechanize and accelerate detection of missing persons using a deep learning-based facial recognition model. It follows a sequential modular architecture offering scalability, accuracy, and real-time operation. As illustrated in Figure 1, the system comprises six operating phases: Report Submission, Backend Processing, Public Photo Upload, Face Recognition and Matching, Admin Validation, and Result Notification.

A. User Report Submission

A registered user or relative of a missing person files a report on FaceTrace, providing essential demographic information including name, age, sex, physical description, last-seen location, and new facial images as references for future comparisons. This submission is transmitted securely to the backend system for processing.

B. Backend Processing

Once a report is submitted, uploaded images are processed through the Dlib-ResNet facial extraction module, which creates 128-dimensional facial embeddings. These unique identity features are stored along with case details in the MongoDB database for future matching. The backend continuously indexes embeddings to enable efficient retrieval and comparison.

C. Public Image Upload

Citizens can upload photos of persons they believe resemble missing individuals, expanding the search effort. All uploaded photos undergo the same preparatory steps including conversion into face embeddings. These, along with metadata such as time and place, are made available in the backend for comparison against existing missing person embeddings.

D. Face Recognition and Matching

The Face Recognition Module compares uploaded "found person" image embeddings against those in the database using Euclidean distance — a lower distance indicates greater similarity. If similarity exceeds a predefined threshold (0.80), the record is flagged as a possible match and displayed on the admin dashboard. This comparison methodology reduces human interference and boosts identification efficacy.

E. Admin Validation and Notification

Flagged matches are handled at the admin dashboard, which displays candidate matches with confidence scores and metadata. The admin may confirm or reject possible matches based on accuracy and additional data. Once verified, an automatic notification is sent through the WhatsApp Business API or email to the reporting family and relevant authorities, along with matched photo, timestamp, and location details.

VI. ALGORITHM DESIGN

The FaceTrace algorithm is designed for automated identification of missing persons through deep learning-based facial recognition. The complete preprocessing, embedding extraction, matching, and alerting pipeline is designed for a real-time, scalable system.

Missing Person Identification Algorithm Based on Facial Recognition:

Step 1 — Report Submission: User submits missing person details along with an image via the web or mobile application.

Step 2 — Embedding Generation: The image is preprocessed in OpenCV, after which Dlib-ResNet creates 128-dimensional facial embeddings.

Step 3 — Database Storage: Embeddings and associated metadata are stored in MongoDB in encrypted format for indexing.

Step 4 — Public Upload: Citizens upload images of found persons; these undergo the same preprocessing and embedding generation steps.

Step 5 — Matching: The Euclidean distance (d) between embeddings is calculated; if $d \leq T$ (threshold), a possible match is flagged.

Step 6 — Admin Validation: Matches are shown on the admin dashboard for confirmation of valid identifications.

Step 7 — Notification: Families and authorities are notified via the WhatsApp API.

Step 8 — Validation: System performance is evaluated using accuracy, precision, recall, and F1-score metrics.

VII. RESULTS AND DISCUSSION

The FaceTrace system was evaluated for efficiency, accuracy, and general feasibility in detecting missing persons. Testing was conducted on 10,000 facial images captured under varying illumination, angles, and expressions. The Dlib-ResNet model generated embeddings, while Euclidean distance served as the comparison metric.

The system demonstrated strong recognition accuracy and stability across repeated tests with diverse scenarios. Image normalization and background correction techniques enhanced feature extraction quality. The Node.js and MongoDB backend enabled effective data storage and retrieval, while the WhatsApp API ensured real-time alerts to concerned users and authorities.

The algorithm achieved accuracy of 96.8%, precision of 94.5%, and recall of 92.7%, confirming reliable matching capability under varied input conditions. The average response time of approximately 2.8 seconds confirms feasibility for real-time deployment. Table 1 summarizes these performance results.

Table 1: Performance Evaluation of the FaceTrace System

Parameter	Metric Used	Result (%) / Value	Remarks
Accuracy	Correctly identified faces / Total test	96.8%	High recognition reliability
Precision	TP/(TP+FP)	94.5%	Low false match rate
Recall	TP/(TP+FN)	92.7%	Effective retrieval of actual matches
F1-Score	Harmonic mean of Precision & Recall	93.6%	Balanced performance
Response Time	Average time per match	2.8 sec	Real-time efficiency
Dataset Size	Total images tested	10,000	Strong validation scope

The results confirm that FaceTrace is a robust and effective tool for missing person identification. The precision-recall balance (F1-score: 93.6%) minimizes false positives while retaining high sensitivity. The modular architecture supports ease of scalability and integration with law enforcement databases. Deep-learning-based embeddings accurately handle complex face variations, and the experimental outcomes confirm that FaceTrace addresses all critical goals of speed, accuracy, and reliability.

VIII. CONCLUSION

FaceTrace is an efficient, novel, and socially useful system for missing person identification using state-of-the-art deep learning-based facial recognition. It stitches together Dlib-ResNet embeddings with Euclidean distance-based matching and a real-time notification mechanism to cut down search time and effort. Experimental results yield recognition accuracy exceeding 96%, affirming robustness and reliability under diverse imaging conditions.

FaceTrace's modular design brings scalability, security, and adaptability, allowing smooth integration with existing law enforcement and public databases. MongoDB enables effective data management and the WhatsApp API ensures real-time alert notifications. The system adheres to ethical norms and data privacy requirements, making it applicable to real-world humanitarian situations.

Future directions include adoption of better CNN architectures, aging study models, and cross-age facial recognition, as well as integration with IoT-based surveillance systems and blockchain-enabled data integrity architectures for a secure and automated operational mode.

In summary, FaceTrace provides a concrete base upon which artificial intelligence can lend a hand to humanity, accelerating missing persons identification through an intelligent and human-centered technological framework.

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