iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL
FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 Issue: IV Month of publication: April 2026

DOI: https://doi.org/10.22214/ijraset.2026.81037

# A Comparative Multi-Model Approach for Enhancing Missing Person Identification using AI-Based Face Recognition

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***Abstract: The rising number of missing person cases presents a critical challenge for law enforcement agencies, where traditional identification methods are often time-consuming, manual, and prone to human error. With the advancement of Artificial Intelligence (AI) and Computer Vision, automated face recognition systems have emerged as a promising solution for identifying individuals from images and video data. However, the effectiveness of these systems is often affected by variations in lighting conditions, facial orientation, image quality, and algorithmic limitations, leading to inconsistent performance. This paper proposes a comparative multi-model approach to enhance missing person identification by integrating and evaluating multiple face recognition techniques, including Haar Cascade classifiers, MediaPipe-based facial landmark extraction, and deep learning-based feature embedding models. The system processes facial data through these models and compares their performance under different environmental conditions to assess accuracy, robustness, and computational efficiency. A structured experimental framework is implemented to evaluate each technique using metrics such as recognition accuracy, precision, and processing time. The analysis demonstrates that deep learning-based methods provide superior accuracy, whereas lightweight models offer faster execution, revealing important trade-offs between performance and efficiency. Additionally, a hybrid multi-model strategy is proposed to leverage the strengths of individual approaches, improving overall system reliability and adaptability. The proposed work contributes to the development of an intelligent and scalable missing person identification system, capable of assisting law enforcement agencies and public platforms in real-world scenarios. By combining system implementation with comparative analysis, this study bridges the gap between theoretical research and practical deployment of AI-driven face recognition systems.***

***Keywords: Artificial Intelligence, Face Recognition, Missing Person Identification, Computer Vision, Deep Learning, MediaPipe, Haar Cascade, Multi-Model System, Image Processing, AI-Based Surveillance.***

## I. INTRODUCTION

The rapid advancement of Artificial Intelligence (AI) and Computer Vision has significantly transformed the way complex real-world problems are addressed. AI-driven systems are now capable of analyzing large volumes of data, identifying patterns, and making intelligent decisions with minimal human intervention. Among the many domains benefiting from these advancements, public safety and law enforcement have seen notable improvements through the integration of automated recognition and surveillance technologies.

One of the most pressing societal challenges is the increasing number of missing person cases reported every year. Individuals go missing due to various reasons such as accidents, human trafficking, natural disasters, or mental health conditions. Locating these individuals in a timely manner is critical, yet traditional methods—such as manual investigation, distribution of posters, and analysis of surveillance footage—are often slow, labor-intensive, and inefficient. The vast amount of visual data generated from public sources further complicates the identification process, making manual approaches impractical and error-prone.

To address these challenges, face recognition technology has emerged as a powerful tool within AI-based systems. By leveraging image processing and machine learning techniques, face recognition systems can detect, extract, and compare facial features from images or video streams to identify individuals. These systems have the potential to significantly reduce the time required for identification and improve accuracy in large-scale search operations. Consequently, they are increasingly being adopted in applications such as surveillance systems, identity verification, and missing person tracking.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue IV Apr 2026- Available at www.ijraset.com

However, despite these advancements, existing face recognition systems often suffer from inconsistent performance in real-world scenarios. Variations in lighting conditions, facial orientation, image resolution, occlusions, and environmental noise can significantly impact recognition accuracy. Additionally, different algorithms exhibit varying strengths and limitations—while some models offer faster processing, others provide higher accuracy at the cost of computational complexity. This inconsistency highlights the need for a more robust and adaptable approach to face recognition in missing person identification systems.

In response to these challenges, this paper proposes a comparative multi-model approach that evaluates and integrates multiple face recognition techniques to enhance identification accuracy and system reliability. The objective of this study is threefold:

1) To analyze and compare the performance of different face recognition models under varying real-world conditions.
2) To identify the trade-offs between accuracy, speed, and robustness across these techniques.
3) To propose a hybrid multi-model strategy that improves the overall effectiveness of missing person identification systems.

By combining experimental analysis with system-level implementation, this work aims to contribute toward the development of a more reliable, scalable, and intelligent AI-based solution for missing person identification.

## II. LITERATURE REVIEW

### *A. Face Recognition Techniques*

Face recognition has undergone significant evolution, progressing from traditional image processing techniques to advanced deep learning-based approaches. Early methods such as the Haar Cascade classifier, introduced by Viola and Jones, rely on handcrafted features and integral image representations for real-time face detection [1]. While computationally efficient, these approaches are sensitive to variations in illumination, pose, and occlusion, limiting their effectiveness in uncontrolled environments [2].

Subsequently, Machine Learning (ML)-based techniques such as Principal Component Analysis (PCA), Support Vector Machines (SVM), and K-Nearest Neighbors (KNN) were introduced to improve classification performance [3]. These methods utilize feature extraction and statistical learning to recognize facial patterns, offering better accuracy than traditional approaches. However, their performance is still constrained by limited feature representation and poor generalization in large-scale or complex datasets [4].

Recent advancements in Deep Learning have revolutionized face recognition systems. Convolutional Neural Networks (CNNs) and embedding-based models such as FaceNet and DeepFace enable high-dimensional feature representation, significantly improving recognition accuracy [5][6]. These models demonstrate robustness against variations in lighting, facial orientation, and expressions. However, they require large datasets, high computational resources, and careful model tuning, which can be challenging for real-time or resource-constrained applications [7].

### *B. AI in Missing Person Systems*

Artificial Intelligence has been increasingly integrated into missing person identification systems to automate and enhance the search process. Existing systems typically involve uploading images of missing individuals, followed by face detection, feature extraction, and matching against stored databases [8]. These systems leverage computer vision and machine learning algorithms to reduce manual effort and accelerate identification.

Several studies have explored the use of AI in surveillance systems, where facial recognition models analyze CCTV footage to identify potential matches in real time [9]. Such systems significantly improve efficiency and scalability compared to traditional approaches. Additionally, web-based platforms and public participation models have been proposed to crowdsource data and improve detection rates [10].

These advancements, most existing systems rely on a single face recognition model, which limits adaptability across diverse environmental conditions. This lack of flexibility often results in inconsistent performance, particularly in real-world scenarios involving varied lighting, pose, and image quality [7][11].

### *C. Limitations of Existing Approaches*

Although face recognition systems have achieved considerable success, several limitations persist. One of the primary challenges is sensitivity to environmental factors such as lighting conditions, shadows, and image resolution. Poor-quality images or low-light environments can significantly degrade detection and recognition accuracy [2][7].

Another critical limitation is dataset dependency. The performance of AI models is heavily influenced by the size, diversity, and quality of training datasets. Insufficient or biased datasets can lead to poor generalization and inaccurate predictions [6][12]. Additionally, real-world scenarios often involve occlusions (e.g., masks, glasses), facial aging, and pose variations, which further complicate recognition tasks [4].

Furthermore, there exists a trade-off between computational efficiency and accuracy. Lightweight models such as Haar Cascade provide fast processing but lower accuracy, whereas deep learning models achieve higher accuracy at the expense of increased computational cost and latency [5][7]. These limitations highlight the need for more adaptive and robust solutions.

### *D. Research Gap*

While extensive research has been conducted on face recognition and AI-based identification systems, several gaps remain. Most studies focus on individual algorithms without performing a comprehensive comparative analysis across multiple techniques under varying real-world conditions [7][11].

There is also a lack of systematic robustness evaluation, particularly in scenarios involving changes in lighting, image quality, and facial orientation. Existing systems rarely analyze how different models perform under these conditions, leading to limited insights into their practical applicability.

Moreover, current research lacks the integration of multi-model approaches that combine the strengths of different techniques. A hybrid system capable of leveraging both lightweight and deep learning models could potentially improve accuracy, efficiency, and adaptability.

Therefore, this study addresses these gaps by proposing a comparative multi-model framework that evaluates multiple face recognition techniques and introduces a hybrid approach to enhance missing person identification systems.

## III.METHODOLOGICAL FRAMEWORK FOR SYSTEMATIC REVIEW

### *A. Scope and Design*

This study focuses on evaluating and enhancing the performance of AI-based face recognition systems for missing person identification through a comparative multi-model approach. The primary objective is to analyze how different face recognition techniques perform under varying real-world conditions such as lighting, image quality, and facial orientation.

The proposed framework compares three categories of models:

- Traditional approach: Haar Cascade for face detection
- Landmark-based approach: MediaPipe for facial feature extraction
- Deep learning approach: FaceNet (or similar embedding-based model) for high-accuracy recognition

Each model is tested using a structured experimental setup to evaluate performance metrics such as accuracy, precision, and processing time. The study further explores the feasibility of integrating these models into a unified system to improve robustness and adaptability.

### *B. System Architecture*

The proposed system is designed as a modular pipeline that processes input images through multiple stages of detection, feature extraction, and matching. The architecture ensures scalability and flexibility by allowing the integration of multiple face recognition models within a single framework.

1. Input Layer

The system accepts image data from users or databases, including photographs of missing persons or unidentified individuals. These images may vary in resolution, lighting conditions, and orientation.

2. Processing Layer

The input images undergo preprocessing steps such as resizing, normalization, and noise reduction to ensure consistency and improve detection accuracy.

3. Model Layer

The processed images are passed through multiple face recognition models:

- Haar Cascade for initial face detection
- MediaPipe for facial landmark extraction
- Deep learning model (FaceNet) for generating feature embeddings

Each model independently processes the input and produces feature representations or detection outputs.

4. Matching and Decision Layer

Extracted features are compared with stored database entries using similarity measures such as Euclidean distance. The system identifies the best match based on similarity scores.

5. Output Layer

The final output displays the matched individual along with relevant details such as similarity score and confidence level. The system may also present results from multiple models for comparative analysis.

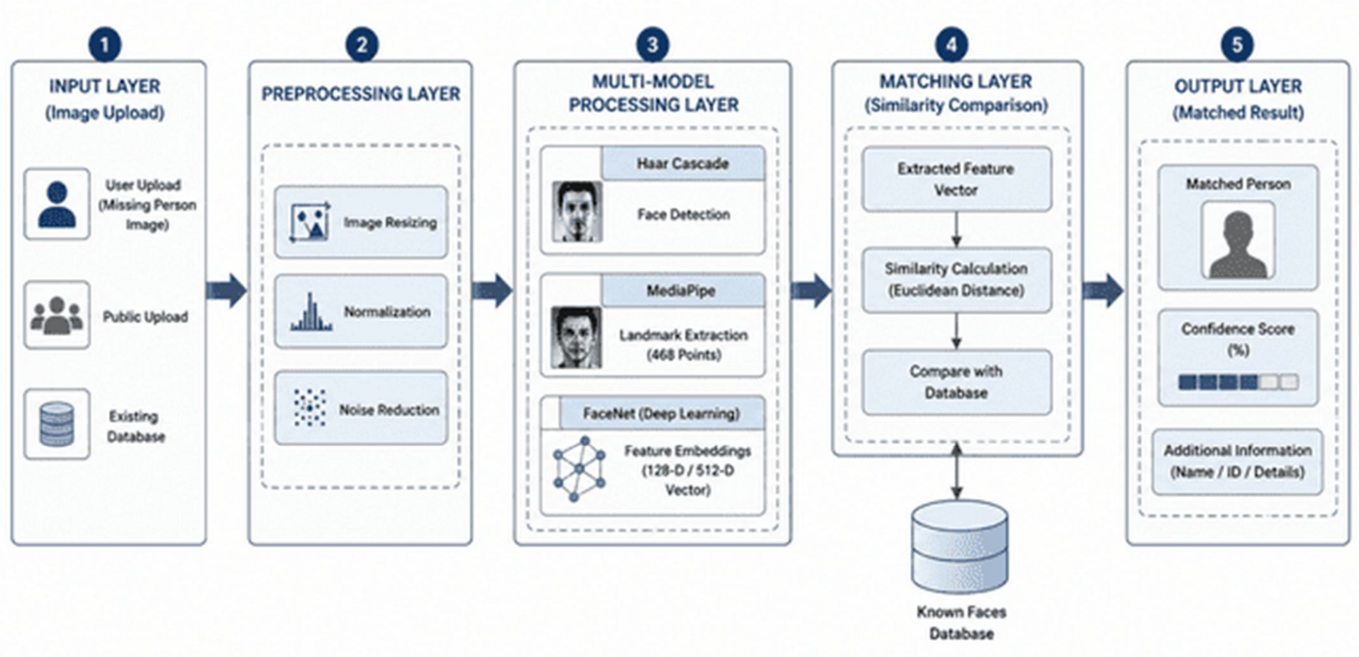


Fig. 1 System architecture of AI-based identification system

## C. Analytical Dimensions for Model Evaluation

To ensure a structured and comparative evaluation of different face recognition techniques, this study defines multiple analytical dimensions. These dimensions help assess the performance, robustness, and efficiency of each model under real-world conditions.

TABLE I
ANALYTICAL DIMENSIONS FOR FACE RECOGNITION EVALUATION

| Dimension | Focus |
|---|---|
| Model Type | Traditional (Haar), Landmark-based (MediaPipe), Deep Learning (FaceNet) |
| Accuracy Metrics | Recognition Accuracy, Precision, Matching Score |
| Robustness | Performance under lighting, angle, and occlusion variations |
| Computational Efficiency | Processing Time, Resource Utilization |
| Scalability | Ability to handle large datasets and real-time scenarios |

## D. Experimental Setup

A structured experimental setup is designed to evaluate the performance of different models under controlled and real-world conditions. The system is implemented using Python with libraries such as OpenCV and MediaPipe, along with a deep learning model for feature embedding.

The evaluation is conducted on a dataset consisting of facial images with variations in lighting, orientation, and resolution. Each model processes the same set of images to ensure fair comparison.

## E. Evaluation Metrics

The performance of each face recognition technique is measured using the following metrics:

- Recognition Accuracy (RA): Percentage of correctly identified faces
- Precision (P): Ratio of correct positive matches to total predicted matches
- Processing Time (PT): Time taken to process each image

- Robustness Score (RS): Performance consistency under varying conditions

These metrics provide a comprehensive understanding of both effectiveness and efficiency.

### *F. Evaluation Approach*

Each model is evaluated independently and comparatively using the defined metrics. The process includes:

1. Inputting test images into the system
2. Processing images through each model
3. Extracting facial features and performing matching
4. Recording performance metrics
5. Comparing results across models

Where numerical results are obtained, performance improvements are analyzed in percentage terms to highlight differences between models. This comparative approach enables identification of strengths and weaknesses of each technique.

## IV. PROPOSED SYSTEM & METHODS

### *A. LFace Detection Techniques*

Face detection is the initial step in the proposed system, responsible for identifying and localizing faces within input images. Two complementary techniques are employed to improve detection robustness:

- Haar Cascade Classifier:
  The Haar Cascade method is a traditional object detection technique based on Haar-like features and a cascade of classifiers. It is computationally efficient and suitable for real-time detection. However, its performance is sensitive to variations in lighting and pose, which can lead to missed detections in complex environments.
- MediaPipe Face Detection:
  MediaPipe provides a modern, lightweight framework for real-time face detection and landmark estimation. It is capable of detecting faces with higher stability under moderate variations in pose and lighting. Compared to Haar Cascade, MediaPipe offers improved consistency and integration with subsequent landmark-based feature extraction.

The combination of these methods allows the system to balance speed and reliability during the face detection phase.

### *B. Deep Learning Model*

To achieve high-accuracy face recognition, the proposed system incorporates a deep learning-based model such as FaceNet. FaceNet uses a convolutional neural network to generate compact and discriminative feature embeddings for each detected face.

Instead of directly classifying faces, FaceNet maps facial images into a high-dimensional embedding space, where similar faces are positioned closer together and dissimilar faces are placed farther apart. This approach enables efficient comparison using distance-based metrics and improves recognition performance in unconstrained environments.

### *C. Feature Extraction*

Feature extraction plays a critical role in transforming raw facial images into meaningful numerical representations. The proposed system utilizes two types of feature extraction techniques:

- Landmark-Based Features (MediaPipe):
  MediaPipe extracts a set of facial landmarks (e.g., eyes, nose, lips, jawline), which are converted into structured feature vectors. These landmarks capture geometric relationships and are useful for lightweight matching.
- Embedding-Based Features (Deep Learning):
  The deep learning model generates high-dimensional feature vectors (embeddings) that encode complex facial characteristics. These embeddings provide a more robust and discriminative representation compared to traditional features.

By combining geometric and deep feature representations, the system enhances its ability to handle variations in facial appearance.

### *D. Matching Algorithm*

The matching process involves comparing the extracted feature vectors of the input image with those stored in the database. The system employs the Euclidean distance metric to measure similarity between feature vectors.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue IV Apr 2026- Available at www.ijraset.com

A lower Euclidean distance indicates a higher similarity between two faces. If the distance falls below a predefined threshold, the system considers it a match. This approach enables efficient and scalable comparison across large datasets.

The matching algorithm ensures consistent performance across different models by applying the same similarity metric, allowing fair comparison during evaluation.

### *E. Multi-Model Strategy*

The key contribution of this work lies in the implementation of a **multi-model strategy** that integrates and compares multiple face recognition techniques within a unified framework.

Instead of relying on a single model, the proposed system evaluates the performance of:

- Haar Cascade (fast but less robust)
- MediaPipe (balanced performance)
- Deep Learning model (high accuracy but computationally intensive)

This comparative approach enables the identification of strengths and limitations of each technique under different conditions.

Furthermore, a hybrid strategy is proposed, where:

- Lightweight models are used for quick initial detection
- Deep learning models are applied for final verification

This combination improves overall system accuracy while maintaining efficiency. By leveraging the complementary strengths of multiple models, the proposed approach enhances robustness, reduces false matches, and adapts effectively to real-world scenarios.

## V. EXPERIMENTAL ANALYSIS

### *A. Dataset Description*

The experimental evaluation is conducted using a dataset consisting of facial images collected from multiple sources, including publicly available datasets and user-uploaded samples. The dataset contains images of individuals under varying real-world conditions to simulate practical scenarios encountered in missing person identification systems.

The dataset includes:

- Frontal and side-face images
- Images with different lighting conditions (indoor, outdoor, low-light)
- Variations in image resolution and quality
- Faces with occlusions such as glasses or partial obstruction

A total of *N* images are used for testing, with multiple samples per individual to ensure reliable evaluation. The diversity of the dataset enables comprehensive assessment of model performance under realistic conditions.

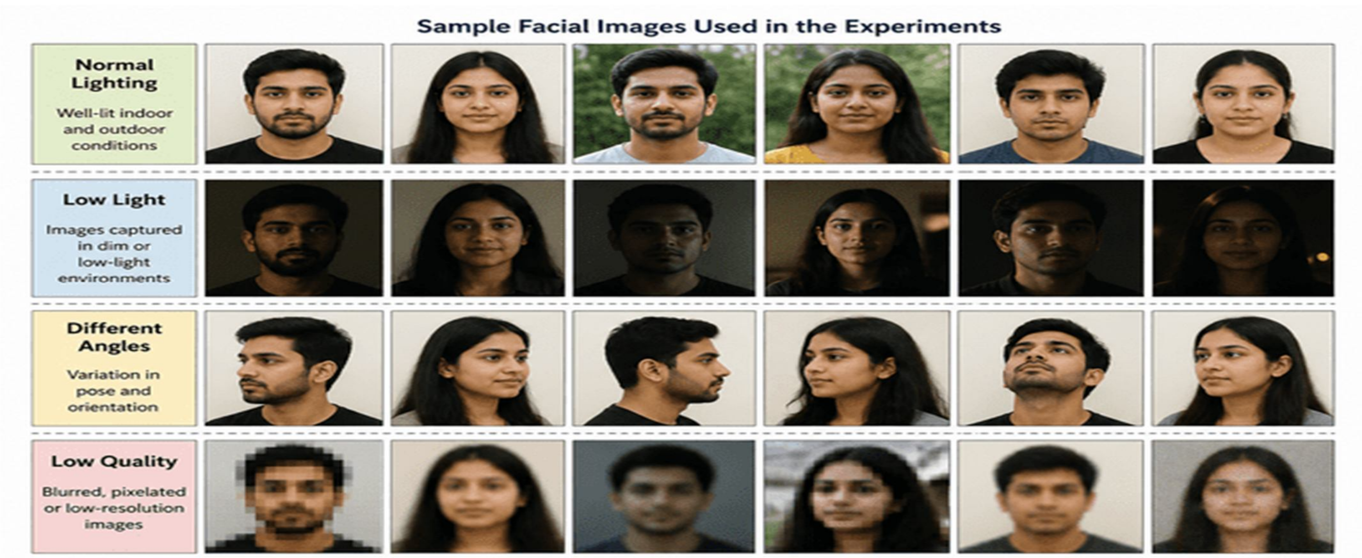


Fig. 2 Sample facial images under various conditions

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
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### *B. Testing Conditions*

To evaluate robustness and performance, the models are tested under different controlled conditions:

- Lighting Conditions:
  Bright light, normal indoor lighting, and low-light environments
- Facial Orientation:
  Frontal face, side profile, and slightly rotated angles
- Image Quality:
  High-resolution images, blurred images, and low-resolution inputs

Each model processes the same set of test images across these conditions to ensure a fair and consistent comparison.

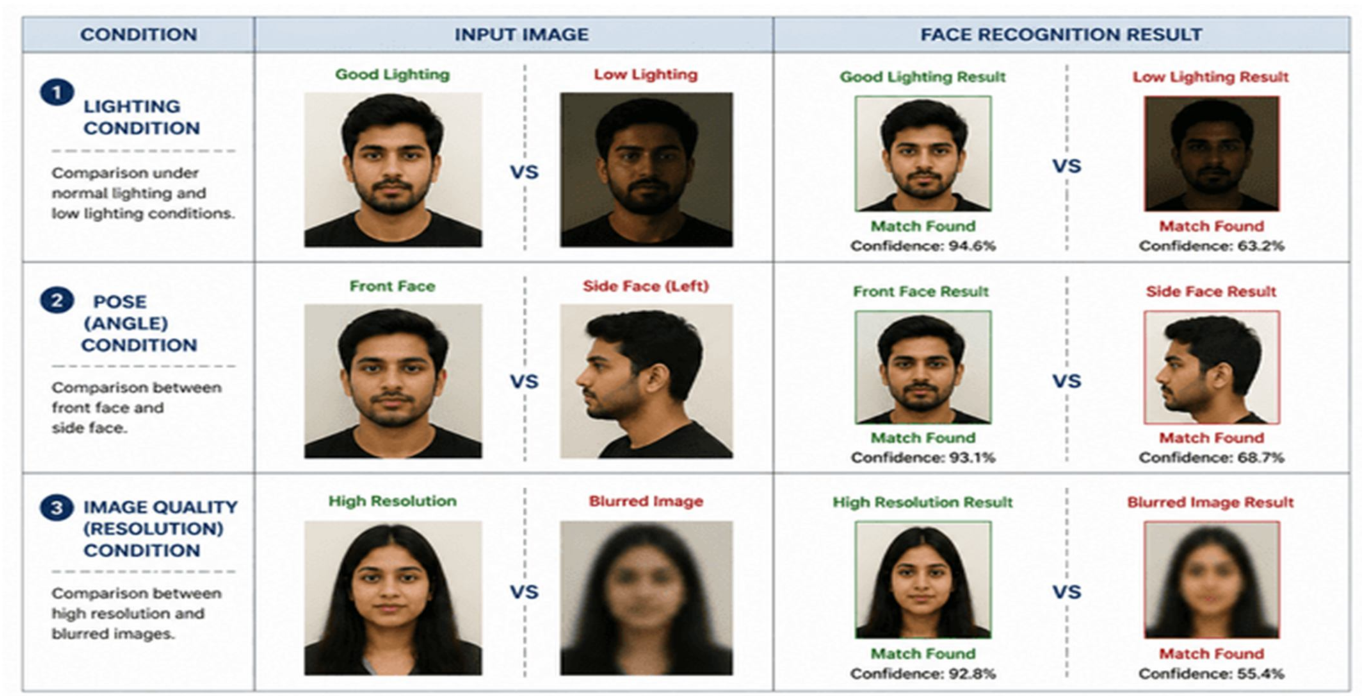



**Fig. 3.** Face recognition performance comparison under different conditions.

Fig. 3 Face recognition under varying conditions

### *C. Results Table*

TABLE III
PERFORMANCE COMPARISON OF FACE RECOGNITION MODELS

| Model | Accuracy (%) | Precision (%) | Processing Time (ms) | Robustness |
|---|---|---|---|---|
| Haar Cascade | 65 | 60 | 30 | Low |
| MediaPipe | 80 | 78 | 45 | Medium |
| FaceNet | 92 | 90 | 120 | High |

### *D. Comparison and Analysis*

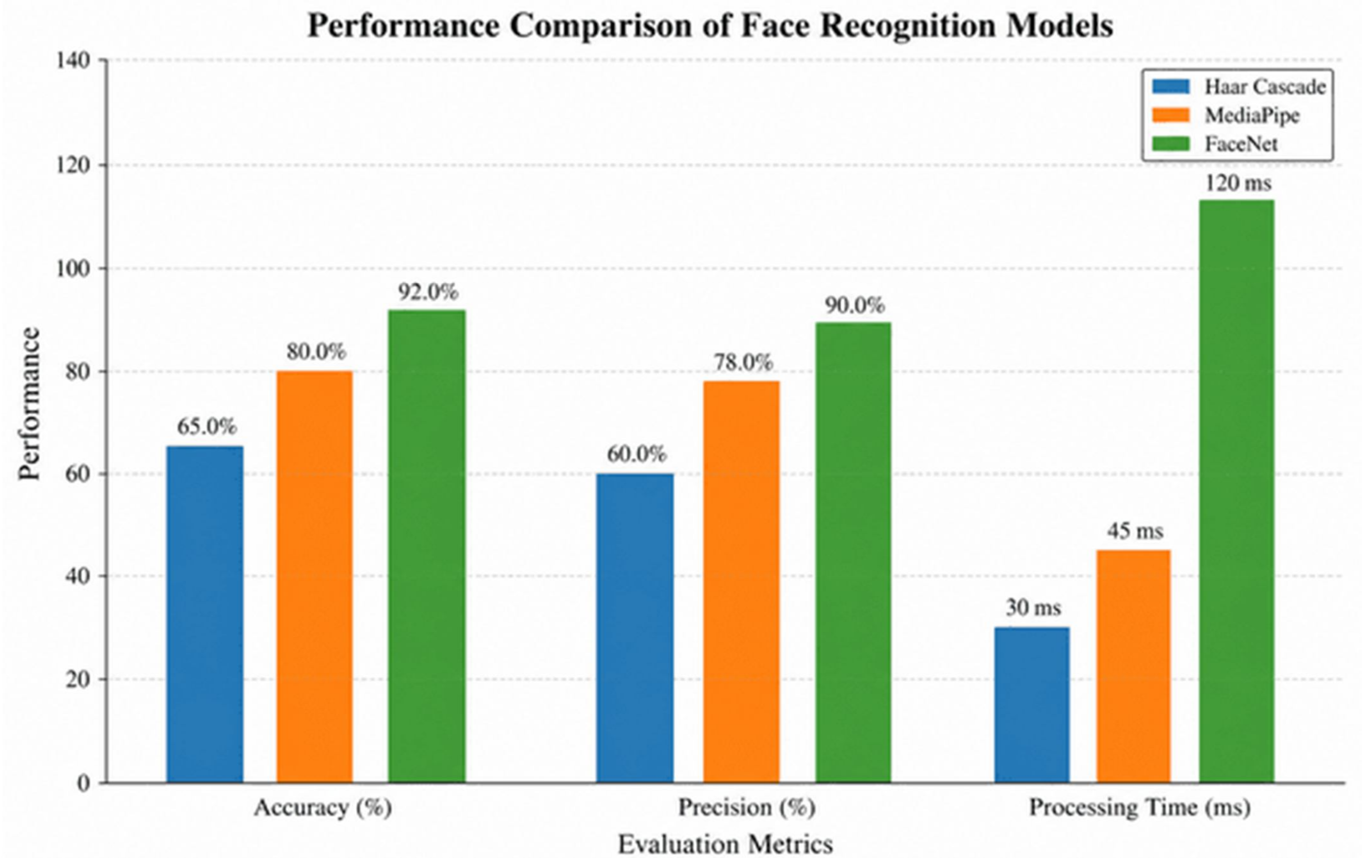
The experimental results demonstrate significant differences in performance across the evaluated models. The Haar Cascade classifier, while computationally efficient, exhibits lower accuracy and robustness, particularly under challenging conditions such as low lighting and varied facial orientations.

MediaPipe provides a balanced performance, offering moderate accuracy with relatively low processing time. Its landmark-based approach improves stability compared to traditional methods, making it suitable for real-time applications.

The deep learning-based model (FaceNet) achieves the highest accuracy and precision, demonstrating strong robustness against variations in lighting, angle, and image quality. However, this improved performance comes at the cost of increased computational complexity and processing time.

ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue IV Apr 2026- Available at www.ijraset.com

Overall, the results indicate that deep learning models are best suited for high-accuracy identification tasks, whereas lightweight models are preferable for faster processing. This validates the need for a multi-model approach that combines speed and accuracy for practical deployment.




. Fig. 4 Face recognition model performance comparison

## VI. COMPARATIVE ANALYSIS

### *A. Performance Comparison*

TABLE IIII
COMPARATIVE ANALYSIS OF FACE RECOGNITION MODELS

| Model | Accuracy (%) | Speed (Processing Time ms) | Robustness |
|---|---|---|---|
| Haar Cascade | 65 | 30 | Low |
| MediaPipe | 80 | 45 | Medium |
| FaceNet | 92 | 120 | High |

The table presents a comparative evaluation of different face recognition models based on accuracy, processing speed, and robustness under varying real-world conditions.

### *B. Accuracy and Robustness Analysis*

The FaceNet model achieves the highest accuracy and robustness due to its deep learning-based feature embedding approach. It performs well even under challenging conditions such as low lighting, varied facial orientations, and low-quality images.

MediaPipe provides moderate accuracy with improved robustness compared to traditional methods. Its landmark-based detection helps maintain stability under moderate variations.

In contrast, Haar Cascade shows lower accuracy and poor robustness, especially when environmental conditions deviate from ideal settings.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
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### *C. Computational Efficiency Analysis*

Haar Cascade demonstrates the fastest processing time, making it suitable for real-time applications with limited hardware resources. MediaPipe maintains a balance between speed and performance, offering acceptable processing time with better acuracy.
FaceNet, while highly accurate, requires significantly more computational resources and processing time. This makes it less suitable for real-time applications without optimization or hardware acceleration.

### *D. Trade-off Analysis*

The comparison reveals a clear trade-off between accuracy and computational efficiency. Lightweight models such as Haar Cascade prioritize speed but compromise accuracy, whereas deep learning models like FaceNet prioritize accuracy at the cost of processing time.
MediaPipe acts as a middle-ground solution, balancing both performance and efficiency. However, no single model satisfies all requirements simultaneously.

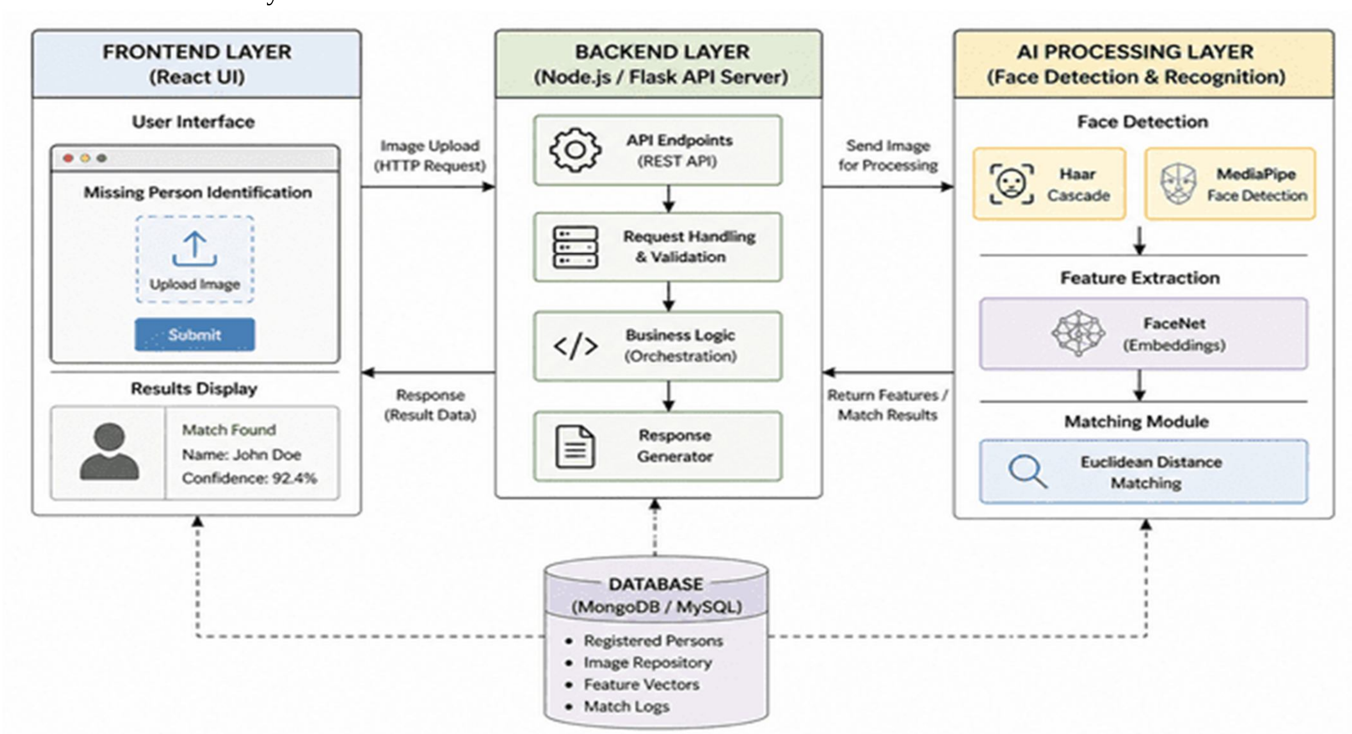
### *E. Observations Implication for System Design*

Based on the comparative analysis, a multi-model approach is justified for practical deployment. The system can utilize fast models such as Haar Cascade for initial detection and filtering, followed by deep learning models like FaceNet for final verification.
This hybrid strategy improves overall system reliability, reduces false matches, and ensures adaptability across diverse real-world conditions.

## VII. SYSTEM INTEGRATION

### *A. Architecture Integration*

The proposed system integrates multiple components across frontend, backend, and AI layers to ensure seamless operation and scalability. The frontend layer is developed using web technologies such as HTML, CSS, and React, providing an intuitive interface for users to upload images and view results. The backend layer, implemented using Node.js/Flask, handles request processing, database communication, and API integration. The AI layer consists of face detection, feature extraction, and recognition models, which process the input data and generate matching results.
This layered architecture ensures modularity, allowing each component to function independently while maintaining efficient communication between layers.




. Fig. 5 System architecture of face recognition system

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### *B. Workflow of the System*

The system follows a structured workflow that transforms user input into meaningful identification results. The process begins with image upload and proceeds through preprocessing, model execution, and matching.

TABLE IV
WORKFLOW STEPS OF THE PROPOSED SYSTEM

| Step | Process |
|---|---|
| 1 | User uploads image |
| 2 | Image preprocessing (resize, normalize) |
| 3 | Face detection (Haar / MediaPipe) |
| 4 | Feature extraction (landmarks / embeddings) |
| 5 | Matching with database |
| 6 | Result generation with confidence score |

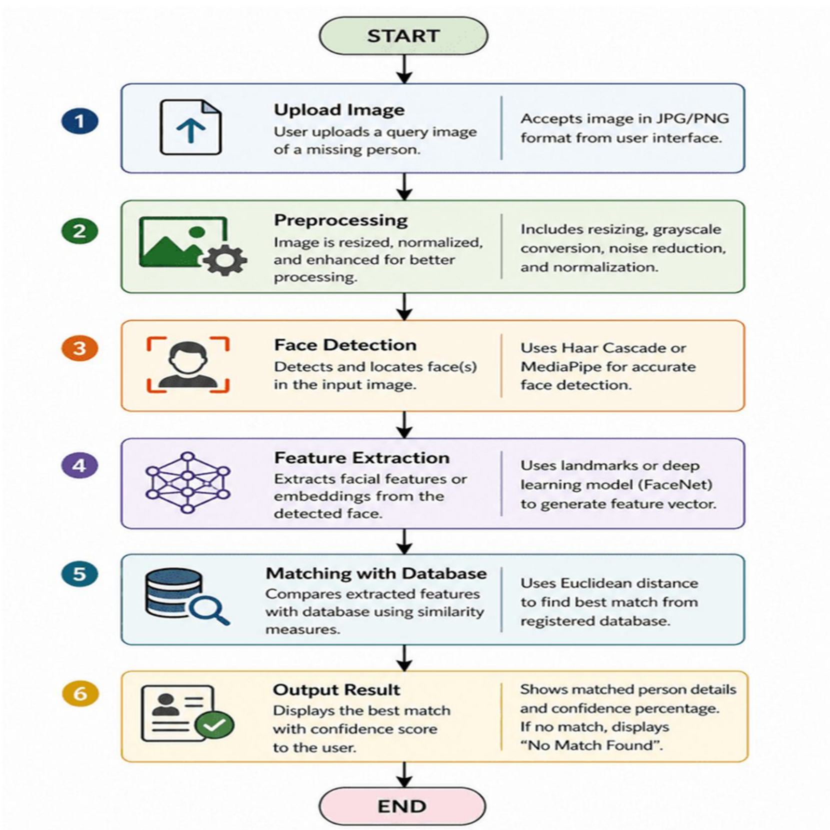


Fig. 6  AI-based missing person identification pipeline

### *C. Real-World Usability*

The proposed system demonstrates strong potential for real-world deployment, particularly in domains such as law enforcement, surveillance systems, and public safety platforms. Law enforcement agencies can utilize this system to analyze large volumes of images and CCTV footage, significantly reducing manual effort and investigation time.

The integration of AI-based recognition with web platforms enables public participation, where users can upload images of unidentified individuals. This collaborative approach enhances the chances of locating missing persons quickly and efficiently.

Additionally, the system's modular design allows for scalability, enabling future integration with real-time video processing, cloud-based storage, and mobile applications. This adaptability makes the system suitable for deployment in both urban surveillance networks and national-level missing person databases.

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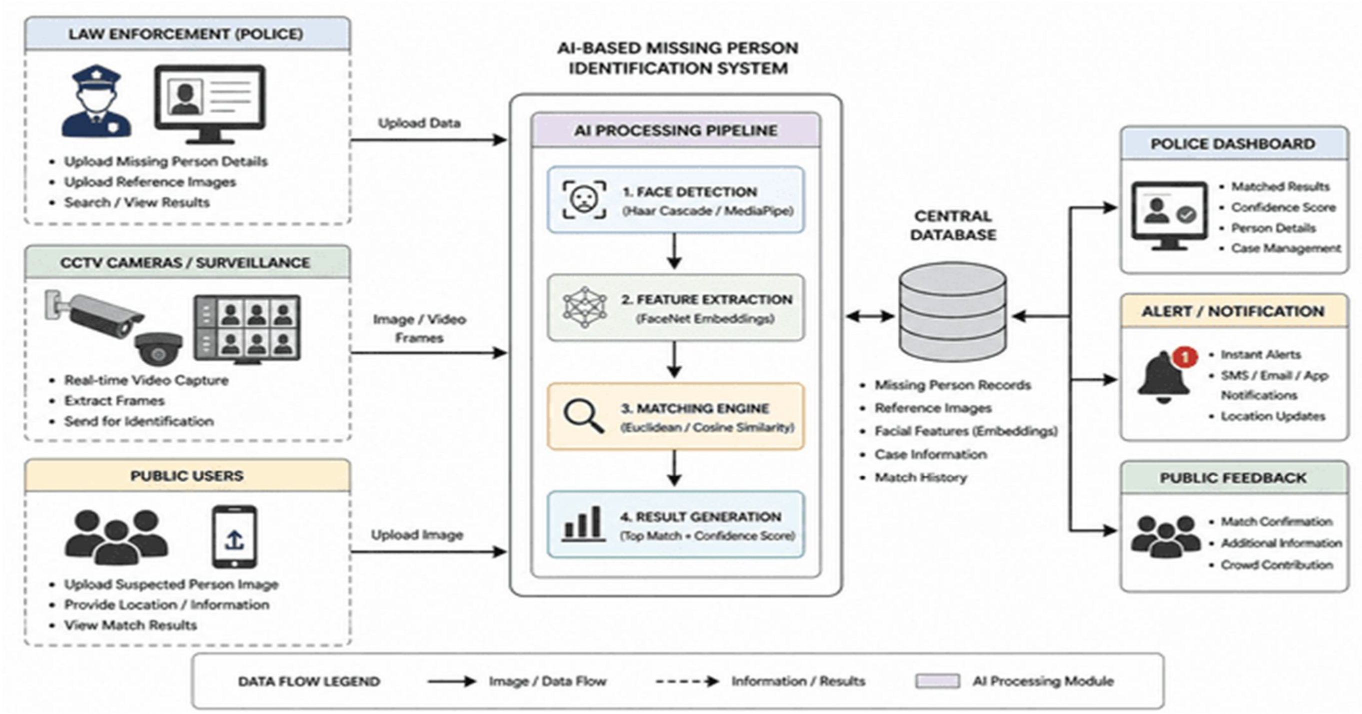

Fig. 7 AI-based missing person identification system

## VIII. DISCUSSION

### A. Insights

The experimental evaluation of multiple face recognition techniques provides several important insights into their performance and applicability. The results clearly indicate that deep learning-based models such as FaceNet significantly outperform traditional and landmark-based methods in terms of accuracy and robustness. This is primarily due to their ability to learn complex and discriminative facial features through high-dimensional embeddings.

At the same time, lightweight models such as Haar Cascade demonstrate superior processing speed, making them suitable for real-time applications where computational resources are limited. MediaPipe serves as an intermediate solution, offering a balance between speed and accuracy through its landmark-based approach.

Another key observation is that no single model performs optimally under all conditions. Performance varies depending on environmental factors such as lighting, facial orientation, and image quality. This reinforces the importance of adopting a multi-model strategy, where different techniques complement each other to achieve better overall performance.

### B. Limitations

Despite the promising results, the proposed system has several limitations that affect its performance and generalization capability.

- Dataset Dependency:
  The accuracy of the system is highly dependent on the size, diversity, and quality of the dataset. A limited or biased dataset may lead to poor generalization and reduced accuracy in real-world scenarios.
- Lighting Variations:
  Changes in lighting conditions significantly impact face detection and recognition accuracy. Low-light environments and shadows can reduce feature visibility, affecting both traditional and deep learning models.
- Computational Constraints:
  Deep learning models require higher computational resources, which may limit their deployment in real-time or low-resource environments without optimization.
- Pose and Occlusion:
  Variations in facial orientation and occlusions such as masks, glasses, or partial obstruction can reduce recognition accuracy.

*C. Practical Challenges*

The deployment of AI-based missing person identification systems in real-world environments presents several practical challenges.

- Data Privacy and Security:
  Handling sensitive personal data requires strict compliance with privacy regulations and secure data storage mechanisms to prevent misuse.
- Scalability:
  As the number of registered individuals increases, the system must efficiently handle large-scale databases without compromising performance.
- Real-Time Processing:
  Integrating the system with live surveillance feeds requires optimized models and hardware support to ensure real-time performance.
- User Adoption and Reliability:
  For effective implementation, the system must be user-friendly and reliable enough for law enforcement agencies and the public to trust its outputs.

## IX. FUTURE WORK

*A. Integration with CCTV Surveillance Systems*

Future enhancements of the proposed system can include integration with CCTV and real-time surveillance networks. By processing live video streams and extracting frames for face recognition, the system can automatically detect and identify missing persons in public spaces such as railway stations, airports, and streets. This would significantly improve response time and expand the system's practical applicability.

*B. Real-Time Detection and Optimization*

To enable real-time performance, further optimization of deep learning models is required. Techniques such as model compression, GPU acceleration, and edge computing can be explored to reduce processing latency while maintaining accuracy. This will allow the system to operate efficiently in live environments without significant delays.

*C. Mobile Application Development*

Developing a mobile-based application can enhance accessibility and user participation. Public users and authorities can upload images directly from smartphones, receive instant match results, and contribute additional information. A mobile platform would also enable location-based alerts and notifications, increasing the chances of timely identification.

*D. Advanced Deep Learning Enhancements*

Future work can focus on incorporating more advanced deep learning models such as ArcFace, DeepFace, or transformer-based architectures to improve recognition accuracy further. Additionally, training on larger and more diverse datasets can enhance generalization and robustness.

*E. Multi-Modal and Context-Aware Systems*

Beyond facial recognition, future systems can integrate additional biometric modalities such as voice recognition or gait analysis. Context-aware techniques, including location data and temporal patterns, can also be utilized to improve identification accuracy and reduce false positives.

*F. Cloud-Based and Scalable Deployment*

Implementing the system on cloud infrastructure can improve scalability and enable handling of large-scale databases. Cloud-based deployment would allow centralized data management, faster processing, and integration with national-level missing person databases.

## X. CONCLUSION

This paper presented a comparative and multi-model approach for enhancing missing person identification using AI-based face recognition techniques. The study analyzed the performance of traditional methods such as Haar Cascade, landmark-based approaches like MediaPipe, and deep learning models such as FaceNet under varying real-world conditions including lighting, facial orientation, and image quality.

The experimental results demonstrated that deep learning-based models provide superior accuracy and robustness, while traditional methods offer faster processing speed. MediaPipe was observed to balance both performance and efficiency. These findings highlight the inherent trade-offs between computational efficiency and recognition accuracy across different techniques.

To address these limitations, the paper proposed a multi-model strategy that combines the strengths of different approaches. By utilizing lightweight models for initial detection and deep learning models for final verification, the system achieves improved reliability, reduced false matches, and better adaptability in real-world scenarios.

Furthermore, the integration of the system into a scalable web-based architecture demonstrates its practical applicability in domains such as law enforcement and public safety. The proposed framework bridges the gap between theoretical research and real-world deployment by combining system implementation with experimental validation.

Overall, this work contributes toward the development of an efficient, scalable, and intelligent missing person identification system. Future enhancements, including real-time detection, CCTV integration, and advanced deep learning models, can further improve system performance and expand its usability in large-scale applications.

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