Payal N. Rathi, 2026, 14:2
ISSN (Online): 2348-4098
ISSN (Print): 2395-4752

International Journal of Science, Engineering and Technology
An Open Access Journal

Missing Person Tracker Using AI And Face Recognition.

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Abstract- Missing person cases are a serious global issue that require fast and accurate identification systems. Traditional methods rely on manual investigation, which is time-consuming and often inefficient. This paper presents an AI-based Missing Person Tracking System that uses face recognition techniques based on computer vision and deep learning [1].The system uses Convolutional Neural Networks (CNNs) to extract facial features and generate embeddings for accurate identification under different conditions such as lighting and facial expressions. OpenCV is used for face detection and preprocessing, [2] and the extracted features are converted into numerical vectors. These vectors are compared with a centralized database using similarity measures like Euclidean distance to find matches.The system also provides a user-friendly interface that allows users and authorities to upload images and retrieve results in real time. This approach improves automation, reduces manual effort, and increases search efficiency. Overall, the system offers a reliable and scalable solution for identifying missing persons and supporting public safety.

Keywords: Face Recognition, Artificial Intelligence, Computer Vision, Deep Learning.

I. INTRODUCTION

In addition to face recognition, modern missing person tracking systems can also incorporate advanced technologies such as machine learning, cloud computing, and big data analytics to further enhance performance. Machine learning algorithms [3] [4] enable the system to continuously improve its accuracy by learning from new data. As more images are added to the database, the system becomes more robust and capable of handling diverse facial variations.Another important aspect of such systems is data preprocessing and normalization. Before performing face detection and recognition, images are often preprocessed to improve their quality. This includes operations such as resizing, grayscale conversion, noise reduction, and contrast enhancement. These preprocessing [5] [6] steps help in improving detection accuracy and ensure consistent results across different image conditions.

Feature extraction is one of the most critical stages in face recognition. In deep learning-based systems, CNN [7] models automatically learn important features from training data. These features include low-level features such as edges and textures, as well as high-level features such as facial structure and identity patterns. This hierarchical learning process makes CNNs [8] highly effective compared to traditional handcrafted feature extraction methods.

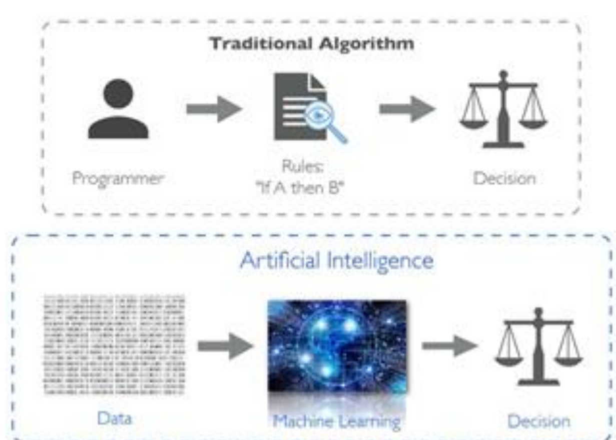

Figure 1 Comparison Between Traditional Methods and AI-Based Approach

Another key concept used in modern systems is feature embedding space. In this space, each face is represented as a point in a multi-dimensional vector space. Similar faces are located closer together, while different faces are placed farther apart. This representation allows efficient comparison and clustering of faces, which is particularly useful when dealing with large databases.

To improve performance, many systems also use threshold-based decision making. A predefined threshold value is used to determine whether two faces match or not. If the calculated similarity score exceeds this threshold, the system considers it a match. Selecting an appropriate threshold is important, as a very high threshold may result in false negatives, while a low threshold may lead to false positives.

Scalability is another important factor in designing such systems. As the number of stored records increases, the system must be able to handle large-scale data efficiently. Techniques such as indexing, database optimization, and parallel processing are used to ensure fast retrieval and comparison of data. Cloud-based storage solutions can also be used to manage large datasets and provide remote access to the system.

Real-time processing is a significant advantage of AI-based systems. By integrating the system with CCTV cameras and surveillance networks, it becomes possible to continuously monitor public spaces and automatically detect missing persons. This can greatly improve response time and increase the chances of locating individuals quickly.

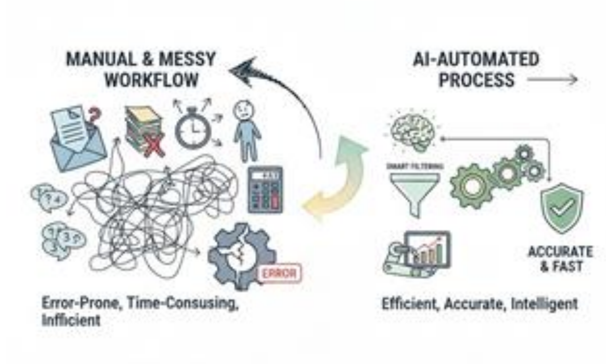

Figure 2 Manual Process vs AI-Based Missing Person Identification System

Security and privacy are critical considerations in face recognition systems. Since facial data is highly sensitive, it is important to implement strong security measures such as data encryption, secure authentication, and access control. Ethical considerations must also be taken into account to prevent misuse of the system and ensure that it is used only for authorized purposes.

Another important area is model training and dataset quality. The accuracy of a face recognition system depends heavily on the quality and diversity of the training dataset. A well-trained model with diverse data can recognize faces under different conditions such as varying lighting, angles, and expressions. Regular updates and retraining of the model can further improve performance over time.

II. THEORY

2.1 Background Theory

Face recognition is a biometric technique used to identify or verify individuals based on their facial features. It is considered one of the most reliable and widely used identification methods because every human face has unique characteristics such as the shape of the eyes, nose, lips, and overall facial structure. These unique features make it possible to distinguish one person from another using digital systems.

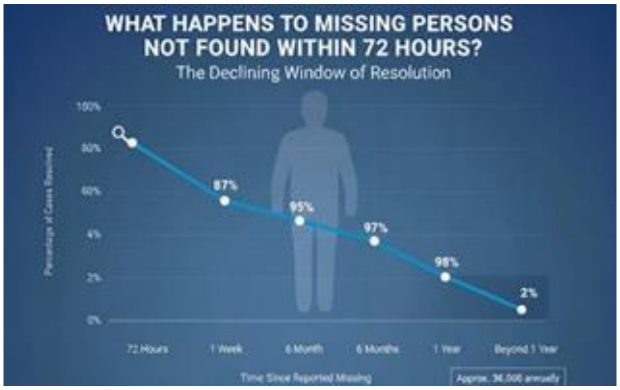

Figure 3 Probability of Finding Missing Persons Over Time

The process of face recognition generally involves multiple steps. The first step is face detection, where the system identifies and locates a human face within an image or video. This is usually done using computer vision techniques such as Haar Cascade [9]classifiers or deep learning-based detection models. Once the face is detected, the next step is feature extraction, where important facial features are identified and analyzed.

In traditional systems, feature extraction was done manually using geometric measurements such as distances between eyes or shape of facial components. However, these methods were not very accurate and failed under different lighting conditions or facial expressions. To overcome these limitations, modern systems use deep learning techniques, especially Convolutional Neural Networks (CNNs) [10].

CNNs [11] are a type of neural network designed specifically for image processing tasks. They consist of multiple layers such as convolution layers, pooling layers, and fully connected layers. The convolution layers extract important features like edges, textures, and patterns from the image. Pooling layers reduce the size of the data while retaining important information, making the system more efficient. The final layers combine all extracted features to create a meaningful representation of the face.

In deep learning-based face recognition, the extracted features are converted into numerical values known as feature vectors or embeddings. These embeddings represent the unique identity of a person in a mathematical form. When a new image is provided, its embedding is generated and compared with stored embeddings in the database. The comparison is usually done using similarity measures such as Euclidean distance or cosine similarity [12] [13]. If the distance between two embeddings is very small, it indicates that both faces belong to the same person. This approach allows the system to achieve high accuracy even when there are variations in lighting, facial expressions, or angles.

Overall, deep learning models such as CNNs have significantly improved the performance of face recognition systems. They provide better accuracy, robustness, and scalability compared to traditional methods. As a result, face recognition is now widely used in applications [14] such as security systems, surveillance, mobile authentication, and missing person tracking systems.

2.2 Literature Review

Various methods have been developed over the years for face detection and recognition, ranging from traditional approaches to modern deep learning techniques [15] [16]. Earlier systems mainly relied on classical computer vision algorithms, while recent advancements have introduced highly accurate deep learning-based models.

One of the most commonly used traditional methods for face detection is the Haar Cascade classifier, which was introduced by Viola and Jones. This method works by detecting patterns such as edges, lines, and textures in an image. It uses a cascade of classifiers trained with positive and negative images to quickly identify the presence of a human face. Haar Cascade is efficient and fast, making it suitable for real-time applications. However, its accuracy is limited, especially under conditions such as poor lighting, different facial angles, or occlusions.

With the advancement of Artificial Intelligence, deep learning-based approaches such as Convolutional Neural Networks (CNNs) have become more popular. CNNs are capable of automatically learning complex patterns from images without the need for manual feature extraction. These models consist of multiple layers that analyze different aspects of the image, such as edges, shapes, and textures. CNN-based models provide higher accuracy compared to traditional methods and perform well even under challenging conditions like variations in lighting, pose, and facial expressions.

Modern face recognition systems use a combination of face detection and feature extraction techniques. After detecting the face, the system extracts unique features and converts them into a numerical representation known as an embedding. These embeddings are compact vectors that capture the essential characteristics of a face.

For matching faces, modern systems compare these embeddings using similarity measures such as Euclidean distance or cosine similarity. Instead of comparing raw images, this approach compares numerical values, which makes the process faster and more efficient. If the distance between two embeddings is below a certain threshold, the system considers them as a match.

Advanced models such as FaceNet [17], DeepFace [18], and other deep learning architectures have further improved the accuracy of face recognition systems. These models are trained on large datasets and can recognize faces with high precision. They are widely used in applications such as security systems, surveillance, mobile authentication, and missing person identification.

Overall, the transition from traditional methods like Haar Cascade to modern deep learning techniques such as CNN and embedding-based matching has significantly improved the performance of face recognition systems. These advancements have made it possible to develop reliable and efficient systems for real-world applications.

The proposed system is designed to provide an efficient and automated solution for identifying missing persons using face recognition technology. It integrates Artificial Intelligence (AI), Computer Vision, and database management to improve the accuracy and speed of identification compared to traditional methods.

The system consists of multiple modules that work together in a structured manner. The first module is the user authentication module, which allows users to securely register and log into the system. This ensures that only authorized users can access and upload information.The second module is the image upload module, where users can upload images of missing persons. These images act as input for the system and are further processed using computer vision techniques.The face detection module is responsible for identifying and extracting the face from the uploaded image. This is achieved using algorithms such as Haar Cascade or deep learning-based models. Once the face is detected, the system moves to the face recognition module.

In the face recognition module, facial features are extracted using deep learning models such as Convolutional Neural Networks (CNNs). These features are converted into numerical representations called embeddings, which uniquely represent each face.

The database module stores all the information related to missing persons, including images and their corresponding feature vectors. The system compares the extracted features with stored data using similarity measures to identify potential matches.

Finally, the system displays the results to the user. If a match is found, relevant details of the person are shown; otherwise, the system indicates that no match is available.

Overall, the proposed system provides a fast, accurate, and user-friendly approach for identifying missing persons, reducing manual effort and improving the efficiency of search operations.

III. SYSTEM ARCHITECTURE

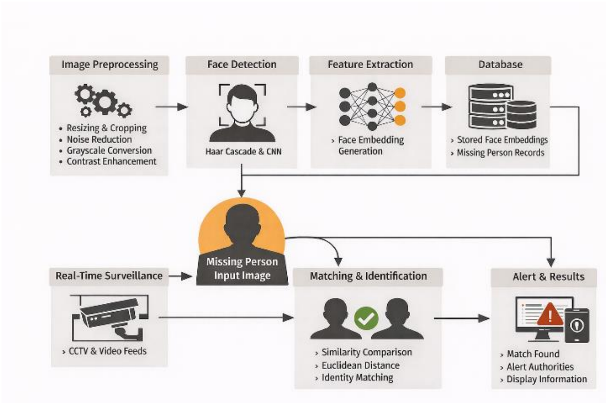

Figure 4 System Architecture of AI-Based Missing Person Tracking System

3.1 Overview

The objective of the proposed system is to identify missing persons using Artificial Intelligence and face recognition techniques. Unlike traditional systems that require manual investigation and physical search operations, this approach relies entirely on visual information captured through images or camera-based systems. The system analyzes facial features and identity patterns to identify individuals accurately in real time.

The framework primarily focuses on detecting and recognizing human faces and matching them with stored records of missing persons, while unmatched cases are considered as unknown individuals. The identification process is based on analyzing facial structures, feature patterns, and similarity between face encodings generated from images.

The workflow of the proposed system is structured as follows:

Input Acquisition: Images of the missing person are captured through user upload or camera systems such as CCTV or mobile devices.

The captured images are resized, converted into appropriate formats, and enhanced to handle variations in lighting conditions.

1. Face Detection: The system detects faces from the image using OpenCV-based detection techniques [19] [20].
2. Feature Extraction: Important facial features are extracted using deep learning techniques such as Convolutional Neural Networks (CNNs).
3. Face Encoding: The extracted features are converted into numerical representations known as face encodings.Database Retrieval: Stored face encodings are retrieved from the database of missing.
4. persons.Matching: The input encoding is compared with database encodings using similarity measures [21].
5. Decision Making: If the similarity is within a predefined threshold, the system identifies a match.Output Visualization [22]:

The system displays the matched result; otherwise, it shows "No Match Found". In addition to the core workflow, the proposed system incorporates advanced optimization techniques to improve accuracy and efficiency. During preprocessing, techniques such as histogram equalization and normalization are applied to enhance image quality and reduce the impact of environmental variations [23] [24].This ensures that the system performs reliably even when images are captured under poor lighting conditions or from low-resolution sources.The face detection stage plays a crucial role in isolating relevant facial regions from complex backgrounds.

Modern approaches may also include deep learning-based detectors such as Single Shot Detectors (SSD) or Multi-task Cascaded Convolutional Networks (MTCNN) to improve detection accuracy. Thesemethods enable the system to detect faces at different angles, scales, and orientations.Feature extraction using Convolutional Neural Networks (CNNs) allows the system to learn hierarchical patterns from facial images.

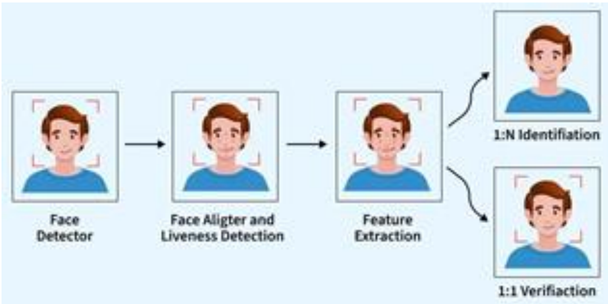

Figure 5 Workflow of Face Detection and Identification System

Lower layers of the network capture basic features such as edges and textures, while deeper layers extract complex facial structures. This hierarchical learning significantly improves the robustness of the system against variations in facial expressions, pose, and occlusions.

Table 1 Driver Fatigue Detection Methods Comparison

Sr. No	Type of Detection	Researchers	Year	Approach	Dataset	Accuracy / Performance / Notes
1	Face Detection	Viola & Jones	2001	Haar Cascade	Ad-hoc	Fast, light-sensitive
2	Deep Learning	Krizhevsky et al.	2012	CNN (AlexNet)	ImageNet	High accuracy
3	Face Recognition	Schroff et al.	2015	FaceNet (Embeddings)	LFW	~99%
4	Feature Extraction	Lowe et al.	2004	SIFT	Benchmark	Robust to scale
5	Feature Extraction	Bay et al.	2006	SURF	Benchmark	Fast & efficient
6	Deep Face Recognition	Taigman et al.	2014	DeepFace	Facebook Data	Near human-level accuracy
7	OpenCV Detection	Bradski	2000	OpenCV Library	Custom	Real-time processing
8	Face Encoding	Various	2020	Embedding + Distance Matching	Custom	Efficient comparison
9	Database Matching	Various	2021	Euclidean Distance	Custom	Fast similarity matching
10	Hybrid (Proposed System)	Your System	2026	CNN + OpenCV + Encoding Matching	Custom Dataset	High accuracy, real-time

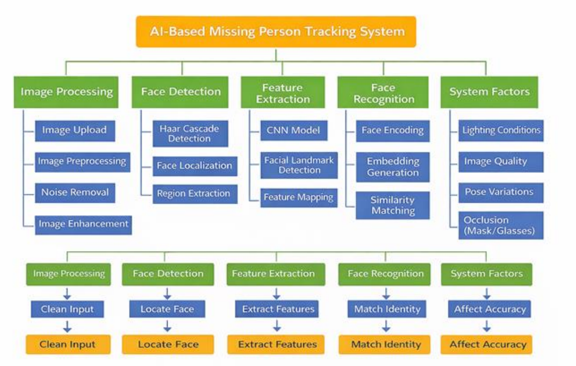

Figure 6 Detailed Workflow of AI-Based Missing Person Tracking System

3.2 Face Recognization Using Facial Features

Face recognition is a critical component in AI-based missing person tracking systems. It is primarily based on analyzing unique facial features, as each individual has distinct facial patterns that can be used for identification. One of the most widely used techniques is facial embedding generation using deep learning models such as Convolutional Neural Networks (CNNs), which convert facial features into numerical representations for accurate comparison.

In this approach, facial landmark [25] detection methods are used to extract key points from the face, such as the eyes, nose, and mouth. These landmarks help in understanding the structure and geometry of the face. The extracted features are then processed to generate embeddings, which represent the identity of a person in a compact vector form. When the similarity between embeddings falls within a predefined threshold, the system identifies a match.

Compared to traditional image-based techniques [26], deep learning-based face recognition methods are more accurate and robust, especially in handling variations in lighting, facial expressions, and pose [27]. These methods are suitable for real-time applications and can efficiently process large datasets.

Additionally, similarity measures such as Euclidean distance or cosine similarity are used to compare facial embeddings. These techniques improve the accuracy of identification by minimizing false matches. However, challenges may arise in situations involving low image quality, occlusions such as masks or glasses, and significant changes in appearance over time.

Overall, face recognition techniques provide a reliable, scalable, and efficient solution for identifying missing persons and are widely used in modern AI-based surveillance and tracking systems.

Figure 7 CCTV-Based Face Matching and Identification System

3.3 Face Recognization and Feature Analysis

Face recognition systems involve detailed analysis of facial features such as eye structure, nose shape, and overall facial geometry to accurately identify individuals (Fig. 7). Unlike image manipulation tasks, this approach focuses on recognizing and matching identities rather than altering visual content.

Identification of individuals relies on extracting unique facial features and generating embeddings that represent each person. Techniques such as Convolutional Neural Networks (CNNs), facial landmark detection, and deep learning-based feature extraction are commonly used to capture these distinguishing characteristics. These methods enable the system to handle variations in lighting, facial expressions, and pose.

Metrics such as feature similarity, embedding distance, and pattern matching are used to compare input images with stored data. Similarity measures like Euclidean distance or cosine similarity help determine whether two faces belong to the same individual. These features allow the system to distinguish between known (matched) and unknown (unmatched) persons, enabling accurate and real-time identification.

Figure 8 Face Detection and Recognition of Unknown Individual Using CCTV Surveillance

3.4 Face Recognization and Matching Process

Face recognition in the proposed system focuses on identifying individuals by comparing facial features with stored database records (Fig. 8). Unlike simple face detection, which only locates faces in to determine identity. When a detected face matches with stored data, the system identifies the person; an image, recognition involves analyzing and matching facial patterns otherwise, it is classified as unknown. Key techniques include:

1. Face Encoding: Generating numerical representations (embeddings) of facial features using deep learning models. These embeddings uniquely represent each individual and are used for comparison.
2. Similarity Matching: Comparing the input face encoding with stored encodings using similarity measures such as Euclidean distance or cosine similarity. A smaller distance indicates a higher probability of a match.
3. Threshold-Based Decision: Defining a similarity threshold to determine whether two faces belong to the same person. If the distance is below the threshold, the system confirms a match; otherwise, it is considered a non-match.
4. Database Search Optimization: Efficiently retrieving and comparing facial encodings from large datasets to ensure fast and scalable performance.
5. Real-Time Processing: Continuously analyzing input images or video frames to detect and identify individuals instantly, enabling quick response in real-world scenarios.

3.5 Face Matching and Identification Process

Face matching in the proposed system focuses on identifying individuals by comparing detected faces with stored records in the database (Fig. 8). Unlike simple face detection, which only identifies the presence of a face, this process involves analyzing facial features and determining identity through similarity comparison. When a detected face matches with a stored record, the system identifies the individual; otherwise, it is considered unknown.

Key techniques include:

1. Face Embedding Generation: Converting facial features into numerical vectors using deep learning models such as CNNs. These embeddings uniquely represent each individual.
2. Similarity Measurement: Comparing input embeddings with stored embeddings using metrics such as Euclidean distance or cosine similarity. A smaller distance indicates a higher likelihood of a match.
3. Threshold-Based Decision: Applying a predefined threshold to determine whether two faces belong to the same individual. If the similarity score is within the threshold, a match is confirmed.
4. Continuous Analysis: Evaluating multiple inputs or frames (in case of video) to improve reliability and reduce false matches.

3.6 Classification-Based Recognization Framework

After feature extraction and encoding, the final step is classification of the input face as either a matched (known) or unmatched (unknown) individual. Instead of relying solely on complex classification models, the proposed system uses similarity-based and threshold-based techniques to perform identification efficiently.

The classification is carried out by comparing the input face encoding with stored encodings in the database. If the similarity between encodings satisfies the predefined threshold condition, the system classifies the input as a known individual and retrieves the corresponding details. Otherwise, it is classified as an unknown person.

This framework offers the following advantages:

Simplicity: Eliminates the need for extensive training processes by using direct similarity comparison methods.

Real-Time Performance: Enables fast processing and instant identification, making it suitable for real-time applications such as surveillance systems.

Efficiency: Requires minimal computational resources while maintaining high accuracy, making it suitable for scalable and practical deployment.

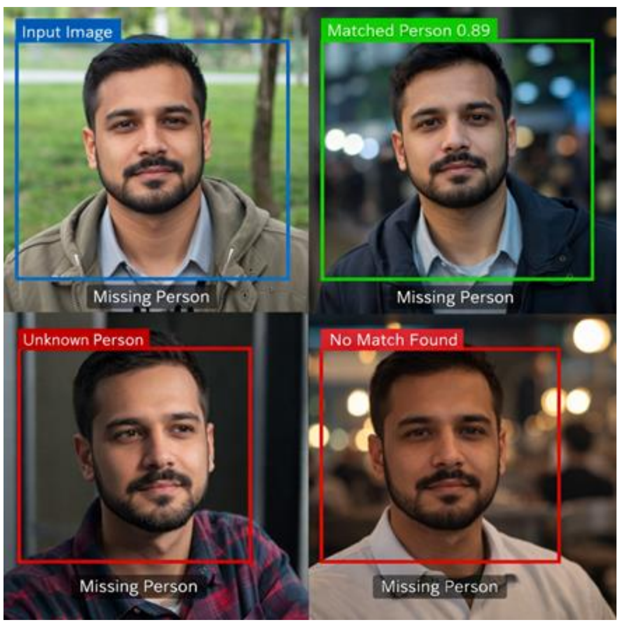

Figure 9 Face Recognition Results Showing Matched and Unmatched Cases

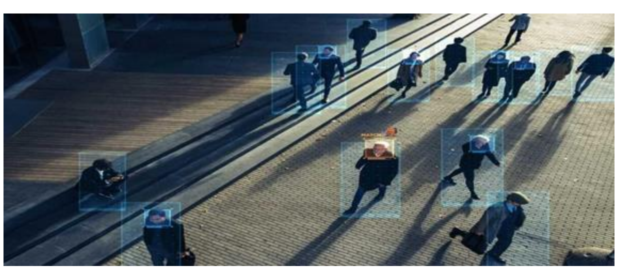

Figure 10 Real-Time Crowd Monitoring for Missing Person Identification

IV. EXPERIMENTAL SETUP AND RESULTS

4.1 Experimental Environment

The experiments were conducted using Python 3.x with support from libraries such as OpenCV, NumPy, and face recognition/deep learning frameworks for image processing [28] and facial feature extraction. These tools were used for tasks such as face detection, feature extraction using Convolutional Neural Networks (CNNs), and generation of facial embeddings for identification.

The system was tested on a standard computing setup with an Intel i5/i7 processor, 8–16 GB RAM, and a webcam or image dataset for input. Unlike traditional manual systems, the proposed approach leverages efficient algorithms and optimized libraries to perform real-time face detection and recognition. Depending on the implementation, optional GPU support can be used to further improve performance, but the system can also run effectively on CPU-based environments.

The database used for testing consisted of facial images of individuals, which were converted into embeddings and stored for comparison. During testing, input images were processed and compared with stored data to identify matches based on similarity measures such as Euclidean distance.

This setup ensured efficient execution of face recognition algorithms with minimal computational overhead. The system demonstrated stable performance and was capable of processing inputs quickly, enabling near real-time identification. The approach is scalable and suitable for practical deployment in real-world applications such as surveillance systems and missing person identification platforms. [29]

4.2 Dataset Description

To evaluate the performance of the proposed AI-based Missing Person Tracking System, both benchmark datasets and custom real-world data were utilized.

Labeled Faces in the Wild (LFW) Dataset:
This dataset contains a large collection of facial images captured under unconstrained conditions, including variations in lighting, pose, and facial expressions. It is widely used for evaluating face recognition systems and helps in testing the robustness of the model under real-world scenarios [30].

Custom Collected Dataset:
A custom dataset was created by collecting facial images of individuals from real-world environments. The dataset includes variations such as different angles, lighting conditions, facial expressions, and occlusions (e.g., glasses, masks). This dataset helps in evaluating the system's performance in practical missing person identification scenarios.

Real-Time Input (Camera/CCTV):
In addition to stored datasets, the system was tested using live input from webcams or CCTV cameras. This allows evaluation under dynamic conditions such as lighting variation, motion, and partial occlusion. It ensures that the system performs effectively in real-time surveillance environments.

These datasets provide diverse facial variations and environmental conditions, making the evaluation more realistic and suitable for real-world deployment of the missing person tracking system.

4.3 Evaluation Metrics

The performance of the proposed AI-based Missing Person Tracking System is evaluated using effective metrics based on face recognition and matching accuracy.

i. Accuracy (ACC):
Represents the proportion of correctly identified faces (matched and unmatched) out of the total inputs. It indicates how accurately the system can recognize missing persons.

ii. Recognition Rate:
Measures how effectively the system identifies and matches input faces with the correct records in the database. A higher recognition rate indicates better system performance.

iii. False Match Rate (FMR):
Indicates the number of incorrect matches where the system falsely identifies two different individuals as the same person.

iv. False Non-Match Rate (FNMR):
Represents the cases where the system fails to identify the same individual correctly, even when the person exists in the database.

v. Processing Speed (Time/FPS):
Measures how quickly the system processes input images or video frames, indicating its capability for real-time performance.

4.4 Results and Observations

The performance of the proposed AI-based Missing Person Tracking System is summarized in Table 1, highlighting its effectiveness in identifying individuals using face recognition techniques. The analysis demonstrates how various components such as face detection, feature extraction using CNN, and embedding-based matching contribute to accurate and efficient identification.

From the results, several important observations can be derived:

1. Impact of Threshold Values:
The system performance is highly dependent on the selection of similarity threshold values used for face matching. Lower thresholds increase sensitivity and allow more matches but may result in higher false matches, while higher thresholds reduce false positives but may fail to detect actual matches.

2. Lighting Conditions:
The system performs best under normal and well-lit conditions. However, accuracy may decrease in low-light environments or under harsh shadows, which can affect face detection and feature extraction.

3. Occlusion Effects:
The presence of occlusions such as masks, glasses, or partial face visibility can reduce recognition accuracy by affecting the extraction of key facial features.

4. Pose and Expression Variations:
Moderate variations in head pose and facial expressions are handled effectively, but extreme angles or expressions may lead to reduced matching accuracy.

5. Real-Time Performance:
The system demonstrates efficient performance and is capable of processing inputs quickly, enabling near real-time identification without requiring high-end computational resources.

6. Multi-Feature Advantage:
Combining multiple techniques such as face detection, CNN-based feature extraction, and embedding comparison improves overall system reliability compared to using a single method alone.

4.5 Discussion
The results demonstrate that the proposed AI-based Missing Person Tracking System can effectively identify individuals using face recognition techniques. The combination of face detection, CNN-based feature extraction, and embedding-based matching enables reliable and accurate identification in near real-time scenarios.

In particular, the use of multi-stage processing improves system performance compared to relying on a single technique. Integrating face detection with deep learning-based feature extraction and similarity matching enhances both accuracy and robustness. The system achieves a good balance between recognition performance and computational efficiency, making it suitable for deployment on standard computing systems without requiring high-end hardware.

However, certain challenges remain. The system performance may decrease under low-light conditions, poor image quality, and face occlusion (such as masks, glasses, or partial visibility), which can affect feature extraction accuracy. Additionally, variations in pose, facial expressions, and aging may impact recognition results. Proper selection of similarity thresholds is also important, as inappropriate values can lead to false matches or missed identifications.

Overall, the proposed framework provides a practical and efficient solution for missing person identification and can be applied in real-world scenarios such as surveillance systems, public safety applications, and law enforcement support systems.

V. DISCUSSION AND CONCLUSION

The study demonstrates that the proposed AI-based Missing Person Tracking System effectively identifies individuals using face recognition techniques. By analyzing key features through face detection, CNN-based feature extraction, and embedding-based matching, the system achieves reliable performance in identifying missing persons. Among these, deep learning-based feature extraction provides the most accurate results, while similarity matching further enhances identification accuracy when combined.A major strength of the proposed framework lies in its ability to maintain a balance between accuracy and computational efficiency. Unlike traditional manual methods, the system automates the identification process and can operate efficiently on standard computing systems without requiring highly complex infrastructure. This makes it suitable for real-world deployment in surveillance systems and law enforcement applications. However, certain limitations exist, particularly under low-light conditions, poor image quality, face occlusion (e.g., masks or glasses), and extreme pose variations, which may affect recognition accuracy.

Future improvements can focus on enhancing system robustness by incorporating advanced deep learning models, adaptive threshold mechanisms, and improved preprocessing techniques. Integration with real-time CCTV surveillance, mobile applications, and cloud-based databases can further extend the system's practical usability and scalability. In conclusion, the proposed system provides an efficient, scalable, and reliable solution for missing person identification. With further advancements, it has strong potential to support public safety systems and assist law enforcement agencies in faster identification and recovery of missing individuals.

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