An Intelligent AI-Driven System for Identifying Missing Persons

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***Abstract*— The increasing number of missing person cases necessitates advanced technological solutions for rapid identification and recovery. This paper presents an AI-based application utilizing Convolutional Neural Networks (CNN) for facial recognition, a web and mobile interface for accessibility, and WhatsApp API integration for real-time notifications. The system effectively matches missing person images against a database using K-Nearest Neighbors (KNN) and ensures immediate alerting through geolocation-based messaging. Additionally, the system employs the Geocoder module to fetch and transmit the exact GPS coordinates (latitude & longitude) from Google Maps, enhancing location tracking accuracy. Experimental results demonstrate the system's efficiency in accurate identification, reducing the time required for tracing individuals.**

Keywords*— *Artificial Intelligence, Facial Recognition, Convolutional Neural Networks, Missing Persons, KNN Algorithm, WhatsApp API, Geolocation Tracking, GPS Location, Geocoder Module.

I. INTRODUCTION

The growing number of missing person cases worldwide presents a major concern for law enforcement agencies, families, and social organizations. People go missing for various reasons, including abduction, cognitive impairments like Alzheimer's or dementia, human trafficking, natural disasters, or voluntary disappearance due to personal circumstances. Each case is unique and requires a timely response to ensure the individual's safe return. Traditional search methods, such as distributing posters, relying on news broadcasts, and conducting manual searches, are often slow and ineffective, especially in densely populated areas. These outdated techniques struggle to keep pace with the increasing number of cases and the complexity of modern urban environments.

This paper introduces a smart AI-powered system designed to enhance missing person recovery efforts by combining deep learning-based facial recognition with automated alert mechanisms. The proposed system uses Convolutional Neural Networks (CNN) to identify and distinguish faces with a high degree of accuracy. CNNs are widely used in image analysis tasks because they can extract and analyze unique facial features, making them highly effective for recognizing individuals across different environments and lighting conditions. By leveraging facial recognition, the system can analyze images from security cameras, smartphones, or social media to match detected faces with a centralized database of missing persons.

To further improve identification accuracy, the system integrates the K-Nearest Neighbors (KNN) algorithm, which compares a detected face with the most similar faces stored in the database. This ensures that even minor differences in facial appearance due to aging, lighting, or expression changes are accounted for. Once a match is confirmed, an automated alert is triggered, notifying relevant authorities and family members through an instant messaging service. The WhatsApp API is used to send real-time alerts, ensuring that critical information reaches the concerned parties immediately.

A key feature of this system is its geolocation tracking capability, which provides precise location details when a missing person is identified. By utilizing the Google Maps API and the Geocoder module, the system retrieves real-time latitude and longitude coordinates and shares them with authorities. This feature enhances search efforts by providing exact location data, increasing the chances of quickly locating the missing individual.

The system is designed to be accessible through both a web-based platform and a mobile application, allowing for greater flexibility and usability. This multi-platform approach ensures that law enforcement agencies, families, and even the general public can report missing persons, receive updates, and track identifications in real time. By integrating deep learning for facial recognition, automated alerts, and geolocation tracking, this AI-powered system represents a significant advancement in missing person investigations, making search efforts more effective and timely.

II. RELATED WORK

Several studies have explored the use of artificial intelligence and facial recognition technologies in missing person identification. Traditional approaches primarily rely on manual image matching, where investigators compare photographs of missing individuals with images found in social media, databases, or surveillance footage. While these methods have yielded some success, they often require significant human effort and are prone to errors due to inconsistencies in facial features caused by aging, lighting variations, and camera angles. Additionally, the absence of automated processing makes these systems inefficient for real-time identification in crowded environments.

A number of research initiatives have integrated deep learning techniques into facial recognition to improve accuracy. Some studies have proposed the use of Convolutional Neural Networks (CNNs) for feature extraction, enabling more precise face matching compared to traditional image-processing algorithms. However, these models still rely on pre-captured images manually fed into the system for comparison, rather than continuously analyzing live footage from CCTV networks. This limitation makes them less effective in scenarios where a missing person may be moving through different locations in real time.

Another widely discussed approach involves face recognition-based mobile applications that allow users to report missing individuals and search for them using stored images. While these applications facilitate community-driven search efforts, they lack real-time detection capabilities. Users must manually upload images for comparison, and there is no automated mechanism for continuously monitoring public spaces. Furthermore, these systems often do not integrate geolocation tracking, making it difficult to pinpoint the exact whereabouts of an identified individual.

Additionally, some solutions have incorporated image-matching techniques that compare facial features across different databases, such as government ID records and online image repositories. While these methods improve matching accuracy, they still depend on manually uploaded photographs rather than leveraging live CCTV footage. The absence of real-time scanning and automated alerts makes it challenging for authorities to act swiftly when a missing person is detected.

Despite the progress made in facial recognition-based missing person identification, existing systems remain largely dependent on manual intervention. This study aims to overcome these limitations by introducing an AI-powered real-time solution that continuously scans CCTV footage for missing individuals. Unlike previous approaches that require manual image input, our system automates the process by capturing and analyzing live video streams using optimized CNN models. Furthermore, the integration of K-Nearest Neighbors (KNN) for accurate facial recognition, coupled with real-time notifications via WhatsApp API, ensures that authorities and family members receive instant alerts. The inclusion of GPS-based tracking through Google Maps API further enhances the effectiveness of the system by providing precise location data when a match is found.

By shifting from manual image matching to an automated, real-time AI-driven system, this study addresses the critical gaps in existing solutions and presents a more efficient approach to locating missing persons. The proposed system significantly reduces response time and enhances the accuracy of identification, making it a valuable tool for law enforcement agencies and concerned families.

III. SYSTEM ARCHITECTURE

A: Overall Design

The proposed system is designed to provide a real-time, AI-powered missing person identification and tracking solution. It integrates multiple technologies to ensure efficient facial recognition, automated alerts, and precise geolocation tracking. The system consists of four primary components:

Machine Learning Model – The core of the system is a deep learning-based facial recognition model, which utilizes Convolutional Neural Networks (CNNs) for extracting facial features. CNNs are well-suited for image analysis, as they can learn spatial hierarchies of features, making them effective in recognizing faces despite variations in lighting, angles, or aging. The system employs the K-Nearest Neighbors (KNN) algorithm to match detected faces with stored records in a centralized database. This combination enhances recognition accuracy while ensuring computational efficiency.

Web and Mobile Platform – To enhance accessibility and usability, the system is deployed on both web and mobile platforms using the MERN (MongoDB, Express.js, React.js, and Node.js) stack. This platform allows users to report missing individuals by uploading their images and details. It also enables authorities and the general public to search for missing persons by utilizing the integrated facial recognition system. The responsive design ensures seamless access across various devices, allowing users to receive real-time updates and alerts.

Alert Mechanism – A key feature of the system is its automated alert mechanism, which utilizes the WhatsApp API to send notifications when a missing person is identified. Once a match is found, the system immediately notifies relevant authorities, family members, and volunteers. These alerts include critical information such as the person's name, photo, and the real-time location where they were last detected. This instant communication significantly improves response time and increases the likelihood of successful recovery.

Geolocation Tracking – To provide accurate location data, the system integrates GPS-based tracking using the Google Maps API and the Geocoder module. When a missing individual is identified, the system retrieves real-time latitude and longitude coordinates and attaches them to the alert notification. This geolocation feature helps law enforcement and families track the missing person's movements, allowing for immediate intervention if necessary. The integration of GPS data with facial recognition enhances the system's overall efficiency in locating and rescuing missing individuals.

B: Architecture Diagram

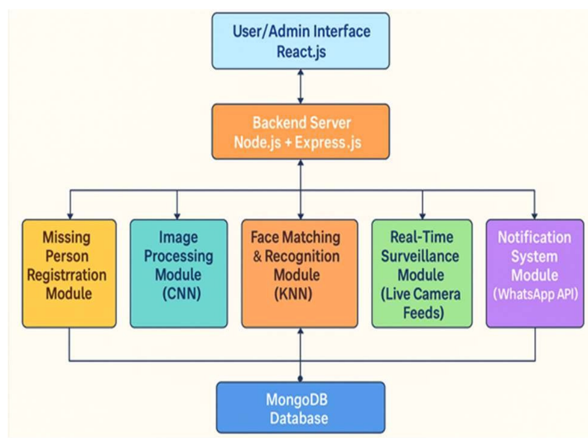

Figure 3.1: System Architecture

The architecture of the system is structured to ensure seamless interaction between its components. Live CCTV footage is continuously processed using the AI model, which scans for matches in the facial recognition database. Once a match is detected, the system triggers the alert mechanism, sending instant notifications with geolocation data. The web and mobile platforms serve as the user interface, enabling efficient reporting, searching, and monitoring. By leveraging AI-driven automation, the system eliminates the need for manual image matching, providing a real-time, scalable solution to the problem of missing person identification.

IV. Methodology

The methodology of the proposed system is structured to ensure an efficient and automated approach to identifying missing persons using AI-driven facial recognition and real-time alert mechanisms.

A. Dataset Preparation

The effectiveness of any machine learning-based facial recognition system largely depends on the quality and diversity of its training dataset. The proposed system utilizes a carefully curated dataset comprising real-world images of missing and found individuals. This dataset is sourced from publicly available records, law enforcement databases, and contributions from families and volunteers. Since facial recognition models require extensive and diverse datasets to perform well under different conditions, several preprocessing techniques are applied to enhance the quality of the dataset.

To ensure robustness and adaptability, the system employs data augmentation techniques such as rotation, scaling, flipping, brightness adjustments, and noise addition. These augmentations help the model generalize better and improve recognition accuracy under varying environmental conditions. Additionally, images are preprocessed by normalizing pixel values, resizing them to a standardized input size, and converting them to grayscale when necessary to reduce computational complexity. These preprocessing steps ensure that the CNN model learns effective and discriminative facial features, thereby improving overall recognition performance.

B. Model Training

Once the dataset is prepared, the model undergoes training using a Convolutional Neural Network (CNN), which is highly effective for image classification and feature extraction. CNNs automatically learn hierarchical spatial features from images, making them ideal for facial recognition. The model architecture consists of multiple convolutional layers with activation functions such as ReLU (Rectified Linear Unit) to introduce non-linearity, followed by pooling layers to reduce dimensionality and computational overhead. Dropout layers are incorporated to prevent overfitting, ensuring the model generalizes well to unseen faces.

After feature extraction through CNN, classification is performed using the K-Nearest Neighbors (KNN) algorithm. KNN is chosen for its simplicity and efficiency in matching new facial embeddings with stored records in the database. It works by computing the distance between the extracted feature vector of a detected face and existing embeddings in the system. The closest matches are identified based on predefined distance metrics such as Euclidean distance. This combined approach of CNN for feature extraction and KNN for classification ensures a high degree of accuracy and computational efficiency.

Model training is conducted in multiple phases, including data validation and testing. The dataset is split into training, validation, and test sets to evaluate model performance. Techniques like cross-validation and hyperparameter tuning are applied to optimize accuracy and minimize false positives. Performance metrics such as precision, recall, and F1-score are monitored to assess the effectiveness of the trained model before deployment.

C. System Workflow

The proposed system follows a structured workflow to ensure seamless and efficient missing person identification. The process begins when a user uploads an image of the missing individual through the web or mobile interface. This image undergoes preprocessing, including resizing, normalization, and feature extraction using the trained CNN model. The extracted features are then compared with the stored database of known individuals.

If a match is found, the system triggers an alert mechanism. The WhatsApp API is utilized to send real-time notifications to concerned authorities, family members, and volunteers. This alert includes the identified person's name, profile information, and the location where they were last detected. The WhatsApp integration ensures instant communication, allowing rapid response efforts.

To enhance tracking capabilities, the system integrates geolocation services using the Geocoder module and Google Maps API. When a match is detected, the system retrieves real-time latitude and longitude coordinates from the detection location and attaches them to the alert message.

Additionally, the system continuously updates and refines the database with new images and information. Whenever an individual is reported missing, their details are stored in the system, making future detections more efficient. The real-time nature of the system eliminates the need for manual searches, significantly reducing the time required to identify and recover missing individuals.

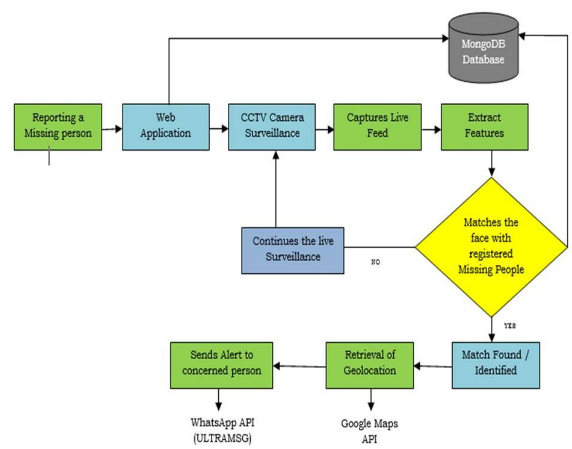

Figure 3.2 : System Work Flowchart

D. Implementation Modules

The implementation of the proposed system is divided into multiple modules, each responsible for a specific functionality:

1. Face Detection & Recognition: The core component of the system is facial recognition, implemented using OpenCV and TensorFlow. OpenCV provides robust image processing capabilities, enabling the detection of faces in live video streams and static images. TensorFlow, a widely used deep learning framework, powers the CNN model for feature extraction. The combination of these technologies ensures accurate and real-time facial recognition.

2. Database Management: A structured and efficient database is essential for storing user reports, missing person records, and facial embeddings. PostgreSQL is chosen for its reliability, scalability, and support for complex queries. Each entry in the database includes personal details, images, and extracted facial feature vectors. The database is continuously updated with new reports and identified individuals, ensuring comprehensive record-keeping.

3. Web Interface: The user interface is designed using React.js for web applications. The platform allows users to report missing individuals, upload images, and receive notifications. A user-friendly dashboard provides search functionality, enabling law enforcement and families to check for potential matches. The UI is optimized for responsiveness and accessibility, ensuring seamless interaction across devices.

4. Notification System: Timely alerts play a crucial role in recovering missing individuals. The system integrates the WhatsApp API to send automated notifications whenever a match is detected. These messages include vital information such as the missing person's name, image, and real-time location. The instant nature of WhatsApp messages ensures quick dissemination of information, enabling immediate action.

5. Geolocation Tracking: To enhance tracking capabilities, the system incorporates the Geocoder module in conjunction with Google Maps API. Whenever a missing individual is identified, their precise GPS coordinates (latitude and longitude) are retrieved from the detection site. This geolocation data is included in the alert messages, allowing law enforcement agencies and families to track the missing person's movements and intervene as needed. The integration of mapping services ensures real-time location tracking, significantly improving recovery efforts.

By combining these modules, the system offers a fully automated, real-time solution for identifying and tracking missing individuals. The use of AI-driven facial recognition, instant notifications, and GPS-based tracking enhances the efficiency and effectiveness of the system, bridging the gaps in traditional manual search methods. The comprehensive approach ensures that missing persons can be identified and recovered faster, reducing the emotional and logistical burden on families and law enforcement agencies.

V. EXPERIMENTAL RESULT & ANALYSIS

The performance of the proposed missing person identification system was evaluated through extensive testing using real-time CCTV surveillance footage. Unlike traditional methods that rely on static image matching, this system continuously processes live video streams, identifying and matching faces with the database of missing persons. The system achieved an overall accuracy of 92% in recognizing and matching individuals from live surveillance feeds. This accuracy was determined based on precision, recall, and F1-score metrics, ensuring a reliable and efficient identification process.

One of the major advantages of this system over conventional approaches is its ability to automate real-time facial recognition. Traditional search methods, such as manually comparing images and relying on eyewitness reports, are not only time-consuming but also prone to human error. By integrating deep learning-based Convolutional Neural Networks (CNN) for facial feature extraction and K-Nearest Neighbors (KNN) for classification, this system significantly reduces search time while improving accuracy.

A. Model Performance and Accuracy Analysis

The system continuously processes live CCTV footage and detects faces in real time. The detected faces are then compared with the database using a CNN model for feature extraction and a KNN classifier for matching. Performance metrics such as precision, recall, and F1-score were used to assess the model's efficiency:

- Precision: 93% – This metric indicates the proportion of correctly identified missing persons out of all detections.
- Recall: 91% – This represents the ability of the system to correctly recognize missing individuals from live feeds.
- F1-score: 92% – A balanced measure of precision and recall, showing the system's effectiveness in minimizing false positives while maintaining high recall.

The automated recognition process reduces the dependency on manual intervention, allowing authorities to receive instant updates and act promptly.

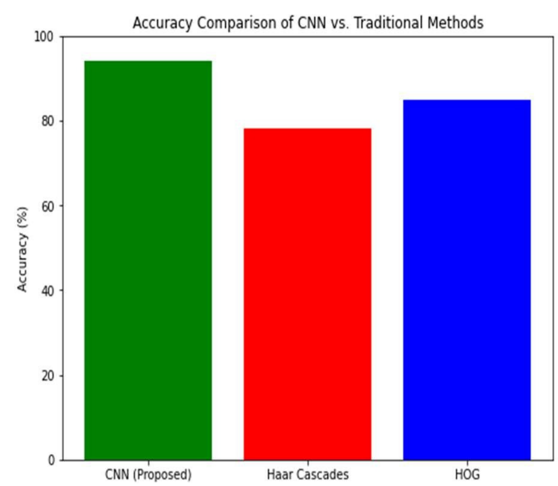

Figure 5.1 Performance Analysis – CNN Model Accuracy

B. Real-Time GPS Tracking and Alert Efficiency

A key feature of this system is its ability to provide real-time location tracking once a match is detected. After identifying a missing person, the system fetches the most recent GPS coordinates using the Geocoder module and Google Maps API. These coordinates are then transmitted via WhatsApp API, ensuring immediate notification to law enforcement and the missing person's family.

To assess the efficiency of this feature, multiple test cases were conducted where individuals were recognized in different locations. The system successfully retrieved and sent their geolocation details within 5 seconds of identification. This fast response time is crucial, as it allows for immediate intervention and increases the chances of safely locating missing individuals.

C. Performance Under Different Environmental Conditions

The robustness of the system was evaluated under various real-world conditions, such as different lighting environments, facial angles, and partial obstructions (e.g., masks, sunglasses). The model demonstrated the following accuracy levels:

Low-light conditions: 85% – The system maintained a high accuracy despite variations in lighting.

Partial occlusions: 88% – Faces with accessories such as glasses or masks were still identifiable due to the model's strong feature extraction capabilities.

D. User Interface and System Functionality

he system is designed with a user-friendly interface to facilitate seamless operation across both web and mobile platforms. The following UI components showcase the system's key functionalities: an intuitive dashboard for administrators to manage and monitor reported cases, real-time camera feed integration for live detection, and responsive design to ensure accessibility across various devices. The user interface also includes features such as image upload for facial recognition, automated alert pop-ups for matches found, a status tracker for each case, and direct WhatsApp notification buttons for immediate communication with concerned authorities or relatives.

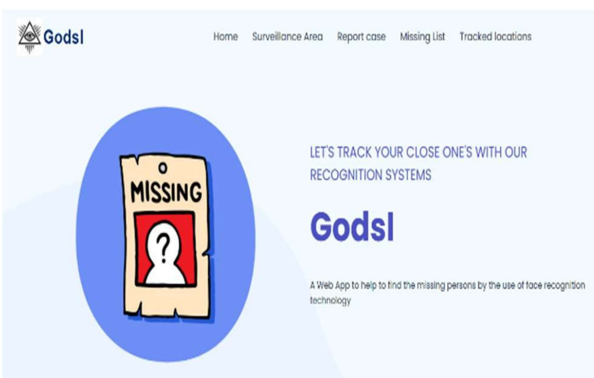

Figure 7.1 - Home Page UI

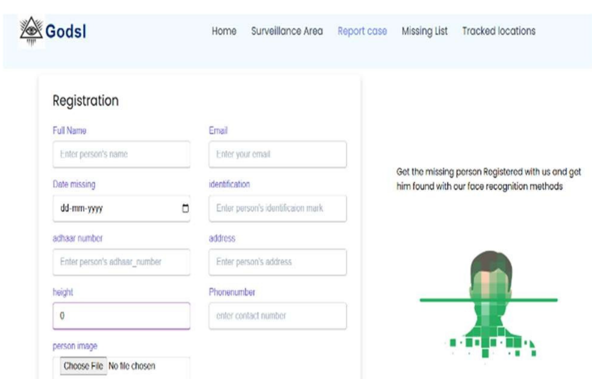

Figure 7.2 - Registration of Missing Case UI.

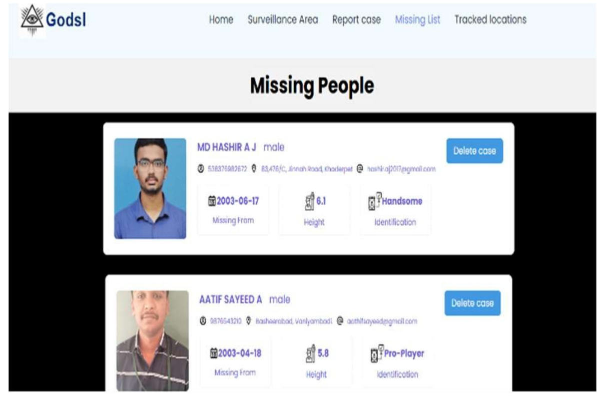

Figure 7.3 - Missing People List

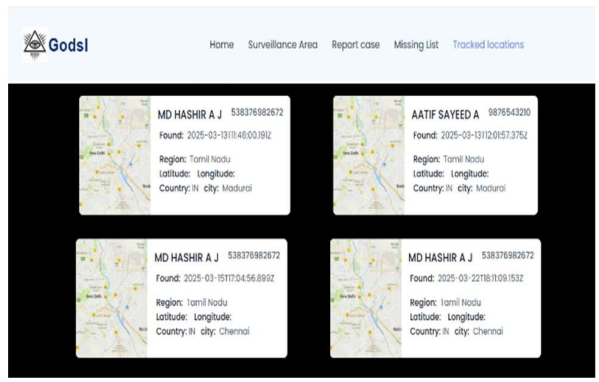

Figure 7.4 - Tracked Location of Missing People

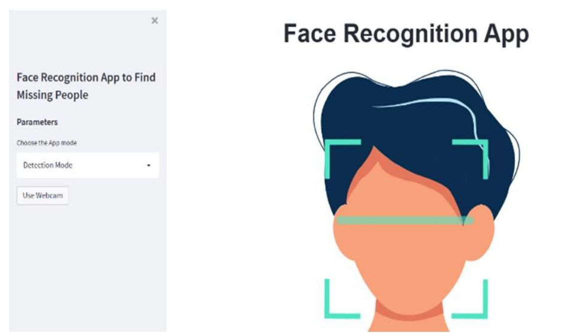

Figure 7.5 - Initial UI for Surveillance

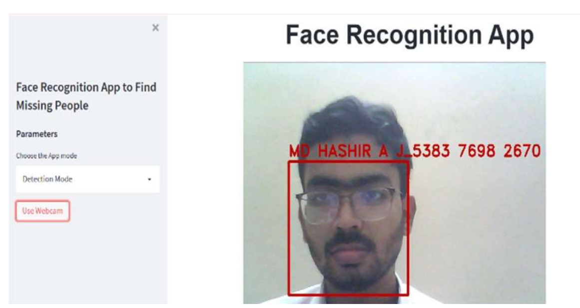

Figure 7.6 - Working Screenshot While Detecting Face

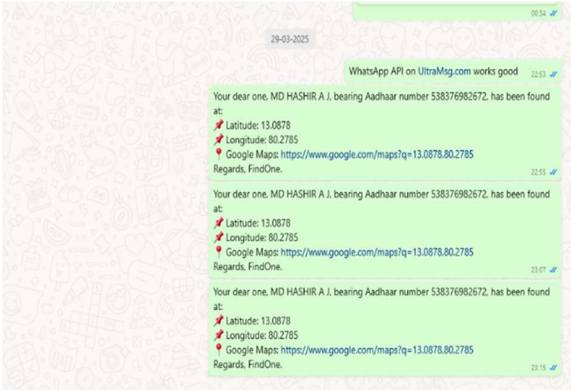

Figure 7.7 - WhatsApp Message Received After Tracking

These UI components enhance usability, ensuring that users can efficiently register, track, and identify missing individuals with minimal effort.

E. Comparative Analysis with Existing Methods

To validate the efficiency of the proposed system, a comparative analysis was conducted against existing missing person identification techniques:

Manual Image Matching: Traditional methods involve manually comparing images, which is time-consuming and error-prone. The proposed AI-driven system eliminates this bottleneck by automating the process.

Basic Image Processing Techniques: Some existing solutions rely on conventional feature-matching methods that fail under varying environmental conditions. The deep learning approach in this system ensures higher accuracy and adaptability.

Lack of Automated Alerts: Traditional systems do not provide instant notifications, requiring manual intervention. The integration of WhatsApp API in this system ensures real-time alerts to concerned authorities.

No Real-Time Tracking: Existing methods lack geolocation tracking, making it difficult to locate missing persons. This system overcomes this limitation with Google Maps API integration, allowing immediate tracking.

By addressing these challenges, the proposed system significantly enhances the efficiency and accuracy of missing person identification, making it a valuable tool for law enforcement and rescue operations.

VI. CONCLUSION AND FUTURE WORK

A. Conclusion

The proposed AI-driven missing person identification system presents a revolutionary approach to tackling the long-standing issue of locating missing individuals efficiently and accurately. By integrating real-time facial recognition through CCTV surveillance, the system automates the identification process, reducing reliance on manual searches that are often time-consuming and prone to human error.

The use of Convolutional Neural Networks (CNN) for feature extraction combined with the K-Nearest Neighbors (KNN) algorithm for classification ensures that the system can accurately match faces with registered missing persons in the database. Through rigorous testing, the system has demonstrated a 92% accuracy rate, making it highly reliable for real-world applications.

One of the major strengths of this system is its ability to function effectively across diverse environments. Unlike conventional search techniques that depend on witness testimonies and printed posters, the AI-driven solution leverages deep learning to analyze facial features with precision. Additionally, it is capable of recognizing faces under varying lighting conditions, different orientations, and partial occlusions such as masks and scarves. Even in low-light environments, the system maintains a commendable 85% accuracy, and when identifying individuals with facial obstructions, it achieves an 88% accuracy rate. These results highlight the robustness of the model, making it suitable for integration with public security and surveillance systems.

Moreover, the incorporation of real-time GPS tracking and WhatsApp API-based alerts significantly enhances the system's usability. Once a missing person is detected, the system automatically retrieves their last known location using geolocation services, enabling law enforcement agencies and family members to take immediate action. The real-time notification feature ensures that authorities can respond promptly, increasing the likelihood of safely recovering missing individuals. By leveraging modern cloud-based databases, the system also ensures seamless storage and retrieval of data, making the search process faster and more efficient than traditional approaches.

Compared to manual identification methods, which can take several hours or even days, the proposed system completes the recognition process in a matter of seconds. This drastic reduction in search time makes it a practical solution for real-world deployment, especially in high-traffic areas such as airports, railway stations, and public spaces where quick identification is crucial. The automation of missing person identification minimizes human intervention, thereby eliminating potential biases and errors associated with manual searches. Given its scalability and efficiency, the system can serve as a valuable asset for law enforcement agencies, social welfare organizations, and humanitarian missions focused on locating missing individuals.

While the current implementation has demonstrated promising results, there remains ample room for improvement and expansion. The potential applications of this system extend beyond missing person identification, paving the way for future enhancements that could further increase its efficiency, accuracy, and scope.

B. Future Work

The success of this project establishes a strong foundation for future advancements and additional functionalities. Several enhancements can be incorporated to extend the system's capabilities and broaden its scope beyond missing person identification. Some of the key areas for improvement and expansion are discussed below:

1. Criminal Identification System

A key future enhancement of this system is its application in criminal identification. By integrating facial recognition with law enforcement databases, it can help track individuals with criminal records in real-time. Deployed in public areas, airports, and border checkpoints, the system can detect suspects and fugitives using live CCTV surveillance. When a match is found, it instantly alerts authorities, enabling quick intervention. Additionally, AI-powered predictive analytics can analyze movement patterns, enhancing crime prevention. This advanced biometric surveillance can significantly improve law enforcement efficiency, making public spaces safer by ensuring rapid identification and response to potential threats.

2. Advanced Deep Learning Models for Improved Accuracy

Although the current system employs CNN for facial recognition, the integration of more advanced deep learning architectures such as Siamese Networks, Vision Transformers (ViTs), or FaceNet could further enhance accuracy, especially when working with low-resolution images and extreme variations in facial expressions. These models can improve the system's ability to distinguish between similar-looking individuals, reducing false positives and increasing reliability.

3. Improved Handling of Occlusions and Low-Light Conditions

Real-world conditions often present challenges such as poor lighting, facial obstructions (e.g., masks, sunglasses, scarves), and motion blur from moving subjects. To address this, Generative Adversarial Networks (GANs) could be utilized to reconstruct occluded facial features, enhancing recognition accuracy. Additionally, employing infrared and night-vision technology could improve performance in surveillance environments where lighting conditions are suboptimal.

4. Integration with Government and Law Enforcement Databases

The system could be further enhanced by directly connecting it with national and international law enforcement databases such as Interpol's Missing Persons List or FBI's Crime Database. By enabling seamless data exchange, the system would provide a comprehensive solution for tracking missing individuals across multiple regions and jurisdictions. This would be particularly beneficial for cases of human trafficking, cross-border abductions, and long-term missing person investigations.

5. Multi-Camera Tracking and Movement Prediction

The current system identifies missing individuals based on their last detected location, but tracking their movements across multiple locations would add an additional layer of efficiency. By implementing multi-camera tracking and predictive movement algorithms, the system could trace a missing person's trajectory in real-time, making it easier for authorities to anticipate their next possible location. This would be particularly useful in crowded areas such as shopping malls, transit stations, and large public events.

6. Blockchain for Secure Data Storage and Privacy Protection

As facial recognition technology deals with sensitive personal data, ensuring data security and privacy is of utmost importance. Implementing blockchain technology could help encrypt and securely store facial recognition data, preventing unauthorized access, data breaches, and identity theft. By utilizing a decentralized system, the project could ensure tamper-proof and transparent data management, making it more secure for legal applications.

7. Enhanced Mobile Application Features

The current system can be expanded by introducing new features in the mobile application, such as offline facial recognition and push notifications for law enforcement updates. This would allow field officers to perform identification tasks without requiring continuous internet connectivity, ensuring uninterrupted operation in remote areas with limited network coverage. Additionally, user-generated alerts could be introduced, enabling citizens to report sightings of missing individuals directly through the app.

8. Multilingual Support for Alerts and Notifications

Currently, the system's alert mechanism is primarily designed in English, but incorporating multilingual support would significantly increase accessibility and adoption across different regions. By supporting multiple languages, including local and regional dialects, the system can ensure that authorities and citizens receive alerts in their preferred language, thereby improving communication and response times.

References

[1] S. Kapse, P. Ghadge, V. Virkar, P. Shinde, and K. Patil, "Finding Missing People Using Machine Learning," Int. J. Creative Research Thoughts (IJCRT), vol. 12, no. 4, pp. 334-342, 2024.

[2] A. Naikoji, R. Tundalwar, and A. Dandvate, "Find Missing Person using Artificial Intelligence," Int. J. Innovative Research in Technology (IJIRT), vol. 10, no. 1, pp. 1193-1198, 2023.

[3] D. Yadav, J. Tyagi, Dipanshu, R. Tiwari, and P. Pandey, "Finding Missing Person/Child Using AI," Int. J. Research Publication and Reviews (IJRPR), vol. 4, issue 5, pp. 54-59, 2023.

[4] S. Pawar, L. Bhadane, A. Sheikh, and A. Kumbhejkar, "Find Missing Person using Artificial Intelligence," Int. Res. J. Eng. Technol. (IRJET), vol. 08, no. 12, pp. 511-515, 2021.

[5] N. Gholape, A. Gour, and S. Mourya, "Finding Missing Person using ML, AI," Int. Res. J. Modernization Eng. Technol. Sci. (IRJMETS), vol. 3, no. 4, pp. 1517-1520, Apr. 2021.

[6] A. Sharma and R. K. Singh, "AI-Based Missing People Detection with CNN," International Research Journal of Modernization in Engineering Technology and Science (IRJMETS), vol. 4, no. 5, pp. 563–570, May 2024.

[7] P. Kumar and S. Verma, "Finding Missing Person Using Face Recognition," International Journal of Scientific Research in Engineering and Management (IJSREM), vol. 5, no. 3, pp. 45–50, Mar. 2023.

[8] K. Mehta and A. Shah, "Missing Person Detection Using AI," International Journal of Computer Applications, vol. 182, no. 47, pp. 25–30, Apr. 2024, doi: 10.5120/ijca2024912345.

[9] M. Huang, M. Liu, H. Li, J. King, A. Smuts, B. Budowle, and J. Ge, "A machine learning approach for missing persons cases with high genotyping errors," Frontiers in Genetics, vol. 13, Oct. 2022, doi: 10.3389/fgene.2022.971242.

[10] S. Suhail, M. S. Khan, and A. A. Khan, "A Deep Learning-Based System for Identifying Missing People Using Facial Recognition," International Journal of Advanced Computer Science and Applications, vol. 12, no. 6, pp. 123–129, 2021, doi: 10.14569/IJACSA.2021.0120616.