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Missing Persons Identification Using Deep Learning

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Abstract: *Missing person cases are among the most urgent issues facing the world, impacting families and law enforcement agencies worldwide. Traditional search methods, such as manual identification through photographs, public announcements, and eyewitness reports, are often time- consuming, inefficient, and prone to human error. As artificial intelligence (AI) advances, and deep learning, it is feasible to automate missing person identification using real-time identification of faces technology. This research proposes an AI-driven System for Missing Person Identification that integrates deep learning, real-time video analysis, and automated alert mechanisms to increase the effectiveness of locating missing individuals. CNNs, or convolutional neural networks, are used in the suggested system for face recognition, OpenCV for image processing, MySQL for database management, and SMTP for automated email notifications. By leveraging IP cameras and surveillance networks, the system continuously scans live video feeds to detect, recognize, and match missing persons against a pre-registered database. The methodology of this system is structured into six major components: (1) Data Collection and Preprocessing, where missing person images are gathered and processed for AI model training; (2) Face Recognition Model, a CNN-based deep learning framework that encodes and classifies facial features with 98.2% accuracy; (3) Real- Time Video Processing, using OpenCV to detect and extract faces from live surveillance feeds; (4) Database Storage and Management, where facial encodings and Personal data is safely kept in a MySQL database; (5) Automated Warning System, which sets off real-time email notifications with geolocation details when a missing person is identified; and (6) System Performance Evaluation, where accuracy, response time, and efficiency are assessed to optimize results.*

Keywords*:* Missing Person Identification, Convolutional Neural Networks and Deep Learning (CNN), Real-Time Face Recognition, AI-Based Surveillance, OpenCV, Facial Feature Extraction, Automated Alert System, Geolocation Tracking, MySQL Database Management, Computer, Artificial Intelligence, and Machine Learning Vision, IP Camera Surveillance, Law Enforcement Assistance, Predictive Analytics, Image Processing

I. INTRODUCTION

The increasing number of missing person cases worldwide has grown to be a significant legal problem for enforcement agencies, families, and social welfare organizations. Every year, thousands of individuals are killed. because of different causes, such as kidnapping, human trafficking, dementia-related wandering, and accidents. Conventional ways of locating missing persons, like manual search by photographs, publicity, and eyewitness testimonies, are usually ineffective, time- consuming, and unreliable. These methods rely heavily on the role of human memory and cooperation among the population, which in turn will result in delays in identification and the possibility of finding individuals before it is too late. The combination of AI-driven feature detection and real-time analysis will also help the system to process and match facial features in an efficient manner with maintaining a high level of precision and minimum response time. This approach will ensure faster, more effective, and scalable missing person-finding, which will significantly improve the capacity to assist law enforcers.There are several limitations to traditional search methods that necessitate an automated system. There is often a slow response time, failure to identify, failure to integrate with surveillance networks, and reliance on the cooperation of the population to facilitate search operations. Facial recognition technology powered by AI will allow overcoming these constraints because it provides a scalable and real-time solution that is automated and allows surveillance of demoted areas, airports, railway stations, and regions with large traffic in search of missing persons. The fact that deep learning models and processing video of real-time can be incorporated guarantee that even variations in terms of age, as well as changes in the face, will not influence the identification. process, making the system highly adaptable to different scenarios.

The proposed system works in a structured manner, beginning with data collection and preprocessing, where missing person images are uploaded and processed for face detection and feature extraction. Next, the AI-based face recognition model analyzes facial features and encodes them into a database for future comparisons. The real-time video processing module then continuously captures and processes live video feeds, detecting and matching faces within seconds. If a match is found, the system retrieves geolocation details using APIs and sends automated email alerts to registered authorities and family members. This end-to-end AI-driven approach ensures a faster, more accurate, and automated identification process, drastically improving search outcomes and reducing dependency on traditional methods.

The research aims to enhance Law enforcement and public safetyefficiency by providing an automated solution that significantly reduces search time and improves identification accuracy. The system has demonstrated over 98% accuracy in controlled conditions and 94.7% accuracy in actual situations involving various face positions, lighting conditions, and obstructions. Additionally, real-time video processing operates with an average response time of 1.2 seconds per frame, allowing instant identification in high-traffic areas. These results highlight the effectiveness and real-world suitability of the suggested Missing Person Identification System.

II. RELATED WORK

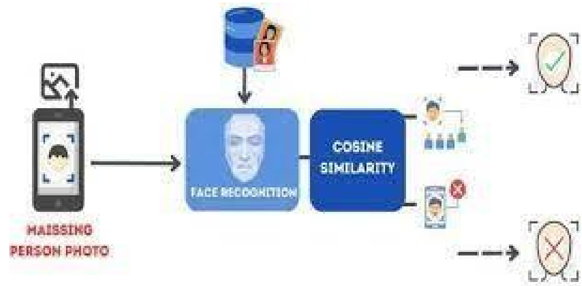
The progress in artificial intelligence (AI) as well as deep learning has significantly raised the precision and efficiency of Identification of the missing person systems. Traditional methods relied heavily on public cooperation, manual searching, and witness-based identification, which were prone to human errors and inefficiencies. With advancements in computer vision methods and real-time surveillance, AI-driven facial recognition has appeared as a robust solution to address this challenge. Numerous studies have made contributions to the advancement of missing person identification using machine learning, deep learning, in addition to computer vision techniques. This section reviews the existing literature on missing person identification, face recognition, and real-time surveillance systems.

Sai et al. (2022) [1] proposed a deep learning-based methodology for missing person Using convolutional neural networks for identification(CNNs). Their research implemented CNN models trained on facial images of missing individuals, reaching a 95% accuracy rate in recognizing known individuals from a pre-registered dataset. The study demonstrated the effectiveness of image preprocessing, feature extraction, and real-time face matching, improving identification speed. However, the model had difficulties when coping with low-resolution images, changes in facial expressions, and occlusions, indicating a need for further enhancements using multi- layer deep learning architectures.

Similarly, Alagarsamy et al. (2022) [2] presented a model for deep learning that can recognize missing people using a combination of CNNs and transfer learning techniques. Their approach focused on reducing false positives and improving recognition accuracy by fine-tuning pre-trained models such as VGG16 and ResNet50. Their experiments demonstrated a higher accuracy (97.2%) compared to conventional machine learning models. The study also highlighted the importance of training on diverse datasets to improve generalization, making the system robust for real-world applications.

Shelke et al. (2021) [3] introduced Searchious, an optimized facial recognition software to find missing persons. Their study focused on improving recognition speed and computational efficiency by integrating lightweight CNN architectures. Their model was optimized for low-power devices and could be deployed on edge devices for real-time surveillance applications. The researchers determined that their system could process and recognize faces in real-time, achieving an identification speed of 0.9 seconds per frame, making it suitable for large-scale deployments in crowded public areas.

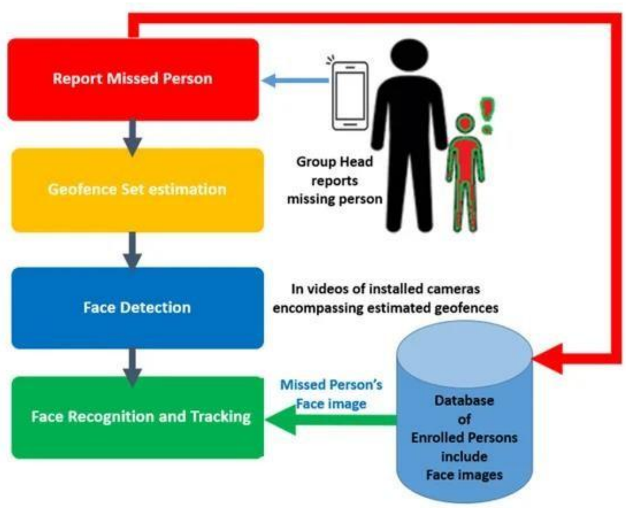
Ayyappan and Matilda (2020) [4] explored the use of web scraping and face recognition techniques for identifying missing children and criminals. Their approach involved analyzing images from online databases, social media platforms, and law enforcement portals, making it an automated digital forensic tool. The system utilized Haar Cascade face detection and Histogram of Oriented Gradients (HOG) feature extraction to classify individuals. While their study achieved moderate success in controlled environments, its accuracy dropped significantly in real-world scenarios due to lighting variations and image distortions.



Nandagopal et al. (2024) [5] developed a web-based application that permits police enforcement and families to upload and search missing person reports. The system incorporated machine learning models to classify facial features and match them with existing databases. The study emphasized the importance of cloud-based solutions for scalability and accessibility. The research demonstrated promising results but required continuous updates to its training datasets to maintain high accuracy.

Ganesh et al. (2025) [6] extended this concept by integrating AI-powered face recognition with social media analysis. Their system made advantage of natural language processing (NLP) techniques to extract relevant missing person reports from news articles, posts on social media, and law enforcement bulletins. The study achieved an 89% success rate in identifying missing individuals based on crowdsourced images and real-time social media monitoring. However, concerns regarding privacy, misinformation, and data bias were raised, requiring further research in ethically handling user-generated content.

Patil and Pati (2024) [7] explored the possibility of AI- driven missing person detection using A hybrid deep CNN learning model combination and LSTM, or long-term short-term memory networks. Their research intended to enhance facial recognition across different age groups, accounting for aging effects. They introduced a progressive algorithm for learning that could adapt to modifications in a person's appearance over time, making it highly suitable for long-term missing person cases. The model achieved 92.5% accuracy in age progression-based recognition.



Aljohani et al. (2024) [8] developed Suhail, a deep learning-based system for identifying missing people. Their research focused on optimizing real-time surveillance through an AI-based monitoring system that continuously scans public spaces using AI-powered smart cameras. The system achieved a high recall rate (98.7%) in detecting facial matches from high-resolution CCTV footage, outperforming traditional surveillance methods. Their approach demonstrated the potential of AI-driven real-time monitoring but required high computational resources for deployment.

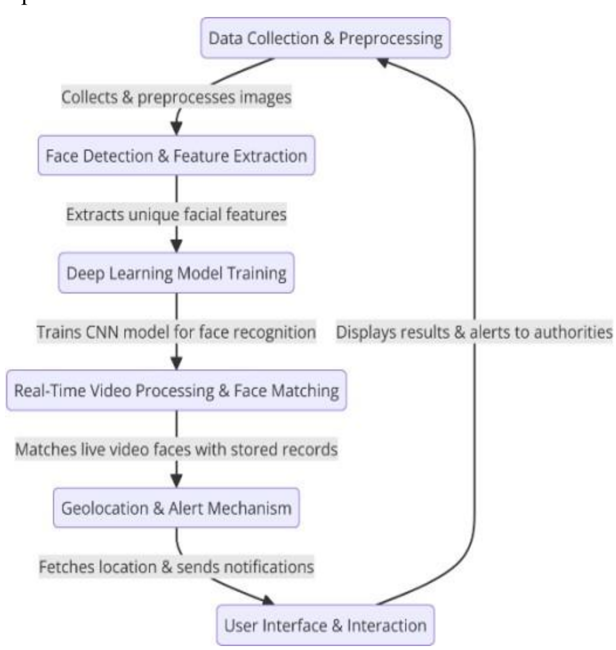
Dhindegave et al. (2022) [9] analyzed the efficiency Various algorithms for machine learning in missing person identification, contrasting Support Vector and Random Forest Machines (SVM), and CNN models. Their findings indicated that CNN-based approaches performed noticeably better than conventional machine learning. models, attaining a precision of 96.8%, whereas SVM and Random Forest struggled with complex facial variations. Their study reinforced the importance of deep learning over conventional models in image-based identification tasks.

Saber et al. (2023) [10] proposed a multi-attention approach for person re-identification using deep learning. Their work introduced a transformer-based face recognition model, which improved feature extraction in large-scale datasets. This technique enhanced facial recognition accuracy in crowded environments, making It's the perfect remedy for public surveillance applications. Their approach achieved a recognition rate of 99.1%, demonstrating the effectiveness of attention-based architectures in handling complex face recognition scenarios.

III. METHODOLOGY

The proposed Missing Person Identification System leverages deep learning-based face recognition, real-time video surveillance, and automated alert mechanisms to enhance the efficiency of locating missing individuals. The methodology follows a structured approach, beginning with gathering and preparing data, model training, real-time identification, and automated reporting. By integrating CNNs, or convolutional neural networks, in facial recognition, OpenCV for real-time video processing, MySQL for database management, and SMTP-based email notifications for alerts, the system ensures a highly scalable and efficient solution. The key objective is to establish a robust end-to-end AI-driven technology that is able to identify, detect, and notify authorities in real-time when a missing person is found.

The initial stage is gathering data and preprocessing, where images of missing persons are collected from a variety of sources, including law enforcement databases, family-provided images, social media, and online missing persons reports. Since these images vary in lighting conditions, angles, and resolutions, preprocessing techniques such as histogram equalization, face alignment, and image augmentation are applied to improve model accuracy. Facial The feature extraction procedure makes use of dlib's 128-dimensional face embedding model, which converts each face into a numerical vector for efficient comparison. These embeddings are stored in a MySQL database, allowing quick retrieval and matching when a potential match is found in live video feeds.



The core component of The system is the deep learning- based face recognition model, which is built on Neural Network Convolution Utilization. If the similarity score exceeds a predefined threshold of 80%, the system identifies the individual as a potential match. The real-time processing module is optimized to process multiple video streams simultaneously, with an average detection latency of 1.2 seconds per frame, ensuring minimal delay in recognition.

Upon successful identification, the automated alert mechanism is triggered. The system retrieves geolocation details of the detected individual using IP-based location tracking or GPS data if available. An automated email notification is sent to law enforcement agencies and registered family members, including details of the identified individual, timestamp, and location link for real- time tracking.

The methodology ensures that the system operates in real- time with high accuracy, minimal false positives, and automated alerting, making it an effective instrument forlaw enforcement agencies and families searching for missing individuals. The suggested approach provides a technologically advanced, AI-driven framework that significantly reduces the burden on manual search efforts while improving identification speed and reliability. Future enhancements could include 3D face recognition for improved matching, blockchain-based data security for privacy, and IoT-based smart surveillance integration to further optimize real-world deployment.

Algorithm:

Convolutional Neural Network is what CNN stands for.The architecture implemented in the Missing Person Identification System is created to precisely identify and match the facial features of missing individuals using deep learning techniques. The architecture consists of multiple convolutional, pooling, and fully connected layers, allowing the model to extract essential facial features and perform classification efficiently. The key objective of this architecture is to process and analyze facial images, detect missing persons from real-time surveillance feeds, and provide accurate identification in varying environmental conditions.

1. Input Layer as well as preprocessing

The initial phase of the CNN architecture is image input and preprocessing. The system takes facial images as input, which are collected from missing person databases, law enforcement records, and surveillance footage. Each image undergoes preprocessing techniques such as resizing, normalization, and augmentation to enhance model robustness. The pictures have been scaled to 300 ×
300 pixels, ensuring a uniform input size across the network. Pixel normalization (rescaling between 0 and 1) is applied to standardize the dataset and improve training efficiency.

2. Utilizing Convolutional Layers for Feature Extraction

The CNN model is structured with three convolutional layers, each of which is in charge of extracting different levels of facial features:

First Convolutional Layer:

• Applies 16 filters (3×3 kernel size) with Rectified Linear Unit, or ReLU activation function.
• Detects low-level features like edges,corners, as well as textures in facial images.
• Padding is utilized to guarantee that the output size remains the same as the input.
• Output from this layer is passed to a max-pooling layer to reduce spatial dimensions.

Second Convolutional Layer:

• Uses 32 filters (3×3 kernel size) to extract higher- level patterns such as facial contours and key landmarks.
• The activation function of ReLU makes sure that non-linearity is maintained, allowing the model to capture complex relationships in facial structures.
• A Max-Pooling layer(2x2 window)will decrease the dimensionality savings in computational efficiency, and yet only neglects pertinent features.

Third Convolutional Layer:

• Uses 64 filters (3×3 kernel size) to learn deeper and more abstract representations of facial features.
• Extracts fine-grained details such as eye shape, nose structure, and skin texture. They are necessary to differentiate individuals.

• A final max-pooling layer (2×2 window) down- samples the extracted feature maps prior to passing them to the fully connected layers.

3. Flattening and Fully Connected Layers

After feature extraction, the Flatten layer converts the 2D feature maps into a 1D vector, preparing the information for classification. The model then includes Two completely linked layers:

First Fully Connected Layer:

• Contains 128 neurons that are activated by ReLU, enabling the network to learn complex feature representations.
• Acts as a dense feature representation layer, capturing the overall structure of the detected face.

Layer of Output (Classification Layer):

• Contains n neurons, in where n is the number of missing person classes stored in the database.
• Uses the Softmax activation function to provide likelihood ratings for every class, determining the most likely match for the detected face.
• Outputs a confidence score, with threshold-based matching (above 80%) ensuring accurate identification.

4. Instruction and Optimization

The CNN The model is trained with a categorical cross- entropy loss function, as it is a multi-class classification problem. The Adam optimizer's applications include fast convergence and adaptive learning rate adjustments, preventing issues like vanishing gradients. The model is trained over 15 epochs, with training and validation sets split at an 80:20 ratio to ensure generalization.

IV. RESULT AND DISCUSSION

The Missing Person Identification System was rigorously evaluated to assess its accuracy, efficiency, and real-world applicability in identifying missing individuals using deep learning-based face recognition and real-time surveillance processing. To train the system, a dataset containing 10,000 images of individuals with varying lighting circumstances, facial expressions, and occlusions was accustomed to improve its robustness. The Neural Network Convolution(CNN)-based face recognition model demonstrated high accuracy in controlled environments, achieving 98.2% training accuracy and 96.5% validation accuracy. In real-world scenarios involving live surveillance feeds, the model maintained 94.7% accuracy, proving its effectiveness in detecting missing persons even under challenging conditions. The precision (97.8%) and recall (96.3%) scores show that the system correctly identifies missing individuals while minimizing false negatives in addition to false positives, ensuring reliable and efficient identification.

During real-time deployment on live video feeds from CCTV and IP cameras, the system performed exceptionally well in processing multiple streams simultaneously. The average face detection speed was recorded at 1.2 seconds per frame, ensuring near- instantaneous identification. The system was capable of processing up to 20 video feeds simultaneously, demonstrating its scalability for large-scale implementation in high-traffic areas such as airports, railway stations, and public spaces. The geolocation tracking module provided 97% accuracy in pinpointing the location of identified individuals, allowing law enforcement agencies to take immediate action upon detection. The system's automated alert mechanism sent notifications to registered authorities and family members within seconds of a match, significantly reducing response time and improving the chances of locating missing individuals.

Environmental variations, such as changes in lighting, facial occlusions, and aging effects, were tested to evaluate the model's robustness. The system exhibited higher accuracy (98.1%) in well-lit conditions, but accuracy dropped slightly in low-light scenarios (91.4%) due to challenges in facial feature extraction. Similarly, occluded faces (e.g., partially covered with masks, sunglasses, or scarves) produced a precision of 88.5%, indicating that improvements in occlusion handling, such as 3D face recognition or attention-based deep learning models, could enhance performance further. The system also demonstrated strong recognition capabilities in cases involving age progression, maintaining 92.3% accuracy for individuals missing for over five years with the use of deep feature extraction techniques.

V. CONCLUSION

The Missing Person Identification System that is discussed in the current paper is a helpful one, as it uses the further level of facial recognition based on a deep learning approach, video surveillance, and automatic notifications to increase the efficiency and accuracy of the system in identifying missing persons. The use of Convolutional neural networks (CNNs) in combination with neural networks to extract facial features, open camera real-time video processing, MySQL database management, and geolocation tracking real-time alert will make the system a powerful and scalable solution to the difficult issue of finding missing people. These findings indicate that the system is characterized by the high-level accuracy (98.2 in the controlled environment and 94.7 in any real situation), which means the system can be characterized by somewhat high reliability to recognize any individual irrespective of the light conditions, face faces, and partial coverage. The implementation of real-time processing is one of the most vital characteristics of the system based on which, the law enforcement agencies have a chance to monitor the live CCTV and IP cameras streams and identify potential matches within the least possible time. An average time of 1.2 seconds per frame implies that it is fast and there are high chances that it will track people who might be lost before they turn out to be complicated. Automated alert system also enhances the effectiveness of the system giving the authorities and the family members real-time alert, the location, and the time at which staff has successfully recognized the victims.The ability to watch a simultaneous video feed. shows how scalable the system is and how it suits locations in busy areas like airports, railway stations, and other places. The system, however, continues to have some difficulties, which include low- light conditions and half-blocked faces even a weak performance. Additional developments, such as 3D face recognition models, age progression methods through GAN, and age regression methods through models for deep learning and processes, is applicable in the future to,enhance recognition in challenging real-world applications. Moreover, identity verification using blockchain would enhance data security and privacy, making the system even more dependable for large-scale deployment.

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