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AI-Powered Missing Person Identification Systems

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ABSTRACT :

Every year, thousands of missing person cases are reported across the world, creating a serious challenge for police and families in locating individuals quickly. Traditional methods such as spreading posters, community announcements, and manual search teams often take time and may not provide the desired results. With the growing availablity of CCTV cameras in public areas, there is now an opportunity to monitor locations continuously and support faster identification of missing people. Linking these live video feeds with facial recognition systems makes the verification of identities more accurate and reduces the heavy reliance on human observation.

In situations where lighting is poor, places are crowded, or the camera angle is unusual, facial recognition alone may struggle. However, adding artificial intelligence (AI) improves its ability to detect and recognize faces under these difficult conditions. AI also increases the speed of analysis and makes the process more reliable. Researchers have further strengthened results by combining deep learning techniques with conventional image processing methods, leading to hybrid models that perform better in real-world scenarios. Based on this review, an effective framework for missing person detection should include real-time video analysis, AI-driven face recognition, and hybrid aproaches. By integrating these elements, such systems can improve the accuracy and speed of searches, while also providing timely alerts to both authorities and families, thereby increasing the chances of locating missing individuals quickly.

Keywords: Missing Persons, Live CCTV, Facial Recognition, Artificial Intelligence, Deep Learning, Hybrid Models, Real-Time Surveillance

Introduction

The issue of missing persons is recognized worldwide as a serious social and public safety problem. Each year, thousands of such cases are reported, affecting families, communities, and the agencies responsible for locating the individuals. Traditional ways of searching—such as community campaigns, putting up posters, making public anouncements, and conducting manual searches—often demand a lot of time and effort but still produce limited results. These methods can also be affected by human mistakes, which makes the process even slower. Delayed action can have severe effects, especially in situations involving children, senior citizens, or people with disabilities who are more vulnerable. To address these challenges, many researchers have proposed technology-based alternatives. Examples include web applications and systems that use the Internet of Things (IoT) to track individuals in real time. These approaches aim to make the identification process faster and improve the ability of authorities to respond quickly (Malarvizhi et al. [1]; Zambrano et al. [2]).

CCTV surveillance has become an important tool for public safety because it can continuously watch streets, crowded places, transport hubs, and other busy regions. Unlike traditional methods, live CCTV allows police and security teams to observe activities as they happen and take quick action when a missing person is noticed. By linking multiple cameras placed in different areas, it is possible to follow movement patterns and find potential matches in real time, which greatly reduces the delay in emergency response. Studies have shown that combining real-time surveilance with AI-based analytics improves awareness of situations and helps ensure faster action when needed (Tsai et al. [3]; Magendiran et al. [4]).

Facial recognition technology is one of the main elements used in modern systems for detecting missing persons. These systems work by analyzing unique facial features to verify identities from both live video feeds and stored recordings. Even under chalenging conditions such as crowded places, poor lighting, unusual camera positions, or when the face is partly hidden, facial recognition can still match images against a database of known missing individuals with reliable results. The use of deep learning methods and other advanced AI models has further improved the accuracy of recognition, making it possible to monitor in real time with minimal human effort (Sudhagar et al. [5]; Bhavani et al. [6]).

When facial recognition is combined with artificial intelligence (AI), the system gains both automation and stronger detection abilities. AI models like convolutional neural networks (CNNs) can process large volumes of video in real time, detect faces, and verify identities, which reduces the effort needed from law enforcement and lowers the chance of missing potential matches. By learning from earlier detections, AI can also adapt to new conditions and improve both accuracy and efficiency. The reliability of such systems is further improved when hybrid approaches are used, as they bring together traditional image processing methods with AI-based recognition. This combination helps the system perform well even under challenging situations such as blurred video, low resolution, or frames containing multiple faces (Bhilawadi et al. [7]; Kaspate et al. [8]; Vishwanatha et al. [9]; Yiming Yao [10]).

The use of live CCTV, artificial intelligence, facial recognition, and hybrid models together has introduced a new approach to missing person identification. These technologies enable quick alerts, tracking, and detailed reports that include time and location, while also making monitoring more scalable and largely automated. By applying these advancements, authorities can work faster and with greater accuracy, improving the reliability of search efforts and increasing the chances of reuniting missing individuals with their families within a shorter time.

Literature Survey: Foundational Technologies and Concepts

Advances in computer vision, deep learning, and artificial intelligence (AI) have brought major changes to how missing persons are identified. In the past, searches mainly relied on manual efforts such as posters, public anouncements, and community help, which were time-consuming and often less effective. The increasing use of live CCTV cameras in public spaces has created new opportunities to automate the process of tracking and detecting missing people in real time. These systems bring together different technologies, including database management, video analytics, facial recognition, and hybrid approaches that mix traditional image processing with AI methods. By studying these core technologies and how they work together, we can better understand the latest techniques being used in AI-based missing person detection and the challenges that come with them.

Real-Time Video Surveillance and Data Acquisition

Real-time video surveillance plays a crucial role in modern missing person detection systems, allowing continuous monitoring of public spaces to locate and track individuals. High- resolution video streams from CCTV cameras serve as the primary input for AI-based analysis. These cameras are typically installed in strategic locations such as metro stations, airports, bus terminals, shopping malls, and busy city streets (Dr. Ambika L G, Kadiri Kavya, Kusuma C, Guddampalli Sravani, and Keerthana M [11]). Early surveillance systems struggled with the sheer volume of video data due to limitations in processing speed, storage, and real-time analysis. As a result, quickly and accurately finding missing people was difficult, with manual monitoring often being slow and prone to human error (Rajeev Ranjan, Swami Sankaranarayanan, Ankan Bansal, Navaneeth Bodla, Jun-Cheng Chen, Vishal M. Patel, Carlos D. Castillo, and Rama Chellappa [12]).

Thanks to advancements in edge computing, distributed processing, and cloud-based analytics, modern surveillance systems have become highly responsive, capable of analyzing video streams almost instantly. By combining live CCTV footage with AI-powered models—such as convolutional neural networks for object tracking and facial recognition—these systems can quickly detect and verify missing persons (Ramavath Ganesh, Chilukuri Srija, Bhuriwale Devesh, and Mrs. Harika Koormala [13]). They are designed to handle real-world challenges like changing lighting conditions, crowded environments, and shiffting camera angles. The integration of high-resolution cameras, intelligent video analytics, and automated motion detection ensures that critical alerts are issued promptly, significantly reducing the response time for family members or law enforcement. By enabling continuous, proactive monitoring in high-risk areas, these capabilities not only enhance search efficiency but also strengthen overall public safety measures.

Preprocessing and Feature Extraction

With advances in edge computing, distributed processing, and cloud-based analytics, modern surveillance systems have become highly responsive, capable of analyzing video streams almost in real time. By integrating live CCTV footage with AI-powered models—such as convolutional neural networks for object tracking and facial recognition—these systems can rapidly identify and verify missing persons (Ramavath Ganesh, Chilukuri Srija, Bhuriwale Devesh, and Mrs. Harika Koormala [13]). They are built to tackle real-world challenges, including fluctuating lighting conditions, crowded spaces, and shifting camera angles. The combination of high-resolution cameras, intelligent video analytics, and automated motion detection ensures that critical alerts are generated promptly, greatly reducing response times for families and law enforcement. By supporting continuous, proactive monitoring in high-risk areas, these systems not only improve the efficiency of search operations but also reinforce public safety measures.

During feature extraction, which begins after preprocesing, key characteristics such as facial landmarks, head position, body posture, and facial expressions are identified. These features form the core input for deep learning models, providing a structured representation of each individual in the scene. By combining these extracted features with robust neural network architectures, the system can accurately recognize and track people even in challenging conditions, such as occlusion, crowded environments, varying camera angles, or partially visible faces (Divyansh Yadav, Janhvi Tyagi, Dipanshu, Ritu Tiwari, and Ms. Pawan Pandey [15]). A thorough preprocessing and feature extraction process is therefore critical for AI-based missing person identification systems to achieve high accuracy and reliability.

Facial Recognition in Missing Person Identification

Facial recognition technology forms the core of AI-powered missing person detection systems. After preprocessing and feature extraction from live CCTV footage, deep neural networks (DNNs) compare the extracted facial features with a database of recorded missing persons (Diego Acuña-Escobar, Julio Ibarra-Fiallo, and Monserrate Intriago-Pazmiño [16]). These features include facial landmarks, distances between the eyes, nose shape, jawline contours, and other distinctive identifiers that remain largely consistent across different expressions and lighting conditions. By encoding these characteristics into numerical representations known as feature embeddings, the system can accurately match live detections with stored records. This capability significantly acelerates response times compared to traditional manual searches, allowing authorities to receive real-time alerts whenever a match is found.

Convolutional neural networks (CNNs) and advanced architectures such as FaceNet, VGG- Face, and ArcFace are central to modern facial recognition techniques. These networks are designed to generate robust and distinctive feature embeddings for each individual (BIRARI HETAL, SANYASHIV RAKESH, PORJE ROHAN, and SALVE HARISH [17]). They are trained on large-scale datasets, which enables them to handle variations in pose, lighting, expression, and partial occlusions—common challenges in crowded public spaces. To further enhance recognition accuracy in difficult scenarios, such as videos with many faces or low- quality footage, hybrid systems often combine CNNs with attention mechanisms and metric learning methods. By leveraging these sophisticated models, AI-based solutions maintain high reliability, reduce false positives, and ensure that missing persons are detected quickly and accurately.

Hybrid Detection Models

Hybrid detection models, which combine AI-based facial recognition with traditional computer vision techniques, significantly enhance the identification of missing persons (Jiankang Deng, Jia Guo, Jing Yang, Niannan Xue, Irene Kotsia, and Stefanos Zafeiriou [18]). Conventional methods such as edge detection, background subtraction, and histogram of oriented gradients (HOG) are effective for detecting general shapes and motion in video frames, but they often struggle under challenging conditions like low lighting, partial occlusion, or unusual camera angles. By integrating these traditional aproaches with deep learning models, hybrid systems
can accurately locate potential faces before confirming identities using CNN-based facial recognition. As noted by Yaniv Taigman, Ming Yang, Marc'Aurelio Ranzato, and Lior Wolf [19], this two-step strategy enhances detection robustness, reduces false positives, and ensures accurate analysis even for partially hidden faces or low-resolution images. Hybrid models are particularly well-suited for large-scale, real-time surveillance, maintaining reliability in dynamic environments such as crowded streets, train stations, and airports.

Moreover, hybrid systems can dynamically adjust the weight given to neural networks versus traditional computer vision methods depending on the environment. For instance, AI-based recognition may dominate in well-lit, clearly visible areas, while conventional edge detection can guide the neural network toward the most relevant facial regions in dimly lit or crowded settings. This flexibility ensures consistent performance across diverse conditions and enables continuous monitoring without significant loss of accuracy. Overall, hybrid detection models provide a practical and scalable framework for large-scale missing person identification systems.

Real-Time Matching and Alert Systems

The system immediately notifies relevant authorities and family members when a potential match is detected (Fahad Parvez Mahdi, Md. Mahmudul Habib, Md. Atiqur Rahman Ahad, Susan Mckeever, A.S.M. Moslehuddin, and Pandian Vasant [20]). These alerts are crucial, as timely action can significantly increase the chances of locating a missing person. To achieve this, the system employs high-performance processing pipelines capable of analyzing multiple CCTV streams simultaneously with minimal delay. Advanced setups often leverage edge computing, cloud-based infrastructure, and GPU parallel processing to ensure that analysis and matching occur almost instantanously.

Modern alerting systems also use mobile applications, IoT devices, and SMS or email notifications to quickly share information (Florian Schroff, Dmitry Kalenichenko, and James Philbin [21]). Alerts typically include the image, location, timestamp, and confidence score of the detected individual, enabling authorities to verify and respond immediately. In addition, dashboards provide a centralized monitoring interface that displays all active matches across surveillance points, helping security personnel eficiently prioritize responses. By combining automated matching, real-time communication, and rapid detection, these technologies enhance public safety and significantly reduce the time between detection and recovery in missing person operations.

Database Management and Big Data Analytics

The effective use of big data analytics and well-organized databases is crucial for the accuracy and reliability of AI-powered missing person identification systems (MR. G Bharath Kumar, Pulivarthi Sandhya, Talathoti Vamsi, Rolla Venkatesh, and Tadiboina Syam Prasad [22]). These databases store not only demographic information and face embeddings but also historical records, previous sightings, and metadata, all of which are essential for accurate identification. By leveraging face embeddings—vector representations of unique facial features—the AI system can consistently recognize individuals even under variations in lighting, angle, or partial occlusion.

Big data analytics enables the system to predict likely locations of missing persons by analyzing movement patterns, cross-referencing information from multiple sites, and processing large volumes of video data from various CCTV feeds simultaneously (Chun-Wei Tsai, Chin-Feng Lai, Han-Chieh Chao, and Athanasios V. Vasilakos [23]). Techniques such as data preprocessing, feature extraction, indexing, and parallel querying ensure real-time responsiveness by allowing rapid comparisons between incoming video and extensive databases. Predictive analytics also supports authorities in decision-making, streamlining search operations, and identifying patterns or hotspots, making the system proactive and adaptable. By integrating structured databases with advanced analytics frameworks, this approach provides the foundation for scalable, accurate, and timely detection of mising persons in urban environments, airports, metro stations, and other high-traffic public areas.

Multi-Source Video Integration

N. Niranjani, B. Tharmila, C. Sukirtha, K. Kamalraj, S. Thanujan, P. Janarthanan, N. Thiruchchelvan, and K. Thiruthanigesan [24] emphasize the importance of integrating multiple CCTV and IP camera streams to track missing persons in complex urban environments. By combining video feeds from different sources through synchronization, spatio-temporal mapping, and data fusion algorithms, AI systems can maintain continous monitoring as individuals move across zones. For instance, the system can track a person's journey from a metro station to nearby streets by comparing appearances across multiple cameras, while accounting for changes in lighting, viewing angle, and resolution.

Integrating multiple camera sources enhances situational awareness for authorities by providing comprehensive alerts that show not only detection events but also movement history and predicted trajectories. AI ensures accurate tracking even in challenging conditions, such as crowded areas or low-light environments, by managing heterogenous video feeds from high- definition private cameras and lower-resolution public cameras. The system's efficiency in
urban settings is greatly improved through cross-camera correlation and real-time processing, enabling rapid and coordinated responses.

Challenges in Data Handling

Despite the advancements in AI, real-world applications of missing person identification still face significant data management challenges (Adnan Nadeem, Muhammad Ashraf, Nauman Qadeer, Kashif Rizwan, Amir Mehmood, Ali AlZahrani, Fazal Noor, and Qammer H. Abbasi [25]; Houlin Zhao, Stephen Ibaraki, Neil Sahota, Niven R. Narain, Josef Akhtman, Dr. Nora Khaldi, Emmet Browne, Mike Hinchey, Frederic Werner, and Amir Banifatemi [26]). In crowded or dynamic environments, video footage may be low-resolution, grainy, or partially obstructed, complicating detection efforts. The massive volume of real-time data from multiple CCTV streams also creates computational challenges, requiring edge computing, optimized processing pipelines, and neural network architectures capable of fast inference.

Maintaining ethical standards and protecting privacy are also essential. To balance security needs with individual rights, systems should employ data anonymization, controlled access, and privacy-preserving facial recognition methods. Additional challenges include minimizing false positives, ensuring synchronization across multiple cameras, and achieving reliable performance under varying motion, weather, and lighting conditions. By adressing these ethical and technical concerns, AI-powered systems can deliver accurate and timely detection and alerts, while remaining dependable, scalable, and socially responsible, ultimately helping authorities locate missing persons more effectively.

Special Applications: Children and Vulnerable Adults

AI-based identification systems are particularly crucial for locating missing children and vulnerable individuals, who are often at higher risk and require immediate intervention (Pratyush Raj, Shubham Kumar S. Dhamodaran, J. Refonaa S. L. Jany Shabu, and Viji Amutha Mary [27]). Detecting children in real time is especially challenging due to their smaller facial features, increased movement in crowded areas, and rapid facial changes with age. Nevertheless, specialized neural networks trained on children's facial characteristics allow the system to accurately recognize their faces, even in cases of occlusion, motion blur, or non- frontal poses.

Similarly, deep learning architectures are employed in adult detection systems to minimize false positives while maintaining reliability across diverse demographic profiles, lighting conditions, and camera angles (Ramavath Ganesh, Chilukuri Srija, Bhuriwale Devesh, and Mrs. Harika Koormala [28]). These systems often rely on hybrid models that integrate traditional computer vision techniques with AI-based motion tracking, facial recognition, and context-aware analytics to enhance accuracy and dependability. They can operate continously, monitor multiple video streams simultaneously, and automatically update the database with new information, enabling proactive surveillance and rapid alerts. These applications highlight the importance of combining advanced AI technologies, real-time video analytics, and effective alert mechanisms to ensure timely responses, providing tangible benefits to families, caregivers, and law enforcement agencies.

AI-Driven Workflow for Real-Time Detection

The workflow for real-time missing person detection begins with continuous video capture from strategically positioned CCTV cameras. Preprocessing steps, such as frame extraction, motion detection, and image enhancement, are applied to improve visibility in challenging conditions (Aswani T. et al. [29]). Deep neural networks then analyze the extracted facial landmarks, expressions, and head orientation, comparing them against a structured database of known missing persons. When a match is identified, the system automatically sends notifications—including timestamps, location coordinates, and images—to authorities or family members for verification (B. B. Saha et al. [30]).

This automated and systematic approach significantly reduces response times, ensuring rapid and acurate identification. By integrating real-time data processing, multi-source video analysis, and hybrid detection models, the system can track individuals across different zones, maintaining continuity even as they move between cameras or locations. These solutions demonstrate the real-world impact of AI-powered missing person identification, combining advanced AI analytics with organized alert mechanisms to enable effective coordination between technology, law enforcement, and families, ultimately helping protect vulnerable populations.

Summary of Methodology used towards identification of Missing Person

Name of Paper	**Methodology Proposed**	**Advantages**	**Limitations**
"FaceNet: A Unified Embedding for Face Recognition and Clustering" by F. Schroff, D. Kalenichenko, and J. Philbin (2015)	Introduced face embeddings, which are compact vector representations of faces. Different faces map to distant vectors, whereas the same person's faces map to neighboring vectors.	Incredibly efficient and scalable—all it takes to match an embedding with thousands of others is a few fast mathematical calculations.	Due to its autoregressive nature, it provides no fine-grained control over the particular characteristics of the generated audio, such as time or mood.

"DeepFace: Closing the Gap Between Human and Machine Performance in Face Verification" by Y. Taigman et al. (2014)	Created 3D face models using a deep neural network, then compared them to determine whether they were created by the same person.	Reached a ground- breaking accuracy rate in facial verification that was almost on par with human performance.	On conventional technology, 3D modeling was too computationally costly for real-time video.
"Face Recognition- Based Real-Time System for Surveillance" by F. P. Mahdi et al. (2016)	A two-step live video system that first recognizes faces using a quick algorithm and then compares them to a database.	Gives a clear, doable road map for developing a system for video streams, which is one of our project's main goals.	Utilized older models (PCA, Viola- Jones); blur, low resolution, and changes in illumination or angle cause performance to suffer.
"Big Data Analytics: A Survey" by Chun- Wei Tsai et al. (2015)	Explains why traditional analytics cannot manage enormous, quick, and diverse data (such as photos and video) and the "3Vs" of big data: volume, velocity, and variety.	Explains why file- based storage isn't scalable and offers a strong basis for creating data-intensive systems.	Focuses on Big Data solutions at the corporate level, which are too resource-intensive and sophisticated for a small project prototype.
"Face Recognition and Tracking of Missing Person using AI" by T. Aswani et al. (2025)	Suggests a comprehensive system similar to ours, complete with machine learning for detection and web-based reporting.	This report validates our project's concept and methodology by offering a very contemporary and pertinent example of the kind of project we've produced.	Lacks the deployment of real-time live camera feeds and instead concentrates on theoretical design.
"Toward Digitalization: A Secure Approach to Find a Missing Person Using Facial Recognition Technology" by Abid Faisal Ayon and S M Maksudul Alam (2024)	Suggests a safe missing-person system that has robust information verification and two- way communication between families and finders.	Demonstrates the value of security and robust design and validates our concept as a workable, safe solution.	Describes a theoretical system that has not been fully implemented and depends on police-based verification that is outside the purview of the project.

Conclusion

The process of identifying missing persons has been revolutionized by the integration of deep learning, artificial intelligence (AI), and real-time video analytics. Traditional methods, such as printed posters, public announcements, and manual searches, are time-consuming and labor- intensive, often delaying critical interventions. In contrast, AI-powered systems provide automated, continuous surveillance, analyzing CCTV footage in real time to detect and track individuals. Even under challenging conditions like occlusion, low lighting, or low-resolution video, these systems can acurately identify missing persons using facial recognition techniques and advanced neural network architectures such as CNNs, FaceNet, VGG-Face, and ArcFace. The integration of hybrid detection models, which combine conventional computer vision methods with AI-based recognition, further enhances reliability and reduces false positives, ensuring consistent performance in crowded and dynamic environments.

One of the key advantages of modern missing person identification systems is their ability to issue real-time alerts. Automated notifications containing details such as location, timestamps, and images are sent to relevant authorities and family members as soon as a potential match is detected, enabling rapid response. By integrating multiple video sources and leveraging big data analytics, these systems can handle numerous CCTV feeds simultanously, track movement patterns, and cross-reference information across various locations, improving overall efficiency and coordination. Structured workflows ensure a systematic process—from video capture to preprocessing, feature extraction, and database comparison—minimizing delays and human error. These capabilities make AI-powered surveillance an invaluable tool for security agencies, law enforcement, and concerned families alike.

AI applications designed for children and other vulnerable individuals illustrate how these systems can address specific high-risk situations. Neural networks trained on age-specific facial features, combined with automated real-time monitoring and alert mechanisms, enable rapid identification and intervention. These customized solutions demonstrate the adaptability of AI- based methods across different locations, demographics, and operational requirements. Overall, the integration of AI, hybrid detection models, real-time video analytics, and comprehensive database management is transforming public safety. These advancements lay the groundwork for future innovations in intelligent surveillance, predictive monitoring, and crisis management, promising faster, more accurate, and responsive identification of missing persons.

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