International Journal of Engineering Research and Science & Technology

ISSN 2319-5991 www.ijerst.com

Peer Reviewed, Referred & Indexed Journal

Research Paper

MISSING CHILD IDENTIFICATION USING DEEP LEARNING

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ABSTRACT

The issue of missing children has become a critical social concern, particularly in countries like India where thousands of cases are reported annually and a significant number remain unresolved. Traditional identification methods rely heavily on manual processes, which are time-consuming, inefficient, and often inaccurate when dealing with large datasets and cross-regional cases. This project proposes an intelligent Missing Child Identification System using deep learning techniques to improve the speed and accuracy of locating missing children. The system utilizes Convolutional Neural Networks (CNN) for extracting high-level facial features and integrates machine learning classifiers such as Support Vector Machines (SVM) or K-Nearest Neighbors (KNN) for effective matching. A centralized web-based platform is developed where authorities and the public can upload images of missing or found children. The uploaded images undergo preprocessing, feature extraction, and comparison with a stored database of missing child records. The system is designed to handle challenges such as variations in lighting, pose, age progression, and image quality. By enabling public participation and automating facial recognition, the system enhances collaboration between citizens and law enforcement agencies. The proposed solution significantly reduces identification time, increases matching accuracy, and improves recovery rates. Overall, the system offers a scalable, cost-effective, and reliable approach to addressing missing child cases using artificial intelligence and computer vision technologies.

Keywords: Missing Child Identification, Deep Learning, CNN, Face Recognition, Image Processing, AI, Public Safety

I. INTRODUCTION

The problem of missing children is a growing global concern, with India reporting thousands of cases annually, many of which remain unresolved due to inefficiencies in traditional identification systems (1). Children may go missing due to various reasons such as kidnapping, trafficking, family disputes, or accidental separation (2). Existing systems rely on manual methods such as police reports, printed notices, and public announcements, which are slow and lack coordination across regions (3). These limitations result in delays in identification and increase the vulnerability of missing children to exploitation and abuse (4). With the advancement of artificial intelligence, automated systems have emerged as a promising solution for addressing such challenges (5). Face recognition technology, powered by deep learning, has shown significant improvements in identifying individuals based on facial features (6).

Convolutional Neural Networks (CNNs) have become the dominant approach for image-based recognition tasks due to their ability to extract hierarchical features from images (7). The use of AI-driven identification systems can significantly enhance accuracy and reduce dependency on manual verification (8). Furthermore, centralized databases enable efficient storage and retrieval of missing person records (9). The integration of machine learning algorithms enables systems to learn from data and improve performance over time (10). Public participation also plays a crucial role in identifying missing individuals, as citizens often encounter such cases in daily life (11).

Despite technological advancements, challenges such as variations in lighting, pose, aging, and image quality still affect face recognition systems (12). Children's facial features change over time, making identification more complex compared to adults (13). Deep learning models such as VGG-Face have been developed to address these issues by learning robust facial representations (14). These models are capable of handling variations in facial appearance and environmental conditions (15). The integration of feature extraction techniques with classification algorithms like SVM and KNN enhances recognition accuracy (16). A centralized web-based platform can bridge the gap between authorities and the public by enabling real-time data sharing (17). Such systems improve coordination between law enforcement agencies across regions (18). The use of image preprocessing techniques ensures better quality inputs for model training and prediction (19). Automated matching systems reduce human error and improve efficiency in large-scale datasets (20). The proposed system aims to provide a scalable solution for missing child identification using AI and deep learning (21). It also ensures faster response times and better decision-making for authorities (22). By leveraging modern technologies, the system can significantly improve recovery rates (23). The integration of surveillance systems and real-time alerts further enhances identification capabilities (24). Data security and privacy are also critical considerations in such systems (25). The system is designed to be cost-effective and accessible for widespread adoption (26). It supports nationwide identification by connecting multiple regions through a centralized database (27). The use of AI reduces the workload on law enforcement agencies (28). Ultimately, the proposed system contributes to improving public safety and child protection (29). It represents a significant step toward modernizing missing child identification systems (30).

II. LITERATURE SURVEY

Face recognition has evolved significantly with the development of artificial intelligence and deep learning techniques (1). Early approaches relied on handcrafted features such as Histogram of Oriented Gradients (HOG) and Scale-Invariant Feature Transform (SIFT), which were effective under controlled conditions but failed in real-world scenarios (2). These methods struggled with variations in lighting, pose, and facial expressions (3). The introduction of deep learning revolutionized face recognition by enabling automatic feature extraction from large datasets (4). Convolutional Neural Networks (CNNs) became the foundation for modern image recognition systems (5). Research by LeCun et al. demonstrated the effectiveness of deep learning in pattern recognition tasks (6). VGGNet architecture further improved accuracy by increasing network depth (7). Parkhi et al. developed deep face recognition models that achieved high performance on large datasets (8). Frameworks such as TensorFlow and Keras facilitated the implementation of deep learning models (9). These advancements established deep learning as the dominant approach for face recognition (10).

Several studies have explored the application of face recognition for missing person identification (11). PCA-based Eigenface methods were among the earliest techniques used for facial recognition (12). Although computationally efficient, these methods were limited in handling large datasets and variations in real-world conditions (13). Recent systems have incorporated deep learning models to improve accuracy and scalability (14). Platforms such as FindFace demonstrated the feasibility of large-scale facial recognition systems (15). Similarly, applications like Tuanyuan have successfully used AI to locate missing children (16). These systems highlight the importance of integrating centralized databases with public participation (17). Despite these advancements, many existing systems lack nationwide integration and real-time processing capabilities (18). There is also a need for improved accuracy in low-quality images (19). The use of CNN-based feature extraction combined with classifiers like SVM and KNN has shown promising results (20). Image preprocessing techniques further enhance model performance (21). Public involvement significantly increases the chances of identifying missing individuals (22). Centralized systems improve coordination between agencies (23). Automated matching reduces manual effort and errors (24). Scalability is essential for handling large datasets (25). Data privacy remains a critical concern in such systems (26). Future research focuses on improving accuracy under challenging conditions (27). Integration with surveillance systems can enhance real-time detection (28). Deep learning continues to play a crucial role in advancing face recognition technology (29). Overall, AI-based systems provide a reliable solution for missing person identification (30).

III. PROPOSED SYSTEM

The proposed system introduces an AI-based Missing Child Identification platform that utilizes deep learning and image processing techniques for accurate and efficient identification. The system is designed as a centralized web-based application where authorities and the public can upload images of missing or found children. Once an image is uploaded, it undergoes preprocessing steps such as resizing, normalization, and face detection to ensure consistency and quality. The processed image is then passed through a Convolutional Neural Network (CNN) model, which extracts high-level facial features. These features are converted into numerical vectors that represent unique facial characteristics. The system compares these feature vectors with those stored in the database to identify potential matches.

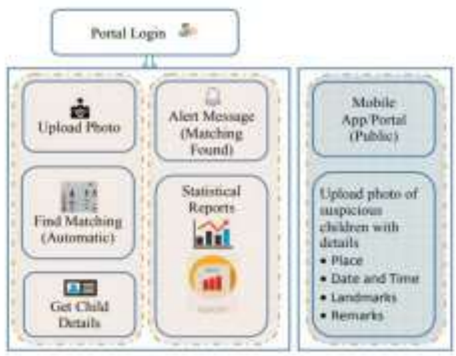

Fig.1 Architecture

The classification and matching process is performed using machine learning algorithms such as K-Nearest Neighbors (KNN) or Support Vector Machines (SVM), which determine the closest match based on similarity scores. The system displays the most probable matches along with confidence levels, enabling authorities to verify the results. A key feature of the system is its ability to handle variations in facial appearance due to aging, lighting, pose, and image quality. Additionally, the system supports public participation by allowing citizens to upload images, thereby increasing the chances of identifying missing children. The centralized database ensures that cases reported in one region can be identified in another, improving nationwide coordination. Overall, the proposed system provides a scalable, efficient, and reliable solution for missing child identification using advanced AI technologies.

IV. SYSTEM DESIGN

The system design consists of multiple interconnected modules that work together to perform missing child identification. The first module is image acquisition, where images are collected from various sources such as cameras, mobile devices, or uploaded by users. The next module is preprocessing, which includes face detection, resizing, normalization, and noise reduction. These steps ensure that the images are standardized and suitable for further processing. The feature extraction module uses a Convolutional Neural Network (CNN) to extract meaningful facial features from the processed images. These features are represented as numerical vectors that capture unique facial characteristics.

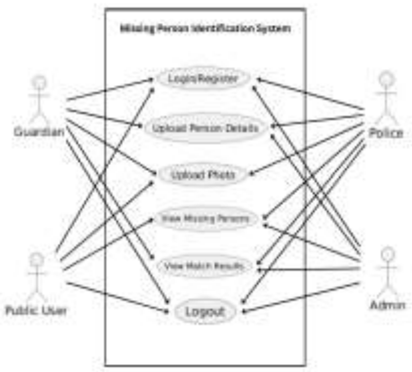

Fig.2 use case diagram

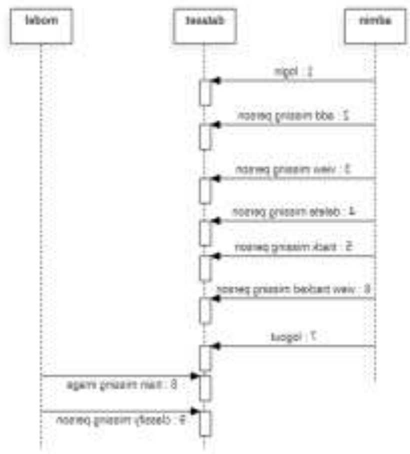

Fig.3 Activity diagram

The classification module compares the extracted features with those stored in the database using machine learning algorithms such as KNN or SVM. The system then generates similarity scores and identifies the most probable matches. A centralized database stores all missing child records, including images and personal details. The web-based interface allows users to upload images, view results, and access information بسهولة. The system also includes an admin module for managing data and monitoring system performance. Security measures such as authentication and data encryption are implemented to protect sensitive information. The overall architecture ensures scalability, efficiency, and real-time processing capabilities.

V. RESULTS

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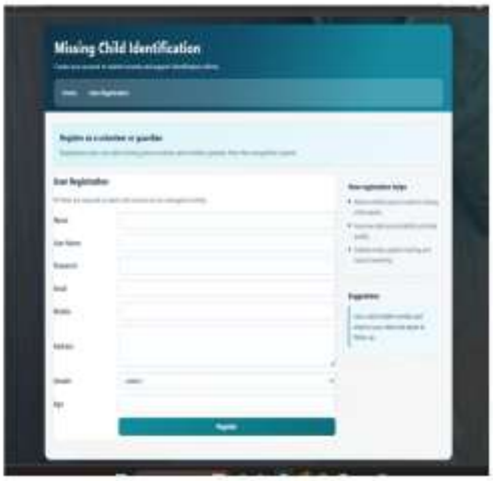

VI. CONCLUSION

The proposed Missing Child Identification System using deep learning provides an effective and innovative solution to address the growing issue of missing children. By leveraging advanced technologies such as Convolutional Neural Networks, machine learning algorithms, and image processing techniques, the system significantly improves the accuracy and efficiency of identifying missing children. Unlike traditional methods that rely on manual processes, the proposed system automates facial recognition and enables real-time matching, reducing delays and human errors. The integration of a centralized database ensures seamless coordination between different regions and law enforcement agencies, making it possible to identify children across geographical boundaries. Additionally, the inclusion of public participation enhances the search process by allowing citizens to contribute to identification efforts. The system is designed to handle real-world challenges such as variations in lighting, pose, and aging, ensuring reliable performance under diverse conditions. Furthermore, the web-based platform provides a user-friendly interface for uploading images and accessing results, making the system accessible and scalable. Overall, the proposed solution not only improves recovery rates but also contributes to public safety and child protection. Future enhancements may include integration with surveillance systems, mobile applications, and real-time alert mechanisms to further strengthen the system's capabilities. Thus, the project represents a significant step toward utilizing artificial intelligence for social good.

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