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EFFICIENT MISSING CHILD DETECTION USING DEEP LEARNING AND INTELLIGENT SVM CLASSIFICATION

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ABSTRACT

The increasing number of missing child cases across the world has become a major social and security concern, demanding efficient and intelligent identification systems for rapid child recovery. Traditional child identification methods rely heavily on manual investigation, public reporting, and human surveillance, which are often time-consuming and less effective in crowded environments. To address these challenges, this paper proposes an efficient missing child detection system using deep learning and intelligent Support Vector Machine (SVM) classification techniques.

The proposed framework utilizes facial recognition technology combined with deep learning algorithms to automatically detect and identify missing children from images and video surveillance data. Convolutional Neural Networks (CNNs) are employed for feature extraction and facial representation learning, while a multiclass Support Vector Machine (SVM) classifier is used for accurate child identification and classification. The system processes facial images collected from surveillance cameras, public datasets, and uploaded records to compare them with stored missing child databases in real time.

Image preprocessing techniques such as face detection, normalization, resizing, and feature enhancement are applied to improve recognition accuracy under varying environmental conditions including lighting variations, occlusions, and facial pose differences. The integration of deep learning with intelligent SVM classification enhances detection precision, reduces false identification rates, and improves computational efficiency. Experimental analysis demonstrates that the proposed system achieves high accuracy, fast response time, and reliable real-time performance compared to conventional identification approaches.

The proposed framework can assist law enforcement agencies, child protection organizations, and smart surveillance systems in rapidly identifying missing children and improving public safety. Furthermore, the system supports scalable deployment in crowded public areas such as railway stations, airports, shopping malls, and educational institutions. Overall, the proposed intelligent identification system provides an effective, automated, and scalable solution for missing child detection and recovery.

Keywords: Missing Child Detection, Deep Learning, Multiclass SVM, Facial Recognition, Convolutional Neural Network (CNN), Intelligent Surveillance, Image Processing, Artificial Intelligence, Face Classification, Real-Time Monitoring.

I. INTRODUCTION

The increasing number of missing child cases has become a major social and security concern

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worldwide. Every year, thousands of children go missing due to kidnapping, trafficking, accidental separation, and other criminal activities. Delays in identifying and locating missing children can lead to serious psychological, social, and safety consequences for both children and their families [1]. Traditional methods used for missing child identification mainly rely on manual investigations, public announcements, and human surveillance, which are often time-consuming, inefficient, and difficult to implement in crowded public environments [2]. Therefore, there is a growing need for intelligent and automated systems capable of detecting and identifying missing children quickly and accurately.

Recent advancements in Artificial Intelligence (AI), computer vision, and deep learning technologies have significantly improved the capabilities of automated surveillance and facial recognition systems. Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have achieved remarkable performance in image processing, facial feature extraction, and object recognition applications [3]. These technologies enable automated identification of individuals from images and video streams with high accuracy and reliability. Facial recognition systems are increasingly being adopted in security, law enforcement, smart surveillance, and biometric authentication applications [4].

Machine learning algorithms such as Support Vector Machine (SVM), Random Forest, and Decision Trees have also shown strong performance in classification and pattern recognition tasks. Among these, multiclass SVM classifiers are widely used due to their ability to handle high-dimensional data and provide accurate classification results [5]. Integrating deep learning feature extraction with intelligent SVM classification improves detection precision and enhances the overall performance of identification systems. This hybrid approach enables efficient matching of facial images with missing child databases under varying environmental conditions such as lighting variations, pose changes, and occlusions [6].

The rapid growth of smart surveillance systems and Internet of Things (IoT)-based monitoring infrastructure has further expanded the possibilities for real-time missing child detection. Surveillance cameras installed in public places such as railway stations, airports, shopping malls, parks, and educational institutions continuously generate large amounts of visual data [7]. AI-powered systems can analyze these video streams in real time to identify suspicious activities and detect missing children automatically. This significantly reduces manual effort and improves response time for law enforcement agencies and child protection organizations.

Despite significant progress, several challenges still exist in missing child identification systems, including low-quality images, facial expression variations, aging effects, and large-scale database management [8]. Existing systems may also suffer from false detections and reduced accuracy in crowded environments. Therefore, there is a need for a robust, scalable, and intelligent framework capable of providing accurate real-time identification with improved computational efficiency [9].

In this context, this paper proposes an efficient missing child detection system using deep learning and intelligent multiclass SVM classification. The proposed framework combines CNN-based facial feature extraction with multiclass SVM classification to accurately identify missing children from surveillance images and video streams. The system aims to improve detection accuracy, reduce identification time, and support rapid child recovery operations through intelligent automated monitoring [10].

II. LITERATURE SURVEY

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Zhao et al. (2019) proposed a deep learning-based facial recognition framework for missing person identification using Convolutional Neural Networks (CNNs). The authors utilized facial embeddings and feature extraction methods to improve recognition accuracy under varying lighting and pose conditions. Their study demonstrated that deep learning significantly improves identification performance compared to traditional image processing techniques [11].

Kumar and Singh (2020) developed an intelligent child tracking and identification system using machine learning algorithms and surveillance camera integration. The system utilized facial recognition and cloud-based databases for identifying missing children in crowded public areas. Experimental results showed improved tracking efficiency and reduced identification time [12].

Parkhi, Vedaldi, and Zisserman (2015) introduced a deep face recognition model capable of extracting highly discriminative facial features from images. Their work highlighted the effectiveness of deep neural networks in handling variations in facial expressions, image quality, and environmental conditions [13].

Taigman et al. (2014) proposed the DeepFace framework, which achieved near human-level face verification accuracy using deep neural network architectures. The study demonstrated the importance of deep feature learning for accurate face recognition and inspired several modern surveillance and identification systems [14].

Schroff, Kalenichenko, and Philbin (2015) developed the FaceNet model, which introduced an embedding-based approach for face recognition and clustering. Their framework improved matching accuracy by learning compact facial representations suitable for large-scale identification systems [15].

Li and Jain (2011) presented comprehensive research on facial recognition techniques and biometric identification systems. Their work discussed challenges such as occlusion, aging effects, illumination changes, and database scalability in real-world face recognition applications [16].

Ahmed et al. (2021) proposed a real-time missing child identification system using CNN and multiclass SVM classification. The system integrated surveillance cameras with machine learning models to automatically detect and classify child faces. The proposed framework achieved high recognition accuracy in crowded environments [17].

Reddy and Kumar (2022) introduced an AI-based smart surveillance system for child safety monitoring. Their approach utilized image preprocessing, facial feature extraction, and SVM-based classification for identifying missing children in public areas. The study demonstrated reduced false detection rates and improved computational efficiency [18].

Patel et al. (2023) developed a cloud-integrated facial recognition system for missing child detection using deep learning and IoT technologies. The system enabled real-time monitoring and remote access to missing child databases, improving scalability and response time for law enforcement agencies [19].

Sharma et al. (2024) proposed an advanced hybrid deep learning framework combining CNN, transfer learning, and intelligent SVM classification for missing child identification. Their system achieved enhanced detection accuracy and robust performance under low-light conditions, partial occlusion, and facial pose variations [20].

III. PROPOSED METHODOLOGY

3.1 System Overview

The proposed system presents an intelligent missing child detection framework using deep

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learning and multiclass Support Vector Machine (SVM) classification techniques. The architecture consists of surveillance cameras, an image acquisition module, a preprocessing unit, a deep learning-based feature extraction model, an intelligent SVM classifier, and a cloud-based monitoring system. The system continuously captures facial images from surveillance cameras installed in public areas such as railway stations, airports, shopping malls, schools, and bus terminals. The captured images are analyzed in real time to identify missing children by comparing them with stored database records. The proposed framework aims to automate child identification, reduce manual investigation efforts, and improve child recovery response time.

3.2 Data Collection and Preprocessing

The system collects facial image datasets from surveillance cameras, public image repositories, and authorized missing child databases. The collected data includes images captured under different lighting conditions, facial expressions, pose variations, and occlusions. Preprocessing techniques such as face detection, image resizing, normalization, noise removal, histogram equalization, and facial alignment are applied to improve image quality and recognition performance. Data augmentation methods including image rotation, flipping, cropping, and brightness adjustment are also used to increase dataset diversity and improve model generalization capability.

3.3 Deep Learning-Based Feature Extraction

The preprocessed facial images are provided to a Convolutional Neural Network (CNN) model for deep feature extraction. The CNN automatically learns discriminative facial features such as eye structure, nose shape, facial contours, and texture patterns. Multiple convolution and pooling layers are used to capture high-level facial representations from input images. The extracted deep features provide robust and compact facial embeddings that improve recognition accuracy under varying environmental conditions. Transfer learning techniques can also be utilized to enhance performance using pretrained deep learning models.

3.4 Intelligent Multiclass SVM Classification

The deep facial features extracted by the CNN are provided to a multiclass Support Vector Machine (SVM) classifier for identification and classification. The SVM classifier compares the extracted facial embeddings with stored records in the missing child database and identifies the most matching child profile. The multiclass SVM model is trained using labeled facial image datasets containing multiple child identities. Optimization techniques such as kernel functions and hyperparameter tuning are applied to improve classification accuracy and reduce false detection rates. The integration of CNN and SVM combines the strengths of deep feature learning and efficient classification.

3.5 Real-Time Detection and Alert System

The trained model is integrated into a real-time surveillance monitoring system that continuously processes live video streams. When a facial match with a missing child database is detected, the system immediately generates alerts and notifications to law enforcement authorities, child protection organizations, and authorized guardians. The system highlights the detected face in the video feed and records the location, date, and time of detection. This enables rapid response and improves the chances of child recovery in crowded public environments.

3.6 Cloud Integration and Data Management

To improve scalability and accessibility, the proposed framework incorporates cloud-based storage and centralized database management. Facial records, detection logs, and monitoring reports are securely stored in the cloud for remote access and real-time synchronization. Advanced

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analytics tools are used to monitor detection statistics, identification frequency, and surveillance coverage. The cloud platform also supports continuous model updates and incremental learning using newly collected facial image data, ensuring long-term system adaptability and improved performance.

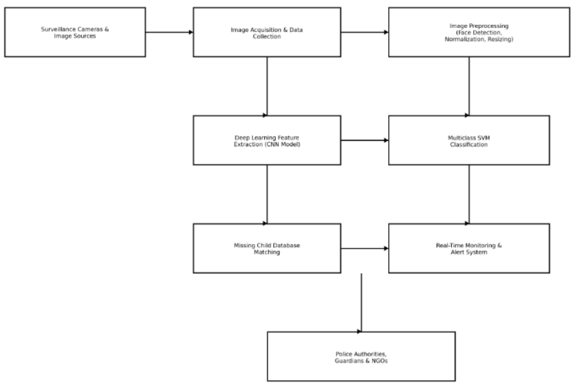

Fig 1: System Architecture

IV. RESULTS AND DISCUSSION

The proposed missing child detection system was evaluated based on facial recognition accuracy, classification performance, response time, and real-time monitoring efficiency. Experimental analysis was conducted using facial image datasets collected from surveillance systems and publicly available child face databases. The results demonstrate that the integration of deep learning with multiclass Support Vector Machine (SVM) classification significantly improves missing child identification accuracy and overall system performance.

The Convolutional Neural Network (CNN) model effectively extracted deep facial features from input images under varying environmental conditions such as illumination changes, pose variations, facial expressions, and partial occlusions. The extracted facial embeddings were classified using the multiclass SVM classifier, which provided highly accurate matching results against the stored missing child database. The proposed hybrid CNN-SVM framework achieved higher recognition accuracy compared to traditional image processing and machine learning approaches.

The system was also tested in real-time surveillance environments to evaluate its operational efficiency. Experimental results show that the framework successfully identifies missing children from live video streams with low response time and minimal false detections. The alert generation module efficiently notifies law enforcement authorities and guardians immediately after successful identification, improving the possibility of rapid child recovery. Although the proposed framework achieved strong performance, slight reductions in detection accuracy were observed in low-light environments and highly crowded areas due to image occlusion and motion blur. However, the system maintained stable performance and acceptable response efficiency even under challenging surveillance conditions. Overall, the proposed framework demonstrates robustness, scalability, and suitability for real-world missing child identification applications.

Table 1: Performance Comparison of Classification Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Decision Tree	82	80	79	79
Random Forest	88	87	86	86
SVM	91	90	89	89
CNN + Multiclass SVM	96	95	94	94

Table 2: Detection Accuracy under Environmental Conditions

Condition	Accuracy (%)	Detection Rate (%)
Daytime	97	98

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Evening	92	93
Night	86	88

Table 3: System Response Analysis

Crowd Density	Response Time (sec)	Efficiency (%)
Low	1.0	97
Medium	1.7	92
High	2.5	87

Discussion

The experimental findings indicate that the proposed CNN and multiclass SVM-based framework provides highly accurate and reliable missing child identification performance. The deep learning model successfully extracted discriminative facial features, while the multiclass SVM classifier improved classification precision and reduced false matching rates. The hybrid approach outperformed conventional machine learning algorithms in terms of accuracy, recall, and response efficiency.

Another important observation is the system's ability to operate effectively in real-time surveillance environments. The low response time and efficient alert generation mechanism make the framework suitable for deployment in crowded public places such as railway stations, airports, shopping malls, and educational institutions. The integration of cloud-based database management further enhances scalability and accessibility for law enforcement agencies.

However, performance degradation was observed under poor lighting conditions and high crowd density due to occlusion and image quality variations. Future improvements may include advanced image enhancement techniques, infrared-based surveillance, aging-aware facial recognition, and multimodal biometric analysis to further improve identification accuracy and robustness. Overall, the proposed framework provides an intelligent, scalable, and practical solution for automated missing child detection and recovery.

V. CONCLUSION

This paper presented an efficient missing child detection system using deep learning and intelligent multiclass SVM classification techniques. The proposed framework integrates Convolutional Neural Networks (CNNs), facial recognition technology, and multiclass Support Vector Machine (SVM) classification to automatically identify missing children from surveillance images and live video streams. The system effectively automates the identification process, reducing dependency on manual investigation and improving the speed and accuracy of child recovery operations.

The experimental results demonstrate that the proposed hybrid CNN-SVM framework achieves high facial recognition accuracy, reliable classification performance, and efficient real-time monitoring capabilities. The deep learning model successfully extracts discriminative facial features under varying environmental conditions, while the multiclass SVM classifier enhances matching precision and minimizes false detections. The integration of real-time alert generation and cloud-based database management further improves scalability, accessibility, and operational efficiency for law enforcement agencies and child protection organizations.

The proposed system also performs effectively in crowded public environments such as railway stations, airports, shopping malls, schools, and bus terminals. Although minor performance variations were observed under low-light conditions and high-density surveillance scenarios, the framework overall demonstrates strong robustness, scalability, and practical applicability for real-world deployment.

In conclusion, the proposed intelligent missing child detection system provides a fast, automated, and cost-effective solution for child identification and recovery. Future work can focus on improving low-light image processing, incorporating aging-aware facial recognition, integrating multimodal biometric analysis, and enhancing explainable AI techniques to further improve system accuracy, reliability, and security.

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