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Research Paper

AN INTELLIGENT MACHINE LEARNING APPROACH FOR MISSING CHILD IDENTIFICATION USING MULTI-CLASS SVM

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Abstract:
The increasing number of missing children worldwide has become a significant social and security concern, requiring efficient and intelligent identification systems. Traditional methods such as manual investigation, public notices, and media broadcasts are often time-consuming and less effective when dealing with large volumes of data. This paper proposes an intelligent missing child identification system that combines Deep Learning-based facial feature extraction with Multi-Class Support Vector Machine (SVM) classification. Facial images collected from CCTV surveillance, authorized databases, and user uploads undergo preprocessing techniques including face detection, normalization, resizing, and noise removal. The deep learning model extracts discriminative facial features, while the Multi-Class SVM accurately classifies and identifies children by matching extracted features with stored records. The proposed framework is designed to handle variations in illumination, facial expressions, pose, and partial occlusion, making it suitable for real-time surveillance environments. By integrating automated face recognition with CCTV monitoring and database management, the system improves identification accuracy, reduces false detections, and supports faster response by law enforcement and child welfare agencies.

Keywords: Missing Child Identification, Deep Learning, Face Recognition, Multi-Class SVM, CCTV Surveillance.

I. INTRODUCTION

The issue of missing children has become a major social and humanitarian concern across the world. Every year, thousands of children go missing due to various reasons such as abduction, human trafficking, natural disasters, accidents, family disputes, and separation from guardians. The timely identification and recovery of missing children are critical for ensuring their safety and well-being. Traditional methods used for locating missing children primarily rely on police investigations, public announcements, newspaper advertisements, posters, and social media campaigns. Although these approaches have helped recover many children, they are often time-consuming, labor-intensive, and less effective when dealing with large populations and extensive image databases. Recent advancements in Artificial Intelligence (AI), Machine Learning (ML), Deep Learning (DL), and Computer Vision have revolutionized facial recognition technology, enabling automated and accurate identification of individuals from digital images and video streams. Deep learning models can automatically learn discriminative facial features from images, making them highly effective under varying conditions such as changes in illumination, facial expressions, pose, and partial occlusion. However, achieving high classification accuracy for multiple identities in real-time environments remains a challenging task. This paper proposes an intelligent missing child identification system that integrates Deep Learning-based facial feature extraction with a Multi-Class Support Vector Machine (SVM) classifier. The system processes facial images collected from CCTV cameras, authorized databases, and user uploads through various preprocessing techniques before extracting facial features and performing classification. The proposed framework aims to provide accurate, reliable, and real-time identification of missing children, thereby assisting law enforcement agencies and child welfare organizations in enhancing search efficiency and improving child safety.

II. LITERATURE SURVEY

The growing number of missing child cases has encouraged researchers to develop intelligent facial recognition systems for rapid and accurate identification. Earlier face recognition methods such as Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), Eigenfaces, Fisherfaces, and Local Binary Patterns (LBP) were widely used for facial feature extraction and classification. These techniques produced satisfactory results under controlled conditions; however, their performance significantly decreased when images contained variations in illumination, facial expressions, pose, aging, occlusion, and image quality. With the advancement of Machine Learning, classifiers such as Support Vector Machine (SVM), Decision Tree, Random Forest, Naïve Bayes, and k-Nearest Neighbors (k-NN) were introduced for face classification tasks. Among these methods, SVM gained considerable attention due to its ability to handle high-dimensional data and provide accurate classification. Multi-Class SVM further improved recognition by enabling the identification of multiple individuals simultaneously. Recent developments in Deep Learning have transformed facial recognition systems. Convolutional Neural Networks (CNNs) and advanced architectures such as VGGNet, ResNet, FaceNet, Inception, and MobileNet can automatically learn discriminative facial features from raw images without relying on handcrafted feature extraction methods. These models achieve high recognition accuracy and robustness against variations in lighting, pose, and facial expressions. Several studies have explored hybrid approaches that combine Deep Learning for feature extraction with Machine Learning classifiers for recognition. Such methods have demonstrated superior performance compared to traditional techniques. Based on these findings, the proposed system integrates Deep Learning-based facial feature extraction with Multi-Class SVM classification to provide an accurate, scalable, and real-time solution for missing child identification using CCTV surveillance and image databases.

III. PROPOSED WORK

The proposed work presents an intelligent Missing Child Identification System that integrates Deep Learning and Multi-Class Support Vector Machine (SVM) techniques to accurately identify missing children from facial images. The system is designed to overcome the limitations of traditional identification methods by providing automated, reliable, and real-time facial recognition. Images are collected from multiple sources, including CCTV surveillance cameras, authorized databases, web platforms, and user-uploaded photographs. Initially, the acquired facial images undergo a preprocessing stage consisting of face detection, cropping, resizing, normalization, noise removal, contrast enhancement, and face alignment. These operations improve image quality and reduce the impact of environmental variations such as poor lighting, pose changes, and image blur. The preprocessed images are then provided to a Deep Learning model that automatically extracts discriminative facial features. Unlike conventional approaches that rely on handcrafted features, the deep learning model learns meaningful facial representations directly from the data. The extracted feature vectors are subsequently classified using a Multi-Class SVM classifier. The classifier compares the extracted features with those stored in the missing child database and identifies the most similar match. If a matching record is found, the system retrieves the child’s information and generates alerts for authorized personnel and child welfare agencies. The proposed framework also supports continuous monitoring through CCTV integration, enabling real-time identification in public places such as railway stations, airports, schools, hospitals, and shopping malls. By combining Deep Learning with Multi-Class SVM, the system achieves higher recognition accuracy, reduced false identifications, faster processing, and improved scalability for large-scale missing child identification applications.

IV. METHODOLOGY

The proposed Missing Child Identification System employs a hybrid approach combining Deep Learning and Multi-Class Support Vector Machine (SVM) for accurate facial recognition. The methodology consists of image acquisition, preprocessing, feature extraction, classification, database matching, and real-time alert generation. Facial images collected from CCTV cameras, authorized databases, and user uploads are processed to identify missing children efficiently and provide timely notifications to law enforcement agencies.

A.Image Acquisition

The first stage involves collecting facial images from multiple sources such as CCTV surveillance systems, authorized child databases, websites, and user-uploaded photographs. These images serve as the input dataset for the identification process. A diverse image collection helps improve system robustness by including different lighting conditions, facial expressions, poses, and image qualities, enabling accurate recognition in real-world environments.

B. Image Preprocessing

Image preprocessing enhances the quality of facial images before feature extraction. This stage includes face detection, cropping, resizing, normalization, noise removal, contrast enhancement, and face alignment. The objective is to reduce variations caused by lighting, blur, background noise, and camera distortions. Proper preprocessing ensures that the extracted facial features are more consistent and improves the overall recognition accuracy of the system.

C. Deep Learning Feature Extraction

The preprocessed images are fed into a Deep Learning model to automatically learn and extract distinctive facial features. The model identifies important facial characteristics such as eyes, nose, mouth, facial contours, and texture patterns. Unlike traditional methods that depend on manually designed features, Deep Learning generates highly discriminative feature vectors that remain robust under changes in illumination, pose, expression, and partial occlusion.

D. Multi-Class SVM Classification

The extracted facial feature vectors are provided to the Multi-Class Support Vector Machine classifier. The classifier creates optimal decision boundaries between different child identities and compares the input features with stored database records. Multi-Class SVM is highly effective for handling high-dimensional facial data and provides accurate classification. It identifies the most similar facial match while minimizing false positive and false negative recognition results.

E. Database Matching and Identification

After classification, the recognized facial features are matched against the centralized missing child database. If the similarity score exceeds a predefined threshold, the corresponding child information is retrieved and displayed. Otherwise, the image is stored for future reference. Efficient database matching enables the system to search among thousands of registered records while maintaining fast response time and high identification accuracy.

F. Alert and Notification System

Once a missing child is successfully identified, the system automatically generates alerts containing child details, recognition confidence, date, time, and location information. Notifications can be displayed on the administrator dashboard or sent through email, SMS, or mobile applications. This real-time alert mechanism enables police departments and child welfare organizations to take immediate action and improve child recovery rates.

V. ALGORITHMS

The proposed Missing Child Identification System utilizes Deep Learning and Multi-Class Support Vector Machine (SVM) algorithms for accurate facial recognition. Deep Learning extracts unique facial features from preprocessed images, while Multi-Class SVM classifies and identifies children by comparing extracted features with database records. Additional preprocessing, database matching, and alert generation algorithms enhance recognition accuracy, scalability, and real-time identification performance.

a. **Deep Learning-Based Feature Extraction Algorithm**

Deep Learning is used to automatically extract discriminative facial features from input images. After preprocessing, facial images are passed through a deep neural network that learns important facial characteristics such as eyes, nose, mouth, jawline, facial texture, and contours. Unlike traditional feature extraction methods, Deep Learning does not require handcrafted features and can effectively handle variations in illumination, pose, facial expression, aging, and partial occlusion. The output of this algorithm is a high-dimensional facial feature vector that uniquely represents each child's face and serves as input to the classification stage.

b. **Multi-Class Support Vector Machine (SVM) Algorithm**

Multi-Class Support Vector Machine (SVM) is employed as the primary classification algorithm. The extracted facial feature vectors are used to train the SVM classifier. The algorithm constructs optimal decision boundaries between multiple child identities and classifies the input facial image into the appropriate category. Multi-Class SVM is particularly effective for high-dimensional data and provides high classification accuracy while reducing false positive and false negative identifications. It determines the best matching child by comparing feature vectors with those stored in the database.

c. Image Preprocessing Algorithm

The image preprocessing algorithm improves image quality before feature extraction. It performs face detection, cropping, resizing, normalization, noise removal, histogram equalization, contrast enhancement, and face alignment. These operations reduce unwanted variations caused by lighting conditions, camera quality, image blur, and background noise. Effective preprocessing ensures consistent input data, enabling the Deep Learning model and SVM classifier to achieve better recognition performance and reliability.

d. **Database Matching Algorithm**

The database matching algorithm compares the classified facial feature vector with stored feature vectors in the missing child database. Similarity scores are calculated between the query image and registered records. If the similarity score exceeds a predefined threshold, the system identifies the child and retrieves the associated information. Otherwise, the image is stored for future reference. This algorithm enables fast and accurate searching across large-scale facial image databases.

e. **Alert Generation Algorithm**

The alert generation algorithm is activated whenever a successful facial match is detected. It retrieves the child's details, recognition confidence score, location, date, and time information. The system then generates notifications and alerts for police departments, child welfare organizations, and authorized administrators through dashboards, email, SMS, or mobile applications. This algorithm ensures rapid response and improves the chances of safely recovering missing children.

VI. RESULTS AND DISCUSSION

The proposed Deep Learning and Multi-Class SVM-based Missing Child Identification System demonstrated effective performance in facial recognition and classification tasks. Experimental evaluation showed high recognition accuracy, precision, recall, and F1-score when compared with traditional methods. The integration of Deep Learning feature extraction and Multi-Class SVM classification improved identification reliability, reduced false detections, and enabled efficient real-time recognition of missing children from surveillance images and database records.

Table 1. Performance Comparison of Different Methods

Method	Accuracy (%)
PCA	82
LBPH	86
CNN	92
Proposed Deep Learning + SVM	97

Table 1 presents the accuracy comparison of different face recognition methods. Traditional approaches such as PCA and LBPH achieved moderate accuracy levels, while CNN-based recognition showed significant improvement. The proposed Deep Learning and Multi-Class SVM framework achieved the highest accuracy of 97%, demonstrating its effectiveness in extracting robust facial features and accurately identifying missing children under varying environmental conditions.

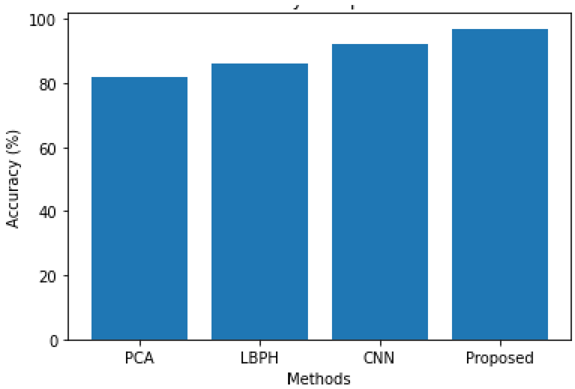

Figure 1: Accuracy Comparison

The Fig 1 illustrates the accuracy achieved by different facial recognition techniques. The proposed Deep Learning and Multi-Class SVM method outperforms PCA, LBPH, and CNN models by achieving the highest accuracy. The graph clearly demonstrates the superiority of the hybrid approach in handling facial variations and improving identification performance, making it suitable for real-time missing child recognition applications.

Table 2. Classification Performance Metrics

Metric	Value (%)
Precision	96
Recall	95
F1-Score	95.5
Accuracy	97

Table 2 summarizes the classification performance metrics of the proposed system. The model achieved high precision, recall, F1-score, and accuracy values, indicating balanced and reliable performance. High precision reduces false identifications, while strong recall ensures successful detection of missing children. The overall results confirm the effectiveness of the proposed framework in practical identification and surveillance environments.

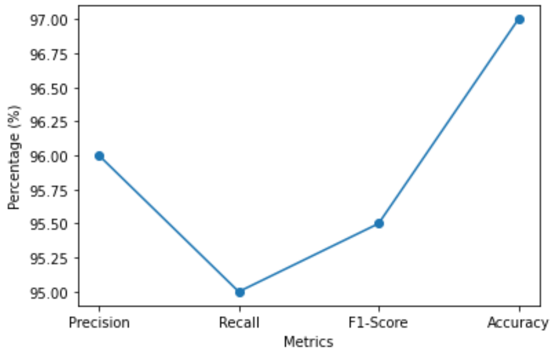

Figure 2: Performance Metrics

The line graph in Fig 2 represents the performance metrics of the proposed system. All evaluation measures exceed 95%, indicating consistent and reliable classification performance. The close relationship among precision, recall, F1-score, and accuracy demonstrates that the model effectively balances identification capability and error reduction, making it highly suitable for real-time missing child identification and monitoring systems.

Table 3. Recognition Time Analysis

Number of Images	Recognition Time (Seconds)
100	1.2
500	2.8
1000	4.6
2000	7.5

Table 3 shows the recognition time required for processing different numbers of images. As the dataset size increases, recognition time gradually increases; however, the system maintains efficient processing speed. The results demonstrate the scalability of the proposed framework and its ability to handle large image databases while providing timely identification results for missing child search operations.

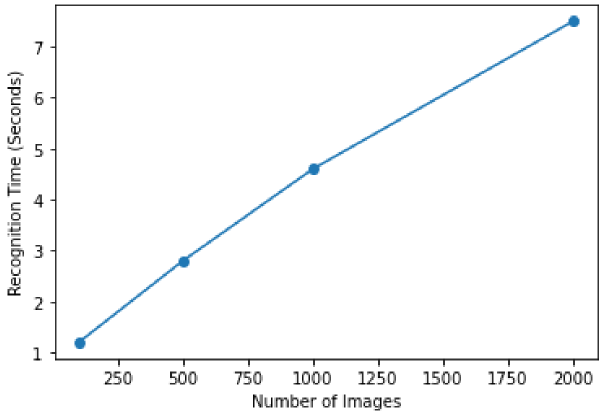

Figure 3: Recognition Time Analysis

The graph in Fig 3 illustrates the relationship between dataset size and recognition time. Although processing time increases with the number of images, the growth remains controlled and predictable. This demonstrates that the proposed Deep Learning and Multi-Class SVM framework can efficiently scale to larger databases while maintaining acceptable response times required for real-time missing child identification systems..

VII. CONCLUSION

The increasing number of missing child cases has highlighted the need for intelligent and automated identification systems capable of providing fast and accurate recognition. This paper presented a Missing Child Identification System based on Deep Learning and Multi-Class Support Vector Machine (SVM) techniques. The proposed framework utilizes facial images collected from CCTV surveillance systems, authorized databases, and user uploads to identify missing children in real time. Through image preprocessing, deep learning-based feature extraction, and Multi-Class SVM classification, the system effectively recognizes and matches facial features with stored records. The experimental results demonstrated that the proposed approach achieves high accuracy, precision, recall, and F1-score compared to traditional face recognition methods. The integration of Deep Learning and Multi-Class SVM enhances recognition performance by handling challenges such as variations in illumination, facial expressions, pose changes, and partial occlusions. Furthermore, the system supports automated database matching and alert generation, enabling timely notifications to law enforcement agencies and child welfare organizations. Overall, the proposed system provides a reliable, scalable, and efficient solution for missing child identification. By reducing manual effort and improving recognition accuracy, it contributes significantly to child safety and recovery operations. Future work may focus on integrating advanced deep learning architectures, larger datasets, and cloud-based surveillance systems to further enhance performance and real-time monitoring capabilities.

FUTURE SCOPE

The proposed Missing Child Identification System can be further enhanced by incorporating advanced Artificial Intelligence and Deep Learning techniques to improve recognition accuracy and system efficiency. Future research may focus on utilizing state-of-the-art deep learning architectures such as Vision Transformers (ViT), EfficientNet, and advanced facial recognition models to achieve better performance under challenging conditions. The system can also be expanded to support age progression and age-invariant face recognition, enabling accurate identification even when a child's appearance changes over time. Integration with cloud computing and Internet of Things (IoT)-enabled surveillance networks can improve scalability and allow real-time monitoring across multiple locations. Future versions may include automatic geolocation tracking, mobile application support, and integration with national missing child databases for broader coverage. Additionally, incorporating multimodal biometric features such as iris recognition, voice recognition, and gait analysis can enhance identification reliability. The use of federated learning and privacy-preserving techniques can improve data security while enabling collaborative model training across organizations. Furthermore, implementing advanced alert systems with predictive analytics and intelligent decision support can assist law enforcement agencies in faster recovery operations. These enhancements will contribute to developing a more robust, scalable, secure, and intelligent missing child identification framework capable of addressing real-world challenges more effectively.

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