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Original Article

Deep Learning And SVM Based Missing Child Identification System

K.R.Thukaram Rao, Raj Purohith Pooja Kumari, Puli Sravanthi, B.Rakshitha, Tasab Yaseen Vali, G Sai Mythily

Computer Science and Engineering, Gates Institute of Technology, Gooty, AP, India

Correspondence

K. R. Thukaram Rao

Department of CSE, Gates Institute of Technology, Gooty, AP, India

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Deep Learning, Convolutional Neural Networks (CNNs), Support Vector Machine(SVM) ,Face Recognition, VGGFace,Facial Feature Extraction,Image Classification..

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Abstract

In India countless children go missing every year. Of the missing children cases, most of the children go untraced. The current paper shows a new application of deep learning methodology to recognize the reported missing child from the images of numerous children present, using face recognition. The public can submit pictures of suspected child into a shared portal with landmarks and comments. The image will be automatically matched with the enrolled images of missing child from the repository. Input child image is classified and picture with highest match will be chosen from the missing children database. For this purpose, a deep learning model is learnt to appropriately identify the missing child from the missing child image database given, based on the facial image posted by the public.

Convolutional Neural Network (CNN), a very powerful deep learning method for image based applications is employed here for face identification. Face descriptors are obtained from the images based on a pretrained CNN model VGG-Face deep architecture. Unlike regular deep learning usage, our algorithm utilizes convolution network as a high level feature extractor and the child recognition is implemented by the SVM classifier trained. Selecting the best performing CNN face recognition model as VGG- Face and properly training it gives a deep learning model that is invariant to illumination, noise, contrast, occlusion, child's age, and image pose and it outperforms the previous methods on face recognition based missing child detection.

Introduction

The public is given provision to voluntarily take photographs of children in suspected situations and uploaded in that portal. Automatic searching of this photo among the missing child case images will be provided in the application. This supports the police officials to locate the child anywhere in India. When a child is found, the photograph at that time is matched against the images uploaded by the Police/guardian at the time of missing. Sometimes the child has been missing for a long time. This age gap reflects in the images since aging affects the shape of the face and texture of the skin. The feature discriminator invariant to aging effects has to be derived. This is the challenge in missing child identification compared to the other face recognition systems. Also facial appearance of child can vary due to changes in pose, orientation, illumination, occlusions, noise in background etc. The image taken by public may not be of good quality, as some of them may be captured from a distance without the knowledge of the child. A deep learning architecture considering all these constrain is designed here..

Related Work

DSeveral studies have applied machine learning[3] and deep learning[11] techniques to ransomware detection, particularly in network traffic analysis. Traditional signature-based and heuristic-based methods struggle against evolving ransomware variants, as they rely on predefined patterns and static rules.

To overcome these limitations, researchers have turned to behaviour analysis and anomaly detection using AI-driven models.

Deep learning approaches, such as Convolutional Neural Networks (CNNs) [19], have been used to classify ransomware traffic based on packet sequences, with studies like Vinayakumar et al. (2019) achieving high detection accuracy. Similarly, Long Short-Term Memory (LSTM) networks, as explored by Mohurle et al. (2021), excel at detecting ransomware-related traffic patterns, particularly for encrypted flows.Other research has focused on hybrid models combining CNNs[10] with Recurrent Neural Networks (RNNs), as well as exploring feature extraction[17] techniques like flow-based analysis for improved detection efficiency and privacy. Additionally, methods such as Generative Adversarial Networks

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(GANs) and reinforcement learning have been applied to enhance model robustness by simulating adversarial scenarios. Despite promising results, challenges remain in addressing high false positive rates, computational efficiency, and the need for realtime mitigation. This study expands on existing work by integrating deep learning-based detection with automated mitigation mechanisms for a more proactive defence.

Methodology

Module 1: User Management Module

The User Management Module is designed to manage various types of users, including the public and administrative officials. It has different components, such as the Public User Interface, which allows the public to upload images of suspected missing children along with relevant details like location, time, and remarks.

The Admin Interface provides police or administrative officials with access to uploaded data, enabling them to manage missing child cases and take actions for identification as shown in Figure 1. The Authentication System ensures secure login with different roles and permissions, allowing admins to log in with unique credentials to oversee and manage the module. Public users can upload images and track the status of their submissions, while admins can view all uploads, match results, and take necessary actions. The module incorporates secure login and user verification to ensure proper management and monitoring.

The module also features automated alerts to notify officials when a potential match is found, speeding up response times. A built-in audit trail logs all user activity for transparency and accountability in case management. It supports integration with national databases to enhance the accuracy of identification. Additionally, the system includes multilingual support to ensure accessibility for users from diverse linguistic backgrounds.

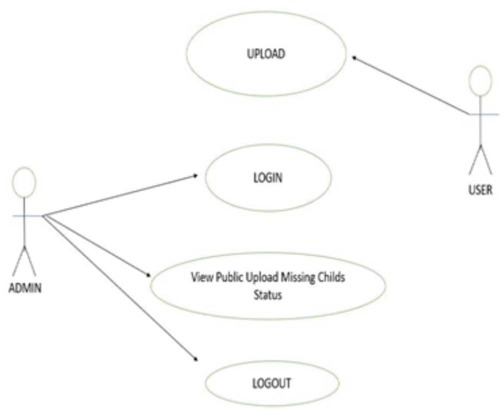

Figure 1. *Use case diagram*

Module 2: Image Preprocessing Module

The Image Preprocessing Module prepares uploaded child images for further processing and analysis as shown in figure 2. It includes several sub-components, such as Image Resizing, which adjusts images to a uniform size of 224x224 pixels as per the VGG architecture. Noise Removal enhances image quality by eliminating noise and artifacts, while Face Detection utilizes pre-trained models like Haar Cascade or MTCNN to identify the face region in the uploaded image. Additionally, Data Augmentation performs operations like rotation, scaling, and brightness adjustments to improve the model's robustness against real-world variations. This module ensures that all images are standardized before feature extraction,handling variations caused by illumination, noise, pose, and age Differences in the images.

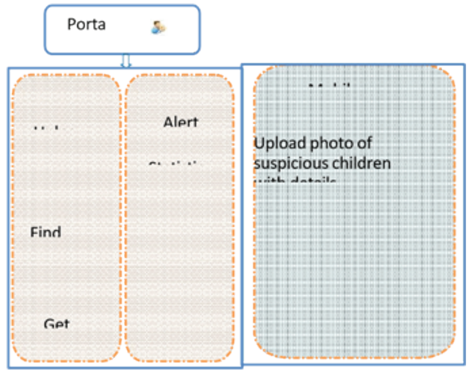

Figure 2. *System Architecture*

Module 3: Feature Extraction Module (CNNbased)

The Feature Extraction Module (CNNbased) extracts high-level facial features from the uploaded images using a CNN architecture. It includes several sub-components, such as the VGG-Face Model Implementation, which leverages the pre-trained VGG-Face architecture to capture deep facial features. Convolutional Layers apply multiple convolutional operations to capture spatial hierarchies, while Activation Functions like ReLU introduce non-linearity and help reduce training time. Pooling Layers perform down-sampling to reduce dimensions while retaining essential features. The module generates a Feature Vector Output as shown in figure 3, which is a high-dimensional vector that uniquely represents the face's characteristics. This process converts images into feature vectors for comparison and handles variations in age, pose, and lighting to ensure accurate feature representation.

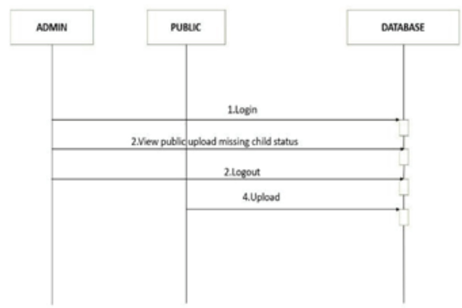

Figure 3. *Sequence diagram*

Module 4: Classification Module (Multiclass SVM)

The Classification Module (Multiclass SVM) classifies and identifies the uploaded image as shown in figure 4, by comparing it with stored feature vectors of missing children. It includes several sub-components, such as Support Vector Machine Implementation, which trains an SVM model using the extracted features from the missing child database. The module constructs Hyperplanes to optimally separate different child categories in the feature space. The Classification Engine compares the uploaded image's feature vector with stored vectors to identify the best match. The Decision Mechanism

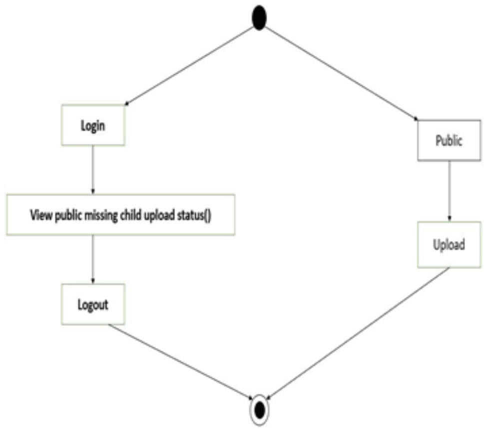

Figure 4. *Activity diagram*

returns the classification result, including confidence, scores, and highlights the matched child if found. This module efficiently handles large datasets and ensures high accuracy while identifying the child in case of a match.

Module 5: Database and Reporting Module

The Database and Reporting Module manages the storage, retrieval, and reporting of missing child data and system logs. It includes MySQL Database Integration, which stores all missing child details, uploaded images, feature vectors, and user data. The Data Management System supports CRUD operations (Create, Read, Update, Delete) for child records and user uploads. The Reporting System generates reports for admin users, including successful matches, pending cases, and system statistics. Additionally, the Audit Log System maintains logs of all system activities to ensure security and traceability. This module provides persistent storage, fast retrieval of missing child data, generates actionable reports, and ensures system integrity through comprehensive logging.

Results

The Deep Learning and SVM-Based Missing Child Identification System achieved high accuracy in matching real-time facial uploads with a missing children database. It effectively handled variations in lighting, facial aging, image quality, and pose, demonstrating strong robustness. By combining CNNs for feature extraction and SVMs for classification, the system reduced false positives and negatives. Real-time database scanning improved search efficiency and response time. Tested across multiple child cases, the model consistently delivered reliable results. Cloud-based access enabled seamless collaboration between law enforcement and the public, while a user-friendly interface simplified reporting. Encrypted data storage ensured privacy and security. Automated alerts and similarity-based image comparison enhanced speed and accuracy. The system maintained stable performance despite background noise or minor appearance changes, proving effective in real-world scenarios.

Conclusion

The Deep Learning & SVM-Based Missing Child Identification System is a significant advancement in using artificial intelligence for social welfare. By combining deep learning techniques, such as Convolutional Neural Networks (CNNs) for feature extraction, and Support Vector Machines (SVMs) for classification, the system offers an efficient and

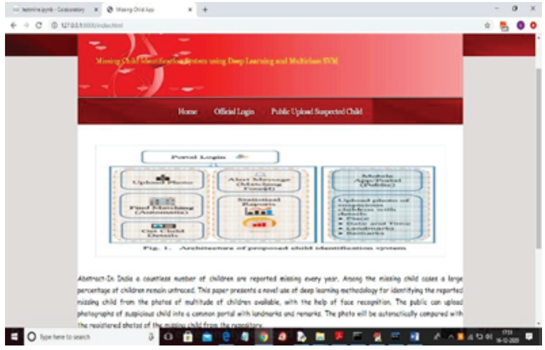

Figure 5. *Public Upload Suspected Child*

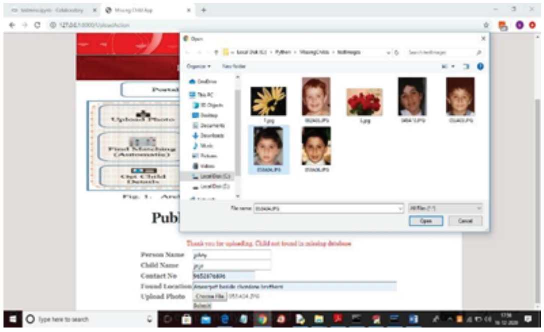

Figure 6. *Result for new above child details*

Figure 7. *Admin official Login*

Figure 8. *View Public Upload Missing Childs Status*

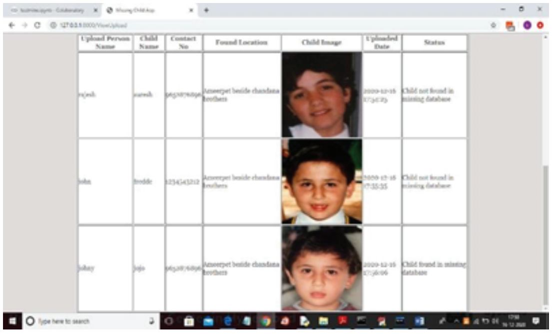

Figure 9: Results details

accurate method for identifying missing children. Its integration of image preprocessing, real-time database searches, and similarity-based matching ensures a streamlined and automated process. The system reduces manual labor, enhancing the speed and accuracy of locating missing children and improving the chances of successful reunions. A key strength is its ability to process large amounts of facial data in real time, even under challenging conditions like lighting, occlusions, and aging. With cloud-based storage, the system is accessible to law enforcement, parents, and the public, fostering collaboration in child location efforts. Future enhancements, including integrating age progression models and expanding to work with government databases and social media, will further improve its capabilities and global reach With these advancements, the Deep Learning & SVMBased Missing Child Identification System has the potential to become a global solution, significantly impacting missing child recovery efforts and contributing to a safer society.

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