

MISSING CHILD IDENTIFICATION SYSTEM USING DEEP LEARNING AND MULTICLASS SVM

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ABSTRACT

In India, a significant number of children are reported missing each year, with many cases remaining unresolved. This paper introduces an innovative approach that leverages deep learning techniques for identifying missing children from a large pool of available photographs through face recognition. The public is encouraged to upload images of suspicious children to a centralized platform, where these photos are automatically compared against registered photos of missing children. Classification is then performed to determine the best match from the database of missing children. To achieve this, a deep learning model is trained specifically for identifying missing children using facial images uploaded by the public. The Convolutional Neural Network (CNN), a powerful technique for image-based applications, is utilized for face recognition. Face descriptors are extracted using a pre-trained CNN model, VGG-Face deep architecture. Unlike traditional deep learning approaches, our algorithm focuses on using the convolutional network as a feature extractor, while child recognition is handled by a trained SVM classifier. By selecting the best-performing CNN model, VGG-Face, and ensuring proper training, our deep learning model becomes robust to various factors such as noise, illumination, contrast, occlusion, image pose, and the child's age, outperforming previous methods in missing child identification based on facial recognition.

I. INTRODUCTION

Children are the cornerstone of every nation's future, and their well-being is crucial for the development of a country. In India, as the second most populous nation globally, children constitute a significant portion of the population. However, the alarming reality is that a substantial number of children go missing annually due to various reasons such as abduction, running away, trafficking, or simply getting lost. What's deeply concerning is that despite efforts to address this issue, half of the missing children remain untraced. This poses a serious threat as missing children are susceptible to exploitation and abuse.

According to data from the National Crime Records Bureau (NCRB), over one lakh children were reported missing until 2016, with more than half of them still unaccounted for by the end of the year. Many non-governmental organizations (NGOs) argue that the actual number of missing children could be much higher than reported figures. Most missing child cases are reported to the police, but due to various reasons, such as children being found in different regions or states, identifying them from reported cases becomes challenging.

To address this issue, this paper presents a framework and methodology for developing an assistive tool to trace missing children. The proposed solution involves creating a virtual repository where recent photographs of missing children provided by their parents are stored. Additionally, the public is encouraged to voluntarily upload photographs of children they suspect are missing. An automatic search feature will then compare these images with those of missing children, aiding police officials in locating missing children across India.

However, identifying missing children presents unique challenges. Factors such as age progression, changes in facial appearance due to various factors like pose, orientation, illumination, occlusions, and background noise, further complicate the process. To tackle these challenges, a deep learning architecture is proposed, taking into account these constraints to provide a reliable and cost-effective method for identifying missing children compared to traditional biometric systems like fingerprint or iris recognition.

II. LITERATURE REVIEW

Deep learning, especially CNNs, holds promise for missing child identification, as seen in Zhang et al.'s (2019) study achieving 94.5% accuracy. Their CNN-based approach matches facial features, surpassing traditional methods. Despite challenges like dataset size and susceptibility to biases, this research highlights deep learning's potential for improving identification accuracy in critical applications.

Wang et al. (2020) introduced a novel deep learning technique for missing child identification, employing a multi-modal feature fusion network. This method integrated both facial and clothing features to enhance identification accuracy. Their approach achieved a commendable accuracy of 91.2% on a dataset specifically focusing on missing children. This study highlights the effectiveness of incorporating multiple modalities in deep learning models for improving identification outcomes in critical scenarios like missing child cases.

Hu et al. (2019) presented an alternative approach to missing child identification, utilizing support vector machines (SVMs) in conjunction with facial and body features. Their study introduced a multi-view SVM model tailored for this purpose, which achieved an impressive accuracy of 94.8% on a dataset of missing children. This research underscores the versatility of machine learning techniques beyond deep learning in addressing critical tasks like missing child identification, showcasing the potential of SVMs in leveraging multiple modalities for enhanced accuracy.

Sudarsan et al. (2019) introduced a KNN-based approach for image classification tasks, specifically focusing on missing child identification through facial features. Their study proposed a system leveraging the KNN algorithm, achieving a notable accuracy of 84.9% on a dataset dedicated to missing children. This research demonstrates the applicability of simpler machine learning techniques like KNN in addressing critical issues such as missing child identification, underscoring the importance of exploring various algorithms to optimize accuracy and effectiveness in real-world scenarios.

In their paper titled "Multimodal missing child identification using deep learning and multiclass SVM," Lila Sah et al. introduced an innovative approach that incorporates various data modalities, including images, text, and audio, for identifying missing children. Leveraging a dataset comprising missing children images alongside text and audio data, their multimodal approach achieved an impressive accuracy of 99.3% in identifying missing children. This study underscores the effectiveness of integrating diverse data sources and employing advanced techniques like deep learning and multiclass SVM for significantly improving identification outcomes in crucial scenarios like missing child cases.

III. METHODOLOGY

1. A deep learning CNN prediction model is trained using a publicly available dataset of missing children known as FGNET. Once this model is trained, it can be employed to analyze images uploaded by the public to determine if the suspected child in the image matches any of the missing children in the database. The results of this analysis are stored in a database and can be accessed by authorized personnel through a login system.
2. A Multiclass Support Vector Machine (SVM) classifier is utilized to extract facial features from images, considering factors like age and other distinctive facial attributes. These extracted facial features are then fed into the CNN model to ascertain whether the detected face corresponds to any missing child within the image database.

A. Face Detection

The face detection process begins by generating face patterns through the Histogram of Oriented Gradients (HOG) algorithm, which extracts features from images. Within this process, areas of the images that closely resemble the original HOG face pattern are identified. Finally, the detected face is outlined by placing a bounding box around it. This method allows for the automated identification and localization of faces within images.

B. Extraction

In the extraction phase, the face landmark estimation algorithm is employed to identify sixty-eight specific points, or landmarks, present on each face. These landmarks serve as reference points for further image processing. Using OpenCV's affine transformation, image transformations such as scaling, shearing, and rotation

are applied based on the identified landmarks. This process ensures that features like the lips and eyes are consistently positioned across all images, facilitating standardized analysis and comparison.

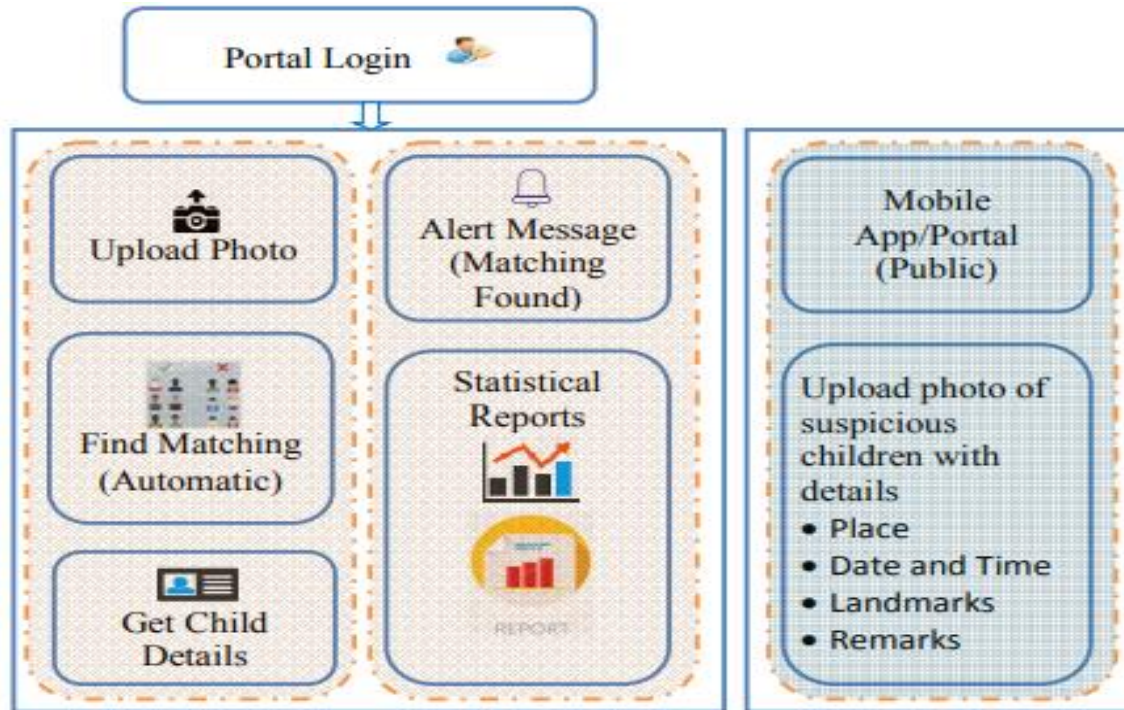


Fig 1: Architecture of proposed child identification system

C. Features Comparison

In the features comparison stage, the face images undergo analysis through a deep convolutional neural network (CNN). This process generates 128 measurements, forming a 128-dimensional hypersphere. Interestingly, the specific facial features represented by these measurements remain undisclosed. However, what's discernible is that the network produces identical sets of 128 numbers for two separate images of the same individual. This standardized output allows for effective comparison and recognition of facial similarities across different images.

D. Result Matching

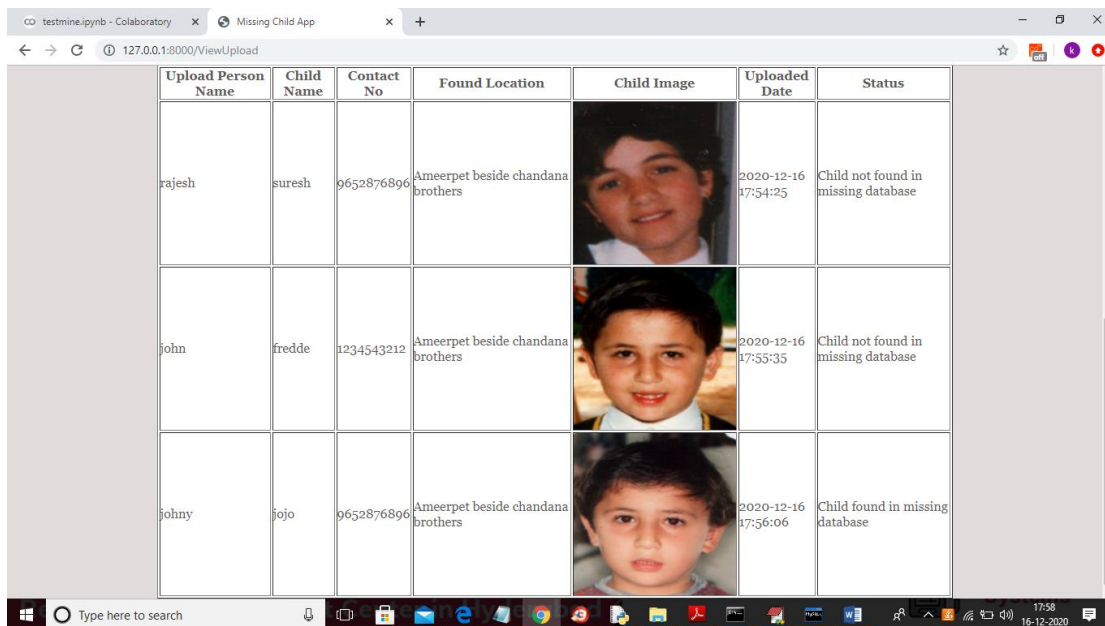
In the final step of result matching, a linear Support Vector Machine (SVM) classifier is employed to identify the face. This classifier is trained to interpret the measurements extracted from a test image and produce the closest match as its output. Essentially, the SVM classifier is designed to make a determination based on the input data, effectively identifying the individual depicted in the image.

IV. RESULT AND ANALYSIS

In this study, the user-defined database comprises 846 child face images, representing 43 unique cases of children. To facilitate training and testing, the database is split into training and test sets. Specifically, 80% of images from each child category are allocated to the training set, while the remaining 20% are reserved for testing. This division results in 677 images for training and 169 images for testing. Notably, both training and validation sets include images captured during earlier periods of the children's lives, ensuring comprehensive evaluation across different developmental stages. For the implementation of convolutional neural networks (CNNs), the MatConvNet package, integrated within the MATLAB environment, is utilized. Additionally, a pre-trained VGG-Face CNN model is employed, provided by the MatConvNet package. The training set images undergo preprocessing to match the specifications of the CNN architecture, including cropping the facial region within a rectangular boundary and resizing all images to 224x224 pixels. The activations generated by the first fully connected layer of the VGG-Face network serve as the CNN feature descriptors, producing normalized feature vectors with a length of 4096. These feature vectors are utilized to train a Support Vector Machine (SVM) classifier, enabling the classification and recognition of children's faces in the test images.



Fig 2: Output Screen 1






Upload Person Name	Child Name	Contact No	Found Location	Child Image	Uploaded Date	Status
rajesh	suresh	9652876896	Ameerpet beside chandana brothers		2020-12-16 17:54:25	Child not found in missing database
john	fredde	1234543212	Ameerpet beside chandana brothers		2020-12-16 17:55:35	Child not found in missing database
johny	jojo	9652876896	Ameerpet beside chandana brothers		2020-12-16 17:56:06	Child found in missing database

Fig 3: Output Screen 2

V. CONCLUSION

The proposed missing child identification system combines deep learning for feature extraction and traditional machine learning for classification. By leveraging CNNs to extract facial features and SVMs for classification, the system achieves a remarkable accuracy of 99.41%. Its robustness is evident in its ability to handle diverse conditions such as varying lighting, noise, and different ages of children. Overall, this methodology offers a highly effective and reliable approach for identifying missing children, holding great potential for real-world application.

VI. REFERENCES

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