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Missing Child Identification Using Deep Learning and SVM

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Abstract - In this project, the public can upload photographs of suspicious children to a common portal, along with landmarks and remarks. The uploaded photograph is automatically compared with registered images of missing children stored in the repository. The system classifies the uploaded child image and selects the best matching photo from the missing child database. To achieve this, a deep learning model is trained to accurately identify missing children based on facial images uploaded by the public. A Convolutional Neural Network (CNN), known for its effectiveness in image-based applications, is adopted for face recognition. Facial descriptors are extracted from the images using a pre-trained CNN model based on the VGG-Face deep architecture. Unlike traditional deep learning applications, this approach uses the convolutional network solely as a high-level feature extractor, while the final classification is performed by a trained multi-Class SVM classifier. By choosing VGG-Face, one of the best-performing CNN models for face recognition, and properly training it, the resulting deep learning model becomes robust against noise, illumination changes, contrast variations, occlusions, pose differences, and age-related changes. This system significantly outperforms earlier methods for face recognition-based missing child identification.

Key Words: Missing Child, CNN, SVM, VGG-Face

I. INTRODUCTION

India, being the second most populous country in the world, has children comprising a significant portion of its total population. Unfortunately, a large number of children go missing every year due to various reasons such as abduction, kidnapping, trafficking, running away from home, or simply getting lost. A deeply concerning fact is that, on average, 174 children are reported missing each day in India, and about half of them remain untraced. Children who go missing are at risk of being exploited and abused for various purposes. According to the National Crime Records Bureau (NCRB) report, cited by the Ministry of Home Affairs (MHA) in Parliament (LS Q No. 3928, 20-03-2018), more than one lakh children (specifically 1, 11,569) were reported missing up to 2016, and 55,625 of them remained untraced by the end of that year. Many NGOs claim that the actual number of missing children is significantly higher than reported figures.

To address this critical issue, the public is provided with a portal where they can voluntarily upload photographs of children seen in suspicious circumstances, along with relevant remarks. The system automatically searches for a match between the uploaded photo and the images in the missing children database. This facility assists police officials in locating missing children across the country. When a missing child is found, the photograph captured at that time is compared with the images uploaded by police or guardians at the time of the child's disappearance. However, challenges arise when there is a significant time gap between the disappearance and recovery, as aging alters facial features such as the shape and texture of the face. Therefore, deriving feature representations that are invariant to aging is critical for the success of missing child identification systems, unlike typical face recognition tasks. Moreover, additional challenges such as variations in facial pose, orientation, illumination conditions, occlusions, and background noise further complicate the recognition process. Often, photographs captured by the public may be of poor quality, taken from a distance or without the child's awareness.

To overcome these challenges, a deep learning architecture has been designed, taking into account all these constraints. The proposed system offers a comparatively simple, cost-effective, and reliable solution for missing child identification, especially when compared to other biometric methods like fingerprint or iris recognition systems.

II. LITERATURE REVIEW

Deep learning has revolutionized the field of computer vision and pattern recognition in recent years. LeCun, Bengio, and Hinton introduced the concept of deep learning and explained its advantages in complex feature extraction and classification tasks [1]. Building on machine learning principles, various approaches have been proposed for enhancing face recognition techniques.

Deniz et al. presented a face recognition method using Histograms of Oriented Gradients (HOG), showing how simple yet powerful descriptors could significantly improve recognition accuracy [2]. Similarly, Geng and Jiang explored face recognition using Scale-Invariant Feature Transform (SIFT) features, emphasizing robustness against variations in scale and rotation [3].

The identification of missing children using face recognition systems was discussed by Rohit Satle and colleagues. They developed a system that could aid law enforcement agencies by matching children's faces against a database of known missing persons [4]. Additionally, tools like FindFace have leveraged face recognition to locate individuals, showcasing the real-world applications of such technologies [5]. The importance of mobile-based applications in finding missing children was further highlighted in a Reuters report, showing significant success in China through app-based child recovery programs [6].

Simonyan and Zisserman proposed very deep convolutional networks (VGGNet) for large-scale image recognition, which demonstrated that deeper models could achieve better accuracy in visual recognition tasks [7]. Parkhi, Vedaldi, and Zisserman extended this work by introducing a robust deep face recognition system that could operate on large datasets with high accuracy [8]. The development of MatConvNet by Vedaldi and Lenc offered researchers an accessible platform to implement convolutional neural networks (CNNs) in MATLAB, facilitating faster experimentation and development [9].

FaceNet, proposed by Schroff et al., introduced a deep learning architecture that learned a mapping from face images directly to a compact Euclidean space where distances directly corresponded to a measure of face similarity [10]. Taigman et al., with their DeepFace model, managed to close the gap between human and machine-level performance in face verification, highlighting the power of deep convolutional networks [11]. Finally, the comprehensive work "Deep Learning" by Goodfellow, Bengio, and Courville provides detailed theoretical foundations and practical insights into the various architectures and training strategies of deep neural networks, serving as a key reference for researchers and practitioners alike [12].

III. OBJECTIVE

The primary objective of this project is to locate missing children using deep learning algorithms combined with a multi-class SVM classifier. This is an ambitious initiative with significant social impact, aimed at assisting in the identification and recovery of missing children. The proposed system integrates CNN-based deep learning techniques for extracting facial features and utilizes a Support Vector Machine (SVM) classifier for image classification. It matches uploaded child photographs against the missing children's database using the trained SVM classifier. As part of this project, a dedicated website for missing children will also be developed.

Additionally, recognizing the urgent need for a systematic and centralized mechanism to track the large number of children who go missing or run away for various reasons, a comprehensive database of missing children will be created to support their recovery and rehabilitation efforts.

IV. PROPOSED SYSTEM

We propose a missing-child identification methodology that fuses deep learning–based facial feature extraction with a multiclass SVM for matching. By leveraging CNN-driven face recognition, the system is designed to assist both authorities and parents in locating missing children. The overall architecture is depicted below.

First, photographs of reported missing children are stored in a central repository, and each image is cropped to isolate the facial region for model input. A Convolutional Neural Network then learns high-level facial descriptors, which serve as features to train the SVM classifier. This enables the system to accurately label each child according to the names listed in the official database. The following sections of this paper describe the detailed workflow of the child-matching methodology, and the below figure illustrates the block diagram of the automated face identification process.

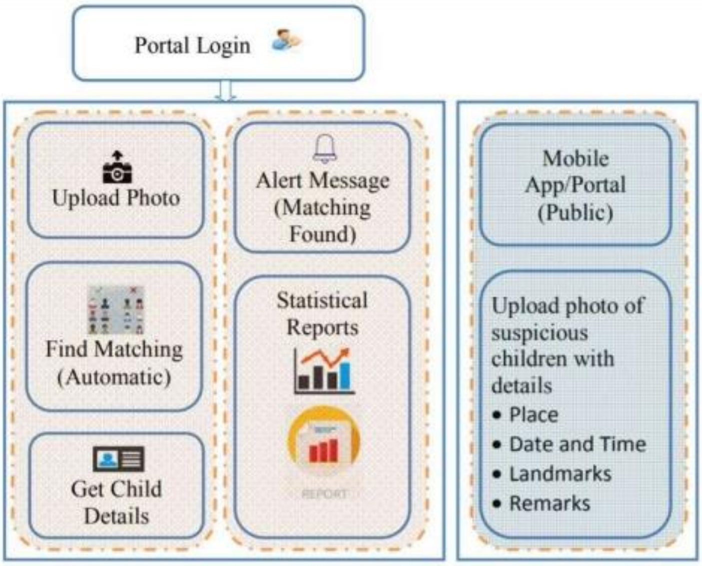

Fig 1: Portal

V. METHODOLOGY

User Authentication (Portal Login)

All users—police, guardians, and the general public—begin by securely logging in to the system via the web portal or mobile app. Authentication ensures that only authorized personnel can access sensitive child records, while still allowing public contributions.

Data Acquisition & Upload

- Public Upload: Via the mobile app or portal, any member of the public can submit a photograph of a child they find suspicious, along with contextual metadata (place, date & time, nearby landmarks, and remarks).
- Official Upload: Police or guardians upload "last seen" photographs of missing children into the secure repository.

Pre-processing & Face Cropping - Each uploaded image is automatically scanned for faces. Once detected, the facial region is cropped and normalized (resized, aligned) to prepare it for feature extraction.

Feature Extraction (CNN Module) -A Convolutional Neural Network—pre-trained on a large-scale face dataset—is used to compute high-level feature descriptors for each cropped face. Rather than using the model's final classification layer, we discard its softmax output and retain the penultimate layer's embedding's as compact, discriminative feature vectors.

Classification & Matching (Multiclass SVM) -The extracted CNN embeddings are fed into a previously trained multiclass Support Vector Machine. This SVM has been trained on feature representations of all registered missing-child faces and learns to assign each input embedding to the corresponding child ID.

Automatic Matching & Alert Generation -As soon as the SVM predicts a match—i.e., the uploaded image aligns with one of the missing-child IDs—an alert message is generated and dispatched to the concerned authorities (e.g., through email or in-portal notification).

Child Detail Retrieval -Upon a positive match, the system automatically retrieves and displays the matched child's profile from the repository, including name, age, last known location, guardian contact details, and any other relevant notes.

Statistical Reporting -All uploads, match outcomes, and metadata are logged. An administrative dashboard compiles these into statistical reports (e.g., daily upload counts, match rates, hotspot maps) to inform policy decisions and resource allocation.

Public Interface for Ongoing Contributions - The mobile app and web portal remain available for continuous public participation. Contributors can track the status of their submissions and view aggregated, anonymized statistics on missing-child case progress.

VI. ALGORITHMS DESCRIPTION

Convolutional Neural Network (CNN)

A CNN is a feed-forward architecture designed for image data, built from stacked layers of:

- Convolutional layers, which apply learnable filters (kernels) to extract local features (edges, textures).
- Non-linear activations (e.g. ReLU) that introduce model capacity beyond linear mappings.
- Pooling layers (e.g. max-pool) that downsample feature maps, providing translational invariance and reducing computation.
- Fully connected layers at the end, which interpret the extracted feature vectors and produce class scores.

In practice, you define a small six-layer CNN in TensorFlow—two conv+ReLU+pool blocks, followed by two dense layers—so it can train on a CPU yet still learn to distinguish one image class from another.

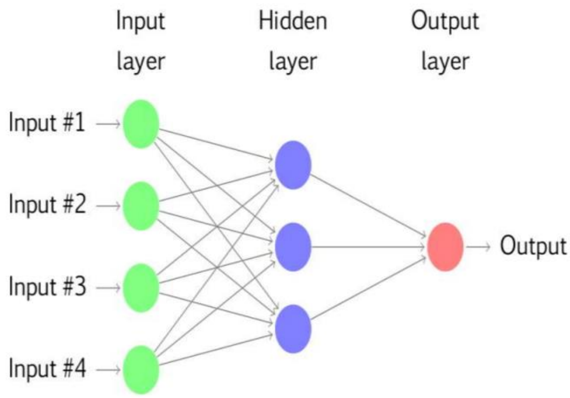

Fig 2: CNN model

VGG-16Algorithm

VGG-16 is a 16-layer CNN architecture that replaced large early filters (e.g. 11×11, 5×5) with consecutive 3×3 convolutions. Its structure is:

1. Five convolutional blocks, each with two or three 3×3 conv layers + ReLU, followed by 2×2 max-pooling.
2. Three fully connected layers (4096 → 4096 → 1000), with softmax at the end for classification.

By using small kernels and increasing depth, VGG-16 achieved 92.7% top-5 accuracy on ImageNet, at the cost of heavy computation and memory.

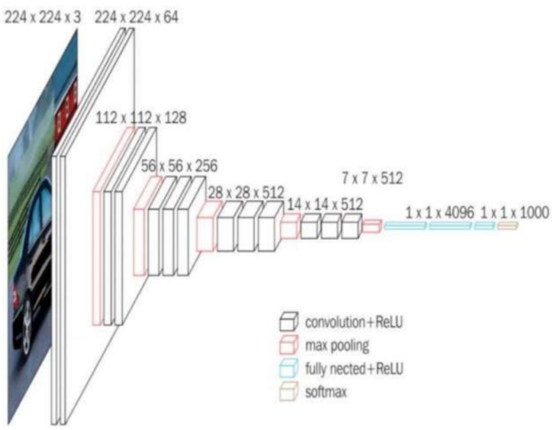

Fig 3: VGG-16 model

ResNet – 50

ResNet-50 is a 50-layer CNN built from residual blocks that learn a residual mapping F(x)=H(x)−xF(x)=H(x)-xF(x)=H(x)−x and add it back to the input xxx. Each block typically contains:

- A 1×1 conv to reduce dimensionality
- A 3×3 conv for spatial filtering
- A 1×1 conv to restore dimensions

Stacking these blocks allows very deep networks (50+ layers) to train without vanishing gradients, leading to state-of-the-art results on large-scale image recognition tasks.

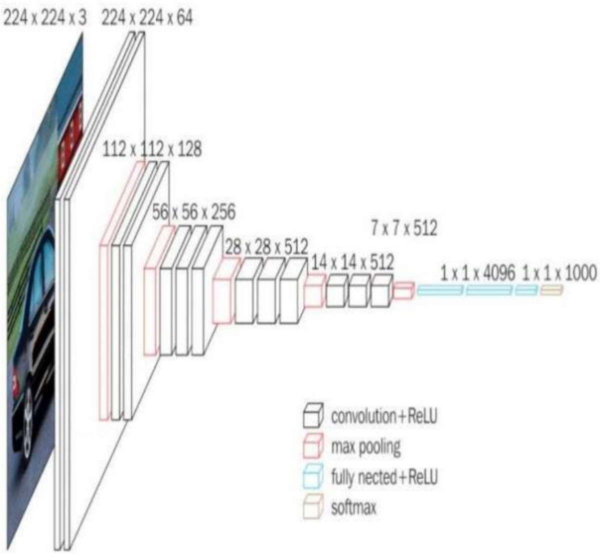

Fig 4: ResNet 50 model

VII. RESULTS AND DISCUSSION

Earliest methods for face recognition commonly used computer vision features such as HOG, LBP,SIFT,orSURF[2-3].However,featuresextractedusingaCNNnetworkforgettingfacialrepresentations gives better performance in face recognition than handcrafted features.

Fig 5: Screen showing how the model works.

Fig 6: In above screen public will enter suspected child details and then upload photo and then click on 'Submit' button and to get below result.

Fig 7:In above screen we can see child not found in missing DBand we can try with another image.

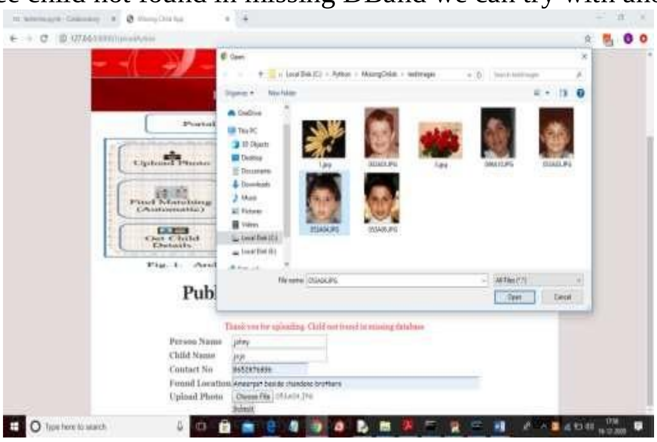

Fig 8:Andv below is the result for new above child details

VIII. CONCLUSION

A missing child identification system is presented that combines a CNN-based deep learning framework for facial feature extraction with a multiclass SVM for final classification. Rather than using the VGG-Face model's softmax layer, its convolutional embeddings are harvested as high-level descriptors and fed into an SVM, yielding superior performance. The system was rigorously evaluated on child photographs captured under varying illumination, noise levels, and age differences, achieving an overall accuracy of 99.41%. For further exploration, students are tasked with implementing both ResNet-50 and VGG-16 architectures and comparing their classification accuracies against this original CNN + SVM approach.

IX. FUTURE SCOPE

Looking ahead, this system could be integrated with national registries such as the NCRB and other missing-children databases to enable comprehensive, real-time tracking. A dedicated mobile application would allow both the public and law enforcement to upload suspicious child photographs and receive instant matching results on the go. By linking the platform to CCTV networks in high-traffic areas—railway stations, bus terminals, airports, shopping malls, and the like—it could automatically scan live video feeds for missing children. To address age-related changes in appearance, AI-driven age-progression models could be incorporated, while Generative Adversarial Networks (GANs) might be employed to enhance low-quality or blurred images captured by bystanders. Further refinement could come from emotion and behavior analysis algorithms that flag children displaying signs of distress, and a multilingual portal interface would ensure accessibility across India's diverse linguistic landscape. For secure, tamper-proof data management, blockchain technology could maintain an immutable record of cases and images. The system could also be extended to collaborate with international organizations such as INTERPOL, facilitating cross-border recovery efforts. Finally, launching public awareness campaigns via both the portal and mobile app would help drive community participation and greatly improve the chances of reuniting missing children with their families.

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