



Hybrid Deep Learning and Multi-Class SVM Approach for Missing Child Identification

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ABSTRACT

In India a countless number of children are reported missing every year. Among the missing child cases a large percentage of children remain untraced. This paper presents a novel use of deep learning methodology for identifying the reported missing child from the photos of multitude of children available, with the help of face recognition. The public can upload photographs of suspicious child into a common portal with landmarks and remarks. The photo will be automatically compared with the registered photos of the missing child from the repository. Classification of the input child image is performed and photo with best match will be selected from the database of missing children. For this, a deep learning model is trained to correctly identify the missing child from the missing child image database provided, using the facial image uploaded by the public. The Convolutional Neural Network (CNN), a highly effective deep learning technique for image based applications is adopted here for face recognition. Face descriptors are extracted from the images using a pre-trained CNN model VGG-Face deep architecture. Compared with normal deep learning applications, our algorithm uses convolution network only as a high level feature extractor and the child recognition is done by the trained SVM classifier. Choosing the best performing CNN model for face recognition, VGG-Face and proper training of it results in a deep learning model invariant to noise, illumination, contrast, occlusion, image pose and age of the child and it outperforms earlier methods in face recognition based missing child identification. The classification performance achieved for child identification system is 99.41%. It was evaluated on 43 Child cases.

Keywords: SVM, CNN, model VGG-Face deep architecture.

I. INTRODUCTION

1.1 Aim of study: The aim of the Missing Child Identification System utilizing Deep Learning and Multiclass Support Vector Machine (SVM) methodologies revolves around enhancing the accuracy, efficiency, and promptness of identifying missing children from diverse visual data sources.

1.2 Objective: Enhanced Accuracy and Efficiency: By employing Deep Learning techniques, the system endeavors to improve the accuracy and efficiency of identifying missing children from diverse sources of visual data.

Comprehensive Database Integration: The integration of a vast database of missing children allows the system to compare and match facial features, optimizing the identification process.

Real-Time Recognition: The system is designed to enable real-time recognition and comparison of facial features, facilitating immediate responses and actions by law enforcement agencies. **Ethical Considerations:** Upholding ethical standards and ensuring the privacy and security of sensitive data remain fundamental aspects of system development and deployment.

1.3 Scope of study Scope includes gathering diverse datasets comprising images of missing children and organizing them into a structured format suitable for analysis and model training. Scope involves the development and training of Convolutional Neural Network (CNN) models to extract intricate facial features, patterns, and representations from images of missing children.

1.4 Introduction The safety and prompt recovery of missing children are paramount concerns in today's society. The ability to swiftly and accurately identify missing children from various sources of information, such as images and databases, is critical in aiding law enforcement agencies and communities in their efforts to locate and reunite these children with their families. Leveraging advancements in Deep Learning and Multiclass Support Vector Machine (SVM) techniques offers a promising approach to address this challenge.

1.4.1 The Need for Advanced Identification Systems Traditional methods for identifying missing children often rely on manual examination and comparison of visual features, which can be time-consuming and prone to errors. In response to these limitations, the implementation of sophisticated technological solutions becomes imperative.

II. LITERATURE SURVEY (WITH EXISTING METHODS)

[1] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning", *Nature*, 521(7553):436–444, 2015. Deep learning allows computational models that are composed of multiple processing layers to learn representations of data with multiple levels of abstraction. These methods have dramatically improved the state-of-the-art in speech recognition, visual object recognition, object detection and many other domains such as drug discovery and genomics. Deep learning discovers intricate structure in large data sets by using the backpropagation algorithm to indicate how a machine should change its internal parameters that are used to compute the representation in each layer from the representation in the previous layer. Deep convolutional nets have brought about breakthroughs in processing images, video,

speech and audio, whereas recurrent nets have shone light on sequential data such as text and speech. Machine-learning technology powers many aspects of modern society: from web searches to content filtering on social networks to recommendations on e-commerce websites, and it is increasingly present in consumer products such as cameras and smartphones. Machine-learning systems are used to identify objects in images, transcribe speech into text, match news items, posts or products with users' interests, and select relevant results of search. Increasingly, these applications make use of a class of techniques called deep learning.

Conventional machine-learning techniques were limited in their ability to process natural data in their raw form. For decades, constructing a pattern-recognition or machine-learning system required careful engineering and considerable domain expertise to design a feature extractor that transformed the raw data (such as the pixel values of an image) into a suitable internal representation or feature vector from which the learning subsystem, often a classifier, could detect or classify patterns in the input.

[2] O. Deniz, G. Bueno, J. Salido, and F. D. la Torre, "Face recognition using histograms of oriented gradients", *Pattern Recognition Letters*, 32(12):1598–1603, 2011. Face recognition has been a long standing problem in computer vision. Recently, Histograms of Oriented Gradients (HOGs) have proven to be an effective descriptor for object recognition in general and face recognition in particular. In this paper, we investigate a simple but powerful approach to make robust use of HOG features for face recognition. The three main contributions of this work are: First, in order to compensate for errors in facial feature detection due to occlusions, pose and illumination changes, we propose to extract HOG descriptors from a regular grid. Second, fusion of HOG descriptors at different scales allows to capture important structure for face recognition. Third, we identify the necessity of performing dimensionality reduction to remove noise and make the classification process less prone to overfitting. This is particularly important if HOG features are extracted from overlapping cells. Finally, experimental results on four databases illustrate the benefits of our approach.

Face recognition has been a long standing problem in computer vision. It has recently attracted significant attention due to the accessibility of inexpensive digital cameras and computers, and its applications in biometrics and surveillance (see Zhao et al. (2003); Chellappa et al. (1995); Samal and Iyengar (1992); Chellappa and Zhao (2005) for recent surveys of face recognition). Central to the success of face recognition are the feature representation and the classification method. In this paper, we will focus on the former. Broadly speaking, we could classify the features for face recognition as geometric or photometric (view based). The latter seem to have prevailed in the literature (Zhao et al., 2003). There exist a large number of features, starting from the influential Eigenfaces (Principal Component Analysis) (Turk and Pentland, 1991), Gabor wavelets (Amin and Yan, 2009), Local Binary Patterns (Ahonen et al., 2004),



Error-Correcting Output Codes (Kittler et al., 2001) and Independent Component Analysis (ICA) (Bartlett et al., 2002) among others

III. EXISTING SYSTEM

Earliest methods for face recognition commonly used computer vision features such as HOG, LBP, SIFT, or SURF [2-3]. However, features extracted using a CNN network for getting facial representations gives better performance in face recognition than handcrafted features. In [4], missing child identification is proposed which employees principal component analysis using Eigen vectors is used for face recognition system.

FindFace is a website that lets users search for members of the social network VK by uploading a photograph [5]. FindFace employs a facial recognition neural network algorithm developed by N-Tech Lab to match faces in the photographs uploaded by its users against faces in photographs published on VK, with a reported accuracy of 70 percent The “Tuanyuan”, or “reunion” in Chinese, app developed by Alibaba Group Holding Ltd. helped Chinese authorities recover hundreds of missing children [6]. The app has allowed police officers to share information and work together with public

IV. PROPOSED METHOD

4.1 WORK FLOW OF FACE RECOGNITION Here we propose a methodology for missing child identification which combines facial feature extraction based on deep learning and matching based on support vector machine. The proposed system utilizes face recognition for missing child identification. This is to help authorities and parents in missing child investigation. The architecture of the proposed frame work is given below, Fig. 1. Architecture of proposed child identification system It consists of a national portal for storing details of missing child along with the photo. Whenever a child missing is reported, along with the FIR, the concerned officer uploads the photo of the missing child into the portal. Public can search for any matching child in the database for the images with them. The system will prompt the most matching cases. Once the matching is found, the officer can get the details of the child. The system also generates various statistical reports.

The public can upload photo of any suspicious child at any time into the portal with details like place, time, landmarks and remarks. The photo uploaded by the public will be automatically compared with photos of the registered missing children and if a matching photo with sufficient score is found, then an alert message will be sent to the concerned officer. The message will also be visible in the message box of the concerned officer login screen. The portal for the public can also be maintained as a mobile app, where he or she can upload photo of suspicious children with details.



V. IMPLEMENTATION

The implementation of the proposed missing child identification system is carried out using a combination of deep learning techniques, image processing, and web-based technologies. The system is developed using Python, with Django serving as the backend framework to manage user interactions, data processing, and database operations.

The implementation begins with data acquisition and preprocessing. A dataset containing facial images of missing children is collected and organized into labeled classes. Each image undergoes preprocessing steps such as resizing, normalization, and noise reduction to ensure uniformity. The images are resized to a fixed dimension (e.g., 64×64 pixels) to maintain consistency for model training. Additionally, grayscale conversion and histogram equalization are applied to improve feature visibility and enhance model performance.

Face detection is performed using the Haar Cascade Classifier provided by OpenCV. This step isolates the facial region from the input image, eliminating background noise and focusing only on relevant features. The detected face is then passed to the classification model for further processing.

The deep learning model is built using a Convolutional Neural Network (CNN) architecture. The CNN consists of multiple convolutional layers for feature extraction, followed by pooling layers to reduce spatial dimensions and prevent overfitting. Fully connected layers are used for classification. The model is trained on the preprocessed dataset to learn distinctive facial features.

To improve classification performance, the extracted deep features are passed to a Multi-Class Support Vector Machine (SVM) classifier. The SVM acts as a robust classifier that separates multiple classes using optimal hyperplanes. This hybrid approach enhances accuracy by combining the feature extraction capability of CNNs with the classification strength of SVMs.

The system is integrated into a Django web application where users can upload images of found children. The uploaded image is stored on the server and processed through the detection and classification pipeline. If a match is found in the database, the system updates the status accordingly and stores the result along with user details in a MySQL database.

The implementation ensures real-time processing, efficient storage, and user-friendly interaction. Error handling mechanisms and validation checks are incorporated to ensure system reliability. Overall, the implementation provides a scalable and efficient solution for missing child identification.

VI. ALGORITHMS

The proposed system utilizes a hybrid algorithm combining Convolutional Neural Networks (CNN) and Multi-Class Support Vector Machine (SVM) for accurate identification.

The first stage involves face detection using the Haar Cascade algorithm. This method scans the image at multiple scales to detect facial regions based on Haar-like features. It is computationally efficient and suitable for real-time applications.

The second stage uses a CNN for feature extraction. The CNN processes the detected face through convolutional layers, which apply filters to extract important features such as edges, textures, and facial patterns. Pooling layers reduce dimensionality, and activation functions such as ReLU introduce non-linearity. The output of the CNN is a feature vector representing the facial characteristics.

In the third stage, the feature vector is passed to a Multi-Class SVM classifier. The SVM constructs multiple hyperplanes in a high-dimensional space to separate different classes. It uses strategies such as one-vs-all or one-vs-one for multi-class classification. The classifier determines the class label corresponding to the highest confidence score.

The overall algorithm flow is as follows: input image → preprocessing → face detection → feature extraction (CNN) → classification (SVM) → result generation. A threshold value is used to determine whether a match is found in the database. This hybrid approach ensures high accuracy, robustness, and efficient classification, making it suitable for real-world deployment.

VII. SYSTEM DESIGN

The system design follows a layered and modular architecture to ensure scalability, flexibility, and efficient processing. The design is divided into three main layers: the presentation layer, the application layer, and the data layer.

The presentation layer consists of a web-based user interface developed using Django templates (HTML, CSS). This layer allows users such as officials or the public to upload images, view results, and access system functionalities. The interface is designed to be user-friendly and accessible. The application layer handles the core logic of the system. It is implemented using Django views, which process user requests and coordinate with backend modules. This layer includes components such as image handling, face detection, classification, and result processing. When a user uploads an image, the application layer saves the file and triggers the processing pipeline.

The data processing module includes the deep learning model and SVM classifier. The CNN extracts features from detected faces, while the SVM performs classification. This module is optimized for performance and accuracy. Pre-trained models are loaded dynamically to reduce processing time.



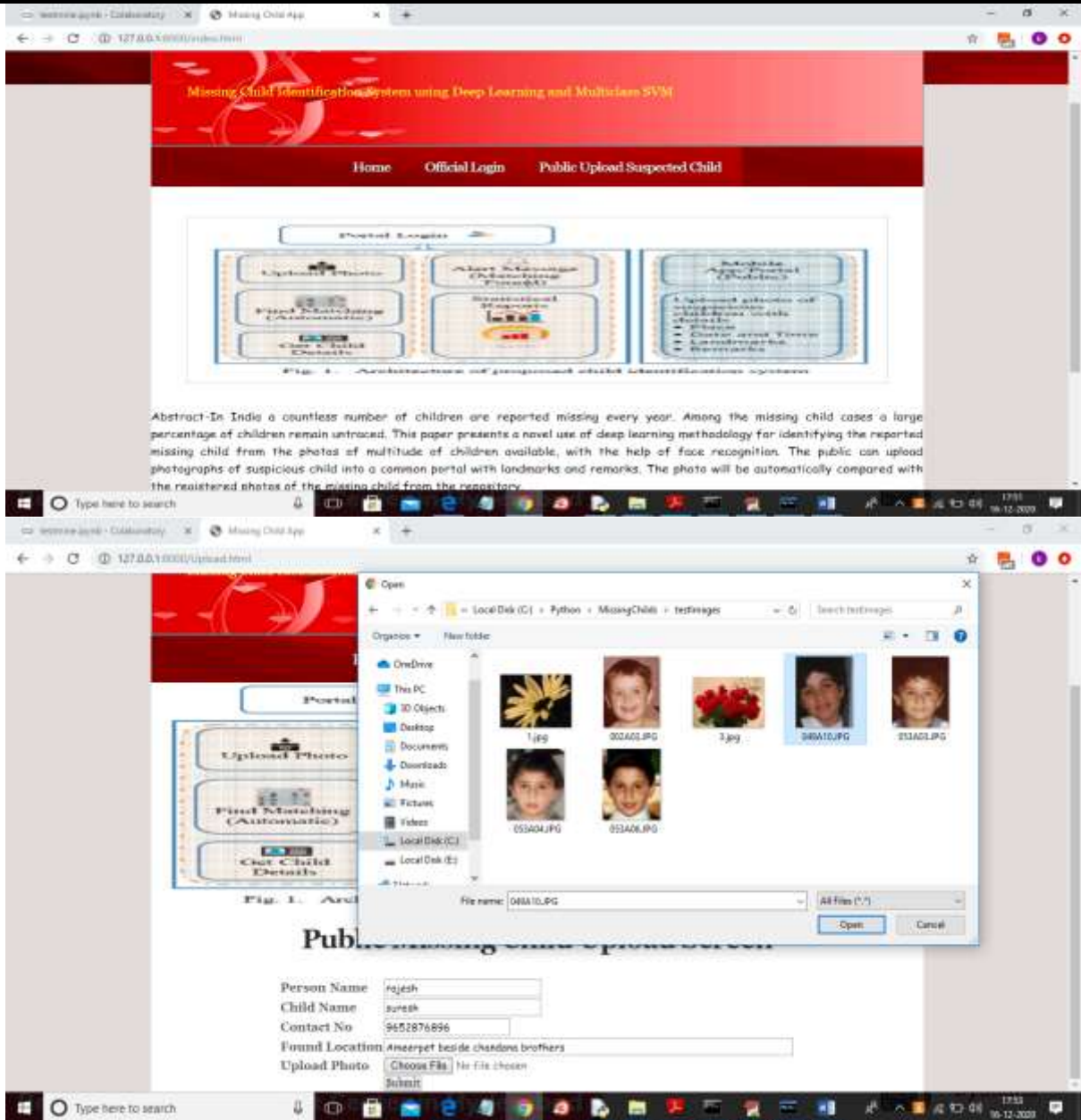
The data layer consists of a MySQL database that stores information about missing children, uploaded images, user details, and identification results. The database ensures efficient data retrieval and management. Each record includes attributes such as child name, contact details, location, image path, timestamp, and identification status.

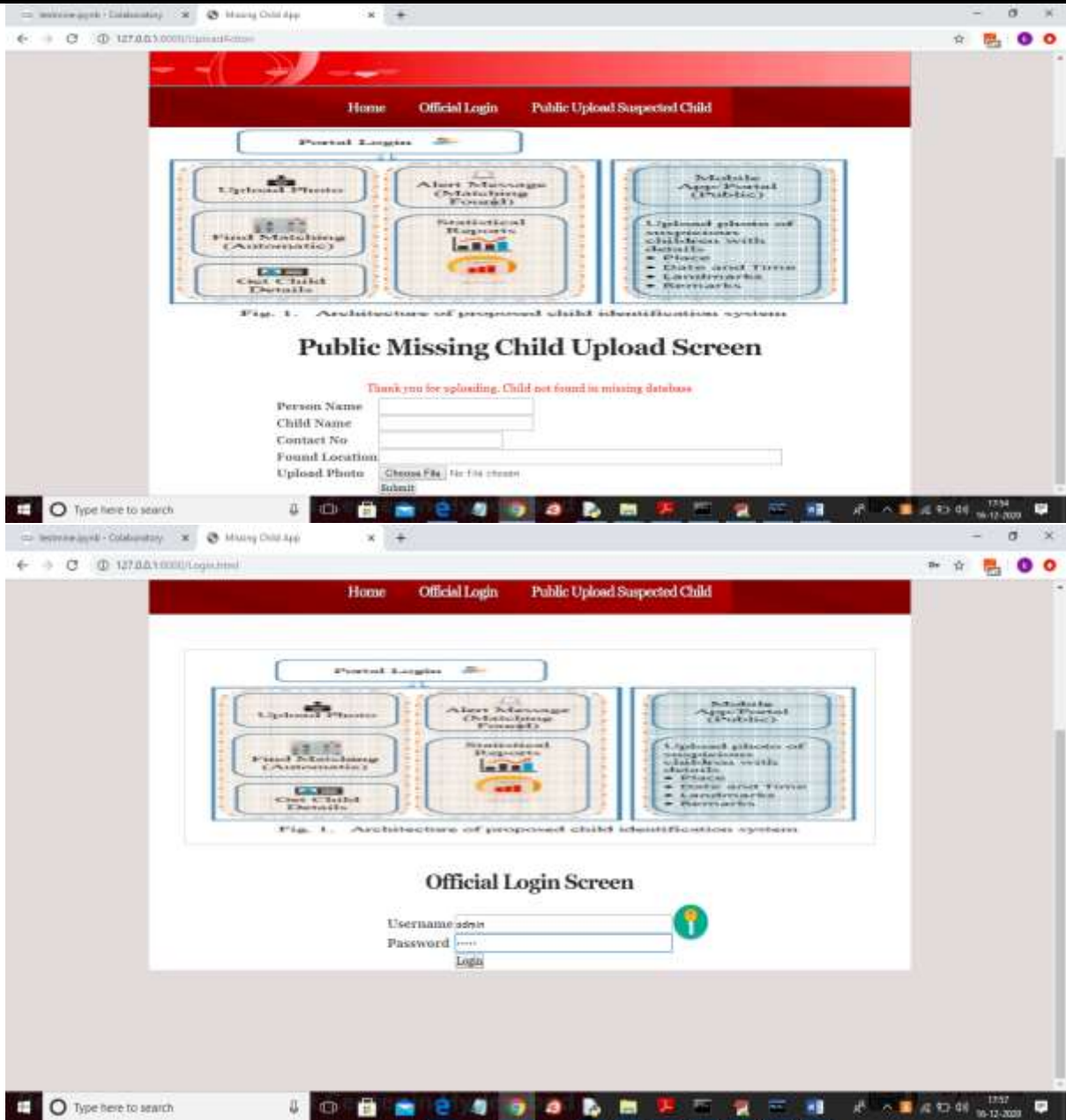
The workflow begins when a user uploads an image through the interface. The image is stored and passed to the face detection module. If a face is detected, it is processed by the CNN and classified using SVM. The result is then compared with existing records in the database. If a match is found, the system updates the status as “Child Found”; otherwise, it remains “Not Found.”

The system also includes error handling mechanisms, such as checking for invalid inputs and handling exceptions during processing. Logging is implemented to track system performance and debugging.

The modular design allows easy integration of additional features such as real-time video analysis, mobile application support, and cloud deployment. This ensures that the system can evolve with technological advancements and increasing data requirements.

SYSTEM DESIGN IMAGES







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

VIII. CONCLUSION

The proposed missing child identification system presents an effective solution for addressing the critical issue of missing children using advanced technologies. By integrating deep learning and Multi-Class SVM, the system achieves accurate and reliable identification of children based on facial features. The use of Convolutional Neural Networks ensures efficient feature extraction, while the SVM classifier enhances classification performance.

The implementation of the system as a web-based application using Django makes it accessible and user-friendly. Users can easily upload images and obtain real-time identification results. The integration with a database enables efficient storage and retrieval of records, supporting large-scale deployment.

Compared to traditional methods, the proposed system eliminates manual intervention and reduces the time required for identification. The use of automated face detection and classification improves accuracy and minimizes human error. Additionally, the system provides a scalable framework that can be extended to include advanced features such as real-time surveillance and integration with law enforcement databases.

One of the key advantages of this system is its hybrid approach, combining deep learning with classical machine learning techniques. This ensures both high accuracy and computational efficiency. The system also demonstrates robustness in handling variations in image quality, lighting conditions, and facial expressions.



In conclusion, the proposed system contributes significantly to the field of computer vision and public safety. It offers a practical and efficient solution for identifying missing children and can play a vital role in reuniting families. Future work may focus on improving model accuracy, expanding the dataset, and integrating advanced technologies such as cloud computing and IoT for enhanced functionality.

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