

# Missing Child Identification System Using Deep Learning and Multiclass SVM

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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 there pository. 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 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 unidentified Child cases

**Key words:** CNN, Deep learning, SVM Classifier

## I. INTRODUCTION

Children are the greatest asset of a nation, as they shape the future of society. India, being the second most populous country in the world, has a significant child population. However, an alarming concern is the large number of children who go missing every year due to various reasons such as abduction,

trafficking, and running away from home. According to the National Crime Records Bureau (NCRB), over one lakh children were reported missing in India until 2016, with nearly half remaining untraced. This issue highlights the urgent need for an efficient and scalable solution to aid in locating missing children. To address this challenge, this paper proposes a deep learning-based Missing Child Identification System that leverages Convolutional Neural Networks (CNNs) for facial feature extraction and a Multiclass Support Vector Machine (SVM) classifier for efficient matching of missing child images. The system utilizes a centralized database where parents and authorities can upload recent photographs of missing children.

Additionally, the public is encouraged to upload images of children in suspected situations, which are then automatically compared with the stored database using advanced facial recognition techniques. Unlike traditional biometric methods such as fingerprint or iris recognition, this system offers a more practical, cost-effective, and scalable approach. By integrating with CCTV networks, law enforcement databases, hospitals, and child welfare organizations, the system significantly enhances the chances of recovering missing children. A mobile application further promotes public participation, allowing citizens to actively contribute to child recovery efforts.

This initiative has significant social impact, offering a systematic, centralized, and technology-driven approach to address the critical issue of missing children. Through the application of deep learning and machine learning techniques, the project aims to improve identification accuracy while overcoming challenges such as aging effects, variations in facial appearance, and poor-quality images.

## II. RELATED WORK

J. Zhang et al.[1] introduced a D-CNN model that can

extract deep features from input images and classify them as real or fake with high accuracy and generalizability. It uses seven different datasets from the reconstruction challenge with 5000 deepfake images and 10000 real images to train and test the model. Improved dense CNN architecture for deepfake image detection. The model using accuracy, precision, recall and F1 score metrics and compares it with existing approaches existing approaches and yields an accuracy of 98.33 percent in AttGAN, 99.33 percent in GDWCT, 95.33 percent in StyleGAN, 94.67 percent in StyleGAN2, and 99.17 percent in StarGAN real and deepfake images.

G. Kiran et al, [2] introduced a Artificial Intelligence techniques, particularly deep learning, play a key role in the enhanced and simplified generation of deepfakes, impacting various aspects of society. The methodology involves a systematic approach, adopting the PRISMA approach, to collect, analyze, and synthesize publications related to deepfakes. Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs) are key techniques in visual and audio deepfake generation. Text-based deepfakes primarily use Natural Language Processing (NLP)-based deep learning models, including Conventional Neural Networks (CNN) and Recurrent Neural Networks (RNN). Highlighting its potential to fuel cybercrimes such as phishing, identity theft, and digital espionage.

S. Li et al., [3] proposed a Deepfake defense methods: Proactive deepfake disruption, Reactive deepfake detection. Data poisoning caused by the coexistence of disruption and detection techniques, which can reduce the detection accuracy. Deepfake detection models that involves purifying the disrupting perturbations using a denoising diffusion probabilistic model (DDPM).

R. Wang et al., [4] introduced A taxonomy of Deepfake detection techniques, which are classified into four categories: machine learning-based, Deep learning-based, Statistical, Blockchain-based methods. The empirical evidence of the various methods, such as the datasets, features, models, and measurement metrics used in the experiments. It also evaluates 3 the performance of the methods based on different criteria and compares them with each other. Limitations and challenges of the current research, such as the lack of a common framework, dataset, and metric for fair and comprehensive evaluation of the methods.

K. Patel et al., [5] introduced the Research in DeepFake detection using deep neural networks is acknowledged as an area of increased interest. DeepFake is defined as regenerated media obtained by injecting or replacing information within the DNN model. DeepFake models are typically trained on DeepFake datasets and tested through experiments. Dataset trends play a crucial role in training and evaluating DeepFake detection models. GANs face challenges in establishing disentangled and controllable syntheses, particularly in the highresolution domain..

H. Liu et al., [6] acknowledged recent advancements in machine learning (ML) and deep learning (DL) techniques, particularly the development of generative adversarial networks (GANs). These advancements have enabled the creation of increasingly realistic deepfake content, making it more challenging to distinguish from authentic media. The various ML/DL approaches used to synthesize deepfake content across different modalities, including images, audio, and video streams.

M. Chen et al., [7] proposed a Generative Adversarial Networks (GANs) can synthesize DEEPFAKE images to augment data. Previous Approaches: Prior studies have utilized various GAN architectures, such as DCGAN, pix2pix, and PGGAN, for synthesizing DEEPFAKE images in medical imaging applications like segmentation and detection

Q. Wu et al.,(2021) [8] proposed technique utilizes a multi-faceted approach to deepfake detection, leveraging both pixel-level analysis and higher-level facial features to accurately identify manipulated images. By addressing multiple aspects of deepfake generation, the algorithm enhances detection capabilities and achieves stable performance across diverse datasets. The DeepFaceLab team released a deepfake face-swapping application. This application likely incorporates advanced techniques

A. Sharma et al., (2021) [9] introduced a Deepfake Face Mask Dataset (DFFMD), a novel dataset and method for detecting deepfake videos with face masks<sup>1</sup>. The paper proposes a novel Inception-ResNet-v2 model with preprocessing stages, featurebased, residual connection, and batch normalization to improve the accuracy and speed of deepfake detection<sup>2</sup>. The paper compares the

proposed model with existing state-of-the-art methods, such as CNN, InceptionResNetV2, and VGG19, and shows that the proposed model achieves the highest accuracy of 99.1.

L. Wang et al.,(2022) [10] introduced a Exposing fake faces through deep neural networks combining content and trace feature extractors. proposes a hybrid face forensics framework based on a convolutional neural network that extracts both content features and trace features from a face image to enhance the manipulation detection performance. uses a public Face2Face dataset and a custom DeepFake dataset to validate the proposed framework and shows that it is more accurate and robust than the previous methods at various video compression rates.

B. Liu et al.,(2022) [11] proposed a method to extract the CT using an ExpectationMaximization algorithm that captures the pixel correlations in the spatial RGB space. The CT is a feature vector that represents the structure of the Transpose Convolution layers used by the Generative Adversarial Networks (GANs) to create Deepfake images. The CT is shown to have high discriminative power, robustness to attacks, and independence to image semantics for the Deepfake detection task. The authors test their method on images generated by ten different GAN architectures.

Y. Zhu et al.,(2021) [12] introduced the Meta-learning based deepfake detection method called Meta Deepfake Detection (MDD), aims to improve the generalization of face forgery detection across different domains and techniques. The MDD algorithm uses meta-weight learning to transfer information from the source domains to the target domains, and meta-optimization to combine the gradients from the metatraining and meta-test sets, which helps the model to learn effective representations of both synthetic and real faces.

### III. METHODOLOGY

#### Data collection:

The system uses supervised machine learning algorithms, specifically Local Binary Pattern Histogram Algorithm combined with Haar Cascade Classifier. This comprehensive strategy aims to enhance the face recognition in realtime using webcam. As you can see, each image are presented in the matrix formats, which are made up of rows and columns. The pixel is an image's fundamental

building block. A group of pixels make up an image. These are all little squares. We may build the entire image by arranging them side by side. The smallest amount of information that can be present in an image is a single pixel. Every grayscale image has pixels with values ranging from 0 to 255. Each pixel is composed of Three values are R, G, and B, which are the basic colours red, green, and blue. The combination of these three basic colours will create all these colours here in the image so we conclude that a single pixel has three channels, one channel for each one of the basic colours. We provide a step-by-step overview of the implementation process, including data collection, model selection, training procedure and evaluation metrics. By adopting this approach, we aim to develop a robust and accurate framework for the missing child identification cases. Images and Videos:

#### Data Preprocessing:

The primary objective of this system is to detect missing children using facial recognition techniques, incorporating Convolutional Neural Networks (CNN) and Support Vector Machine (SVM) classifiers.

#### System Components:

##### Image Acquisition:

Collect images from CCTV footage, social media platforms, and public camera feeds.

##### Face Detection (CNN-Based):

Utilize a trained CNN model to detect and extract facial features from the acquired images.

##### Feature Classification (SVM):

Extract facial features using an SVM multiclass classifier based on age and other distinctive characteristics.

Compare extracted features against a database of missing children.

##### Face Matching and Database Comparison:

Utilize the CNN model to predict whether the detected face belongs to a missing child by comparing it with a pre-trained dataset.

Store detected matches in a database for further analysis.

##### Post-processing and Alerts:

Provide real-time match alerts to concerned authorities.

Flag uncertain cases for manual review by officials.

#### Process Flow:

1. Preprocess and standardize the input images.
2. Detect faces using a trained CNN model and extract unique facial features.
3. Classify and match detected faces against the missing children's database using an SVM classifier.
4. Generate real-time alerts when a match is found.
5. Store detected results in a secure database accessible to authorized personnel.

**Training and Implementation**

A publicly available dataset of missing children, such as FGNET, is used to train the deep learning-based CNN model.

After training, when an image is uploaded by the public, the model will check against the trained database to detect potential matches.

Law enforcement officials can access the system to review and verify the detected results.

Data Pre-processing can be done in four different ways: data cleaning, data integration, data transformation, normalization, and data reduction.

**Data Cleaning**

Data in the real world is frequently incomplete, noisy, and inconsistent. Many bits of the data may be irrelevant or missing. Data cleaning is carried out to handle this aspect. Data cleaning methods aim to fill in missing values, smooth out noise while identifying outliers, and fix data discrepancies. Unclean data can confuse data and the model. Therefore, running the data through various Data Cleaning/Cleansing methods is an important Data Pre-processing step.

**SYSTEM ARCHITECTURE:**

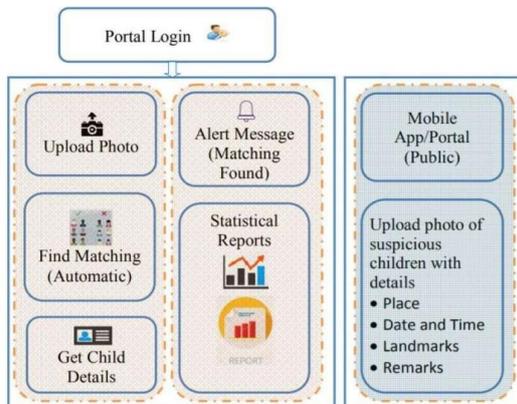


Figure 1: Architecture diagram

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 framework is given below. Images of reported missing children are saved in a repository and the face area is selected for cropping to obtain input face images. Learned features from a Convolutional Neural Network (CNN), a specific type of deep learning algorithm, are used for training a multi class SVM classifier. This machine learning approach is used to correctly label the child using the name indicated in the database provided by the concerned authority. In the following sections the paper details the work flow for child matching methodology. The block diagram of the automatic child face identification methodology.

**Model Architecture Design:**

This module involves designing the architecture of the hybrid neural network model. Defining the input layer and its shape. Designing the convolutional layers with ResNet-like architecture. Designing the inception blocks with inception modules, concatenation, batch normalization, and ReLU activation. Designing the attention mechanisms with spatial and channel attention blocks and fusion with feature maps.

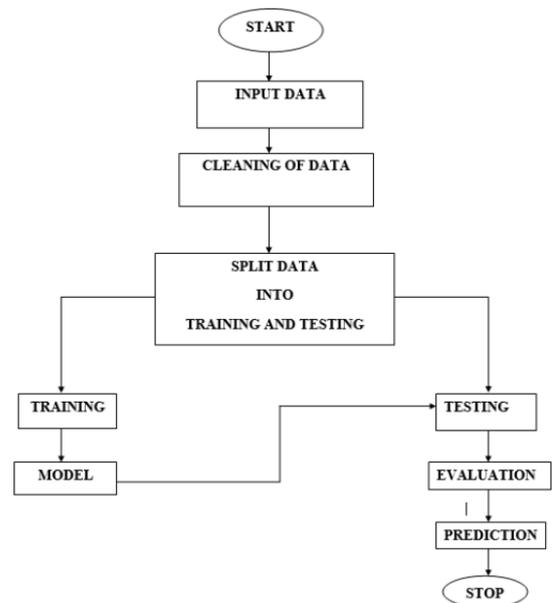


Figure 2: Workflow Diagram

**Data Preprocessing:-**

In this context, NVIDIA provides a comprehensive dataset selected for research. With approximately 4GB of highly curated data, this dataset contains a wide selection of authentic media samples, including photographs and videos from a variety of instances and contexts. This module involves collecting and

preprocessing the dataset of altered and unaltered media. The steps involved in this module are, Collecting a large dataset of altered and unaltered media from various sources such as online repositories, social media platforms, and news websites Preprocessing the dataset by removing any duplicates, irrelevant data, and noise. Labeling the dataset with appropriate categories such as "altered" or "unaltered". Splitting the dataset into training, validation, and testing sets

#### IV RESULT AND DISCUSSION

A deep learning-based missing child identification system is developed using the FGNET dataset. A Convolutional Neural Network (CNN) is trained to detect and match uploaded child images with the missing children database. The system allows officials to review detected results upon login.

##### Methodology:

SVM Multiclass Classifier extracts facial features (age, facial attributes) before feeding them into the CNN model for identification.

Comparison of CNN, ResNet-50, and VGG-16: Accuracy improves with increasing epochs. The results show that VGG 16 and CNN exhibit accuracy improvements, with ResNet-50 performing better in some cases.

This study demonstrates the potential of deep learning for missing child detection, leveraging CNN-based classification and feature extraction for improved accuracy.

##### Adversarial Manipulation:

Although the model performs well on traditional image manipulations (e.g., splicing, deepfakes), it may struggle with very sophisticated adversarial manipulations or unknown forms of media alteration. As AI-generated media continues to evolve, the system might need to be updated periodically.

##### Effectiveness of the Model:

The hybrid model combining CNN, ResNet, and Inception layers has shown promising results in detecting altered media with high accuracy, precision, and recall. The use of deep learning architectures like ResNet allows for effective feature extraction even in very deep networks without losing important information due to the residual connections. The Inception layers help the model capture multi-scale features, which is particularly useful in detecting subtle manipulations in images.

##### Computational Complexity:

The model architecture combining CNN, ResNet, and Inception is computationally intensive. This could be a challenge if the model needs to be deployed in real-time environments, such as detecting manipulated media on social media platforms. Techniques like model pruning or knowledge distillation could help reduce the model size and make it more efficient for deployment.

Report the final accuracy/\* of the model, which shows the percentage of correct predictions made by the model. For example, if your model achieved an accuracy of 95%, it means the model correctly classified 95% of the manipulated and non-manipulated images in the dataset.

To run this project we need to follow this steps

- 1) First create database in MYSQL by copying content from 'DB.txt' file and paste in MYQL
- 2) Install python, DJANGO and MYSQL software
- 3) Create 'Python' folder in C directory and put 'Missing Childs' folder in it
- 4) start DJANGO server and run in browser to get first page

In above screen public can click on 'Public Upload Suspected Child' link to get below page and to add missing child details



Official Login Screen

Username   
 Password

Figure 3: Login Page

In above screen admin can login by entering username and password as 'admin' and 'admin' and after clicking on 'Login' button will get below screen



Figure4: Upload Screen



Figure 5: upload image From Device

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



Figure 6: Output

In above screen officials can see all details and then take action to find that child

### CONCLUSION

A missing child spotting system is proposed that combines a powerful CNN-based deep learning approach for feature extraction and a support vector machine classifier to classify different categories of children. This system is evaluated using a deep learning model that is trained with feature representations of children's faces. By discarding the soft max of the VGG-Face model and extracting the CNN image features for multi-class SVM training, excellent performance could be achieved. The performance of the proposed system is tested on photos of children with different lighting conditions, noise, and also on photos of children of different ages. The classification achieved a higher accuracy of 99.41%, which shows that the proposed face recognition methodology could be used for reliable identification

This system is evaluated with the deep learning model which is trained with feature representations of children faces. By discarding the soft max of the VGG-Face model and extracting CNN image features to train a multi class SVM, it was possible to achieve superior performance. Performance of the proposed system is tested using the photographs of

children with different lighting conditions, noises and also images at different ages of children. The classification achieved a higher accuracy of 99.41%.

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