

# Missing Child Identification System using Deep Learning and Multiclass SVM for E-police

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**Abstract:** *Countless children go missing in India every year. In missing children, most children are not included. This article presents a deep learning method to identify missing children from multiple existing images of children with the help of face recognition. Citizens can send pictures of suspicious children to public places with signs and writings. The photo will be automatically compared to the saved photo of the missing child in the warehouse. Sort the photos of the children and choose the best photos from the missing children file. To this end, a deep learning model was trained to accurately identify missing children by matching information about missing children using face images provided by the public. Convolutional Neural Networks (CNNs) are deep learning techniques for image-based applications, this is face recognition. Extract face identifiers from images using the CNN pre-trained VGG-Face deep architecture. Compared to ordinary deep learning applications, our algorithm only uses network connection as high-level input and child identification is done by SVM trainers. Choose VGG-Face, the most effective CNN face recognition model, and train it appropriately to make deep learning models that are not affected by noise, light, contrast, obscuration, image posture and child age, and perform better based on previous Face recognition methods. In identifying missing children, Child identification achieved a 99.41% classification rate. Forty-three patients were evaluated.*

**Keywords:** Missing Child Recognition, Face Recognition, Deep Learning, CNN, VGG-Face, Multiclass SVM

## I. INTRODUCTION

Children are the richest of all nations. The future of a country depends on the development of its children. Our country is the second most populous country in the world and children make up a large part of the total population. But unfortunately, every year in India, a large number of children go missing for various reasons such as kidnapping, kidnapping, running away from home, kidnapping, disappearing. The most disturbing fact about the missing children in India is that while an average of 174 children go missing every day, half of them cannot be reached.

## II. RELATED WORKS

Early face recognition techniques usually use computer vision such as HOG, LBP, SIFT or SURF [2-3]. However, features extracted using CNN have been proposed for the detection of missing children in [4], where key analysts using vectors in face recognition are used. FindFace is a website that allows users to search for social network VK members by uploading a photo [5]. FindFace uses a face recognition neural network algorithm developed by N-Tech Lab to match faces in photos uploaded by users with faces in photos uploaded to VK with 70% accuracy. Alibaba Group Holding Ltd. "Reunion" application developed by He helped the Chinese police rescue hundreds of missing children [6]. The app allows the police to share information and work with the public.

**III. WORK FLOW OFFACE RECOGNITION**

Here, we propose a missing child recognition method that supports deep learning-based face extraction and vector machine-based matching. The system plans to use facial recognition to identify missing children. This is to help authorities and parents search for missing children. The architecture of the conceptual framework is shown below,

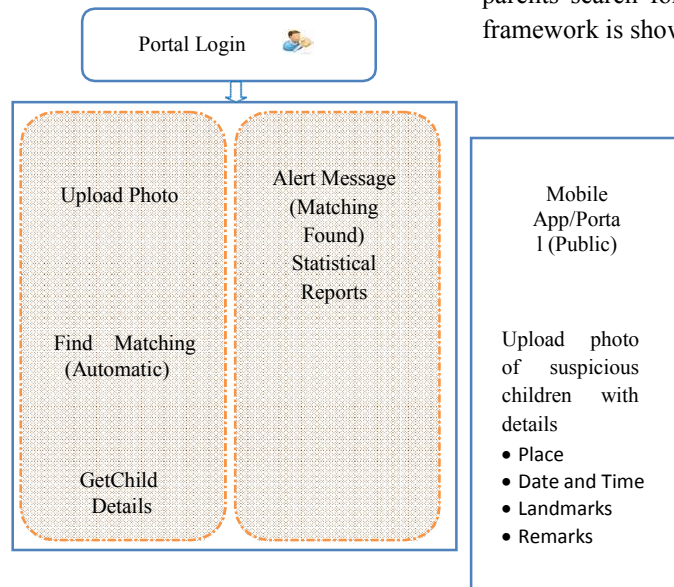


Fig.1. Architecture of proposed child identification system

It contains a national portal where details and pictures of missing children are stored. When a child is reported missing, authorities upload a photo of the missing child to the portal along with the FIR. The public can search for information about all the children corresponding to the pictures next to them. Alert system for the best information. When a match is found, the authorities can get the child's details. The system also generates a lot of statistical information. Citizens can send the photograph of the child they see as suspicious to the portal at any time, including details such as place, time, area and text. Photos shared by the public will be compared with those of missing children, and if a photo matching the scores is found, a warning will be sent to the relevant personnel. The message will also be displayed in the mailbox of the login ID of the affected person. The public website can also be stored as a mobile application from which the child can download pictures and content. The location of the person who edited this image in the mobile application is automatically turned off. Once everyone has uploaded pictures of expected children, the system will generate vector images of faces based on the uploaded pictures. If a match is found in the warehouse, the system will show the best picture and send the message to the official website or send a warning message via SMS to the relevant child. Likewise, authorities can check all matches with information using the prepared system. Images of missing children are stored in storage and the area of the face is selected to be cropped to obtain the face image. Features learned from convolutional neural network (CNN) is a type of deep learning used to train different types of DVM classifiers. This machine learning method is used to accurately enroll children with the names shown in the data provided by the authorities

**IV. CONVOLUTIONAL NEURAL NETWORKS(CNN)**

A CNN or ConvNet consists of a mesh network of recursive layers, ReLUs (Rectified Linear Units), connected layers, and fully connected layers. The Convolutional Neural Network (CNN) combines input face image data with different nuclei to generate convolution layers, activation maps, or feature maps representing low-level features such as edges or curves. This particular map feeds into the next convolution process, creating a high-level representation function that shows the position of the face. A convolutional layer defines a filter layer that is initially changed during network training. A ReLU is followed by all convolutional layers and introduces nonlinearity to the body. This method uses  $f(x) = \max(0,x)$  to layer the input data. The pooling layer combines similar features by reducing the size. The basic idea behind merging layers is that the relative position relative to other attributes is more important than the actual position of a particular attribute. It reduces the dimensionality of feature maps and network parameters. The last procedure is

called a fully bound procedure that displays the class count. There are many layers that convert 2D feature maps to 1D feature vectors for additional feature representation. A VGG-Face CNN Identifier For face recognition, a deep CNN named VGG-Face network [8] is used, the structure of which is detailed in Figure 3. One or more parameters such as ReLU and maximum pooling. Since the linear operator is a set of filters (linear convolution), the first eight blocks are called convolutions. It uses 3 x 3 dimensional filters with pitch and padding 1 across the mesh. All convolutional processes are based on layer correction (ReLU). The maximum pooling layer is only used in 2x2 with 2 steps. The last three blocks are full layers, similar to layers, but containing filters whose size is the size of the input data; whole image. The output of the first two FC layers is 4096 size and the last FC layer is 2622 size based on L size dimension embedding. Optimization was performed by stochastic gradient descent using a mini-batch of 64 samples and a power factor of 0.9.

layer	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
type	input	conv	relu	conv	relu	mpool	conv	relu	conv	relu	mpool	conv	relu	conv	relu	conv	relu	mpool	conv
name	-	conv1_1	relu1_1	conv1_2	relu1_2	pool1	conv2_1	relu2_1	conv2_2	relu2_2	pool2	conv3_1	relu3_1	conv3_2	relu3_2	conv3_3	relu3_3	pool3	conv4_1
support	-	3	1	3	1	2	3	1	3	1	2	3	1	3	1	3	1	2	3
filt dim	-	3	-	64	-	-	64	-	128	-	-	128	-	256	-	256	-	-	256
num flts	-	64	-	64	-	-	128	-	128	-	-	256	-	256	-	256	-	-	512
stride	-	1	1	1	1	2	1	1	1	1	2	1	1	1	1	1	1	2	1
pad	-	1	0	1	0	0	1	0	1	0	0	1	0	1	0	1	0	0	1
layer	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37
type	relu	conv	relu	conv	relu	mpool	conv	relu	conv	relu	conv	relu	mpool	conv	relu	conv	relu	conv	softmax
name	relu4_1	conv4_2	relu4_2	conv4_3	relu4_3	pool4	conv5_1	relu5_1	conv5_2	relu5_2	conv5_3	relu5_3	pool5	fc6	relu6	fc7	relu7	fc8	prob
support	1	3	1	3	1	2	3	1	3	1	3	1	2	7	1	1	1	1	1
filt dim	-	512	-	512	-	-	512	-	512	-	512	-	-	512	-	4096	-	4096	-
num flts	-	512	-	512	-	-	512	-	512	-	512	-	-	4096	-	4096	-	2622	-
stride	1	1	1	1	1	2	1	1	1	1	1	1	2	1	1	1	1	1	1
pad	0	1	0	1	0	0	1	0	1	0	1	0	0	0	0	0	0	0	0

## V. PREPROCESSING

Preprocessing a raw input image in face context knows how to use face space and normalizes the image in a format compatible with business CNN architecture. Each CNN has different input size requirements. Take photos of missing children obtained from a digital camera or cell phone and share them to create a face recognition database. The face region in each image is identified and cropped to obtain the face image. The image of the face has been changed to 224x224 because the VGG-face mesh can handle RGB images of this feature.

## VI. EXTRACTION OFFACIAL FEATURES

VGG-Face is trained to recognize 2622 ID and other groups cannot be identified using this ID. However, activation vectors extracted from the VGG-Face architecture can be used as a proxy for classifying each group. Remove the last layer of classification and completely remove 4K dimensional features from the first layer. The resulting positive vectors are normalized by dividing each component by the L2 standard of this 4096-dimensional vector. Therefore, the pre-trained CNN VGG-Face is used as an automatic facial feature extractor to train a classifier.

## VII. MULTI CLASS SVM CLASSIFIER

Each face image corresponds to a child and the recognition of the child's face is considered as an image classification problem. The task is to identify images entered into one of the classrooms by the public, based on the image representation. Basically, the CNN architecture consists of a computational process for inference and a classification process at the final stage. The VGG-faced CNN model uses a softmax activation function for the list of prediction classes, which shows the classes each image belongs to. The softmax in the CNN layer is replaced by a multiclass SVM trained with a set of feature vectors for each image. Use a one-to-one linear SVM classifier and train it on the data. The extracted feature vector array is used to train the classifier.

## VIII. RESULTS AND DISCUSSIONS

The face recognition algorithm is implemented by the MATLAB 2018a platform. Tests conducted on Microsoft Windows 7, 64-bit operating system and Intel Core i7, 3.60GHz processor and 32GB RAM. Additional processing

power is required to manage CNN architectures. A GPU was recommended for the training model and used an Nvidia GeForce TitanX 12GB card. The user database contains 846 baby face photos and 43 baby scenes. Schedule training and testing by sharing the image database. From each group, 80% of the images were selected for training and 20% for testing, resulting in 677 training sets and 169 test images. The training and validation tests include images of all early children and were tested using images of later children of different ages to test the system in all conditions. The CNN implementation is based on the MatConvNet package [9], which integrates CNN building blocks into the MATLAB environment. Pre-trained VGG-Face CNN is also provided by MatConvNet. Download and use MatConvNet version 1.0-beta25 for this experiment. The training images were preprocessed to the size defined by the CNN architecture before switching to the CNN model. The image fed into VGG-Face is resized by rescaling to 224x224. The operation of the input image produced by the first layer connected to the VGG-Face network architecture is handled according to the CNN description. Normalized vectors, each 4096 long, are used to train an SVM classifier to classify face images and identify children. A low quality image was created to test the flexibility of deep architectures for face recognition against changes in image quality. Images obtained by changing noise, brightness, contrast, illumination, contrast, blur, contrast and face position were used to measure the child's knowledge. Face recognition is calculated as the ratio of recognized face images to all face images in the child's test form. Accuracy =  $\frac{\text{Recognized face image}}{\text{Total Images}}$  The recognition accuracy of the multiclass SVM calculation using features learned from CNN is 99.41%

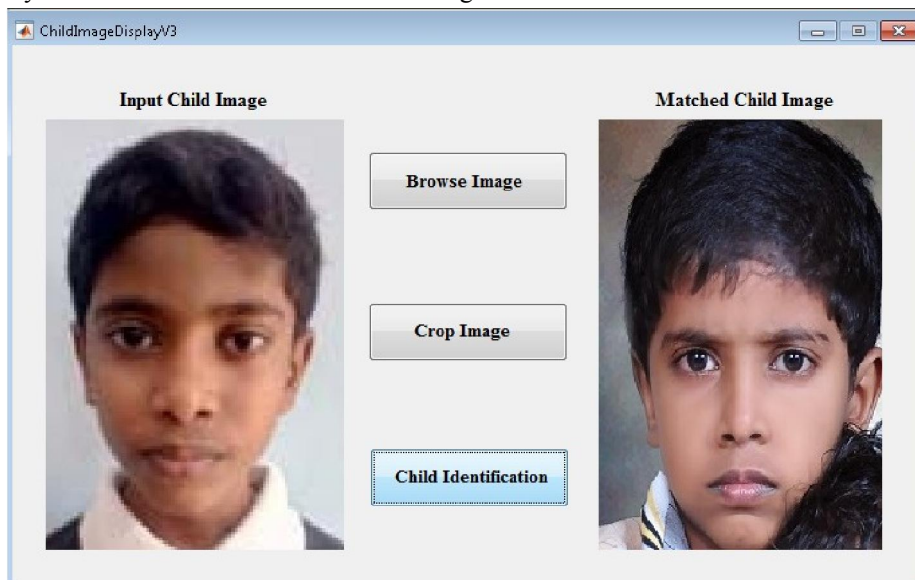


Fig. 4. GUI for child identification showing an input image and matched output image in the database



Fig.5. Images with variations correctly classified by the system

### **IX. CONCLUSION**

A missing child detection system is proposed to combine a CNN-based deep learning method for feature extraction and a support vector machine classifier for classification of different children. The system was evaluated using a deep learning model that learned the representation of the child's face. Very good performance can be achieved by training the multiclass SVM by placing the softmax of the VGG-Face model and extracting the CNN image features. The effectiveness of the proposed method was tested using different lighting, noise and images of children of different ages and images of children. This classification provides an accuracy of more than 99%.41% This shows that facial recognition is effective in detecting a missing child.

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