Lost + Found: The Lost Angel Investigator

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Each year, a large number of youngsters are found missing in India. Among them, a large number of cases are never solved due to various difficulties faced by the police ranging from heavy paperwork to lacking technology. Therefore, one of this work's key goals is to provide an application that may assist people whose children have been missing and rescued by the public. This will also reduce the time required to find the missing child to reunite the child with their loved ones as soon as possible. The pictures of child victims can be uploaded by the citizens along with landmarks, to our web app. The photographs will be matched to the missing child's registered photographs if existing in the database. A deep neural network model is trained to locate the lost youngster using a facial picture uploaded by the citizens. Multi-Tasking CNN (MTCNN), the most efficient DNN technique for image-based apps, is used for facial Identification. The images were passed through an augmentation layer to get images of different orientations, brightness, and contrast, which were used ahead to train the EfficientNetB0 model. This model is then used to recognize faces in photographs. Using the MTCNN model for facial recognition with EfficientNetB0 and developing it yields a deep learning model that is free from all types of distortion. The model's training accuracy is 96.66 percent and its testing accuracy is 76.81 percent, implying that there is approximately 77 percent possibility of finding a match for the missing kid. It was evaluated using 25 Child classes. Each Child class has around 15 to 20 images. These images are taken with different backgrounds and real-time settings so that model will work even when noise is present in the image.

Keywords: Deep Learning Model, Face Detection, Face Recognition, MTCNN, EfficientNetB0.

1. INTRODUCTION

Each country's most valuable asset is its children. Each year, a significant number of youngsters go lost due to a variety of factors such as kidnapping, desertion, trafficking, and lost youngsters. Traditional procedure involves notifying the police about missing children. The police filed an FIR and begin their search which is a very time-consuming and tedious process. For a variety of circumstances, a kid lost in one location may be located in another region or state. Even if a child is located, identifying him or her from the reported missing instances is challenging as there is no properly maintained easy-to-use common database. This project describes a structure and methods for designing an assistance tool and webpage specialized in locating missing kids. The objective of our project is

- A architecture and technique for developing missing children tracing software.
- A common database where every report is maintained.
- Encouraging people to give back to society by helping find missing children by capturing the images of children in suspicious settings and uploading them on our webpage.
- Depreciating the chock-a-block in the police system by providing them a hassle-free technology.
- Terminating the glut of Venal Practices from the system reduces the undue advantage given to the privileged.
- Promoting Digitalization/Automation.

Our project includes an automated search for the picture provided by the citizen among missing kid case photographs. These assist officials in searching for the youngster. Whenever a kid is found, the image taken at the time is matched to the photograph provided by the authority/guardian when the kid went missing. Sometimes the child's facial look can also alter according to variations. The image taken by the citizen might be of low quality because it was taken from a faraway position without the child's awareness. All of these restrictions are taken into account while designing a deep learning framework. Compared to other technologies such as iris or fingerprint recognition systems, the proposed method is simple, inexpensive, and trustworthy.

2. LITERATURE REVIEW

The work by Singh et al. [2022] discuss face recognition which was employed as a search method. In the event of a missing person, the person's guardian can upload the photo, which will subsequently be saved in the database. The database will then be checked by their system's facial recognition model for a match of that person. Pupala et al. [2021] discuss that their system has mainly based on the FaceNet technique for facial feature recognition and extraction as well as C-GAN technique for facial ageing. Singh and Jasmine [2019] and Satle et al. [2016] employ the KLT method, the Viola-Jones technique for face detection (which uses a Haar cascade classifier to detect human faces, but the camera constantly detects faces with each frame), and the PCA algorithm for feature selection. To match the geometrical features of the human face, we combine a model. The study by Kasar et al. [2016] provides an overview of face detection experiments and systems that use various ANN techniques and algorithms. Their research study also analyses the performance of various ANN approaches and algorithms in addition to the strengths and weaknesses of these literature studies and systems. Another research team of Chandran et al. [2018] and Sai et al. [2022] have used technique to obtain facial descriptors from photos using the VGG-Face model. In contrast to normal deep learning applications, the trained classification algorithm conducts kid identification in the approach, which employs the neural network just as a high dimensional extractor. Experiments conducted by Boyko et al. [2018] and Ayyappan and Matilda [2020] proposed the development of a full recognition system and the scientific underpinnings of facial recognition were discussed. The fundamental tenets of facial recognition software are established. The productivity of the Dlib and OpenCV libraries was compared in terms of implementation time and the total number of times the utilised algorithms were iterated. They offer a system that can correctly detect many faces, which is important for swiftly looking for suspects because the calculation time is relatively short. It generates a unique pattern for each face and compares it to other photos in the collection. Wang et al. [2020] present attentive feature distillation and selection (AFDS), which dynamically selects the key features to transfer while also adjusting the level of transfer learning regularization. A research team of Kaipeng Zhang et al. [2016] employ an architecture that is a pipelined structure consisting of three levels of precisely developed deep neural networks to predict facial and landmarks placement from basic to high level. Their method surpasses other algorithms on the tough FDDB and WIDER FACE facial identification benchmarks, as well as the AFLW facial alignment test, while preserving actual performance level. Tan and Le [2019] thoroughly investigated the framework scalability and observed that balancing network length, breadth, and quality can boost results. They illustrated the efficiency of this approach for scaling ResNet and MobileNets and employed neural architecture to advance much further to explore for ways to build a new foundation network in order to develop the EfficientNets family of models

3. PROPOSED WORK

3.1 Workflow of the Lost Angel Investigator

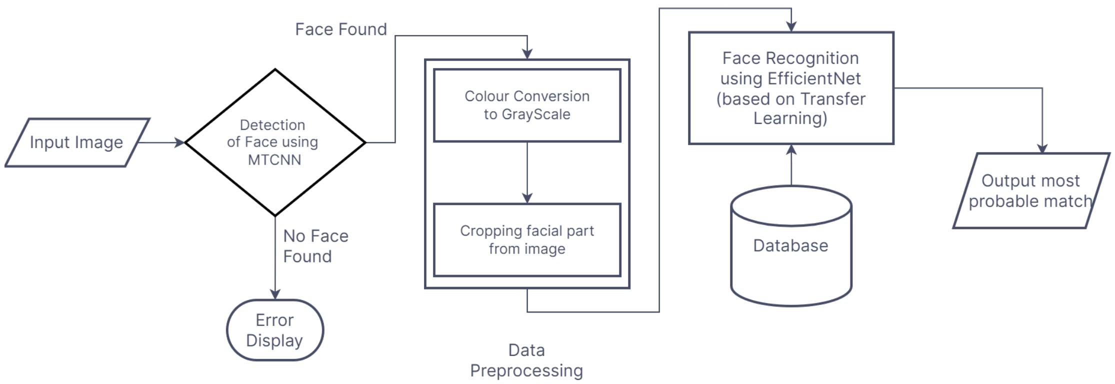

Figure 1: Workflow of the Lost Angel Investigator

3.2 Dataset

The dataset of 25 children was created by collecting the images from relatives and friends obtaining 15 to 20 images of each child. These images were taken from different angles, varying the amount of real-world ground and capturing devices to stimulate the real world. These images were later used to train the deep-learning model.

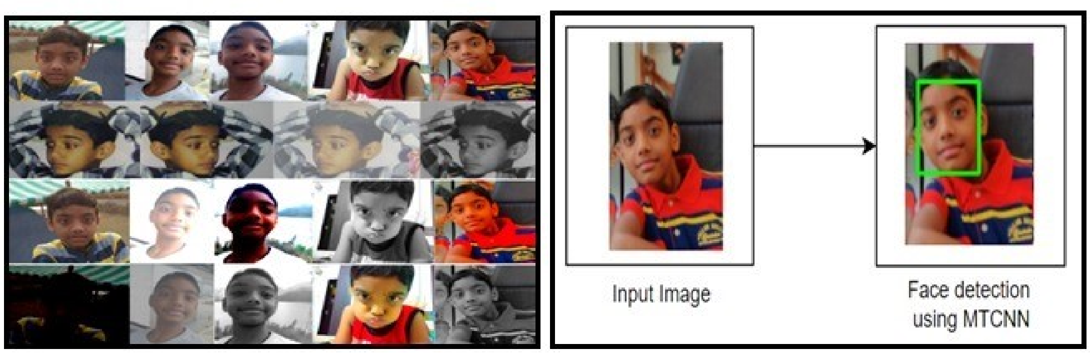

Figure 2 (i) Figure 2 (ii)

Figure 2: (i) Images of the subject from the dataset used to train the model, (ii) Face detection using MTCNN

3.3 MTCNN Model

Face detection and recognition are the two phases of a lost angel investigator. Lots of ways have been used to implement these phases. The MTCNN is used for face detection. This method is quicker than viola jones's and recognizes faces with varying sizes, illumination, and rotations. In the MTCNN model, first, the image is scaled many times to detect faces of various sizes. The P-network (proposal) then searches pictures, conducting initial detection. It has a low detection threshold and hence identifies numerous false positives, even after NMS (non-maximum suppression), but does so on design. The recommended areas (which contain many false positives) are sent into the second network, the R-network (refine), which, as the name implies, filters detections (also using NMS) to produce very accurate bounding boxes. The O-network (output) conducts the final refining of the bounding boxes in the final step. Not only are faces recognized in this manner, but bounding boxes are also incredibly accurate and exact. Detecting facial landmarks, such as the eyes, nose, and corners of the mouth is an optional function of MTCNN.

It is nearly free because they are utilized for facial detection in the process, which is an added benefit if one requires those.

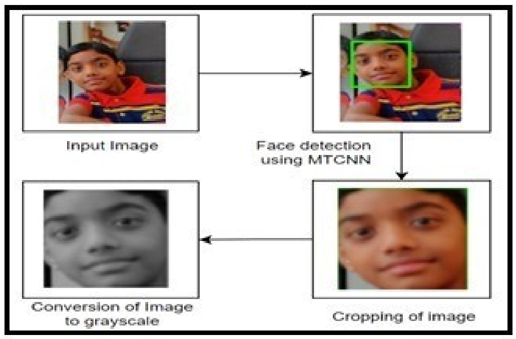

Figure 3 (i)

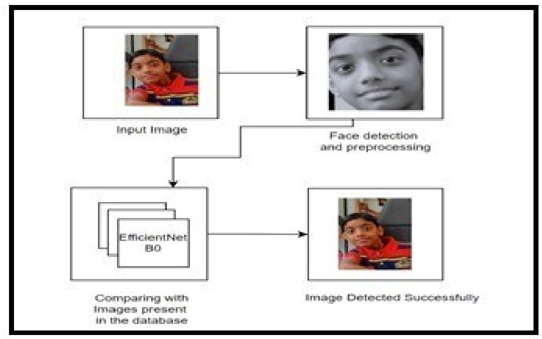

Figure 3 (ii)

Figure - 3: (i) Face Detection using MTCNN and Pre-processing, (ii) Workflow of the Recognition Phase

3.4 Data Pre-processing

After the face has been detected successfully, the image is converted to grayscale and the facial part is cropped. The image is passed ahead for face recognition and verification. This cropping is done using the OpenCV library in python. The coordinates received from the MTCNN face detector are used to get the coordinates of the facial part in that specific image and are further cropped in a rectangular shape. This cropped image is then converted to grayscale. This is done to normalize all the images concerning the color. This conversion is again done using OpenCV python.

3.5 Face Recognition

Predictions are made using the transfer learning model based on EfficientNet-B0. The first layer in this model has a data augmentation layer, followed by an EfficientNetB0 model with a removed topmost layer. Then comes a GlobalAveragePooling2D layer, accompanied by a dense output layer. Initially, layers of EfficientNetB0 are not allowed to train with this data. While training, the input images will be passed through the data augmentation layer, which includes augmenting the images with random flipping, rotation, height, width, brightness, and contrast. For every image in the training dataset, 6 augmented images with 1 original image are passed to the model. All these images are given as input to the EfficientNetB0 model which is followed by a globalaveragepooling2d layer to get summarized weights. Finally, A dense layer is applied to each picture to categorize it into one of the pre-defined classes. Next, to fine-tune this model, only the top 5 layers from the base EfficientNet-B0 model are allowed to train on our data, by lowering the learning constant to 1e-4 we ensure that we get the advantage of this model concerning the data we provided. This model is stored in JSON format and the weights are stored in h5 format. These two files are used in our Django Web application to make predictions. The pre-predictions image is passed in this model to make a prediction and find the matching child class.

4. SIMULATION RESULTS

The accuracy of the conventional Face Recognition algorithm Eigen face is 60%. For face identification and recognition, we employed MTCNN and EfficientNet-B0 deep learning models. Both methods were simple to put into action. This approach achieved an accuracy of 76.81%. It was discovered that during the recognition phase of the process, the photographs needed to be educated for the machine to learn about the facial traits of the provided individual. The testing accuracy of the model rises as the frequency of epochs grows, as seen in Figure 4 (i). The testing loss of the model reduces as the frequency of epochs increases, as seen in Figure 4 (ii). The increase in the frequency of epochs after fine-tuning enhances the overall testing accuracy of the model, as seen in Figure 4 (iii). Figure 4 (iv) demonstrates that after fine-tuning, the total testing loss of the model reduces as the frequency of epochs increases. The formula used for loss calculation is Categorical Cross Entropy. The calculation of the above loss is done using the given formula.

$$Loss = -\sum_{i=1}^{outputsize}\left(E_i.log\hat{E}_i\right)$$

Here Ê is the considered i-th numeric attribute present in the model output and Ei is the target value, and the output size is the frequency of numeric attributes in the output of the model.

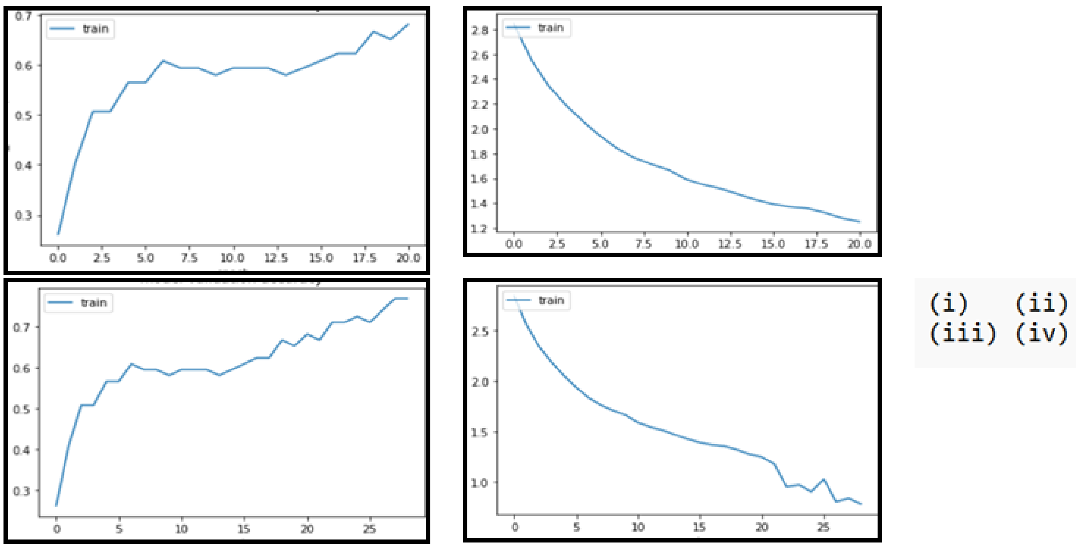

Figure 4: (i) Model Testing Accuracy Graph For 21 Epochs (Before Fine Tuning), (ii) Model Testing Loss Graph For 21 Epochs (Before Fine Tuning), (iii) Model Testing Accuracy Graph for 28 Epochs (After Fine Tuning), (iv) Model Testing Loss Graph For 28 Epochs (After Fine Tuning)

Epochs	Training Accuracy	Testing Accuracy	Training Loss	Testing Loss
21	0.8967	0.6812	0.8065	1.2503
28	0.9666	0.7681	0.1613	0.7849

Table I: Training Accuracy , Testing Accuracy, Training Loss for 21 Epochs (Before Fine Tuning) and 28 Epochs (After Fine Tuning)

Table 1 shows the Training Accuracy, Training Loss, Testing Accuracy, and Testing Loss. We can see a significant improvement in the accuracy after the model was fine-tuned. Fine Tuning resulted in decreasing loss thus improving the accuracy from 68.12% to 76.81%. A callback function was set to terminate training when no improvement in training loss was found which terminated the regular training at 21 epochs and after fine-tuning at 28 epochs. Training loss was reduced at a certain level improving the training and testing accuracy.

5. CONCLUSION

Face recognition technique using a deep learning model EfficientNetB0 has been used to make predictions on the uploaded image to find the nearest match possible. Using our model, one can get the search results in minutes, thus reducing the time required for the tedious manual process to follow and helping in improving the lost children detection process. The proposed model achieved a testing accuracy of 76.81% even when trained only on 423 images. However, this model may be improved by training it on additional photos and eliminating as much background noise from the images as feasible. Our proposal will result in a system assisting police and parents in finding missing children effectively and this initiative will aid in the promotion of digitization in the police sector to provide a database for officers from multi-states. The dataset created by us using the images of relatives and friends is quite helpful for future studies. This model can act as a basis for testing different noise reduction techniques. For security purposes, this web app can be integrated with Aadhar authentication.

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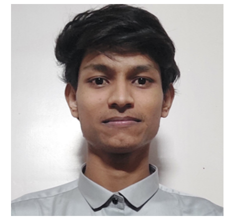

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