Identifying Lost Children using Deep Learning

B.E. Project Report

Submitted in partial fulfillment of the requirements

For the degree of

Bachelor of Engineering in Computer Engineering

Submitted by

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April 2021



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CERTIFICATE

This is to certify that, the project 'A' titled

"Identifying Lost Children Using Deep Learning"

is a bonafide work done by

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Bachelor of Engineering
in
Computer Engineering
to the
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Abstract

A countless number of children go missing in India every year. And a large number of children remain untraced due to the problem in the identification of children using the photograph. As the state-of-the-art missing children identification systems using face recognition fall short in identifying children at later stages because of aging. We have proposed a novel use of face recognition with face aging to overcome the limitation of existing systems. We have proposed a solution using deep learning, in which we have created a virtual space where the public can upload images of missing children and can also search for a lost child. We have used the Age C-GAN algorithm for face aging and the FaceNet algorithm for face feature extraction and face recognition.

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Chapter 1

Introduction

Children represent a significant percentage of the total population of India. Unfortunately, many children go missing every year due to various reasons like kidnapping, trafficked children and lost children, run-away children, and abduction. According To the National Crime Record Bureau 2019 report, the number of missing children has increased by 8.9% since 2019 giving a total of 73,137 children reported missing last year. Many NGOs claim that the actual number of missing children cases is much more than reported. A child lost in one location can be found in some other location. Even if the child is found it gets difficult to recognize him/her. The face of Face recognition is thus the most promising biometric technology for recognizing missing children. But if the child is found after many years from the date when he/she is lost the state-of-art face recognition systems fall short to identify children from the photograph because a child's face undergoes many temporal variations due to aging like a change in skin texture, change in the shape of the face, color, weight, facial hair growth, etc. Hence as the time difference between a probe image and a true mate image gets larger, the performance of the face recognition algorithm decrease, and thus the search gets harder. Thus the primary goal of the proposed system is to generate an age-progressed image of the child rather than enhancing the face recognition performance. Thus this system enhances the ability of face matches to identify and locate children who are lost at a young age by aging face features to reunite them back with their families. Our system will be helpful to the police and higher authorities for tracking down missing children quickly.

1.1 Overview

As children's are the important aspect of our country, but due to cases of missing children's arising it is becoming like a threat to the future of our country. And finding any missing child with one photograph is a difficult job for the officials, as recognition plays a vital role in solving the case of missing children. And when the barriers come in the part of the recognition it becomes very difficult to solve the case and find the children who is missing, which can take 5 to 10 years and that's why many children's are interested till date which is becoming the main reason into the increasing cases of the missing children. Sometimes it takes 5 to 10 years to solve case so the aging also becomes barrier in the recognition and then it becomes more difficult to recognize the children from the photograph which was given at the time of reporting, So the aging also plays an important role in the recognition and then it becomes more difficult to recognize the children from the photograph which was given at the time of reporting, So the aging also plays an important role in the recognition. Our system overcomes all these barriers which create difficulties in the recognition part. Using the deep learning features like FaceNet algorithm for recognizing any children using the aging feature (C-gan) can solve the issues and the process can go smoothly which will be very helpful for solving the cases.

1.2 Objective

Recognizing a missing child is a difficult job for the police and also for the higher authority, and even if a child is found, it becomes difficult to recognize him/her from the reported missing cases which include the photograph. Recognizing or identifying a child using face detection will make the process much easier. The proposed idea is based on the maintaining database, such that at the time of the reporting photograph (recent photographs) of the missing child which is given by the parents will get stored and the provision will be given to the public to voluntarily take the photographs of the children so they can add the photograph to the portal, so the automatic searching will take place. So, the objective of this project is to help Police and higher authorities track down missing children quickly.

1.3 Motivation

- Children are an important factor in our society, after all, they are the future which we look up to.
- But many children are get reported missing every year, which creates a big issue as most
 of them are interested.
- This problem arises because of the difficulties that come with the identification of the missing child. It is needed to solve this problem so these missing children can have a better future and to reduce the number of cases that are increasing day by day.

1.4 Organization of report

The report is organized by considering the topics as Literature Survey, Proposed Work, Results and Analysis, Conclusion and Future Works. Where the literature survey is consisting of the survey we have gone through, for example, the papers that we have used for our survey which have helped us to understand the condition and also the design of our system. Whereas the actual work and the methodologies are the algorithms we have used for our system is consisting of the topics as proposed work which have the details of the algorithm with the working of it and the software used for the implementation, fulfilled with the whole implementation details. The actual working means how the system will actually work in real life and implementation of the system is shown in the result and analysis with the actual pictures (snapshots) of the system which has been implemented. And the last is the conclusion of the project "Lost Children Identification using Deep Learning" with the future work which is given in detail that we can do further improvement in the system and the implementation which we can carry out in future so it will be more beneficial.

Chapter 2

Literature Survey

2.1 Survey of Existing System

| NAME OF THE PAPER | NAME OF THE TECHNOLOGY | INTRODUCTION | ADVANTAGES | DISADVANTAGES |
|--|---|--|---|--|
| 1) Missing Child Identification System Using Deep Learning and Multiclass SVM | CONVOLUTIO- NAL NEURAL NETWORKS (CNN) VGG-FACE CNN DESCRIPTOR | In deep learning methods, CNN are important tools that works appropriately with image data. Blocks of convolutional ReLU pooling layers and fully connected layers are composed in CNNs.In this paper, For face recognition VGG-Face network is used. | CNN and VGG- Face network applied on photos of children. These photos are taken in uneasy environment. It gives higher accuracy of 99.41 for classification. | CNN and VGG- Face networks slower the process of classification and extraction of faces from images. |

| 2) Double-Blinded Finder: A Two- Side Privacy- Preserving Approach for Finding Missing Children | MULTITASK FACENET MODEL AND IPE METHOD FOR BLIND FACE MATCHING | Face-to-face matching method is based on IPE- based blind computing which is used to restrict access to photos | Using these technologies, the system can safely run and provides the privacy for both the unsure and missing children parts. | To provide more effective face recognition module, the output of images with threshold encryption schemes should be improved. |
|---|--|---|---|--|
| 3) Child Face Recognition with Deep Learning. | VGG16, RESNET50, MOBILE- FACENET | In this paper, VGG16,ResNet50 and MobileFaceNet these three Convolutional neural networks algorithms were used. | MobileFaceNet provides highe accuracy than VGG16 and ResNet50 and also it is lightweight model. | MobileFaceNet has a smallest model size and VGG16 has largest model in size. At the beginning |
| 4)Optimizing deep neural network structure for face Recognition | DEEPID MODULES WITH WIDE MODULE. | In this paper, DeepId, FaceNet networks are used by acquiring modified Inception structures which contains different type such as DeepId2,DeepId3. | A deep face network gives the best performance with higher accuracy when there is very less difference between wide module and deep module. | as the width increases, The mutual information of a single image in the same layer of different designed module also increases. However, the mutual information goes down with additional branches such as DeepId3 in wide module. |
| 5)Face Aging with Conditional Generative Adversarial Networks | AGE-CGAN | This system used Age-cGAN to generate artificial images within different age categories. And apply latent vector optimization method which protects the original photo's identity while recreating images using Age-cGAN. | Identity preserving latent vector optimization method used to conserve original photo's identity while face aging and also for other operations such as face alterations. | The face recognition method which is being used by this system can be improved by combining Pixelwize and Identity-Preserving methods into one singular method. |

 Table 1: Literature survey of Existing System

- In paper [1] the author has used CNN and VGG face technologies for the identification of missing children. The faces of children are detected and features are extracted by using CNN. CNN is an important tool that works appropriately with image data. Blocks of convolutional, ReLU pooling layers, and fully connected layers are composed in CNNs or ConvNets. For classification, they used SVM Classifier. But these technologies slower the process of classification and extraction of faces from images.
- In paper [2] a Face-to-face matching method is used which is based on IPE-based blind computing which is used to restrict access to photos. Using Multitask FaceNet Model, the system can safely run and provides privacy for both the unsure and missing children parts. To provide a more effective face recognition module, the output of images with encryption schemes needs to be improved.
- In paper [3] Three Convolutional neural network algorithms were using which are: VGG16, ResNet50, and Mobile-FaceNet. From which Mobile-FaceNet has the smallest model size and provides higher accuracy than VGG16 and ResNet50 and VGG16 has the largest model in size.
- In paper [4] the author has used DeepId and modified Inception structures which contain different types such as DeepId2, DeepId3 modules which give the best performance with higher accuracy when there is very little difference between a wide module and deep module. however, the mutual information goes down with additional branches such as DeepId3 in a wide module.
- In paper [5] the author had used Age-cGAN to generate artificial images within different age categories. The face recognition method used by this system is the Identity preserving latent vector optimization method used to conserve the original photo's identity while face aging which can be improved by combining Pixelwize and Identity-Preserving methods into one singular method.

2.2 Limitations of Existing System

• Existing systems do not contain an Age-progression module that can recognize images of the child having an age gap larger than 5 years or more.

- The existing system does not give high accuracy while recognizing the face in an uncontrolled environment like low light, blur images, images are taken from a distance, changes of a pose, illumination, expression, etc.
- The system uses the technologies which involve complex algorithm which make the process of extraction and classification of images slower.

2.3 Problem Statement

India is one of the countries that control a fifty fifth of the population of youth and kids. And this fifty-fifth is taken into account because the vital facet of our country, however, several ranges of kids are getting rumored missing each year that creates a giant issue as most of them are interested. This downside arises as a result of the difficulties that come with the identification of the missing kid. However, this downside may be solved using a system that is predicated on the deep learning methodology for the identifying of the reported missing child from the photos with face recognition. Because the missing kid may be found in any region, thus with the landmarks and remarks public will upload the photograph of the suspicious kid into the common portal. Automatic comparison can present itself with the photo that the public has posted and therefore the registered photo of the missing kid from the repository. A deep learning model is trained as there is going to be a method of classification for the input photo of the kid and therefore the photo that is matching best can get selected from the information of the missing children. To help the authorities in the cases of the missing children which will be beneficial for our society.

2.4 Scope

Missing children cases are arising day by day because of the problem in the identification, and this problem arises because it is difficult to find a child with a photograph with hundred percent surety and when the time goes by like after 5 to 0 years the problem of age gap creates more difficulties in the identification and after 5 or 10 years later identifying a child with an old photograph is much harder than we think. And police officers and other higher authorities have to go through these difficulties and more importantly the missing child and his/her parents have to face all these difficulties. So, by observing such conditions our system will not only help in the identification but even after 5 or 10 years later if any suspected child gets found the system will recognize the child correctly with the feature of an age gap and deep learning. Therefore,

it will be much easier for the police officer and the parents of the missing child to identify the missing child quickly and easily, it will help the process go smoothly and perfectly.

Chapter 3

Project Proposal

3.1 Proposed Work

It is known that the performance of the face recognition algorithm is affected due to aging. It is still a problem to consider the aging parameter under consideration for face recognition as most of the algorithm fails to detect the face of the child after a few years. A child's face undergoes various changes including facial hair, weight, the texture of the skin, shape, and size of the face, etc. Several studies were performed to analyze the extent to which facial aging affects the performance of face recognition algorithms. Two conclusions can be drawn from these studies: The performance of traditional face recognition algorithms decreases with an increase in time-lapse. Performance of face recognition and detection algorithms decreases more rapidly in the case of younger individuals as compared to older individuals. Hence it is important to consider the age progression of the face for enhancing the performance of the face recognition algorithm, especially when enrolled at a young age. In particular, our contributions are as follows:

- A portal for finding missing children that compare the image of the missing child with the images of the already registered missing children.
- To take into consideration many kinds of variations in face images which are taken under uncontrolled conditions such as change of expression, illumination, pose, change in lighting condition, presence of noise, and blurred image.

Using Age Conditional Generative Adversarial Network to reconstruct high-quality synthetic images of the required age group preserving the original person's identity. Using methodology like Facenet and C-Gan the process of recognition gets easier which will help the authorities to find the missing children quickly and solve many cases which have been untraceable because of the above issues.

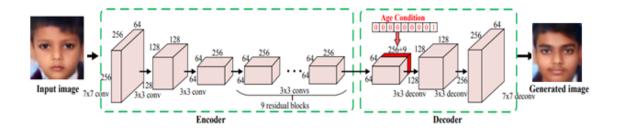


Figure 1: Layers used in Aging cGAN

Here we propose a methodology for missing child identification and recognition to make the process of finding a missing child less painful and faster. As compared to the existing system we are solving the problem of face variations caused due to the age gap by combining facial feature extraction and age progression based on deep Learning.

Thus the proposed system presents a novel deep learning methodology to find the missing children using the photo of the children currently available using face recognition. Whenever anyone finds any suspicious child on the road he/she can click the photograph of the child and upload it into the common portal with landmarks and remarks. The public can upload the photograph of the missing child into the portal. Then the photo will automatically be compared with the already registered images in the repository. If no matching record is found then the image will be age progressed and again the age-progressed image will be compared with the registered photos. For this, a deep learning model Aging C-GAN is used. And the face recognition is done using FaceNet. Thus the proposed system outperforms the earlier methods in face recognition based on missing child identification.

As mentioned earlier face aging model is based on an age-conditional generative adversarial network, a model for synthesis and generation of human faces of the required age category. Thus the task of our cGAN network is to generate the image of a child at different ages based on the input image and target age. The structure of the model consists of three parts: encoder, age condition, and decoder. The encoder is used for feature extraction of the input face image. We

are using three groups of convolution layer and nine residual blocks. Each convolution layer consists of a ReLU non-linearity layer, spatial batch normalization layer stride, and a convolution layer. After this, we get a 56 feature map of the image. Since there is a huge range of images of a large number of age groups in our dataset we are dividing the image into y number of groups which is represented as a one-hot age vector. Each block represents a specific age group. The task of the decoder is to convert the face to generate an image of the required age group based on the features.

3.2 Proposed Methodology

3.2.1 Age-cGAN:

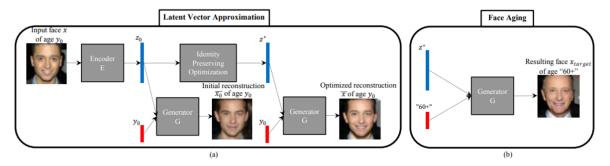


Figure 2: Face Aging Method. (a) approximation of the latent vector to reconstruct the input image; (b) switching the age condition at the input of the generator G to perform face aging. [5]

Conditional Generative Adversarial Network is conditioned on extra information and is based on the idea of Vanilla GAN which allows us to control the output of the generator network. In this, we have to give extra information y as an additional layer to the generator. As compared to vanilla GAN, In vanilla GANs we cannot control the category of the retrieved images as it can learn only one category, however, in CGAN we can generate images of the specific category using condition y. y can we any data depending on the application for which we are building the model for like integer data or class label. Thus CGAN can be used to generate models with different categories and conditions.

The Face Aging-cGAN has four networks:

Encoder: Encoder is a deep convolution neural network used to generate the latent vector of images. It is used to learn the inverse mapping of input image and age condition with the latent vector Z.

- It generates a latent vector of 100 dimensions of the input face images of dimension (64,64,3).
- There are 2 dense layers and 4 convolution blocks.
- All the convolution blocks except the first layer have a convolution layer which is followed by a batch normalization layer and then an activation function.

Generator Network: It is a deep convolutional network that takes a face image and condition vector and tries to generate realistic images of the face.

• It is a CNN having upsampling, convolutional, and dense layers which take a condition vector which is additional information added to the network which is age, and a latent vector to generate a realistic image of a dimension of (64, 64, 3). The condition vector is the additional information that is provided to the network. For the Age-cGAN, this will be the age.

Discriminator Network: It is CNN that is used to discriminate between the real image and the fake image. It contains several convolutional blocks which contain a batch normalization layer, convolutional layer, and an activation function.

FaceNet: It is a face recognition model that learns the difference between the original image x (input image) and the generated image x'. it is used to recognize the person's identity in the image. We are using a ResNet2. For FaceNet Inception ResNet, ResNet-50, or pre-trained Inception can be used. We are using the ResNet2 model without fully connected layers. FaceNet is used to identify the person's identity in the given input image. The extracted embeddings for the original input image and the reconstructed image can be found by calculated Euclidean distance between the embeddings.

Stages of the Age-cGAN:

Age-cGAN has four networks and it is trained in three stages:

- 1. **Conditional GAN training:** In this stage, we have trained the generator network which generates the blurred images of the face after training and the discriminator network.
- 2. **Initial latent vector approximation:** In this stage, we have trained the encoder network to approximate the latent vector using both the real images and the generated images which generates the latent vector from learned distribution.
- 3. **Latent vector optimization:** In this stage, we have optimized both the encoder and the generator network.

3.2.2 FaceNet:

We are using FaceNet in our work for feature extraction and face recognition. We have first passed all the images through Multi-Task Cascaded Convolutional Neural Network (MTCNN) for finding and extracting faces from the images. Then we have used FaceNet for extracting high-quality features from children's faces which we have used to train a face identification system. It uses Convolution layers to learn embeddings from the face directly which are used for face verification and face recognition. These embeddings are of 128 dimensions and insert them into feature space such that the squared distance between faces of the same person is less whereas the squared distance between images to two different people is large.



Figure 3: Model architecture of FaceNet.

3.2.3 Dataset:

We have used two separate datasets for the training of face recognition and the Age Progression model. For face recognition, we have created our dataset by collecting images of children from various sources. We have created a directory structure where each child to be recognized has a

dedicated directory with their images saved in it. The photos in the directory provide a range of orientation, sizes, lighting conditions. If an image contains multiple faces then the face having the highest probability will be considered for further steps. We are using this dataset as the basis for our classifier which is trained on a training dataset only.

For training the Age progression model we have used the IMDB WIKI-crop dataset which is the largest publically available dataset of human faces. It contains about 400 thousand images where each image is labeled in the format gender_age_name with all the metadata information like dob, the year when the photo was taken, gender, face location, face, and secondary face score, etc in .mat file. The dataset contains images of all the age categories from 0 to 100 years of age which is not required for the model. So we have first filtered the dataset and considered the images of children in the age group from 0-15 years of age and have deleted the rest of the images. The dataset contains images with huge variations in facial expression, illumination, resolution, occlusion, pose, etc. The dataset also provides the corresponding landmarks. This dataset can be used for a variety of tasks including age estimation, age progression, landmark localization, progression/ regression, face detection, etc.



Figure 4: Sample images of children from IMDB Wiki- Crop face dataset

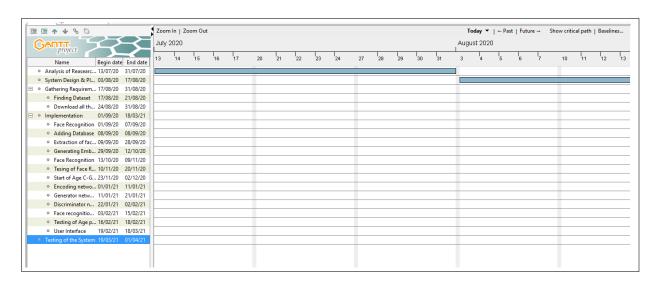
3.3 Details of Hardware/Software Requirement

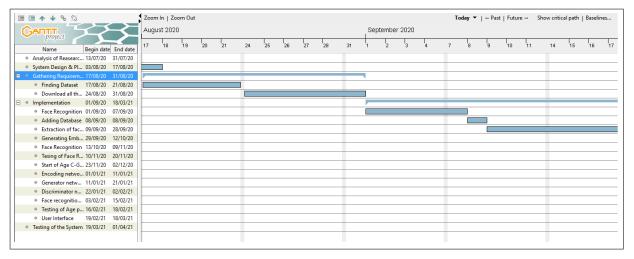
- python 3.8.5
- Anaconda v4.8.3: Conda is an open-source distribution of R and Python programming language for data science and scientific computation which is used to simplify deployment and package management.
- **Jupyter Notebook**: The Jupyter Notebook is an web application which is used to share and create documents containing narrative text, visualization, equations, live code. Uses include machine learning, data visualization, statistical modeling, numerical simulation data cleaning and transformation, and much more.
- **NumPy 1.19.2**: NumPy is a library that is used for working with large, multidimensional matrices arrays.
- pandas 1.1.3: pandas is a fast and powerful open-source data manipulation and analysis tool.
- scikit-image 0.17.2
- matplotlib 3.3.2
- **Keras** is written in Python and it is one of the leading high-level neural network APIs which supports multiple back-end neural network computation engines.
- **Tensorflow v2.3.1:** TensorFlow is a flexible and comprehensive end-to-end open-source platform for machine learning.

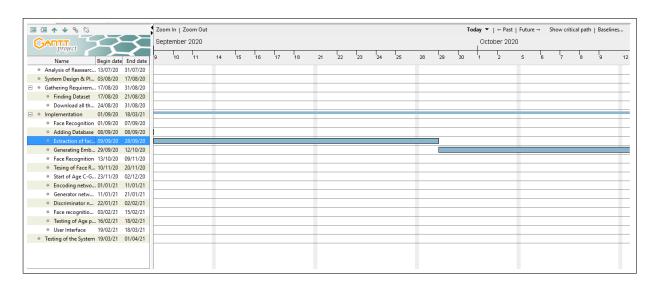
Chapter 4

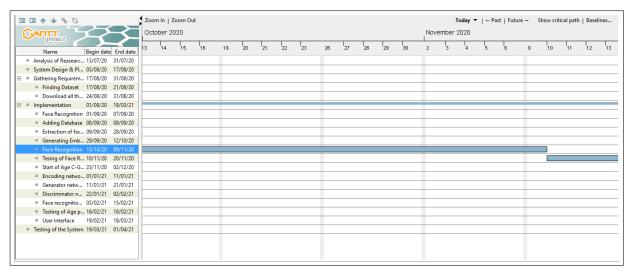
Planning And Formulation

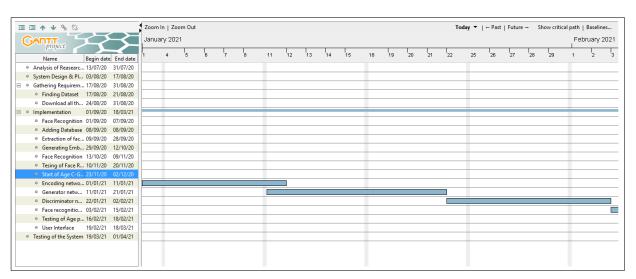
4.1 Schedule for Project

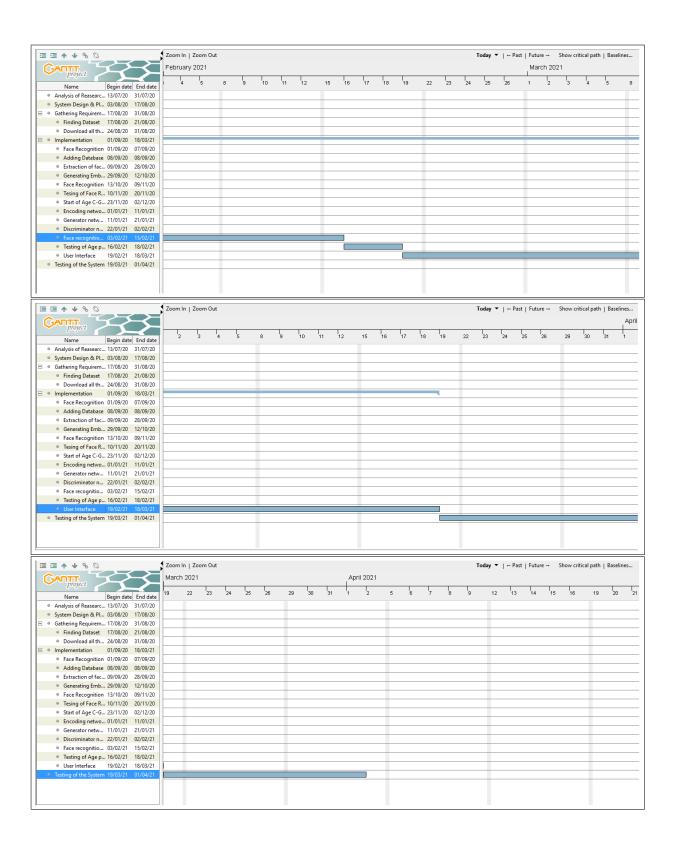












4.2 Detail Plan of Execution

- Existing System Study: At the start of July, We started gathering the research papers that are related to the Lost child identification topic. After going through many research papers, we have done the analysis of papers and Literature survey through which we come to know that there are some limitations present in the existing system.
- System Design and Planning: At the start of August, We started designing our system after analyzing the existing system. To overcome the limitations of the existing system we decided to work on the Aging invariant module in face recognition. After much research, we decided to use a Conditional- Generative Adversarial Network and we decided the further planning of our system.
- Gathering System Requirements: From the middle of August week, we started gathering the Child dataset that is required for the system. After testing some child datasets, we start creating our dataset from scratch for more accuracy. For our system as we are going to use Keras and Tensorflow, we started downloading all the important libraries that are required for implementation.

• Implementation:

Face Recognition : At the start of September, We started the implementation process of our system. We started implementing the Face recognition module. First, we loaded the dataset that we created from scratch into the Jupyter notebook that we created from scratch. After that, we started implementing the module which extracts the faces of children from images. After completing the Extracting face module, we started to generate embeddings of images and after that, we started work on face recognition. After completing the face recognition module we started testing.

Age C-GAN: At end of November, we started implementing the Aging invariant module. First, we have started implementing an Encoding vector which used for feature extraction. After that, we have created a Generator network to generate realistic images. Then we have implemented the Discriminator module to discriminate between the real image and the fake image. At the start of February, we have done with face recognition network used for Age progressed images. Then we started testing the Age progression module. After completing testing we started creating the user interface of the system. In the middle of March, we are done with the implementation of our system. At the end of the march, we have done the testing of the whole system.

Chapter 5

Design of System

5.1 Design Diagram with Explanation

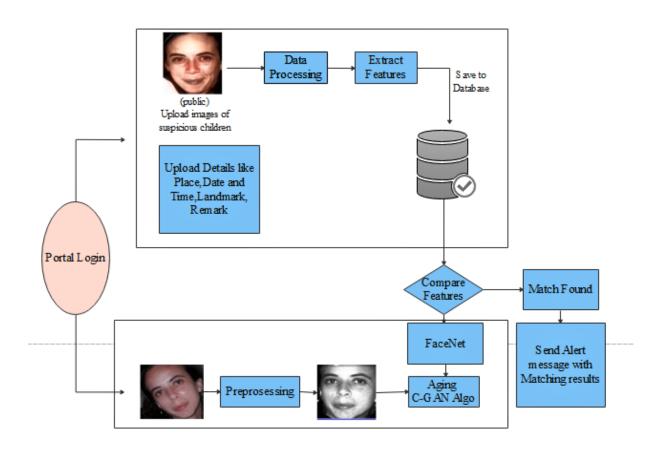


Figure 5: System design for lost child identification using FaceNet and C-GAN

The proposed system will consist of a portal where the public can store the details with a photograph of the missing child. The public here refers to the parent of the missing child or the police officer. By using the photograph the public can find the matching children from the already stored data. The system will prompt the most matching cases after applying a face recognition algorithm to the uploaded image. Once the matching is done then the concerned person will get the details of the child.

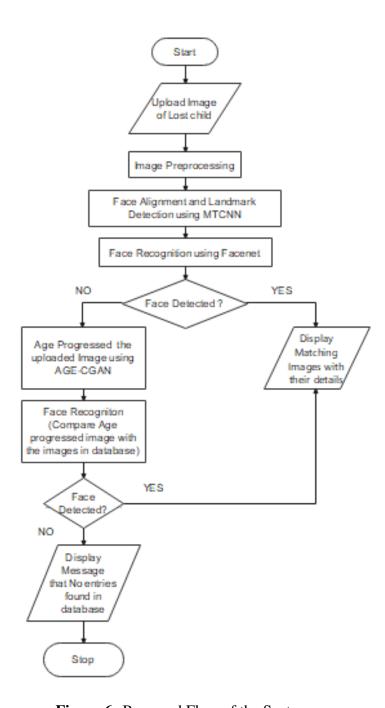


Figure 6: Proposed Flow of the System

The proposed model is divided into various phases. First, whenever the public finds any missing or suspicious child they can upload the photograph of the child with the details like name of the child, age, place where the child was found, date and time when the child was found and remarks like what clothes the child was wearing when he was spotted or any information the child might have told to the person which can be helpful to find the child.

This uploaded image goes through an image pre-processing phase. The input to this is the raw image that is uploaded by the public and the output of this phase is an aligned frontal face image. The main purpose of this step is to align all the face images based on eye coordinates such that all the images are aligned with the same standard size.

The next stage is to extract the required face features. In this stage, we have used a Multitask Cascaded Convolutional Networks (MTCNN) model which is a framework used for face alignment and face detection which consists of three stages of convolutional networks that can detect landmark location such as eyes, nose, and mouth and can recognize face very efficiently. The preprocessing step includes removing noise from the image, straighten the image, and detecting and cropping the face from the whole image. The extracted face features will be stored in the database for further processing.

To search for a missing child parent of the child need to upload a photograph of the child then this image will go through the face recognition algorithm after the pre-processing and feature extraction step for face recognition. If any matching photo is found in the database then the image of the child will be displayed on the screen. If no matching image is found then the uploaded image goes through the Age CGAN algorithm. The GAN algorithm is used to generate a new age-progressed image with the same statistics as the training images. As the child may be spotted after many years, the face of the child changes from the last known photograph taken before the child had gone missing. So this model will be used to synthesis the child's face to produce an age-progressed facial image of the child. So basically this model will be used to synthesis child face to required age categories.

This face synthesized and age-progressed image goes through the FaceNet algorithm for feature extraction and face recognition. The main distinction between FaceNet and other face recognition algorithms is that faceNet does not use any bottleneck layer for verification and recognition tasks but rather learns the mapping directly from images and creates embedding.

The FaceNet is used to automatically compare the age-progressed photo of the missing child with the already present images in the database and if the photo matches with any of the photos present in the database then it will be displayed on the screen of the parent of the missing child along with details like name and location and time where the child was found.

Chapter 6

Results And Discussion

6.1 Implementation Details

Age Progression Module: To generate high-quality synthetic images of the required age group by protecting the original person's identity we have used Age Conditional Generative Network(Age C-GAN). The face aging with Age CGAN is done in two steps: 1. To find the optimal latent vector from the given input image and age which is used to generate a face as close as possible to the original image. 2. Given target age, the generated image is equal to latent vector by simply switching age at the input of the generator. The structure of the Age C-GAN model is consists of four networks: Encoder, FaceNet, Generator network, and Discriminator network.

The Encoder is used for feature extraction of the input face image. It is used to learn the inverse mapping of input image and age condition with the latent vector Z. Encoder network is a Convolutional Neural Network that generates a latent vector of 100 dimensions of the input face image of dimension (64,64,3). There are two dense layers and four convolution blocks. All the convolution blocks except the first layer have a convolution layer followed by a batch normalization layer and then an activation function.

The Generator network takes face image and condition vector in this case it will be Age and tries to generate realistic images. It is a CNN having upsampling, convolutional, and dense layers which take a condition vector and a latent vector to generate a realistic image of a dimension of (64, 64, 3). The condition vector is the additional information that is provided to the network. For the Age-cGAN, this will be the age.

The Discriminator network is used to discriminate between the real image and the fake image. FaceNet is used to recognize a person's identity in a given image. The extracted embeddings

for the original input image and reconstructed image can be found by calculated Euclidean distance. FaceNet is used to improve generator and encoder networks.

When any person finds any suspicious child on the road then that person can upload the photograph of the missing child into the portal. Then the photo will automatically be compared with the already registered images in the repository. If no matching record is found then the image will be age progressed and again the age-progressed image will be compared with the registered images if the match is found the system will give the message that the child is found.

Face Recognition

Detecting and Extracting Faces: The first step in Face recognition is to detect faces present in the images and extract faces of children from the images. To detect and extracting faces we have used Multi-Task Cascaded Convolutional Neural Network(MTCNN). To detect faces MTCNN has three stages of convolution networks that are used to recognize faces and mark the features of the face such as eyes, mouth, and nose. After detecting a face from the image it will generate a border around the face by marking features there are five landmarks which are right eye, left eye, nose, right mouth corner, and left mouth corner. After extracting a face from images, Extracted faces and original faces are saved into a compressed NumPy array file.

Generating Embedding from faces: The next step is to create Embedding from extracted faces. Features extracted from the face are represented as a vector which is called Face embedding. We have used the FaceNet model to generate embeddings for a given image. FaceNet uses deep convolutional neural networks. The difference between FaceNet and other technologies is that it doesn't use any bottleneck layer for recognition instead it trains the mapping from images and generates embeddings from images. After generating embedding we can use those embeddings for face recognition or verification. Once the dataset is converted into face embeddings those embeddings are then saved to a compressed NumPy array file.

Classification, Normalization, and Prediction: For Face recognition, the Last step is to classify the face embeddings. For classification, we have used the K-neighbors algorithm which is the simplest supervised learning algorithm. It stores all the face embeddings and classifies a new embedding based on similarity. When new face embedding is given for prediction it can be easily classified into the right category and predicts correctly. Before that data require some preparation concerning modeling for that we have to normalize the embedding vector and for

normalization, we have used normalize class. After that the variables for each child's name need to be converted to integers for that labelization is required for that we have used Label Encoder. The last step is prediction, When we load all the embeddings, the Classifier classifies all the stored embedding vectors. Whenever a new image is loaded to the system for prediction from the image, the system will detect face and extracted features and generates an embedding vector and that vector can be classified by the classifier and it will predict the given image according to the highest probability.

6.2 Result Analysis

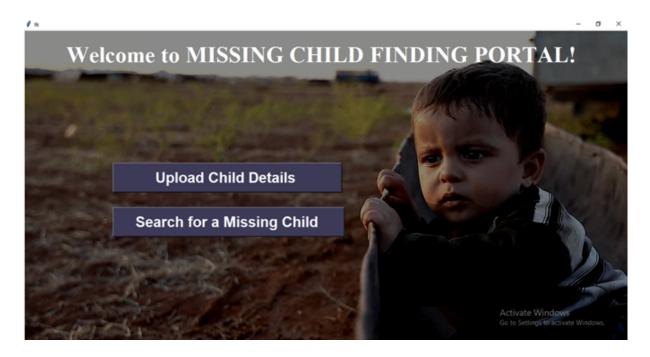


Figure 7: Welcome page of a missing child finding portal

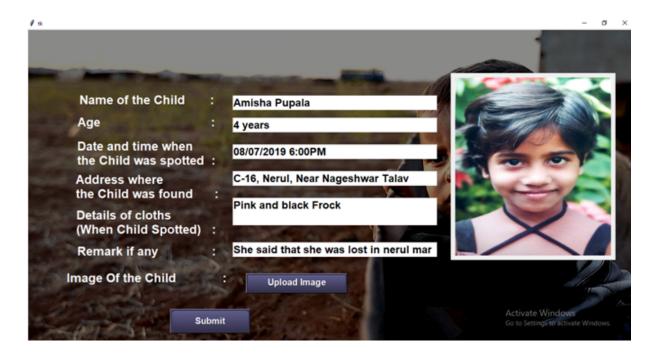


Figure 8: Page where the public can upload details of a suspicious or lost child

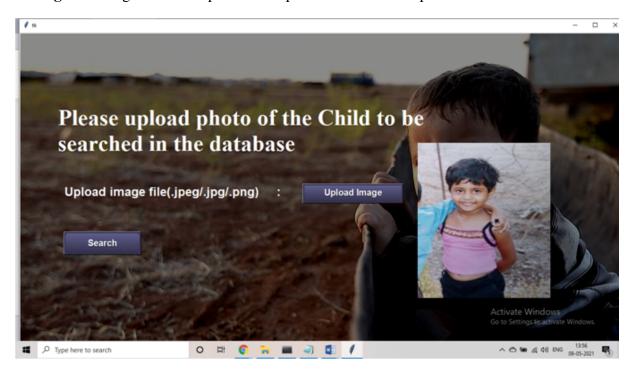


Figure 9:Page to search for a lost child using his/her photograph



Figure 10: The system requires some time to age progress the photograph and search in the database



Figure 11:: Details of the child found in the database

Performance of face recognition algorithm was evaluated on child dataset before and after age progressing the child images. The Age cGAN model was trained on the IMBD Wiki-Crop dataset. The IMDB Wiki-Crop Dataset contains more than 400k images with different age

groups ranging from 0-100 years. We have first filtered that dataset and have just used images from age group 0-15 years to train the model. Based on their experiments, the following conclusions are derived:

- 1. The accuracy of face recognition algorithm with the images of same age category is: train accuracy: 87.38 percent and test accuracy is:81.07 percent
- 2. The Accuracy of face recognition algorithm with images if different age category: 44.76 percent
- 3. The Accuracy of FaceNet algorithm with images of different age category after age progressing images using Age-cGAN algorithm: 47.32 percent

| MODEL | AGE CATEGORY | ACCURACY |
|---|--------------|----------|
| Face Recognition | Same | 81.07 |
| Face Recognition | Different | 44.76 |
| Face Recognition on Age Progressed images | Different | 47.32 |

Table 2: Accuracy Table

Based on the experiments, the following conclusions are derived:

- 1. The model is correctly recognizing the misaligned faces and images clicked in an uncontrolled environment like the change of expression, illumination, pose, change in lighting condition, and presence of noise.
- 2. Average decrease in the performance of face recognition is more than 40 percent due to age variation in the faces of the children.
- 3. Intra-person variations like expression and pose are degrading the performance of the system is similar to face aging. Also, large self-occlusion, blur, and misaligned faces are slightly degrading the performance of the model.

6.3 Cost and Benefit Analysis

Limitations:

- 1. Training of the deep learning model which requires a large dataset remains a challenge when training with a small dataset hence accuracy is compromised.
- 2. The age-progressed images get blurred which eventually affects the performance of the model.

- 3. The performance of the face recognition model heavily depends on the accuracy of ageprogressed images which are obtained.
- 4. Due to the long duration of code execution and heaviness of the model we have trained the model for 300 epochs due to which the performance of the model is compromised

Suggested Solutions:

- 1. As face aging depends on various other factors other than aging, it is required to consider all the other factors like having a single face aging database with correct demographic details and a lot of images of the child of various age groups is need of the hour for better accuracy of the face aging model.
- 2. The model age progresses the images of the child to just one age group, this can further be improved in the future by using a bigger dataset and categorizing the images in the dataset in various required age groups.
- 3. The Age progression model should be trained for at least 500 epochs for getting better accuracy for age-progressed images.

Chapter 7

Conclusion and Future Work

Conclusion:

In this work, a system is proposed for an age-invariant face recognition system for finding missing children. This system reduces the manual work of scanning through all the photographs of the lost children to find a match. We have tried to solve the problem of age variation by age progressing the images of the child using the Aging cGAN deep learning algorithm. The model improves the performance of the FaceNet model which we have used for face recognition from 44.76 percent to 47.32 percent. These results suggest that age progressing the faces of the children before face recognition enhances the ability of the system to identify the lost children who are possible victims of child abduction and trafficking. This will be beneficial for solving cases of untraced missing children and thus will help to reduce the increasing number of missing child cases.

Future Work:

- The model age progresses the images of the child to just one age group, this can further be improved in the future by using a bigger dataset and categorizing the images in the dataset in various required age groups.
- The system can be further extended by connecting it to public cameras to detect real-time faces which can be continuously monitored by the system.
- Facial aging is stricken by numerous intrinsic still as alien factors, however, their qualitative analysis is missing. additionally, analysis of the impact of gender and race is a prominent future direction within the development of a strong face recognition system.
 Therefore, coming up with strong age invariant options and corresponding generalizable

matching framework effective across aging and non-aging situations each may be a viable future direction.

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