Age and Gender Prediction Model

A PROJECT REPORT

Submitted by

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in partial fulfilment for the award of the degree of

BACHELOR OF ENGINEERING

IN

COMPUTER SCIENCE & ENGINEERING

CHANDIGARH UNIVERSITY, GHARUAN

May 2023

BONAFIDE CERTIFICATE

Certified that this project report **"Age and Gender Prediction Model"** is the bonafide work of "Shikhar Bhardwaj", "Shubham Chauhan", "Dipanshu Kansal" and "Ritik Kumar", who carried out the project work under my/our supervision.

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INTERNAL EXAMINER **EXTERNAL EXAMINER**

ACKNOWLEDGEMENT

I thank the almighty for giving us the courage and perseverance in completing the project report. This project itself is acknowledgements for all those people who have given us their heartfelt co-operation in making this project a grand success.

We extend our sincere thanks to Supervisor- "**Shiwali Yadav"**, Co-Supervisor: "**Parveen Kumar**", for providing sufficient infrastructure and good environment in the College to complete our Discussions, Researches.

I am thankful to our secretary for providing the necessary Infrastructure, labs and also permitting to carry out this project. With extreme jubilance and deepest gratitude, I would like to thank Head of the CSE Department 3rd Year for his constant encouragement.

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ABSTRACT

Age and gender prediction from images is an important application of computer vision. Because of its wide range of applications in a variety of facial investigations, automatic age and gender prediction from face photos has recently gained a lot of attention. We can leverage the aforementioned technologies to determine a person's age and gender just on a single glimpse from a camera, image, or video. Technology will also underline its importance and how it may be used to better our everyday lives. The project's prime objective of use openCV and deep learning to develop a gender and age detector that can roughly predict the gender and age of a human face in an image. Further, the map shows how this technology might be applied to our benefit and look at the broad array of applications where it could be used: from intelligence agencies, CCTV cameras, and policing to matrimony sites.

GRAPHICAL ABSTRACT

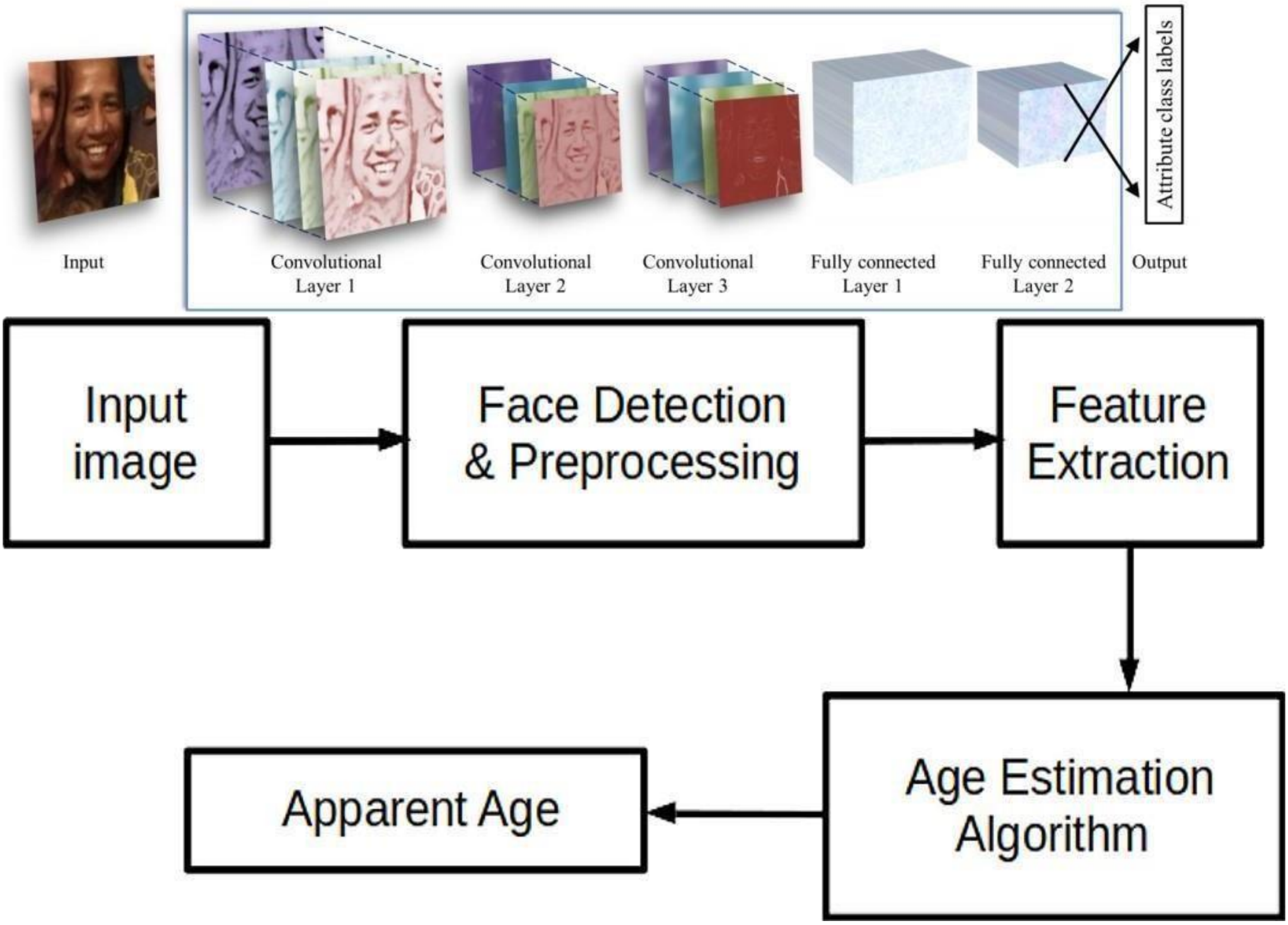


Fig:1.1- SYSTEM ARCHITECTURE

CHAPTER 1.
INTRODUCTION

Client Identification/Need Identification/Identification of relevant Contemporary issue.

Age and gender information are very important for various real-world applications, such as social understanding, biometrics, identity verification, video surveillance, human-computer interaction, electronic customer, crowd behaviour analysis, online advertisement, item recommendation, and many more. Despite their huge applications, being able to automatically predicting age and gender from face images is a very hard problem, mainly due to the various sources of intra-class variations on the facial images of people, which makes the use of these models in real world applications limited. these applications, facial photographs are commonly employed since they contain useful information that may be used to extract human interaction. For gender detection and age prediction, Image processing, feature extraction, and classification steps are usually used. These steps may change based on the objective of the study and the characteristics to be used. The face images were processed using a variety of approaches, and calculations were performed based on the results of the investigations. For image processing, there are two basic and typical which we need to follow. Image enhancement is the process of improving an image so that the resultant image is of higher quality and can be used by other applications.

Identification of Problem

These systems offer the potential to perform complex tasks at a speed and scale far beyond the capacity of humans. But unlike people, deep learning systems typically cannot provide explanations or rationales for their individual choices. And unlike traditional computer programs, which follow a highly prescribed set of steps to reach their outcomes, these systems are sometimes so complex that even the data scientists who designed them do not fully understand how they come to their decisions.

One common limitation of many gender classification systems is that they cannot account for individuals who do not identify as either a woman or a man, and they have no concept of gender identity as separate from physical appearance. But even beyond these known limitations, we learned that the training data used to train these models matters greatly. The models that we trained using more diverse sets of images which includes their demographic composition as well as the quality and types of images used in each set were better at identifying gender in a similarly diverse group of photos than models that were trained on more limited data.

We also noticed variation in the performance of these models that was sometimes surprising and difficult to explain. For instance, even though the models that were trained using greater diversity were the most accurate, some models that were trained on less diverse images were more accurate than others. Similarly, some of these models were better at identifying men than women, while others over performed on women rather than men.

Identification of Tasks

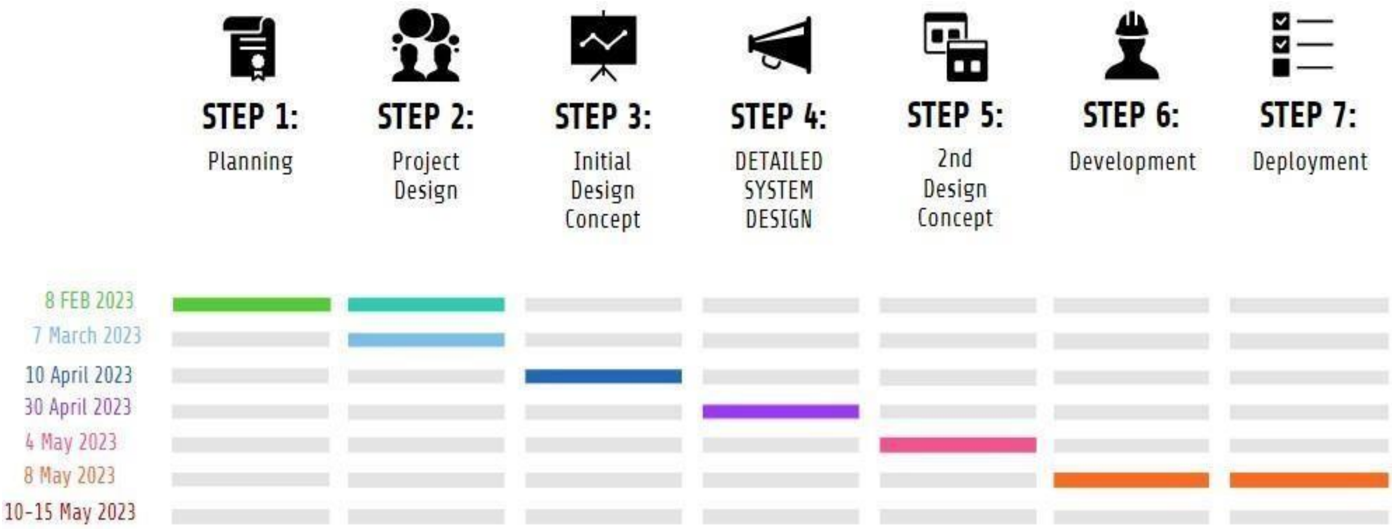
As predicting age and gender from faces are very related, we use a single model with multi-task learning approach to jointly predict both gender and age bucket. Also, given that knowing the gender of someone, we can better estimate her/his age, we augment the feature of the age-prediction branch with the predicted gender output. Through experimental results, we show that adding the predicted gender information to the age prediction branch, improves the model performance. To further improve the prediction accuracy of our model, we combine the prediction of attentional network with the residual network, and use their ensemble model as the final predictor.

Here are the contributions of this work:

- We propose a multi-task learning framework to jointly predict the age and gender of individuals from their face images.
- We develop an ensemble of attentional and residual networks, which outperforms both individual models. The attention layers of our model learn to focus on the most important and salient parts of the face.
- We further propose to feed the predicted gender label to the age prediction branch, and show that doing this will improve the accuracy of age prediction branch.

- With the help of the attention mechanism, we can explain the predictions of the classifiers after they are trained, by locating the salient facial regions they are focusing on each image.

Timeline



Organization of the Report

- In chapter 1 basically we have discussed about introduction of Age and Gender Prediction Model
- In chapter 2 we will discuss Literature survey
- In chapter 3 we will discuss Design flow/process of Age and Gender Prediction Model.
- In chapter 4 we will discuss about Result analysis and validation approach.
- In last chapter we will discuss about Conclusion and future work deviation from expected results and way ahead References.

CHAPTER 2

LITERATURE REVIEW/BACKGROUND STUDY

Timeline of the reported problem

In 2017, k. Zang, proposed Residual network of Residual network (ROR) for automatic prediction of age and gender from face images of unconstrained condition. The architecture is for high resolution facial images age and gender classification. Two mechanisms such as pretrained by gender and training with weighted loss layer, and used to improve the performance of age estimation. In order to future improve the performance and alleviate overfitting problem, ROR is pretrained on ImageNet, then it is fine-tuned on IMBD-WIKI 101dataset for further learning the features of face images and finally tuned on Adience dataset. High accuracy is achieved for gender classification task works well for high resolution facial images. Age estimation accuracy of 67.37% and gender estimation accuracy of 93.27%. Lower age estimation accuracy and ROR model is slower than other models make this challenging.

In 2018, Philip smith, transfer learning is employed to tackle the issue of recognizing a person's age and gender from an image using deep CNNs. Transfer learning to use VGG19 and VGGFace pretrained models are used to increase the efficiency. Training techniques such as input standardization, data augmentation, label distribution age encoding is compared. Dataset used is MORPII.VGGFace produce better result than VGG19.

In 2019, Ningning Yu, proposed an ensemble learning used for facial age estimation within non-ideal facial imagery in Fig[2.1] . The method consists of mainly image pre-processing, feature extraction, and age predication. Separately, the input face image is pre-processed in RGB Stream, Luminance Modified Stream, and YIQ Stream. Three different pretrained DCNNs equipped with SoftMax are wont to implement feature extraction and age estimation because the weak classifiers. Finally, the ensemble learning module fuses the three weak classifiers to get a more accurate estimation.

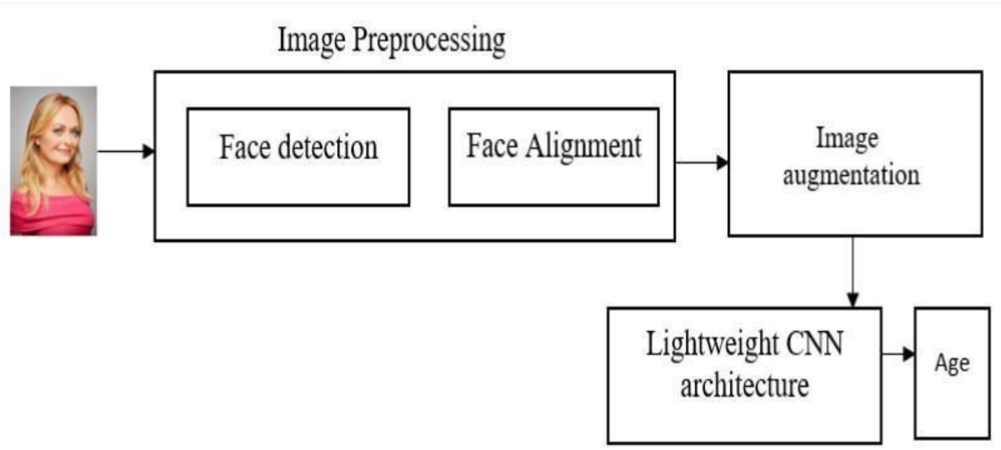


Fig 2.1 Block diagram for Lightweight CNN Age estimation

In 2020, Olatunbosun, proposed a Lightweight Convolutional neural network for real and apparent age estimation of human faces in Fig [1]. Real and apparent age estimation has numerous real-world applications such as medical diagnosis, forensic, facial beauty product production. CNN model is larger, more complex, too large network parameters and layers, training time is long, huge training dataset which increases computation cost and storage overhead. So, proposed to design a lightweight CNN layer of fewer layers to estimate real and apparent age. Input is real-world face image. First step is, image preprocessing i.e., face detection and alignment. Then, followed by image augmentation where random scaling, random horizontal flipping, color channel shifting, standard color jittering, random rotation and also generate an alter copies of every training image. Next step, is estimate real and apparent age using light CNN model.

In 2021, Avishek Garain, proposed a model GRANET (Gated Residual Attention Network) for classification of age and gender from facial images in Fig [2.2]. Some common shortcomings of previous researches are: higher MAE, lower age estimation accuracy, Gender classification accuracy is not at all high, Performance is impacted by minor change in alignment, some model works well on high resolution images but others not. So suggested multiple attention blocks are gated together to form the model.

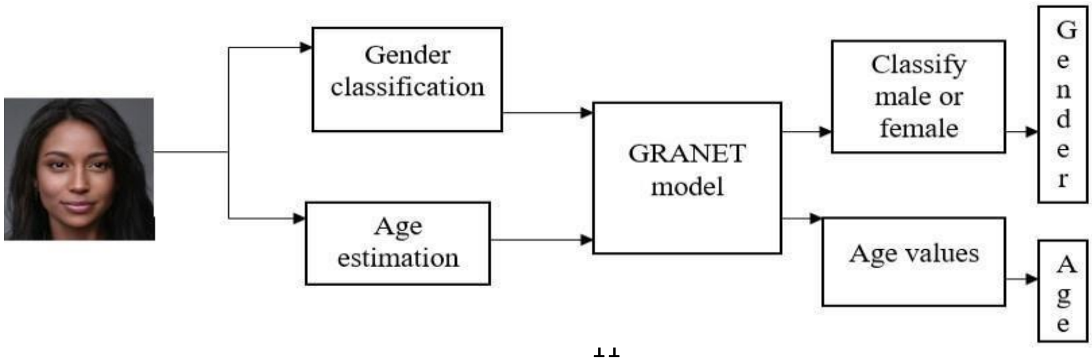


Fig [2.2] Block diagram of GRANET model, Avishek Garain

Proposed solutions

➢ Convolutional Neural Network

Convolutional Neural Networks (CNN) are a type of neural network that generalizes better than previous neural networks (e.g., multi-layer perceptron). CNN is designed to process data in the form of multiple arrays, passing the input between layers that extract the necessary features of the input and assign to those features calculated weights (filters) that will decide which are more important.

➢ Siamese Networks

A Siamese Network is a type of network made up by two or more identical subnetworks, which use the same shared parameters and weights. These networks accept distinct inputs but are joined by a function at the top that computes some metric to perform a comparison between the inputs. This metric is computed over the highest-level feature representation on each side and gives an estimate to which extent image one is similar to image two.

➢ One-Shot Learning

One-shot learning is a type of machine learning that involves training a model to recognize new objects or concepts based on a single example. Unlike traditional machine learning, where large amounts of labelled training data are required, one-shot learning aims to learn from just one or a few examples.

One-shot learning is often used in computer vision tasks, such as object recognition and image classification. For example, a one-shot learning algorithm could be trained to recognize a specific object, such as a particular breed of dog, based on a single image of that breed. Once trained, the algorithm could then be used to recognize new instances of that breed, even if it has never seen them before.

➢ Wide Residual Networks

Wide Residual Networks (WRNs) are a type of neural network architecture that were introduced in 2016 by Sergey Zagoruyko and Nikos Komodakis. This allows for more features to be extracted at each layer and can lead to better performance on image classification tasks.

Bibliometric analysis

➢ Methodology

To be able to understand how we could achieve our goals, an investigation was done to study what kind of methods and techniques were being applied by other authors to provide a model that could solve our proposed problem. The investigation regarding the literature review was done using several known platforms like Google Scholar, ACM Digital Library, and IEEE Digital Library.

A separate investigation was done for both face detection and age/gender classification tasks, analysing separate papers for each of them. All the methods applied were analysed as part of the specific paper, and the results achieved for each of the problems presented were extracted and registered. With this, we were able to have a summary of performances achieved and which techniques were used so that we can make an informed decision on how to create our system. The scope was focused to only include research from 2015 onwards, although a few older documents were used as well. With this, we wanted to have only recent papers related to the specified subjects, since recognition models are improving and evolving at a fast pace, and what was used in the last decade may not be the best approach today. Furthermore, an additional investigation was done to find existing models that could be used for our own purposes and testing.

Methods

➢ Image Processing

Image-quality analysis and standardization were performed by Haut. AI's Image Quality software. First, the system checked the position of the face and the head's rotation angle on the *x* (yaw), *y* (pitch) and *z* (roll) axes based on 400+ predicted facial key points. Then, the system standardized the face image by aligning the centre of the face, calculated from the geometry of the facial features. Next, the following image-quality metrics were analysed.

- Dataset

The author used the private Beauty.AI dataset, which constitutes a collection of fully anonymized skin data derived from selfie pictures. The Beauty.AI dataset includes 17,700 selfies captured with smartphone cameras. From this dataset, the images of 433 subjects whose selfie photographs had sufficient image quality were selected.

The images contained key facial landmarks, adequate illumination and head position, no face occlusion, no distortion and no image noise. The inclusion criteria were set to filter out photographs that lacked at least one quality requirement.

Review Summary

In plastic surgery and cosmetic dermatology, photographic data are an invaluable element of research and clinical practice. Additionally, the use of before and after images is a standard documentation method for procedures, and these images are particularly useful in consultations for effective communication with the patient. An artificial intelligence (AI)-based approach has been proven to have significant results in medical dermatology, plastic surgery, and antiaging procedures in recent years, with applications ranging from skin cancer screening to 3D face reconstructions, the prediction of biological age and perceived age. The increasing use of AI and computer vision methods is due to their non-invasive nature and their potential to provide remote diagnostics. This is especially helpful in instances where traveling to a physical office is complicated, as we have experienced in recent years with the global coronavirus pandemic.

Problem Definition

- Age and gender prediction models are used to predict the age and gender of individuals based on various factors such as facial features, voice, and other demographic information. The problem definition for such a model is to develop an accurate and reliable system that can predict the age and gender of an individual with high precision.
- The first step in building an age and gender prediction model is to define the problem clearly. This includes defining the input data, the output variables, and the evaluation metric. The input data can be images, audio recordings, or other demographic information such as name, address, and date of birth. The output variables are the predicted age and gender of the individual.
- To evaluate the performance of the model, various metrics can be used such as accuracy, precision, recall, and F1 score. The choice of evaluation metric depends on the specific application and the goals of the model.
- Once the problem is defined, the next step is to collect and pre-process the data. This involves gathering a large dataset of labelled examples, cleaning the data, and performing feature extraction. Feature extraction is an important step in which relevant features are selected from the input data and transformed into a format that can be used by the model.
- After the data is pre-processed, the model can be trained using various machine learning algorithms such as neural networks, decision trees, or support vector machines. The performance of the model can be optimized by tuning the hyper parameters and using techniques such as regularization and data augmentation.
- Finally, the model can be evaluated on a test set to determine its accuracy and reliability. If the model performs well on the test set, it can be deployed in real-world applications to predict the age and gender of individuals.

Goals/Objectives

The main objective of this research work is to create an efficient system that is able to detect faces in images and to classify such faces based on age and gender. Thus, the goals below can be derived from this:

- The system should be able to detect faces in images;
- The system should be able to classify a face into a set of age and gender classes;
- The system should be configurable in terms of age classes used;
- Evaluate currently available models for both face detection and age/gender classification;
- Create a system integrating the identified best available models;
- Evaluate the failing outputs of the integrated models in order to find an underlying reasons for such failures;
- Adapt the system to overcome the identified failing outputs to improve the classification accuracy.

For the first goal to be considered complete, the system needs to be able, provided an image with people, to identify most faces correctly and provide good images as input to the next part of the system, which is the age and gender classification model.

For the second goal to be reached, we need an accurate approach to provide a good age and gender classification on the customers, so that we can have a high categorization accuracy. When it comes to age prediction, a high accuracy could be troublesome to achieve as even humans find it hard to predict the age of a person based on their facial characteristics alone; hence, in this case, a lower accuracy might be acceptable.

The third goal allows the user to have some control over which classes to use. So the system should allow the user to configure the age classes as he sees fit, without requiring to re-train the underlying model.

Since AI systems have grown rapidly over the last years, there are multiple models that are capable of detecting faces and others capable of classifying faces by age and gender. Therefore, an analysis needs to be conducted in order to validate which ones achieve better results for our problem, enabling us to decide which models to use in our system.

Finally, an analysis of the outputs that are wrongly predicted needs to be done in order to understand why such failures occur. The objective of this is to, after understanding why such images tend to fail, find a possible solution and adapt the system to increase the accuracy further.

CHAPTER 3.
DESIGN FLOW/PROCESS

Evaluation & Selection of Specifications/Features

Gender and age play a significant role in interpersonal interactions among people who live in communities. The use of smart gadgets has expanded as technology has progressed, and social media has begun to draw everyone's attention. Daily studies on gender and age prediction have grown in prominence, it increases the number of apps that use such techniques. In these applications, facial photographs are commonly employed since they contain useful information that may be used to extract human interaction. For gender detection and age prediction, Image processing, feature extraction, and classification steps are usually used.

Image Pre-processing: It has a strong favourable impact on the quality of feature retrieval and the outcomes of image exploration. This is a combination comprising enhancements and enrichments that is required for a face recognition pipeline. Thus, image processing chores include noise subdual, contrast enrichments, and removal of undesirable effects on detention such as blurring by motion effects and colour alterations.

Face Detection and Alignment Using Landmark Localisation: Facial detection is the fundamental phase in any face recognition process. A face detection method assists in finding any face portion of an image. A face detection system must be resistant to changes in stance, lighting, emotion, scale, skin colour, occlusions, disguises, make-up, and on. The proposed method identifies the 68 landmark points in the face using the Dlib library. Facial key points include the nasal tip, ear margins, mouths edges, eye contours, and so on. Certain face landmarks are required for face orientation that is required for facial registration. Face alignment utilizes the eye position and the centre point in the face. Based on these factors, the input photo is cropped and scaled, having the size of the image set to 110×110. Facial recognition and alignment are crucial aspects in biometrics, gender categorization, and age estimation.

CNN Model: We must first extract the face from a webcam image before proceeding with the implementation. The OpenCV library in Python is used to accomplish this. An effective object detection method is face detection utilizing Haar feature-based cascade classifiers, which is a machine learning-based approach. There will be many positive and negative photos, on which the classifier will be trained. It's then utilised to find faces in other pictures.

We have three linear layers and two convolutional layers. PyTorch's neural network module class is a module for creating neural networks. This module is extended by each of our layers. The forward function definition and a weight tensor at each layer will be the two main components wrapped within. As the learning process begins, the Network will learn the weight values, which are then modified to the weight tensor within each layer. The values for each argument are passed to the constructor when creating a layer. The linear layers have two parameters, while the convolutional layers have three.

Design Constraints

Functional Requirements of the system:

We have classified these functional requirements as follow:

- Choosing the dataset for training.

- Image processing and prediction. Accuracy and speed of the model.

Non-Functional requirements:

After the functional requirements, my teammate and I have been able to classify the non-functional requirements as follows:

A. Product Requirements:

a) Usability Requirements:

The application shall be used friendly and does not require any guidance to be used. In other words, the application has to be as simple as possible, so its users shall use it easily. The interface is quite simple and straight forward so that anyone can understand it. The user just must open their camera and the model will predict their age and gender.

b) Reliability Requirements:

- **Stability:** The model should produce consistent results over time, even as data inputs change.
- **Availability:** The model should be available to users when they need it and have a high level of uptime.
- **Fault tolerance:** The model should be able to continue operating even in the event of data errors or processing issues.
- **Performance:** The model should be able to perform well under different conditions, including with low-quality or missing data.

B. Efficiency Requirements:

a) **Response Time:** The model produces predictions within a reasonable time frame, ideally in real-time or near real-time.

b) **Minimal Data Storage:** The model should require minimal data storage and be able to operate on small, manageable datasets.

Accuracy vs. Efficiency Trade-off: The model should be optimized for a balance between accuracy and efficiency, depending on the specific use case and performance requirements.

Attributes of the Software:

- **Maintainability:**

  The application shall respond to any change on the requirements.

- **Adaptability:**

  The application shall be compatible to any Android OS version or any web browser.

- **Availability:**

  The application shall be available on the store whenever users want to download it.

- **Flexibility:**

  The architecture shall be flexible to any change of the requirements.

Design Flow

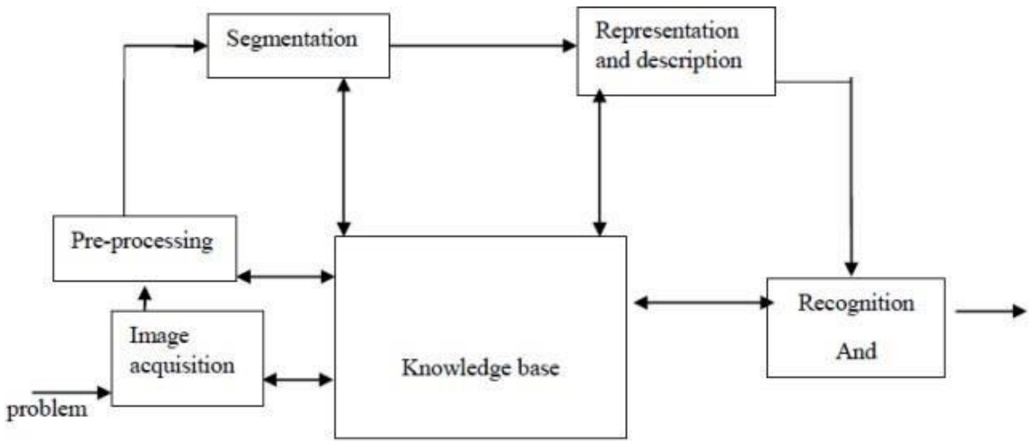


Fig 3.3.1 Data Flow Diagram

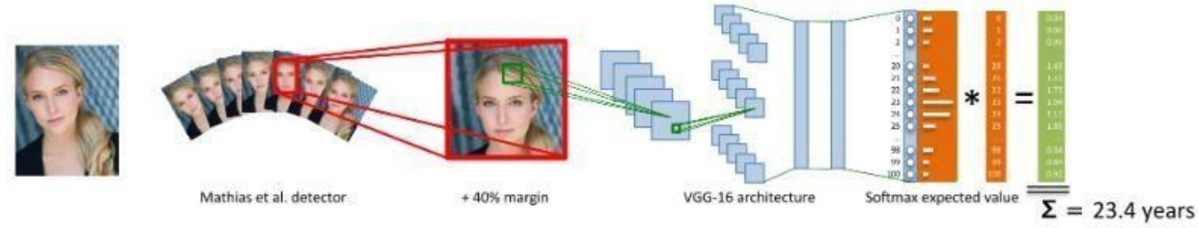


Fig. 3.3.2 Data Flow Diagram (II)

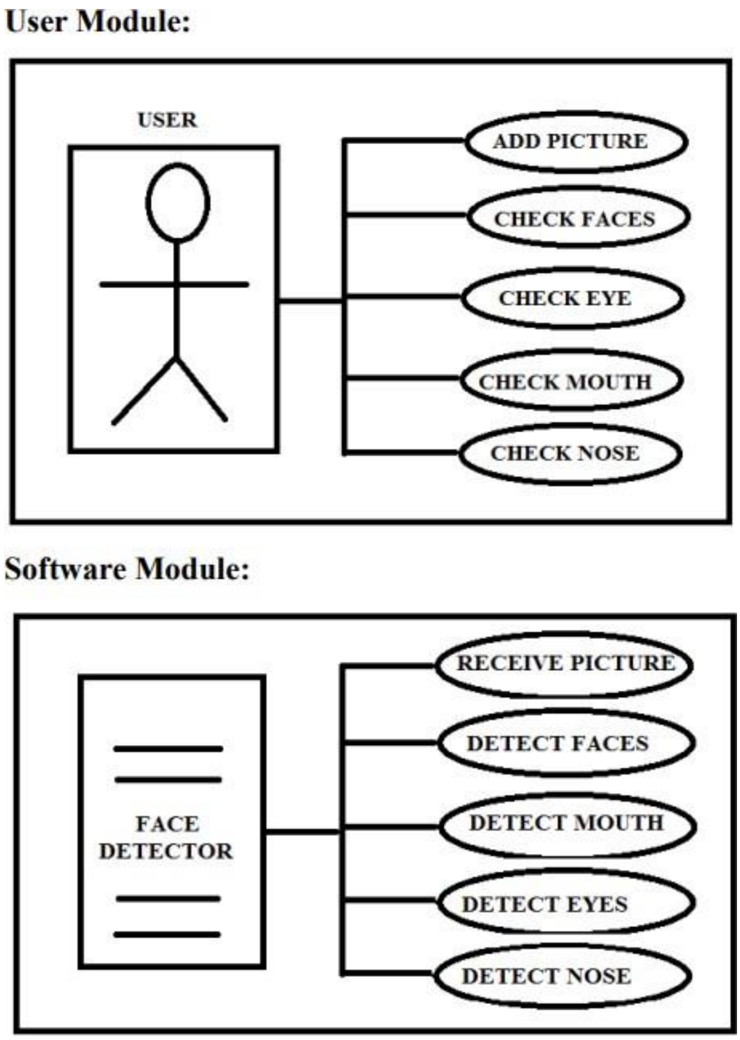


Fig 3.3.3 Use Case Diagram

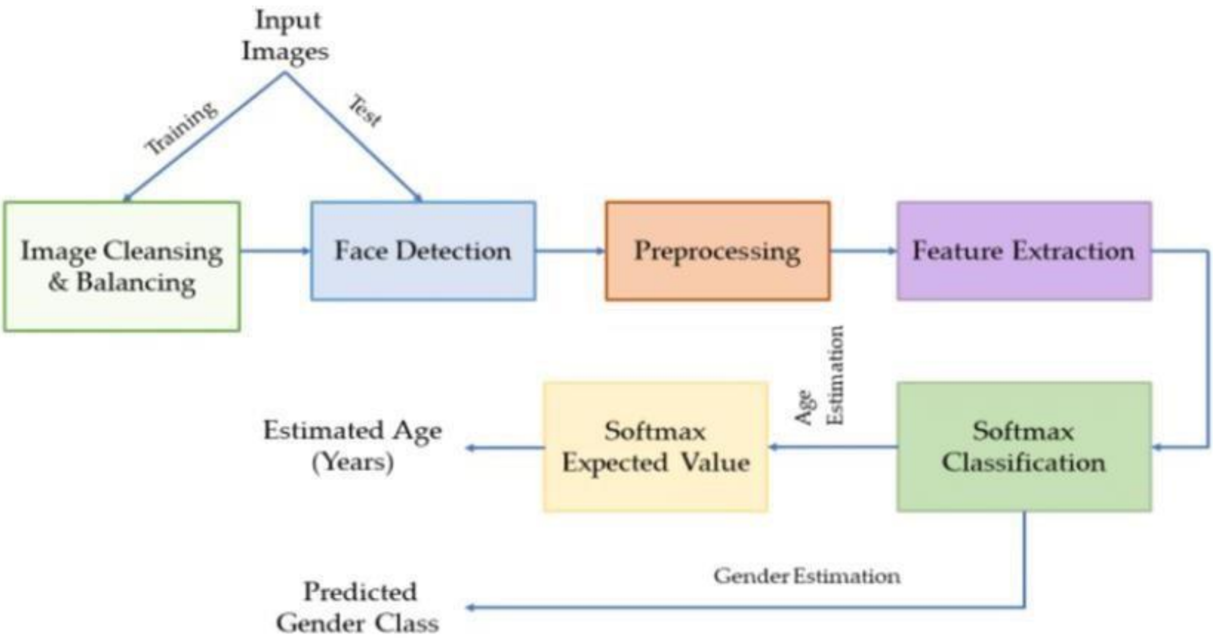


Fig 3.3.4 Sequence Diagram for Processing

Implementation plan/methodology

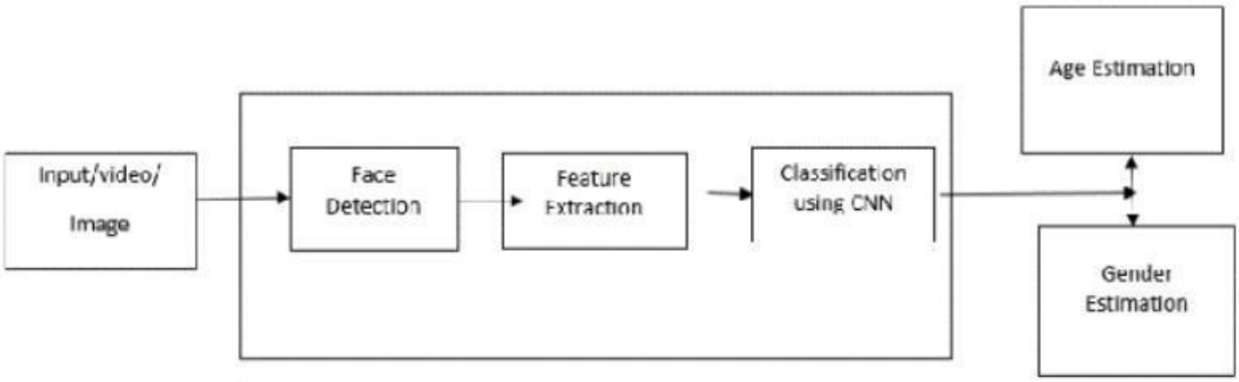


Fig 3.4.1 Structure of AGP Model

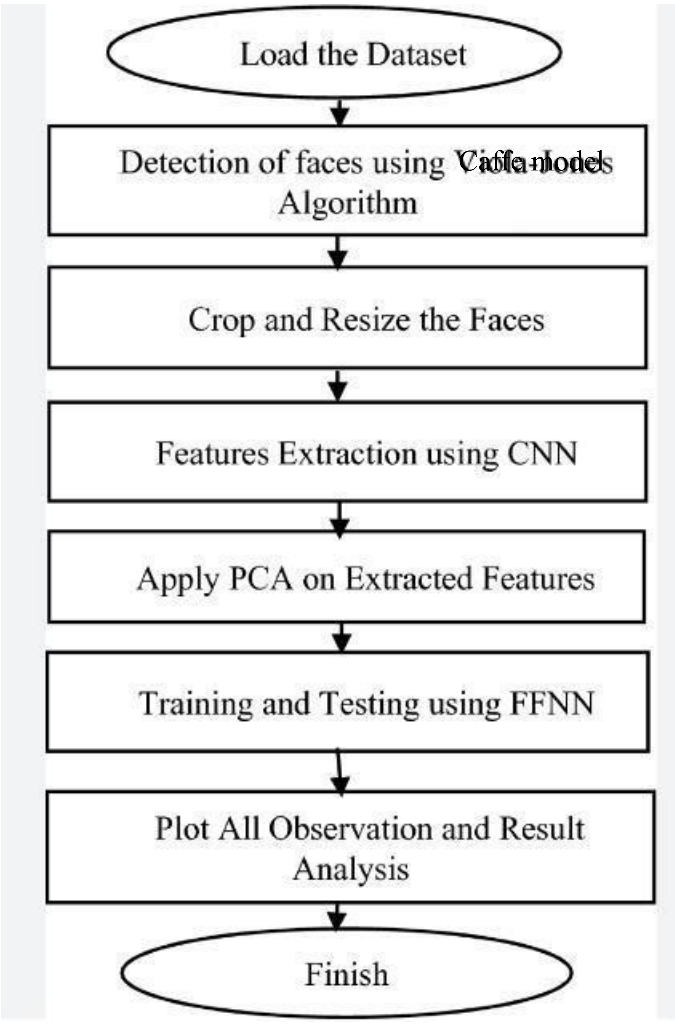


Fig 3.4.2 Block Diagram of AGP Model

CHAPTER 4.
RESULTS ANALYSIS AND VALIDATION

4.1 Experimental Settings

Because of a high number of parameters, CNN requires plenty of training data. Furthermore, training is extremely time-consuming, optimization may need hours or months. In order to solve this obstacle, two stages are used to develop a transfer learning strategy:

Prior to training: randomly initialized networks are initially trained by an accompanying task which has sufficient pictures labelled.

Fine-tune step: settings which have been learned during pretraining are utilized to begin a new job.

4.2 Design drawings/ schematics

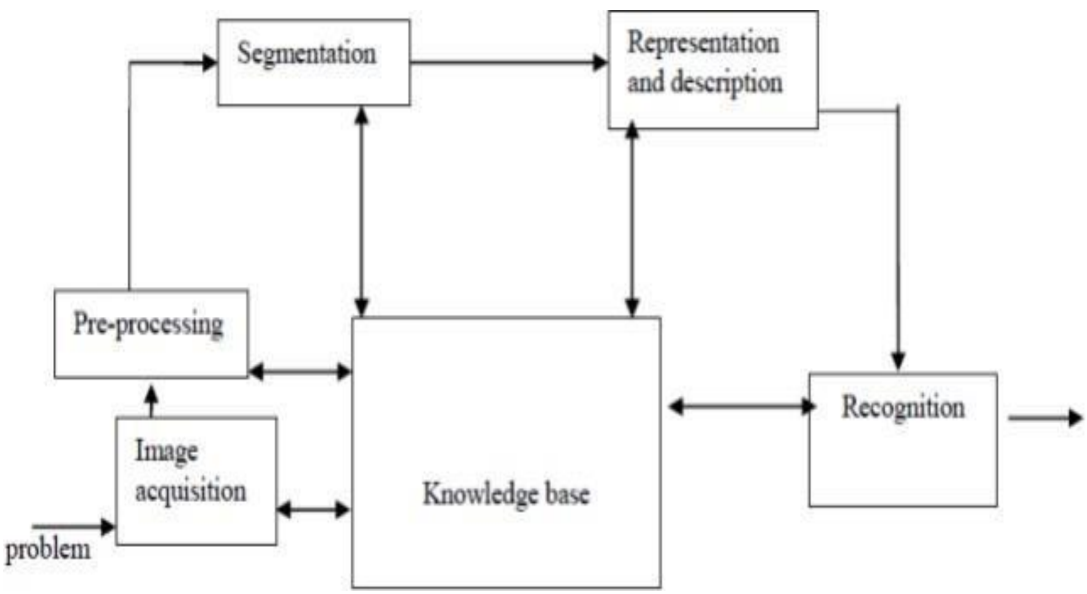
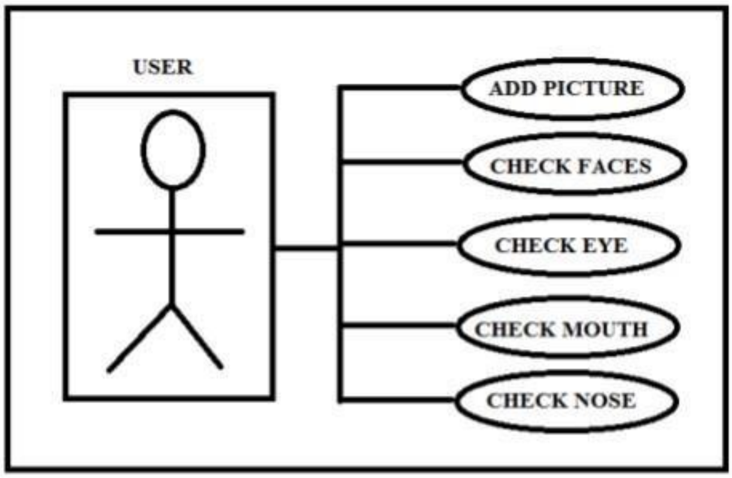


Fig 4.2.1 AGP Design Flow

User Module:



Software Module:

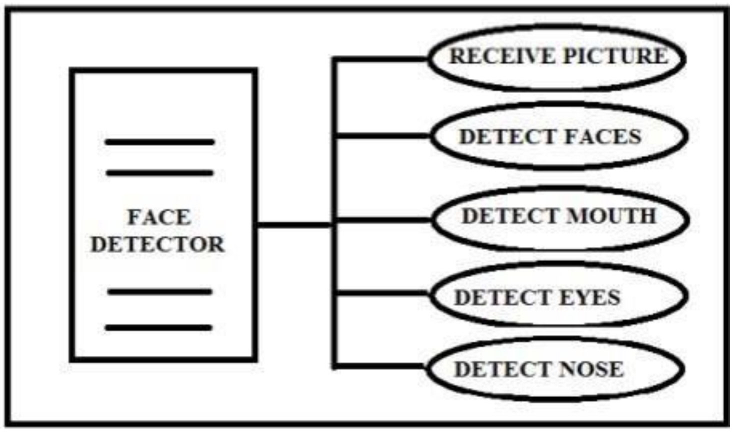


Fig 4.2.2

4.3 Results and Analysis

The input can be either taken from the webcam or the images can be given as the input. Here, the input image is taken from webcam. The age and gender are found. This method achieves high to medium accuracy. For testing we take sample images estimating age and gender. For classification we use Caffe model. Figure 4.3.1 and Fig 4.3.2 represents the sample images with correct age and gender classifications. Figure 4.3.3 represents the pictures of age misclassifications. Results of using Caffe Deep Learning Framework If the detected face is a male, the output is “Male”. If the detected face is a female, the output is “Female”.

For the age prediction, the CNN's output layer (probability layer) in this CNN consists of 8 values for 8 age classes of the following ranges- (0 – 2), (4 – 6), (8 – 12), (15 – 20), (25 – 32), (38 – 43), (48 – 53), (60 – 100).

Testing:

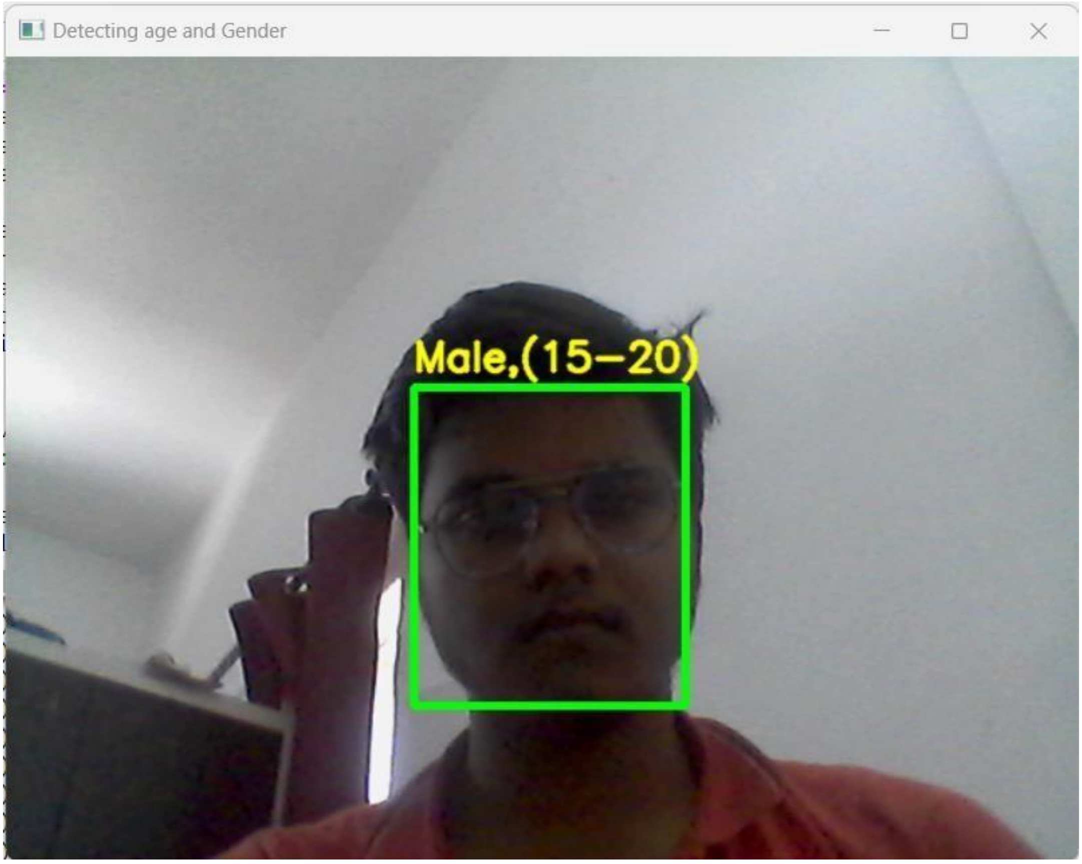


Fig – 4.3.1

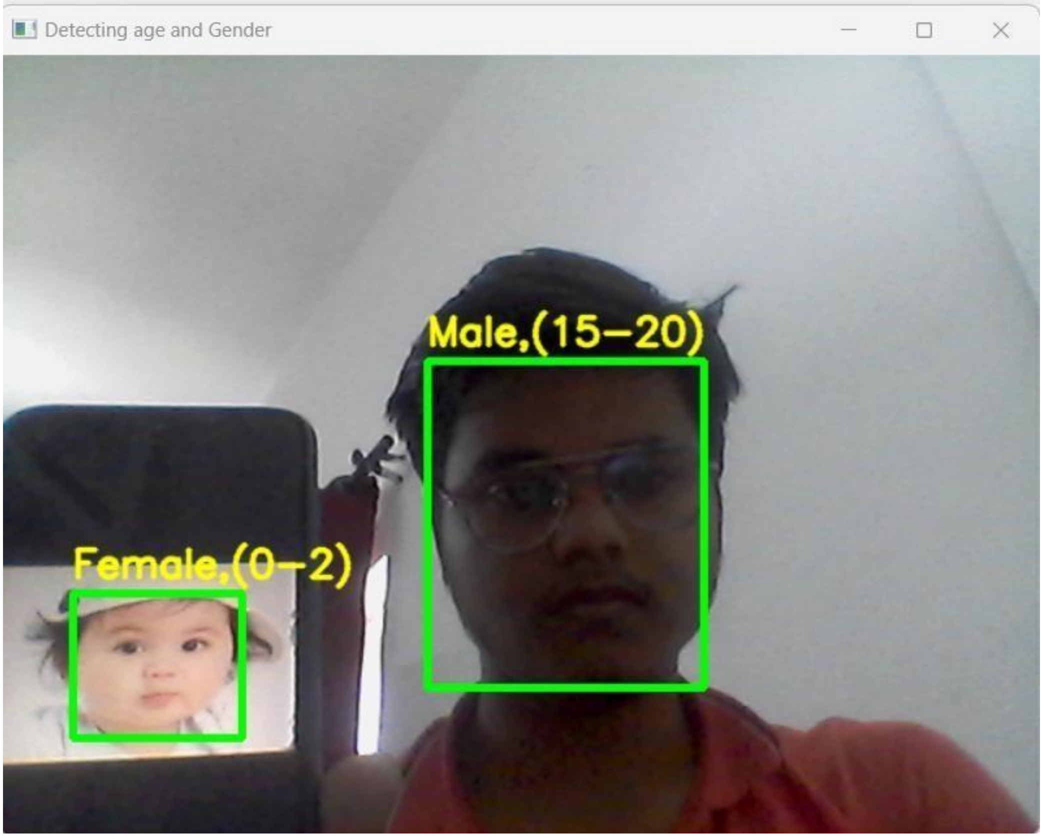


Fig – 4.3.2

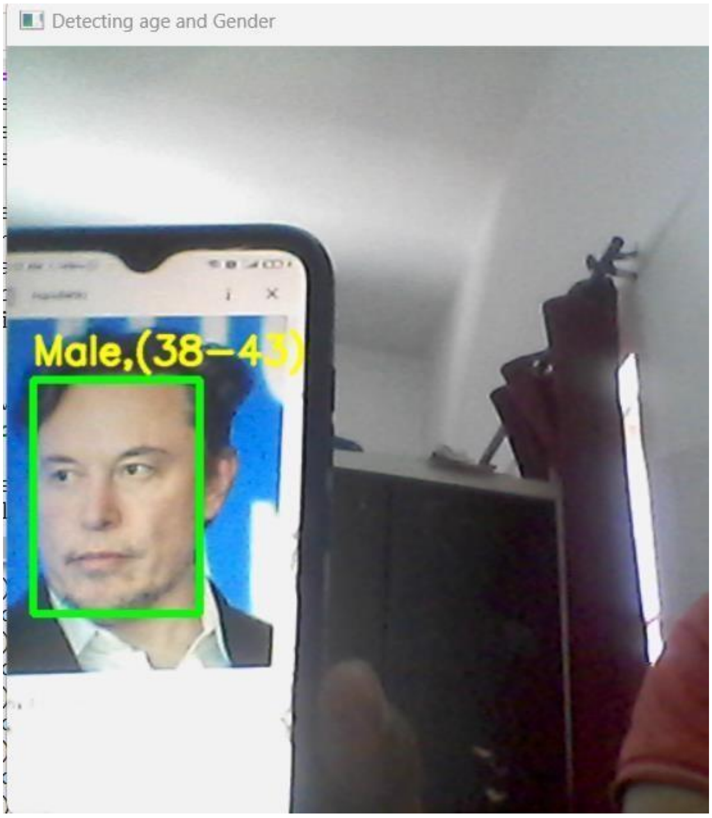


Fig – 4.3.3

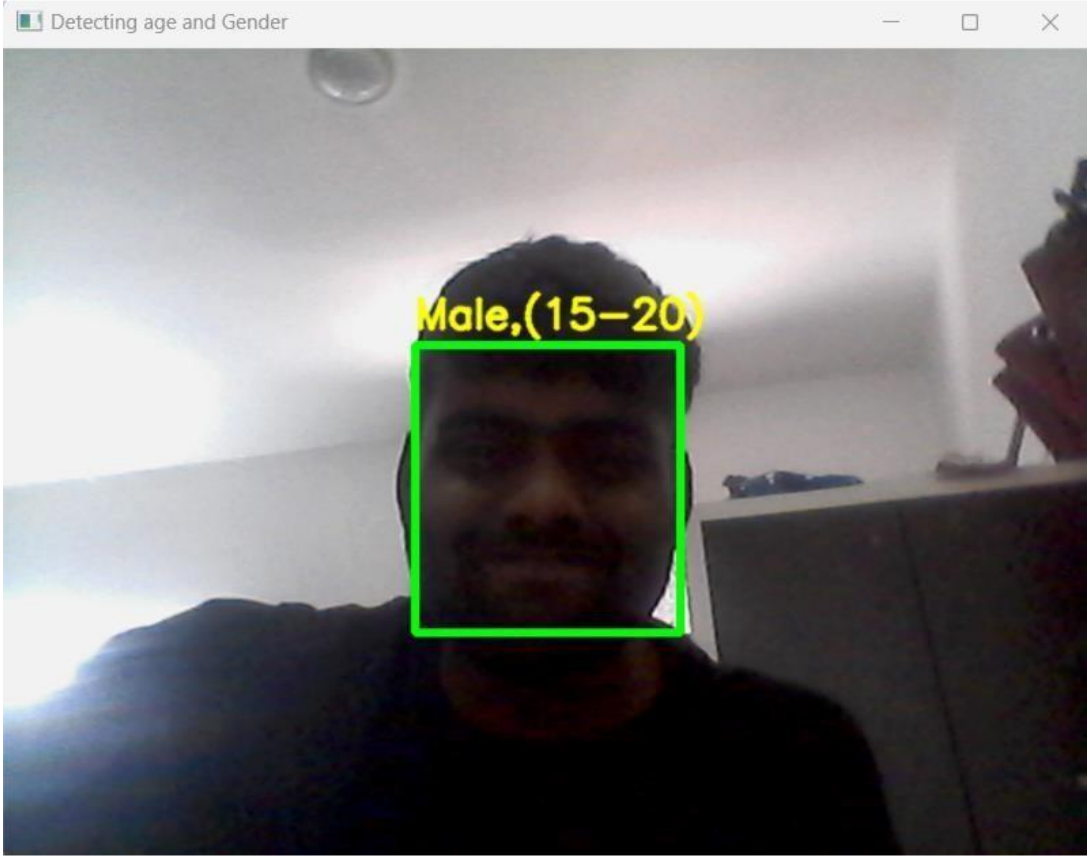


Fig – 4.3.4

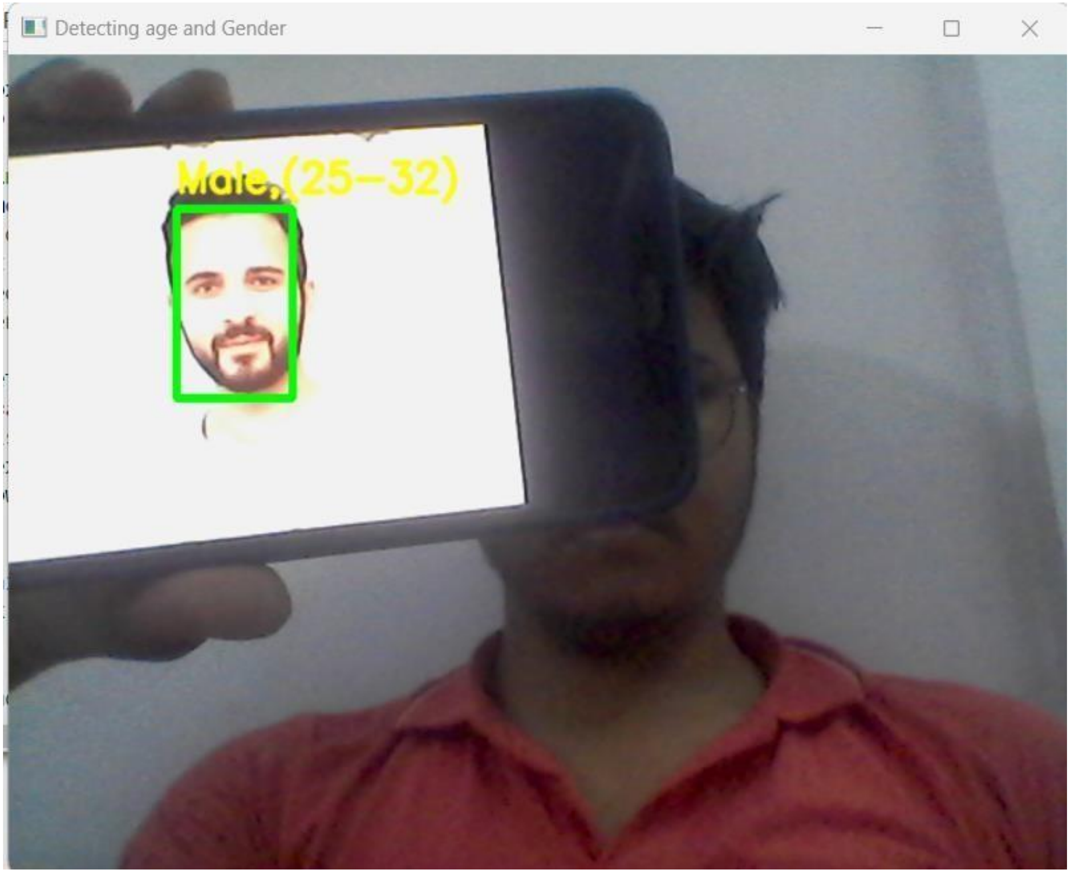


Fig – 4.3.5

Analysis:

Accuracy = No. of accurate prediction / Total no. of prediction
The overall accuracy of the system using caffe deep learning framework is 78%.

Caffe Model	Exact Match	
Males Total: 50	38	76%
Females Total: 50	40	80%
Total : 100	78	78%

CHAPTER 5

CONCLUSION & SCOPE FOR THE FUTURE WORK

CONCLUSION

We implemented an application for age and gender prediction. The application can be used both as a Python module imported into another project and as a standalone application with command line interface. The application provides two different face detection method. One is based on computing histogram of oriented gradients, the second is based on cascade of convolutional networks.

Additionally, the application provides a way to filter faces which are turned away from the camera. We also enable the usage of our application in conjunction with person detection tools by accepting a person id parameter and computing the average result.

To select the basis of our application we evaluated 3 different methods. We then trained our own model that implements the best method using a dataset made by combining all evaluated publicly available datasets and the dataset we manually labelled. The trained model performed better on all dataset in age estimation. The most significant improvement was on FG-NET dataset where mean absolute error improved from 12.85 to 6.61. In gender estimation the model performed better on most of the datasets. On UTKFace dataset it improved from 20.45% error rate to 10.6%. Furthermore, we evaluated in detail the trained model on the manually labelled dataset. We achieved age mean absolute error of 5.66. In some cases, the mean absolute error gets as low as 3.96. The model is also able to correctly classify all male subjects. We demonstrated that our implementation is able to estimate age and gender in a real-world situation. We also trained one age model and one gender model using integral image as an additional colour channel. This did not improve the performance and the results on most datasets were worse that the pretrained models. It is possible that training with integral images requires a different neural network architecture or different set of hyper parameters.

FUTURE WORK

Age and gender detection is essential for authentication, human-computer interaction, behaviour analysis, product recommendation based on user preferences, and many other areas. Many companies needed age and gender data capture, but few solutions were available. Significant developments have been made in the past few years to meet this need. In the last decade, artificial intelligence classification systems have been used instead of manual classification systems for age and gender detection. With the introduction of artificial intelligence, the success rate of solving the problem has increased.

Age detection: Age detection can be used to place ads in the types of media most consumed by your target audience.

Gender detection: Gender detection can be used to determine whether a social media platform is more likely to show your product to men or women.

There are many possibilities in age and gender estimation research. An immediate idea would be to look more deeply into training models with integral images as additional colour channels using more varied neural network architectures.

Another idea would be to use more varied neural network architecture specifically for gender prediction. Many current tools use the same architecture for both age and gender prediction.

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