Facial Image Classification based on Age & Gender

Submitted in partial fulfillment of the requirements
of the degree of

T. E. Computer Engineering

By

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CERTIFICATE

This is to certify that the project entitled **"Facial Image Classification based on Age & Gender"** is a bonafide work of **"Shravani Dhuri(06), Clare Rebello(07), Kate Rebello(08)"** submitted to the University of Mumbai in partial fulfillment of the requirement for the award of the degree of T.E. in Computer Engineering

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Project Report Approval for T.E.

This project report entitled (***Facial Image Classification based on Age & Gender***) by (***Shravani Dhuri, Clare Rebello, Kate Rebello***) is approved for the degree of ***T.E. in Computer Engineering.***

Examiners

1.--

2.--

Date: 15-05-2021

Place: Mumbai

Declaration

I declare that this written submission represents my ideas in my own words and where others' ideas or words have been included, I have adequately cited and referenced the original sources. I also declare that I have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in my submission. I understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

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Abstract

In this project, we introduce an approach to classify gender and age from images of human faces which is an essential part of our method for autonomous detection of anomalous human behaviour. Human behaviour is often uncertain, and sometimes it is affected by emotion or environment. Automatic detection can help to recognise human behaviour which later can assist in investigating suspicious events. Automatic face identification and verification from facial images attain good accuracy with large sets of training data while face attribute recognition from facial images still remain challenging. Hence introducing an efficient and accurate facial image classification based on facial attributes is an important task. This project proposes a methodology for automatic age and gender classification based on feature extraction from facial images. It includes three main iterations: Preprocessing, Feature extraction and Classification. This study has been carried out using facial images of gender consisting of both gender types and the age classification has been done according to predefined age ranges using Caffemodel. Proposed solution is able to classify images in different lighting conditions and different illumination conditions.

In this project, an investigation has been made on gender classification through facial images using principal component analysis (PCA), and support vector machine (SVM). PCA is a dimensionality reduction technique, which is used to represent each image as a feature vector in a low dimensional subspace. SVM is a binary classifier for which PCA is the input in the form of features and predicts which of the two possible classes forms the output. Age Classification is done using a pre-trained CNN caffe model.

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List of Abbreviations

Sr. No.	Abbreviation	Expanded form
1	SVM	Support Vector Machine
2	CNN	Convolutional Neural Network
3	PCA	Principal Component Analysis
4	LBP	Local Binary Pattern
5	LAR	Least Angle Regression
6	PLO	Piecewise Linear Orthonormal
7	MUCT	Milborrow / University of Cape Town
8	OSH	Optimal Searching Hyper-plane

Chapter 1

Introduction

Facial analysis has gained much recognition in the computer vision community in the recent past. Human face contains features that determine identity, age, gender, emotions, and the ethnicity of people. There has been an increase in the development of automatic facial analysis techniques with a view for developing machine-based systems that mimic these abilities of the human visual system. Age and gender classification can be especially helpful in several real-world applications including security and video surveillance, biometrics, human-computer interaction and forensic art. With much progress in automatic face detection and recognition, much research is now focused on automatic demographic identification.

1.1 Description

Age and gender predictions of unfiltered faces classify unconstrained real-world facial images into predefined age and gender. Significant improvements have been made in this research area due to its usefulness in intelligent real-world applications. However, the traditional methods on the unfiltered benchmarks show their incompetency to handle large degrees of variations in those unconstrained images. More recently, Convolutional Neural Networks (CNNs) based methods have been extensively used for the classification task due to their excellent performance in facial analysis. In this work, we propose a model for gender prediction using SVM ,a classification algorithm, and CNN caffemodel to achieve robust age classification of unfiltered real-world faces. The architecture includes feature extraction and classification itself. The feature extraction extracts features corresponding to age and gender, while the classification classifies the face images to the correct age group and gender. Particularly, we address the large variations in the unfiltered real-world faces with a robust image preprocessing algorithm that prepares and processes those faces before being fed into the CNN and SVM model.

1.2 Problem Formulation

The recent growth in social media and the social platform has given rise to an increasing amount of applications. The automatic classification of age and gender has become relevant for an increasing request of applications. The performance which is reported for the related task of face recognition, the performance of current methods on real-world images is lacking considerably. Age detection plays a key role in many fields like Multimedia Retrieval and Human-Machine Interaction. Vocabulary used to address people changes according to the age groups very often. Gender Identification is one of the major components for developing gender-dependent acoustic modules for speech recognition etc. Salutations and grammar rules of languages vary from one gender to the other.

The aim of this project is to classify humans according to age and gender. The model training includes preprocessing, face extraction, feature extraction and classification.

1.3 Motivation

Age and gender prediction systems have been growing rapidly in recent days due its important modules and beneficial uses for many computer vision applications such as human-computer interaction, security systems, and visual surveillance. There are many examples that demonstrate the importance of a gender and age prediction. For Instance, there is a specific age for getting alcohol, driving vehicles, traveling alone abroad, smoking cigarettes, etc. But the problem is that human skills of age prediction are limited and not accurate. Therefore, computer vision systems would be helpful todeny under-aged people. Another example is that following the increase of terrorist threats, airports are considering security measures at the security checkpoints to collect the gender information of the passengers automatically, which may help in observing a certain segment of people.

Besides the security applications, age and gender prediction techniques are used also in health care systems, information retrieval, academic studies and researches, and Electronic Customer Relationship Management (ECRM) systems, where customers are distributed to different gender and age groups like children, teenagers, adults and senior adults in addition to determine whether they male or female. Furthermore,gathering some customer's daily life information like activities, habits, traditions,priorities etc. may help the corporations to classify products and services depending on their gender or age groups, which lead to increase their incomes and earn more money. For example, clothes stores may offer appropriate fashions for males or females according to their age groups; restaurants want to know the most popular meals for each age or gender group; many companies want to make specific advertising to specific audiences depending on their gender or age groups.

1.4 Proposed Solution

Gender classification is a binary classification problem, which can be stated as inferring female or male from a collection of facial images. Although there exist different methods for gender classification, such as gait, iris, hand shape and hair, yet the prominent methods to achieve the goal are based on facial features.

In age estimation, the algorithms usually take one of two approaches: age group or age-specific estimation. This model classifies a person based on age group. This approach is further decomposed into two key steps: feature extraction and pattern learning/classification.

1.5 Scope of the project

Face recognition is one of the most important social perception skills. Human face processing allows us to identify and store patterns for thousands of individual faces. Human face perception depends on identifying specific features, such as the eyes, nose, and mouth, and on perceiving the specific spatial arrangement of those features.

Face recognition technology has a fast processing nature and it doesn’t need any contact with users. This model commonly encompasses a range of tasks, including gender classification, age prediction and the analysis of facial expression. This model helps us to determine the results.

Chapter 2

Review of Literature

Estimating the age and gender of a person appearing in a photo, from that person's facial features, has been studied at length in the past, though far less than the related problem of face recognition. Here we provide a cursory overview of this work, referring the reader to those papers for a more in-depth treatment.

Most age estimation and gender classification studies have utilized face images captured in controlled conditions. Many variations may appear in the image of a person's face. These variations may affect the ability of the computer vision system to estimate the age or recognize the gender. They are due to many factors which can be divided into: human factors (race, facial expression etc.) and capture process factors (pose, illumination, quality etc.).

Gallagher et al. [3] studied contextual features for capturing the structure of people's images. Instead of treating each face independently, they extracted features which cover the structure of the group from persons' faces. Firstly, they used the social context features, then they tried to use appearance features.Finally, they combined context and appearance features together achieving the accuracy of 42.9% and 74.1% for age and gender respectively.

Shan [4] investigated age estimation and gender classification by treating each face independently. He focused on appearance features exactly on Local Binary Patterns (LBP) and Gabor features as face representation, then he adopted Adaboost to learn the discriminative local features. The best performance in his experiments is with the boosted LBP based on SVM classifier with an accuracy of 50.3% for age and 74.9% for gender.

Li et al. [5] focused on facial age estimation based on ordinal discriminative feature learning. They tried to remove redundant information from both the locality information and ordinal information by minimizing non linear correlation and rank correlation, using different feature selection algorithms (Laplacian Score, LAR, Fisher Score, Rank Boost and PLO).The Piecewise Linear Orthonormal (PLO) gave the best results for the age estimation with an accuracy of 48.5%.

Ylioinas et al. [6] studied automatic age classification using LBP variants. They proposed a method based on a combination of LBP variants encoding the structure of elongated facial micro-patterns and their strength. Their experimental results gave an accuracy of 51.7% for age classification.

Fu et al. [7] wrote a survey about age synthesis and estimation. They divided the age estimation systems into two concatenated modules: age image representation and age estimation techniques. There are five main models in age image representation, they are: Anthropometric Models, Active Appearance Models, Aging Pattern Subspace, Age Manifold and Appearance Models. And the age estimation techniques are: Classification, Regression and Hybrid techniques. They mentioned the majority of the aging databases including the Images of Groups Dataset. They summarize and compare different age estimation methods on different databases.

Ng et al. [8] wrote a survey about human gender recognition from face, gait and body. They mentioned some face preprocessing methods that may be applied in gender classification systems like normalization for contrast and brightness. They also categorized feature extraction methods for face gender classification into geometric-based and appearance based methods. As in any survey, a comparison of different methods and databases was summarized.

In our work, we propose an easy approach to estimate the age and recognize the gender in uncontrolled conditions based on facial images. Principal Component Analysis (PCA) and Support Vector Machines (SVM) are the 2 backbones of our approach for gender classification while CNN is used for age estimation. PCA is mainly used for reducing the dimensionality of the analysed data by converting them into a small number of uncorrelated principal components. First few principal components contain the maximum variability of the data and the degree of variability decreases down the line. In this way, we can neglect the other principal components without loss of valuable data. SVM is a machine learning tool useful for classification purposes. We implemented a supervised learning approach with SVM, and operated upon 3755 images from the MUCT database.

Chapter 3
System Analysis

3.1 Functional Requirements:

Dataset: The **MUCT database** was used for gender prediction**,** which consists of 3,755 faces with 76 manual landmarks. The database was created to provide more diversity of lighting, age, and ethnicity than currently available landmarked 2D face databases.A wide range of subjects was photographed, with approximately equal numbers of males and females, and a cross section of ages and races.

Libraries in python:

- Numpy
- cv2
- os,sys
- gradio
- argparse
- exposure
- model_selection, preprocessing, svm
- PCA
- math
- dump,load

3.2 Non-Functional Requirements:

These are basically the quality constraints that the system must satisfy according to the project contract. The priority or extent to which these factors are implemented varies from one project to another. They are also called non-behavioral requirements.

- The processing of each request should be done within 10 seconds.
- The site should load in 3 seconds when the number of simultaneous users are > 10000
- The system should provide better accuracy.
- User friendly.

3.3 Specific Requirements

Hardware

The hardware environment consists of the following:

CPU	:	Intel Pentium IV 600MHz or above
Motherboard	:	Intel 810 or above
Hard disk space	:	20GB or more
Display	:	Color Monitor
Memory	:	128 MB RAM
Other Devices	:	Mouse.

a) Server side

The web application will be hosted on a web server which is listening on the web standard port, port 7860.

b) Client side

Monitor screen – the software shall display information to the user via the monitor screen Mouse – the software shall interact with the movement of the mouse and the mouse buttons. The mouse shall activate areas for data input, command buttons and select options from menus.

3.4 Use-Case Diagrams and description

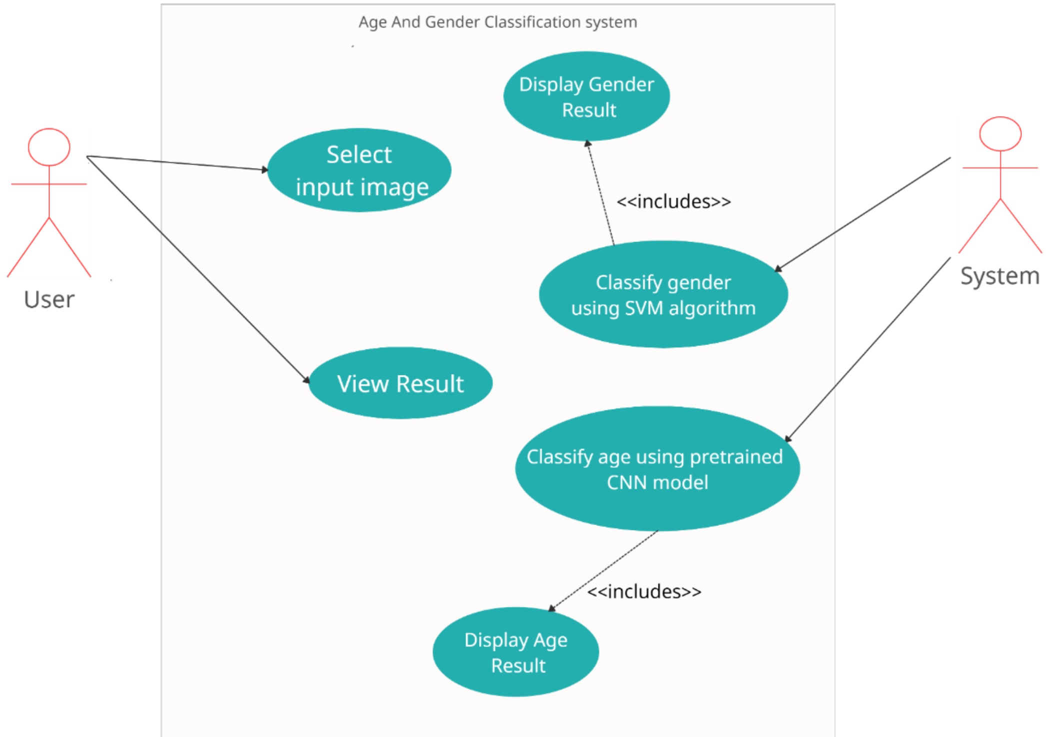

Fig3.1. Use Case of Age and Gender System

Use case1: Select input image

Actor: User

Description: In this activity the user uploads an input image.

Pre-condition: The frontend is loaded and the image field takes an image input.

Post-condition: The user uploaded image is visible in the image field of the frontend.

Basic Course of Action:

1)User clicks on upload image /Drag the image to be classified

2)Select the image to be uploaded

3)Press Enter

Use case2: View Result

Actor: User

Description: In this activity the final predicted age and gender is displayed.

Pre-condition: The User has clicked the submit button.

Post-condition: The Predicted age and gender is displayed to the user.

Use case3:classify gender using svm Algorithm

Actor: System

Description: In this activity the SVM model is given the input image for gender classification.

Pre-condition: The user must upload a valid image file as input.

Post-condition: The Predicted gender is given to the frontend function.

Use case4: Classify age using pre trained CNN model

Actor: System

Description: In this activity a pretrained CNN model is given the input image for age classification.

Pre-condition:The user must upload a valid image file as input.

Post-condition:The Predicted age is given to the frontend function.

Use case5: Display gender result

Actor: System

Description: In this activity the predicted gender is displayed in the gender field.

Pre-condition: The Predicted gender is given to the frontend function.

Post-condition: The Predicted gender is displayed on the frontend.

Use case6: Display age result

Actor: System

Description: In this activity the age is predicted by the model.

Pre-condition: The Predicted age is given to the frontend function.

Post-condition: The Predicted age is displayed on the frontend.

Chapter 4

Analysis Modeling

4.1 Activity Diagram

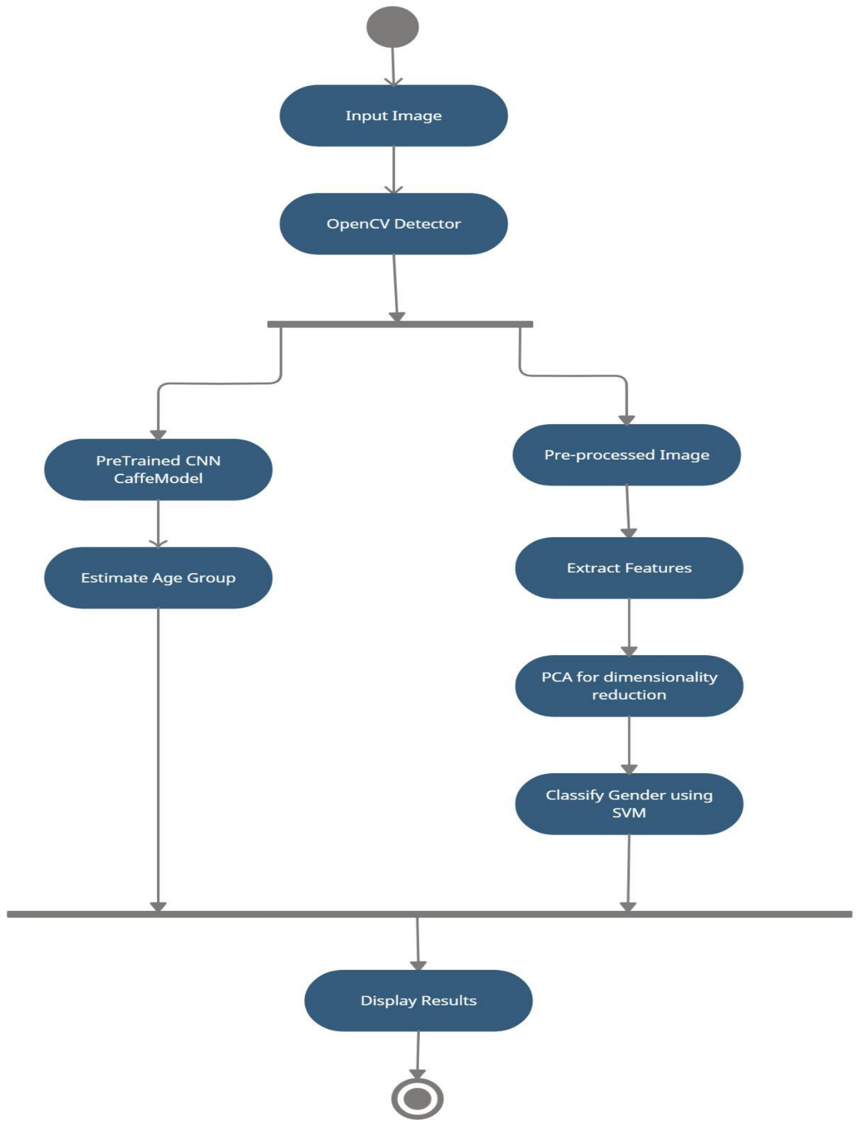

Fig4.1. Activity Diagram of Age and Gender System

This diagram shows a sequential flow of one activity to another.Here it begins with the input image which is followed by the face detector wherein the face is detected using OpenCV Detector. The detected face further goes into the pretrained caffe model for age detection. The same detected face is also used for gender detection for which it is pre-processed where the image is resized,cropped and aligned,then the features are extracted.Further PCA dimensionality reduction is done and then the gender is classified using SVM. The results of age and gender are displayed at the end.

4.2 Functional Modeling

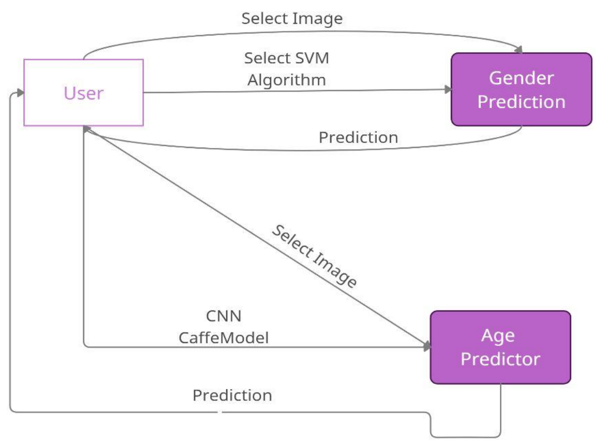

Fig4.2. Level 0 Data Flow Diagram of Age and Gender System

Level 0:

The user selects an image for age and gender classification. The SVM algorithm is applied on the selected input image for gender classification. The classified gender is displayed on the screen.For age, a pre-trained CNN model is used to predict the age group of the selected input image and the output of predicted age is displayed.

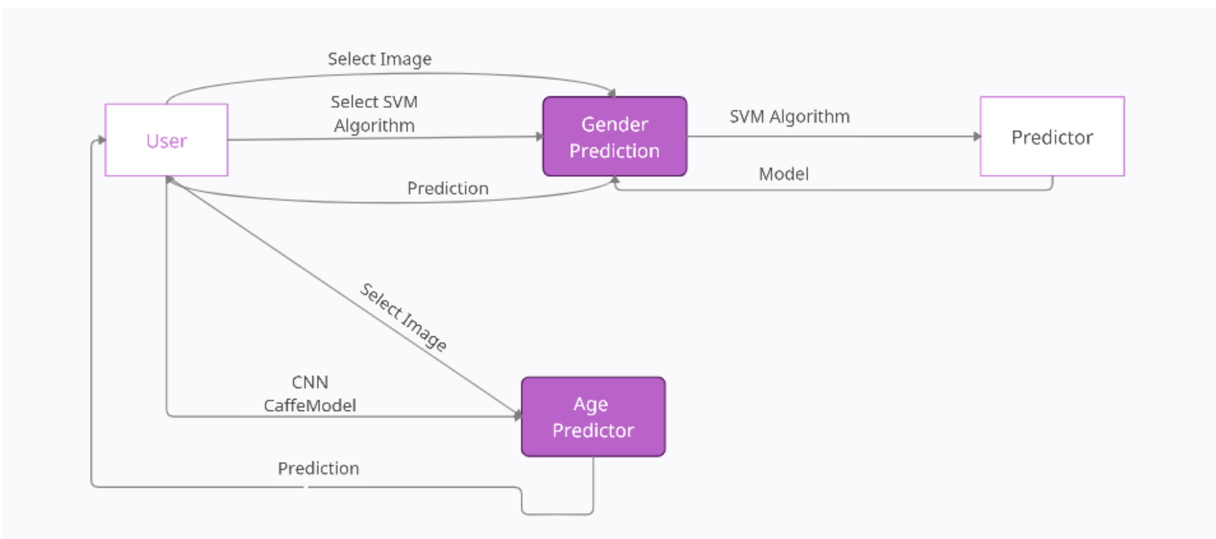

Fig4.3. Level 1 Data Flow Diagram of Age and Gender System

Level 1:

The user selects an image for age and gender classification. The SVM algorithm is trained for a dataset and a model for gender classification is developed. Using the trained model the gender of the selected input image is classified. The classified gender is displayed on the screen.For age, a pre-trained CNN model is used to predict the age group of the selected input image and the output of predicted age group is displayed.

Chapter 5

Design

5.1 Architectural Design

Firstly, we will be giving an image as an input to the model which will go through the following three major steps:

Face detection - Using openCV it maps facial features from the input image.

Gender classification - Further PCA was applied to reduce dimensionality of the vectors that serve as inputs to the SVM model. Svm library from sklearn in python is used.

Age prediction - For the estimation of age, a pretrained CNN caffemodel is used to predict the age group. Age and gender are finally produced as the result of the model design.

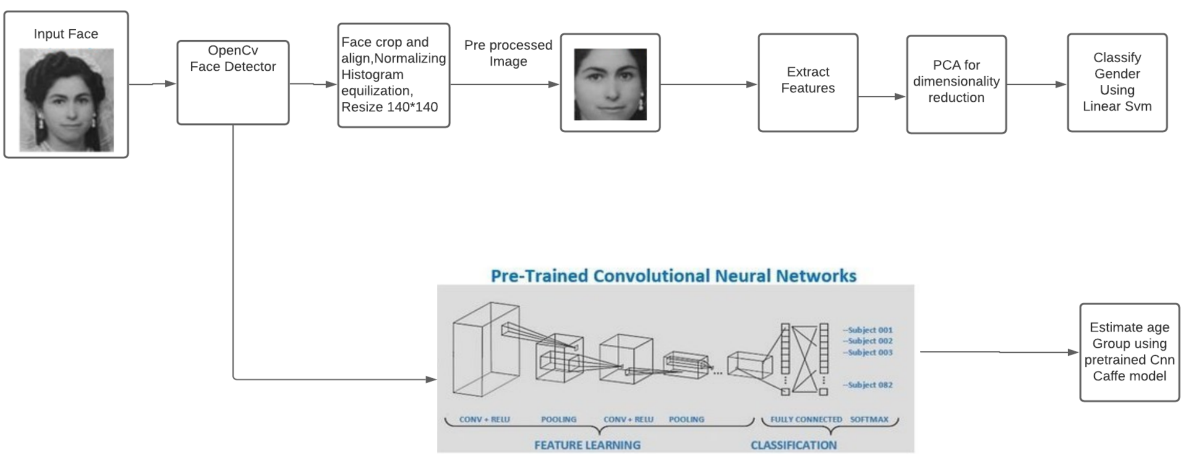

Fig5.1. Workflow/Architecture Design of Age and Gender System

5.2 User Interface Design

Gradio is an open source library and free which allows you to quickly create customizable UI components around your TensorFlow or PyTorch models, or even arbitrary Python functions in a few lines of code. Gradio is a great tool for deploying models to the web. Gradio can wrap almost any Python function with an easy to use interface. That function could be anything from a simple tax calculator to a pretrained model. You can integrate the GUI directly into your Python notebook, or you can share the link to anyone.

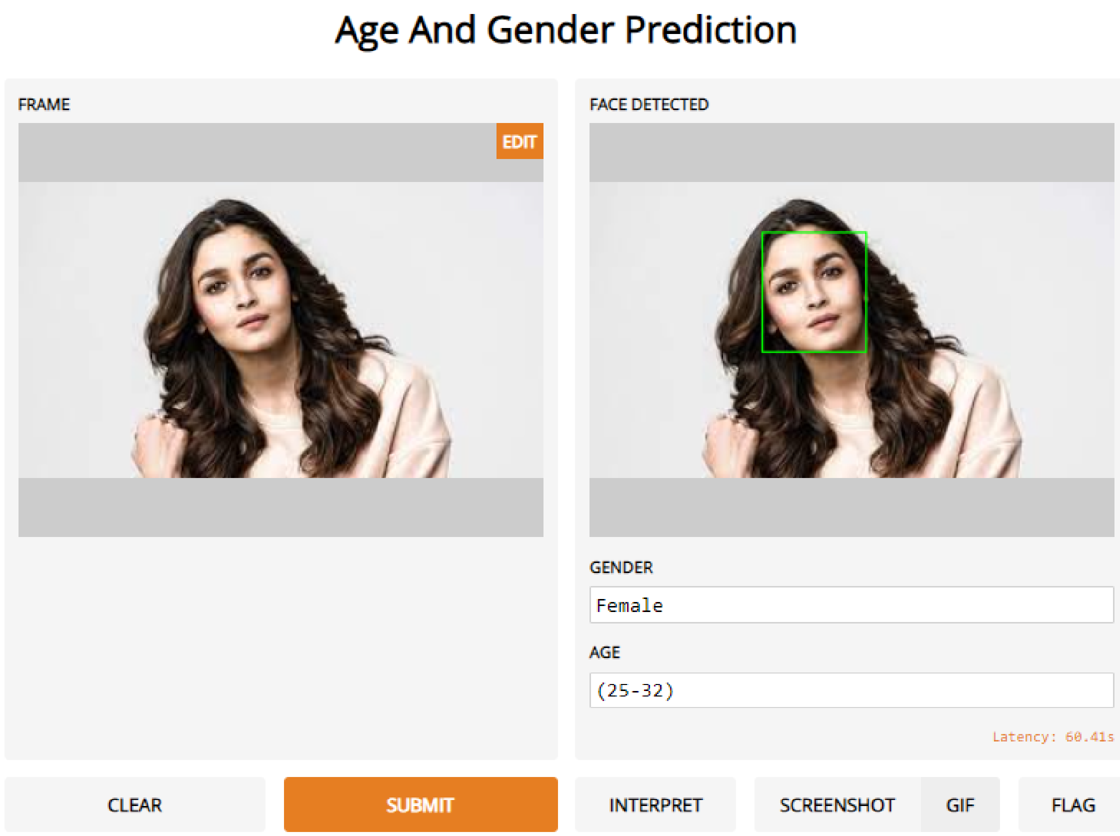

Fig5.2. User Interface of Age and Gender System

First, drag or upload any image into the frame, you can crop or edit or align the image as per your convenience. Click on submit to check the results. After some time you'll be able to see the face detected, gender and the age predicted. You can also clear the output and add any other image of your choice. You may also take a screenshot of the output by clicking on the "SCREENSHOT" button.

Chapter 6

Implementation

6.1 Algorithms / Methods Used:

1. PCA (Principal component analysis)

Principal Components Analysis is a very well known approach for reducing the dimensionality of data. For applying PCA to images, the image is first represented as a column of vectors. A matrix is formed by concatenating the column of training set images. Let this matrix be X,

X = [x1 x2 … xn] , where xi is the ith column vector representing the ith training image.

Then the mean is subtracted from each column and the covariance matrix is computed.

Let the mean image be –

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$$

And Y = [$x_i - \bar{x}$ … x_n - $\bar{x}$]

The covariance matrix Q = cov(Y) = $Y\ Y^T$

Finally, eigenvalue decomposition is performed to find the highest ranking (based on eigenvalues) eigenvectors. These vectors, known as principal components span the low dimensional subspace. Out of these eigenvectors m most significant vectors are chosen, let these vectors be – $e_1, e_2, \ldots, e_m$. The value of m is chosen by considering the cumulative sum of the eigenvalues.

The features of an image x is then computed by projecting it onto the space spanned by the eigenvectors as follows –

g = [$e_1 e_2 \ldots e_m]T$ (x − $\bar{x}$)

, where g is an m dimensional vector of features.

This feature vector g is used during training and classification.

2. SVM (Support vector machine)

SVM was developed by Cortes and Vapnik in 1995 and has extensively been used as a popular and powerful supervised learning tool for general pattern recognition applications. In addition, it gives promising and excellent performance on the range of machine learning and many other fields by applying it to different classification problems, data separation, regression, and density estimation.SVM classifier has many advantages, which make it one of the most accurate and robust algorithm, such as:

- Gives high performance even with a small number of images in the training set.
- Not sensitive to the number of dimensions, which gives it promising performance with any image size.
- Ability to minimize both empirical and structural risk, which leads to better generalization for data classification even when the number of test sets is high.

The main task of SVM is based on searching for the OSH "Optimal Separating Hyper-plane", which is the closest point between two classes (positive and negative samples)of data in the training set. By increasing the margin between these classes, SVM can modify the input data into a high-dimensional feature space where a hyper-plane may be found. Furthermore, it can reduce the structural risk; hence reducing the number of predictable errors. However, the nearest OSH data to the border of each class are called the "Support Vectors".

3. CNN (Convolutional Neural Network)

A Convolutional Neural Network (CNN) is a Deep Learning algorithm which can take an image as an input, assign importance to various aspects in the image and be able to differentiate them one from the other. CNNs perform very well on visual recognition tasks.

In the OpenCV’s dnn package ,OpenCV has provided a class called Net which can be used to populate a neural network. Furthermore, these packages support importing neural network models from well known deep learning frameworks like caffe, pytorch etc.

Caffe is a deep learning framework which has 2 associated files

.prototxt: This file defines the layers in the neural network, each layer's inputs, outputs and functionality

.caffemodel: Contains the information of the trained neural network

4. Preprocessing:

Train Test Split is one of the important steps in Machine Learning. It is very important because your model needs to be evaluated before it has been deployed. And that evaluation needs to be done on unseen data because when it is deployed, all incoming data is unseen.

The main idea behind the train test split is to convert original data set into 2 parts

- train
- test

where train consists of training data and training labels and test consists of testing data and testing labels.

6.2 Working of the project:

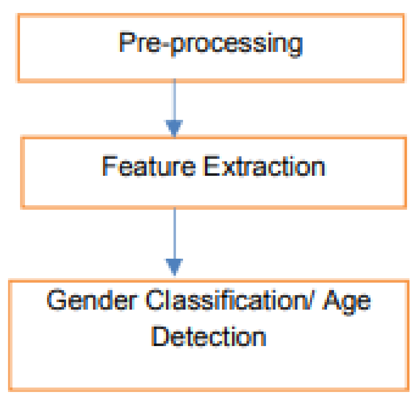

Fig6.1. Steps involved in gender/age prediction

Face detection:

```
class FaceRecognition():
    def __init__(self):
        self.faceProto="models/opencv_face_detector.pbtxt"
        self.faceModel="models/opencv_face_detector_uint8.pb"
        self.face_net = cv2.dnn.readNet(self.faceModel, self.faceProto)
    def detect_face(self, image, threshold = 0.7):
        temp_image = image.copy()
        height, width, channels = temp_image.shape
        blob = cv2.dnn.blobFromImage(temp_image, 1.0, (300, 300), [104, 117, 123], True, False)
        self.face_net.setInput(blob)
        detected = self.face_net.forward()
        faceBoxes = []
        for row in range(detected.shape[2]):
            confidence = detected[0, 0, row, 2]
            if confidence > threshold:
                left = int(detected[0, 0, row, 3] * (width ))
                top = int(detected[0, 0,row, 4] * height )
                right = int(detected[0, 0, row, 5] * width )
                bottom = int(detected[0, 0, row, 6] * height )
                faceBoxes.append([left, top, right, bottom])
                cv2.rectangle(temp_image, (left, top), (right, bottom), (0, 255, 0), int(round(height / 150)), 8)
        return temp_image, faceBoxes
```

Gender Classification:

```
# Samples split into train set and testset
        traineddata, testdata, trainingLabel, testLabel = train_test_split(whole_data, sample_label,
test_size = 0.2, random_state = 30)
        PCA_cnt = int(self.samples_cnt / 10) # Principal Component Analysis - Numbers
        train_PCA = PCA(n_components = PCA_cnt)
```

```
        train_PCA.fit(traineddata)
        test_PCA = PCA(n_components = PCA_cnt)
        test_PCA.fit(testdata)
        # Create SVM Classifier
        svm_classifier = svm.SVC(kernel = 'poly', C = 1.0, gamma = 0.10000000000000001)
        trainLabels = np.array(trainingLabel[:])
        testLabels = np.array(testLabel[:])
        model = svm_classifier.fit(traineddata, trainLabels)
        # Save SVM Classifier
        dump(svm_classifier, self.svm_model)
        # Test the Classifier & Show the result
        test_classifier = svm_classifier.predict(testdata)
        T_F_N_P = confusion_matrix(testLabels, test_classifier)
        print("True & False - Negative & Positive:\n", T_F_N_P)
        accuracy = accuracy_score(testLabels, test_classifier)
        print("Accuracy is ", accuracy)
        report = classification_report(testLabels, test_classifier)
        print("Model Report is - \n", report)
```

Age prediction:

```
class AgeRecognition():
    """docstring for Age"""
    def __init__(self):
        self.ageProto="models/age_deploy.prototxt"
        self.ageModel="models/age_net.caffemodel"
        self.ageNet = cv2.dnn.readNet(self.ageModel, self.ageProto)
        self.age_category = ['(0-2)', '(4-6)', '(8-12)', '(15-20)', '(25-32)', '(38-43)', '(48-53)', '(60-100)']
        self.MODEL_MEAN_VALUES = (78.4263377603, 87.7689143744, 114.895847746)

    def predict_age(self, face):
```

```
    blob = cv2.dnn.blobFromImage(face, 1.0, (227,227), self.MODEL_MEAN_VALUES,
swapRB=False)
    self.ageNet.setInput(blob)
    guess_age = self.ageNet.forward()
    age = self.age_category[guess_age[0].argmax()]
    print("Age:{},confidence={:.3f}".format(age, guess_age[0].max()))
    return self.age_category[guess_age[0].argmax()]
```

Chapter 7

Conclusions & Future Scope

Conclusions

In this report, gender classification using dimensionality reduction techniques namely PCA along with SVM is presented.Along with age classification using deep learning CNN's Caffe model. Appearance-based approach is taken with the assumption that the input images are aligned and free of background clutter. Features are extracted after performing dimensionality reduction and classification is performed using SVM with Polynomial kernel.

There exist several algorithms which have been already implemented to generate a solution to the same project. We have implemented the kmeans algorithm (accuracy-53.72%) and EigenFace algorithm (accuracy-59.82%) which helped us to understand better about classification problems and finally we were able to pick the efficient one which was SVM (accuracy-94.70%) for gender classification.The accuracy using caffemodel was found to be 86.8% for age classification.In the current work, the database size was small. The performance of the approach can be better understood by using a larger database. It would also be interesting to see how the accuracy varies for people of different ethnicities. For this work all the highest ranking vectors found by PCA were used. For a large training set it would be computationally efficient to choose a subset of these components.

Future Scope

Proposed methodology can be improved further to gain higher accuracy in classification. More parameters can be added to represent the geometric variation of gender to the existing classifier in order to increase the performance. Reducing the gap between age ranges would result with a better classification of images into several age groups.

The joint efforts of all our members have made few applications of real-world face recognition achievable, but there are still several challenges to address and opportunities to explore for designing mature face recognition systems that can work in highly challenging environments and with images typically found within the social media environment. Hence, significant new research is required to face the technical challenges of face recognition.

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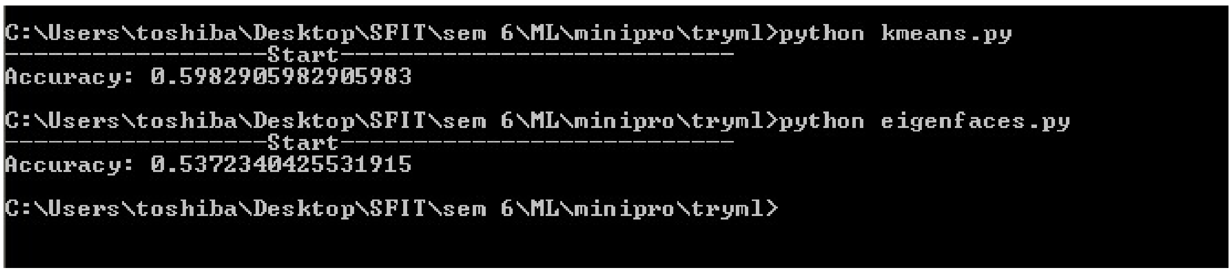
Appendix

Age and gender prediction using other algorithms :

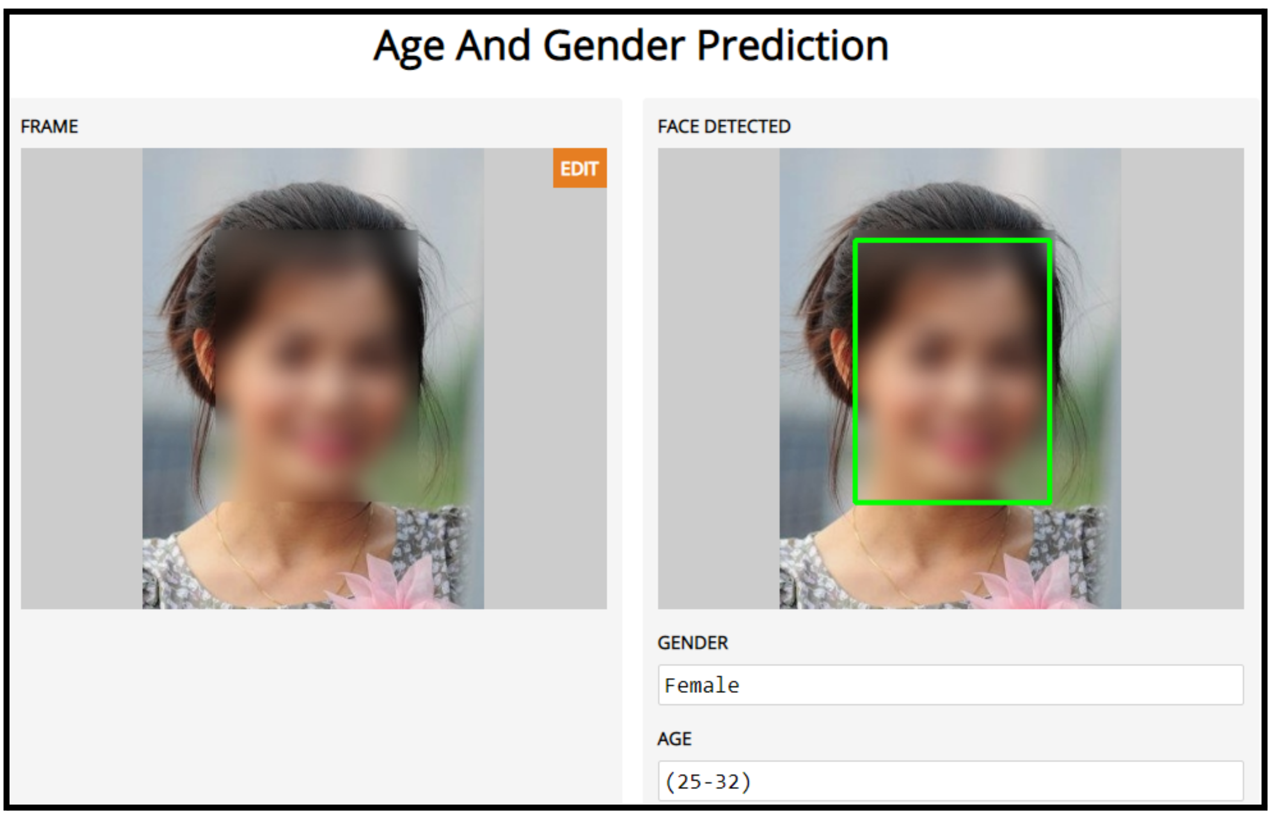
Sr no	Algorithms	Accuracy
I	K-means	53.72%
II	EigenFace	59.82%



```
C:\Users\toshiba\Desktop\SFIT\sem 6\ML\minipro\tryml>python kmeans.py
------------------Start---------------------------
Accuracy: 0.5982905982905983

C:\Users\toshiba\Desktop\SFIT\sem 6\ML\minipro\tryml>python eigenfaces.py
------------------Start---------------------------
Accuracy: 0.5372340425531915

C:\Users\toshiba\Desktop\SFIT\sem 6\ML\minipro\tryml>
```

FigA.1. Accuracy of k-means and eigenfaces

Age and gender prediction for blur image:

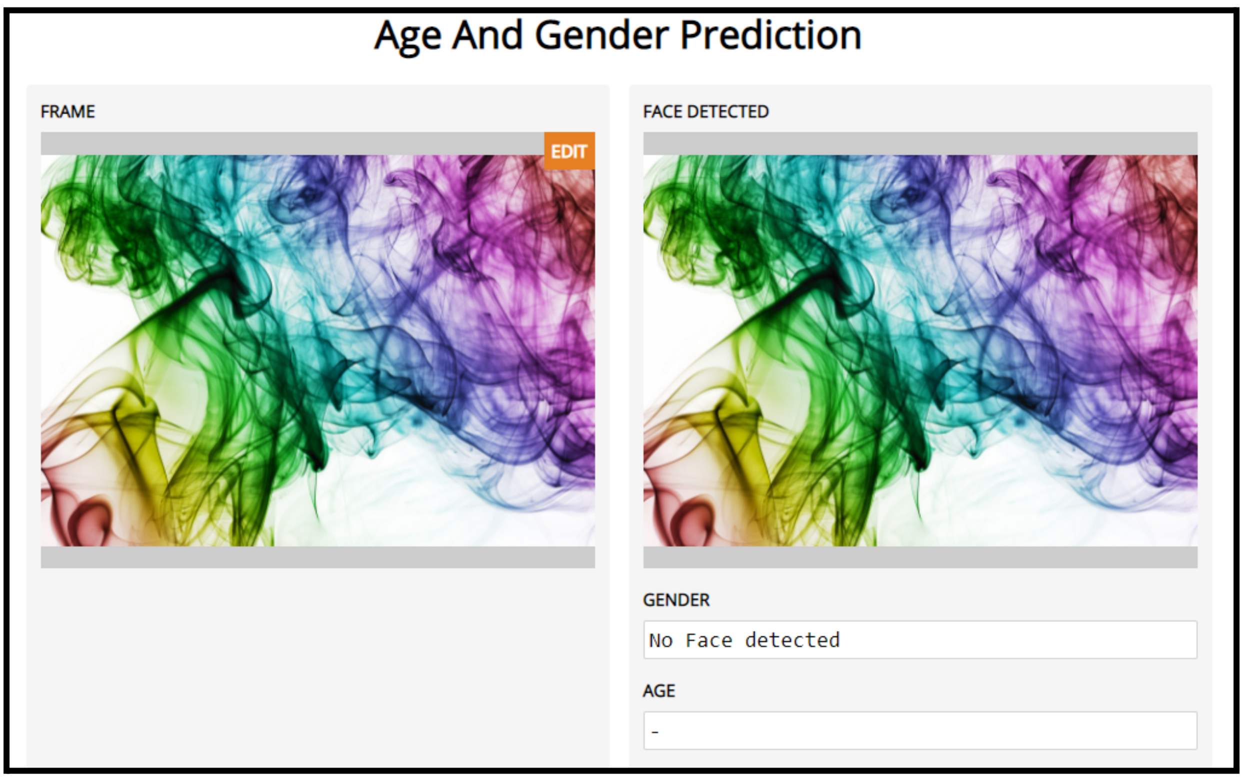


FigA.2. Output for blur face image

```
True & False - Negative & Positive:
 [[60  3]
 [ 5 83]]
Accuracy is  0.9470198675496688
Model Report is -
               precision    recall  f1-score   support

           f       0.92      0.95      0.94        63
           m       0.97      0.94      0.95        88

    accuracy                           0.95       151
   macro avg       0.94      0.95      0.95       151
weighted avg       0.95      0.95      0.95       151

Age:(25-32),confidence=0.309
```

FigA.3. Accuracy of the blur image

Age and gender prediction when no face is detected:



FigA.4. Output for no face detected