RAJKIYA ENGINEERING COLLEGE, BANDA, U.P.(INDIA)

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PROJECT REPORT

(BACHELOR THESIS)

ON

GENDER AND AGE DETECTION USING DEEP LEARNING

Session 2020-2021

Submitted to

Department of Information Technology

Under the Supervision of

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ABSTRACT

In the present scenario, the research under image processing has been rapidly transformed from machine learning to deep learning. The deep learning algorithms are usually applied in various areas like images to be classified or identified more accurately. In this Project, I will use Deep learning to accurately identify the gender and age of the person from a single image of a face. The predicted gender may be one of 'Male' and 'Female', and the predicted age maybe one of the following ranges-(0-2), (4-6), (8-12), (15-20), (25-32), (38-43), (48-53), (60-100). It is very difficult to accurately guess an exact age from a single image because of factors like makeup, lighting, obstruction and facial expression. And so, we make this a classification problem instead of making it one of regression. This task is accomplished using deep convolutional neural networks to achieve higher accuracy. Image pre-processing, feature extraction and recognition are three main identification steps which are taken under consideration. Proposed CNN classifier learns the features of facial images such as classification of age and gender by using hidden layers like convolutional layer, max pooling layer, dropout layers and fully connected layers. The model acquires knowledge related to features of OUI-Adience benchmark dataset in which 26,000 images are available, which helps to predict the correct category of unknown facial images with accuracy of 85% and minimum losses. Result is slightly better than the previous work that analyzes 80% of accuracy.

ACKNOWLEDGEMENT

I would like to express my deepest appreciation to all those who provided us the necessary support to complete this report. We would like to give special gratitude to our project guide, **Dr. Dhananjay Bisen Sir**, whose contribution in stimulating suggestions and encouragement, helped us to coordinate our project especially in writing this report. We want to express our sincere gratitude to all the faculty members without which we were incapable of bringing this report to its completion. I am grateful to (Project Coordinator) who guided us throughout the project and has also helped us mentally to be active to make the project meet its end. I also want to convey our sincere regards to **Dr. Vibhas Yadav** (Head of the department, Information Technology). I would also like to thank our colleagues for their precious suggestions.

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CHAPTER 1

INTRODUCTION

Facial analysis has gained much recognition in the computer vision community in the recent past. Human's face contains features that determine identity, age, gender, emotions, and the ethnicity of people. Among these features, age and gender classification can be especially helpful in several real-world applications including security and video surveillance, electronic customer relationship management, biometrics, electronic vending machines, human-computer interaction, entertainment, cosmetology, and forensic art. However, several issues in age and gender classification are still open problems. Age and gender predictions of unfiltered real-life faces are yet to meet the requirements of commercial and real-world applications in spite of the progress computer vision community keeps making with the continuous improvement of the new techniques that improve the state of the art.

Over the past years, a lot of methods have been proposed to solve the classifications problem. Many of those methods are handcrafted which perform unsatisfactorily on the age and gender predictions of unconstrained in-the-wild images.These conventional hand-engineered methods relied on the differences in dimensions of facial features and face descriptors which do not have the ability to handle the varying degrees of variation observed in these challenging unconstrained imaging conditions. The images in these categories have some variations in appearance, noise, pose, and lighting which may affect the ability of those manually designed computer vision methods to accurately classify the age and gender of the images. Recently, deep learning-based methods have shown encouraging performance in this field especially on the age and gender classification of unfiltered face images. In light of the current works in age and gender classification and encouraging signs of progress in deep learning and CNN, we therefore propose a novel end-to-end deep learning-based classification model that predicts age group and gender of unfiltered in-the-wild facial images. We formulate the age and gender classifications task as a classification problem in which the CNN model learns to predict the age and gender from a face image.

The contributions of this work are summarized as follows:
(1) We propose a model that uses CNN architecture to predict the age group and gender of human's faces from unfiltered real-world environments. The novel CNN approach addresses the age and gender labels as a set of discrete annotations and train the classifiers that predict the human's age group and gender.

(2) We design a quality and robust image preprocessing algorithm that prepare and preprocess the unfiltered images for the CNN model and this greatly has a very strong impact on the performance accuracy of our age and gender classifiers.
(3) We demonstrate that pretraining on large-scale datasets allows an effective training of our age and gender CNN model which enable the classifiers to generalize on the test images and then avoid overfitting.
(4) Finally, OIU-Adience benchmark is used to evaluate the performance of our novel CNN model, and despite the very challenging nature of the images in the dataset, our approach produces significant improvements in age group and gender classification accuracy over the state-of-the-art methods; the result can satisfy the requirements of several real-world applications.

CHAPTER 2

LITERATURE SURVEY

We began our background search with research papers and blog posts online, related to our topic. Face detection is used in biometrics, often as a part of (or together with) a facial recognition system. It is also used in video surveillance, human computer interface and image database management. Some recent digital cameras use face detection for autofocus [DCRP Review: Canon PowerShot S5 IS]. Face detection is also important for selecting regions of interest in images slideshows that use a pan-andscale Ken Burns effect. Face detection is gaining the interest of marketers. A webcam can be integrated into a television and detect any face that walks by. The system then estimates the race, gender, and age range of the face. Once the information is collected, a series of advertisements can be played that is specific toward the detected race/gender/age. This paper shows prototype or partial implementation of this type of work. Face detection is also being researched in the area of energy conservation [Energy Conservation].

Lanitis et al. proposed the first approach applying AAM to age estimation, which extracts craniofacial growth and skin aging during childhood and adulthood. Different classifiers (including shortest-distance classifier, quadratic function and neural networks) are compared when AAM is employed as the feature representation. The approach also differentiated between age-specific estimation, which is based on the assumption that the aging process is identical for everyone appearance-specific estimation, which follows the assumption that people who look similar tend to have similar aging processes.

Here is the table showing the some known researchers who worked on the “age and gender predection” using different methods and datasets.

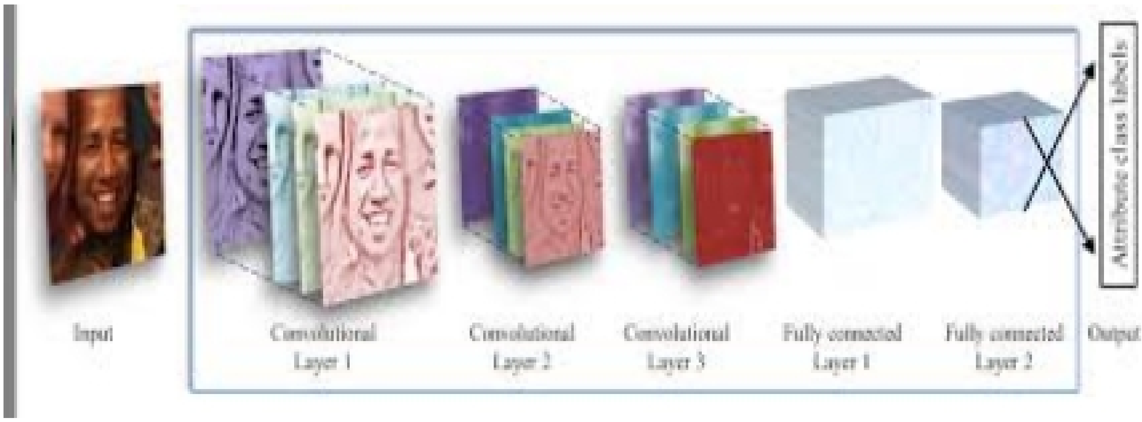
Author and publication	**Objective**	**Feature Extraction**	**Dataset**	**Performance**

Eidinger, Eran, Roee Enbar, and Tal Hassner.	Age and gender detection of unfiltered faces	SVM	LFW	88.8%
Amilia, Sindi, Mahmud Dwi Sulistiyo, and Retno Novi Dayawati.	Face image based gender recognition using neural network	ANN	FERET	80.7%
Nagpal, Shruti, Maneet Singh, Richa Singh, and Mayank Vatsa	Regularized DL for Face Recognition With Weight variable.	DEEP NEURAL NETWORK	FQ-NET	84.7%
Gil Levi and Tal Hassner	Age and Gender Classification Using CNN	CNN	ADIENCE DATASET	81%
Bulbul Agrawal, Manish Dixit	Age Estimation and Gender Prediction	CNN	IMDB-WIKI	86% approx.

CHAPTER 3

PROPOSED METHODOLOGY

The method that we used in our project is deep Convolutional Neural Network (deep CNN). A Convolutional neural network (CNN) is a deep learning algorithm and is one of the main categories to do images recognition, images classifications. CNN image classifications take an input image, process it and classify it under certain categories.



Before diving into the Convolution Neural Network, let us first revisit some concepts of Neural Network. In a regular Neural Network there are three types of layers:

Input Layers: It's the layer in which we give input to our model. The number of neurons in this layer is equal to total number of features in our data (number of pixels incase of an image).
Hidden Layer: The input from Input layer is then feed into the hidden layer. There can be many hidden layers depending upon our model and data size. Each hidden layers can have different numbers of neurons which are generally greater than the number of features. The output from each layer is computed by matrix multiplication of output of the previous layer with learnable weights of that layer and then by addition of learnable biases followed by activation function which makes the network nonlinear.
Output Layer: The output from the hidden layer is then fed into a logistic function like sigmoid or softmax which converts the output of each class into probability score of each class.
The data is then fed into the model and output from each layer is obtained this step is called feedforward, we then calculate the error using an error function, some common error functions are cross entropy, square loss error etc. After that, we backpropagate into the model by calculating the derivatives. This step is called Backpropagation which basically is used to minimize the loss.

Convolution Neural Networks or covnets are neural networks that share their parameters. Imagine you have an image. It can be represented as a cuboid having its length, width (dimension of the image) and height (as image generally have red, green, and blue channels). Now imagine taking a small patch of this image and running a small neural network on it, with say, k outputs and represent them vertically. Now slide that neural network across the whole image, as a result, we will get another image with different width, height, and depth. Instead of just R, G and B channels now we have more channels but lesser width and height. his operation is called Convolution. If patch size is same as that of the image it will be a regular neural network. Because of this small patch, we have fewer weights.

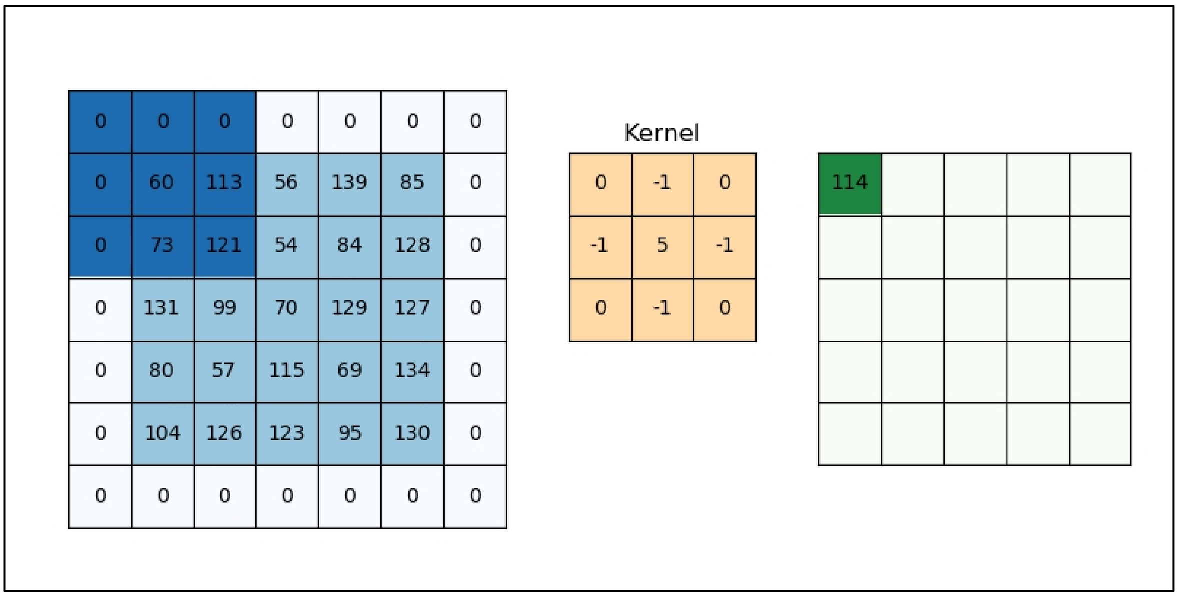
Layers used to build ConvNets:

A covnets is a sequence of layers, and every layer transforms one volume to another through differentiable function.

Let’s take an example by running a covnets on of image of dimension 227 x 227 x 3.

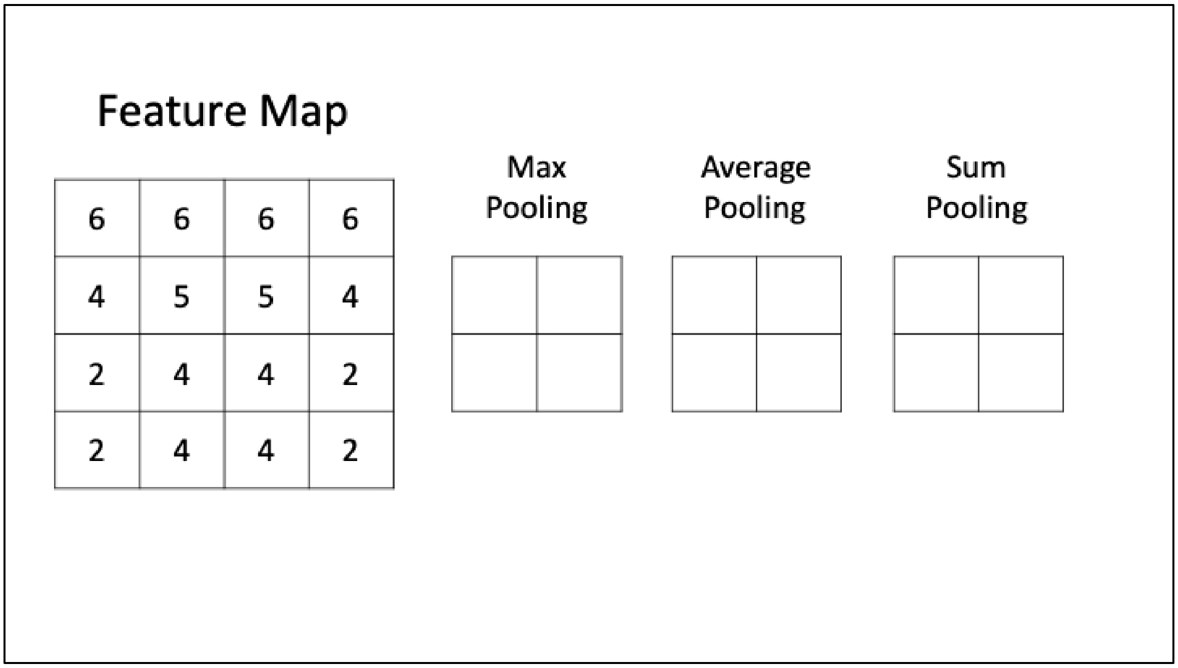
Input Layer: This layer holds the raw input of image with width 227, height 227 and depth 3.

Convolution Layer: This layer computes the output volume by computing dot product between all filters and image patch. Suppose we use total 96 filters for this layer we’ll get output volume of dimension 109 x 109 x 96.



Activation Function Layer: This layer will apply element wise activation function to the output of convolution layer. Some common activation functions are **RELU: max(0, x), Sigmoid: 1/(1+e^-x),** Tanh, Leaky RELU, etc. The volume remains unchanged hence output volume will have dimension 109 x 109 x 96.

Pool Layer: This layer is periodically inserted in the covnets and its main function is to reduce the size of volume which makes the computation fast reduces memory and also prevents from overfitting. Two common types of pooling layers are max pooling and average pooling. If we use a max pool with 2 x 2 filters and stride 2, the resultant volume will be of dimension 54x54x96.



Fully-Connected Layer: This layer is regular neural network layer which takes input from the previous layer and computes the class scores and outputs the 1-D array of size equal to the number of classes.

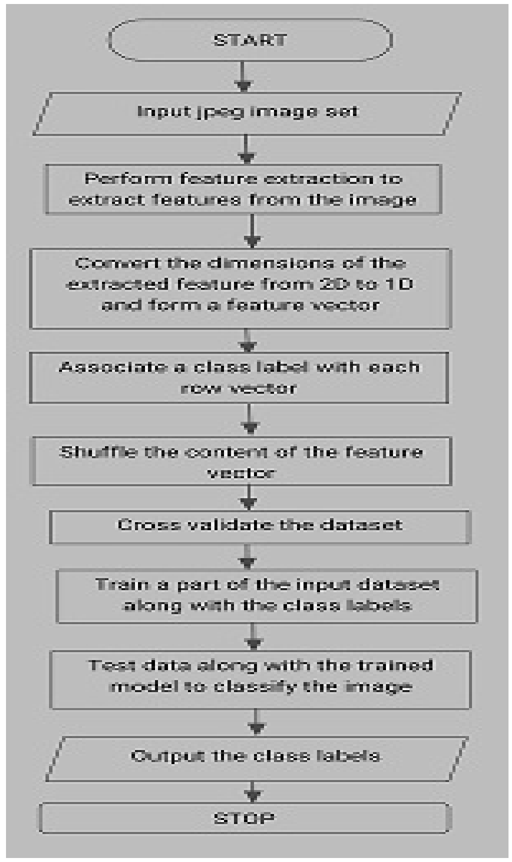
Dataset

For the age group and gender classification, we evaluate the proposed method on OIU-Adience dataset. OIU-Adience is a collection of face images from ideal real-life and unconstrained environments. It reflects all the features that are expected from an image collected from challenging real-world scenarios. They are face images that were uploaded to Flickr website from smartphone without any filtering. Adience images, therefore, display a high-level of variations in noise, pose, and appearance, among others. The entire collection of OIU-Adience dataset is about 26,580 face images of 2,284 subjects and with an age group label of eight comprising 0–2, 4–6, 8–13, 15–20, 25–32, 38–43, 48–53, and 60+.

	0-2	**4-6**	**8-13**	**15-20**	**25-32**	**38-43**	**48-53**	**60-**	**Total**
Male	745	928	934	734	2308	1294	392	442	8192
Female	682	1234	1360	919	2589	1056	433	427	9411
Both	1427	2162	2294	1653	4897	2350	825	869	19487

Table The AdienceFaces benchmark. Breakdown of the AdienceFaces benchmark into the different Age and Gender classes.

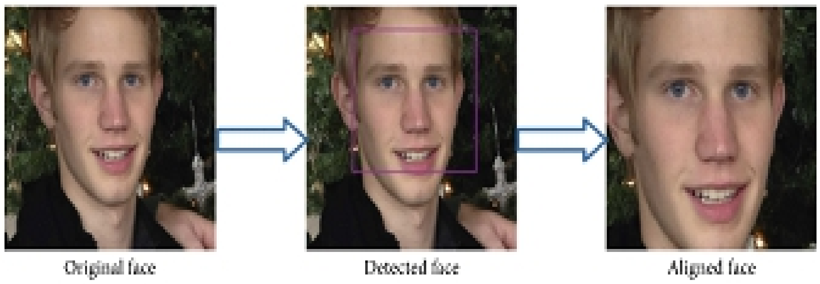
FLOW CHART



IMPLEMENTATION STEPS

1. Image Preprocessing

Intelligent age and gender classifiers tackle the classification task under unfiltered real-world settings. Most of those face images are not aligned and nonfrontal and also with different degrees of variations in pose, appearance, lighting, and background conditions. Therefore, those in-the-wild face images need first to be detected, then aligned, and, finally, used as input for the classifiers. The image preprocessing phase as shown in Figure.



2. Face Detection

The first stage of image preprocessing is face detection. The face detection phase locates the face in an input image. In this work, we employ an open-source face detector: Head Hunter described in. In order to detect a face, all the input images are rotated in the range of −90° to 90° angles and with the step of 5°. After that, the detector selects the input image with the best output of the face detector and in a case where the face is not detected in all the modifications of the input image, the original input image is upscaled and face detection algorithm is repeated until a face is detected. The upscaling helps in detecting faces in all the input images.

3. Landmark Detection and Face Alignment

After face detection, is the facial landmark detection and face alignment phase, where we employ the state-of-the-art solution in [55]. This image preprocessing solution is an open-source multiview facial landmark detection algorithm that uses five landmark detection models, including a frontal model, two half-profile models, and two full profile models. All of these five models are trained to work on one of the corresponding facial poses. The face alignment phase, on the other hand, entails running of all the five facial landmark models, on the detected faces. An affine transformation is then performed on the model, with the highest confidence score, to the predefined optimal settings of those landmarks.

4.CNN Architecture

- Provide input image into convolution layer
- Choose parameters, apply filters with strides, padding if requires. Perform convolution on the image and apply ReLU activation to the matrix.
- Perform pooling to reduce dimensionality size
- Add as many convolutional layers until satisfied
- Flatten the output and feed into a fully connected layer (FC Layer)

- Output the class using an activation function (Logistic Regression with cost functions) and classifies images.

5. Training Details

We describe the training details for age group and gender classifiers on OIU-Adience datasets benchmark. The age group classifier will be responsible for predicting the age groups of unfiltered human's face images into eight different classes, while gender classifier will classify those face images into two gender classes.

For all our experiments, we initialized and trained our CNN model from scratch, using the images and the labels of Adience datasets benchmark. We primarily pretrained the novel CNN architecture on the unfiltered facial aging dataset whose images are obtained directly from the website with some degree of variability and then fine-tuned the CNN on the images from the Adience dataset, to avoid overfitting and also to adapt the CNN model to face image contents of the task to perform. Finally, we tuned the network on the training part of the actual dataset (OIU-Adience) on which we evaluated. The fine-tuning allows the CNN to pick up the distribution, the particularities, and the bias of each dataset, hence improving the performance. For datasets we split it into two: 80% for training and 20% for validation. On the original OIU-Adience dataset, training and testing for both age and gender classification are performed using the standard 5-fold cross-validation procedure that is defined in recent literature.

6. Age Group Classification

We evaluate our method for classifying a person to the correct age group. We train our network to classify face images into eight age group classes and report the performance of our classifier on OIU-Adience dataset, a standard dataset benchmark for the existing methods for age group and gender classification. Our model, when evaluated on the dataset, obtains an exact accuracy of____. This improves over the best-reported state-of-the-art result for exact accuracy in Gil Levi and Tal Hassner by _____.

7. Gender Classification

We also evaluate our method for classifying a person to the correct gender. We assess the performance on the same Adience dataset consisting of labels for gender. For this task, we train our network for classification of two classes and report the result on exact accuracy, with pretraining on the datasets. We achieve an accuracy of _____compared to the previous state-of-the-art of Gil Levi and Tal Hassner showing an improvement of 3.0%. Our approach, therefore, achieves the best results not only on the age group estimation but also on gender classification.

8. Accuracy

Exact accuracy calculates the exact age group and gender results. It measures the percentage of face images that were classified into correct age group and gender, which is the ratio of the accurate predictions to the total number of the ground-truth labels.

$$\text{Exact Accuracy} = \frac{\text{No. Of accurate Prediction}}{\text{Total no. Of Predicion}}$$

CHAPTER 4

HARDWARE/SOFTWARE REQUIREMENTS AND SPECIFICATIONS

4.1 HARDWARE REQUIREMENT

4.1.1 PROCESSOR INTEL i5 2.1 GHZ

Developed and manufactured by Intel, the Core i5 is a computer processor, available as dual-core or quad-core. It can be used in both desktop and laptop computers, and is one of four types of processors in the "i" (Intel Core family) series. The first i5 processor was released in September 2009 and new generations of the i5 continue to be released (2020).

4.1.4 GPU 2 GB

A graphics processing unit (GPU) is a specialized electronic circuit designed to rapidly manipulate and alter memory to accelerate the creation of images in a frame buffer intended for output to a display device. GPUs are used in embedded systems, mobile phones, personal computers, workstations, and game consoles.

Open the Start menu on your PC, type "Device Manager," and press Enter. You should see an option near the top for Display Adapters. Click the drop-down arrow, and it should list the name of your GPU right there.

4.2 SOFTWARE REQUIREMENT

Software that are needed for the implementation of the model are Anaconda Navigator, It is a desktop graphical user interface (GUI) included in Anaconda distribution that allows you to launch applications and easily manage conda packages, environments, and channels without using command-line commands. Navigator can search for packages on Anaconda.org or in a local Anaconda Repository. It is available for Windows, macOS, and Linux. It offers many applications for the development like Jupyter Notebook, JupyterLab, Spyder, Pycharm, Rstudio and many more.

4.3 LIBRARY USED

NUMPY

NumPy is a basic level external library in Python used for complex mathematical operations. NumPy overcomes slower executions with the use of multi-dimensional array objects. It has built-in functions for manipulating arrays. We can convert different algorithms to can into functions for applying on arrays

PANDAS

Pandas is a must for data-science, It provides fast, expressive, and flexible data structures to easily (and intuitively) work with structured (tabular, multidimensional, potentially heterogeneous) and time-series data.

OPENCV

OpenCV is a huge open-source library for computer vision, machine learning, and image processing. OpenCV supports a wide variety of programming languages like Python, C++, Java, etc. It can process images and videos to identify objects, faces, or even the handwriting of a human. When it is integrated with various libraries, such as Numpy which is a highly optimized library for numerical operations, then the number of weapons increases in your Arsenal i.e whatever operations one can do in Numpy can be combined with OpenCV.

KERAS

It is an open-source neural network library written in Python designed to enable fast experimentation with deep neural networks. With deep learning becoming ubiquitous, Keras becomes the ideal choice as it is API designed for humans and not machines according to the creators.

SKLEARN

Scikit-learn is probably the most useful library for machine learning in Python. The sklearn library contains a lot of efficient tools for machine learning and statistical modeling including classification, regression, clustering and dimensionality reduction.

TENSORFLOW

TensorFlow is an open-source library developed by Google primarily for deep learning applications. It also supports traditional machine learning. TensorFlow was originally developed for large numerical computations without keeping deep learning in mind. However, it proved to be very useful for deep learning development as well, and therefore Google open-sourced it.

TensorFlow accepts data in the form of multi-dimensional arrays of higher dimensions called tensors. Multi-dimensional arrays are very handy in handling large amounts of data.

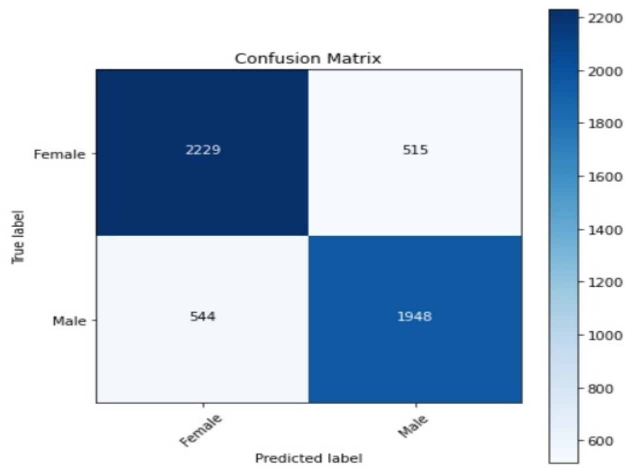
CHAPTER 5

RESULT AND DISCUSSION

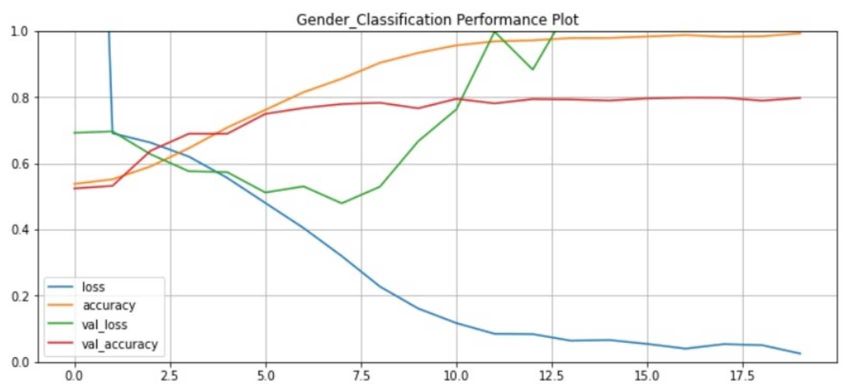
Gender Classification

We evaluate our method for classifying a person to the correct age group. We train our network to classify face images into eight age group classes and report the performance of our classifier on OIU-Adience dataset, a standard dataset benchmark for the existing methods for age group and gender classification. Our model, when evaluated on the dataset, obtains an exact accuracy of 79.89%.

Confusion Matrix for gender classification is shown below:



Graphical Calculation of Accuracy, val_accuracy, Loss and val_loss.



Accuracy 79.89%

F1 Score 0.797680800

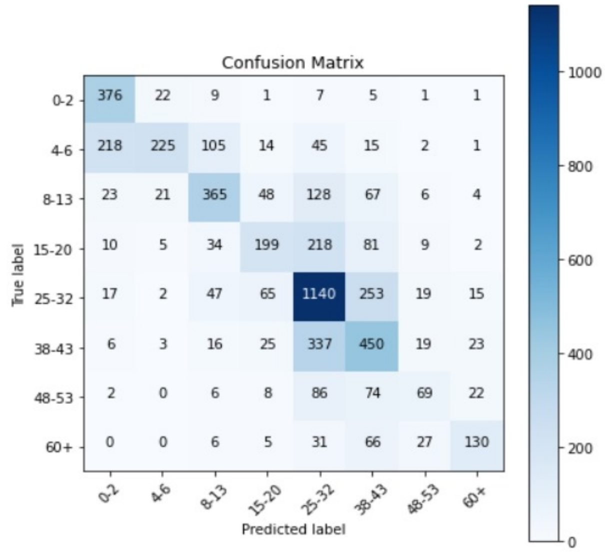
Recall Score 0.797746371

Precision Score 0.79764828

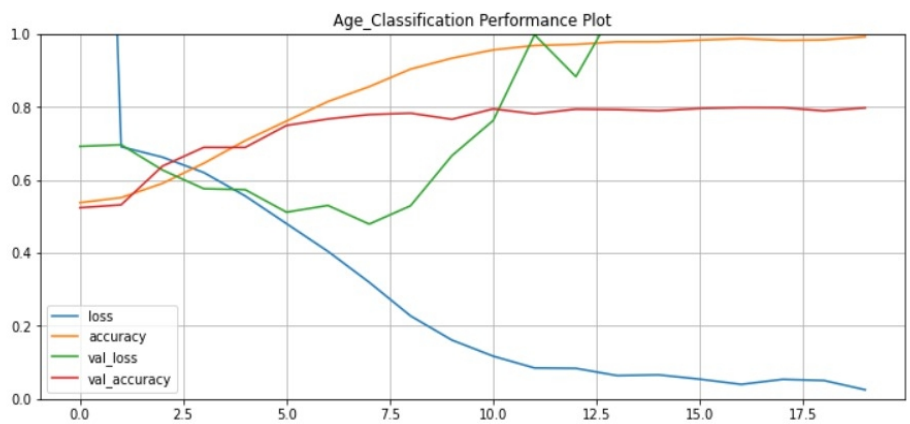
Age Classification

We also evaluate our method for classifying a person to the correct gender. We assess the performance on the same Adience dataset consisting of labels for gender. For this task, we train our network for classification of two classes and report the result on exact accuracy, with pretraining on the datasets. We achieve an accuracy of 60% approx.

Confusion Matrix for Age Classification is shown below:



Graphical Calculation of Accuracy, val_accuracy, Loss and val_loss.



Accuracy 60%

F1 Score 0.55159694

Recall Score 0.564171

Precision Score 0.58106072

CHAPTER 6

CONCLUSION AND FUTURE SCOPE

Though many previous methods have addressed the problems of age and gender classification, until recently, much of this work has focused on constrained images taken in lab settings. Such settings do not adequately reflect appearance variations common to the real-world images in social websites and online repositories. Internet images, however, are not simply more challenging: they are also abundant. The easy availability of huge image collections provides modern machine learning based systems with effectively endless training data, though this data is not always suitably labeled for supervised learning. Taking example from the related problem of face recognition we explore how well deep CNN perform on these tasks using Internet data. We provide results with a lean deep-learning architecture designed to avoid overfitting due to the limitation of limited labeled data. Our network is "shallow" compared to some of the recent network architectures, thereby reducing the number of its parameters and the chance for overfitting. We further inflate the size of the training data by artificially adding cropped versions of the images in our training set. The resulting system was tested on the Adience benchmark of unfiltered images and shown to significantly outperform recent state of the art. Two important conclusions can be made from our results. First, CNN can be used to provide improved age and gender classification results, even considering the much smaller size of contemporary unconstrained image sets labeled for age and gender. Second, the simplicity of our model implies that more elaborate systems using more training data may well be capable of substantially improving results beyond those reported here.

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