

# EXTRAPOLATION OF AGE AND GENDER USING CONVOLUTIONAL NEURAL NETWORKS

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## ABSTRACT

Age and sexual orientation order has gotten pertinent to an expanding measure of uses, especially since the ascent of social stages and web-based social networking. In the current paper, we will formulate and carry out estimation of age and extrapolation of gender from scratch with Keras. The face detection is accomplished by practicing a pre-trained facenet model. Our work is carried out by handling a UTK dataset. We produced an image output along with the confidence and accuracy of an image regarding the age and gender of a singular personality.

**Key-words:** Keras, Facenet Model, Convolutional neural networks.

## 1. INTRODUCTION

Practical facial element extraction is critical for face arrangement, which is a fundamental handling step between face discovery and acknowledgment. This paper expects to fabricate a face acknowledgment framework to anticipate age and sexual orientation which are utilized in inserted or potentially buyer applications.

In this context, a very comprehensive, distributed input dataset is practiced so that the Neural Network can read the numerous features it constrains for the classification. Training a model from scratch requires thousands of detailed, high-quality training data. As training data, we are going to scrape a few images using the UTK dataset. The confusion matrix unveils how the classification model is confused when it performs predictions. It provides us insight not only about the errors being made by a classifier but also the types of errors that are being made.

This paper is composed of different sections. It starts with a literature survey in the context of present work. We will start by explaining about problem statement. Then we will move on to the process flow. Further we talk about methodology. Then we present results that we had obtained by performance evaluation. Lastly about the conclusion and future scope.

## 2. LITERATURE SURVEY

By contemplating portrayals through the utilization of profound convolutional neural systems (CNN), a huge promotion in execution is caught on the actualized assignments [1]. The VGG engineering concerning the facenet model is utilized. The UTK dataset having face pictures with sexual orientation and age labels was favored as the dataset [2]

FaceNet empowers us to legitimately recognize a associating from face pictures to a compacted Euclidean space where separates undeviatingly epistolize to a proportion of face distinguishing proof. When this space has been imagined, tasks, for example, face acknowledgment, check, and grouping can be easily executed utilizing standard systems with FaceNet embeddings as highlight vectors [3]. A subset of properties is planned over the transferred pictures dependent on the appropriation power. A one of a kind trait is assessed at one time [4]. Face photos of characters are prepared to use convolutional neural systems [2].

Another inclusion of highlights like inclusion of picture smoothing, skeletonization, edge recognition, ebb and flow, and shape depictions are accessible for a superior impact of extrapolation old enough and sexual orientation of individual characters [5]. Through the course, we proposed an oversimplified neural network which can be utilized in any event, when the essentialness of preparing information is limited [1]. Executing the UTK face dataset we transferred single front confronted symbols with the end goal that no combined examples are polished. Two systems are exacted on encoder and generator for extrapolating the precise age and sex of an individual [8].

Two differentiating models are sketched out utilizing the convolutional neural system. The structures are created for the extrapolation old enough and sexual orientation separately [6]. We marshaled the venture utilizing the Keras which is written in Python. Through this, we were able in encouraging quickened experimentation with profound neural systems that combine on being negligible, measured and extensible [7]. The yield exactness of about 99.69 % is conveyed utilizing the strategy [3]. The results are shown by the engaging presentation and adaptability of the presented structure by standing out it from the best in class and ground truth.

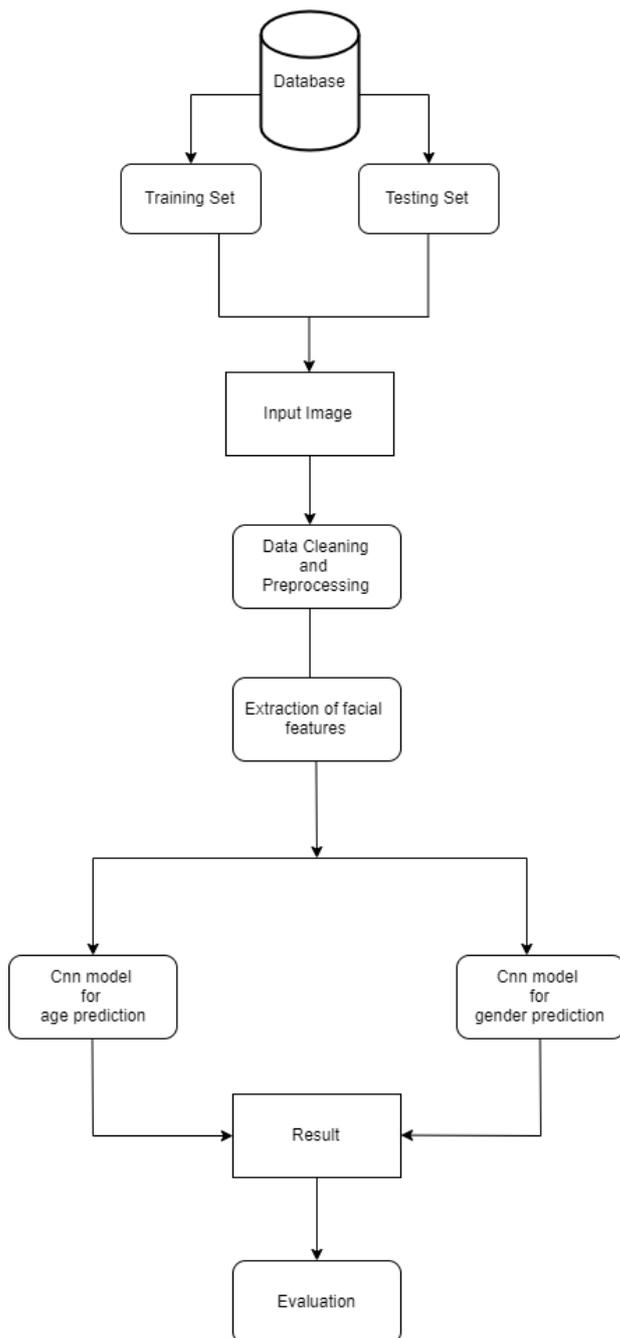
## 3. PROBLEM STATEMENT

There is a need to identify age and gender for preventing credit card fraudulent activities or imposing gender based constraints in dating sites. The manual way of identifying age and gender has become difficult. Thus there has been a dire necessity that compelled researchers to work on predicting age and gender. Estimating age and gender using thumbnails of people is actively going research.

Gender has been treated as a classification problem. As opposed to treating age as a regression problem Although we expect age to be a number as output, we treated age as categorical problem and divided into 100 classes. Keras, a python library has been used for modeling. Estimating model accuracy and loss has become easy with the use of Keras.

## 4. PROCESS FLOW

This flow will give the demonstration of how the project is carried out.



## 5. METHODOLOGY

### 5.1 Data Acquisition:

Data acquisition is all about curating the data we need to carry our study on. We can apply an analogy of the foundation of a house as to data to a model. The data we collect should be sound enough when we are working on developing a solution to the problem.

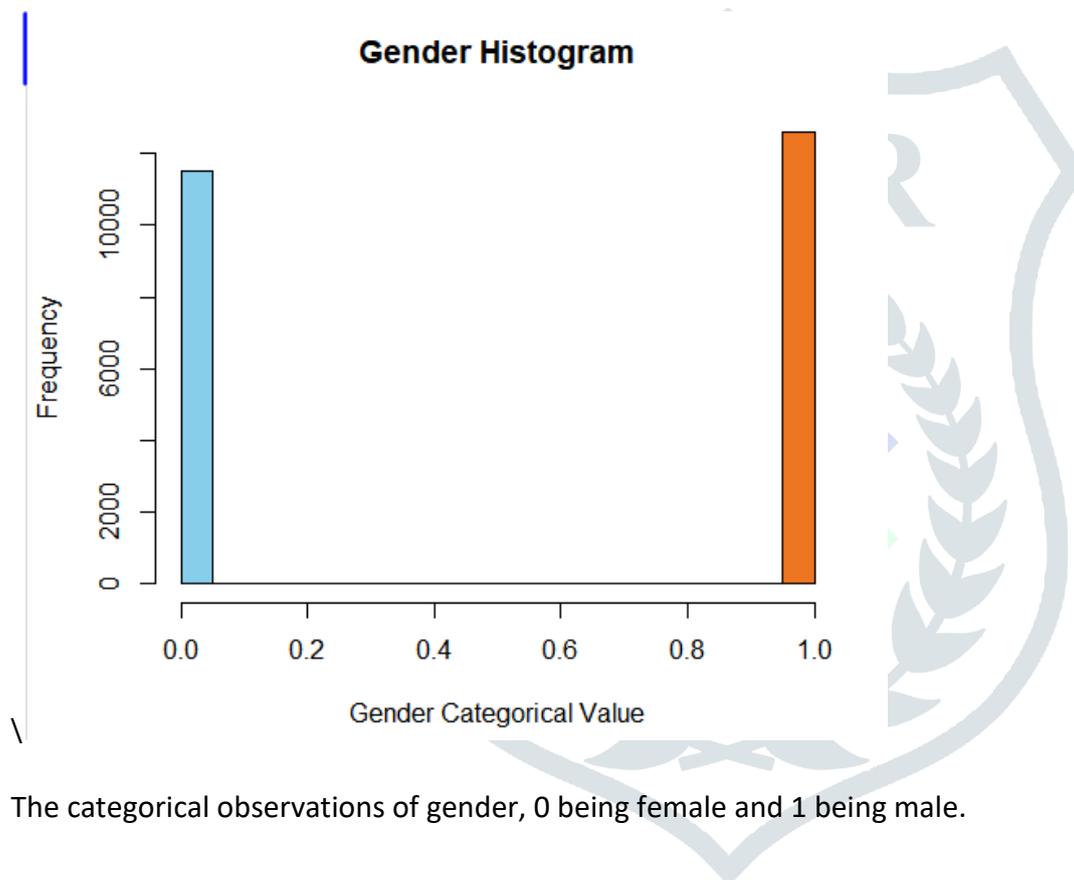
In this project we used utk face dataset [ ] which consists about 20,000 facial images of people of various ages, genders and ethnicity. It contains demographic characteristics like age, gender of the person and the race, the person belongs to along with the time at which the image was collected.

## 5.2 Data Preparation:

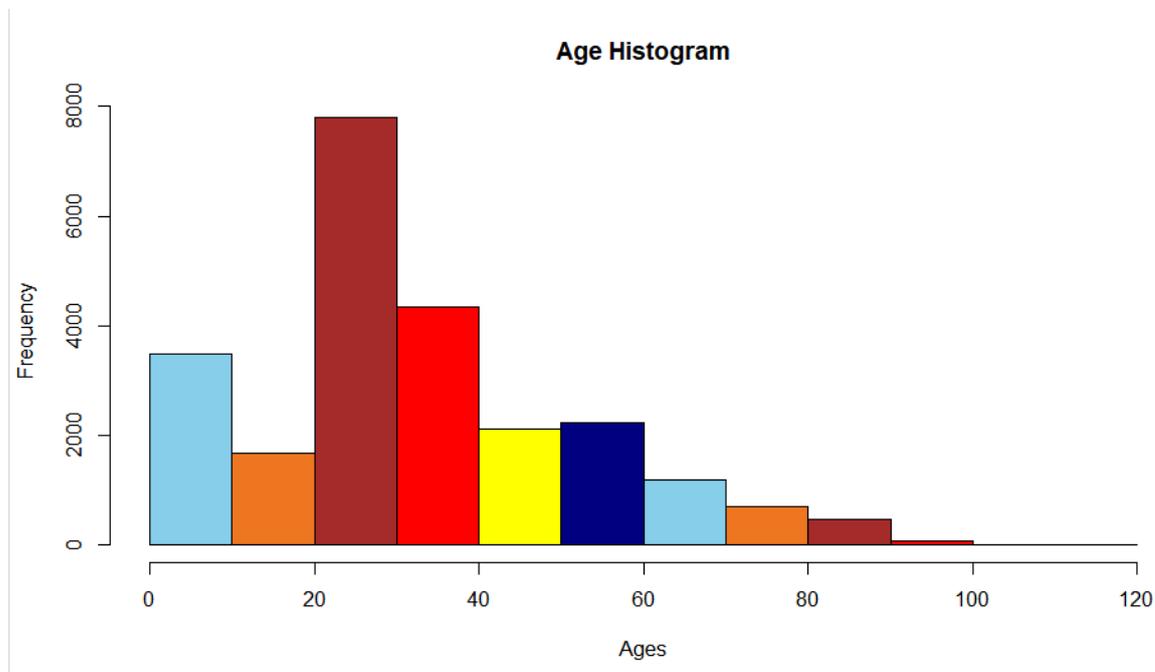
Oftentimes the success rate is attributed to the extent we preprocess the data. Erroneous and faulty data heads to deteriorated results. The competence of the model depends on the quality of data we choose. Various practices like feature scaling, normalization, handling outliers, etc should be employed when we are preprocessing the data.

## 5.3 Data Visualization:

Visualizing the data to see give the insight of our data set.



The categorical observations of gender, 0 being female and 1 being male.



The ages are plotted in the histogram based on the frequency count.

#### 5.4 Modeling Using Convolutional Neural Network

Cnn is the spine of today's frontline innovations which includes facial recognition, humanoids, self-driving cars and many more. The key of a cnn model relies in the convolutional layers. In this project we have employed 3 cnn layers.

It takes in parameters such as inputs, filters and kernel size. We apply input only to the first layer of the cnn.

##### Conv2D

This layer generates a convolution kernel which helps to produce a tensor of outputs with input layers. Conv2D is the first layer of the model, it takes input shape and 32 filters are provided with a kernel size of 3 along with relu as activation function.

##### Pooling Layer

Maxpooling aids in diminishing the dimensions where further assumptions can be made about features contained. We have given pool size as 2 in the model.

##### Dropout Layer

Dropout is a method adopted which helps in enhancing over-fitting in neural networks. We use dropout layers after maxpooling layers. In dropout we randomly shutdown fraction of a layer's neurons at each training step by zeroing out the neuron values. We took a dropout rate of 0.3.

##### Flatten

Using flatten we convert the data into a 1-d array so that we can give it as input to the following layer. Also, we create a single feature vector to flatten the output which is further connected to the ultimate classification model also known as a fully-connected layer.

## Dense

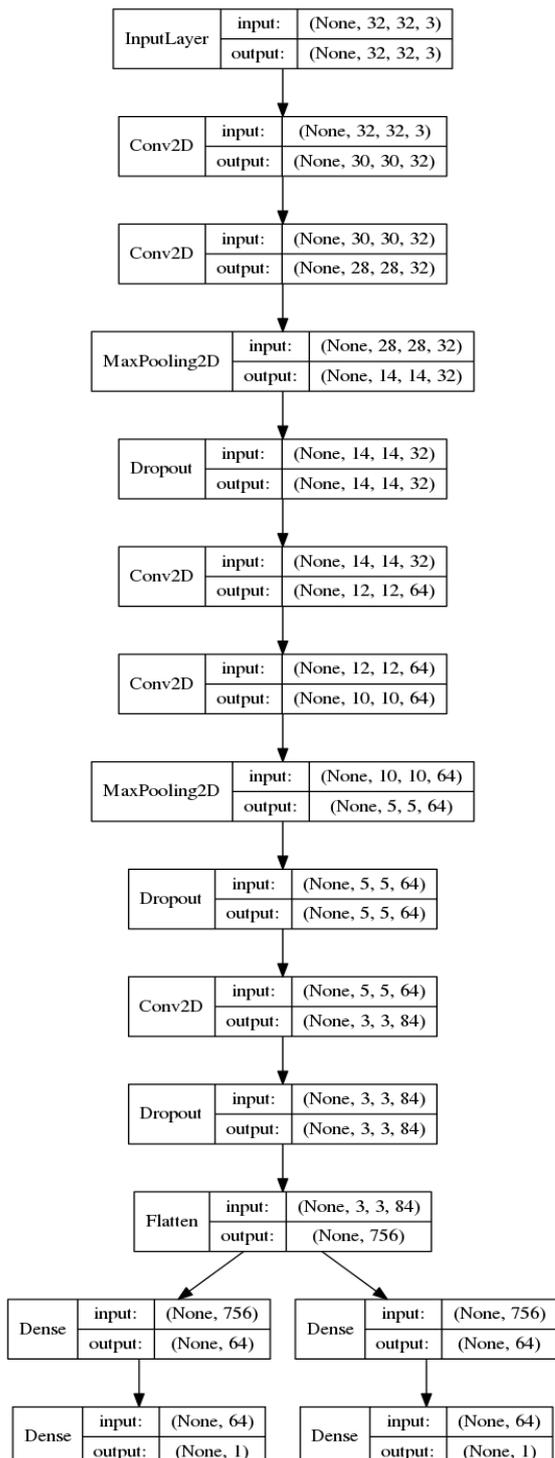
Individually every neuron gets an input from the ones which are present in the former layer, which makes them densely connected. 64 units are given, which denotes the output constraint space dimensions.

## Relu

Relu is an activation function which returns 0 for negative input and the same value incase of positive input.

$$f(x) = \begin{cases} x & \text{if } x > 0, \\ 0.01x & \text{otherwise.} \end{cases}$$

Below is the flow diagram of cnn model employed in our project.



## 6. PERFORMANCE EVALUATION

### Accuracy

It tells the number of accurate predictions made to the number of total predictions.

$$\text{Accuracy} = \frac{\text{Number of Correct predictions}}{\text{Total number of predictions made}}$$

The model has yielded an gender classification accuracy of 0.8935 and 0.7735 for age prediction

### Precision

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

The model recorded a precision of 0.8835 for gender classification and 0.8211 for age prediction respectively

### F1 score

$$F_1 = \left( \frac{\text{recall}^{-1} + \text{precision}^{-1}}{2} \right)^{-1} = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}$$

The model recorded a f1 score of 0.8732 for gender and 0.8923 for age prediction.

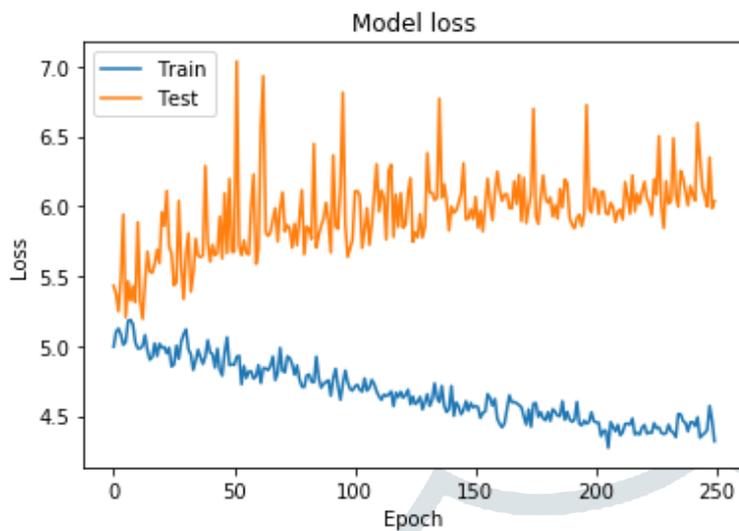
### Mean Absolute Error (MAE)

$$\text{MAE} = \frac{\sum_{i=1}^n |y_i - x_i|}{n} = \frac{\sum_{i=1}^n |e_i|}{n}$$

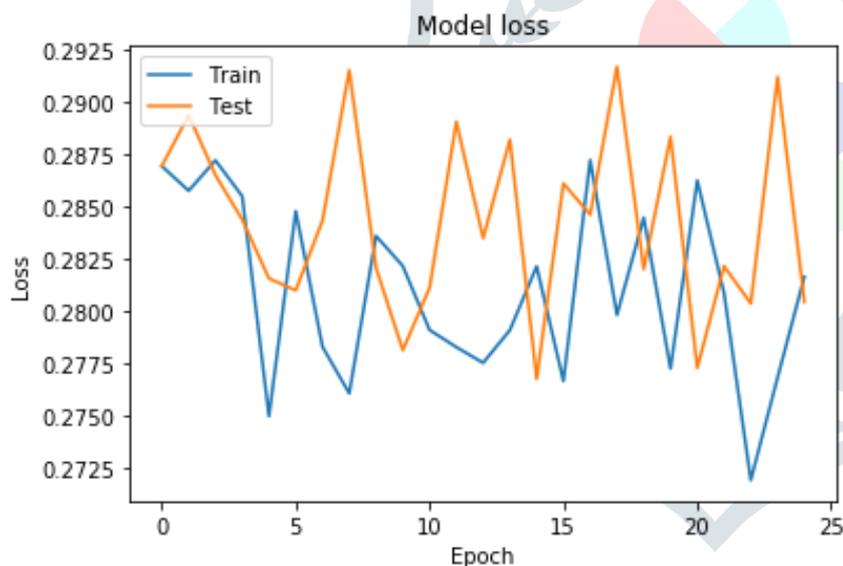
MAE is one of the several ways of comparing estimations with their final results. Used Adam Optimizer alongside binary cross-entropy loss . This motivates in the calculation of the loss for every cnn output vector independently.

## Loss

Plotted loss versus epoch for age prediction.



Plotted loss versus epoch for gender prediction.



## 7. CONCLUSION

This paper focuses on extrapolation old enough and sexual orientation from facial pictures utilizing Convolutional Neural Networks. We have built up an apparent age and sexual orientation indicators without any preparation based pictures using the UTK dataset. This task is exceptionally convenient, reasonable and can effectively be actualized. The proposed approach is increasingly helpful regarding velocity and exactness. Single frontal human appearances with two sexual orientation gatherings and age gatherings (0-100 classes) are recognized effectively with a decent achievement rate.

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