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# Human Age and Gender Prediction from Facial Images Using Deep Learning Methods

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**Abstract**

Human age and gender prediction from facial images has garnered significant attention due to its importance in various applications. Traditional models struggle with large-scale variations in unfiltered images. Convolutional Neural Networks (CNNs) have emerged as effective tools for facial analysis due to their robust performance. This paper presents a novel CNN approach for robust age and gender classification using unconstrained real-world images. The CNN architecture includes convolution, pooling, and fully connected layers for feature extraction, dimension reduction, and mapping to output classes. Adience and UTKFace datasets were utilized, with the best training and testing accuracies achieved using an 80% training and 20% testing data split. Robust image pre-processing and data augmentation techniques were applied to handle dataset variations. The proposed approach outperformed existing methods, achieving age prediction accuracies of 86.42% and 81.96%, and gender prediction accuracies of 97.65% and 96.32% on the Adience and UTKFace datasets, respectively.



*Keywords:* Convolutional neural network; Pre-processing; batch normalization ; Pooling ;Dropout ; Optimizers

## 1. Introduction

From a face image of human being we can predict age, gender, ethnic, emotion etc. Normally, human being can easily predict human age and gender from the face structure, hair style, skin texture, wrinkles etc. But it becomes a challenging matter if we want to make a system to estimate age as well as gender of human from their picture.

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Because machines don't have ability to think like human being. So, we will have to make machine understand that using some sample dataset and classification algorithm. Automatic age and gender prediction study has a huge amount of untapped potential. There is a continuously rising interest in this area due to the immense potential it shows in several fields of computer science. This field has many dynamic applications such as - age related restriction system, law enforcement, human-computer interaction, security control, cosmetics suggesting, forensics, automated translation service and speech generation etc. It can provide very effective applications in the field of IoT. For example, clothe stores can offer appropriate fashions, restaurants can select their themes, based on the average age or gender of customers who have come until then.

In past years, research on human age and gender classification has explored various methods, including face, ear, and wrinkle features [37]. Techniques such as Principal Component Analysis (PCA)[31], Support Vector Machine (SVM)[22, 24, 25, 26], and Neural Networks (NN)[28] have been utilized for age and gender classification [7]. Traditional hand-engineered methods rely on facial descriptors and features, but struggle with the diverse complexities of unfiltered image variations [13]. Deep learning approaches have shown significant success in image classification, with Convolutional Neural Networks (CNNs)[9] emerging as the top performer for age and gender prediction from unconstrained images [33, 4]. Our proposed CNN model leverages this capability, trained with ample data to achieve optimal performance metrics.

The significant contributions of our work are:

1. We suggest a CNN model which is used to predicting the age and the gender group from unconstrained real world images. This model is designed in such a way that it can mitigate the computational cost.
2. We utilise a standard and vigorous image pre-processing technique which processed the unconstrained images for the CNN model. It strongly affects the performances of age and gender classification.
3. Normalization is used to remove redundant data, reduce cost. Further augmentation is employed to decrease overfitting.
4. We evaluate the proposed model using two different dataset, which include variations and different age and gender label.
5. Optimization is utilised to reduce the error between predicted and real value.
6. We have also applied several pre-trained CNN models to identify which model is batter.

The next chapters of the paper are organized accordingly: Section 2 describes some previous work on age and gender prediction, Section 3 narrates the methodology that has been applied to design our proposed model, Section 4 provides the result of our system and comparison with other approaches, finally Section 5 concludes the research and mentions future scopes.

## 2. Literature Review

Age and gender prediction in image processing and machine learning has been addressed by various methods. Early systems employed conventional techniques such as Support Vector Machine [12, 5], Local Binary Pattern [6], and Linear Regression [10]. In recent studies, pre-trained approaches like VGG16, Squeeze-and-Excitation (SENet50), and Residual Networks (ResNet50) have been utilized with fine-tuning for age prediction [36]. CNN architectures have also been applied, achieving 82.2% accuracy for gender and 57.5% for age prediction [32]. Liu et al. employed a CNN with a multi-class focal loss function, reaching 60.4% accuracy on the Adience dataset [20]. Afnan et al. developed a CNN for age and gender classification, achieving 79.122% and 94.94% accuracy, respectively [34]. Rojas et al. utilized Efficient-Net models, with B4 providing accuracies of 73.5% and 81.1% on UTKface and Adience datasets [3]. Ranjan et al. achieved 52.9% accuracy for age estimation using a DCNN model [8]. These studies highlight the diverse approaches and accuracies in age and gender prediction using CNNs and pre-trained models.

## 3. Methodology

In our implemented system, Convolutional Neural Network has been utilized. This deep learning model is able to differentiate images using their characteristics [15] . It is normally used for video recognition, image analysis, image segmentation, image classification etc [14]. In this research work, first of all we have applied pre-processing technique to convert the primary data into an efficient format. After that the CNN model has been employed which has been comprised of feature extraction and classification. In our system, convolution and pooling layers are used for extracting features of image for making decision. And fully connected layer is used for classification.

### *3.1. Dataset*

The first step of age and gender prediction from face image is collection of dataset with age and gender level. There are several ways of collecting dataset. We can capture image from camera or can collect a large number of images from internet. Except this, there are several datasets of face images with age and gender label. From several available datasets of age and gender prediction in this paper, we have used Adience dataset and UTKFace dataset.

#### *3.1.1. Adience*

Adience dataset is a collection of large amount of unfiltered data [12] . We have categorized all images based on their age and gender. There are eight categories for age prediction - (0-2), (4-6), (8-12), (15-20), (25-30), (38-43), (48-53), (60+). And two categories for gender prediction- man and woman.

#### *3.1.2. UTKFace*

UTKFace is a dataset of 20000+ facial images of people between 0 to 100 years[38]. The images have variations in facial expressions, poses, lightening conditions, resolution, etc. It can be used face detection, age classification, gender classification etc. This dataset is also categorized as like Adience dataset.

Figure 1 shows samples of dataset from Adience benchmark and UTKFace.

(a)

(b)

Fig. 1: Dataset : a)Adience, b)UTKFace

### *3.2. Pre-processing*

The images of the datasets that have been used in this paper need to be pre-processed before being input into the CNN. Face detection, landmark detection, face alignment and normalization are performed here. These steps help normalizing and aligning faces to a standard position, which allow proper comparison and measurement.

#### *3.2.1. Face Detection*

At first, a face detection algorithm has been applied which spontaneously detects the facial location and localizes them with a four-sided demarking box in the images. Facenet has been used to extract some features such as nose, eyes, and mouth by providing the bottom, right, the top, and left coordinates of the face. If any face is identified in an image, then the algorithm crops out the face, if no face is identified, then the image is dispelled. We have selected this algorithm for it's ability of handling images of different orientations, detecting faces across diverse scales, and appropriately handling occlusions.

#### *3.2.2. Facial Landmark Detection and Alignment*

After identifying the face, the landmark identification and the face alignment have been performed utilizing the same Facenet. The algorithm chooses the spatial points on the faces for the important notations. Upon detecting the facial keypoint, the algorithm has been used to measure the distances between these points, considering the obtained values as the features of face. In the procedure of face alignment, facial keypoints have been utilised for capturing images from various corner, enabling to match the extracted features.

### 3.2.3. Data Normalisation

Then the Min-Max technique has been used to normalise the images as neural networks perform superior on normalized data. Normalization is a rescaling technique over actual images which turn all values into a new range between 0 to 1. The Min-Max normalisation carries out linear transformation over the actual data and preserves the connection among the actual data values.

$$N' = \frac{\mathrm{N - minvalueofN}}{\mathrm{maxvalueofN - minvalueofN}}(\mathrm{D - K}) + \mathrm{K}$$

### 3.2.4. Data Augmentation

After the normalization process, augmentation technique has been employed over the images. Various methods have been explored for observing the impact of overfitting and investigating how augmentation can increase the accuracy of classification[21]. The ImageDataGenerator function has been used for augmenting data. The settings that have been applied for data augmentation - Rotation(45), Shear(0.2), Zoom(0.15), Horizontal flip(True).

### 3.3. CNN model

The Convolutional Neural Network (CNN), inspired by the human brain [19], consists of layers like Convolution, Activation, Pooling, and Fully Connected. Convolution applies filters to extract texture and edges from images, while Pooling reduces dimensionality. Flattening converts data for Fully Connected layers, and Dropout prevents overfitting [35]. The architecture starts with a 32-filter convolutional layer, ReLU activation, and batch normalization, followed by max pooling. Subsequent layers include sets of convolutional layers with increasing filters, ReLU activation, batch normalization, and max pooling. The final layers include a fully connected layer with ReLU activation, dropout, and softmax and sigmoid functions for age and gender classification. This architecture effectively processes features for age and gender classification.

## 4. Result and Discussion

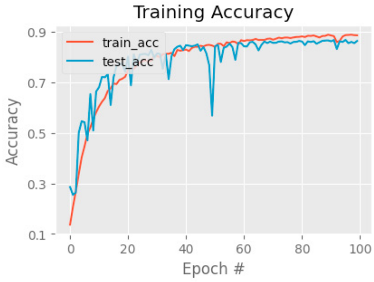
### 4.1. Comparison of results among different optimizers

Table 1 illustrates the accuracies for both dataset using different optimizers. We used Adam, Adamax, Adagrad, SGD and Adadelta optimizers in our system and have got best accuracy using Adam optimizer for both age and gender prediction.

Table 1: Accuracy using different optimizers

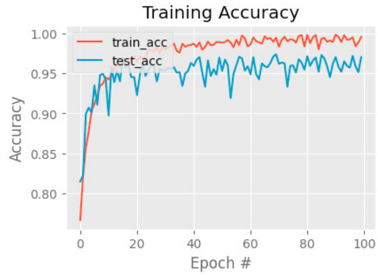
| | Adience Dataset | | UTKFace Dataset | |
|---|---|---|---|---|
| Optimizers | Age Acc | Gender Acc | Age Acc | Gender Acc |
| Adam | 86.42% | 97.65% | 81.96% | 96.32% |
| Adamax | 79.31% | 90.53% | 76.88% | 90.02% |
| Adagrad | 75.22% | 84.37% | 72.56% | 82.89% |
| SGD | 69.56% | 79.43% | 67.69% | 77.92% |
| Adadelta | 62.56% | 76.65% | 59.12% | 73.25% |

Accuracy measures how accurately a model can predict compared to the correct data value. In addition, loss is the quantity of errors created for each example in training or testing sets. From the loss value we can see how faintly or clearly a model treats each iteration of optimization. Figure 2 shows the accuracy and loss curves of both age and gender prediction model using Adience dataset.




a) Age accuracy


b) Age loss



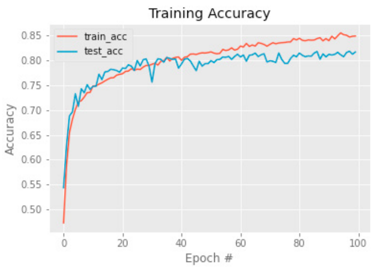

a) Gender accuracy


b) Gender loss

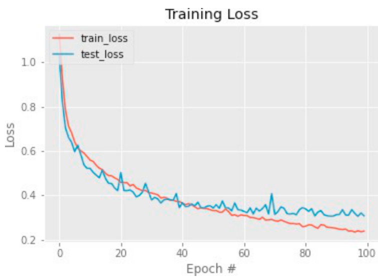
Fig. 2: Training accuracy and loss curves of both age and gender prediction model using Adience dataset.

In the above curves the training and testing accuracy of age prediction increasing respectively from 13.57% to 89.91% and from 29.96% to 86.42%. And the training and testing loss of age prediction decreasing respectively from 1.58 to .06 and from 1.57 to .16. Whereas the training and testing accuracy of gender prediction increasing respectively from 76.23% to 99.94% and from 81.37% to 97.65%. And the training and testing loss of age prediction decreasing respectively from .68 to .02 and from .48 to .15.

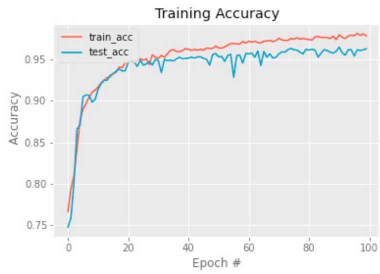
And Figure 3 shows the accuracy and loss curves of both age and gender prediction model using UTKFace dataset.



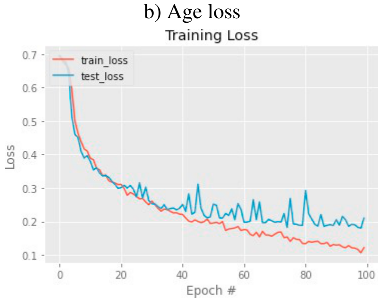

a) Age accuracy




b) Age loss




a) Gender accuracy



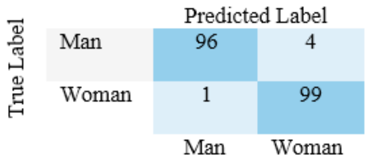

b) Gender loss

Fig. 3: Training accuracy and loss curves of both age and gender prediction model using UTKFace dataset.

In figure 3 the training and testing accuracy of age prediction increasing respectively from 46.05% to 85.01% and from 54.89% to 81.96%. And the training and testing loss of age prediction decreasing respectively from 1.17 to .22 and from 1.02 to .31. Whereas the training and testing accuracy of gender prediction increasing respectively from 77.05% to 98.25% and from 75.99% to 96.32%. And the training and testing loss of age prediction decreasing respectively from .69 to .12 and from .70 to .22.

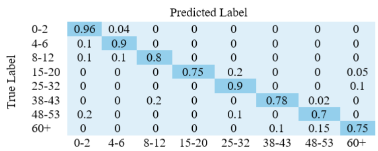
Generally, confusion matrix summarizes the prediction outcomes of a classification problem. Figure 4 and 5 show the confusion matrices of Adience dataset and UTKFace dataset respectively. From these confusion matrices we can determine the performances of our system.


a)Age

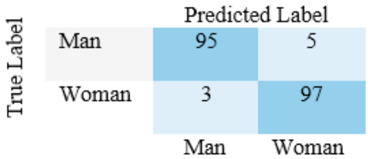



b)Gender

Fig. 4: Confusion matrix using Adience dataset.




a)Age




b)Gender

Fig. 5: Confusion matrix using UTKFace dataset.

### 4.2. *Comparison of proposed model*

To train the above pre-processed datasets, some pre-trained approaches such as- VGG-16, VGG-19, ResNet50, have also been employed. Table 2 and 3 show a comparison of these models with our proposed model. From the table we see that our proposed model is the best performed model as it outperformed other models in terms of accuracy, precision, recall, and f1-score. By placing our proposed model to the test, we have evaluated the performance of our model against other models.

Table 2: Comparison of performance among different models Adience dataset.

| | Age Prediction | | | | Gender Prediction | | | |
|---|---|---|---|---|---|---|---|---|
| Models | Accuracy | Precision | Recall | F1-score | Accuracy | Precision | Recall | F1-score |
| VGG-16 | 77.22% | 78.54% | 76.41% | 77.46% | 86.79% | 86.5% | 87% | 86.75% |
| VGG-19 | 72.81% | 72.63% | 71.38% | 71.99% | 85.82% | 86% | 85.5% | 85.75% |
| ResNet50 | 69.84% | 66.18% | 67.43% | 66.79% | 84.28% | 84.5% | 84.5% | 84.5% |
| Proposed model | 86.42% | 88.16% | 86.38% | 87.26% | 97.65% | 97.54% | 97.5% | 97.52% |

In table 4, we have showed a comparison of our proposed system with other previous work which have done on this topic. Here, we mentioned the methods and dataset that have been used in the previous papers. We also mentioned about the accuracy of their model. And we see that our proposed method is the best method as it outperforms other method. Using Adience dataset, the system achieved 86.42% accuracy for age prediction and 97.65% accuracy for gender prediction. And using UTKFace dataset, the system achieved 81.96% accuracy for age prediction and 96.32% accuracy for gender prediction.

Table 3: Comparison of performance among different models using UTKFace dataset.

| | Age Prediction | | | | Gender Prediction | | | |
|---|---|---|---|---|---|---|---|---|
| Models | Accuracy | Precision | Recall | F1-score | Accuracy | Precision | Recall | F1-score |
| VGG-16 | 72.09% | 71.68% | 70.49% | 71.08% | 85.19% | 85.5% | 84.5% | 85% |
| VGG-19 | 69.97% | 70.04% | 69.56% | 69.79% | 82.89% | 82% | 82.5% | 85.25% |
| ResNet50 | 65.56% | 64.18% | 65.31% | 64.74% | 79.95% | 78.5% | 78% | 78.25% |
| Proposed model | 81.96% | 82.27% | 81.75% | 82.01% | 96.32% | 97.5% | 97.5% | 97.5% |

Table 4: Best reported performance from previous work and our approach

| Reference | Method | Dataset | Accuracy (Age) | Accuracy (Gender) |
|---|---|---|---|---|
| [2] | CNN | Adience | 83.1% | 96.2% |
| [17] | DCNN | Adience | 69.4% | 93.6% |
| [20] | CNN | Adience | | 60.4% |
| [3] | EfficientNet | Adience<br>UTKFace | 81.1%<br>73.5% | |
| [36] | Pre-trained CNN | UTKFace | 71.84% | |
| [1] | CNN | Adience | 84.8% | 89.7% |
| [34] | CNN(age)<br>SENet50(gender) | UTKFace | 79.12% | 94.94% |
| [11] | CNN-ELM | Adience | 52.3% | 77.8% |
| [18] | MLP | Adience | 67.47% | |
| Proposed method | CNN with 5 conv. layers | Adience<br>UTKFace | 86.42%<br>81.96% | 97.65%<br>96.32% |

## 5. Conclusion and Future work

The study combines computer vision and machine learning, leveraging image processing techniques for quality enhancement and preparation. It employs softmax and sigmoid functions for age and gender prediction, respectively, with various optimizers for improved performance. Utilizing extensive datasets enhances feature observation. Comparative analysis highlights superior system performance. Future endeavors include multiple classifications based on image subjects, integrating BRBES[23, 16, 27, 29, 30], K-fold cross-validation, extending gender detection, predicting from video, and exploring emotion detection.

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