Human Gender Detection from Facial Images Using Convolution Neural Network

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Abstract. Human gender detection which is a part of facial recognition has received extensive attention because of it's different kind of application. Previous research works on gender detection have been accomplished based on different static body feature for example face, eyebrow, hand-shape, body-shape, finger nail etc. In this research work, we have presented human gender classification using Convolution Neural Network (CNN) from human face images as CNN has been recognised as best algorithm in the field of image classification. To implement our system, at first a pre-processing technique has been applied on each image using image processing. The pre-processed image is passed through the Convolution, RELU and Pooling layer for feature extraction. A fully connected layer and a classifier is applied in the classification part of the image. To obtain a better result, we have implemented our system using different optimizers and also have used k fold cross-validation as deep learning approach. The whole method has been evaluated on two dataset collected from Kaggle website and Nottingham Scan Database. The experimented result shows a highest accuracy which is 97.44% using Kaggle dataset and 90% accuracy using Nottingham Scan Database.

Keywords: Convolution neural network · Convolution · RELU · Pooling layer · Fully connected layer · K-fold cross-validation · Optimizers · Kaggle datset · Nottingham Scan Database

1 Introduction

Gender detection plays a significant role in modern technology. The detection of gender has many dynamic applications such as social interaction, security maintenance and surveillance, video games, human-computer interaction, criminal identification, mobile application, commercial development, monitoring application etc. It has occupied a great space in the field of facial recognition. The main

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purpose of gender detection is to differentiate male and female based on different features of human.

In recent years, various research papers have been published regarding human gender classification using different methods. Human gender can be classified using different features such as face, eyebrow [12], hand-shape [5], body-shape [8], finger nail [32]. Among these, the majority of the gender detection research have been accomplished using face images. The feature extraction is classified into two categories [7], namely geometric based and appearance based.

In the geometric based feature extraction, different facial components or feature points are extracted which mainly represents the face geometry [11]. In the appearance based feature extraction, the features are extracted applying image filter the whole image or particular component of an image [11]. The appearance based feature extraction has an advantage over the geometric based feature extraction. In the geometric based feature extraction, only some fixed points of face image are used where in the appearance based feature extraction, information is extracted from the whole face image. The training process of classifying gender includes several methods such as Support Vector Machine (SVM), Principal Component Analysis (PCA), and Neural Networks (NN) [7]. However, in the field of image classification the Convolution Neural Network (CNN) has been proved to perform as best algorithm comparing with other machine learning algorithms [3,27]. The filters are optimized through automated learning in CNN [6,33] whereas they are hand-engineered in other traditional algorithms. This is a major advantage of CNN as it is independent of human intervention in feature extraction. Moreover, while using an algorithm with pixel vector, a lot of spatial interaction between pixels are lost. A CNN can effectively use adjacent pixel information by convolution and then uses a prediction layer at the end.

Our main purpose of this research is to detect human gender from facial images where we have used an image processing technique for appearance based feature extraction and Convolution Neural Network (CNN) for the classification of human gender. In this regard, at first we have applied an image processing technique where we have converted the face image into a two dimensional array where the values of the array indicates the pixel values of the image. After that, all the pixel values have been divided by 255 so that all the values of the array come to a range between 0 to 1. This is done to reduce the difference among the values. After this pre-processing step, a machine learning algorithm called Convolution Neural Network is applied for the classification of gender using a compact variant of VGGNet architecture on 2 dataset which are Kaggle dataset and Nottingham Scan Database. After implementation, a highest accuracy 97.44% has been gained using Kaggle dataset and 90% has been gained using Nottingham Scan Database. The significant contributions of our research are:

1. Performance comparison has been shown among different optimizers.
2. K-fold cross validation has been applied as a deep learning approach.
3. Performance comparison has been shown among different activation function.
4. Dataset has been splitted into different ratio to gain a best accuracy.

The next sections of the paper are arranged accordingly: Sect. 2 contains the previous works regarding gender classification. Section 3 describes the methodology where Convolution Neural Network is discussed broadly. Section 4 shows experimental setup where the experimental tools used in implementing our system has been stated. Section 5 is about the result and discussion and finally in Sect. 6 conclusion and future work has been discussed.

2 Literature Review

In the field of image processing and machine learning, a lot of research work has been done on human gender estimation. In this section, a brief overview of previous work on human gender estimation has been presented.

Lian HC [20] obtained an accuracy of 94.81% applying local binary pattern (LBP) and SVM with polynomial kernel on the CAS-PEAL face database. According to this method, a good accuracy can be achieved if the block size for the LBP operator is correctly selected, which is really a difficult task. Li et al. [19] performed the classification of gender utilizing only five facial features (eyes, nose, mouth, brows, forehead). One drawback of this research is that the feature extraction method they have used is affected by complex backgrounds. Saeed Mozaffari, Hamid Behravan and Rohollah Akbari [23] used geometric based feature for male female classification where they have used AR and Ethnic dataset containing 126 frontal images in each dataset. Here they have achieved 80.3% and 86.6% accuracy respectively. In [10] a texture based local binary pattern has been used for feature extraction and as classification algorithm naïve Bayes, ANN and linear SVM has been applied. They achieved 63% accuracy with only 100 face images that has been collected from Nottingham Scan database which is quite low. Sajja, T. K., Kalluri, H. K. [28] have worked on gender classification from face images using LBP, SVM and Back Propagation. In this research they have used ORL dataset which contains 400 images and Nottingham Scan database which contains 100 images. After implementation they gained 100% accuracy for ORL dataset and 71% accuracy for Nottingham Scan database respectively. The work in [24] showed a high classification accuracy of 99.30% using SUMS face database. In this work, the researchers applied 2D-DCT feature extraction, Viola and Jones face detection and the K-means nearest neighbor (KNN) algorithm as classifier. Being a compute-intensive algorithm, 2D-DCT is not suitable for real-time applications. Using principal component analysis (PCA), researchers in [30] processed the face image to reduce the dimensionality. After that, a good subset of eigenfeatures has been selected using genetic algorithm (GA). Here, they reported an average error rate of 11.30%. The main drawback of this method is that, the GA exhibits high computational complexity. Althnian et al. [4] used hand crafted and fused features for face gender recognition where they have used both SVM and CNN and gained best accuracy 86.60% using CNN which can be improved further. Serna et al. [29] worked on gender detection using VGG and ResNet where they analyzed how bias affects deep learning. They divided the images into 3 ethnic groups and also experimented on an unbiased group. Here they achieved best average accuracy 95.27% for unbiased group using VGG and 95.67% Biased group 3 using ResNet.

Deviating from only facial based gender recognition, some researchers have worked on estimating human gender from different body parts for example body shape, eyebrow, hand shape, finger nail etc. Dong, Yujie & Woodard, Damon [12] approached a new technique where they classified gender using eyebrow shape. For classification MD, LDA and SVM were used in this paper and they gained 96% and 97% accuracy for MBGC and FRGC dataset respectively. In [5] they investigated human gender from hand shape from a small dataset containing 40 images and they achieved 98% accuracy. As classification algorithm Score-level fusion and LDA have been applied here. HongáLim et al. [32] presented a novel method for gender classification using finger nail with 80 samples donated by 40 people. With the use of PCA and SVM as classification algorithm, they showed about 90% accuracy in this research.

So considering the whole literature review, it is clear that an improvement in gender classification is needed. The main disadvantages of the above gender classification research works is that, the feature extraction and the classification are performed separately. To obtain an optimum pre-processing and feature extraction design, prior knowledge is needed here. In case of CNN which is a multilayer neural network model [21,22], it can optimize filters through automated learning where it is independent of prior knowledge which demonstrate a superior performance can be achieved using CNN.

3 Methodology

In our proposed system, we have utilized a CNN (Convolutional Neural Network) architecture. CNN which is a deep learning algorithm is capable of distinguishing images from their characteristics [1,9,14]. CNN is generally used for image analysis, image segmentation, image classification, medical image analysis, image and video recognition, etc. [2,13]. In this research, at first we have applied an image processing technique as pre-processing on images to transform the raw data into an efficient and useful format. Later, the CNN architecture has been applied. Here, it has been decomposed into two parts:

- Feature Extraction
- Classification

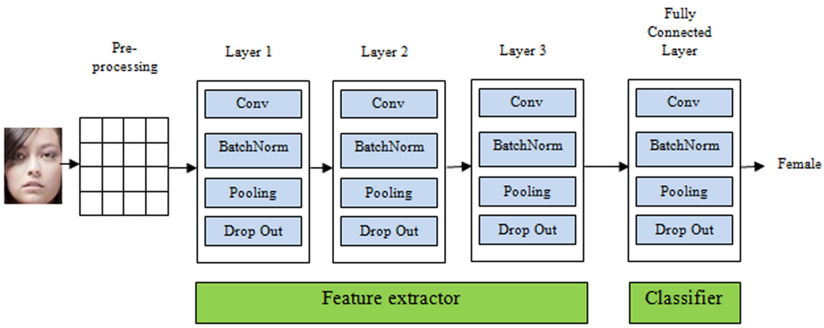


Fig. 1. Network architecture

The convolution and the pooling layers performs the feature extraction of image which actually extract information from input for decision making. Finally, fully connected layer performs as the classification part. Our basic network architecture has been illustrated in Fig. 1.

3.1 Dataset

In the field of gender estimation, there are several global datasets used in different research works. In this paper, we have used two global datasets so that we can show the comparison of the result achieved using different datasets. One of the two datasets is collected from kaggle website and the other is Nottingham Scan database.

Kaggle Dataset. The CELEBA aligned data set has been used in kaggle dataset to provide image. This dataset is of good quality and large. Here, the images are separated into 1747 female and 1747 male as training images, 100 male and 100 female as test image and 100 male, 100 female as validation images. A face cropping function using MTCNN has been applied here to crop the images so that only face images are included here. In Fig. 2 a sample of Kaggle Database have been shown.

Fig. 2. Sample of Kaggle Dataset

Nottingham Scan Database. Nottingham Scan database is comprise of 100 human faces where half of the images are of male and half images are of female. The format of images used in this database is .gif format. 438×538 pixel size image hase been used here with 256 a gray-levels. As per our requirement, the images have been converted to .jpg format from .gif format. In Fig. 3 a sample of Nottingham Scan Database have been shown.

3.2 Pre-processing

Pre-processing of image generally removes low frequency background noise, normalizes the intensification of the individual practical image, removes reflection of light to get rid of the image noise, and prepares the face image to better feature extraction. In our system, we have first resized the images into 96×96 dimension. Then We have converted the image to an array of pixel value. Each pixel value of the array is converted to float and divided by 255.0 so that all the pixel values comes to a range between 0 to 1. In Fig. 4, the whole pre-processing system has been illustrated.

Fig. 3. Sample of Nottingham Scan database

3.3 Feature Extraction

In Convolutional Neural Network (CNN), the feature extraction is performed by the Convolution and the Pooling layer. In our proposed system these layers are defined as follows:

1. The convolution layer contains 32 filters with a 3×3 kernel. Here RELU is used as the activation function followed by batch normalization.
2. The POOL layer uses a 3×3 pool size to reduce spatial dimension from 96×96 to 32×32. A dropout is used in our network architecture which disconnects nodes arbitrarily from layer to layer.
3. Next the convolution and ReLU layers are applied twice before applying another POOL layer. This operation of multiple convolutional and ReLU layers allow to learn a richer set of features. Here-

  - The filter size is being increased from 32 to 64. As we go deep into the network, we will learn the filters more.
  - The max pooling size is decreased from 3 × 3 to 2 × 2 so that spatial dimensions don't get reduced too quickly. Dropout is again performed at this stage.
4. Again the convolution and ReLU layers is applied twice before applying another POOL layer. The filter size is increased to 128. And 25% dropout of the nodes is executed in this step for the reduction of over fitting.

3.4 Classification

Fully Connected and RELU operation is performed and a sigmoid classifier is used for classification. Here-

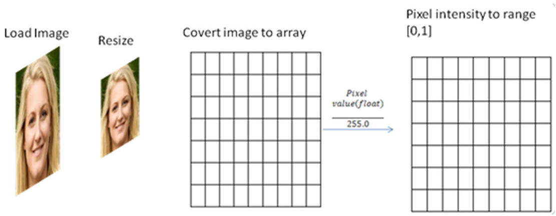


Fig. 4. Pre-processing steps

1. RELU and batch normalization with dense (1024) defines the fully connected layer where dropout is executed for the last time. This time 50% of the node is being dropped during training.
2. Finally, sigmoid function is used as classifier to return the predicted probabilities for each class label.

$$Sigmoid(x) = \frac{1}{1 + e^{-}\theta^{T} x}$$

In Fig. 5 the whole schematic diagram of our network architecture has been provided.

4 Experimental Setup

Our system has been implemented using python programming language. Matplotlib, keras, numpy libraries has been used for system implementation. Keras provides some built in functions such as activation functions, optimizers, layers etc. Tensorflow has also been used as the system backend. In Table 1, the experimental tools used in this system implementation has been showed.

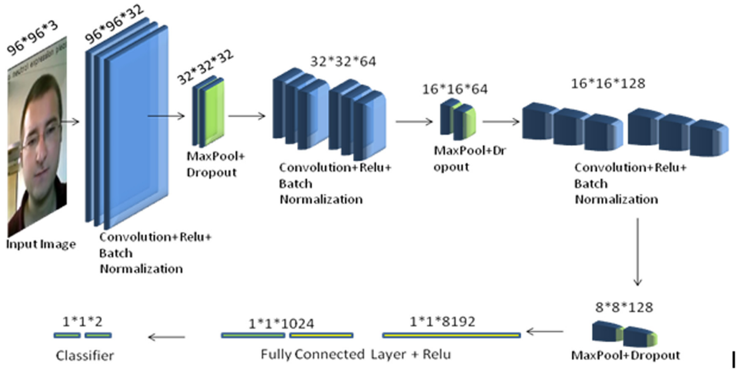


Fig. 5. A full schematic diagram of network architecture

Table 1. Experimental tools

Name	Experimental tool
Hardware	i. Microsoft Windows 8.1 pro ii. Processor Intel (R) core (TM) i3-5005U, 4 GB RAM
Software	Spyder (Python3.7)
Programming Language	Pythonn
Method implementation	i. Keras 2.2.4 ii. Tensorflow 1.15.0

5 Result and Discussion

As stated in earlier section, we have used two dataset to evaluate our model. For both dataset, we have implemented our model using different optimizers so that best accuracy can be obtained. After that we have trained our model using 5 fold cross validation as deep learning approach.

5.1 Comparison of Result Among Different Optimizers and Activation Functions

Table 2 shows the training and testing accuracy for different optimizers for both Kaggle and Nottingham Scan Database.

As we can see using Kaggle dataset, we have achieved satisfactory accuracy using Adam, Adamax, RMSprop and Adagrad optimizer which is above 90%. Using SGD and Adadelta optimizer the accuracy gained less comparing with the others. Among all of these, the best accuracy has been gained using the Adam optimizer. For Nottingham Scan Database, the Adam optimizer shows the best accuracy and also it maintains a good balance between training and testing accuracy. So, we can say that for both dataset the best accuracy is obtained using adam optimizer.

Table 2. Accuracy using different optimizers

Optimizers	Kaggle Dataset		Nottingham Scan Dataset	
	Training accuracy	Testing accuracy	Training accuracy	Testing accuracy
Adam	98%	95%	90.62%	90%
Adamax	96%	94%	78.12%	85%
RMSprop	97%	93%	93.75%	65%
Adagrad	91%	93%	87.50%	85%
SGD	84%	86%	53.12%	82.50%
Adadelta	70%	76%	40.62%	65%

Figure 6 and 7 shows Loss/Accuracy curve using Adam optimizer for Kaggle dataset and nottingham scan database respectively.

In Table 3, we have shown the accuracy acquired by splitting the dataset into different ratio. Here, the best training and testing accuracy we have achieved by splitting both dataset into 80% training and 20% testing which is 98.09% training accuracy and 95% testing accuracy for Kaggle dataset and 87.50% training accuracy and 80.50% testing accuracy for Nottingham Scan Dataset.

Table 3. Accuracy comparison of splitting dataset

Split Ratio	Kaggle Dataset		Nottingham Scan Dataset	
	Training accuracy	Testing accuracy	Training accuracy	Testing accuracy
60%–40%	96.49%	93.63%	80.77%	80%
70%–30%	96.63%	93.03%	75.67%	80%
80%–20%	98.09%	95%	87.50%	80.50%
90%–10%	93.41%	94%	80.62%	75%

Table 4 shows the result of our system implementation using different activation functions to see which activation function generates the best result. In this case we have considered the splitting ratio as 80%-20% as we achieved a satisfactory accuracy by splitting the dataset into 80% training and 20% testing. Here as we can see, the sigmoid function results the best for each dataset. Softmax function performs well for Kaggle dataset but it shows overfitting problem in Nottingham Scan Dataset. On the other hand, Relu activation function shows a poor accuracy for both dataset.

5.2 K-Fold Cross Validation

Cross validation is a re-sampling method which is used to evaluate machine learning models on a limited data sample. Here we have implemented our model

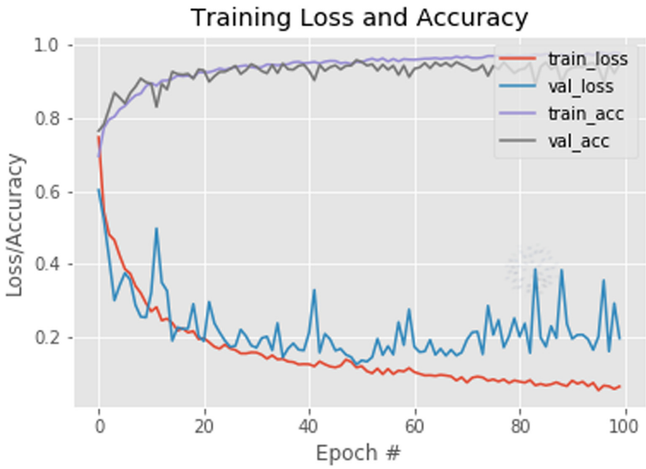


Fig. 6. The Loss vs Accuracy curve using Adam optimizer for Kaggle dataset

Table 4. Accuracy using different activation function

Activation function	Kaggle Dataset		Nottingham Scan Dataset	
	Training accuracy	Testing accuracy	Training accuracy	Testing accuracy
Sigmoid	98%	95%	90.62%	90%
Softmax	93.20%	87.98%	93.10%	60%
Relu	28.35%	26.20%	28.12%	50%

using K-fold cross validation as a deep learning approach on both Kaggle Dataset and Nottingham Scan Database. We have chosen the value of k=5 here as 5 fold cross-validation.

Table 5 shows the result of our model using 5 fold cross-validation and also the average accuracy and the best accuracy achieved after the 5 fold cross-validation. As we can see, the average accuracy and the best accuracy we have achieved are respectively 95.06% and 97.44% for Kaggle Dataset and 83.50% and 90% for Nottingham Scan Database.

In Table 6, we have shown the comparison of our proposed method with two existing method where Nottingham Scan Database have been used. Datta et al. [10] applied texture based LBP for feature extraction. Artificial Neural Network (ANN), Naïve Bayes, Linear SVM algorithms have been applied for classification. They have achieved a highest accuracy of 63% using ANN classification algorithm. In [28], the researchers used a combination of LBP and SVM where they achieved 55% accuracy and used a combination of LBP and NN where they

Fig. 7. The Loss vs Accuracy curve using Adam optimizer for Nottingham Scan database

Table 5. Accuracy using K-fold cross validation

Fold	Kaggle Dataset		Nottingham Scan Dataset	
	Training accuracy	Testing accuracy	Training accuracy	Testing accuracy
1	98.07%	93.92%	90.62%	90%
2	97.62%	94.28%	96.88%	82.85%
3	98.09%	97.44%	87.50%	77.50%
4	96.93%	94.28%	90.62%	85%
5	97.44%	95.42%	90%	82.50%
Average Accuracy	97.51%	95.06%	90%	83.50%
Best Accuracy	98.09%	97.44%	96.88%	90%

Table 6. Comparison of the proposed approach with existing method

Serial No	Reference	Method	Database	Accuracy
1	Datta et al. [10]	LBP+ANN	Nottingham Scan Database	63%
2	Sajja, T.K. [28]	LBP+NN	Nottingham Scan Database	71%
3	Our proposed method	CNN	Nottingham Scan Database	83.5%

achieved 71% from the Nottingham Scan database. But in our proposed method, we have got a best accuracy 90% using CNN model with 5 fold cross-validation and the average accuracy of the 5 folds is 83.50%.

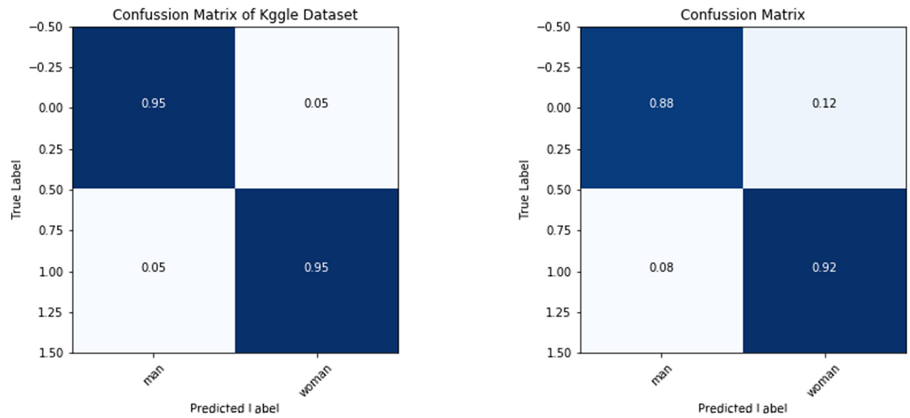


Fig. 8. Confusion matrix of 5-fold cross-validation on Kaggle dataset and Nottingham Scan Database

Figure 8 shows the confusion matrix of 5-fold cross-validation on Nottingham Scan Database and Kaggle Dataset respectively.

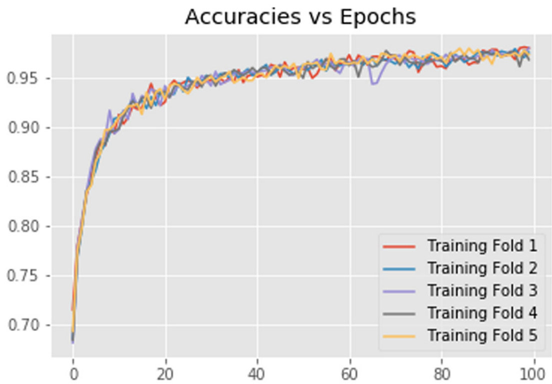
Figure 9 shows accuracy vs epoch curve using 5 fold cross-validation for kaggle dataset and nottingham scan database respectively. As we can see here, we have achieved a satisfactory accuracy after 100 epoch.

5.3 Performance Metrics

Researchers generally evaluate the overall performance and also the efficiency of machine learning algorithms using these factors [26]. In our model we have evaluated performance metrics to understand how well our model is performing on given dataset. In this study, the performances have been evaluated based on three criteria- Recall, Precision, F1-score. In Table 7, the comparison of the performance metrics for both datasets are shown.

Table 7. Different parameters

Performance matrices	Kaggle Dataset			Nottingham Scan Dataset		
	Man	Woman	Macro Average	Man	Woman	Macro Average
Precision	0.95	0.95	0.95	0.88	0.92	0.90
Recall	0.95	0.95	0.95	0.88	0.92	0.90
F1-score	0.95	0.95	0.95	0.88	0.92	0.90



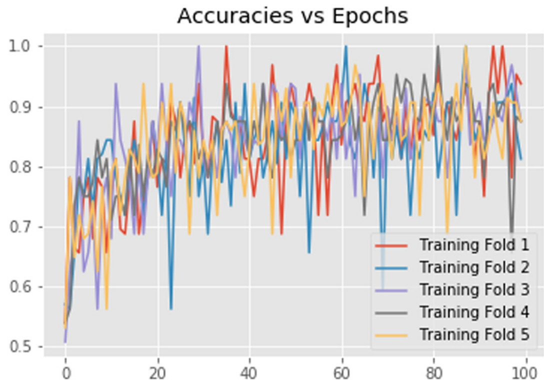


Fig. 9. The Accuracy vs Epoch curve using 5 fold for Kaggle dataset and Nottinghum scan database

6 Conclusion and Future Work

In this paper, we have used both image processing technique and machine learning algorithm for implementation and achieved a promising result for both Kaggle dataset and Nottingham Scan Database. As part of image processing, a pre-processing technique has been applied first. After pre-processing, feature extraction and classification are implemented in this system. A sigmoid function has been used as classifier in our model. Different optimizers have been used to determine which optimizer gives a better result. For assessing the effectiveness of our model, we have applied 5 fold cross-validation which has helped to evaluate our model. After analysing the result, a comparison of two previous work with our paper has also been shown where our system gives better result than them.

However, our system can be improved using different classifier for example softmax function and ReLU. A more efficient system can be built for human gender classification using Belief Rule Based Expert Systems (BRBES) [15–18, 25, 31]. So in future, we will implement all these for human gender classification.

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