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GENDER CLASSIFICATION FROM FACIAL IMAGES USING CONVOLUTIONAL NEURAL NETWORK (CONVNET)

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ABSTRACT

Classification is a techniques used for solving problems. Several problems are solved with this technique. Gender classification is gaining grounds due to different areas of applications such as surveillance, security and monitory etc. Different authors have presented different research areas in the domain of gender classification and

INTRODUCTION

Biometrics verification acts as a measure for security and safety have gained popularity over decades in the area of image verification and identification. Biometric which is used for identity authentication takes biological input which may be inform of scanning or capturing of some parts of the human body such as face, voice, palm, iris, and finger features.

Images such as animals, things and human beings are captured through biometric devices or any other capturing devices. Facial images datasets are tremendous on the internet in the recent time; this has brought a large research area in face recognition and verification domain (Sharma, Jain and Mishra, 2018).

Face recognition system is one of the way people display their emotion and it is a fundamental biometric system that proves effective, efficient and highly authenticated (Dahghan, Ortiz, Shu and Masood, 2017). Several important information are expressed through human faces such as emotion, race, gender, age and etc. (Yang, Chen, R icanek and Sun, 2011). These expressions can be processed in other to be able to detect or classify facial images by the means of digital computer and with the use of machine learning algorithms. Classification has been a wider and a popular techniques used in fields such as medical, security etc. Every image has features to be extracted; these features are extracted from the shape, colour, edge etc. of an image. Also, all images have picture element (pixel) that are represented with values. Some values that are closer to 0 are denoted with black while those values closer to 255 are denoted with bright colour.

Gender classification can be easily identified by human being but it is problematic for machine. The gender classification will help to identify, authenticate and control access of people from some restricted areas such as security zone by

used several methods for analysing facial images in other to predict or classify the images. These methods adopted are either traditional algorithms, hybridised techniques or neural network so as to obtain better accuracy and reliability. We know that successful classification needs a robust method with good experimental setups that is why we present a gender classification using Convolutional Neural Network (ConvNet) for the purpose of reliability and accuracy using a local dataset. Although, majority of works done on this research area made use of the popular datasets such as FERET, AT & T, FACE94, AR to mention but few and/or compare two or more datasets to know the one with the best performance accuracy. Our state of heart method was used on local data set where sizable numbers of images were captured and five different augmentations were done on the images. The experimental result showed that our proposed ConvNet on our local dataset improve gender classification accuracy with the ***Precision (%) - 89.6276-; Recall (%) - 89.6276; Accuracy (%) - 92.8094*** and ***F1-score (%) - 89.6237.***

Keywords: *Gender classification, Convolutional Neural Network,*

allowing individual face as an identifier instead of using password, username or even key. This paper presents a novel way of classifying gender using convolutional neural network (ConvNet or CNN) as a deep learning algorithm that is trending in this.

LITERATURE REVIEW

Gender Classification

According to Makkinen and Raisamo (2008), gender classification dated back to early 1990 with the use of both feature based and appearance based methods where mult-layer neural network approach was used (Khan, Nazir, Akram and Riaz, n.d). Several algorithms have been used in the area of facial analysis such as facial detection algorithm, features extraction algorithms or classifying algorithm. The lists below are the popular algorithms and classifiers used for face analysis.

i. Discrete Cosine Transformation (DCT): is an algorithm used to change illumination condition of the facial images (Haider, et al. 2014). This algorithm is applied on the captured images by keeping the coefficient in a zigzag form in other to convert the 2D images to feature vector (Hemalatha, 2014; Sumathi, 2014).
ii. Local Binary Pattern (LBP): is an algorithm used in the area of face detection localisation which produced highest ranking matching level (Haider, et al. 2014). According to Gaur, et al (2019) LBP was formally used face texture investigation but now it is used for outward appearance extraction and opposes the variation to illumination with easy way of computing. There is extension of LBP which is VLBP (Volume Local Binary Pattern) which augmented LBP).
iii. Elastic Bunch Graph Map (EBGM): This algorithm is used for distance optimisation amongst face images (Haider, et al. 2014)
iv. Linear Discriminant Analysis (LDA): This is a facial recognition algorithm used for high dimensional data (Haider, et al. 2014) where faces and non-faces are categories into some different parts (Mishra, & Dubey, 2015). It is used to represent the face vector space by using the class information which is referred to as Fisher's faces Delac, Grgic, Lintsis, (2005). The problem which

limits the success of PCA was achieved with LDA. (Bhele & Mankar, (2012) mentioned that the LDA is mostly used for feature selection and use to optimise the discriminating power of the feature selection.

v. Principal Components Analysis: This is an algorithm was first developed by Turk and Pentland in 1991 as recorded by (Bhele & Mankar 2012; Gan, 2018). The algorithms used to extract the main components of the faces by approximate individual face in the database and combined the largest eigenvectors (Mishra, & Dubey, 2015). Delac et al. (2005) in their paper explained PCA as a techniques used to represent collection of sample points and dimensionality reduction of the description by projecting points onto the major parts and compressing the data. The reduced data space is used for recognition due to the elimination of the information that is not needed. The major challenge with this algorithm is the poor discriminating power coupled with large computation and small size of dataset.

vi. Independent Components Analysis**:** This algorithm is used for searching the essential components from the multi-level statistical data. The imperative use of ICA for face images with distinguishing orientation and illumination condition is overwhelming. The distinction in ICA is that it examines a component that are statically independent and non-Gaussian (Bhele & Mankar 2012; Sutara, Rokadiab and Shah (2016).

vii. Support Vector Machine (SVM): Is an algorithm used for classifying and recognising emotions (Gaur, et al 2019). Bhele & Mankar (2012) explain that SVM can only be used where there is no omission in the features vectors defining sample. It also attains good generalisation performance. SVM finds the hyperplane that distinguish the largest probable fraction point on the same area of the same class (Chawngsangpuii & Singh, 2015). This technique is popularly used for forecasting (Kumar et al., 2019).

viii. Artificial Neural Network: This is a classifying algorithm popularly used for harmonising the facial feature extraction

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which moves muscles. There is a hidden layer in NN which is likened to the parts of the face (Gaur, et al 2019). This classifier which is popularly used in object recognition and the likes is used to extract the complex class of face feature or pattern (Chawngsangpuii & Singh, 2015). There are series of layers which is made up of neurons; neurons are connected by weighted combinations of all other neurons in the group (Shehina & Joseph, 2017).

Convolutional Neural Network in History
Convolutional Neural Network as a Classifier

Coskin (n.d) and Kamencay (2017) defined CNN as an artificial neural network that extract features from input data. It was developed by Lecum and was first used for handwriting recognition. It is a feed forward network that consists of multiple layer where the output of the previous layer enters the next layer as an input.

The multitasking ability of CNN has made it an appreciative algorithm in the several areas of applications and couple with its recognisable performance. Areas of application such as pattern recognition such as hand writing recognition were the historic area where CNN architecture introduced. The area of imageNet with several grouping of the image datasets (Sharma et al., 2018).

CNN Layers

Convolutional Neural Network (CNN or CovNet) is a learning algorithm for image classification and recognition with a deep learning architecture. There are layers that datasets have to pass through when using CNN algorithm before faces are recognised. According to Sharma et al., 2018) there are five layers that CNN go through. These are;

i. Input Layer: Is the layer that takes captured images, resize them and later pass it to second stage for feature extraction.
ii. Convolution Layer: This is the second layer; this layer is used to filter images and to extract the features which are used to determine the match feature point during testing.
iii. Pooling Layer: This is a layer where all images are resized to a reduced shape while protecting the useful information in them. It

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keeps the useful features within the window where the maximum value is kept. The related features of each training test are combined together (Zafar, Ghafoor, Zia, Ahmed, Latif, Malik and Sharif 2019).

iv. Rectified Linear Unit Layer (ReLU): This layer swaps all negative number to zero which makes the CNN to be stable.

v. Fully Connected Layer: This layer takes highly filtered images and classified those using labels. It makes sure that each layer is fully connected.

Several pre-trained CNN datasets such as GooLeNet, AlexNet, and ResNet meaning Residual Network etc. are mentioned by (Sharma et al., 2018) these algorithms have proofed powerful and have effectively been used for image or object classifications, this is because it reduces the time for feature selection because convolution filters that convolve round the images to extract features that is basically called feature map (Zhang, Dind, Shang, Shao and Fu 2018).

Typical Convolutional Neural Network Architectures

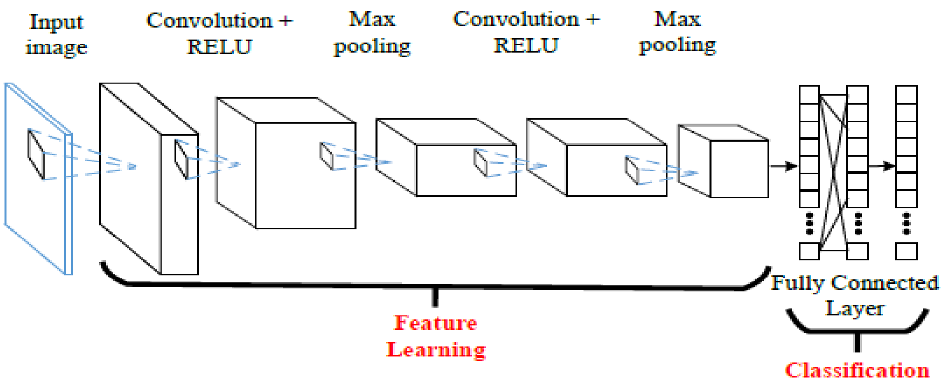

Figure 1: Typical CNN Architecture

Source: Kamencay P et. al. (2017).

METHODOLOGY

Gender Recognition

The MTL-CNN model is to recognize the gender of the facial image. The loss function used for gender attribute, L_g, is the cross-entropy loss given as:

$$L_g = -(1-G)\log(1-P_G) - G\log(P_G) \quad (3.1)$$

where $G = 0$ for male and 1 for female. The P_G is the predicted probability that the facial image is a female.

Overview of the System Setup

For the sake of deep learning, the variables used were discrete values of (0 and 1) where 0 is used for male and 1 is used for female. All images are reduced to the dimension of 227by227 which is allowed by our model program to work with. The entire dataset was randomly divided by the CNN algorithm into two: the training and testing dataset.

The input layer of the CNN consists of filters. The filters are applied to the input image to produce feature map output. The feature map produced by the CNN layer ConvL1 is passed as input to the second layer ConvL2 for learning. The learned features from ConvL2 become the inputs for the next layer ConvL3. The process is repeated up to the final Fully Connected (FC) layer. Finally, the learned features become a trained CNN model as the classifier.

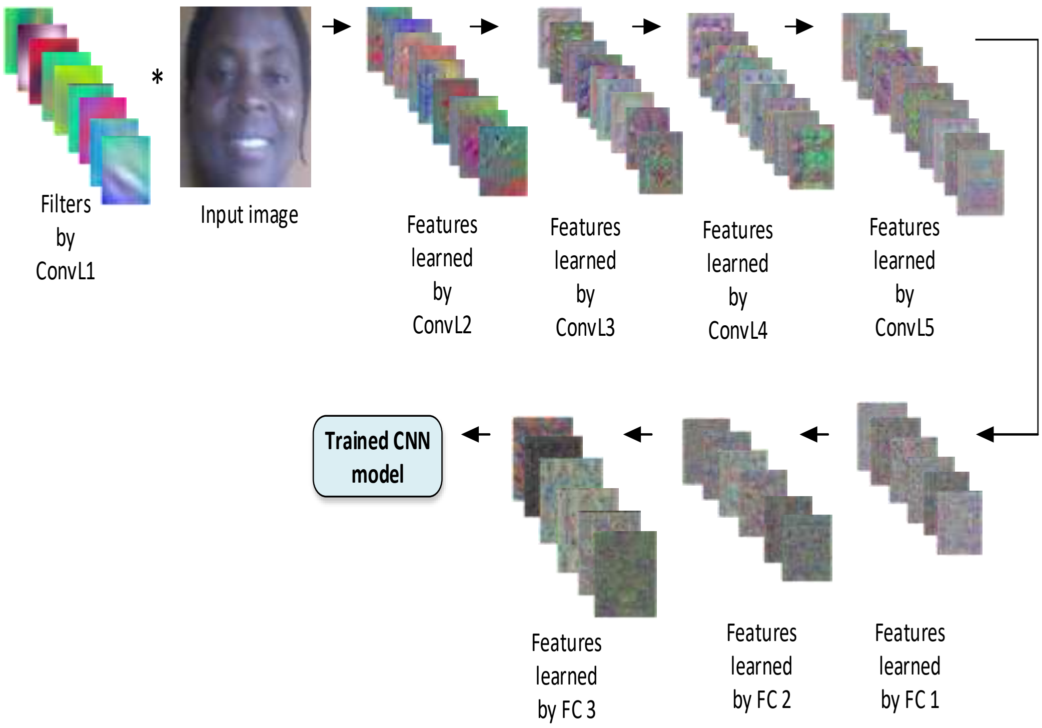

Figure 2: Architectural overview of the Model

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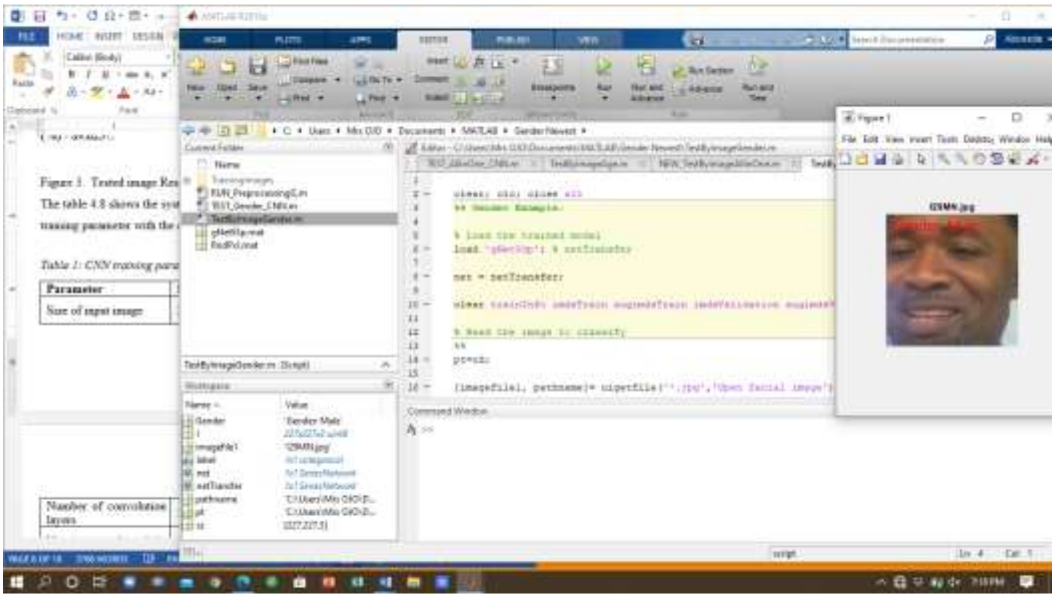

Figure 3: Tested image Result of the Implemented Gender Classification using MATLAB

The table 1 shows the system requirements for the PC used for the simulation and the CNN training parameter with the description of each of the parameter.

Table 1: CNN training parameters for Gender and its description

Parameter	Specification	Description
Size of input image	227-by-227-by-3	The acceptable dimension required by the pre-trained algorithm (AlexNet)
Number of convolution layers	5	This is building blocks used in convolutional neural network
Number of fully connected layers	3	These are layers where all the inputs from previous layer are connected to every activation unit of the next layer.
Activation function	Softmax	This is used to transform the unnormalised elements of fully connected layer to a normalised output

Optimizer	Stochastic gradient descent	This is an iterative method used to optimise an object function with appropriate smoothness properties.
Momentum	0.9	This is a designed method or techniques used as group of trick to speed up the convergence of the first order optimisation methods.
Maximum epoch	23	This the maximum number of times the algorithm sees the entire dataset
Learning rate	0.0001	This is the parameter that controls how much we are adjusting the weights of our network with respect to the loss gradient
PC used for simulation	64-bit OS, Core i5-5200U CPU @ 2.2GHz, 4GB RAM	PC Specifications for the simulation

Table 2: Testing of the created CNN model for Gender detection

Test Image ID	Gender (Actual or ground truth) Female/Male	Gender (Predicted by CNN) Female/Male
1	Male	Male
2	Male	Male
3	Male	Male
4	Male	Male
5	Male	Male
6	Male	Male
7	Male	Male

8	Male	Male
9	Male	Male
10	Male	Male
….	….	….
420	Female	**Male**
421	Female	Female
422	Female	Female
423	Female	Female
424	Female	Female
425	Female	Female
426	Female	Female
427	Female	Female
428	Female	Female
429	Female	Female
430	Female	**Male**
….	….	….
598	Female	Female

Table 3: Results of the created CNN model for Gender detection

Gender	Number of images tested	Correct classification	Misclassification	Precision (%)	Recall (%)	Accuracy (%)	F1-score (%)
Female (1)	292	260	32	89.0411	90.2141	92.8094	89.6237
Male (0)	306	295	11	90.2141	89.0411	92.8094	89.6237
Average				**89.6276**	**89.6276**	**92.8094**	**89.6237**

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Table 4: Comparison of the training set and testing set

	Training set	Testing set
Number of images	1394	598
Testing time (s)	3952	40.7549

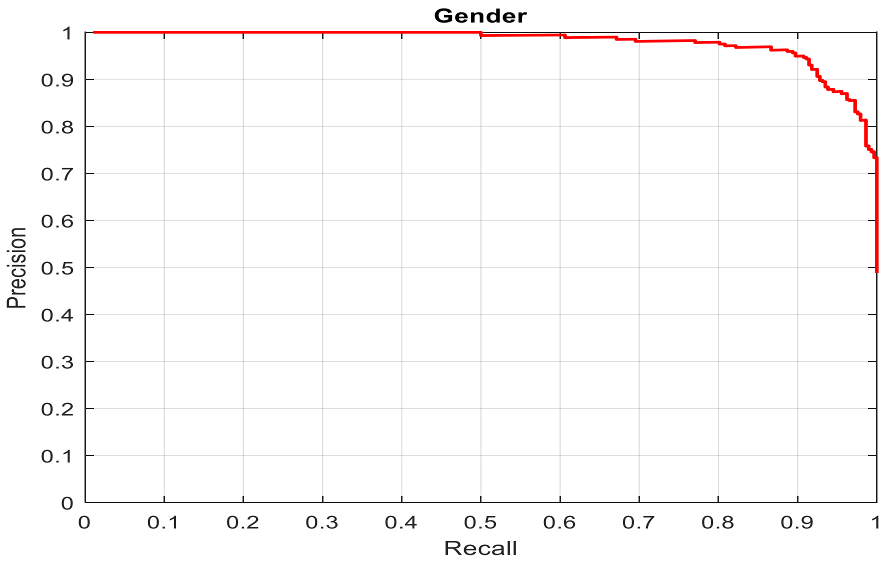

Figure 4: Precision vs. Recall on Gender

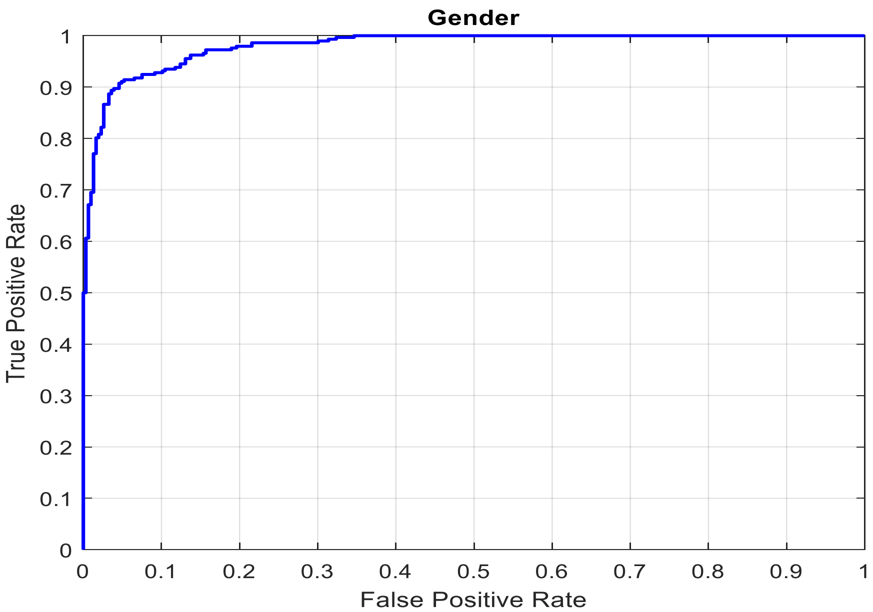

Figure 5: True Positive Rate vs. False Positive Rate on Gender

Table 5: Accuracy and Loss versus Epoch

Epoch	Training Accuracy	Testing Accuracy	Training Loss	Testing Loss
0	65.6250	52.6756	0.6817	0.7148
1	60.9375	57.3579	0.6944	0.6816
2	71.8750	69.2308	0.5731	0.5687
3	73.4375	73.9130	0.5512	0.4989
4	68.7500	75.0836	0.5553	0.4908
5	82.8125	81.1037	0.4502	0.3876
6	82.8125	85.2843	0.4297	0.3408
7	90.6250	84.4482	0.2804	0.3511
8	81.2500	85.7860	0.3915	0.3335
9	93.7500	82.7759	0.2320	0.3704
10	85.9375	87.7926	0.3609	0.2895
11	90.6250	85.1171	0.1984	0.3305
12	84.3750	88.7960	0.3241	0.2714
13	81.2500	80.1003	0.4224	0.4309
14	89.0625	90.4682	0.2998	0.2375
15	85.9375	90.1338	0.2947	0.2209
16	89.0625	92.1405	0.2768	0.2188
17	93.7500	91.4716	0.1494	0.2278
18	95.3125	90.9699	0.1025	0.2238
19	82.8125	93.3110	0.2345	0.1703
20	98.4375	93.6455	0.1144	0.1653
21	92.1875	91.8060	0.1372	0.2076
22	84.3750	92.8094	0.2340	0.1861
23	89.0625	92.8094	0.2602	0.2039

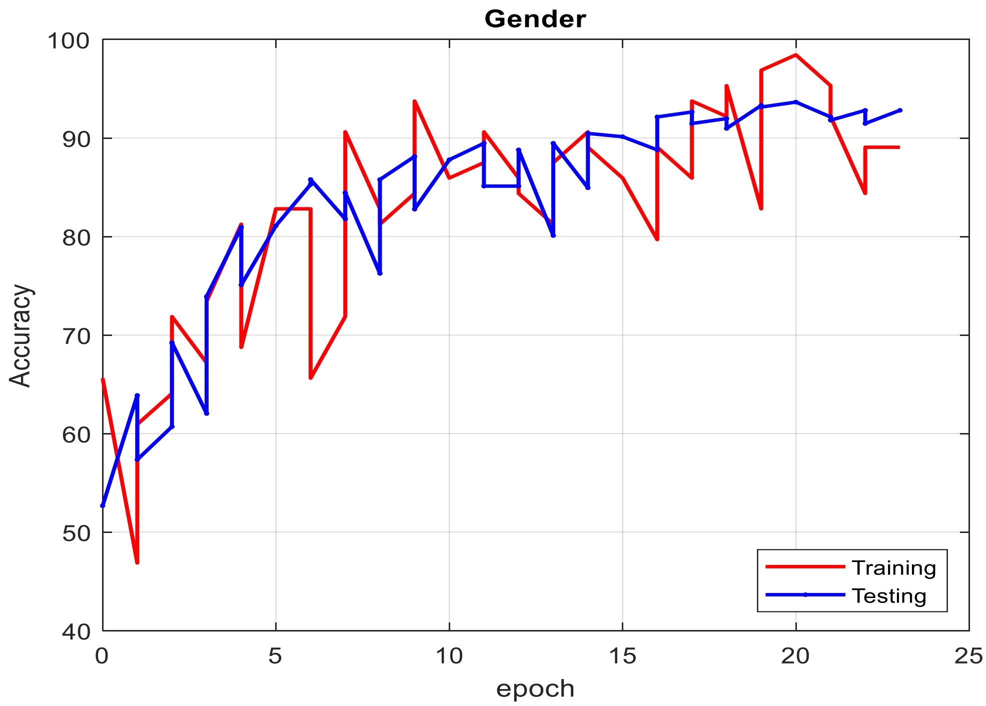

Figure 6: Accuracy vs. Epoch

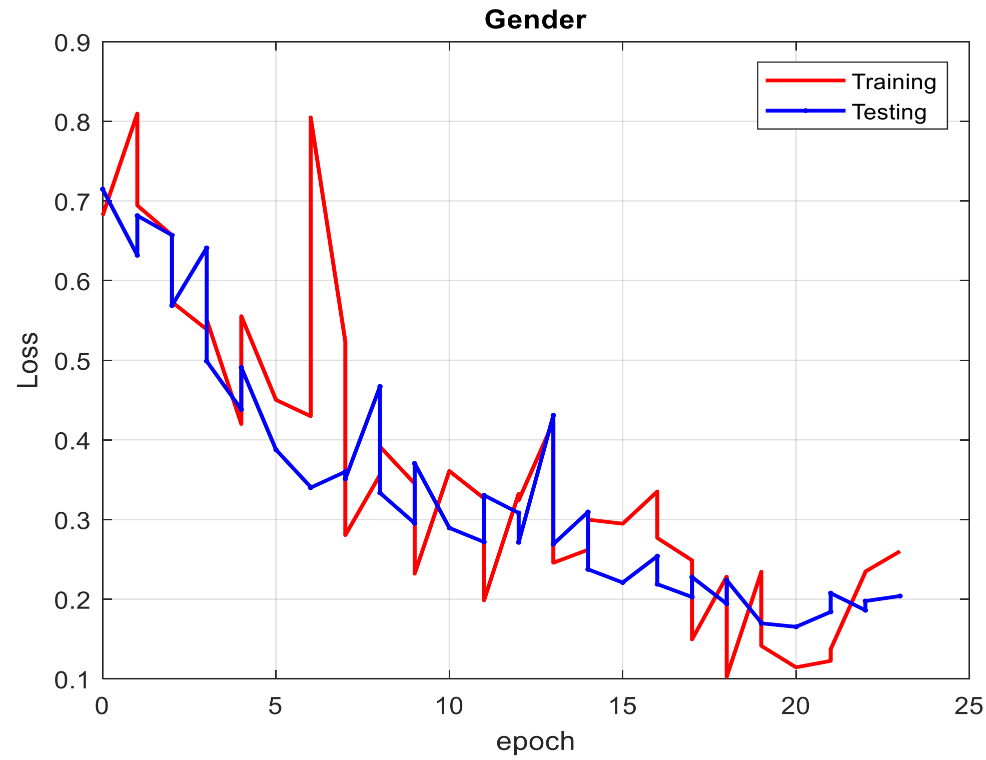

Figure 7: Loss vs. Epoch

Table 6: Confusion Matrix for Gender Classification

Confusion Matrix

Output Class \ Target Class	0	1	
0	**295** 49.3%	**32** 5.4%	90.2% 9.8%
1	**11** 1.8%	**260** 43.5%	95.9% 4.1%
	96.4% 3.6%	89.0% 11.0%	**92.8%** **7.2%**

Figure 8: "Female" is denoted by digit 1 while "Male" is denoted by digit 0

Figure 9 Tested input samples for Gender classification

DISCUSSION

Discussion on Gender Classification

The table 2 is the result of testing CNN model for gender detection where 598 images were tested with brief discussion.

1. Test Image ID: the Test imageId column represents the total number of Images tested. These images were randomly selected from the testing images.
2. The Gender Actual or ground truth: is the column that shows the true sex of the image selected where digit 1 denote female and digit 0 denote male.
3. Gender Predicted by CNN: This column shows what the CNN classifier classified on the Test ImageId.

For example from the table 2, the first Test imageId (1) which represent the first image was male on the ground truth and correctly predicted as male by CNN classifier. But a cursory look at the Test ImageId (420) which was female and was misclassified by CNN classifier. So also the Test ImageId (430) that was female but predicted as male.

The table 3 shows the result of created CNN models for gender detection where the total number of 598 images was tested. With 292 images females (1) and 306 images males (0). 260 images from 292 female images were correctly classified, while the remaining 32 images were misclassified. Also, 295 male images (0) out of the 306 images was correctly classified was correctly while 11 images was misclassified.

The Precision, Recall, Accuracy and F1-score that are parameters for evaluation of performance were calculated and their Average performance scores were highlighted in bold. For **Precision (89.6272); Recall (89.6276); Accuracy (92.8094) and F1-score (89.6237).** The best performance average score was **92.8094** under the Accuracy

The table 4 shows the comparison of the number of training images and testing images with their testing time. The total number of 1394 images was used for training and 598 images were used for testing with 3952(s) for training and 40.7549(s) for testing.

The table 5 shows the Recall vs. Precision and False Positive rate vs. True Positive Rate with their graph. While, table 4.6 shows the training/testing Accuracy vs. the Training/ Testing Loss. With a cursory look at the table, there is stable increase in the training accuracy column from epoch 0 to epoch 3. But, at epoch 4 there was a decrease in the accuracy that later increase in epoch 5 with obvious increase. On the other hand, a steady increase was observed under the testing accuracy from epoch 1 to 12 with a decrease in epoch 13. All these fluctuations were as a result of the update in the weights at every epoch iteration and these resulted in different validation error and invariably the network accuracy during the training.

Finally, the Confusion Matrix for the Gender Classification represents the result of the gender classification. From table 3, it was observed that the total percentage number of correctly classified images for female (0) was 260 out of 292 images with percentage score of (89.0%) and 32 misclassified as male with percentage score of 11.0%. 295 out of 306 images trained was correctly classified with percentage score of 96.4% while 11 images was misclassified as female with the percentage score of 3.6%. The overall average **accuracy was 92.8%** and the overall average loss was 7.2%.

CONCLUSION

We implemented our state-of –the art gender classification using MATLAB R2018a where we used a local dataset of 490 images. These images were cropped to the required dimension of 277by277 as required by the AlexNet pertained architecture. Five different augmentations were performed on the images in other to populate the dataset and to be able to enhance the classification process. We observed that our method was able to classify people on glasses.

Finally, the CNN model has a very high accuracy with significantly better performance where we have **89.6276** for **Precision (%); 89.6276** for **Recall (%) ; 92.8094** for **Accuracy (%)** and for **F1-score (%)** is **89.6237.**

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