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## FOREWORD

Compliment of the season to all our contributors, well-wishers and world of Academia in general. I respectfully appreciate and welcome you all to the volume 3 issue 2 of Federal Polytechnic – Journal of Pure and Applied Sciences (FEPI-JOPAS) which is a peer reviewed multi-disciplinary accredited Journal of International repute. It is imperative to re-affirm that FEPI-JOPAS publishes full length research work, short communications, critical reviews and other review articles. In this issue, readers will find a series of manuscripts of top-rated significance in pure and applied sciences, engineering and built environment. This issue is the last of its kind for 2021 calendar year which features findings from basic and applied researches of high societal impacts from the seasoned authors. These articles have been reviewed and packaged for wider readership through the collective efforts of our managing editor, publishing editors, our valuable reviewers and editorial board members.

In this particular issue, you will find that Ilelaboye and Jesusina evaluated the quality of biscuits and chin-chin made from okara enriched plantain-sorghum flour blends. Ojo and Ebisin utlilized convolutional neural network for gender classification through facial analysis. Omotayo and Fafioye investigated antimalarial potential of ethyl acetate fraction of Phyllanthus niruri while Olubodun and Adetona examined landscaping as a strategy for combating air pollution in Lagos megacity. Buoye and Ojuawo provided imperative dataset on Covid-19 crisis management in Nigeria and Brazil. Obun-Andy and Banjo investigated effective communication as a tool for good governance in Nigeria. Yusuff and co-workers conducted a field survey on fish hatcheries in Yewa South and Yewa North Local Government of Ogun State. Akinlade and co-workers meticulously expatiated on the effect of aqueous blend of three herbs on haemato-biochemical indices of broiler chicken at starter phase.  Ajeigbe, Sangosina, Ogunseitan, Lawal, & Yusuff analysed the Effects of Neem Leaves (Azadirachta Indica) and Cassava Peels on the Performance of West African Dware Goat. Abdussalam & Adewole in their paper  carefully explained the Formulation of Natural Products Repellents for the Control of Cockroaches (Periplaneta americana). Elesin & Obafunmiso gave as Assessment of Public Toilets Facilities Provision and Management in Tertiary Institutions in Nigeria- An Overview of The Federal Polytechnic, Ilaro, Ogun State.

I would like to deeply appreciate and extend my profound gratitude to my co-editors, editorial board members, reviewers, members of FEPI-JOPAS, especially the Managing Editor, as well as all the contributing authors for making the production and publishing of this volume 3 issue 2 a reality. I will like to appreciate the authors in this issue for allowing their works to be subjected to our thorough and rigorous peer-review processes and for taking all the constructive criticism in good fate. The authors are solely responsible for the information, date and authenticity of data provided in their articles submitted for publication in the Federal Polytechnic Ilaro – Journal of Pure and Applied Sciences (FEPI-JOPAS). I am looking forward to receiving your manuscripts for the subsequent publications.

You can visit our website (https://fepi-jopas.federalpolyilaro.edu.ng) for more information, or contact us via e-mail us at fepi.jopas@federalpolyilaro.edu.ng.

Thank you and best regards.

Prof. Olayinka O. AJANI

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# Framework Model of Facial Analysis for Gender Classification Using Convolutional Neural Network

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## Abstract

Classification is a technique used for solving problems. Several problems are solved with this technique. Gender classification is gaining ground due to different areas of applications such as surveillance, security, and monitory, etc. Different authors have presented different research articles in the domain of gender classification and adopted 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 networks to obtain better accuracy and reliability. This article is aimed at developing a model where gender can be classified. Successful classification needs a robust method with good experimental analysis that is why we present a gender classification using a Convolutional Neural Network for reliability and accuracy using a local dataset. Although, most of the articles in this research area made use of 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 (490 images) were captured and five different augmentations such as blur, top hat, lightening, etc were carried out on the images. The dataset was divided into two with 70% of the images used for training and the remaining 30% for testing. This was done with the use of a random selection algorithm. Required 227by227by3 image size was pre-trained by AlexNet a CNN. The experimental results generated several tables, Area under Curve (AUC) and Confusion Matrix. Our proposed ConvNet on our local dataset improves gender classification accuracy. In conclusion, the 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.

**Keywords: Gender, Facial Images, Facial Analysis, Classification, Convolutional Neural Network.**

## INTRODUCTION

Biometrics verification acts as a measure for security and safety, it has 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 informed of scanning or capturing of some parts of the human body such as the face, voice, palm, iris, and finger features.

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

Face recognition system is one of the ways people display their emotions and it is a fundamental biometric system that proves effective, efficient, and highly authenticated (Dahghan, Ortiz, Shu, and Masood, 2017). Several important information is expressed through human faces such as emotion, race, gender, age, etc. (Yang, Chen, Ricanek and Sun, 2011). These expressions can be processed in other to be able to detect or classify facial images by the means of a digital computer and with the use of machine learning algorithms. Classification as a technique is widely 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 elements (pixels) 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 is easily carried out by human beings but it is problematic for a machine. The gender classification will help to identify, authenticate and control access of people from some restricted areas such as security zone by allowing individual face as an identifier instead of using password, username, or even key. This paper presents a novel way of classifying gender using a convolutional neural network (ConvNet or CNN) as a deep machine learning algorithm that can multi-task and learn robust features for different tasks(Ranjan, Sankaranarayanan, Castillo, and Chellappa, 2016)

## LITERATURE REVIEW

### Gender Classification

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

i. Discrete Cosine Transformation (DCT): is an algorithm used to change e illumination condition of the facial images (Haider, Bashir, Sharif, Sharif, and Wahab 2014). This algorithm applied the captured images by keeping the coefficient in a zigzag form in other to convert the 2D images to vector (Hemalatha, 2014).
ii. Local Binary Pattern (LBP): is an algorithm used in the area of face detection localization that produced the highest-ranking matching level (Haider, et al. 2014). According to Gaur, Dixit, Hasan, Wani, Kaz, I, and Rizvi (2019) LBP has form been ally used in face texture investigation but now it is used for outward appearance extraction and opposes the variation to illumination with an easy way of computing. There is an 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 optimization amongst facial images. It helps to locate the nodes in the facial landmarks which include the corner of the eyes, nose tip, mouth, etc. The face graph is constructed by feature matching and manual correction which compares the graph. (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, and 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 and 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 algorithm was first developed by Turk and Pentland in 1991 as recorded by (Bhele and Mankar 2012; Gan, 2018). The algorithm was used to extract the main components of the individual face in the database and combine the largest eigenvectors (Mishra and Dubey, 2015). Delac et al. (2005) in their paper explained PCA as a technique used to represent a 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 the large computation and small size of the 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 conditions is overwhelming. The distinction in ICA is that it examines a component that is statically independent and non-Gaussian (Bhele and Mankar 2012; Sutara, Rokadiab, and Shah 2016).
vii. Support Vector Machine (SVM): This is an algorithm used for classifying and recognising emotions (Gaur, et al 2019). Bhele and Mankar (2012) explain that SVM can only be used where there is no omission in the feature vectors defining sample. It also attains good generalisation performance. SVM finds the hyperplane that distinguishes the largest probable fraction point on the same area of the same class (Chawngsangpuii and 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 which moves muscles. There is a hidden layer in NN that is likened to the parts of the face (Gaur, et al 2019). This classifier which is popularly used in object recognition and likes is used to extract the complex class of face features or patterns (Chawngsangpuii and Singh, 2015). There are a series of layers which is made up of neurons; neurons are connected by weighted combinations of all other neurons in the group (Shehina and Joseph, 2017).

### Convolutional Neural Network in History

Convolutional Neural Network as a Classifier

Coskun (n.d) and Kamencay (2017) defined CNN as an artificial neural network that extracts 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 layers 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 several areas of applications and couple with its recognisable performance (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 the CNN algorithm before faces are recognised. According to Sharma et al., 2018) there are five layers that CNN goes through. These are;

i. Input Layer: This is the layer that takes captured images, resizes them, and later passes it to the 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 keeps the useful features within the window where the maximum value is kept. The related features of each training test are combined (Zafar, Ghafoor, Zia, Ahmed, Latif, Malik, and Sharif 2019).

iv. Rectified Linear Unit Layer (ReLU): This layer swaps all negative numbers to zero which makes the CNN 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 around the images to extract features that are called feature map (Zhang, Dind, Shang, Shao and Fu 2018).

Typical Convolutional Neural Network Architectures

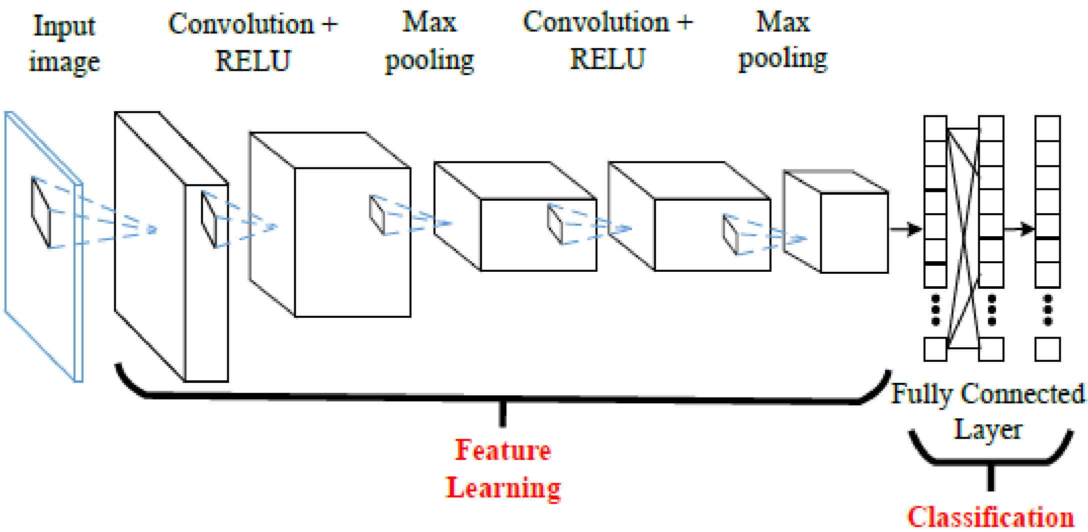



**Figure 1: Typical CNN Architecture**
**Source: Kamencay P et. al. (2017).**

## MATERIALS AND METHOD

### Image Acquisition

The image dataset consists of 490 images that involve males and females of different age brackets. Figure 3.1 shows the samples of images from the local dataset.

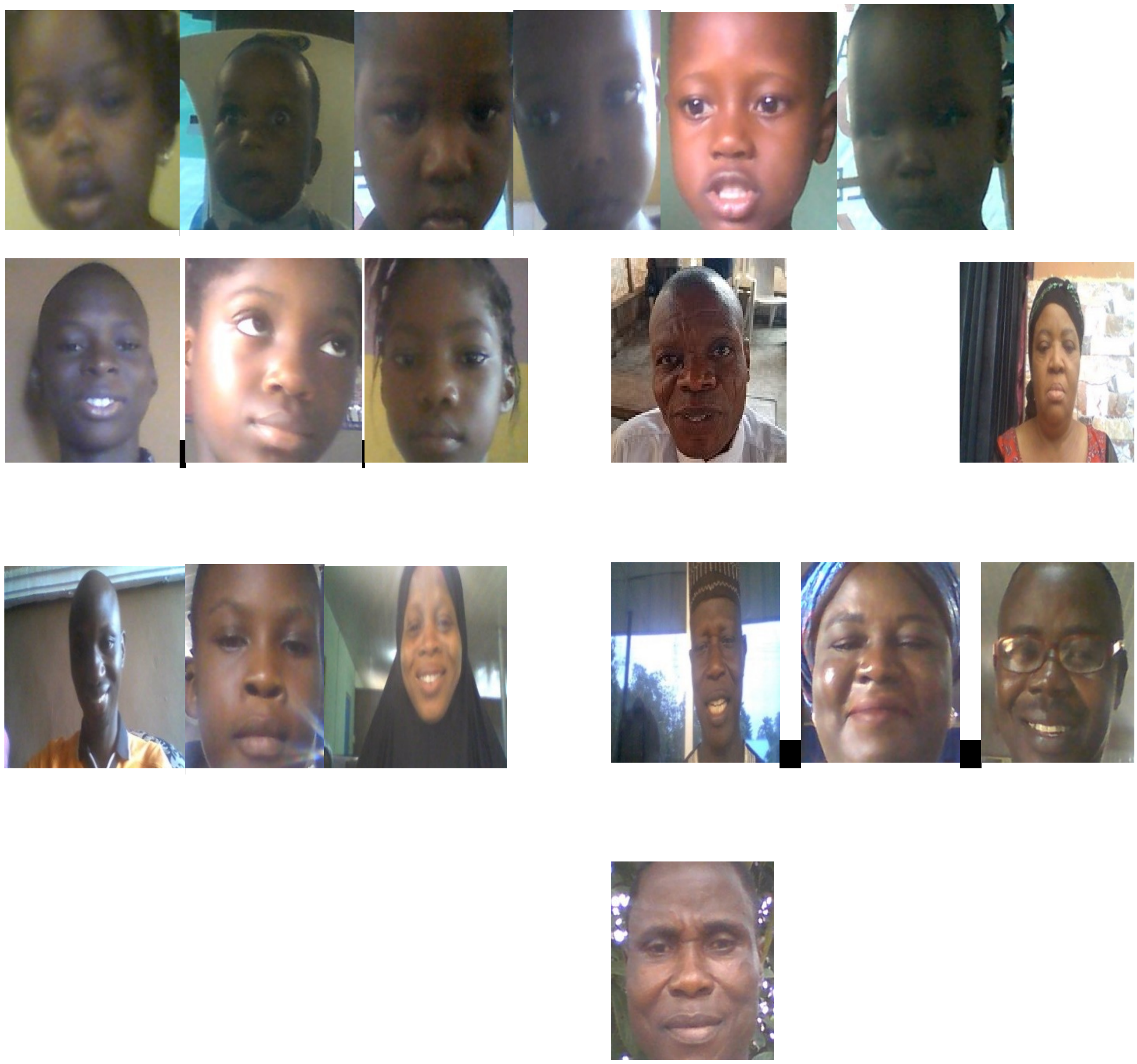


**Fig. 3.1 Some Images from the Local Dataset**

**Gender Recognition**

The MTL-CNN model is to recognize the gender of the facial images. The loss function also known as error function is a function that maps the values of one or more variables onto a real number automatically representing some cost associated with an event. It describes how well an algorithms model dataset.

The loss function used for gender classification, $L_g$, 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 females. 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.

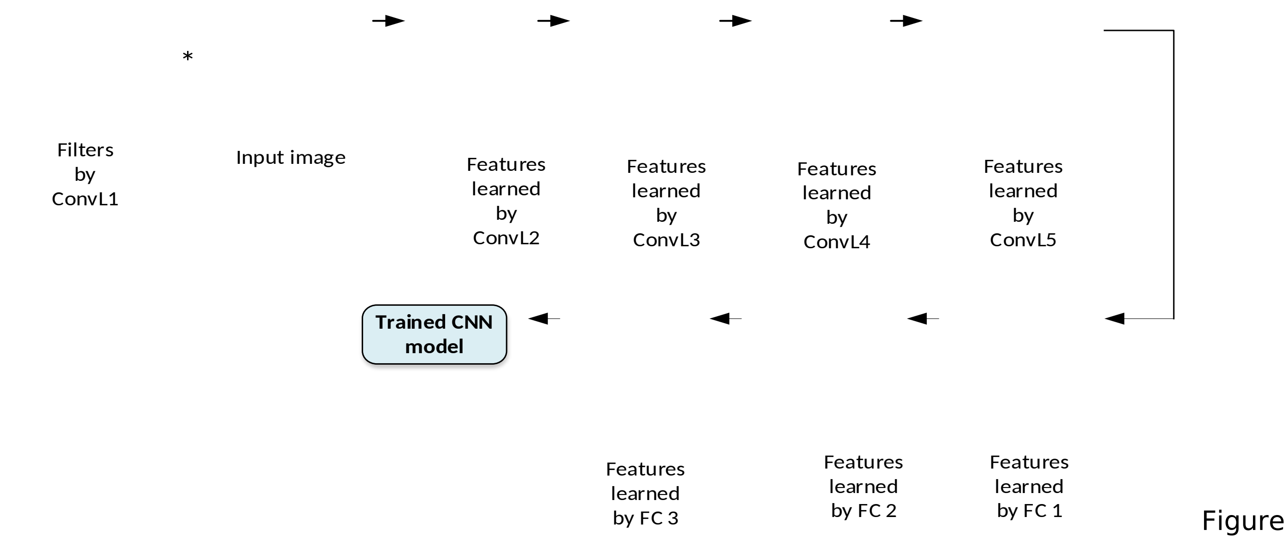



Figure 2: Architectural overview of the Model

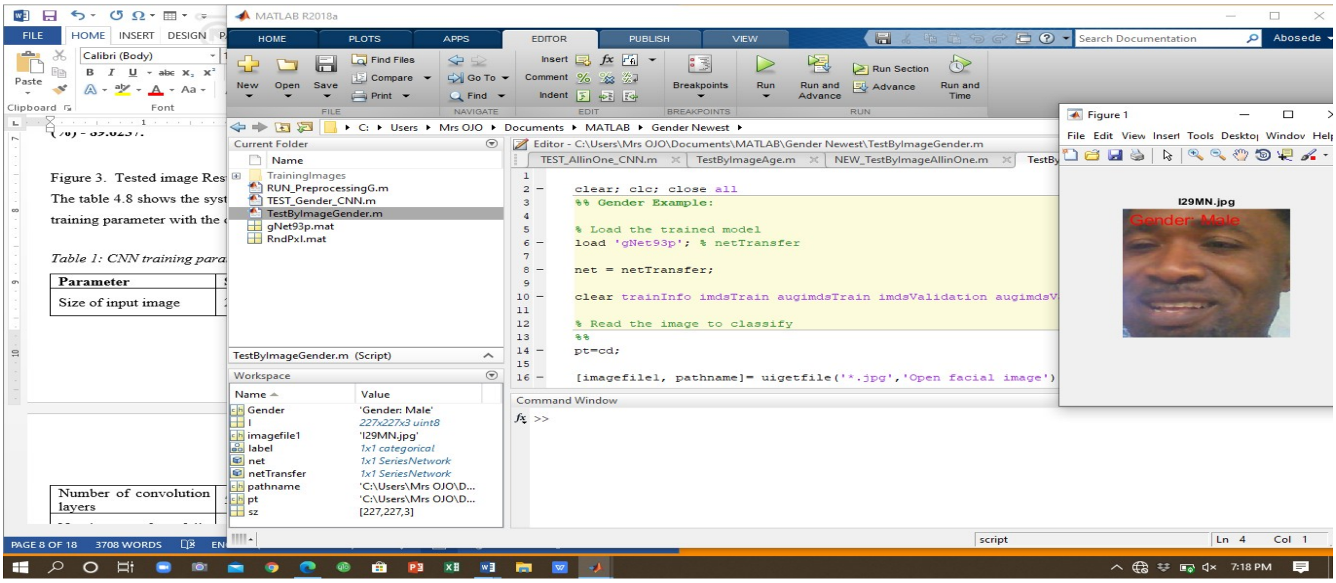



**Figure 3: Tested image Result of the Implemented Gender Classification using MATLAB**

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 parameters.

**Table 1: CNN training parameters for Gender and its description**

| **Parameter** | **Specification** | **Description** |
|---|---|---|
| Size of the input image | 227-by-227-by-3 | The acceptable dimension required by the pre-trained algorithm (AlexNet) |
| Number of convolution layers | 5 | These are building blocks used in convolutional neural network |
| Number of fully connected layers | 3 | These are layers where all the inputs from the previous layer are connected to every activation unit of the next layer. |
| Activation function | Softmax | This is used to transform the unnormalised elements of a fully connected layer into a normalised output |
| Optimizer | Stochastic gradient descent | This is an iterative method used to optimise an objective function with appropriate smoothness properties. |
| Momentum | 0.9 | This is a designed method or technique used as a group of tricks to speed up the convergence of the first-order optimisation methods. |
| Maximum epoch | 23 | This is 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 concerning 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**

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

**Table 4: Comparison of the training set and testing set**

| **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** |

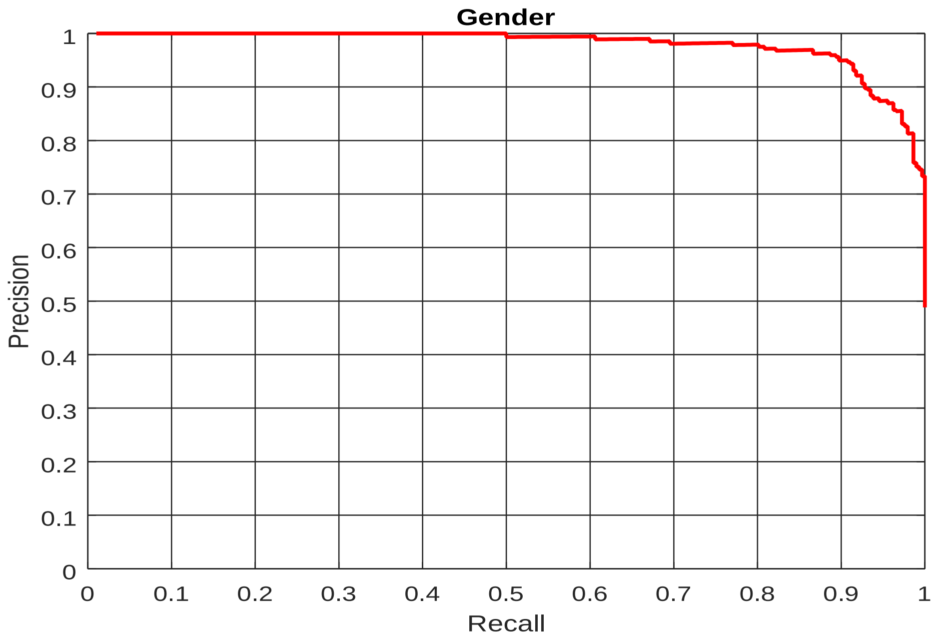



**Figure 4: Precision vs. Recall on Gender**

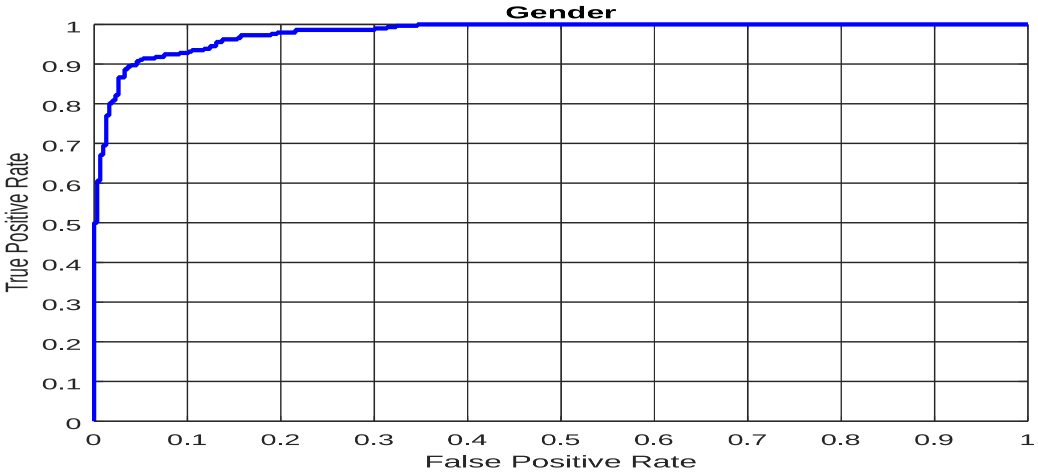



**Figure 5: True Positive Rate vs. False Positive Rate on Gender**

**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 |

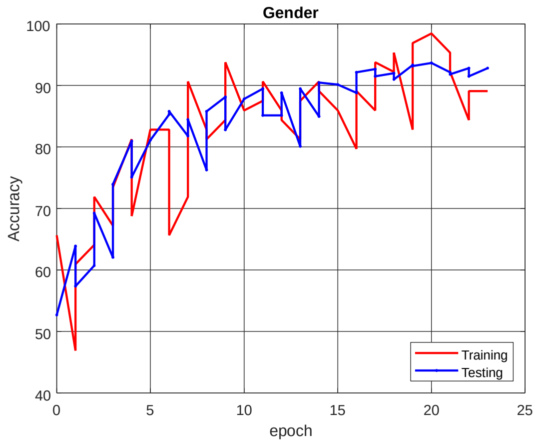



**Figure 6: Accuracy vs. Epoch**

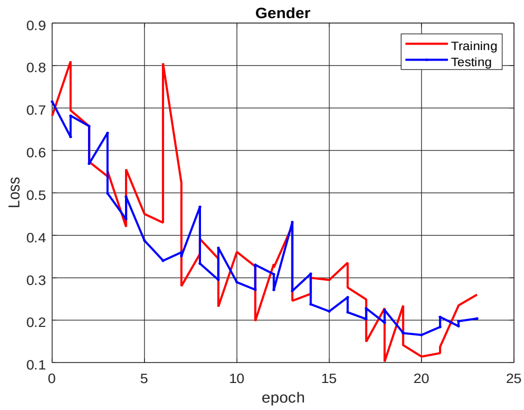
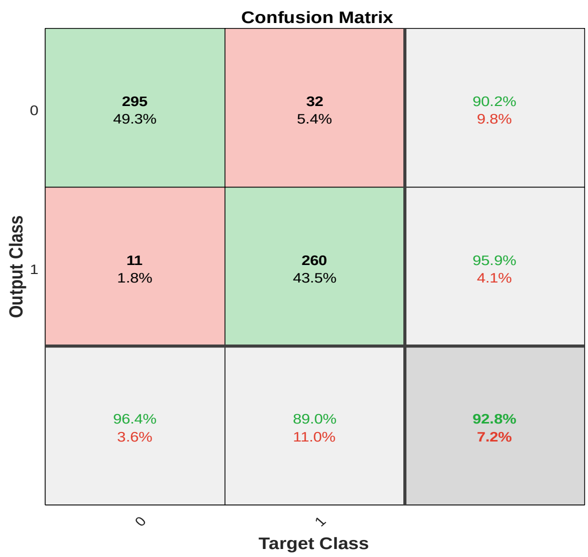



**Figure 7: Loss vs. Epoch**

**Table 6: Confusion Matrix for Gender Classification**



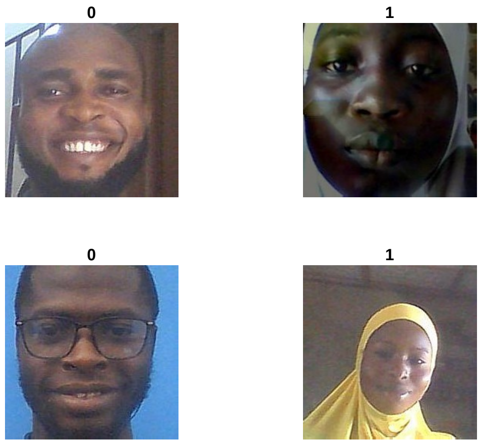



**Figure 8: Sample of trained images - "Female" is denoted by digit 1 while "Male" is denoted by digit 0**

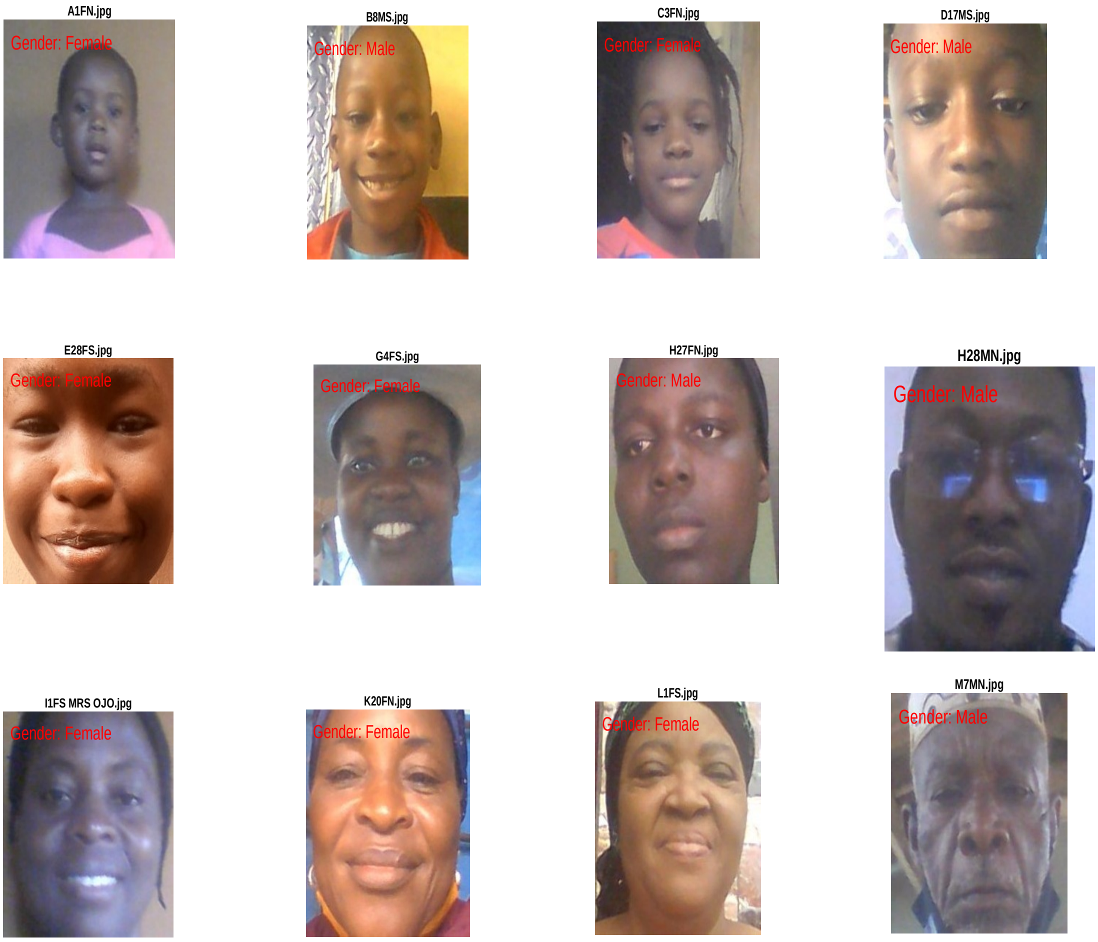



**Figure 9 Tested input samples for Gender classification**

## DISCUSSION

### Discussion on Gender Classification

Table 2 represents the result of testing the CNN model for gender detection where 598 images were tested with a 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 using random selection algorithms.
2. The Gender Actual or ground truth: is the column that shows the true sex of the image selected where digit 1 denotes female and digit 0 denotes male.
3. Gender Predicted by CNN: This column shows what the CNN classifier classified on the Test ImageId.

The Precision, Recall, Accuracy, and F1-score which 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 Accuracy with two different epoch that is epoch 22 and epoch 23.

Table 4 shows the comparison of the number of training images and testing images with their testing time. A total number of 1394 images were used for training and 598 images were used for testing with 3952(s) for training and 40.7549(s) for testing with the use of an algorithm called random selection algorithm. The total number of the figure for both the training and the testing images was gotten from the number of the images stored as a dataset which was 490 images multiplied with the five different augmentations performed on each image.

Table 5 shows the Recall vs. Precision and False Positive rate vs. True Positive Rate with their graphs. While table 4.6 shows the training/testing Accuracy vs. the Training/ Testing Loss. With a cursory look at the table, there is a 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 an 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 a result of the update in the weights at every epoch iteration and these resulted in different validation errors 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

In table 2, the first Test imageId (1) which represents the first image was male on the ground truth and correctly predicted as male by the 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) was female but predicted as male.

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 were correctly classified while 11 images were misclassified.

for females (0) was 260 out of 292 images with a percentage score of (89.0%) and 32 misclassified as male with a percentage score of 11.0%. 295 out of 306 images trained were correctly classified with a percentage score of 96.4% while 11 images were misclassified as female with a 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. Finally, the CNN model has very high accuracy with significantly better performance where we have **89.6276** for **Precision (%); 89.6276** for **Recall (%); 92.8094** for **Accuracy (%)** and **F1-score (%)** is **89.6237.**

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