Menoufia J. of Electronic Engineering Research (MJEER), Vol. 31, No. 2, July,2022

Faces Recognition and Facial Gender Classification using Convolutional Neural Network

Mohamed A. Berbar
Dept. of Computer Engineering and sciences
Faculty of Electronic Engineering, Menofia University
Menouf 32952, Egypt
m_berbar@el-eng.menofia.edu.eg
0000-0001-5405-159X

Abstract— **Computational power in deep convolutional neural networks has made it possible to have robust classifiers for faces and facial gender for many security issues and computer vision problems. This paper proposes two convolutional neural network (CNN) models for face recognition and facial gender classification. The models consist of an image input layer, followed by three blocks of convolutional, normalization, activation, and max-pooling layers, and three fully connected layers. The performance of the proposed CNN solutions is evaluated using five publicly available face datasets. Two greyscale face datasets: Sheffield and AT & T. Three color face datasets, Faces94, Ferret, and Celebrity Face Images from Kaggle. The achieved classification accuracy ranged between 99.0% and 100% on the Faces94, Ferret, Sheffield, and AT&T datasets, and classification accuracy of 93.6% to 95.0% on the Kaggle dataset. The proposed CNN can process and classify a small-size face image 32 × 32-pixel from the Faces94, Sheffield, and AT&T datasets and 100 × 100 pixels from the Ferret and Kaggle datasets. The obtained results prove that the proposed CNN models are an effective solution for face image recognition and facial gender image classification. The proposed model produces competitive accuracy compared to several state-of-the-art methods.**

Keywords— **Face recognition; facial gender classification; convolutional neural network; max pooling layer, fully connected layer.**

I. Introduction

Face recognition is one of the most popular identity recognition issues in security issues. Facial gender classification focuses on recognizing key features used to differentiate between male and female people [1]. Inequality between facial virility and femininity can be used to improve the performance of face recognition applications in biometrics. In recent years, the field of automatic facial gender recognition has received increasing attention. The challenges are how to deal with the real-world facial images obtained from uncontrolled environments such as customs, airports, and stadiums in varying conditions such as illumination changes or facial occlusion (i.e., glass, beard). Recently, the computational power in deep convolutional neural networks and the availability of a large amount of data for the public have made it possible to have robust classifiers for faces and facial gender as well as for many other computer vision problems. The traditional methods of face recognition and facial gender classification include stages of image preprocessing, feature extraction, and classification. Both feature extraction and classification are performed within a single network structure through learning from data samples. Feature selection is also integrated into the training process by learning the weights in CNN. Convolutional layers are responsible for extracting features [2]. The CNN has advantages over the traditional approach because of its resistance to geometric distortions and transformations [2]. Unfortunately, a traditional feature extractor is designed independently of the classifier, so it is characterized as a static approach as it is not part of the training procedure [3]. Hence, the CNN is designed to overcome the weakness of the traditional feature extractor. The biggest benefit of CNNs is that they are considered easier to train. CNN has fewer parameters compared to fully connected multi-layer perceptron (MLP) networks with the same number of hidden layers. The CNN approval promises success in a wide range of applications like character recognition [4], face recognition [5], human tracking [6], traffic sign recognition, and many others. In this paper, we propose a novel CNN model for gender classification and another model for face recognition. The gender classifier model demonstrated its robustness, especially when trained on a dataset and tested using a different dataset. The binary gender classifier model scores high accuracy on the Celeb Kaggle dataset, which is a large dataset (168550 images) and images have different backgrounds. The developed code for preprocessing and machine learning was written using Matlab-19. The used computer was an XPS 18 all-in-one with a single CPU, 4GB of RAM, and a 1TB HD.

II. Related works

Although gender classification can play a significant role in many computer vision applications, it has not been studied well compared to many popular problems of recognition and identification. This section discusses previous works from the perspective of the classification methods applied. In [7-11], the authors used local binary patterns (LBP) and SVM. Ihsan Ullah et al. (2014) [7] used the spatially enhanced versions of the local binary pattern (LBP) and Weber’s law descriptor (WLD) (SLBP and SWLD) for gender classification. They got an accuracy of 99.1% at best on the FERET database. Lian and Lu (2006) [8] obtained an accuracy of 94.81% on the CAS-PEAL face dataset. Some methods, such as [7,8,9], divide the image into blocks and use LBP to extract features for each block.A good performance could be achieved if the block size for the LBP operator is selected and calculated with care, which is a rather difficult task because the choice of the block size is dependent on the resolution of the images.

Fekri-Ersha (2019) [9] classified genders in human face images based on modified local binary patterns (MLBP). They got 93.29% accuracy on the ICPR dataset. Wang et al. (2012) [10] proposed a variant of Local Binary Patterns (LBP), namely Local Circular Patterns (LCP). The maximum accuracy was 94.64%. Sajja and Kalluri (2019) [11] have worked on gender classification from face images using LBP, SVM, and back propagation. In this research, they have used the ORL dataset, which contains only 400 images, and the Nottingham Scan dataset, which contains 100 images. After implementation, they gained 100% accuracy for the ORL dataset and 71% accuracy for the Nottingham Scan dataset, respectively. Sami et al. (2021) [12] proposed facial gender classification using their proposed CNN. A preprocessing stage is preceded by the classification process. Their method achieved 95.0% using the Kaggle dataset and 90% accuracy using the Nottingham Scan Dataset database, which is quite low in the number of samples. Nazir et al. (2010) [13] used the 2D-DCT method for feature extraction and the K-means nearest neighbour (KNN) classifier. They achieved an accuracy of 99.30% on the SUMS face dataset. Berbar (2013) [14] used the 2D-DCT method to extract features and SVM for gender classification. With 2-fold cross-validation, they achieved accuracies of 99.90%, 93.3%, 98.6%, and 99.97% for the UMIST, FERET, AT@T, and Faces94 datasets.Berbar (2013) [14] also used GLCM for feature extraction. Accuracy rates for UMIST and FERET, AT@T, and Faces94 datasets were 100%, 93.11%, 98.8%, and 99.6%, respectively. The drawback of 2D-DCT is that it is an intensive computation algorithm. Sun et al. (2002) [15], used a hybrid approach of principal component analysis and genetic algorithms. The error rate of 11.30% was reported. Duffner (2009) [5] proposed a CNN with six layers. On the FERET dataset, a classification rate of 94.7% was achieved. Liew et al. (2016) [16] proposed a CNN architecture for gender classification based on face images. They got classification accuracies of 99.38% and 98.75% on the AT & T and SUMS datasets, respectively. Athenian et al. (2021) [18] used 191 hand-crafted and fused features for face gender recognition. They used both SVM and CNN and gained the best accuracy of 86.60% using CNN. Serna et al. (2021) [19] worked on gender detection using VGG-Net and Res-Net, where they analyzed how bias affects deep learning. They divided the images into 3 ethnic groups and experimented on a test group. They achieved the best average accuracy of 95.27% for the test group using VGG and 95.67% using Res-Net. 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 work are that the feature extraction and the classification are performed separately. In the case of CNN, which is a multilayer neural network model [20, 21], it can optimize filters through automated learning that is independent of prior knowledge, which demonstrates a superior performance that can be achieved using CNN. Tilki et al. (2021) [17] used their convolutional neural network (CNN) and the popular pre-trained model Alex Net. Experiments were performed to evaluate the performance of both models for the identification of male and female classes from selected 5000 face images (KAGGLE, 2018). Their results are accurate to 94.4%.

III. Datasets Under Processing

Except Kaggle dataset, the most used datasets are unbalanced in the number of terms of females compared to the number of males. In most of the public datasets, the number of females is usually much smaller than the number of males. To resolve this problem, we evaluated the proposed models with a mix of two datasets. The images of males and females of people of various racial origins, some people have glasses, and some have beards.

A. Faces94 dataset

The number of images per individual is 20 taken under artificial lighting. The number of individuals is 152, and the image resolution is 180 by 200 pixels (portrait format). The dataset contains 2,660 male and 399 female images. This dataset contains a considerable number of images. Samples of the dataset are shown in Figure 1 [22].

Figure 1: Samples of images from the faces94 dataset [22]

B. AT&T (Olivettti) dataset (ORL)

The dataset contains 380 images of male persons and 50 images of femaleS. This dataset contains 34 subjects (5 females and 29 males), and 10 images per subject. All images are represented in grayscale levels and 92×112-pixel size. This dataset is available in [23] and samples are shown in Figure 2.

Figure 2: Samples of images from the AT@T dataset [23]

C. FERET dataset

The FERET dataset contains 631 males and 66 females. Figure 3 shows some samples of the FERET dataset [24].

Figure 3: Samples of images from the FERET dataset [24].

D. UMIST & Sheffield dataset

The Sheffield (previously UMIST) Face Dataset consists of 564 images of 20 individuals of mixed race/gender/appearance. Figure 4 shows samples of some subjects. The dataset contains 480 male and 172 female images with different pose positions. The images have different sizes ranging from 248×258 to 202×233.

Figure 4: Sheffield Dataset are grayscale images mixed of frontal and side view faces [31].

E. *Kaggle Celeb Face dataset*

The Celeb Face dataset from Kaggle [28, 29] is a large dataset for faces gender classification. The dataset consists of almost 200K images of various celebrities of mixed race/gender/appearance. The images are all taken in different conditions and are of different poses. It contains an unbalanced number of male/female images. In this paper, the used number of images is 168550, half of them are female images and the same number for male images to balance the training. The original image resolution is 178×218 but in this paper, the resolution is resized to 100×150. Figure 5 shows samples of images and the challenges in the detection of faces and gender.

Figure 5: Samples of CELEB-aligned images [29].

IV. Solutions Methodology

In our proposed system, we have utilized a CNN architecture. CNN which is a deep learning algorithm is capable of distinguishing images from their characteristics. In this research, we proposed a CNN architecture model for facial gender classification. Later, we modified the classification part in the same CNN model to classify faces and recognize personal identity. The convolution and the pooling layers perform the feature extraction of the image which extracts information from the input for decision making. Finally, three fully connected layers perform the classification part. Our basic network architecture for facial gender classification has been illustrated in Figure 6.

In Convolutional Neural Network (CNN), the feature extraction is performed by the convolution and the pooling layer. The proposed CNN model architecture comprises an image input layer, followed by three blocks of convolutional, normalization, activation, and max-pooling layers. The first block of layers consists of a convolution layer containing 16 filters with 3 × 3 kernels followed by batch normalization and RELU is used as the activation function then max-pooling layer uses a 2x2 pool size to reduce spatial dimension. The second block is repeating the first block of layers using 32 filters. The third group contains a convolution layer containing 64 filters with a 3 × 3 kernel size followed by batch normalization and RELU without a max-pooling layer. This third block of layers is followed by classification layers. The classification layers are three fully connected layers (fc_1, fc_2, and fc_3). Fc_1 and fc_2 are ten neurons and fc_3 two neurons. At the end of the CNN a SoftMax layer and classification layer. To use the proposed model for face recognition, we increased the size of classification layers (fc_1, and fc_2) to 500 neurons. fc_3 size is dependent on how many subjects are required to recognize them. It is 152 neurons to handle the problem of recognizing the faces of 152 people in the faces_94 dataset. The basic network architecture for face recognition has been illustrated in Figure 7.

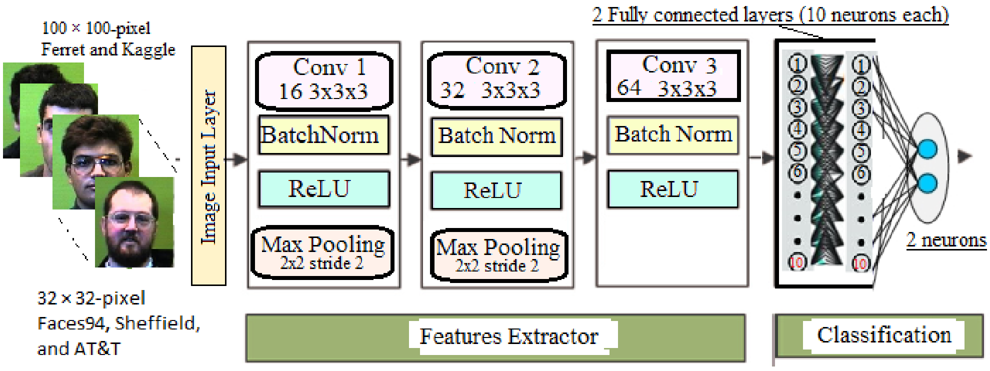


Figure 6: The proposed basic network architecture for gender classification.

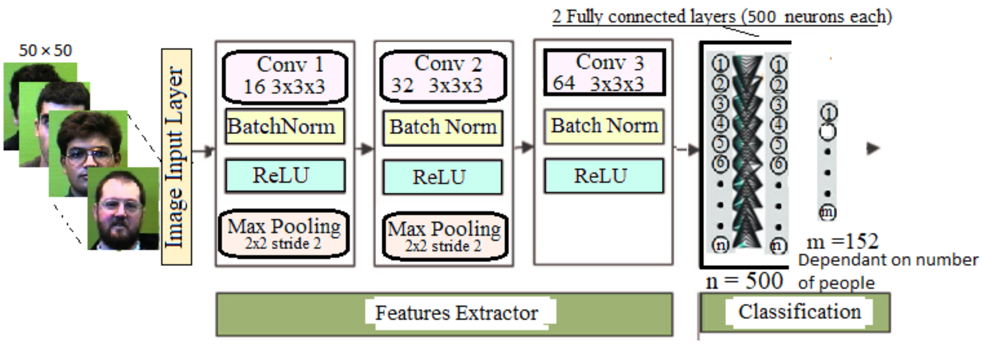


Figure 7: The proposed basic network architecture for face recognition.

V. Performance Evaluation Metrics

The results will be measured using the confusion matrix. The confusion matrix gives a clear measure to the system, and it does not mislead by only the total accuracy measure, especially when the number of classes is unbalanced (see Table 1). The performance will be measured using the receiver operating characteristic curve (ROC) and the area under the curve (AUC). ROC is a probability curve, and AUC represents the degree or measure of separability. It shows how much the model is capable of distinguishing between classes. Our models deal with greyscale and color images. The main contributions of this research are as follows: Efficient and effective CNN models for face-based gender classification and also for face recognition are proposed. The proposed CNN model has a reduced design complexity compared with pre-trained CNN models (Alex-Net, Google-Net, Res50-Net, etc.). Our models have a small number of layers, neurons, trainable parameters, and connections.

Table 1: Confusion Matrix

	Positive Female (PF)	Positive Male (PM)	
Female (F)	Number of True Classification of Female **(TF)**	Number of False Classification of Female **(FF)**	True Female rate % (TFR), selectivity of female = TF/F
Male (M)	Number of False Classification of Male **(FM)**	Number of True Classification of Male **(TM)**	True Male rate % (TMR), sensitivity of male = TM/M
	Female predictive value % (FPV)=TF/PF	Male predictive value % (MPV) = TM/PM	
Accuracy (ACC) % = (**TM** + **TF**) / (**FM** + **FF** + **TM** + **TF**)			

VI. Results and Discussions

As explained in section 3, the datasets under processing contain images of different sizes. Some datasets contain color images, while other datasets contain greyscale images. Our model expects the input images to be in color and of a size 100×100 pixels for the Ferret and Kaggle datasets and of a size 32×32 pixels for the Faces94, Sheffield, and AT&T datasets. The training and test images are automatically resized and converted to RGB before they are input into the network. We create augmented image datastores before training, determine the desired image size, and use these datastores as input arguments to CNN. We decided to use a split ratio of testing and training samples of 50/50. 50% of the number of dataset samples under processing is used for training and the other 50% is for testing.

A. *Results of Facial Gender Classifier Model*

Table 2 shows the results of the facial gender classifier on four datasets and the result of the facial gender classifier on a combination of Ferret and Faces94 datasets. It also shows a comparison with the best available results in the literature using the same datasets. The proposed CNN model for facial gender classifier shows excellent performance on color face datasets such as Faces94 and Ferret and on greyscale face datasets such as Sheffield and AT&T with a split ratio of training/testing sets of 50/50. Figures 8-11 show the details of the results in Table 2. For example, Figure 10 shows the results of the Sheffield dataset. 85 of 86 female samples are predicted correctly, while one sample is classified as male. On the other hand, 420 samples of males were classified correctly. The true female rate (sensitivity of female detection) equals (85/86) about 98.8%. The true male rate (sensitivity of male detection) is equal to (420/420) to 100%. The female predictive value is equal to 100%. The male predictive value is equal to 99.8%.

Table 2: Results of facial gender classifier with a comparison with the best available results in the literature using the same datasets.

Dataset	Method	Input image size	Accuracy	AUC
Sheffield	Proposed	32 × 32	99.8%	0.9896
AT&T	Proposed	32 × 32	99.53%	0.9674
	Liew et al. (2016) [16]	NA	99.38%	NA
Faces94	Proposed	32 × 32	99.80%	0.9951
	Mahesh and Raj (2018) [25]	112 × 92	100 .0%	
Ferret	Proposed	100 × 100	99.13%	0.9438
	Duffner (2009) [5]	NA	94.70%	NA
Ferret & Faces94	Proposed		99.84%	0.9955

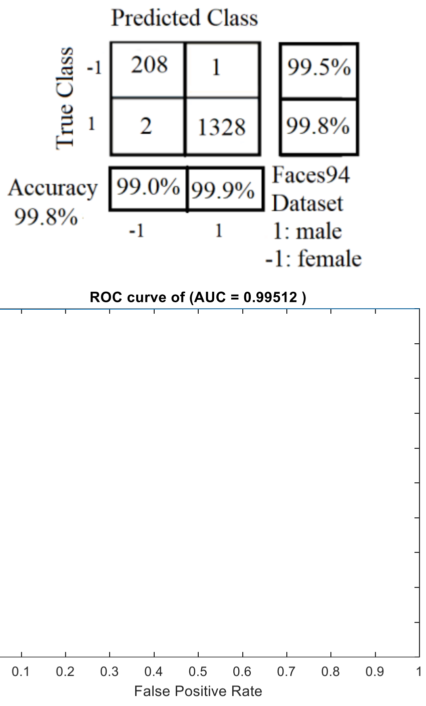


Figure 8: The Confusion Matrix and ROC curve of Gender classifier on color Faces94 Dataset.

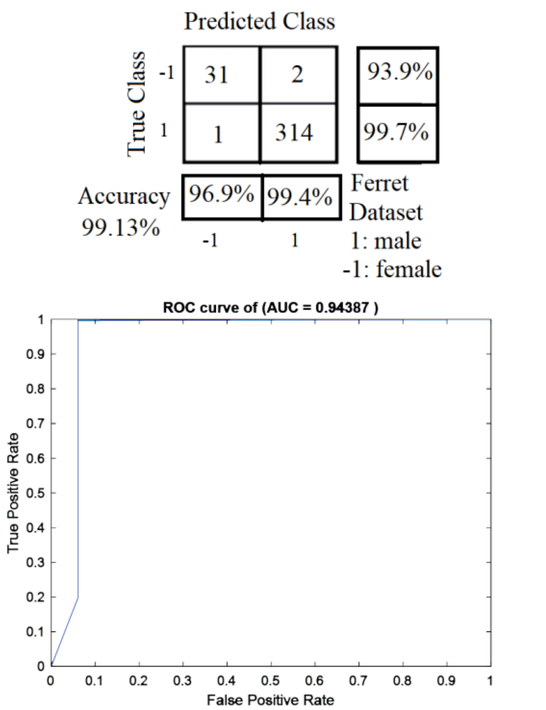


Figure 9: The Confusion Matrix and ROC curve of Gender classifier on color Ferret Dataset.

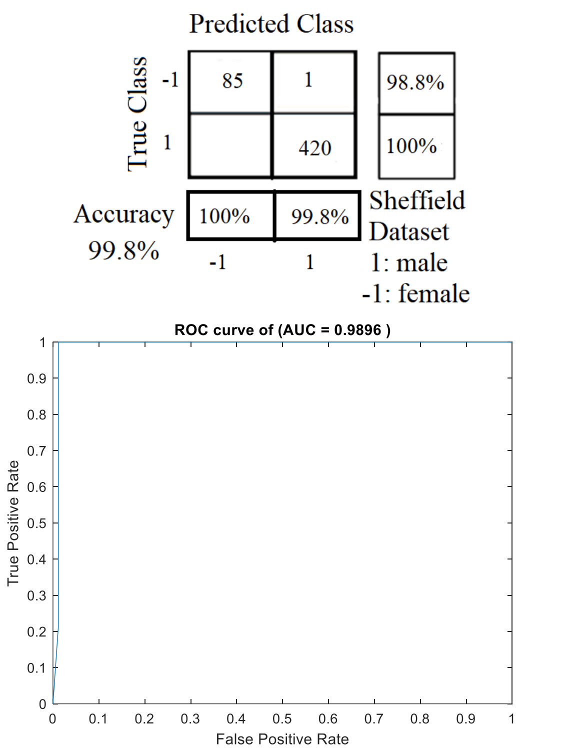


Figure 10: The Confusion Matrix and ROC curve of Gender classifier on Sheffield Dataset.

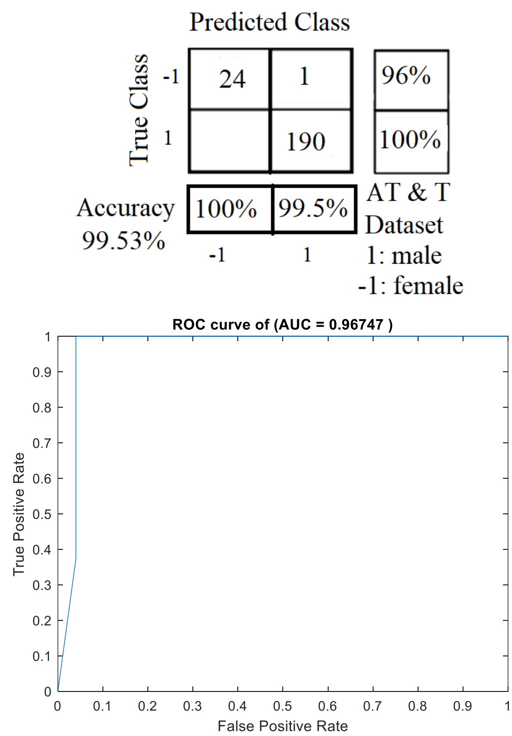


Figure 11: The Confusion Matrix and ROC curve of Gender classifier on the AT&T dataset using split ratio 50/50.

We also noticed that increasing the number of training samples to 70% of the dataset (split ratio 70/30) will increase the accuracy to 100% (see Figure 11 and Figure 12).

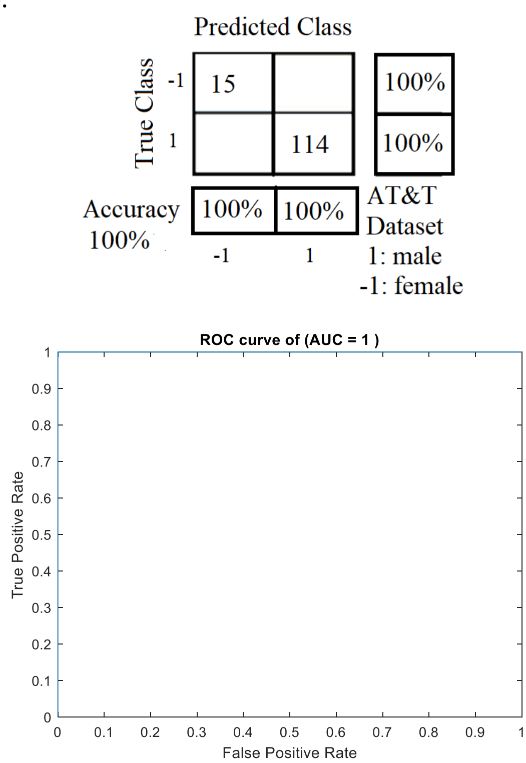


Figure 12: The Confusion Matrix and ROC curve of gender classifier using a splitting ratio 70/30 of AT&T dataset for training.

For more evaluation of the proposed model, we combined two datasets, Ferret and faces94 (3775 images), and the results confirmed the robustness of the model (see Figure 13-14). The CNN training converges within less than 4 epochs. Its accuracy reached 100%. The input image size affects the performance of the proposed CNN. We noticed that reducing the size of the image will reduce the classification accuracy in the case of the color ferret dataset, while in the case of color faces94 it keeps its performance down to a size of 32×32 pixels, which is the smallest size not affecting performance (see Figure 15). For more evaluation of the proposed facial gender classifier model, we trained the model using one dataset (faces94) and tested the model using a different dataset (ferret). The confusion matrix shows 100% classification accuracy of (697) images from the ferret dataset on the gender classifier CNN model, which was trained on the faces94 dataset (see Figure 16).

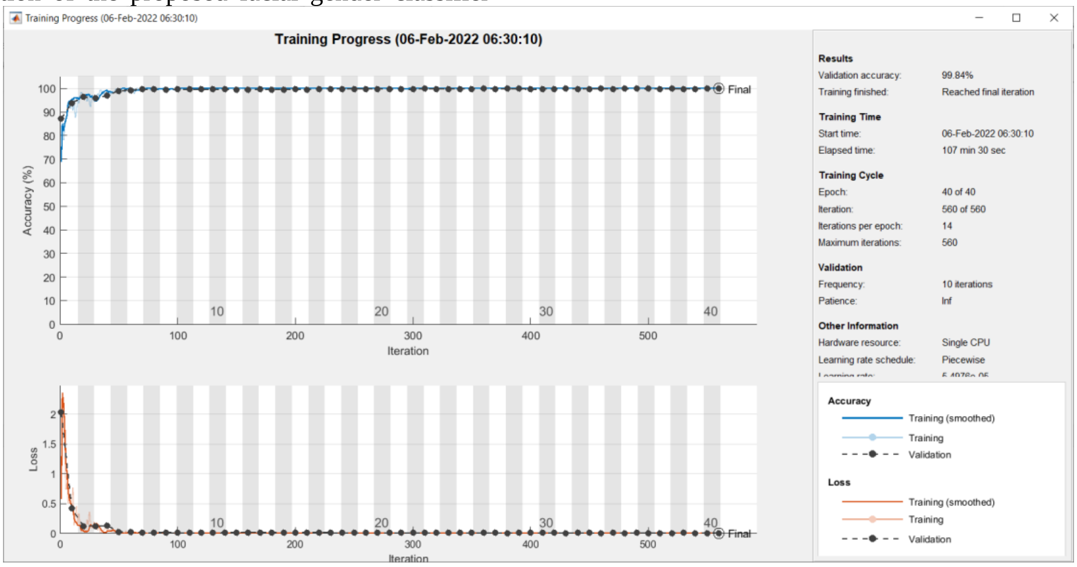


Figure 13: The training and validation progress of gender classifier on the combination of Ferret /Faces94 datasets.

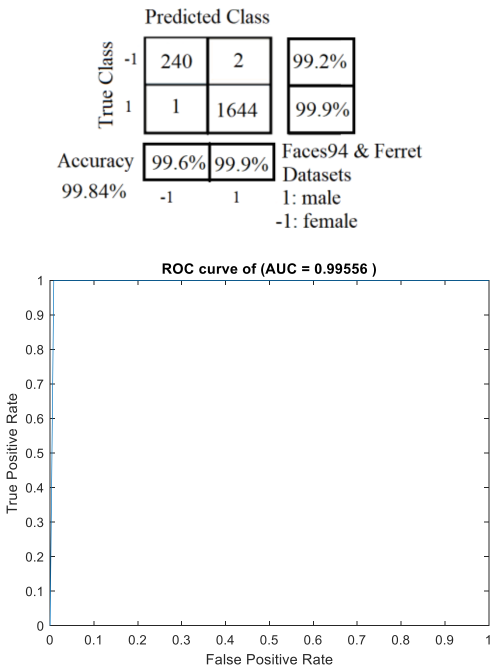


Figure 14: The confusion matrix and ROC curve of gender classifier model on a combination of Ferret /Faces94 datasets (3775 images resized to 100×100) and the model trained with splitting ratio 50/50.

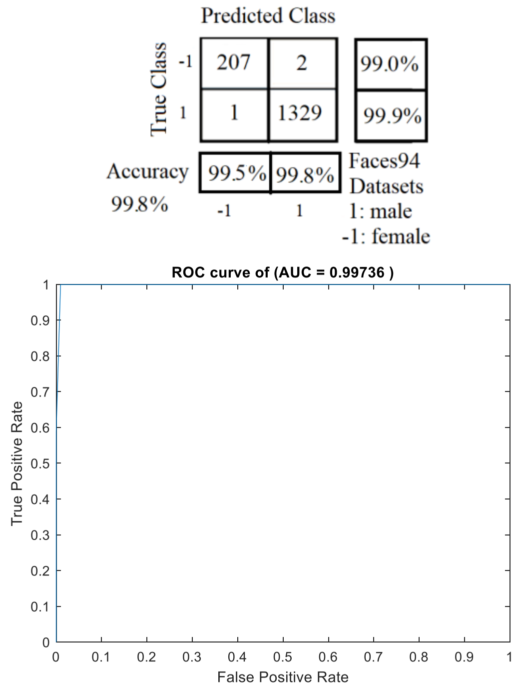


Figure 15: The Confusion Matrix and ROC curve of Gender classifier on Faces94 Datasets using 32x32 image size and a split ratio 50/50.

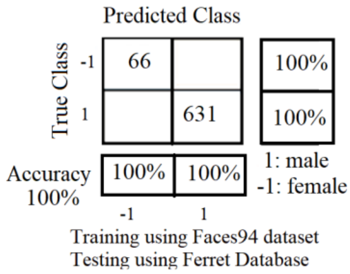
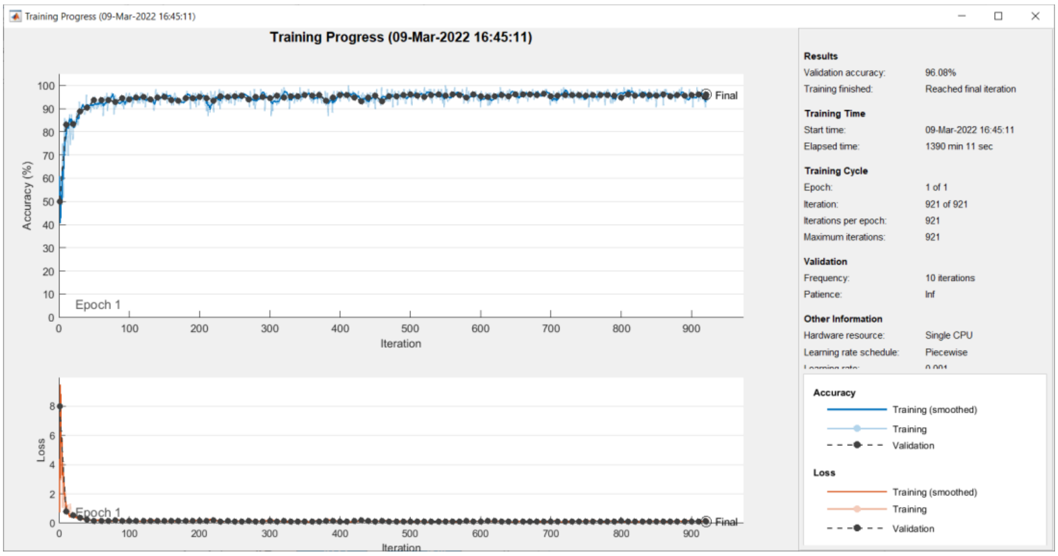


Figure 16: Confusion matrix of results of testing the gender classifier model with Ferret dataset on the proposed model which trained on 90% of Faces94 dataset.

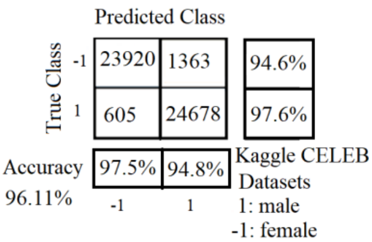
The Kaggle Celeb face dataset is the most difficult dataset because the images were taken in unconstrained environments and the faces were not cropped. The results of testing the binary CNN classifier model on the Kaggle Celeb Face dataset were encouraging (see Table 3 and Figure 17). Its results confirmed the robustness of the model.

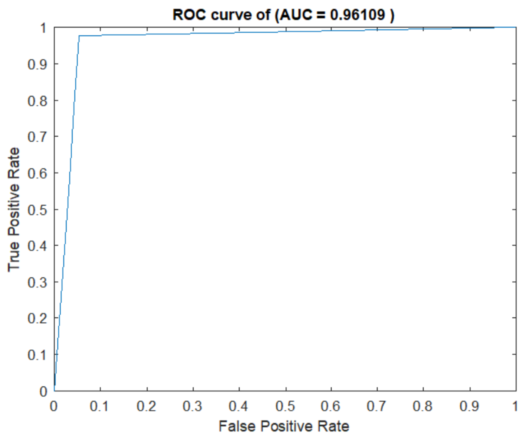
Table 3: Testing the model using the Kaggle Celeb Face dataset.

Dataset	Method	Input image	Accuracy	AUC
Kaggle	Proposed 168550 images	100 × 150	96.11%	0.96109
	ELKarazle et al (2022) [30] only 11649 images	64 × 64	94.87%	NA
	Tilki et al. (2021) [17] only 5000 images	NA	92.4%	NA



(a)Training/Validation progress.





(b) Confusion Matrix (c) ROC curve

Figure 17: Gender classifier on CELEB Dataset (168550 images)

B. Results o**f Faces Recognition Model**

The faces recognition model shown in figure 7 is evaluated using the colored Faces94 dataset. The mentioned dataset contains 152 classes; each class has 20 images. The images have been resized to 50×50 pixels. The training and validation progress of the face recognition model on the color Faces94 dataset is shown in Figure 18. The CNN training converges within less than 40 iterations. 152 people have been recognized with an accuracy rate of 100%.

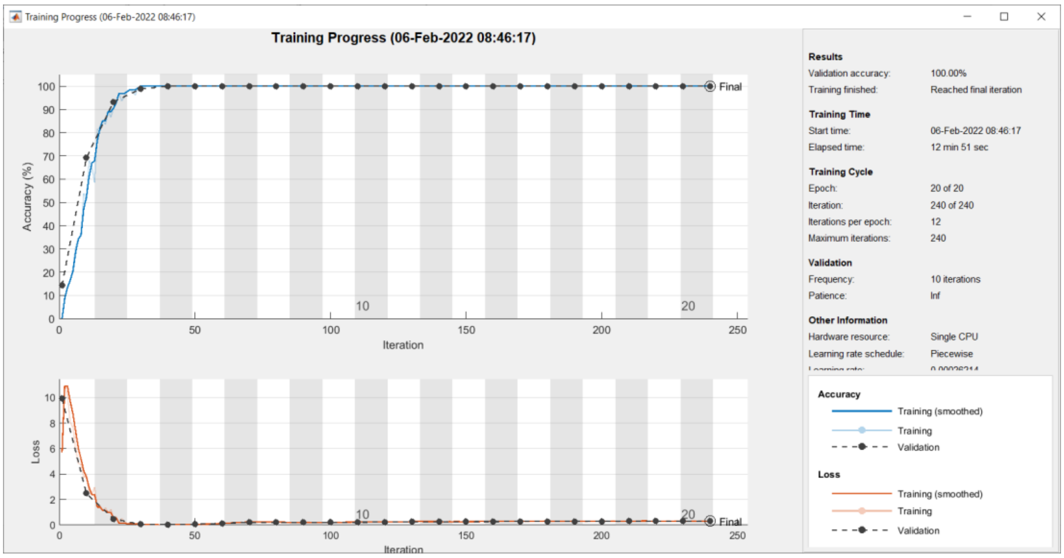


Figure 18: Training and validation progress of the face recognition model on the Faces94 dataset (152 people).

The training and validation progress of the face's recognition model on the greyscale Sheffield dataset is shown in Figure 19. The CNN training converges within less than 25 iterations. Figure 20 shows the confusion matrix results of the proposed face recognition model on 20 people from the Sheffield dataset. The images have been resized to 50×50 pixels. The numbers shown on the x-y coordinates are the codes given to each person's name. For example, the recognition errors for people with code "13" and "18", two red arrows pointing to them (see Figure 20) are explained as follows. The person with code "13" was recognized with an accuracy of 91% as 2 samples were recognized as belonging to the person with code "12" and the remaining 11 samples were recognized correctly. For the person with code "18", 10 samples are recognized correctly, while one sample is recognized as it belonging to the person with code "15." Other people were recognized with 100% accuracy.

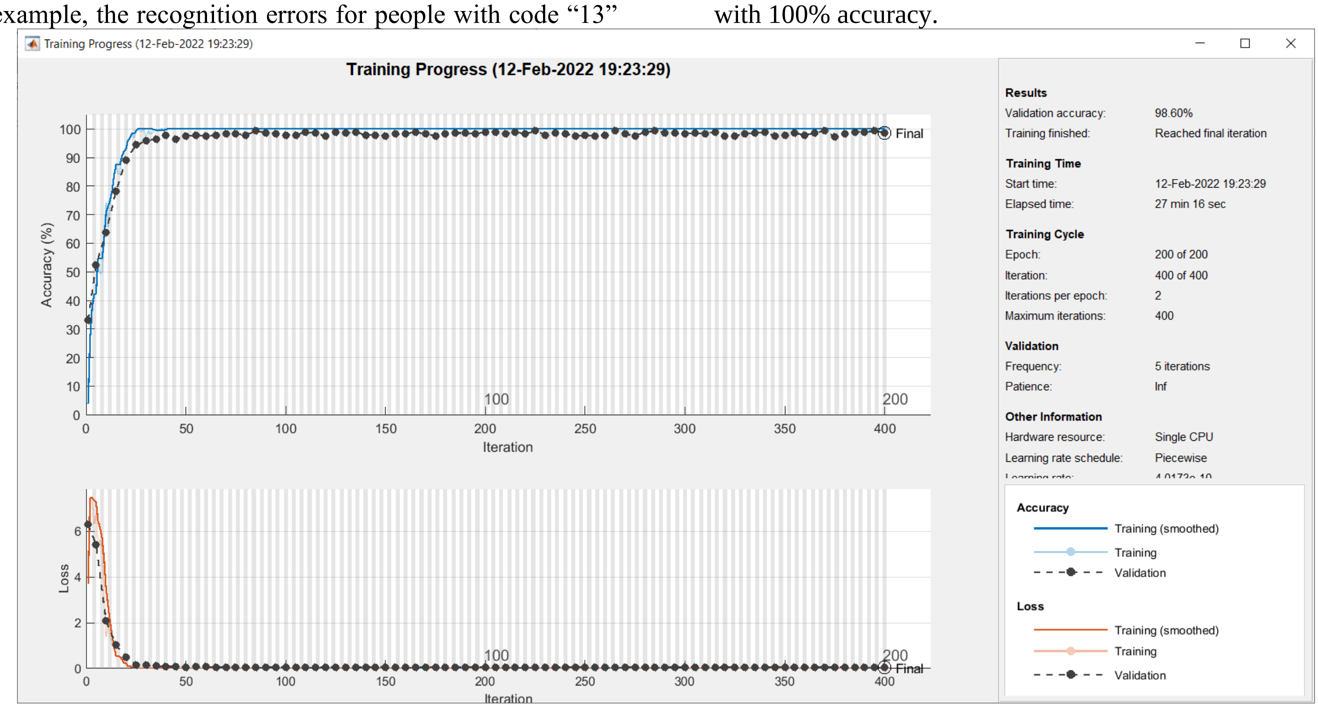


Figure 19: Training and validation progress of faces recognition model on Sheffield dataset.

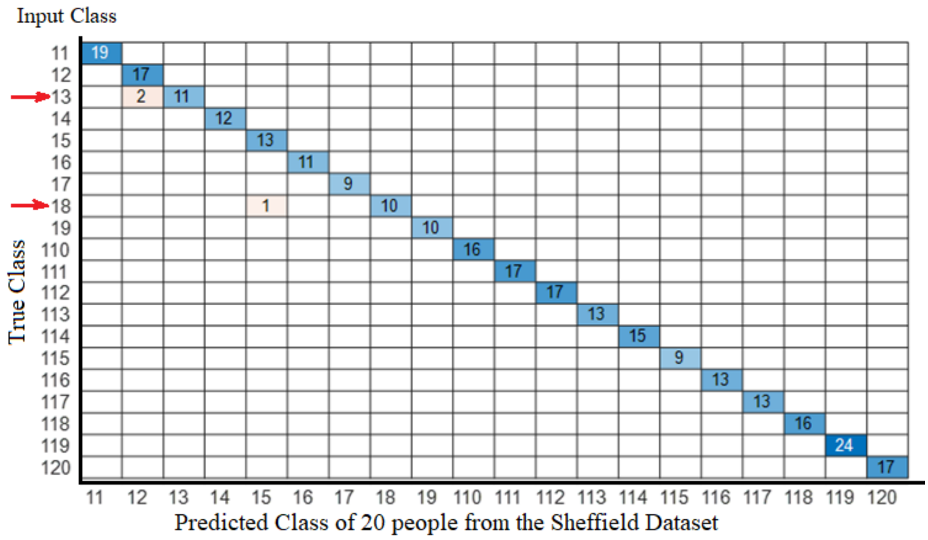


Figure 20: The confusion matrix results of 20 persons from Sheffield Dataset.

The mentioned results of the colored Faces94 dataset and the greyscale Sheffield dataset proved the robustness of the proposed CNN model, and the model is better at dealing with color images than greyscale ones. It can recognize 20 human images from the color faces94 dataset with 98.94% accuracy.

VII. Conclusions

The first CNN model is for facial gender classification. It achieved high accuracy compared to current state-of-art methods. Its robustness has been approved, especially when trained on the faces94 dataset and tested using a different dataset (Ferret). The binary gender classifier model scores high accuracy on the Celeb Kaggle dataset, which is a large dataset (168550 images). The second model is for the face recognition CNN model. Its reliability has been approved as it can recognize 152 human images from the color faces94 dataset with 100% accuracy. It can recognize 20 human images from the Sheffield dataset with 98.94% accuracy. From the results, we can conclude that the binary gender classifier is robust and superior to other researchers' works, and the face recognition model is doing well in general and better with color face images than grayscale ones. It needs more testing on more datasets.

VIII. Statements and Declarations

The author confirms that there is no conflict of interest and there are no financial funds.

IX. References

[1] Tivive F. H. C. and Bouzerdoum A., "A Gender Recognition System using Shunting Inhibitory Convolutional Neural Networks," *The 2006 IEEE International Joint Conference on Neural Network Proceedings*, 2006, pp. 5336-5341, doi: 10.1109/IJCNN.2006.247311.

[2] Lecun Y., Bottou L., Bengio Y. and Haffner P., "Gradient-based learning applied to document recognition," in *Proceedings of the IEEE*, vol. 86, no. 11, pp. 2278-2324, Nov. 1998, doi: 10.1109/5.726791.

[3] Strigl D., Kofler K. and Podlipnig S., "Performance and Scalability of GPU-Based Convolutional Neural Networks," *2010 18th Euromicro Conference on Parallel, Distributed and Network-based Processing*, 2010, pp. 317-324, doi: 10.1109/PDP.2010.43.

[4] Khalajzadeh, H., Mansouri, M., Teshnehlab, M. (2014). Face Recognition Using Convolutional Neural Network and Simple Logistic Classifier. In: Snášel, V., Krömer, P., Köppen, M., Schaefer, G. (eds) Soft Computing in Industrial Applications. Advances in Intelligent Systems and Computing, vol 223. Springer, Cham. https://doi.org/10.1007/978-3-319-00930-8_18

[5] Duffner S., "Face Image Analysis with Convolutional Neural Networks." Dissertation To obtain the doctoral degree the Faculty of Applied Sciences at the Albert-Ludwigs-University in Freiburg im Breisgau, Munich, Germany": GRIN Verlag, (2009).

[6] J. Fan, W. Xu, Y. Wu and Y. Gong, "Human Tracking Using Convolutional Neural Networks," in *IEEE Transactions on Neural Networks*, vol. 21, no. 10, pp. 1610-1623, Oct. 2010, doi: 10.1109/TNN.2010.2066286.

[7] Ihsan Ullah, Aboalsamh H. , Hussain M. , Bebis G. , " Gender Classification from Facial Images Using Texture", Journal of Internet Technology 15(5):801-812, (2014). DOI: 10.6138/JIT.2014.15.5.10

[8] Lian H.C., Lu, B. L.," Multi-view gender classification using local binary patterns and support vector machines." In: Wang, J. Z., Zurada J.M., Lu B.L., Yin, H. (eds.) ISNN 2006. LNCS, vol. 3972, pp. 202–209. Springer, Heidelberg (2006). https://doi.org/10.1007/11760023_30

[9] Fekri-Ersha S., "Developing a Gender Classification Approach in Human Face Images using Modified Local Binary Patterns and Tani-Moto based Nearest Neighbor Algorithm", International Journal of Signal Processing, Image Processing and Pattern Recognition Vol. 12, No. 4, pp.1-12, (2019). http//dx.doi.org/10.33832/ijsip.2019.12.4.01

[10] Wang C., Huang D., Wang Y., Zhang G.,"Facial image-based gender classification using Local Circular Patterns," *Proceedings of the 21st International Conference on Pattern Recognition (ICPR2012)*, 2012, pp. 2432-2435.

[11] Sajja, T.K., Kalluri, H.K. "Gender classification based on face images of local binary pattern using support vector machine and back propagation neural networks." Adv. Modell. Anal. B **62**(1), 31–35, (2019). DOI:10.18280/ama_b.620105

[12] Sumi T.A., Hossain M.S., Islam R.U., Andersson K.," Human Gender Detection from Facial Images Using Convolution Neural Network. In: Mahmud M., Kaiser M.S., Kasabov N., Iftekharuddin K., Zhong N. (eds) Applied Intelligence and Informatics. AII 2021. Communications in Computer and Information Science, vol 1435. Springer, Cham. https://doi.org/10.1007/978-3-030-82269-9_15, (2021)..

[13] Nazir M, Ishtiaq M, Batool A, Jaffar MA, Mirza AM. “Feature selection for efficient gender classification.” In: Proceedings of the 11th WSEAS International Conference; pp. 70–75, (2010). Doi:10.5555/1863431.1863444
[14] Berbar, M.A. Three robust features extraction approaches for facial gender classification. Vis Comput 30, 19–31 (2014). https://doi.org/10.1007/s00371-013-0774-8
[15] Zehang Sun, Xiaojing Yuan, G. Bebis and S. J. Louis, "Neural-network-based gender classification using genetic search for eigen-feature selection," *Proceedings of the 2002 International Joint Conference on Neural Networks. IJCNN'02 (Cat. No.02CH37290)*, 2002, pp. 2433-2438 vol.3, doi: 10.1109/IJCNN.2002.1007523.
[16] Liew S. S., Hani M. K., Radzi S. A. “Gender classification: a convolutional neural network approach”. Turk J Elec Eng & Comp Sci 24: 1248 – 1264, (2016). DOI: 10.3906/elk-1311-58
[17] Tilki, S., Dogru, H.B., Hameed, A.A., Jamil, A., Rasheed, J., Alimovski, E.,” Gender Classification using Deep Learning Techniques.”, Manchester journal of Artificial Intelligence and Applied sciences, V. 02, NO: 01, pp 126-131, (2021).
[18] Althnian, A., Aloboud, N., Alkharashi, N., Alduwaish, F., Alrshoud, M., Kurdi, H.: “Face gender recognition in the wild: an extensive performance comparison of deep-learned, hand-crafted, and fused features with deep and traditional models.” journal Applied Sciences, ISSN: 2076-3417, Volume: 11 Issue: 89, pp: 102-451 (2021).
[19] Serna, I., Peña, A., Morales, A., Fierrez, J., “InsideBias: measuring bias in deep networks and application to face gender biometrics.”. 25th ICPR 2020, pp. 3720–3727. IEEE (2021).
[20] Mahmud, M., Kaiser, M.S., McGinnity, T.M. et al. Deep Learning in Mining Biological Data. Cogn Comput 13, 1–33 (2021). https://doi.org/10.1007/s12559-020-09773-x
[21] Mahmud M, Kaiser MS, Hussain A, Vassanelli S. Applications of Deep Learning and Reinforcement Learning to Biological Data. IEEE Trans Neural Netw Learn Syst. 2018 Jun;29(6):2063-2079. doi:10.1109/TNNLS.2018.2790388. PMID: 29771663.
[22] http://cswww.essex.ac.uk/mv/allfaces/faces94.html
[23] F. S. Samaria and A. C. Harter, "Parameterisation of a stochastic model for human face identification," *Proceedings of 1994 IEEE Workshop on Applications of Computer Vision*, 1994, pp. 138-142, doi: 10.1109/ACV.1994.341300.
[24] Phillips, P.J., Wechsler, H., Huang, J., Rauss, P.: The FERET database and evaluation procedure for face classification algorithms. Image Vision Computing 16(5), pp: 295–306 (1998). https://doi.org/10.1016/S0262-8856(97)00070-X
[25] Mahesh, V.G.V., Raj, A.N.J. (2018). Zernike Moments and Machine Learning Based Gender Classification Using Facial Images. In: Abraham, A., Cherukuri, A., Madureira, A., Muda, A. (eds) Proceedings of the Eighth International Conference on Soft Computing and Pattern Recognition (SoCPaR 2016). SoCPaR 2016. Advances in Intelligent Systems and Computing, vol 614. Springer, Cham. https://doi.org/10.1007/978-3-319-60618-7_39
[26] Kishore G D K, Mukamalla B.R., Detecting Human and Classification of Gender using Facial Images MSIFT Features Based GSVM, International Journal of Recent Technology and Engineering (IJRTE) ISSN: 2277-3878, Volume-8 Issue-3, September (2019).
[27] Al-wajih E., Ahmed M., “A New Application for Gabor Filters in Face-Based Gender Classification”, International Arab Journal of Information Technology 17(2), (2020), DOI: 10.34028/iajit/17/2/5.
[28]https://www.kaggle.com/ashishjangra27/gender-recognition-200k-images-celeba.
[29] S. Yang, P. Luo, C. Loy and X. Tang, "From Facial Parts Responses to Face Detection: A Deep Learning Approach," IEEE International Conference on Computer Vision (ICCV), Santiago, Chile, 2015 pp. 3676-3684, (2015). doi: 10.1109/ICCV.2015.419
[30] ELKarazle, K., Raman, V., Then, P. (2022). Facial Gender Classification Using Deep Learning. In: , et al. Proceedings of the 13th International Conference on Soft Computing and Pattern Recognition (SoCPaR 2021). SoCPaR 2021. Lecture Notes in Networks and Systems, vol 417. Springer, Cham. https://doi.org/10.1007/978-3-030-96302-6_56
[31] https://www.visioneng.org.uk/datasets/