Journal of University of Kerbala , Vol. 21, Issue 1, June 2024

Available at https://www.iasj.net/iasj
Iraqi Academic Scientific Journals
Journal homepage:
https://journals.uokerbala.edu.iq/index.php/UOKJ

Research Article

Human Gender Prediction by Face Images Based on Convolution Neural Network

Mais Saad Safoq

Information Technology Department, College of Computer Science and Information Technology, University of Kerbala, Kerbala, Iraq

Article Info

Article history:

Received 16 -3 -2024

Received in revised form 29-4 -2024

Accepted 9-6 -2024

Available online 30 -6-2024

Keywords: Gender Prediction, Convolutional Neural Network, Facial Features, K-fold cross-validation.

Abstract

Gender prediction involves the detection of an individual's gender by facial features analysis. The growth of applications that require facial recognition has created an urgent need for such techniques for security and commercial rationales. Gender identification via facial recognition has received great interest among researchers, as well as various techniques used in the field of artificial intelligence and machine learning, with a particular focus on the use of convolutional neural networks (CNNs) for gender classification tasks. This paper proposes an excellent convolutional neural network (CNN) architecture for gender identification based on facial features. The model is trained and evaluated using a dataset sourced from Kaggle. In addition to the suggested Convolutional Neural Network (CNN) model, the performance of a pre-trained MobileNetV2 model and InceptionV3 model is evaluated on the same dataset. The CNN model achieved a commendable accuracy rate of 96.28%, while the MobileNetV2 and InceptionV3 models achieved 95.81% and 97.09%, respectively. The k-fold cross-validation is occupied for the CNN model as a trial for enhancing the accuracy rate to achieve 97.75% accuracy.

Corresponding Author E-mail : mais.s@uokerbala.edu.iq

Peer review under responsibility of Iraqi Academic Scientific Journal and University of Kerbala.

1. Introduction

The identification of gender holds substantial importance within the fields of computer vision and artificial intelligence since it encompasses a wide variety of applications spanning from security systems to personalized marketing.

Throughout decades, experts have conducted investigations into diverse methodologies and frameworks to categorize gender based on facial features effectively. In contemporary times, deep convolutional neural networks (CNNs) have appeared as an effective tool for gender classification thanks to their capability to autonomously acquire distinguishing features from raw input.

In the last decade, there has been a notable increase in research investigations concentrating on the identification of gender based on facial features. The research in [1] utilised convolutional neural networks (CNN) for gender classification, experimenting with the proposed technique with collected data from three different datasets Age-Faces-Dataset (AAF), UTKFace and IMDBWIKI dataset, a similar methodology also employed by [2] in their study on real-time face image analysis. In their study, the researchers in [3] introduced a Convolutional Neural Network (CNN) model enhanced with an Ant Colony Optimizer for gender classification. In their study [4], the authors investigated the application of facial recognition techniques for age and gender prediction. Similarly, the authors in [5] employed Convolutional Neural Networks in their research to achieve gender classification. In [6] the study conducted a study on the application of deep learning techniques to accurately estimate the genuine age and gender of individuals. Furthermore, a multi-feature approach was utilised by the authors in [7], while [8] explored the application of deep learning in age detection. The foundational research on gender classification approaches was conducted by researchers in [9] and [10]. The field of landscape analysis has witnessed ongoing developments as evidenced by the research proposed in [11], [12], and [13]. These works have placed significant emphasis on the use of customised convolutional neural network (CNN) architectures for gender identification and smile recognition. This highlights the fluid nature of the discipline, as extensively examined by the authors of [14].

In general, these researches demonstrate the progress achieved in gender detection through the utilisation of deep convolutional neural networks, alongside supplementary methodologies like transfer learning and machine learning techniques. The existing studies have made substantial advancements in enhancing the accuracy as well as effectiveness of gender identification systems. As a result, these advancements have created opportunities for practical implementation in several fields that require precise identification of individuals' genders.

2. Literature Review

The topic of gender classification based on facial images has attracted considerable interest among researchers, who have been investigating various approaches to improve the accuracy as well as efficiency of this purpose. This literature review provides a comprehensive summary of their results derived from various kinds of investigations. In [15], a comparative analysis is performed on seven datasets that are employed for model training and evaluation. These datasets include LFW, CPLFW, CFP-FP, VGG2-FP, UTKFace, and their data. The proposed model improved the accuracy over the MobileFaceNet model, achieving the highest results of 99.52 on the LFW dataset and 99.94 on the prepared dataset. Moreover, the proposed system in [16] implemented a gender identification mechanism Deep Belief Networks employ Shifted Filter Responses as a means of feature identification. The proposed model shows a high level of accuracy, getting 98% and 99% on the adopted dataset. In another attempt, the researchers in [17] demonstrate a novel approach that integrates a combination of convolutional neural network (CNN) with support vector machine (SVM) algorithms for gender classification. The approach described in this study shows favourable results when applied to the adopted dataset. Deep learning approaches are employed in [18] to address the challenges of face, gender, and emotion detection in scenarios where the face is partially disguised. The VGG19 architecture in [19], is a famous deep-learning model adopted for real-time age and gender classification, recording an accuracy of 93.42%. The authors of the research in [20] employ machine learning and convolutional neural network techniques to integrate facial feature analysis and object identification for the sake of age and gender classification. The methodology in [21] investigates gender classification based on facial images utilising Central Difference Convolutional Networks (CDCN). The training was performed using the Casia WebFace dataset and two datasets used for testing (LFW) dataset and the FEI dataset. The recognition rate achieved by this approach is 97.79% for the LFW dataset and 99.10% for the FEI dataset. A novel multichannel deep learning framework is proposed in [22] for the task of gender identification from face images. The framework aims to investigate a more complex and sophisticated method of feature extraction. This study in [23] centres on the task of gender recognition from unconstrained selfie images by employing a Convolutional Neural Network (CNN) methodology. The main focus is placed on the difficulties encountered while dealing with a wide range of different and unregulated selfie data. The system is tested over multiple datasets Adience, LFW, FERET, NIVE, Caltech WebFaces and CAS-PEAL-R1 and acquired an accuracy of 89%.

The utilisation of Convolutional Neural Networks (CNNs) for gender classification is explored in the study conducted by the authors in [1]. This work provides valuable information on the utilisation of deep learning techniques to precisely identify gender based on face images, the system achieved a classification accuracy of about 97%.

The study proposed in [2] concentrates on the application of Convolutional Neural Networks (CNN) for the real-time estimation of gender and age, This article introduces an original technique for simultaneously collecting gender and age information from facial images, highlighting the capabilities of convolutional neural networks (CNNs) in perform multiple tasks in facial recognition. In [3] provide a convolutional neural network (CNN) model that integrates Ant Colony Optimization to address the task of gender detection. The combined use of optimisation approaches with deep learning is demonstrated in this distinctive combination, resulting in enhanced gender identification, the system was experimented on two databases of gender classification, the MIT dataset and the PKU-Reid dataset. Their model obtained the highest rate of accuracy 93% on the PKU-Reid dataset. The authors in [4] investigate the concurrent identification of both age and gender. This study enhances the overall comprehension of facial image analysis by incorporating predictions of several aspects. In [5] the study employs Convolutional Neural Networks (CNNs) to do gender identification. This work highlights the significance of employing deep learning techniques in order to achieve precise gender identification based on facial images. The study is experimented using the UTKFace dataset and the system performed an accuracy of 90%. The study conducted in [6] centres on the estimate of genuine age and gender based on unconstrained face images. This paper presents an original technique based on deep learning for predicting age and gender, providing valuable knowledge into the possible applications in customer relationship management within smart stores. The proposed model was adopted for the gender classification using the Adience dataset and obtained an accuracy of 97%. In their study, the authors in [7] investigate the utilisation of machine learning techniques for gender identification. This study examines many characteristics, demonstrating the wide range of approaches utilised in gender prediction. In [8], the researchers propose a complete methodology for the identification of gender and age, with a particular focus on the incorporation of deep learning techniques to enhance the accuracy of predicting the two classes. The research in

[10] offers valuable insights into the initial investigation of Convolutional Neural Networks (CNNs) for gender classification. This study enhances the fundamental comprehension of deep learning methodologies in the domain of gender prediction. The study in [14] provides an extensive examination of several approaches currently employed in the field of gender classification. The research paper consolidates different techniques and serves as a significant reference for researchers in the respective area. The authors in [9] conducted a comprehensive investigation into the different approaches employed in gender classification. Although the main topic of this study is not concentrated on deep learning, it offers valuable insights into the historical background and progression of gender classification techniques. The researchers in [11] offer essential perspectives into the use of Convolutional Neural Networks (CNNs) for efficient gender classification, establishing a fundamental basis for future investigations in this particular field. The study implements the gender classification task by collecting a dataset and the accuracy achieved was approximately 94%. In his study, [12] investigates the concept of gender classification by employing a specialised Convolutional Neural Network (CNN) architecture. It highlights the importance of customised network architectures in improving the accuracy of gender prediction. Three datasets CelebA, IMDB and WIKI were investigated for gender classification task where it obtained the best accuracy as 96% , 97% and 96% respectively. This study proposes that adapting networks to individual tasks can improve the accuracy of classification. The research produced in [13] expands its scope beyond gender classification by including the detection of smiles. The incorporation of many characteristics illustrates the adaptability of convolutional neural networks (CNNs) in the field of facial analysis. This multifaceted approach reflects the adaptability of CNNs for handling diverse facial attributes simultaneously. The experiments provided in these researches offer specific designs and diverse technique that provide useful insights. These findings can guide future research in the development of more advanced applications of Convolutional Neural Networks (CNNs) in the fields of facial recognition and gender classification. The present study proceeds as follows. At first, the proposed system was implemented and the subsequent sections will present the experimental findings derived from the progress of this research. The last section involves a comparative analysis with other relevant research studies. In the end, a conclusion is derived.

3. The proposed system

A gender prediction system is proposed based on the facial image analysis. The block diagram of the system phases is introduced in Figure 1

.

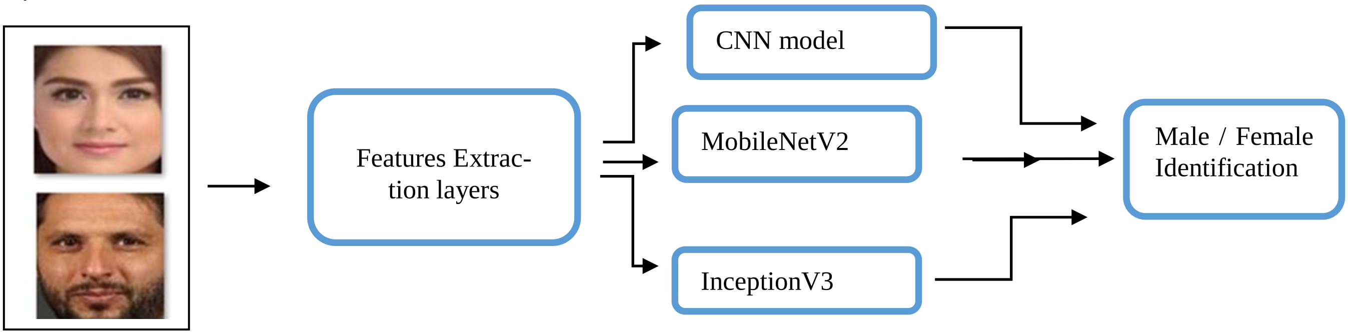

Fig. 1: The proposed gender Identification model system

The proposed system employs a convolutional neural network with a new architecture to predict the gender of the human face based on facial features illustrated from the face. The main phases of the system are preprocessing and gender identification.

3.1. The Dataset

In this article, we adopted a Kaggle dataset for the training and evaluation of the proposed model. The dataset is composed of a cropped 'jpg' images for males and females. The training set contains 23,766 images of males and 23,243 images of females and the validation set contains approximately 5,500 images of each class; Figure 2 shows some samples of the dataset.

Fig 2: some samples of the dataset

The dataset is well prepared so that it contains the bounding box of the face, the training split into train and test sets (80% for training,20% for testing), and the number of samples in each set is illustrated in Table 1

Table 1: Dataset

Train set	Validation set	Test set
37607	11649	9402

3.2. Architecture of the proposed System

To compare and analyze the results of the proposed system, other experiments were conducted using the MobileNetV2 model and the InceptionV3 model.

The proposed model architecture consists of several convolutional layers interleaved with max-pooling and dropout layers adopted for feature extraction hierarchical features from the input images. The convolutional neural network (CNN) was implemented using the Keras. It's designed for gender image classification tasks and comprises several layers that aim to extract features from the input images and make predictions. The proposed model composed of an input layer and five layers responsible of features extraction followed by a fully connected dense layers, figure 3 illustrate the proposed architecture.

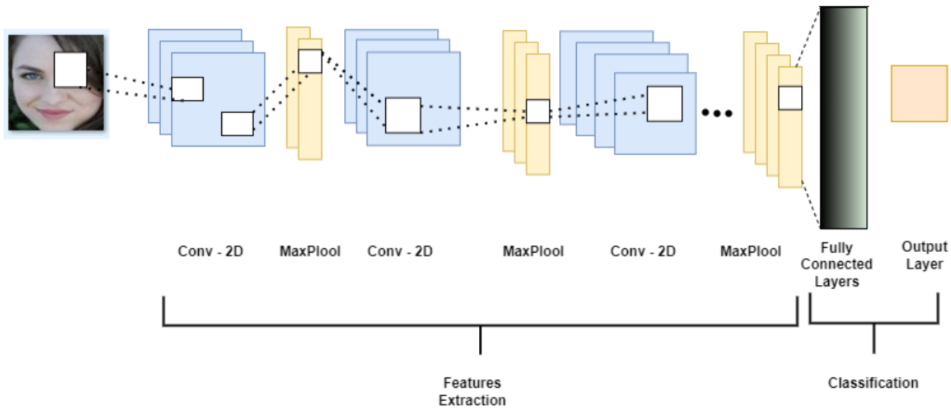

Fig. 3: The proposed gender Identification model system

The input Layer is the first convolutional layer with 16 filters of kernel size 3x3. Followed by 4 more Convolutional layers. It's then followed by fully connected layers (5 Dense layers), the output layer uses a sigmoid activation function to further process the obtained features before producing the final classification prediction, the result is a binary classification to identify a male or female, see Table 2.

The number of parameters in the Convolutional layer relayed on the size of kernels (filters), while the number of parameters of the Dense layer depends on the weights and biases of the dense layer, during training the model parameters set as following: batch size (16), learning rate (0.001) and the dataset trained for 30 epochs this can be seen as parameter in Table 2.

Table 2: Convolutional Neural Network model

Layer (type)	Output Shape	Params #
conv2d_1 (Conv2D)	(None, 98, 98, 16)	448
max_pooling2d_1 (MaxPooling 2D)	(None, 49, 49, 16)	0
dropout_1 (Dropout)	(None, 49, 49, 16)	0
conv2d_2 (Conv2D)	(None, 47, 47, 32)	4640
max_pooling2d_2 (MaxPooling 2D)	(None, 23, 23, 32)	0
conv2d_3 (Conv2D)	(None, 21, 21, 64)	18496
max_pooling2d_3 (MaxPooling 2D)	(None, 10, 10, 64)	0
conv2d_4 (Conv2D)	(None, 8, 8, 128)	73856
max_pooling2d_4 (MaxPooling 2D)	(None, 4, 4, 128)	0
conv2d_5 (Conv2D)	(None, 2, 2, 256)	295168
max_pooling2d_5 (MaxPooling 2D)	(None, 1, 1, 256)	0
dropout_2 (Dropout)	(None, 1, 1, 256)	0
flatten_1 (Flatten)	(None, 256)	0
dense_1 (Dense)	(None, 500)	128500
dense_2 (Dense)	(None, 250)	125250
dense_3 (Dense)	(None, 30)	7530
dropout_3 (Dropout)	(None, 30)	0
dense_4 (Dense)	(None, 1)	31

Total params: 653,919
Trainable params: 653,919
Non-trainable params: 0

4. Experimental Results

Analyzing the training and validation sets after each epoch and creating a learning curve allows for an accurate understanding of how the model learns on the dataset. Accuracy is a commonly employed metric to assess a deep learning model's performance while it is being trained and offer feedback for enhancements; the accuracy curve is illustrated in Figure 4.

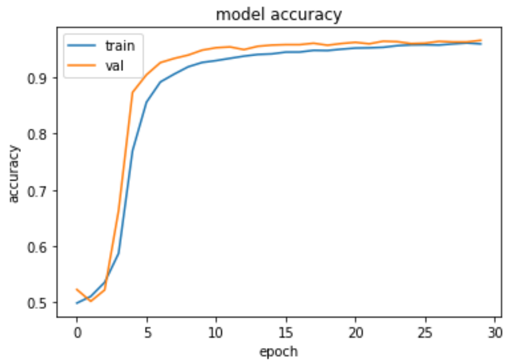

Fig.4. Accuracy Learning Curve of the Proposed Model

The loss function curve of a Convolutional Neural Network (CNN) model is a graphical representation of how the loss, often measured as a function of the model's error, changes over time during the training process, see Figure 3. The loss function curve typically shows the relationship between the number of training iterations or epochs (x-axis) and the value of the loss function (y-axis). In the early stages of training, the loss is usually high, as the model's predictions are far from the actual target values. As training progresses, the loss decreases, indicating that the model is improving its ability to make accurate predictions, figure 5.
Visualizing the accuracy curve and the loss function curve is a crucial part of monitoring and fine-tuning CNN models to achieve the best possible performance on a given task.

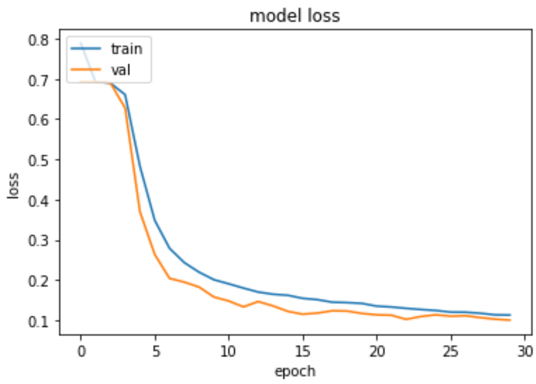

Fig.5. Loss Function Learning Curve of the Proposed Model

4.1. Evaluation of the Models

Deep learning models are inherently stochastic, meaning that when the same model is trained on the same data multiple times, it can yield varying predictions with varying levels of proficiency. The assessment of the proposed architectural model is conducted according to accuracy evaluation, k-fold cv evaluation and estimating precision, recall and f1-score evaluation.

4.1.1. K-Fold Cross-Validation Estimation

The Assessment of model skill is evaluated using k-fold cross-validation, in this step the model's performance is estimated across different subsets of the data. k-fold cross-validation where the data is split into k folds and the model is trained and evaluated k times, in this experiment a 5-fold cross-validation is employed. Each time, a different fold is used as the test set, while the remaining folds are used for training. The result of the model is calculated as the average of all the performances of the 5-fold. Table 3, illustrates the results of a 5-fold CV.

Table 3. 5-Fold CV for the proposed model

Fold number	Fold accuracy	Accuracy of the model
1	0.9777	97.75% ±0.035
2	0.9809	
3	0.9815	
4	0.9821	
5	0.9778	

4.1.2. Evaluation of the proposed CNN model based on precision, recall, and F1-measure

This experiment evaluates the proposed CNN model based on precision, recall, and F1-measure. Collectively, these metrics give a comprehensive view of the model's performance in binary classification tasks. A good model would have high precision, high recall and, consequently, a high F1 measure. Precision focuses on the accuracy of positive predictions, recall emphasizes capturing all positive instances, and F1-measure balances both precision and recall. A high F1 measure indicates a model that performs well in terms of both precision and recall. Table 4, explains the results of the precision, recall and F1-measure of the adopted CNN model.

Table 4: Precision, Recall and F1-score of the CNN model

	precision	recall	f1-score	support
female	0.93	0.98	0.96	5841
male	0.98	0.93	0.96	5808
accuracy			0.96	11649
macro avg	0.96	0.96	0.96	11649
weighted avg	0.96	0.96	0.96	11649

The same evaluation was conducted using the MobileNetV2 model and InceptionV3 model, the results of these models are illustrated in Table 5 and Table 6, respectively.

Table 5: Precision, Recall and F1-score of the MobileNetV2 model

	precision	recall	f1-score	support
female	0.93	0.99	0.96	5841
male	0.99	0.93	0.96	5808
accuracy			0.96	11649
macro avg	0.96	0.96	0.96	11649
weighted avg	0.96	0.96	0.96	11649

Table 6: Precision, Recall and F1-score of the InceptionV3 model

	precision	recall	f1-score	support
female	0.97	0.97	0.97	5841
male	0.97	0.97	0.97	5808
accuracy			0.97	11649
macro avg	0.97	0.97	0.97	11649
weighted avg	0.97	0.97	0.97	11649

The proposed model demonstrates good behaviour in comparison to the pre-trained model adopted for the same task, the accuracy of the CNN model gained 96.28% while the MobileNetV2 reported 95.81% and the InceptionV3 produced 97.09%.

4.2. Discussion

The literature review provides significant findings in the field of gender prediction, while every study makes a distinct contribution to the area, their collective agreement on the efficacy of Convolutional Neural Networks (CNNs) emphasises the crucial role of deep learning in enhancing the accuracy of gender classification.

The overall results highlight the increasing prevalence of specialised convolutional neural network designs and the investigation of several facial features to achieve a more accurate gender classification. The experimental results are illustrated in Table 7 with a comparison to the previous works.

Table 7: Comparison of the proposed CNN, MobileNetV2, and InceptionV3 models and previous work

Previous Works	Dataset	Model	Accuracy
Alvarado-Diaz *et al*.[1]	collected dataset	CNN	97%
Abbas *et al*.[3]	MIT dataset and PKU-Reid dataset	CNN	93%
Saha D *et al*.[5]	UTKFace dataset	CNN	90%
Islam *et al*.[6]	Audience dataset	CNN	97%.
Yuda *et al*.[11]	Collected dataset	CNN	94%
Zaman F *et al*[12]	Celebi IMDB WIKI	CNN	96% 97% 96%
Rastgoo *et al*.[15]	LFW, CPLFW, CFP-FP, VGG2-FP, UTKFace, and collected dataset	MobileFaceNet	99.52 on LFW 99.94 on the collected dataset
Proposed CNN model	**Kaggle Dataset**	**CNN** **MobileNetV2** **InceptionV3**	**96.28%** **95.81%** **97.09%**

Conclusion

Gender identification refers to the process of classifying a person's face according to the facial features to determine the person's gender, Different applications encourage the development of convolutional neural networks (CNN) in gender classification tasks. In this paper a convolutional neural network (CNN) framework is designed for gender classification using facial features; furthermore, the assessment of the performance of a pre-trained MobileNetV2 model and InceptionV3 model is investigated. The model has been trained and evaluated using a dataset obtained from Kaggle. The CNN model demonstrated a notable accuracy rate of 96.28% due to its remarkable design, whereas the MobileNetV2 and InceptionV3 models attained accuracy rates of 95.81% and 97.09%, respectively. In the second experiment the K-Fold Cross-Validation evaluation is adopted for the same CNN model and the recorded accuracy improved to 97.75%.

References

[1] W. Alvarado-Diaz, B. Meneses-Claudio, and A. Roman-Gonzalez, "Classification and Prediction of Gender in Facial Images with CNN," 2021, pp. 53–62. doi: 10.1007/978-3-030-72208-1_5.

[2] B. Abirami, T. S. Subashini, and V. Mahavaishnavi, "Gender and age prediction from real-time facial images using CNN," *Mater. Today Proc.*, vol. 33, pp. 4708–4712, Jan. 2020, doi: 10.1016/j.matpr.2020.08.350.

[3] F. Abbas, M. Yasmin, M. Fayyaz, M. Abd Elaziz, S. Lu, and A. A. A. El-Latif, "Gender Classification Using Proposed CNN-Based Model and Ant Colony Optimization," *Mathematics*, vol. 9, no. 19, p. 2499, Oct. 2021, doi: 10.3390/math9192499.

[4] S. T. Challa, S. Jindam, R. R. Reddy, and K. Uthej, "Age and Gender Prediction using Face Recognition," *Int. J. Eng. Adv. Technol.*, vol. 11, no. 2, pp. 48–51, Dec. 2021, doi: 10.35940/ijeat.B3275.1211221.

[5] D. D. P. G. S. S. and T. M. Devjyoti Saha, "Classification of Gender from Human Facial Images using Convolutional Neural Networks", Accessed: Nov. 14, 2023. [Online]. Available: https://doi.org/10.36375/prepare_u.a61

[6] M. M. Islam and J.-H. Baek, "Deep Learning Based Real Age and Gender Estimation from Unconstrained Face Image towards Smart Store Customer Relationship Management," *Appl. Sci.*, vol. 11, no. 10, p. 4549, May 2021, doi 10.3390/app11104549.

[7] S. Kumar, S. Singh, and J. Kumar, "Gender Classification Using Machine Learning with Multi-Feature Method," in *2019 IEEE 9th Annual Computing and Communication Workshop and Conference (CCWC)*, Jan. 2019, pp. 0648–0653. doi: 10.1109/CCWC.2019.8666601.

[8] U. Kumbhar and P. A. S. Shingare, "Gender and Age Detection using Deep Learning," *Int. J. Sci. Res. Comput. Sci. Eng. Inf. Technol.*, pp. 604–610, Jun. 2021, doi: 10.32628/CSEIT2173128.

[9] P. Rai and P. Khanna, "Gender Classification Techniques: A Review," 2012, pp. 51–59. doi: 10.1007/978-3-642-30157-5_6.

[10] S. S. LIEW, M. KHALIL-HANI, S. AHMAD RADZI, and R. BAKHTERI, "Gender classification: a convolutional neural network approach," *TURKISH J. Electron. Eng. Comput. Sci.*, vol. 24, pp. 1248–1264, 2016, doi: 10.3906/elk-1311-58.

[11] R. P. Yuda, C. Aroef, Z. Rustam, and H. Alatas, "Gender Classification Based on Face Recognition using Convolutional Neural Networks (CNNs)," *J. Phys. Conf. Ser.*, vol. 1490, no. 1, p. 012042, Mar. 2020, doi: 10.1088/1742-6596/1490/1/012042.

[12] F. H. K. Zaman, "Gender classification using custom convolutional neural networks architecture," *Int. J. Electr. Comput. Eng.*, vol. 10, no. 6, pp. 5758–5771, Dec. 2020, doi: 10.11591/IJECE.V10I6.PP5758-5771.

[13] K. Zhang, L. Tan, Z. Li, and Y. Qiao, “Gender and Smile Classification Using Deep Convolutional Neural Networks,” in *2016 IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, Jun. 2016, pp. 739–743. doi: 10.1109/CVPRW.2016.97.

[14] B. Patel and S. Degadawala, “A Survey Paper on Gender Classification using Deep Learning,” *Int. J. Sci. Res. Comput. Sci. Eng. Inf. Technol.*, pp. 20–25, Jan. 2020, doi: 10.32628/CSEIT20613.

[15] R. Rastgoo, K. Kiani, and F. Alinezhadand, “A Deep Learning-based Model for Gender Recognition in Mobile Devices,” *J. AI Data Min.*, vol. 11, no. 2, pp. 229–236, Apr. 2023, doi: 10.22044/JADM.2023.12487.2398.

[16] M. Patel and U. Singh, “Age and Gender Recognition using Deep Learning Technique,” *Proc. - 2023 3rd Int. Conf. Smart Data Intell. ICSMDI 2023*, pp. 238–245, 2023, doi 10.1109/ICSMDI57622.2023.00052.

[17] S. Mandara and N. Manohar, “A Gender Recognition System from Human Face Images Using VGG16 with SVM,” *Lect. Notes Data Eng. Commun. Technol.*, vol. 101, pp. 309–320, 2022, doi: 10.1007/978-981-16-7610-9_22/COVER.

[18] A. B. A. Hassanat *et al.*, “DeepVeil: deep learning for identification of face, gender, expression recognition under veiled conditions,” *Int. J. Biom.*, vol. 14, no. 3–4, pp. 453–480, 2022, doi: 10.1504/IJBM.2022.124683.

[19] M. Tariq, A. Akram, S. Yaqoob, M. Rasheed, and M. S. Ali, “Real-time Age and Gender Classification using VGG19,” *Adv Mach Lear Art Inte*, vol. 4, no. 2, pp. 56–65, 2023.

[20] M. Karahan, F. Lacinkaya, K. Erdonmez, E. D. Eminagaoglu, and C. Kasnakoglu, “Age and gender classification from facial features and object detection with machine learning,” *J. Fuzzy Ext. Appl.*, vol. 3, no. 3, pp. 219–230, Jul. 2022, doi: 10.22105/JFEA.2022.328472.1201.

[21] M. Sheikh Fathollahi and R. Heidari, “Gender classification from face images using central difference convolutional networks,” *Int. J. Multimed. Inf. Retr.*, vol. 11, no. 4, pp. 695–703, Dec. 2022, doi: 10.1007/S13735-022-00259-0/METRICS .

[22] R. Ramya, A. Anandh, K. Muthulakshmi, and S. Venkatesh, “Gender recognition from facial images using multichannel deep learning framework,” *Mach. Learn. Biometrics Concepts, Algorithms Appl.*, pp. 105–128, Jan. 2022, doi: 10.1016/B978-0-323-85209-8.00009-2.

[23] S. Bekhet, A. M. Alghamdi, and I. Taj-Eddin, “Gender recognition from unconstrained selfie images: a convolutional neural network approach,” *Int. J. Electr. Comput. Eng. (IJECE*, vol. 12, no. 2, pp. 2066–2078, 2022, doi: 10.11591/ijece.v12i2.pp2066-2078.