

# An innovative deep learning approach for Arabic race recognition

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## ABSTRACT

In computer vision, human race detection has become a critical application across many domains, such as security and customized marketing. Deep learning approaches, such as convolutional neural network (CNN), have played an essential role in improving human race detection. Nevertheless, detecting Arabic race is still a field that has received little attention. In this paper, an Arabic human race dataset comprising the following classes: Gulf, Levant, Sudan, Egypt, and North Africa (excluding Egypt) has been collected and proposed as a starting point for Arabic race classification. This dataset has been evaluated using a simple CNN-based model and other transfer learning models: DenseNet121, VGG16, and ResNet50. The difficulty in classifying these regions lies in the similarity of border areas in people's features and in intermarriage between different regions, which helps transfer genetic traits that distinguish one region from another. The best results in recall, F1-score, precision, and accuracy were obtained by the DenseNet121 model, which achieved an average accuracy of 0.746 across five folds.

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## 1. INTRODUCTION

Facial analysis gained huge attention in the computer vision realm [1]. It has evolved to encompass various properties and characteristics known as soft biometrics, including gender, age, race, and other physical attributes [2], [3]. Soft biometrics are essential in several applications [4], spanning human-computer interaction (HCI) to security measures. In HCI, these metrics enhance user interaction based on individual characteristics [5]. They also play an important role in security and surveillance, aiding in identifying and verifying individuals across different scenarios accurately, ranging from routine verification to more complex law enforcement situations [6]. Also, they have been applied to refine database search mechanisms in identification systems and to enhance facial image search engines, thereby improving their efficiency and interaction within technological frameworks [7]. The study of human facial races first appeared in psychology, where it was analyzed from a cognitive science perspective. It has since evolved into an important area of research in computer vision [8].

Deep learning (DL) technology has become essential in refining race recognition technologies [9]. Using advanced neural networks, DL techniques learn from large datasets to enhance their ability to distinguish

and classify races based on facial images. These systems are excellent at extracting detailed features and recognizing intricate patterns in facial attributes critical to race identification, such as variations in skin tone and facial structure [10]. This level of reliability improves the accuracy of race recognition systems and enables them to function effectively across multiple settings, making them critical in applications ranging from security to customized marketing. One of the most important applications of race classification is to achieve health equity, where it is essential for diagnosing disparities and tailoring care [11].

Convolutional neural network (CNN) architectures play a crucial role in race classification. A method aimed at predicting the ethnicity of Iraqi males, concentrating on the two predominant race groups: Arabs and Kurds, was proposed by applying the faster region-based convolutional neural network (Faster-RCNN) to classify facial images from these groups. Given their dataset's limited size and diversity, the authors turned to transfer learning, utilizing several pre-trained models—EfficientNetB4, ResNet-50, SqueezeNet, VGG16, and MobileNetV2—to extract features and improve classification accuracy. Among these, ResNet50 was chosen as the core framework for their race classification model, striking a balance between accuracy and inference speed [12]. Additionally, a proposed method for race identification focused on four broad racial groups: Caucasian, African, Asian, and Indian. The study developed and trained a deep CNN, R-Net, using the BUPT Equalised Face dataset, which contains approximately 1.3 million images captured in unrestricted environments. This model achieved a state-of-the-art accuracy of 97% [13]. Other research papers chose to use hybrid models to enhance classification accuracy, such as integrating the VGG16 pretrained model with the support vector machine (SVM) to classify a dataset of Bangladeshi, Chinese, and Indian faces [14]. Another approach combines a CNN with an SVM to classify the race of 3D images [15], achieving 90% accuracy in classifying the races into three categories: White, Asian, and African.

The authors of paper [16] represented a significant advancement by being the first to focus specifically on classifying the Arabic race using facial images, in addition to Asian and Caucasian categories. The framework established in this study employs principal component analysis (PCA) to reduce the dimensionality of facial images, along with a feedforward neural network that is optimized using the scaled conjugate gradient algorithm for classification. The proposed method achieves an impressive correct classification rate of around 83.5%, surpassing the standard backpropagation algorithm by approximately 15%. A significant contribution of their paper is the development of a new dataset for the Arabic category, which addresses the existing gap in datasets for this demographic. However, a limitation of their study is the relatively small dataset size, especially for the Arabic category, which contains only 120 images. This limitation suggests that, although the initial results are encouraging, further research with larger and more diverse datasets is necessary to validate and expand upon the findings. Many other works on race classification focused on non-Arab races, or the Arab races were subcategorized in their classification with other races, or they were all classified as one class [17]–[20]. This may be due to the lack of sub-Arab races availability in known datasets in this field, such as the video-based multi-expression recognition (VMER) [21], Chinese Academy of Sciences – pose, expression, accessories, and lighting (CAS-PEAL) [22], and face recognition technology (FERET) [23] datasets, which have been used in numerous research studies [20], [24]–[26].

The most related work presented an Arab dataset that contains Gulf Cooperation Council (GCC), Levant, and Egypt classes [8]. This work used supervised and unsupervised deep learning models to classify the data. The best accuracy results were 0.56 for the supervised model and 0.59 for the unsupervised model. Some limitations were mentioned in their work, such as a class containing different images of the same person (subject). For example, 784 subjects produced 5,589 images in the GCC class. Data augmentation was applied, the dataset covered limited regions, and 67% of the subjects were from the GCC region.

Contributions: due to the lack of research papers that discuss approaches for classifying the Arabic races, our contributions are summarized in the following points:

- Advanced race recognition within Arabic populations by developing a DL model to classify various Arabic groups only, without being biased towards any other different races.
- Compile a comprehensive dataset that reflects various facial features across different Arabic regions that are subdivided into five categories: Gulf, Levant, Sudan, Egypt, and North Africa except Egypt, based on collected images from public resources. To the best of our knowledge, this is the first study that has these classes in Arabic race classification. We made every effort to have one image for each person.
- Different CNN models were examined for classifying races, and we achieved an accuracy of 0.746.
- To avoid biasing, 5-fold cross-validation was used to evaluate the models, and a face detection step was applied to all images to prevent the models from training based on similar backgrounds or traditional dress.

Paper organization: in section 2, the method is described, starting with a detailed discussion of the Arabic human race dataset collected, followed by the preprocessing steps conducted on this dataset to enhance its quality for model training. Next, a detailed description of the CNN-based models used in the experiments is provided. The section ends with specifying the evaluation metrics used in the testing phase. As for section 3, the experimental results are illustrated by tables and figures, then discussed and justified. Finally, section 4 concludes the paper's work and results in addition to recommended future work.

## 2. METHOD

In this section, the research method is described in detail. The work is mainly conducted in two steps: collecting images representing several regions and classifying these sub-Arab race groups into five regions using a basic CNN model and other transfer learning models. The method overview is summarized in Figure 1.

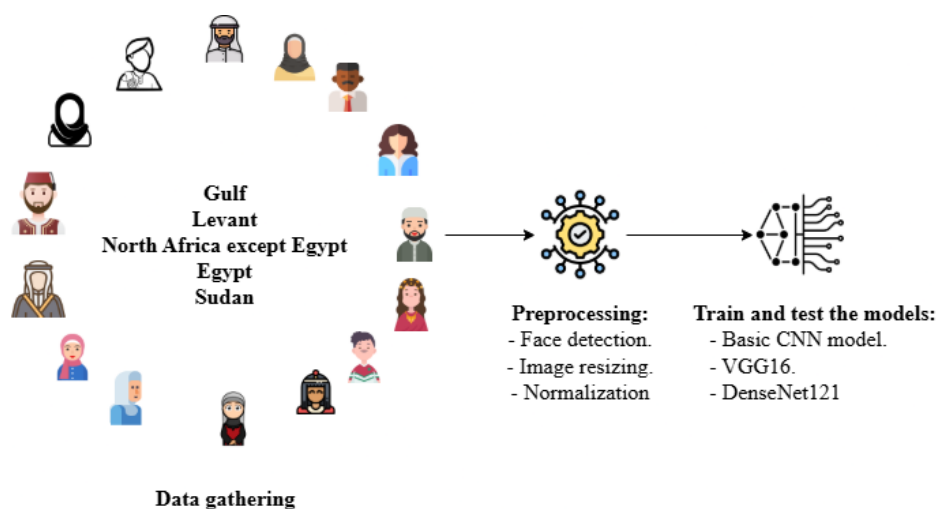


Figure 1. Proposed method

### 2.1. The Arabic human race dataset

An Arabic human race dataset has been collected from public sources and classified into five classes: Gulf, Sudan, Egypt, North Africa (excluding Egypt), and Levant. Table 1 shows the dataset distribution. As shown in Table 1, the dataset used in this study was carefully assembled to include various individuals from different regions, specifically the Gulf countries, Sudan, Egypt, North Africa (excluding Egypt), and Levant. During the image collection phase, it became clear that most search results prominently featured well-known figures such as singers, actors, and social media influencers. This trend highlights the significant impact of these public figures on their respective areas. We have double-checked their origins whenever possible and have tried to obtain only one sample for each person. As a result, the dataset contains numerous images of famous individuals, thereby enhancing its relevance for research on facial recognition and demographic analysis. Importantly, all images collected are free from personal or sensitive information, ensuring compliance with ethical standards by focusing on public images from resources that do not require a copyright.

Table 1. Counts of classified samples in the Arabic human race dataset

Class	Count
Gulf	1,920
Sudan	1,624
Egypt	1,720
North Africa except Egypt	1,086
Levant	1,917

Regarding regional classification, Egypt was designated as a separate category due to its substantial population of approximately 100 million [27], which significantly shapes the demographic landscape of the Arab world. The dataset comprises 1,720 images from Egypt, making it a larger segment than groups of

countries (Gulf, North Africa except Egypt, and Levant). This choice was made to capture the diverse facial features of the Egyptian population. Other regions were grouped according to their unique facial characteristics and population density. For example, the Gulf region, represented by 1,920 images, was treated as a distinct group due to its unique facial traits shaped by a diverse ethnic background. Sudan (1,624 images) and North Africa (excluding Egypt; 1,086 images) were also categorized separately to accurately represent the specific facial features typical of these regions. With 1,917 images, Levant region was grouped based on its rich ethnic diversity and cultural heritage. The numbers provided for each class were obtained after duplicates were removed.

The dataset offers a thorough and varied representation of the Arab world, comprising 8,267 images. Each region was carefully selected to capture the distinct facial features and demographic traits of these populations. This method ensures that the dataset is robust and appropriate for different analytical studies, such as facial recognition and demographic research, while strictly adhering to ethical guidelines. Some dataset samples are shown in Figure 2; they have been intentionally blurred for privacy preservation.

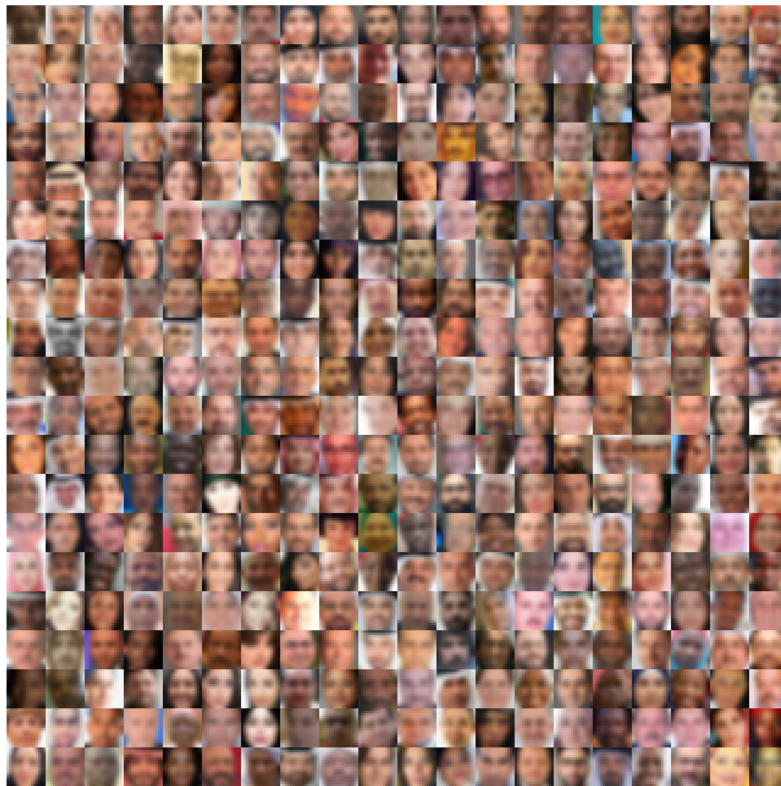


Figure 2. Arabic human race dataset

## 2.2. Preprocessing steps

Data preprocessing is a vital operation that significantly affects the quality of a dataset, thereby enhancing training performance and evaluation results. In our work, we have conducted three main preprocessing steps on the created dataset, including:

- Face detection step: this step was taken to enhance the model's understanding of image context. Some of the collected images may include a background or a traditional outfit. Our work should focus solely on facial features to avoid the model's bias. Thus, face detection is a critical step in enhancing our work. To detect faces, we used a Viola-Jones-based algorithm, specifically the MATLAB cascade object detector. The vision.CascadeObjectDetector() function was chosen for several reasons. Firstly, we have a limited dataset without ground-truth samples. Secondly, it is a fast algorithm with a simple implementation. Lastly, we do not need to train the model [28].

- Images resizing: resizing all images in the dataset to the same size ( $128 \times 128 \times 3$ ) so that they can be input to the same deep-learning model.
- Images normalization: normalizing the values of pixels of the images by dividing their values by 255.0. This step is crucial for converting pixel values to the range 0-1, ensuring that differences between values do not exceed 1/2. As a result, the model will not prioritize pixels with large values over others.

### 2.3. Convolutional neural network-based models

Several CNN-based models have been used to train the collected dataset. Starting with a basic CNN model that has been designed to consist of a sequence of traditional convolution and max pooling layers, as illustrated in Figure 3. The following is a detailed description of this model:

- 2D convolution layer, with 32 filters of size  $3 \times 3$  and ReLU as activation function.
- 2D max pooling layer of size  $2 \times 2$ .
- 0.25 dropout layer.
- 2D convolution layer, with 64 filters of size  $3 \times 3$ , and ReLU as activation function.
- 0.25 dropout layer.
- Flatten layer.
- Dense layer with 125 neurons and ReLU as activation function.
- 0.5 dropout layer.
- Output dense layer with five neurons (classes to predict) and SoftMax as activation function.

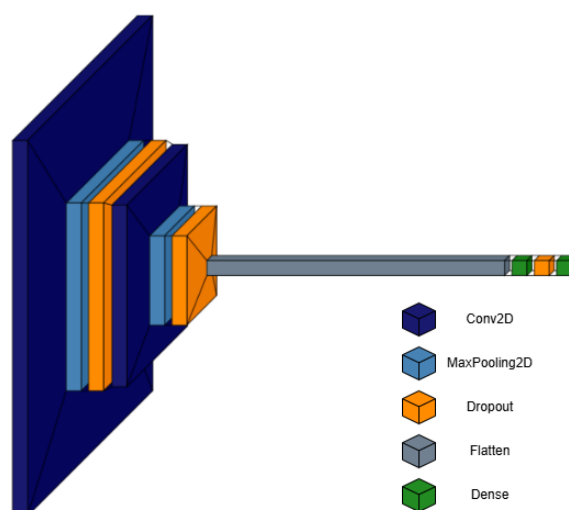


Figure 3. The basic CNN model architecture

In addition, we applied transfer-learning models, including DenseNet121 [29], VGG16 [30], and ResNet50 [31], to provide comparisons with the basic CNN model. Our motivation is to train large-CNN models with many more layers and more complex connections. In our experiments, all three transfer-learning models have been extended with additional layers, which are:

- Global average pooling layer.
- A fully connected (dense) layer with 128 neurons and ReLU as activation function.
- 0.5 dropout layer.
- A dense output layer with five neurons (classes to predict) and SoftMax as activation function.

We trained and tested the models using a 5-fold stratified cross-validation method, with 60 epochs, early-stopping callbacks that monitor the validation loss, and a batch size of 32. To compile the models, we have used the Adam optimizer and sparse categorical cross-entropy as the loss function.

### 2.4. Evaluation metrics

For evaluation, the standard classification metrics are used [32]. These metrics are described in (1) (accuracy), (2) (precision), (3) recall, and (4) (F1-score):

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \quad (1)$$

$$Precision(Prec) = \frac{TP}{TP + FP} \quad (2)$$

$$Recall(TPR) = \frac{TP}{TP + FN} \quad (3)$$

$$F1 - score(F_1) = \frac{2 * (Recall * Precision)}{Recall + Precision} \quad (4)$$

where TP is the true positive, TN the true negative, FP the false positive, and FN the false negative.

### 3. RESULTS AND DISCUSSION

This study classifies the sub-Arab races into five classes, whereas previous works either treated the Arab race as a single class or merged it with other classes. The only work that focused on the races within the Arabic regions depends on three classes [8]. We have achieved better results, worked to overcome their limitations, and expanded into new regions.

Table 2 shows the averaged precision, recall, F1-score, and accuracy for all folds among each class utilizing four CNN architectures: basic CNN, VGG16, ResNet50, and DenseNet121. VGG16 and DenseNet121 exhibit similar overall performance. DenseNet121 outperforms other models, while the basic CNN model performance indicates that the optimization of simple models can outperform these complex models, especially since the basic CNN model outperforms the ResNet50 model, which was not a suitable model for our data.

Table 2. Models' performance across five folds

Class	Basic CNN			VGG16			ResNet50			DenseNet121		
	Prec	TPR	F <sub>1</sub>	Prec	TPR	F <sub>1</sub>	Prec	TPR	F <sub>1</sub>	Prec	TPR	F <sub>1</sub>
Egypt	0.59	0.52	0.55	0.61	<b>0.58</b>	0.60	0.49	0.35	0.40	<b>0.65</b>	<b>0.58</b>	<b>0.61</b>
Sudan	<b>0.80</b>	<b>0.86</b>	<b>0.83</b>	0.78	0.82	0.80	0.62	0.62	0.62	<b>0.80</b>	0.84	0.82
Gulf	0.74	0.71	0.72	0.76	0.71	0.73	0.65	0.63	0.64	<b>0.77</b>	<b>0.74</b>	<b>0.76</b>
North Africa	0.81	0.79	0.80	0.82	0.79	0.81	0.62	0.66	0.64	<b>0.83</b>	<b>0.81</b>	<b>0.82</b>
Levant	0.67	0.72	0.69	0.68	0.73	0.71	0.51	0.60	0.55	<b>0.69</b>	<b>0.76</b>	<b>0.72</b>
Accuracy	0.718			0.726			0.57			<b>0.746</b>		

As the only recent study to classify the human Arabic race into five classes, achieving these values across different metrics is commendable. The North Africa class had the best performance across all models, except the basic CNN model, while the lowest values were for the Egypt class, which may be due to the quality of the images, since their sizes after cropping were the smallest, as shown in Figure 4. The basic CNN model achieved slightly better classification performance than the DenseNet121 model.

For more details about the DenseNet121 results, which achieved the best performance and was the most robust model, Figures 5 demonstrates how the model performs in each fold for each class (Figure 5(a) for recall, Figure 5(b) for precision, and Figure 5(c) for F1-score). The best recall was for the Sudan class, while the best recall was for the North Africa class. That yields an F1-score that is similar for both classes. The Egypt class's performance was not close to the rest of the classes in recall and F1-score, indicating that we need to modify and provide this class with more images. Since DenseNet121 was the best model, the confusion matrices for the five folds are shown in Figure 6. The most intersection was between the Egypt and Levant classes.

Viewing the data from another perspective using t-distributed stochastic neighbor embedding (t-SNE), which projects the data feature vectors into a 2D visualization, can help interpret the results. As shown in Figure 7, the axes are the embedding coordinates, and each point is a sample from the dataset. Similar feature vectors will be closer to each other. Noticing that the North Africa class is a tight cluster more than other classes, which demonstrates why it was the class that achieved the highest results, while other classes are more spread out.

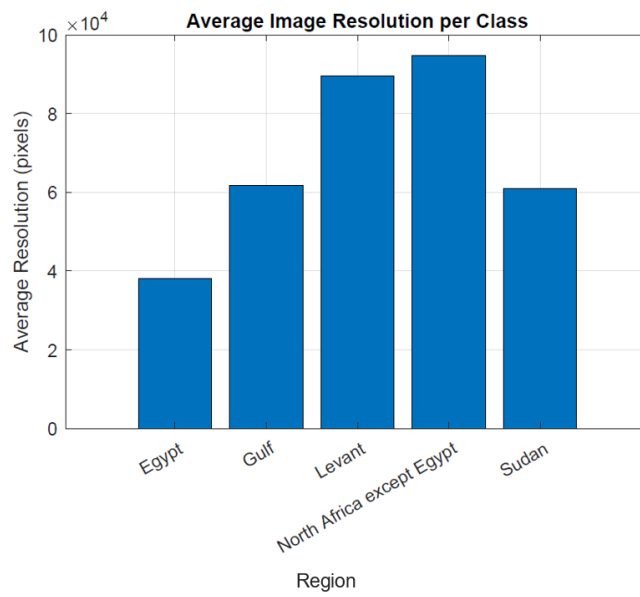


Figure 4. The average image resolution (pixel) per class

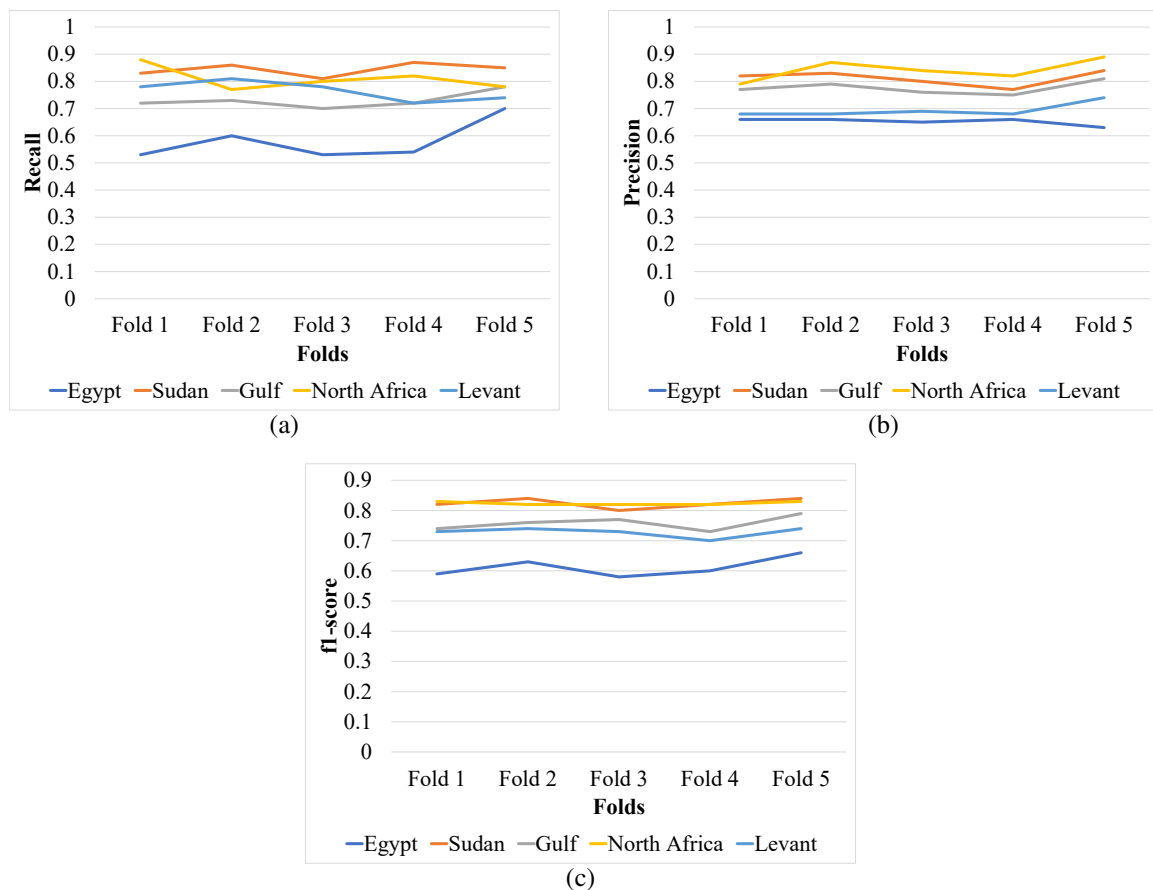


Figure 5. DenseNet121 performance across different metrics; (a) recall, (b) precision, and (c) F1-score

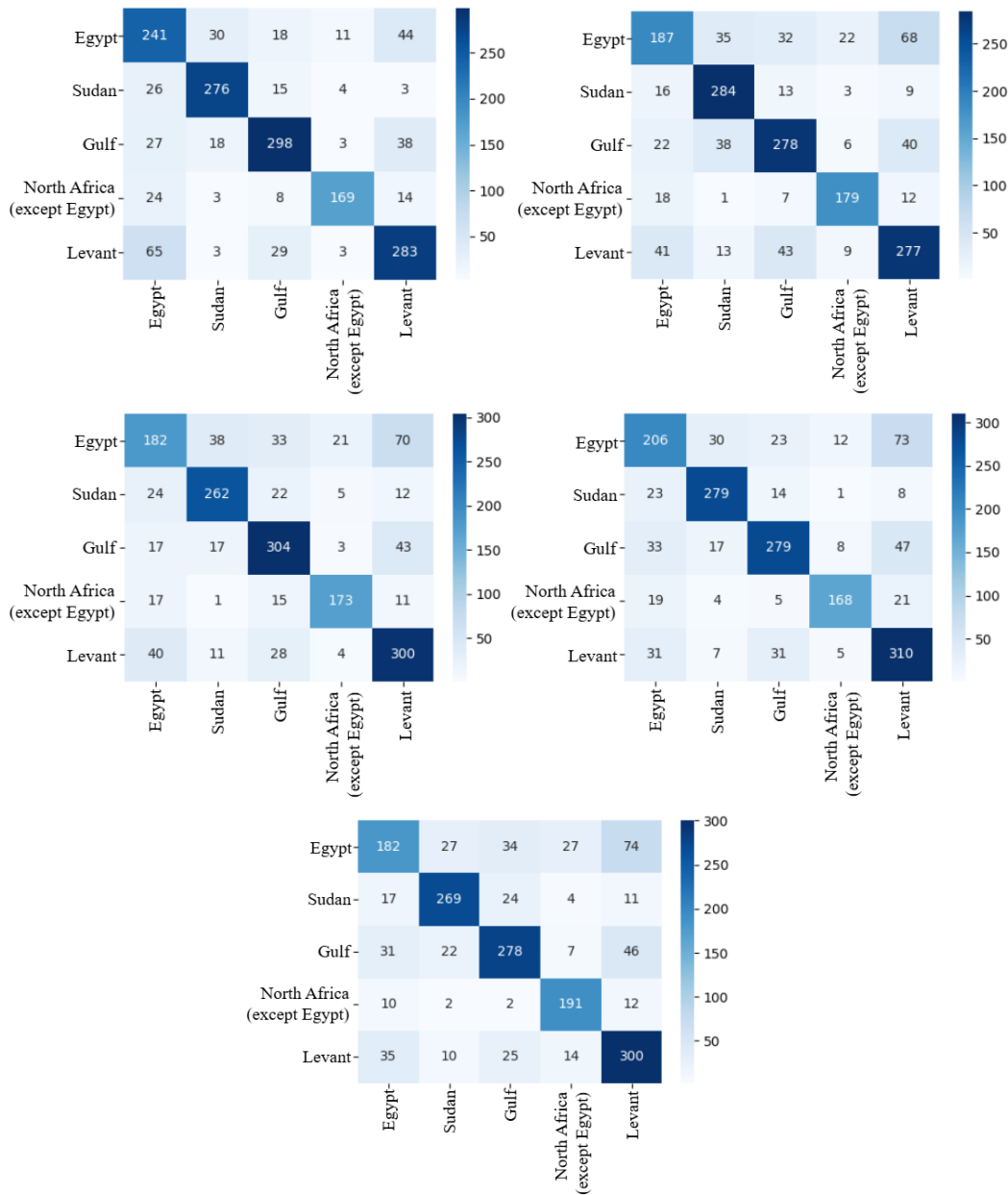


Figure 6. DenseNet121 confusion matrix (y-axis is the true labels and the x-axis is the predicted labels)

The results showed a good start in classifying the Arab sub-races. However, we have a limited dataset with varying resolutions and sizes, so expanding the dataset and optimizing the model can yield better results and pave the way for understanding Arab features by region.

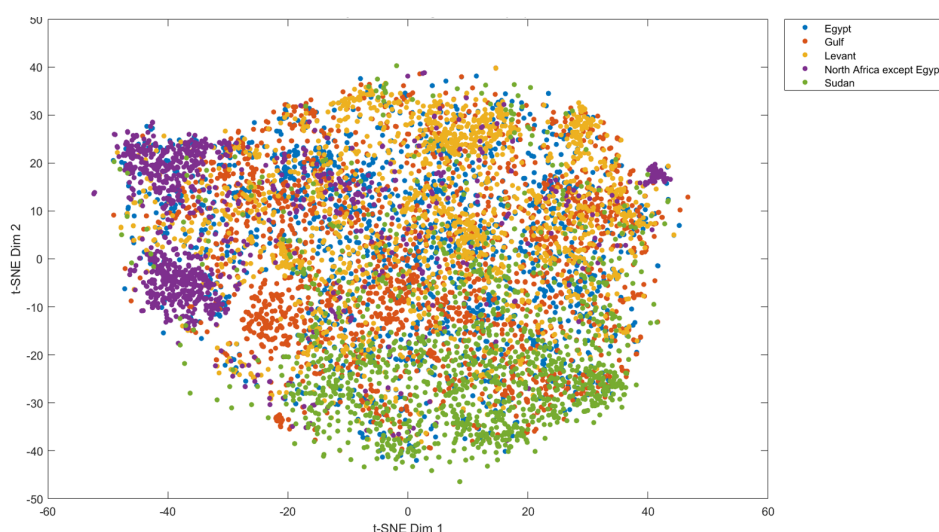


Figure 7. t-SNE projection of image features (2D)

#### 4. CONCLUSION

Developing a race classification model requires a meticulous approach to feature selection, data diversity, and algorithm choice. Our research serves as a foundational step toward sub-race classification in Arab regions by utilizing several CNN models, achieving a high accuracy of around 75%, given the challenges in this field.

Our approach will exhibit promise when trained on reliable and representative data, since our data was collected from multiple sources. Our comprehensive analysis and findings set the stage for subsequent studies aimed at developing more equitable and accurate race classification systems. Future research will build upon this groundwork, focusing on refining algorithms and enhancing data diversity.

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#### AUTHOR CONTRIBUTIONS STATEMENT

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Rahmeh Ibrahim	✓	✓	✓	✓	✓	✓		✓	✓		✓			
Eman Alnagi	✓	✓	✓	✓	✓	✓		✓	✓		✓			
Ashraf Ahmad	✓	✓		✓	✓					✓		✓	✓	
Abdullah Aref		✓			✓			✓		✓				

C : Conceptualization  
 M : Methodology  
 So : Software  
 Va : Validation  
 Fo : Formal Analysis

I : Investigation  
 R : Resources  
 D : Data Curation  
 O : Writing - Original Draft  
 E : Writing - Review & Editing

Vi : Visualization  
 Su : Supervision  
 P : Project Administration  
 Fu : Funding Acquisition

#### CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest.

## DATA AVAILABILITY

The data used in this study are private and not publicly available.




## REFERENCES

- [1] G. Ali *et al.*, "Artificial neural network based ensemble approach for multicultural facial expressions analysis," *IEEE Access*, vol. 8, pp. 134950-134963, 2020, doi: 10.1109/ACCESS.2020.3009908.
- [2] B. Hassan, E. Izquierdo, and T. Piatrik, "Soft biometrics: A survey: Benchmark analysis, open challenges and recommendations," *Multimedia Tools and Applications*, vol. 83, pp. 1–44, 2021, doi: 10.1007/s11042-021-10622-8.
- [3] R. E. Jack and P. G. Schyns, "The human face as a dynamic tool for social communication," *Current Biology*, vol. 25, no. 14, pp. R621–R634, 2015, doi: 10.1016/j.cub.2015.05.052.
- [4] N. Narang and T. Bourlai, "Gender and ethnicity classification using deep learning in heterogeneous face recognition," in *2016 International Conference on Biometrics (ICB)*, Halmstad, Sweden, 2016, pp. 1-8, doi: 10.1109/ICB.2016.7550082.
- [5] Y. Hu, Y. Fu, U. Tariq, and T. S. Huang, "Subjective experiments on gender and ethnicity recognition from different face representations," in *Advances in Multimedia Modeling: 16th International Multimedia Modeling Conference*, Chongqing, China, 2010, pp. 66–75, doi: 10.1007/978-3-642-11301-7\_10.
- [6] G. Sunitha, K. Geetha, S. Neelakandan, A. K. S. Pundir, S. Hemalatha, and V. Kumar, "Intelligent deep learning based ethnicity recognition and classification using facial images," *Image and Vision Computing*, vol. 121, p. 104404, 2022, doi: 10.1016/j.imavis.2022.104404.
- [7] K.-H. Chow, S. Hu, T. Huang, F. Ilhan, W. Wei, and L. Li, "Diversity-driven privacy protection masks against unauthorized face recognition," in *Proceedings on Privacy Enhancing Technologies*, 2024, doi: 10.56553/popets-2024-0122.
- [8] N. A. Al-Humaidan and M. Prince, "A classification of arab ethnicity based on face image using deep learning approach," *IEEE Access*, vol. 9, pp. 50755-50766, 2021, doi: 10.1109/ACCESS.2021.3069022.
- [9] A. H. Sham *et al.*, "Ethical AI in facial expression analysis: Racial bias," *Signal, Image and Video Processing*, Halmstad, vol. 17, no. 2, pp. 399–406, 2023, doi: 10.1007/s11760-022-02246-8.
- [10] D. Belcar, P. Grd, and I. Tomičić, "Automatic ethnicity classification from middle part of the face using convolutional neural networks," *Informatics*, vol. 9, no. 1, p. 18, 2022, doi: 10.3390/informatics9010018.
- [11] C. Lu, R. Ahmed, A. Lamri, and S. S. Anand, "Use of race, ethnicity, and ancestry data in health research," *PLOS Global Public Health*, vol. 2, no. 9, p. e0001060, 2022, doi: 10.1371/journal.pgph.0001060.
- [12] B. A. Abdulrahman and N. E. Mustafa, "Iraqi kurd or arab male authenticity detection based on facial feature," *UHD Journal of Science and Technology*, vol. 8, no. 1, pp. 64–77, 2024, doi: 10.21928/uhdjt.v8n1y2024.pp64-77.
- [13] M. A. Ahmed, R. D. Choudhury, and K. Kashyap, "Race estimation with deep networks," *Journal of King Saud University-Computer and Information Sciences*, vol. 34, no. 7, pp. 4579–4591, 2022, doi: 10.1016/j.jksuci.2020.11.029.
- [14] Z. Heng, M. Dipu, and K.-H. Yap, "Hybrid supervised deep learning for ethnicity classification using face images," in *2018 IEEE International Symposium on Circuits and Systems (ISCAS)*, Florence, Italy, 2018, pp. 1-5, doi: 10.1109/ISCAS.2018.8351370.
- [15] N. Reda and H. Abbas, "3D human facial traits' analysis for ethnicity recognition using deep learning," *Ingénierie des Systèmes d'Information*, vol. 29, pp. 501–514, 2024, doi: 10.18280/isi.290211.
- [16] A. Awwad, A. Ahmad, and A. Salameh, "Arabic race classification of face images," *International Journal of Computer Technology*, vol. 4, pp. 234–239, 2013.
- [17] W. Wang, F. He, and Q. Zhao, "Facial ethnicity classification with deep convolutional neural networks," in *Biometric Recognition: Chinese Conference, Chengdu, China*, 2016, pp. 176–185, doi: 10.1007/978-3-319-46654-5\_20.
- [18] S. Masood, S. Gupta, A. Wajid, S. Gupta, and M. Ahmed, "Prediction of human ethnicity from facial images using neural networks," *Data Engineering and Intelligent Computing*, 2018, pp. 217–226, doi: 10.1007/978-981-10-3223-3\_20.
- [19] H. Chen, Y. Deng, and S. Zhang, "Where am i from?—east asian ethnicity classification from facial recognition," *Project study in Stanford University*, 2016.
- [20] K. Khan, R. U. Khan, J. Ali, I. Uddin, S. Khan, and Byeong-hee Roh, "Race classification using deep learning," *Computers, Materials & Continua*, vol. 68, no. 3, pp. 3484–3498, 2021, doi: 10.32604/cmc.2021.016535.
- [21] Q. Cao, L. Shen, W. Xie, O. M. Parkhi, and A. Zisserman, "VGGFace2: A dataset for recognising faces across pose and age," in *2018 13th IEEE International Conference on Automatic Face & Gesture Recognition (FG 2018)*, Xi'an, China, 2018, pp. 67-74, doi: 10.1109/FG.2018.00020.
- [22] W. Gao *et al.*, "The CAS-PEAL large-scale Chinese face database and baseline evaluations," in *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans*, vol. 38, no. 1, pp. 149-161, Jan. 2008, doi: 10.1109/TSMCA.2007.909557.
- [23] P. J. Phillips, H. Wechsler, J. Huang, and P. J. Rauss, "The FERET database and evaluation procedure for face-recognition algorithms," *Image and Vision Computing*, vol. 16, no. 5, pp. 295–306, 1998, doi: 10.1016/S0262-8856(97)00070-X.
- [24] S. Mezzoudj, B. Ali, and R. Seghir, "Towards large-scale face-based race classification on spark frame- work," *Multimedia Tools and Applications*, vol. 78, pp. 26729–26746, 2019, doi: 10.1007/s11042-019-7672-7.
- [25] A. A. Abdulwahid, "Classification of ethnicity using efficient cnn models on morph and feret datasets based on face biometrics," *Applied Sciences*, vol. 13, no. 12, 2023, doi: 10.3390/app13127288.
- [26] K. Khan, M. Attique, R. U. Khan, I. Syed, and T.-S. Chung, "A multi-task framework for facial attributes classification through end-to-end face parsing and deep convolutional neural networks," *Sensors*, vol. 20, no. 2, 2020, doi: 10.3390/s20020328.
- [27] Worldometer, "Countries in the world by population (2025). [Online]. Available: <https://www.worldometers.info/world-population/population-by-country/>. (Accessed: 2025, Oct. 01).
- [28] N. M. Sapari, K. H. Yusof, N. T. K. Lung, M. M. Rasid, and S. M. Hussin, "Determining image deblur, de- tecting faces, and enhancing appearance using image processing techniques," in *2024 IEEE International Conference on Automatic Control and Intelligent Systems (I2CACIS)*, Shah Alam, Malaysia, 2024, pp. 363-367, doi: 10.1109/I2CACIS61270.2024.10649627.
- [29] B. Li, "Facial expression recognition by densenet-121," *Multi-chaos, fractal and multi-fractional artificial intelligence of different complex systems*, 2022, pp. 263–276, doi: 10.1016/B978-0-323-90032-4.00019-5.




- [30] S. Tammina, "Transfer learning using vgg-16 with deep convolutional neural network for classifying images," *International Journal of Scientific and Research Publications (IJSRP)*, vol. 9, no. 10, pp. 143–150, 2019, doi: 10.29322/IJSRP.9.10.2019.p9420.
- [31] M. Elpeltagy and H. Sallam, "Automatic prediction of COVID-19 from chest images using modified ResNet50," *Multimedia tools and applications*, vol. 80, no. 17, pp. 26451–26463, 2021, doi: 10.1007/s11042-021-10783-6.
- [32] Ž. Vujović, "Classification model evaluation metrics," *International Journal of Advanced Computer Science and Applications*, vol. 12, no. 6, pp. 599–606, 2021, doi: 10.14569/IJACSA.2021.0120670.

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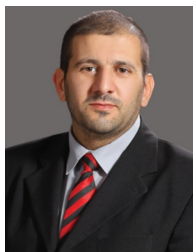
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