AUTOMATED ETHNICITY RECOGNITION USING EQUILIBRIUM OPTIMIZER WITH MACHINE LEARNING ON FACIAL IMAGES

by

Yousef ASIRI[a], Abdullah ALHABEEB[b], Aisha M. MASHRAQI[a], Abeer D. ALGARNI[c] and Sayed ABDEL-KHALEK[d*]

aDepartment of Computer Science, College of Computer Science and Information Systems, Najran University, Najran, Saudi Arabia
bDepartment of Information Science, College of Arts, King Saud University, Riyadh, Saudi Arabia
cDepartment of Information Technology, College of Computer and Information Sciences, Princess Nourah bint Abdulrahman University, Riyadh, Saudi Arabia
dDepartment of Mathematics, College of Science, Taif University, Taif, Saudi Arabia

Original scientific paper
https://doi.org/10.2298/TSCI22S1353A

In recent times, computer vision related face image analysis has gained significant attention in various applications namely biometrics, surveillance, security, data retrieval, informatics, etc. The main objective of the facial analysis is to extract facial soft biometrics like expression, identity, age, ethnicity, gender, etc. Of these, ethnicity recognition is considered a hot search topic, a major part of community with deep connections to many social and ecological concerns. The deep learning and machine learning methods is merit for effective ethnicity classification and recognition. This study develops a facial imaging based ethnicity recognition using equilibrium optimizer with machine learning (FIER-EOML) model. The goal of the FIER-EOML technique is to detect and classify different kinds of ethnicities on facial images. To accomplish this, the presented FIER-EOML technique applies an EfficientNet model to generate a set of feature vectors. For ethnicity recognition, the presented model uses long short-term memory method. To improve the recognition performance, the FIER-EOML technique utilizes EO algorithm for hyperparameter tuning process. The performance validation of the FIER-EOML technique is tested on BUPT-GLOBALFACE dataset and the results are examined under several measures. The comprehensive comparison study reported the enhanced performance of the FIER-EOML technique over other recent approaches.

Keywords: *machine learning, ethnicity recognition, informatics, facial images, deep learning, computer vision*

Introduction

Recently, deep learning (DL) method makes an effort to automatically learn good representations from raw data with multi-layers stacked on each other, has grabbed substantial interest in research community because of its different applications in natural language processing, speech processing, and computer vision (CV), [1]. One type of DL is the convolu-

*Corresponding author, e-mail: sabotalb@tu.edu.sa

tional neural network (CNN) that reached promising results in video and large-scale image recognition. Facial feature-oriented analysis of ethnical groups, races, and nations is becoming a renowned research domain in face recognition society [2]. Particularly, with swift advancements in human globalization, facial detection and identification approaches monitor the nation's borders and regulate movement of individuals at the border, providing security to public, and also in customs check [3]. Commonly, some of the factors that determine the facial features of an individual are society, genes, and environment. Of these, genes will be considered as one significant component which has a crucial part in ethnical groups. It was unique and extremely difficult to scrutinize other ethnical groups [4]. One solution was by understanding several gene systems and investigating similarity among them. This analysis was important to identify the similarities among facial features for various ethnicities [5].

Ethnicity detection is the efficiency of a technique to determine an individual's belonging to one of ethnicity groups related to facial appearance observation like other explicit patterns [6], morphology, and skin colour has not gained equivalent consideration from the authors. The curiosity in ethnicity recognition was certainly increasing [7, 8], given that new techniques and datasets were presented recently to enhance the precision level of realtime applications recently providing a force to the application in forensics or attaining an efficiency biased with ethnicity [9]. However, the research workers of a recent comprehensive work showed that the advances of this study can be mostly hindered by absence of ethnicity information; certainly, at this period of DL, there comes a demand for a vast amount of data available to train CNN efficiently [10].

This study develops a FIER-EOML model. The goal of the FIER-EOML technique is to detect and classify different kinds of ethnicities on facial images. To accomplish this, the presented FIER-EOML technique applies an EfficientNet model to generate a feature vector set. For ethnicity recognition, the presented model uses long short-term memory (LSTM) method. To improve the recognition performance, the FIER-EOML technique utilizes EO algorithm for hyperparameter tuning process. The performance validation of the FIER-EOML technique is tested on BUPT-GLOBALFACE dataset and the results are examined under several measures.

Related works

In [11], the authors proposed a new classification algorithm based on machine learning mechanism. Particularly, a new DL technique relevant to a DCNN method was introduced that outperform a consistent determination of the ethnicity of persons related to facial feature. Hence, it is essential to apply particular high-performance computing hardware to construct a workable DCNN-oriented FR technique because of lower computational energy provided by the CPU. In [12], the authors designed an IDL-ERCFI method based on intelligent DL tool. The study aims to classify and distinguish ethnicity according to facial images. Since the retrieved feature was higher dimensional, feature reduction process applies the PCA method that can be efficient to overcome *curse of dimensionality*. Moreover, the ethnicity classification method is performed through optimum KELM, with parameter tuning of KELM mechanism performed by glow-worm swarm optimization method.

Terada *et al.* [13] developed a 3-D facial ethnicity detection technique based on cylindrical projection and DL. In this work, the author first uses cylindrical projection to transform a 3-D facial image (scanned 3-D dataset) into a 2-D grayscale imagery. Then, converted 2-D images are fed into CNN for ethnicity detection. Ng *et al.* [14] introduced an Ensemble of Convolutional Autoencoder mechanisms to try to differentiate Korean, Chinese, and Japanese individuals and faces from distinct areas of China. Lei *et al*. [15] employed a DL based on the algorithm to recognize and classify ethnic costume image of Wa and Yi people. In the DL architecture Tensorflow, the deep convolutional network VGG method has been migrated to the ethnic costume detection method, and the image detecting of ethnic costume related VGG was realized.

Christy *et al*. [16] developed an ethnicity detection method related to CNN. Furthermore, a chaotic encryption-oriented blind digital image watermarking technique was used for the recognition image for the security imageries. Cover images are used to hide e recognized image to defend the image from third parties or attackers. Heng *et al*. [17] introduced an innovative hybrid supervised learning mechanism for performing ethnicity categorization that employs strength of CNN and rich characteristics attained from the network. A supervised SVM hybrid learning was introduced for training feature vector to carry out ethnicity classification.

The proposed model

In this study, we have developed an automated FIER-EOML approach for ethnicity detection and classification on facial images. The presented FIER-EOML technique employed the EfficientNet model to generate a set of feature vectors. For ethnicity recognition, the presented model utilized the EO algorithm with LSTM model. Figure 1 illustrates the overall process of FIER-EOML system.

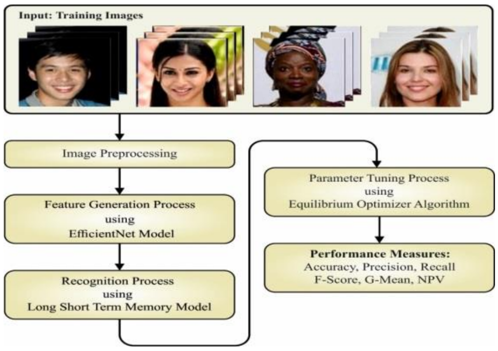

Figure 1. Overall process of FIER-EOML system

Feature extraction: EfficientNet model

Primarily, the input facial images are processed by the EfficientNet model to create a set of feature vectors. EfficientNet refers to a CNN method established by Google Brain Team [18]. Such researchers inspected network scaling and initiate that optimized network width, resolution, and depth are boosting performance. For creating a novel approach, it can be scaled to a NN for constructing further DL approaches which produce much more efficiency and accuracy related to the earlier utilized CNN. In order to ImageNet, EfficientNet carried out large-scale visual detection with consistency and accuracy. Related to optimum recognized systems like Xception, VGGNets, InceptionResNet, GoogleNet, and ResNets, this sequence of CNN infrastructure was around eight times lesser and six times quicker than infer. EfficientNet-B0 utilizes a composite scaling approach that generates distinct approaches in CNN family. The count of layers in network equals network depth. The convolutional (Conv) layer width has proportional to count of filters it comprises [19-22]. The heights and widths of input images defined resolution. The latest EfficientNet-B0 baseline approach which accepts an $224 \times 224 \times 3$ input image. This technique takes features across layers utilizing several Conv layers with 3×3 receptive domain and mobile inverted bottleneck Conv. Equations (1)-(5) showcase that present scaling resolution, depth, and width assuming, φ:

$$d = \alpha^{\varphi} \tag{1}$$

$$w = \beta^{\varphi} \tag{2}$$

$$r = \gamma^{\varphi} \tag{3}$$

$$\text{s.t}\alpha\chi^2\gamma^2 \approx 2 \tag{4}$$

$$\alpha \ge 1,\ \beta \ge 1,\ \gamma \ge 1 \tag{5}$$

where w, d, and r refer network width, depth, and resolution correspondingly, and constant terms α, β, γ are defined utilizing the grid search hyperparameter tune system. The co-efficient was a user-defined variable which controls every method scaling resource. This system regulates network resolution, depth, and width for optimizing network accuracy and memory utilization dependent upon accessible resources. Different other deep CNN, EfficientNet-B0 used all the dimensions utilizing an existing group of scaling co-efficient, demonstrating other cutting-edge methods training on ImageNet database. Even with TL system, EfficientNet created outstanding outcomes and illustrated their efficacy away from the ImageNet database. This method has been released with scales range in (0-7), comprising enhancements in the accuracy and parameter size. With new progress of EfficientNet, users and developers are now apply and give enhanced ubiquitous connectivity capable with DL abilities in distinct platforms for meeting distinct requires.

Ethnicity recognition: Optimal LSTM model

For ethnicity recognition, the FIER-EOML technique uses LSTM model. The LSTM was a kind of recurrent neural network (RNN), has chained recurrent module. But distinct LSTM cells are highly complicated than typical RNN [23]. Each rectangle characterizes the FC layer with their respective activations sigma, σ, and tan$h$. Input dataset in, t, timestep can be denoted as x_t. Likewise, the present cell state and output can be denoted as C_t and h_t. The present cell state, C_t based on minor linear interaction associated with the preceding cell state, C_{t-1}. The LSTM gate was generated by the sigmoid, σ, layer and point wise multiplication such the output lies in-between 0 and 1 (discarded as well as valid information). The f_t forget gate operation can be given in eq. (6), whereby w_f indicates the corresponding weight matrices for that gate and remains constant. This assessment defines that data is needed to be kept related to the preceding output and present data, b_f indicates a bias. Likewise i_t can be attained with a similar procedure, W_i and b_i represent bias and weights. This gate is called an input gate; it chooses which value gets upgraded. The output i_t get integrated with the vector of candidate value, C_t attained with tan$h$ layer, weight W_C and b_C, as seen in eq. (8). Figure 2 illustrates the infrastructure of LSTM.

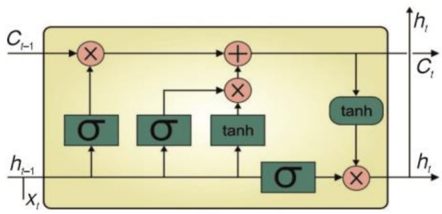

Figure 2. Architecture of LSTM

The previous cell state C_{t-1} upgrades resulting in eq. (9). The C_t then a tan$h$ pushes toward the value amongst t − l and 1 beforehand multiplied with the output of another sigmoid gate and it can be given:

$$f_t = \sigma\left(W_f\left[h_{t-1'}x_t\right] + b_f\right) \tag{6}$$

$$i_t = \sigma\left(W_i\left[h_{t-1'}x_t\right] + b_i\right) \tag{7}$$

$$C_t = \tanh\left(W_C\left[h_{t-1}, x_t\right] + b_C\right) \tag{8}$$

$$C_t = f_t C_{t-1} + i_t C_t \tag{9}$$

$$0_t = \sigma\left(W_0\left[h_{t-1'} x_t\right] + b_0\right) \tag{10}$$

$$h_t = 0_t \times \tanh\left(C_t\right) \tag{11}$$

To execute a multi-layered LSTM, output series of LSTM cells in a time step, h_t, was returned and fed into following layer. Where T signifies the maximal amount of time steps. The last layer does not need to retrieve each hidden cell output but only the output in the final timestep. The last output corresponds to $h_T^{'}$.

Consequently, there exist 2 hyperparameters to set:

- Hidden neuron (n): amount of hidden neurons in the LSTM cell gate.
- Hidden layer (L): amount of LSTM layers to be connected.

To enhance the efficacy of the ethnicity recognition process, the EO algorithm is used here. The EO algorithm was based on physical mass balance equation that gives physical basis by controlling controller's quantity weight input, production qualities, and output [24]:

$$C = C_{\mathrm{eq}} + \left(C_0 - C_{\mathrm{eq}}\right)F + \frac{G}{\lambda V}\left(1 - F\right) \tag{12}$$

where C is the existing particle concentration, G signifies mass generation rate in control product, C_{eq} indicates concentration at an equilibrium states where there exists no generation inside control volume, λ indicates a random value within zero and one, C_0 represent original concentration of particles, F index to balance exploration and development, and V shows the unit quantity.

Equilibrium pool and its candidate solution

The equilibrium state can be globally optimal and is the last convergence state. The EO method creates vector named equilibrium pool that gives equilibrium candidate particles. Five candidate solutions presented in equilibrium pools can be determined through experimentations, four of which will be the optimal particles recognized in entire optimization technique. Others are the mathematical average of above four. The average was helpful for exploitation and four best particles are useful for exploration as:

$$\vec{c}_{\mathrm{eq,pool}} = \left\{\vec{C}_{\mathrm{eq}(1)}, \vec{C}_{\mathrm{eq}(2)}, \vec{C}_{\mathrm{eq}(3)}, \vec{C}_{\mathrm{eq}(4)}, \vec{C}_{\mathrm{eq(ave)}}\right\} \tag{13}$$

where $\vec{c}_{\mathrm{eq,pool}}$ indicates candidate solutions chosen with a similar probability in equilibrium pools.

F index

The F index acts a crucial role in the exploitation and exploration stages of balanced EO algorithm:

$$F = e^{\left[-\lambda\left(t - t_0\right)\right]} \tag{14}$$

where λ denotes the random number ranges from zero to one and t represents the iterative function:

$$t = \left(1 - \frac{Iter}{\mathrm{Max}\_Iter}\right)^{\alpha_2 \frac{Iter}{\mathrm{Max}\_Iter}} \tag{15}$$

where *Iter* and Max_*iter* indicates the number of presents and maximal iterations correspondingly:

$$\vec{t} = \frac{1}{\vec{\lambda}} \ln\left(-\alpha_1 sign\left(\vec{r} - 0.5\right)\left[1 - e^{-\lambda t}\right]\right) + t \tag{16}$$

where α_1 and α_2 denotes constant utilized for controlling the exploration and exploitation capabilities and greater the values of α_1 and α_2 the stronger exploration and exploitation abilities:

$$F = \alpha_1 sign\left(\vec{r} - 0.5\right)\left[e^{-\vec{\lambda} t} - 1\right] \tag{17}$$

Generation rate G

The generation rate *G* allows EO method to offer precise solutions by enhancing the exploitation phase and it can be formulated in the following equation:

$$\vec{G} = \vec{G}_0 e^{-k_{(t-t_0)}} \tag{18}$$

where $\vec{G}$ denotes initial value, *k* refers to attenuation constant equivalent to λ, hence the last expression of generation rate was given:

$$\vec{G} = \vec{G} e^{-k_{(t-t_0)}} = \vec{G}_0 \vec{F} \tag{19}$$

whereas

$$\vec{G} = \overrightarrow{GCP}\left(\vec{C}_{\text{eq}} - \vec{\lambda}\vec{C}\right) \tag{20}$$

$$\overrightarrow{GCP} = \begin{cases} 0.5 r_1, & r_2 \geq GP \\ 0, & r_2 < GP \end{cases} \tag{21}$$

where r_1 and r_2 neutralization is a random integer ranges from zero to one and *GCP* denotes the probability that generation contributed towards the updating method named the generation rate control parameter. The incomparable input of probabilities uses this generation term to upgrade the state. The *GCP* could attain from eq. (17). The *GP* (*GP* = 0.5) is named generic possibility to accomplish better balance amongst exploitation and exploration:

$$\vec{C} = \vec{C}_{\text{eq}} + \left(\vec{C}_0 - \vec{c}_{\text{eq}}\right)\vec{F} + \frac{\vec{G}}{\vec{\lambda} V}\left(1 - \vec{F}\right) \tag{22}$$

The EO algorithm will derive a fitness function (FF) to have enhanced classifier outcome. It sets a positive values for signifying superior outcome of the candidate solutions. The reduction of the classifier error rate was designated as the FF in this study, as given:

$$\text{fitness}\left(x_i\right) = \text{classifier error rate}\left(x_i\right) = \frac{\text{number of misclassified samples}}{\text{total number of samples}} \times 100 \tag{23}$$

Results and discussion

The experimental validation of the FIER-EOML method is tested using the facial image dataset, comprising 8000 samples and four classes as represented in tab. 1. Figure 3 demonstrates the some sample images.

Figure 4 showcases the confusion matrices produced by the FIER-EOML model on ethnicity recognition process. The results identified that the FIER-EOML model has properly recognized four different types of ethnicities.

Table 1. Dataset details

Class	No. of Samples
Cauca	2000
African	2000
Asian	2000
Indian	2000
Total No. of samples	8000

Figure 3. Sample images

Table 2 reports an overall ethnicity recognition outcome of the FIER-EOML model. Figure 5 illustrates an overall result of the FIER-EOML model interms of $accu_y$, $prec_n$, and $reca_l$. The results denoted that the FIER-EOML model has obtained effectual outcome under all classes. For instance, on entire dataset, the FIER-EOML model has attained average $accu_y$, $prec_n$, and $reca_l$ of 98.94%, 97.89%, and 97.89% respectively. Meanwhile, on 70% of TR database, the FIER-EOML method has achieved average $accu_y$, $prec_n$, and $reca_l$ of 98.96%, 97.91%, and 97.91% respectively.

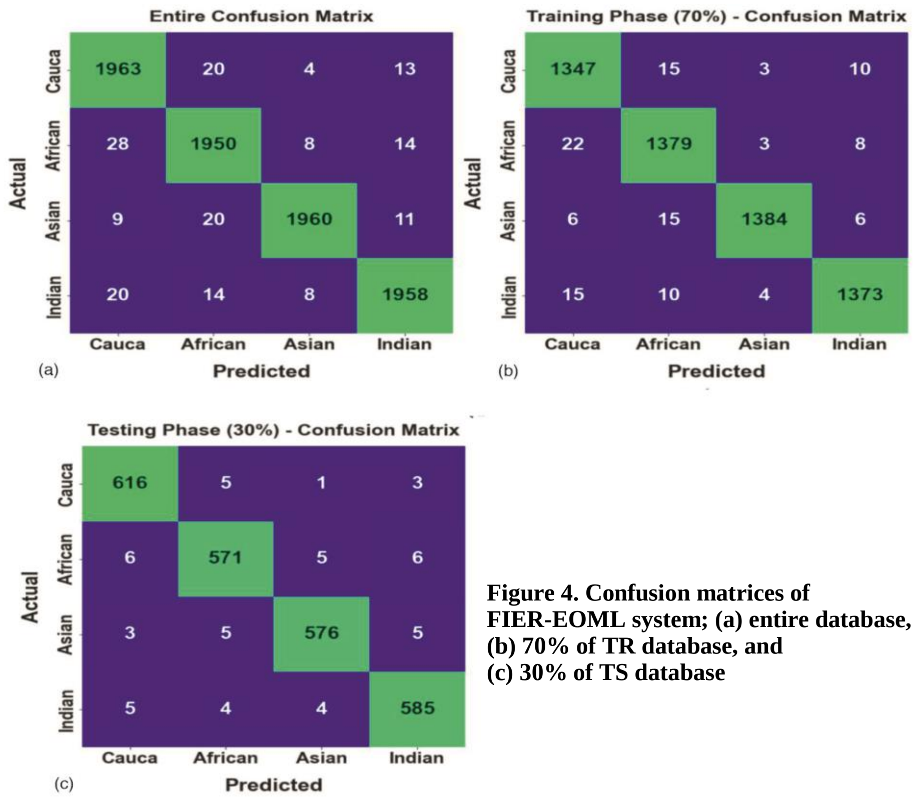

Figure 4. Confusion matrices of FIER-EOML system; (a) entire database, (b) 70% of TR database, and (c) 30% of TS database

Table 2. Ethnicity recognition outcome of FIER-EOML approach with distinct classes

Class	Accuracy	Precision	Recall	F-Score	G-Mean	NPV
Entire dataset						
Cauca	98.82	97.18	98.15	97.66	98.60	99.38
African	98.70	97.31	97.50	97.40	98.30	99.17
Asian	99.25	98.99	98.00	98.49	98.83	99.34
Indian	99.00	98.10	97.90	98.00	98.63	99.30
Average	98.94	97.89	97.89	97.89	98.59	99.30
Training phase (70%)						
Cauca	98.73	96.91	97.96	97.43	98.47	99.33
African	98.70	97.18	97.66	97.42	98.35	99.21
Asian	99.34	99.28	98.09	98.68	98.92	99.36
Indian	99.05	98.28	97.93	98.11	98.68	99.31
Average	98.96	97.91	97.91	97.91	98.61	99.30
Testing phase (30%)						
Cauca	99.04	97.78	98.56	98.17	98.89	99.49
African	98.71	97.61	97.11	97.36	98.16	99.06
Asian	99.04	98.29	97.79	98.04	98.62	99.28
Indian	98.88	97.66	97.83	97.74	98.52	99.28
Average	98.92	97.84	97.82	97.83	98.55	99.28

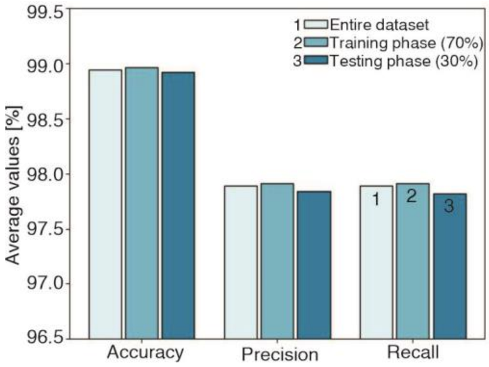

Figure 5. The $accu_y$, $prec_n$, and $reca_l$ analysis of FIER-EOML approach

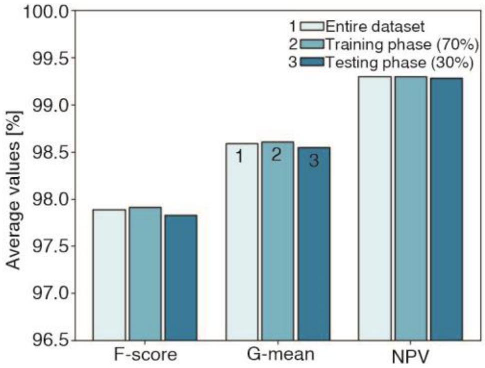

Figure 6. The F-score, G-mean, and NPV analysis of FIER-EOML approach

Figure 6 shows an overall result of the FIER-EOML approach interms of F-score, G-mean, and NPV. The results exhibited the FIER-EOML technique has gained effectual outcome under all classes. For example, on entire dataset, the FIER-EOML methodology has achieved average F-score, G-mean, and NPV of 97.89%, 98.59%, and 99.30% correspondingly. In the meantime, on 70% of TR database, the FIER-EOML technique has reached average F-score, G-mean, and NPV of 97.91%, 98.61%, and 99.30% correspondingly.

The TACC and VACC of the FIER-EOML approach is investigated on ethnicity recognition performance in fig. 7. The figure displayed the FIER-EOML approach has signified improved performance with increased values of TACC and VACC. It is noted that the FIER-EOML approach has reached maximal TACC outcomes.

The TLS and VLS of the FIER-EOML approach are tested on ethnicity recognition performance in fig. 8. The figure displayed the FIER-EOML technique has shown superior performance with minimal values of TLS and VLS. It is noted that the FIER-EOML approach has resulted to reduced VLS outcomes.

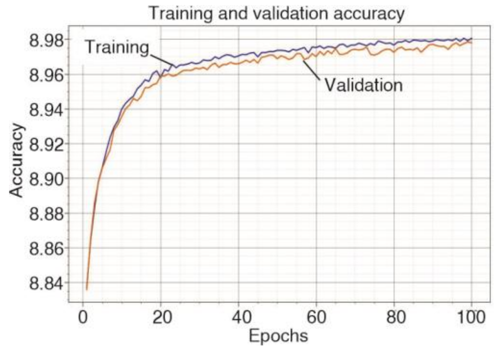

Figure 7. The TACC and VACC analysis of FIER-EOML approach

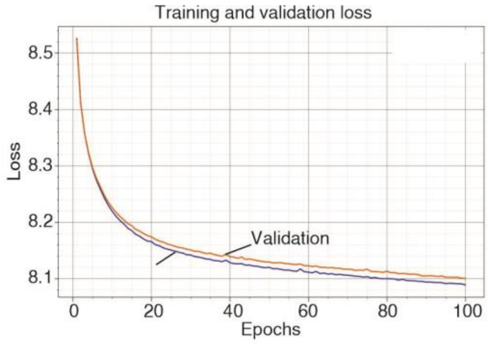

Figure 8. The TLS and VLS analysis of FIER-EOML approach

A clear precision-recall inspection of the FIER-EOML technique in test database is shown in fig. 9. The figure specified the FIER-EOML approach has resulted to enhanced values of precision-recall values in every class labels.

Table 3 demonstrates an overall comparative study of the FIER-EOML method with other existing methods.

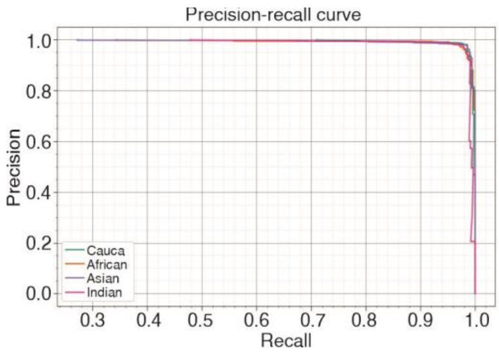

Figure 9. Precision-recall analysis of FIER-EOML approach

Table 3. Comparative analysis of FIER-EOML system with existing approaches

Methods	Accuracy	Precision	Recall	F1-score
FIER-EOML	98.96	97.91	97.91	97.91
R-Net	97.03	96.43	97.60	97.25
VGGFace-SVM	98.34	97.50	97.34	97.55
Inception-ResNet-v2	96.71	96.51	96.60	96.72
SeNet	95.57	96.34	95.60	96.13
Mobilenet	96.11	96.89	96.18	96.81
IDL-ERCFI	98.85	97.78	96.57	97.46

Figure 10 represents a comparative examination of the FIER-EOML model in terms of $accu_y$ and F1-score. The results indicated that the FIER-EOML model has reached maximum performance over other models. For instance, based on $accu_y$ the FIER-EOML model has attained higher $accu_y$ of 98.96% whereas the R-Net, VGGFace-SVM, Inception-ResNet-v2, SeNet, Mobilenet, and IDL-ERCFI models have obtained lower $accu_y$ of 97.03%, 98.34%, 96.71%, 95.57%, 96.11%, and 98.85% respectively. At the same time, based on F1-score the FIER-EOML approach has reached higher F1-score of 97.91% where the R-Net, VGGFace-SVM, Inception-ResNet-v2, SeNet, Mobilenet, and IDL-ERCFI algorithms have gained lower F1-score of 97.25%, 97.55%, 96.72%, 96.13%, 96.81%, and 97.46% correspondingly.

Figure 11 signifies the detailed study of the FIER-EOML model in terms of $prec_n$ and $reca_l$. The results show the FIER-EOML approach has reached maximal performance over other models. For example, based on $prec_n$ the FIER-EOML technique has attained higher $prec_n$ of 97.91% whereas the R-Net, VGGFace-SVM, Inception-ResNet-v2, SeNet, Mobilenet, and IDL-ERCFI algorithms have attained lower $prec_n$ of 96.43%, 97.50%, 96.51%, 96.34%, 96.89%, and 97.78% correspondingly. Simultaneously, based on $reca_l$, the FIER-EOML approach has achieved higher $reca_l$ of 97.91% whereas the R-Net, VGGFace-SVM, Inception-ResNet-v2, SeNet, Mobilenet, and IDL-ERCFI methodologies have attained lower $reca_l$ of 97.60%, 97.34%, 96.60%, 95.60%, 96.18%, and 96.57% correspondingly.

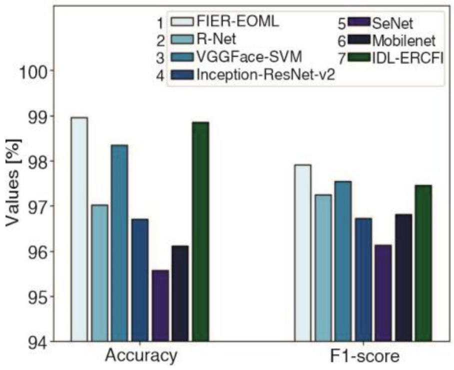

Figure 10. The $accu_y$ and F1-score analysis of FIER-EOML system with existing approaches

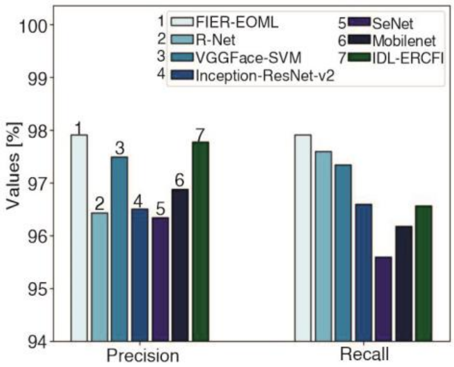

Figure 11. The $prec_n$ and $reca_l$ analysis of FIER-EOML system with existing approaches

Finally, a comprehensive computation time (CT) examination of the FIER-EOML method with other DL methods in tab. 4 and fig. 12. The results represented that the R-Net method has shown worse outcome with increased CT of 8.87 seconds. Next, the other existing models such as VGGFace-SVM, Inception-ResNet-v2, SeNet, and MobileNet methods have reached moderately closer CT values. Although the IDL-ERCFI technique has resulted to near optimal CT of 3.59 seconds, the FIER-EOML model has shown maximum performance with least CT of 3.12 seconds. Thus, the presented FIER-EOML model can be employed for enhanced performance over other models.

Table 4. The CT analysis of FIER-EOML system with other existing approaches

Methods	Computational time [s]
FIER-EOML	3.12
R-Net	8.87
VGGFace-SVM	7.26
Inception-ResNet-v2	7.20
SeNet	7.73
Mobilenet	7.74
IDL-ERCFI	3.59

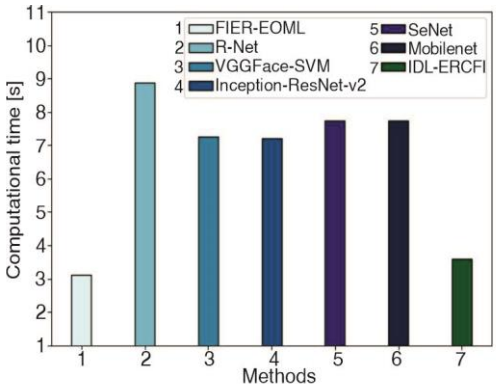

Figure 12. The CT analysis of FIER-EOML system with existing approaches

Conclusion

In this study, we have developed an automated FIER-EOML approach for ethnicity detection and classification on facial images. The presented FIER-EOML technique employed the EfficientNet model to generate a set of feature vectors. For ethnicity recognition, the presented model utilized the EO algorithm with LSTM model. The application of EO algorithm for hyperparameter tuning process considerable improve the recognition performance, the FIER-EOML technique utilizes. The performance validation of the FIER-EOML technique is tested on BUPT-GLOBALFACE dataset and the results are examined under several measures. The comprehensive comparison study reported the enhanced performance of the FIER-EOML technique over other recent approaches. In future, the performance of the FIER-EOML technique can be improved by hybrid DL models.

Acknowledgment

The authors are thankful to the Deanship of Scientific Research at Najran University for funding this work under the Research Collaboration Funding program grant code (NU/RC/SERC/11/5) and Princess Nourah bint Abdulrahman University Researchers Supporting Project number (PNURSP2022R51), Princess Nourah bint Abdulrahman University, Riyadh, Saudi Arabia.

References

[1] Belcar, D., *et al*., Automatic Ethnicity Classification from Middle Part of the Face Using Convolutional Neural Networks, *Informatics, 9* (2022), 1, p. 18
[2] Devaraj, S. J., *et al*., *Deep Learning Based Facial Feature Detection for Ethnicity Recognition*, *Smart Computing Techniques and Applications*, Springer, Singapore, 2021, pp. 527-534
[3] Noseworthy, P. A., *et al*., Assessing and Mitigating Bias in Medical Artificial Intelligence: The Effects of Race and Ethnicity on a Deep Learning Model for ECG Analysis, *Circulation: Arrhythmia and Electrophysiology, 13* (2020), 3, e007988
[4] Liu, A., *et al*., Cross-Ethnicity Face Anti-Spoofing Recognition Challenge: A Review, *IET Biometrics, 10* (2021), 1, pp. 24-43
[5] Wang, C., *et al*., Expression of Concern: Facial Feature Discovery for Ethnicity Recognition, *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 9* (2019), 1, e1278
[6] Dahlan, H. A.,. A Survey on Deep Learning Face Age Estimation Model: Method and Ethnicity, *International Journal of Advanced Computer Science and Applications, 12* (2021), 11
[7] Amali, G., *et al*., A Deep Learning-Based Framework for Accurate Facial Ethnicity Classification and Efficient Query Retrieval, in: *Handbook of Research on Deep Learning-Based Image Analysis Under Constrained and Unconstrained Environments*, IGI Global, Hershey, Penn., USA, 2021, pp. 216-240
[8] Li, J., *et al*., Machine Learning Approach to Predict Race and Ethnicity of Twitter Users Discussing HIV Prep Prevention Therapy, *Proceedings*, APHA Annual Meeting and Expo, Denver, Col., USA, 2021
[9] Greco, A., *et al*., Benchmarking Deep Network Architectures for Ethnicity Recognition Using a New Large Face Dataset, *Machine Vision and Applications, 31* (2020), 7, pp. 1-13
[10] Aworinde, H. O., *et al*., Performance Evaluation of Feature Extraction Techniques in Multi-Layer-Based Fingerprint Ethnicity Recognition System, *Asian J. of Research in Computer Sci., 3* (2019), 1, pp. 1-9
[11] AlBdairi, A. J. A., *et al*., Face Recognition Based on Deep Learning and FPGA for Ethnicity Identification, *Applied Sciences, 12* (2022), 5, 2605
[12] Sunitha, G., *et al*., Intelligent Deep Learning-Based Ethnicity Recognition and Classification Using Facial Images, *Image and Vision Computing, 121* (2022), 104404
[13] Terada, T., *et al*., Three-Dimensional Facial Ethnicity Identification Based on Cylindrical Projection and Deep Learning, *Proceedings*, IEEE International Conference on Consumer Electronics, Las Vegas, Nev, USA, 2022, pp. 01-04
[14] Ng, W. W., *et al*., Fine-Grained Facial Ethnicity Recognition Based on Dual Convolutional Autoencoders, *Proceedings*, 11th International Conference on Intelligent Control and Information Processing, Dali, China, 2021, pp. 235-240
[15] Lei, Q., *et al*., Research on Image Recognition Method of Ethnic Costume Based on VGG, *Proceedings*, International Conference on Machine Learning for Cyber Security, Guangzhou, China, 2020, pp. 312-325
[16] Christy, C., *et al*., Deep Learning with Chaotic Encryption Based Secured Ethnicity Recognition, *Proceedings*, 3rd International Conference on Electronics, Communication and Aerospace Technology, Coimbatore, India, pp. 515-520

[17] Heng, Z., *et al*., Hybrid Supervised Deep Learning for Ethnicity Classification Using Face Images, *Proceedings*, IEEE International Symposium on Circuits and Systems, Florence, Italy, pp. 1-5
[18] Shah, H. A., *et al*., A Robust Approach for Brain Tumor Detection in Magnetic Resonance Images Using Finetuned EfficientNet, *IEEE Access, 10* (2022), June, pp. 65426-65438
[19] Alabdulkreem, E., *et al*., Optimal Weighted Fusion-Based Insider Data Leakage Detection and Classification Model for Ubiquitous Computing Systems, *Sustainable Energy Technologies and Assessments, 54* (2022), 102815
[20] Alsubai, S., *et al*., Bald Eagle Search Optimization with Deep Transfer Learning Enabled Age-Invariant Face Recognition Model, *Image and Vision Computing, 126* (2022), 104545
[21] Abukhodair, F., *et al*., An Intelligent Metaheuristic Binary Pigeon Optimization-Based Feature Selection and Big Data Classification in a MapReduce Environment, *Mathematics, 9* (2021), 20, 2627
[22] Mansour, R. F., *et al*., Optimal Deep Learning-Based Fusion Model for Biomedical Image Classification, *Expert Systems, 39* (2022), 3, e12764
[23] Tirado-Martin, P., Sanchez-Reillo, R., BioECG: Improving ECG Biometrics with Deep Learning and Enhanced Datasets, *Applied Sciences, 11* (2021), 13, 5880
[24] Yu, B. C., Shao, L. S., An Optimization Method of Mine Ventilation System Based on R2 Index Hybrid Multi-Objective Equilibrium Optimization Algorithm, *Energy Reports, 8* (2022), Nov., pp. 11003-11021

Paper submitted: October 2, 2022
Paper revised: November 17, 2022
Paper accepted: November 21, 2022