A Novel Method for Gender and Age Detection Based on EEG Brain Signals

Haitham Issa[1], Sali Issa[2], and Wahab Shah[3]
[1]Department of Electrical Engineering, Zarqa University, Jordan
[2]Department of Computer Engineering, Hubei University of Education, China
[3]Department of Electrical Engineering, Namal University, Pakistan

Abstract: *This paper presents a new gender and age classification system based on Electroencephalography (EEG) brain signals. First, Continuous Wavelet Transform (CWT) technique is used to get the time-frequency information of only one EEG electrode for eight distinct emotional states instead of the ordinary neutral or relax states. Then, sequential steps are implemented to extract the improved grayscale image feature. For system evaluation, a three-fold-cross validation strategy is applied to construct four different classifiers. The experimental test shows that the proposed extracted feature with Convolutional Neural Network (CNN) classifier improves the performance of both gender and age classification, and achieves an average accuracy of 96.3% and 89% for gender and age classification, respectively. Moreover, the ability to predict human gender and age during the mood of different emotional states is practically approved.*

Keywords: *EEG, Gender, Age, CWT, CNN.*

Received September 27, 2020; accepted February 9, 2021
https://doi.org/10.34028/iajit/18/5/10

1. Introduction

Brain-Computer Interface (BCI) technology is considered as a fantastic sign of the modern era, where machines could measure and detect human brain response, analyze the collected information, and produce useful decisions or signals that serve several essential and critical daily applications [2, 12, 25]. Several techniques are implemented to detect and measure our brain information, such as the famous Electroencephalography (EEG) test.

The EEG is a safe and cheap test that measures the electrical activity response of human brain neurons using a scalp with pasted metal discs or electrodes and then transmits the collected brain signals to the computer or especial machines through tinny wires or wireless connectors. The measured EEG voltages are minimal, recorded in microvolts within the range of 10-20 mV, and cover the area frequency of delta, theta, alpha, beta, and gamma [3, 13, 29].

Due to the relation between internal brain neurons and external environment interaction, researchers have started using EEG brain signals for useful and vital applications such as checking the disorder of brain tasks [8, 10, 31], testing drugs and alcohol addiction [21], monitoring several diseases as Epilepsy and Alzheimer [23, 33], enhancing criminal investigation, security, and helping disabled people [33]. Human gender and age classification are also examples of these challenging applications. Although it is possible to classify gender and age depending on other signals or information such as the human face, voice, and body gestures [1, 16, 32], EEG signals are robust and accurate methods. It is direct information that spread out of the brain and nobody can hide, change, or fake the generated brain signals [4, 7, 28]. Hence, gender and age classification based on EEG brain signals will give systems more reality.

During the past decade, several studies of gender and age classification based on EEG brain signals have been done, but still have many challenges, limitations, and need more enhancements. Most of them used a large number of EEG electrodes, extraction features, and feature selection methods to get robust systems [9, 10, 15], others used additional peripheral signals such as heartbeats, and temperature to upgrade the classification results, as well as, all of them selected the recorded EEG channels during the neutral or rest emotional state [15, 17, 18].

In this paper, a new gender and age classification system is introduced based on EEG brain signals. Continuous Wavelet Transform (CWT) is implemented to get the time-frequency voltage information of only one EEG electrode, and then sequential mathematical calculations are applied to get the grayscale image feature from the time-frequency information. In classification, four different classifiers of Convolutional Neural Network (CNN), Linear Discriminant Analysis (LDA), Support Vector Machine (SVM), and K Nearest Neighbor (KNN) were trained and tested for evaluation and comparison purpose. As a result, the proposed extracted gray image feature with the CNN classifier achieved the highest results for both gender and age classification. The main contributions of this paper are as follows:

1. An enhanced grayscale image feature is proposed, with its ability to present the EEG voltage distribution or variation, where image rows number related to the brain frequency range of 1-45 Hz, image columns related to the time pass as sequential batches, and image intensity related to the brain voltage distribution.
2. Person independent gender and age classification system is introduced with robust and stable results using only one EEG electrode without any peripheral signals.
3. The proposed system proves the possibility of human gender and age prediction in eight different emotional cases rather than the usual neutral or relaxed state.

The remainder of this paper is as follows; section 2 gives a brief description for the previous related works. Section 3 shows the implemented database acquisition and preprocessing. Section 4 illustrates the proposed extracted feature in detail; section 5 provides the experimental results of the framework, and section 6 is the conclusion.

2. Literature Review

According to the importance of BCI technology in our modern daily life, scientists are doing intensive work to enhance the performance of BCI technologies, and solve the concurrent challenges. For example, Nguyen *et al*. [17] selected the rest state or the neutral emotion recordings of eight EEG electrodes to extract two different features; popular and paralinguistic. For popular features, the common Power Spectral Density (PSD), relative power, and Hjorth parameters were produced. For paralinguistic features, Mel-Frequency Cepstral Coefficients (MFCC), Log Filter-Bank Powers (LFBP), and Line Spectral Pairs (LSP) were extracted. SVM classifier was trained to identify the participant gender and age category, which is divided into three main categories of Young, Middle, and Old participants. In gender classification, the trained SVM classifier achieved an average accuracy of 97.7% and 97.1% for paralinguistic and popular feature groups, respectively. While, in age classification, the trained SVM classifier achieved an average accuracy of 97.5% and 96.7% for paralinguistic and popular feature groups, respectively.

Liu *et al*. [15] depended on the rest state emotional recordings of all EEG channels. Then, Fourier transform is used to get the frequency domain information, CNN classifier was trained for gender and age classification, where age label are divided into three different groups: Young, Middle, and Old groups. The classification system produced an average accuracy of 62.7% and 51.2% for gender and age, respectively.

Nguyen *et al*. [18] used the rest state emotion recordings of eight EEG electrodes to extract several features, which are the popular features such as Hjorth parameters, and the speech processing features such as Log Filter-Bank Powers (LFBP), and LSP. The extracted features were used to construct a third-order tensor with the modes of time epochs, features, and electrodes. Later, PARallelFACtor (PARAFAC) was implemented to split the tensor into the sum of rank-one tensors. The decomposed tensors were applied to derive the system features. Moreover, Multi-linear Partial Less Square (N-PLS) regression model was used to enhance the classification performance because it helps in extracting the components which fit the tensor and also predicts the class category together. According to age prediction, the participants are divided into three main categories: Young, Middle, and Old. In experiments, the trained SVM classifier achieved an average accuracy of 93.8% and 92.5% for gender and age, respectively.

Kaur *et al*. [9] used wireless EEG sensors to record fourteen EEG electrodes during the rest state, Discrete Wavelet Transform (DWT) was implemented for frequency decomposition. According to age prediction, the participant's age ranges from 6 to 55 years old and divided into six categories. In feature extraction, mean, energy, and Root-Mean-Square (RMS) were produced for all frequency bands. Average accuracy of 88.33% and 96.66% was produced using random forest classifier for age and gender, respectively.

Oral *et al*. [19] used only one EEG channel for the two states of awake and sleep. EEG cepstrum coefficients were driven, and some frequency domain features were calculated. SVM classifier was constructed and trained for gender classification purposes, and an average accuracy of 77.84% and 89.66% were produced for awake and sleep states, respectively.

Kaushik *et al*. [10] depended on fourteen EEG channels during the rest state. Then, in feature extraction, DWT was applied to get the five frequency bands for each channel. The Deep Bidirectional Long Short-Term Memory- Long Short-Term Memory (BLSTM-LSTM) classifier was constructed and trained for gender classification. Experiments showed that the best results were achieved for the beta frequency band with an average accuracy of 97.5%.

Actually, this topic still needs more work and suffers from critical challenges. All previous researches used the EEG signals under the condition of rest or neutral state [9, 10, 15, 17, 18], this is not practical or logical in daily life applications, and alternated system is needed to detect subject age and gender whatever the emotional state is. Another essential thing is aimed to minimize the number of used EEG channels for feature extraction calculation as much as possible [9, 10, 15], moreover, avoid using any peripheral signals such as human face and voice expression. Reducing the calculation size or dimension without effect the classification robustness is an extreme challenge and needs more researches that are new.

Comparing with the previous related works, a novel gender and age prediction system is enhanced using only one EEG channel and one extraction feature. The proposed method proves the possibility of having an accurate, practical and reliable prediction system in case of using up to eight different emotions together.

3. Database Acquisition and Pre-processing

Database for Emotion Analysis using Physiological Signals (DEAP) public database [11] was made as a database acquisition since 2012, and it is a multi-modal database implemented for recording 32 EEG channel electrodes and other peripheral psychological signals of 32 participants (16 males and 16 females). During the stimuli experiment, each participant watched 40 excerpts of movies 60 s long, and rated each video in terms of the levels of arousal, valence, dominance, liking and familiarity with a scale from 1 to 9. EEG recordings were sampled to 128 Hz, EOG artifacts were removed, and a band pass frequency filter (4-45Hz) was applied. The standard international 10/20 system is used during experiment recordings. This system describes the position of EEG electrodes on the scalp; it is based on the relation between the electrode location and the underlying area of the cerebral cortex [30]. Figure 1 illustrates the international 10/20 EEG electrodes positions used in collecting the DEAP database.

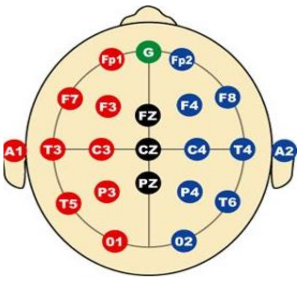


Figure 1. The EEG 10/20 system electrode distances.

4. Feature Extraction

In feature extraction calculation, the powerful CWT technique is utilized to derive the grayscale image feature from EEG signals. Wavelet transform presents the ordinary 1D EEG time-domain signal into 2D time-frequency domain data, so, it is possible to have a full and clear EEG voltage activation information in both time and frequency domains together. However, the sequential steps of extracting the image feature can be summarized into the followings:

1. Select only Fz electrode

Choosing the minimum number of EEG electrodes is considered as a primary challenge in this field, because a large number of EEG channels produce sophisticated features with enormous dimensions, consumes time and memory space for the needed huge calculation. On the other side, the frontal Fz electrode achieved excellent results in previous BCI researches [5, 6]. Accordingly, it is selected for feature calculation.

2. Select the second half of Fz channel data

All DEAP database recording channels are 60 seconds. In this proposed study, the second half (30 seconds) data is selected to minimize the feature extraction size. Also, the possibility of having sufficient features with accurate results is approved using parts of EEG electrodes [14]. In other words, there is no need to use the complete recording of EEG channels.

3. Apply Continuous Wavelet Transform (CWT)

In this step, the CWT is applied to generate the time-frequency domain conversion of Fz electrode. The wavelet conversion is calculated using the following equation [22]:

$$CWT_x^{\varphi}(\tau, s) = \Psi_x^{\varphi}(\tau, s) = \frac{1}{\sqrt{s}} \int X(t) \Psi^* \left(\frac{t-\tau}{s}\right) \quad (1)$$

Where $X(t)$ is the time domain voltage signal of Fz electrode; τ and s are the signal translation and scale parameters, and Ψ is the mother wavelet function.

4. Reform the time-frequency data into 45x45 data matrix

Split the converted time-frequency signal into 45 sequential parts as in Equation (2), where each part is the maximum voltage magnitude for the entire voltage distribution in each frequency value.

$$\forall_c \in C \{ M = Max\, M(r = 1,2,\dots,45 ;\ c = 1,2,\dots,45) \} \quad (2)$$

Where M is the reformed CWT matrix of size 45x45; c is the part sequence (1-45), and r is the brain frequency magnitude (1-45 Hz).

The total rows number (45 rows) refers to the possible brain frequency ranges, and the purpose of calculating M matrix is to detect the high EEG voltages in each brain frequency value. The total columns number is selected to produce a square and convenient matrix.

5. Convert the 2D 45x45 CWT matrix to agrayscale image.

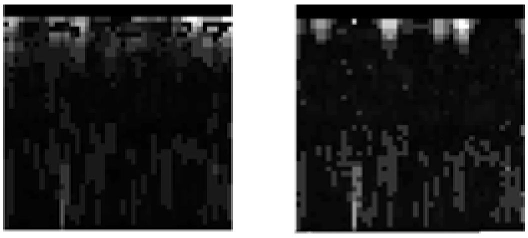
Algorithm 1 illustrates the procedure of converting the 2D matrix into a grayscale image of range (0-1). In grayscale image, black color has value of ‘0’ and reflects the tinny EEG voltages, value ‘1’ for white color and reflects the high EEG voltages. While the gray color pixels within the range of 0-1 reflects the EEG voltage variation. Figure 2 provides examples of grayscale images for the frontal Fz channel.

The produced grayscale image is not only a calculated feature; it is further simulating the variation of the brain signals’ voltages during time.

Consequently, EEG voltages could be seen and tracked as images.

Algorithm 1: Grayscale image feature extraction

```
procedure GRAYSCALE (M)
min ← minimum (M), max ← maximum (M)
    delta ← 1 / (max – min)
    Image ← (M x delta) - (delta x min)
    return Image
end procedure
```



a) Negative emotion. b) Positive emotion.

Figure 2. Examples of grayscale images for Fz electrode.

5. Results and Discussion

According to the DEAP database, the watched movies were rated by the participants due to the Arousal Valence Dominance (AVD) scale of range 1-9, where 1 is the lowest value. Eight different recordings were selected for each participant, as illustrated in Table 1.

The gray image features were calculated for the selected recordings of each participant, hence, the total database size is 256 grayscale images (32 participants x 8 emotional recording), and then, the produced images were randomly divided into training and testing groups using a three-fold cross-validation strategy.

The CNN with the other three classifiers were trained and tested to classify both gender and age. The description of each classifier construction can be summarized as follows:

Table 1. The eight selected EEG recordings, L ≤ 3.5, H ≥ 6.

No	Parameters Value		
	Arousal	**Valence**	**Dominance**
1	L	L	L
2	H	L	L
3	L	H	L
4	H	H	L
5	L	L	H
6	H	L	H
7	L	H	H
8	H	H	H

- Gender Classification

For gender classification, CNN was constructed and trained using five basic layers as in Figure 3; Input Layer to pass the gray scale image of size 45x45; Convolutional layer to compute the convolutional neurons using five filters of size 5x5 and a stride movement of one steps; Pooling layer of size 2x2 and a stride movement of one step; Fully connected layer with soft max lose function; and output layer.

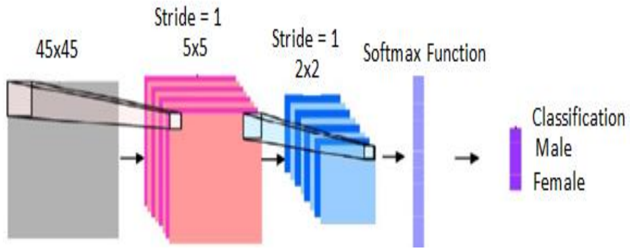


Figure 3. The constructed CNN classifier for gender classification.

KNN was trained using Euclidean distance, and the number of nearest neighbors is 3. SVM was trained using the kernel RBF function. While LDA was trained using the pseudo-Linear discriminant choice.

Table 2 presents the average accuracy and the F1 score [26] (as shown in Equation (3)) of different gender classifiers. The P test value [27] (as shown in Equation (4)) among the tested four classifiers was also calculated, it shows the significance measure for the statistical results and the data pattern distributions, where small P values (≤ 0.05) indicates that the tested classifiers results are significant.

From Table 2, it is clear that the CNN classifier has the best results where its P value is less than 0.01 (< 0.01). CNN classifier has the dominant performance in recognition, and it can deal directly with images [20, 24].

$$F1\ Score = \frac{TP}{TP+0.5(FP+FN)} \tag{3}$$

Where *TP* is number of true positives; *FP* is number of false positives; and *FN* is number of false negatives.

$$P\ Value = CDF\ (\frac{\overline{Ac.}}{\sigma(Ac.)+\sqrt{k}} \tag{4}$$

Where CDF is the Accumulative Distribution Function; $\overline{Ac.}$ and $\sigma(Ac.)$are the mean and standard deviation values of the classifiers' results; and k is the number used in k-fold cross validation.

Table 2. The average accuracy results of gender classification experiment.

Classifier	Accuracy	F1 Score
CNN	0.963 ± 0.017	0.95 ± 0.03
KNN	0.92 ± 0.03	0.91 ± 0.05
SVM	0.885 ± 0.06	0.87 ± 0.02
LDA	0.90 ± 0.04	0.89 0.07

- Age Classification

The participant's age is ranged between 19 and 37 years old, accordingly, the participants were divided into three categories or groups; the first group includes the participants of age between 19 and 24 years old, the second group includes the participants of age between 25 and 29 years old, and the third group includes the participants of age between 30 and 37 years old.

For age classification, CNN was constructed and trained using five basic layers as in Figure 4; Input Layer of size 45x45; Convolutional layer with three filters of size 3x3 and a stride movement of two steps;

Pooling layer of size 2x2 and a stride movement of one step; Fully connected layer with soft max lose function; and output layer.

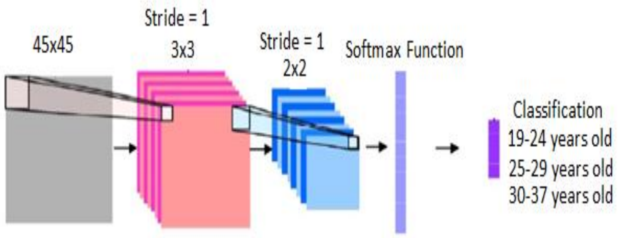


Figure 4. The constructed CNN classifier for age classification.

KNN was trained using Euclidean distance, and the number of nearest neighbors is 1. SVM was trained using the kernel RBF function. While LDA was trained using the pseudo-Linear discriminant choice. Table 3 presents the average accuracy and F1 score results of age classification. It is clear that CNN classifier has the best results among the others with P value < 0.01, followed by KNN, SVM and LDA, respectively.

Table 3. The average accuracy results of age classification experiment.

Classifier	Accuracy	F1 Score
CNN	0.89 ± 0.01	0.88 ± 0.03
KNN	0.78 ± 0.02	0.78 ± 0.06
SVM	0.75 ± 0.07	0.74 ± 0.02
LDA	0.74 ± 0.08	0.73 ± 0.06

Figure 5 shows the bar chart for the tested classifiers in both gender and age classification.

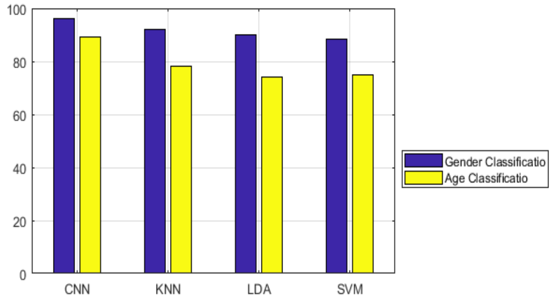


Figure 5. The result of the tested classifiers in both gender and age classification.

To sum up, the proposed feature achieved robust, useful, and accurate results even in different emotional EEG recordings. In other words, the previous related works used the EEG recordings of neutral or relax emotional state to predict both gender and age, but in this research, the used or taken EEG recordings are related to eight different emotions, and it is proved the possibility of gender and age prediction under different emotional states.

Table 4 below provides a comparison between the proposed method and other recent trends in this field. Several previous related works used a large number of EEG electrodes, which generates huge feature dimensions [9, 10, 15]. Moreover, it is clear that most of accurate results are based on rest or neutral emotions. Researches of other emotions have much lower accuracies [19]. In contrast, our proposed method produces robust and accurate results using only one EEG electrode for eight distinct emotions.

Table 4. Comparison between the proposed work and current previous works.

Research	Feature Extraction	EEG Channels	Classifier	Results
Nguyen *et al.* [17] 2013	Time-domain features + Frequency Domain Features	8 Channels Rest state	SVM	97.1% Gender 96.1% Age
Liu *et al.* [15] 2019	Frequency Domain Features	All Channels Rest state	CNN	62.7% Gender 51.2% Age
Nguyen *et al.* [18] 2013	Time-domain features + Speech features	8 Channels Rest state	SVM	93.8% Gender 92.5% Age
Kaur *et al.* [9] 2019	Time-frequency features	14 Channels Rest state	RF	96.6% Gender 88.3% Age
Oral *et al.* [19] 2017	Frequency Domain Features	1 Channel Awake and sleep state	SVM	89.6% Gender
Kaushik *et al.* [10] 2019	Time domain features + Frequency Domain Features	14 Channels Rest state	Deep BLSTM-LSTM	97.5% Gender
Proposed Work	Time-frequency features	1 Channel 8 different emotions	CNN	96.3% Gender 89% Age

6. Conclusions

This paper produces an efficient gender and age classification system based on EEG brain signals. An enhanced proposed grayscale feature has been introduced using the CWT for only one EEG frontal electrode. Accurate and robust results have been achieved using the DEAP dataset for eight different emotional states instead of the ordinary rest or neutral emotion state. In future work, further experiments will be performed to improve learning classifiers, and apply the classification system in real-time applications.

References

[1] Al-Wajih E. and Ahmed M., “A New Application for Gabor Filters in Face-Based Gender Classification,” *The International Arab Journal of Information Technology*, vol. 17, no. 2, pp. 178-187, 2020.

[2] Chaudhary U., Birbaumer N., and Ramos-Murguialday A., “Brain-Computer Interfaces For Communication and Rehabilitation,” *Nature Reviews Neurology*, vol. 12, no. 9, pp. 513-525, 2016.

[3] Fisher J., Huang S., Ye M., Nabili M., Wilent

W., Krauthamer V., Myers M., and Welle C., "Real-Time Detection and Monitoring of Acute Brain Injury Utilizing Evoked Electroencephalographic Potentials," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 24, no. 9, pp. 1003-1012, 2016.

[4] Gunes H. and Pantic M., "Automatic, Dimensional and Continuous Emotion Recognition," *International Journal of Synthetic Emotions*, vol. 1, no. 1, pp. 68-99, 2010.

[5] Issa S., Peng Q., You X., and Ali W., "Emotion Assessment Using EEG Brain Signals and Stacked Sparse Autoencoder," *Journal of Information Assurance and Security*, vol. 14, no. 1, pp. 20-29, 2019.

[6] Issa S., Peng Q., and You X., "Emotion Classification Using EEG Brain Signals and the Broad Learning System," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, pp. 1-10, 2020.

[7] Jatupaiboon N., Pan-ngum S., and Israsena P., "Real-Time Eeg-Based Happiness Detection System," *The Scientific World Journal*, pp. 618-649, 2013.

[8] Joysly L. and Tamilselvi R., "Abnormality Recognition During Drowsy State from ECG and EEG," *in Proceedings of International Conference on Innovations in Information Embedded and Communication Systems*, Coimbatore, 2015.

[9] Kaur B., Singh D., and Roy P., "Age and Gender Classification Using Brain-Computer Interface," *Neural Computing and Applications*, vol. 31, pp. 5887-5900, 2019.

[10] Kaushik P., Gupta A., Roy P., and Dogra D., "EEG-based Age and Gender Prediction Using Deep BLSTM-LSTM Network Model," *IEEE Sensors Journal*, vol. 19, no. 7, pp. 2634-2641, 2019.

[11] Koelstra S., Muhl C., Soleymani M., Lee J., Yazdani A., Ebrahimi T., Pun T., Nijholt A., and Patras I., "Deap: A Database for Emotion Analysis Using Physiological Signals," *IEEE Transactions on Affective Computing*, vol. 3, no. 1, pp. 18-31, 2012.

[12] Kübler A., "The History of bci: from a Vision for the Future to Real Support for Personhood In People with Locked-in Syndom," *Neuroethics*, vol. 13, pp. 163-180, 2019.

[13] Kumar J. and Bhuvaneswari P., "Analysis of Electroencephalography (EEG) Signals and its Categorization- A Study," *Procedia Engineering*, vol. 38, pp. 2525-2536, 2012.

[14] Kumara N., Khaunda K., and Hazarikaa S., "Bispectral Analysis of EEG for Emotion Recognition," *in Proceedings of The 7th International Conference on Intelligent Human Computer Interaction*, India, pp. 31-35, 2015.

[15] Liu H., He L., Shang S., Lu J., Wan M., and Liu S., "Convolutional Neural Network For Resting State EEG Signal Analysis," *in Proceedings of IEEE 16th International Conference on Networking, Sensing and Control*, Banff, pp.138-143, 2019.

[16] Meena K., Subramaniam K., and Gomathy M., "Gender Classification in Speech Recognition using Fuzzy Logic and Neural Network," *The International Arab Journal of Information Technology*, vol. 10, no. 5, pp. 477-485, 2013.

[17] Nguyen P., Tran D., Huang X., Ma W., "Age and Gender Classification Using EEG Paralinguistic Features," *in Proceedings of Annual International IEEE EMBS Conference on Neural Engineering*, San Diego, pp. 1295-1298, 2013.

[18] Nguyen P., Tran D., Vo T., Huang X., Ma W., and Phung D., "EEG-Based Age and Gender Recognition Using Tensor Decomposition and Speech Features," *in Proceedings of International Conference on Neural Information Processing*, Daegu, pp. 632-639, 2013.

[19] Oral E., Ozbek I., and Codur M., "Gender Classification Based on Single Channel EEG Signal," *in Proceedings of International Artificial Intelligence and Data Processing Symposium*, Malatya, pp.1-4, 2017.

[20] Peng M., Wang C., Chen T., and Liu G., "Nirfacenet: A Convolutional Neural Network for Near Infrared Face Identification," *Information*, vol. 7, no. 4, pp. 1-14, 2016.

[21] Poza J., Caminal P., Vallverdu M., Hornero R., Romero S., and Barbanoj M., "Study of the EEG Changes During the Combined Ingestion of Alcohol and H1-Antihistamines by Using the Wavelet Transform," *in Proceedings of 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, Lyon, pp. 23-26, 2007.

[22] Polikar R., *The Wavelet Tutorial, Rowan University*, Glassboro, Camden, Stratford, New Jersey, 1999.

[23] Sharma R., Varshney P., Pachori R., and Vishvakarma S., "Automated System for Epileptic Eeg Detection Using Iterative Filtering," *IEEE Sensors Letters*, vol. 2, no. 4, pp. 2472-2475, 2018.

[24] Simonyan K. and Zisserman A., "Very Deep Convolutional Networks for Large-Scale Image Recognition," CoRR, vol. abs/1409.1556, 2014.

[25] "The Bci-brain computer interfaces," Brain Vision UK, Zeal House, 8 Deer Park Road, London, 2014.

[26] "The Calculation of F1 Score", at: https://towardsdatascience.com/accuracy-precision-recall-or-f1-331fb37c5cb9, Last Visited, 2021.

[27] "The Calculation of P value," at: https://stats.stackexchange.com/questions/240453/statistical-significance-of-multiple-classifiers-by-using-p-value, Last Visited, 2021.
[28] "The Eeg signals", at: http://www.hopkinsmedicine.org, Last Visited, 2019.
[29] "The Electroencephalography (EEG)," Mayo Clinic, at: https://www.mayoclinic.org/tests-procedures/eeg/about/pac-20393875, Last Visited, 2021.
[30] Trans Cranial Technologies, at :https://www.transcranial.com, Last Visited 2019.
[31] Ueno S., Iramina K., Harada K., and Matsuoka S., "MEG and EEG Topography and A Source Model of Slow Wave Types of Abnormality," *IEEE Translation Journal on Magnetics in Japan*, vol. 3, no. 3, pp. 281-287, 1988.
[32] Yılmaz A. and Nabiyev V., "A Novel Age Classification Method Using Morph Based Models," *The International Arab Journal of Information Technology*, vol. 16, no. 4, pp. 677-685, 2019.
[33] Yuan Y., Xun G., Jia K., and Zhang A., "A multi-View Deep Learning Framework for Eeg Seizure Detection," *IEEE Journal of Biomedical and Health Informatics*, vol. 23, no. 1, pp. 83-94, 2013.

Haitham Issa received his Ph.D. in Communications and Information systems from Zhejiang University, Hangzhou, China, in 2002. He is currently teaching in the Department of Electrical Engineering in Zarqa University, Zarqa, Jordan. His current research interests include image processing, signal Processing, pattern recognition, machine learning, communication, and renewable energy.

Sali Issa received her Ph.D. in Electrical Information and Communication Engineering from Huazhong University of Science and Technology, Wuhan, China, in 2020. Her main research interests include artificial intelligence, signal processing, pattern recognition, and brain computer interface.

Wahab Shah received his Ph.D. in Electrical and Electronic Engineering from Huazhong University of Science and Technology, Wuhan, China, in 2019. His main research interests include the artificial neural networks, insulation design of power systems and long air-gap discharge.