Person-Independent Emotion and Gender Prediction (EGP) System Using EEG Signals

Haitham Issa
Department of Electrical Engineering, Zarqa University, Jordan
hissa@zu.edu.jo

Qinmu Peng
Department of Information and Communication Engineering, Huazhong University of Science and Technology, China
pengqinmu@hust.edu.cn

Sali Issa
Department of Electrical Information of Science and Technology, Hubei University of Education, China
sword-lily@hotmail.com

Xinge You
Department of Information and Communication Engineering, Huazhong University of Science and Technology, China
youxg@hust.edu.cn

Ruijiao Peng
Baiguo Hospital, Huanggang, China
ruijiaowork.peng@gmail.com

Jing Wang
Department of Radiology, Union Hospital, Wuhan, China
jwinflower@126.com

Abstract: *This paper presents a person-independent Emotion and Gender Prediction (EGP) system using Electroencephalography (EEG) brain signals. First, Short Time Fourier Transform (STFT) technique is implemented to get the time-frequency information for the selected electrode (Fz Electrode). Then, it is splitted into twenty sequential batches according to the electrode recorded time in seconds, and the maximum EEG activation voltage is located for every frequency level within each batch to create a 2D time-frequency extraction feature. Next, sparse auto encoder is applied to convert the distribution of the extracted feature into more compact and distinguished one instead. For system evaluation, Human-Computer Interaction) database (MAHNOB-HCI) public dataset with five-fold-cross validation classifier are used and implemented. In experiments, the proposed extracted feature improves the results of both emotion and gender prediction. For emotion prediction, the highest average accuracy is 97.07\%, 93.27% and 91.72\% for three, four and six emotions with Convolutional Neural Network (CNN) classifier, respectively. While, for gender prediction, experiments are tested related to neutral, amusement, happy, sad, and the mix of all these emotions, the highest average accuracy is obtained with CNN classifier in all emotion states (>95%) including the state of mixing all emotions together. As well as, the ability to distinguish between genders in case of mixing different emotions together is practically approved.*

Keywords: *Emotion, gender, EEG, brain signals, STFT.*

Received October 17, 2020; accepted July 27, 2021
https://doi.org/10.34028/iajit/19/4/7

1. Introduction

Human brain is alive and active all the time. It is collecting and analysing information, controlling responses, and sending signals inside/outside human bodies during dream, work, rest, think, feel and sense. The brain comprises billions of cells, half of them are neurons which interconnected via synapses, and the other half assists and manages the activity of neurons. Any interaction or activity in one synapse produces tinny electrical impulse which is called a postsynaptic potential, the activity of thousands of neurons generate an electrical field which is possible to detect and spread outside brain skull [11]. Actually, several techniques are followed to detect and record brain activity such as the well-known Electroencephalography (EEG) test.

The EEG is a safe and cheap method to measure the electrical activity of the brain neurons through the scalp, where a small metal discs or electrodes are pasted on the scalp, and then transmit brain signals to computer or especial devices by using thin wires or wireless connections. The recorded EEG voltages are very small, measured in microvolts (mV), and cover the frequency range of delta, theta, alpha, beta, and [36].

According to the deep relation between EEG signals and brain response or interaction with internal/external environment, scientists has started using these signals for important and useful applications such as checking the abnormality of brain tasks, testing drugs and alcohol addiction [18], predicting and monitoring several diseases as epilepsy and Alzheimer [33], understanding brain learning factors [23] and much more.

Emotion and gender detections are examples of these important and hot applications; it could be used in psychological therapy, disabled assistance, criminal detection, control environments, and security services [40]. Although it is possible to classify emotions and genders using other signals or data such as human face, voice and body gestures [6, 7, 27, 28], EEG is considered as a direct information or response out of brain without change or fake, nobody can hide or fake brain signals [12], consequently, emotion and gender classification based on EEG signals will give more realistic results.

Many recent emotion and gender researches related to EEG brain signals have been done, but still face many challenges and need more improvement [1, 2, 41]. Most of researches depended on using large amounts of EEG channels, extraction features and feature selection methods to get robust systems, others used additional peripheral signals such as heart beats, and temperature to enhance the classification process and produce more accurate results.

In this paper, a new person-independent Emotion and Gender prediction (EGP) system is produced based on EEG brain signals. Short Time Fourier Transform (STFT) is utilized to get the time-frequency voltage spectrum of only one EEG channel, and then several mathematical calculations are applied to have a two dimensional information for EEG voltage propagation during time. Finally, the sparse autoencoder tool is used to transform the calculated feature into more compact representation instead.

In classification, four different classifiers of Convolutional Neural Network (CNN) [17], Linear Discriminant Analysis (LDA) [26], Support Vector Machine (SVM) [21], K Nearest Neighbour (KNN) [42] were constructed trained, and tested for evaluation and comparison purpose. As a result, the proposed extracted feature with CNN classifier produced the best results for both emotion and gender predictions.

The main contributions of this paper are as follows:

1. An enhanced feature extraction with more predictable distribution is obtained by sparse autoencoder for only one EEG Channel. It guides the feature to have a better presentation, and improves the recognizing efficiency in both emotion and gender prediction.
2. Person-independent emotion classification system is achieved with higher accuracy results compared with previous person-independent systems, it enhanced the prediction results up to six emotions, and more suitable in real life applications.
3. Gender prediction system produces high and accurate results not only in relax or neutral emotion states, but also in other happy, sad, and amusement emotion states. Moreover, it proves the possibility of identifying between the two genders in case of mixed emotions, or unstable emotion data entry.

The remainder of this paper is as follows; Section 2 provides a literature review and a brief description for the previous works. Section 3 illustrates the proposed method in detail. Section 4 provides the experimental results of the framework, and Section 5 is the conclusion.

2. Literature Review

Brain Computer Interface (BCI) technology is considered as the hotspot area in recent era. Although several researches with its broad applications have been produced, they still need to be improved and addressed before usage in real life scenarios [1, 2].

In emotion classification based on EEG brain signals, various methodologies, extraction features, classification methods, and stimuli datasets to produce a robust and accurate emotion assessment system.

According to feature extraction process, the majority of previous related work used the traditional methods of time domain, frequency domain, and time-frequency domain analysis. In time domain analysis, there are common calculated features such as the statistical relations, fractal dimension, and the Hjorth parameters of EEG signal. For example, Qing *et al*. [32] derived the first and second order difference features for the time domain data of all EEG electrodes, the normalized first and second order derivatives were also calculated. Next, an autoencoder is used to process these calculated features and get more compact magnitudes. In classification, they construct two different experiments; all and later stage of EEG data, respectively. The latter stage of EEG data experiments had better results of an average accuracy of 63.09% and 75% for two different EEG datasets.

In frequency domain analysis, the calculated features depend on the Fourier transform for the original EEG time domain signal such as Power Spectral Density (PSD) and relative power. For example, Soleymani *et al*. [34] used ten EEG channels with other peripheral signals. PSD feature was extracted for each EEG channel, and Analysis Of Variance (ANOVA) test was applied as a feature selection for all extracted features. In classification, SVM was constructed to classify six distinct emotions with the average accuracy of 72.45%. Xing *et al*. [39] provided a feature fusion for the PSD of all EEG frequency bands and the privileged video audio-visual features. MLP binary classifier was constructed and achieved the average accuracy of 97.29%. Wang *et al*. [38] used MAHNOB-HCI and other two databases for evaluation purpose. All EEG electrodes were selected to calculate the power spectrum, and combined with the extracted features of other peripheral signals. SVM classifier was constructed to classify four different emotions and achieved an average accuracy of 60.79%, 71.32%, and 57.53% for MAHNOB-HCI and the other two datasets, respectively.

Several researches used a collection of both time domain and frequency domain features such as Habib Ullah *et al*. [13], they selected all EEG signals and divided each channel into several segments. For each segment the following statistical features of mean, median, maximum, minimum, variance, standard deviation, range, kurtosis, skewness, fisher information ratio, Petrosian fractal dimension, and entropy were calculated and combined into one vector. Also, another frequency domain features of PSD, Differential Entropy (DE), Discrete Cosine Transform (DCT) features and Spectrogram based features. Next, they applied ensemble learning to select the discriminative and active features, and the sparse projection coefficients are performed to learn the final classifier where the maximum average accuracy was 78.67% for two emotions. Li *et al*. [22] extracted spatial, temporal, and frequency domain features from all EEG channels, then, all these features were mapped to form a Multidimensional Feature Image (MFI). In classification, the combination of CNN and Long Short-Term-Memory (LSTM) Recurrent Neural Networks (RNN) was implemented and achieved an average accuracy of 75.21% for four emotions.

For time-frequency domain analysis, an advanced transform techniques such as Wavelet Transform (WT), Short Time Fourier Transform (STFT), and Gabor function are implemented to get the time-frequency domain for EEG signals, and then use these transforms in feature extraction. For example, Liu *et al*. [25] calculated various features using time domain, frequency domain, and time-frequency domain analysis for fourteen EEG electrodes. Then, both Principal Component Analysis (PCA) and Maximum Relevance Minimum Redundancy (mRMR) were used in feature selection stage. Later, Random Forest classifier was trained and achieved an average accuracy of 75% ± 10. Issa *et al*. [14] applied Continuous Wavelet Transform (CWT) to get the time- frequency data of only one EEG channel. Next, the feature extraction was extracted using several calculation combined with the statistical standard variation of alpha and beta frequency bands. Deep Stacked Sparse Autoencoder (SSAE) was trained to classify three different emotions with an accuracy of 96.7%.

Other researchers try to use non-traditional features such as functional connectivity network methods. In Al-Shargie *et al*. [5] study, they based on feature fusion of cortical activations with functional connectivity network, and achieved high accuracy of 90.3% for three different emotions.

Due to the previous related works, most of them depended on selecting large number of EEG electrodes, calculating a plenty of time domain, frequency domain, and time-frequency domain features, and/or using complex feature selection methods to control the size of calculated features, as well as select the discriminative ones. Many previous works of emotion prediction are person-dependent systems where emotion classifier is constructed and accuracy is calculated for a specific participant. Actually, general user-independent systems are more practical and suitable to human real life applications. Moreover, distinct recent researches still combining other peripheral data with/without EEG brain signals such as heart beats, eye movement, ECG, EMG, temperature, response face images and videos, ...etc.

For Gender identification using EEG brain signals, several techniques have been introduced, their results sound better than emotion classification applications. However, it is possible to enhance the system in terms of decreasing the selected EEG channels, minimizing feature extraction calculations, as well as, producing a stable and robust gender recognition system in different emotional states rather than resting or neutral emotional state. Nguyen *et al.* [29] used eight EEG channels to provide two features groups; popular and paralinguistic groups. In popular EEG features, PSD, relative power, and Hjorth parameters were calculated. While, in paralinguistic group, Mel-frequency Cepstral Coefficients (MFCC), Log Filter-Bank Powers (LFBP), and Line Spectral Pairs (LSP) was calculated. SVM classifier was trained to identify the subject gender and achieved an average accuracy of 97.7% and 97.1% for paralinguistic and popular feature groups, respectively.

Oral *et al*. [31] depended on one EEG electrode to have EEG cepstrum coefficients and calculate a frequency domain features for two type of datasets; awake and sleep phase activities. SVM classifier was trained and provided an accuracy of 77.84% and 89.66% for awake and sleep dataset, respectively. Kaushik *et al*. [20] processed fourteen EEG electrodes using Discrete Wavelet Transform (DWT) to get five frequency bands for each electrode. Beta frequency band with deep BLSTM-LSTM classifier were used for classification, and the average accuracy was 97.5%. Liu *et al.* [24] applied Fourier transform to get the frequency domain of all EEG electrodes; CNN classifier was trained for gender classification and got an average accuracy of 62.7%. While, in Kaur et al. [19] research, they used wireless EEG sensors to capture fourteen EEG channels, DWT was performed for frequency decomposition. Then, Mean, Energy, and Root-Mean-Square (RMS) features were calculated for all frequency bands. An average accuracy of 96.66% was produced using random forest classifier.

Al-Qazzaz [3] used the spectral relative power ratios (PR) features, and implemented SVM and KNN classifiers. The results showed that the maximum average accuracy was 92% for KNN gender classifier. A recent research for Al-Qazzaz [4] used linear spectral mean frequency (meanF) and nonlinear Multiscale Fuzzy Entropy (MFE) features. The ANOVA, Binary Gravitation Search Algorithm (BGSA) and Binary Particle Swarm Optimization (BPSO) were implemented on the extracted features to get the optimal channels for gender prediction. Next, KNN classifier was trained and got a maximum average accuracy of 93.71% in natural emotion case.

To sum up, BCI applications of emotion and gender detection still face additional challenges. More stable and robust system is necessary without certain restrictions such as using peripheral signals, large size of EEG electrodes and feature selection methods.

3. Methodology

The proposed EGP system diagram is illustrated in Figure 1. It consists of three basic steps: EEG dataset recording and preprocessing, feature extraction, and classification.

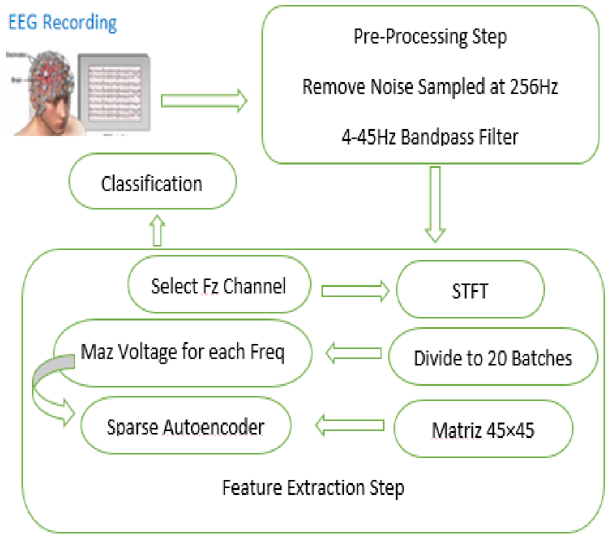


Figure 1. The proposed Emotion-Gender Prediction (EGP) system process.

3.1. EEG Dataset Description and Preprocessing

For GEP system evaluation, the public well-known MAHNOB-HCI [35] multi modal dataset was selected for data acquisition. Where 27 subjects (11 male and 16 female) of ages between 19 and 40 years old (M=26.06 and SD=4.39) were shown a fragments of 20 movies. The stimuli movies duration was between 34.9 and 117 s long and covered nine different emotions of happy, sad, angry, fear, surprise, disgust, anxious, amusement, and neutral.

During experiment, a total of 32 EEG channels were recording using the EEG 10/20 electrode cap system, Also, other sensors and/or tools were added for measuring different physiological data such as ECG, respiration amplitude, and skin temperature.

In preprocessing step, EEG signals noise, interference and EOG artifacts were removed; then, a bandpass filter was applied to get the frequency range of 4-45Hz.

3.2. Feature Extraction

In feature extraction, STFT spectrogram is implemented to get the time-frequency data. Next, a series of mathematical calculations are applied to have a two dimensional information matrix. Finally, the sparse auto encoder tool is used to get more compact and predictable features.

The proposed feature extraction can be divided into the following sequential stages:

1. Select the middle frontal Fz electrode: According to medical and anatomy science, the seven frontal electrodes of FP1, Af3, F3, FP2, Af4, F4, and Fz are related to human emotion stimuli process [37]. Moreover, a previous related work [14] has proved the efficiency of using only Fz electrode in emotion classification based on EEG brain signals.
2. Derived the time-frequency information data of Fz electrode: The common STFT spectrogram is used for this purpose by applying a sliding window to divide the time domain signal into smaller parts and then analyze each part using Fourier transform to get its frequencies. The STFT transform can be derived using the following common equation [8]:

$$x\,(n, w) = \sum_{\infty}^{-\infty} x[m]\, w[n \;\; - m]\, e^{-i\omega n} \tag{1}$$

Where $x[m]$ is the original time domain signal of Fz electrode; $w[m]$ is the sliding window function centered at time n and multiplied with the signal $x[m]$.

3. Divide the transformed time-frequency voltage data into twenty sequential and equal batches, and then find the maximum EEG voltage for each frequency in all batches [15, 16].

$$\forall_b \in B\,\{M = Max\ M(\forall_f \in F, b)\}\ (2 \tag{2}$$

Where M a is 2D 45x20 time-frequency information; f is the frequency value {f = 1,...., 45 Hz}; b is the batch block number {b = 1, ..., 20}.

Apply the sparse autoencoder: To get the sparse features from M matrix, the optimization of the following equation should be solved [30]:

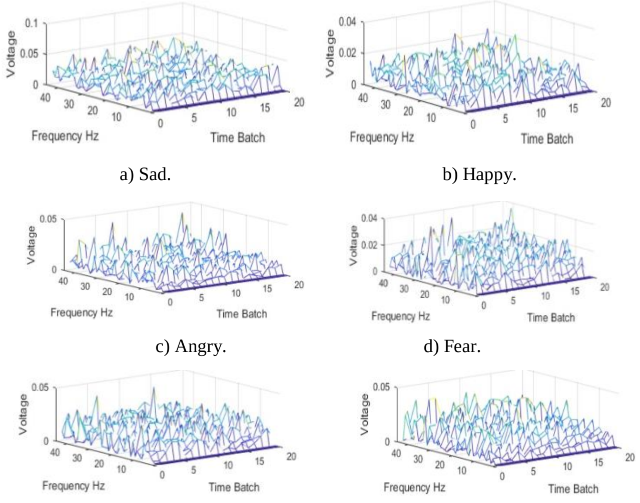
$$\underset{\hat{x}}{\arg\min}:\ \|Y\hat{x} - M\|_v^{\sigma_1} + \gamma\, \|\hat{x}\|_u^{\sigma_2} \tag{3}$$

Where σ_1, σ_2, v, u are norm regularizations; $\hat{x}$ is the solution result of sparse autoencoder; and Y is the solution output of the equation. Next, Alternating Direction Method of Multipliers (ADMM) technique [9, 10] is used to solve Equation (6), and the iterative process of Equation (4) is utilized for the proximal problem [26]:

$$\begin{cases} x_{n+1} = (Y^T Y + \rho I)^{-1}\left(Y^T m + \rho(o^n + u^n)\right) \\ o_{n+1} = S_{\frac{Y}{\rho}}(x_{n+1} + u_n) \\ u_{n+1} = u_n + (x_{n+1} - o_{n+1}) \end{cases} \tag{4}$$

Where ρ is a positive value; and S parameter is the soft threshold.

Figure 2 provides extracted features examples for the individual emotions.



a) Sad. b) Happy.

c) Angry. d) Fear.

e) Amusement. f) Neutral.

Figure 2. Extracted feature examples for sad, happy, angry, fear, amusement, and neutral.

3.3. Classification

For feature extraction evaluation, CNN [17], Linear Discriminate Analysis (LDA) [26], SVM [21], and KNN [42] were constructed and trained.

1. CNN [17] is different from the ordinary neural networks, because its neurons are organized in three dimensions: width, height, and depth. The additional depth dimension points to the activation volume dimension, not to the total number of layers. The neurons within a specific layer are connected to a small part from the previous layer. Moreover, the final output layer is a single vector of class scores, arranged along the depth dimension. A fully stacked CNN is considered as a simple deep learning structure and should has the following basic layers (Figure 3); Input layer to get the input image or 2D matrix; Convolution layer to Calculate the output neurons which are connected to the local parts in the input image or matrix, where the calculation process is a simple product between neurons weights and a small part through its connection in the input; Pool layer to performs a down sampling process for the spatial dimensions; Fully connected layer to find the output class scores.

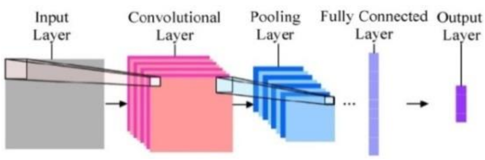


Figure 3. The structure of DCNN classifier.

2. LDA [26]: It is a generalization of Fisher's linear discriminant, its solution principle depends on assuming that the conditional probability density functions of $P(\vec{x}, c) = 0$ and $P(\vec{x}, c) = 1$ are normally distributed, where $\vec{x}$ is the sample features; and c is the corresponding class of $\vec{x}$. As shown in Equation (5) [26],

$$\sum b = \frac{1}{c}\sum_{i=1}^{c}(\mu_i - \mu)(\mu_i - \mu)^T \tag{5}$$

Where μ is the class mean.

3. SVM [21]: It is a common supervised learning classifier in machine learning. Suppose that X is the training sets or features where X=x1, x2, ..., xi, and Y is the corresponding class labels of X where Y= y1, y2, ..., yi, therefore, Equation (6) should be solved [21]

$$sgn(w^T \emptyset(x_i) + b) = sgn\left(\sum_{i=1}^{l} y_i \alpha_i K(x_i, x) + b\right) \tag{6}$$

Where $K(x_i,x)$ represents the kernel function; $\emptyset(x_i)$ manipulates with x_i in a higher dimensional space.

4. KNN [42]: it is a non-parametric classifier, where the input includes the k closest training samples, and the output is its corresponding class membership or the plurality vote of its neighbours, so if K = 1, then the tested sample is assigned to the class of its nearest neighbour. Suppose that X1={f1,...,fl} and X2=={f1,...,fl} are two different samples with l number of features for each one, if the voting decision measure related to Euclidean distance, then Equation (7) will be applied [42]:

$$d = \sqrt{\sum_{i=1}^{l}(X_{1i} - X_{2i})^2} \tag{7}$$

Where *d* is the distance between *X1* and *X2* samples.

4. Results and Discussion

The extracted features were calculated for all subjects, and then five-fold cross-validation strategy was performed for the classification experiments. For comparison and evaluation purpose, Convolutional Neural Network (CNN) with other three classifiers were constructed, trained, and tested for emotion and gender prediction.

1. CNN: the construction CNN comprises five basic layers; Input Layer that deals with the input feature of size 45x20. Convolutional layer with five filters of size 5x5 and a stride of one step. Pooling Layer with one filter of size 5x5 and a stride of one step. Fully connected layer of softmax lose function. Final output layer to get the class category.

For emotion prediction, CNN has 250 epochs, 250 batches, and a learning rate of 0.0001. It was constructed and trained to classify four and six different emotions of happy, sad, angry, fear, amusement, and neutral. The result average accuracy was approximately of 93.27% and 91.72% for four and six emotions, respectively.

For gender prediction, CNN has 150 epochs, 250 batches, and a learning rate of 0.0001. It was constructed and trained to classify the subject gender during neutral, happy, sad, and amusement emotion state, as well as, predict the subject gender for the mix of all these emotions state. Angry and fear emotion states are not included in gender prediction dataset because there is no balance in EEG database size for male and female genders. However, the result average accuracy was approximately of 97.11%, 97.50%, 96.25%, 96.76%, and 95.60% for neutral, amusement, happy, sad, and mixed emotions state, respectively.

2. Linear Discriminant Analysis (LDA): 'pseudolinear' discriminant type is selected.
3. Support Vector Machine (SVM): 'polynomial' kernel function is applied.
4. K-Nearest Neighbours (KNN): euclidean distance is used and the number of nearest neighbour is 3.

Tables 1, and 2 provide the average accuracy and F1 score of the tested classifiers for emotion and gender classification, respectively. The bar plot in Figure 4 shows the average accuracy of the tested classifiers for emotion prediction, while, Figure 5 show the average accuracy of the tested classifiers for gender prediction in Neutral, amusement, happy, sad, and the mix of all emotions state, respectively.

Table 1. The average accuracy and F1 score of the tested classifiers for emotion prediction.

	3 Emotions		4 Emotions	
Class.	**Accuracy**	**F1 Score**	**Accuracy**	**F1 Score**
CNN	**0.9707 ± 0.0231**	**0.9685 ± 0.0421**	**0.9327 ± 0.0442**	**0.9401 ± 0.0321**
KNN	0.7753 ± 0.0211	0.7632 ± 0.0523	0.6671 ± 0.0855	0.6700 ± 0.0755
LDA	0.9350 ± 0.0452	0.9401 ± 0.0321	0.9294 ± 0.1578	0.9323 ± 0.0425
SVM	0.6201 ± 0.0325	0.6189 ± 0.0321	0.3000 ± 0.0535	0.2823 ± 0.0423
	6 Emotions			
CNN	**0.9172 ± 0.0215**		**0.9046 ± 0.0360**	
KNN	0.6755 ± 0.1399		0.6954 ± 0.1235	
LDA	0.9040 ± 0.2146		0.8953 ± 0.2013	
SVM	0.4846 ± 0.2146		0.5012 ± 0.0932	

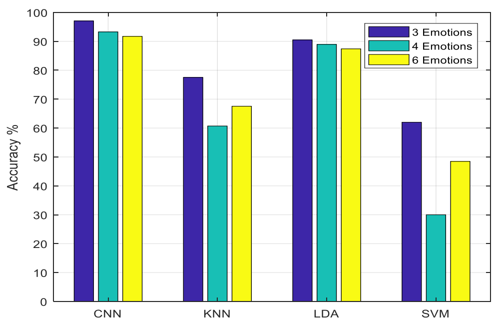
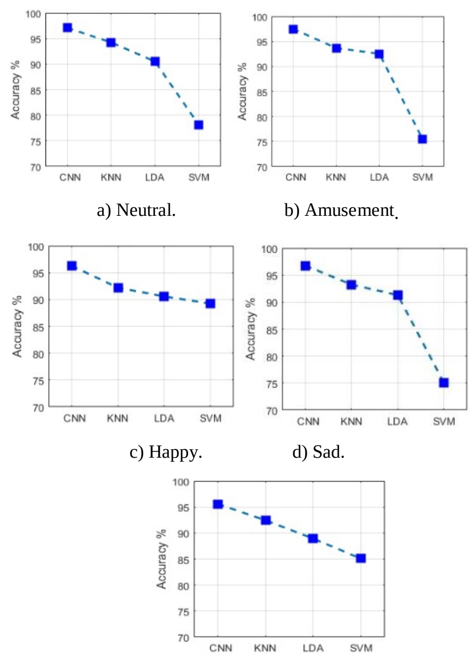


Figure 4. The average accuracy of the tested classifiers for emotion prediction.

For emotion prediction, CNN classifier achieved the highest accuracy of 93.27% and 91.72% for four and six emotions, respectively. It followed by LDA classifier with 92.94% and 90.40% for four and six emotions, respectively. F1 score value for both CNN and LDA classifiers was high, P<0.01 which means that the improvement of these classifiers are significant, they provide robust and accurate results.

Table 2. The average accuracy and F1 score of the tested classifiers for gender prediction.

	Neutral		Amusement	
Class.	**Accuracy**	**F1 Score**	**Accuracy**	**F1 Score**
CNN	**0.9711 ± 0.0566**	**0.9685 ± 0.0453**	**0.9750 ± 0.0294**	**0.9701 ± 0.0211**
KNN	0.9426 ± 0.0239	0.9553 ± 0.0325	0.9367 ± 0.0279	0.9346 ± 0.0246
LDA	0.9052 ± 0.0477	0.9001 ± 0.0235	0.9253 ± 0.0123	0.9183 ± 0.0223
SVM	0.7811 ± 0.2508	0.7956 ± 0.2534	0.7550 ± 0.0342	0.7653 ± 0.0423
	Happy		**Sad**	
CNN	**0.9625 ± 0.0235**	**0.9685 ± 0.0256**	**0.9676 ± 0.0745**	**0.9686 ± 0.0562**
KNN	0.9220 ± 0.0321	0.9273 ± 0.0352	0.9324 ± 0.0324	0.9401 ± 0.0335
LDA	0.9056 ± 0.0706	0.9089 ± 0.0653	0.9129 ± 0.1277	0.9100 ± 0.1128
SVM	0.8923 ± 0.0823	0.8885 ± 0.0963	0.7500 ± 0.0353	0.7646 ± 0.0453
	Mixed All Emotions			
CNN	**0.9560 ± 0.0356**		**0.9499 ± 0.0253**	
KNN	0.9245 ± 0.0277		0.9301 ± 0.0234	
LDA	0.8893 ± 0.0641		0.8953 ± 0.0752	
SVM	0.8508 ± 0.0542		0.8637 ± 0.0456	



a) Neutral. b) Amusement.

c) Happy. d) Sad.

e) Mix all emotions.

Figure 5. The average accuracy of the tested classifiers for gender prediction.

For gender prediction, CNN classifier also achieved the highest accuracy for all emotion states, the maximum average results of neutral, amusement, happy, and sad emotions were 97.11%, 97.50%, 96.25%, and 96.75% respectively. Also, the mix of all emotions case gave good and acceptable results for all classifiers, the maximum accuracy was 95.60% for CNN classifier, F1 score value is high and P<0.01 which means that the improvement of this classifier is significant. It is obvious from Table 1 that the extraction features of amusement emotional state are more predictable to distinguish between male and female genders; it has the maximum average accuracy among other emotion states. Furthermore, it is possible to detect the subject gender even if the constructed classifier based on different emotions (mixed emotions).

Tables 3 and 4 present a summary of some current trends in the field of gender and emotion prediction, respectively. Some of them focused on selecting a large number of EEG electrodes or using large number of extraction features with huge calculation space and feature selection methods [5, 13, 19, 20, 24, 25, 32, 41]. Other works used additional peripheral signals or data, such as blood pressure, body temperature, eye movement, ECG, EMG, face expressions, and voice effects to increase system reliability and stability [34, 39]. Also, several researches provided person-dependent systems, or person-independent systems with not acceptable or high accuracy results.

In previous works related to emotion classification, the calculated accuracy decreases with the increase of classified emotion number [34, 38]. In contrast, our classifier works well with the increase of classified emotion number, it is still accurate, robust and produces 91.72% for six emotions. As well as, compared with previous works which used the same database [14, 34, 38], our proposed feature based on only one EEG channel and improved emotion prediction results.

While, for previous works related to gender detection, although most of the results are very high and exceed 96%, their methodologies depended on one emotional state which is the rest or neutral emotion state in most cases [3, 4, 19, 20, 24, 29], while our classifier works well in several different emotions states, as well as, the state of mixing different emotions together. In fact, the last point is the great contribution of our proposed system (Table 3), where it is more practical and useful to distinguish between genders in real life applications in case of mixed emotions, or unstable emotion data entry.

However, compared to the previous related works, this paper presents an efficient extracted feature using one EEG channel and sparse autoencoder, as well as, a robust person-independent classification system for both emotion and gender applications.

5. Conclusions

This paper provides an enhanced Emotion-Gender Prediction (EGP) system. An efficient proposed feature extraction has been introduced using the spares autoencoding presentation of the time-frequency information for only one EEG frontal channel. High and robust experimental results have been achieved for both emotion and gender classification using MAHNOB-HCI dataset, as well as, an accurate gender classifier has been improved to distinguish between the two genders in case of mixed emotions and/or unstable emotion data entry. In future work, further experiments will be performed to improve the system results, and apply in real time applications.

Table 3. Comparison between the proposed work and some current trends in gender prediction.

Research	Feature Extraction	No. Channels	Classifier	Results
Nguyen *et al.* [29]	Time Dom. Features Frequency Dom. features	8 Channels	SVM	97.7% Rest state
Oral *et al.* [31]	Frequency Dom. features	1 Channel	SVM	89.66% Sleep 77.84% Awake
Kaushik *et al.* [20]	Time Dom. Features Frequency Dom. features	14 Channels	Deep BLSTM-LSTM	97.5% Rest state
Liu *et al.* [24]	Frequency Dom. features	All Channel	CNN	62.7% Rest state
Kaur *et al.* [19]	Time-Frequency features	14 Channels	RF	96.66% Rest state
Al-Qazzaz *et al.* [3]	Spectral Relative Power ratios (PR)	All Channel	KNN	92% Neutral
Al-Qazzaz *et al.* [4]	(MeanF) and (MFE)	14 Channels	KNN	93.71% Neutral
Proposed work	Time-frequency feature+Sparse autoencoder	1 Channel	CNN	97.11% Neutral 95.60% Mix state

Table 4. Comparison between the proposed work and some current trends in emotion prediction.

Research	Feature Extraction	No. Channels	Classifier	Results
Soleymani *et al.* [34]	Frequency Dom. features+ Feature selection	10 Channels MAHNOB-HCI	SVM	72.45%, 6 Emotions
Wang *et al.* [38]	Frequency Dom. features	All Channels MAHNOB-HCI	SVM	60.79%, 4 Emotions
Liu *et al.* [25]	Time Dom. Features, Frequency Dom. features Time-Frequency features + Feature selection	14 EEG Channels	RF	75% ± 10
Habib Ullah *et al.* [13]	Time Dom. Features, Frequency Dom. Features + Feature selection	All Channels	EL	78.67%, 2 Emotions
Qing *et al.* [32]	Time Dom. Features + Smoothing feature	All Channels	Voting	75%, Binary
AL-Shargie *et al.* [5]	Function connectivity net- work	All Channels		90.3%, 3 Emotions
Issa *et al.* [14]	Time-Frequency features	1 Channel MAHNOB-HCI	Deep SAE	96.7%, 3 Emotions
Xing *et al.* [39]	Frequency Dom. features	All Channels	MLP	97.7%, Binary
Proposed work	Time-frequency feature + Sparse autoencoder	1 Channels MAHNOB-HCI	CNN	97.07% 3 Emotions 93.27% 4 Emotions 91.72% 6 Emotions

References

[1] Alarcao S. and Fonseca M., "Emotions Recognition Using EEG Signals: A Survey," *IEEE Transactions on Affective Computing*, vol. PP, no. 99, pp. 1-20, 2017.

[2] Al-Nafjan A., Hosny M., Al-Ohali Y., and Al-Wabil A., "Review and Classification of Emotion Recognition Based on EEG Brain-Computer Interface System Research: A Systematic Review," *Applied Sciences*, vol. 7, no. 12, pp. 1239, 2017.

[3] Al-Qazzaz N., Sabir M., Ali S., Ahmad S., and Grammer K., "The Role of Spectral Power Ratio in Characterizing Emotional EEG for Gender Identification," *in Proceedings of IEEE-EMBS Conference on Biomedical Engineering and Sciences (IECBES)*, Langkawi Island, pp. 334-338, 2020.

[4] Al-Qazzaz N., Sabir M., Ali S., Ahmad S., and Grammer K., "Multichannel Optimization with Hybrid Spectral- Entropy Markers for Gender Identification Enhancement of Emotional-Based EEGs," *IEEE Access*, vol. 9, pp. 107059- 107078, 2021.

[5] AL-Shargie F., Tariq U., Alex M., Mir H., and AL-Nashash H., "Emotion Recognition Based on Fusion of Local Cortical Activations and Dynamic Functional Networks Connectivity: An EEG Study," *IEEE Access*, vol. 7, pp. 143550- 143562, 2019.

[6] 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.

[7] Bansal A., Agarwal R., and Sharma R., "SVM Based Gender Classification Using Iris Images," *in Proceedings of the 4th International Conference on Computational Intelligence and Communication Networks*, Mathura, pp. 425-429, 2012.

[8] Boashash B., *Time-Frequency Signal Analysis and Processing*, Oxford, 2016.

[9] Boyd S., Parikh N., Chu E., Peleato B., and Eckstein J., "Distributed Optimization and Statistical Learning Via The Alternating Direction Method of Multipliers," *Found Trends Machine Learning*, vol. 3, no. 1, pp. 1-12, 2011.

[10] Chen C. and Liu Z., "Broad Learning System: An Effective and Efficient Incremental Learning System without the Need for Deep Architecture," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 29, no. 10, pp. 10-24, 2018.

[11] Farnsworth B., "What is EEG?," at: https://imotions.com, Last Visited, 2021.

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

[13] Habib Ullah H., Uzair M., Mahmood A., Ullah M., Khan S., and Cheikh F., "Internal Emotion Classification Using EEG Signal With Sparse Discriminative Ensemble," *IEEE Access*, vol. 7, pp. 40144-40153, 2019.

[14] Issa S., Peng Q., You X., and Shah W., "Emotion Assessment Using EEG Brain Signals and Stacked Sparse Autoencoder," *Journal of Information Assurance and Security*, vol. 14, pp. 20-29, 2019.

[15] 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*, vol. 51, no. 21, pp. 7382-7391, 2020.

[16] Issa H., Peng Q., and Issa S., "A Novel Method for Gender and Age Detection Based on EEG Brain Signals," *The International Arab Journal of Information Technology*, vol. 18, no. 5, pp. 1-8, 2021.

[17] Johnson J., Karpathy A., and Git R., "Fully Connected Nets, Batch Normalization, Dropout, Convolutional Nets," Assignment 2, Computer Science Department, Stanford University, California, at: https://cs231n.github.io/assignments2022/assignment2/, Last Visited, 2022.

[18] Jonathan A., Huang S., Ye M., Nabili M., Bryan Wilent W., Krauthamer V., Matthew R., and Cristin G., "Real-Time Detection and Monitoring of Acute Brain Injury Utilizing Evoked Electroencephalographic Potentials, *IEEE TNSRE*, vol. 24, no. 9, 2016.

[19] Kaur B., Singh D., and Roy P., "Age and Gender Classification Using Brain-Computer Interface," *Neural Computing and Applications*, vol. 31, no. 15, pp. 5887-5900, 2019.

[20] 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.

[21] Kim S. and Choi J., "An SVM-Based High-Quality Article Classifier for Systematic Reviews," *Journal of Biomedical Informatics*, vol. 47, pp. 153-159, 2014.

[22] Li Y., Huang J., Zhou H., and Zhong N., "Human Emotion Recognition with Electroencephalographic Multidimensional Features by Hybrid Deep Neural Networks," *Sensors*, vol. 7, no. 10, pp. 1-20, 2017.

[23] Lin C., Wu C., and Chaovalitwongse W., "Integrating Human Behavior Modeling and Data Mining Techniques to Predict Human Errors in Numerical Typing," *IEEE Transactions on Human-Machine Systems*, vol. 45, no. 1, pp. 39-50, 2015.

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

[25] Liu J., Meng H., Li M., Zhang F., Qin R., and Nandi A., "Emotion detection from EEG Recordings Based on Supervised and Unsupervised Dimension Reduction, Concurrency and Computation: Practice and Experience," *Wiley Online Library*, vol. 30, no. 23, 2018.

[26] Loh W., "On Linear Discriminant Analysis with Adaptive Ridge Classification Rules," *Journal of Multivariate Analysis*, vol. 53, no. 2, pp. 264-278, 1995.

[27] Lu L., Xu Z., and Shi P., "Gender Classification of Facial Images Based on Multiple Facial Regions," *in Proceedings of WRI World Congress on Computer Science and Information Engineering, Los Angeles*, Los Angeles, pp. 48-52, 2009.

[28] 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.

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

[30] Olshausen B. and Field D., "Sparse Coding with an over Complete Basis Set: A Strategy Employed by V1," *Vision Research*, vol. 37, no. 23, pp. 3311-3325, 1997.

[31] Oral E., Ozbek I., and Çodur M., "Gender Clasification Based on Single Channel EEG Signal," *in Proceedings International Artificial Intelligence and Data Processing Symposium (IDAP)*, Malatya, pp. 1-4, 2017.

[32] Qing Ch., Qiao R., Xu X., and Cheng Y., "Interpretable Emotion Recognition Using EEG Signals," *IEEE Access*, vol. 7, pp. 94160- 94170, 2019.

[33] 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.

[34] Soleymani M., Pantic M., and Pun T., "Multimodal Emotion Recognition in Response to Videos," *in Proceedings of International Conference on Affective Computing and Intelligent Interaction ACII*, Xian, China, pp. 491-497, 2015.

[35] Soleymani M., Lichtenauer J., Pun T., and Pantic M., "A Multimodal Database for Affect Recognition and Implicit Tagging," *IEEE Transactions on Affective Computing*, vol. 3, no. 1, pp. 42-55, 2012.

[36] "The Biomedical Signals Acquisition: EEG," at: https://www.medicine.mcgill.ca/physio/vlab/biomed_signals, Last Visited, 2021.

[37] "The EEG: Electrode Positions and Broadmann atlas," at: https://www.cnblogs.com, Last Visited, 2021.

[38] Wang S., Zhu Y., Yue L., and Ji Q., "Emotion Recognition with the Help of Privileged Information," *IEEE Transactions on Autonomous Mental Development*, vol. 7, no. 3, pp. 189-200, 2015.

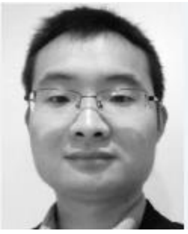
[39] Xing B., Zhang H., Zhang K., Zhang L. Wu X., Shi X., Yu S., and Zhang S., "Exploiting EEG Signals and Audiovisual Feature Fusion for Video Emotion Recognition," *IEEE Access*, vol. 7, pp. 59844-59861, 2019.

[40] Yu S., Yu Q., Luo J., Wu B., Yang F., Li Y., Zhuang Y., Zheng X., and Chen W., "A Hybrid Brain-Computer Interface Control Strategy in A Virtual Environment," *Journal of Zhejiang University-SCIENCE C (Computers and Electronics)*, vol. 12, pp. 351-361, 2011.

[41] Yulita I., Julviar R., Triwahyuni A., and Widiastuti T., "Multichannel Electroencephalography-based Emotion Recognition Using Machine Learning," *in Proceedings International 2nd International Conference on Mechanical, Electronics, Computer, and Industrial Technology, Journal of Physics*, Medan, North Sumatera, Indonesia, pp. 1-8, 2018.

[42] Zhang Z., "Introduction to Machine Learning: K-Nearest Neighbors," *Annals of Translational Medicine*, vo. 4, no. 11, 2016.

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 main research interests include machine learning, signal processing, electronics and communications.



Qinmu Peng received the Ph.D. in Computer Science, Hong Kong Baptist University, Hong Kong, in 2015. He is currently teaching in the Department of Electrical Information and Communications, Huazhong University of Science and Technology, Wuhan, China. His main research interests include machine learning, medical image processing, and pattern recognition.

Sali Issa received her Ph.D. in Electrical Information and Communication Engineering from Huazhong University of Science and Technology, Wuhan, China, in 2020. She is currently teaching in the Department of Electrical Information of Science and Technology in Hubei University of Education, Wuhan, China. Her main research interests include artificial intelligence, signal processing, and brain computer interface.

Xinge You received the Ph.D. degree in computer Science from Hong Kong Baptist University, Hong Kong, in 2004. He is currently a professor in the School of Electrical Information and Communications, Huazhong University of Science and Technology, Wuhan, China.

Ruijiao Peng graduated from Hubei University of Traditional Chinese Medicine in 1995. She is currently a doctor at Baiguo Hospital, Macheng City, China.

Jing Wang received Ph.D. degree in Radiology from Huazhong University of Science and Technology, Wuhan, China, in 2010. She is currently an associate professor in Radiology Department in Union hospital, Wuhan, China.