© Universiti Tun Hussein Onn Malaysia Publisher's Office

IJIE

Journal homepage: http://penerbit.uthm.edu.my/ojs/index.php/ijie
ISSN : 2229-838X e-ISSN : 2600-7916

The International Journal of Integrated Engineering

Spectro-spatial Profile for Gender Identification Using Emotional-based EEG Signals

Noor Kamal Al-Qazzaz[1*], Mohannad K. Sabir[1], Sawal Hamid Md Ali[2], Siti Anom Ahmad[3], Karl Grammer[5]

[1]Department of Biomedical Engineering, Al-Khwarizmi College of Engineering, University of Baghdad, 47146, IRAQ

[2]Department of Electrical, Electronic and Systems Engineering, Faculty of Engineering and Built Environment, Universiti Kebangsaan Malaysia; UKM Bangi, Selangor 43600, MALAYSIA

[3]Department of Electrical and Electronic Engineering, Faculty of Engineering, Universiti Putra Malaysia; UPM Serdang, Selangor 43400, MALAYSIA

[4]Malaysian Research Institute of Ageing (MyAgeing™), Universiti Putra Malaysia 43400 Serdang, Selangor, MALAYSIA

[5]Department of Evolutionary Anthropology, University of Vienna, Althan strasse 14, A-1090 Vienna, AUSTRIA

*Corresponding Author

DOI: https://doi.org/10.30880/ijie.2021.13.05.008
Received 24 April 2021; Accepted 3 May 2021; Available online 31 July 2021

Abstract: Identifying gender has become essential specially to support automatic human-computer interface applications and to customize interactions based on affective responses. The electroencephalogram (EEG) has been adopted for recording the neuronal information as waveforms from the scalp. The objective of this study was twofold. First, to identify genders from four different emotional states using spectral relative power biomarkers. Second, to develop Spectro-spatial profiles that afford additional information for gender identification using emotional-based EEGs. The dataset has been collected from ten healthful volunteer students from the University of Vienna while watching short emotional audio-visual clips of angry, happiness, sadness, and neutral emotions. Wavelet (WT) has been used as a denoising technique, the spectral relative power features of delta (δ), theta (θ), alpha (α), beta (β) and gamma (γ) were extracted from each recorded EEG channel. In the subsequent steps, analysis of variance (ANOVA) and Pearson's correlation analysis were performed to characterize the emotional-based EEG biomarkers towards developing the Spectro-spatial profile to identify gender differences. The results show that the spectral set of features may provide and convey reliable biomarkers for identifying Spectro-spatial profiles from four different emotional states. EEG biomarkers and profiles enable more comprehensive insights into various human behavior effects and as an intervention on the brain. The results revealed that almost high relative powers from all emotional states appear in females compared to males. Particularly, δ was the most prominent for anger, θ and β were widely observed in happiness, γ was the most appears in sadness, β and γ were the powers that appears widely in neutral. Moreover, in females, δ_neut was correlated with and δ_ang, θ_neut was mostly correlated with θ_ang. Besides, α_neut was correlated with α_ang, β_neut was correlated with α_ang, γ_neut was mostly correlated with γ_sad. Moreover, in males, α_neut showed a very strong correlation with α_sadness whereas β_neut was correlated with γ_hap and γ_neut wa s correlated with γ_hap. Therefore, the

*Corresponding author: noorbme@kecbu.uobaghdad.edu.iqo

proposed system using the WT denoising method, spectral relative power markers, and the spectro-spatial profile plays a crucial role in characterizing the emotional-based EEGs towards gender identification. The classification results were 89.46% for SVM and 90% for the KNN. Therefore, the proposed system using the WT denoising method, spectral relative powers features, SVM, and KNN classifiers were crucial in gender identification and characterizing the emotional EEG signals.

Keywords: Emotion, electroencephalography, wavelet, relative power, ANOVA, Pearson's correlation, SVM, KNN

1. Introduction

Emotions are an immediate impression of mental procedures, perspectives, physiological incitement, conduct reactions and inspirational inclinations which happen because of the associations of different types of knowledge, including perceptual, verbal and numerical, which are available in the mind [1, 2].

A common stereotype in both Western and Eastern societies proposes that females and males have various aptitudes identified with the sending and accepting of emotional tasks. In general, females are all the more genuinely expressive, while males can control their passionate presentations [3-5]. Notwithstanding their encoding capacity, females will in general express feeling through outward appearance and relational correspondence, while males commonly express feeling through activities, for example, participating in forceful conduct [6, 7].

An assortment of passionate states can also be comprised of the essential feelings which are anger, disgust, surprise, fear, happiness and sadness [8]. These feelings have been portrayed based on the dimensional model. This model is described through its two-dimensional (2D) nature and uncovers the connection amongst polarity and valance arousal of emotion. This, thus, encourages the mapping of all feelings on the valance-excitement diagram, as depicted in the Circumplex model of emotion [9].

Recently, various examinations on emotional recognition have been explored utilizing electroencephalograph (EEG) [10, 11]. EEG signals have been demonstrated to give educational attributes in reactions to the diverse mental states [12]. Diverse learning stages can trigger distinctive enthusiastic states, in this way the passionate procedures as psychological exercises covering with neural circuitry.

EEG investigation can be inside and out influenced by the covering of non-cerebral sources known as artifacts with the physiological action of the mind. In any case, end of such antiquities can be done through a few techniques including the independent component analysis method [13], empirical mode decomposition method [14] and wavelet transform technique which are able to eliminate EEG artefacts and decompose the EEG signals into the required frequency bands [15, 16].

Features like the correlation dimension, Lyapunov exponent [17, 18], approximate entropy [19], Hurst exponent, Hjorth Parameters [20] and Fractal dimension [21] have been widely applied to investigate EEG signals. Moreover, spectrum analysis has been utilized to identified any EEG-signal-related anomalies through the investigation of the EEG frequency bands [15, 22].

EEG signal contains useful information that has proven to be a potential biomarker to realize the brain behaviour [11, 23-26]. Thus, the motivation of this work is twofold. First, to identify genders from four different emotional states using spectral relative power biomarkers. Second, to obtained additional gender discrimination information from the spectro-spatial profiles using emotional-based EEGs.

The preprocessing stage was including the conventional filters and wavelet (WT) denoising technique. Besides, spectral relative biomarkers were obtained across the recorded signals by extracting EEG sub-bands powers including the relative powers of delta (δ), theta (θ), alpha (α), beta (β), and gamma (γ). In the subsequent step, five stages of two-way analysis of variance (ANOVA) were conducted to obtain the spectral biomarkers followed by Pearson's correlations to obtain the spectro-spatial profile to identify the gender-related differences from anger, happiness, sadness and neutral emotional states. To the author's best knowledge this study has two contributions: firstly, it is the first use of the wavelet-based spectral relative powers biomarkers to develop spectro-spatial profile to identify genders from emotional-based EEG signals, the EEG elicitation protocol and EEG measurement procedure have never been used before for emotion data acquisition.

2. Materials and Methods

Fig. 1 shows the block diagram of the proposed spectro-spatial profile for gender identification from emotional-based EEGs.

2.1 EEG Acquisition and Recording

Altogether, the signals from 14 EEG electrodes were checked using a versatile Emotiv Epoc EEG 14-channel headset (Emotive Systems, Inc., San Francisco, CA) to record the signs relegated as in the following arrangements:

AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4 referring to the essential common mode sense left mastoid and the determined right leg mastoid as ground with an example recurrence of 128 Hz.

The assessment enrolled four females and six males, all college understudies. Going before the beginning of the investigation, each part gave an informed consent structure the educated assent structure (ICF) which they were referenced to sign prior to participating in the assessment. The appraisal of the four feeling states (sadness, happiness, and anger) alongside the neutral condition was driven by allowing the individuals to see diverse short emotionally-stimulating audio-visual clips, after which the individuals were allowed exactly an occasion to evaluate their responses utilizing a self-assessment questionnaire followed by a break of 45 seconds before review the following video cut Fig. 2. The emotional video clips utilized were picked subject to those recommended by Rottenberg [27].

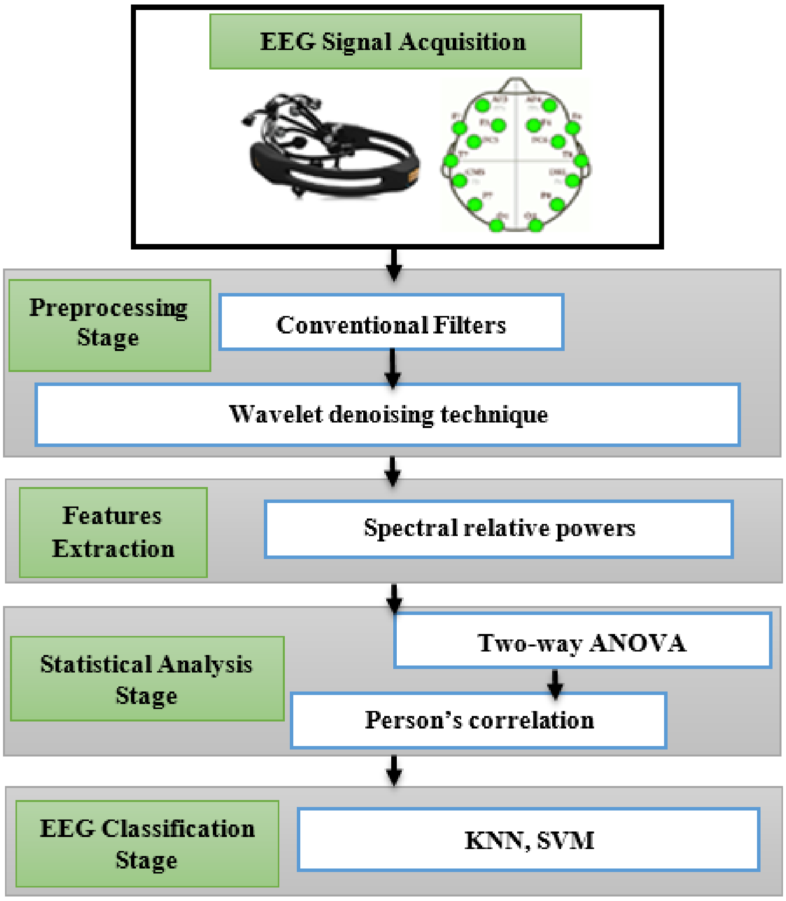

Fig. 1 - The block diagram of the proposed study

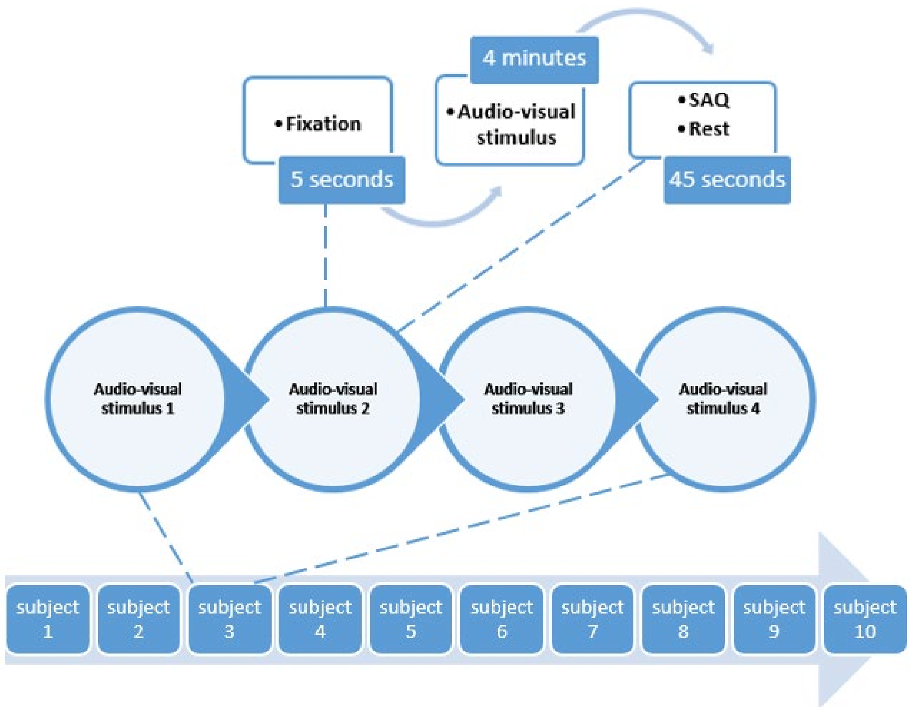

Fig. 2 - The experimental protocol of emotion

2.2 Pre-processing Stage

Preprocessing stage has involved the conventional filters including notch filters _ with 50Hz cutoff frequency to remove the A/C electricity power line interference [12]_ and the band pass _ with a low cutoff frequency of 0.5Hz a higher cutoff frequency around 64Hz [28]_ to remove the artifacts that may overlapped the EEG frequencies of interest. Moreover, wavelet transform was carried out as an additional denoising method to filtered EEG dataset. It has been widely used with the non-stationary signals, like EEG and EMG [ref]. The mathematical states of the discrete wavelet transform can be achieved by estimating the parameters a and b as in Equation 1.

$$DWT_{m,n}(f) = a_0^{-m/2} \int f(t)\, \psi(a_0^{-m} t - n b_0) dt \quad (1)$$

Where $\psi(t)$ is the mother wavelet function, a_0 scaling parameter for dilating or contracting and b_0 parameter for shifting as in Equation 2. The values of a_0 and b_0 are set to 2 and 1, respectively. which is shifted by the location (b) and (a).

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}} \psi\left(\frac{t-b}{a}\right), a\epsilon R^{+}, b\epsilon R \quad (2)$$

Discrete wavelet change was utilized for denoising purposes, the symlets mother wavelet function of ‘order 9’ was utilized to give the excellent denoising results [29]. Four decomposition levels for the recorded EEG signals were chosen based on the sampling frequency of 128 Hz [10]. The Stein’s unbiased risk estimation (SURE) threshold has been applied [30]. In the present work, each video-clip was examined for the last 30 seconds and was divided into three 10 second parts comprising of 1280 information points per part, providing 3840 information points overall from which the EEG signal spectral biomarkers were calculated.

2.3 Features Extraction Stage

To identify the gender-related differences from anger, happiness, sadness and neutral emotional states, the relative power in delta (δ), theta (θ), alpha (α), beta (β), and gamma (γ) were investigated to get insight the impact of various multi-channel EEG signals’ in gender discrimination, Welch’s technique was applied to calculate the EEG information’s power spectral density (PSD), with the specific frequency bands of gamma (γ: $32 \leq f \leq 60$) Hz, beta (β: $16 \leq f \leq 32$) Hz, alpha (α: $8 \leq f \leq 16$) Hz, theta (θ: $4 \leq f \leq 8$) Hz, and delta (δ: $0 \leq f \leq 4$) Hz being distinguished as particular frequency bands for the EEG signals’ PSD [31]. A single band’s level of EEG activity autonomous of different bands’ activity is indicated by the following Equation (3) [32].

$$RP(\%) = \frac{\sum \text{Selected frequency range}}{\sum \text{Total range } (0.5 - 60 \text{ Hz})} \quad (3)$$

2.4 Statistical Analysis Stage

This study intends to investigate the spectral biomarkers towards develop the spectro-spatial profile to identify the gender-related differences from anger, happiness, sadness and neutral emotional states. Therefore, statistical analysis has been conducting using SPSS statistical tool version 22. Normality tests were assessed using the Kolmogorov–Smirnov test. Five sessions of two-way analyses of variance (ANOVA) were performed to realize the significant differences among the emotions (i.e. angry, happiness, sadness and neutral) and relative powers of (δ, θ, α, β and γ) as dependent variables were evaluated. The group factor (i.e., female and male) was the independent variable. The significance was set at $p < 0.05$.

After obtaining the spectral biomarkers from the previous ANOVA sessions, the spectral biomarkers were further investigated by spatial domain, thus enabling an appropriate understanding of gender differences from emotional significance EEG signals. Consequently, Pearson's correlation was implemented to develop spectro-spatial profile for gender identification from anger, happiness, sadness and neutral emotions.

During the Pearson's correlation coefficient (r) was calculated so as to establish the biomarkers' correlations, including the relative powers from anger, happiness, sadness emotions and the relative powers of neutral emotional state. The spectro-spatial profile for females and males were examined at $p < 0.05$, reflecting statistical significance. All correlation sessions were implemented for every participant.

2.5 Gender Classification Stage

To investigate gender differences based on emotional states two classifiers were utilized namely, KNN and SVM. KNN is the most universal and least complicated non-parametric classification algorithms in which the classifier labels the samples in the training set based totally on their closeness. The KNN computation portrays objects reliant on the closest planning insights that are shown in the significant features system [33]. The article is distributed to the class that is for the most part fundamental among its k nearest neighbors, where k is continually a positive entire number. KNN is dynamically effective when $k > 1$, and a bigger k worth can help decrease the impact of loud focuses inside the training set [34]. The parameter k is for the most part dictated by the attributes of the datasets, and the closest examples are accepted to offer more than the far examples. The unknown sample belongs to the class that is frequent amongest the KNN [35]. SVM was proposed by Vapnik and made subject to computational learning hypothesis [36], SVM has been extensively utilized in biomedical engineering [37]. In this study, the kernel functions used to be radial basis function (RBF) kernel function [36]. The best results for the classifiers were gotten by performing a 10-fold cross-validation (CV). For KNN classifier, k was used to be diverse between 1 and 10 at intervals of 2. The classifier was prepared to locate the best estimation of k, which was gotten at $k = 5$, and to maximize the classification accuracy. The Euclidean distance was utilized as a similarity measure to classify each trial by KNN. The presentation of the proposed framework was assessed utilizing average classification accuracy.

3. Results and Discussion

3.1 Results of Denoising Stage

All the EEG signals were experienced to be denoised by the WT Denoising procedure. Fig. 3 outlines a case of the WT Denoising impact contrast with the first boisterous sign utilizing the third channel from the frontal locale (F3) when the volunteer was exposed to anger emotional state. It can watch the suspension of the artefactual sign (the blue line) when contrasted with the raw noisy EEG signal (the red line).

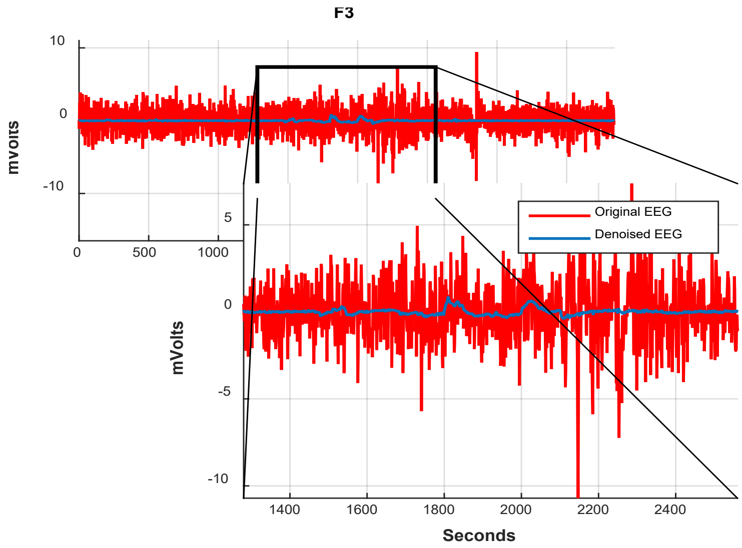

Fig. 3 - F3 channel before and after using WT denoising technique

3.2 Results of Statistical Analysis Stage

Fig. 4 shows the comparative plot that illustrates the changes in the relative powers of the four emotional states in both females and males. It can be observed a relatively high rlative powers for all emotional states in females compared to males particularly in α power. For δ power, the relative power of anger and neutral were significantly higher than sadness and happiness in females, whereas the anger, happiness and sadness were significantly higher than neutral in males. Therefore, for δ , females' show relatively higher relative power for anger, neutral and sadness compare to male, whereas happiness in males was significantly higher than females.

Moreover, for θ power, the relative powers of sadness and happiness were higher and significantly different from each other. However, the sadness and happiness for females were significantly different from neutral and happiness. Therefore, for θ, females' show relatively higher relative powers for sadness and happiness compare to male, whereas anger and neutral were significantly higher in males compare to females. Moreover, for β power, the relative powers of sadness were higher and significantly higher than anger, neutral and happiness. However, in males' the sadness, neutral and anger were significantly different from happiness. Therefore, for β, females' show relatively higher relative powers for sadness and happiness compare to male, whereas anger and neutral were significantly higher in males compare to females. Moreover, for γ power, the relative powers of sadness were higher and significantly differ than anger, neutral and happiness in females. However, in males' the sadness, neutral and anger were significantly different from happiness. Therefore, for γ, females' show relatively higher relative powers for sadness and anger compare to males, whereas neutral and happiness were significantly higher in males compare to females.

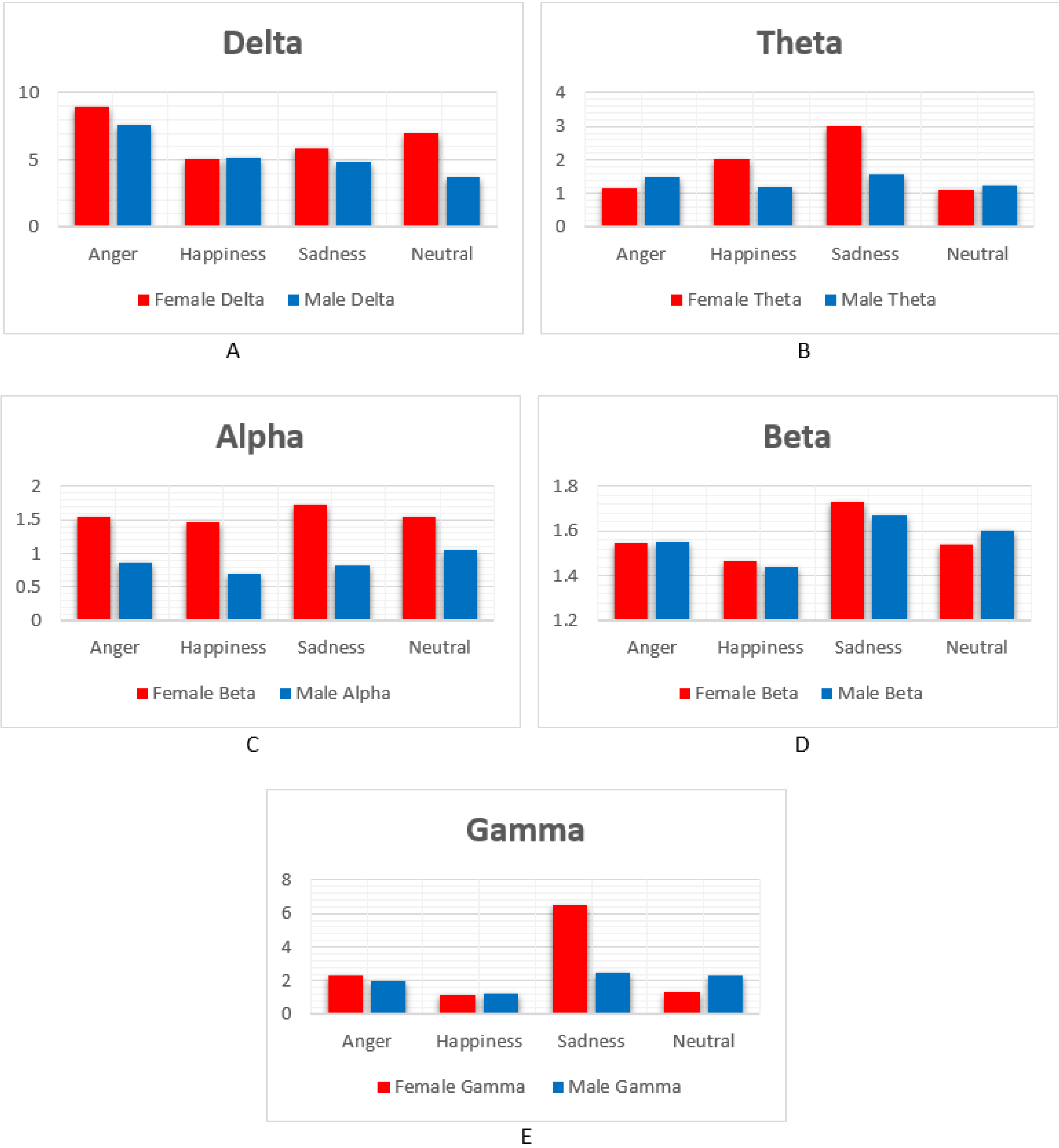

Fig. 4 - Comparative plot between females and males illustrates the emotional responses using (a) delta; (b) theta; (c) alpha; (d) beta; (e) gamma relative powers

The Bonferroni post hoc test has been conducted to examine multiple comparisons. Table 1 shows the post-hoc emotion multiple comparisons using Bonferroni adjustments for spectral relative power biomarker. The post hoc tests using the Bonferroni correction revealed that theta, alpha and gamma were illustrated a statistically significant different between females and males.

Table 1 - Gender comparison test using Bonferroni for the spectral biomarker

Relative powers	(I) Gender	(J) Gender	Mean Difference (I-J)	*p*-value[a]
Delta	Female	Male	1.375	0.058
Theta	Female	Male	**0.457***	0.05
Alpha	Female	Male	**0.113***	0.049
Beta	Female	Male	0.003	0.942
Gamma	Female	Male	**0.828***	0.048

* The mean difference is significant at the 0.05 level.
a Adjustment for multiple comparisons: Bonferroni

Moreover, the Bonferroni post hoc test has been conducted to examine multiple comparisons among emotions at delta, theta, alpha, beta and gamma. Table 2 shows the post-hoc emotion multiple comparisons using Bonferroni adjustments for spectral relative power biomarker. The post hoc tests using the Bonferroni correction revealed that for delta, anger was statistically significant from happiness, sadness, neutral (p =0.013,0.024,0.03) respectively, whereas for theta, anger was statistically significant from sadness (p =0.05), and happiness was statistically significant from sadness and neutral (p =0.05, 0.04) respectively, and sadness was statistically significant from neutral (p =0.05). Moreover, for alpha and beta, happiness was statistically significant from neutral (p =0.05) and sadness (p=0.002) respectively. Finally, for gamma, anger was statistically significant from sadness (p =0.05), happiness was statistically significant from sadness (p =0.05) and sadness was statistically significant from neutral (p =0.05).

Table 2 - Emotions multiple comparison test using Bonferroni for the spectral biomarker

Dependent Variable	(I) Emotion	(J) Emotion	Mean Difference (I-J)	*p*-value[a]
Delta	Anger	Happiness	**3.174***	0.013
		Sadness	**2.970***	0.024
		Neutral	**2.896***	0.03
	Happiness	Sadness	-0.204	1
		Neutral	-0.279	1
	Sadness	Neutral	-0.075	1
Theta	Anger	Happiness	-0.273	0.514
		Sadness	**-0.958***	0.05
		Neutral	0.157	1
	Happiness	Sadness	**-0.684***	0.05
		Neutral	**0.431***	0.04
	Sadness	Neutral	1.115*	0.05
Alpha	Anger	Happiness	0.129	0.674
		Sadness	-0.031	1
		Neutral	-0.207	0.066
	Happiness	Sadness	-0.16	0.287
		Neutral	**-0.336***	0.05
	Sadness	Neutral	-0.175	0.182
Beta	Anger	Happiness	0.094	1
		Sadness	-0.151	0.166
		Neutral	-0.021	1
	Happiness	Sadness	**-0.245***	0.002
		Neutral	-0.116	0.538
	Sadness	Neutral	0.129	0.347
Gamma	Anger	Happiness	0.93	0.701
		Sadness	**-2.335***	0.001
		Neutral	0.346	1
	happiness	Sadness	**-3.265***	0.05
		Neutral	-0.584	1
	Sadness	Neutral	**2.681***	0.05

* The mean difference is significant at the 0.05 level.
a Adjustment for multiple comparisons: Bonferroni

During the second statistical analysis stage, Pearson's correlation coefficients were calculated relating to the spectral biomarkers for the neutral state as well as four emotional states (anger, happiness and sadness) for the females and males. Significant differences were calculated as existing between the various emotions with regard to EEG-based correlation alterations.

The spectro-spatial correlations for females and males of the relative powers of neutral emotional state and the relative powers of anger, happiness, sadness emotions were almost significantly positive in all cases, as in Table 3.

In females, δ_neut showed a strong positive correlation especially with and δ_ang (r=0.646, p=0.05). θ_neut showed a strong positive correlation with δ_ang (r=0.759, p=0.05), a very strong positive correlation with θ_ang (r=0.905, p=0.05) and a strong negative correlation with and α_hap (r=-0.790, p=0.05). α_neut showed a strong positive correlation especially with θ_ang (r=0.602, p=0.05), α_ang (r=0.661, p=0.05), α_hap (r=0.806, p=0.05) respectively. Besides, β_neut had a negative strong correlation with α_ang (r=0.663, p=0.05). Additionally, γ_neut had a strong positive correlation particularly with θ_ang (r=0.620, p=0.05), β_ang (r=0.622, p=0.05), θ_hap (r=0.652, p=0.05), β_hap (r=0.670, p=0.05), θ_sad (r=0.670, p=0.05) and γ_sad (r=0.765, p=0.05).

Moreover, in males, α_neut showed a very strong positive correlation especially with α_ang (r=0.715, p=0.05), β_ang (r=0.790, p=0.05), α_hap (r=0.809, p=0.05), β_hap (r=0.745, p=0.05), γ_hap (r=0.866, p=0.05) and α_sadness (r=0.873, p=0.05) respectively. β_neut had a strong positive correlation particularly with with α_ang (r=0.702, p=0.05), β_ang (r=0.775, p=0.05), α_hap (r=0.778, p=0.05), γ_hap (r=0.806, p=0.05) and α_sadness (r=0.709, p=0.05) respectively. γ_neut showed a very strong positive correlation with α_ang (r=0.726, p=0.05), β_ang (r=0.792, p=0.05), α_hap (r=0.834, p=0.05), β_hap (r=0.719, p=0.05), γ_hap (r=0.897, p=0.05) and α_sadness (r=0.844, p=0.05) respectively. These correlations might be interpreted as evidence for a relationship with the relative powers particularly identification gender related emotions from emotional-based EEG signals.

3.3 Results of Gender Classification Stage

The SVM characterization exactness was 90.4% while for the KNN arrangement in general precision was 92%. Accordingly, KNN was remembered for the investigation as a benchmark method just as being straightforward and demonstrated to show great outcomes. KNN bolsters multi-class arrangement, to segregate females and males dependent on their EEG enthusiastic states.

4. Conclusion

Gender identification from emotional-based EEGs is become essential to support brain computer interface applications and to customize their interactions. 14 channels were used to record the EEG signals of four different emotions including: anger, happiness, sadness and neutral of each EEG channel.

WT denoising method has been used; the spectral relative power features were computed for each multi-channel EEG signal. ANOVA and Pearson's correlation analysis were computed to illustrate the emotional-based EEG biomarkers towards develop the the spectro-spatial profile to identify gender differences.

The results evidence that the spectral set of features may provide and convey reliable biomarkers for identifying spectro-spatial profile from four different emotional states. In summary, δ was the dominant wave in anger, θ and β were mostly noted in happiness, γ was the most appears in sadness, β and γ were the powers that appears widely in neutral.

Moreover, in females, δ_neut was correlation with and δ_ang, θ_neut was mostly correlation with θ_ang. Besides, α_neut was correlation with α_ang, β_neut was correlation with α_ang, γ_neut was mostly correlation with γ_sad. Moreover, in males, α_neut showed a very strong correlation with α_sadness whereas β_neut was correlation with γ_hap and γ_neut was correlation with γ_hap.

This examination was exposed to various confinements for example little example size bringing about a necessity to do promote examinations with a bigger database later on. However, our results were consented to different investigations, for example Kring et al. [38, 39] have indicated that both females and males detailed encountering more sadness because of the sad movies than fear in response to the fear movies and and happiness in response to the happy movies. Besides, both females and males have displayed more positive expressions in response to the happy movies than to either of the negative movies, and more negative expressions in response to the fear movies than to the sad movies [40].

The grouping results was 89.46% for SVM and 90% for the KNN. Consequently, the proposed framework utilizing WT Denoising method, spectral relative power features, KNN and SVM classifiers were crucial role in gender identification and characterizing the emotional EEG signals.

Table 3 - Spectro-spatial correlations of the relative powers for neutral emotional state and the relative powers of anger, happiness, sadness emotions for females and males. Correlations of significance at 0.05 level (2-tailed)

Gender	RP_Emotion		δ_ang	θ_ang	α_ang	β_ang	γ_ang	δ_hap	θ_hap	α_hap	β_hap	γ_hap	δ_sad	θ_sad	α_sad	β_sad	γ_sad
Female	δ_neut	r	**0.646****	0.561**	0.021	0.152	0.310*	0.287*	0.563**	-0.322*	0.451**	0.282*	0.083	0.480**	0.106	-0.176	0.393**
			0.05	0.05	0.876	0.268	0.021	0.034	0.05	0.017	0.001	0.037	0.545	0.05	0.44	0.198	0.003
	θ_neut	r	**0.759****	**0.905****	-0.295*	0.292*	0.492**	0.343*	0.792**	**-0.790****	0.527**	-0.124	-0.287*	0.720**	-0.307*	0.23	0.587**
			0.05	0.05	0.029	0.031	0.05	0.01	0.05	0.05	0.05	0.367	0.034	0.05	0.022	0.091	0.05
	α_neut	r	-0.433**	**-0.602****	**0.661****	0.055	-0.173	-0.431**	-0.463**	**0.806****	-0.134	0.443**	0.328*	-0.399**	0.566**	-0.065	-0.19
			0.001	0.05	0.05	0.688	0.207	0.001	0.05	0.05	0.328	0.001	0.015	0.003	0.05	0.636	0.165
	β_neut	r	-0.126	-0.206	**0.663****	0.373**	0.101	-0.402**	-0.06	0.514**	0.219	0.448**	0.15	-0.016	0.520**	0.218	0.182
			0.361	0.132	0.05	0.005	0.462	0.002	0.662	0.05	0.109	0.001	0.273	0.908	0.05	0.109	0.184
	γ_neut	r	0.555**	**0.620****	0.354**	**0.622****	0.597**	-0.071	**0.652****	-0.24	**0.670****	0.219	-0.118	**0.670****	0.224	0.449**	**0.765****
			0.05	0.05	0.008	0.05	0.05	0.607	0.05	0.078	0.05	0.109	0.392	0.05	0.1	0.001	0.05
Male	δ_neut	r	-0.009	0.272*	-0.268*	-0.361**	-0.034	0.096	-0.044	-0.297**	-.471**	-0.381**	0.203	0.077	-0.405**	-0.055	0.02
			0.937	0.012	0.014	0.001	0.761	0.385	0.688	0.006	0.05	0.05	0.064	0.487	0.05	0.62	0.855
	θ_neut	r	0.036	0.363**	-0.374**	-0.402**	-0.014	0.048	0.19	-0.353**	-0.388**	-0.388**	0.055	-0.046	-0.547**	-0.521**	-0.444**
			0.746	0.001	0.05	0.05	0.9	0.667	0.083	0.001	0.05	0.05	0.619	0.678	0.05	0.05	0.05
	α_neut	r	-0.035	-0.477**	**0.715****	**0.790****	0.17	-0.172	-0.203	**0.809****	**0.745****	**0.866****	-0.258*	-0.145	**0.873****	**0.604****	0.493**
			0.755	0.05	0.05	0.05	0.123	0.117	0.064	0.05	0.05	0.05	0.018	0.188	0.05	0.05	0.05
	β_neut	r	-0.142	-0.377**	**0.702****	**0.775****	0.246*	-0.273*	-0.328**	**0.778****	0.445**	**0.806****	-0.431**	-0.407**	**0.709****	0.427**	0.268*
			0.198	0.05	0.05	0.05	0.024	0.012	0.002	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.014
	γ_neut	r	-0.057	-0.430**	**0.726****	**0.792****	0.209	-0.205	-0.199	**0.834****	**0.719****	**0.897****	-0.287**	-0.204	**0.844****	0.550**	0.441**
	δ_neut		0.609	0.05	0.05	0.05	0.056	0.061	0.07	0.05	0.05	0.05	0.008	0.063	0.05	0.05	0.05

* Correlation is significant at the 0.05 level (2-tailed).

** Correlation is significant at the 0.01 level (2-tailed).

Acknowledgments

This research was supported by Universiti Kebangsaan Malaysia and Ministry of Education, Malaysia, Grant Code GUP-2020-009.

Conflicts of Interest

The authors declare no conflict of interest.

References

[1] S. Jerritta, M. Murugappan, W. Khairunizam, and S. Yaacob. (2014). Electrocardiogram-based emotion recognition system using empirical mode decomposition and discrete Fourier transform. Expert Systems, 31, 110-120.
[2] N. K. Al-Qazzaz, M. K. Sabir, S. H. B. M. Ali, S. A. Ahmad, and K. Grammer (2020). Electroencephalogram Profiles for Emotion Identification over the Brain Regions Using Spectral, Entropy and Temporal Biomarkers, Sensors, 20, 59.
[3] N. K. Al-Qazzaz, M. K. Sabir, and K. Grammer. (2019). Gender Differences identification from Brain Regions using Spectral Relative Powers of Emotional EEG," in Proceedings of the 2019 7th International work-conference on Bioinformatics and biomedical engineering, 38-42.
[4] N. K. Al-Qazzaz, M. K. Sabir, and K. Grammer. (2019). Correlation Indices of Electroencephalogram-Based Relative Powers during Human Emotion Processing. in Proceedings of the 2019 9th International Conference on Biomedical Engineering and Technology, 64-70.
[5] N. K. Al-Qazzaz, M. K. Sabir, S. Ali, S. A. Ahmad, and K. Grammer. (2019). Effective EEG Channels for Emotion Identification over the Brain Regions using Differential Evolution Algorithm. 2019 41th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC).
[6] Y. Deng, L. Chang, M. Yang, M. Huo, and R. Zhou. (2016). Gender differences in emotional response: inconsistency between experience and expressivity. PloS one, 11, 0158666.
[7] K. Chellappan, N. K. Mohsin, S. H. B. M. Ali, and M. S. Islam. (2012,). Post-stroke brain memory assessment framework," in 2012 IEEE-EMBS Conference on Biomedical Engineering and Sciences, 189-194.
[8] E. A. Kensinger (2004). Remembering emotional experiences: The contribution of valence and arousal. Reviews in the Neurosciences, 15, 241-252.
[9] A. Mehrabian. (1996). Pleasure-arousal-dominance: A general framework for describing and measuring individual differences in temperament. Current Psychology, 14, 261-292.
[10] N. K. Al-Qazzaz, M. K. Sabir, S. H. M. Ali, S. A. Ahmad, and K. Grammer. (2021). The Role of Spectral Power Ratio in Characterizing Emotional EEG for Gender Identification. 2020 IEEE-EMBS Conference on Biomedical Engineering and Sciences (IECBES), 334-338.
[11] N. K. Al-Qazzaz, S. Ali, S. A. Ahmad, M. S. Islam, and J. Escudero. (2016). Entropy-based markers of EEG background activity of stroke-related mild cognitive impairment and vascular dementia patients. 2nd International Conference on Sensors Engineering and Electronics Instrumental Advances (SEIA 2016), Barcelona, Spain.
[12] N. K. Al-Qazzaz, S. H. B. Ali, S. A. Ahmad, K. Chellappan, M. S. Islam, and J. Escudero. (2014). Role of EEG as Biomarker in the Early Detection and Classification of Dementia. The Scientific World Journal, 2014.
[13] A. Mert and A. Akan. (2018). Emotion recognition based on time–frequency distribution of EEG signals using multivariate synchrosqueezing transform. Digital Signal Processing, 106-115.
[14] H. Ali, M. Hariharan, S. Yaacob, and A. H. Adom. (2015). Facial emotion recognition using empirical mode decomposition. Expert Systems with Applications, 42, 1261-1277.
[15] M. Murugappan, N. Ramachandran, and Y. Sazali. (2010). Classification of human emotion from EEG using discrete wavelet transform. Journal of Biomedical Science and Engineering, 390.
[16] N. K. Al-Qazzaz, S. Hamid Bin Mohd Ali, S. A. Ahmad, M. S. Islam, and J. Escudero. (2017). Automatic Artifact Removal in EEG of Normal and Demented Individuals Using ICA–WT during Working Memory Tasks. Sensors, 17, 1326.
[17] J. Gao, J. Hu, and W.-w. Tung. (2011). Facilitating joint chaos and fractal analysis of biosignals through nonlinear adaptive filtering. PloS one, 6, 24331.
[18] J. Selvaraj, M. Murugappan, K. Wan, and S. Yaacob. (2013). Classification of emotional states from electrocardiogram signals: a non-linear approach based on hurst. Biomedical engineering online, 12, 44.
[19] N. K. Al-Qazzaz, S. Ali, S. A. Ahmad, and J. Escudero. (2017). Stroke-related mild cognitive impairment detection during working memory tasks using EEG signal processing. Advances in Biomedical Engineering (ICABME), 2017 Fourth International Conference on, 1-4.
[20] A. Patil, C. Deshmukh, and A. Panat. (2016).Feature extraction of EEG for emotion recognition using Hjorth features and higher order crossings. Advances in Signal Processing (CASP), Conference on, 429-434.

[21] O. Sourina and Y. Liu. (2011).A Fractal-based Algorithm of Emotion Recognition from EEG using Arousal-Valence Model. Biosignals, 209-214.
[22] K.-E. Ko, H.-C. Yang, and K.-B. Sim. (2009). Emotion recognition using EEG signals with relative power values and Bayesian network. International Journal of Control, Automation and Systems, 7, 865-870.
[23] S. Xie and S. Krishnan. (2013).Wavelet-based sparse functional linear model with applications to EEGs seizure detection and epilepsy diagnosis. Medical & biological engineering & computing, vol, 51, 49-60.
[24] D. Abásolo, R. Hornero, P. Espino, D. Alvarez, and J. Poza. (2006).Entropy analysis of the EEG background activity in Alzheimer's disease patients. Physiological measurement, 27, 241.
[25] N. K. Al-Qazzaz, S. Ali, M. S. Islam, S. A. Ahmad, and J. Escudero. (2016). EEG markers for early detection and characterization of vascular dementia during working memory tasks. in Biomedical Engineering and Sciences (IECBES), 2016 IEEE EMBS Conference on, 347-351.
[26] N. K. Al-Qazzaz, S. Ali, S. Islam, S. Ahmad, and J. Escudero. (2016). EEG Wavelet Spectral Analysis During a Working Memory Tasks in Stroke-Related Mild Cognitive Impairment Patients. International Conference for Innovation in Biomedical Engineering and Life Sciences, 82-85.
[27] J. Rottenberg, J. J. Gross, F. H. Wilhelm, S. Najmi, and I. H. Gotlib. (2002).Crying threshold and intensity in major depressive disorder. Journal of abnormal psychology, 111, 302.
[28] D. Abásolo, J. Escudero, R. Hornero, C. Gómez, and P. Espino. (2008). Approximate entropy and auto mutual information analysis of the electroencephalogram in Alzheimer's disease patients. Medical & biological engineering & computing, 46, 1019-1028.
[29] N. K. Al-Qazzaz, S. Ali, S. A. Ahmad, M. S. Islam, and M. I. Ariff. (2014). Selection of mother wavelets thresholding methods in denoising multi-channel EEG signals during working memory task. in Biomedical Engineering and Sciences (IECBES), 2014 IEEE Conference, 214-219.
[30] N. Al-Qazzaz, S. Hamid Bin Mohd Ali, S. Ahmad, M. Islam, and J. Escudero. (2015). Selection of mother wavelet functions for multi-channel EEG signal analysis during a working memory task. Sensors, 15, 29015-29035.
[31] M. Teplan, A. Krakovská, and M. Špajdel. (2014). Spectral EEG features of a Short Psycho-physiological Relaxation. Measurement Science Review, 14, 237-242.
[32] J. Kang, T. Zhou, J. Han, and X. Li. (2018). EEG-based multi-feature fusion assessment for autism. Journal of Clinical Neuroscience, 56, 101-107.
[33] R. O. Duda, P. E. Hart, and D. G. Stork. (2012) Pattern classification: John Wiley & Sons.
[34] M. Kantardzic. (2011). Data mining: concepts, models, methods, and algorithms: John Wiley & Sons.
[35] C. Lehmann, T. Koenig, V. Jelic, L. Prichep, R. E. John, L.-O. Wahlund, et al.. (2007). Application and comparison of classification algorithms for recognition of Alzheimer's disease in electrical brain activity (EEG). Journal of neuroscience methods, 161, 342-350.
[36] V. Vapnik. (2000) The nature of statistical learning theory: springer.
[37] N. K. Al-Qazzaz, S. Ali, S. A. Ahmad, and J. Escudero. (2017). Classification enhancement for post-stroke dementia using fuzzy neighborhood preserving analysis with QR-decomposition. 2017 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 3174-3177.
[38] M. M. Bradley, M. Codispoti, D. Sabatinelli, and P. J. Lang. (2001).Emotion and motivation II: sex differences in picture processing. Emotion. 1, 300.
[39] A. M. Kring and A. H. Gordon. (1998). Sex differences in emotion: expression, experience, and physiology. Journal of personality and social psychology, 74, 686.
[40] N. K. Al-Qazzaz, M. K. Sabir, S. H. M. Ali, S. A. Ahmad, and K. Grammer. (2021). The Role of Spectral Power Ratio in Characterizing Emotional EEG for Gender Identification," in 2020 IEEE-EMBS Conference on Biomedical Engineering and Sciences (IECBES), 334-338.