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Multichannel Optimization With Hybrid Spectral-Entropy Markers for Gender Identification Enhancement of Emotional-Based EEGs

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ABSTRACT Investigating gender differences based on emotional changes supports automatic interpretation of human intentions and preferences. This allows emotion applications to respond better to requirements and customize interactions based on affective responses. The electroencephalogram (EEG) is a tool that potentially can be used to detect gender differences. The main purpose of this paper is twofold. Firstly, it aims to use both linear and nonlinear features of EEG signals to identify emotional influences on gender behavior. Secondly, it aims to develop an automatic gender recognition model by employing optimization algorithms to identify the most effective channels for gender identification from emotional-based EEG signals. The EEGs of thirty healthy students from the University of Vienna were recorded while they were watched four short video clips depicting the emotions of anger, happiness, sadness and neutral. In this study, the wavelet transform (WT) de-noising technique, linear spectral mean frequency ($meanF$) and nonlinear multiscale fuzzy entropy (MFE) features were used. The individual performance of these attributes was statistically examined using analysis of variance (ANOVA) to represent the gender behavior in the brain-emotion in females and males. Then, these two features were fused into a set of hybrid spectral-entropy attributes (SEA). Consequently, optimization algorithms including binary gravitation search algorithm (BGSA) and binary particle swarm optimization (BPSO), were employed to identify the optimal channels for gender classification. Finally, the k-nearest neighbors (kNN) classification technique was used for automatic gender identification of an emotional-based EEG dataset. The results show linear and nonlinear features are remarkable neuromarkers for investigating gender-based differences in emotional states. Moreover, the results show significant enhancement in the overall accuracy of classification achieved by using the BGSA optimization algorithm with the proposed hybrid SEA set when compared to individual features. Therefore, the proposed methods were effective in improving the process of automatic gender recognition from the emotional-based EEG signals.

INDEX TERMS ANOVA, channel selection, electroencephalography, emotion, entropy, features, gender, optimization.

I. INTRODUCTION

Investigating gender-based differences in emotions is essential to understanding the changes in behavior of individuals across their lifespan. Automatic interpretation of human emotions, intentions and preferences helping in emotion applications to respond better to users' requirements and customize interactions based on affective responses [1], [2]. Gender contrasts have been archived in intellectual cycles, for example, memory and feeling. Subsequently, gender differences

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dependent on emotional processing has attracted particular interest because of its possible application in understanding human psychopathologies, such as depression and anxiety. The responses of females and males to stress differ and this difference may affect psychopathologies [3].

Psychologically, two emotional models are identified to classify the emotional levels; these are the discrete model and the dimensional model. The discrete model is comprise of multiple, distinct emotional states that identifies basic feelings (anger, fear, disgust, surprise, happiness, and sadness), and all different feelings are viewed as an aspect of these essential emotions or a combination of them [4], [5]. The dimensional model is a two-dimensional (2D) cognitive-emotional state model that is used to broadly utilized in mapping the emotion onto the valance-arousal graph, as described in the Russell's circumplex model of emotion [6], [7].

Recently, researchers indicated that to provide the best environment for recognition of emotion, they need to get the combined effect of both visual and auditory stimuli to elicit a specific emotional state [8]. Using short audio-visual video clips to create conditions that elicit various feelings has been found to be more effective than other modalities [9]. Therefore, to reveal personal characteristics that would be valuable in recognizing individual gender accurately in daily life, visual and auditory stimuli are considered as the two common ways for human beings to elicit different emotional states [3]. Thus, in this work, emotions were initiated by using short audio-visual video clips.

So far, few studies have examined gender differences based on emotional changes [10]–[12], and the greater part of these studies report significant differences [8]. However, some limitations of the EEG-based emotion recognition model have been identified. For instance, the accuracy of the model decreases as the number of emotions to be classified increases. Another challenge that emerges while acquiring the EEG signals from different emotional states, is that emotions tend to propagate from one brain area to another. Indeed, recording common information with better convey of the stimulants will be a breakthrough of substance significance.

To address the above problem, this paper proposes a novel method to identify the optimal EEG channels for differentiating gender-based emotions. Determining the most effective EEG channels can help to remove task-independent from the recorded signals, reducing the complexity of the system. This achieves better classification performance and decreases the computational load while producing a robust and reliable gender recognition model. Thus, in this research, optimization algorithms were used to detect the effective EEG channels automatically.

To do this, the emotional-based EEG dataset is initially filtered using a conventional filter and wavelet (WT) de-noising technique. Linear spectral mean frequency (meanF) and nonlinear multiscale fuzzy entropy (MFE) features were computed [13], [14]. The individual performance of these features was statistically examined using a three-way ANOVA. Then the linear spectral *meanF* and nonlinear *MFE* features were combined into a hybrid *SEA* feature set to illustrate the simple brain activities with sophisticated complex information. BGSA and BPSO optimization algorithms were employed to detect the optimal EEG channels. Finally, *k*NN classifier was used to automatically identify the gender of an emotional-based EEG dataset.

To the authors best of knowledge the contribution of a gender-specific role in the brain-emotion relationship has been addressed in this work. So, the main purpose of this paper is twofold. First, it aims to propose gender recognition indices using linear *meanF* and nonlinear *MFE* markers from EEG data of different emotional states acquired using low-cost EEG devices. Second, proposed an automatic gender recognition model using optimization algorithms for optimal channel selections to empower the gender identification process from emotional-based EEGs. This study is the first to use BGSA and BPSO optimization algorithms to select the channels that are most effective in enhancing the accuracy of classification the different genders' emotional-based EEGs. Additionally, the EEG elicitation protocol, which uses audio-visual video clips as external stimuli have never been used for information about feelings that may make gender contrasts more pronounced.

II. RELATED WORK

Over the last decade, different tools that detect physiological signals, such as electrocardiogram (ECG) and electroencephalogram (EEG), can be used to recognize emotions [15]–[17]. Minhad *et al.* have illustrated the emotional differences from ECG signal with a classification accuracy of 83.33% [18]. EEG is a neurophysiological tool used to screen and distinguish brain activity. EEG is a generally accessible, cost-effective, and non-obtrusive apparatus that tracks data preparing with milliseconds exactness and high temporal resolution [19]. EEG signals are helpful markers of various mental states; for example, seizure discovery/expectation, motor imagery of stroke patients rehabilitation, mental task characterization, emotion recognition, sleep state classification, analyzing the impact of medication, attention deficit hyperactivity disorder (ADHD), Alzheimer's disease (AD), depression, and various emotional information [20]–[25].

Indeed, the strong correlation between different emotional states and EEG signals is most likely attributable to the signals coming directly from the central nervous system (CNS), thereby providing information about internal emotional states [2], [11], [15], [26]–[28]. Recently, EEGs have been used to assess human emotional states with excellent time resolution [9]. Therefore, recognizing emotion supports automatic interpretation of human intentions and preferences, allowing human computer interface applications to respond better to users' requirements and customize interactions according to affective responses. Moreover, EEG signals have been described as a potential biomarker of gender differences from emotional-based EEG dataset with a classification accuracy of 92% [8], [11].

A. EEG FEATURES EXTRACTION

Investigating gender differences based on emotional changes become essential to understand various human behavior in our daily life [29]. Although, there is no common agreement on the most suitable EEG features, researches have suggested extracting features from time-domain [8], [30], [31], frequency-domain [32], time-frequency domain using wavelet transform [33]–[35] and the users of the statistical features [10] as in Table 1.

However, EEG signals illustrate non-linear behaviour, in this demand, entropy has been considered as a non-linear parametric index that can be utilized to evaluate the vulnerability of a framework and unstable dynamic EEG signal. Moreover, the entropy evaluators can quantify the complexity of a time series degree and have been broadly applied to the EEG signal to investigate the psychological mental states and rest states lately [36]–[39]. For instance, Wang *et al.* have used, including sample entropy (*SampEn*), approximate entropy (*ApEn*), permutation entropy (*PerEn*) to quantify the complexity of a time series [27]. Moreover, EEG-based gender recognition acknowledgment by utilizing various entropies has an expected application for clinical investigates, referred to as social emotion, person identification, treatment uptake, clinical efficacy and adverse reactions [26]. Thul *et al.* have adopted (*PerEn*) and Symbolic Transfer entropy to analyze EEG signals for clinical assessments, which suggests that the utilized EEG entropy analyses were able to relate to patient groups with various disorders of consciousness [40]. Add to that, fuzzy entropy (*FuzEn*) [41], amplitude-aware permutation entropy (*AAPE*) which relatively quantifies the complexity of a time series for EEG analysis [13], [42]. Research shows that *FuzEn* alleviates the problem of entropy mutation; however, these methods analyze at a single scale, which loses useful information. Thus, multiscale *FuzEn* (*MFE*) was put forward to explore deeper information [43]. Therefore, *MFE* entropy features were selected to be used as a diagnostic index that would be able to discriminate gender using an emotional-based EEG dataset.

Indeed, features extracted from single domain are mostly simple and may lead to insufficient EEG information that affecting the overarching performance of classification [44], a robust feature set using hybrid feature methods provide a solution for emotion recognition system aforementioned problem [44]. Hence, in this study, the linear spectral *meanF* and nonlinear *MFE* features were evaluated individually and were combined into a hybrid spectral-entropy attributes (*SEA*) feature set to illustrate the simple brain activities with sophisticated complex information.

B. EEG FEATURES AND CHANNELS SELECTION

Detection of different human emotions from EEG signals is usually a prone to the curse of dimensionality due to the high dimensional feature matrix which will modulate the final classification performance. Multi-channels may cause noise due to motion artefacts, and/or dataset outliers resulting in a poor classification accuracies. To solve this issue, channels selection methods have applied to decrease the dataset dimensionality, reduce the computational complexity, reduce the amount of overfitting that may arise due to the utilization of unnecessary channels which leads to enhance classification accuracy. Therefore, most particular channels selection techniques are filtering and embedded methods [45]. The filtering methods have been used to select and combine discriminative channels and classify a set of emotions [46]. Moreover, researchers have used conventional canonical correlation analysis algorithm to model the corresponding EEG feature vectors to simultaneously cope with both automatic channel selection and emotion recognition [45], [47].

Table 1 shows the state-of-the-art methods for EEG features and channels selection. Studies [45], [46], [48]–[53] attempted to estimate the best features using features selection (FS) methods including sequential feedforward selection (SFFS), Minimum Redundancy Maximum Relevance (mRMR), genetic algorithm (GA), evolutionary computation (EC) and sparse discriminative ensemble learning (SDEL), Sparse Discriminative Ensemble Learning (SDEL) algorithm, sparse linear discriminant analysis (LDA), (SBS), and principle component analysis (PCA) whereas study [54] used binary adaptive differential evolution bat algorithm (BADEBA) channels selection (ChS) method.

However, in different emotional states, brain areas associated with emotional elicitations are not exactly the same, which will result in the inability of traditional channel selection methods to extract effective EEG features. Thus, the problem of channels selection could be solved using optimization algorithms. Several studies have been employed metaheuristic algorithms for selecting efficient learning operators through solving the optimization problems [55] including the artificial bee colony (ABC) [56], flower pollination algorithm (FPA) [57] and particle swarm optimization (PSO) [58]. Huang *et al.* [59] proposed a new ant colony optimization (ACO) for electromyography signals classification. Venugopal *et al.* [60] applied the genetic algorithm (GA) for measuring the muscle fatigue conditions. Moreover, Purushothaman and Vikas [61] made use of particle swarm optimization (PSO) and ACO to solve the feature selection problem in finger movement recognition. Another study proposed a binary grey wolf optimization (BGWO) in evaluating the optimal feature subset [55]. Moreover, Roman *et al.* [62] have used a hybrid controller to optimally tune by a Grey Wolf Optimizer algorithm. Recently, the Cuckoo search (CS) algorithm [63] has been used to diagnose the epilepsy based on EEG dataset classification [64].

C. EEG EMOTION CLASSIFICATION

Emotion recognition supports automatic interpretation of human intentions and preferences, allowing human computer interface applications to better respond to users' requirements

TABLE 1. State-of-the-art: Methods of EEG features extractions, features-channels selection and classification.

Study	Features types	Method	Classifiers
Kortelainen et al. [48]	Frequency domain	FS: SFFS	kNN
P. Ackermann et al. [46]	Statistical	FS: mRMR	SVM, RF
J. Atkinson et al. [49]	Statistical, frequency	FS: GA	SVM
Nakisa et al. [50]	Frequency domain, time domain	FS: EC	probabilistic neural network (PNN)
H. Ullah et al. [45]	Statistical, frequency domain	FS: SDEL	SVM
Y. Zhang et al. [65]	EMD-SE	–	SVM
G. Zhao et al. [51]	STFT	FS: Sparse LDA	SVM
Z.-T. Liu et al. [52]	EMD-LZC	FS: SBS	kNN
E. S. Pane et al. [66]	PSD, statistical, wavelet	–	RF
Z. Wang et al. [54]	Statistical, WT Time domain,	ChS: BADEBA	SVM
R. Nawaz et al. [53]	Power, entropy, FD, statistical, wavelet entropy	FS: PCA	DT
Z. Li et al. [67]	Frequency domain, time domain, time-frequency domain	FS: PSO	SVM

TABLE 2. The operation of the proposed methodology.

Algorithm 1 : Operation of the proposed methodology
1. The capture of raw input emotional-based EEG dataset of 14 channels. 2. For EEG dataset, preprocess all the 14 channels to remove artifacts using conventional filters and wavelet transform (WT) technique. 3. Extract the linear $meanF$ and the nonlinear MFE features from each channel and store these attributes as features database. 4. Randomly initialize the particle/object of the BPSO and BGSA optimization algorithms. 5. Set particle/object size to 30. 6. Each particle/object randomly select (j) channels and select only those channel features from features database. 7. For the particle/object size, calculate the classification accuracies . 8. For the particle/object size, evaluate fitness functions $fiti$. 9. if (fit=1 or maximum iteration occurs) Go to step 10 else Find position $Mi(t)$, $Fi(t)$, $ai(t)$, $worst(t)$, and $vi(t)$ velocity of each particle/object; Update the position of each particle/object and go to step 7 10. Selected channels are optimal for classification of gender from emotional-based EEG dataset. 11. Exit.

and customize interactions based on affective responses. Table 1 illustrates the most popular machine learning algorithms that have been used are Support Vector Machine (SVM), k-Nearest Neighbor (kNN), Random Forest (RF) and decision tree (DT) particularly in the study of the EEG emotion classification [12]. These classification models all directly use EEG set of features for classification without considering the EEG signals' internal temporal dynamic information [17].

III. MATERIALS AND METHODS

This study is intended to investigate the gender differences by estimating two methods which are linear *meanF* and nonlinear *MFE*. These features were combined as a hybrid spectral-entropy attributes (*SEA*) feature set to illustrate the neural behavior and complexity changes over the brain regions. Therefore, for achieving good classification performances this study involves representing two optimization algorithms from different metaheuristic categories using BPSO and BGSA for optimal channel selection and gender identification enhancement of emotional-based EEGs for the four emotional states over the brain regions. The novel proposed model is validated on multi-channels emotional-based EEG datasets.

Table 2 shows the pseudocode of the proposed method framework. The proposed methodology run through successive stages where the result of each stage is an input to the consecutive one. Figure 1 illustrates the block diagram of the proposed study.

A. EEG ACQUISITION AND RECORDING

The emotion elicitation procedure starts by examination, every member went through an assessment to guarantee no earlier history of neurological or mental issues and was then given an educated assent structure (ICF) which they were mentioned to sign before partaking in the investigation. Then, the EEGs of thirty volunteer were recorded while they were demonstrated three, short video-clips for anger, happiness and sadness emotions Table 3. In addition, a video-clip for neutral emotion have been used as a baseline. This procedure was suggested by Rottenberg [68]. Every video clip has a different length, but none is longer than four minutes. The video clips have been presented to volunteers with a Virtual Emotion Presenter (VEP) software developed at the University of Vienna. This software allows random presentation and recording of additional data sources. The picture shows the VEP in the Anthropology lab Figure 2. Moreover, the emotion elicitation procedure includes self-statements questionnaire (*SAQ*) to assess and grade their reactions to the clips, followed by a break of 45 seconds before review the following video clip (Figure 3). The film stimuli we will use are recommended and tested for emotion perception by Rottenberg [68].

After that, the EEG signals were recorded using Emotiv EPOC EEG headset, inertial sensors, wireless connectivity (Emotive Systems, Inc., San Francisco, CA) of 14-channel ($AF3$, $F7$, $F3$, $FC5$, $T7$, $P7$, $O1$, $O2$, $P8$, $T8$, $FC6$, $F4$, $F8$, $AF4$) plus two references, the common mode sense (CMS) at the left mastoid and the determined right leg (DRL) at the right mastoid. The Emotiv EPOC EEG utilizes wipe based terminals which were found dependent on the 10–20 framework, and recently employed in [69], [70]. The anode data was sifted through a 0.5-70 Hz band-pass channel. A 128 Hz examining recurrence was utilized with a goal of 0.51 mV.

B. PREPROCESSING STAGE

Most of the artifacts are lying in EEG waves and it may overlap with different brain activities. The filtration process gets a crucial role in EEG signal preprocessing. Therefore, to successfully carry out the research objectives of this study, the EEG dataset were preprocessed to remove artifacts using

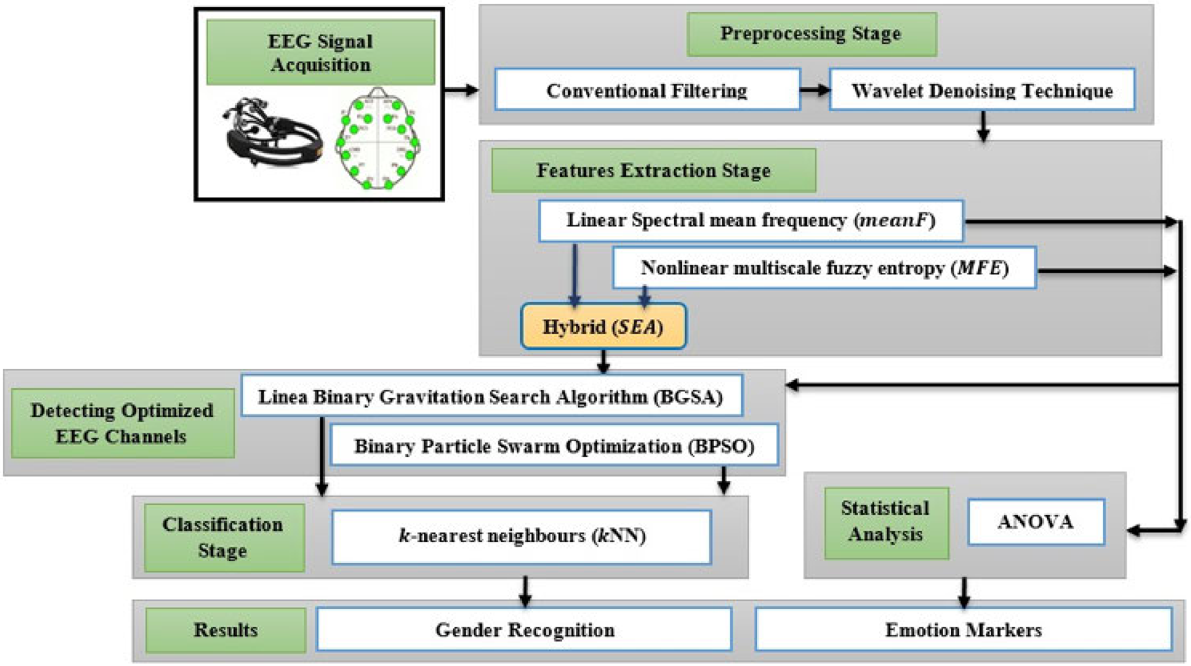

FIGURE 1. Block diagram of this study.

TABLE 3. Sociodemographic information of the subjects with *SAQ* scores, (Age in years, mean ± standard deviation).

Demographic and clinical features	Subjects
Number	30
Age	22.933±2.581
Female/Male	17F/13M
Anger	1.867±0.01
Happiness	2.249±0.052
Sadness	2.897±0.842

conventional filters and wavelet transform (WT) technique which is discussed in details in the following section.

1) CONVENTIONAL FILTERING

To perform filtering, additional software filters (notch and bandpass filters) have to be applied to the EEG signals. In this study, a bandpass filter with a lower cutoff corresponding to 3 dB is 0.5 Hz and the upper cutoff frequency was selected to be 64 Hz, these conventional filters were applied to limit the frequencies of the EEG signals as in [8]. A notch band stop filter was utilized to remove the AC power line interference noise (PLIN) and it was set to the cutoff frequency of 50 Hz [8], [31].

2) WAVELET (WT) DE-NOISING TECHNIQUE

WT has the capacity in settling EEG into explicit time and frequency components by giving a good time-resolution and a poor frequency-resolution at high frequencies and a good frequency-resolution and a poor time-resolution at low frequencies. The discrete wavelet (DWT) can be processed by getting the discrete estimation of the parameters a and b, as in Equation 1. It can be performed by finding the correlation between the EEG signal $f(t)$ and the mother wavelet (MWT) function, $\Psi(t)$. In this study, symlet mother wavelet of order 9 was chosen to be used by applying DWT. MWT is shifted by the location parameter b and contracted by frequency scaling parameter a, as in Equation 2 [71]:

$$DWT_{m,n}(f) = a_0^{\frac{-m}{2}} \int f(t)\psi(a_0^{-m}t - nb_0)dt. \qquad (1)$$

a_0 and b_0 values are set to 2 and 1, respectively.

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi(\frac{t-b}{a}), a \in \mathbb{R}^+, b \in \mathbb{R}. \qquad (2)$$

C. FEATURES EXTRACTION STAGE

Investigating EEG signals to identify gender differences from emotional-based background activity remains a crucial goal for improving the process of gender recognition. Recently, EEG markers play the important role in reveal information from brain activity. Therefore, different attributes can be quantified and derived from the EEG signal to identify gender from different emotional states. Since the patterns of recorded EEG signals were varied among the different case of study, studies have been declared that the success of the results was mainly depending on the quality of the extracted set of features as the choice of the feature set has a stronger influence on the classification accuracy than the choice of classifier [72]. In this direction, this study is intended to investigate the linear spectral *meanF* and nonlinear *MFE* dynamical entropy attributes to characterize gender behavior according to different emotional states over the brain regions.

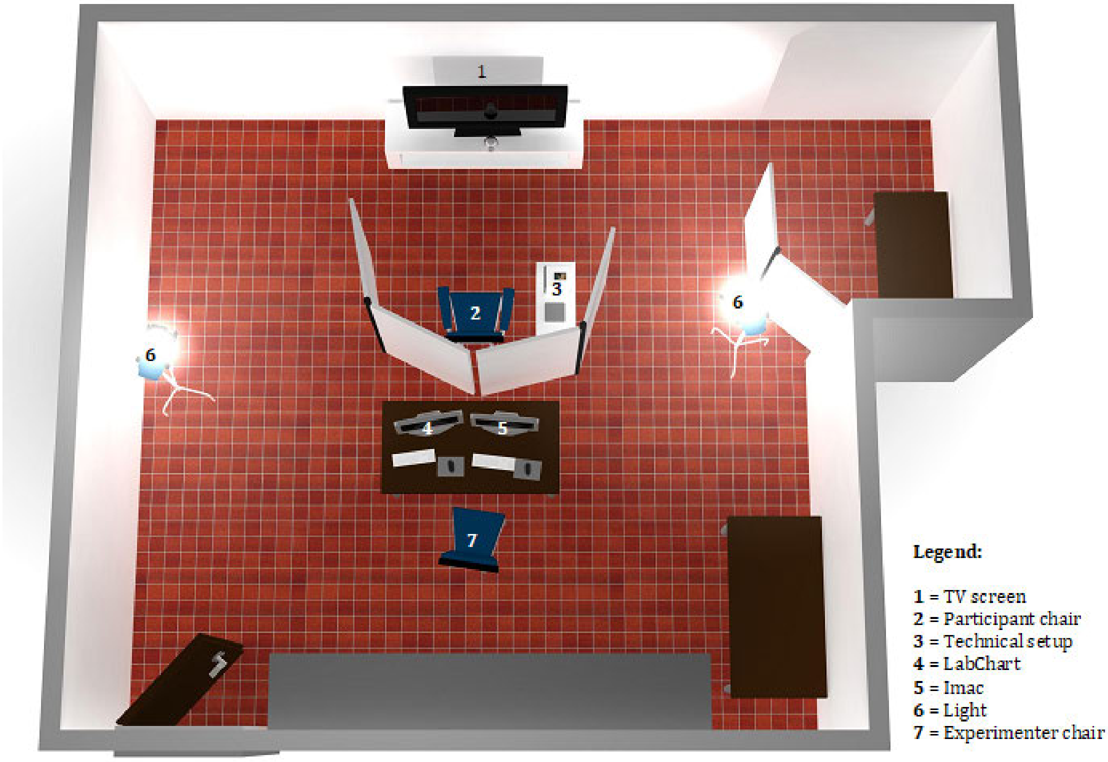

FIGURE 2. Setup of the experimental room with presentation TV and the recorders.

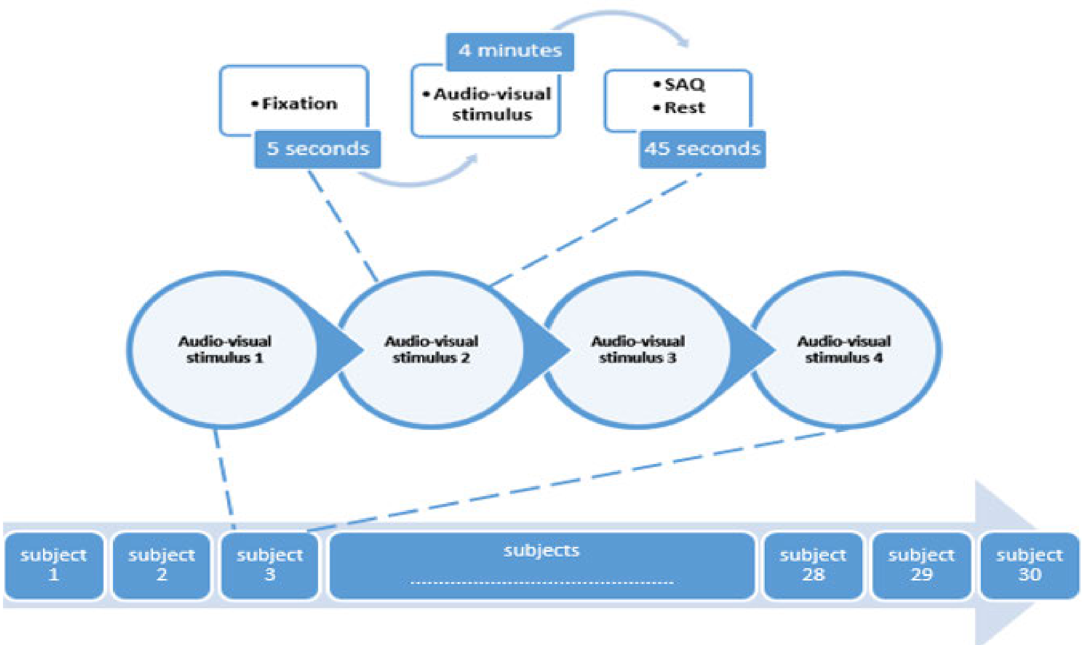

FIGURE 3. The experimental protocol of emotion.

1) MEAN FREQUENCY (*meanF*)

The changes in EEG were investigated by using *meanF* to be an indicator of the general slowing of neural activity [73]. To compute the *meanF*, first, normalized the power spectral density (*PSD*) obtained by Welch Method to the total power to get normalized *PSD* (PSD_{norm}) so that $\frac{PSD(i)}{\sum_i PSD(i)}$. Then, the *meanF* was then defined as in Equation 3.

$$meanF = \sum_i f(i) PSD_{norm(i)}. \tag{3}$$

where, the index i denotes the frequency bin, $f(i)$ the mean frequency in Hz for each frequency bin, and $PSD_norm(i)$ the relative power in that frequency bin [14].

2) MULTISCALE FUZZY ENTROPY (*MFE*)

Due to the capability of the brain to perform sophisticated cognitive tasks, in this study, the nonlinear *MFE* was also used to analyze the recorded EEG signals. *MFE* method is based on the used of *FuzEn* values on multiple scales [8], the EEG time series is denoted as $Y = y(i) : 1 \leq i \leq N$ and the coarse-grained time series $y(\tau)$ is constructed as $y_1(\tau), y_2(\tau), \ldots, y_{\frac{N}{\tau}(\tau)}$, and can be computed based on Equation 4:

$$y_i(\tau) = \frac{1}{\tau} \sum_{i=(j-1)+1}^{i\tau} y(i), \quad 1 \leq j \leq \frac{N}{\tau}. \tag{4}$$

where N is the length of time series and τ is a positive integer. The *FuzEn* of each coarse-grained time series can be computed as in [74]. Then, *MFE* is a function of scale factor τ, it can be computed by the following Equation 5:

$$MFE(Y, \tau, m, n, r) = FE(y(\tau), m, n, r). \tag{5}$$

where, τ is a defined scale factor, m is the embedding dimension, n is the power, and tolerance r for all of the approaches were respectively chosen as $\tau = 1$, $m = 3$, $n = 2$, $r = 0.25 \times SD$, and SD is the standard deviation of the original X time series [74]. In this study, *meanF* and *MFE* features would be derived from the EEG signals of 30 seconds length (N=3840) samples, 3 windows of 10-second length (1280 samples) were extracted from the original EEG time series for every 14 channels. Subsequently, the linear *meanF* and nonlinear *MFE* features were fused via the concatenation process into a hybrid spectral-entropy attributes (*SEA*) to get insight into the mechanism responses of neural behavior and the complexity changes over the brain regions that help in understanding the gender differences better. The hybrid *SEA* set was utilized to represent the most prominent attributes that enhance the gender classification from emotional-based EEGs.

D. GENDER DIFFERENCES INVESTIGATION BY STATISTICAL ANALYSIS

Statistical analyses were performed to describe the gender differences based on the physiological meaning of the extracted features. In this study, the hypothesis to characterize gender based on their behavior from different emotional states was considered. Linear spectral *meanF* and nonlinear dynamic *MFE* were used based on the past investigations that demonstrated their usefulness in recognizing the EEGs of various cognitive tasks subjects' [13], [14]. Subsequently, to assess the *meanF* and *MFE* performance influences in personal gender identification due to anger, happiness, sadness and neutral emotional stimuli two sessions of three-way ANOVA were employed. To perform ANOVA, entropy features of the 14-channels from the EEG dataset of the 30 healthy participants were, to begin with, assembled into 4 account areas that relate to the scalp area of the cerebral cortex, these are the frontal ($AF3, F7, F3, FC5, F4, FC6, F8$, and $AF4$ channels), parietal ($P7$ and $P8$ channels), temporal ($T7$ and $T8$ channels), and occipital ($O1$ and $O2$ channels). IBM USA's SPSS program version 25 was adopted to attempt statistical analysis. So, in each of the two sessions, the group factors of gender (i.e. females and males), the brain regions (i.e. frontal, temporal, parietal and occipital) and the four emotional states (i.e. angry, sadness and happiness) were set as the independent variables and the features including (*meanF* and *MFE*) were set as the dependent variables. Subsequently, Levene's test for homoscedasticity was applied, as well as the Kolmogorov-Smirnov assessments for the normality test. Duncan's test was applied to provide the post-hoc contrast, with $p < 0.05$ established as each statistical assessments' level of significance. Regionally averaged features helped in considering the differences between females and males over the scalp areas which can directly display their behavioral responses to the emotional changes on the mind.

E. DETECTING OPTIMIZED EEG CHANNELS

To propose the most effective EEG channels that involve in gender identification enhancement with better classification performance from emotional-based EEGs, optimization algorithms including BPSO and BGSA were used. This study is the first to use BGSA and BPSO optimization algorithms to select the most effective channels to enhance the classification accuracy of genders from anger, happiness, sadness and neutral emotional-based EEGs.

1) BINARY PARTICLE SWARM OPTIMIZATION (BPSO)

Binary particle swarm optimization (BPSO) is a binary version of particle swarm optimization (PSO) that was created by Kennedy and Eberhart in 1995 dependent on the behavior of bird flocks called a swarm [58]. In this algorithm, each solution is shown as a vector under the name of the particle (bird) and the population (swarm) which may have any random number of initial solutions (particles). Each particle begins with its initial position and velocity, then moves in the solution space to achieve the optimum result. BPSO can be computed by incorporate producing the starting position and velocity of every generation in the populace to get the optimal solution. The mathematical computation of BPSO algorithm is as in below. Let any particle x_i (solution) in d-dimensional space is represented in Equation 6.

$$x_i = x_{i1}, x_{i2}, x_{i3}, \ldots, x_{id}. \tag{6}$$

where, $i = 1, 2, 3, \ldots, d$ and d is the number of particles in the swarm. every particle keeps up its own velocity, as given in Equation 7.

$$v_i = v_{i1}, v_{i2}, v_{i3}, \ldots, v_{id}. \tag{7}$$

Additionally, in this calculation, every particle keeps up its own best position called p_{best} and the best solution among all the particles called g_{best}. In every iteration or generation, the particles move towards an optimal solution by updating their velocity and position according to the formula given in Equations 8 and 9.

$$v_i^d(t+1) = \omega v_i^d(t) + c_1 r_1 (pbest_i^d(t) - x_i^d(t)) + c_2 r_2 (gbest_i^d(t) - x_i^d(t)). \tag{8}$$

$$x_i(t+1) = x_i(t) + v_i(t+1). \tag{9}$$

where $v_i(d+1)$ represents the velocity of $i^t h$ particle at $d+1$ iteration. ω is the inertia weight, $v_i(d)$ represents the velocity of $i^t h$ particle at d iteration. $pbest_i$, $gbest_i$ represents the personal best of the particle and global best of the swarm at t iteration respectively. i is the order of particle in the population, d is the dimension of search space, and t is the number of iterations. $x_i(t)$, $x_i(t+1)$ are the previous and present solutions respectively. c_1 and c_2 are two positive real constants known as self-confidence factor and swarm confidence factor respectively. r_1 and r_2 are any random numbers generated in between (0,1). Note that the velocity is bounded by the maximum velocity, v_{max} and minimum velocity, v_{min} which were set at 6 and -6, respectively [64]. Then, the velocity is converted into probability value using Equation 10, and the position of particle is updated as shown in Equation 10.

$$S(v_i^d(t+1)) = \frac{1}{1 + exp(-v_i^d(t+1))}. \tag{10}$$

$$x_i^d(t+1) = \begin{cases} 1 & if\ rand < S(v_i^d(t+1)) \\ 0 & otherwise. \end{cases} \tag{11}$$

where $rand$ is a random number uniformly distributed between 0 and 1. In BPSO, pbest and $gbest$ play an important role in guiding the particle to move toward the global optimum. Considering the minimization function was applied in this paper. Iteratively, the $pbest$ and $gbest$ are updated as follows:

$$pbest_i(t+1) = \begin{cases} x_i(t+1) & if\ F(x_i(t+1)) < F(pbest_i(t) \\ pbest_i(t) & otherwise. \end{cases} \tag{12}$$

$$gbest_i(t+1) = \begin{cases} pbest_i(t+1) & if\ F(pbest_i(t+1)) < F(gbest_i(t) \\ gbest_i(t) & otherwise. \end{cases} \tag{13}$$

where x is the solution, $pbest$ is the personal best solution, $gbest$ is the global best solution for the entire population, $F(.)$ is the fitness function, and t is the number of iterations. Notably, the larger inertia weight performs more efficient global search and the smaller inertia weight performs efficient local search [75]. Hence, this inertia weight can be considered as an important parameter to tune the performance of PSO algorithm [75]. The pseudocode of the BPSO is shown if Figure 4 [76].

TABLE 4. The Binary Particle Swarm Optimization (BPSO) pseudocode.

Algorithm 2: The binary particle swarm optimization (BPSO) pseudocode.
1. Begin 2. Initialization a population of particles x , and parameters N, $c1$, $c2$, $vmax$, $vmin$. 3. Fitness evaluation of the particles. 4. Set $pbest$ and $gbest$. 5. Compute the inertia weight w. 6. Updating the velocity and the position of particles. 7. Evaluate the fitness of new particles. 8. Update the and . 9. Repeat steps (5) to (8) until the stopping criteria is met. 10. End.

2) BINARY GRAVITATION SEARCH ALGORITHM (BGSA)

BGSA algorithm has been used to reduce the amount of information in terms of detecting the optimal channels and it has been proposed by Rashedi *et al.* [77]. GSA is an effective optimization algorithm that was designed based on Newtonian laws of gravity and motion and it was introduced for solving binary-valued problems in [77]. BGSA can be computed by considering a system with m masses. Each mass has a position that is an answer to the problem. p_i^d represents the position of the i^{th} mass in the d^{th} dimension.

$$P_i = (p_i^1, \ldots, p_i^d, \ldots, p_i^D). \tag{14}$$

In this system, the force acting on the i^{th} mass from the j^{th} mass at time t is calculated as follows:

$$F_{ij}^d(t) = \frac{G(t) \times Mg_j(t)}{R_ij(t) + \epsilon}(p_j^d(t) - p_i^d(t)). \tag{15}$$

where, Mg_j is the gravitational mass related to mass j, $G(t)$ is gravitational constant at time t, ϵ is a small constant, and R_{ij} is the Euclidean distance between two masses i and j.

$$R_{ij}(t) = \left\| P_i(t), P_j(t) \right\|^2. \tag{16}$$

The total acting force on the i^{th} mass in the dimension d is a random weighted sum of the d^{th} components of applied forces from other masses:

$$F_i^d(t) = \sum_{j=1, ji}^{m} r_j F_{ij}^d(t). \tag{17}$$

Based on Newton's second law, the acceleration of the i^{th} mass at time t in the th dimension is given as follows:

$$a_i^d(t) = \frac{F_i^d(t)}{Mi_i(t)}. \tag{18}$$

The velocity of a mass in the next step is considered as a fraction of its current velocity added to its acceleration. Therefore, its position and velocity could be updated as follows:

$$V_i^d(t+1) = r_i \times V_i^d(t) + a_i^d(t). \tag{19}$$

$$p_i^d(t+1) = p_i^d(t) + V_i^d(t+1). \tag{20}$$

where r_i are random numbers with uniform distribution in the interval [78]. The gravitational and inertial mass are evaluated by the fitness $fit_i(t)$ function as follows:

$$Mg_j = \frac{(fit_i(t) - worst(t))}{(best(t) - worst(t))}. \tag{21}$$

$$Mi_i = 1 + Mg_i. \tag{22}$$

$$best = \min_{j \in 1,2,\ldots,m} fit_i(t). \tag{23}$$

$$worst = \min_{j \in 1,2,\ldots,m} fit_i(t). \tag{24}$$

In the binary environment, every dimension has a value of 0 or 1. Moving in every dimension means that its value changes from 0 to 1 or vice versa. BGSA updates the velocity based on the Equation 19 and considers the new position to be 1 or 0 with probability. In other words, moving velocity is defined in terms of changes of probabilities that a bit will be in one state or the other. Thus V_i^d shows the probability of changing the value of x_i^d from 0 to 1 or vice versa. Function $S(V_i^d)$ is defined to transform V_i^d into a probability function. Therefore, $S(V_i^d)$ must be bounded between 0 and 1:

$$S(V_i^d(t)) = \left| tanh(S(V_i^d(t)) \right|. \tag{25}$$

After calculating $S(V_i^d$, masses will move according to the following equation:

$$p_i^d(t+1) = \begin{cases} p_i^d(t) & rand < S(V_i^d(t+1)) \\ p_i^d(t) & rand \geq S(V_i^d(t+1)) \end{cases}. \tag{26}$$

In BGSA, $G(t)$ is decreased linearly with time according to the following equation:

$$G(t) = G_0(1 - \frac{t}{T}). \tag{27}$$

where T is the total number of iterations (the total age of the system). The BGSA pseudocode is shown in Figure 5 [78].

TABLE 5. The Binary gravitation search algorithm (BGSA) pseudocode.

Algorithm 3: The binary gravitational search algorithm (BGSA) pseudocode.
1. Begin
2. Search space identification.
3. Random initialization.
4. Fitness evaluation of objects.
5. Update $G(t)$, $worst(t)$ and $Mi(t)$.
6. Calculation of the objects' total force in different directions.
7. Calculation of the objects' acceleration and velocity.
8. Calculation of the transfer function for all objects.
9. Updating the position of the objects.
10. Repeat steps (4) to (9) until the stopping criteria is met.
11. End.

3) K-NEAREST NEIGHBOR METHOD

The k-nearest neighbor (kNN) method is one of the most popular nonparametric methods, the k- nearest neighbors are a positive integer that is considered as a key factor in the classifier performance [32]. kNN classifier checks for the closest training observations that are presented in the proposed features matrix based on the minimum Euclidean distance [11]. The observation is assigned to the class that is most common among its k- nearest neighbors and the nearest samples are assumed to contribute more than the far samples [11]. In this paper, to enhance the classification accuracies, the leave-one-out cross-validation (LOOCV) method was performed to choose the parameter k.

4) FITNESS FUNCTION

This study was searched for the most effective channels that provide better gender identification performance evaluation in terms of the fitness function (fit_i). A good fitness value yields higher classification accuracy with lower-dimensional numbers in terms of EEG channels. Therefore, fit_i is designed and computed using Equation 28 [79]:

$$fit_i = \omega_1 \times accu_i + \omega_2 \times \left[1 - \frac{\sum_{j=1}^{p} f_j}{p} \right]. \tag{28}$$

There are two predefined weight factors ω_1 and ω_2; ω_1 is the weight factor for the classification accuracy of the 1-nearest neighbor (1-NN) determined by the LOOCV method; $accu_i$ is the 1-NN classification accuracy; ω_2 is the weight factor for the number of selected features and f_j is the value of feature mask. The weight factor of accuracy can be adjusted to a high value to improve the final classification accuracy. The object with high fitness value has a high probability of affecting the other objects' positions of the next iteration, so it should be set appropriately [80]. The $accu_i$ is obtained by Equation 29, in which corr represents the number of correctly classified examples and incorr represents the number of incorrectly classified examples [79]. kNN method based on Euclidean distance calculations serves as a classifier for evaluating classification accuracies.

$$accu_i = \frac{corr}{corr + incorr} \times 100\%. \tag{29}$$

5) OPTIMIZATION ALGORITHMS SETUP

The BPSO and BGSA parameters were selected among the values suggested in [81], [82]. Both optimization algorithms were computed utilizing $M = 30$ particles until a fitness value equal to 1 was achieved or until 100 iterations were exceeded. For the real part, the inertia parameter W was a random number varied from 0.9 to 0.2 linearly across 100 iterations and had a constant value equal to 1 for the binary part. The two exploration and exploitation constants c_1 and c_2 are fixed variables which are determined by user and were set to $c_1 = c_2 = 2$. r_1 and r_2 are two random variable in the range of (0,1) which are updated each iteration. The search space of the only real component was constrained to $[-1, 1]$. The maximum and minimum velocities were set to -0.1 and 0.1, respectively, for the real part, and -6 and 6, respectively, for the binary part. The BPSO and BGSA particle's initial conditions were set for each binary component with randomly initialized to either 0 or 1 with equal probability. BPSO and BGSA, like other heuristic search algorithms works randomly and produces different results in every run. Therefore, to find the optimal channels that are selected in different runs of channel selection algorithm, the BGSA performed for 50 independent runs in subject one. Then the numbers of each selected channel was counted for all of the 14 channels independently.

F. GENDER RECOGNITION BY CLASSIFICATION AND PERFORMANCE EVALUATION

The development of an automatic system for gender identification based on emotional responses arouses considerable interest due to their impact in medical diagnosis. In the classification stage, the accuracy of classifiers strongly relies upon the quality of the extracted attributes [11]. Consequently, in this section, a comparative study of using *meanF*, *MFE* and hybrid *SEA* features before and after applying the BGSA and BPSO optimization algorithms was run to check the proposed system abilities in classifying the subjects' gender into (females and males) based on their response to anger, happiness, sadness and neutral emotional states using kNN classifier.

kNN classification technique was chosen due to their dependence on the sizes of the training and test sets. kNN classifier was trained to find the best value of k. The k value was varied between 1 and 9 at intervals of 2 and it was chosen empirically at $k = 7$. The Euclidean distance has been computed as a similarity measure to classify each trial. After that, ten-fold cross-validation was used to avoid overfitting and bias in the classification analysis [12]. Finally, the results of the classification stage to classify the subjects' gender-based EEG dataset of 4 emotional states were demonstrated and evaluated by using the average classification accuracies (AvClassifAcc). The average classification accuracy is computed as a percentage as in Equations 30:

$$AvClassifAcc = \left(\frac{Number\ of\ correctly\ classified\ instances}{total\ number\ of\ instances}\right) \times 100. \quad (30)$$

IV. RESULTS

The gender differences from the emotional-based EEG signals were investigated using statistical analysis, firstly and through the performance of optimization algorithms with kNN classifier secondly. The results were illustrated in the following sections.

A. RESULTS OF GENDER RECOGNITION BY STATISTICAL ANALYSIS

Statistical analyses were performed to describe the gender differences based on the physiological meaning of the extracted features. In this study, the hypothesis to characterize gender based on their behavior from different emotional states was considered. Linear spectral *meanF* and nonlinear dynamic *MFE* were used based on the previous studies that showed their usefulness in distinguishing the EEGs of different cognitive tasks subjects'. Therefore, to evaluate the *meanF* and *MFE* performance influences in personal gender identification due to anger, happiness, sadness and neutral emotional stimuli two sessions of three-way ANOVA were employed.

To identify females and males based on their emotional behavior, the statistical qualifications of anger, sadness, happiness and neutral emotions among the frontal, temporal, parietal and occipital brain regions have been assigned individually using *meanF* and *MFE* features. The significant differences were established at $p < 0.05$ level of significance.

In the first session of ANOVA, three-way ANOVA was applied on the *meanF* feature. From the first glance at Table 6, it can be observed that all the emotions but happiness were illustrated significant differences between females and males ($p < 0.05$). The *meanF* marker of anger, sadness and happiness for males were significantly higher than the ($meanF_{anger,sadness,happiness}(Males) > meanF_{anger,sadness,happiness}(Females)$), whereas

$$(meanF_{neutral}(Females) > meanF_{neutral}(Males)).$$

Moreover, Figure 4 shows gender discrimination based on the brain regions' point of view. The females' investigations show that the frontal lobes have the lowest effects, whereas the parietal and temporal lobes particularly significantly had the highest effect from the neutral, anger and sadness emotions. Notably, happiness has the highest effect in the temporal lobes whereas sadness has the highest effect in the occipital lobes with significance differences ($p < 0.05$). Further investigations to Figure 4 shows that the frontal lobes have the lowest effects, whereas the temporal, parietal and occipital lobes significantly had the same effect for the neutral emotional state in males. Notably, sadness, happiness and neutral have the highest effect in the occipital lobes, whereas anger has the highest effect in the temporal regions ($p < 0.05$).

TABLE 6. The average values (Mean ± SD) of *meanF* for the female and male over the scalp regions. Significant group differences are marked with an asterisk.

Features	Emotions	Female	Male	value
meanF	anger	14.804±4.299	15.519±4.252	**0.033***
	sadness	12.797±4.721	15.51±5.113	**0.05***
	happiness	13.536±4.681	13.669±4.404	0.677
	neutral	15.33±3.803	13.532±3.048	**0.05***

Thus, in males, the *meanF* could serve as an index of anger in the temporal regions ($meanF^{anger}_{Temporal}(Males)$) and as an index of sadness, happiness and neutral in the occipital lobe ($meanF^{sadness,happiness,neutral}_{Occipital}(Males)$). In females, *meanF* could be as an index of neutral, anger and sadness in the parietal brain regions ($meanF^{neutral,anger,sadness}_{Parietal}(Females)$) and an index of happiness in the temporal lobes ($mean^{happiness}_{Temporal}(Females)$). Given that anger and sadness emotions are situated in the upper and lower-right quadrant of the valence-arousal Circumplex model of emotions, respectively and the neutral emotion is located in the lower-left quadrant of the valence-arousal Circumplex model.

In the second session of ANOVA, three-way ANOVA was applied on the *MFE* feature. From the first glance at Table 7, it can be observed that all the emotions were significant differences between females and males ($p < 0.05$). The *MFE* markers of anger, sadness and neutral for males were higher than the *MFE* markers of the same emotions for females ($MFE_{anger,sadness,neutral}(Males) > MFE_{anger,sadness,neutral}(Females)$), whereas

$$(MFE_{happiness}(Females) > MFE_{happiness}(Males)).$$

Figure 5 shows the gender discrimination based on the brain regions' point of view, the females show that the frontal lobes have the lowest effects, whereas the parietal and the occipital lobes were significantly highest in anger, sadness and happiness emotions ($p < 0.05$). Notably, the neutral has the highest effect in the temporal lobes with almost the same effect in the parietal and occipital regions. Further investigations to Figure 5 show that the males' frontal lobes have the lowest effects, whereas the parietal, occipital and temporal lobes significantly had the highest effects in all emotions. Notably, anger, neutral and happiness have the highest effect in the parietal regions, the sadness has the highest effect in the occipital region with significance differences ($p < 0.05$).

Thus, in males, the *MFE* could serve as an index of anger, neutral and happiness in the parietal regions ($MFE^{anger,neutral,happiness}_{Parietal}(Males)$), and as an index of sadness in the occipital region ($MFE^{sadness}_{Occipital}(Males)$). In females, the *MFE* could serve as an index of anger, sadness and happiness in the parietal regions ($MFE^{anger,sadness,happiness}_{Parietal}(Female)$), whereas *MFE* in the temporal regions could serve as an index of neutral ($MFE^{neutral}_{Temporal}(Female)$). Given that anger and neutral emotions are situated in the upper-right and lower-left quadrant of the valence-arousal model respectively and the neutral emotion is located in the lower-left quadrant of the valence-arousal model.

TABLE 7. The average values (Mean ± SD) of *MFE* for the female and male over the scalp regions. Significant group differences are marked with an asterisk.

Features	Emotions	Female	Male	value
MFE	anger	0.241±0.099	0.267±0.113	**0.001***
	sadness	0.179±0.155	0.201±0.082	**0.014***
	happiness	0.185±0.116	0.158±0.123	**0.001***
	neutral	0.212±0.232	0.096±0.111	**0.041***

B. RESULTS OF DETECTING OPTIMIZED EEG CHANNELS

The proposed optimization algorithms were tended to choose the most effective EEG channels over the stimulated brain regions. Therefore, the comparative analysis of the BGSA and BPSO algorithms were obtained to identify the most effective channels for gender identification enhancement from emotional-based EEG signals. Table 2 reports the optimal channels from the implemented *meanF*, *MFE* entropy and hybrid *SEA* features to the BGSA and PBSO optimization algorithms.

From Table 8, it can be observed that almost all the brain regions were participated to discriminate females and males while the emotion elicitation. However, it could be noted that there were different groups of channels that could be considered as the most effective channels to discriminate females and males from both BGSA and BPSO.

In this manner, from *meanF* marker, the results suggest that the most effective channels that separated females and males were covered mainly the frontal, parietal and occipital lobes in left and right hemispheres in anger, whereas other groups of channels were considered as the most effective channels in the sadness emotional state. Moreover, for happiness and neutral emotions, the most frequent channels to discriminate females and males were almost achieved by specific channels from the left and right brain lobes. Additionally, from *MFE* marker, the results were mainly related to left frontal and temporal lobes with right parietal and occipital lobes during anger, left brain hemisphere during sadness, left and right frontal and parietal with right temporal and left occipital during happiness and the lateral regions of the brain during neutral emotions.

According to the results, the number of selected channels is much lower than the original 14 channels. For instance, by selecting 5 channels 64% of the channels were ignored compared to the total 14 channels and that will reduce the amount of unimportant information to be focused on the most relevant brain regions that involve emotion elicitations'.

Accordingly, for the hybrid *SEA* marker, the more considerably active channels were mainly related to the left brain hemisphere in anger and sadness, left frontal and temporal with left and right parietal in happiness and the lateral regions in neutral emotions. Consecutively, the intersection between the most effective channels obtained from both BGSA and BPSO algorithms was achieved to build up an EEG brain mapping over the scalp view as in Figure 6.

Figures 7, 8 and 9 illustrate the convergence curves of *meanF*, *MFE* and *SEA* features using BPSO and BGSA, respectively for 30 independent runs. In these Figures, it can be observed that the performance of BGSA was outperformed the BPSO for emotional-based EEG datasets to seek out the optimal solution.

C. RESULTS OF GENDER RECOGNITION BY CLASSIFICATION

The development of an automatic gender recognition model from emotional-based EEG signals is essential in the processing chain of this study. For achieving strong robustness identifications with good classification performances this article compares the classification performance results of the *meanF*, *MFE* and hybrid *SEA* features obtained before and after using BGSA and BPSO optimization algorithms on the emotional response to anger, happiness, sadness and neutral emotional states.

In this stage, the classification accuracies were strongly depended on the quality of the extracted features. Table 3 reports the performances of the *k*NN classifier

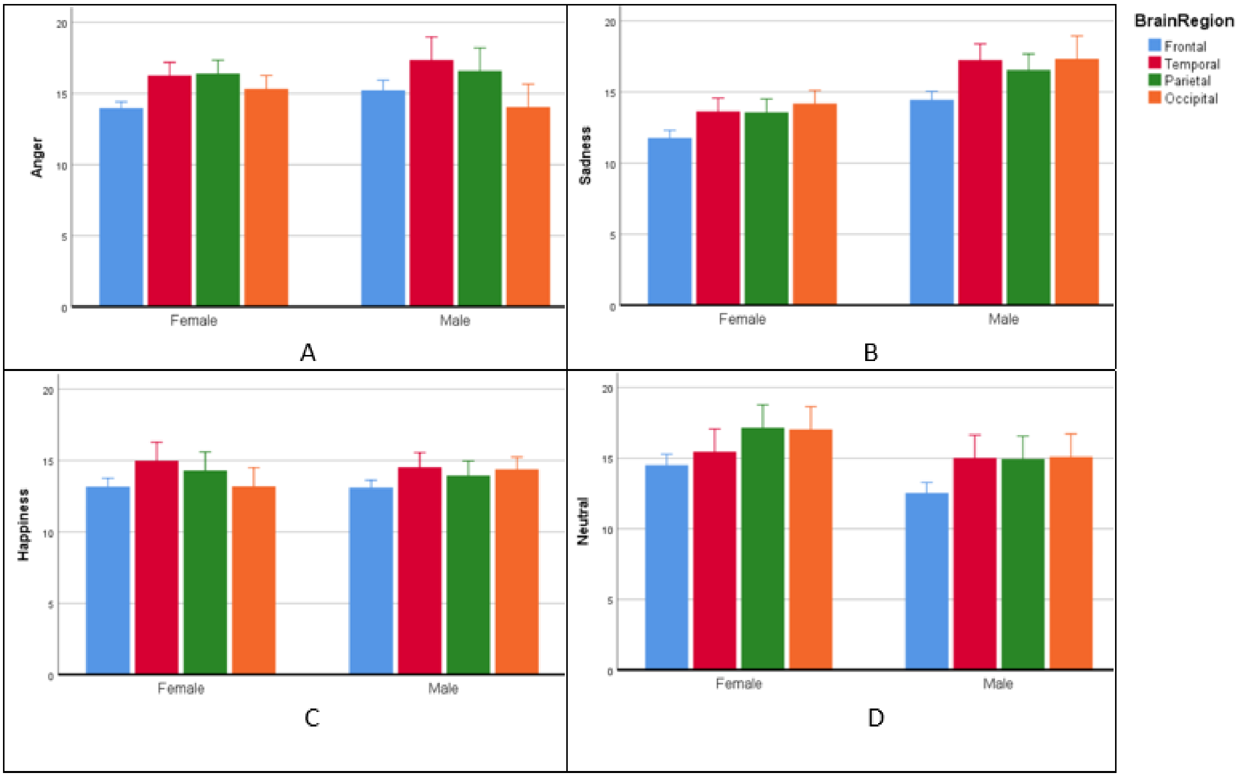

FIGURE 4. The *meanF* marker comparative plot for female and male due to A: anger, B: sadness, C: happiness and D: neutral emotional states.

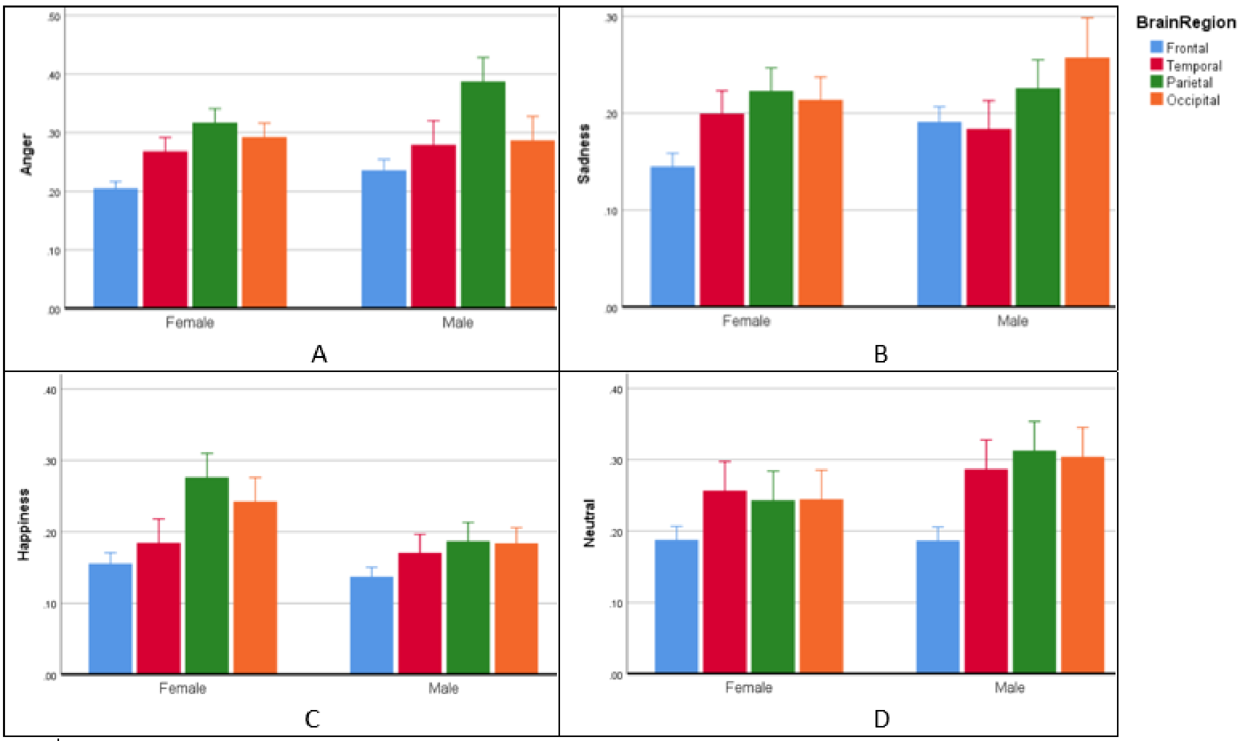

FIGURE 5. The *MFE* marker comparative plot for female and male due to A: anger, B: sadness, C: happiness and D: neutral emotional states.

to get insights into assessing the differences in personal gender before and after using BGSA and BPSO optimization algorithms.

The classification accuracies of the 14 EEG channels using *meanF*, *MFE* and hybrid *SEA* feature sets were illustrated lower performances compared to the accuracies after using

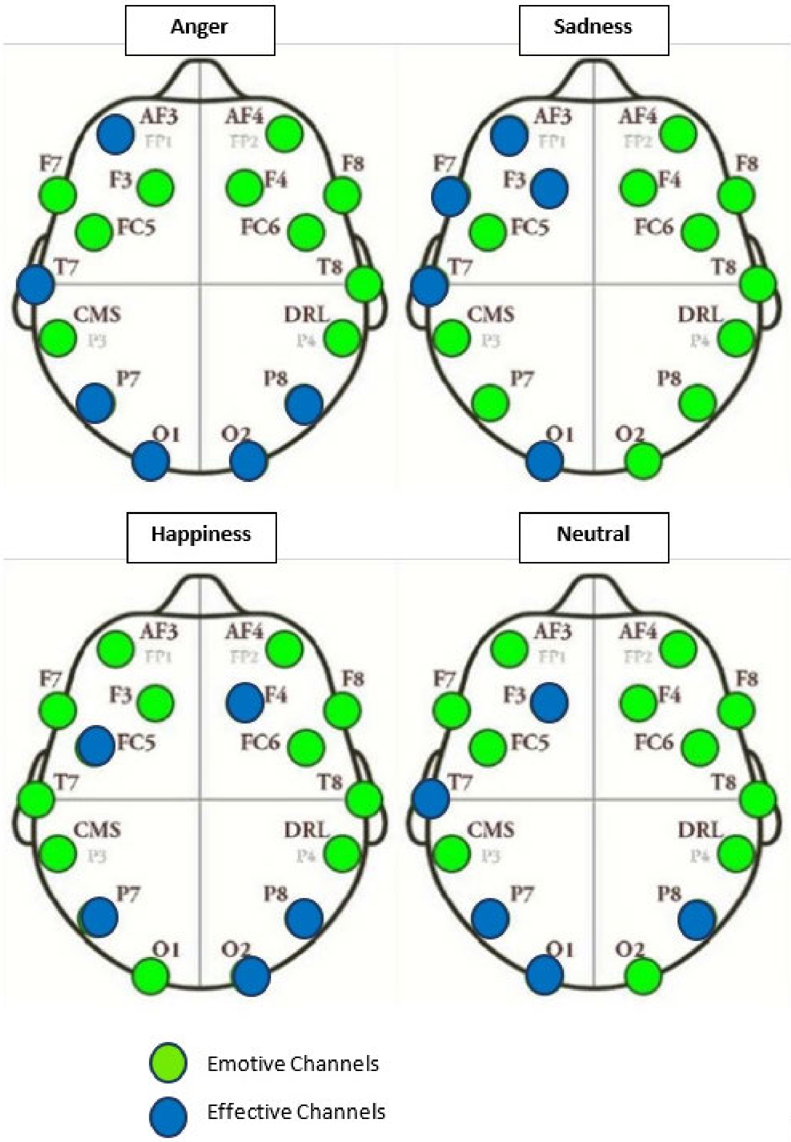

FIGURE 6. The EMOTIV EPOC EEG configuration of 14 EEG channels, the blue filled circles are the most effective channels obtained by hybrid *SEA* from both BGSA and BPSO optimization algorithms.

optimization algorithms. However, it can be noticed that the proposed *SEA* set can yield useful information that outperforms the other features by improving the gender classification overall accuracies of the 14 EEG channels for all emotions.

It is noteworthy that, the classification accuracies after using the effective channels obtained by BGSA and BPSO were improved, however, the most improvements were obtained from the hybrid *SEA* set, for instance, the females and males identification based on anger emotional state was increased from 73.89% to 85.62% and 79.77% for BGSA and BPSO, respectively.

In the same manner, the overall accuracy of gender identification based on sadness emotional state was increased from 70% to 85.44% and 83.95% for BGSA and BPSO, respectively. Moreover, the accuracies of gender differences based on happiness emotional state were increased from 76.67% to 85.80% and 83.91% for BGSA and BPSO, respectively. Furthermore, for the neutral emotional state, the overall accuracy of females and males' identification was increased from 82.22% to 93.71% and 91.80% for BGSA and BPSO, respectively.

On the other hand, Table 9 also shows the classification accuracies enhancement obtained after using BGSA and BPSO optimization algorithms. Indeed, the BGSA algorithm enhanced the classification performances achieved by 12% for anger and neutral, 15% for sadness and 9% for happiness emotions after reducing the number of used channels.

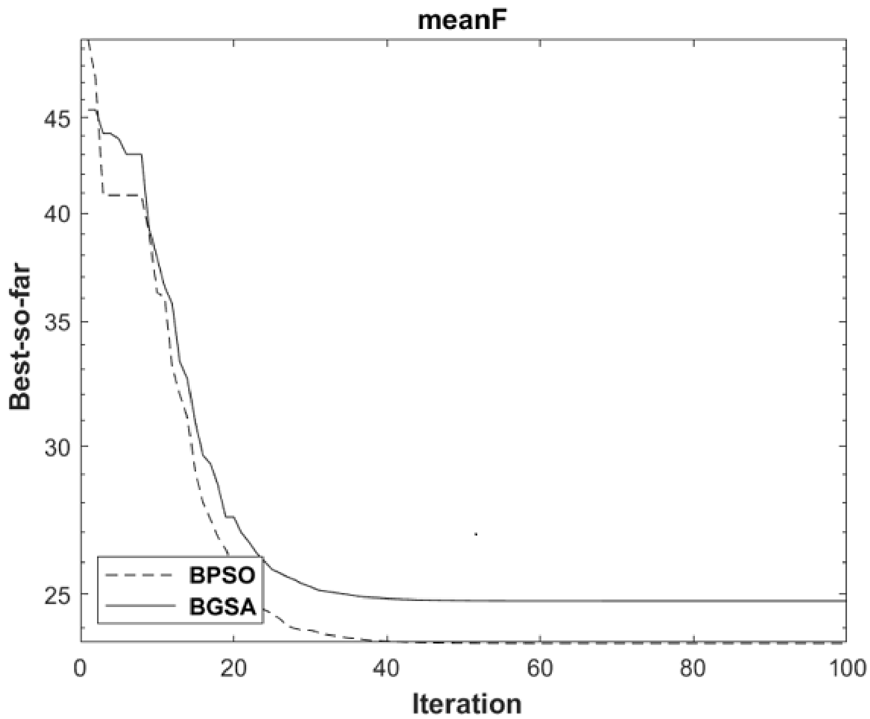

FIGURE 7. The convergence curves of *meanF* feature on emotional-based EEG dataset from both BGSA and BPSO optimization algorithms.

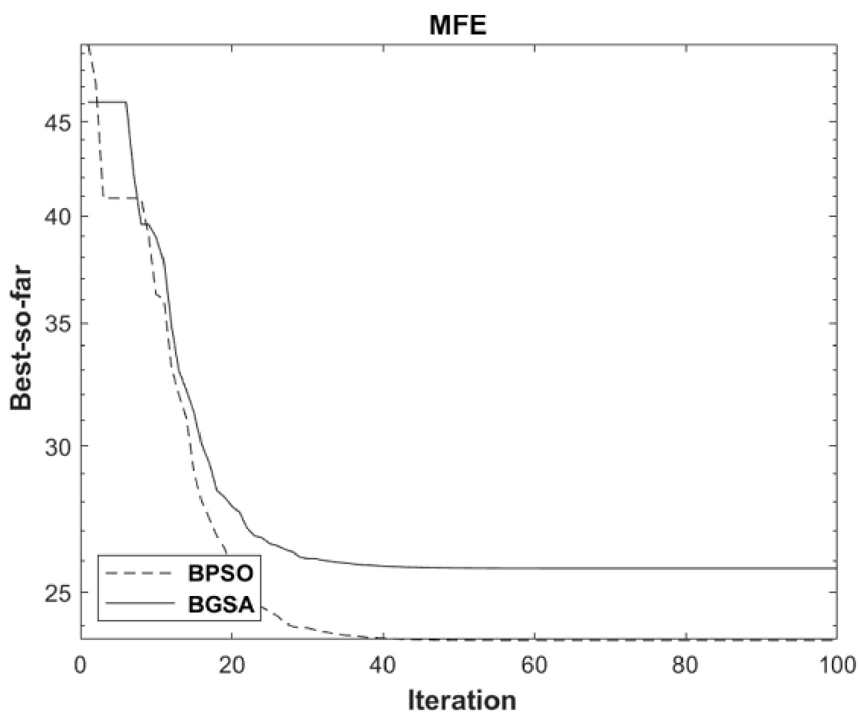

FIGURE 8. The convergence curves of *MFE* feature on emotional-based EEG dataset from both BGSA and BPSO optimization algorithms.

Table 11 provides the comparative analysis of the proposed method with existing methodologies. Studies attempted to estimate the best features using FS methods and ChS method. However, these methods were obtained with reduction in detection accuracy due to complicated computational calculations due to the redundant channels. This study presents

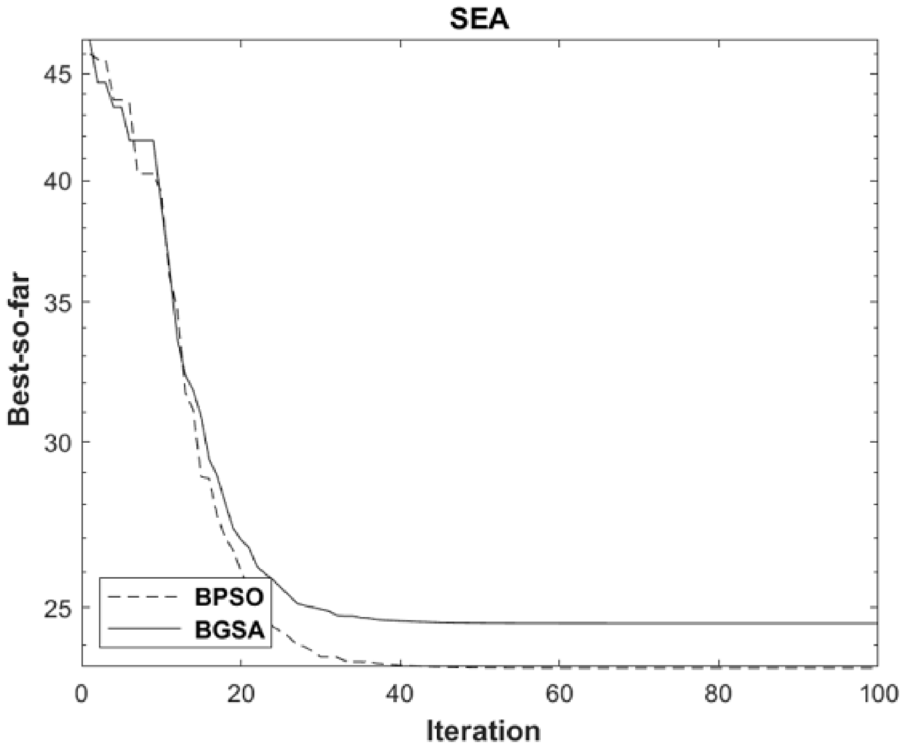

FIGURE 9. The convergence curves of *SEA* hybrid feature on emotional-based EEG dataset from both BGSA and BPSO optimization algorithms.

TABLE 8. Effective EEG channels for gender identification obtained by BGSA and BPSO optimization algorithms.

Features	Emotion	Most frequent channels using BGSA	No. of Chs
$meanF$	Anger	F7,F3,T7,P7,O1,O2	6
	Sadness	F3,P7,O1,O2,P8,T8,F4	7
	Happiness	F3,O1,P8,T8,FC6	5
	Neutral	AF3,F3,FC5,T7,O2,P8,F4	7
MFE	Anger	AF3,F7,F3,T7,P7,O2,P8	7
	Sadness	AF3,F7,F3,T7,P7,O1,P8	7
	Happiness	AF3,FC5,T7,P7,O2,P8,F4	7
	Neutral	AF3,F7,T7,P7,O1,P8,F4	7
SEA	Anger	AF3,F7,T7,P7,O1,O2,P8	7
	Sadness	AF3,F7,F3,T7,P7,O1,O2	7
	Happiness	FC5,T7,P7,O2,P8,F4	6
	Neutral	F3,T7,P7,O1,P8,F4	6
	Emotion	Most frequent channels using PSO	No. of Chs
$meanF$	Anger	F7,F3,P7,O1,O2	5
	Sadness	AF3,F3,P7,O1,P8,T8,FC6	7
	Happiness	F3,P8,T8,FC6,F4	5
	Neutral	F7,F3,FC5,T7,O2,P8,AF4	7
MFE	Anger	AF3,F7,F3,T7,O2,P8	6
	Sadness	AF3,F7,F3,T7,P7,O1,F4	7
	Happiness	AF3,F3,T7,P7,O2,P8,F4	7
	Neutral	AF3,F7,F3,T7,P7,O1,P8,F4	8
SEA	Anger	AF3,FC5,T7,P7,O1,O2,P8	8
	Sadness	AF3,F7,F3,T7,O1,P8	7
	Happiness	FC5,P7,O2,P8,F4	5
	Neutral	F7,F3,T7,P7,O1,P8	6

an automatic gender recognition model using BGSA and BPSO optimization algorithms for optimal channel selections to empower the gender identification process from emotional-based EEGs. With the proposed method there is a relatively reduction in the number of channels for the gender detection process with a good classification accuracies. Moreover, these methods have been used to study emotional-based EEGs, however gender recognition from emotional-based EEG using BGSA and BPSO optimization algorithms is the first to be considered in this study to select the most effective channels that enhanced the classification accuracy of genders from anger, happiness, sadness and neutral emotional-based EEGs. Additionally, the previous studies have used already existing public dataset datasets (MAHNOB, DEAP) whereas in this study the EEG dataset elicitation protocol and the EEG estimation system have never been utilized for feeling information securing and that may make gender contrasts more articulated.

Therefore, the best performance can be achieved by using the hybrid *SEA* feature set with the BGSA optimization algorithm which has the influence on gender recognition from the EEG signals and helps identify the gender differences based on different emotional states to provide prompt feedback for clinical practices. The proposed model using the WT de-noising technique, hybrid *SEA* set with BGSA optimization algorithm achieves superior results than the use of all the 14 EEG channels with traditional *meanF* and *MFE* methods with kNN classifier to characterize and identify gender from emotional-based EEG signals.

V. DISCUSSION

The current study has illustrated the gender behavior from the emotional-based EEG and their relation with the brain

TABLE 9. Comparing the gender-based classification accuracies obtained before and after using BGSA and BPSO optimization algorithms.

Features	Emotion	Classification all channels	accuracy (%) using BGSA	enhancement	using BGSA	enhancement
$meanF$	Anger	61.67	71.86	10	71.34	10
	Sadness	60	72.78	13	70.78	11
	Happiness	60.56	72.78	12	71.67	11
	Neutral	72.22	91.5	19	90.6	18
MFE	Anger	70.56	80.38	10	76.53	6
	Sadness	67.22	82.41	15	80.73	14
	Happiness	68.89	84.67	16	82.41	14
	Neutral	81.67	92.17	11	91.63	10
SEA	Anger	73.89	85.62	12	79.77	6
	Sadness	70	85.44	15	83.95	14
	Happiness	76.67	85.8	9	83.91	7
	Neutral	82.22	93.71	12	91.8	10

regions which is important in the cognitive sciences. Moreover, it has been able to successfully identify gender from the emotional-based EEGs by adapting a fully-automated algorithm to serve the purpose. This work proposed a novel approach in gender detection through applying the WT de-noising technique, hybrid *SEA* set, BGSA optimization algorithm for optimal channels selection, and implementation of kNN classifier as well. The improvement in the results was achieved by identifying the most effective channels through the optimization algorithms.

Table 10 represents the role of each brain lobe in gender behavior detection from the emotional-based EEGs. It is clear that parietal and temporal lobes have the most significant impact to identify females during anger, sadness, neutral and happiness, whereas to identify males, temporal, occipital and parietal lobes were played an essential role in anger, sadness, happiness and neutral and the results agree with Morteza *et al.* [83]. In contrast to other brain regions, the frontal lobe has an impact in both females and males for all the mentioned emotions, it seems to be more prominent for emotions associated with valence like anger, happiness, neutral and sadness, respectively [83]. These differences were mainly related to that the females and males recruited almost dissimilar neuronal brain networking for processing the anger, sadness, happiness and neutral audio-visual stimuli [8].

Table 10 shows the effect of *meanF* and *MFE* features as markers for investigating gender behavior based on anger, sadness, happiness and neutral emotional state over the brain lobes.

Therefore, almost all brain lobes are play crucial role in differencing females and males from emotional-based EEG. From the structure anatomical point of view, every one of our discoveries is predictable with key elements of the frontal, temporal, parietal, and occipital lobes of the brain. The frontal lobe is considered as our emotional control center [84], the temporal lobes which are related to emotion perception [28], and all the mentioned emotional states were identified by channels related to these two regions. The parietal lobe is located immediately behind the frontal lobe, and it is associated with handling data from the body's senses [8], the happiness and sadness emotional states were distinguished by channels delighted from this region. The occipital lobe contains most of the anatomical location of the visual cortex [12], the happiness, sadness and neutral emotions were recognized by channels from this area.

Besides, the proposed hybrid *SEA* with BGSA optimization algorithm consistently produced better performance results than the other feature extraction and selection methods. The utility of EEG as a clinical tool to assess functional changes related to different emotional states (i.e. anger, sadness, happiness and neutral) for different brain areas (i.e. frontal, temporal, parietal and occipital scalp) is of great interest.

However, several limitations also need to be considered including first that the algorithm relied on the regularized dimensionality reduction stage to reduce the number of features rather than including the sample size was small and a requirement to carry out further investigations with a larger database in the future is needed. The feature sets have been used in this study were compared, and some other measures such as Wavelet entropy, dispersion entropy, multi-scale entropy also have been widely used and should be studied further for EEG-based gender recognition in our ongoing researches. One problem with the proposed approach using EEG signals is that these signals cannot be easily acquired unobtrusively. In other words, subjects need to wear sensors to acquire data. The invasiveness makes such signals difficult to acquire and are not practical for real-time applications. For this actual application, an offline analysis on EEG datasets was performed and recorded from online experiments in this study. However, since the offline and online classifications have distinct characteristics, a further study in a real-time online experimental environment should be conducted to confirm the present findings.

TABLE 10. Effective biomarkers for identifying gender-based on anger, happiness, sadness and neutral emotional states over the brain region.

Marker	Gender	Emotions	Brain Regions
$meanF$	Female	anger, sadness, neutral	Parietal
		Happiness	Temporal
	Male	anger	Temporal
		sadness, happiness, neutral	Occipital
MFE	Female	anger, sadness, happiness	Parietal
		Neutral	Temporal
	Male	anger, happiness, neutral	Parietal
		sadness	Occipital

Despite these drawbacks, all our results are consistent with those of other researchers, whose findings showed that the EEG signals can detect the most corresponding differences between the females' and males' groups for anger, sadness, happiness and neutral, this agrees with EEG bands showed the gender differences [12], [28]. Therefore, the WT de-noising technique, the proposed hybrid *SEA* with BGSA optimization algorithm can yield useful information for characterizing and identifying gender from emotional-based EEGs.

For the future work, the proposed method will be extend by applying the given markers for automatic gender identification method experimentally. Moreover, another recommended direction is to perform the real application of

TABLE 11. Qualitative comparative analysis of the proposed method with the state-of-the-art.

Study	Dataset	Features types	Classes	method	No. of optimal channels				Classifiers	Accuracy (%)		
Kortelainen et al. [48]	MAHNOB	Frequency domain	Arousal, Valence	FS: SFFS	–				kNN	Valence: 63 Arousal: 65		
P. Ackermann et al. [46]	DEAP	Statistical	Anger, Surprise, Others	FS: mRMR	–				SVM, RF	55		
J. Atkinson et al. [49]	DEAP	Statistical, frequency	Arousal, Valence	FS: GA	–				SVM	Arousal: 60.7, Valence :62.33		
Nakisa et al. [50]	DEAP, MAHNOB, video EEG dataset	Frequency, Time domain	HA-P, HA-N, LA-P, LA-N	FS: EC	–				probabilistic neural network (PNN)	DEAP: 67.47, MAHNOB: 96.97, video EEG dataset:65.04		
H. Ullah et al. [45]	DEAP	Statistical, frequency	Arousal, Valence	FS: SDEL	–				SVM	Arousal: 70.1, Valence: 77.4		
Z. Wang et al. [54]	DEAP	Statistical, Time, WT	Arousal, Valence	ChS: BADEBA	7, 8				SVM	Arousal: 75.98, Valence: 75.26		
Our Proposed Method	Our emotional-based EEG dataset	Frequency domain, entropy domain, hybrid	anger, happiness, sadness and neutral	ChS: BGSA, BPSO	$meanF$	anger	8	11	kNN	$meanF$	71.86	71.34
						sadness	7	7			72.78	70.78
						happiness	8	8			72.78	71.67
						neutral	7	7			91.5	90.6
					MFE	anger	8	6		MFE	80.38	76.53
						sadness	8	9			82.41	80.73
						happiness	8	7			84.67	82.41
						neutral	9	8			92.17	91.63
					SEA	anger	8	9		SEA	85.62	79.77
						sadness	9	9			85.44	83.95
						happiness	8	8			85.8	83.91
						neutral	8	9			93.71	91.8

automatic gender recognition model from emotional-based EEGs.

To sum up, the conceptual link between *meanF* and *MFE* features were statistically used to illustrate the mechanism responses of neural behavior and the complexity changes over the brain regions that help in understanding the gender differences better. The novel automatic model was introduced from the WT, hybrid *SEA* with BGSA algorithms to characterize gender differences according to different emotional states over the brain regions through providing an alternative way to the existing channel selection techniques.

VI. CONCLUSION

Developing an automatic gender recognition model remains a crucial goal for improving the process of automatically identifying gender differences in EEG-based emotional signals. In this study, the WT de-noising technique has been used. Linear *meanF* and nonlinear *MFE* features have been extracted to characterize gender behavior statistically. Data obtained from different emotional states in different brain regions were analyzed using three-way ANOVA. Then, these two features have been combined into a hybrid *SEA*. Optimization algorithms, including BGSA and BPSO, were employed to identify the most effective channels for gender classification. Finally, a kNN classifier was used to automatically identify the gender of an emotional-based EEG dataset. The results indicate that *meanF* and *MFE* features are remarkable neuromarkers for investigating gender-based differences in emotional states occurring in the brain. Moreover, the classification results showed that in comparison to individual features, the proposed BGSA optimization algorithm with a hybrid *SEA* set, significantly enhanced the overall accuracy of classification. Therefore, the proposed methods were effective in improving the process of using emotional-based EEG signals to automatically recognize gender.

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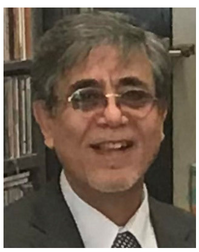

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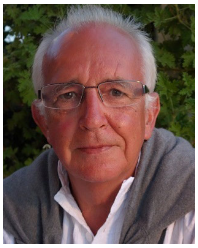

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