Proceedings of the Indian National Science Academy (2023) 89:858–868
https://doi.org/10.1007/s43538-023-00201-w

RESEARCH PAPER

Automated diagnosis of bipolar depression through Welch periodogram and machine learning techniques

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Received: 13 June 2023 / Accepted: 16 August 2023 / Published online: 7 September 2023

Abstract
Bipolar depression is a chronic mood disorder that causes severe shifts in mood, behaviors and energy levels. Very few studies to date have utilized these electroencephalogram (EEG) band abnormalities for the diagnosis of bipolar depression. Considering that bipolar depression affects millions of people around the world and its correct early diagnosis is of great importance in the treatment process. Considering the importance of EEG frequency bands in investigating the neuropathology of neuropsychiatric disorders, in this study, we intend to use a Welch periodogram and support vector machine (SVM) for the automatic diagnosis of bipolar depression from EEG signals. Therefore, in this research, 20 patients with bipolar depression aged 20 to 45 years and 25 healthy individuals with the same age range were subjected to electroencephalography in a resting state. After rejecting the artifact and reducing the noise in the preprocessing stage, the Welch periodogram was applied to the EEG and five statistical features (power, mean, variance, skewness and Shannon entropy) were calculated in delta, theta, alpha, beta and gamma frequency bands. SVM with linear, polynomial, RBF and sigmoid kernels, LDA, KNN, SOM and RBF were used as classifiers. The results showed that the features selected by statistical analysis and SOM neural network could achieve good accuracy, sensitivity and specificity of 97.62, 98.70 and 97.02%, respectively, in diagnosing bipolar depression. Considering that our simple system gives promising results in diagnosing patients with bipolar depression from EEG, there is scope for further work with a larger sample size and different ages and genders.

Keywords Bipolar depression · EEG · Support vector machine · Welch periodogram · Classification

Introduction

In the last two decades, the integration of physics, mathematics and computer rules in clinical sciences has led to various biomedical engineering techniques and algorithms related to medicine, which have many applications in various fields of medicine, including neuroscience (Zhang et al. 2023). These engineering techniques help clinicians diagnose and monitor patients with an acceptable accuracy (Khaleghi et al. 2020a). Therefore, computational approaches have found a special place in medical sciences in recent years (Khaleghi et al. 2023). Data mining and artificial intelligence are two such computational approaches that are widely used in medical data analysis. These approaches are particularly useful in the analysis of genetic and brain data (Zia et al. 2022). For example, recent reviews have highlighted important applications of computational approaches, including machine learning and biological modeling, in neuroscience and psychiatry (Khaleghi et al. 2022).

The analysis of brain electrical activity and brain waves is a hot topic in biomedical engineering, neuropsychology and neuroscience because these electrical oscillations contain very important information about the typical and atypical functioning of people in real life. Electroencephalogram (EEG) signals, which originate directly from neuronal activity within different brain regions during resting or executive cognitive functions, are rich sources of brain functioning with several useful applications in neuropsychiatry for the purposes of prediction, diagnosis, classification and monitoring (Khaleghi et al. 2021; Moeini et al. 2014). Considering that a neuropsychiatric disease involves various brain abnormalities, examining brain

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fluctuations can provide helpful endophenotypes (Zarafshan et al. 2016; Moeini et al. 2017). These important fluctuations may provide reliable quantitative biomarkers to help clinicians understand the underlying neuropathological mechanisms involved in a disorder (Khaleghi et al. 2020b; Afzali et al. 2023). Accordingly, several EEG researchers have investigated bipolar depression and tried to reveal the relationship between this disorder and impairments in brain oscillations (Khaleghi et al. 2015a; Moeini et al. 2015). These EEG studies have shown disturbances in various EEG frequency bands in patients with bipolar depression (Degabriele and Lagopoulos 2009). For example, gamma and alpha bands are frequently reported to be impaired in bipolar depression, possibly due to dysfunction of the GABAergic system and the thalamus, respectively (Zhang et al. 2022). However, there is still doubt whether these impairments are caused by abnormal shifts in brain waves to lower/higher frequency bands or abnormalities in specific brain regions responsible for generating these oscillations. In addition, very few studies to date have utilized these EEG band abnormalities for the diagnosis of bipolar depression (Campos-Ugaz et al. 2023). In a recent study, alpha band abnormalities and K-nearest-neighbor classifier have been used for EEG classification of bipolar II disorder and healthy individuals, and an accuracy of 95.8% has been obtained (Khaleghi et al. 2019). In another study, convolutional neural network and deep learning based features have been proposed to diagnose bipolar disorder, and an accuracy of 96% has been obtained through this complex automatic system (Metin et al. 2022). In a resting-state EEG research, both linear and nonlinear analyzes along with gradient boosting classifier have been proposed to automatic diagnosis of bipolar disorder, and an accuracy of 94% has been obtained (Mateo-Sotos et al. 2022).

Considering that bipolar depression affects millions of people around the world and its correct early diagnosis is of great importance in the treatment process (Mohammadi et al. 2019, 2017, 2022; Khaleghi et al. 2018). Considering the importance of EEG frequency bands in investigating the neuropathology of neuropsychiatric disorders, in this study, we intend to use a Welch periodogram and different machine learning techniques for the automatic diagnosis of bipolar depression from EEG signals. The Welch technique is a method for estimating the power of EEG signals at different frequencies.

Materials and methods

Participants

20 patients with bipolar depression (15 females and 5 males) in the age range of 20 to 45 years (34.19 ± 4.79 years) and 25 healthy individuals (18 females and 7 males) in the age range of 20 to 45 years (33.62 ± 3.49 years) have participated in this research. The Edinburgh test was utilized to determine the handedness of participants, and only the right-handed subjects were included in the research. The patients with bipolar depression were diagnosed according to DSM-5 criteria (American Psychiatric Association and Association 2013), and this diagnosis was confirmed through psychiatric interviews performed by two experienced psychiatrists. Any intellectual disabilities and psychiatric comorbidities were ruled out by applying Raven's IQ test and Structured Clinical Interview for DSM Disorders (SCID) for all participants. Moreover, any neurological disorders (such as head trauma or epilepsy) were ruled out in all subjects. All patients were drug-naïve newly diagnosed people. Before starting the research, informed consent was obtained from all the subjects.

EEG data

EEG signal was recorded from each subject at a private psychiatric clinic using a standard digital electroencephalography apparatus (Nihon Kohden Cor., Tokyo, Japan). The signal recording was done in a quiet and noiseless environment while resting with eyes open for 8–10 min. The 10–20 electrode placement system was recruited to locate 19 Ag/AgCl electrodes on the scalp. These 19 EEG channels were placed on: FP1, FP2, F7, F3, FZ, F4, F8, T3, C3, CZ, C4, T4, T5, P3, PZ, P4, T6, O1, O2. A1 and A2 electrodes were utilized as references on the earlobes. The signals were recorded between 0.1 and 50 Hz, and the sampling frequency was fixed at 256 Hz.

Signal preprocessing

Figure 1 shows the flow diagram of our proposed system in this work. Preprocessing of EEGs was conducted through a Python program. Makoto's preprocessing pipeline was followed in this research to perform this step of signal processing. A Butterworth band pass finite impulse response (FIR) of 0.5–50 Hz was applied to brain signals. In this step, an FIR filter with zero phase shift was utilized to prevent distorting phase responses. Electrode interpolation was conducted through neighboring electrodes for the electrodes with very high artifacts and very low quality. Signals were re-referenced to the common average and then were decomposed through independent component analysis (ICA). Components containing muscle artifacts, movement artifact and eye blinks were determined using ICA and were then eliminated according to scalp maps, time courses and frequency spectrum. The cleaned components were then reconstructed, and an artifact-free EEG signal was formed for each subject.

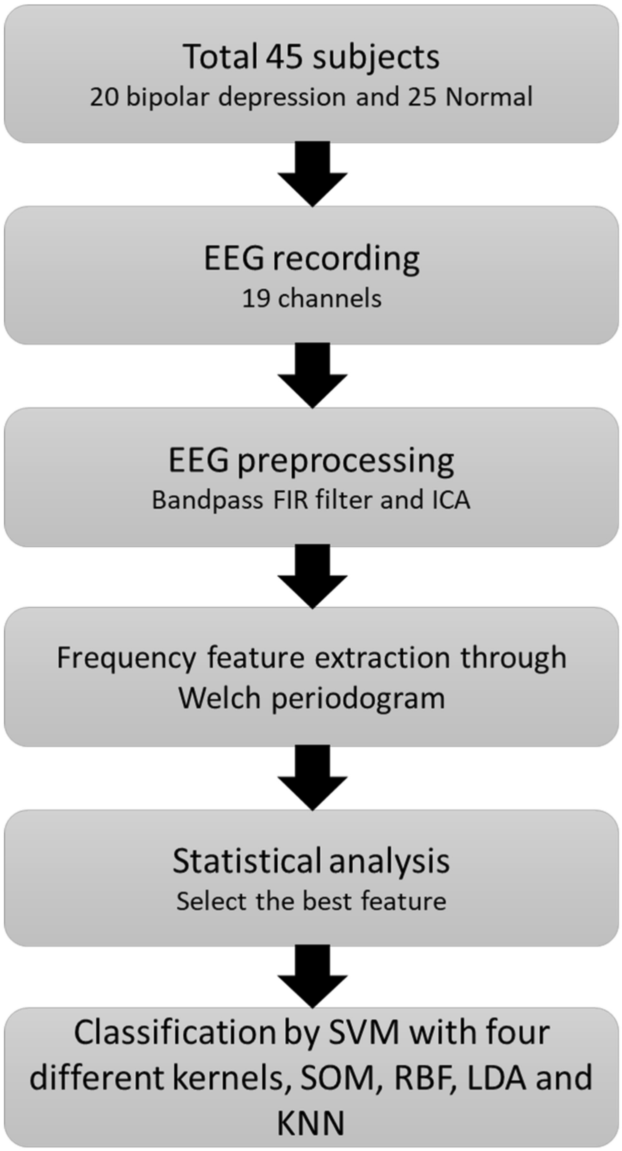

Fig. 1 Flow diagram of the proposed system to diagnose bipolar depression

Welch periodogram

Periodogram is a method based on fast Fourier transform (FFT) to estimate the power spectrum density (PSD) of a time series. Consider the time series s(n) of finite length. The PSD and FFT of this time series are (Zhao et al. 2013):

$$\hat{P}(f) = \frac{1}{N}|s(f)|^2 \tag{1}$$

where N is the length of S(n). At discrete frequency samples f(kΔf), observed through the above equation:

$$\hat{P}(f) = \frac{1}{N}|S(k)|^2 = \frac{1}{N}|FFT[s(n)]|^2 \, for \, K = 0.1.2 \ldots .N-1 \tag{2}$$

This method is convenient, and the computational cost is not too bad, but when the length of the time series is fixed or too small/large, the variance of the spectral estimation increases and the accuracy of the spectrum decreases. Therefore, Welch's method has been proposed to improve the accuracy of spectral estimation. In this study, Welch's method was used to extract relevant features from EEG frequency bands. This technique uses periodogram spectrum estimates, which are the outcome of converting EEG from the time domain to the frequency domain. In this method, the sampled data are segmented to decrease the variance of the periodogram, which can enhance the direct estimate of the spectrum. In this study, we used a Hanning window with a length of 128 samples and an overlap of 64. Therefore, we had a frequency resolution of 0.5 Hz. It should be noted that using the Hanning window as a non-rectangular window causes the relative independence of the segmentations and thus reduces the variance of the spectrum estimation (Mohammadi et al. 2016).

$$D_i(\omega) = \frac{1}{PQ}\left|\sum_{n=0}^{P-1} s_i(n)w(n)e^{-j\omega n}\right|^2. \quad for \, i = 1.2.3 \ldots .L \tag{3}$$

The mean energy of the window function Q is:

$$Q = \frac{1}{P}\sum_{n=0}^{P-1} w^2(n) \tag{4}$$

Finally, the PSD is obtained by:

$$PSD_w(\omega) = \frac{1}{L}\sum_{i=1}^{L} D_i(\omega) \tag{5}$$

Frequency features

After estimating the PSD using the Welch periodogram, the standard EEG frequency bands were determined: delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz) and gamma (30–45 Hz). Then the statistical features of power, mean, variance, skewness and Shannon entropy were extracted from each of the estimated frequency bands. The use of statistical features in the characterization of EEG signals is common because these features are easily implemented and have a low computational cost. At the same time, they contain important information about the EEG signal (Khaleghi et al. 2015b).

Statistical analysis

All statistical analyses in this study were done using SPSS version 21 software. First, the Shapiro–Wilk test was used to determine the distribution of the data. This test showed that our data has a normal distribution. Then, in order to compare the features extracted in two groups, analysis of variance (ANOVA) was used. The ANOVA test provides us with two parameters, P-value and F-value, based on which the best features can be selected to separate the two groups. In this way, the features that have the lowest P value and the highest F value will give us very good discrimination and separation.

Support vector machine (SVM)

SVM was proposed by Vapnik and Cortes in 1995 for two-class classification problems (Cortes and Vapnik 1995). This powerful classifier has been widely utilized by researchers to solve various nonlinear problems and classification tasks with small data samples (Zhang and Chen 2016; Ma et al. 2016). The important idea of SVM is how to discriminate two classes of data through a dimensionless vector space, which separates a vector space into two groups, called a hyperplane. We used SVM in this study because this classifier minimizes the expected risk in the test data and considers a margin around the class boundaries, which leads to increased generalizability of the results.

SVM uses a kernel function to transform the nonlinear classification problem into a linear one by increasing the dimensionality of the dataset. In this work, we examined four different SVM kernels to obtain the best classification performance in the diagnosis of bipolar depression. The original function of SVM is:

$$a_i = \left[\left(\omega \cdot b_i\right) + x\right] - 1 \geq 0 \,.\, i = 1.2 \ldots .l \tag{6}$$

where a_i represents the identifier generated by SVM ($a_i \in -1. + 1$). This can be transformed into a dual problem via the Lagrange coefficient as follows:

$$\min Q(y) = \frac{1}{2} \sum_{i.j=1}^{l} y_i y_j a_i a_j \cdot K\left(b_i b_j\right) - \sum_{i=1}^{l} y_i \tag{7}$$

where y_i represents Lagrange coefficients. K is the kernel function with the following equation:

$$K\left(a.a_i\right) = \frac{\exp\left(-\left|a - a_i\right|^2\right)}{g^2} \tag{8}$$

SVM with linear kernel

The linear kernel is the simplest type of kernel in SVM. In this model, SVM does not transform the data into higher dimensions. It is given by:

$$\min \frac{1}{m} \sum_{i=1}^{m} \xi_i + \frac{1}{c} \sum_{i=1}^{m} a_i \tag{9}$$

where i = 1,…, m and $\xi_i \geq 0$ are the stack variables. This kernel is very simple and only has the constant term c as the parameter. The linear kernel is usually utilized on relatively large datasets as raising the dimensionality on them does not certainly increase separability. Moreover, this kernel type is usually less prone to overfitting than nonlinear kernels (Wijayanto et al. 2019).

SVM with polynomial kernel

Unlike the linear kernel, this kernel works by inner product from a higher dimension space. This kernel is a generalized version of the linear kernel. The polynomial kernel is given by:

$$K\left(x_i.x_j\right) = \left(\gamma x_i^T x_j + r\right)^d .\gamma > 0 \tag{10}$$

where d, r and γ are kernel parameters. d = 2 is usually used in different problems because larger values may result in overfitting. We set the other two parameters to γ = 1 and r = 0.5 (Zhou and Jetter 2006).

SVM with radial basis function (RBF) kernel

The RBF kernel is the most widely utilized kernel in SVMs. The RBF kernel has good performance in various classification problems, and it is expressed as:

$$K\left(x_i.x_j\right) = \exp\left(-\gamma \|x_i - x_j\|^2\right).\gamma > 0 \tag{11}$$

where γ is the free parameter to scale the extent of influence, two samples have on each other. Here, we set γ = 0.5 ().

SVM with sigmoid kernel

The idea of this kernel originates from artificial neural networks. The sigmoid kernel is defined by:

$$K\left(x_i.x_j\right) = \tanh\left(\gamma x_i^T x_j + r\right) \tag{12}$$

This kernel is commonly applied in a neural network for classification purposes. The SVM with a sigmoid kernel has a complicated structure that makes its results difficult to interpret (Prajapati et al. 2010).

Self-organizing map (SOM)

In our study, we employed the self-organizing map (SOM) technique to categorize features derived from EEG data of individuals with autism and those without autism. The SOM method, widely used in various domains such as prediction, classification, and clustering problems, is an unsupervised neural network approach. In this algorithm, each neuron 'i' is associated with a weight vector whose dimension matches that of the input data. Initially, the winning neuron is determined using the following equation:

$$i^*(t) = argmin\{g_i(x(t))\}.g_i(x(t)) = \|x(t) - w_i(t)\| \tag{13}$$

where $w_i(t)$ is the weight vector that must be updated based on the following equation:

$$\Delta w_i(t) = \alpha(t)h(i^*.i;t)\left[x(t) - w_i(t)\right] \tag{14}$$

where h(.) denotes the neighborhood function with the following definition:

$$h(i^*.i;t) = \exp\left(-\|r_i(t) - r_{i^*}(t)\|^2/\sigma^2(t)\right) \tag{15}$$

$\|r_i(t) - r_{i^*}(t)\|$ defines the distance between i and i^*, σ(t) is the neighborhood radius and α(t) is the learning rate parameter.

In order for SOM to categorize data, it is necessary to assign labels to the output neurons. Once the SOM has been trained, a winning neuron is assigned to each training vector. Subsequently, the label of each training vector is established. Finally, the label of the winning neuron is determined based on the most frequently occurring class labels among the training vectors. For this particular study, the initial neighborhood parameter was initially set at 3 and then decreased to 1 after 100 iterations. Additionally, α(t) was fixed at 0.8.

Radial basis function (RBF)

The Radial Basis Function (RBF) consists of three layers: an input layer, a hidden layer, and an output layer. The number of neurons in the input layer is determined by the number of extracted features. The optimal number of neurons in the hidden layer is determined based on the training data to achieve the best classification performance. In the output layer, a hard limiter function is used in the neuron to assign the feature to a specific class. A value of 0 represents the normal group, while a value of 1 represents the patient group. To calculate the activation of the hidden layer, the weighted inputs to the radial basis transfer function are determined by calculating the Euclidean distance between the input vector(s) and a weight matrix. This distance is then multiplied by a bias value. Increasing the distance between the input vector(s) and the weight vector leads to a decrease in the output value, and vice versa. During the RBF training process, the biases and weights are updated to minimize the classification error using the mean squared error criterion.

Linear discriminant analysis (LDA)

LDA is an expansion of Fisher's linear discriminant to find linear combinations of samples that separate two classes of events or objects. It is very associated with regression analysis and analy-sis of variance, which attempt to specify one dependent variable as a linear combination of other samples. LDA attempts to solve an optimal discrimination projection matrix W_{opt}:

$$W_{opt} = \underset{W}{\operatorname{argmax}}\left|\frac{W^T S_b W}{W^T S_t W}\right| \tag{16}$$

where S_b and S_t are the scatter matrices with the following definitions:

$$S_b = \sum_{p=1}^{q} n_p(\mu_p - \mu)(\mu_p - \mu)^T \tag{17}$$

$$S_t = \sum_{p=1}^{q} n_p(\mu_p - \mu)(\mu_p - \mu)^T + \sum_{p}(x_p - \mu_{k_p})(x_p - \mu_{k_p})^T \tag{18}$$

where S_b is the between-class dispersion matrix and S_t is the overall dispersion matrix.

K-nearest neighborhoods (KNN)

It is a nonparametric approach of pattern identification utilized for various classification prob-lems. Using KNN, samples are classified based on the majority vote of their closest neighbors. Indeed, samples are appointed to the class that is most common among their K nearest neighbors. Here, we considered KNN as a distinguishing nonlinear classifier that operates according to the Mahalabonis distance:

$$D_c(x) = \sqrt{(x - \mu_c)M_c^{-1}(x - \mu_c)^T} \tag{19}$$

$D_c(x)$ denotes the Mahalabonis distance which is determined by the correlation between data points through the covariance matrix (M_c) and the mean (μ_c) of data points. In the present re-search, K = 6.

Results

Statistical analysis showed no significant difference between the two groups in terms of age and gender ($P > 0.05$). The Welch periodogram was applied to all 19 EEG channels, and the five mentioned statistical features were calculated from the five mentioned frequency bands for each subject. Therefore, the total feature vector contained 475 components (5 features × 5 bands × 19 channels). Figure 2 shows an example of the PSD of frontal channels (F3 and F4) for a patient with bipolar depression and a healthy subject. Also, Fig. 3 shows an example of a spectrogram and beta band spectrogram of FP2 channel for a patient with bipolar depression and a healthy subject. As seen in these two figures, there is a difference in the frequency patterns of EEG signals of the two groups, which is the basis of our proposed system for disease diagnosis.

Figure 4 shows the grand average of the power of five frequency bands, delta, theta, alpha, beta and gamma, for both groups. As shown, the difference between the two groups is more evident in the delta, alpha and beta frequency bands. The features selected by the statistical analysis based on the P-value and F-statistics that provide us with the most discriminability between the two groups are shown in Table 1. As shown in this table, 17 features were selected by statistical analysis as a subset of features for classification in the next step. It is worth noting that most of these features are

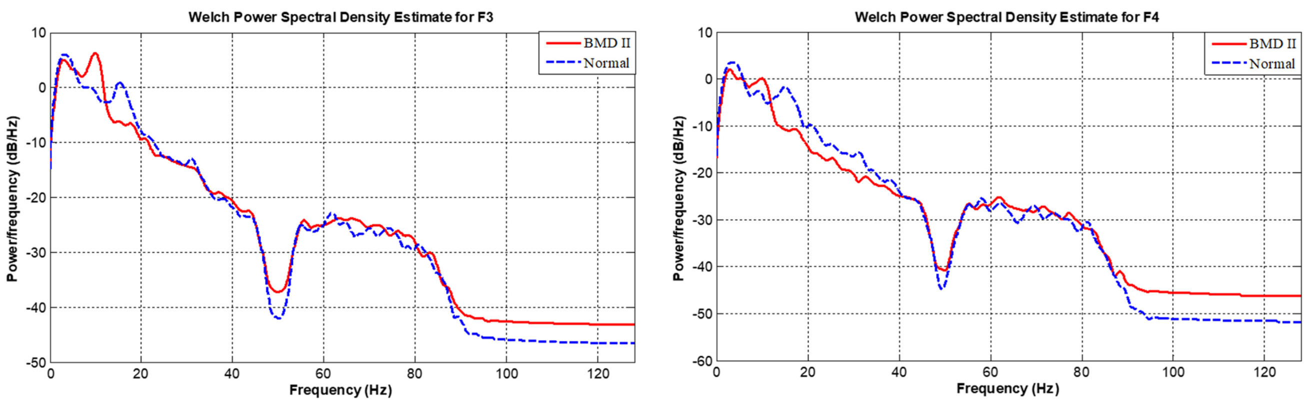

Fig. 2 An example of the power spectrum density of F3 and F4 channels for a patient with bipolar depression (red line) and a healthy person (blue line)

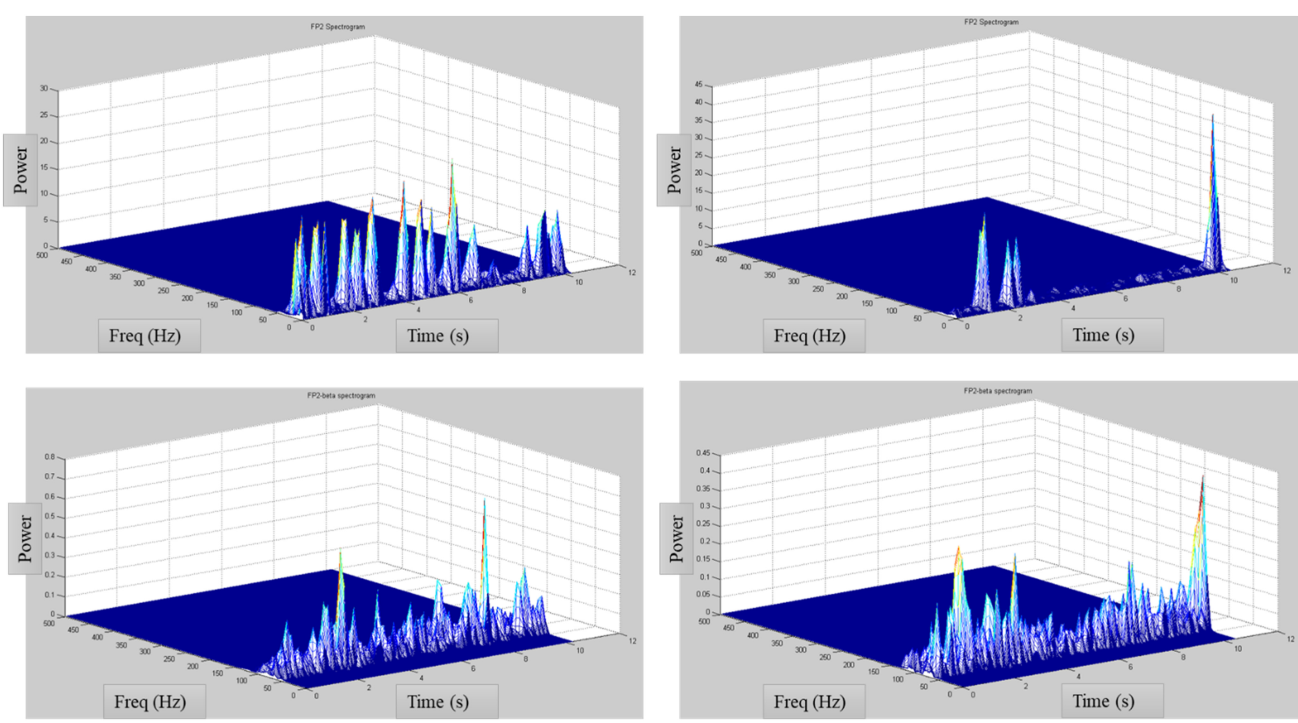

Fig. 3 An example of the spectrogram (top diagrams) and beta band spectrogram (bottom diagrams) of FP2 channel for a healthy subject (left diagrams) and a patient with bipolar depression (right diagrams)

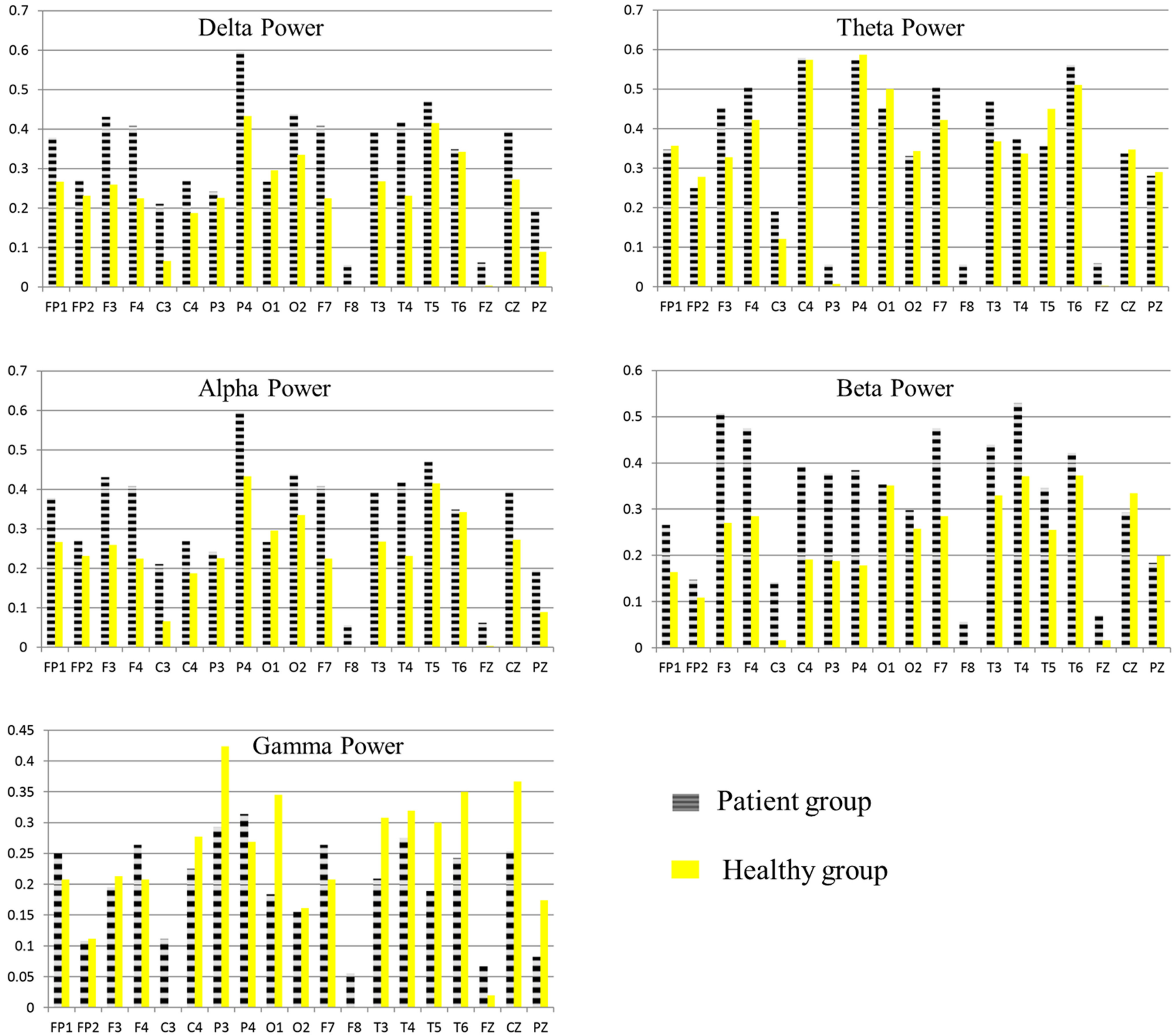

Fig. 4 The grand average of the power of EEG frequency bands in both patient and healthy groups

located in the frontal area and are entropy-type. In the classification stage, we used both the total feature vector with 475 components and this subset of features with 17 components. It should be noted that the training and testing processes of the classifiers were carried out with the leave-one-out cross-validation method.

Accuracy, sensitivity and specificity were calculated in this study to measure classification performance. These metrics were calculated based on the concepts of false negative (FN), false positive (FP), true negative (TN), and true positive (TP), which represent cases that were incorrectly or correctly identified as negative or positive cases (Lever 2016).

$$\begin{aligned} Accuracy &= \frac{TP+TN}{N+P}. Sensitivity \\ &= \frac{TP}{TP+FN}. Spesificity \\ &= \frac{TN}{TN+FP} \end{aligned} \tag{20}$$

The performance of different classifiers is assessed based on the above metrics, as shown in Tables 2 and 3.

Table 2 shows the performance of different classifiers for diagnosing bipolar depression using all features extracted from EEG frequency bands (i.e., 475 features). According to this table, SVM with RBF kernel outperformed other kernels with accuracy, sensitivity and specificity of 92.85%,

Table 1 The results of the ANOVA test to identify features with significant differences ($P < 0.01$) with larger F-values between two groups (bipolar depression group and healthy control group)

Features	Patients group (n = 16) mean ± SD	Healthy group (n = 16) mean ± SD	F-statistics	P-value
F3-alpha-entropy	0.018 ± 0.169	0.013 ± 0.132	20.301	0.001
F3-alpha-mean	0.248 ± 0.030	0.062 ± 0.139	10.070	0.007
F3-beta-mean	0.120 ± 0.025	0.063 ± 0.039	9.577	0.008
F3-alpha-skewness	0.257 ± 0.001	0.259 ± 0.002	9.250	0.009
F3-beta-entropy	0.173 ± 0.023	0.206 ± 0.018	9.501	0.008
C3-alpha-entropy	0.171 ± 0.024	0.134 ± 0.013	13.412	0.003
C4-gamma-skewness	0.244 ± 0.009	0.246 ± 0.001	13.510	0.002
C4-alpha-entropy	0.162 ± 0.018	0.133 ± 0.013	13.360	0.003
F4-gamma-skewness	0.245 ± 0.001	0.243 ± 0.001	9.372	0.008
F4-alpha-entropy	0.114 ± 0.190	0.143 ± 0.153	11.544	0.004
P3-gamma-skewness	0.246 ± 0.001	0.242 ± 0.002	10.835	0.005
P4-alpha-entropy	0.129 ± 0.019	0.158 ± 0.019	9.146	0.009
P4-beta-entropy	0.156 ± 0.023	0.194 ± 0.021	10.394	0.006
O2-alpha-skewness	0.257 ± 0.001	0.261 ± 0.001	10.822	0.005
F7-gamma-skewness	0.240 ± 0.003	0.232 ± 0.002	9.372	0.008
F7-alpha-entropy	0.114 ± 0.020	0.147 ± 0.015	11.544	0.004
T4-alpha-entropy	0.120 ± 0.021	0.154 ± 0.014	11.039	0.005

Table 2 Classification results for the diagnosis of bipolar depression using different machine learning techniques and total feature vector

Classifiers	Accuracy (%)	Sensitivity (%)	Specificity (%)
SVM with linear kernel	90.14	89.36	88.97
SVM with polynomial kernel	90.41	91.20	90.05
SVM with RBF kernel	92.85	93.62	92.00
SVM with sigmoid kernel	89.64	88.37	90.12
SOM	94.14	94.88	93.69
RBF	93.02	92.27	93.38
LDA	91.50	91.94	91.11
KNN	88.76	90.26	87.10

Table 3 Classification results for the diagnosis of bipolar depression using different machine learning techniques and selected features through statistical analysis

Classifiers	Accuracy (%)	Sensitivity (%)	Specificity (%)
SVM with linear kernel	93.08	94.10	93.68
SVM with polynomial kernel	94.41	94.49	93.60
SVM with RBF kernel	96.12	98.21	94.04
SVM with sigmoid kernel	94.23	92.59	93.98
SOM	97.62	98.70	97.02
RBF	96.41	96.49	95.32
LDA	93.49	93.98	92.80
KNN	91.71	92.63	90.47

93.62% and 92%, respectively. However, neural networks (i.e., SOM and RBF) showed better performance than other classifiers. Classification using RBF resulted in 93.02% accuracy, 92.27% sensitivity and 93.38% specificity. Also, SOM achieved 94.14% accuracy, 94.88% sensitivity and 93.69% specificity in our two-class classification problem. Furthermore, Table 3 shows the performance of different classifiers for diagnosing bipolar depression using selected features through statistical analysis (i.e., the subset with 17 features). Again, SVM with RBF kernel outperformed other kernels with accuracy, sensitivity and specificity of 96.12%, 98.21% and 94.04%, respectively. Again, SOM and RBF neural networks outperformed other classification models. Classification using RBF resulted in 96.41%

accuracy, 96.49% sensitivity and 95.32% specificity. Also, SOM achieved 97.62% accuracy, 98.70% sensitivity and 97.02% specificity in our two-class classification problem.

Figure 5 compares the accuracy obtained from different SVM kernels for the entire feature set and feature subset selected by statistical analysis. As indicated, the classification performance increased by 3–5% using the selected feature subset.

Discussion

In this study, we investigated the potential of Welch periodogram-based features and different machine learning techniques to diagnose bipolar depression through EEG analysis. Our results showed that SOM neural network and features selected by statistical analysis could provide good accuracy (about 97.50%) for this task. The classification results obtained in this work are similar to previous similar studies. As mentioned in the introduction, the accuracy obtained in previous studies for the diagnosis of bipolar depression was in the range of 94–96% (Khaleghi et al. 2019; Metin et al. 2022; Mateo-Sotos et al. 2022). However, very few similar studies have been conducted so far, and the heterogeneity between these studies makes it difficult to compare results. Considering there is no public EEG database for bipolar depression, each study was conducted on a unique (researcher-made) database. A different sample size was used in previous studies compared to the present study, and the signal recording protocol was not the same in all studies. In addition, the characteristics of the participants in each study are different. As a result, it is not possible to provide a precise comparison between the proposed methods of each study. However, considering the lower computational complexity and cost of our proposed method and the good accuracy obtained in this study compared to previous studies, it seems that our diagnostic system has more applicability in clinical settings.

In this work, we compared four SVM kernels for our two-group classification task. Although all kernels did well on this problem, the RBF kernel had the best classification performance. Kernel functions are very strong mathematical tools for exploring high-dimensional spaces. They enable us to perform linear discriminant on a nonlinear manifold, which may lead to greater accuracy and robustness than conventional linear models (). RBF kernel is a strong and widely used kernel in SVM. Unlike polynomial or linear kernel functions, RBF is more efficient and complex at the same time, which can combine several polynomial kernels multiple times with different degrees to project separable nonlinear data into higher dimensional spaces so that using a hyperplane can be separated (Kuo et al. 2013). However, SOM and RBF neural networks provided better classification results than other conventional classifiers for the diagnosis of bipolar depression. Non-linearity, flexibility and robustness against noise are among the advantages of neural networks over classifiers such as SVM, LDA and KNN, which improve the classification performance.

Entropy, among other features, made the most difference between the two groups. When viewed from an information theory perspective, entropy determines the amount of information in the system required to describe the microstate of the system clearly. Entropy is a measurable physical property to describe the state of randomness and uncertainty in a system (Jie et al. 2014). Due to the enormous complexity of the human brain system and the highly nonlinear nature of the EEG signal, entropy can potentially explore more and finer details of the brain's electrical activity and reveal the neuropathological mechanisms of bipolar depression compared to healthy brain function. Consistent with this finding, there are many EEG studies that have used the entropy feature to diagnose and classify various diseases (Catherine Joy et al.

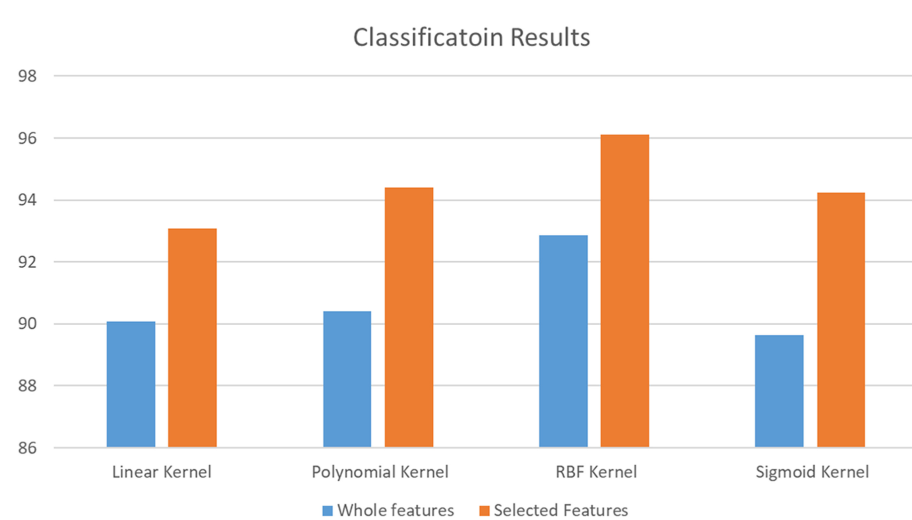

Fig. 5 Comparison of accuracy of SVM classifier with different kernels based on input data (total feature vector or features selected by statistical analysis

2022; Srinivasan et al. 2007; Acharya et al. 2015; Hadoush et al. 2019). In addition, most of the significant differences between the two groups were located in the frontal region of the brain. Consistent with this finding, previous EEG and neuroimaging studies have reported different pathologies and abnormalities in this brain region in patients with bipolar depression compared to healthy individuals (Scaini et al. 2020; Başar et al. 2012).

The strength of our work is to present a simple semi-automatic system based on the Welch periodogram and different machine learning techniques with the minimal computational cost for diagnosing bipolar depression from EEG signals. However, limitations such as the small sample size could reduce the generalizability of the findings of the present study. In addition, in this study, the resting state EEG signal was analyzed. In contrast, previous neurophysiological studies have shown that patients with bipolar depression exhibit important neuropathological mechanisms in different states of arousal. Therefore, different EEG recording protocols should be considered in future studies.

Conclusion

In this article, the diagnosis of bipolar depression from EEGs has been investigated through Welch periodogram-based features with different classifiers, including SVM with different kernels, LDA, KNN, and RBF and SOM neural networks. The effectiveness of these features was checked by statistical analysis, and it was observed that entropy has more discrimination in diagnosing patients. In addition, the effectiveness of differeng classifiers were evaluated, and the SOM neural network yielded the maximum classification accuracy, sensitivity, and specificity. Considering that our simple system gives promising results in diagnosing patients with bipolar depression from EEG, there is scope for further work with a larger sample size and different ages and genders.

Author contributions HW: methodology, formal analysis, software, validation. SZ: writing-original draft preparation, conceptualization, supervision, project administration. YL: language review, methodology, software, formal analysis. YS: methodology, software, validation, language review.

Data availability statement The authors do not have permissions to share data.

Declarations

Conflict of interest The authors declare no competing interests.

References

Acharya, U.R., Fujita, H., Sudarshan, V.K., Bhat, S., Koh, J.E.: Application of entropies for automated diagnosis of epilepsy using EEG signals: a review. Knowl.-Based Syst. **88**, 85–96 (2015)

Afzali, A., Khaleghi, A., Hatef, B., Akbari Movahed, R., Pirzad, J.G.: Automated major depressive disorder diagnosis using a dual-input deep learning model and image generation from EEG signals. Waves Random and Complex Media (2023). https://doi.org/10.1080/17455030.2023.2187237

American Psychiatric Association, D., Association, A.P.: Diagnostic and statistical manual of mental disorders. American psychiatric association, Washington DC (2013)

Başar, E., Güntekin, B., Atagün, I., Turp Gölbaşı, B., Tülay, E., Özerdem, A.: Brain's alpha activity is highly reduced in euthymic bipolar disorder patients. Cogn. Neurodyn. **6**, 11–20 (2012)

Campos-Ugaz, W.A., Garay, J.P.P., Rivera-Lozada, O., Diaz, M.A.A., Fuster-Guillén, D., Arana, A.A.T.: An overview of bipolar disorder diagnosis using machine learning approaches: clinical opportunities and challenges. Iran. J. Psychiatry **18**(2), 237–247 (2023)

Catherine Joy, R., Thomas George, S., Albert Rajan, A., Subathra, M.: Detection of ADHD from EEG signals using different entropy measures and ANN. Clin. EEG Neurosci. **53**(1), 12–23 (2022)

Cortes, C., Vapnik, V.: Support-Vector Networks. Machine Learn. **20**, 273–297 (1995)

Degabriele, R., Lagopoulos, J.: A review of EEG and ERP studies in bipolar disorder. Acta Neuropsychiatrica. **21**(2), 58–66 (2009)

Hadoush, H., Alafeef, M., Abdulhay, E.: Brain complexity in children with mild and severe autism spectrum disorders: analysis of multiscale entropy in EEG. Brain Topogr. **32**, 914–921 (2019)

Jie, X., Cao, R., Li, L.: Emotion recognition based on the sample entropy of EEG. Bio-Med. Mater. Eng. **24**(1), 1185–1192 (2014)

Khaleghi, A., Sheikhani, A., Mohammadi, M.R., Nasrabadi, A.M.: Evaluation of cerebral cortex function in clients with bipolar mood disorder I (BMD I) compared with BMD II using QEEG analysis. Iran. J. Psychiatry **10**(2), 93 (2015a)

Khaleghi, A., Sheikhani, A., Mohammadi, M.R., Nasrabadi, A.M., Vand, S.R., Zarafshan, H., et al.: EEG classification of adolescents with type I and type II of bipolar disorder. Australas. Phys. Eng. Sci. Med. **38**, 551–559 (2015b)

Khaleghi, A., Mohammadi, M.R., Zandifar, A., Ahmadi, N., Alavi, S.S., Ahmadi, A., et al.: Epidemiology of psychiatric disorders in children and adolescents; in Tehran, 2017. Asian J. Psychiatr. **37**, 146–153 (2018)

Khaleghi, A., Mohammadi, M.R., Moeini, M., Zarafshan, H., Fadaei, F.M.: Abnormalities of alpha activity in frontocentral region of the brain as a biomarker to diagnose adolescents with bipolar disorder. Clin. EEG Neurosci. **50**(5), 311–318 (2019)

Khaleghi, A., Mohammadi, M.R., Jahromi, G.P., Zarafshan, H.: New ways to manage pandemics: Using technologies in the era of covid-19: a narrative review. Iran. J. Psychiatry **15**(3), 236 (2020a)

Khaleghi, A., Birgani, P.M., Fooladi, M.F., Mohammadi, M.R.: Applicable features of electroencephalogram for ADHD diagnosis. Res. Biomed. Eng. **36**, 1–11 (2020b)

Khaleghi, A., Mohammadi, M.R., Shahi, K., Motie, N.A.: A neuronal population model based on cellular automata to simulate the electrical waves of the brain. Waves Random Complex Media (2021). https://doi.org/10.1080/17455030.2021.1938746

Khaleghi, A., Mohammadi, M.R., Shahi, K., Nasrabadi, A.M.: Computational neuroscience approach to psychiatry: a review on theory-driven approaches. Clin. Psychopharm. Neurosci. **20**(1), 26 (2022)

Khaleghi, A., Mohammadi, M.R., Shahi, K., Nasrabadi, A.M.: Possible neuropathological mechanisms underlying the increased complexity of brain electrical activity in schizophrenia: a computational study. Iran. J. Psychiatry (2023). https://doi.org/10.18502/ijps.v18i2.12363

Kuo, B.-C., Ho, H.-H., Li, C.-H., Hung, C.-C., Taur, J.-S.: A kernel-based feature selection method for SVM with RBF kernel for hyperspectral image classification. IEEE J. Select. Topics Appl. Earth Obs. Remote Sens. **7**(1), 317–326 (2013)

Lever, J.: Classification evaluation: It is important to understand both what a classification metric expresses and what it hides. Nat. Methods **13**(8), 603–605 (2016)

Ma, Y., Ding, X., She, Q., Luo, Z., Potter, T., Zhang, Y.: Classification of motor imagery EEG signals with support vector machines and particle swarm optimization. Comput. Math. Methods Med. **2016**, 1–8 (2016)

Mateo-Sotos, J., Torres, A., Santos, J., Quevedo, O., Basar, C.: A machine learning-based method to identify bipolar disorder patients. Circ. Syst. Signal Process. **41**(4), 2244–2265 (2022)

Metin, B., Uyulan, Ç., Ergüzel, T.T., Farhad, S., Çifçi, E., Türk, Ö., et al.: The deep learning method differentiates patients with bipolar disorder from controls with high accuracy using EEG data. Clin. EEG and Neurosci. (2022). https://doi.org/10.1177/15500594221137234

Moeini, M., Khaleghi, A., Amiri, N., Niknam, Z.: Quantitative electroencephalogram (QEEG) spectrum analysis of patients with schizoaffective disorder compared to normal subjects. Iran. J. Psychiatry **9**(4), 216 (2014)

Moeini, M., Khaleghi, A., Mohammadi, M.R.: Characteristics of alpha band frequency in adolescents with bipolar II disorder: a resting-state QEEG study. Iran. J. Psychiatry **10**(1), 8 (2015)

Moeini, M., Khaleghi, A., Mohammadi, M.R., Zarafshan, H., Fazio, R.L., Majidi, H.: Cortical alpha activity in schizoaffective patients. Iran. J. Psychiatry **12**(1), 1 (2017)

Mohammadi, M.R., Khaleghi, A., Nasrabadi, A.M., Rafieivand, S., Begol, M., Zarafshan, H.: EEG classification of ADHD and normal children using non-linear features and neural network. Biomed. Eng. Lett. **6**, 66–73 (2016)

Mohammadi, M.R., Ahmadi, N., Kamali, K., Khaleghi, A., Ahmadi, A.: Epidemiology of psychiatric disorders in iranian children and adolescents (ircap) and its relationship with social capital, life style and parents' personality disorders: study protocol. Iran. J. Psychiatry **12**(1), 66 (2017)

Mohammadi, M.R., Ahmadi, N., Khaleghi, A., Mostafavi, S.A., Kamali, K., Rahgozar, M., et al.: Prevalence and correlates of psychiatric disorders in a national survey of Iranian children and adolescents. Iran. J. Psychiatry **14**(1), 1 (2019)

Mohammadi, M.R.S., Alavi, S.S., Gharaati Sotoudeh, H., Khaleghi, A., Ahmadi, N., Hooshyari, Z., et al.: Prevalence and socio-demographic factors of bipolar mood disorders in children and adolescents: identification of the principal predictors. Iran. Rehabilitation J **20**(2), 149–160 (2022)

Patle A, Chouhan DS, editors. SVM kernel functions for classification. 2013 International Conference on Advances in Technology and Engineering (ICATE); 2013: IEEE.

Prajapati GL, Patle A, editors. On performing classification using SVM with radial basis and polynomial kernel functions. 2010 3rd International Conference on Emerging Trends in Engineering and Technology; 2010: IEEE.

Scaini, G., Valvassori, S.S., Diaz, A.P., Lima, C.N., Benevenuto, D., Fries, G.R., et al.: Neurobiology of bipolar disorders: a review of genetic components, signaling pathways, biochemical changes, and neuroimaging findings. Brazi. J. Psychiatry **42**, 536–551 (2020)

Srinivasan, V., Eswaran, C., Sriraam, N.: Approximate entropy-based epileptic EEG detection using artificial neural networks. IEEE Trans. Inf Technol. Biomed. **11**(3), 288–295 (2007)

Wijayanto I, Hartanto R, Nugroho HA, editors. Higuchi and katz fractal dimension for detecting interictal and ictal state in electroencephalogram signal. 2019 11th International Conference on Information Technology and Electrical Engineering (ICITEE); 2019

Zarafshan, H., Khaleghi, A., Mohammadi, M.R., Moeini, M., Malmir, N.: Electroencephalogram complexity analysis in children with attention-deficit/hyperactivity disorder during a visual cognitive task. J. Clin. Exp. Neuropsychol. **38**(3), 361–369 (2016)

Zhang, T., Chen, W.: LMD based features for the automatic seizure detection of EEG signals using SVM. IEEE Trans. Neural Syst. Rehabil. Eng. **25**(8), 1100–1108 (2016)

Zhang, G., Li, H., Xiao, C., Sobhani, B.: Multi-aspect analysis and multi-objective optimization of a novel biomass-driven heat and power cogeneration system; utilization of grey wolf optimizer. J. Clean. Prod. **355**, 131442 (2022)

Zhang, L., Guo, Q., Liu, M., Yang, Na., Gao, R., Sobhani, B.: Optimal dispatch of dynamic power and heat considering load management, water pump system, and renewable resources by grasshopper optimization algorithm. J. Energy Storage **57**, 106166 (2023)

Zhao, L., He, Y.: Power spectrum estimation of the welch method based on imagery EEG. Appl. Mech. Mater. **278–280**, 1260–1264 (2013)

Zhou, D.-X., Jetter, K.: Approximation with polynomial kernels and SVM classifiers. Adv. Comput. Math. **25**(1–3), 323–344 (2006)

Zia, A., Aziz, M., Popa, I., Khan, S.A., Hamedani, A.F., Asif, A.R.: Artificial intelligence-based medical data mining. J. Personal. Med. **12**(9), 1359 (2022)