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Statistical feature-based EEG signals classification using ANN and SVM classifiers for Parkinson's disease detection

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Abstract: Parkinson's disease (PD) is a neurological disorder which is progressive in nature. Although there is no cure to this disease, symptomatic treatments are available. These treatments can slow the progressive development of the symptoms. Medications can treat some of the symptoms of the PD up to a great extent that in turn may help the patients to live a normal life. Besides these medications, the patients can also be provided with various therapies based on the types of their symptoms. But for providing any treatment, detection of its symptoms at an early stage is very important. This can reduce its future complexities considerably. Early diagnosis along with proper medications may treat the symptoms of PD significantly. This motivates to propose a new and effective methodology for detection and analysis of PD. In this work, an approach has been proposed for identification of PD patients by using Electroencephalogram (EEG) signals. Here, the EEG signals of normal persons and PD patients are processed in three stages. First, the raw EEG signals are pre-processed for removal of noises and artefacts present. Out of various techniques, Wavelet transform is used for this purpose. In the MATLAB environment, de-noising can be executed by using the in-built functions. Performances of the de-noising techniques are examined with the performance parameters namely Root Mean Square Error (RMSE) as well as Signal to Noise Ratio (SNR). In the second stage, statistical features are extracted from the pre-processed EEG signals. In this work, five statistical features are considered for performing the classification. In the final stage, the extracted features are classified using Artificial Neural Network (ANN) and Support Vector Machine (SVM) techniques. ANN is an efficient classifier that predicts the human brain's working manners. SVM on the other hand has been proven as one of the most prevailing classification algorithms that gives highly accurate and robust results. This is a novel approach of analyzing the performances of the classification techniques by evaluating the best performing feature. In both the classifiers accuracy, precision, sensitivity and specificity are calculated from the confusion matrix evaluated from the values of the statistical features. In ANN, results using six different training algorithms at different hidden layers are calculated and compared. This proves the training algorithm Levenberg-Marquardt back-propagation with hidden layer 20 as the best combination for performing the classification. From the results it is seen that both ANN and SVM classifiers provide significant classification accuracies of 94.7% and 96.5% respectively. Amongst the five considered features, Mean performs the best in terms of classification accuracy.

Introduction

The peripheral or central nervous system stimulates neurological disorders. Functional and structural degeneration of this nervous system in a progressive manner is characteristic of neurodegenerative disorders. Parkinson's is one of the common diseases of this type.

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Although it is not fatal early diagnosis of PD carries great importance as it affects not only the patient's physical health but also the mental health. Some PD cases are found to be hereditary, whereas, in others, there was no history of PD in their families. Now a day, many studies claim that PD may be caused by genetic factors, environmental issues or a combination of these two. The majority of the symptoms of PD are of motor types. Besides this, some non-motor types of symptoms are also experienced by the patients. Through simple observation, the neurological symptoms of PD cannot be assessed. For this purpose, advanced methodologies need to be formulated to analyse the human brain or the whole nervous system of human beings (Mostafa et al., 2018).

PD occurs due to the loss of Dopamine in the brain. Dopamine is the neurotransmitter of the brain. Loss of Dopamine has resulted from the loss of neurons in one specific area of the brain called substancia migra. The neurons of this region produce Dopamine. The Dopamine produced in the substancia migra regulates all the motor movement of the body. Hence PD is sometimes called a movement disorder. It functions in a suitable balance with other neurotransmitters to maintain coordination with numerous nervous system cells. Insufficient Dopamine causes a misbalance of this coordination, resulting in various PD symptoms in the patient. The person suffering from PD does not lose neurons from the substancia migra only. There are losses of neurons in some other parts of the brain too. This results in various non-movement types of symptoms in those patients.

Diagnosis of PD completely depends on its clinical symptoms. Motor-related symptoms get more importance in such cases. But these symptoms appear very late, which results in a delayed diagnosis of the disease (Yang et al., 2022). Although it has no cure, detection of its symptoms at an early stage can help doctors to provide appropriate treatment to the patient. Proper medications can treat some of the symptoms of PD up to a great extent that, in turn, may help the patients to live a normal life. Besides these medications, the patient can also be provided various therapies by simulating their brains in order to reactivate the neurons that produce dopamine. This may result in lowering the rate of progress of its symptoms (Govindu and Palwe, 2023).

For analyzing the brain dynamics of the patient for the purpose of identification of PD, several tools exist. For the current analysis we are using Electroencephalogram (EEG). EEGs are basically the electrical activities of the brain. Although the electrical signal generated by a single neuron is very hard to record, but the signals generated by thousands of neurons can be well recorded. It can be recorded by using appropriate electrodes. Based on the kind of application, these electrodes are placed over the scalp (non-invasive) or on some interior brain sections (invasive) (Kumar and Bhubaneswari, 2012).

In this reported work, EEGs of two categories of persons are considered for carrying out the analysis. One category of persons is with PD and the other is without the PD. As an initial phase of the processing, an appropriate de-noising technique is applied in order to remove any unwanted information contained in the raw EEG. After the application of the pre-processing steps, features from these EEGs are extracted through some statistical means. Mean, energy, standard deviation, skewness and kurtosis are the features considered in this work (Gopika et al., 2016). In order to differentiate the features of the two categories of persons, ANN and SVM classifiers are applied.

Studies have revealed that in last few years, researchers have significantly adopted machine learning algorithms in research related to the detection or diagnosis of PD. Applications of these algorithms in the medical sector have also increased considerably. Machine learning techniques have enabled healthcare practitioners to extract meaningful information from biomedical signals or samples in an automatic or semi automatic manner (Mei et al., 2021).

Artificial Neural Network (ANN) is a computational technique often used in machine learning (Belakhdar et al., 2016). This technique is inspired by the anatomical and functional structure of the human neural network and hence nodes are designed to create an artificial network in analogous to the networks of the biological neurons to solve various complex problems. ANN predicts the human brain's working ways, although it is significantly distinct from the brain. A basic model of ANN is shown in Figure 1.

SVM is another machine learning algorithm that can be effectively used for the classification of two classes. SVM is a supervised type of machine-learning algorithm (Hosseini et al., 2021). In this algorithm, data are plotted as points in the space of n-dimensions, where n represents the number of features considered for the classification. The data points nearest to the hyper planes are called the support vectors. The coordinates of the data points of the space are the values of the features. Classification is then performed by identifying hyper planes that differentiate the two classes in the best possible way. A basic model of the SVM classifier is shown in Figure 2.

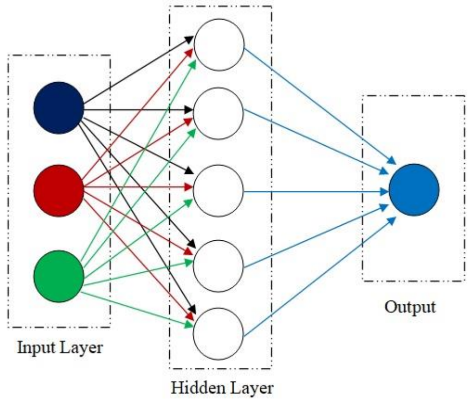

Figure 1. Basic model of ANN

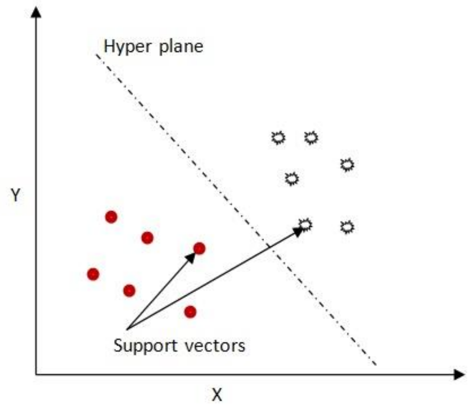

Figure 2. Basic model of SVM

Using SVM algorithm, both linear and non-linear classification problems can be solved. In the case of linear separation problems, linear hyper planes solve the purpose. Again in the case of Non-linear separation problems, Karnel trick can be used. Over time, researchers have established the SVM as one of the most prevailing classification algorithms by evaluating highly accurate and robust results (Rana et al., 2022).

The primary goal of this research is to detect PD by classifying the EEG signals of the affected and the normal categories of persons with good accuracies. ANN and the SVM are the types of classifiers selected for the purpose. For the said classifications, five statistical features are considered. The aim also includes providing the best-performing feature out of those considered for the current work in terms of classification accuracies.

Various approaches for the detection and diagnosis of PD were reported by researchers. Some of them have used speech or audio signals as a tool for the purpose while some others have analysed EEG signals to evaluate the outcomes. Some of these methodologies, considered in the literature, are provided in the following section for giving an overview.

Mohamed (2016) reported a work for the detection of PD by using four classification techniques. The work was carried out on voice signals of PD as well as of normal persons. In this work, the highest accuracy of 70 % was achieved using the SVM classifier. Ouhmida et al. (2021) used nine different machine-learning algorithms for the classification of PD. The results evaluated gave the highest accuracy of 97.22% in the KNN classifier. This work was based on 240 speech measurements. Another work reported by Roobini et al. (2022) proposed a methodology in which PD was detected with the highest accuracy of 96%. This work was also carried out on audio features of patients.

Various other approaches, on the other hand, are reported by researchers where the dynamics of EEG signals are widely used. Nour et al. (2023) presented a work for classifying EEG signals for detecting PD in patients. In this work, the authors proposed a reliable methodology with an accuracy of 99.3% using deep learning techniques. Aljala et al. (2022) presented work on PD detection by applying machine learning techniques to EEG signals. This work proposed discrete wavelet transform-based techniques for efficient detection of the disease. Han et al. (2013) reported a paper in which the abnormalities associated with the brain activities of persons with PD were studied. In this work, the author used AR burg and WPE methods for analyzing the EEG dynamics related to the brain abnormalities of the targeted patients.

In order to extract fruitful information from the EEG signals, pre-processing is very important. Different approaches were reported by various researchers in this regard. SNR is often used as a performance parameter for the application of these methods. Khatwani and Tiwari (2013) reported a survey on the PCA and ICA techniques for the rejection of artifacts in time domain. The author also reported a survey on the wavelet transform methods for noise removal in time as well as frequency domain. Statistical-based approaches were also implemented by many researchers in pre-processing of EEG signals for numerous applications. Such a method, called fully automated statistical thresholding, was reported by Nolan et al. (2010).

Analysis of bio-potentials recorded from different parts of the human body is analyzed with respect to some specific features selected depending on the type of requirements. Selection and extraction of the features of the EEG signals have crucial roles in its processing. Many approaches have been suggested by the researchers in this regard. Azlan and Low (2014) provided a review on some very commonly used feature extraction

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techniques used for schizophrenia. Hilbert-Huang transform, PCA, IDA and Local discriminate bases (LDB) were the techniques that were compared in this paper. Besides these methods, modified LDB was also represented as a significant tool for analysis of the said disease. An approach of using various statistical features for the analysis of the dynamics of EEG was reported by Gopika et al. (2016). In this work, SVM and K-nearest neighbours (KNN) classifiers were applied to the considered features for the purpose of classification.

Based on the extracted features, the EEG signals are classified in order to differentiate the classes of EEGs of interest. In recent years, several techniques for EEG classifications were described by many authors. The performance and accuracy of any classification method depends on the ability of the method to find out the degree of differences that exists between the features of both the classes. Ouhmida et al. (2021) proposed a method for identifying PD using ANN and KNN algorithms. The author reported the highest accuracy of 97.7 % while using ANN algorithm in this work which was based on the acoustic features of subjects. Çimen and Bolat (2016) experimented application of ANN in diagnosing PD. In this work, the authors used Multi-layer perception (MLP) and Generalized Regression Neural Network (GRNN). Comparative analyses of both these methods were represented in the paper. The comparison shows that the GNRR method classifies the PD persons more accurately. Rumman et al. (2018) used ANN and image-processing techniques to detect early-stage PD. This study was carried out based on SPECT images of PD persons. An accuracy of 94% was reported by the authors for this proposed ANN model. A comparative analysis of several techniques of classification, such as SVM, ANN, Hidden Markov Model (HMM), KNN, Fuzzy and K-means clustering, was reported by Mrozik et al. (2017). Alshammri et al. (2023) have shown a few approaches for identifying PD from audio signal features. Along with some other methods of classification, SVM has also been used by the author in their work which gave 95% accuracy of classification. Based on the results presented, the author commented that the proposed method could be used reliably in the prediction of PD. Shahbakhi et al. (2014) have presented a method of classifying healthy and PD-affected person by using SVM and genetic algorithm as a combination. An accuracy of classification up to 94.5% was achieved by them in that approach. Nanthini and Santhi (2014) published a paper in which SVM was used for the categorization of EEG signals for automatic finding of seizure. Bourouhou et al. (2016) provided a comparison of three methods of classifications i.e., KNN, Naïve Bayes and SVM, while detecting Parkinson's disease based on voice signals of persons. The author concludes the paper with the findings that the SVM performs best for detecting Parkinson's disease in the reported approach. Rejith and Subramaniam (2018) have employed six emotional states to classify PD and non-PD persons using EEG signals. They used two classifiers i.e., Probabilistic Neural Network (PNN) and KNN, for determining classification accuracy employing four feature extraction methods. A study on the automatic identification of Parkinson's disease is reported by Çaglar et al. (2010), where two ANN classifiers (MLP and Radial Basis Function) and an Adaptive Neuro-Fuzzy classifier (ANFC) are employed with the help of features collected from 195 sustained vowel phonation of 31 people. Ene (2008) has applied three variants of PNN to differentiate between normal people and people with Parkinson's disease. The author also used characteristics of biomedical voice signals for the detection.

The above-mentioned literature provides an idea of various tools and methods that can effectively be used for processing EEG signals. Various researchers have proposed various methodologies for classifying signals and their relevant pre-processing. The performances of these reported approaches motivated to set the goal of this work as the classification of EEG signals of diseased and normal persons.

Materials and Methods

Materials

For any research objective, the availability of reliable raw data is a crucial parameter for its implementation. In this work, the major challenge was the non-availability of real-time EEG signals of PD patients. Hence, the reported work is being carried out based on the dataset available in Figshare, an online open-access platform (Yoshida et al., 2018). Various researchers used to share their research output in Figshare. The EEG signals collected from this source for this work were recorded from 19 different brain locations through a 10-10 system of EEG recording, which is a modified version of its earlier 10-20 system (Sharbrough et al., 1991). These locations were C1, C2, C3, C4, Cz, CP1, CP2, CPz, Pz, F1, F2, F3, F4, Fz, FC1, FC2, FC3, FC4 and FCz. These were recorded from two classes of persons, one being normal and the other having PD symptoms. The dataset contains separate files for each participant in MATLAB file (.mat) format. The signals were sampled at 1200 Hz of frequencies. For both classes, 171 signals are considered while performing the analysis.

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Proposed Methodology

The diagrammatic demonstration of the proposed methodology for detection of the EEG signals of PD patients is shown in Figure 3. The methodology can be described in three significant steps as follows.

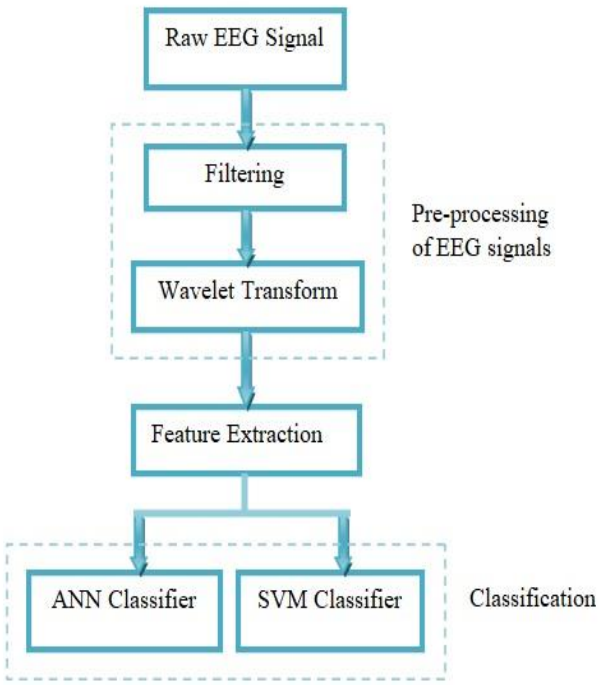

Figure 3. Schematic representation of the methodology

Pre-processing of EEG signals

Raw EEG signals collected or recorded from any subject contain different types of noises and artifacts. EEG signals which are generated from non-cerebral sources can be termed as artifacts. EEG signals are often polluted by these artifacts. The amplitude of the artifact is mostly relative to the signals of interest. Hence, interpreting the correct EEG signal for any clinical purpose becomes very important.

Pre-processing is necessary for extracting fruitful information from the raw EEG signal. Various techniques for pre-processing or de-noising of EEG signals are being used by many researchers. Most of these techniques have given significant results. Amongst these existing techniques, we have used wavelet transform for its benefit of having localization of both time and frequency (Haloi et al., 2019). Each raw version of the EEG signal is passed through a notch filter of 50 Hz to remove the power line interference. The signal frequency is then resampled from 1200 Hz to 128 Hz. This is done to reduce the computational complexities of the process. Discrete Meyer wavelet functions, Coiflet functions (order 1 to 5), Daubechies functions (order 1 to 20) and Symlet functions (order 1 to 20) are the orthogonal mother wavelet functions used in this work.

In the MATLAB environment, de-noising can be executed by using the in-built functions available in it. ‘rigrsure’, ‘heursure’, ‘sqtwolog’ and ‘minimaxi’ are the functions used in this work for the said purpose. Performances of the de-noising techniques are examined with the performance parameters Root Mean Square Error (RMSE) as well as Signal Noise Ratio (SNR). Considering these two parameters, several combinations of mother wavelet functions and wavelet thresholding methods are iterated. Both soft and hard thresholding techniques are considered while carrying out the analysis.

Feature extraction

After pre-processing, the noise and artifact present in the raw EEG gets eliminated. Some distinctive properties of these EEGs can now be extracted by used of appropriate feature extraction techniques. These properties or the features of the EEG signals carry valuable information about the dynamics of the signals. The selected features are evaluated for EEGs of both the classes of interest. In this work, the below-mentioned statistical features of the EEG signals are considered.

Mean: The average values calculated from various data points of a signal are termed as Mean. This can be found in Eq. (1)

$$M = \frac{1}{J}\sum_{x=1}^{J} p_x \quad \text{......(1)}$$

Here J is the number of data samples and p_x is the signal.

Standard Deviation: Dispersion of values of the data points about their mean can be found out by calculating the Standard deviation. It can be evaluated from the Eq. (2).

$$\sigma = \sqrt{\frac{1}{J}\sum_{x=1}^{J}(p_x - M)^2} \quad \text{......(2)}$$

Energy: Energy of signals considered can be evaluated by using Eq. (3).

$$e_r = \sum_{x=1}^{J} {p_x}^2 \quad \text{...... (3)}$$

Kurtosis: In a probabilistic distribution, for measuring the outliers present, Kurtosis can be calculated by the Eq. (4).

$$k_r = \frac{M_4}{\sigma^4} \quad \text{......(4)}$$

where M_4 is the 4^{th} moment about the mean. It can be found from Eq. (5).

$$M_4 = \frac{1}{J}\sum_{x=1}^{J}(p_x - M)^4 \quad \text{......(5)}$$

Skewness: The asymmetry existing in a distribution of probability can be interpreted from Skewness. It is formulated by the Eq. (6).

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$$S_k = \frac{M_3}{\sigma^3} \quad \text{.. (6)}$$

Here M_3 is the 3rd moment about its mean and is evaluated in Eq. (7).

$$M_3 = \frac{1}{J}\sum_{x=1}^{J}(p_x - M)^3 \quad \text{................................ (7)}$$

Values of these features evaluated shows distinctive behaviour for both the categories of EEG signals, which fulfills the purpose of selecting these feature for the current work. Comparison of these results obtained for both the referred classes of the signals enables this methodology to differentiate them. This can be achieved by the use of a significant classification technique.

Results and Discussion

The dataset considered or the EEG signals of both the classes of subjects were processed in the MATLAB environment. Due to the flexibility of operations and greater graphic user interface, MATLAB was considered as the most suitable environment for processing of EEGs. For calculating threshold, the MATLAB functions 'rigrsure', 'heursure', 'sqtwolog' and 'minimaxi' are used. In the process of de-noising, SNR and RMSE are selected as performance parameters to signify the standard of de-noising. Multiple pairs of mother wavelet functions and threshold techniques of wavelets are iterated for finding out the performances. The best pair is evaluated based on the highest SNR and the lowest RMSE. In both the classes of EEG, rigrsure thresholding with hard thresholding method gives the best results. In all conditions discrete meyer wavelet performs the best. The summarized findings of the de-noising stage are shown in Table 1.

Table 1. Results of de-noising in case of persons with PD and without PD

Subject class	Hard thresholding		Soft thresholding	
	RMSE	SNR	RMSE	SNR
Normal persons (Non-PD)	2.97	58.43	3.70	56.33
Persons with PD	3.61	65.09	4.97	62.65

Five statistical features were then calculated from the 171 numbers of de-noised EEGs of PD and the Non-PD subjects. These features obtained from the EEGs of both the categories of persons are then classified using ANN and SVM classifiers in MATLAB. In MATLAB environment, there are several algorithms for ANN classification. In this work, we have used Scaled Conjugate Gradient (SCG), Gradient descent with adaptive learning rate back-propagation (GDB), Gradient descent with momentum back-propagation (GDMB), Gradient descent with momentum and adaptive learning rate back-propagation (GDMLB), Levenberg-Marquardt back-propagation (LMB), Resilient back-propagation (RB) and BFGS quasi-Newton back-propagation (BFGS). The results of classification of features obtained by using ANN algorithms for diverse hidden layers are shown in Table 2. The results shown in Table 2 illustrates that the best classification accuracy is obtained with the algorithm Levenberg-Marquardt back-propagation with hidden layer 20.

Based on this outcome, the process of classification was repeated for each feature individually. For each of the features accuracy, sensitivity, specificity and precision were calculated. A comparative analysis of these parameters was obtained from the ANN

Classification

Statistical features were calculated for each EEG signal considered for the work. After evaluating the features of the EEGs for both the subjects with PD and without PD, ANN and SVM were used for classification. In the ANN classification, the known sets of features of both the classes were used for training the network. The same values of the features were then applied to the ANN for the required classification. Results were calculated for six different training algorithms. For each of the algorithm, values of accuracies were evaluated changing the hidden layers eight times. Like ANN, in the SVM algorithm also, accuracy, precision, sensitivity and specificity are calculated from the confusion matrix evaluated from the sets of values of the five statistical features. The accuracy can be calculated from the Eq. (8)

$$\text{Accuracy} = \frac{\text{True Positive (TP)} + \text{True Negative (TN)}}{\text{Positive (P)} + \text{Negative (N)}} \text{.......(8)}$$

Here TP and TN are true positive and true negative respectively. While summation of all positives and negatives are represented by P and N respectively.

The precision can be calculated from the Eq. (9)

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False positive}} \quad \text{................(9)}$$

The Sensitivity gives how fairly the experiment detects all the true positives. It is calculated by the Eq. (10)

$$\text{Sensitivity} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} \text{.............. (10)}$$

In a similar way, the Specificity gives how fairly the experiment detects all the true negatives. It can be calculated by Eq. (11)

$$\text{Specificity} = \frac{\text{True Negative}}{\text{True Negative} + \text{False Positive}} \text{............ (11)}$$

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classification of the five features considered for this study, as shown in Table 3. It shows that the feature Mean best significantly differentiate the EEG signals of both the classes of persons.

In case of SVM classifier also, accuracy along with other parameters like sensitivity, precision and specificity were calculated. The results evaluated from SVM classifier are shown in Table 4. The comparison shows that the features mean and the standard deviation classify the features with the highest and the lowest accuracies respectively.

Table 2. Accuracies obtained in ANN classification

Training algorithm	Accuracy at different hidden layers							
	5	10	20	30	50	100	150	200
SCG	91.2	92.5	89.3	85.7	86.1	89.3	89.3	90.6
GDB	88.0	89.0	89.3	91.6	89.0	88.0	92.9	89.6
GDMB	81.8	89.0	86.4	93.5	89.0	90.3	93.4	89.6
GDMLB	88.6	92.9	90.6	92.5	92.9	74.4	81.5	81.5
LMB	91.2	88.0	94.7	91.9	89.9	91.9	92.2	90.6
RB	88.3	91.6	90.6	91.9	86.7	89.3	92.9	90.3
BFGS	89.9	90.3	89.0	89.6	93.2	91.6	87.7	89.3

Table 3. Feature-wise accuracies obtained in ANN classification (LMB algorithm and 20 hidden layers)

Features	Accuracy	Sensitivity	Specificity	Precision
Mean	94.8	93	98.2	98.5
Standard deviation	77.1	74.7	79.9	78.4
Energy	84	96.3	86.3	84.3
Kurtosis	91.4	93.5	92.6	89.8
Skewness	94.2	97.8	94.9	93.7

As the final step of the analysis, the performance parameters were evaluated for both the classifiers of ANN and SVM considering all the five features simultaneously. A comparison of performances of ANN and SVM classifiers are presented in Table 5. The evaluated results are graphically shown in Figure 4.

Table 4. Results obtained in SVM Classifiers

Features	Accuracy	Sensitivity	Precision	Specificity
Mean	95.2	97.5	94.3	94.1
Standard Deviation	79.4	80.1	89.2	83.2
Energy	91.3	96.4	93.2	92.2
Kurtosis	88	83.7	92.5	90.6
Skewness	92.5	91.3	91.8	94.8

These results clearly show that the classification was performed more efficiently by the SVM classifier than the ANN classifier. The ANN and SVM provide significant classification accuracies of 94.7% and 96.5% respectively.

Table 5. Comparison of results obtained in ANN and SVM classifiers

Classification method	Accuracy	Sensitivity	Precision	Specificity
ANN	94.7	92.3	95.6	94.7
SVM	96.5	93.5	96.8	96.2

Conclusion

Besides the complexities associated with neurological diseases, this work was carried out to show an appropriate approach to the classification of EEG signals of PD and normal persons for the detection of PD. One of the major challenges faced during the study was the non-availability of a real-time dataset of PD patients. Hence this study was based on EEG signals of PD and normal categories of persons collected from a reliable online source. Statistical features were extracted from these signals and were classified using ANN and SVM classifiers. The work provides a comparison of performances of ANN and SVM classifiers in terms of accuracies and other performance parameters considered, which clearly shows that the classifier SVM provides significant classification outcome with accuracy of 96.5% for detection of PD compared to the ANN classifier having accuracy of 94.7%. The results also exhibit that the mean feature classify both the classes of EEGs with highest accuracy in both the classification techniques. As a future scope, the classification of the EEGs may be carried out by using hybrid combinations of some efficient algorithms to evaluate the best possible results.

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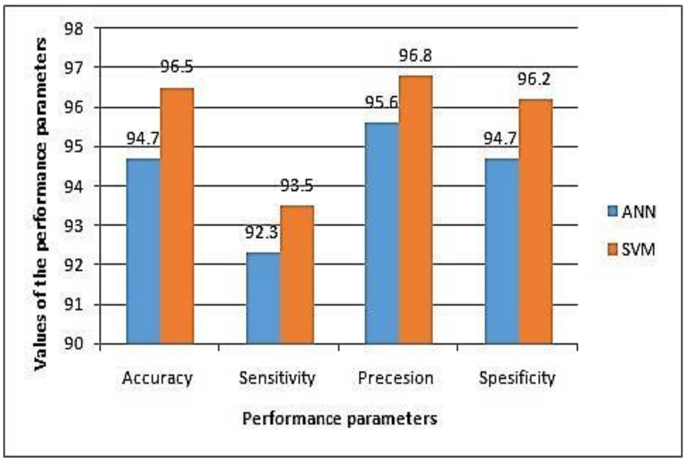

Figure 4. Comparative graph of results of ANN and SVM classifiers

Conflict of interest statement

The author declares that in this work, there is no conflict of interest.

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