DOI: https://doi.org/10.52756/ijerr.2024.v43spl.003 *Int. J. Exp. Res. Rev.*, Vol. 43: 32-41 (2024)

Original Article | Peer Reviewed | Open Access

International Journal of Experimental Research and Review (IJERR)

ISSN: 2455-4855 (Online)
www.iaph.in

# Performance Analysis of KNN, Naïve Bayes, and Extreme Learning Machine Techniques on EEG Signals for Detection of Parkinson's Disease



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**Article History**:

**Received:** 12th Jun., 2024
**Accepted:** 15th Sep., 2024
**Published:** 30th Sep., 2024

**Keywords:**
EEG classification, ELM, KNN, Naïve Bayes, Neurodegenerative disorder, Parkinson's disease, statistical features

**How to cite this Article:**
Rupjyoti Haloi and Dipankar Chanda (2024). Performance Analysis of KNN, Naïve Bayes, and Extreme Learning Machine Techniques on EEG Signals for Detection of Parkinson's Disease. *International Journal of Experimental Research and Review*, *43*, 32-41.
**DOI**: https://doi.org/10.52756/ijerr.2024.v43spl.003

**Abstract:** The application of bio-potentials for diagnosing neurological disorders has become highly effective nowadays. This work focuses on using Electroencephalogram **(**EEG**)** to detect Parkinson's disease (PD), a significant neurological disorder. PD is considered the second most common neurological disorder in the world. Being degenerative in nature, it affects the patients progressively. The progression of the severity of this disease can be restricted by a certain limit if its symptoms can be well-treated on time. This work presents a relative analysis of the performances of three machine learning (ML) techniques in detecting PD. These are K-nearest Neighbor (KNN), Naïve Bayes and Extreme Learning Machine (ELM) techniques. Statistical-based features are evaluated from the EEG data signals of normal as well as persons with PD after preprocessing. The features evaluated are then classified using the three techniques. The results of the classifiers are evaluated with the help of some performance parameters such as accuracy, precision, sensitivity, specificity and F1 score. Based on the values of these parameters, the performances of all these techniques are compared. The comparison shows that ELM performs the best, with an accuracy of 98.84% in detecting PD. The reported methodology holds significant clinical relevance. It can offer an early, non-invasive, and objective method for diagnosing, tracking, and managing PD.

## Introduction

Parkinson's disease **(**PD) is a brain disorder caused due to the death of dopaminergic neurons in the substantia nigra of the brain, which controls motor-related activities. The neurotransmitter, Dopamine is produced by the neurons of this region. The disease affects the neurons of not only the substantia nigra but also the neurons of other parts of the brain. Hence, PD is characterised by the symptoms of both movement and non-movement types. While genetic factors are a common cause of PD, environmental factors also contribute to it. The diagnosis of PD has been a challenge since it was first described in the early 1800's. Researchers have formulated various methodologies over time using modern technologies for the diagnosis of PD based on its symptoms. Although not fatal, to avoid progressive severities, the symptoms of PD are being diagnosed and treated with proper medications nowadays (Beitz, 2014). The diagnosis of PD always depends on some specific type of bio-potential or tool. EEG is one such non-invasive tool used for the analysis of the brain dynamics of PD patients. It is used because of its significant advantages like high temporal resolution and low cost. The EEG signals recorded from any subjects generally contain various types of noises. These noises are some unwanted information contained in the raw EEG signals. This information does not carry any significant characteristics of the original EEG signal and sometimes makes the analysis results incorrect. Hence, eliminating these noises is very important for evaluating the actual performance of the process. Researchers are reporting various methodologies for the removal of noise. Out of the available methods, the Wavelet Transform technique is selected in this work for the

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reduction of noises from the raw EEG signals due to its unique benefit of having both time and frequency localization (Alturki et al., 2020; Maitín et al., 2022). The Kruskal-Wallis and the mRMR feature selection method employed in online signature verification can also be applied in classification improvement in EEG signal processing, as shown by Chetry and Kar (2024) in their work using SVM and KNN techniques.

The denoised EEG signals are then fed to the process of feature extraction. Features of these data signals carry crucial information regarding the dynamics of the brain. The selection of appropriate features for the signal processing steps is crucial. Depending on the application type and the methodology's desired goal, features are used to be selected. In the context of the current analysis, statistical-based features of the data signals are selected to identify Parkinson's disease (Gopika et al., 2016; Haloi et al., 2023; Madhu et al., 2024; Roy et al., 2024). Classification techniques are applied to identify any signals of interest from a group of two or more classes of similar signals. These classification methods act on the extracted features of the selected data signals. The performance of these techniques can be analysed in terms of some performance parameters. For this reported work, classifications of the data signals are done by the supervised ML algorithms, namely KNN, Naive Bayes and Extreme Learning Machine classifiers (Govindu and Palwe, 2023).

The main focus of this paper is to assess the successes yielded by the classification techniques used in the diagnosis of PD. These performances rely on the successful classification of the features of EEG signals of people with PD. The next section gives an overview of the related literature on detecting PD and its associated methodologies.

In any signal processing analysis, it is essential to denoise the raw signals before processing. Researchers have reported various techniques for denoising EEG signals. Dautov et al. (2018) presented an approach for denoising signals using Wavelet Transforms (WT). They have experimented with the use of multiple types of mother wavelets and thresholding to determine the most appropriate combinations. Their work showed that Daubechies' family and the soft thresholding gave the best results. Choudhry et al. (2016) presented another approach to denoising EEG signals by the use of WT tools. This work specifically considered the noises imposed by EMG during the recording of the EEG. Five different WT techniques and five different thresholding methods were also used here. RMSE and SNR were used as performance parameters in this work. The work results showed that soft thresholding and DDDT-DWT performed the best. To carry out the analysis further, it is very important to select and take out the features of the denoised EEG signals. Depending on the type of application, various features may be selected. Statistical features are one such variety which is widely used nowadays. Priyanka et al. (2017) carried out a study on persons suffering from Epilepsy. The author used classification methods on pre-processed EEG signals in this work by extracting features like mean, variance, skewness, kurtosis and standard deviation. The accuracy of classification reported in this work was 96.9%. Another study on the neurological disorder was reported by Malini et al. (2016). This work also selected statistical features such as mean, mode, minimum, maximum, etc., to perform the analysis, which gave favourable results.

Appropriate classification methods are to be used to segregate any features of interest. The performance of classification is assessed based on its accuracy. Awan et al. (2016) published a paper presenting the classification of feature vectors for identifying different facial expressions of the subjects. Classification in this work was performed by applying the KNN method. Another work using a KNN classifier was reported by Rahmawati et al. (2017). This work reported the identification of epilepsy from the patient's EEG signal. The results of the experiments reported in this publication showed an accuracy of classification of 99.83%. Bablani et al. (2018) reported a work which used KNN as the classification method for developing a concealed information test. The work used EEG signals of both innocent and guilty persons and carried out the classification with an accuracy of 96.7%. Ouhmida et al. (2022) reported an approach to detecting PD from the speech signals of patients. The authors used 44 different features to evaluate the performances of nine classification techniques considered for the study. The comparison results showed that the KNN classifier gave the highest accuracy rate, with 97.22%. Oktavia et al. (2019) reported a work on the detection of human emotions by the use of Naïve Bayes classification method. The emotions of Happy and Sad were classified in this work from the features of the EEG signals. The authors achieved the highest accuracy of 87.5% in detecting emotions in this work. Mawalid et al. (2018) presented a work for analysis of cybersickness from EEG signals. KNN and Naïve Bayes classifiers were applied for the classification of features in this work. The classification accuracy of 83.8% was reported by the authors in the work. Jose et al. (2020) presented a work

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for the detection of epileptic seizures using ELM classifiers. This work uses features extracted from EEG signals to carry out the desired classification. Wei et al. (2023) reported a work for the automatic detection of Schizophrenia from Scalp EEG Using an ELM classifier. The author proposed a hybrid model combining CNN with an ELM and a wide convolution kernel in this work. An accuracy of 95.59% was achieved in the proposed methodology. Murugappan et al. (2020) reported a work for identifying emotional impairment due to PD from EEG signals. In the experimental analysis of the work, the ELM classifier provided the highest mean accuracy while identifying emotions in PD.

## Materials and Methods

### Materials

The dataset made accessible on the internet open access platform "Figshare" is the basis for the reported work. Researchers from different fields used to exchange their findings on "Figshare" (Yoshida et al., 2018). The dataset on "Figshare" is openly available to the public, ensuring transparency in the study and enabling other researchers to replicate or build upon the findings. The dataset considered for this work was taken from two groups of people: those with PD symptoms and those who were normal. Using a 10-10 approach of EEG recording, these EEG signals were recorded from 19 distinct brain regions (Sharbrough et al., 1991) viz., C1, C2, C3, C4, Cz, CP1, CP2, CPz, Pz, F1, F2, F3, F4, Fz, FC1, FC2, FC3, FC4 and FCz were these regions. A frequency sampling of 1200 Hz was used for these signals. Nine subjects from each of the groups were considered for generating this dataset. Thus, a total of 171 signals for each group are considered during the work. This specific dataset was selected for several factors that support the validity and applicability of the research, particularly when contrasted with other accessible datasets. The dataset has been organized to align with the research approaches utilized. The said "Figshare" dataset was chosen for its relevance to the EEG and PD-related research. It was well-documented and of high quality, which was essential for carrying out precise and trustworthy research.

### Proposed Methodology

The methodology proposed in the current work for performance analysis of the three classification methods used on EEG signals for the detection of PD is presented in the block diagram shown in Figure 1. It consists of three prime functional blocks. These blocks can be illustrated as follows.

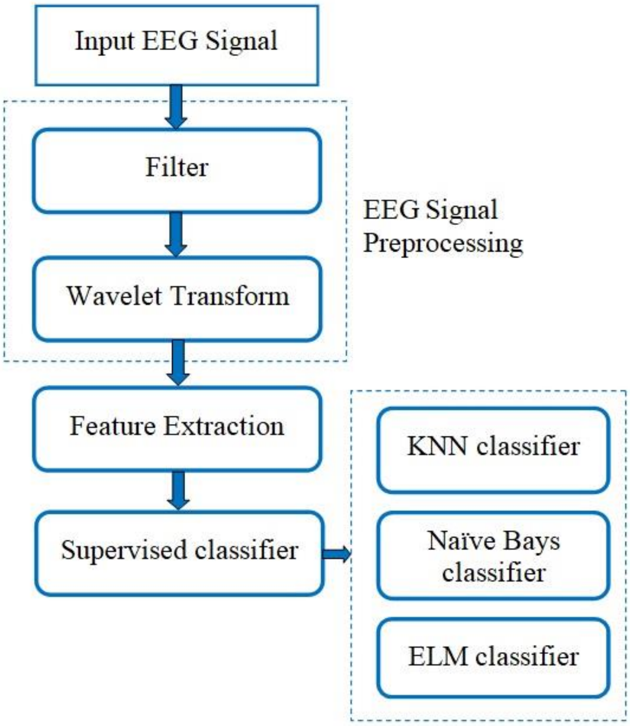


**Figure 1. Block representation of the proposed methodology.**

### Pre-processing of the data signal

The raw EEG signals considered for any application generally contain some unwanted components. These noises or artifacts may pollute the EEG signals at the stage of its acquisition or recording. Their magnitude is very much relative to the original signal. Before applying to any clinical application, removing these components from the raw EEGs is essential as these may sometimes suppress the actual information of interest contained in the signals. Removal of the noises and artifacts carries significant importance in any signal processing applications as it may affect the performance of the process. Researchers have formulated various methodologies for this purpose. The majority of these techniques have shown good results. Wavelet transform is one such technique which is used effectively for denoising EEG signals. It has the unique benefit of having localization of both time and frequency. Being non-stationary in nature, the statistical properties of the EEG signals change over time. Wavelet transforms are highly effective in analyzing such signals because they provide both time and frequency resolution**.** This is particularly useful for identifying and isolating transient features in EEG signals associated with PD, like tremors or irregular brain rhythms. Moreover, the wavelet transform makes it possible to perform multi-resolution analysis (MRA), which breaks down the EEG signal into various frequency bands (scales). This is important for denoising since noise in EEG signals frequently occurs at

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different frequencies. The signal's clarity for PD identification can be increased by using the wavelet transform, which can efficiently separate noise from the valuable EEG components at several resolutions. MATLAB environment has some built-in functions that enable the denoising of EEG signals to be executed. In this reported work, functions like rigrsure', 'heursure', 'sqtwolog' and 'minimaxi' are used for denoising the raw signals. Root Mean Square Error (RMSE) and Signal Noise Ratio (SNR) are the performance parameters selected in this work to evaluate the performance of the denoising techniques. These performances are analysed using several combinations of mother wavelet functions and thresholding techniques. Both hard and soft thresholding methods are considered while carrying out the experiments.

## Feature extraction of the pre-processed signals

The EEG signals after being denoised become free from noises and artefacts present in them. Some distinct properties of the signals should be extracted to process these signals for further steps. The selection of these properties plays a vital role as they should carry all the valuable information of interest about the dynamics of the EEGs. These extractions can be done by using appropriate feature extraction techniques. The features chosen in this work are then evaluated and analysed for both the categories of EEG signals considered for classification. The statistical features mean, energy, standard deviation, skewness, and kurtosis are selected for this work. To diagnose PD using EEG data, these statistical parameters are frequently chosen as they provide important details about the signal's distribution, variability, and structure. Because these features may represent both the general and complex components of EEG signal patterns that are frequently affected in patients with Parkinson's disease, they have significant advantages over other features. Therefore, These characteristics are excellent for PD classification from EEG data because they are easy to compute, computationally efficient, and reliable.

**Mean:** The term "Mean" refers to the average values that are computed from different signal data points. Eq. (1) can be used to determine this.

$$M = \frac{1}{J}\sum_{x=1}^{J} p_x \tag{1}$$

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

**Standard Deviation:** Standard Deviation is used to determine the values of the data points' dispersion around their mean. Equation (2) can be used to evaluate it.

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

**Energy:** To evaluate the energy of the signals under consideration Eq. (3) can be used.

$$e_r = \sum_{x=1}^{J} {p_x}^2 \tag{3}$$

**Kurtosis:** Kurtosis in a probabilistic distribution can be computed using Eq. (4) to measure the outliers that are present.

$$k_r = \frac{M_4}{\sigma^4} \tag{4}$$

M4 denotes the fourth moment about the mean. It is derived from Equation (5).

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

**Skewness:** A probability distribution's asymmetry can be understood based on its skewness. It is expressed using Equation (6).

$$S_k = \frac{M_3}{\sigma^3} \tag{6}$$

Here, $M_3$, or the third moment around its mean, is calculated using Equation (7).

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

The values of the selected features are thus calculated for the EEG signals of interest. By use of appropriate classification techniques, these features extracted from the two classes of the EEGs can be well differentiated.

## Classification

As the motive of this work is to differentiate EEG signals of subjects with PD and without it, statistical-based features were extracted for both categories of EEGs. Evaluated features are then classified by using KNN, Naïve Bayes and Extreme Learning Machine techniques.

## K-nearest neighbour classifier

KNN is one of the best well-liked supervised ML techniques. This approach has been thoroughly tested for regression, pattern recognition, data mining, and classification applications (Narayan, 2024). This non-parametric approach predicts the fresh data points using similar features. This indicates that a new class shall be allocated to the newly collected data points according to how strongly they resemble the training set's points. Only data are stored using this technique during the training phase. The real classification work is completed every time the algorithm is fed relevant data. As a result, the technique groups the input data according to how similar it is to the previously saved data during training. The algorithm first loads the training and test datasets. The closest numbers from data point k, a positive integer that is typically small are then chosen. Every row in the training data is used to compute the distances of each

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point in the set of data. Thereafter, the top k rows in the sorted array were selected and placed in ascending order according to the distance value. Lastly, the class allocated to the test point will be based on the most common class among these rows.

The **KNN** classifier is a simple and effective machine learning algorithm often used to detect PD from EEG signals for classification task**s**. The number of neighbours (k) considered in the classifier when classifying EEG signals plays an important role in its performance. A small value of k makes the classifier more sensitive to noise, while a larger k provides more robust predictions. In this reported work, this value was set to nine. A value like **nine** provides a balance between the two extremes of overfitting and underfitting. A larger neighborhood is useful for classifying noisy datasets like EEG signals because patterns tend to develop over a greater range, even when individual readings may be noisy.

### Naïve Bayes classifier

Another significant supervised ML technique that comes from the Bayes theorem is the Naïve Bayes classifier. It works on the assumption that the features are not statistically related and is named after Thomas Bayes. Since it is a probabilistic approach, it operates under the assumption that the existence of one attribute in a class does not affect the existence of any other attributes. This method's requirement for a limited dataset for training purposes is one of its key advantages. This method allows for the estimation of parameters needed for categorization. This approach seeks to determine posterior probability. It is a family of probabilistic classifiers with an assumption of predictor independence. Naïve Bayes is a straightforward and effective technique used by researchers for classifying EEG data. Bayes' theorem can be written mathematically as shown in equation (8).

$$P(C \mid X) = \frac{P(X|C).P(C)}{P(X)} \tag{8}$$

Where P(C|X) represents the posterior probability or the likelihood of class C in light of feature X. P(X|C) is expressed as the likelihood or probability of detecting feature X given that the class is C. P(C) is the prior probability of class C and P(X) is the evidence which means the probability of observing the feature set X across all possible classes. Prior probabilities play a crucial role in the functioning of Naïve Bayes classifiers. They represent the initial assumption of each class is likelihood before considering any specific features or evidence. If prior probabilities are not explicitly provided, Naïve Bayes classifiers will estimate them from the class distribution in the training data. These priors play a vital role in calculating the posterior probability during the classification process, allowing the classifier to determine which class a new data point is most likely to belong.

### Extreme Learning Machine (ELM)

ELM emerged as one new ML technique proposed by Huang et al. (2004). This feed-forward neural network was proposed with a single hidden layer in that paper. They compared the classification performance of ELM with other neural networks on the medical diabetic dataset and found many advantages of ELM over conventional neural networks. ELM is simple and exceptionally fast, where input weights are arbitrarily chosen, and the output weights are analytically determined. Several researchers applied this algorithm thereafter to detect various diseases in the medical field with promising results. The general inverse of the hidden layer output matrix determines the output layer weights in this network, which operates with input layer weights and biases that are assigned randomly. An ELM structure's layout is shown in Fig. 2.

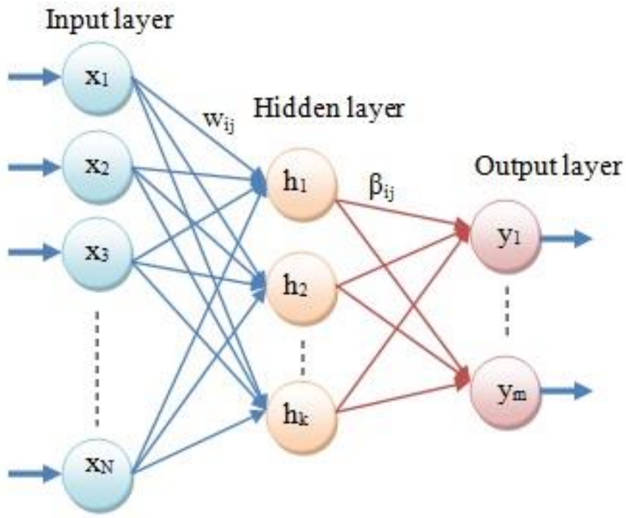


**Figure 2. ELM classifier's basic model.**

The ELM output with hidden nodes of K is:

$$f_K(p) = \sum_{i=1}^{K} \beta_i g(w_i * p_j + b_i)\, j = 1,2,\ldots,S \tag{6}$$

where, $\beta_i =$ weight of output layer of the $i^{th}$ neuron of hidden layer, $g$ = activation function, $w_i$ = input layer weights related to $i^{th}$ neuron of hidden layer, $p_j$ = $j^{th}$ input sample, $b_i$ = bias, $S$= no. of training samples.

Eq. (6) may be shortened and rewritten as:

$$T = G\beta \tag{7}$$

Here,

$$G = \begin{bmatrix} g(w_1 * p_1 + b_1) & \cdots & g(w_K * p_1 + b_1) \\ \vdots & \cdots & \vdots \\ g(w_1 * p_S + b_1) & \cdots & g(w_K * p_S + b_K) \end{bmatrix}_{S\times K} \tag{8}$$

$$\beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_K^T \end{bmatrix}_{K\times m} \quad (9)$$

and

$$T = \begin{bmatrix} t_1^T \\ \vdots \\ t_S^T \end{bmatrix}_{S\times m} \quad (10)$$

Where, $m$ = no. of output, $G$= hidden layer output matrix, $T$= training data target matrix.

ELM is a linear system if the parameters of the hidden layer $w_i$ and $b_i$ can be assigned randomly. Then cost function is created:

$$\|G\hat{\beta} - T\| = {}^{min}{}_{\delta}\|G\beta - T\| \quad (11)$$

The values of δ are calculated by determining a least square solution as:

$$\hat{\beta} = G^{\dagger}T \quad (12)$$

Where, $G^{\dagger}$ = generalized inverse of $G$ (Moore-Penrose). Therefore, a mathematical transformation is used to determine the output weights (Huang et al., 2006; Ding et al., 2014).

In detecting PD from EEG signals, the ELM classifier is a powerful tool for classifying EEG data based on extracted features. The key advantage of ELM is that the input weights and hidden biases are randomly generated and fixed, while the output weights are calculated analytically. This significantly speeds up the training process compared to conventional neural networks, as it avoids iterative backpropagation.

The performances of all the selected classifiers are evaluated with the help of some performance parameters. These parameters are accuracy, precision, sensitivity, specificity, and F1 score. These parameters are evaluated from the values of the five statistical features considered in this work to find out how well these classification techniques perform. The parameter accuracy is defined as the ratio of true positives and true negatives among all the instances examined. Percentages of true positive outcomes in all positive predictions are known as precision. The percentage of true positive outcomes in all actual positive cases is called sensitivity or recall. The percentage of true negative outcomes in all actual negative cases can be termed as specificity. The harmonic mean of recall and precision can be used to calculate the F1 score, which brings a balance between the two measures. When false positives as well as false negatives are considered, it is especially helpful.

## Results and Discussion

Denoising of the raw EEG data under consideration was the first step in the presented work. Wavelet transforms were used during the denoising process in this work. This method iterated many combinations of mother wavelet functions and thresholding techniques within the MATLAB environment. The parameters SNR and RMSE were used to assess the performances of each iteration. Rigrsure thresholding with hard thresholding works best in denoising the EEGs of both PD and non-PD individuals. Under all iterated conditions, the Discrete Meyer wavelet produces the best-intended outcomes. After reducing the noise and artifacts from the EEG dataset under consideration, five statistical features were

**Table 1. Classification results of the KNN technique.**

| Features | Performance measuring parameters (in percentage) | | | | |
|---|---|---|---|---|---|
| | Accuracy | Sensitivity | Specificity | Precision | F1 Score |
| Mean feature | 98 | 98.4 | 97 | 97 | 97.7 |
| Standard Deviation feature | 97.5 | 97 | 96.7 | 97.4 | 97.1 |
| Kurtosis feature | 97.7 | 97.2 | 97.3 | 97.5 | 97.3 |
| Energy feature | 98.3 | 96.8 | 98 | 96.6 | 96.7 |
| Skewness feature | 97.8 | 97.2 | 97.2 | 97.3 | 97.2 |

**Table 2. Results of classification of Naïve Bayes technique.**

| Features | Performance measuring parameters (in percentage) | | | | |
|---|---|---|---|---|---|
| | Accuracy | Sensitivity | Specificity | Precision | F1 Score |
| Mean feature | 96.8 | 97 | 97.1 | 97 | 97 |
| Standard Deviation feature | 96.4 | 96.2 | 96.8 | 96.8 | 96.5 |
| Kurtosis feature | 97 | 97.3 | 97 | 96.7 | 97 |
| Energy feature | 97.8 | 96.8 | 96.2 | 97 | 96.9 |
| Skewness feature | 96.8 | 97 | 97.2 | 97.2 | 97.1 |

computed from the 171 de-noised EEGs of PD and non-PD subjects. The KNN, Naïve Bayes, and ELM classifiers were used to classify the features that were calculated from the EEG signals of both classes. These results of feature classifications obtained using KNN, Naïve Bayes and ELM algorithms are presented in Tables 1, 2 and 3, respectively.

The results evaluated in terms of the performance parameters considered show significant classification capabilities of all three classifiers. A comparative analysis of the performances of KNN, Naïve Bayes and ELM classifiers was finally carried out. The outcomes of this comparison in the form of various selected parameters are tabulated in Table 4.

The comparison clearly shows that the classification was performed more efficiently by the ELM classifier than the KNN and Naïve Bayes classifiers. The KNN and Naïve Bayes offer remarkable classification accuracy of 97.86% and 96.96%, respectively, while the ELM performs the best with an accuracy of 98.84%.

Although Naïve Bayes, KNN, and ELM are popular classifiers for identifying PD they also face limitations when applied to EEG-based PD detection. One major limitation is that EEG signals are non-stationary, intrinsically noisy, and prone to a variety of artefacts. This is a problem for all classifiers since they might not be able to handle noise and temporal variability in the absence of appropriate pre-processing techniques.

**Table 3. Evaluated results of classification of ELM classifier.**

| Features | Performance measuring parameters (in percentage) | | | | |
|---|---|---|---|---|---|
| | Accuracy | Sensitivity | Specificity | Precision | F1 Score |
| Mean feature | 99.1 | 98.2 | 99.1 | 98.8 | 98.5 |
| Standard Deviation feature | 99 | 98.6 | 98.4 | 98.4 | 98.5 |
| Kurtosis feature | 98.7 | 98.3 | 98.6 | 98.4 | 98.3 |
| Energy feature | 98.4 | 98.6 | 98.5 | 99 | 98.8 |
| Skewness feature | 99 | 98.8 | 98.7 | 98.8 | 98.8 |

**Table 4. Comparison of performances of KNN, Naïve Bayes and ELM classifiers.**

| Classifiers | Performance measuring parameters (in percentage) | | | | |
|---|---|---|---|---|---|
| | Accuracy | Sensitivity | Specificity | Precision | F1 Score |
| KNN | 97.86 | 97.32 | 97.24 | 97.16 | 97.20 |
| Naïve Bayes | 96.96 | 96.86 | 96.86 | 96.94 | 96.90 |
| ELM | **98.84** | **98.5** | **98.66** | **98.68** | **98.58** |

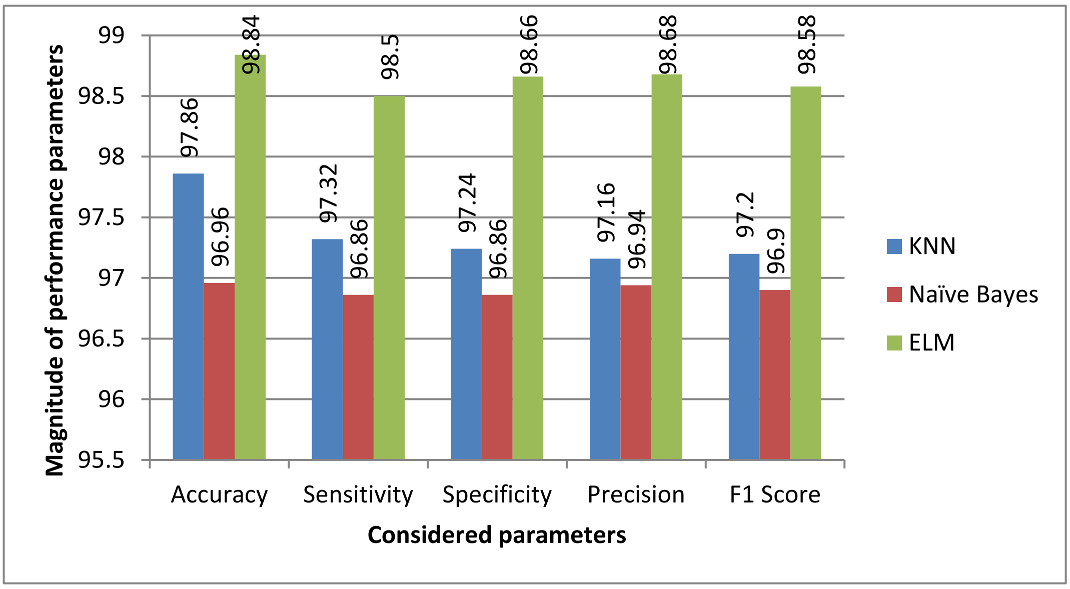


**Figure 3. Comparison of performances of classifiers.**

The results of the comparison of the performances of the three classifiers are graphically depicted in Figure 3.

Secondly, large EEG datasets are hard to obtain for PD identification, which makes most classifiers overfit. Poor generalization can also be caused by small sample numbers, particularly when using sophisticated classifiers like ELM. Lastly, selecting the appropriate characteristics is also essential. While statistical features are frequently employed, more advanced features may offer superior discrimination for PD identification. These characteristics, however, could make model interpretation and training more difficult.

## Conclusion

The work was carried out to compare the performances of three supervised types of ML techniques while sensing Parkinson's disease. Although the detection of neurological disorders has various complexities, the reported approach gives significant output in the detection of PD. This detection was done by classification of EEG signals from PD and non-PD patients by use of three classification techniques namely KNN, Naïve Bayes and ELM. The said classifications were done based on five statistical features of EEGs. In terms of the selected performance parameters, the performances of the classifiers were compared. The comparison shows that the ELM classifier gives the best result of classification with an accuracy of 98.84% in contrast to the KNN and the Naïve Bayes classifiers which give accuracies of 97.86% and 96.96%, respectively. The ELM performs better than KNN and Naïve Bayes classifiers in the detection of PD from EEG signals because of its faster training time, better handling of complex, nonlinear relationships, superior generalization capability, scalability to high-dimensional data, and robustness to noisy signals. These characteristics make ELM particularly well-suited for the challenging task of EEG-based PD detection, where the data can be high-dimensional, noisy, and complex.

Although there have been encouraging results in detecting PD using classifiers like KNN, Naïve Bayes, and ELM on EEG data, some approaches still exist to expand and enhance this work. This includes developing ensemble and hybrid models, enhancing feature extraction and selection methods, managing unbalanced and noisy data, customizing and implementing real-time detection systems and enhancing model interpretability. These developments have the potential to greatly enhance the precision, resilience, and clinical usefulness of PD detection systems, which will ultimately benefit the patients.

## Conflict of interest statement

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

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**How to cite this Article:**

Rupjyoti Haloi* and Dipankar Chanda (2024). Performance Analysis of KNN, Naïve Bayes, and Extreme Learning Machine Techniques on EEG Signals for Detection of Parkinson's Disease. *International Journal of Experimental Research and Review*, *43*, 32-41.

**DOI :** https://doi.org/10.52756/ijerr.2024.v43spl.003