

# Diagnosis of Parkinson's disease through EEG signals based on artificial neural network and cuckoo search algorithm

Rzgar Sirwan<sup>1, a,\*</sup>, Adil Hussein Mohammed<sup>2, b</sup>

<sup>1</sup> Department of Computer Science, College of Science and Technology, University of Human Development, Sulaymaniyah, Iraq

<sup>2</sup> Department of Communication and Computer Engineering, Faculty of Engineering, Cihan University-Erbil, Kurdistan Region, Iraq

**Abstract**—Parkinson's disease is a degenerative nervous system condition that impairs mobility. If the condition is not detected early enough, it might have permanent effects for the sufferer. A novel approach for identifying Parkinson's disease is provided in this research, which employs machine optimization and learning techniques. The suggested method's diagnosis procedure may be broken down into three primary steps: "preprocessing," "feature extraction," and "classification." Preprocessing the EEG data is the initial stage in the suggested technique. Database samples are treated using discrete wavelet analysis to remove the destructive influence of noise on the input signals using signal analysis for this aim. The suggested method's second phase will employ principal component analysis to remove duplicate features and minimize data dimensionality. The artificial neural network model is trained and the classification model is built using the retrieved features. The effectiveness of the suggested technique is examined in terms of criteria such as accuracy, sensitivity, and specificity during the experimentation phase, and the results are compared to existing learning models. The findings revealed that the suggested technique enhances illness diagnostic accuracy by at least 8.25% and may be utilized as a useful tool in disease diagnosis.

**Index Terms**—Parkinson's disease diagnosis, machine learning, artificial neural network, cuckoo search algorithm.

## I. INTRODUCTION

Parkinson's disease (PD) is a common neurological condition caused by a lack of dopamine in the brain and other subcutaneous neurons. Motor abilities are frequently compromised in Parkinson's sufferers [1]. Tremors at rest, muscular stiffness, lethargy (or slowness in movement), instability in posture, and walking difficulties are all frequent side symptoms of this condition, in addition to bending. Patients' feet are frequently affected by impaired mobility (paralysis) during walking. Patient reports are being used in the clinical assessment of Parkinson's disease [2]. Parkinson's disease is a prevalent central nervous system progressive neurological illness. If the condition is not detected early enough, it might have disastrous consequences for the affected patient. The condition is more common in adults over the age of 55 than in other age groups [1, 3]. Infected people make up around 1% of the world's population. However, diagnosing Parkinson's disease purely on clinical indicators is extremely challenging, especially in the early stages when there is little to

no trustworthy evidence. As a result, there have been various attempts in recent years to use machine learning techniques to automatically identify the condition [4]. One of the most useful methods for identifying Parkinson's disease is the electroencephalography (EEG) signal. Electroencephalography (EEG) is a non-invasive way of measuring the electric field created by the brain's neuronal activity. According to new study, there is a link between EEG signal patterns and the presence of Parkinson's disease [5]. However, finding a link between EEG signal patterns and the existence of Parkinson's disease is a key issue in the illness's automated diagnosis [6]. Machine learning algorithms have been applied to identify Parkinson's disease using a collection of EEG signal features in recent years. However, there has been little advancement in terms of identifying the condition. Using the learning benefits of neural networks and optimization algorithms, this article attempts to solve the drawbacks of the previously reported strategies for forecasting Parkinson's disease. To diagnose the issue, the suggested technique combines an artificial neural network with a cuckoo search optimization algorithm, which sets it apart from previously offered methods. The following is how the rest of the article is structured: The scientific background is covered in the second section, and the proposed approach for diagnosing Parkinson's disease is described in the third section. The results of the implementation and assessment of the suggested approach are shown in the fourth part, and the findings are discussed in the fifth section. Finally, recommendations for further study in this area are made.

## II. LITERATURE REVIEW

The area of research relating to the diagnosis of Parkinson's disease using EEG signals is vast, and we will look at a few instances in this section. Using deep learning techniques, Oh et al. [7] suggested a method for identifying Parkinson's disease using EEG waves. The CNN convolution neural network was employed as the learning model in this study. The CNN network contains four layers of two-dimensional cloning that can depict Parkinson's disease symptoms in distinct bands of the EEG data at different degrees of abstraction. The size of the EEG signal descriptor characteristics are then reduced using two successive fully linked layers. As a result, an input EEG signal in this neural network will be defined by ten features, and the ailment will be identified using these features. One of this method's merits is the simplicity of the convolution network topology utilized in it. However, when compared to other learning models with comparable performance, this learning model still has a high computational complexity. Anjum et al. [8] presented a technique for defining the spectrum properties of Parkinson's disease-related EEG data. The feature extraction technique is accomplished utilizing spectral density parameters to characterize each signal, and these attributes are also merged using the LPC linear predictor coding scheme. The Burg technique is used to calculate LPC coefficients in this study. Finally, the collected characteristics are classified and the illness is diagnosed using a new classification based on principal component analysis. Each class is separated from the

other classes in this classification by a hyperpage, which is determined by assessing the primary components of the attributes. This method's key benefit is its fast computational speed, which makes it suited for real-time applications. However, when compared to comparable algorithms, the approach suggested in this study has a lesser accuracy. Silva et al. [9] employed EEG signal channel correlation to identify Parkinson's illness. To extract the ideal characteristics, this technique employs a genetic algorithm and binary classification, as well as an artificial neural network with a hidden layer to categorize the extracted features. EEG signals have been proposed by Barua et al. [10] as a three-step technique for diagnosing Parkinson's disease. The initial stage in this approach is to generate multilevel characteristics for the input signal, from which a collection of pattern and statistical properties may be retrieved. The Neighborhood Component Analysis (NCA) approach is utilized in the second stage to pick the suitable features. Finally, the property categorization procedure is carried out in the third stage utilizing the closest neighbour K method. Khare et al. [11] provide a deep learning-based automated method for identifying Parkinson's illness. In this approach, the field of EEG signals is first transformed into matrices in terms of time and frequency, and then the signals are classified using a CNN network. To diagnose Parkinson's disease, Loh et al. [12] employ an approach similar to that provided in [11]. The main difference is that they employed Gabor conversion to transform the field of EEG signals in their technique. Cuckoo Search Algorithm is an optimization algorithm that in addition to faster convergence than other optimization methods does not require the determination of multiple parameters. This algorithm's basic trend is to start with a set of random solutions and then refine it using various operators. The three rules that govern this algorithm are as follows:

Each cuckoo lays one egg at a time and sleeps on it in a nest chosen at random. The best nests with the finest eggs are saved for the following cycle. In other words, the best answers will be available in the following search algorithm iteration. The number of host nests available is constant, and the host bird with a probability of  $P_a \in (0,1)$  finds an egg on which the cuckoo is lying. The code of the multi-objective cuckoo search algorithm is as follows [13]:

#### Algorithm 1: Cuckoo Search

- 1- Defining the fitting function of the algorithm as  $f(x) = (x_1, \dots, x_d)$
2. Production of the initial population consists of  $n$  nests, each of which contains  $K$  eggs.
3. Repeat the instructions in this step until  $(t < T)$  or one of the stop conditions occurs:
  - 3-1- Select a random cuckoo like  $i$  by Levy algorithm.
  - 3-2- Evaluate the optimality of the selected cuckoo by the fitting function.
  - 3-3- Choose a random nest like  $j$  from  $n$ .
  - 3-4- If the solutions in  $j$  prevail over the cases in  $i$ , then replace  $i$  with the answers in  $j$ .

- 3-5- Leave the  $P_a$  ratio of the worst nests and replace them with new nests.
- 3-6- Keep the best answers / nests.
- 3-7- Increase the value of  $t$  by one unit.
- 4- The end.

The search method starts by producing a collection of random solutions for the nests based on the pseudocode above. Then, using an iterative cycle, a cuckoo named  $i$  is chosen at random and its beam optimality determined. The next step is to choose a second random nest (solution set) such as  $j$  and compare its beam optimality to that of nest  $i$ . If nest  $j$  outnumbers nest  $i$  nest  $j$ 's solution set is considered to be the best response set to nest  $i$  and  $j$  is replaced by  $i$ . The  $P_a$  nest ratio is left with a poorer fit in the following stage of this method, and a fresh set of solutions is randomly produced. The optimum set of maintenance options is supplied at the conclusion of each cycle. These stages are continued until the algorithm's number of iterations exceeds a preset value of  $T$  [13].

### III. RESEARCH METHODS

The proposed system for diagnosing Parkinson's disease using a combination of neural network and cuckoo search algorithm includes the following steps:

1. Pre-processing EEG signals to eliminate noise
2. Reduce data dimensions based on principal component analysis
3. Classification based on artificial neural network and cuckoo search algorithm.

Preprocessing the EEG data is the initial stage in the suggested technique. To remove noise in the input signals, database training samples are treated using discrete wavelet analysis. The suggested method's second phase will employ principal component analysis to remove duplicate features and minimize data dimensionality. The artificial neural network model is trained and the classification model is built using the retrieved features. The cuckoo search algorithm is employed in the proposed technique to train the neural network and discover the best weight vector of neurons and their biases. The new EEG readings will be utilized to test this enhanced neural network for the existence of Parkinson's disease. Figure depicts the suggested method's steps as a diagram (1).

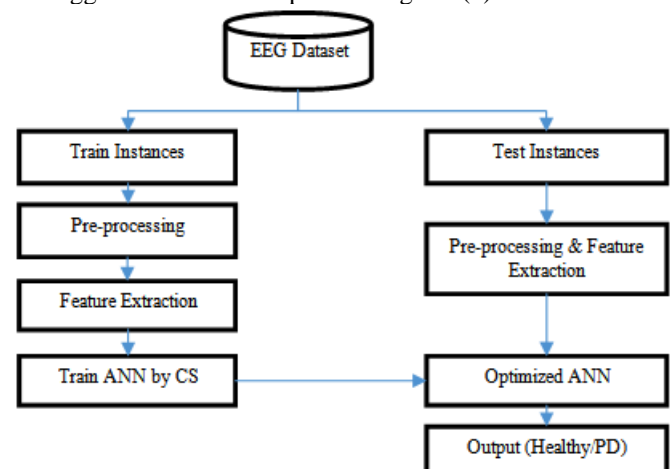


Fig. 1. Diagram of the process of diagnosing Parkinson's disease using the

*proposed method*

Each of the steps of the proposed method will be explained below.

**A. Data Processing**

The goal of data preprocessing is to get the input EEG signals ready for the following phases of processing. Noise's detrimental influence on EEG signals must be minimized for this to happen. Discrete wavelet analysis (DWT) is utilized to eliminate noise from EEG data in this work. A large range of fundamental functions are included in wavelet discrete analysis. These functions offer a variety of processing choices for EEG signals in various settings that can be matched to the peculiarities of EEG signals in epileptic episodes [14]. Single channel EEG recordings may be divided into numerous subband signals using discrete wavelet analysis. More characteristics may then be retrieved using these breakdown signals, boosting the accuracy of Parkinson's diagnosis. The wavelet transform is used to deconstruct the original data into layers, which is then used to decompose the signal using discrete wavelet analysis. In a time series, the wavelet transform may be thought of as a piece-by-piece information decomposition. The raw data is initially evaluated by transforming the wavelet into layers, which is known as function analysis, in this procedure. Each decomposed signal segment may be seen as a wavelet coefficient and a scale factor. In each stage of applying the wavelet filter and scaling filter to the main time series, which is repeated in the form of the pyramidal algorithm depicted in Figure, wavelet coefficients and scaling coefficients are acquired (2). S denotes the major EEG signal in Figure 2. In layer I  $A_i$  denotes low frequency data, whereas  $D_i$  denotes high frequency data. In reality, data is separated into two series in wavelet analysis: high frequency and low frequency data. The key aspects of the series are revealed by the limited quantity of data produced by applying the parent wavelet to the main series. High-frequency data may also be created by applying the mother wavelet to the main series, which is generally referred to as noise, and the chance of noise in high-frequency data is lowered as the decomposition levels go [14]. Figure (2) shows that the chance of noise in  $A_1$  data is quite high, but the probability of noise in  $A_5$  data is extremely low. In reality, wavelet decomposition's primary goal is to isolate the important characteristics from a slew of noise.

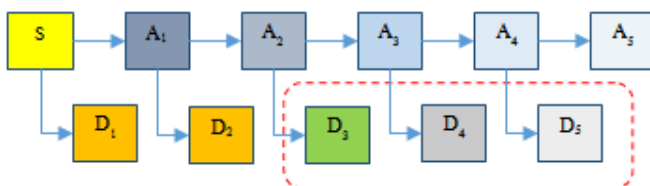


Fig. 2. Pyramidal algorithm of discrete wavelet analysis in the proposed method

According to Figure (2), in the proposed method, EEG signals are decomposed into six subband signals ( $a_5, d_1, d_2, d_3, d_4, d_5$ ). Also, the decomposition function used to decompose EEG signals by wavelet discrete decomposition is

the DB4 function. Figure (3) shows an example of subbands resulting from the application of DB4-based wavelet discrete analysis to six subbands. The conversion of the S and F signal domains from time to frequency indicates that the frequency range of the subbands extracted from the decomposition of the EEG signals is as follows:

The remaining signal  $a_5$  in the frequency range 0-3 Hz

- Signal  $d_1$  in the frequency range 50-100 Hz
- Signal  $d_2$  in the frequency range 25-50 Hz
- Signal  $d_3$  in the frequency range 12-25 Hz
- Signal  $d_4$  in the frequency range 6-12 Hz
- Signal  $d_5$  in the frequency range of 3-6 Hz

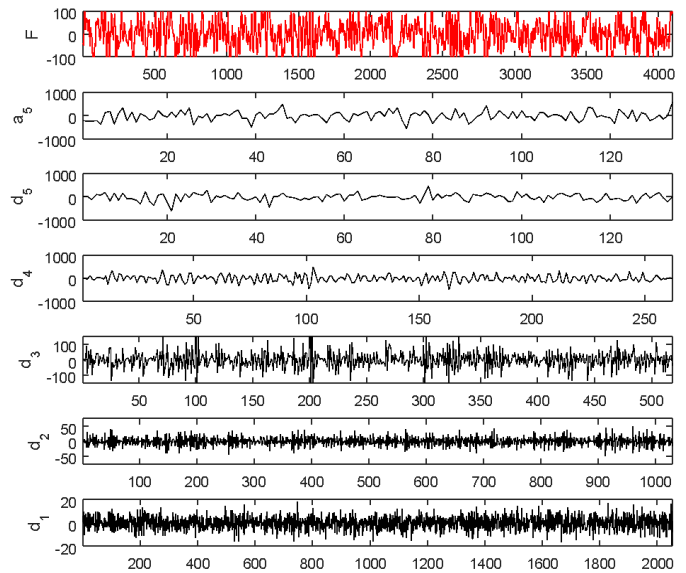


Fig. 3. Subbands resulting from the decomposition of an EEG sample signal by discrete wavelet decomposition

The frequency of Parkinson's-related patterns in EEG signals is usually in the range of 3 to 25 Hz. The frequency of signals  $d_1$  and  $d_2$  is out of this range. Therefore, in the proposed method,  $d_3, d_4$  and  $d_5$  subbands will be used to extract the feature.

**B. Feature extraction using principal component analysis**

After extracting the  $d_3, d_4$  and  $d_5$  subbands from the EEG signals, the feature extraction operation is performed using principal component analysis. For this purpose, the process of analyzing the main components of each of these subbands will be applied and the characteristics of each subband will be extracted. Considering the  $X^T$  data matrix with zero experimental mean value, where each row represents an instance and each column represents a property, the principal component analysis can be defined as follows [15]:

$$Y^T = X^T W = V S \tag{1}$$

In the above relation,  $V S W^T$  represents the decomposition of the individual values of the  $X^T$  matrix. According to the basic definition of principal component

analysis, the purpose of this algorithm is to convert the data matrix X with dimensions M to the data matrix Y with dimensions L. Therefore, it is assumed that the matrix X consists of columnar vectors  $X_1, \dots, X_N$ , each of which represents a property in X-. Thus, the X data matrix will have dimensions  $M \times N$ . With this structure in mind, the steps for extracting X principal components based on the covariance matrix will be as follows:

A) Calculating the experimental average of the data and its normalization: The experimental average of the data is a vector that is calculated as the following relation [15]:

$$u[m] = \frac{1}{N} \sum_{i=1}^N X[m, i] \tag{2}$$

The experimental mean of the data in the above relation is specifically applied to the rows of the matrix. The data distance matrix is then calculated with the experimental mean as follows [15]:

$$B = X - uh \tag{3}$$

In the above relation, h is an all-in-one vector of size  $1 \times N$ .

B) Calculation of the covariance matrix: In the second step, the covariance matrix C with  $M \times M$  is calculated through the following equation [15]:

$$C = E[B \otimes B] = E[B \cdot B^*] = \frac{1}{N} B \cdot B^* \tag{4}$$

In the above relation, E indicates the arithmetic mean. Also, the operator  $\otimes$  represents the external multiplication of the matrix, and  $B^*$  represents the conjugate of the matrix B.

C) Estimation of eigenvalues of covariance matrix and permutation of eigenvectors: In this step, eigenvalues and eigenvectors in covariance matrix C are calculated using the following equation [15].

$$V^{-1}CV = D \tag{5}$$

Which in the above relation; V is a matrix of special vectors and D is a diagonal matrix whose objects whose principal diameter is the eigenvalues of the matrix. Each eigenvalue in this matrix corresponds to an eigenvector. This means that the matrix V has dimensions  $M \times M$  and its columns are special vectors; So that the specific vector  $V_q$  is in the q-th column of this matrix and the specific value q of the corresponding matrix D is corresponding to it ( $\lambda_q = D(q, q)$ ). The permutations of special vectors are based on the magnitude of the corresponding eigenvalues. In this case, special vectors are sorted according to the descending order of the eigenvalues.

D) Selection of a subset of special vectors as a base set: Selection of a subset of special vectors is done through analysis of special values. The final subset is determined based on the permutation obtained from the previous step as  $V_1, \dots, V_l$ . In this step, cumulative energy can be used based on which [15]:

$$g[m] = \sum_{q=1}^m \lambda_q \tag{6}$$

The value of l should be chosen so that it has a minimum value and at the same time g has an acceptable value. For example, at least l can be selected as  $g[m=1] \leq 90\%$ .

E) Transferring data to a new coordinate space: For this purpose, the following transformations must be applied first:

The matrix  $s_l (M, l)$ , which represents the standard deviation of the data set, is calculated as  $s[i] = \sqrt{C[i, i]}$ .

The data is converted to  $Z = B / s$ .

The data are mapped to the new space based on the following relation [15]:

$$Y = W^* \cdot Z \tag{7}$$

After integrating the wavelet bandwidth characteristics, the detection model is built using a mix of artificial neural networks and the cuckoo search optimization technique, which we'll go over in the next part.

C. Classification of properties extracted by the proposed method

The data categorization operation may be done once the properties have been extracted using the suggested technique. The classification operation is conducted in the suggested technique by merging an artificial neural network with a cuckoo search optimization algorithm. The suggested classification model for the diagnosis of Parkinson's disease based on features retrieved from EEG signals is discussed in length in this section. This neural network is a prospectron network with two hidden layers. The lattice layers of this network have 6 and 4 neurons, respectively, and the transmission function of the first lattice of the logarithmic sigmoid type and the second lattice of the tangent sigmoid type has been determined. Also, the number of input layer neurons is equal to the number of features extracted for each sample (P) and the number of output layer neurons is equal to the number of output groups (normal / Parkinson's). The structure of this network is shown in Figure (4).

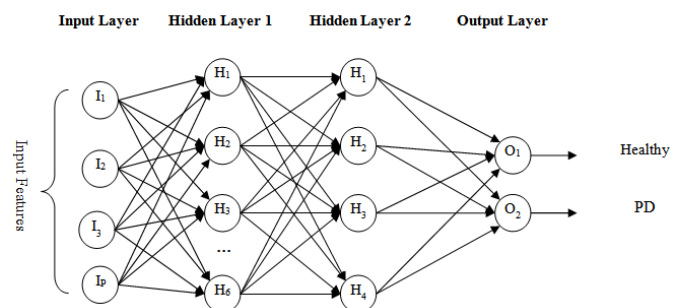


Fig. 4. Neural network structure for the diagnosis of Parkinson's disease

The cuckoo search optimization technique is employed in the detection phase of the suggested method and to establish the ideal weights for the specified neural network. Changing the weights of communication between neurons and neural network

biases, and then calculating the prediction error, is employed in this technique. The cuckoo search algorithm's optimal answer search mechanism is based on the strategy provided in [13]. Assuming the reader is familiar with this approach, the fitting function and response vector structure are given in the next sections. The response vector in the optimization algorithm used in this section determines the weight of communication between neurons as well as neural network biases. Therefore, for a neural network with I input neurons, H1 hidden neurons in the first layer, H2 neurons in the second layer, and P output neurons, the length of each response vector in the cuckoo search algorithm is equal to  $H_1 \times (I + 1) + H_2 \times (H_1 + 1) + P \times (H_2 + 1)$  will be. After determining the neural network weights by this response vector, the neural network outputs are generated for the training samples and compared with the actual target values. The mean square error (MSE) criterion is then used to evaluate the neural network performance and the optimality of the generated response. Therefore, the fitting function of the cuckoo search algorithm will be defined as follows:

$$MSE = \frac{1}{N} \sum_{i=1}^N (T_i - Z_i)^2 \tag{8}$$

In the above relation, N represents the number of training samples and  $T_i$  indicates the target value for the  $i$  training sample.  $Z_i$  also represents the output generated by the neural network for the  $i$ -th training example. An example of weight determination and neural network fit evaluation in the proposed method using the cuckoo search optimization algorithm is shown in Figure (5).

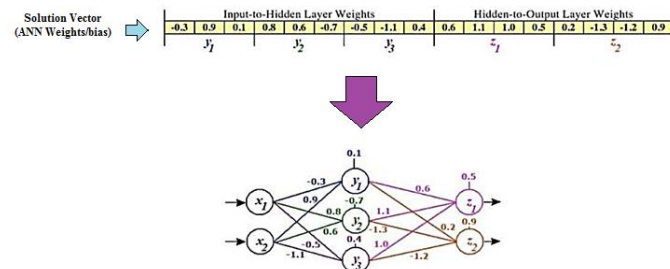


Fig. 5. An example of determining neural network weights by a cuckoo search algorithm

Using the cuckoo search optimization technique, the suggested method computes the neural network weight vector depending on its prediction error for training samples.

#### IV. IMPLEMENTATION AND RESULT

The suggested approach is implemented using MATLAB software in this section, and the proposed method's performance is evaluated. The suggested method's efficiency is also compared to that of alternative learning methods. The University of Oxford prepared the data collection utilised in this chapter's experiments. This collection is made up of two EEG signal datasets, each of which comprises 100 signal samples. These two datasets' samples are separated into two categories: normal (100 samples) and Parkinson's disease (200 samples) (containing 100 samples). A sample rate of 512 Hz was used to

record the data. Each signal has a total duration of around 8 seconds. Each EEG signal in the database is characterized as a vector with a length of 4096 bytes using this description. Each input signal is processed using discrete wavelet analysis and an attempt is made to reduce the signal's destructive effect of noise using the technique outlined in the preceding section. The feature dimensions of each sample were then reduced to 320 features using principal component analysis on the preprocessed signal set. The database samples are separated into two groups in the proposed method's performance test: training samples and test samples. A cross-evaluation approach with 10 repetitions of the experiment was used to categorize the training and test samples in order to retain the validity of the test results. The following are the parameters that were utilized in the cuckoo search optimization technique to optimize the neural network weight vector:

- Population size: 50
- Number of repetitions: 100
- Probability of leaving the nest: 0.25

Figure (6) shows the fitting diagram (MSE) obtained from one run of the cuckoo search algorithm to train the neural network.

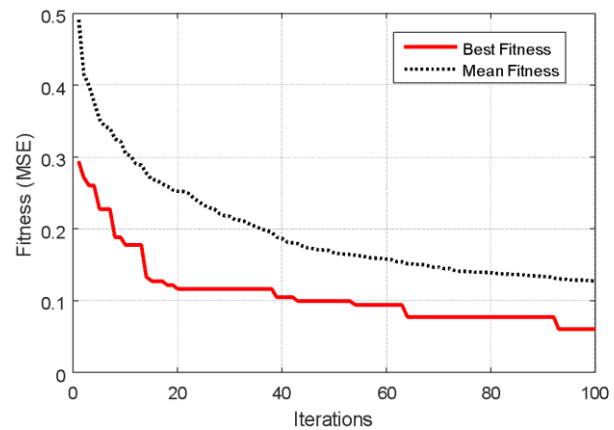


Fig. 6. Graph of fitting changes resulting from neural network training by cuckoo search algorithm

The graph of changes in the fit of the cuckoo search algorithm in Figure (6) illustrates that this algorithm may minimize neural network error and operates as an efficient training procedure for the neural network throughout different iterations. Figure (7) depicts the outcomes of the suggested model's proper diagnosis for each iteration. The accuracy of the suggested strategy is compared against three support vector machine learning (SVM), New Biz (NB), and K nearest neighbor (KNN) models in this graphic (and following trials).

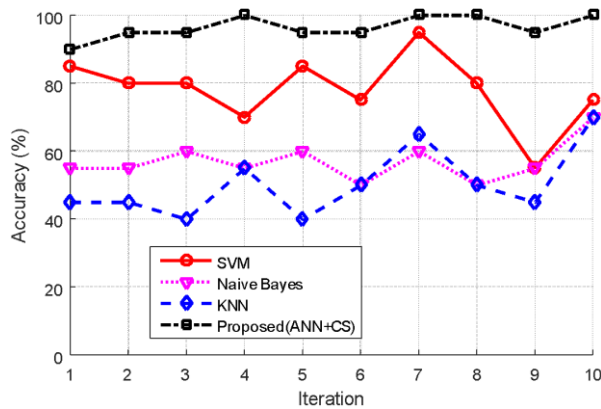


Fig. 7. Results related to the correct diagnosis of the proposed method

The proportion of right diagnosis for each of the 10 repeats of the test is displayed in Figure (7). Using the suggested strategy, as illustrated in this figure, can enhance the accuracy of Parkinson's disease diagnosis when compared to other instances. The findings of this experiment reveal that when utilizing the suggested approach, the lowest accuracy of accurate diagnosis of the complication is equal to 90%, the greatest accuracy is equal to 100%, and the average correct diagnosis is equivalent to 96.5 %. Table 1 shows the accuracy results for each of these methods (1). The findings in this table demonstrate that the suggested method, which uses a mix of optimization techniques and machine learning, has a smaller range of changes during various repetitions, in addition to having a better average accuracy. According to the findings of the trials, the suggested technique had a detection accuracy of less than 95% in only one iteration and was able to accurately categorize more than 95% of the test samples in subsequent iterations.

TABLE I  
SUMMARY OF PREDICTION RESULTS OF EACH OF THE TESTED ALGORITHMS

Title	Average accuracy	The least accuracy	The most accuracy	Standard deviation
suggested method	96.5%	90%	100%	3.37
SVM	78%	55%	95%	10.59
KNN	50.5%	40%	70%	10.12
NB	57%	50%	70%	8.86

Figure (8) shows the confusion matrix resulting from the diagnosis of Parkinson's disease in the proposed model. In the displayed clutter matrix, the number 100 in the first row and column indicates the number of healthy samples tested that have been correctly identified by the proposed method. This number is identified in the clutter matrix as TN. The number 0 in the second row and first column indicates the number of healthy specimens tested that were incorrectly diagnosed with Parkinson's disease. This number is identified in the clutter matrix as FP. The clutter matrix's second row and second column, which reflect the number 93, identifies samples with Parkinson's disease that have been accurately detected by the patient's suggested method and are designated as TP samples. In addition, the number 7 in the first row and second column represents the number of diseased specimens diagnosed wrongly by the suggested healthy approach. The clutter matrix

identifies this number as FN. These findings reveal that the suggested approach for identifying Parkinson's disease in healthy specimens had an average accuracy of 96.5 percent, with just 7 of the 200 specimens in the database misclassified.

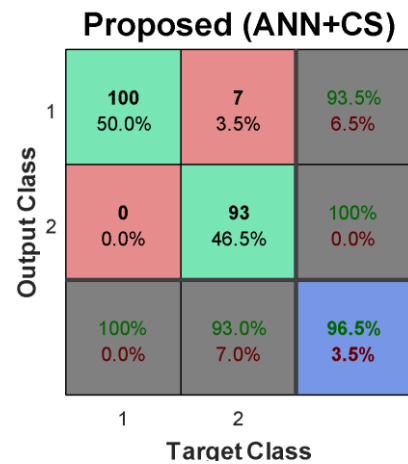
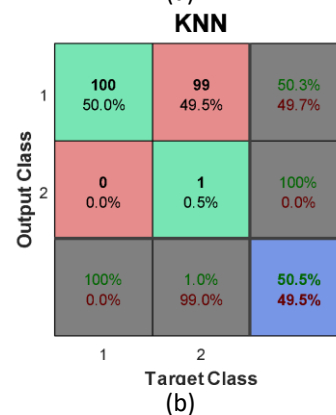
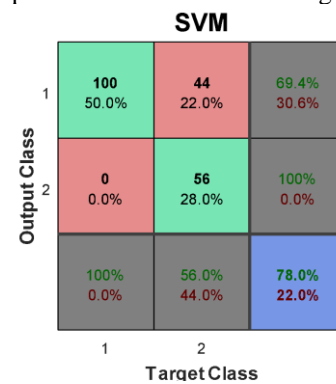


Fig. 8. Disorder matrix resulting from the diagnosis of Parkinson's disease in the proposed model

Also, the results of the perturbation matrix related to the other three compared modes are shown in Figure (9).



**Naive Bayes**

Output Class	1	37 18.5%	23 11.5%	61.7% 38.3%
	2	63 31.5%	77 38.5%	55.0% 45.0%
		37.0% 63.0%	77.0% 23.0%	57.0% 43.0%
		1	2	
		Target Class		

(c)

Fig. 9. Disorder matrix resulting from Parkinson's diagnosis by (a) SVM (b) KNN (c) NB

Table (2) shows the performance measures of the experiments performed. All methods compared in this table use the same database and training and test samples as the proposed method. In this table, the criteria of sensitivity, specificity and area under the ROC or AUC curve are compared. Sensitivity criteria are used to measure the proportion of total positive group samples (with Parkinson's disease) that have been correctly diagnosed and are calculated as follows [16]:

$$\text{Sensitivity} = \frac{TP}{TP + FN} \quad (9)$$

On the other hand, the characteristic criterion is used to measure negatively categorized negative samples. This criterion is calculated as follows [16]:

$$\text{Specificity} = \frac{TN}{TN + FP} \quad (10)$$

Finally, the AUC criterion is obtained by calculating the area under the ROC curve for each method. Comparison of AUC values in Table (2) confirms that the area under the ROC curve is higher than other compared algorithms when using the proposed method. This diagram shows that using the proposed method will reduce the FP rate and increase the TP rate compared to other algorithms. On the other hand, the proposed method has better performance than the compared algorithms both in terms of correct detection percentage and in terms of sensitivity and specificity criteria. As a result, the proposed algorithm is more efficient in diagnosing Parkinson's disease.

TABLE II  
COMPARISON OF THE EFFICIENCY OF THE PROPOSED METHOD WITH  
OTHER CLASSIFICATION MODELS AND PREVIOUS METHODS

Algorithm	Sensitivity	Property	AUC	Accuracy (%)
Backup vector machine	0.6944	1	0.847 2	78
New Bay	0.6167	0.5500	0.583 3	57.0000
K nearest neighbor	0.5025	1	0.751 3	50.5000

CNN [7]	0.8471	0.9177	0.871 2	88.2500
LPC [8]	0.8700	0.8370	0.917 8	85.4000
suggested method	0.9346	1	<b>0.967</b> <b>3</b>	96.5000

## V. DISCUSSION AND CONCLUSION

Parkinson's disease is a degenerative and progressive nervous system illness that impairs a person's ability to regulate their movements. Analyzing EEG patterns is one approach to identify Parkinson's disease. However, finding a link between EEG signal patterns and the existence of Parkinson's disease is a key issue in the illness's automated diagnosis. This research proposes a new method for identifying Parkinson's disease based on optimization and machine learning techniques to address this issue. Using discrete wavelet analysis, the suggested approach conducts signal preprocessing to limit the damaging influence of noise. Principal component analysis has also been used to minimize data dimensionality and eliminate duplicate characteristics. Finally, the cuckoo search optimization technique was utilized to train the neural network and identify the best weight vector of its neurons. The presence of Parkinson's disease in fresh EEG data was predicted using this improved neural network. During the studies, the suggested method's efficiency was analyzed in terms of criteria such as accuracy, sensitivity, and specificity, and the findings were compared to existing learning models. Other optimization strategies for optimizing the weight vector of the artificial neural network can be researched in future study. The optimization approach may be utilized to concurrently optimize the structure of the network topology and its weight vector in future work. Future study may focus on determining the efficacy of the suggested approach for detecting various difficulties via EEG data, such as epileptic seizures or depressive illnesses.

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