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RESEARCH

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Predicting UPDRS in Parkinson's disease using ensembles of self-organizing map and neuro-fuzzy

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Abstract

Parkinson's Disease (PD) is a complex, degenerative disease that affects nerve cells that are responsible for body movement. Artificial Intelligence (AI) algorithms are widely used to diagnose and track the progression of this disease, which causes symptoms of Parkinson's disease in its early stages, by predicting the results of the Unified Parkinson's Disease Rating Scale (UPDRS). In this study, we aim to develop a method based on the integration of two methods, one complementary to the other, Ensembles of Self-Organizing Map and Neuro-Fuzzy, and an unsupervised learning algorithm. The proposed method relied on the higher effect of the variables resulting from the analysis of the initial readings to obtain a correct and accurate preliminary prediction. We evaluate the developed approach on a PD dataset including speech cues. The process was evaluated with root mean square error (RMSE) and modified R square (modified R2). Our findings reveal that the proposed method is effective in predicting UPDRS outcomes by a combination of speech signals (measures of hoarseness). As the preliminary results during the evaluation showed numbers that proved the worth of the proposed method, such as UPDRS = 0.955 and RMSE approximately 0.2769 during the prediction process.

Keywords Parkinson's disease, Neuro-Fuzzy, Machine learning, Self-organizing map, Classification, Features extraction

Introduction

Parkinson's disease (PD) is a complex disease that affects the brain and leads to movement differences that greatly impair a patient's life. One of the symptoms suspected of this disease is aging, which is accompanied by health consequences that negatively affect the nervous system [1]. With age, the incidence of this disease increases in all cities of the world. The risk associated with Parkinson's disease is age and is mostly affected by age groups over 60 years [2]. As for the percentage of young people, it was a weak percentage, not exceeding 20%, which was diagnosed and who are before the age of fifty. Parkinson's disease (PD) affects a large number of people around the world, approximately 3.6 million people are affected [3]. And it is increasing, depending on the age group and quality of life. Awareness and social costs also affect the increase in the disease rate. Statistics show that the disease rate will increase to more than 8 million in the middle of 2030. In fact, there is no specific and real test that can diagnose the disease [4]. The doctor's task is to research the patient's medical history, some neurological examinations, etc.

Because of the great heterogeneity between infected people and those suffering from Parkinson's disease, therefore, each individual suffers from different symptoms from the other. At the beginning of the disease, the

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symptoms are mild, so the disease disappears for a long time until it is discovered. As well as 60% of people who suffer from Parkinson's disease, the symptoms are not clear or consistent, there are many symptoms that have been counted, some patients participate in them and others do not, including motor and non-motor [5]. Among these symptoms are constipation, sleep disturbance, rapid eye movement, bladder disorder, and many non-motor symptoms. They represent the early stages of the disease. There are also secondary symptoms such as a defect in walking, a defect in smell, difficulty in remembering or thinking, and sexual weakness. Since there is no cure for such a disease, but symptoms can be reduced in some cases [6]. The treatment currently available is either to replace the dopamine that is present in the brain or to reduce the risk of problems caused by the lack of dopamine. Also, dysarthria is one of the symptoms that can be inferred from the disease.

The UPDRS, or the so-called Unified Parkinson's Disease Rating Scale, is the most important measure for measuring the severity and diagnosis of Parkinson's disease [7]. This scale can measure the severity of the disease, but the cause of the disease cannot be known. UPDRS consists of three main sections, sequentially motor symptoms, daily activities, and human behavior [8]. One of the most important things that must be taken is to monitor the development of the disease and is considered one of the necessary things to stop the disease from getting worse. Monitoring also reduces the expenses that come from frequent visits and medications to the patient, so attention has been turned to remote monitoring using smart devices [9]. Thus, the visit to the doctor is reduced and greater accuracy is obtained through health care.

Machine learning is an effective tool in diagnosing diseases. There are many traditional methods for diagnosing Parkinson's disease, but artificial intelligence methods are almost few, especially the extraction and grouping of features and selecting the best ones for use in predicting UPDRS by machine learning. Machine learning techniques can be used in prediction and development in terms of extracting features or improving prediction algorithms. And it is possible to classify a group of points as belonging to a certain category and others not belonging, thus it can be predicted that a strong probability will be obtained in places where the specifications should be present. Similar data of a certain type are in one direction, which are heterogeneous in the last direction in order to be easy to classify. In this way, the patterns and behavior followed by the disease can be understood and thus controlled [10].

This study aims to diagnose Parkinson's disease early so that we can control it by one of the Artificial Intelligence (AI) algorithms. In this study, the extracted features are collected and the features with the highest weight that affects the result are selected and dealt with in another new treatment within the algorithm. The algorithm was developed using a developed neural network based on feedback and the method of choosing the Most Influential Variable (MIV).

Much previous research focused on feature extraction, but good extraction still requires exceptional efforts. Many workbooks have been used for this purpose, but they still require additions to the workbook in order for its work to be integrated and to give better results than traditional methods.

Related work

One of the most important actions that can be taken in this field is the effective diagnosis of Parkinson's disease. Lots of ratings and different ways by researcher illustrated in literature [11]. As well as the accuracy of the classifier was calculated by various evaluation methods, and based on the results that were extracted [12], they found that the best classifier is the neural networks (NNs) classifier [13], which leads to good results compared to other methods, exceeding 92% in accuracy [14]. The Weka program was used to extract the important data and perform its primary processing [15]. In the context of machine learning, some researchers used the Support Vector Machine (SVM) as a well-known and well-known qualifier for the diagnosis and indication of Parkinson's disease, as well as to distinguish infected people from non-infected people [16]. They used the LIBSVM application many times to reach high accuracy in the kernel values for a group of experimental images of the disease [17]. In addition to the use of statistical methods such as the receiver operating characteristic (ROC) curve, through which the disease was monitored remotely and inferred by artificial intelligence about the causes [18]. Another famous classifier that many researchers relied on is Fuzzy K-Nearest Neighbor (FKNN) [19], which depends on the proximity of the extracted features to each other and their relationship to one another. One of the methods that did not find much popularity is the weighting of features based on fuzzy mass (FCM) (FCMFW) [20], which depends on the largest effect of the feature extracted from within the same group or class and was used to detect Parkinson's disease in its early beginnings [21]. One of the systems that also had a good impact in the early diagnosis of Parkinson's disease is the K-NN classifier [22], which considers adjacent points as the basis and from which it expands in order to classify the area to be diagnosed. Among the applications that relied on extracting groups with sub-specifications is the application of Principal Components Analysis (PCA)

[23]. On this basis, researchers developed an approach that relies on important features from secondary features, which in most applications are neglected.

The local radiological projection technique (PBL-McRBFN) was used for images taken from various sources and devices to be adopted in predicting the presence of Parkinson's disease [24]. An algorithm called Random Forest has been tested to predict the progression of Parkinson's disease and supports early diagnosis of the disease, thus obtaining satisfactory results [25]. Some studies relied on recognizing the patient's voice, through which the vocal features are extracted during the stage of the disease from its inception to its final diagnosis and thus its treatment [26]. The features in this case have different dimensions for ease of merging and classification. The threshold method is one of the rapid methods that were used for the final diagnosis of the disease and the use of medical images from a database had an impact on the accuracy of the output and achieved good results based on the classification among the extracted features. New Technique also based on SVM classifier suggested and based on CMBA-SVM for clinical issue then try to find the chaotic behavior for the patient [27]. The well-known SVM classifier was developed with specific additions such as Least Square SVM (LS-SVM), which gave the most accuracy during the training process on images from a standard database, and the disease diagnosis rate was very high in this way [28].

Neuro-Fuzzy System

The Neural Fuzzy System (NFS) combines the learning capabilities of a normal neural network with inferences to explain the flow of data within the layers of the neural network [29]. As well as the NFS system works to develop business rules with ambiguity in the event that the condition of doing the specific action is fulfilled. The if–then rule has the best role in making decisions within the neural network. In this case, the fuzziness of the system will be removed, in many cases it is dealt with during the training phase. There are two main types that are dealt with in the proposed neural network, which are Conditional Feedback (CF) and High Weight Variables (HWV). The first type uses fuzzy values in making decisions related to the establishment of data return paths and procedures that are clear in the next stage. As for the second type, it uses linear systems that are affected by the fuzzy variables generated in the previous stages to decide which one to use in the next stage of training.

$$\textit{if } I_1 \textit{ is } X_{1j} \textit{ and } I_2 \textit{ is } X_{2j} \textit{ and} \ldots\ldots I_n \textit{ is } X_{nj} \textit{ then } y_j = \sum_{i=1}^{n} x_{ij}a_i + b_v \tag{1}$$

Where X is the input parameter from vector $V = \{x_1.x_2 \ldots x_n\}$ for each layer and j represent how many parameters in certain hidden layer, while a consider as threshold parameters and b is bias.

Any fuzzy neural network used to detect or work with Parkinson's disease is based on a fuzzy type of HWV and consists mostly of more than 6 layers [30], in the first layer it is specialized to configure the passages as inputs to the network. $V_p = \sum L1.L2 \ldots .Ln$,as for the second layer, it is the one that performs preliminary processing to decide whether the system can generate feedback in the later stages or not. In every signal that enters the system, the network performs complex calculations in order to distinguish which of the data is important and is the product of the advanced stages as a kind of prediction. The Gaussian distribution helps in the process of determining the variables as well [31], which are usually in the third layer of the neural network. And the linguistic discretion illustrates in the following equation.

$$\mu_{1j}(x_i) = e^{-\frac{(x_i - y_{ij})^2}{\rho_{ij}^2}} \textit{ such as } i = 1 \ldots m \; j = 1 \ldots n \tag{2}$$

Where x *and* y represent the two parameters of the Gaussian function and the μ_{1j} is the membership function. The third layer in the neural network notice as the rule layer and the node inside are variables as distributed in each layer.

Then the rules of the layers collected in the network to make the proposed output result by achieving the AND operation with fixed the parameters inside each layer. As shown in the equation.

$$\mu j(x) = \prod_i \mu 1j\ (x_i) \textit{ where } i = 1 \ldots m \textit{ and } j = 1 \ldots n \tag{3}$$

Where $\prod \mu$ consider the main AND operation of the signal in the next 5 layers. The layer represents the linear system behavior and the significant value illustrate in the equation bellow:

$$y_i = \sum_{j=1}^{m} x_j w_{ji} + ba_i \tag{4}$$

Consider y as the layer with corresponding nodes x, and results features with w weights. This is the process of the signal inside the layer in Fuzzy system while the output signal can be calculated as in equation bellow:

$$y_{i=}\mu_i(x) \times y1_i \; i = 1 \ldots n \tag{5}$$

Where y represent the layers with x nodes, and the whole system of NFS can calculate the output as:

$$U_K = \frac{\sum_{i=1}^{n} w_{ik} y_i}{\sum_{i=1}^{n} \mu_i(x)} \tag{6}$$

Such that U is the final output system to the layers $k=1...n$ numbers of nodes, w is weight that control the whole system. Fuzzy design identifies information that is predictable and unknown to later stages of work in the fuzzy if–then rule. In this context, we divide the regions into smaller, fuzzy regions, and the small part describes the small base. Thus, by grouping the descriptions, we can make a comprehensive description of the system.

Self-organizing map

A self-organizing map (SOM) is an algorithm proposed by Teuvo Kohonen, through which data is visualized in a special ordering manner, and it works on high-dimensional data because it has the ability to reduce its dimension in the map. It collects similar data together and arranges them hierarchically so that the next level can be selected according to certain priorities [32].

In fact, the data points extracted from the features compete with each other to get an appropriate representation in the network. In the beginning, the network is done by means of weights that are extracted from the features in the data provided, while the distance between nodes is calculated accurately and with known directions. The short distance here is considered the ideal distance that the contract should follow and is considered the winner. During the training process, the weights and distances are changed, as they are in constant change until the end of the treatment. As shown in Fig. 1.

Algorithm for SOF

This algorithm works on one principle, which is the winning node. The winning node has the shortest distance to a predetermined vector through the weight function. The algorithm can be improved by this weight or function. Determining the distance is in different ways, and the most used is the Euclidean distance, and it is used to measure the distance depending on the weights. The algorithm description illustrates as bellow:

Algorithm 1. Initialize the network

For i=1: *number of iteration*

- **Calculate** neighborhood radius **by** $nr = nr_0(T)e^{-\left(\frac{T}{\gamma}\right)}$ $such\ that\ \gamma =$ *Maximum radius of Grid*/ number of iteration
- **Learning** rate **by** $\beta = n\beta r_0(T)e^{-\left(\frac{T}{\gamma}\right)}$ $such\ that\ \gamma = Maximum\ radius\ of\ Grid/$ number of iteration
- **For** All input
    - Winner=short path **by** $D\left(w_i.w_j\right) = \sum(w_{im}.w_{jm})^2$
    - **For** All weight find distance *(w-k)< nr*

    Adjust weight by $w(t+1) = w(t) + \delta(t)\beta(t)\left(x - w(t)\right)\ where\ \delta\ is\ e^{-\left(\frac{d}{nr}\right)}$

    END

END

END

With regard to learning and prediction in this algorithm by achieving the general goal of making certain parts of the network behave similar to the entered patterns. The distributions depend on the pre-calculated weights of the neurons in the network, and initially they are small random values taken from the fundamental vectors. In each cycle, the algorithm calculates the weight more accurately and changes its paths until it reaches the best path, which is due to the calculated ideal weight.

Methodology

Artificial Intelligence (AI) methods have proven effective in many prediction and diagnosis processes [33]. This study uses one of the unsupervised artificial

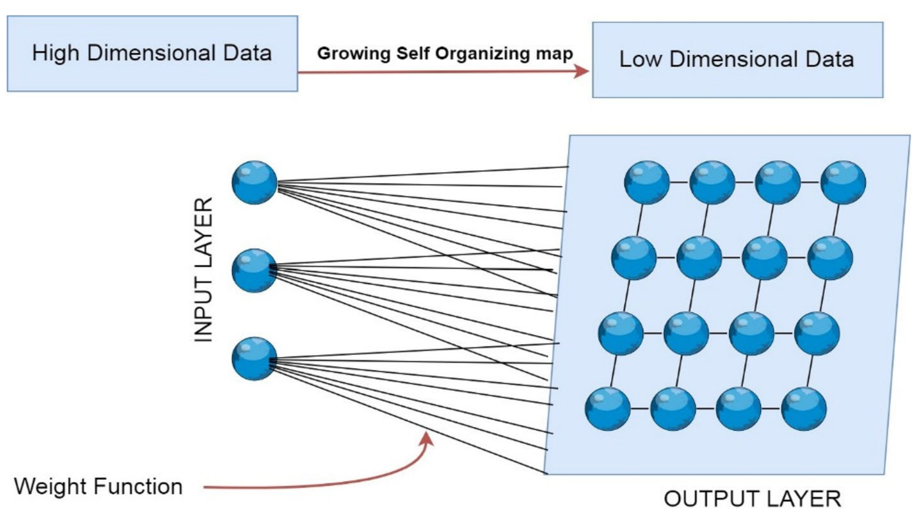

Fig. 1 Self-organizing map within AI algorithm

intelligence techniques to diagnose Parkinson's disease in its initial stages. Through the prediction of the UPDRS, many of the methods that were used include the beginning of collecting data, analyzing that data, reducing its dimensions, passing through the preliminary treatment, and extracting the features that are considered the basis in the prediction process.

The proposed method consists of several stages, each stage has its own characteristics, beginning with data collection, analysis and processing, and thus extracting advantages from it. We can explain the stages in detail as follows.

1. *Collecting data* in order to predict Parkinson's disease from different places, the most important of which is the standard database and data of individuals in the hospital, both healthy and patients diagnosed with the disease. The data must contain the features to be extracted that help in prediction.

This study consists of data from 276 still images from several sources of the human brain from X-rays and MRI. 178 of them are late cases of the disease that can be easily diagnosed, and the rest differ from one to the other according to the quality of the image. The goal of treatment is to distinguish healthy people from those infected with the disease. The data generally contains a sign in the image to distinguish the percentage of the disease and not just that it is infected or not [34].

Dataset have many attributes that help in prediction some of these attributes illustrate in Fig. 2.

The dataset should provide clinical assessments such as a rating scale for measuring motor and non-motor symptoms. Demographic information is also important in providing age, gender, race, and family history of Parkinson's disease. And brain imaging, which is the basis on which the proposed method depends.

2. *Data Preprocessing*: Clean and preprocess the collected data to handle missing values, normalize features, and remove any noise or irrelevant information. The pre- processing is done to increase the accuracy of the results and to obtain a satisfactory result. The goal here is to deal with values with large dimensions and process them to unify the dimensions of all values, and thus the data extraction is optimal. The pre- processing here is the first step

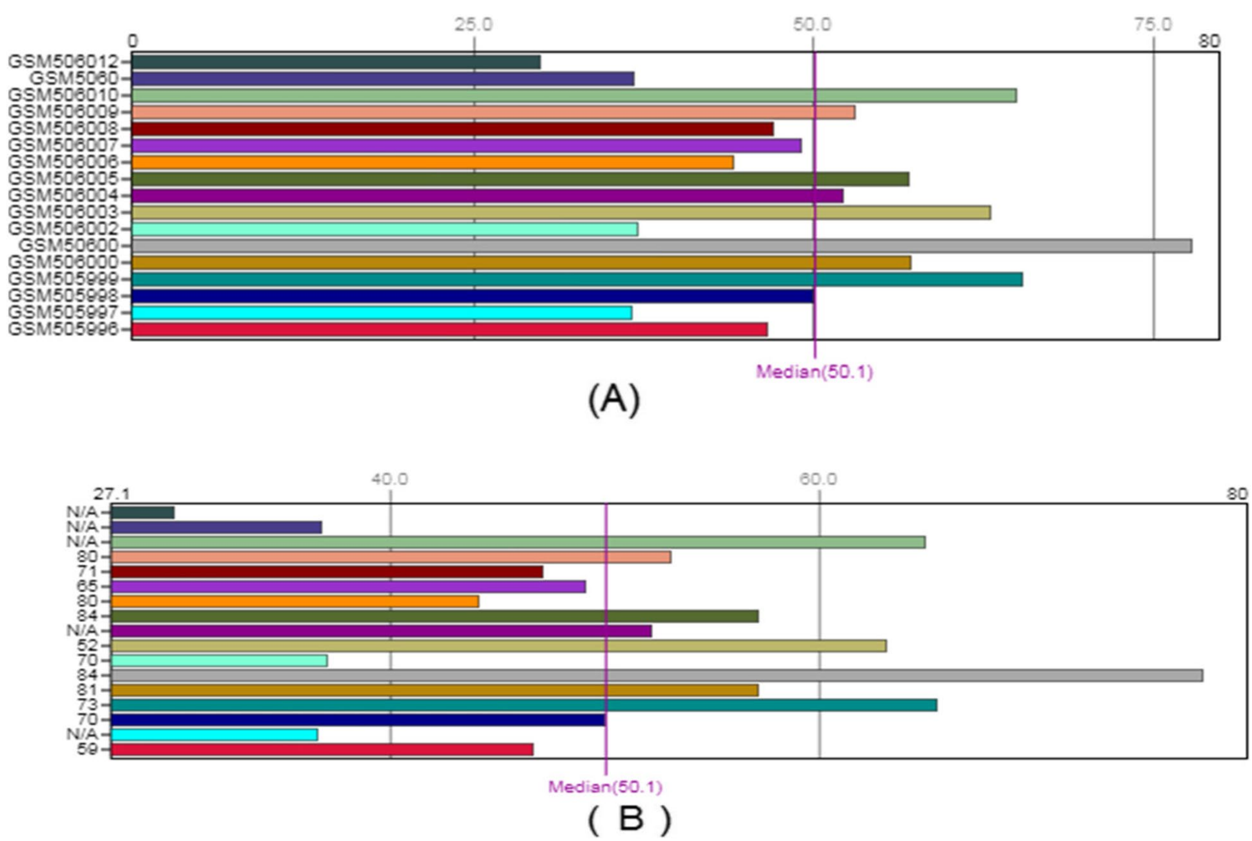

Fig. 2 Attribures Dataset **A** including names and **B** ages

towards prediction, which is the basis of the study and the desired outcome of the study. There are empty groups and others that contain incomplete data. During the pre-processing, the data is distributed sequentially to those groups.

General framework illustrate the stages flowed in this study with the sequence of these stages including the data flow among them. In Fig. 3 the stages will shows the priority interest of the processing with impact of them on the prediction.

3. *Feature Extraction*: Identify the most informative features from the preprocessed data. This step aims to reduce dimensionality and enhance the predictive power of the model.

The features extracted from these inputs are of **two types**, the first and the basic type, which is the one that is at the beginning of processing, which is in the first layer of the neural network and is called the input layer, as follows:

$$v_X = \sum_{i=1}^{n} X_i b + w_{i\times 0.02} \tag{7}$$

Considering v is the feature vector for feature item x, controlled by the weight w in factor decomposition, all the features stored in vectors before processing then may reduce the dimension of them or not according to processing manner.

The basic vectors are solved as they are the main components of a group of feature vectors, using the statistical method, and then binary vectors consisting of columns and rows are made.

$$z = [z_1 . z_2 \ldots z_m] \tag{8}$$

$$\acute{z} = H_\theta + v_{select} \tag{9}$$

Where z is the vector in input layer with dimension m, and $\acute{z}$ consider as the vector under process within neural network (in the other layers). H is the matrix model such as $H = [\varnothing_1 \ldots \varnothing_j] \in \mathbb{R}^{m\times j}$ andθ vector of $\theta_1 \ldots \theta_n$.

4. *Classification*: Parkinson's Disease classification involves using neural network to classify individuals into two groups: those who have Parkinson's Disease (PD) and those who do not (healthy individuals). This task is typically framed as a binary classification problem, where the model is trained on labeled data to distinguish between the two classes based on input features.

Many variables control the neural network, and these variables are trained to obtain the best result in prediction. In medical images or medical information, many advantages are extracted. The feature with the most impact is the feature that can be taken advantage of and thus re-processed. The fuzzy processing of the neural network allows many improvements in the results of artificial intelligence and thus the accuracy of the prediction result for patients with Parkinson's disease. The important

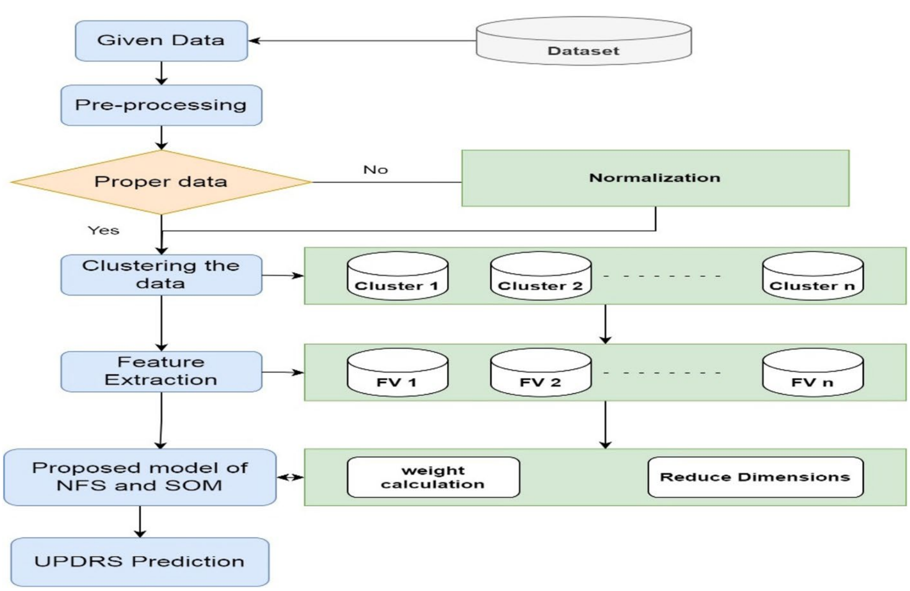

Fig. 3 General Framwork

contribution here when the neural network works, the output of the most influential from a particular layer can be returned feedback to the layer that precedes it to take advantage of the weight of this variable. The flow of data from one layer to another is controlled by the weights that accompany the features from one layer to another in the neural network. As shown in Fig. 4.

The nervous system, according to the standard behavior, collects infinitely weighted variables that come from the previous stages *(x_j(n-1))*, and in relation to the current stage *(xj(n))*, it represents the signal, and thus it is delayed by a certain amount and goes to the next stage with a specific and calculated delay time.

$$y_k(n) = \sum_{i=0}^{\infty} w^{i+1} x_j(n-1) \quad (10)$$

Consider w as the weight that control the flow of the data through layers, and the i is the iteration number of how many times start this network. In fuzzy system we propose to control the feedback by the derived weight of extracted features and the feature that comes from layers in the network as shown in Fig. 5.

There are three cases for controlling the weight in proposed Fuzzy neural system, first, when $|w| < 1$ for the output signal, $y_k(n)$ that reflect system stability. And when $|w| = 1$ consider the linear behavior, finally when, $|w| > 1$ lead to negative exponential.

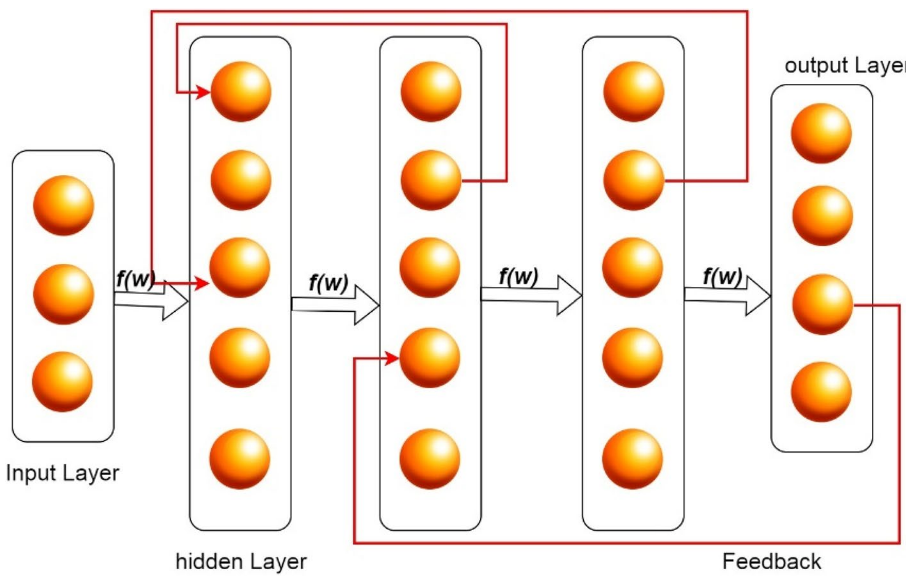

Fig. 4 Strategy of neural network

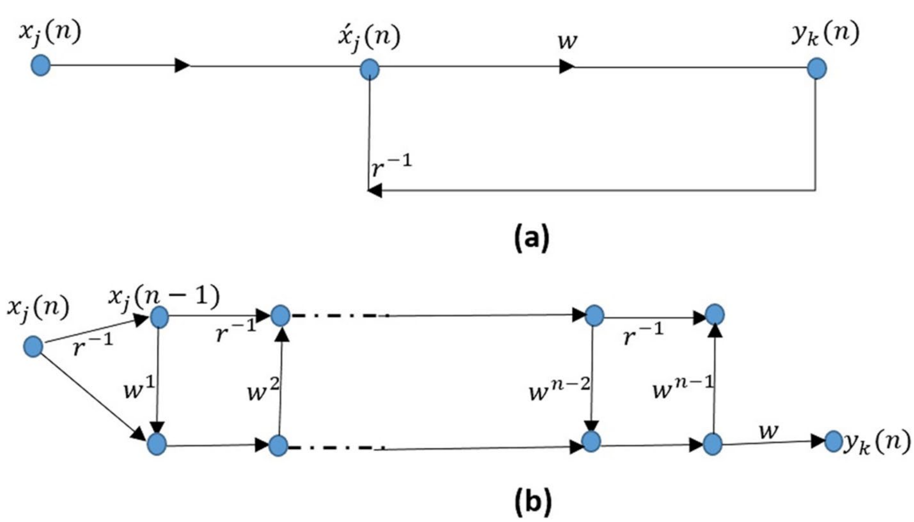

Fig. 5 (**a**) data flow on neural system (**b**) data flow with corresponding weights

For N power the weight will be not enough for achieving results in case of w^N so that infinite sum will produced as a y_k.

$$y_k(n) \approx \sum_{l=0}^{N-1} w^{l+1} x_j(n-1) \tag{11}$$

then we can consider the weight in each layer in neural system derived according to the following:

$$y_k(n) = wx_j(n) + w^2 x_j(n-1) + w^3 x_j(n-2) + \cdots + w^N x_j(n-N+1) \tag{12}$$

All the weight should be store in certain vector for new processing actually in the next iterations.

The method relies primarily on the outputs of the hidden layers in the neural network, and the outputs of those layers are variable depending on the feed they are provided with from the previous layers. The feedback that results from one hidden layer to another hidden layer preceding it can be calculated using precedence marks called weights. The weight is calculated according to its effect on the average result, and therefore important weights can be determined and fixed during the testing mode.

Results

In order to classify Parkinson's disease, the NFS is used in a way that divides people into two main categories: the normal one who does not carry the disease, and the PD one who is infected. For this purpose, we used the previously mentioned standard dataset, which is basically classified according to the proposed method. Which includes multiple images from more than one source and contains specific specifications and signs for each image. The images contain infected and non-infected people, and the data is indexed in the form of integrated tables. These data were used for training. In order to initialize the classification method, the NFS framework is constructed with a sibling of inputs and 18 neurons per output. The proposed method on the used database has proven its worth in relation to the rest of the methods.

When designing the proposed method, we divide the input space and determine the dimensions of the hypothesis. In the second layer, the input differs from other information because of the initial processing. The input space is usually less than the space for the hidden layers and therefore for the outer layer. The algorithm automatically scales the fuzzy parts and duplicates the data as it passes through the hidden layers. Data training input and output in the classification process begins with the transfer process and then with data processing in hidden layers and decision making. As for the two-dimensional output group, the data is different. The training process is in the form of 80% training and 20% testing.

The results obtained from the simulations of the NFS algorithm are compared with the results with other algorithms that classify the PD. For evaluation, the following equation should be used:

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \left(u_i^d - u_i\right)^2} \tag{13}$$

Consider u_i^d output desired value and u_i the real value from the system. To estimate the performance of the NFS system, we take the values resulting from Eq. 13 and the resulting signals. In another iteration, the RMSE values are calculated, and from them we can measure the recognition rate by the number of completely classified variables divided by the total number of variables:

$$Recognition\ Rate = \frac{Number\ of\ item\ correctly\ classified}{Total\ number\ of\ item} \times 100\% \tag{14}$$

While training the NFS algorithm, all input data are measured in the form [0, 1]. And after the process of collecting the data in the form of groups and according to priority. The structure of the NFS at Layer 2 is variable from the input source. Modified RMSE consider the MSE after each iteration until reach appropriate one that achieve the objective. Every cycle can be reflecting the certain behavior with MSE and system should be stable. The learning process was conducted for 18 h in a fuzzy algorithm and with a different number of bases: 2, 5, 8, 12 and 16. By imaging and decreasing the RMSE values in each cycle, we can increase the accuracy of the output. The results illustrated in Table 1.

In the table we note that the increase in neurons leads to an increase in the result to a certain extent. The result can be excellent, and any increase in the number of neurons is useless, so it causes an increase in time with an unnecessary increase in the number of program cycles.

Reducing the error rate is one of the priorities that the methods used aim at. The error rate is proportional to the number of neurons, but the result remains the dividing line. For the training mode, it is better for it to be close to the examination mode, and for the training session when there are two neurons in the hidden layer, there will be a certain error rate and it decreases with each increase in the number of neurons, as shown in Table 1.

RMSE result differ from one iteration to other and depends on the strength of algorithm while the best result was 0.5836 during training as shown in Fig. 6.

Table 1 Result simulation of NFS

Hidden neurons	Training	Evaluation	Testing	Accuracy (%)
2	0.5836	0.5687	0.5763	82
5	0.3876	0.4431	0.3871	91
8	0.3821	0.4715	0.4329	96
12	0.3981	0.3209	0.3925	97
16	0.2769	0.2915	0.2835	100

Through the results of Table 1, increasing the number of neurons in the hidden layers exclusively leads to a decrease in the RMSE values and the performance of the NFS algorithm is improved. While comparing the result of PD, the result that we get is compared with some algorithms from previous studies within the same criteria. At the Figure can recognize the RMSE with start training as 0.58 and decrease during the running the neural system, most of existing systems starting with 0.9 and going with decreasing. As shown in Table 2, the performance of the proposed algorithm is better than other algorithms in the literature.

The Features play an important role in the expected result, so care is taken to analyze them and reduce their dimensions. Among the criteria by which the algorithm was evaluated is Mean Absolute Error (MAE) as well as Prediction Accuracy. The values of these two variables are related to the previously extracted features and in the initial processing stage. As shown in Table 3, the variation in values and according to the fit of the features with the fuzzy technique used in this study.in the following equation used to find the MAE and prediction accuracy.

$$MAE = \frac{\sum_{i=1}^{N} \left|Predicted_i - Observed_i\right|^2}{n} \tag{15}$$

$$Prediction\ accuracy = \frac{\sum_{i=1}^{N} \left(Predicted_i - \overline{Observed_i}\right)^2}{\sum_{i=1}^{N} \left(Observed_i - \overline{Observed_i}\right)^2} \tag{16}$$

Table 2 shows the methods used for previous methods in the literature for benchmarking with the proposed method, while Table 3 is the algorithms that were used during the training mode in order to increase the efficiency of the proposed method.

Conclusion

This study presents the diagnosis of Parkinson's Disease (PD) using one of the techniques of Artificial Intelligence (AI), which is the neural fuzzy system. Two of the important techniques used here are NFS and SOM, one complementary to the other. The features were extracted and stored in special vectors in order to reduce their dimensions and use them in the workbook later. A standard database was used to train the algorithm and thus obtain a large accuracy later. The accuracy was 97.8, while the study proved its worth in terms of the criteria used while

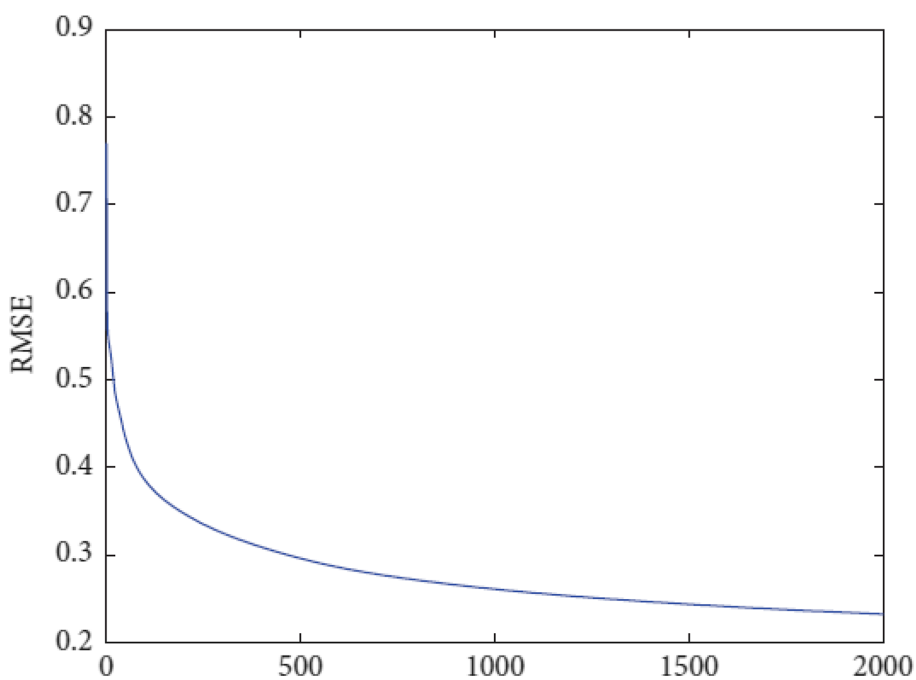

Fig. 6 RMSE results through Fuzzy algorithm

Table 2 Benchmarking results with existing algorithms

Models	Accuracy (through testing mode)
Decision Tree [15]	85.4
Regression [35]	87.3
DMneural [36]	83.9
Neural Network [37]	92.4
FCM + weight [38]	97.3
SVM [39]	93.6
Proposed	97.8

Table 3 Two criteria evaluation of PD

Technique	MAE	Prediction Accuracy
FNS + V_3	0.436	0.915
FNS + V_5	0.4521	0.927
FNS + SOM	0.427	0.942
FNS + SOM + V_3	0.416	0.932
FNS + SOM + V_4	0.468	0.974
FNS + SOM + V_5	0.498	0.982

comparing it to previous studies. During the simulations, you showed that the results of the proposed method are better than previous results in the literature. This method can be a classification mechanism because the organization is subjective and variable according to the data of the neural network and the feedback that determines the features of the map used to organize the input and output.

Authors' contributions
Conception and design of study: Siren Zhao. Acquisition of data (laboratory or clinical): Siren Zhao, Jilun Zhang. Data analysis and/or interpretation: Siren Zhao, Jilun Zhang. Drafting of manuscript and/or critical revision: Siren Zhao, Jilun Zhang, Jianbin Zhang. Approval of final version of manuscript: Siren Zhao, Jilun Zhang, Jianbin Zhang.

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Availability of data and materials
Data for this study is available from the corresponding author upon reasonable request.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
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Competing interests
The authors declare no competing interests.

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