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Research Article

Online Sequential Extreme Learning Machine for Parkinson Disease Diagnosis Using Voice Data

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ABSTRACT

In recent times, it has been reported by researchers that almost 90% of people infected with (Parkinson Disease) infected people show some forms of vocal disorders when the disease is at its early stage. Consequently, the focus of the most recent researches on PD diagnosis is on the detection of vocal disorders that emerges from running speech or sustained vowel pronunciation of those who suffer from the disease. In order to be able to detect PD diseases with high accuracy, this group of researchers has employed the use of various speech processing methods to deduce clinically relevant information and feed it as input to a wide range of ML (Machine Learning) algorithms. Despite all these efforts geared towards achieving a more accurate detection rate for PD, the accuracy rates obtained by many new PD diagnosing systems remain unsatisfactory, and necessitates the need for improvement. Consequently, in this study, a PD diagnosing system is proposed using the MFCC (Mel Frequency Cepstral Coefficients) together with the OSELM (Online Sequential Extreme Learning Machine) classifier which is among the ML algorithms with high level of accuracy deployed in the classifying Parkinson's disease. In this work, samples of voices used for experiments were acquired from the PDCD (Parkinson Disease Classification Dataset) database. The outcomes of the experimentations have revealed that the highest OSELM classifier's performance has been accomplished with an accuracy reached up to 93.38%. Consequently, it can be concluded that the OSLEM is a technique with high efficiency for diagnosing Parkinson Disease through the use of voice data.

Keywords: Parkinson Disease, MFCC, OSELM, Machine Learning, Indonesia

I. INTRODUCTION

PD (Parkinson Disease) is described as a neurodegenerative condition that advances slowly and is characterized through a many motor and non-motor features [1]. The Parkinson Disease is ranked as the second after Alzheimer's, which is the number one most neurodegenerative ailment that affects persons above the age of 60 [2].

It has become paramount to develop health systems that are capable of diagnosing and monitoring PD accurately and reliably due to its high prevalence rate in person above 60 years, and the prolonged lifespan of patients who are affected by Parkinson Disease with the use of pharmacological and surgical interventions.

Most recently, several works have focused on proposing diagnosis and monitoring systems for: i) early detection of PD. ii) Reduction of the frequency of hospital visits for clinical screenings due to body discomforts. iii) Minimization of doctors' workload. Most of the systems designed for the detection of Parkinson disease are able to diagnose the disease through the measurement and analysis of the indications by means of devices and equipment that are non-invasive in nature. Out of the symptoms used in determining the disease, vocal abnormality is the most dominant symptom exhibited by almost 90% of people affected by PD at the early stage [3]. Due to this, a large of studies conducted on PD diagnosis have primarily employed the use of speech processing techniques to obtain clinically relevant data, after which a variety of ML algorithms are fed with the feature that were extracted at the initial stage for the recognition of Parkinson Disease [4-6]. For instance, in a study carried out by the authors in [7] a system which automatically detects PD was proposed. The system performs the detection of PD in four (4) stages including extraction of acoustic attributes, feature augmentation using statistical pooling techniques, selection of feature using (ReliefF algorithm); and feature classification by the utilization of KNN (K-Nearest Neighbor) and SVM (Support Vector Machine). The authors conducted an assessment of the suggested system's performance by applying the system on a PD data base which is made up of a total of 240 voice samples collected from a total of 80 people, out of which 40 were in good health and the other 40 were patients. Observation of the results derived from the experiments carried out by the authors revealed that the best performance was demonstrated by the Support Vector Machine, achieving 91.25% accuracy.

Similarly, a group of authors in [8] proposed a classification application which is able to perform classification. In their work, the use of acoustic features was employed, and the use of four different feature was employed including Self-organizing maps, Kendall correlation coefficient, Pearson correlation coefficient, and principal component analysis. Besides, the authors made use of NN (Neural Network) algorithm for the purpose of classification. The proposed application performance assessment was conducted on a database of PD, using 40 samples (20 healthy persons and 20 persons that were patients. Their experimentations results showed that their proposed application performed optimally, achieving the highest rate of 86.47% by using the features selection, acoustic features, NN classifier, and Kendall correlation coefficient.

In another study carried out by the authors in [9], a CNN classifier was proposed based on speech parameters features to carry out the automatic diagnosis of PD. To test the performance and efficiency of the proposed PD diagnosis system, the authors applied it on a PD database with a total of 240 samples of voice obtained from 80 people. Out of the 40 were patients, and the other 40 were people affected by Parkinson Disease. Based on the outcomes of the experiments performed by the researchers, it was reported that the proposed system yielded the finest results with an accuracy rate of the 87.76%.

Similarly, the authors in [10] introduced a system for PD diagnosis, and they employed the use of the SVM classifier and the MFCC features and SVM classifier. The testing of their proposed system was carried out on a database that is made up of 17 healthy persons, out of which 9 were males and the remaining 8 were females, and 17 patients (11 males and 6 females). Results of the experiments showed that the system demonstrated the finest performance with a rate of accuracy hit up to 91.00%.

A Parkinson Disease diagnosis system was proposed in study [11]. In the study, the use of MFCC features alongside GMM classifier. The proposed system was tested through the use of two dissimilar databases. The voices contained in the first database were recorded using a professional microphone, while the voices in the second database were recorded through phone call. The 1st database is made up of 122 samples, out of which 74 were affected by Parkinson disease, and the remaining 48 were in good health without PD. On the other hand, the second database was made up of 99 samples, out of which 63 were affected by Parkinson disease and the other 36 were unaffected by PD. The experimentations results revealed that when the proposed system was applied on the first database, accuracy rate of 83% was attained, and when applied to the second database, an accuracy rate of 75% was recorded.

The authors in study [12] focused on developing a system that is able to automatically detect PD by combining PCA (Principal Components Analysis), with the x-Vector (using MFCC), and PLDA (Probabilistic Linear

Discriminant Analysis) classifier. A database containing a total of 89 subjects (43 affected by Parkinson and 46 unaffected) was used to evaluate the performance of the proposed system. The experimentations results showed that an accuracy rate of 90% was recorded by the proposed system.

In addition, in another study [13] the researchers proposed an application for the diagnosis of PD. This application was proposed based on i-vector features obtained from MFCC features together with SVM. The evaluation of the proposed application was done using a data algorithm, and a database containing 90 subjects, out of which 49 were affected by Parkinson Disease and the remaining 41 were healthy. The results of the experimentations showed that the proposed application yielded the utmost accuracy rate of 79.40%.

In the study carried out by the authors in [14], an application that automatically diagnoses Parkinson Disease was suggested using the MFCC features, SVM, and LDA (Linear Discriminant Analysis) dimensionality reduction. The suggested application's performance was tested using a PD database that is made up of 160 voice samples, and out the total number of 160 samples, 100 were healthy and 60 were affected by Parkinson disease. The experimentations results showed that the suggested application which is the MFCC-LDA-SVM, yielded the finest results with a high accuracy rate of 97.5%.

In addition, in another study, the authors [15] suggested a diagnosis system for the PD, using a combination of MFCC features and the MLP classifier. To evaluate the suggested system, the authors employed the utilization of a database containing 200 voice samples. The results of the experiments performed by the authors showed that the suggested system accomplished the finest accuracy rate of 95.5%.

Similar effort was made in study [16], where a PD diagnosis system was proposed, and the performance of two classifiers, namely SVM and HMM was tested using 3 different techniques of feature extraction, which are Wavelet Packets, MFCC, and a combination of MFCC and WPT. The evaluation of the proposed system involved the use of a database containing a total of 40 subjects, out of which 20 were patients and the remaining 20 were healthy. Results obtained from the experiments revealed that by deploying a mixture of the fusion features from both WPT and MFCC together with HMM classifier the finest result was yielded with an accuracy hit up to 95.16%. The previous studies that have proposed PD diagnosis systems and applications using ML and DL algorithms reviewed in this section have been summarized in Table 1 below.

The following conclusions can be made based on the aforementioned studies on Parkinson diagnosing systems and applications:

- Majority of the studies reviewed were evaluated using a small database, and hence, there is a need for a study that employs a larger database.
- The accuracy rates achieved by the systems proposed in previous studies are not potentially promising, and as such, there is need for improvement in the systems to achieve higher accuracy rates in PD diagnosis.
- The metrics used for evaluation in many of the reviewed studies were limited, and hence the need for a more robust assessment metrics.

TABLE I

SUMMARY OF THE FORMER PD PROGNOSIS' WORKS USING DL AND ML APPROACHES

Ref.	Dataset	Features	Method	Accuracy	Weaknesses
[7]	240 audio samples	Acoustic features with feature increasing alongside with Relief feature selection.	KNN and SVM	91.25%	• Testing of proposed systems conducted on a small database, and thus, there is need for the use of a more robust database
[8]	20 healthy and 20 patients	Acoustic features and four different feature selection	NN	86.47%	• The proposed systems produced results that

		approaches.			are not satisfactory, and therefore, there is need for more work to improve the results.
[9]	240 audio samples	Speech parameters features.	CNN	87.76%	
[10]	17 patients and 17 healthy	MFCC	SVM	91.17%	• The evaluations of the performances of the proposed systems have been carried out using a limited set of evaluation benchmarks. There is need to use a more robust set of evaluation metrics.
[11]	First dataset: 48 healthy and 74 Parkinson. Second dataset: 36 healthy and 63 Parkinson.	MFCC	GMM	83.00% for the first dataset. 75.00% for the second dataset.	
[12]	46 healthy and 43 Parkinson	x-Vector	PLDA	90.00%	
[13]	49 Parkinson and 41 healthy	i-vector features	SVM	79.40%	
[14]	100 healthy and 60 patients	MFCC and LDA dimensionality reduction.	SVM	97.5%	• The proposed systems have been tested on a small database. • The proposed systems have been assessed based on limited set of evaluation metrics.
[15]	200 Samples	Combining the phonetic and MFCC features	MLP	95.5%	
[16]	20 healthy and 20 patients	Fusion features: MFCC and WPT	HMM	95.16%	

One of the utmost recent and widely-used ML algorithms is known as the Online Sequential Extreme Learning Machine (OSELM), which is also a Single-hidden Layer feedforward Neural Networks (SLFNs)) that consists of three layers in total including input; hidden; and output [17]. The nodes in the input layer are connected to the nodes embedded within the hidden layer through the biases and weights that were produced in a random manner. While the output-weights are connecting the nodes within the hidden layer to the nodes embedded within the output layer. The values of the output-weights are computed using the least squares solution [18]. Researchers in more recent times have shown more preference for OSLEM due to its superior performance as compared to the traditional SVM and Back Propagation Neural Network (BPNN) [19, 20]. The OSLEM is famous and preferred due to the benefits it offers including: a) prevention of overfitting; b) wide application in both multi and binary classification; and c). More so, the OSLEM demonstrates a comparable capability to kernel-based SVM and functionality within the NN framework. Due to all the aforementioned reasons, the OSLEM technique is regarded as more efficient in the realization of superior learning performance. Despite the huge benefits that can derived from the use of OSLEM, there is no study that has employed the use of OSLEM algorithm in Parkinson's Disease detection. Consequently, this research seeks to achieve the following objectives:

- Propose a novel model for PD diagnosis based on the MFCC features together with OSLEM classifier using voice data.
- Carry out the performance evaluation of the novel model by means of a more robust evaluation metrics including (G-M) G-Mean; (A) Accuracy; (S) Specificity; (F-M) F-Measure; (MCC) Matthews Correlation Coefficient; (R) Recall; (ROC) Receiver Operating Characteristic; and (P) Precision.
- Make an accuracy rate comparison of the novel proposed PD classifier with PD classifiers proposed in recent researches that employed the use of similar database.

This article is structured as follow: the materials alongside with the proposed method are provided in Section 2.

While the experiments setup and outcomes are deeply explained in Section 3. Finally, the conclusion of this research is delivered in Section 5.

II. Materials and Proposed Method

In this work, a PD diagnosis model is proposed based on the OSLEM technique. The PDCD (Parkinson Disease Classification Dataset) is used to test the performance of the proposed OSELM method in prognosis the PD. The PDCD database contains voice data (i.e., sustained pronunciation of the vowel /a/) for both healthy persons and persons affected by PD. During the classification stage, the OSLEM technique is used for the diagnosis, determining whether the voice sample inputted into the proposed system is healthy or infected by Parkinson Disease. The entire architecture of the proposed model of PD diagnosis is represented in the Figure 1 below.

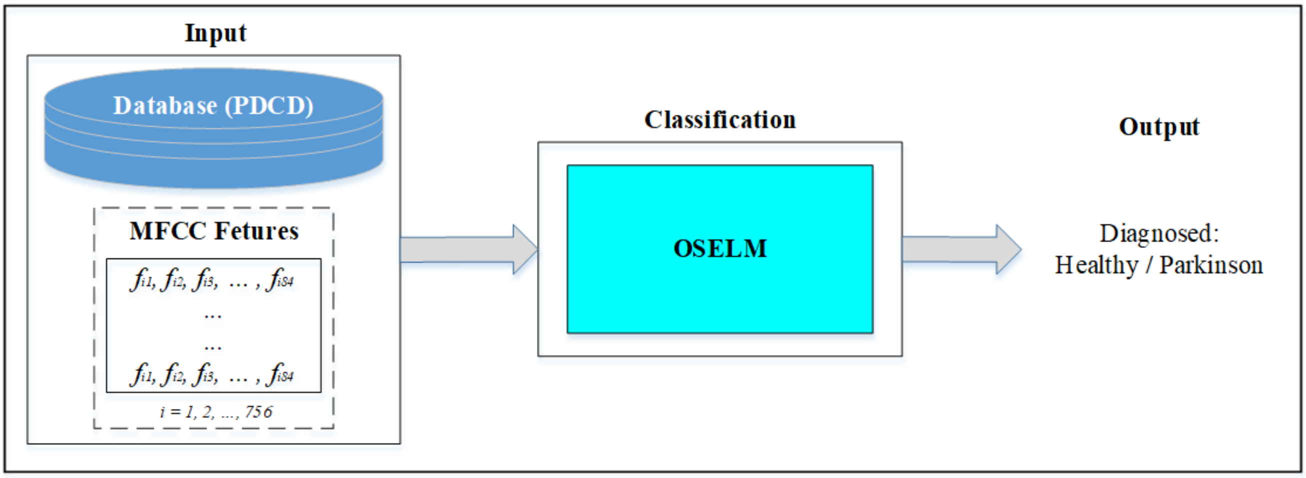

Fig. 1. The general diagram of the novel proposed PD prognosis model.

A. Database: PDCD

The PD diagnosis model proposed in this study has been evaluated using the PDCD database which was obtained from [21]. It is also made available online by the University of California, Irvine website through its ML repository [22]. The aforementioned PDCD is considered as a standard database that has been deployed by many researchers in former studies for the evaluation of numerous ML approaches like GMM [22], which is a hybrid technique that combines SMOTE and RF in [24], as well as and SVM in [23]. The aforementioned database is made up of 188 patients affected by Parkinson disease. Out of the 188 patients, 107 were males while the remaining 81 were women within the age range of 33 to 87 years. The 188 subjects were patients at the neurology depart of Istanbul University. Also, the database contained samples from 64 healthy persons that were within the age range of 41 and 82 years, with 41 of them being males and 81 being females. The authors in study [21] noted that the frequency of the microphone used for the voice recording was set at 44,100 Hz for the entire period of data collection. After the assessment of the doctor each person was recorded three times, bringing to a total of three samples from each person. In the signals, the prolonged vowel /a/ was included. More so, the PDCD is a database that includes a collection of all relevant features including baseline time frequency, vocal fold, Wavelet Transform, MFCC, and TQWT (Tunable Q-factor Wavelet Transform). In [21] the extracted features contained in the PDCD database are described in details. Nevertheless, the focus of this work will be on the use of MFCC feature alone because of its popularity in features extraction, and its proven effectiveness in numerous speech applications including detection off voice pathology [24-26], identification of spoken language [27-29], and recognition of emotion speech [30]. Table 2 below provides a detailed description of the PDCD database. Worth of note is the fact that all the study experiments were carried out based on the 80:20 ratio, where 80% of the sample which is 605 samples were employed in training the proposed system and the remaining 20%, which is 151 samples were deployed in testing the level to which the proposed system is efficient in the detection of PD.

In this study, the PDCD is utilized to assess the proposed PD diagnosing model. The PDCD database was taken from [21], as well as it is available online at the University of California, Irvine website, that has a ML repository [31]. The PDCD is a standard database which has been utilized in numerous prior PD diagnosing studies in order to assess several ML approaches such as GMM [22], a hybrid method through combining RF and SMOTE in [32], and SVM in [23]. The PDCD database was collected from 188 patients with Parkinson disease (i.e., 107 men and 81 women), ranging in age (33 - 87), at the department of Istanbul University's neurology. Whilst only 64 healthy persons with ages ranging (41 - 82) were considered (i.e., 23 males and 41 women). The setting of the microphone frequency was set at 44,100 Hz, according to [21] authors, who also note this throughout the procedure of the data collection. Three repetitions have been also collected for each person following the doctor's assessment. In the signals, the prolonged vowel /a/ was included. In addition, the PDCD database was made accessible as a collection of several extracted features including baseline, time frequency, MFCC, WT (Wavelet Transform), vocal fold, and TQWT (Tunable Q-factor Wavelet Transform). A deep description and explanation of these extracted features of the PDCD database are delivered in [21]. However, this study will focus on using the MFCC feature only, due to the MFCC is one of the utmost popular techniques (i.e., features extraction techniques) that's proved its effectiveness in various speech applications including voice pathology detection [24-26], spoken language identification [27-29], and emotion speech recognition [30]. The description of the PDCD database is delivered in table 2. It's worth mentioning that all the experiments of the current study were conducted based on the ratio of 80% for training which is equal to 605 samples and 20% for testing which is equal to 151 samples.

TABLE II

PDCD DATABASE DEPICTION.

Class	Total Samples	Women's Voice Samples	Men's voice samples	Label
Parkinson	564	243	321	1
Healthy	192	123	69	2

B. Classification: OSELM

The authors in [33] made the proposal for the OSLEM which is made up of 3 layers including the input, hidden, and output. The first layer which is the input layer is fed with the extracted tumor features, the hidden layer which is the second layer contains the biases, while the last layer which is the output layer is made up of the algorithm's final classifications. The equation 1 below represents the hidden-layer output matrix (H) computation:

$$H = W_1 \cdot X_1 + B_1 \qquad (1)$$

Where: W denotes the weights of input that serve as a linkage between the first (i.e., input) and second (i.e., hidden) layers. The 30 features extracted in the input layer is represented by X, while B denotes the biases of the hidden layer. The input weights (W) and the hidden layer biases (B) are generated stochastically in [-1 to 1] range. For N arbitrary distinct samples (x_j, t_j), where $x_j \in R^d$ and $t_j \in R^m$; SLFNs with g(x) activation function and n hidden nodes can be represented statistically as given below:

$$f(X) = \sum_{i=1}^{n} \beta_i g(w_i \cdot x_j + b_i) = t_{j,} \qquad j = 1, 2 \ldots, \mathrm{N} \qquad (2)$$

Similarly, equation (2) can be denoted as follow:

$$H\beta = T \qquad (3)$$

Where:

$$H = \begin{bmatrix} g(w_1.x_1 + b_1) & \cdots & g(w_n.x_1 + b_n) \\ \vdots & \ldots & \vdots \\ g(w_1.x_N + b_1) & \cdots & g(w_n.x_N + b_n) \end{bmatrix}_{N \times n}$$

$$\beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_n^T \end{bmatrix}_{n*m} \quad , T = \begin{bmatrix} t_1^T \\ \vdots \\ t_N^T \end{bmatrix}_{N*m}$$

The output weights ($\hat{\beta}$) are then calculated using the following equation (4):

$$\hat{\beta} = H^{\dagger}T \quad (4)$$

Where: $H^{\dagger}$ is an inverse representation of the generalized Moore-Penrose for the hidden-layer output matrix (H), with the following computation:

$$H^{\dagger} = (H^T H)^{-1} H^T \quad (5)$$

The application of the OSELM algorithm is done so that the training samples can be learned in a successive and gradual manner. The OSLEM algorithm's process of learning involves two critical steps including sequential learning and initialization. The process of sequential learning was initiated with the aim of training samples gradually and successively. The OSELM algorithm learning operation is consisted of 2 main steps which are initialization and sequential learning. The computation of H_0 (hidden layer output matrix), and the β_0 (initial output weights) in the initialization phase is represented in the equations below:

$$H_{k+1} = g(W_1 \cdot X_{k+1} + B_1) \quad (6)$$

$$P_0 = (H_0^T H_0)^{-1} \quad (7)$$

$$\beta_0 = P_0 H_0^T T_0 \quad (8)$$

At the second stage, which is the stage of sequential learning, an update will be made to the output matrix (H_{k+1}) of the hidden layer for the fresh sample as represented in equation (6). In addition, the equation below would be used to update the β_{k+1} (output weights matrix):

$$P_{k+1} = P_k - P_k H_{k+1}^T (1 + H_{k+1} P_k H_{k+1}^T)^{-1} H_{k+1} P_k \quad (9)$$

$$\beta_{k+1} = \beta_k + P_{k+1} H_{k+1}^T (T_{k+1} - H_{k+1} \beta^k) \quad (10)$$

The set = k + 1 and move back to the equations (6; 9; and 10) so that the following sample can be trained. The training of all the samples makes it possible to use the OSLEM algorithm to predict an input-vector that is unknown. The diagram of the OSLEM algorithm is presented in Figure 2, where the final classifications are represented as T1 and T2, denoting Parkinson Disease and healthy, respectively.

The OSLEM algorithm is made up of two primary stages, which are the boosting stage and data the learning stage. At the boosting stage, the ELM method is utilized to train the SLFNs alongside some of the training data at the initialization stage. Upon the completion of the boosting stage, the boosting-training data is discarded. Subsequent to the boosting stage, the training data is learned by the OSLEM algorithm in chunks, and afterwards the training data is discarded upon the completion of data learning process.

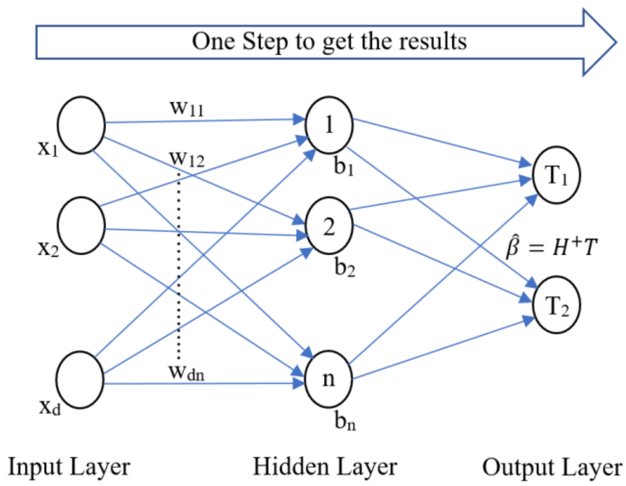

Fig. 2. Diagram of the OSELM model. ([34] owned by the author)

III. Experiment Setup and Results

The use of MFCC features alongside OSLEM classifier was employed in conducting several experiments for the diagnosis of PD. Every experiment was conducted based on using 20% of the database for testing, and the remaining 80% of the dataset for training. In total 6 experiments were performed using the proposed OSLEM classifier together with a wide range of concealed nodes ranging from 50 to 400, and 50 increment step. The whole experiments were implemented on a PC that has the following features: processor = Core i7 running at 3.20 GHz, RAM = 16 GB, SSD = 1 TB, and operating system = Windows 10. In this study, the proposed OSELM classifier was evaluated utilizing a variety of valuation metrics. These evaluation metrics are including (TN) True Negative, (TP) True Positive, (FN) False Negative, (FP) False Positive, (G-M) G-Mean; (A) Accuracy; (S) Specificity; (F-M) F-Measure; (MCC) Matthews Correlation Coefficient; (R) Recall; (ROC) Receiver Operating Characteristic; and (P) Precision. Equations (11-17) [35-40] demonstrations these evaluation metrics.

$$\text{accuracy} = \frac{TP+TN}{TP+TN+FN+FP} \quad (11)$$

$$\text{precision} = \frac{TP}{TP+FP} \quad (12)$$

$$\text{recall} = \frac{TP}{TP+FN} \quad (13)$$

$$\text{F} - \text{Measure} = \frac{(2 \times precision \times recall)}{(precision + recall)} \quad (14)$$

$$\text{G} - \text{Mean} = \sqrt{recall \times precision} \quad (15)$$

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (16)$$

$$\text{MCC} = \frac{TP \times TN - FP \times FN}{\sqrt{(TP+FP) \times (TP+FN) \times (TN+FP) \times (TN+FN)}} \quad (17)$$

All results of the experiments for the proposed OSLEM classifier are presented in table 3 below. The results for the highest G-M, A, S, F-M, MCC, R, and P are conveyed in bold font. More so, figure 3 shows the results for the highest achieved G-M, A, S, F-M, MCC, R, and P.

TABLE III

THE EXPERIMENTAL OUTCOMES OF THE PROPOSED OSELM METHOD

Hidden Neurons	A	P	R	S	MCC	F-M	G-M
50	92.72	**99.12**	91.80	**96.55**	80.20	95.32	95.39
100	**93.38**	94.69	**96.40**	85.00	**82.77**	**95.54**	**95.54**
150	90.73	96.46	91.60	87.50	74.49	93.97	94.00
200	91.39	94.69	93.86	83.78	76.95	94.27	94.27
250	92.05	96.46	93.16	88.24	78.35	94.78	94.80
300	89.40	94.69	91.45	82.35	71.04	93.04	93.06

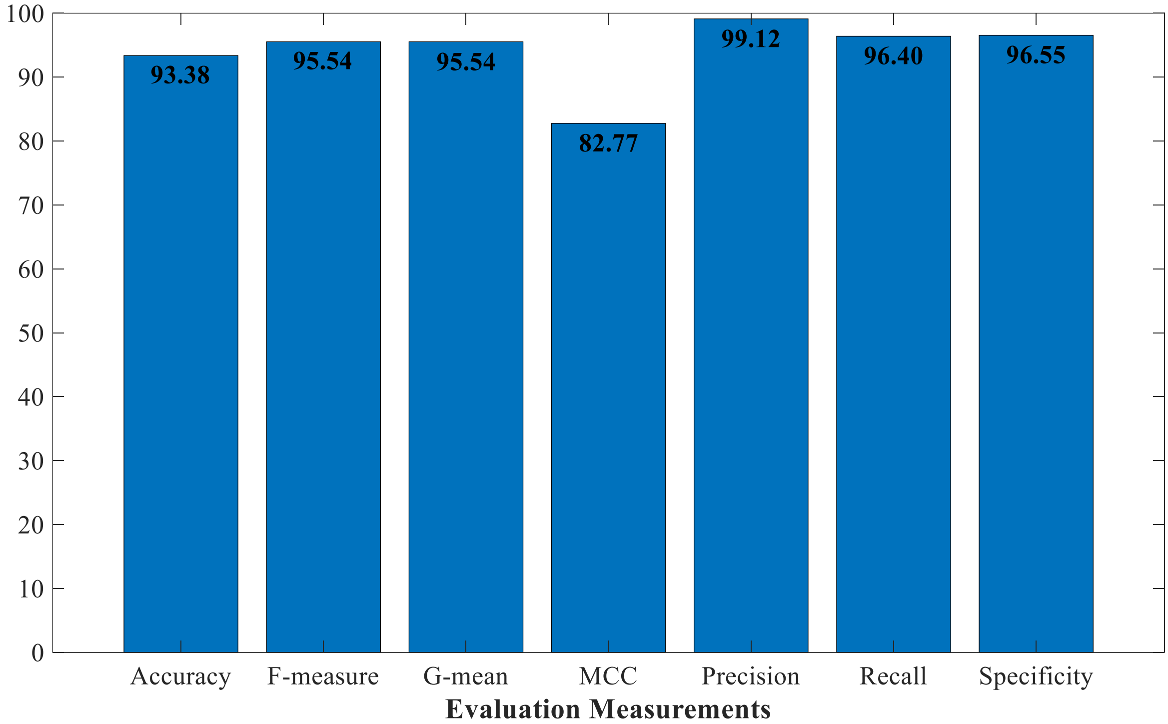

Fig. 3. The utmost achieved results

Based on the experimental results presented on table 3 and figure 3, the highest R, A, F-M, MCC, and G-M were attained by the proposed OSLEM when the hidden neurons number was equal to 100. The OSLEM yielded the highest A rate of 93.38%, R rate of 96.40%, MCC rate of 82.77%, F-M score of 95.54%, and G-M score of 95.54%. Furthermore, the highest P rate of 99.12%, and S rate of 96.55% were achieved by the proposed OSLEM when the hidden neurons number was equal to 50. Consequently, the proposed OSLEM may be a suitable technique for the PD prognosis utilizing voice data. The confusion matrix as well as the ROC outcomes for the utmost (A) Accuracy yielded by the proposed OSLEM classifier are depicted in Figures (4 and 5).

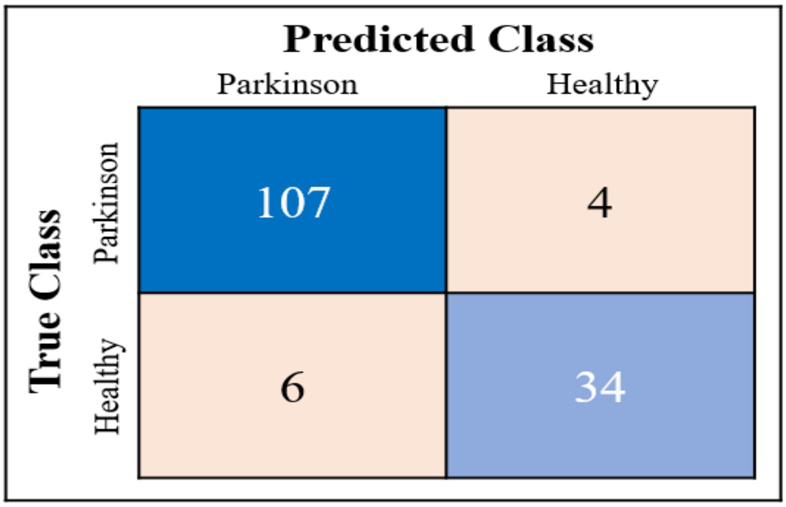

Fig. 4. Confusion matrix of the uppermost attained accuracy by the proposed OSELM classifier

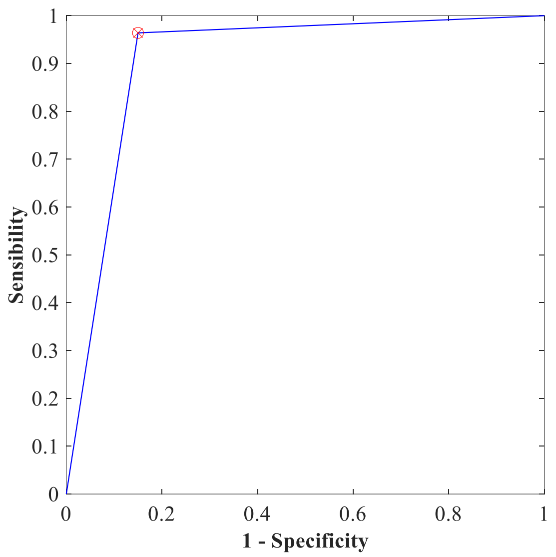

Fig. 5. ROC result of the uppermost attained accuracy by the proposed OSELM classifier

More so, the statistical assessment of the proposed OSLEM model has been carried out through the implementation of addition experiment to gain further evidence on the effectiveness of OSLEM in the prognosis of PD. The experimental results conveyed in table 4 shows that the uppermost accuracy rate was attained by the proposed OSLEM with 100 nodes based on 30 runs. Table 4 shows that statistical results obtained from the additional experiments. In addition, figure 6 shows all the evaluation measurements boxplot throughout the 30 runs.

TABLE IV

THE STATISTICAL RESULTS OF THE PROPOSED OSELM MODEL

Mean						
A	**P**	**R**	**S**	**F-M**	**G-M**	**MCC**
91.28%	98.81%	89.66%	95.35%	93.98%	94.11%	73.67%
RMSE						
A	**P**	**R**	**S**	**F-M**	**G-M**	**MCC**
8.7583	1.8149	10.5766	6.9693	6.0663	5.9332	26.5460
STD						
A	**P**	**R**	**S**	**F-M**	**G-M**	**MCC**
0.8215	1.3664	2.2259	5.1884	0.7335	0.6761	3.3440
Max						
A	**P**	**R**	**S**	**F-M**	**G-M**	**MCC**
93.38%	100.00%	95.69%	100.00%	95.94%	95.96%	81.40%
Min						
A	**P**	**R**	**S**	**F-M**	**G-M**	**MCC**
90.07%	95.65%	87.60%	83.33%	93.39%	93.60%	67.73%

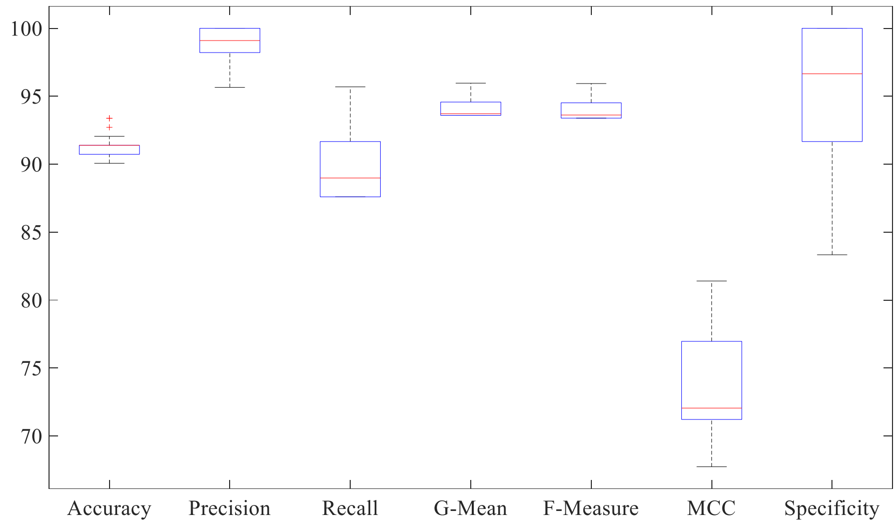

Fig. 6. The evaluation measurements' boxplots throughout the 30 runs

The results presented on table IV show that all the metrics used in evaluating the proposed OSLEM approach achieved mean values that were close to the optimal/observed value of 100%. This implies that the OSLEM technique achieved P, F-M, A, G-M, R, S, and MCC values that are very close to the optimal/observed value of 100% within the 30 runs, while the RMSE and the STD were low (close to zero). This provides evidence that the proposed OSLEM model is effective and demonstrates high performance in the classification of PD in 30 runs. The results of the statistical evaluation presented in Table IV reveals that the following were achieved by the proposed OSLEM approach:

a) The mean value for the A was 91.28%, P was 98.81%, R was 89.66%, F-M was 93.98%, G-M was 94.11%, MCC was 73.67%, and S was 95.35%.
b) The RMSE value for the A 8.7583, P 1.8149, R 10.5766, F-M 6.0663, G-M 5.9332, MCC 26.5460, and S 6.9693.
c) The STD value for the A was 0.8215, P was 1.3664, R was 2.2259, F-M was 0.7335, G-M was 0.6761, MCC was 3.3440, and S was 5.1884.

In addition, the performance of the proposed OSLEM model in terms of accuracy in diagnosing PD was compared with some recent works that used the identical database [21, 41-43]. The accuracy comparison results for the proposed OSLEM and the former works are presented in Table 5. Based on the outcomes presented in Table 5, the OSLEM classifier revealed superior performance in terms of accuracy. Thus, this study provides evidence that shows that the proposed OSLEM classifier is effective in classifying PD using voice data that can support doctors in a more accurate and easy diagnosis of the Parkinson Disease in clinical.

TABLE V

THE COMPARISON OF THE HIGHEST ACCURACY OUTCOMES

Method	Accuracy
SVM + mRMR [21]	86.00%
ANOVA+RF [42]	91.00%
ReliefF + NN [43]	92.50%
CNN (9-layered) [41]	86.90%
Proposed Method (OSELM)	**93.38%**

IV. Conclusion

This work primarily focused in proposing a model for the accurate diagnosis of PD based on MFCC features with

OSLEM classifier. The testing of the performance of the proposed PD diagnosis (MFCC-OSLEM) was carried out using the PDCD database made up of voice signals of prolonged pronunciation of the vowel /a/. Results of the experiments showed that superior performance was demonstrated by the OSLEM classifier as compared with other classifier proposed in previous studies as shown in Table 5. The proposed OSLEM classifier demonstrated remarkable performance with an A rate of 93.38%. More so, the proposed OSELM classifier has attained 96.40%, 82.77%, 95.54%, 95.54%, 99.12%, and 96.55% for R, MCC, F-M, G-M, P and S, R. Nevertheless, this study is only concerned with the classification of the voice signals into two classes which are PD and healthy, while neglecting other diseases. Thus, future work can be focused on the implementation of the proposed OSLEM classifier on a database with more voice signals of many more diseases. More so, the biases and input weights of the OSLEM can optimized through the use of optimization methods so that more appropriate input weights as well as biases can be generated, thereby resulting in the minimization of errors that may occur in the process of classification.

References

[1] R. Li *et al.*, "Basal ganglia atrophy–associated causal structural network degeneration in Parkinson's disease," *Human Brain Mapping,* 2021.

[2] L. M. Bekris, C.-E. Yu, T. D. Bird, and D. Tsuang, "The Genetics of Alzheimer’s Disease and Parkinson’s Disease," *Neurochemical Mechanisms in Disease,* pp. 695-755, 2011.

[3] C. Ma, J. Ouyang, H.-L. Chen, and X.-H. Zhao, "An efficient diagnosis system for Parkinson’s disease using kernel-based extreme learning machine with subtractive clustering features weighting approach," *Computational and mathematical methods in medicine,* vol. 2014, 2014.

[4] J. Mei, C. Desrosiers, and J. Frasnelli, "Machine learning for the diagnosis of parkinson's disease: A review of literature," *Frontiers in aging neuroscience,* vol. 13, p. 184, 2021.

[5] I. Nissar, W. A. Mir, and T. A. Shaikh, "Machine Learning Approaches for Detection and Diagnosis of Parkinson’s Disease-A Review," in *2021 7th International Conference on Advanced Computing and Communication Systems (ICACCS)*, 2021, vol. 1: IEEE, pp. 898-905.

[6] D. Tulbă, L. Cozma, P. Bălănescu, A. Buzea, C. Băicuș, and B. O. Popescu, "Blood pressure patterns in patients with Parkinson’s disease: A systematic review," *Journal of personalized medicine,* vol. 11, no. 2, p. 129, 2021.

[7] O. Yaman, F. Ertam, and T. Tuncer, "Automated Parkinson’s disease recognition based on statistical pooling method using acoustic features," *Medical Hypotheses,* vol. 135, p. 109483, 2020.

[8] L. Berus, S. Klancnik, M. Brezocnik, and M. Ficko, "Classifying Parkinson’s disease based on acoustic measures using artificial neural networks," *Sensors,* vol. 19, no. 1, p. 16, 2019.

[9] A. Krishna, S. prakash Sahu, R. R. Janghel, and B. K. Singh, "Speech Parameter and Deep Learning Based Approach for the Detection of Parkinson’s Disease," in *Computer Networks, Big Data and IoT*: Springer, 2021, pp. 507-517.

[10] A. Benba, A. Jilbab, A. Hammouch, and S. Sandabad, "Voiceprints analysis using MFCC and SVM for detecting patients with Parkinson's disease," in *2015 International conference on electrical and information technologies (ICEIT)*, 2015: IEEE, pp. 300-304.

[11] L. Jeancolas *et al.*, "Comparison of telephone recordings and professional microphone recordings for early detection of Parkinson's disease, using mel-frequency cepstral coefficients with Gaussian mixture models," in *INTERSPEECH 2019: 20th annual conference of the International Speech Communication Association*, 2019: International Speech Communication Association (ISCA), pp. 3033-3037.

[12] L. Moro-Velazquez, J. Villalba, and N. Dehak, "Using x-vectors to automatically detect parkinson’s disease from speech," in *ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2020: IEEE, pp. 1155-1159.

[13] N. García, J. C. Vásquez-Correa, J. R. Orozco-Arroyave, and E. Nöth, "Multimodal I-vectors to Detect and Evaluate Parkinson's Disease," in *INTERSPEECH*, 2018, pp. 2349-2353.

[14] A. Rahman, S. S. Rizvi, A. Khan, A. Afzaal Abbasi, S. U. Khan, and T.-S. Chung, "Parkinson’s disease diagnosis in cepstral domain using MFCC and dimensionality reduction with svm classifier," *Mobile Information Systems,* vol. 2021, 2021.

[15] A. Jafari, "Classification of Parkinson's disease patients using nonlinear phonetic features and Mel-frequency cepstral analysis," *Biomedical Engineering: Applications, Basis and Communications,* vol. 25, no. 04, p. 1350001, 2013.

[16] H. Kuresan, D. Samiappan, and S. Masunda, "Fusion of WPT and MFCC feature extraction in Parkinson's disease diagnosis," *Technology and Health Care,* vol. 27, no. 4, pp. 363-372, 2019.

[17] M. A. A. Albadra and S. Tiuna, "Extreme learning machine: a review," *International Journal of Applied Engineering Research,* vol. 12, no. 14, pp. 4610-4623, 2017.

[18] G. Huang, G.-B. Huang, S. Song, and K. You, "Trends in extreme learning machines: A review," *Neural Networks,* vol. 61, pp. 32-48, 2015.

[19] M. A. A. Albadr, S. Tiun, M. Ayob, M. Mohammed, and F. T. AL-Dhief, "Mel-frequency cepstral coefficient features based on standard deviation and principal component analysis for language identification systems," *Cognitive Computation,* vol. 13, no. 5, pp. 1136-1153, 2021.

[20] M. A. A. Albadr, S. Tiun, M. Ayob, and F. T. AL-Dhief, "Spoken language identification based on optimised genetic algorithm–extreme learning machine approach," *International Journal of Speech Technology,* vol. 22, no. 3, pp. 711-727, 2019.

[21] C. O. Sakar *et al.*, "A comparative analysis of speech signal processing algorithms for Parkinson's disease classification and the use of the tunable Q-factor wavelet transform," *Applied Soft Computing,* vol. 74, pp. 255-263, 2019.

[22] O. Bchir, "Parkinson's Disease Classification using Gaussian Mixture Models with Relevance Feature Weights on Vocal Feature Sets," *International Journal of Advanced Computer Science and Applications,* vol. 11, no. 4, 2020.

[23] A. Rawat, S. Mishra, Y. Sharma, and P. Khetarpal, "High accuracy multilayer autoencoder trained classification method for diagnosis of Parkinson's disease using vocal signals," *Journal of Information and Optimization Sciences,* vol. 43, no. 1, pp. 93-99, 2022.

[24] F. T. AL-Dhief, N. M. a. A. Latiff, M. M. Baki, N. N. N. A. Malik, N. Sabri, and M. A. A. Albadr, "Voice Pathology Detection Using Support Vector Machine Based on Different Number of Voice Signals," in *2021 26th IEEE Asia-Pacific Conference on Communications (APCC)*, 2021: IEEE, pp. 1-6.

[25] Khirbeet, A. S., & Muniyandi, R. C. (2017). New Heuristic Model for Optimal CRC Polynomial. *International Journal of Electrical and Computer Engineering*, *7*(1), 521.

[26] Al-Khaleefa, A. S., Hassan, R., Ahmad, M. R., Qamar, F., Wen, Z., Aman, A. H. M., & Yu, K. (2021). Performance evaluation of online machine learning models based on cyclic dynamic and feature-adaptive time series. *IEICE TRANSACTIONS on Information and Systems*, *104*(8), 1172-1184.

[27] M. A. A. Albadr and S. Tiun, "Spoken language identification based on particle swarm optimisation–extreme learning machine approach," *Circuits, Systems, and Signal Processing,* vol. 39, no. 9, pp. 4596-4622, 2020.

[28] Al-Khaleefa, A. S., Ahmad, M. R., Isa, A. A. M., Esa, M. R. M., Al-Saffar, A., & Aljeroudi, Y. (2018). Infinite-term memory classifier for Wi-Fi localization based on dynamic Wi-Fi simulator. *IEEE Access*, *6*, 54769-54785.

[29] Malik, R. F., Gustifa, R., Farissi, A., Stiawan, D., Ubaya, H., Ahmad, M. R., & Khirbeet, A. S. (2019, March). The indoor positioning system using fingerprint method based deep neural network. In *IOP Conference Series: Earth and Environmental Science* (Vol. 248, No. 1, p. 012077). IOP Publishing.

[30] M. A. A. Albadr, S. Tiun, M. Ayob, F. T. AL-Dhief, K. Omar, and M. K. Maen, "Speech emotion recognition using optimized genetic algorithm-extreme learning machine," *Multimedia Tools and Applications,* pp. 1-27, 2022.

[31] C. O. Sakar, et al.,. Parkinson's Disease Classification Data Set

[32] K. Polat, "A hybrid approach to Parkinson disease classification using speech signal: the combination of smote and random forests," in *2019 Scientific Meeting on Electrical-Electronics & Biomedical Engineering and Computer Science (EBBT)*, 2019: Ieee, pp. 1-3.

[33] G.-B. Huang, N.-Y. Liang, H.-J. Rong, P. Saratchandran, and N. Sundararajan, "On-line sequential extreme learning machine," *Computational Intelligence,* vol. 2005, pp. 232-237, 2005.

[34] F. T. Al-Dhief *et al.*, "Voice pathology detection and classification by adopting online sequential extreme learning machine," *IEEE Access,* vol. 9, pp. 77293-77306, 2021.

[35] V. Mayya, V. Tummala, C. U. Reddy, P. Mishra, R. Boddu, and D. Olivia, "Applications of Machine Learning in Diabetic Foot Ulcer Diagnosis using Multimodal Images: A Review," *IAENG International Journal of Applied Mathematics,* vol. 53, no. 3, 2023.

[36] S. Verma, S. P. Sahu, and T. P. Sahu, "Stock Market Forecasting with Different Input Indicators using Machine Learning and Deep Learning Techniques: A Review," *Engineering Letters,* vol. 31, no. 1, 2023.

[37] Al-Khaleefa, A. S., Ahmad, M. R., Isa, A. A. M., Al-Saffar, A., Esa, M. R. M., & Malik, R. F. (2019). Mfa-oselm algorithm for wifi-based indoor positioning system. *Information*, *10*(4), 146.

[38] Al-Saffar, A., Awang, S., Al-Saiagh, W., Al-Khaleefa, A. S., & Abed, S. A. (2021). A Sequential Handwriting Recognition Model Based on a Dynamically Configurable CRNN. *Sensors*, *21*(21), 7306.

[39] Alammari, A., Alkahtani, A. A., Ahmad, M. R., Noman, F., Mohd Esa, M. R., Sabri, M. H. M., ... & Agelidis, V. (2020). Kalman filter and wavelet cross-correlation for VHF broadband interferometer lightning mapping. *Applied Sciences*, *10*(12), 4238.

[40] Naser Abdali, T. A., Hassan, R., Mohd Aman, A. H., Nguyen, Q. N., & Al-Khaleefa, A. S. (2021). Hyper-angle exploitative searching for enabling multi-objective optimization of fog computing. *Sensors*, *21*(2), 558.

[41] H. Gunduz, "Deep learning-based Parkinson’s disease classification using vocal feature sets," *IEEE Access,* vol. 7, pp. 115540-115551, 2019.

[42] K. A. Hasan and M. A. M. Hasan, "Classification of Parkinson's Disease by Analyzing Multiple Vocal Features Sets," in *2020 IEEE Region 10 Symposium (TENSYMP)*, 2020: IEEE, pp. 758-761.

[43] T. Parlar, "A heuristic approach with artificial neural network for Parkinson’s disease," *International Journal of Applied Mathematics Electronics and Computers,* vol. 9, no. 1, pp. 1-6, 2021.