An Enhanced Voice Record Recognition System for Parkinson's Disease Progression using Deep Neural Networks

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Abstract: Parkinson's disease (PD) is a progressive neurodegenerative disease that manifests itself with a variety of motor and non-motor symptoms. Many PD patients have difficulty moving in a normal manner in the early stages. One of the most common symptoms is vocal disorders. Recent PD detection studies have focused on diagnostic systems based on vocal disorders that hold a lot of promise as an excitingly new field of research. Deep Learning has grown in prominence in recent years for a variety of prediction issues that are challenging the medical professionals. In this paper, Back Propagation Deep Neural Networks (BPDNN) is applied with multiple architectures to create better predictive models for detection of Parkinson's disease (PD) based on the analysis of the features collected from different speech samples of patients. Significantly, even without the use of a feature selection method, Deep Neural Networks has emerged as the best classification tool for PD diagnosis. Finally, DNN was fine-tuned, resulting in a train precision of 99.35%.

Keywords: Parkinson's disease, Deep Learning, Deep Neural Networks, Classification

1. Introduction

Parkinson's disease (PD) is a major neurodegenerative disease that affects 1% of the population above 60 years age, affecting 1 - 2 persons per 1000[1]. The estimated global population affected by PD has more than doubled from 1990 to 2016 (from2.5 million to 6.1 million), which is a result of increased number of elderly people and age-standardized prevalence rates [2]. PD is a progressive neurological disorder associated with motor and non-motor features [3] which comprises multiple aspects of movements, including planning, initiation, and execution [4]. During its development, movement-related symptoms such as tremor, rigidity and difficulties in initiation can be observed, prior to cognitive and behavioural deficits [5]. PD severely affects patients' quality of life (QoL), social functions and family relationships, and places heavy economic burdens at individual and society levels [6-8]. The diagnosis of PD is traditionally based on motor symptoms. Despite the establishment of cardinal signs of PD in clinical assessments, most of the rating scales used in the evaluation of disease severity have not been fully evaluated and validated [3]. Although non-motor symptoms (e.g., cognitive, and behavioural abnormalities, sleep disorders, sensory abnormalities such as olfactory dysfunction) are present in many patients prior to the onset of PD [3, 9], they lack specificity, are complicated to assess and/or yield variability from patient to patient [10]. Therefore, non-motor symptoms do not yet allow for diagnosis of PD independently [11], although some have been used as supportive diagnostic criteria.

1.1. Different stages of Parkinson's Disease

There are different stages of Parkinson's disease that are listed below.

- **Mildest Stage (Stage 1):** At this point, patients with Parkinson's disease have the least interference with daily activities. Other signs, such as tremors, are limited to one side of the body.
- **Moderate Stage (Stage 2):** At this point symptoms such as stiffness, resting tremors, and shaking can be felt on both sides of the body at this time. Patients with Parkinson's disease can also experience changes in their facial expressions.
- **Mid-Stage (Stage 3):** In PD patients, significant changes such as lack of balance, reduced flexes, and stage II symptoms can be noted at this stage. Combining occupational therapy with medicine can help to alleviate symptoms.
- **Progressive Stage (Stage 4):** At this point, the PD patient's health can deteriorate, making it impossible for the patient to travel without the use of an assistive device such as a walker.
- **Advanced stage (Stage 5):** At this point, patients experience the most debilitating and painful condition in Parkinson's disease. Standing can be difficult if the legs are stiff. Patients also find it difficult to stand without collapsing. They may hallucinate and paranoia on occasion.

Most of the common sicknesses or diseases can be segregated into communicable and non-communicable categories offering varying degrees of symptoms and prognosis. While certain illnesses respond to treatment and patients can be revived, there are other ailments that offer no solution to patients and trouble them for a long time or the entire lifetime. This illness affects almost 11 million people worldwide. Many studies have been carried out

in order to find a better treatment for the disease. Machine learning is the process of analyzing empirical data in order to come up with a suitable solution for the future. [10][12].

1.2 Parkinson's Disease Symptoms

In terms of symptoms, Parkinson disease has two broad categories:

- Motor Symptoms
- Non-Motor Symptoms

1.2.1 Motor Symptoms

This is a medical condition wherein a patient has trouble in taking voluntary actions. Tremor, rigidity, freezing, Bradykinesia, or other voluntary muscle contraction are some symptoms of movement disorders [14].

1.2.2 Non-Motor Symptoms

Apathy, cognitive dysfunction, and complex personality disorders are symptoms that are known as non-motor symptoms. Physicians primarily divide them as primary and secondary symptoms of Parkinson disease.

1.2.3 Primary Symptoms

It is the most critical symptom. Rigidity, tremor, and slowness of movement commonly manifest as regular symptoms.[14][17].

1.2.4 Secondary Symptoms

Such a symptom has a significant effect on a person's life. These can either be motorised or non-motorized. Its impact varies from person to person. Parkinson's disease manifests itself in a wide variety of symptoms. Around 90% of people with Parkinson's disease experience vocal dysfunction [6]. Vocal defects should not come out of nowhere. They are the culmination of a long phase that can go overlooked in its early stages. As a result, early detection and tele-monitoring technologies based on precise, effective, and impartial predictive models are critical for patients and researchers. Latest experiments have used machine learning techniques to diagnose speech problems using acoustic tests (features) of dysphonia [16]. The diagnosed conditions reflect basic frequency fluctuations or changes in pitch of vocal oscillation (F0). Other conditions include absolute sound pressure level that signifies the relative loudness of speech. Among other conditions, jitter represents the cyclic changes in fundamental frequency, while shimmer represents cyclic variation in speech amplitude. A condition like harmonicity represents the degree of acoustic periodicity. Here, we have sought to apply Back Propagation Deep Neural Networks (BPDNN) to the extracted features from different voice samples of tested persons with different configurations to predict possibility of Parkinson's disease (PD) [17]. When the DNN is training, the model obtains better initial parameters through unsupervised parameter pre-training algorithm. On this basis, the model uses the supervised training method to optimize parameters further [18][22].

2. Proposed Work

Typically, it is a challenging exercise to classify persons with Parkinson's disease, wherein control efficiency is a pattern classification problem. The data is divided into sub-datasets containing tests of individuals having a unique form of expression, referred to as speech samples, to successfully identify such patterns. Thereafter, voice sample features are selected, after which, their role in the presence of PD is assessed. Then, the selected features extracted from each voice sample (m denotes the number of samples) are used in a Classifier as input. Each classifier predicts its own class name, with a majority preference deciding the outcome. A block diagram of the proposed method is shown in Fig.1.
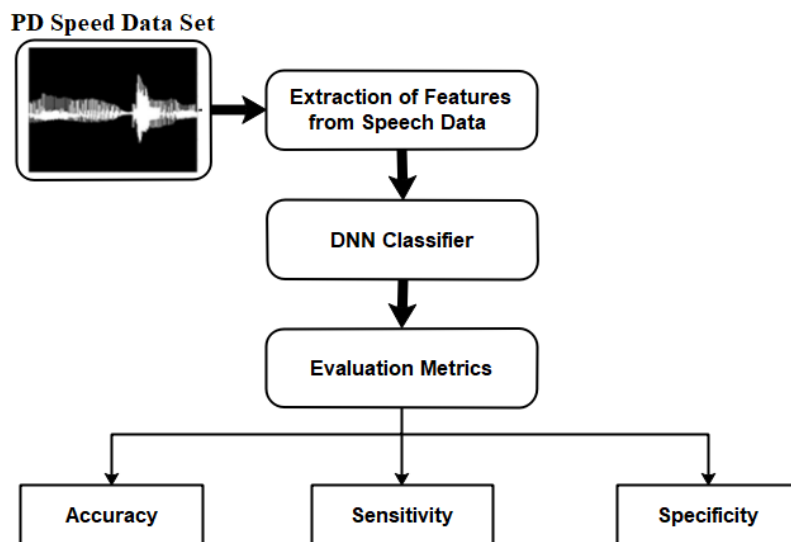
Fig.1. PD Patients Identification/Classification System Model

2.1. Feature Extraction from Speech PD Data

The extraction of speech feature parameters is crucial in voiceprint recognition. The speech signal changes at a slower rate. When it is perceived in a short time, the speech signal is generally considered to be stable at intervals of 10-30 ms. Hence, short-time spectrum analysis can be applied for calculation [20]. The frequency perception of the human ear is estimated by applying Mel scale, and it is calculated by 1000 Hz corresponding to 1000 Mel. This study uses temporal speech quality, spectrum, and cestrum domains to develop more objective assessments to detect speech impairments [19][21]. Factors like the fundamental frequency of vocal cord vibration (F0), absolute sound pressure level, jitter, shimmer, and harmonics noise ratio (HNR) are marked as the basic measurements.

Table.1. Acoustic Analysis results of Healthy with PD

Condition	Sex	Age (Range)	F0(HZ)	Jitter (%)	Shimmer (%)	HNR(dB)
Person Healthy	M	12.6 ± 58.5	127.4 ± 17.4	0.05 ± 0.37	0.24 ± 0.11	14.9 ± 4.7
Person Healthy	F	11.8 ± 55.7	205.6 ± 37.8	1.24 ± 1.27	0.36 ± 0.47	11.2 ± 7.2
Person with Disease	M	62.3 ± 9.8	120.6 ± 20.7	0.96 ± 0.78	0.38 ± 0.17	10.5 ± 3.8
Person with Disease	F	61.9 ± 10.8	193.6 ± 16.6	1.92 ± 1.34	0.69 ± 0.92	8.2 ± 5.2

Based on the pronunciation characteristics of PD patients, the characteristic parameters were extracted for analysis. However, each component contained in the feature parameters has different speech characterization capabilities for different speech samples.

2.2. DNN Classification

Various features are extracted to train the DNN with Back Propagation for classification as follows.

Input Layer $\in \mathbb{R}^3$ Hidden Layer $\in \mathbb{R}^5$ Hidden Layer $\in \mathbb{R}^5$ Hidden Layer $\in \mathbb{R}^5$ Output Layer $\in \mathbb{R}^2$
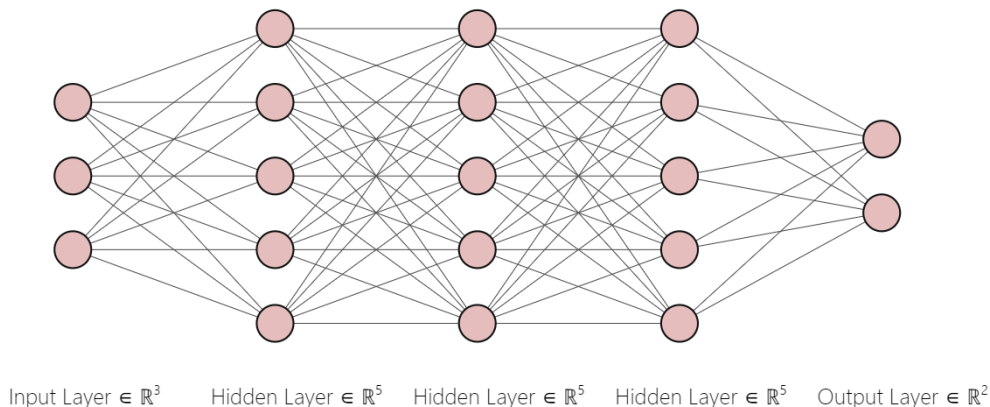
Fig.2. Schematic Diagram of the DNN Structure

DNN is a multilayer perceptron with multiple hidden layers. Because it contains multiple hidden layers, it can abstract useful high-level features or attributes from high redundant low-level features, and then discover the inherent distribution of data. The neural network designed in this paper includes input layer, hidden layer, and output layer. Fig.3 shows the input layer written as Layer 0, while the output layer is written as layer L [19]. A DNN can have multiple hidden layers, and the output of the current hidden layer is the input of the next hidden layer or the output layer. This study uses the Back propagation (BP) algorithm to calculate the gradient of each layer's parameters. The activation function is a Rectified Linear Unit (ReLU), which has the advantage that the network can introduces sparsity on its own and greatly improve the training speed.

For any $l(\,0 < l < L\,)$ layer,

$$z^l = W^l v^{l-1} + b^l$$

$$v^l = f(\,z^l\,)$$

where $z^l \in R^{N_L \times 1}$ is the excitation vector, $v^l \in R^{N_l \times 1}$ is the activation vector, $W^l \in R^{N_l \times N_{l-1}}$ is the weight, $b^l \in R^{N_l \times 1}$ is the bias, and $N_l \in R$ is the number of neurons in the lth layer. $f(\,\bullet\,)$ is the activation function ReLU, with a mathematical expression:

$$\mathrm{Re\,LU}(z) = \max(0, z)$$

When using back propagation for parameter training, the model parameters of the DNN are trained through a set of training $(\,x^i, y^i\,), 1 \le i \le N$, where x^i is the feature vector of the first i samples, and y^i is the corresponding label. The back propagation algorithm is explicitly summarized below.

Back Propagation Deep Neural Networks (BPDNN) Model

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1. Input x: Set the corresponding activation value for the input layer.

2. Forward Propagation: For each layer calculate.

$$z^l = W^l v^{l-1} + b^l$$

$$v^l = f(\,z^l\,)$$

3. Output layer e^L: The error vector is calculated by:

$$e^L = \frac{\partial J(W, b; x, y)}{\partial z^L}$$

4. Back propagation: The error of defining the layer 1node is:

$$e^l = diag(f_l^{'}(z^l)) \bullet (W^{l+1})^T . e^{l+1}$$

5. Output: The weight matrix and bias of each layer are calculated by Equations:

$$x(n) = x(0)\,\hat{x}(n) + \sum_{k=0}^{n-1} \frac{k}{n} x(k) x(n-k)$$

$$\begin{cases} 0 & n < 0 \\ \dfrac{x(n)}{x(0)} - \displaystyle\sum_{k=0}^{n-1} \frac{k}{n} \hat{x}(k) \frac{x(n-k)}{x(0)} & n < 0 \end{cases}$$

The BP algorithm is the core algorithm for training DNN. It optimizes the parameter values in the network according to the predefined loss function. An important step in determining. the quality of the network model is the optimization of the parameters in the neural network model. The optimization algorithm randomly extracts m samples from all samples, where m is the total number of training samples. The m samples are m

$X_1, X_2, ..., X_i, ..., X_m$. ω and b are the sets of weights and bias in the network. Y_i and A_i are the expected output and the actual output of the first i samples input, and $\|\bullet\|$ is a norm operation. The mean squared error is calculated as follows:

$$C(w,b)= \frac{1}{2m}\sum_{i=1}^{m}\|Y_i - A_i\|^2 = \frac{1}{m}\sum_{i=1}^{m}C_{X_i} \text{ where } C_{X_i} = \frac{\|Y_i - A_i\|^2}{2}$$

According to the gradient, the representation of ∇C is

$$\nabla C = \frac{1}{m}\sum_{i=1}^{m}\nabla C_{X_i}$$

The above equation estimates the overall gradient using m sample data, and larger the m is, the more accurate the estimates result is. At this point, the formula for the update is.

$$\omega_k' = \omega_k - \eta\frac{\partial C}{\partial \omega_k} = \omega_k - \frac{\eta}{m}\sum_{i=1}^{m}\frac{\partial C_{X_i}}{\partial \omega_k}$$

$$b_k' = b_l - \eta\frac{\partial C}{\partial \omega_k} = b_l - \frac{\eta}{m}\sum_{i=1}^{m}\frac{\partial C_{X_i}}{\partial b_l}$$

Wherein, η is a positive number, whose range of value is [0,1], and is called the learning rate.

3. Parkinson's Disease Dataset

In the present study, the implementation of the developed system is based on a Parkinson's disease dataset selectively extracted from the UCI Machine Learning repository (https://archive.ics.uci.edu/ml/datasets/parkinsons). The selected PD dataset includes 195 voice recordings from 31 people with each having 22 characteristics (referred to as "predictors" or "explanatory variables" throughout this study). Among these 31 individuals, 23 of them are in good health. In the 22 characteristics, a range of biomedical voice measurements like the average of fundamental speech frequency, maximum and minimum changes in fundamental frequency, changes in amplitude, noise- to- tonal components over voice ratio, dynamic nonlinear complexities, focus fractal scale of the signal exponents and nonlinear channels of fundamental frequency variations. All the characteristics describing the characteristics of the speech presented in the recordings are calculated from speech and voice signals. The detailed characteristics of each element are presented in Table 2. In addition, each observation is labelled with a response variable indicating whether people have PD or not. The response variable is referred to as "status" in the PD dataset.

4. Results and Discussion

In our work, to analyse the models and network implemented, performance metrics like Accuracy, Sensitivity and Specificity have been used. Various performance metrics are taken considering Confusion Matrix that provides the True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN)

$$\text{Accuracy}= \frac{TP+TN}{(TP+FP+FN+TN)}*100\%$$

$$\text{Specificity}= \frac{TN}{FP+TN}\times100\%$$

$$\text{Sensitivity}= \frac{TP}{TP+FN}$$

The machine learning models used audio samples that were just 10 seconds long. We expect that voice can be best used as a dense biomarker for PD diagnosis as such models are highly accurate in their performance. In contrast to the most recognised biomarkers for diagnosis, such as DaT scans or clinician-scored/monitored motor test in the Unified Parkinson's Disease Rating Scale, our model only uses self-reported indicators of clinical diagnosis (UPDRS). Better machine learning models can be built and applied with better disease severity benchmarks. Furthermore, while conducting analysis, insignificant volumes of data have been used in comparison to the

number of samples analysed as well as the data type. A ten-second vocalisation of /aa/ by a patient is less informative as compared to the clinical assessment of many symptoms as done by a doctor. The outcomes of various DNN configurations for determining test accuracy (of the test population) and training precision are shown in Tables 3 and 4

Table.2. Characteristic characteristics of the PD dataset

F_No	F_Name	Description
X1	Jitter (local)	
X2	Jitter (local, absolute)	
X3	Jitter (rap)	Frequency Parameter
X4	Jitter (ppq5)	
X5	Jitter (ddp)	
X6	Number of Pulses	
X7	Number of Periods	
X8	Mean Period	Pulse Parameters
X9	Standard Deviation of Period	
X10	Shimmer (local)	
X11	Shimmer (local, dB)	
X12	Shimmer (apq3)	
X13	Shimmer (apq5)	Amplitude Parameters
X14	Shimmer (apq11)	
X15	Shimmer (dda)	
X16	Fraction of locally unvoiced frames	
X17	Number of voice breaks	Voicing Parameters
X18	Degree of voice breaks	
X19	Median pitch	
X20	Mean pitch	
X21	Standard deviation	Pitch Parameters
X22	Minimum pitch	
X23	Maximum pitch	
X24	Autocorrelation	
X25	Noise-to-harmonic	Harmonicity Parameters
X26	Harmonic-to-noise	

Table.3. Test Accuracy of different DNN Configuration.

	$r > \lvert 0 \rvert$	$r > \lvert 0.25 \rvert$	$r > \lvert 0.3 \rvert$	$r > \lvert 0.35 \rvert$	$r > \lvert 0.4 \rvert$
DNN_5	0.6537	0.6588	0.6931	0.6979	0.6822
DNN_10	0.6837	0.6654	0.6515	0.7313	0.6780
DNN_5-5	0.6445	0.6514	0.6873	0.7296	0.7089
DNN_10-10	0.6779	0.7019	0.6623	0.7188	0.6522
DNN_5-10-5	0.6487	0.6676	0.6681	0.7355	0.6777

Table.4. Training Accuracy of different DNN Configuration.

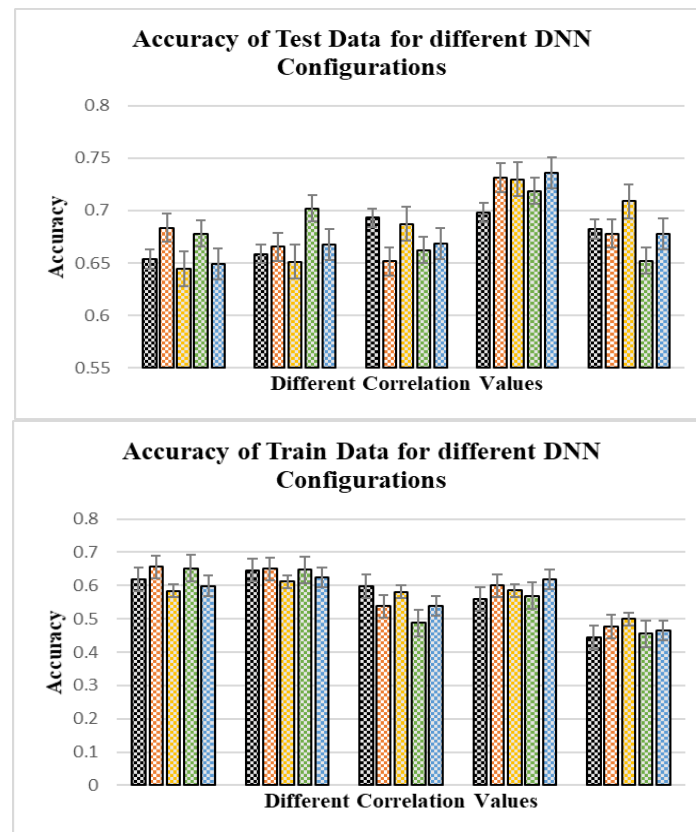|	$r > \lvert 0 \rvert$	$r > \lvert 0.25 \rvert$	$r > \lvert 0.3 \rvert$	$r > \lvert 0.35 \rvert$	$r > \lvert 0.4 \rvert$
DNN_5	0.9908	0.8833	0.8914	0.8835	0.8436
DNN_10	0.9923	0.9275	0.9265	0.9264	0.8767
DNN_5-5	0.9968	0.9185	0.9187	0.9212	0.8796
DNN_10-10	0.9935	0.9613	0.9679	0.9627	0.9250
DNN_5-10-5	0.9924	0.9417	0.9499	0.9393	0.8843

Fig.3. Accuracy of Test and Train Data for different DNN Configurations

This work uses various correlation coefficients $\text{i.e.} (r > |0|, r > |0.25|, r > |0.3|, r > |0.35|, r > |0.4|)$ on both test and train data. Amongst the tested DNN configurations, a result of $r > |0.35|$ is recorded as showing the best accuracy, while the training accuracy is seen gradually decreasing with higher correlation coefficients as shown in fig.3.

Table.5. Sensitivity of different DNN Configuration

	$r > |0|$	$r > |0.25|$	$r > |0.3|$	$r > |0.35|$	$r > |0.4|$
DNN_5	0.6783	0.6621	0.7687	0.8299	0.8936
DNN_10	0.6957	0.6695	0.7475	0.849	0.8667
DNN_5-5	0.6836	0.6608	0.7712	0.8555	0.8996
DNN_10-10	0.7022	0.7366	0.8177	0.8588	0.8250
DNN_5-10-5	0.6880	0.6937	0.7792	0.8385	0.8651

Table.6. Specificity of different DNN Configuration

	$r > |0|$	$r > |0.25|$	$r > |0.3|$	$r > |0.35|$	$r > |0.4|$
DNN_5	0.6183	0.6465	0.5987	0.5599	0.4436
DNN_10	0.6557	0.6495	0.5375	0.5994	0.4767
DNN_5-5	0.5836	0.6117	0.5812	0.5855	0.4996
DNN_10-10	0.6524	0.6466	0.4877	0.5688	0.4552
DNN_5-10-5	0.5989	0.6237	0.5394	0.6185	0.4651

The sensitivity and specificity outcomes of various DNN configurations are shown in Tables 5. & 6. Sensitivity measures the true positive rate that increases in gradual steps when the rate of feature selection rises. Also, higher precision is achieved for nearly all DNN configurations when the correlation coefficient kept increasing. DNN 5-5 produced the best sensitivity outcomes among all configurations with $r > |0.4|$. As a measure of the true negative rate, Specificity is seen as being increasingly unstable when the rate of feature selection kept increasing. DNN 10-10 configuration produced the best specificity levels with $r > |0|$ as shown in fig.4.
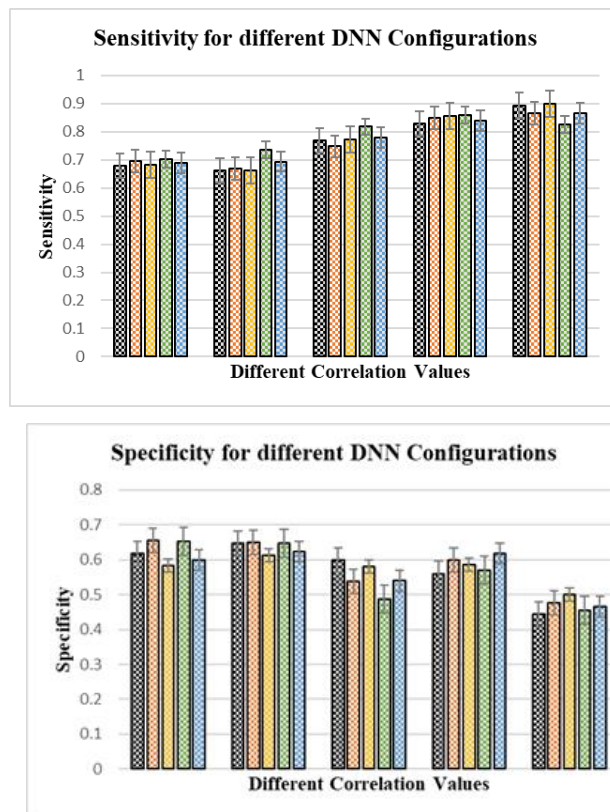
Fig.4. Sensitivity and Specificity for different DNN Configurations

5. Conclusion

Multiple DNNs aligned to different correlation coefficients are examined in this study to resolve problems in accurate diagnosis of Parkinson's disease. Individuals are classified into classes by using various DNN algorithms. Based on a majority voting mechanism, each subject is listed as either "healthy" or "PD." One of the challenges of Machine Learning is finding a typical collection of features for building a classification model for performing a specific task. By reducing the dimensionality of the data with feature selection, the procedure size of the problem is minimized, while DNN efficiency can be improved by eliminating noisy or irrelevant features and avoiding too many attempts at fixing noisy data. When more neurons are added to the existing layers, in addition to the use of multiple concealed layers, significant changes in outcomes is noticed, thus implying that DNN architecture has capacity to determine DNN response. To sum up, our experimental outcomes prove ANN 10-10 as the best ANN topology to address problems in accurate diagnosis of Parkinson's disease with accuracy levels reaching up to 99.35%.

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