Parkinson's Disease Detection by Processing Different ANN Architecture Using Vocal Dataset

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Abstract: Parkinson's Disease (PD) is a long-standing neurodegenerative condition of the central nervous system that mainly affects the motor system and origins full or partial damage in behavior, speech, motor reflexes, mental processing, and other energetic functions. Doctors use different types of datasets such as speech, movement and images from the people to diagnose the disease. In this paper, the speech dataset is collected from people with and without PD to detect the disease. The voice recording samples are analyzed and the feature vectors are extracted from the voice samples. A supervised ANN Multi-Layer Perceptron with a backpropagation algorithm is presented to accurately diagnose and distinguish between healthy and PD individuals. Different Architecture with diverse neuron numbers in the hidden layers are tested to utilize the model and the result of each architecture is compared to select the best ANN architecture for PD recognition. So far, our model score is the highest which is 93% for the testing dataset.

Keywords: Parkinson Disease, Voice Disorder, Artificial Intelligent, Artificial Neural Network, ANN, Multilayer Perceptron, MLP

1. Introduction

The second common neurological disease after Alzheimer is Parkinson Disease (PD). PD is a degenerative neurological disease noticeable by decreased dopamine levels in the brain. Its symptoms occur through a weakening of gesture, including the occurrence of stiffness and shivers. Another common symptom of the disease is marked as the effect on speech, including dysarthria (difficulty pronouncing sounds), hypophonia (lowered volume), and monotone (pitch range decrease). Furthermore, the risk of dementia is increased with mental deterioration and unstable temper. Early diagnosis of PD has been recognized to help with treatment, reducing the severity of symptoms, and providing an improved quality of life for those who suffer from PD. Clinically, various diagnostic tests and various symptoms are carried out to understand and develop the understanding of PD detection.

In recent year, Machine Learning Approaches are being progressively applied in the healthcare sector for predicting, classifying, and diagnosing diseases. machine learning algorithms including Regression, Classification, Image Processing, and Data-mining operations allows a computer program to acquire and extract meaningful illustration from data in a semi-automatic manner.

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For the PD diagnosis, machine learning models have been applied to a collection of data sensory system, including handwritten diagrams (Drot, 2014)(Moshkova et al., n.d.)(Basnin & B, 2021), movement (Wahid et al., n.d.), neuroimaging (Wahid et al., n.d.)(Prashanth et al., 2014)(Quan et al., 2019)(Thakur et al., 2022), and voice (Wibawa et al., 2016)(T. J. Wroge et al., 2019)(Pramanik & Sarker, 2021)(Ozcift, 2012)(Karapinar Senturk, 2020). By using machine learning approaches, we may therefore identify relevant features that are not traditionally used in the clinical diagnosis of PD and rely on these alternative measures to detect PD in preclinical stages or atypical forms.

In this study, we have used a supervised Machine Learning algorithm (MLPANN) on speech dataset for the detection of Parkinson disease. For this case the dataset is collected from the machine learning repository which is formerly done at University of Oxford by M.A. Little (Little MA, McSharry PE, Roberts SJ, Costello DAE, 2007)(Little et al., 2009). The dataset is created from extracted samples from each voice speech of the person. The dataset is preprocessed, feature extracted and normalized to be suitable for the proposed model. Two different architectures of the Multilayer Perceptron Artificial Neural Network are designed with different number of neurons and iterations for the purpose detecting PD. A performance comparative analysis is illustrated between the proposed ANN architectures and the best performed architecture is selected to detect the PD with less training time and a preferable amount of data. The best proposed ANN architecture in this study performed an excellent accuracy with 100% on training dataset and 93% on the test dataset.

The succeeding sections of the paper is organized correspondingly: Previous related works in the literature are presented in Section 2. In Section 3, Data Collection and Preprocessing, Experimental Framework of the study, proposed ANN architecture and Evaluation Metrices are explained. Section 4, The Result of each Proposed ANN architectures are illustrated and a comparative performance analysis is discussed. Lastly, the study is concluded in the section 5.

2. Literature Review

Researches has shown that the dysphonia and gait variability are the most significant symptoms of PD. In literature, it is accused that approximately 90% of people with Parkinson's disease perform some form of vocal weakening. The people with Parkinson's regularly express a pattern of vocal symptom dysphonia, which contains loss in the normal production of vocal sounds (Das, 2010). Most of the recent approaches used for evaluating Parkinson's disease (PD) seriously depend on human expertise. In literature of PD diagnosis, there have been wide-ranging studies of speech measurement for general voice conditions (T. J. Wroge et al., 2019).

Artificial intelligence, precisely machine learning (ML), has found various applications in computer-aided diagnostics, monitoring and management in healthcare (Belić et al., 2019). Recent researches have been conducted on detecting PD by using speech vocals and different ML algorithms.

Researchers in (Islam et al., 2014) proposed a comparative analysis for Parkinson's disease detection using SVM, Random tree (RT) and Feed-forward back-propagation neural network (FBANN). The UCL Machine Learning Respiratory is used to collect the sound dataset. A 10-flod cross validation analysis with 100 iterations has been carried out for all classification. The proposed model achieved 97.37%.

In (Abdurraqeeb & Alturki, 2022), the researchers aimed two cases of Parkinson's disease detection, off–medication and on–medication. They used two different EGG datasets and UNM dataset for this

study. Machine Learning Techniques (random forest, linear/quadratic discriminant analysis, support vector machine, and k-nearest neighbor) were utilized to classify the extracted features. The achieved results in term of off-medication PD detection for classification accuracy, sensitivity, and specificity were approximately 99%, and in term of on-medication PD were between 95% to 98%.

In (Pramanik & Sarker, 2021), Researchers investigates a comparative analysis for PD detection using sound dataset from Department of Neurology in Cerrahpasa, Faculty of Medicine, Istanbul University. Various Machine Learning (ML) classifiers were used to classify the PD such as (AdaBoost, Logistic Regression, Support Vector Machine, k-nearest Neighbor and Random Forest). 10- cross fold validation and grid search have been used for all algorithms. The SVM algorithm performed very high accuracy by 94.10% among all conducted algorithms.

Researchers in (Karapinar Senturk, 2020), has used feature selection and different ML algorithms for PD detection. Feature Selection process has been performed using Feature Importance and Recursive Feature Elimination and the classification process has been executed for PD detection using Artificial Neural Networks, Regression Trees, and Support Vector Machines. Support Vector Machines with Recursive Feature Elimination has achieved better accuracy 93.84% with minimal voice features number for Parkinson's diagnosis.

Researchers in (Çimen & Bolat, 2016), has proposed a comparative study using Multi-Layer Perceptron (MLP) with one hidden layer and Generalized Regression Neural Networks (GRNN) with spread parameters to classify the PD. The sound dataset is used a sample for the models. As comparison, the GRNN achieved the maximum classification rate in the result 100% with a spreading process.

In (T. Wroge et al., 2018), Researchers utilized the mPower Voice dataset with virous Machine Learning Algorithms such as Random Forest, ANN, Decision Tree and Support Vector Machine to classify PD. The classification analysis has been carried out and the Evaluation metrices are calculated using 10-fold cross validation. The DT performed a good result compared to others with accuracy of 86%.

3. Data Collection and Experimental Framework

3.1 Data Collection

In this study, we had used a voice recording data set from the machine learning repository which is formerly done at University of Oxford by M.A. Little (Little MA, McSharry PE, Roberts SJ, Costello DAE, 2007)(Little et al., 2009). The data contains of 6 vocal recorded biomedical voice measurements from 195 recordings extracted from 31 people whom 23 are diagnosed with PD and 8 of them are healthy. the age of the persons ranged from 46 to 85 years with average range of diagnosis 0-28 years. Each recorded vocal is ranging from 1 to 36 seconds, the total phonations of vocal sounds are 147 PD phonations and the total of 48 healthy phonations (Islam et al., 2014).

The data used for this experiment are in ASCII CSV format. The file contains instances corresponding to single vocal recording. Particular voice measures are represented in the columns and each row represents one of 195 vocal soundtracks from these persons. The primary goal of the data is to single out healthy persons from those with PD, the dataset contains of 22 input attributes with one output ‘‘status” attribute which is set to 0 for healthy and 1 for PD. Table 1 shows the features used in this experiment(Little MA, McSharry PE, Roberts SJ, Costello DAE, 2007).

Table 1: Dataset Features used for the Proposed model.

#	Attribute Name	Explanation
1	Name	ASCII Patient name and recording ID
2	MDVP:Fo(Hz)	Average vocal frequency fundamental
3	MDVP:Fhi(Hz)	Maximum vocal frequency fundamental
4	MDVP:Flo(Hz)	Minimum vocal frequency fundamental
5	MDVP: Jitter (%), MDVP: Jitter (Abs), MDVP: RAP, MDVP: PPQ, Jitter: DDP	various measures of differences in frequency fundamental
6	MDVP: Shimmer, MDVP: Shimmer(dB), Shimmer: APQ3, Shimmer: APQ5, MDVP: APQ, Shimmer: DDA	various measures of differences in amplitude
7	NHR, HNR	Two measures of ratio of noise to tonal components in the voice
8	RPDE, D2	Two nonlinear dynamical complexity measures
9	DFA	Signal fractal scaling exponent
10	spread1, spread2, PPE	Three nonlinear measures of fundamental frequency variation
11	status	Person’s Health condition, (one) - Parkinson, (zero) - Healthy

People with Parkinsonism of medical personnel (Sakar et al., 2013) . People with Parkinsonism (PWP) suffer from speech impairments like dysphonia (defective use of the voice), hypophonia (reduced volume), monotone (reduced pitch range), and dysarthria difficulty with articulation (reduced pitch range).

Data is collected throughout the examination procedure by a physician. The doctor instructs the patient to read or repeat a predetermined text that includes voice samples. During this procedure, each patient's speech is recorded. Following that, the speech is parsed to be separated into 6 sub-voice samples, and time-frequency based features are collected from the voice samples. (Sakar et al., 2013). The overall scheme of the PD diagnosis system is shown in Figure 1.

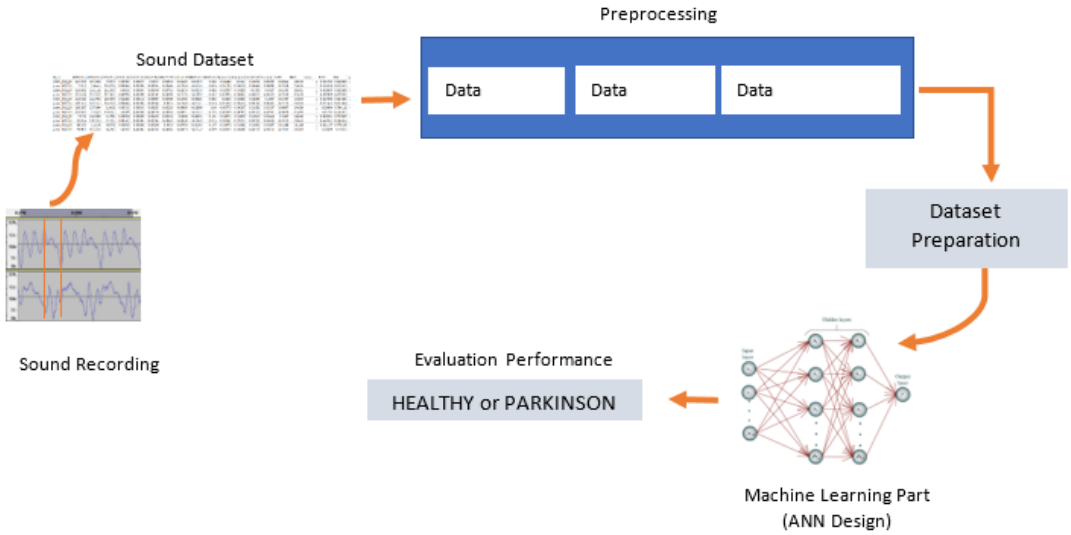


Figure 1: The proposed Framework for the paper.

3.2 Data Preprocessing and Normalization

Processing the dataset is containing the stages data cleaning, data selection, data normalization. During the data cleaning stage, a reliable data format is produced in which missing data are checked, duplicated data is identified, and inadequate data is cleaned up. Essentially, the cleaned data were converted into a format suited for the proposed ANN design.

In the data selection stage, the number of input variables are reduced by removing the features that are not correlated to the target output. The remaining 11 columns of the dataset is assigned as input variables for the proposed ANN design and the status column is stated as a target output. The status sample 0 is assigned for healthy person and 1 to patients with PD.

In the data normalization stage, the dataset values are altered to a new range of values between 0 and 1 using the mix-max method (1) which is more suitable for the proposed ANN method to get the better result.

$$z_i = \frac{x_i - \min(x)}{\max(x) - \min(x)} \times 100 \qquad [1]$$

3.3 Proposed ANN Machine Learning Tool

ANN is an intelligent AI model inspired by the framework of biological human neurons (Niazkar, 2020). neurons are considered as processing units which they are typically consist of three types: Receive impulses or external signals, internal elements to process input information and output units (Veintimilla-reyes et al., 2016). ANN model is used to solve any complicated problems in many application fields such as pattern recognitions, classifications, optimizations, clustering, modeling, prediction, simulations and others.

The ANN model is composed of three layers: an input layer that contains the collected data, one or more hidden layers that connect the input and output levels, and an output layer that contains the computed information from the input layer. (Mohamed, 2019). Each input is multiplied by connection

weights, and its products and biases are added and then passed through an activation function to produce an output as shown in the Figure 2.

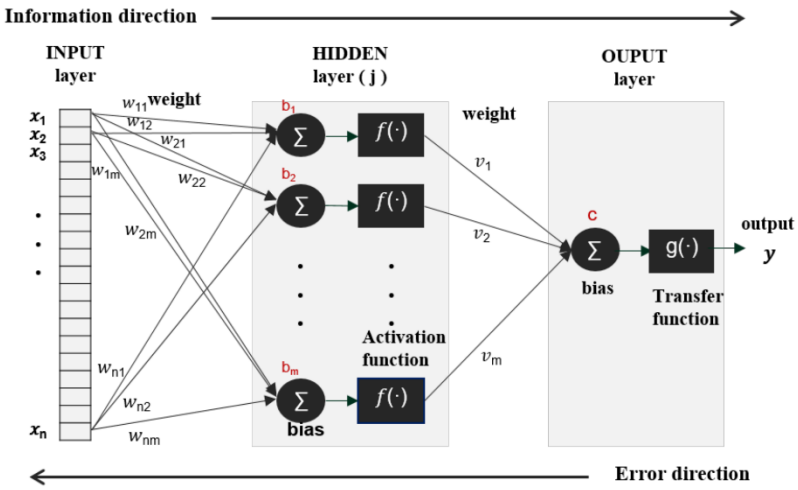


Figure 2: The structure of ANN and

The Back Propagation (BP) algorithm is the most commonly used approach for training feedforward ANNs, which is based on supervised learning and is dependent on the gradient descent optimization technique. The process of BP is, the best weight values are calculated iteratively and the error is defined as difference between network output and the target output. For each training model the weights are adjusted to minimize the mean squared error between the estimated network and the measured data. The updating process of weights are completed as the error reaches the minimum error rate. The weight update equations for the back propagation algorithm are given in the equations below.

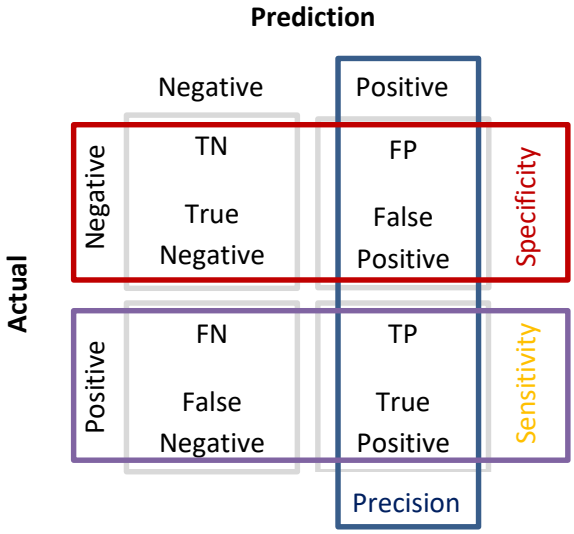
$$\Delta w_{ij}\,(t) = -\alpha \frac{\partial E}{\partial W_{ij}} + \beta\, \Delta w_{ij}\,(t-1) \qquad [2a]$$

$$\Delta w_{ij}\,(t+1) = w_{ij}\,(t) + \Delta w_{ij}\,(t) \qquad [2b]$$

The BP algorithm of ANN based on supervised learning method. To evaluate your model, the dataset is separated into two percentage parts Train and Test split. The training part which trains the model to find the optimal output to the model. And a testing part which is extracted from the original dataset. This testing is to evaluate the model to find the output which is equal to the target output.

3.4 Evaluation Metrices (Recall, Precession, F, confusion Matrix, Roc Curve Accuracy)

The common classification metrices used to evaluate the performance of ANN model are, precession, recall (Sensitivity), Specificity which are calculated from confusion matrix, accuracy, F1-measure and ROC Curve (Wibawa et al., 2016)(Mohammed, 2020). The Confusion matrix contains TP (True Positive), TN (True Negative), FP (False Positive) and FN (False Negative). The values of confusion matrix with the performance evaluation metrices are explained in the Figure 3.



$$Sensitivity\ or\ Recall = \frac{TP}{TP+FP} \quad [3a]$$

$$Specificity = \frac{TN}{TN+FP} \quad [3b]$$

$$Precision = \frac{TP}{TP+FP} \quad [3c]$$

$$F - Measure = \frac{2*Recall*Precision}{Precision+Recall} \quad [3d]$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Figure 3: Evaluation Metrices for the ANN model

True Positives (TP): Number of results that are truly positive and are predicted positive.

True Negatives (TN): Number of results that are truly negative and are predicted negative.

False Positives (FP): Number of results that are truly negative but predicted positive.

False Negatives (FN): Number of results that are truly positive but predicted negative.

ROC curve (Reciever Operating Characterstic curve) is a graph showing the performance of the proposed ANN model. It is visualizing the adjustment between the True Positive Rate (TPR) and False Positive Rate (FPR) using the choice threshold value. The value of TPR and FPR are calculated usinf the equations below

$$TruePositiveRate = \frac{TruePositive}{FalseNegative+TruePositive} \quad [4a]$$

$$FalsePositiveRate = \frac{FalsePositive}{TrueNegative+FalsePositive} \quad [4b]$$

4. Result and Discussions

The total of 195 voice samples is collected from the dataset including PD and healthy phonations. The dataset is arbitrarily partitioned into two parts: 70 % (136 Samples) of the data is used as training (training and validation of the dataset) and the remaining 30% (59) of the dataset is used as test dataset to appraise the performance accuracy of the trained model for PD detection. AN Interactive Colab Notebook environment with a Python programming language and libraries are used for Evaluation and Performance Prediction on the dataset (Welcome to Colab, n.d.).

For the ANN MLP architecture two hidden layer with different number of neurons, which initial weights prefered randomly, has been designed. Best activation functions (relu) are selected for the hidden layers and the sigmoid activation function is selected for the output layer. The training progress for the model is completed using different number of neurons and iterations then the most appropriate one is selected to Evaluate the ANN model.

The first structure of the model contains two hidden layers, the first layer with 20 neurons and the second layer with 40 neurons. The maximum iteration of the model is assigned to be 500 with number of batches to be 100. The accuracy score for the validation set of the model is 100 % and the Test set Accuracy of the model is 91%. 15 samples are correctly identified as healthy and 39 samples as PD out of 59 samples with MSE of 0.085 the confusion matrix for the trained model is presented in the Figure 4a. The ROC area under the curve is illustrated in Figure 4b.

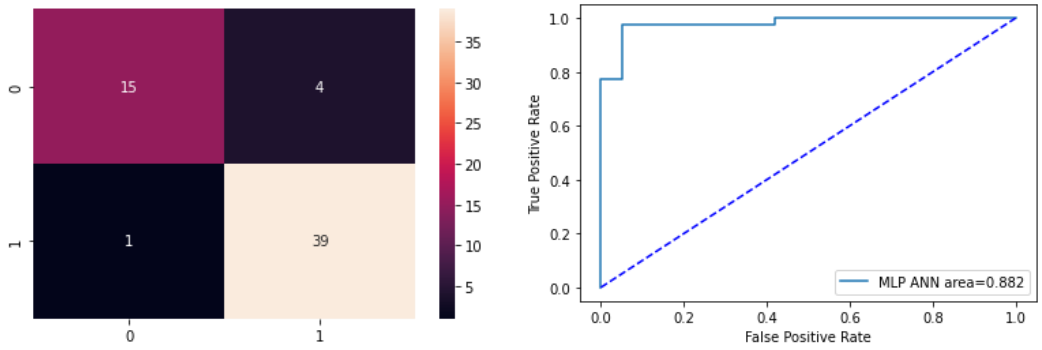


Figure 4a Figure 4b

Figure 4: ROC area ANN with 20 and 40 with 500 iteration structure

The loss for the ANN model during the training is illustrated in the Figure 5. As shown in the figure, the blue line determines the loss value of training set and the orange line denotes the loss value for the validation test set; while X-axis represent the number of each epoch and Y-axis represent the decreasing Loss. The training and validation loss decreases at a stable point and the difference between them is very low which indicates the model is resulting a good performance.

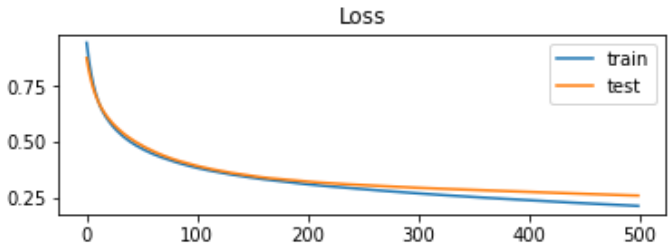


Figure 5: The training loss versus test loss

Figure 6, demonstrates the Accuracy for the training and validation set of the ANN model. the blue line determines the performance of the accuracy of the training set and the orange line determines the accuracy of the validation test set; while X-axis represent the number of each epoch and Y-axis represent the increasing accuracy. As shown in the graph the performance on the validation dataset is giving a good performance with the accuracy 91% compared to the training set.

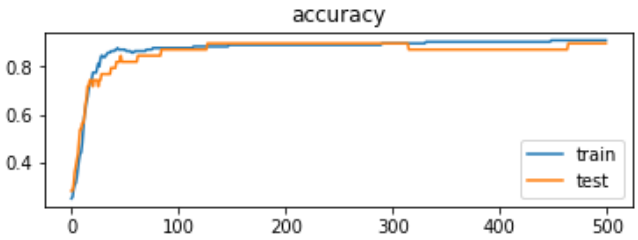


Figure 6: The training accuracy versus test accuracy

The second structure of the model contains two hidden layers, the first layer with 20 neurons and the second layer with 20 neurons. The maximum iteration of the model is assigned to be 1000 with number of batches to be 100. The validation set accuracy score of the model is 100 % and the Accuracy of the Test set is 93%. 16 samples are correctly identified as healthy person and 39 samples of the test dataset ae correctly identified as PD out of 59 samples with MSE of 0.067, the confusion matrix for the trained model is shown in the Figure 7a. The ROC area under the curve is illustrated in Figure 7b.

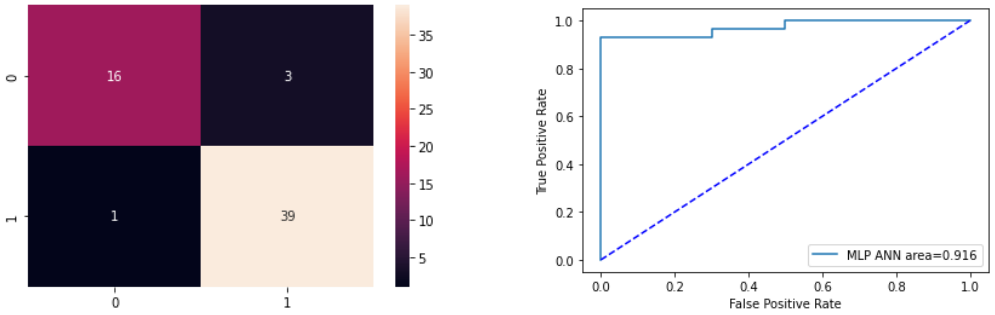


Figure 7a Figure 7b

Figure 7: ROC area ANN with 20 and 40 with 500 iteration structure and confusion matrix

The loss during the training of the ANN model is illustrated in the Figure 8. As shown in the figure, the blue line determines the training loss value and the orange line represents the validation loss; while X-axis represent the number of each epoch and Y-axis represent the decreasing Loss. The training and

validation loss decreases at a stable point and the difference gap between them is very low which indicates the model is resulting a good performance

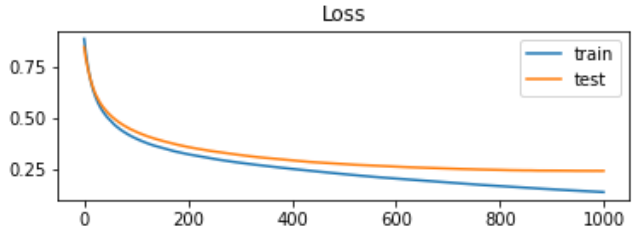


Figure 8: The training loss versus test loss

Figure 9, shows the training and validation Accuracy of the ANN model. the blue line determines the performance of the training accuracy and the orange line represents the validation accuracy; while X-axis represent the number of each epoch and Y-axis represent the increasing accuracy. As shown in the graph the performance on the validation dataset is giving a good performance with the accuracy 93% compared to the training set.

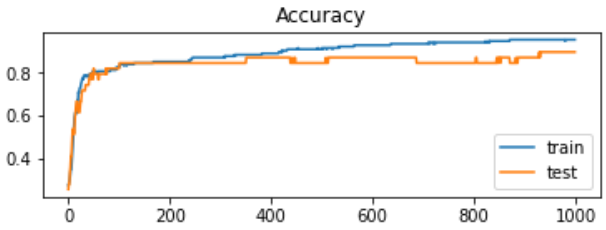


Figure 9: The training accuracy versus test accuracy

The Evaluation Metrices for both ANN Architecture is described in the Table 2. As shown in the table the second structure of the ANN model with 20 neurons in each hidden layer and 1000 iteration gives the best accuracy for predicting the PD with 93%.

Table 2: The comparative analysis for both MLPANN architecture.

No of neurons in the hidden Layers		Iteration	Precision		Recall		F-Measure		Accuracy
1st	2nd		0	1	0	1	0	1	
20	40	500	0.94	0.91	0.79	0.97	0.86	0.94	0.915
20	20	1000	0.94	0.93	0.84	0.97	0.89	0.95	0.932

The preferred model for the ANN is tested using a random sample of data is selected and inserted to the model to predict the output. The model accurately predicted the sample as Healthy or Parkinson disease. This means the model has a good accuracy to detect the Disease.

5. Conclusion

EEG data analysis has lately been utilized to diagnose brain disorders. In this study, Parkinson's Disease detection was achieved by employing our proposed MLPANN model on the PD Speech

dataset. Extensive data pre-processing was applied to improve the dataset quality and the normalized dataset is used for the detection of PD. A MLPANN with two hidden layers is investigated to classify the extracted features. Different numbers of neurons with different number of iterations are used for the model optimization. In terms of classification accuracy, recall, precision, and F-score for PD detection, the MLPANN with two hidden layers (20,20) and 1000 iterations achieves 0.932, 0.93, 0.97, and 0.95, respectively. The Experimental result shows that the proposed predictive model suggestively outperformed the experiments on the test dataset to easily identify the healthy persons from people with PD using voice impairment measurements. For forthcoming work, we suggest to use the dataset in the hospitals in the region to investigate the model using local dataset with more consideration to inspect the enhancement of methods for strength by applying different ML algorithms, extracting features dynamically and selection approach.

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