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A Deep Learning Technique to Clinch the Detection of Parkinson's Disease using Speech and Voice Attributes

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Abstract- Among the neurodegenerative diseases Parkinson's Disease ranks second only to Alzheimer's disease. Though extensive research is carried out in this area there have been no biomarker suggested. At present the diagnosis and monitoring of the disease progression is possible only through clinical examination and function symptoms observation. Voice impairment has been identified as an early marker for Parkinson's Disease and hence the research in this field is gaining popularity. Machine Learning algorithms have proved useful in analyzing the enormous data with high dimensionality. But this has not been successful in extricating features that will have a strong correlation in predicting the disease accurately. This calls for a more effective and powerful technique like Deep Learning that uses deep neural networks that can select the optimal features and can contribute in the identification of the disease. In this paper an initial step was made by designing an Artificial Neural Network model. This yielded a train and test accuracy more than ninety-nine percentage and seventy-five percentage respectively for classifying the disease but showed overfitting problem which resulted in a decrease in the performance. Hence, the Artificial Neural Network model was hyper-tuned to reduce this problem and there was a slight improvement in the performance. Two methods were employed for optimization – a regularization method early stop and another validation method called Stratified K -Fold Cross Validation. Among these the second approach showed better results by slightly reducing the overfitting issue and it yielded a train and test accuracy score of approximately ninety-nine percentage and ninety-seven percentage with K-fold as five and Stochastic Gradient Descent as the optimizer. Even though the results were promising it was unable to unravel the prime attributes that would eventually identify the disease.

Keywords - Parkinson's Disease, Machine Learning, Deep Learning, Deep Neural Networks, Artificial Neural Network (ANN), Stratified K -Fold Cross Validation, Overfitting, Stochastic Gradient Descent (SGD).

I. INTRODUCTION

Parkinson's Disease is one of the most extensively researched neurodegenerative disease. The symptoms of Parkinson's Disease can be compiled into two groups namely motor and non-motor entities. Normally non-motor symptoms manifest early in PD patients and includes the following signs - mood disorders, pain, sensory dysfunction, and cognitive dysfunction, dysautonomia etc., [1]. Motor symptoms which include tremor, slowness of movement (bradykinesia), stiffness (rigidity), and poor balance (postural instability) are common among PD patients. Speech impairments such as soft, breathy and hurried speech occur in more than half of the Parkinson's patients [2]. The analysis of speech and voice signals involves non-invasive techniques that are quite economical, viable and requires complicated procedures.

This makes it attractive for clinicians, neurologists and helps them in predicting the disease before the onset of disabling physical symptoms and thus providing better health care deliverance and improving the quality of life of patients.

Studies involving speech analysis of PD have shown that people affected with PD have shorter maximum phonation time, decreased pitch range, higher jitter, shimmer and increased phonation threshold pressure [3]. Machine learning models have been tried on these instances with an aim to detect PD early [4] – [10]. The machine learning models that are being employed falls into two categories. First one being the traditional methods like Support Vector Machine (SVM) [11][12], K-Nearest Neighbor (KNN) [13], Naïve Bayes (NB) [14], [15], [16], Decision tree [14], Genetic Algorithm [17], and their combinations [18], [19] and the second category involves Deep Learning models.

Traditional models uses global static parameters based on different acoustic measurements like Mel- Frequency Cepstral Coefficients (MFCC), baseline features like jitter, shimmer, fundamental frequency etc., from voice signals. Subsequently dimensionality reduction method like Principal Component Analysis (PCA) is applied to the dataset which helps in reducing the model complexity and avoiding overfitting problems. Some of the best feature selection algorithms like Minimum Redundancy Maximum Relevance (MRMR), Local Learning-Base Feature Selection (LLBFS) etc., are applied to extract the best features. These studies though have yielded some useful results but was not sufficient in identifying the prime attributes and detecting patterns that has strong affinity in predicting the disease.

This necessitates the need for a robust tool that can enable hierarchical feature selection by increasing the level of abstraction for detecting patterns. Several studies have explored PD detection from speech based on Deep Learning models, such as Convolutional Neural Network (CNN) [20]– [23].

This paper aims at building an experimental model using Artificial Neural Network to bring out drastic changes in the performance compared to the existing machine learning models. It is also proposed to elaborate the search for identifying plausible patterns by extracting prime attributes that have strong propensity for Parkinson's disease. In order to achieve this we have to use higher deep learning architectures like CNN, RNN etc.

II. RELATED WORKS

Some of the major studies conducted in the area of machine learning related to speech disorders and PD is a mentioned above. Other than this, the deep learning models which are employed to study any possible presence of an early signs showing PD by analyzing speech and voice parameters is presented here.

In a study by Castro et al. [24] the dataset was obtained from UCI Machine Learning repository. In this study an Artificial Neural Network (ANN) using n MLPs (Multilayer Perceptron) was designed to classify PD patients. Their collections comprised of voice recordings of PD patients. They used many networks containing 10 – 6000 neurons for training. Maximum number of neurons were added in the hidden layer. The speech parameter were analyzed by ANN to assess PD patients.

A hybrid model using Artificial Intelligence was proposed by Parisi et al. [25] to examine PD patients. The UCI Machine Learning repository was chosen for the study from which 68 patient's dysphonic values were subjected to processing. The feature selection was based on MLP weights. To rank input features different weight values were given for physiological and pathological patterns. The proposed model well compared to existing schemes and thus could be used for clinical detection of PD patients.

In the study by Gunduz [20] two architectures based on Convolutional Neural Networks (CNN) were proposed to classify PD using speech parameters. The first framework used combination of different feature sets which were passed as input to a nine – layered CNN model whereas the second model fed feature sets to parallel input layers. These layers were directly connected to CNN layers. To validate the performance of the model the Leave-One-Person -Out Cross Validation (LOPO CV) was used. Between the two frameworks the latter one showed promising results.

III. METHODOLOGY – DEEP LEARNING MODELS AND PD CLASSSIFICATION

Deep learning is the next generation technology that has been successfully employed in the pd studies in the contemporary machine learning methods. Deep learning uses Artificial Neural Networks (ANN) which is a basic model designed to mimic human brain. Neural network which are composed of nodes in each layers just like the human brain which are made of neurons. The nodes in each layer are interconnected and through which the information is transmitted for processing and the final outcome is obtained. Deep learning is instrumental in predicting patterns and trends from plethora of data by critically analyzing it and by using multiple predictive models.

IV. IMPLEMENTATION

A functional basic model of deep neural network called Artificial Neural Network (ANN) was designed to understand the performance of the system in classifying PD from healthy cohorts. The dataset when analyzed using the ANN could obtain an accuracy of 98.7%. The ANN model is designed with three layers. The first layer is the input layer through which the data is fed. The next layer called the hidden layer that takes weighted inputs from the data and produce an output based on the activation function. The last layer is the output layer that produces the ultimate result of the predictive model. Since the dataset used in this study is not balanced some preprocessing and normalization was done before applying it to the proposed model.

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(A) Data Collection

The source of the dataset used in this study is from the Department of Neurology in Cerrahpasa Faculty of Medicine of Istanbul University. It contains totally 252 cohorts out of which 188 are affected with Parkinson's disease and 64 are healthy individuals. The mean age of the population with PD ranges from 33 -88 years and healthy individuals from 41 – 82 years. The number of males and females affected with PD is 107 and 81 whereas the healthy cohorts are 23 and 41 respectively. Total attributes are 754.The data was recorded using a microphone with 44.1 kHz frequency. The cohorts were instructed to utter vowel /a/ three times. This information about sustained phonation was recorded and examined by physicians using different signal processing algorithms to derive clinically usual information. Some of the algorithms employed for this include Time – Frequency Features, Mel Frequency Cepstral Coefficients (MFCCs), Tunable Q-factor Wavelet Transform (TWQT), Vocal Fold features etc. The Praat acoustic analysis software is used to extract the baseline features.

(B) Data Preparation and Preprocessing

Initial data preparation and pre-processing were done on the dataset by checking null values, missing values etc. The dimensionality was reduced by applying correlation. A correlation matrix is created which helps created which helps to identify variables that have high degree of correlation thus reducing the number of features in the dataset. The correlation coefficient the value of which ranges from -1 and +1 were plotted with the aid of a heat map. The values having high positive and negative correlation was removed. The resultant matrix was subjected to sampling. The dataset used in this study contains more number of PD patients than healthy cohorts. In order to make the distribution uniform and to further reduce the number of features sampling was applied.The number of attributes reduced to 384 rows and 197 columns. Normalization was carried out using Standard Scalar function. This function is used to standardize features by removing the mean and scaling to unit variance. The standard score of a sample 'x' is calculated as: $z = (x - u) / s$ where 'u' is the mean of the training samples and's' is the standard deviation of the training samples.

(C) Model Creation, Training, and Testing

Keras a high-level API that runs on top of TensorFlow (is an open -source set of libraries offered by Python for creating and working with machine learning models) is used for model creation and evaluation. It helps in building complex neural networks by providing user friendly and easy to use API. Another advantage of using Keras is that it is less error prone and thus the models are more likely to produce accurate results than with Tensor Flow. In this study Keras are used for creating and evaluating the model. A sequential API is used to create an ANN with three layers. The first layer called input layer contains 60 nodes, with RELU activation function. This accepts input parameters with input shape that is 754 features from the dataset.

RELU (Rectifier Linear Function) is a piecewise linear function that will output the input directly if it is positive, otherwise, it will output zero. For this model RELU was used because it is easier to train the model and can achieve better performance. Next layer called hidden layer consist of 30 nodes. This layer also uses RELU activation function that facilitates the processing. This information is then passed to the final layer which is called the output layer. This layer has only one node that predicts the output as a binary classifier. The activation function used is SIGMOID.

This function takes any real value as input and outputs value in the range of 0 to 1. The larger the input (more positive), the closer the output value will be to 1.0, whereas the smaller the input (more negative), the closer the output will be to 0.0. The model is then compiled using the loss function as BINARY_CROSSENTROPY and the three different optimizer functions were used. This model was trained with 80% data and 20% was used for testing and validating the model. Accuracy is the metric used for assessment. The figure 1 shows the architecture diagram of the proposed model.

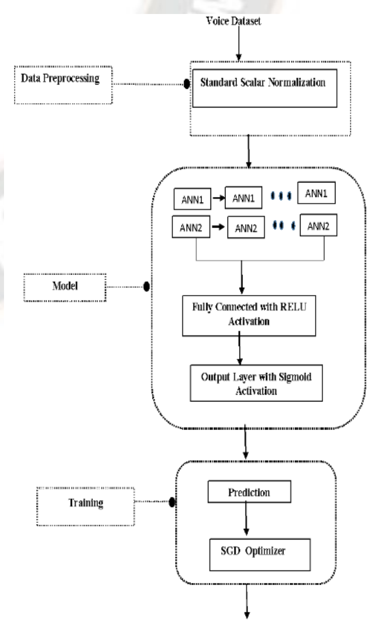

Figure 1: Architecture diagram of proposed ANN model

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The model was over fitted and in order to solve this problem it was subjected to hyper-tuning. Regularization which is a method for hyper-tuning was carried out engaging the early stop technique. In this a validation dataset is defined in addition to the train and test dataset. As we proceed training the model the loss function is computed and recorded for the validation data. The model did not show much improvement on the validation set. Hence the learning was stopped in between rather than executing all epochs. This method of stopping early which is based on validation dataset performance is termed as early stopping.

This not only prevents overfitting but also helps to considerably reduce the number of epochs used for training the model. Here validation accuracy was checked for saturation that is min_delta was set to 0.001 and it was used as an indicator to stop training the model further that might lead to overfitting problem.

Early stop method was not effective in solving the problem of overfitting since it stopped learning after 2 or 3 epochs. Hence, another technique called stratified cross fold validation was applied which could possibly reduce the overfitting issue. In this method the instances are selected from the dataset in the same proportion by dividing them into groups or classes or strata based on a characteristic. This ensures the training and test sets have same proportion of the features of interest as the original dataset. Hence, the model will not have a bias and thus does not go into overfitting state. The K-fold was randomly chosen and the one which provided the best results was selected for the model. This technique yielded better performance compared to early stop method to reduce the problem of overfitting.

V. RESULTS AND DISCUSSIONS

The model showed a train accuracy of 99.6% and testaccuracy of 75% without validation. This points to aproblem of overfitting. In order to solve this problemthe model was subjected to hyper-tuning. This resultedin a slight improvement in the test and train accuraciesof the model. On applying stratified k-fold validationtechnique the model showed a train accuracy of 98.7%and a test accuracy of 97% which could slightly reducethe overfitting problem.

ADAM, SGD and RMS PROP optimizers wereused to fine tune the model. The results as shown in the table 1(A) below shows that using optimizerSGD(Stochastic Gradient Descent) the modelgave the best result of 99.6% training accuracy and 75% test accuracy. Since the model showedoverfitting it was subjected to hyper tuning usingearly stop regularization method and stratifiedcross fold validation. The results obtained usingthe above two methods are summarized in table1(B) and table 1 (C) respectively.

The SGD optimizer yielded the best results in both methods with a train and test accuracy of both 81% for early stop and 98.7 and 97% for stratified k-fold validation (with k-fold =5). Out of these two methods the stratified cross fold validation was chosen as it could slightly reduce the problem of overfitting.

TABLE 1(A): ANN TEST AND TRAIN ACCURACY AND LOSS – WITHOUT VALIDATION

Train Accuracy	Test Accuracy	Training Loss	Testing Loss	Optimizer
100%	74%	0.0035	0.8331	ADAM
99.6%	75%	0.855	0.5682	SGD
100%	72%	1.354	0.0958	RMS PROP

TABLE 1(B): ANN TEST AND TRAIN ACCURACY AND LOSS – WITH VALIDATION (EARLY STOP)

Train Accuracy	Test Accuracy	Training Loss	Testing Loss	Optimizer
98%	87%	0.707	0.3701	ADAM
81%	81%	0.466	0.495	SGD
96%	85%	1.092	0.3796	RMS PROP

TABLE 1(C): ANN TEST AND TRAIN ACCURACY AND LOSS – WITH STRATIFIED K-FOLD =5 VALIDATION

Train Accuracy	Test Accuracy	Training Loss	Testing Loss	Optimizer
100%	100%	9.3	8.2	ADAM
98.70%	97%	0.12	0.08	SGD
100%	97%	1.32	1.009	RMS PROP

The following metrics were used for evaluating the model's performance.

(A) Accuracy

Accuracy is the number of correctly predicted data points out of all the data points Accuracy = (TN+TP)/(TN+FP+TP+FN) For the model the train and test accuracyobtained without optimization is 99.6%and 75%. This showed overfitting of themodel. To overcome this problem the model was subjected to two optimization methods like early stop and stratified cross fold validation. The second method yielded better results by slightly reducing the problem of overfitting. The train and test accuracies achieved using this technique was 98.7% and 97% respectively. The following plot shows the accuracy of the model

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before and after optimization (using stratified cross fold validation).

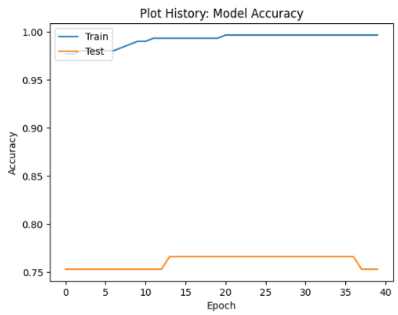

Figure 2(A): Train and Test Accuracy of the model without optimization

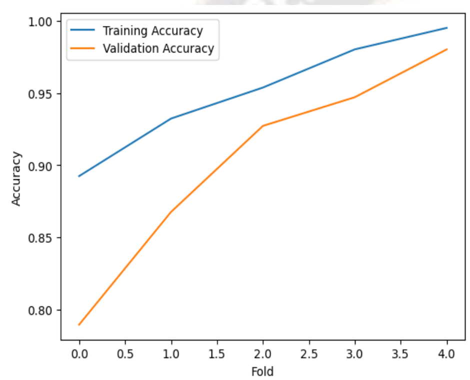

Figure 2(B) Train and Test Accuracy of the model with stratified k-fold optimization

Since accuracy is not a good metric for an unbalanced dataset the following metrics are used for evaluation.

(B) Precision

Precision = (TP)/(TP +FP) FP) which determine the proposition of positive predictions that was actually correct.

(C) Recall /Sensitivity

TPR (Recall/Sensitivity) = TP / (TP+FN) This score is similar to precision but it calculates the proportion of actual positive that was identified incorrectly.

(D) Specificity

Specificity is the proportion of true negatives that are correctly predicted by the model.

FPR (1-Specificity) = FP / **(TN + FP)**

(E) F1-Score

This metric is used to evaluate a binary classification model on the basis of predictions that are made for the positive class. It is calculated with the help of Precision and Recall.

F1-Score = 2* (Precision * Recall) / (Precision + Recall)

The best score is 1.0 and the worst is 0.0. Better the f1- score better the model.

(F) Support

Support is the number of samples of the true response that lies in each class of target values. Macro Average is computed using the arithmetic mean of all F1-Scores whereas the Weighted Average is calculated by taking the mean of all per-class F1-scores while considering each class's support. A high weighted average score indicates fairly good performance of the model.

The following table shows the classification report.

TABLE 2: CLASSIFICATION REPORT

	Precision	**Recall**	**F1-score**	**Support**
0	0.72	0.68	0.7	38
1	0.9	0.91	0.9	114
Accuracy			0.86	152
Macro Average	0.81	0.8	0.8	152
Weighted Average	0.85	0.86	0.85	152

(G) Loss Function

This measure is used to evaluate how well a neural network model performs a certain task. BINARY_CROSSENTROPY is used here. The following plot shows the loss during testing and training phases after optimizing the model.

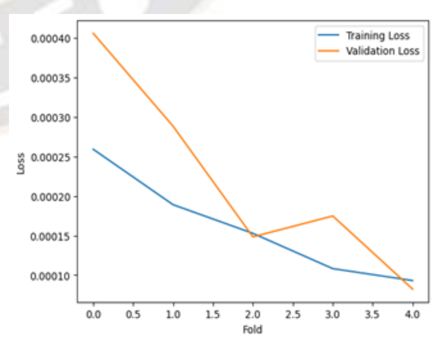

Figure 3: Training and Testing Loss for the optimized model

(H) ROC Curve

To evaluate the prediction power of the classifier the ROC (Receiver Operating Characteristic) curve is plotted This curve shows the behavior of the classifier for every threshold by plotting the two variables the True Positive Rate (TPR) and the False Positive Rate (FPR)

TP = True Positive, TN = True Negative
FP = False Positive, FN = False Negative.

(I) The Interpretation of ROC Curve

To evaluate the ROC curve the Area Under ROC (AUROC) Curve is plotted. This AUC score is a metric that compares different ROC curves. If the value is 1 then the model is set to predict perfectly well by separating classes better. When we use y_predict, the ROC curve has '1's and '0's to calculate the variables which results in the ROC curve to be an approximation. Hence, to avoid this effect and to get more accurate results, we use y_proba and get the probabilities of class '1' when calculating the ROC AUC. The figure below shows the output of the ROC AUC curve obtained for the model.

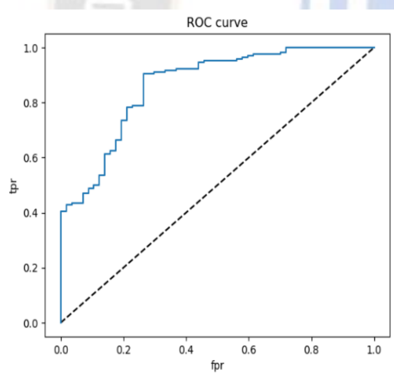

Figure 4: ROC- AUC Curve

From the figure 4 we can understand that the ROC- AUC score is nearly equal to 1 which means the model was able to predict with a fairly good score. Even though the model was able to achieve good prediction results, it can be further improved by employing higher architectures like Convolutional Neural Network (CNN), Recurrent Neural Network (RNN) or a hybrid model by combining any two or more architectures or through pretrained techniques like Transfer Learning.

VI. CONCLUSION AND FUTURE PERSECTIVES

Parkinson's disease is a multifaceted neurodegenerative disease affecting more and more people to such an extent that it is creating a formidable challenge to the research community. Will they be able to expose the true nature of its pathogenicity and a cure for this disease is a distant proposition to conjure at the present. Parkinson's disease has several aspects which merits the need for the appraisal by a novel method to bring out the real cause. It influences several aspects of human functions in which speech disorder is the most prominent. Several types of research have been proposed for diagnosis of PD with voice analysis. In this paper, an Artificial Neural Network was designed to classify healthy cohorts and Parkinson's diseased patients. Various attributes were considered. Results showed that a fairly good accuracy can be achieved. But the model was showing overfitting which adversely affected its performance. In an attempt to improve the performance the model was subjected to hyper tuning. Although hyper tuning could reduce overfitting problem to a satisfactory level it still was not forthcoming to provide a superior performance. This has triggered the idea of employing more sophisticated deep learning architectures like Convolutional Neural Networks, Recurrent Neural Networks etc. or developing hybrid models or to employ transfer learning techniques.

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