Deep Learning based prediction and monitoring of Parkinson’s Disease using Voice Data

Sohom Sen   
Computer Science and Engineering  
Herit*age Institute Of Technology*Kolkata, India  
sensohom2002@gmail.com

Rituparna Mondal  
Department Of Computer Application   
Techno India UniversityKolkata, India  
mondal.rituparna@gmail.comSamaresh Maiti  
Computer Science and Engineering  
Herit*age Institute Of Technology*Kolkata, India  
samareshmaiti02@gmail.com

Alok Kole  
Electrical Engineering  
RCC Institute of Information TechnologyKolkata, India  
alok.kole@rcciit.org.inSumanta Manna  
Computer Science and Engineering  
Herit*age Institute Of Technology*Kolkata, India  
mannasumanta9903@gmail.com

*Abstract*—With recent progress in digitized data acquisition, machine learning and computing infrastructures, the application of AI has stretched its wings far and wide. One such field of application is medical science. Artificial intelligence is gradually changing traditional medical practices and approaches to various problems. Even when medical science is growing with leaps and bounds there are still some problems which are beyond the province of human expertise. The infamous name of Parkinson’s disease haunts the human race even in this era of rapid scientific advancements since it has no cure to date. Thus early detection of the disease is very necessary to be better safe than sorry. PD is a progressive neurological disorder which affects the Central Nervous System (CNS) preventing the proper functioning of the same. This results in tremors, stiffness, slow movements, difficulty in balance and coordination, speech disorders and many more. In this study, data on the speech of affected and healthy people have been gathered. The data has been analyzed using acoustic features such as jitter, shimmer, intensity, pitch, etc. A Deep Learning model (Residual Neural Network) has been implemented for the prediction and monitoring of Parkinson’s Disease using voice data. A comparative performance analysis is performed with different Machine Learning models namely K-Nearest Neighbors, Support Vector Classifier, Decision Tree, Random Forest, Naïve Bayes, Logistic Regression, Extreme Gradient Boost and Gradient Boosting along with modern neural network techniques like Artificial Neural Network and Multi-Layer Perceptron. Using Residual Neural Network will help us in the early and accurate detection of this deadly disease.

Keywords—Artificial Intelligence, Comparative performance analysis, Dimensionality reduction, Machine Learning models, Neural Networks, Parkinson’s Disease, Residual Neural Networks.

# Introduction

Parkinson’s disease is a chronic and progressive movement disorder that affects the human brain and central nervous system.

It is caused by the degeneration of dopamine-releasing neurons in the brain. Dopamine is a key neurotransmitter responsible for controlling the motor movements. With the decrease in dopamine the person gradually loses motor abilities resulting in tremors, inability to control movements etc.

To this day the cause of Parkinson’s disease is not fully understood and hence no complete cure is also available.

The disease usually progresses slowly and hence the physical symptoms are usually not visible until the patient is already in the advanced stages of the disease.

This is where modern medical science with the help of machine learning can intervene, with early and automatic detection of Parkinson’s disease, patients can undergo different supportive treatments that can reduce the symptoms and slow the progression of the disease.

In this article, eight (08) traditional machine learning (ML) and three (03) neural network models namely, K-Nearest Neighbor (KNN) Classifier, Support Vector Machine (SVM) Classifier, Decision Tree Classifier (DTC), Random Forest Classifier (RFC), Naive Bayes Classifier (NBC), Logistic Regression Classifier (LR), XGBoost Classifier (XGBC), Gradient Boost Classifier (GBC), Artificial Neural Network (ANN), Multi-Layer Perceptron (MLP) Classifier and Residual Neural Network (ResNet) have been implemented to classify whether a patient is suffering from Parkinson’s disease or not based on their speech patterns and thorough performance analysis of all the models implemented has been done by testing each of them using a dataset.

# Related Work

Agarwal et al. [1] proposed an efficient approach to implement Extreme Machine Learning on a reliable dataset of speech samples of Parkinson's patients sourced from the UCI repository. They were able to achieve an accuracy of 90.76% and 0.81 MCC in distinguishing between Parkinson’s positive and Parkinson’s negative patients. Their work is mainly focused on Neural Networks and Support Vector Machines.

Ouhmida et al. [2] deployed Convolution Neural Networks (CNN) and Artificial Neural Networks (ANN) for the classification of healthy patients from Parkinson’s Disease (PD) positive patients on two datasets from UCI Machine Learning repository databases. The datasets were denoted by database I and database II consisting of 22 and 45 acoustic features respectively. CNN model achieved the highest accuracy of 93.10% on database I.

Ogawa and Yang [3] worked on the early detection of Parkinson’s Disease using 10-layered 1-d Convolution Neural Networks (CNN) and novel Residual Network (ResNet) type 1-d CNN, on a dataset consisting of the vocal features of healthy and PD-positive patients. They were able to achieve an accuracy of 0.888, an F-measure of 0.928 and an MCC of 0.692 in classifying.

Aghzal and Mourhir [4] combined a Histogram of Oriented Gradients with Convolution Neural Networks (CNN) to automate the detection process of Parkinson’s Disease based on the handwriting patterns of both positive and negative patients. Their model was able to achieve an accuracy of 87% and an F1-Score of 83.21%, outperforming the then-present clinical diagnostic techniques.

Anand et al. [5] deployed state-of-the-art machine learning and deep learning models equipped with varying dimensional reduction (DR) techniques to boost the efficiency, precision, recall and F1-Score of the models on the Parkinson’s Speech Dataset gathered from the UCI Machine Learning Repository. A comparative analysis was performed among the implemented models to come up with a conclusion of the best working model.

# Methodology

## Dataset Description

The dataset on which ResNet has been implemented is sourced from UCI Machine Learning Repository [6]. The dataset has been prepared with the help of 188 PD positive patients and 64 healthy individuals comprising of 130 men and 122 women. Their age ranges from 33 to 87. The dataset has a dimension of 755 columns with 756 data. The dataset has 564 Parkinson’s positive data points and 192 Parkinson’s negative data points.

The attributes involve for the classification of PD positive and negative patients consists of various speech signal processing algorithms such as Time Frequency Features, MEL Frequency Cepstral Coefficients (MFCCs), Wavelet Transform based Features, Vocal Fold Features and TWQT Features.

Although the dataset is relatively small, the high amount of attributes although good for training the models made the implemented algorithm susceptible to overfitting, which have been taken care of by using Principal Component Analysis (PCA) to reduce the number of attributes without losing the training ability. This enabled the training of traditional ML algorithms and especially the Neural Network models to achieve a very high level of precision and accuracy. However, it is certain that with the inclusion of more data points, further improvement of the models would be feasible.

## Data Pre-Processing

Data pre-processing [7] is a very important step in machine learning. The goal of data preprocessing is to prepare and clean the raw dataset so that the efficiency and accuracy of the machine learning algorithms can be maximized.

The Processes gone through to prepare the dataset are:

1. *Null Value Replacement: [8] Real World datasets can have missing data which needs to be replaced by the mean value of the missing attribute. The dataset was checked for missing values and as the dataset did not have any nothing was needed to be done.*
2. *Skewness Reduction: [9] Skewness is the measure of the asymmetry of the probability distribution of an attribute. Excessive skewness can lead to bias in the final model. For this dataset, first checking of each attribute for its skewness is done and for any attribute which has an absolute skewness value of greater than 1 that attribute column is appended to a list named skewedCols. Table I has listed 5 attributes each of which has the highest and lowest skewness before skewness reduction refer to Fig. 2. for the distribution plot of those attributes:*

TABLE I.

|  |  |  |
| --- | --- | --- |
| **Attribute Name** | **Skew value before reducing** | **Skew value after reducing** |
| tqwt\_TKEO\_mean\_dec\_32 | 26.48 | 0.198 |
| tqwt\_TKEO\_std\_dec\_32 | 26.06 | 0.019 |
| tqwt\_TKEO\_mean\_dec\_33 | 24.94 | 0.310 |
| tqwt\_TKEO\_std\_dec\_33 | 24.28 | 0.075 |
| det\_TKEO\_mean\_3\_coef | 20.87 | 1.443 |
| det\_LT\_entropy\_shannon\_7\_coef | -21.41 | -4.780 |
| tqwt\_medianValue\_dec\_29 | -21.62 | -0.315 |
| tqwt\_skewnessValue\_dec\_24 | -22.68 | -1.69 |
| tqwt\_entropy\_shannon\_dec\_33 | -25.06 | -2.023 |
| tqwt\_entropy\_shannon\_dec\_32 | -25.67 | -2.12 |

Fig. 1. Table showing skewness of 5 most skewed attributes

*Further classification of the skewedCols based on whether that attribute contains any positive, zero or negative values into three separate lists named skewedCols\_PositiveVals, skewedCols\_ZeroVals, and SkewedCols\_NegativeVals respectively is done.*

*Then for the attributes present in the list skewedCols\_PositiveVals Box-Cox Transformation is first used to reduce the skewness of the attributes.*

*Box-Cox transformation [10] works by applying a power function to the dependent variable which allows it to be transformed into a normal distribution and reduce its skewness.*

*Cube root transformation is also used to reduce the skewness of the attributes which are present in the lists skewedCols\_ZeroVals, SkewedCols\_NegativeVals. Cube Root transformation works by taking the cube root of each value of the attribute and making the attribute more closely resemble a normal distribution and reduce its skewness. Refer to Fig. 3. to view the changes after skewness reduction.*

1. *Kurtosis Reduction: [11] Kurtosis of an attribute is the measure of the peakedness/flatness of the probability distribution when measured relative to the normal distribution. The kurtosis of the normal distribution is considered zero. High kurtosis can lead to biases in the final model and hence it is needed to reduce kurtosis before processing the data. The dataset is checked for attributes which have a kurtosis value greater than 3. For this dataset, there was no such attribute and hence it was not necessary to do any kurtosis reduction.*
2. *Outlier Detection: [12] Outliers are data points in an attribute which are significantly different from the rest of the data. Outliers are bad for machine learning as they can bias the results of the final model. Each attribute of the dataset is checked for data points which are lower than the 25 percentile or higher than the 75 percentile of that attribute any data point which falls outside of this criteria is replaced by the mean of that attribute. Refer to Fig. 4. to view the distribution plot after the outlier distribution.*
3. *PCA: [13] For the 148 principal components were obtained after looping through it which gave us the optimal results.*

## Model Selection

Supervised Deep Learning models used in the process is the Residual Neural Network (ResNet).

Residual Neural Network (ResNet) is an extension of the Convolution Neural Network (CNN). ResNet and CNN are primarily deployed for image processing as an application of Computer Vision.

The CNN was able to handle a particular number of hidden layers. For updating the weights, the Backpropagation method is used. After going back, a certain number of layers, there is a shift down of loss function. Over a significant number of layers, the gradient “vanishes” leading to the vanishing gradient problem, leading to a saturation in the performance of the CNN model. To overcome this issue, the ResNet model is deployed.

ResNet developed a unique solution, known as “skip connections”. It stacks multiple identity mappings (convolutional layers that do nothing at first), ignores those particular sets of layers and again reuses the activation functions of the previous layer. Skipping or ignoring speeds up initial training by compressing the network into compact layers.

While the network is again trained, all the layers are uncompressed and the remaining parts of the network, known as the residual parts, are allowed to elaborate more on the feature space of the input image.

The majority of the ResNet models skip two or three layers at a time with nonlinearity and batch normalization in between. More advanced ResNet models, known as HighwayNets, can learn to “skip weights”, which dynamically determine the number of layers to skip.

Fig. 5. shows the working of the Residual Block, which is responsible for skip connections in ResNet.

## Experimental Result

Residual Neural Network outperformed the Traditional Machine Learning models, Artificial Neural Network and Multi-Layered Perceptron Classifier. ResNet was able to achieve an accuracy of 98%, PD positive precision of 0.98, PD negative precision of 0.94, PD positive recall of 0.98, PD negative recall of 0.94, PD positive F1-score of 0.98 and PD negative F1-score of 0.94.

TABLE II

|  |  |  |
| --- | --- | --- |
| Actual Values | Positive | Negative |
| Predicted values |
| Positive | 15 | 1 |
| Negative | 0 | 60 |

Fig. 6. Table of Confusion matrix of ResNet.

# Comparative Performance Analysis

After preprocessing the dataset, each of the machine learning and neural network models was trained using the dataset. The dataset was split into a training set comprising of 85% of the dataset and a testing set comprising the rest. The training set is utilized for the training purpose of the traditional ML models and also the Neural Networks. The testing set is utilized to portray a comparative performance analysis showing how ResNet outperformed all other proposed models.

* **Confusion Matrix:** A confusion matrix (CM) is an evaluation metric very useful for the performance analysis of binary classification algorithms. It is a 2x2 matrix comprised in the order True Positive (TP), False Positive (FP), False Negative (FN) and True Negative (TN). In Table II, the CM of the implemented ML models is displayed for comparative analysis.

TABLE III.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Name Of Model** | **True Positive** | **False Positive** | **False Negative** | **True Negative** |
| KNN | 14 | 3 | 1 | 58 |
| SVC | 11 | 6 | 1 | 58 |
| DTC | 12 | 5 | 5 | 54 |
| RFC | 10 | 7 | 1 | 58 |
| NBC | 11 | 6 | 3 | 56 |
| LR | 12 | 5 | 5 | 54 |
| XGBC | 15 | 2 | 5 | 54 |
| GBC | 12 | 5 | 4 | 55 |
| ANN | 14 | 2 | 1 | 59 |
| MLP | 14 | 3 | 1 | 54 |
| ResNet | 15 | 1 | 0 | 60 |

Fig. 10. Table for confusion matrix of ML models

* **Accuracy -** The accuracies of the different models for the training split have been recorded in table IV. From the table, it is evident that the Residual Neural Network and the ANN Classifier have the highest accuracy in classifying whether a patient has Parkinson’s disease or not based on their attributes. Refer to Fig. 12.
* Error - Error is the difference between the true result and the result predicted by the model. The traditional ML models rely on different loss functions such as Mean Square Error (MSE), Log Loss, Hinge Loss, Quantile Loss, Cross Entropy Loss and other important ones. For the Neural Network models, mainly rely on the Backpropagation Algorithm to update and tweak their weights and biases. The Backpropagation Algorithm is entirely based on the Gradient Descent Algorithm (GDA) proposed by Newton. However, nowadays the Gradient Descent Algorithm is replaced by Genetic Algorithm to overcome the shortcomings associated with GDA. In Fig. 11. a detailed visual representation is provided to understand how the error increase or decreases with the tweak of certain important parameters.

From the above graphs, it is evident the models are able to learn to a certain accuracy where the loss or error is minimum.

* **Recall -** The recall values of the different models have been accrued for the training split in the table above. Recall measures the proportion of actual positive cases that are correctly identified by the model as positive. It is a very important metric for the use case as a high recall signifies that the model does not miss many positive cases as negative. From table IV, it is evident that Residual Neural Network and the ANN Classifier are the best-performing models in terms of recall. Refer to Fig. 12.
* **Precision -** The precision values of the different models have been accrued for the training split in table IV. Precision is the measure the fraction of correctly predicted positive instances out of all the instances the model has predicted as positive. It is also a very important metric for this use case as a high precision value implies that the model does not misclassify too many positive patients as negative and vice versa. From the above table, it is also evident that the Residual Neural Network is the optimal model in terms of precision. Refer to Fig. 12.
* **F1-Score -** The F1-scores of the different models have accrued for the training split in table IV. F1 - Score is calculated by combining both the Precision and recall values of the model and hence is a important metric to consider for this use case as a high F1 - Score implies that the model is making accurate predictions and also minimizes false negatives reducing the risk of miss-diagnosis. From the above table it is evident that Residual Neural Network is the optimal model as it has the highest F1 - Score for both the classes. Refer to Fig. 12.

TABLE IV

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Name of Model | Acc | Precision | | Recall | | F1-Score | |
| PD  -ve | PD  +ve | PD  -ve | PD  +ve | PD  -ve | PD  +ve |
| KNN | 95% | 0.93 | 0.95 | 0.82 | 0.98 | 0.87 | 0.97 |
| SVM | 91% | 0.92 | 0.91 | 0.65 | 0.98 | 0.76 | 0.94 |
| DTC | 87% | 0.71 | 0.92 | 0.71 | 0.92 | 0.71 | 0.92 |
| RFC | 89% | 0.91 | 0.89 | 0.59 | 0.98 | 0.71 | 0.94 |
| NBC | 88% | 0.79 | 0.90 | 0.65 | 0.95 | 0.71 | 0.93 |
| LR | 87% | 0.71 | 0.92 | 0.71 | 0.92 | 0.71 | 0.92 |
| XGBC | 91% | 0.75 | 0.96 | 0.88 | 0.92 | 0.81 | 0.94 |
| GBC | 88% | 0.75 | 0.92 | 0.71 | 0.93 | 0.73 | 0.92 |
| ANN | 96% | 0.94 | 0.97 | 0.90 | 0.98 | 0.92 | 0.97 |
| MLP | 94% | 0.82 | 0.98 | 0.93 | 0.95 | 0.87 | 0.96 |
| ResNet | 98% | 0.94 | 0.98 | 0.94 | 0.98 | 0.94 | 0.98 |

Fig. 12. Graphs of AUC-ROC for different ML models.

* **AUC-ROC Curve -** AUC-ROC stands for Area Under the Receiver Operating Characteristics Curve. The AUC-ROC curve is a very useful and commonly used metric which evaluates the performance of binary classification models. It is a graphical representation of how well the model can distinguish between positive and negative classes over a range of threshold values. The AUC-ROC curve is made by plotting the model’s true positive rate against its false positive rate. A high AUC value in the ROC curve (Close to 1) implies that the model can precisely distinguish between Parkinson’s Positive and Parkinson’s Negative patients. It is very robust against imbalanced class distributions and provides a single value summarizing the performance of the model. Refer to Fig. 13. for the AUC-ROC curves of all the implemented Machine Learning and Neural Network Models.

From the above graphs, it is evident that the Neural Networks are the optimal model as they have the highest AUC-ROC.

* AUC-PR Curve - The AUC-PR curve is made by plotting the model’s precision against the recall of the model. In medical use cases, it is a particularly important metric to consider as it can provide a more accurate evaluation of the performance model when the class distribution is imbalanced. The same is true for this dataset as well. Refer to Fig. 14. for the AUC-PR curves of all the implemented Machine Learning and Neural Network Models.

From the above graphs, it is evident that the Neural Networks are the optimal model as they have the highest AUC-PR.

# Conclusion and scope for future work

The research article focuses on a comparative study between Traditional Machine Learning Algorithms and Neural Networks. From the study, it is evident that both Models have their own positive and negative aspects. The Traditional Model focuses on a simplistic approach to automate the learning process of machines and find hidden and unseen patterns. The Neural Networks, on the other hand, try to mimic the working of the human brain, by setting up processing nodes called neurons in a systematic plan and each neuron is interconnected with each other giving rise to a fully connected network.

Traditional ML models are very useful for small to medium-sized datasets, whereas, neural networks are well known for their ability to handle complicated and high-dimensional datasets. Due to the simplicity of traditional ML models, their computing time is often faster than neural networks. Thus, Neural Networks are much more resource hungry and complex to implement.

The factors responsible for choosing between implementing the traditional ML models or the Neural Networks depend upon the type and quality of the dataset, the computing resources and the budget.

As the field of Machine Learning and Artificial Intelligence continues to evolve at an exponential rate, both the Traditional Machine Learning Models and the Neural Networks will continue to upgrade themselves in terms of accuracy, computation time and resource needs. It is important to continue to explore and develop new approaches that combine the strengths of these models and address their limitations, to improve accuracy, interpretability, and scalability.

From the comparative analysis of the selected dataset, it can be concluded, Residual Neural Network (ResNet) has worked exceptionally better than all the traditional Machine Learning Models with an accuracy of 98%, a precision of 0.98, a recall of 0.98 and an F1-Score of 0.98. Standing next to the ResNet is ANN with an accuracy of 96%, a precision of 0.97, a recall of 0.98 and an F1-Score of 0.97. Thus, in conclusion, for the chosen dataset, the Neural Networks have performed exceptionally better in terms of the evaluation metrics. With the advent of more precise attributes in the future, the accuracy of the ML Models and Neural Networks can be boosted to a great extent using Feature Selection, Dimension Reduction and all the other effective and essential Data Pre-processing Techniques.

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