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

Sohom Sen[1*], Samaresh Maiti[1†], Sumanta Manna[1†], Rituparna Mondal[2], Alok Kole[3], Banashree Chatterjee[4]

[1*]Computer Science and Engineering, Heritage Institute of Technology, Kolkata, 700107, West Bengal, India.
[2]Department Of Computer Application, Techno India University, Kolkata, 700091, West Bengal, India.
[3]Electrical Engineering, RCC Institute of Information Technology, Kolkata, 700015, West Bengal, India.
[4]Information Technology, Dr. B.C. Roy Engineering College, Durgapur, 713206, West Bengal, India.

*Corresponding author(s). E-mail(s): sensohom2002@gmail.com;
Contributing authors: samareshmaiti02@gmail.com;
mannasumanta9903@gmail.com; mondal.rituparna@gmail.com;
alok.kole@rcciit.org.in; banashree2014@gmail.com;
[†]These authors contributed equally to this work.

Abstract

This paper focuses on Deep Learning based prediction and monitoring of Parkinson's Disease (PD) using voice data. 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. As per recent studies and surveys conducted by World Health Organization (WHO), the mortality rate (per 100,000 population) in 1994 was 1.76 and reached 5.67 in 2019 and that in women increased from 1.63 (per 100,000 population) in 1994 to 4.81 in 2019. The incorporation of Machine Learning for early detection and assessment of the severity of Parkinson's disease is deemed imperative in light of the current circumstances. PD diagnosis is mainly on the analysis of symptoms, so speech recognition can introduce a new methodology of investigation in the diagno- sis and monitoring of PD. Machine Learning models with Deep Learning features

are proposed in this research work for the automatic detection and the severity of PD. In this proposed research work, a dataset based on the speech of PD patients and healthy people has been gathered. The dataset has been analyzed using acoustic features such as jitter, shimmer, intensity, pitch, etc. A Deep Learning model with Residual Neural Net- work architecture has been implemented for the prediction and monitoring of PD using voice data. Comparative performance analysis of the proposed Residual Neural Network architecture is performed with different Machine Learning models namely K-Nearest Neighbors, Support Vector Classifier, Decision Tree, Random Forest, Na ıve Bayes, Lo- gistic Regression, Extreme Gradient Boost and Gradient Boosting along with modern neural network techniques like Artificial Neural Network and Multi-Layer Perceptron. The results demonstrate that the proposed Residual Neural Network architecture yields favourable performance superior to that of the rest of the implemented other standard Machine Learning models in terms of accuracy, F1-score, precision, recall, AUC-ROC and AUC-PR.

1 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 motor movements. With the decrease in dopamine the person gradually loses motor abilities resulting in tremors, inability to control move- ments 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 arti- cle, eight (08) traditional machine learning (ML) and three (03) neural network Deep Learning based prediction and monitoring of Parkinson's Disease using Voice Data 3 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 Clas- sifier (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.

2 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 90.760.81 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 accu- racy of 93.10

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 87diagnostic 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 anal- ysis was performed among the implemented models to come up with a conclusion of the best working model.

3 Methodology

3.1 Dataset

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 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 size of the dataset on disk is 5.3 mb.

The attributes involved in the classification of PD positive and negative patients consist 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 has 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.

3.2 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:

3.2.1 Null Value Replacement

Real World datasets can have missing data which needs to be replaced by the mean value of the missing attribute [8]. The dataset was checked for missing values and as the dataset did not have any nothing was needed to be done.

3.2.2 Skewness Reduction

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 in the code implementation. Table 1 has listed 5 attributes each of which has the highest and lowest skewness before skewness reduction [9]. Fig. 1 shows the distribution of the ten (10) highly skewed attributes before skewness reduction.
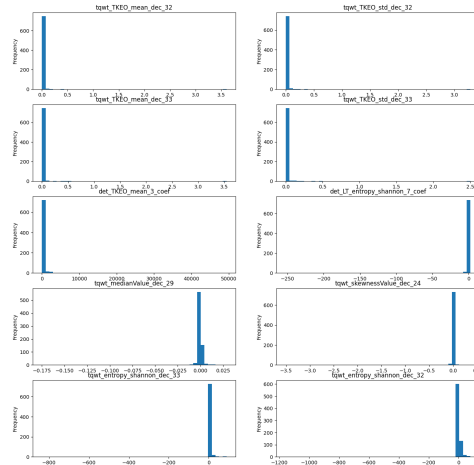

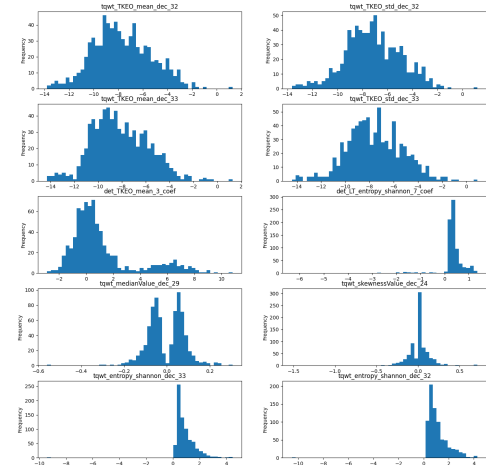**Fig. 1** Attribute skewness pre skewness reduction.

Fig. 2 Attribute skewness post skewness reduction.

4

Table 1 Skewness of 10 most skewed attributes (centered)

Attribute Name	Skew value pre-reduction	Skew value post-reduction
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

3.2.3 Kurtosis Reduction

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 [11] 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.

3.2.4 Outlier Detection

Outliers are data points in an attribute which are significantly different from the rest of the data. Outliers [12] 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. The distribution plot after the outlier reduction is portrayed in Fig. 3.

3.2.5 Principal Component Analysis

One approach to reduce the dimensionality of a dataset while retaining most of the variability is Principal Component Analysis (PCA). For the 148 principal components [13] were obtained after looping through them which gave us the optimal results.

3.3 Model Selection

In this proposed research work, Residual Neural Network (ResNet) is used as a Supervised Deep Learning Model.

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
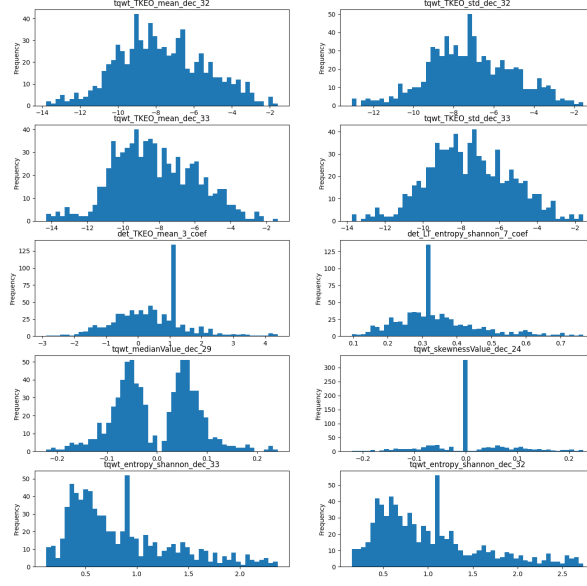
Fig. 3 Attributes with the highest skewness after outlier removal.

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.

3.4 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.
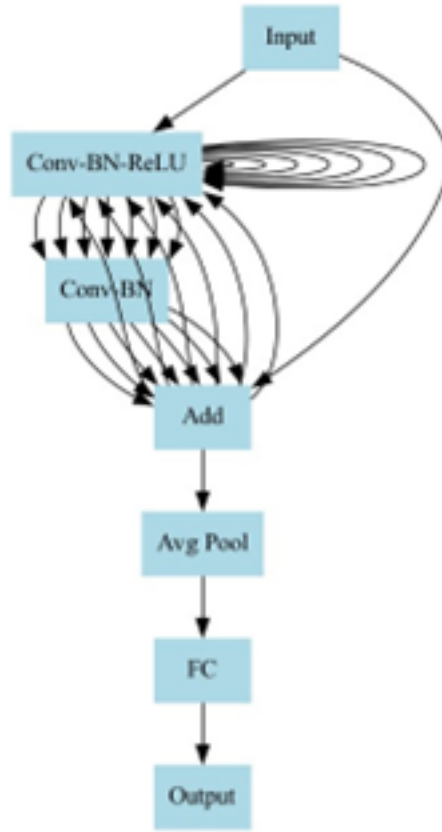
Fig. 4 Residual block of Resnet.

Table 2 Confusion Matrix of ResNet.

| Predicted values | Actual values | |
	Positive	Negative
Positive	15 (TP)	1 (FP)
Negative	0 (FN)	60 (TN)

Table II describes the confusion matrix of ResNet showing 15 True Positive (TP), 1 False Positive (FP), 0 False Negative (FN) and 60 True Negative (TN) classifications. The negative sloping Error Vs Epoch Curve is illustrated in Fig. 5. The AUC-ROC curve with an AUC of 0.984 and AUC-PR curve with an AUC of 0.996 is depicted in Fig. 6 and 7 respectively.
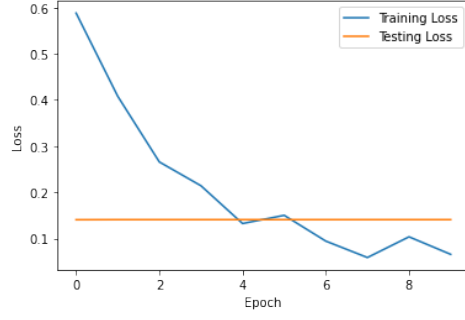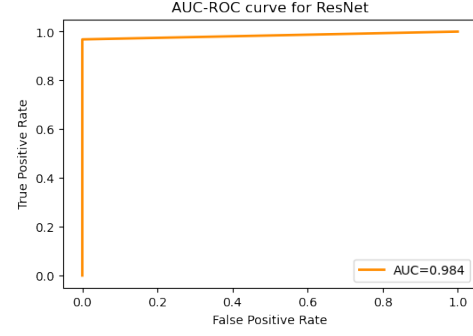
7

Fig. 5 Error graph for ResNet.

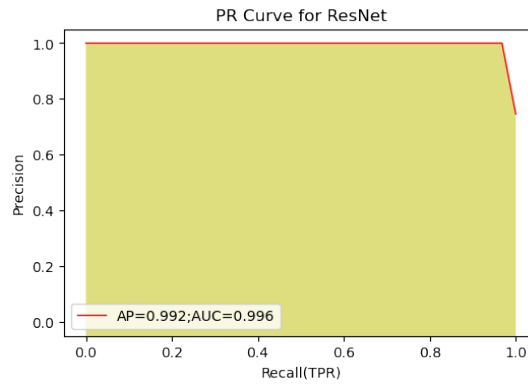**Fig. 6** AUC - ROC curve for ResNet.

Fig. 7 AUC-PR curve for ResNet.

4 Comparitive 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.

4.1 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).

8

In Table II, the CM of the implemented ML and Deep Learning models is displayed for comparative analysis. ResNet has achieved the highest TP and TN values and the lowest FP and FN values.

Table 3 Confusion Matrix of ML models

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

4.2 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 have the highest accuracy of 98% in classifying whether a patient has Parkinson's disease or not based on their attributes.

4.3 Error

Error is the difference between the true result and the result predicted by the model. In Fig. 8. a detailed visual representation is provided to understand how the error increase or decreases with the tweak of certain important parameters. ResNet however has shown the greatest improvement over iterations.

4.4 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. From Table IV, it is evident that Residual Neural Network is the best-performing model in terms of recall.
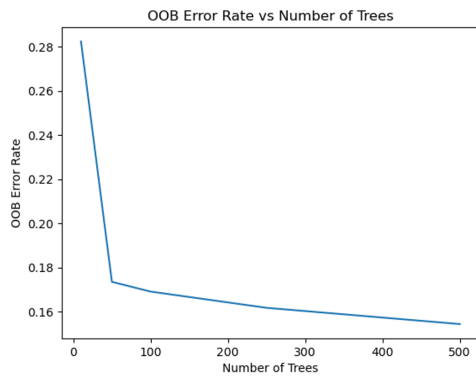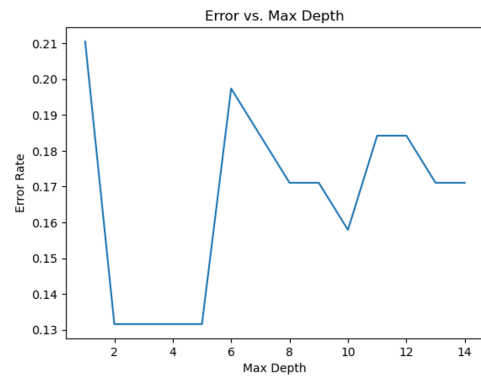
Fig. 8 Error Curve for RF Classifier
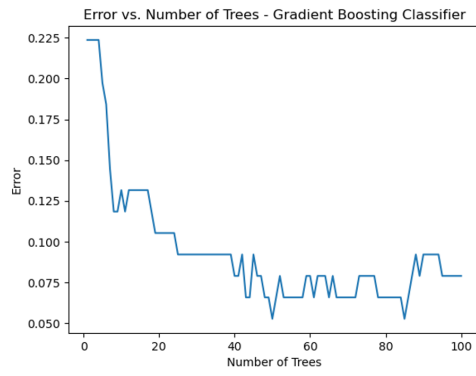

Fig. 9 Error Curve for DT Classifier

Fig. 10 Error Curve for GB Classifier
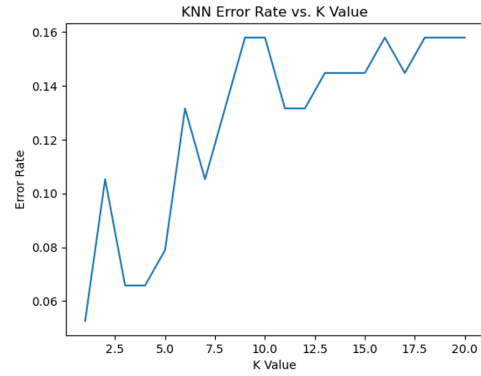

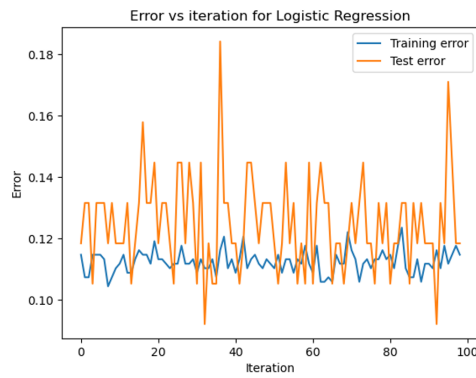**Fig. 11** Error Curve for KNN Classifier

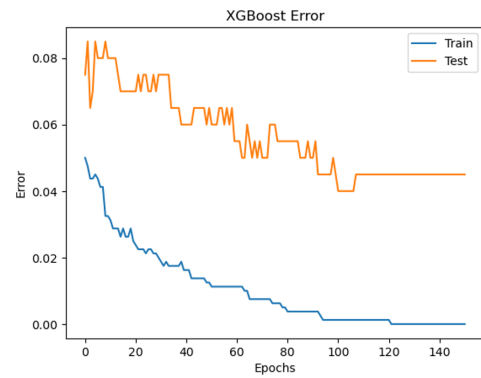**Fig. 12** Error Curve for LR Classifier

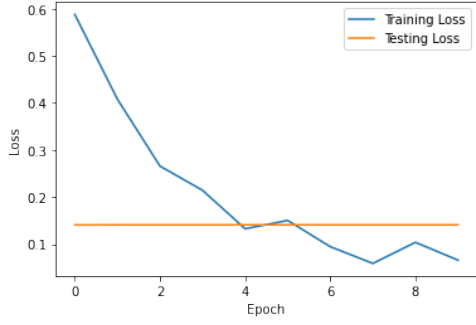**Fig. 13** Error Curve for XGB Classifier

Fig. 14 Error Curve for ResNet
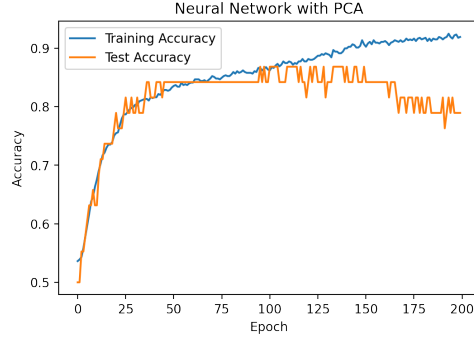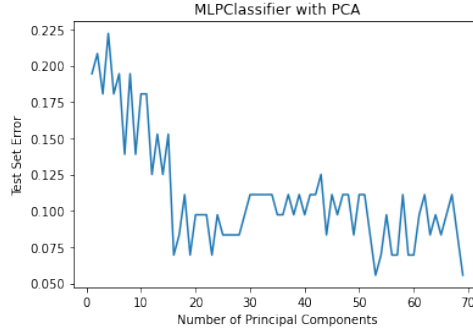

Fig. 15 Error Curve for ANN

Fig. 16 Error Curve for MLP

4.5 Precision

The precision values of the different models have been accrued for the training split in Table IV. Precision is the measure of the fraction of correctly predicted positive instances out of all the instances the model has predicted as positive. From the above table, it is also evident that the Residual Neural Network is the optimal model in terms of precision.

4.6 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. For this use case, a high F1-Score implies that the model is making accurate predictions and also minimizes False Negatives, reducing the risk of misdiagnosis. From Table IV, it is evident that Residual Neural Network is the optimal model as it has the highest F1-Score for both classes.

11

Table 4 Evaluation Metrics for ML models

Name of models	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

4.7 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 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. The AUC-ROC curves of all the implemented Machine Learning and Neural Network Models are illustrated in Fig. 9.

From the above graphs, it is evident that the Residual Neural Network is the optimal model as it has the highest AUC-ROC of 0.984 in comparison to others.

4.8 AUC-PR Curve

The AUC-PR curve is made by plotting the model's precision against the recall of the model. It is a particularly important metric to consider in medical use 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. The AUC-PR curves of all the implemented Machine Learning and Neural Network Models are illustrated in Fig.10.

From the above graphs, it is evident that the Residual Neural Network is the optimal model as they have the highest AUC-PR value of 0.996 in comparison to others.

5 Conclusion and scope for future work

The research article focuses on the Deep Learning Based prediction and monitoring of Parkinson's Disease using the Voice Data sourced from UCI Machine Learning Repository. To accomplish this objective, Residual Neural Network architecture was used as a Supervised Classification Model.

The factors responsible for choosing Residual Neural Network over other standard models is the concept of "skip connections". The Residual Neural Network brings forth an innovative solution to the vanishing gradient problem in the form of skip connections. ResNet reuses the activation of previous layers, speeding up the initial training by compressing the network layers.

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 Residual Neural Network has 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.

Further advancements in this field of study are certain to occur. A few of the possible enhancements can be utilising the MRI images of the human brain [15] in predicting Parkinson's disease using various advanced networks[16] for optimal results. Another approach to the prediction of PD can be done using the datasets comprising Spiral writing test images [17] and Speech [18]. Also rather than depending on only one source of input dataset for prediction, a cumulated form of training data comprising not only numerical inputs but also images and sounds [19] [20] can be prepared for even more accurate and precise results

References

[1] A. Agarwal, S. Chandrayan and S. S. Sahu, "Prediction of Parkinson's disease using speech signal with Extreme Learning Machine," *2016 International Conference on Electrical, Electronics, and Optimization Techniques (ICEEOT)* Chennai, India, 2016, pp. 3776-3779, doi: 10.1109/ICEEOT.2016.7755419.

[2] A. Ouhmida, O. Terrada, A. Raihani, B. Cherradi and S. Hamida, "Voice-Based Deep Learning Medical Diagnosis System for Parkinson's Disease Prediction," , *2021 International Congress of Advanced Technology and Engineering (ICOTEN)*, Taiz, Yemen, 2021, pp. 1-5, doi: 10.1109/ICOTEN52080.2021.9493456.

[3] M. Ogawa and Y. Yang, "Residual-Network -Based Deep Learning for Parkinson's Disease Classification using Vocal Datasets," *2021 IEEE 3rd Global Conference on Life Sciences and Technologies (LifeTech)*, Nara, Japan, 2021, pp. 275-277,

doi: 10.1109/LifeTech52111.2021.9391925.

[4] M. Aghzal and A. Mourhir, "Early Diagnosis of Parkinson's Disease based on Handwritten Patterns using Deep Learning," *2020 Fourth International Conference On Intelligent Computing in Data Sciences (ICDS)*, Fez, Morocco, 2020, pp. 1-6, doi: 10.1109/ICDS50568.2020.9268738.

[5] A. Anand, M. A. Haque, J. S. R. Alex and N. Venkatesan, "Evaluation of Machine learning and Deep learning algorithms combined with dimensionality reduction techniques for classification of Parkinson's Disease," *2018 IEEE International Symposium on Signal Processing and Information Technology (ISSPIT)*, Louisville, KY, USA, 2018, pp. 342-347, doi: 10.1109/ISSPIT.2018.8642776.

[6] Sakar, C.O., Serbes, G., Gunduz, A., Tunc, H.C., Nizam, H., Sakar, B.E., Tutuncu, M., Aydin, T., Isenkul, M.E. and Apaydin, H., 2018. A comparative analysis of speech signal processing algorithms for Parkinsonâ€™s disease classification and the use of the tunable Q-factor wavelet transform. Applied Soft Computing, DOI: https://doi.org/10.1016/j.asoc.2018.10.022

[7] Sen, Sohom; GHOSH, ANKIT (2022): Analysis and Prediction of Parkinson's Disease using Machine Learning Algorithms. TechRxiv. Preprint. https://doi.org/10.36227/techrxiv.20005703.v1

[8] G. A. Mirza, "Null Value Conflict: Formal Definition and Resolution," 2015 13th International Conference on Frontiers of Information Technology (FIT), Islamabad, Pakistan, 2015, pp. 132-137, doi: 10.1109/FIT.2015.32.

[9] P. L. Kevin Ding, S. Martin and B. Li, "Improving Batch Normalization with Skewness Reduction for Deep Neural Networks," 2020 25th International Conference on Pattern Recognition (ICPR), Milan, Italy, 2021, pp. 7165-7172, doi: 10.1109/ICPR48806.2021.9412949.

[10] X. Li, Y. Sun, X. Chen, Y. Li, T. Jiang and Z. Liang, "Saline-Sodic Soil EC Retrieval Based on Box-Cox Transformation and Machine Learning," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 15, pp. 1692-1700, 2022, doi: 10.1109/JSTARS.2022.3145874.

[11] T. Thaiupathump and R. Chompu-inwai, "Impact of kurtosis on performance of mixture control chart patterns recognition using Independent Component Analysis and neural networks," 2015 4th International Conference on Advanced Logistics and Transport (ICALT), Valenciennes, France, 2015, pp. 94-99, doi: 10.1109/ICAdLT.2015.7136600.

[12] H. Du, Q. Ye, Z. Sun, C. Liu and W. Xu, "FAST-ODT: A Lightweight Outlier Detection Scheme for Categorical Data Sets," in IEEE Transactions on Network Science and Engineering, vol. 8, no. 1, pp. 13-24, 1 Jan.-March 2021, doi: 10.1109/TNSE.2020.3022869..

[13] Y. Li and J. Zhang, "Principal Component Analysis Based on Different Starting Points," 2022 IEEE/ACIS 22nd International Conference on Computer and Information Science (ICIS), Zhuhai, China, 2022, pp. 245-251, doi: 10.1109/ICIS54925.2022.9882417.

[14] Pal, Sankar K., and Dinabandhu Bhandari. "Selection of optimal set of weights in a layered network using genetic algorithms." *Information Sciences—Informatics and Computer Science, Intelligent Systems, Applications: An International Journal* 80.3-4 (1994): 213-234.

[15] GHOSH, ANKIT; KOLE, ALOK (2021). A Comparative Study of Enhanced Machine Learning Algorithms for Brain Tumor Detection and Classification. TechRxiv. Preprint. https://doi.org/10.36227/techrxiv.16863136.v1

[16] Md. Abdul Alim Sheikh, Alok Kole, Tanmoy Maity ," Deep Learning Approach using Patch-based Deep Belief Network for Road Extraction from Remote Sensing Imagery",International Journal of Applied Mathematics, Volume 52, Issue-4, pp.750-775 , 2022.

[17] A. Talitckii et al., "Comparative Study of Wearable Sensors, Video, and Handwriting to Detect Parkinson's Disease," in IEEE Transactions on Instrumentation and Measurement, vol. 71, pp. 1-10, 2022, Art no. 2509910, doi: 10.1109/TIM.2022.3176898.

[18] M. K. Reddy and P. Alku, "Exemplar-Based Sparse Representations for Detection of Parkinson's Disease From Speech," in IEEE/ACM Transactions on Audio, Speech, and Language Processing, vol. 31, pp. 1386-1396, 2023, doi: 10.1109/TASLP.2023.3260709.

[19] J. P. Devarajan, V. R. Sreedharan and G. Narayanamurthy, "Decision Making in Health Care Diagnosis: Evidence From Parkinson's Disease Via Hybrid Machine Learning," in IEEE Transactions on Engineering Management, doi: 10.1109/TEM.2021.3096862.

[20] Chinmaya Kumar Pradhan, Shariar Rahaman, Md Abdul Alim Sheikh, Alok Kole, Tanmoy Maity," EEG signal analysis using different clustering techniques", Emerging Technologies in Data Mining and Information Security: Proceedings of IEMIS 2018, Volume 2,Page 99-105, Springer Singapore.