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

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***Abstract*—This paper focuses on using Deep Learning for predicting and monitoring Parkinson's Disease (PD) through voice data and Unified Parkinson's Disease Rating Scale (UPDRS) score. PD is a progressive neurological disorder that affects the Central Nervous System (CNS), leading to symptoms like tremors, stiffness, slow movements, balance and coordination difficulties, and speech disorders. Neurons in the substantia nigra region undergo degeneration or functional impairment, leading to a deceleration or cessation of dopamine synthesis. As per recent studies by the World Health Organization (WHO), the mortality rate for PD has increased significantly over the years. Early detection and severity assessment of PD using Machine Learning is crucial. Speech recognition offers a new approach for diagnosis and monitoring. The research proposes using Deep Learning models with acoustic features like jitter, shimmer, intensity, and pitch for automatic detection and use of UPDRS score for severity assessment. Two datasets, one of them containing speech samples from PD patients and healthy individuals and another containing voice data and UPDRS score, are used in this work. A Residual Neural Network (ResNet) architecture is implemented and compared to other Machine Learning models like K-Nearest Neighbors, Support Vector Classifier, Decision Tree, Random Forest, Naïve Bayes, Logistic Regression, Extreme Gradient Boost, Gradient Boosting, as well as modern neural network techniques like Artificial Neural Network and Multi-Layer Perceptron. The results show that the proposed Residual Neural Network outperforms all other standard Machine Learning models in terms of accuracy, F1- score, precision, recall, AUC-ROC, and AUC-PR for PD prediction and monitoring using voice data.**

***Index Terms*—Artificial Intelligence, Dimensionality reduction, Machine Learning models, Neural Networks, Parkinson's Disease, Residual Neural Networks, Voice dataset.**

I. Introduction

Parkinson's disease is a progressive movement disorder impacting the brain and central nervous system due to the degeneration of dopamine-releasing neurons, affecting motor control and causing tremors and impaired movements. The exact cause remains unknown, and a cure is yet to be discovered. Early detection is vital for managing symptoms and slowing down the disease's progression. This article explores eight traditional machine learning (ML) models and two neural network models (K-Nearest Neighbour, Support Vector Machine, Decision Tree, Random Forest, Naive Bayes, Logistic Regression, XGBoost, Gradient Boost, Fully Connected Neural Network and Residual Neural Network). The goal is to classify whether a patient has Parkinson's disease based on their speech patterns as well as determine its severity. Thorough performance analysis using two datasets has been conducted to evaluate the effectiveness of each model.

II. Related Work

Ouhmida et al. [1] have employed two deep learning models, namely Convolutional Neural Network (CNN) and Artificial Neural Network (ANN), for the purpose of classifying healthy individuals and those afflicted with Parkinson's Disease based on vocal features. The researchers have given preference to utilizing two datasets sourced from the UCI Machine Learning Repository to underpin their investigative efforts. Notably, the CNN model has demonstrated significant efficacy, yielding an accuracy rate of 93.1% in the classification of patients.

Mounika et al. [2] investigates the early diagnosis of Parkinson's Disease using Deep Learning and Machine Learning on a substantial UCI dataset. Employing various performance metrics, the K-Nearest Neighbors (KNN) algorithm with k=5 stands out with an impressive 97.43% accuracy, showcasing its potential as a robust approach for early PD detection.

Jahan et al. [3] addresses the escalating challenge of Parkinson's Disease (PD) by proposing a novel diagnostic system using fine motor symptom-based sketch analysis. Employing Convolutional Neural Network (CNN) models, specifically Inception-v3 and ResNet50 with transfer learning, their system had achieved a commendable 96.67% accuracy in distinguishing PD patients from a Healthy control group based on spiral sketching.

Burri et al. [4] proposed a DBN-based solution, which exhibits superior performance, surpassing competitors with a remarkable 92% success rate in Parkinson's disease diagnosis. The evaluation, incorporated F1 score, sensitivity, specificity, and accuracy measures, underscores the consistency of the achieved results. This study underscores the potential of language-trained Machine Learning (ML) models in Parkinson's disease diagnosis, offering significant implications for both research and treatment in the field.

Ogawa and Yang [5] presented a non-invasive approach for Parkinson's disease diagnosis and early detection, focusing on abnormal motor signs. A 10-layered 1-dimensional Convolutional Neural Network (CNN) and a novel-residual-network-type 1-dimensional CNN have been introduced for classifying Parkinson's disease using vocal feature datasets. The proposed residual network yields favourable classification results, achieving an accuracy of 0.888, F-measure of 0.928, and Matthews Correlation Coefficient (MCC) of 0.692. These findings highlight the efficacy of the introduced models in the context of Parkinson's disease classification based on vocal features.

Sandhiya et al. [6] utilized spiral/wave drawing datasets from 102 individuals (51 healthy and 51 with Parkinson's disease) employing Histogram of Oriented Gradients (HOG) for feature extraction. Classification is accomplished through the Random Forest Classifier in the Scikit-learn package, alongside OpenCV and NumPy for statistical data generation. Emphasizing the expanding applications of image processing, particularly in Parkinson's disease detection, classification, and diagnosis, Random Forest Classifier achieved a classification accuracy of 71.33%, sensitivity of 69.33%, and specificity of 73.3%. This analysis streamlines pattern classification involving Parkinson's disease and healthy individuals, offering time-saving benefits and enhanced productivity.

A deep learning approach for early Parkinson's disease detection is introduced in this paper [7], employing a long short-term memory (LSTM) model with features extracted from speech signals. Promising results are achieved by the LSTM model, with a testing accuracy of 93%, utilizing a dataset that includes features from 188 Parkinson's patients and 64 healthy individuals. The emphasis on speech signal features highlights the potential of this methodology for early Parkinson's disease diagnosis and intervention, with contributions to the enhanced quality of life for affected individuals.

III. Methodology

A. Dataset

In this study, two distinct datasets are utilized to develop and evaluate the proposed deep learning-based prediction and monitoring model for Parkinson's Disease (PD). The selection of multiple datasets was motivated by the need for a comprehensive and diverse set of samples, enhancing the generalizability and robustness of our model.

1) Dataset - 1: This dataset was sourced from UCI Machine Learning Repository. The dataset consists data from 188 PD positive patients and 64 healthy individuals with a gender ratio of 130 males to 122 females. The age of the individuals vary between 33 to 87. This dataset employs several signal and frequency analysis techniques such as Time-Frequency Features, MEL Frequency Cepstral Coefficients (MFCCs), Wavelet Transform based Features, Vocal Fold Features, and TWQT Features to identify patterns and features in voice signals that correlate with the progression of the disease or can be used for early detection. The dataset contains 755 attributes with 756 data points consisting 564 Parkinson's positive and 192 Parkinson's negative cases. The dataset size on disk was 5.3 MB. The abundance of attributes posed a risk of overfitting. To address this, Principal Component Analysis (PCA) was employed to reduce the attributes without compromising the training capability. However, incorporating more data points could further enhance the models' performance.

2) Dataset - 2: This dataset was developed by Athanasios Tsanas and Max Little of Oxford University, in close cooperation of 10 medical centres in the US and Intel Corporation, This dataset consists voice data from 42 individual patients with a gender ratio of 28 males to 14 females. The age of the patients vary between 36 and 85. The dataset contains 21 attributes with 5875 data points. The dataset size on disk was 1.01 MB.

The different parameters recorded by the dataset includes:

- **subject#**: Subject Number.
- **Age**: Subject age.
- **Sex**: Subject sex: '0' indicating Male and '1' indicating female.
- **test_time**: Indicates the time since the induction of the subject into the trial.
- **motor_UPDRS**: Indicates linearly interpolated clinician's motor UPDRS score.
- **total_UPDRS**: Indicates linearly interpolated clinician's total UPDRS score.
- **jitter**: A measure of frequency variation in voice signals.
- **Shimmer**: A measure of amplitude variation in voice signals.

B. Data Pre-Processing

Data pre-processing 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 datasets are:

- **Null Value Replacement**: Real World datasets can have missing data which needs to be replaced by the mean value of the missing attribute. Both the datasets were checked for missing datapoints but none were found hence no measures were required for null value replacement.
- **Skewness Reduction**: Skewness measures attribute distribution asymmetry. High skewness can introduce bias in the model. In the code, attributes with absolute skewness greater than 1 are added to the "skewedCols" list. Table I and Table II list the most skewed attributes of Dataset 1 and Dataset 2 respectively. Fig. 1 displays the distribution

of ten(10) highly skewed attributes pre-skewness reduction of Dataset 1. Fig. 2 shows the distribution change after skewness reduction.

Attribute Name	Skew Value Pre-Reduction	Skew Value Post-Reduction
tqwt_TKEO_mean _ dec_32	26.48	0.498
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

TABLE I: Most skewed attributes of Dataset 1

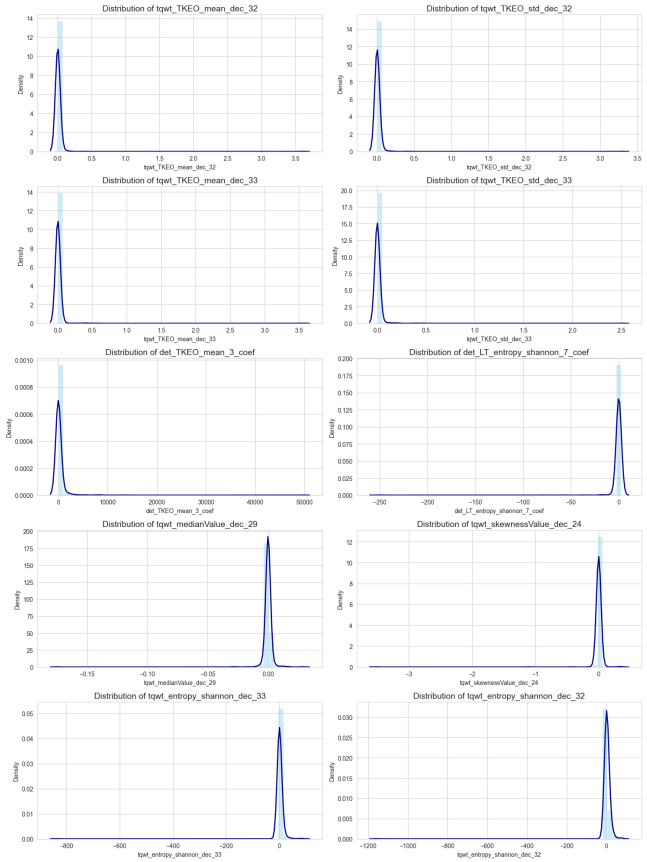

Fig. 1: Histogram of skewed attributes.

Attribute Name	Skew Value Pre-Reduction	Skew Value Post-Reduction
Jitter:PPQ5	7.586205	0.156774
Jitter:RAP	6.945438	0.202510
Jitter:DDP	6.945376	0.206550
Jitter(%)	6.451846	0.166790
NHR	6.549123	-0.092540
Shimmer:APQ5	3.698061	0.081308
Shimmer:APQ11	3.406958	0.093378
Shimmer	3.312793	0.126127
Shimmer:APQ3	3.097223	0.091697
Shimmer	3.312793	0.126127

TABLE II: Most skewed attributes of Dataset 2

- **Kurtosis Reduction**: Kurtosis measures peakedness or flatness of a distribution relative to the normal distribution. High kurtosis levels can bias the model thus kurtosis reduction is required. The kurtosis level of the normal distribution is considered zero. Both the Datasets were checked for attributes with kurtosis levels greater than 3 but no such attributes were found.

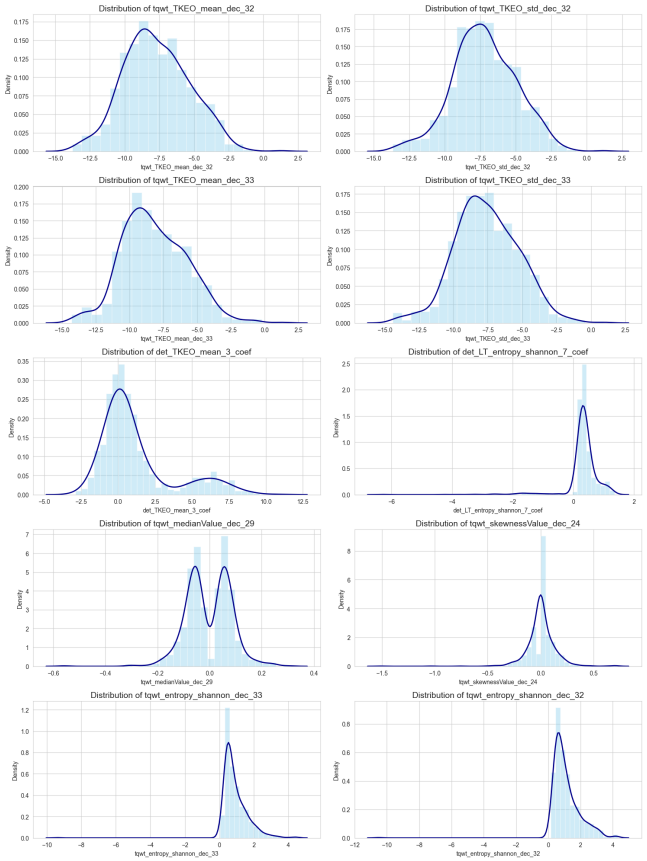

Fig. 2: Attributes with the highest skewness after skewness Reduction.

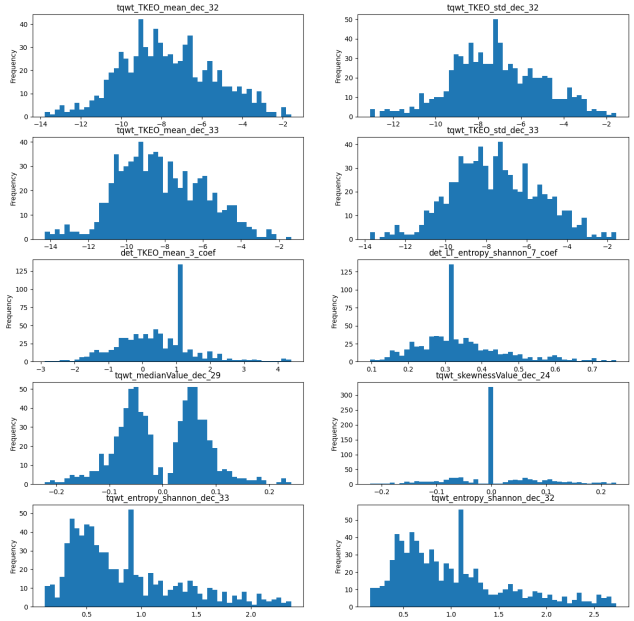

Fig. 3: Attributes with the highest skewness after outlier Reduction

- **Outlier Detection**: Outliers are data points significantly different from others and can bias machine learning models. Each attribute is checked for points below the 25th or above the 75th percentile. Outliers are replaced by the attribute mean. Fig. 3 shows the distribution plot after outlier reduction for Dataset 1.
- **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 were obtained after looping through them which gave us the optimal results for the dataset with acoustic features.
- **Standard Scaling**: Standard scaling or Z-score normalization, is a statistical process of transforming numerical attributes to have a mean 0 and standard deviation of 1. The application of this normalization technique ensures that the features with different scales do not unduly influence the model's performance, particularly those sensitive to the magnitude of input variables.

C. Model Selection

In this research, Residual Neural Network (ResNet) is utilized as a Supervised Deep Learning Model, for analysing acoustic features. Fig. 4 is a schematic architecture of ResNet 18. ResNet is an extension of Convolution Neural Network (CNN) commonly used for Computer Vision tasks, particularly in image processing. CNN faced limitations in handling a specific number of hidden layers, leading to the vanishing gradient problem when updating weights through Backpropagation. This issue resulted in performance saturation. To overcome this, ResNet was introduced with "skip connections," which stack identity mappings, accelerating training by reusing activations from previous layers, and compressing the network.

In retraining, ResNet expands and allows residual parts to enhance the input image's feature space. Skipping two or three layers at a time with nonlinearity and batch normalization in between. Advanced versions, like HighwayNets, introduce "skip weights" dynamically determining the number of layers to skip, thereby improving flexibility and performance.

A fully connected neural network architecture is implemented to process and predict the severity of PD based on the UPDRS scores. The neural network has three hidden layers comprising of 64, 32 and 64 neurons respectively. The activation function used is ReLU.

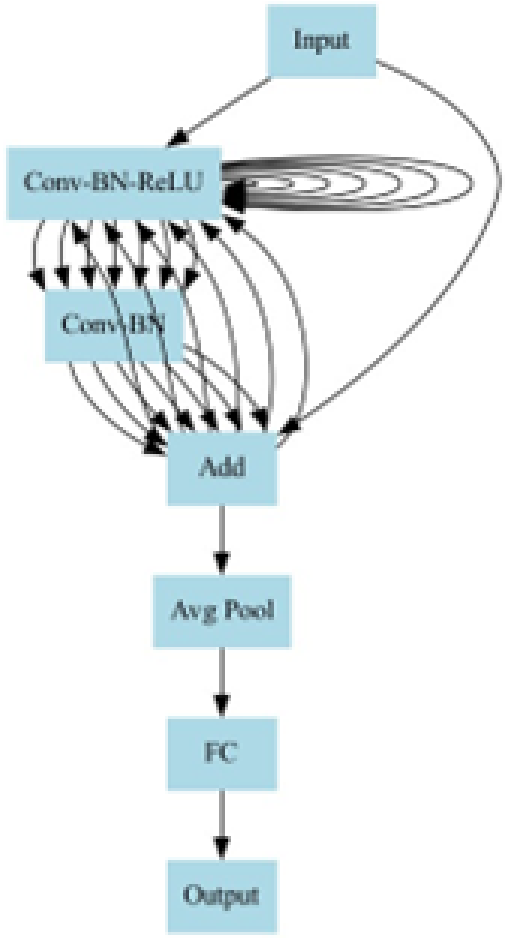

Fig. 4: Residual Block of ResNet

D. Experimental Result

Residual Neural Network outperformed not only the Traditional Machine Learning models, but also 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.

Actual Values / Predicted Values	Positive	Negative
Positive	15 (TP)	1 (FP)
Negative	0 (FN)	60 (TN)

TABLE III: Confusion matrix of ResNet

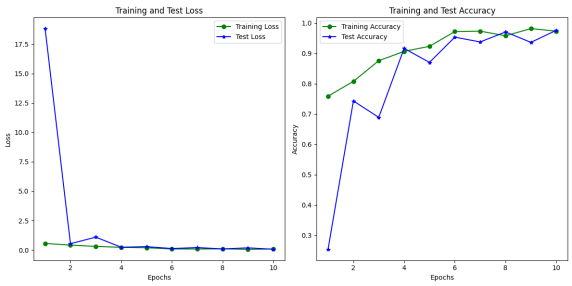

Fig. 5: Training graphs for ResNet18.

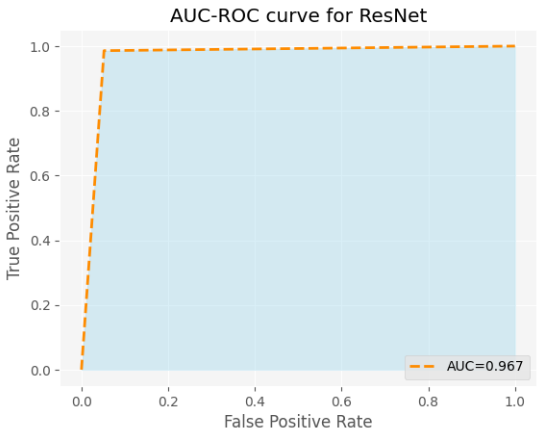

Fig. 6: AUC-ROC curve for ResNet18.

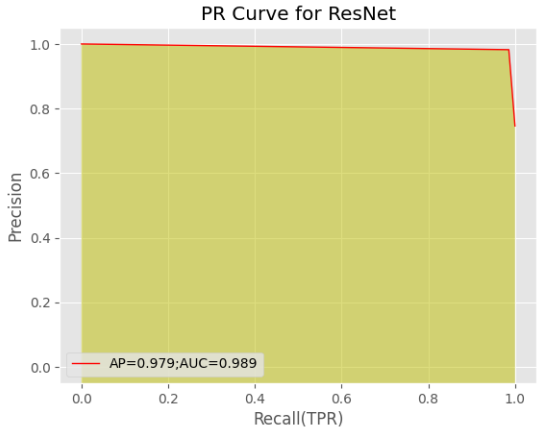

Fig. 7: AUC-PR curve for ResNet18.

Table III 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.

The fully connected neural network demonstrated auspicious outcomes in prognosticating both total and motor UPDRS scores, achieving R2 scores of 0.9709 (total UPDRS) and 0.9696 (motor UPDRS) during training, coupled with Huber Loss/Smooth Mean Absolute Error values of 2.0247 and 3.1705, respectively. Subsequent testing revealed R2 scores of 0.9430 (total UPDRS) and 0.9486 (motor UPDRS), accompanied by Huber Loss values of 3.3553 and 6.0932, respectively.

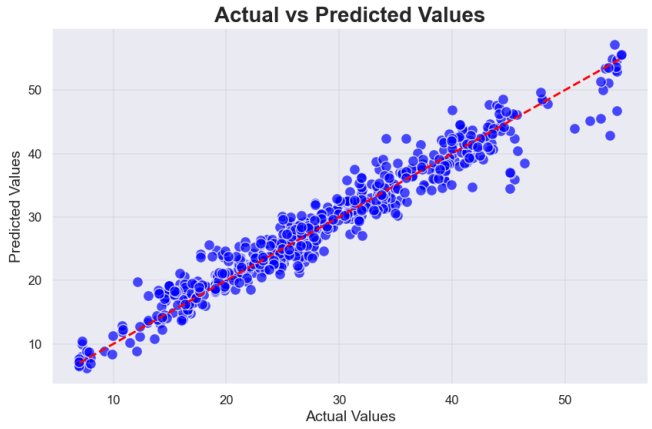

Fig. 8: Actual vs Predicted values based on total UPDRS score.

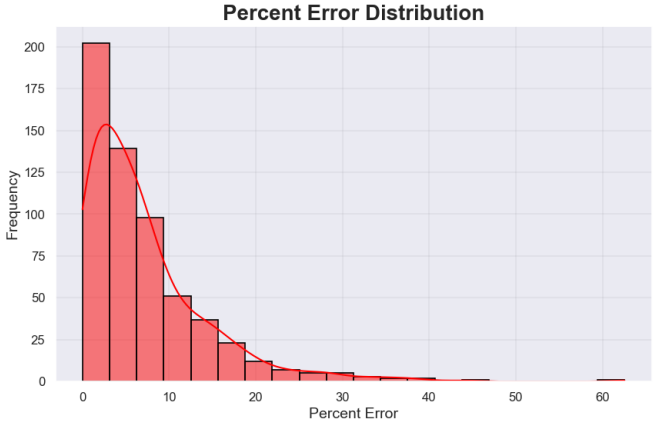

Fig. 9: Percentage error distribution of total UPDRS score.

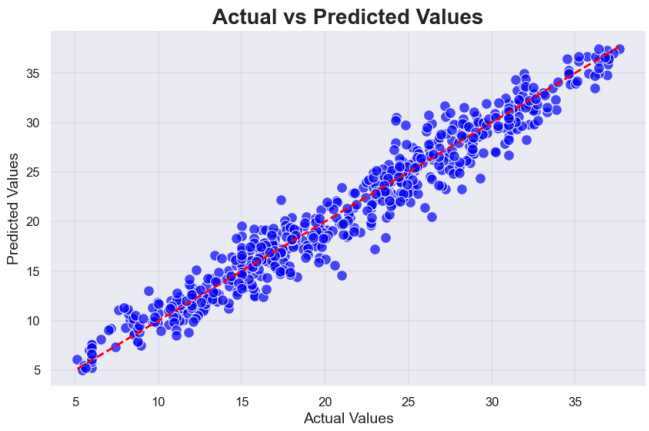

Fig. 10: Actual vs Predicted values based on motor UPDRS score.

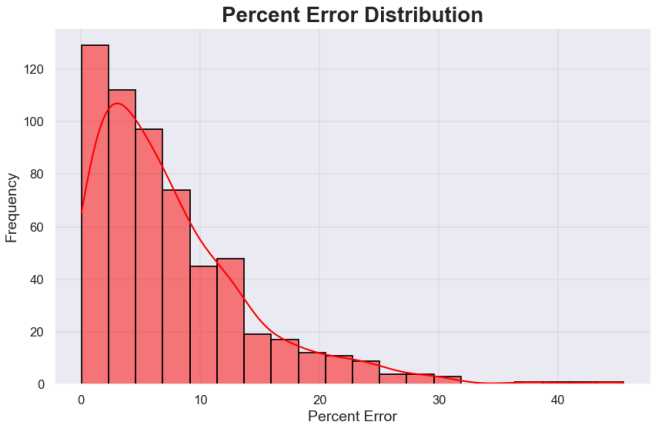

Fig. 11: Percentage error distribution of motor UPDRS score.

IV. COMPARATIVE PERFORMANCE ANALYSIS

A. *Based on acoustic data*

After preprocessing, each model was trained on a dataset split into a training set (85%) and a testing set. Traditional ML models and Neural Networks were trained on the training set. ResNet's superior performance was demonstrated through comparative analysis on the testing set.

- **Confusion Matrix** - Confusion Matrix (CM) evaluates binary classification algorithms with True Positive (TP), False Positive (FP), False Negative (FN) and True Negative (TN). Table IV shows CM for ML and Deep Learning models. ResNet had the highest TP and TN, and the lowest FP and FN values.
- **Accuracy** - Table V displays model accuracies for the training split. Residual Neural Network achieved the highest accuracy of 98% in classifying Parkinson's disease presence based on attributes.
- **Error** - Error is the difference between true and predicted results produced by the models. Fig. 12 shows how error changes with parameter tweaks. ResNet exhibits the most improvement over iterations.

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

TABLE IV: Confusion matrix of ML models

- **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 V, it is evident that Residual Neural Network is the best-performing model in terms of recall.
- **Precision** - In Table V, Precision is the fraction of correctly predicted positive instances among all instances classified as positive. The Residual Neural Network (ResNet) achieved the highest precision, accurately predicting positive instances in its classification.
- **F1-Score** - Table V displays the F1-Scores for the training split, which consider both Precision and recall. A high F1-Score implies accurate predictions and fewer False Negatives. The Residual Neural Network achieved the highest F1-Score, establishing it as the optimal model for both classes.

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

TABLE V: Evaluation Metrics for ML models

- **AUC-ROC Curve** - Area Under the Receiver Operating Characteristics Curve (AUC-ROC) evaluates classification models graphically. It represents the model's ability to distinguish positive and negative classes across various

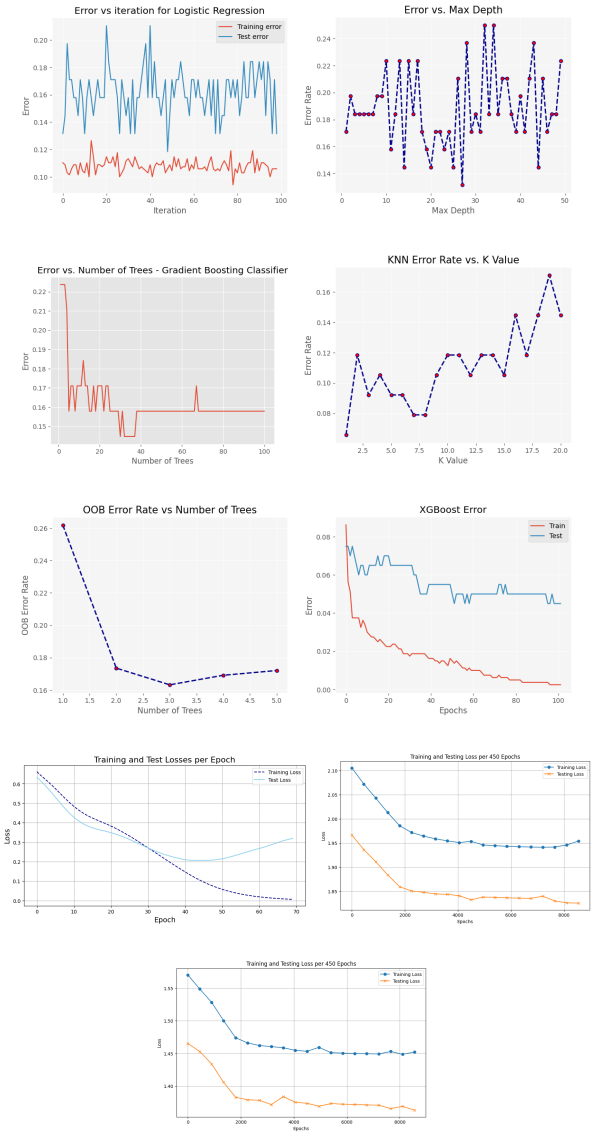

Fig. 12: Error curves.

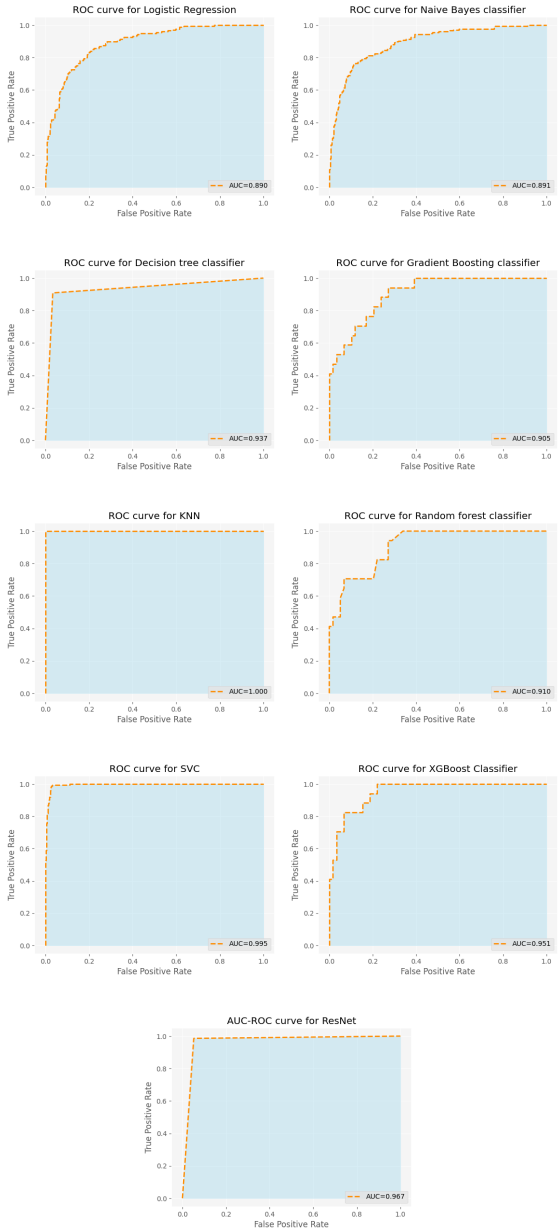

Fig. 13: AUC-ROC Curves.

threshold values. A high AUC value (close to 1) indicates precise discrimination between Parkinson's Positive and Negative patients. Fig. 9 shows the AUC-ROC curves for all models. Residual Neural Network stands out with the highest AUC-ROC of 0.984, making it the optimal model compared to others

- **AUC-PR Curve** - The AUC-PR curve is crucial for evaluating the model's performance, especially in medical applications with imbalanced class distributions. In this study, the AUC-PR curves for all implemented Machine Learning and Neural Network Models are shown 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.

B. Based on UPDRS score

The results of the proposed model used for prediction of severity of Parkinsons disease based on total UPDRS and motor UPDRS are listed below.

1) Based on total UPDRS score: The implemented model attains 97.09% training and 94.30% testing accuracies, employing Huber Loss / Smooth Mean Absolute error with values of 3.3553 and 6.0932 during training and testing, respectively. Comparative analysis with traditional machine learning models reveals the proposed model's competitive performance, marking a notable improvement. Fig. 15 illustrates the training and testing performance of the neural network model.

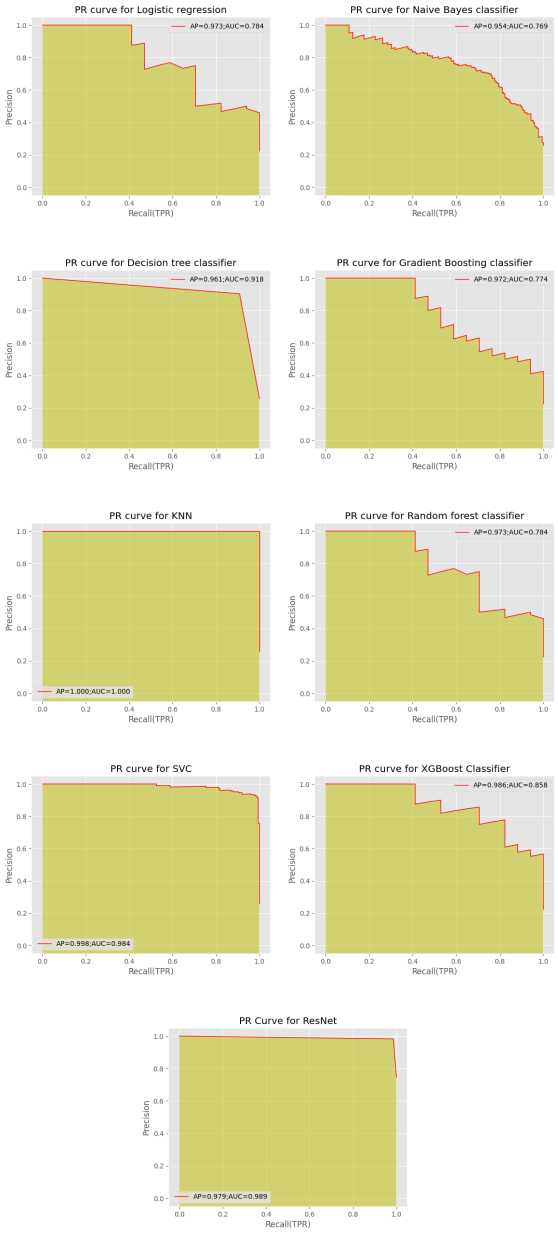

Fig. 14: AUC-PR Curves.

2) Based on motor UPDRS score: The implemented model attains 96.96% training and 94.86% testing accuracies, employing Huber Loss / Smooth Mean Absolute error with values of 2.0247 and 3.1705 during training and testing, respectively. Comparative analysis with traditional machine learning models reveals the proposed model's competitive performance, marking a notable improvement. Fig. 16 illustrates the training and testing performance of the neural network model.

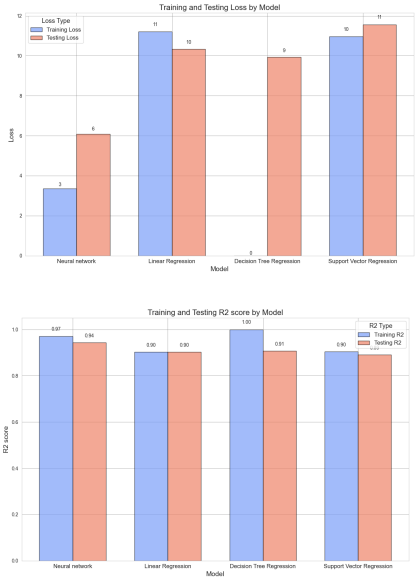

Fig. 15: Training & testing plots based on total UPDRS

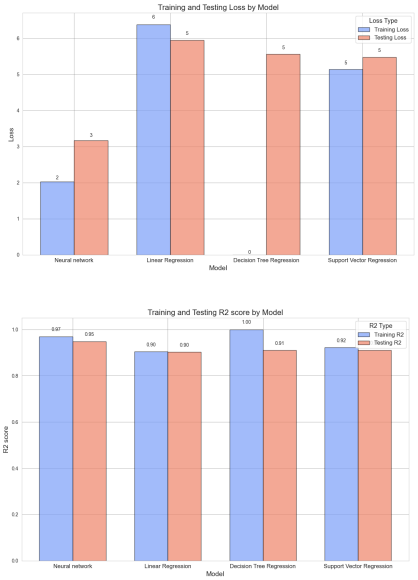

Fig. 16: Training & testing plots based on motor UPDRS

C. Comparison with Recent Publications

The best validation accuracy achieved by the proposed model by Igene et al. [8] for holdout validation was 92.6%, accompanied by a test accuracy of 95.2%. The success of SVM classifiers is demonstrated by an AUC score of 0.95 which is observed for the test dataset, utilizing K-fold validation on the model, and an AUC test score of 0.92 is noted when employing holdout validation at a PCA variance of 95. The results indicate that the model's validation and test accuracy are more balanced at a PCA variance of 95 compared to results obtained at a PCA variance of 85.

To attain one of the top results, various machine learning techniques were applied by Hussain and Sharma [9] using diverse voice features of the patients obtained from the UCI Machine Learning Repository. The analysis concluded that the Stacking Model outperforms other utilized models in terms of Accuracy and F1 scoring. The Stacking Model demonstrates a mean Accuracy of 93% with a standard deviation of 5% and a mean F1-Score of 0.94.

In the study conducted by Alapati et al. [10], a comparative analysis was performed to discern total performance indicators, specifically focusing on precision, recall, and F1-score. Results indicated that Random Forest (RF) models surpassed K-Nearest Neighbors (KNN) models, exhibiting superior accuracy and enhanced predictive capabilities for Parkinson's Disease (PD). The RF model, distinguished for its proficiency in processing extensive datasets, demonstrated reduced training time in contrast to other machine learning algorithms. The derived conclusion posited that the RF Algorithm achieved a notable accuracy rate of 93%, while KNN attained an accuracy rate of 89%.

In the research by Goyal et al. [11], various Machine Learning (ML) and Ensemble Learning (EL)-based classifiers were compared for the purpose of predicting PD. To optimize classifier performance and mitigate overfitting concerns, diverse preprocessing techniques, coupled with Principal Component Analysis (PCA) as a feature selection method, were implemented. The Random Forest, a representative ML model, emerged as the top performer, achieving an accuracy of 82.37%. Additionally, the Ensemble Learning model Light Gradient Boosted Machine (LGBM) demonstrated superior performance with an accuracy of 85.90%.

Good accuracy, precision, recall, and F1 score were exhibited by all models presented by Bajaj et al. [12] highlighting their potential for early Parkinson's disease detection. According to their findings, the Random Forest and XG-Boost models surpassed the others, achieving accuracy rates of over 95%.

The dataset sourced from the UCI Machine Learning Repository for the identification of Parkinson's Disease-positive patients was utilized to evaluate the performance of ResNet18 and the proposed Fully Connected Neural Network in this paper. A significant improvement is observed in the performance of these models compared to recently implemented counterparts.

Proposed by	**Implementation Method**	**Accuracy(%)**
Igene et al.	SVM	95.2%
Hussain and Sharma	Stacking Model	93%
Alapati et al.	Random Forest	93%
Goyel et al.	Ensemble Learning & LGBMs	85.9%
Bajaj et al.	Random Forest & XG-Boost	95%
Proposed model	ResNet18	98%

TABLE VI: Comparison of relevant recent publications

V. CONCLUSION AND SCOPE FOR FUTURE WORK

The research article focused on using Deep Learning to predict and monitor Parkinson's Disease using voice data from the UCI Machine Learning Repository. The chosen model was the Residual Neural Network (ResNet) due to its innovative skip connections, which address the vanishing gradient problem and accelerate training Comparing the dataset, ResNet outperformed all traditional Machine Learning Models with 98% accuracy, 0.98 precision, 0.98 recall, and 0.98 F1-Score. ANN followed closely with 96% accuracy, 0.97 precision, 0.98 recall, and 0.97 F1-Score. ResNet demonstrated superior performance in all evaluation metrics. Future enhancements in this field may involve incorporating MRI brain images for improved predictions, using advanced networks. Additionally, leveraging datasets with spiral writing test images and speech could be explored. Combining numerical, image, and sound data could lead to even more accurate results

REFERENCES

[1] 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.

[2] P. Mounika and S. G. Rao, "Machine Learning and Deep Learning Models for Diagnosis of Parkinson's Disease: A Performance Analysis," 2021 Fifth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC), Palladam, India, 2021, pp. 381-388, doi: 10.1109/I-SMAC52330.2021.9640632.

[3] N. Jahan, A. Nesa and M. A. Layek, "Parkinson's Disease Detection Using CNN Architectures withTransfer Learning," 2021 International Conference on Innovative Computing, Intelligent Communication and Smart Electrical Systems (ICSES), Chennai, India, 2021, pp. 1-5, doi: 10.1109/ICSES52305.2021.9633872.

[4] S. R. Burri, D. K. Agarwal, N. Vyas and R. Duggar, "A Machine Learning Framework for Accurate Prediction of Parkinson's Disease from Speech Data," 2023 3rd International Conference on Innovative Sustainable Computational Technologies (CISCT), Dehradun, India, 2023, pp. 1-6, doi: 10.1109/CISCT57197.2023.10351422.

[5] 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.

[6] S. S, A. S, G. V. V. Rao, P. V, K. Mohanraj and R. Azhagumurugan, "Parkinson's Disease Prediction Using Machine Learning Algorithm," 2022 International Conference on Power, Energy, Control and Transmission Systems (ICPECTS), Chennai, India, 2022, pp. 1-5, doi: 10.1109/ICPECTS56089.2022.10047447.

[7] J. Naanoue, R. Ayoub, F. E. Sayyadi, L. Hamawy, A. Hage-Diab and F. Sbeity, "Parkinson's disease detection from speech analysis using deep learning," 2023 Seventh International Conference on Advances in Biomedical Engineering (ICABME), Beirut, Lebanon, 2023, pp. 102-105, doi: 10.1109/ICABME59496.2023.10293142.

[8] L. Igene, A. Alim, M. H. Imtiaz and S. Schuckers, "A Machine Learning Model for Early Prediction of Parkinson's Disease from Wearable Sensors," 2023 IEEE 13th Annual Computing and Communication Workshop and Conference (CCWC), Las Vegas, NV, USA, 2023, pp. 0734-0737, doi: 10.1109/CCWC57344.2023.10099230.

[9] A. Hussain and A. Sharma, "Machine Learning Techniques for Voice-based Early Detection of Parkinson's Disease," 2022 2nd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE), Greater Noida, India, 2022, pp. 1436-1439, doi: 10.1109/ICACITE53722.2022.9823467.

[10] N. Alapati, N. Anusha, P. Joharika, N. J. Jerusha and P. Tanuja, "Prediction of Parkinson's Disease using Machine Learning," 2023 Second International Conference on Electronics and Renewable Systems (ICEARS), Tuticorin, India, 2023, pp. 1357-1361, doi: 10.1109/ICEARS56392.2023.10085443.

[11] P. Goyal, R. Rani and K. Singh, ”Comparative Analysis of Machine Learning and Ensemble Learning Classifiers for Parkinson’s Disease Detection,” 2022 3rd International Conference on Computing, Analytics and Networks (ICAN), Rajpura, Punjab, India, 2022, pp. 1-6, doi: 10.1109/ICAN56228.2022.10007376.

[12] M. Bajaj, P. Rawat, V. Sharma, S. Vats, S. P. Yadav and V. Kukreja, ”Study on Degenerative Parkinson’s Disease Using Various Machine Learning Algorithms,” 2023 3rd Asian Conference on Innovation in Technology (ASIANCON), Ravet IN, India, 2023, pp. 1-6, doi: 10.1109/ASIANCON58793.2023.10270216.