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Parkinson's Disease Detection Using Acoustic features from Speech recordings

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***Abstract*— With more than 10 million cases globally, Parkinson's disease is the second most common neurological disorder after Alzheimer's. Parkinson's disease is generally distinguished by a decline in motor and cognitive function. There isn't a single test that can be used to make a diagnosis. Instead, a thorough clinical analysis of the patient's medical history is what medical professionals must conduct. According to National Institute of Neurological Disorders research, the accuracy of an early diagnosis—defined as five years or less of symptoms—is only 53%. Although this isn't much better than winging it, prompt diagnosis is essential for successful treatment. The obtained most heavily weighted feature vector is used for classification. The proposed method makes use of the methods for linear discriminant analysis (LDA), K Nearest Neighbor (KNN), decision tree (DT), and neural network (NN). Three major contributions are made by the suggested method. Finding features from the Parkinson's acoustic dataset is the initial step. The second step is choosing the most important characteristics from the numerous produced feature vectors. The third is the addition of UPDRS-defined data, which includes motor symptoms for Parkinson's disease detection. As a consequence, KNN, LDA, DT, NN, and GB algorithms produced effective results for both acoustic characteristics and UPDRS specified data. The compared results unmistakably demonstrate that, among the chosen state-of-the-art procedures, the UPDRS established parameters attained the best success rate. Given the proposed approach and the outcomes, the approach is effective for identifying Parkinson's disease.**

Keywords*— Parkinson's disease recognition, Voice, Acoustic features Statistical pooling KNN, NN, LDA, Decision tree classifier, GB, UPDRS

I. INTRODUCTION

One of the most prevalent neurological conditions affecting the human central, periphery, and enteric nervous systems is Parkinson's disease. According to a recent study, the prevalence of Parkinson's disease rises steadily with age, from 41/100000 in those between the ages of 40 and 49 to 1903/100000 in people over the age of 80. Prior research revealed standardised occurrences of 16 to 19 per 100000 per year. It is also mentioned that this can be due to the challenge in recognising really elderly people, though. These results demonstrate that the general population's ageing will result in a sharp rise in the number of people with PD. Building dependable telemedicine solutions that lessen the stress of frequent in-person clinic visits and uninsured medical expenses is thus becoming more and more important. Parkinson's disease has no known cure, however some symptoms can be managed with medication and surgical procedures.

II. BACKGROUND

Recent years have seen the performance of scientific investigations to generate various sorts of diseases automatically using the developing technology, such as Parkinson's disease. The approaches for detecting diseases using handwriting and voice are widely developed in the literature. The diagnosis of Parkinson's disease has been the subject of numerous research in the literature. A review of gender disparities in Parkinson's disease was done by Georgiev et al. Georgiev looked at the papers and conducted extensive research on Parkinson's disease. A total of 238 studies on Parkinson's disease were evaluated and examined. 9.

Using an auditory dataset, Naranjo et al. suggested a two-stage variable selection and classification strategy for the diagnosis of Parkinson's disease. The Bayesian technique, a two-stage variable selection that deals with replicated measurements, is suggested in the study that is being recommended.

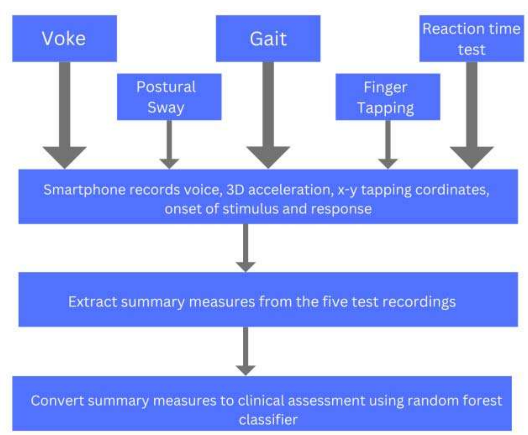
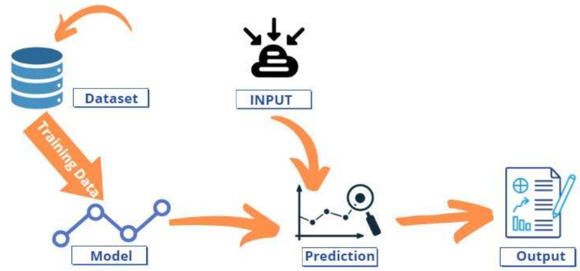


Fig. 1 contains the proposed method's block diagram. With high success, Tsanas et al. suggested an approach to acoustic signal processing for the classification of Parkinson's disease. Using vowels from Parkinson's sufferers, four fundamental characteristics were discovered. Applying Random Forest and Support Vector Machine algorithms to the resultant feature subset allows for disease identification. The success rate for 263 sample datasets from 43 patients was over 99%. PCA and NPCA were suggested by Benba et al. as a technique for Parkinson's disease detection.

III METHODOLOGY



Dataset: The dataset consists of 23 acoustic features which are obtained from applying dysphonia pitch periond entropy on sounds. A concept of MDVP (Multidimensional voice program) has several paramters that can assess voice quality based on various parameters.

Table-1

Feature description of various parameters

MDVP: Jitter(%)	MDVP jitter as percentage
MDVP:Jitter(Abs)	MDVP absolute jitter in microseconds
MDVP:RAP	MDVP relative amplitude perturbation
MDVP:PPQ	MDVP five-point period perturbation quotient
Jitter:DDP	The average period divided by the average absolute difference of the difference between cycles.
MDVP:Shimmer	MDVP local shimmer
MDVP:Shimmer(dB)	MDVP local shimmer in decibels
Shimmer:APQ3	Three point amplitude perturbation quotient
Shimmer:APQ5	Five point amplitude perturbation quotient.
MDVP:APQ	11 point amplitude perturbation quotient
Shimmer:DDA	Between sequential differences between the amplitudes of subsequent periods, there is an average absolute difference.
NHR	Noise-to-Harmonics ratio
HNR	Harmonics-to-Noise ratio
DFA	Detrended fluctuation analysis
PPE	Pitch period entropy

A rating scale called the Unified Parkinson Disease Rating Scale (UPDRS) is used to gauge a patient's parkinson's disease's severity and course. The widespread use, thorough coverage of motor symptoms, and clinimetric features of UPDRS are some of its advantages. The use of UPDRS data also aims to correlate with the clinically relevant terms "minimal," "mild," "moderate," and "severe" parkinson's.

The input data was divided using classification algorithms into several auditory features. To obtain the optimal outcome, various splits of the validation set to the training set are applied. These range from 75% and 25%, through 80% training/20% validation, to 70% and 30%. In order to lessen the impact of outliers, the dataset is rescaled in the range of 0 to 1. There have been a total of 5 trials, and the results are an average.

Different machine learning algorithms, including linear discriminant analysis (LDA), k closest neighbours (kNN), decision trees, neural networks, and gradient boost, are used to train the model.

The linear discriminant analysis algorithm makes the assumption that the data are gaussian and that each feature has the same variance. It uses training data to estimate the mean and variance for each class before applying statistical principles to determine the likelihood that a specific instance belongs to a particular class.

The k nearest neighbours (kNN) algorithm uses the complete training set to make predictions about the validation set. KNN determines the closest examples before making a prediction regarding new input. A proximity measurement (Euclidean) over all features is used to establish "closeness". The class that the model predicts the new instance to be is the class that the majority of the k nearest instances belong to.

Decision tree: A binary tree is used to represent a decision tree, and each leaf node has an output that is utilised to create a prediction. Each root node represents an input variable and a split point.

Neural network: Simulates how the human brain processes information. Each neuron receives one or more inputs, processes them with weights and biases using an activation function, and then produces an output. Neurons can be grouped into layers, and a network made up of several layers can be used to simulate complex decisions.

Gradient boost: This technique is frequently used to find models with exceptionally high predictive performance. It is used to generate a strong model by combining several weak models, hence reducing bias and variance. It consists of three components: an error function that is optimised, a prediction model that is weak, and an additive model that adds trees to reduce the loss function.

Output: The models trained using different machine learning algorithms were validated to find the accuracy and the mathews correlation coefficient (MCC).
A method for evaluating models is the Mathews correlation coefficient. It measures the discrepancies between actual values and projected values and is comparable to the 2x2 contingency table of the chi-square statistic.

$$MCC = \frac{TP\ X\ TN - FP\ X\ FN}{\left((TP+FP)(TP+FN)(TN+FP)(TN+FN)\right)^{0.5}}$$

TP = True positive
TN = True negative
FP = False positive
FN = False negative

IV. RESULTS AND DISCUSSION

Two datasets Parkinsons_data and Parkinson_UPDRS are taken from the **UC Irvine's** dataset repository specifically the Parkinsons ML database. The first database consists of 195 rows x 24 columns and UPDRS database consists of 5875 rows x 22 columns.

In general, the models tended to perform the best (both for the case of accuracy and Mathews correlation coefficient) for 86% to 14% train test split.

For the dataset consisting of 24 different acoustic features and 195 different inputs, results are as follow:

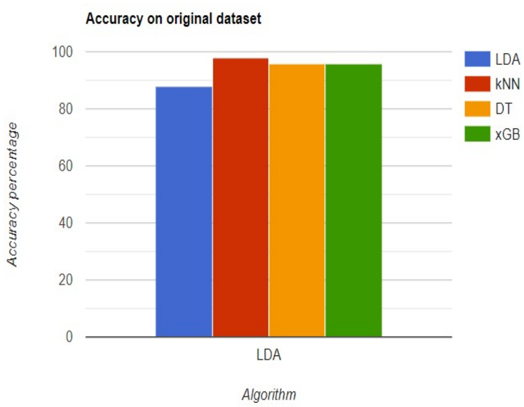


Figure-1 (Accuracy scores)

From the above figure, the model trained through kNN had highest accuracy score of 97.959% followed by decision tree classifier and X-gradient boost algorithms having same accuracy scores of 95.918%. Linear discriminant analysis method posted an accuracy of 87.755%.

From the above figure, kNN algorithm had the highest MCC (0.93674) proving that it is close to perfect agreement between the input and the trained model. While X-gradient boost and DT algorithms posted almost similar MCC of 0.87. Linear discriminant analysis was proven to be away from the expected out with coefficient of 0.58.

A performance metric for machine learning classification problems where the output can be two or more classes is the confusion matrix. There are four possible anticipated and actual value combinations in the table. For each of the 4 different machine learning techniques, confusion matrices were discovered.

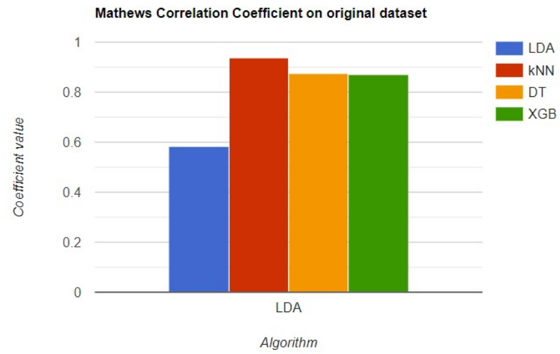


Figure-2 (Mathews correlation coefficient)

For kNN:

9	1
0	39

For LDA:

5	5
1	38

For X-Gradient Boost:

8	2
0	39

For DT:

9	1
1	38

The confusion matrix is a 2x2 matrix. As kNN produced the highest accuracy score we can conclude through its confusion matrix that it gives only 1 False positive case out of the 10 total cases reported. While LDA reported the least accuracy score and hence produces 5 False positive and 1 false negative result after giving input.

For Parkinson_UPDRS dataset which consists of 22 different acoustic/motor features and 5875 rows, a neural network model was trained using the keras library. It was found that a train-test-split of 75% to 25% achieved the best result. A total of 75 epochs were trained till the time loss almost stopped decreasing.

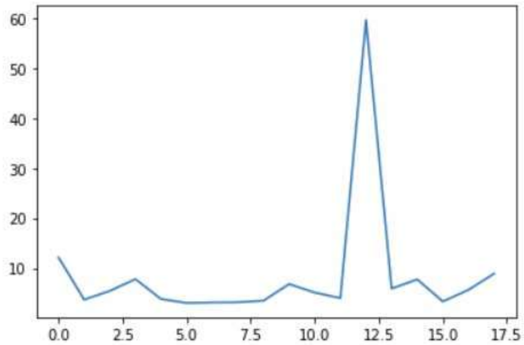


Figure-3 (Error plot for UPDRS dataset)

From the above figure, the error was high at a particular point for the UPDRS data, but the overall error was low.

V. CONCLUSION

These reliable results indicate that it is possible to considerably enhance Parkinson's disease diagnosis techniques by using a machine learning methodology. Our machine learning models offer a very promising alternative to the current, relatively poor technique of diagnosis given the requirement of early diagnosis for appropriate therapy. While my machine learning model delivers 98% accuracy, current techniques of early detection are just 53% accurate. This 45% increase is crucial since a precise, early diagnosis is required for the condition to be adequately treated. Typically, 80% of the striatal dopamine has been depleted and 60% of the nigrostriatal neurons have died by the time the condition is recognised. Much of this degeneration may have been stopped or addressed with an earlier diagnosis.

In addition to being more scalable, less expensive, and hence more accessible to people who might not have access to well-established medical institutions and specialists, our machine learning technique is also more accurate in terms of diagnostic accuracy.

A major source of worry is the comparison between the auditory properties and the inclusion of motor-related symptoms in the UPDRS data. It demonstrates that the most accurate way to detect Parkinson's disease is by using UPDRS data. A 10-15 second voice recording is all that is necessary for the diagnosis, which results in a quick diagnosis.

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