A comparative study of machine learning algorithms for detection of Parkinson's disease at an early stage.

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I. ABSTRACT

Parkinson's disease (PD) is one among many leading public health diseases in the world. This disease has impacted many people and is alarmingly increasing. Thus, it is very important to predict it at an early stage and has been a difficult task among researchers as the symptoms of the disease are evident in either the mid or late stages. Thus, this chapter concentrates on the symptoms of speech articulation difficulty of persons with PD and formulates the model using various machine learning like support vector machine, decision tree, random decision forest, and linear regression, adaptive boosting, bagging, neural networks. The performance of these graders are assessed through various measurements, e.g. Accuracy, receptor ope rating characteristics (ROC) curve, sensitivity,Precision, as wellas specificity. Finally, xgboost is used to find the most important features of any feature to predict Parkinson's disease.

II. INTRODUCTION

Parkinson's disease (PD) is a long-term degenerative disorder of the central nervous system that causes a variety of symptoms to tremors to a cognitive disability, hallucination, sleep disorders, etc. Over 10 million people worldwide are affected by Parkinson's disease. In the world every year, approximately 100 thousand people die from Parkinson's disease.

Until now, there has been no cure for PD. However, approximately 10 years before the onset of tremors or motor symptoms, The human brain has Dopaminergic neurons which are the main source of dopamine (DA) in the central nervous system. The change or loss of these neurons is associated with neurological disorders. Certain premotor symptoms of PD (at an early stage) include a reduction in sense of smell, the disruption in Rapid Eye Movement (REM) sleep, handwriting, difficulty in moving, etc.

Early PD diagnosis makes it possible to effectively manage and avoid unnecessary medical tests, therapies, costs, safety risks, etc.. Early-stage Parkinson's disease is most often detected using brain studies such as MRI, fMRI, SPECT, PET, etc. So far, in most centers, clinicians are interpreting these images which are prone to human error. It was reported that the pooled accuracy of clinical diagnosis of Parkinson's disease is only 80.6%.

III.LITERATURE SURVEY

We collected handwritten samples and used each sample to extract a handwritten scale [9]. New entropy based handwriting measures, signal energy, and empirical mode decomposition of handwriting signals were computed in addition to conventional kinematic and spatiotemporal handwriting measurements. The maximal sensitivity and specificity for PD categorization were 89.47% and 91.89%, respectively, with an

accuracy of up to 88.13% [9]. A useful marker for diagnostic and screening purposes is handwriting. Evaluation of speech captured by cellphones in Parkinson's disease using freely accessible pitch detection algorithms at various noise levels. measurement of the vocal fold's fundamental frequency The assessment of language impairment in Parkinson's disease has identified F0 as a crucial criterion (PD). Pitch Determination Algorithms (PDA) are a broad category of techniques for F0 estimate . The purpose of the study was to examine and compare the performance of several PDAs [1].Different PDAs which they have examined were:

- Harvest
- RAPT
- PRAAT
- Swipe
- SHRP

To evaluate the PDA's tolerance to additional background noise, they added five distinct types of nonstationary noise to each recording at SNR levels of 20, 10, and 6 dB, respectively. The 6 dB restriction was chosen because it represents the worst-case scenario that is most likely to occur in a typical circumstance [1]. When employing a smartphone device for recording, the SWIPE algorithm can measure mono pitch accurately even in non-stationary urban noise with an SNR of up to 10 dB. To obtain sufficient robustness at lower SNR levels, a variety of techniques may need to be combined. SWIPE mono pitches have a significant ability to detect PDs.

SNR 6 dB

		HARVEST	RAPT	PRAAT AC	PRAAT SHS	REAPER	YANGsaf	SHRP	SWIPE	BANA	YAAPT
Noise condition 1											
Mean	MAE	0.75	1.32	0.88	1.87	3.21	0.76	2.38	0.64	0.80	1.82
	NRMSE	0.09	0.17	0.10	0.27	0.37	0.07	0.43	0.05	0.07	0.22
	Spearman r	0.98	0.90	0.93	0.93	0.85	0.97	0.90	0.98	0.97	0.82
SD	MAE	1.87	1.72	0.69	1.96	2.47	1.75	3.02	0.29	0.98	1.51
	NRMSE	0.58	0.34	0.21	0.43	0.55	1.08	0.77	0.10	0.31	0.33
	Spearman r	0.72	0.52	0.64	0.59	0.42	0.65	0.55	0.92	0.58	0.59
Noise condition 2											
Mean	MAE	0.60	0.72	1.79	0.97	2.98	0.94	1.81	0.75	2.54	0.89
	NRMSE	0.07	0.11	0.21	0.15	0.36	0.07	0.39	0.06	0.20	0.12
	Spearman r	0.99	0.92	0.88	0.95	0.82	0.98	0.86	0.98	0.86	0.88
SD	MAE	1.92	1.82	1.70	2.01	2.41	1.50	3.25	0.50	2.98	0.46
	NRMSE	0.58	0.42	0.35	0.57	0.52	0.60	1.04	0.19	0.65	0.12
	Spearman r	0.66	0.55	0.33*	0.74	0.43	0.55	0.57	0.68	0.02*	0.83
Noise condition 3											
Mean	MAE	0.48	0.56	0.66	0.91	1.17	0.14	1.01	0.25	0.40	0.42
	NRMSE	0.05	0.08	0.08	0.11	0.14	0.01	0.14	0.02	0.04	0.08
	Spearman r	0.99	0.92	0.95	0.95	0.92	0.99	0.95	0.99	0.98	0.92
SD	MAE	1.11	0.76	0.93	1.13	1.10	0.25	2.27	0.19	0.53	0.28
	NRMSE	0.36	0.21	0.24	0.34	0.31	0.12	0.74	0.07	0.20	0.12
	Spearman r	0.87	0.76	0.48	0.78	0.77	0.90	0.65	0.95	0.78	0.87
Noise condition 4											
Mean	MAE	0.26	0.49	0.66	0.39	0.65	0.12	0.87	0.32	0.74	0.38
	NRMSE	0.02	0.08	0.06	0.05	0.09	0.01	0.11	0.03	0.06	0.07
	Spearman r	0.99	0.92	0.96	0.97	0.93	0.99	0.95	0.99	0.97	0.93
SD	MAE	0.89	0.54	0.56	0.85	0.74	0.21	2.29	0.23	0.55	0.31
	NRMSE	0.24	0.20	0.20	0.23	0.24	0.09	0.68	0.08	0.23	0.11
	Spearman r	0.87	0.76	0.60	0.81	0.85	0.93	0.61	0.96	0.55	0.88
Noise condition 5											
Mean	MAE	0.37	2.25	2.01	0.49	1.25	0.13	1.90	0.25	1.09	0.43
	NRMSE	0.04	0.21	0.17	0.07	0.14	0.01	0.24	0.02	0.09	0.07
	Spearman r	0.99	0.85	0.85	0.95	0.91	0.99	0.90	0.99	0.93	0.92
SD	MAE	1.26	4.70	2.79	1.48	1.49	0.24	3.39	0.15	1.58	0.29
	NRMSE	0.38	0.56	0.49	0.39	0.39	0.11	0.86	0.06	0.33	0.12
	Spearman r	0.82	0.16*	0.10**	0.75	0.69	0.92	0.31*	0.95	0.35	0.87

MAE = mean absolute error, NRMSE = normalized root mean square error, SD = standard deviation. All correlations reached significance $p < 0.001$ except for * and ** which

Fig 1. Factors Affecting Voice of the Normal Person

A more accurate Parkinson's diagnosis is always preferred to ensure that the right steps are taken to decrease the disease's progression and enhance quality of life. There is evidence that older people and adults have different neural characteristics from men and women. In this paper [5], they developed a sex-specific and age-dependent classification method to diagnose Parkinson's disease using the online handwriting recorded from individuals with Parkinson's (n = 37; m/f-19/18; age-69.310.9yrs) and healthy controls (n = 38; m/f-20/18; age- 62.411.3yrs). However, the potential of such gender and age information have not yet been exploited for Parkinson's identification.

An SVM ranking algorithm is used to show the characteristics specific to their dominance in sex and age group for Parkinson's diagnosis. It was discovered that the generalised classifier performed significantly worse than the sex- and age-specific classifiers [5]. The female-specific classifier's accuracy was observed to be 83.75% (SD = 1.63) and 79.55% (SD = 1.58), respectively, in compared to the general classifier's accuracy of 75.76% (SD = 1.17) and 79.55% (SD = 1.58). Combining the sex and age information was found to improve categorisation [5]. A specific set of traits was demonstrated to be predominating in a different classification category for increased classification accuracy.

Parkinson's disease (PD) is a progressive neurological disorder that causes both motor and non-motor symptoms. PD patients frequently experience vocal problems early on in the course of the disease. Therefore, diagnostic techniques based on voice issues have received a lot of attention in new PD detection investigations. This paper proposes two convolutional neural network-based frameworks for categorising Parkinson's disease (PD) using sets of vocal (voice) features. Both frameworks are used to merge several feature sets, although they go about it in different ways [7]. While the second architecture passes feature sets to parallel input layers that are directly connected to convolution layers [7], the first framework integrates different feature sets before transferring them as inputs to a 9-layered CNN. As a consequence, deep features are simultaneously extracted from each parallel combination before being pooled in the merge layer. The proposed models are evaluated using Leave-One-Person-Out Cross Validation after being trained on data from the UCI Machine Learning Repository. (LOPO CV). F-Measure and Matthews Correlation Coefficient metrics are employed for the assessment along with accuracy due to the unbalanced class distribution in our data.

Voice fundamental frequency, measurements of fundamental frequency variation, amplitude variation measurements, etc. are commonly extracted features. Since most PD detection research conducts experiments using both datasets, the features derived from both datasets are commonly referred to as baseline features. In addition to the baseline features, other features based on signal processing techniques were applied in PD identification. Using techniques like the signal-to-noise ratio (SNR), Mel-frequency cepstral coefficients (MFCC), and tunable Q-factor Wavelet Transform (TQWT), it is crucial to be able to to extract relevant features for PD classification. Rather than using different feature types for model training, the majority of research incorporates individual feature types to perform classification tasks [7].

The DNN model's accuracy rate of 85% exceeded the typical clinical diagnosis accuracy of non-experts, which was roughly 73.8%. The CNN model worked well,

with rates of accuracy, sensitivity, and specificity of 88.25%, 84.71%, and 91.77%, respectively [7]. By merging feature subsets and then utilising mRMR feature selection to choose the informative features, the model produced an accuracy rate of 0.869, an F-Measure of 0.917, and an MCC of 0.632.

IV.DATASET ANALYSIS

The speech signals were recorded by the National Centre for Voice and Speech in Denver, Colorado, and Max Little of the University of Oxford worked together to create the dataset. A variety of biological voice measurements from 31 people, 23 of whom have Parkinson's disease, were part of this collection (PD). Amplitude metrics, Pulse metrics, Frequency metrics, Voicing metrics, Pitch metrics, and Harmonicity metrics are the six categories that Table 2 breaks down the parameters into. There are 195 instances in the collection. A specific voice measure is represented by each column in the table, and each row corresponds to one of the 195 voice recordings from these people. The "Status" parameter is the one that matters the most out of all the others because it is the only one that can tell healthy people from those who have Parkinson's disease apart. While a value of 0 indicates overall health, a value of 1 indicates Parkinson's disease. The sample data **set that was used is depicted in table1.**

FEATURE DESCRIPTION	ABBREVIATIONS
Average vocal fundamental frequency	MDVP:F0 (Hz)
Maximum vocal fundamental frequency	MDVP:PHI (Hz)
Minimum vocal fundamental frequency	MDVP:FLO (Hz)
MDVP jitter in percentage	MDVP:ITTER(%)
MDVP absolute jitter in ms	MDVP:JITTER(ABS)
MDVP relative amplitude perturbation	MDVP:RAP
MDVP five-point period perturbation quotient	MDVP:PPQ
Average absolute difference of differences between jitter cycles	JITER:DDP
MDVP local shimmer	MDVP:SHIMMER
MDVP local shimmer in dB	MDVP:SHIMMER(DB)
Three-point amplitude perturbation quotient	SHIMMER:APQ3
Five-point amplitude perturbation quotient	SHIMMER:APQS
MDVP 11-point amplitude perturbation quotient	MDVP:APQII
Average absolute differences between the amplitudes of consecutive periods,	SHIMMER:DDA
Noise-to-harmonics ratio	NHR
Harmonics-to-noise ratio	HNR

Table 1. Parameters affecting the movement of muscles

Shimmer:APQ5	MDVP:APQ	Shimmer:DDA	NHR	HNR	status	RPDE	DFA	spread1	spread2	D2	PPE
0.0313	0.02971	0.06545	0.0...	21....	1	0.41...	0.8...	-4.813...	0.2664...	2....	0....
0.04518	0.04368	0.09403	0.0...	19....	1	0.45...	0.8...	-4.075...	0.33559	2....	0....
0.03858	0.0359	0.0827	0.0...	20....	1	0.42...	0.8...	-4.443...	0.3111...	2....	0....
0.04005	0.03772	0.08771	0.0...	20....	1	0.43...	0.8...	-4.1175	0.3341...	2....	0....
0.04825	0.04465	0.1047	0.0...	19....	1	0.41...	0.8...	-3.747...	0.2345...	2....	0....
0.03526	0.03243	0.06985	0.0...	21....	1	0.41...	0.8...	-4.242...	0.2991...	2....	0....
0.00937	0.01351	0.02137	0.0...	24....	1	0.59...	0.7...	-5.634...	0.2576...	1....	0....
0.00946	0.01256	0.02487	0.0...	26....	1	0.63...	0.7...	-6.1676	0.1837...	2....	0....
0.01277	0.01717	0.03218	0.0...	21....	1	0.61...	0.7...	-5.498...	0.3277...	2....	0....
0.01725	0.02444	0.04324	0.0...	21....	1	0.54...	0.7...	-5.011...	0.3259...	2....	0....

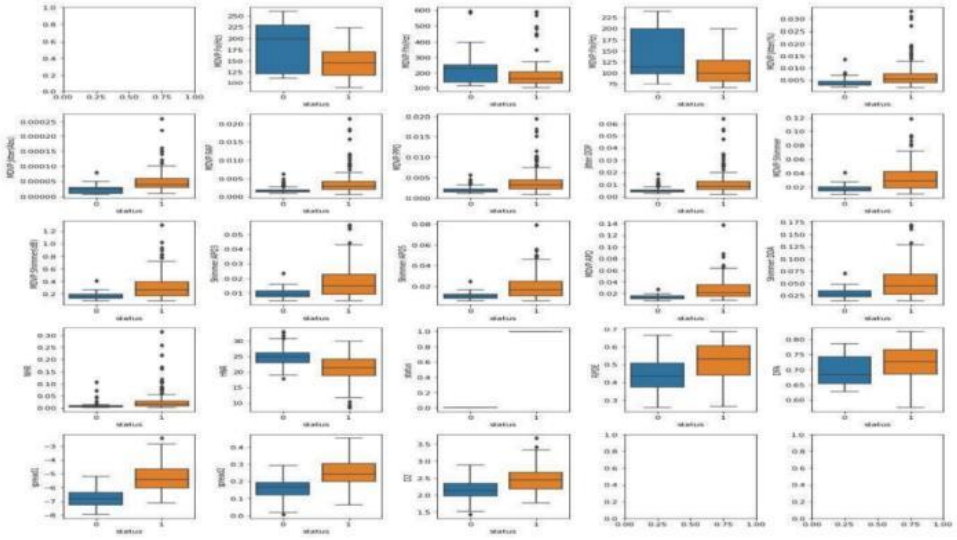


Fig 2. Vocal Features of the dataset

Fig 3. Graphical representation of disease characteristics v/s the status of the person

V.BLOCK DIAGRAM

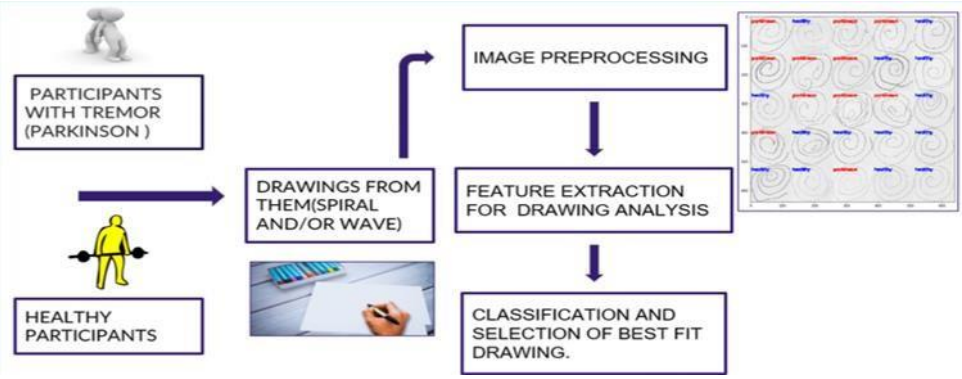


Fig 4. Flow Chart for Classification and Testing

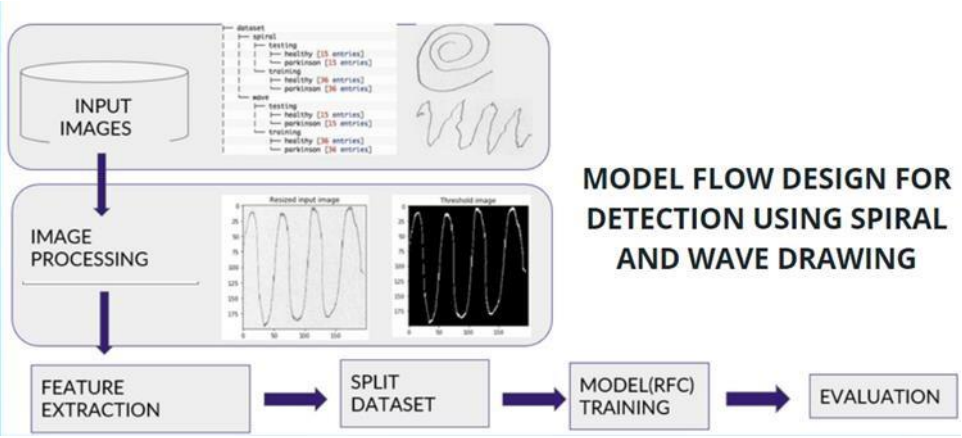


Fig 5. Flow Design for Detection using Spiral and Wave Drawing

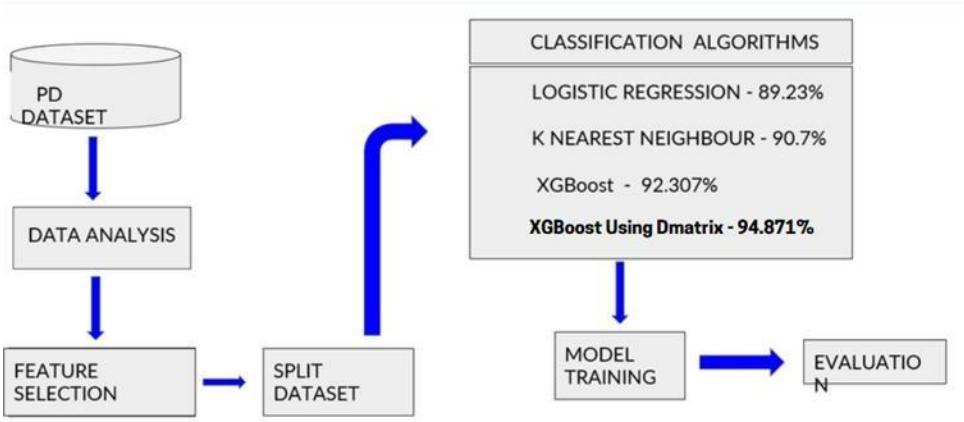


Fig 6. Design Flow for Voice Detection of affected person

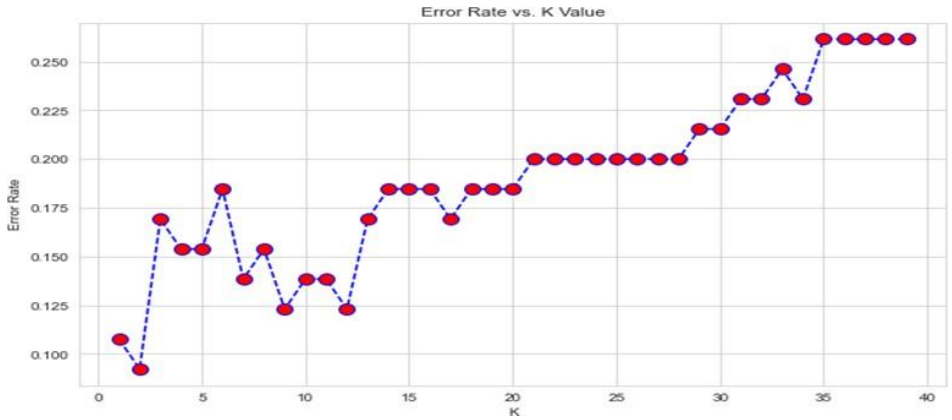
VI. RESULTS AND DISCUSSIONS

The Parkinson Dataset (PD dataset) parameters are classified into 5 categories namely i) Frequency parameters, ii) Pitch parameters, iii) Amplitude Parameters, iv) Voicing Parameters, v) Pulse parameters. The parameter values are then analyzed to identify outliners and errand values, padded with zero for empty values and removal of the parameter which are not contributing for classification. The data set was split into test and training data to train the model, it was trained on different classification algorithms which has functions that balances the characteristics of the input so that the output separates one class with positive traits and the other into negative.The dataset was subjected to the following different classification algorithms:

A. Logistic regression:

As logistic regression only uses log function which statistically is a logit transformation applied to the data. The performance is calculated as the ratio of probability of success to the probability of failure. Logistic regression does not show very trust worthy results. The accuracy was 89.23%.

B. K-Nearest Neighbor (KNN): K-Nearest Neighbour algorithm expects large amount of training data to give benefiting result, as The K-NN algorithm puts the new entity in the category that is most similar to the existing classes on the premise that the new case/data and the current cases are comparable. Due to availability of small dataset of



this disease, the algorithm was capable of producing an accuracy of. 90.7%.

Fig 7. Results using KNN Algorithm

C. Random Forest: Collectively, Random Decision Forest is a classification learning process and uses regression and other tasks during training to build a large number of decision trees. When Random Forest regression model was employed for the PD dataset, it provided an accuracy of 86.15%, which was quite less when compared to other algorithms.

D. XGBoost: The next promising classification algorithm was XGBoost is a distributed gradient boosting library developed to be very portable, effective, and flexible. It uses Gradient Boosting framework and implements classification learning algorithms. The distributed gradient boosting library is efficient for small datasets and it gave us an approximate accuracy of92.30%.

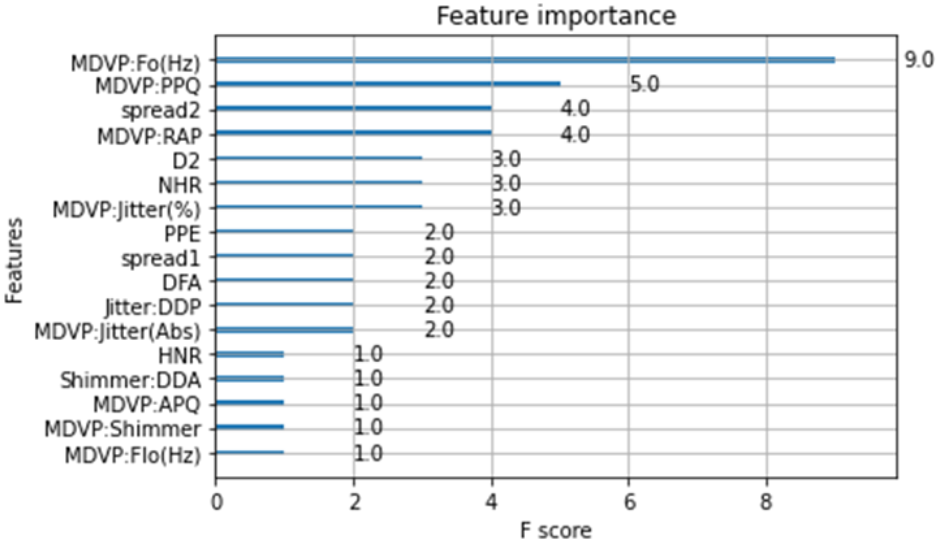
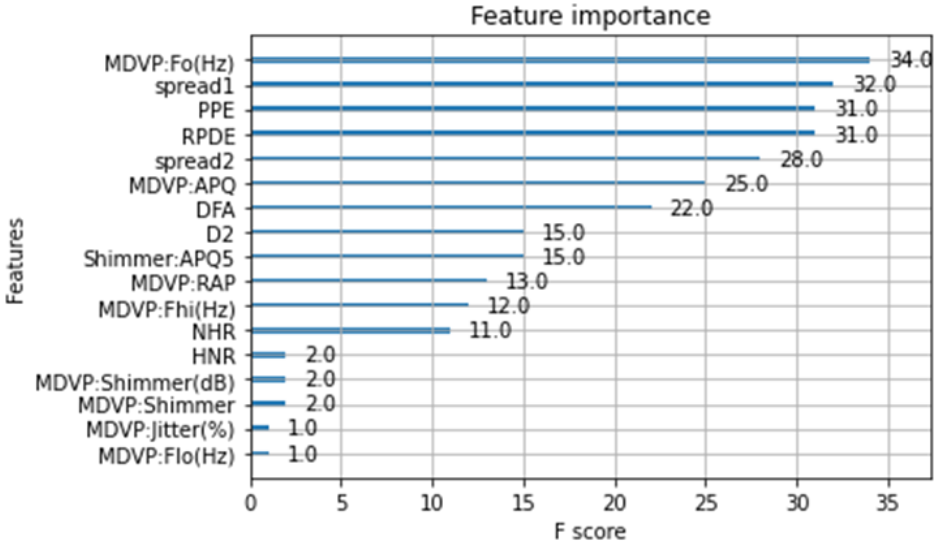


Fig 8. Results using XGBoost Algorithm

E. XGBoost Using Dmatrix: XGBoost when it employed DMAtrix showed the most efficient and accurate results. XGBoost utilises an internal data structure that is designed for both memory effectiveness and training speed in DMatrix. XGBoost with



DMatrix provided a high accuracy of 94.871% and a precision of 88.88%. We must use the DMatrix format as the model and convert our PD dataset into the format so that XGBoost can use in order for it to work.

Fig 9. Results using XGBoost with D-Matrix Algorithm

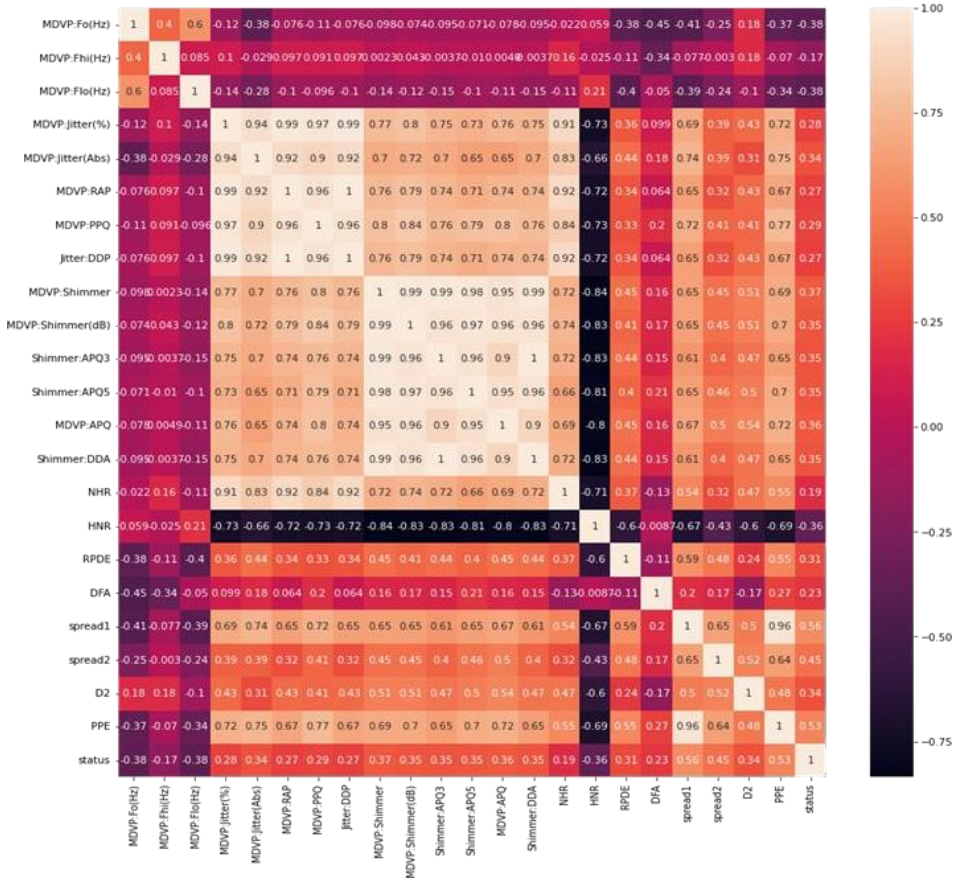


Fig 10. Heatmaps using XGBoost with D-Matrix Algorithm

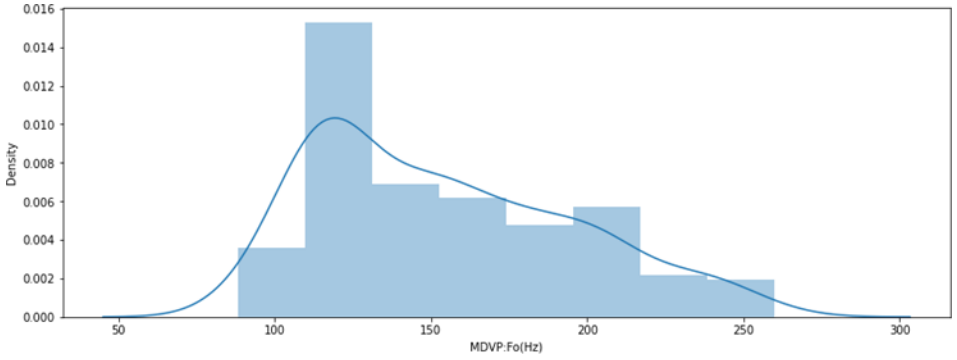


Fig 11. Graphs using XGBoost with D-Matrix Algorithm

VII. CONCLUSION

For the patient to obtain the right care and decrease the consequences of Parkinson's disease, the condition must be recognised as soon as feasible. In this study, we propose an artificial intelligence-powered prediction model that is used to increase the precision of disease diagnosis in people and enable early detection. We intend to aid physicians in accurately diagnosing and forecasting Parkinsons Disease, The two activities that are currently challenging for them to do due to the present method of diagnosis process is the ability to acculately detect and further provide prediction. We divided the task of detection and prediction, and we used that data in a neural model to pinpoint and quantify the region of the brain that is impacted.

The proposed technique resulted in accuracy of 94.871%, sensitivity of 100%, and specificity of 88%. The research has made the following contributions: I This model is quite helpful to doctors as it only makes use of five features. (ii) Because of the substantial and consistent sample that was applied, this model is precise. (iii) By using neural networks and image processing separately, this process uses relatively minimal system resources and has reliable accuracy, which makes it simpler to apply this model to real-world applications. According to the proposed model, objective evaluation and the use of fundamental neural networks are useful in the development of prediction models that can help a doctor diagnose a patient more efficiently and with a smaller chance of human error.

FUTURE SCOPE

Compared to earlier approaches, the model presented in this study took a distinct approach to the problem of Parkinson's disease recognition, but the outcomes are still highly applicable to real-world conditions. Although the conclusions are factual, The model must be improved and used in circumstances that actually occur in the real world. These results are not the end aim. A model with more records in the dataset can deliver better accuracy and more reliable. The effectiveness of this approach can also be more clearly demonstrated by evaluating it with established approaches in term of accuracy, effectiveness and applicability in real-world circumstances. With the use of this technique, clinicians will be able to identify Parkinson's disease more precisely than before. More research may be done on datasets to include more relevant information and include more variables that reflect the disease. Lack of awareness is a major contributing factor to this illness, as is the fact that complications often appear or become apparent only after the person has already begun to experience neuronal degeneration for a while. Hence, datasets generated from patients taken earlier than one week if documented, can generate better outcomes.

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