Detection of Parkinson's Disease using Extreme Gradient Boosting

L. V. Rajani Kumari,
Department of Electronics and Communication Engineering, VNR Vignana Jyothi Institute of Engineering &Technology,
Hyderabad, TG, India.
rajanikumari_lv@vnrvjiet.in

Mohammad Aatif Jaffery,
Department of Electronics and Communication Engineering, VNR Vignana Jyothi Institute of Engineering &Technology,
Hyderabad, TG, India.
aatifjaffery_md17@vnrvjiet.in

K. Saketh Sai Nigam,
Department of Electronics and Communication Engineering, VNR Vignana Jyothi Institute of Engineering &Technology,
Hyderabad, TG, India.
saketh1506@gmail.com

G. Manaswi,
Department of Electronics and Communication Engineering, VNR Vignana Jyothi Institute of Engineering &Technology,
Hyderabad, TG, India.
reddymanaswi696@gmail.com

P Tharangini,
Department of Electronics and Communication Engineering, VNR Vignana Jyothi Institute of Engineering &Technology,
Hyderabad, TG, India.
tharangini15253@gmail.com

Abstract—**Parkinson's disease is a brain-related disease that is common in every person mainly persons above age 45 years. This disease causes numbness in muscles, swallowing problems, bending of the back, shivering in hands, smell dysfunction, speaking problem, Hearing problem, and many more. Parkinson's disease has to be diagnosed as early as possible since the clinical tests, which take hours to detect, may cost a loss of time and money. An automated model for detecting Parkinson's disease in a person with greater accuracy is proposed in this paper. While several models for detecting Parkinson's disease have been established, they are all less reliable and precise. Our model is created using the gradient boosted decision tree, which not only reliably predicts Parkinson's disease in a human, but also predicts it quickly. The feature set contains 22 parameters of the voice signal, which are given to the XGBoost classifier. The developed model predicts Parkinson's disease with 96.6% of accuracy, 95.6% of sensitivity, 100% of specificity, 100% of Precision, F-Score 97.7%.**

Keywords—Parkinson's disease, Detection, Gradient boosted decision tree, Voice signal, XGBoost classifier

I. INTRODUCTION

The growing auditory clutter is a Parkinson's disease. The first symptom is a snag in the movement phase. Dopamine is a gleaming, coordinated muscle in the body that is moved by brain chemicals and a drug found naturally in the human body. It's a neurotransmitter, which means it carries impulses from the body to the brain. It influences a person's gestures and psychic reaction. The cells of the substantia nigra continue to die in patients with this condition, resulting in a drop in dopamine levels. Parkinson's signs tend to occur when the scale is between 60% and 80%. According to a few experts, toxins can induce Parkinson's disease. The bigger the dopamine molecule, the more it controls disease of Parkinson's. In the brains of Parkinson's affected patients, there are isolated Lewy bodies. The fundamental frequency variations, amplitude differences, and nonlinear measurements are all called speech parameters, but many researchers are unsure what role these bodies play. In normal speech experiments, electroglottographic signals are often used to measure variation of behavioral and cognitive intensity, differential amplitude of speech (shimmer), speed, and nonlinear zestful parameters. For further pattern classifications using attribute mixture techniques, the most peculiar vocal parameters must be selected. This paper examines the sensitivity of existing standards and traditional diagnostic approaches by distinguishing between healthy patients and Parkinson's disease (PD). They introduce a "Pitch Period Entropy" alternative dysphonic measure, which is useful in dealing with certain unmanageable confounding effects such as distorted acoustic environments and true, steady voice frequency shifts. Significant phonations have been collected from 31 individuals, 23 of whom are PD. In a thorough examination of all possible combinations of these measures, we chose ten highly unrelated measures and discovered four that, when combined, resulted in a correct overall classification score of 91.4 percent [1]. Speech signal analyses are critical in identifying dysphony and associated phonation issues. This paper provides a description of the relationships between 22 different speech characteristics, signal amplitude variations, and some nonlinear measures [2]. In order to assess nonlinear dynamics in continuous vowel sounds, certain nonlinear and entropy parameters were measured for Parkinson's disease patients and control subjects in speech trials. Studies of disabled speech and phonation in Parkinson's disease patients have shown a substantial improvement in auditory signal sophistication in terms of fractal measurements and time entropies [3].

Changes in Parkinson's disease patients' voices are found in all speech subsystems, phonatory and joint. Despite this, voice research has more accurate and repeatable results than clinical analysis. Acoustic voice analysis can also be used to more accurately describe voice disturbances in Parkinson's disease patients, as well as to estimate improvements in voice tone caused by the disease. Historically, Parkinson's disease patients with articulation and fluidity problems have difficulty expressing themselves [4]. According to the article cited in [5], the research performed by doctors and experts in the early

diagnosis and control of dysarthria would increase patients' quality of life and assess the efficacy of therapies. They looked into the link between speech signal and Parkinson's affected patients speech patterns.

The syndrome may cause problems with simultaneous or concurrent motor movements, as well as impair intelligibility. After the disorder has begun, humans with Parkinson's disease undergo changes in their language ability. Patients may experience visible language abnormalities, such as dysarthria, which include tedious and diminished vocal tone, short bursts of sound, inexact consonants, joint and prosody [6]. An author exposes the connection between a person suffering from Parkinson's disease's seriousness of speech and Parkinsonian dysarthria in a cited paper [7]. There is a strong link between labial pain, speech volume, and disease length. Multiple speech exercises, as described in the report, can be used to determine the degree of speech and voice disabilities in Parkinson's disease. Talking to validate the level of PD speakers, including lifelong phonation, rapid syllables, and variable readings of short sentences, longer passages for diagnosis, and learning about Parkinson's people's speech actions [8].

Shock, trouble walking, gaiting, and communication are the most noticeable motor manifestations. Sensory system, sleep, and emotional symptoms Though treatment reduces the number of symptoms, there is currently no causal solution, and early diagnosis is important to optimize medication effectiveness and improve the patient's quality of life [9]. Voices have been shown to be azoic markers of Parkinson's disease in several studies. The question in this research is whether Parkinson's disease immediately impairs a person's speech or expression. Sustainable phonations, syllabus repetitions, translated texts, and monologues are features that use vocal signals, viral features, and functionalities extracted from a two-weighted model of vocal folds on various types of speech tests [10].

Since our bodies use dopamine to regulate muscles, a decrease in dopamine in the bloodstream makes it more difficult to control motions, actions, and sensations, which can also cause tremors and numbness in the extremities. Neurologists classify Parkinson's disease as a neurodegenerative syndrome that involves problems with muscle function, such as walking and balancing [12]. Parkinson's disorder can be identified using speech examination at an earlier stage when the person's voice improves at an earlier stage. Speech qualities noticeable in Parkinson's disease voice include a 10 decibel decrease in voice pitch, whispering, breathiness, tremors, and shifting to higher tones [13]. The focus of this paper was on evaluating and evaluating speech disorders in the cepstral region using coefficients extracted from the Perceptual Linear Prediction model (PLP). This technique was traditionally used in speaker identification and tracking applications [14]. In certain important speech processing systems such as voice understanding, speaker recognition and speech coding, the ability to remove all characteristics of the vocal tract and the signal generator independently are beneficial [15]. The feature formation studies the creation of new functionality through the projection to a lower dimension of raw data from the ordinary feature space. The goal is to represent less featured data while maintaining the ability to discriminate [16]. The clinical-perceptual method was used in this research to further investigate the nature of Parkinsonian speech disabilities by analyzing the speech deficit profiles (voice, articulation, and fluency) of a cross-section of speech affected patients with Parkinson's disease. They recorded the voices of 200 patients and categorized their total speech function into five intensity categories [17]. Orozco reached a 60 percent accuracy by using the multi-taper Thomson windowing method to identify Parkinson's disease by Mel-frequency cepstral coefficients extraction and the Mel-frequency cepstral coefficients extraction coefficient as recognition accuracy. Combining the Mel-frequency cepstral coefficients extraction and the SVM on a database of 17 stable patients and 17 Parkinson patients resulted in an accuracy of 80 percent [18]. Disorders are also detected using artificial neural networks [19,20].

The structure of the paper is given as follows: Section 2 explains the new work and its novelty. Section 3 presents the findings, as well as a comparison of existing approaches. Section 4 concludes the paper.

II. MATERIALS AND METHODS

A. Dataset

The UCI Machine learning library was supported by Oxford University and the National Voice and Speech Centre. This data set includes 31 subjects, 23 Parkinson's disease patients, and other biomedical speech trials (PD). Each column represents a different aspect of a tone, and each row refers to one of the 194 voice records. Each column reflects a sound characteristic that corresponds to one of the 194 speech records in each row. The data mostly helps to distinguish between stable and Parkinson's disease (PD) patients by using the 'Status' column, which sets the number for 0 in healthy people and 1 in PD patients. The data is available in ASCII CSV format. Each row of the CSV file contains a single speech event. The name of the patient appears in the first column, which contains approximately six reports per patient [11].

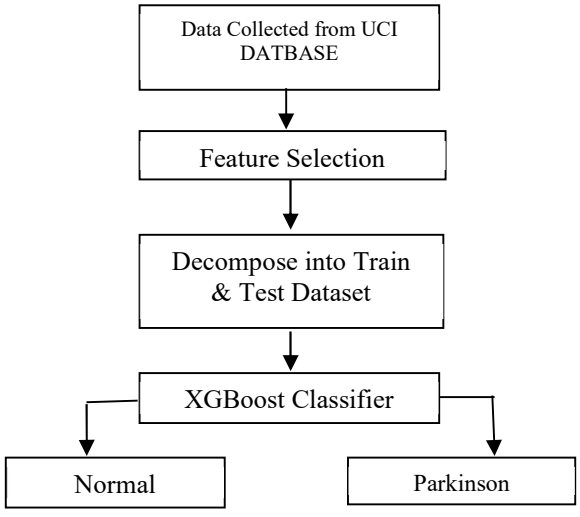

Fig. 1. Flow chart of our model to predict Parkinson's disease.

The figure.1. First downloaded from the UCI Machine Learning Repository, the data collection consists of 195

row and 24 columns with each column containing the calculation of individual voice parameters and a status column that distinguishes the average person from the Parkinson's affected person. This dataset contains 147 Parkinson's patients and 48 non-Parkinson's patients, so it is divided into 70% for training and 30% for testing. There are 101 Parkinson's affected rows and 35 non-affected patients rows Parkinson's in the training dataset, for a total of 136 rows out of 194 provided to the Classifier for training the model. There are 46 Parkinson's affected rows and 13 non Parkinson's rows in the testing dataset, for a total of 59 rows out of 194 provided to the classifier for testing the model.

The XGBoost Classifier employs four algorithms: the Exact Greedy Algorithm, the Estimated Algorithm, the Weighted Quantile Sketch, and the Sparsity Aware Split Finding.

Exact Greedy Algorithm goes through all of the potential splits on all of the functions. Enumerating all feasible breaks for continuous features is computationally demanding. But the exact greedy algorithm is highly efficient as it lists gullibly all conceivable division points. However, it is impossible to do this successfully because the data does not entirely fit into the memory. The Approximate Algorithm proposes that candidates divide points based on percentiles of feature distribution. Then the algorithm breaks the features into buckets which are specified by the candidates' points, adds the statistics and selects from the proposals the best solution based on aggregate statistics. Proposing candidate split points is a critical step in the approximate algorithm. To efficiently manage weighted results, XGBoost employs a distributed weighted quantile sketch algorithm. It is very normal for the input x in many real-world problems to be sparse. Sparsity can be caused by a variety of factors, including:

The info contains missing values.

In numbers, there are a lot of zero entries.

One-hot encoding is an example of a feature engineering artefact.

It is critical to inform the algorithm of the sparsity trend in the results. Both sparsity patterns are handled uniformly by XGBoost.

B. XGBoost Classifier

XGBoost is a fine-tuned distributed gradient boosting library that is logical, structured, scalable, and portable. Under the Gradient Boosting paradigm, it runs deep learning algorithms. XGBoost uses parallel tree boosting (also known as GBDT, GBM) to quickly and accurately solve a variety of data science problems. On a large amount, the homogeneous code darts Hadoop, SGE, and MPI are examples of distributed environments that could solve problems with billions of examples. Extreme Gradient Boosting (XGBoost) is an open-source version of the gradient boosted trees algorithm. It has become one of the most popular techniques in machine learning in Kaggle competitions because of its ability to forecast and easily use it. The algorithm for regression and classification is monitored. Despite its futuristic moniker, It is not difficult to learn if we first understand two concepts: decision trees and gradient boosting. Decision trees are arguably the most readily interpretable machine learning algorithms available, and when used in conjunction with the right techniques, they can be very effective. A decision tree gets its name from its optical form, which resembles a tree with a base and several branches nodes and leaves are the nodes and leaves of a tree. So at iteration n equation (1) means that the following objective function must be minimized (loss function and regularization):

$$\boldsymbol{K^{(n)} = \sum_{j=1}^{m} \left| y\left(p_j, p_j^{(n-1)}\right) + g_n(q_j) \right| + \Omega(g_j)} \quad (1)$$

It is obvious that the XGBoost goal is functional (i.e. y is a function of CART learners).

As an example, for a function ***g(y)*** at point t, the best linear approximation is:

Take as an example in the equation(2) the shortest linear approach to Function g.

$$\boldsymbol{g(y) = g(t) + g'(t)(y - t)} \quad (2)$$

The "trick" here is to use Taylor's theorem to turn a function ***g(y)*** into the simplest function of $\boldsymbol{g}$ around a certain point ***"t"***.

Equation (3) can be written as the objective (loss) function, as a simple function of the current additional student, using the above of each iteration n.

As previously said, t represents the prediction made at step (n-1) and ***(y-t)*** represents the new learner that must be added in step (n) in order to greedily minimize the target.

$$\boldsymbol{g(y) = g(t) + g'(t)(y - t) + (1/2)g'(t)(y - t)^2} \quad (3)$$

So, on rewriting equation 1 we get equation (4) :-

$$K^{(n)} = \sum_{j=1}^{m} \left| y(p_j, p_j{}^{(n-1)}) + l_j g_n(q_j) + \left(\frac{1}{2}\right) m_j (g_j(q_j)^2) \right| + \Omega(g_j) \quad (4)$$

Where,

$$\boldsymbol{l_j = \partial(p(n-1))y\left(p_j, p_j^{(n-1)}\right)} \text{ And}$$
$$\boldsymbol{m_j = \partial^2(p(n-1))y\left(p_j, p_j^{(n-1)}\right)}$$

Finally, by removing the constant pieces leaves us with the following simpler goal to achieve at stage n we get equation (5):

$$\boldsymbol{K^{(n)} = \sum_{j=1}^{m} \left| l_j g_n(q_j) + \left(\frac{1}{2}\right) m_j (g_j(q_j)^2) \right| + \Omega(g_j)} \quad (5)$$

C. Feature Extraction

The phonation data collection provided contains a total of 22 vocal characteristics. The meanings of the roles are defined in Table (I). We have designated an average, maximum, and minimum fundamental vocal frequency (in Hz), as defined by the Kay Pentex, with the abbreviations MDVP:F0, MDVP:Fhi, and MDVP:Flo, respectively, for the purposes of presenting speech interruption . MDVP:jitterh two values one is proportions and other is gross jitter values (Absolute). For MDVP:PPQ and MDVP:RAP, the MDVP specifies the five-point disturbance quotient and relative degree perturbation

features. The average absolute deviation of jitter cycles is represented by the Jitter:DDP ratio. The shortcuts Shimmer has two values one is APQ 3 and APQ 5 which is nothing but the three-point and five-point shimmer destructive quotient values, respectively. The disorder quotient value of an 11-point magnitude is MDVP:APQ11. Shimmer: DDA is the average absolute difference between constant amplitudes. NHR and HNR are abbreviations for the noise-to-harmonics acoustic signal ratio and the harmonic-to-noise ratio, respectively. Nonlinear characteristics include correlation (D2), recurrent density entropy (RPDE), trended fluctuations regression (DFA), and entropy pitch intervals, to name a few (PPE). Spreads 1 and 2 are up against two nonlinear simple frequency variance scales.

TABLE I. FEATURES AND ITS DESCRIPTION OF VOICE SIGNAL MEASURENTS

Features	Description
MDVP: F0 (Hz)	Fundamental frequency of speech on average.
MDVP: Fhi (Hz)	The fundamental pitch of the voice at its highest.
MDVP: Flo (Hz)	The fundamental pitch of the voice should be as low as possible.
MDVP: Jitter (%)	MDVP jitter expressed as a percentage
MDVP: Jitter (Abs)	MDVP absolute jitter in milliseconds.
MDVP: RAP	Modification of the relative amplitude of MDVP.
MDVP: PPQ	The five-point duration perturbation quotient of MDVP.
Jitter: DDP	The average absolute variance between jitter intervals.
MDVP: Shimmer	MDVP shimmer on the local level.
MDVP: Shimmer(dB)	MDVP local glow in decibels (dB).
Shimmer: APQ3	The amplitude perturbat-ion quotient at three points.
Shimmer: APQ5	The amplitude perturbat-ion quotient at five points.
MDVP: APQ11	The 11-point amplitude perturbation quotient of MDVP.
Shimmer: DDA	The average absolute difference in the amplit-udes of successive phases.
NHR	Ratio of noise to harmonics.
HNR	The ratio of harmonics to noise.
RPDE	The density entropy of recurrence periods is a measure of entropy.
D2	Dimension of correlation
DFA	Exponent of signal fractal scaling in detrended fluct-uation analysis.
Spread 1	Two nonlinear fundamental tests.
Spread 2	Variation of frequency.
PPE	Entropy of pitch duration.

The validation test algorithm is tested at each stage, the machine learning parameters are modified, and the model is iterated again for the testing dataset with revised parameters. Before validation and training parameters are set, the procedure is repeated to ensure the model performs better. In order to estimate the precision and failure of the algorithm, the finished Parkinson Prediction model is tested on the test data set separate from the actual data set. Finally, the built in model is converted to binary format before being stored in real-world applications for testing and use.

III. EXPERIMENTAL RESULTS

The UCI Machine Learning library contains a total of 194 registered speech signals with 23 voice measures for detecting Parkinson's disease. In evaluating the

performance of the Parkinson's Disease detection model, the following parameters were taken into account:
Confusion matrix is a table that shows how well a classification model (or "classifier") does on a set of test results on which the actuality values are defined. The uncertainty matrix itself is deceptively easy to understand, but the associated words can be perplexing. True positives (***Tp***) are a type of false positive. There are cases where we can say yes (they have the disease) and yes (they have a problem) based on the evidence. True negatives (***Tn***): We expected that they would be pessimistic and that they would not have the disorder. False positives (***Fp***): We expected yes, but the disease will not be present. False negatives (***Fn***): We hoped the values would not be negative, but they are. The Confusion matrix is a noticeable method may be a good place to start when it comes to adding classification metrics. The way one details the confusion matrix's row- and column-axes can differ depending on the domain.

$$Accuracy = \frac{T_p+T_n}{T_p+T_n+F_p+F_n} \quad (6)$$

Precision is defined as the percentage of correctly identified positive labels **(*Tp*)** out of all expected positive labels **(*Tp* + *Fp*).** Precision is a glorious measure when it comes to minimizing false-positives when less FP produces extreme precision (e.g., a spam filter misidentifies legitimate emails

as spam). When positive cases are scarce, however, accuracy solitary is insufficient notify us if there are so many false negatives.

$$Precision = \frac{T_p}{T_p + F_p} \quad (7)$$

In contrast, remember that the proportion of positive labels accurately identified ($\boldsymbol{Tp} + \boldsymbol{Fn}$) ($\boldsymbol{Tp}$). We can see right away that a classifier with more false-negative counts has a fault in the recall score production. When false positives are a priority (e.g., checking for a deadly contagious disease; a false negative will convey a message to the patient), the recall value is a source of joy patient is sent home without receiving prompt treatment).

$$Sensitivity = \frac{T_p}{T_p + F_n} \quad (8)$$

The specificities of all negative labels ($\boldsymbol{Tn} + \boldsymbol{Fp}$) are classified as the proportion of correctly identified negatives ($\boldsymbol{Tn}$).

$$Specificity = \frac{T_n}{T_n + F_p} \quad (9)$$

F1-score, which is the mean (refresher: mean value gives lower values a better weighting) of precision and recall, is the go-to metric for assessing classifiers when both precision and recall are significant [23].

$$F1 = \frac{2}{\left(\frac{1}{Precision} + \frac{1}{Sensitivity}\right)} = 2 * \frac{(Precision * Sensitivity)}{(Precision + Sensitivity)} \quad (10)$$

TABLE II. CONFUSION MATRIX OF PROPOSED MODEL

	Actual Value	
Predicted Value	$T_p = 13$	$F_p = 0$
	$F_n = 2$	$T_n = 44$

TABLE III. PERFORMANCE PARAMETERS OF PROPOSED MODEL

Performance Parameter	**Obtained Value**
Accuracy	96.61%
Sensitivity	95.6%
Specificity	100%
Precision	100%
F-Score	97.7%

TABLE IV. COMPARISION OF PERFORMANCE PARAMETERS OF PROPOSED MODEL WITH OTHER'S PROPOSED MODEL

Authors	**Parameters of Performance**				
	Accuracy	***Sensitivity***	***Specificity***	***Precision***	***F1 Score***
Little, M. A., McSharry, P. E., Hunter, E. J., Spielman, J., & Ramig, L. O. [1]	91.4%	84.36%	91.5%	-	-
Yunfeng Wu, Pinnan Chen, Yuchen Yao, Xiaoquan Ye, Yugui Xiao, Lifang Liao, Meihong Wu, and Jian Chen. [2]	90%	95.58%	84.37%	-	-
Bocklet, T., Noth, E., Stemmer, G., Ruzickova, H., & Rusz, J. [13]	68.04%	75.34%	45.83%	80.88%	78.01%
Our Proposed Model	96.61%	95.6%	100%	100%	97.7%

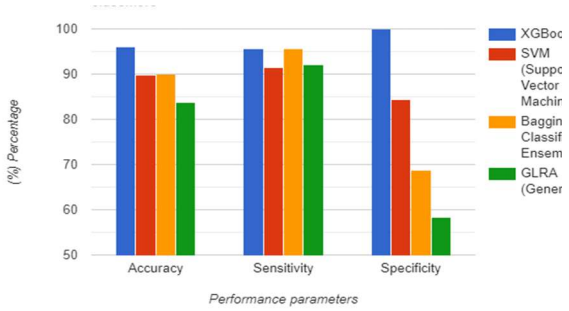

Fig. 2. Comparision of performance parameters of our proposed model classifier with other model classifier's.

Table II shows the confusion matrix of our proposed model this matrix plays a vital role in extracting other performance parameters of our model this confusion matrix, for testingthe model about 59 rows of dataset is

taken in which 46 rows are parkinson's patients dataset and 13 are normal person dataset.
The performance parameters in Table III has the values that are obtain from our proposed model.
The Table IV is the comparision of performance parameters of our model with other reference model's.
Figure 1 indicates a higher result than the current classifiers in the proposed model.

IV. Conclusion

For improved Parkinson's disease diagnosis in sufferer's voice signals, the most reliable, finest Machine learning model in which classifier XGBOOST has been used is developed for predicting the disease. The results were compared to those of other approaches, with a dataset of 22 voice signal measurements which are drawn from the UCI machine learning database.
The developed model has 96.61 percent accuracy, 95.6 percent recall, 100 percent precision and sensitivity, and a 97.6 percent F-score. At the end the result obtain for the Parkinson's disease prediction model could be used to diagnose Parkinson's disease more reliably and easily, potentially aiding in the disease's early detection.

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