A Nature Inspired Algorithm for Parkinson's disease Prediction through Speech Signal

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Abstract:

Neuro Degenerative Diseases (NDD) are rapidly evolving, and the victims gets increasing. It is estimated that the NDD victims have doubles during the past decade. NDDs can be prioritized and in which Parkinson's Disease, Alzheimer's Disease and Dementia are the more prominent ones. Notably, the victims of PD are not aware of it until the symptoms gets severe. This is because there is no specific test for PD hitherto. The available tests are not up to the mark. Hence research in the field of early detection of PD is imperative. In this research work we employ Speech Signals (SS) for early detection of PD. The SS is packed with several medical information. To decipher the SS would help in early detection of PD. The proposed method involves transformation of SS using Discrete Wavelet Transform (DWT). The transformed signals is preprocessed using Hamming window. Then, the vectors of twenty-one features of SS are obtained. These obtained features are selected using the proposed algorithm. Finally, the classification is done using Support Vector Machine (SVM). The feature selection is done using the Cosmic Inception based algorithm. The concept is allured from the Big Bang Theory (BBT) and the Theory of Cosmic Inflation. The concept underlying BBT is that the maximum Bang happened during the Plank's time. Also, after a maximum phase we initiate Big Crunch Phase which inverses the expansion and hence moving the cosmic particles in reverse direction towards Plank's time. The pareto optimal front is obtained in the Plank's time and it is taken as the optimal solutions. In this way, the optimal features are selected, and they are classified using SVM. The experimental results provided convincing results compared to other diagnostic methods of PD

Key words: Nature Inspired Computing, Predictive Science, Parkinson's Disease Prediction

1. Introduction:

Neuro Degenerative Diseases are very common and the victim of is rapidly increasing. The reasons are primarily due to the lifestyle and the dietary style adopted by people. Neurological Diseases in India have escalated from 4% to 8.2% during 1990-2019 [1]. India accounts for about 0.58 million [2] to non-communicable neurological diseases which eventually end in Parkinson's Disease (PD), Alzheimer's Disease (AD) and Dementia. PD is a brain disorder that leads to shaking, stiffness and difficulty with walking, balance, and coordination. Parkinson's symptoms usually begin gradually and get worse over time. As the disease progresses, people may have difficulty walking and talking. They may also have mental and behavioural changes,

sleep problems, depression, memory difficulties and fatigue. This disease cannot be diagnosed very earlier and if it is so, it could be cured with medications. One of the important analysis tools for the diagnosis of PD and AD is Speech Analysis of the victim. Vocal impairment in pertinence to PD is called *dysphonia* which is analysed. PD is caused by the degeneration of the nerve cells in the substantia nigra part of the brain which produce a chemical called 'Dopamine'. Subsequently, this dopamine is responsible for the coordination of body movements. Whence the amount of dopamine is reduced considerably, the locomotion becomes faded eventually leading to PD. The degenerative process of nerve cells whence affected by PD is very gradual. Most symptoms develop in the victim after 80% of the nerve cells are degenerated. Reportedly there are no specific tests for detecting PD [3]. Imaging tests too are not helpful in the diagnosis of PD. Notably, the speech of the victim of PD is altered [4]. Hence the victim may slur certain words, mumble, or trail at the end of a sentence. An experienced physician may diagnose the victim through a one-to-one conversation. Subsequently, automating the diagnosis process by a system was a tedious process previously. But, advancement in the field of computing using Artificial Intelligence (AI) Models and highly sophisticated Multi Objective Optimization (MOO) tools in mathematics have paved the way for developing an automated system for the early detection of PD. This paper aims to design a tool that would diagnosis PD using speech signals. The system uses Naturally Inspired Algorithms for the feature selection phase. A novel Big Bang algorithm is proposed which takes its inspiration for the inception of the cosmos. Interestingly, we use SVM which classifies the processed signals for the detection of PD. A Graphical User Interface (GUI) is developed for the ease in detection of PD. Section two briefs the theoretical background of the proposed design. Section three provides some information about the previous anthologies used for the detection of PD and other NDDs. Section four portrays the proposed Big Bang inspired algorithm and its mathematical formulations. Also, it adds the proposed methodology employed for the early detection of PD. Section five projects the results obtained and gives a detailed interpretation on it. Finally section six informs the possible way ahead for increasing the effectiveness of the proposed design.

2. Theoretical background

The SS contains several medical information contained in it. However, extraction of the information requires high end computing, sophisticated machine learning methodologies and advanced optimization techniques.

- To Design a framework for the early detection of Parkinson's disease using Multi Objective naturally inspired algorithms using speech signals.
- To devise a naturally inspired algorithm based on the traits of Lion and Big Bang (BB) and employ it in the Feature selection of speech signals of PD victim.
- To Model an Adaptive Support Vector Machine for the Classification of Speech Signals of PD victims.

In order to simulate the proposed methodology, data sets which were used in [5] are used. The mentioned data set holds data of 34 patients affected by PD and also it contains 18 healthy patients. It was noted that, the vowel 'a' is pronounced using the sampling frequency 44.100 Hz. The vocal have been recorded in stereo mode and processed in .wav format. From the windowed signal $a_1(t)$, the features were extracted.

2.1 Feature Extraction Process

The features of the SS are extracted and processed to obtain the various parameters. It involves DWT, the features of time domain energy and Zero Crossing Rate (ZCR), Mel Frequency Cepstral Coefficient (MFCC), Shannon Entropy decompositional features and such.

2.2 Discrete Wavelet Transform:

One among the major process in the extraction of features is the DWT. It is done by discretization the scaling and shifting parameters in the continuous wavelet transform. Mathematically,

$$w_s(a,b) = \frac{1}{\sqrt{a}}\int_{-\propto}^{\propto} s(t).\omega * \left(\frac{t-x}{y}\right) dt \tag{1}$$

In the above equation (1), the $\omega(t)$ is the mother wavelet and $\omega *$ is the complex conjugate. Also to be noted that 'x' is the scaling factor for the signal *s(t)* and *'y'* is the transition parameter. In addition, formant frequency is also considered as the frequency character. In a given speech spectrum, the formant frequency would be noted as a keen peak which in turn represents the vocal's resonant frequency. The information for figuring out the difference is quantitatively observed in the amplitude or frequency spectrum.

2.3 Time Domain Energy and ZCR:

For the given samples, the time domain energy is calculated by summing up the square of individual samples. Mathematically,

$$\text{Energy} = E_n = \sum_{n=1}^{N} |x(n)^2| \tag{2}$$

In addition, to calculate the Zero Crossing Rate, the rate of change of signal's sign during the frame is computed from the lower extreme to the maximum divided by the total length. Mathematically,

$$\text{ZCR} = \frac{1}{N}\left[\sum_{n=1}^{n-1}(x(n+1) - x(n))\right] \tag{3}$$

Where n is the length of the windowed frame.

2.4 MFCC

It is common in the SS processing that most of the computation is done in the cepstrum domain. It is just because of the convolution of the source by the vocal tract. This convolution produces a product that makes it difficult to distinguish between the contributions of the source and the conduit. Cepstral analysis can solve this problem by passing through the log spectral domain [6]. MFCC analysis involves utilising the features of the human auditory system by converting the linear frequency scale to the Mel scale. The conversion of linear scale to Mel Scale is done by the eqn. (4)

$$\text{Mel}(f) = 2595 \times \log\left(1 + \frac{f}{700}\right) \tag{4}$$

2.5 Shannon Entropy Decompositional Features

Shannon Entropy Decompositional Features are applied after the extraction of the vector ($a_m, d_m, d_{m-1}, \ldots d_1$). In general, the Shannon entropy decompositional features are usually incorporated to express the degree of confusion in a given system. It is like, the more orderly the system is, the lesser its entropy will be. Shannon Entropy Decompositional Features 'H' is defined as

$$H = \sum_{j=1}^{J} P_j \, log_2(P_j) \tag{5}$$

3. Previous anthologies

One of the first studies on speech signals for PD detection was conducted by [7], who explored the use of a nonlinear dynamical systems approach for PD detection. The authors discovered that vocal tremor was a robust predictor of PD and could be used as a diagnostic marker. Since then, several studies have investigated the use of different acoustic and prosodic features for PD detection. Acoustic features refer to the physical properties of sound, such as pitch, loudness, and duration, while prosodic features refer to the patterns of stress and intonation in speech. [8] investigated the use of prosodic features for PD detection and found that pitch was the most important feature for distinguishing between PD patients and healthy controls. The authors [9] proposed a method for PD detection using a combination of acoustic and prosodic features and found that the accuracy of PD detection improved with the addition of prosodic features.

Spectral features, such as Mel-frequency cepstral coefficients (MFCCs), have also been explored for PD detection. It was found [10] that a combination of spectral features and machine learning algorithms improved the accuracy of PD detection. Convolutional neural networks (CNNs) have also been used for PD detection using speech signals. The authors [11] proposed a method for PD detection using speech signals and CNNs, and found that the CNN achieved high accuracy in distinguishing between PD patients and healthy controls.

Deep learning techniques have also been investigated for PD detection using speech signals. Aujla et al. [12] used a dataset of speech samples from PD patients and healthy controls and trained a deep neural network to classify the samples. Their results showed high accuracy in distinguishing between PD patients and healthy controls. Zhang et al. [13] investigated the use of deep learning techniques for PD detection using a large dataset of speech samples from PD patients and healthy controls. The authors trained a convolutional neural network to classify the samples and found that the network achieved high accuracy in distinguishing between PD patients and healthy controls.

One limitation of many studies on speech signals for PD detection is the small sample sizes used. However, recent studies have used larger datasets to train and test their models. Raghavendra et al. [14] proposed a novel approach for PD detection using vocal signals and artificial intelligence techniques. The authors used a dataset of speech samples from PD patients and healthy controls and extracted several acoustic features for classification using a neural network algorithm. Their results showed high accuracy in distinguishing between PD patients and healthy controls.

Another limitation of many studies is the use of speech signals collected in controlled laboratory settings. However, several studies have investigated the use of speech signals collected in naturalistic settings for PD detection. Gravina-Dominiak et al. [15] used a dataset of speech samples collected from PD patients and healthy controls in a naturalistic setting and found that the accuracy of PD detection was comparable to previous studies that used speech signals collected in a laboratory setting.

Speech signal analysis has emerged as a promising method for PD detection, providing objective and quantitative measures of speech impairment. Several studies have investigated the use of different acoustic and prosodic features, as well as machine learning algorithms, for PD detection.[16] While there are limitations in terms of small sample sizes and controlled laboratory settings in some studies, recent research has addressed these issues with larger datasets and speech signals collected in naturalistic settings. Overall, the results suggest that speech signal analysis can provide an effective and non-invasive method for early detection and monitoring of PD, which could significantly improve the quality of life for patients. [17] Further research is needed to optimize the selection of features and algorithms for PD detection and to validate these methods in larger and more diverse populations.

4. Feature Selection : Proposed Big Bang Algorithm

The Big Bang is the formulation of cosmological model of this universe. This model is widely accepted for its convincing mathematical interpretation for the inception of this cosmos. Physicists compute the Big Bang (BB) from the observable Cosmic Microwave Background (CMW). The basic ideology behind BB is that the universe was once dense and extremely hot and once after there was a bang, the particles were shattered in the space in every direction. [18] These hot elements then gradually cooled down to form the sub-atomic particles in the cosmos. These sub-atomic particles mostly consisted of the Helium and Hydrogen atoms which could cooldown and coalesced through gravity to form the stars, galaxies and everything which exists today as heavenly bodies. [19] In this thesis, we attempted to pry into the cosmic formation and the theory of inflation and thus to devise an algorithm which would provide an optimality for a given problem. BB algorithm depicts that most of the so formed celestial bodies which are hovering in the space are positioned optimally so that there isn't any bang or damage further. That seems to be the motivation behind prying unto BB for optimization problems. Theory of inflation is also studied and incorporated in the proposed algorithm where based on the cosmological constant, the universe inflates. However, after a particular density, there would be a Big Crunch which initiates the symmetric contraction of the universe.

The proposed Big Bangs Inspired Algorithm (BBIA) involves around the inception of the universe from singularity, and it also invokes the idea of BC occasionally for better convergence. The maximum solutions were thrown during the plank time which is also mimicked in the BBIA.

The process involves several stages (i) Initial population generation, (ii) The Big Bang, (iii) Calculation of Centre of Mass, (iv) Inflation Phase, (v) The Big Crunch (vi) Stopping Criteria.

Initially, a feasible solution is calculated from where the algorithm begins. This feasible solution is generated using a random function. [20] The feasible solution is not the optimal solution but it is approximation of the optimal solution. Next, another group of solutions named the initial population is generated with reference to the initial feasible solution. The initial population is group of solution and it is fixed to be 1000. However, this solution set can vary according to the user requirement. But it has to be noted that higher the initial population, higher is the computational time. Hence the initial population is placed in an optimal number.

Once after the feasible solution is set, the other generated population is thrown in the search space and this process is termed as the BB phase. [21] The solutions are thrown in a random manner. The process is initiated by a random function**.**

After the BB phase, the centre of mass of the solutions which is the cost function is calculated. Based on the calculated cost, the one which is near to the plank's time is set as the centre of mass. And based on this point, all the solutions revolve. Once the centre of mass is calculated, the immediate phase is the inflation phase. The inflation happens based on the cosmological constant. The value of cosmological constant is positive during this phase and the solutions evolve as new solutions in a new location.

After a while, (say 1000 iterations of Inflation), the inflation phase reverses, and deflation occurs. This is called the Big Crunch phase where the cosmological constant or the scaling factor is negative. All the solutions tend to move towards the centre of mass position.

Once after a 1000 iteration on whole, the process is stopped and the solutions which are in the plank time are tabulated as the optimal solutions. [22] The reason is because, based on BB theory, maximum expansion took place at plank's time and hence we choose to select the solutions in the plank time.

5. Mathematical Modelling

The initial solutions are created by using the formula in equations

$$|\mathbf{x}-\mathbf{x_0}| \leq \mu \tag{6}$$

$$\sqrt{(\mathbf{x_1}-\mathbf{y_1})^2+(\mathbf{x_2}-\mathbf{y_2})^2+\cdots+(\mathbf{x_n}-\mathbf{y_n})^2} \leq \mu \tag{7}$$

Where μ is a very small positive number. And x_0 is the initial solution.

After the BB, every solution undergoes the inflation phase and the position of the solutions will be modified as in equation

$$\mathbf{x_{k+1} = x_k + \delta d_{ok}} \tag{8}$$

d_0 is the vector from x_0 to x_k, such that;

$$0 < d_{0k} \leq \mu \text{ and } 0 \leq \boldsymbol{\delta} \leq \infty. \tag{9}$$

The state of the $\boldsymbol{\delta}$ will be as follows,

$$\mathbf{x_{k+1} \leq x_k + \delta d_{ok}} + \mu \tag{10}$$

Hence x_{k+1} will be changed. However, the changes should not be small in BB and hence,

$$\mathbf{x_{k+1} \geq x_k + \frac{j}{n\mu} d_{ok} = x_k + \frac{j}{n\mu}} \mu = \mathbf{x_k + \frac{j}{n}} \tag{11}$$

'n' can be varied and it is assumed to be 10 as in this case.

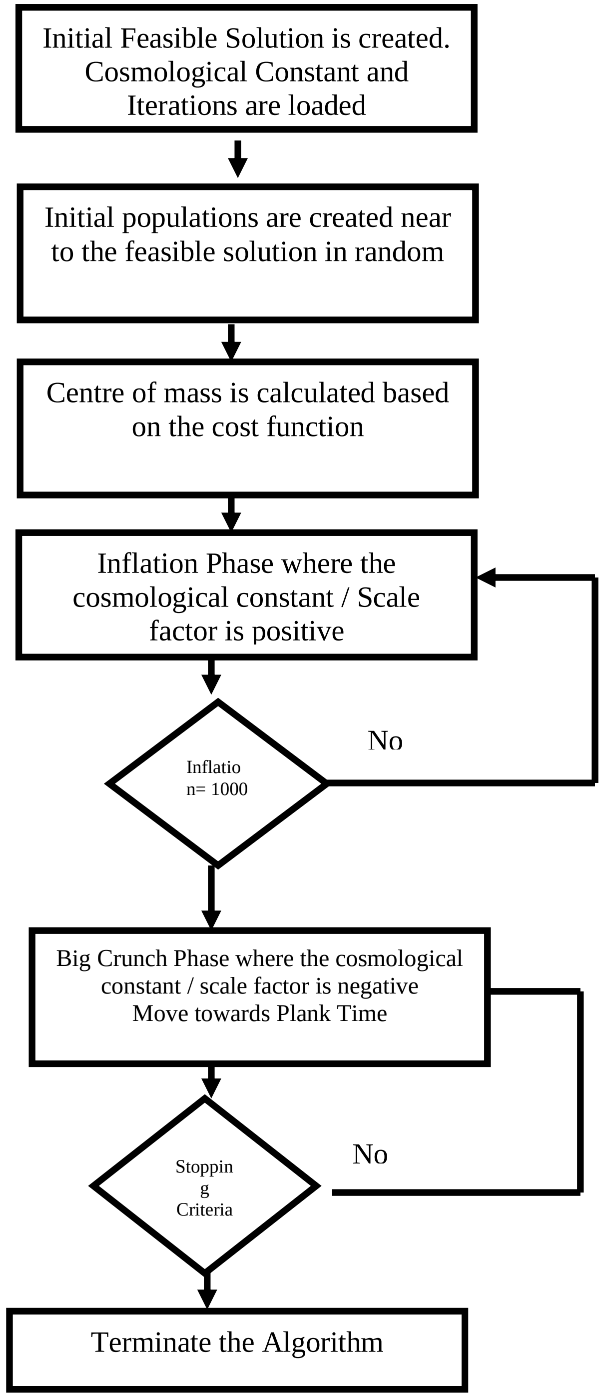

Fig. 1 Flowchart of Big Bang Algorithm

Step1: The initial feasible solution set is created ($x_{01}, x_{02}, \ldots. x_{0n}$). The number of solutions, cosmological constant μ is set and the number of iteration is loaded.

Step 2: Initial population is generated in random near to the feasible solution. And the centre of mass is calculated for the solutions based on the cost function.

Step 3: The solutions undergo a inflation phase where the expansion is governed by equation and the solutions set is updated from ($x_{01}, x_{02}, \ldots x_{0n}$) to ($x_{best1}, x_{best2}, \ldots x_{best\ n}$)

Step 4: After 1000 iterations of inflation, the cosmological constant value is negative and deflation takes place and the solutions enter into a BC phase where all the solutions are taken back to singularity or near to the plank time.

Step 5: The iteration count is checked and if the current iteration is found to be more than the pre-set iteration, then the stopping criteria is met and the algorithm is terminated. Finally, elitism is adopted to sort out the final optimum solution.

If the stopping criteria is not met then the solutions are continually moved towards

Step 6: the plank time. And there is a provision for another BB if needed. As the result of a BC is another BB.

6. Feature Classification : Support Vector Machine

Support Vector Machines (SVM) is a machine learning algorithm that is commonly used for feature classification in speech processing applications such as speech recognition, speaker identification, emotion recognition, and language identification. SVM is particularly effective at handling high-dimensional feature spaces and finding the optimal hyperplane that maximizes the margin between different classes.

The SVM algorithm works by mapping the feature space into a higher-dimensional space using a kernel function. This higher-dimensional space allows SVM to find the hyperplane that separates the data points into different classes. The SVM algorithm maximizes the margin between the hyperplane and the closest data points, which improves the generalization ability of the classifier.

One of the strengths of SVM for feature classification is its ability to handle non-linearly separable data by using non-linear kernel functions. These functions map the feature space into a higher-dimensional space where the data becomes linearly separable. Commonly used non-linear kernel functions include the Gaussian kernel, polynomial kernel, and sigmoid kernel.

SVM is also able to handle imbalanced data sets, where the number of data points in one class is much smaller than the number of data points in the other class. SVM can adjust the class weights to give more importance to the minority class, which helps to improve the accuracy of the classifier. In speech processing applications, the first step in feature classification using SVM is to extract relevant features from the speech signal. These features are then used to train an SVM model, which is trained using a set of labeled training data. Each data point in the training set is labeled with its corresponding class, and the SVM algorithm learns to classify the data into different classes based on the selected features.

After the SVM classifier is trained, it is evaluated using a set of labeled testing data. This testing data is unseen data that is not used in the training process. The SVM classifier is used to predict the class labels of the testing data based on the selected features, and the accuracy of the classifier is evaluated based on the classification error. SVM is a powerful machine learning algorithm that is particularly effective for feature classification in speech processing applications. By mapping the feature space into a higher-dimensional space using kernel functions, SVM can handle high-dimensional feature spaces and non-linearly separable data. Additionally, SVM can adjust the class weights to handle imbalanced data sets. Overall, SVM is a highly accurate classifier for speech processing applications.

7. Results

Table 1
Parkinson's Disease – Healthy Controls

	Parkinson's Disease	Healthy Controls
True Positive	90	5
False Negative	10	95
False Positive	05	90
True Negative	95	10

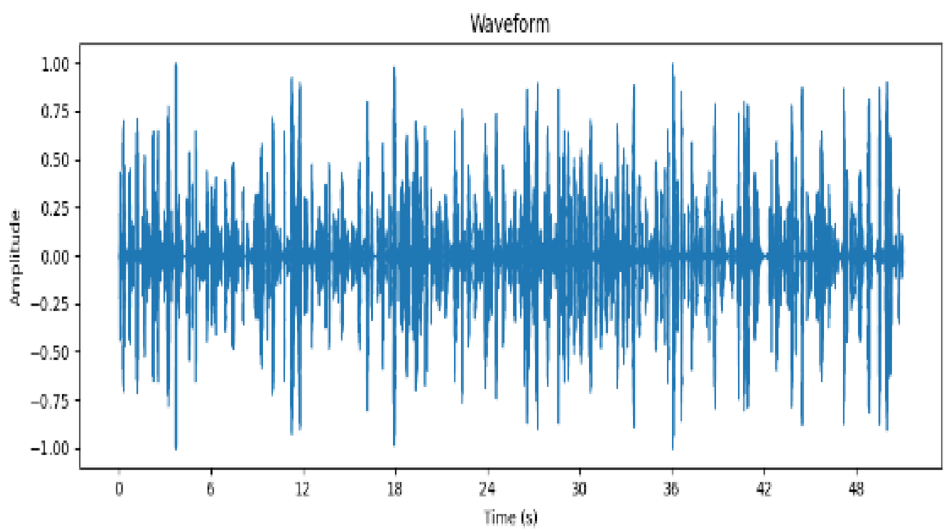

Fig. 1 Sample Speech Signal

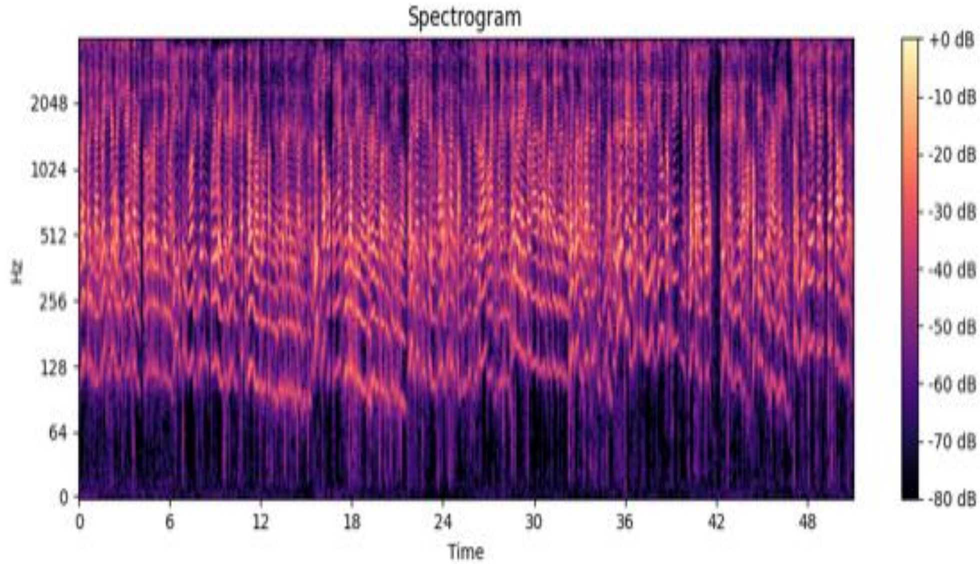

Fig. 2 Spectrogram representation of Sample Speech Signal

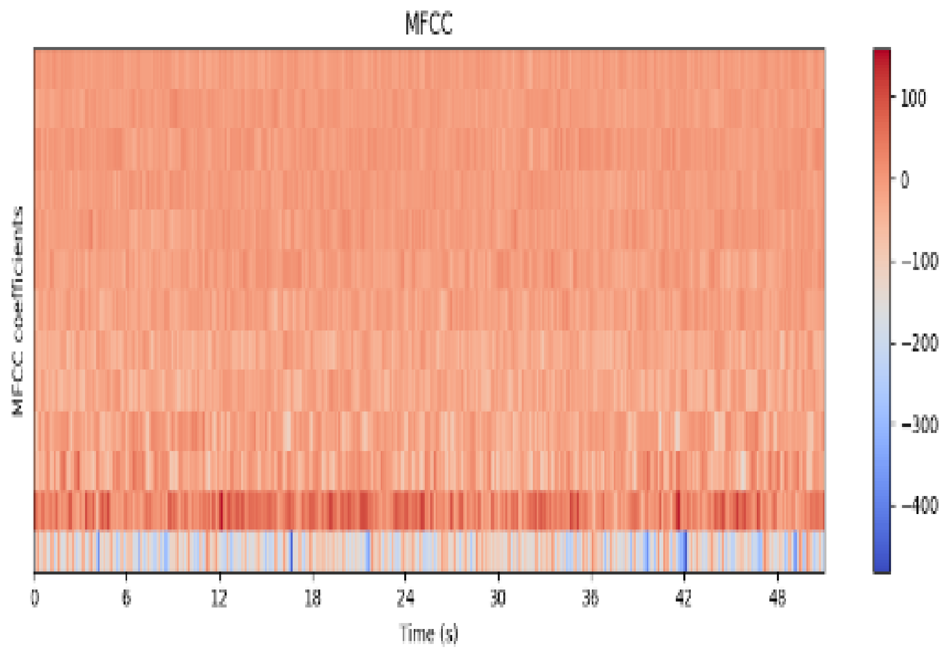

Fig. 3 Extraction of MFCC of the Sample Speech Signal

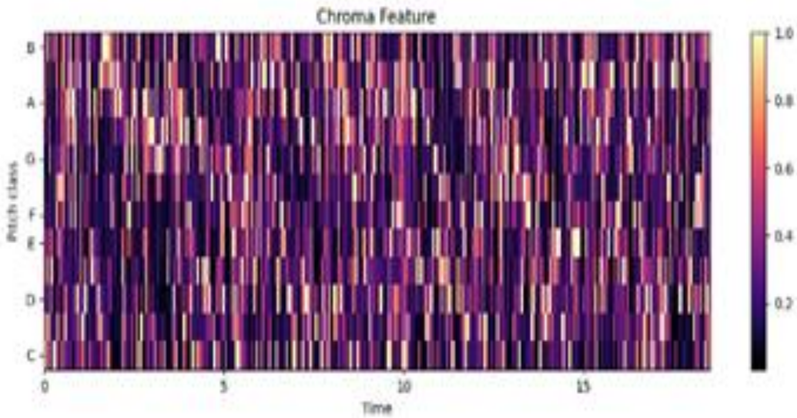

Fig. 4 Extraction of Chroma Feature of Sample Speech Signal

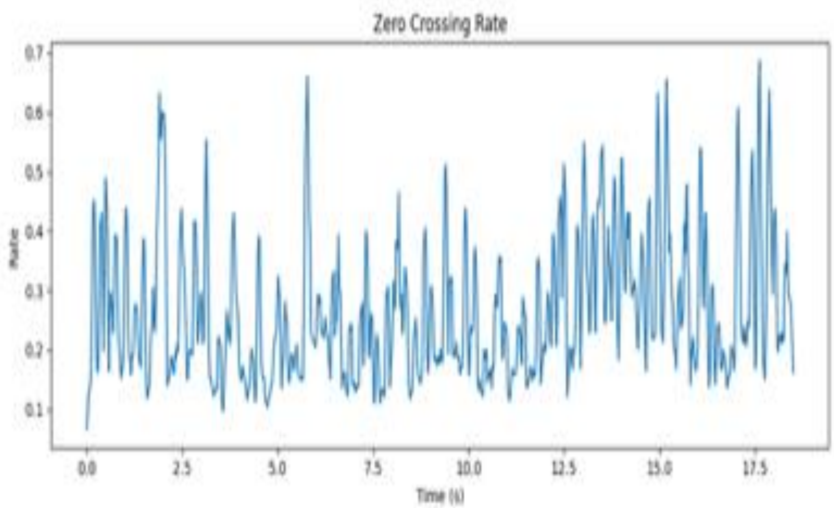

Fig. 5 ZCR of Sample Signal

Table 2
Classification Results For Time Domain Energy And Zero Crossing Rate (ZCR) Features Selected Using Various Optimization Algorithms In Parkinson's Disease Prediction

Features Selected	Classifier	Accuracy	Sensitivity	Specificity
Time Domain Energy, ZCR	Big Bang Algorithm	81.2%	79.5%	83.5%
Time Domain Energy, ZCR	Particle Swarm Optimization (PSO)	77.8%	75%	81.5%
Time Domain Energy, ZCR	Genetic Algorithm (GA)	80.3%	77.5%	83.5%
Time Domain Energy, ZCR	Ant Colony Optimization (ACO)	76.9%	73.5%	80.5%

Table 3
Classification Results For Features Selected Using The Big Bang Algorithm In Parkinson's Disease Prediction

Features Selected	Classifier	Accuracy	Sensitivity	Specificity
MFCCs 1-12	Support Vector Machine (SVM)	79.5%	76%	82.5%
Spectral Entropy, Shannon Entropy, Kurtosis, Mean, Skewness, MFCCs 1-12	Random Forest	84.8%	83%	86.5%
Spectral Entropy, Shannon Entropy, Kurtosis, Mean, Skewness, MFCCs 1-12	Naive Bayes	79.8%	76%	83%
Spectral Entropy, Shannon Entropy, Kurtosis, Mean, Skewness, MFCCs 1-12	Decision Tree	81.7%	79%	84.5%

8. Conclusion

In conclusion, Neuro Degenerative Diseases (NDD) pose a growing challenge as their prevalence continues to increase. The lack of specific tests for diseases like Parkinson's Disease (PD) has hindered early detection and intervention, leading to delayed diagnosis and worsening symptoms for many patients. This research work that explores the use of Speech Signals (SS) as a potential tool for early detection of PD. By employing the Discrete Wavelet Transform (DWT) and Hamming window preprocessing, the researchers extract a set of twenty-one features from the transformed signals. These features are then selected using a novel algorithm inspired by the Big Bang Theory (BBT) and the Theory of Cosmic Inflation, known as the Cosmic Inception based algorithm. The selected features are subsequently classified using Support Vector Machine (SVM).

The experimental results demonstrate the effectiveness of the proposed method in achieving accurate and convincing results compared to other diagnostic methods for PD. This approach not only holds promise for early detection of PD but also provides insights into the potential utility of speech signals as a valuable source of medical information. By harnessing the power of signal processing techniques and advanced algorithms, researchers are taking significant strides towards improving the diagnosis and management of PD and other NDDs. Continued research in this field is crucial to refine and expand upon these findings, ultimately leading to earlier intervention, improved patient outcomes, and a better understanding of these debilitating diseases.

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