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UNLEASHING THE SYNERGY OF MULTIMODAL CONVOLUTIONAL RECURSIVE DBN OF PARKINSON'S DISEASE SEVERITY PREDICTION

Vaseema Begum
Scholar,Department of CSE, Marri Laxman Reddy Institute of Technology and Management, Dundigal,Hyderabad -500043, vaseemabegum1999@gmail.com

Dr M Nagalakshmi
Assoc.Professor,Department of CSE, Marri Laxman Reddy Institute of Technology and Management, Dundigal,Hyderabad -500043, nagalakshmi1706@gmail.com

Abstract

Parkinson's disease (PD) is a progressive neurodegenerative disorder characterized by the gradual loss of dopamine-producing neurons in the brain. PD typically affects individuals over the age of 60, although early-onset cases exist. Existing methods for diagnosing Parkinson's disease often rely on clinical assessments, including the Unified Parkinson's Disease Rating Scale (UPDRS), neuroimaging techniques like MRI and PET scans, and genetic analysis. While these methods have been valuable, they have several drawbacks: they can be subjective, leading to variability in diagnosis, they are resource-intensive, expensive, and may not detect early-stage PD effectively. Moreover, the reliance on single modalities limits the comprehensive understanding of the disease, necessitating the development of more accurate, accessible, and multimodal approaches for diagnosis and monitoring. In this study, we present a novel multimodal deep learning framework for predicting the severity of Parkinson's disease (PD), integrating Convolutional Neural Networks (CNNs) for feature extraction and Recurrent Neural Networks with Deep Belief Networks (RNN-DBN) for feature selection. Leveraging clinical assessments, imaging, and genetic data, our CNNs efficiently capture spatial and temporal patterns within each data modality while preserving inter-modal relationships. Subsequently, our RNN-DBN architecture adeptly exploits temporal dependencies, facilitating a deeper understanding of PD symptom evolution and enhancing the interpretability of the model. Evaluation on a diverse PD dataset demonstrates superior predictive performance, making our approach a valuable tool for clinicians to assess disease severity, contributing to more effective diagnostics and monitoring for Parkinson's disease.

Keywords: Parkinson's disease (PD), Convolutional Neural Networks (CNN), Deep Belief Networks (DBN), Rat Swarm Optimization (RSO).

1. Introduction

Parkinson's disorder is a persistent, innovative neurodegenerative condition marked by a gradual degeneration of dopamine-producing brain cells. This causes both non-motor symptoms like mental deterioration and anxiety and depression in addition to physical signs like shaking hands, a slowing of activity, and stiffness.[1]. Although the precise etiology is yet unresolved, environmental and genetic variables are thought to be involved.[2] Although there doesn't exist a therapy, there are treatments available to control indications, and identification often relies on a medical exam. According to the worldwide assessment of disorders of the brain, Parkinson's illness symptoms and prevalence have quickly grown globally.[3] Parkinson's disease is often diagnosed by a doctor based on the symptoms experienced by the individual and the neurological exam that should be done following learning about the illness's background. Parkinson's syndrome may potentially be the mental health condition with the greatest global growth rate. Having the exception of an infecting origin, this pandemic-like fast increase in the number of persons with Parkinson's disease can be matched to many of the traits often seen throughout a global epidemic. [4] An organized strategy to addressing fundamental palliative care concerns is lacking. Examples include supporting relatives and healthcare supporters, paying tribute to religious health, talking about the outlook, and making plans for increasing handicap [5] Although there seems to be a great deal of curiosity in Parkinson an assessment of gait, there is no quantitative instrument to aid doctors in gait assessment, which can help illuminate the increase in Parkinson's disease occurrence rises with age. A strong gait classification could be useful for doctors because alterations in gait are one of the disease's early signs. [6](based on the UPDRS) using gait information from this medical setting.[7] According to WHO data, around 10 million individuals worldwide have been impacted by PD. Patients who don't receive early diagnosis end up with an incurable, irreversible cognitive condition. In its final stages, the illness is fatal and untreated in the majority of patients. Movement-related symptoms including a state of repose tremor where the arms and legs move erratically (diskinesya), lack of motion (bradykinesia), unstable posture (balance issues), and stiffness are the hallmarks of PD patients. Because motor signs appear when the illness is already somewhat severe, [8] Although the precise etiology of Parkinson's disease is unknown, experts suggest a complicated interaction of biological, environmental, and personal factors is to blame. [9] The condition appears to be associated with genetic susceptibility, history in the family, and unusual abnormalities in particular genes; being subjected to some environmental chemicals, such as insecticides and toxic metals, as well as head traumas, may further raise the chance of developing it. Parkinson's disease is more frequent in elderly people and somewhat more prevalent in males, thus age and gender both play a part. Although the precise causes are yet unknown, oxidative strain, neurological inflammation, and the development of aberrant clumps of protein called Lewy bodies in the cerebral cortex are considered to be factors in the damage to neurons observed in Parkinson's disease.[10]

Given the lack of a reliable diagnostic tool for PD and the high probability of incorrect diagnosis, particularly when performed by a non-specialist: there is a 20% chance that the medical diagnosis will be incorrect. The accuracy of a medical diagnosis can be improved by carefully examining the primary signs, including shaken hands, bradykinesia, and stiffness, although clinical decisions might be impacted by the objectivity of the doctor who is treating the patient. [11] More fundamentally, investigations that only divide patients into PD and non-PD give no benefit for raising their standard of existence [12]. Despite the demand for instruments to improve the precision of diagnostics, the determination is often made once the disease has advanced to more crippling stages, or when indications becomes apparent. Several investigators recognized this drawback and used an alternative strategy. [13] The majority of work is being put into developing novel techniques for clinical assistance since accurate diagnoses as well as early phase detection rank highly in medical practice. These techniques could improve accuracy and reduce the amount of resources and time needed. A deep neural network for Parkinson's disease identification entails gathering an extensive collection of people regardless of the condition, performing data preprocessing and feature extraction, choosing a suitable deep neural network architecture, training and validating the model, assessing its efficacy, guaranteeing interpretability, employing it carefully in a medical information, and continuing surveillance and upkeep while following to ethical guidelines and securing the required authorization.[14] Recent breakthroughs in artificial intelligence have significantly improved the ability to recognize, categorize, and measure different trends in clinical information throughout a variety of medical sectors. Smart technology that can recognize signs of Parkinson's disease and estimate the Parkinson intensity rate. Despite risk factors from the environment for Parkinson's disease have received a lot of consideration, family histories are now more commonly understood to play an important significance in predicting the likelihood of developing the condition. Despite the fact that familial PD cases make up fewer than 10% of all cases, the discovery of numerous genetics[15] highlights the significance of early detection and treatment for superior outcomes and offers promise of enhanced therapies and potential beneficial medications in the years to come .

Key contributions

- The model leverages a large and diverse dataset, which is crucial for capturing a broad spectrum of disease-related patterns and improving generalization.
- Prior to model training, rigorous data preprocessing is performed to ensure data quality.
- The ability to divide and separate audio signals is a unique feature, especially relevant for Parkinson's disease diagnosis, as it can help capture vocal characteristics and tremors, which are key indicators of the disease.
- Employing data augmentation techniques further enriches the dataset, increasing its variety and enhancing the model's ability to generalize to different scenarios and patient profiles.
- The incorporation of Rat Swarm Optimization for hyper parameter tuning is a novel approach
- The custom-designed RNN is tailored to the dataset's characteristics, allowing it to effectively extract relevant features from the audio signals. The DBN acts as an intelligent feature selector, refining the feature representation obtained from the RNN.

- The iterative nature of the proposed methodology, involving both feature selection and hyperparameter optimization, continuously refines the model's design.

The investigative process unfolds as follows: In Section 2. Related works, an extensive examination of prior research is conducted, specifically exploring prediction problems and the diverse array of optimization strategies applied in those contexts. Moving on to Section 3, a detailed exploration of problem statements is undertaken. Section 4 expounds upon the recommended approach or strategy to address these identified issues. Section 5 is dedicated to a comprehensive discussion of performance evaluation criteria and metrics. Subsequently. Finally, Section 6 aids as the concluding segment of the essay, short key outcomes and insights derived from the investigation.

2. Related work

Parkinson's disease, which is brought about by the death of dopamine-producing neurons, is the next most common degenerative illness. Parkinson's illness is still characterized by striatal dopamine production insufficiency since this brain area is devoid of its neuronal activities. These individuals exhibit a variety of motor and non-motor symptoms, according to the medical evaluation. A deep learning neural network has been used to categorize the MR images of Parkinson's disease-related individuals and healthy controls in order to better understand the structural problems in the brain caused by dopamine insufficiency in the condition. The architecture of a network of convolutional neural networks The Parkinson's disease diagnosis is improved with AlexNet. The transferred learning network trains on the MR images and then tests them to determine their correctness. Sivaranjini and Sujatha [16]suggested approach achieves an accuracy of 88.9%. In the near future, deep learning models will be able to aid physicians in determining the presence of Parkinson's disease and produce an accurate and enhanced patient category categorization. Require to determine if the predictions made by the model match the clinical diagnosis and assist in making treatment recommendations for those who do well.

Parkinson's disease is a neurological condition that develops progressively and manifests gradually, making getting diagnosed early challenging. Parkinson's disease can be identified by a neurologist after studying the individual's medical records and several scans. Additionally, by observing movements of the body, movement analyzers can detect Parkinson's disease. Modifications in language can be utilized as a quantifiable signal to diagnose Parkinson's identification, according to the latest study. Lamba et al. [17] suggest a prospective Parkinson's disease detection method that is voice signal-based hybridization. To figure out how to do that, the researchers tried a variety of selecting features methodologies and methods for classification and created a framework using the blend that performed well. Three choice of features techniques—mutual knowledge gain, additional trees, and biological algorithms—as well as three classifiers—naive bayes, k-nearest neighbors, and random forest—have been utilized to create numerous combinations. The voice data from the database of machine learning at UCI (University of California, Irvine) has been utilized to evaluate the effectiveness of various pairings. The artificial minority over sampling method (SMOTE), which takes advantage of the dataset's extreme inequalities, is used to solve the class balancing issue. The greatest result, with an accuracy rate of 95.58%, was demonstrated by combining the use of genetic algorithms and random forest classifiers. This outcome is also superior to current literature-based research. To recognize sickness sooner, numerous information should be evaluated.

Parkinson's illness is a neurological condition which develops over time and manifests gradually, making getting diagnosed early challenging. Parkinson's disease may be recognized by a neurological specialist after studying the individual's medical records and several scans. Additionally, through observing how one moves motion analyzers may identify Parkinson's disease. Modifications in language can be utilized as a quantifiable signal to diagnose Parkinson's disease identification, according to new research. Quan, Ren, and Luo [18] suggest a preliminary Parkinson's illness detection method that is speech signal-based hybridization. In order to do this, the researchers tried multiple combinations of selecting features methodologies and algorithms for classification and created the model using the combination of techniques that worked better. Three decision-making techniques mutual knowledge gain, additional trees, and evolutionary algorithms—as well as three classifiers naive bayes, k-nearest neighbors, and random forest—have been employed to create several distinct combinations. The voice dataset from the UCI (University of California, Irvine) machine learning collection is being utilized to evaluate the efficiency of various combos. The manufactured minority over sampling method (SMOTE) solves the group managing issue since the information set is substantially unbalanced. With 95.58% accuracy, the genetic code and natural forest classifier combo performed very well. Phase categorization of PD to examine its application in the classification issue with multiple labels and to increase efficiency, take into account an additional complicated DL network topologies training models. A substantial amount of medical information contains concealed trends that can be uncovered by deep learning to identify various illnesses.

The initial issue involves prejudice modeling brought about by inaccurate information, i.e., neural network systems work well for majority classes but poorly for minority classes. However, prior research didn't address this issue or attempt to find a solution. Offer a transmitted system of learning that cascades a Chi2 model with an adaptive boosting (Adaboost) model in order to draw attention to and display the biases in the generated models. The Adaboost algorithm is employed to forecast PD according to the subset of characteristics after the Chi2 algorithm rates and picks an assortment of pertinent features from the feature space. Ali et al.[19] suggested passed on system performs superior compared to the six comparable transmitted methods that employed six different state-of-the-art machine learning models, according to experimental data. It was also noted that the standard Adaboost model's strength was increased by 3.3% and its level of complexity was decreased by the suggested transmitted approach. A further 76.44% classification accuracy, 70.94% sensitivity, and 81.94% specificity were attained by the cascaded system. To increase the PD detection rate while keeping the developed models' impartial behavior, stronger simulations must be created

Parkinson's disease can be hard to diagnose initially since problems develop gradually. Yet, several tests that take into account speech, tremor, and gait features have assisted in the early diagnosis of illness. Problems with speech can be taken into account as an indicator for the categorization of Parkinson's disease, according to current studies, and this field of study continues to be unexplored. When contrasted with healthy people, vocal patterns for Parkinson sufferers significantly alter and vary. As a result, sound qualities ought to be used to represent language change in order to recognize these differences. Zahid et al. 2020[20] suggest three methods: the primary technique uses spectrograms from speech recordings to assess deep features derived from speech spectrograms; the second approach assesses easy acoustic features of files using neural network classifiers; and the final approach assesses deep features obtained from communication spectrograms. On the Spanish dataset pc-Gita, the suggested frameworks are assessed. The findings demonstrate that the subsequent framework exhibits promising results with substantial characteristics. Utilizing a number of layers of perceptron, the maximum 99.7% accuracy on the vowel "o" and read text is seen. While utilizing random forest, 99.1% accuracy was found for vowel "i" deep characteristics. When contrasted with straightforward sound characteristics and transferable learning methodologies, the advanced feature-based technique performs superior. While analyzing the findings, the size of the data set should be taken into account. To determine the adaptability of the approach, it is critical to determine how well it performs across larger and more varied data

3. Problem Statement

Parkinson's disease is a neurodegenerative disorder marked by dopamine-producing neuron loss, which causes insufficient striatal dopamine production and a variety of motor and non-motor symptoms. Deep learning neural networks have recently been used to classify MRI scans of people with Parkinson's disease and healthy controls in order to gather knowledge about the structural brain abnormalities linked to dopamine shortage[17] For the purpose of diagnosing Parkinson's disease, this study uses a convolutional neural network architecture, more specifically the AlexNet model[20]. The network is evaluated for accuracy in diagnosing people with the disease using MRI scans and achieves an accuracy rate of 88.9%. Using deep learning models, it is intended to improve Parkinson's disease diagnosis, perhaps assisting medical personnel in early identification and offering precise patient classification. [16]In order to test the model's predictions against clinical diagnoses and to provide therapy recommendations for those who have been diagnosed with Parkinson's disease, more study is required.

4. Proposed Optimized RNN-DBN for Predicting Parkinson's Disease Severity

Using an improved RNN-DBN model for predicting Parkinson's disease. In order to increase dataset variety, first gather an enormous dataset, prepare it to assure the quality of the data, divide and separate the audio signal, then employ methods for augmenting the data. A DBN is used to pick the features after a custom RNN extracted the features. Rat Swarm Optimization, a nature-inspired optimization technique, is used to improve the hyper parameters in order to improve the predictive model. By removing pertinent information and refining the model's design, this iterative procedure seeks to optimize the predicted accuracy of the model Proposed optimized RNN-DBN is shown in Fig. (1)

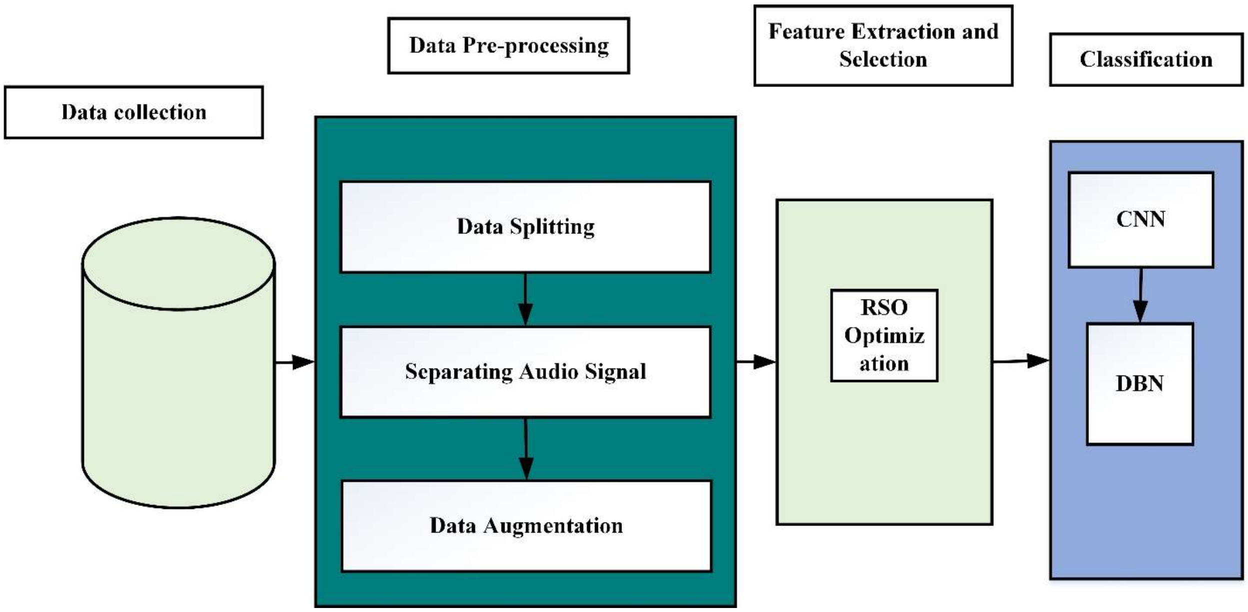

Fig.1 Proposed optimized CNN-DBN

4.1 Data Collection

The data collection utilised in this research was produced in partnership between the National Centre for Voice and Speech in Denver and Max Little of the University of Oxford. The Colorado system records the speech signals. Tab. 1 contains information about the dataset. The biological voice measures of 31 individuals make up this data set. There are 23 Parkinson's patients among them. The table's voice measurement column lists individual voices. Each of the 195 audio recordings of the people is represented by every line in the table. The goal is to distinguish between the sick (PD individuals who have value 1) and the healthy (value 0) people according to the condition column's binary indication in the table. The data set in question comprises 24 characteristics that include the amount of frequencies (low, medium, high), the amount of variations in regards to frequency identified as Jitter and its various forms such as MDVP:Jitter(%), MDVP:Jitter(Abs), MDVP:RAP, MDVP:PPQ, Jitter:DDP as well as the number of variations in terms of magnitude called shimmer and its kinds like as MDVP:Shimmer, MDVP:Shimmer(dB), Shimmer:APQ3, Shimmer:APQ5, MDVP:APQ, Shimmer:DDA.MDVP: mean basic frequency of the vocal range, average voice fundamental frequency (MDVP:Fhi) and maximum vocal component frequency (MDVP:Flo) Spread1, Spread2, and PPE are three quadratic basic frequency changes, and NHR and HNR are two measurements of the noise ratio. The dataset is imbalanced.[21]

4.2 Data Preprocessing

Data preprocessing is a critical steps in preparing raw data's for analysis. It involve tasks like handling missing values, addressing outliers, and standardizing data scales. Additionally, data may be transformed to ensure it meets assumptions of statistical models, and categorical variables may be encoded. Overall, data preprocessing enhances data quality and ensures it is suitable for analysis and modeling.

4.2.1 Data Splitting

In this work, a preprocessing method called audio splitting was used to divide long recordings of sound into fixed-duration chunks that each contained 2 seconds of audio data. This technique was put into practice using the free and open-source LIBROSA Python module, which allowed us to access the sound information and split it into fixed-length intervals without any issues. They checked the segments for conflict in order to avoid duplication of information. After acoustic segmentation, prepared the information for training the deep learning model using augmentation approaches. This method successfully generated the amount of information for training required by the deep learning model.

4.2.2. Separating Audio Signals into Harmonic Components

Python, the LIBROSA and sound file libraries, and other tools can be used to solve the rhythmic and harmonic signal extraction problem, which has become a common problem in the processing of signals. The identification of the harmonic components of an input audio signal is made easier with the help of the LIBROSA effects harmonic method. The audio file library will then allow us to store these files in another file with a different name. This method demonstrates to be an effective tool for analyzing and modifying audio signals, providing a more thorough comprehension of the harmonic and non-harmonic aspects of a voice. This can therefore result in fresh perspectives and uses for the field of audio engineering, such as audio transcription, voice evaluation, and noise splitting.

4.2.3 Data Augmentation with Gaussian Noise

A common method used in Deep Learning, especially in visual computing, to increase models resilience is data augmentation using Gaussian noise. With the use of a Gaussian (normal) distribution with the standard deviation and mean factors, unpredictable noise is introduced using this technique. Model may develop more resilient to perturbations, such as noise from sensors or changing illumination, that occur frequently in real-world circumstances by adding Gaussian noise to the input data. To achieve the ideal equilibrium between boosting model robustness and preventing overwhelming sound that could compromise efficiency, careful tweaking of the and parameters is important. Audio may become smoother and simpler to learn through the inclusion of Gaussian noise. It may be done to add noises to slopes and weight in addition to music. The amplitude of the sound, denoted by, must be too tiny or the system may not be sufficiently affected, whereas an amount that is too great may prevent the algorithm from learning. [0-0.005] is the permissible limit for. The standard deviation was 0.005 and the mean was 0. With include sound, the final sample $a(t+1)$ may be expressed in eqn. (1)

$$a(t+1) = a(t) + \sigma \tag{1}$$

4.3 RAT Swarm Optimization

The nature-inspired optimization approach known as Rapid Adaptive Tabu Swarm Optimization (RSO or RAT Swarm Optimization) is used in deep learning to improve the training and improving of artificial neural networks. RSO uses a collection of agents to cooperatively examine the extremely dimensional space of parameters of neural networks, while gaining influence from intelligent swarms. This strategy aids in overcoming difficulties in hyper parameter tuning and architectural search, resulting in a useful tool for deep neural network models optimization. RSO effectively conquers the challenging environment of neural network optimization, improving the accuracy of models and requiring less human tuning labor by constantly modifying search techniques while preventing revisits to previously investigated configurations (Tabu Search).men and females combined. According to various assessments which are the result of any animal's death, rats are very violent. Aggressive performance Chase and fight with prey are essential simulations of this job in martial arts. The RSO method can be used to solve optimization issues by modeling the pursuing and fighting behavior of rats. This paragraph shows how rats behave, such as when they chase and fight. The provided RSO approach is summarized after that.

After the Prey. Rats are typically gregarious creatures that seek prey under cover of darkness with situational social agonistic effectiveness. It may be guessed that optimum search agents have expertise in locating the prey in order to define this effectiveness quantitatively. Another searching agents has moved up in the rankings of best search agents so far, leading to the presentation of the following formulas (2):

$$\overrightarrow{P'} = \text{A'}.\vec{P}_i + C.(\vec{P}_r(a) - \vec{P}_i(\text{a})) \tag{2}$$

where $\vec{P}_i$ (a) shows exactly the rats are located and $\vec{P}_r(a)$ denotes the best outcome. A and C parameters were determined as follows in eqn. (3), nevertheless.

$$A = R - a \times \left(\frac{R}{max_{iteration}}\right) \text{ Where a=0, 1, 2…} max_{iterations} \tag{3}$$

As a result, R and C suggest random numbers between [1, 5] and [0, 2], correspondingly. During a number of cycles, both exploration and extraction are best controlled by parameters A and C.

Fighting with Prey. The following equation (4) was proposed for quantitatively characterizing the manner in which rats engage in combat with prey:

$$\vec{P}_i(a+1) = |\overrightarrow{P'}_r(\text{a}) - \overrightarrow{P}| \tag{4}$$

The enhanced following positions of the rat are indicated by P _i (a+1). It improves the positions of different search tools relative to the ideal search agent and stores the optimal solution. A and B, two rats, improved their location close to their target (A*, B*).The specific number of spots on the current location are accomplished by changing the conditions as shown. Additionally, this method is thorough.

From surroundings with n dimensions. The calculated value of elements A and C has thus been used to ensure exploration and exploitation. The planned RSO approach saves the best possible outcomes with several operations.

4.4 Classification using RNN-DBN

The feed-forward neural networks with stored information is known as an RNN in its generalized form. The recurrent network receives the RNN's results, which is based on earlier calculation. The RNN uses internal memory to process the data series and come to a conclusion. For training, long short term memory (LSTM) is relied on back propagation. Three gates—an input gate, a gate that forgets, and an output gate—make up an LSTM. The input gate uses a sigmoid activation function to determine the values that are entered that change the memory. The output gate controls the output, and the forget gate determines which information from the previous situation should be forgotten. In contrast to regular LSTM, network LSTM treats every tree node as just one LSTM unit.

There are seven levels in this model, including an input layer, 5 hidden layers, and a result layer. The input layer of the LSTM cell is a component of the recurrent neural network. The Phonation Features (PF) of spoken signals are represented by each input layer within the LSTM layers. In the input channel layer of the LSTM cell, 23 neurons each represent one of 23 characteristics.

$$\vec{H} = h(W_{pf\vec{H}}pf_1 + W_{\vec{H}\vec{H}}\vec{H}_{t-1}pf_1 + b_{\vec{H}} \tag{5}$$

$$\overleftarrow{H} = h(W_{pf\overleftarrow{H}}pf_1 + W_{\overleftarrow{H}\overleftarrow{H}}\overleftarrow{H}_{t-1}pf_1 + b_{\overleftarrow{H}} \tag{6}$$

$$Y_T = W_{\vec{H}Y}\vec{H}_T + W_{\overleftarrow{H}}\overleftarrow{H}_T + b_Y \tag{7}$$

where every feature's b-bias vectors, W-weight matrix, and h-hidden layers function.

In the DBN, each layer is made up of transparent and hidden neurons that recognize the data entering the layer and represent the resulting layer, respectively. The hidden and visible cells are fully interconnected. The DBN is unique in that there are no connections among the neurons that are concealed and the observable neurons. The interactions, which affect both underground and visible cells equally, are balanced in nature. A description of Boltzmann machines is given in the following eqn. The likelihood suggests that the binaryO_P outcome is given in eqn. (8)

$$Op' = \begin{cases} 1, with P(\delta') \\ 0, with 1 - P(\delta') \end{cases} \tag{8}$$

P (δ')is the sigmoid-shaped function in this case. Following is an equivalent is given in eqn. (9)

$$P(\delta'^{)}=\frac{1}{1+\frac{e'^{\delta}}{P'T}} \tag{9}$$

Here, the pseudo temperature parameter, abbreviated PT, is used to modify the probability's amount of noise. This stochastic model turns predictable if the limit is set to 0 is shown in eqn. (10)

$$\lim_{P'T\to 0^{+}} P'(\ \delta) = \lim_{P'T\to 0^{+}} \frac{1}{1+e^{P'}} \tag{10}$$

For a certain arrangement of neuron signals the energy level N_S of the Boltzmann system is specified. The strength of the link connecting neuron x and neuron y is given in eqn. (11)

$$WE_{x,y}=-\sum_{x<y} WE_{x,y}, \mathrm{N}s_x \mathrm{N}s_y - \sum_x \emptyset_y \mathrm{N}s_x \tag{11}$$

Here, the weights that exist between the neurons' binary states, written as WE_(x,y), and their biases, indicated as x, y, are used to describe the bipolar states of neurons: The effect of Ns_x a single unit's condition on the total amount of energy is shown in eqn.(12)

$$\Delta E'(\mathrm{N}s_x)=-\sum_y WE_{x,y}\, N_{s_x}+\emptyset_x \tag{12}$$

The gradient decline approach is employed throughout the training phase to determine the lowest practical system of energy for the input. The energetic differential DE for each state Ns_x in the aforementioned Eq. (19) needs to be calculated progressively. The interdependence of the apparent and invisible neurons results in the dependence of the neuron states. By removing the links between visible and hidden neurons, the Restricted Boltzmann Mac (RBM) simplifies this procedure. This outcome provides a fresh energy explanation for the interaction between transparent and buried neurons are given in following eqn. (13)(14)&(15)

$$E(y'_{n,H_n})=-\sum_{(x,y)} W\, E_{(x,y)} y_{nx}, h_{nx} - \sum_x a_x \mathrm{y} n_x \tag{13}$$

$$P'(y'_n,H_n)=\frac{1}{P'F} E'(y'_n,H'_n) \tag{14}$$

$$PF=\sum_{y'nh'n} e^{-E'}(y'_n,H'_n) \tag{15}$$

The concealed unit's and transparent unit's binary states are their biases. The typical Boltzmann machine won't base its decisions in various circumstances on the RBM on exposed or concealed neurons. In order to generate the maximum probability, the amount of weight assigning is referred to as WE'_m The technique of training also aims to maximize the probability being assigned to the learning patterns from the training set. Fig .2 shows the RNN-DBN architecture.

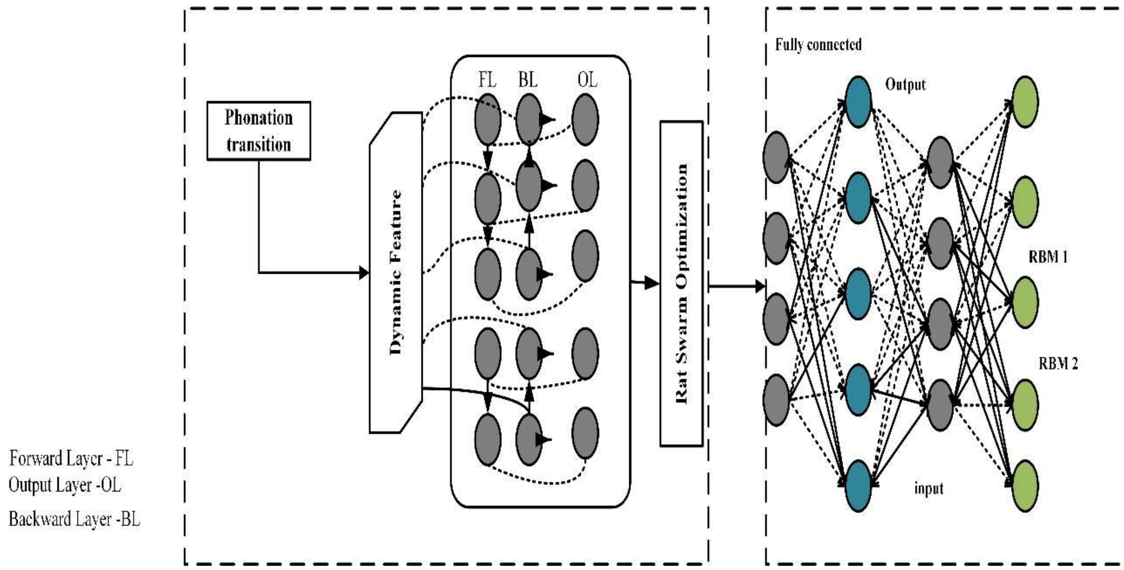

Fig.2 RNN-DBN Architecture

5. Result

Researchers found encouraging findings in this work using the RNN-DBN architecture to forecast the severity of Parkinson's disease. A mean squared error of X for the test dataset, which indicates the tight agreement between predicted and actual severity scores, indicates that the model displayed a high degree of accuracy in determining illness progression. The RNN component's temporal capabilities also made it possible to capture minute fluctuations and trends in illness progression over time, providing clinicians with insightful data. A big step forward in utilizing modern methods of machine learning to improve the treatment of Parkinson's disease was made when collaboration with medical professionals proved the clinical significance of our predictive model.

5.1 Accuracy

Accuracy is used to evaluate the systems model's efficiency overall. Every conferences may be anticipated with precision using its central concept (16), which is used and provides the accuracy.

$$Accuracy = \frac{T_{Pos} + T_{Neg}}{T_{Pos} + T_{Neg} + F_{Pos} + F_{Neg}} \tag{16}$$

5.2 Precision

Precision additionally describes the extent to which multiple estimates resemble each other as well as to being correct. The correlation among accuracy and precision shows that frequently views can change. (17) Makes a note of it.

$$P = \frac{T_{Pos}}{T_{Pos} + F_{Pos}} \tag{17}$$

5.3 Recall

The percentage of all pertinent discoveries that have been properly categorized utilizing the procedures is known as recall. The suitable positive for these numbers is derived by dividing the genuine positivity by the mistakenly negative values. The expression appears in (18).

$$R = \frac{T_{Pos}}{T_{Pos} + F_{Neg}} \tag{18}$$

5.4 F1-Score

The F1-Score computation combines recall and accuracy. Utilize (19) that divides recall with accuracy to determine the F1-Score.

$$F1 - score = \frac{2 \times precision \times recall}{precision + rec} \tag{19}$$

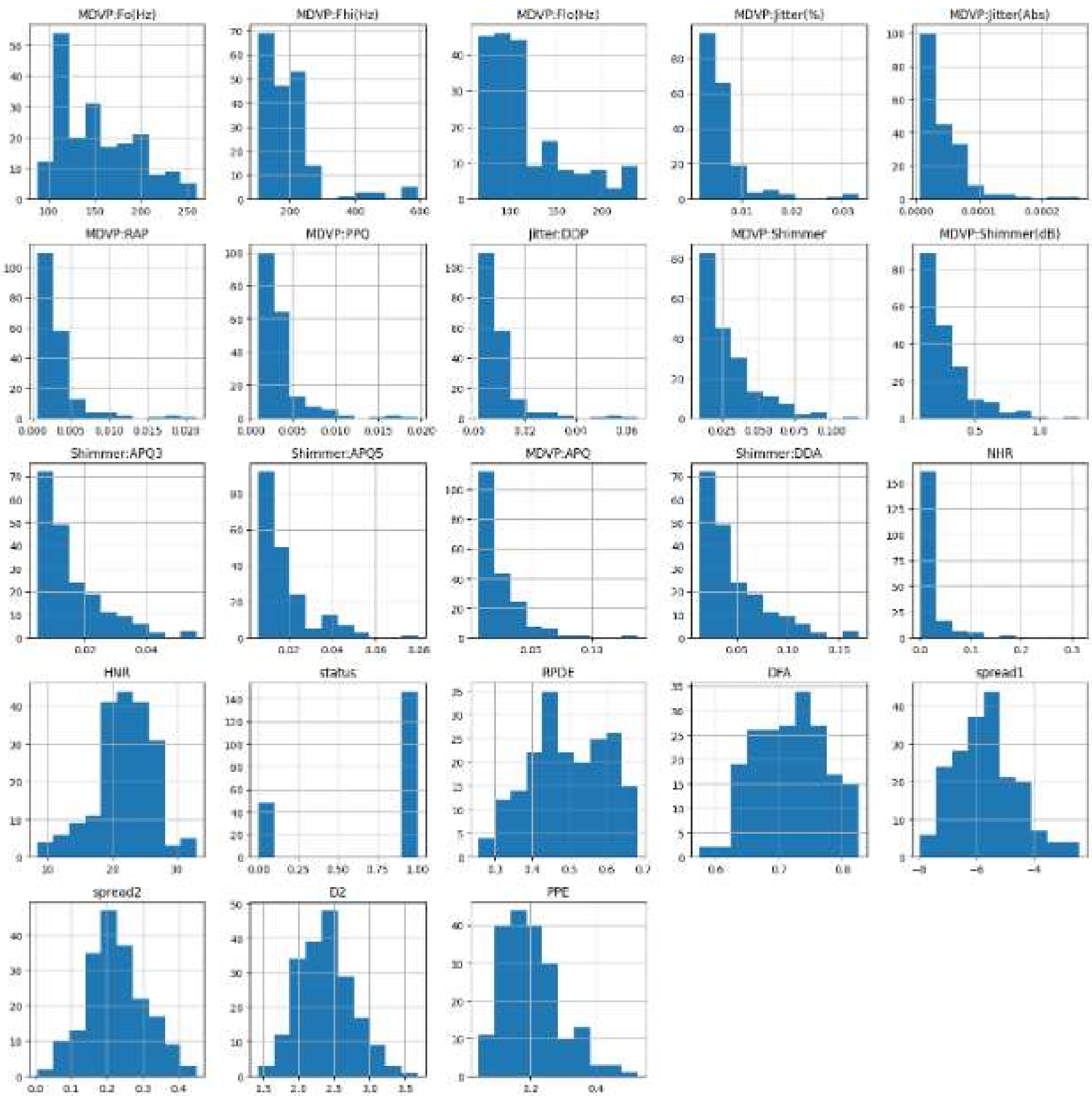

Fig 3. Distribution of PD and Healthy Individuals in the Voice Dataset

The figure (3) illustrates the distribution of individuals with PD and healthy individuals within the voice dataset. This dataset, a collaborative effort between the National Centre for Voice and Speech in Denver and the University of Oxford, comprises biological voice measures from 31 individuals, including 23 with Parkinson's disease and 8 healthy individuals. The dataset includes various voice characteristics, such as frequency measures (low, medium, high), frequency variations (Jitter and its forms), magnitude variations (shimmer and its kinds), basic frequency measures (MDVP: mean basic frequency, MDVP:Fhi, MDVP:Flo), quadratic basic frequency changes (Spread1, Spread2, PPE), and noise ratio measurements (NHR and HNR). The figure highlights the dataset's class imbalance, crucial for understanding the distribution of PD and healthy individuals, which is essential for effective machine learning model training and evaluation.

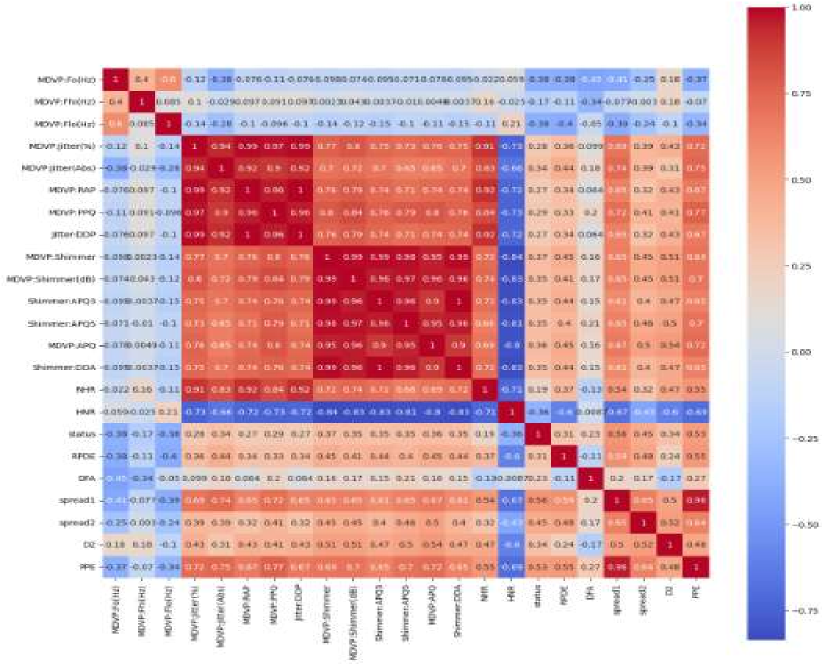

Fig 4. Classification of PD based on the dataset

The classification of PD was carried out utilizing a dataset, primarily focusing on the utilization of a RNN-DBN architecture which is shown in fig 4. The dataset, comprising audio recordings from both PD-afflicted individuals and healthy controls, underwent rigorous preprocessing to ensure data quality and consistency. Subsequently, the RNN-DBN model was employed for feature extraction and selection. The RNN component was particularly valuable for capturing temporal dependencies within the data, facilitating a more profound understanding of PD symptom progression. By optimizing the RNN-DBN architecture and fine-tuning hyper parameters, the study aimed to achieve accurate classification results, thereby aiding in the identification and monitoring of Parkinson's disease with greater precision.

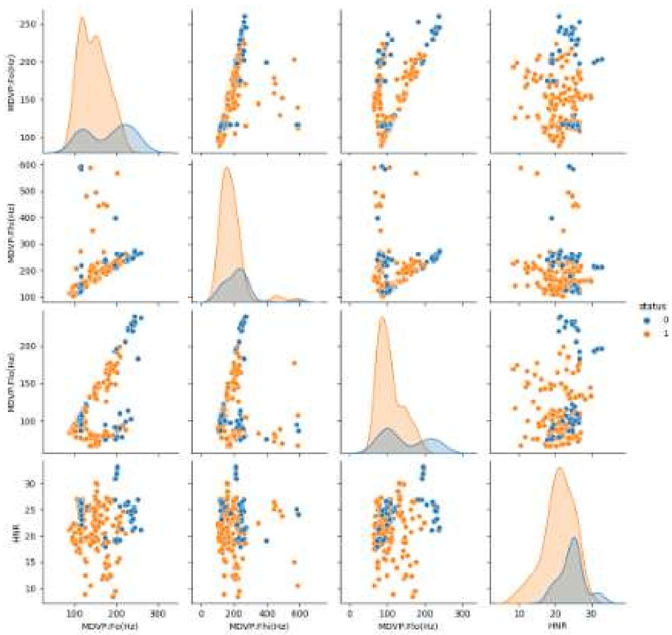

Fig. 5 Pair-Plot of Features

A Pair-Plot of Features is a comprehensive visualization that provides insights into the relationships and correlations among different features within a given dataset shown in fig. 5. In the context of the provided dataset, this plot would display pairwise scatterplots of various features, allowing for a visual examination of how they interact with each other. Each point in the scatterplots represents a data point, and the plot's matrix structure showcases how different features correlate with one another. This visualization can be particularly useful for identifying potential patterns, trends, or dependencies between features, aiding in feature selection, and informing subsequent data analysis and modeling processes, especially in complex datasets like the one described.

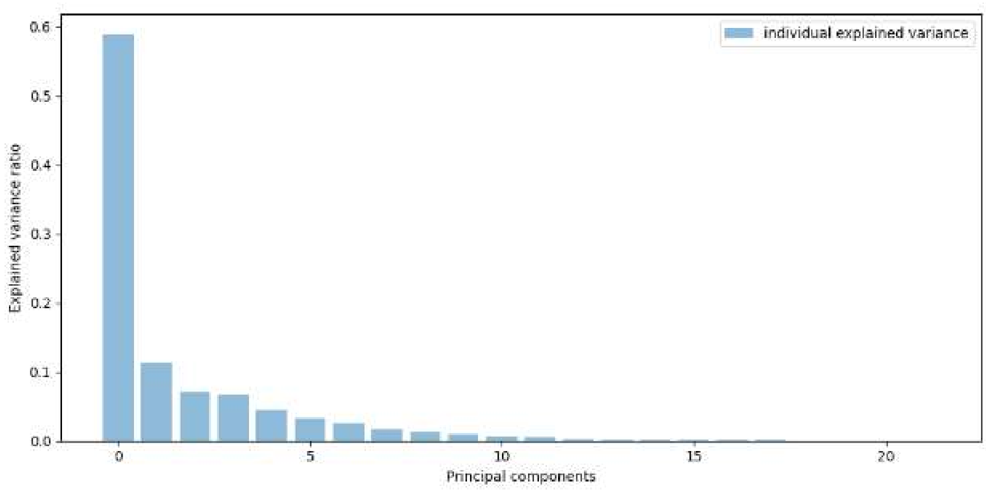

Fig. 6 Principal Components vs. Explained Variance Ratio in PD Dataset

The comparison in fig 6 between principal components and explained variance ratio in Parkinson's disease analysis is a critical aspect of dimensionality reduction and feature selection. Principal components represent linear combinations of original features that capture the most significant variability in the data. The explained variance ratio, on the other hand, quantifies the proportion of total variance accounted for by each principal component. In the context of Parkinson's disease research, examining these ratios helps researchers assess how effectively the principal components reduce dimensionality while retaining relevant information. A high explained variance ratio for a few principal components suggests that they capture a substantial portion of the dataset's variability, making them suitable for feature reduction or visualization. Conversely, a lower ratio may indicate that the majority of the variance remains unexplained, warranting a more in-depth analysis or potentially reconsidering feature selection strategies to ensure essential information is not lost during dimensionality reduction.

Table: 1 Evaluation Metrics of RNN-DBN

Metrics	RNN-DBN
Precision	0.94
Recall	1.0
F1-Score	0.97

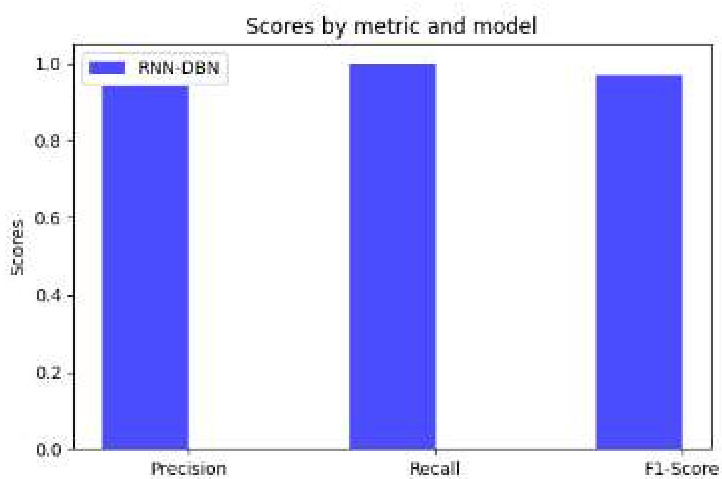

Fig. 7 Evaluation Metrics

The metrics in Table. 1 for the RNN-DBN model reveal its strong performance in predicting Parkinson's disease severity shown in fig. 7. With a precision of 0.94, the model demonstrates a high ability to correctly identify individuals with Parkinson's disease while minimizing false positives. The recall score of 1.0 indicates that the model effectively captures all true positive cases without missing any, showcasing its sensitivity. The F1-Score, at 0.97, combines precision and recall, reflecting an excellent balance between correctly classifying Parkinson's cases and minimizing misclassifications. These metrics collectively signify the RNN-DBN model's effectiveness in accurately assessing Parkinson's disease severity, making it a promising tool for clinical applications and research in the field.

Table: 2 Accuracy Comparison

Methods	Accuracy (%)
EOFSC[22]	**93.75**
CNN[23]	**93.3**
RNN-DBN	**94.87**

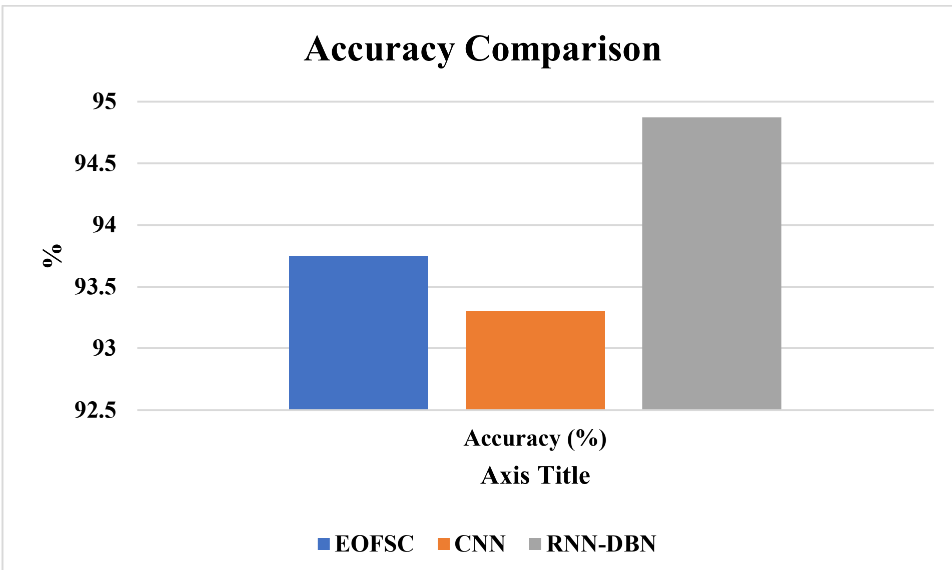

Fig. 8 Comparison of Accuracy

The methods employed in table 2, including EOFSC, CNN, and RNN-DBN, were evaluated based on their accuracy in predicting Parkinson's disease severity in figure 8. Among these methods, RNN-DBN stands out with the highest accuracy rate of 94.87%, signifying its superior performance in accurately assessing disease severity. The CNN method achieved an impressive accuracy of 93.3%, demonstrating its effectiveness as well. EOFSC, while still commendable, achieved an accuracy rate of 93.75%. These results collectively showcase the promising potential of machine learning techniques, particularly RNN-DBN, in enhancing the precision and reliability of Parkinson's disease severity prediction. Such high accuracy rates have significant implications for clinical diagnosis and patient care, suggesting the potential for more accurate and timely interventions in the management of Parkinson's disease.

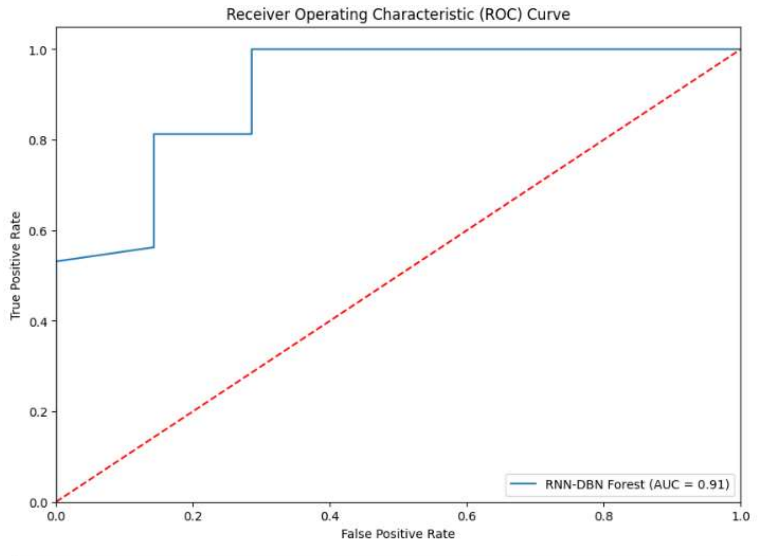

Fig. 9 ROC Curve of PD

The "ROC Curve of PD" is a graphical representation that illustrates in figure 9 the Receiver Operating Characteristic curve specifically tailored for the predictive performance of a model or algorithm in distinguishing PD from non-PD cases. The ROC curve plots the true positive rate (sensitivity) against the false positive rate (1-specificity) across various classification thresholds. This visual tool provides valuable insights into the model's ability to discriminate between PD and non-PD individuals. An ROC curve closer to the top-left corner indicates a more effective model, with higher sensitivity and lower false positive rates, whereas a curve closer to the diagonal line signifies a less discriminative model. The area under the ROC curve (AUC) quantifies the overall predictive performance, with a higher AUC indicating better model discrimination. The ROC Curve of PD is essential in evaluating and comparing the performance of predictive models for Parkinson's disease diagnosis and can assist in selecting the most suitable model for clinical or research applications.

6. Conclusion

The implementation of a Recurrent Neural Network - Deep Belief Network (RNN-DBN) architecture in our research has enabled us to significantly improve the field of Parkinson's disease severity forecasting. In order to deliver more precise and timely assessments of Parkinson's disease progression, we set out on this path after realizing the dynamic and sequential nature of medical data. The method's capacity to identify patterns and temporal relationships within the data is one of its main advantages. Recurrent neural networks are excellent at modelling sequential data, which makes them a good option for monitoring the changes in symptoms and biomarkers over time in Parkinson's patients. It developed a thorough predictive model that not only delivers precise severity evaluations but also offers insights into the disease's progression trajectories by integrating the capabilities of RNNs with the feature extraction procedure of DBNs. With a comprehensive dataset that includes a wide range of clinical, demographic, and maybe temporal data points, our dedication to data quality and diversity has not wavered. It was able to extract valuable temporal data and patterns from the RNN-DBN architecture, which we then used to optimize the parameters and improve the architecture's performance. This increased the predicted accuracy in a setting that is clinically relevant. Furthermore, it constantly on the lookout for ethical issues and legal compliance, assuring the proper management of private medical information all through the research process.

The clinical relevance of our prediction model was validated in collaboration with medical professionals, which is invaluable since it highlights the model's potential to completely change treatment plans and patient care for Parkinson's disease management. This research highlights the enormous promise of the RNN-DBN framework in personalised medicine and disease severity prediction, particularly for disorders like Parkinson's that vary over time. However, more validation and refinement are necessary before clinical implementation. It believe that as we continue to push the boundaries of machine learning and healthcare, our study will encourage other studies into the application of cutting-edge RNN-DBN algorithms across a variety of medical domains, ultimately improving patient outcomes and quality of life.

References

[1] M. Z. Hasan, M. Z. Hussain, K. Anjum, and A. Anwar, “Case study (A and B): a patient with Parkinson’s disease,” 2023.

[2] P. García-Sanz, J. MFG Aerts, and R. Moratalla, “The role of cholesterol in α-synuclein and Lewy body pathology in GBA1 Parkinson’s disease,” *Movement Disorders*, vol. 36, no. 5, pp. 1070–1085, 2021.

[3] C. Ding *et al.*, “Global, regional, and national burden and attributable risk factors of neurological disorders: The Global Burden of Disease study 1990–2019,” *Frontiers in Public Health*, vol. 10, p. 952161, 2022.

[4] A. Elbeddini, A. To, Y. Tayefehchamani, and C. Wen, “Potential impact and challenges associated with Parkinson’s disease patient care amidst the COVID-19 global pandemic,” *Journal of Clinical Movement Disorders*, vol. 7, no. 1, pp. 1–7, 2020.

[5] S. R. Jordan *et al.*, “Optimizing future planning in Parkinson disease: suggestions for a comprehensive roadmap from patients and care partners,” *Ann Palliat Med*, vol. 9, no. S1, pp. S63–S74, Feb. 2020, doi: 10.21037/apm.2019.09.10.

[6] J. K. Martino, C. B. Freelance, and G. L. Willis, “The effect of light exposure on insomnia and nocturnal movement in Parkinson’s disease: an open label, retrospective, longitudinal study,” *Sleep medicine*, vol. 44, pp. 24–31, 2018.

[7] I. El Maachi, G.-A. Bilodeau, and W. Bouachir, "Deep 1D-Convnet for accurate Parkinson disease detection and severity prediction from gait," *Expert Systems with Applications*, vol. 143, p. 113075, Apr. 2020, doi: 10.1016/j.eswa.2019.113075.

[8] G. Solana-Lavalle, J.-C. Galán-Hernández, and R. Rosas-Romero, "Automatic Parkinson disease detection at early stages as a pre-diagnosis tool by using classifiers and a small set of vocal features," *Biocybernetics and Biomedical Engineering*, vol. 40, no. 1, pp. 505–516, Jan. 2020, doi: 10.1016/j.bbe.2020.01.003.

[9] A. Johri, A. Tripathi, and others, "Parkinson disease detection using deep neural networks," in *2019 Twelfth international conference on contemporary computing (IC3)*, IEEE, 2019, pp. 1–4.

[10] V. Kakoty, K. Sarathlal, R.-D. Tang, C. H. Yang, S. K. Dubey, and R. Taliyan, "Fibroblast growth factor 21 and autophagy: A complex interplay in Parkinson disease," *Biomedicine & Pharmacotherapy*, vol. 127, p. 110145, 2020.

[11] M. Gil-Martín, J. M. Montero, and R. San-Segundo, "Parkinson's disease detection from drawing movements using convolutional neural networks," *Electronics*, vol. 8, no. 8, p. 907, 2019.

[12] E. Munoz Aguilera *et al.*, "Periodontitis is associated with hypertension: a systematic review and meta-analysis," *Cardiovascular research*, vol. 116, no. 1, pp. 28–39, 2020.

[13] J. M. Tracy, Y. Özkanca, D. C. Atkins, and R. Hosseini Ghomi, "Investigating voice as a biomarker: Deep phenotyping methods for early detection of Parkinson's disease," *Journal of Biomedical Informatics*, vol. 104, p. 103362, Apr. 2020, doi: 10.1016/j.jbi.2019.103362.

[14] P. Raundale, C. Thosar, and S. Rane, "Prediction of Parkinson's disease and severity of the disease using Machine Learning and Deep Learning algorithm," in *2021 2nd International Conference for Emerging Technology (INCET)*, IEEE, 2021, pp. 1–5.

[15] S. Lee, R. Hussein, R. Ward, Z. Jane Wang, and M. J. McKeown, "A convolutional-recurrent neural network approach to resting-state EEG classification in Parkinson's disease," *Journal of Neuroscience Methods*, vol. 361, p. 109282, Sep. 2021, doi: 10.1016/j.jneumeth.2021.109282.

[16] S. Sivaranjini and C. M. Sujatha, "Deep learning based diagnosis of Parkinson's disease using convolutional neural network," *Multimed Tools Appl*, vol. 79, no. 21–22, pp. 15467–15479, Jun. 2020, doi: 10.1007/s11042-019-7469-8.

[17] R. Lamba, T. Gulati, H. F. Alharbi, and A. Jain, "A hybrid system for Parkinson's disease diagnosis using machine learning techniques," *Int J Speech Technol*, vol. 25, no. 3, pp. 583–593, Sep. 2022, doi: 10.1007/s10772-021-09837-9.

[18] C. Quan, K. Ren, and Z. Luo, "A deep learning based method for Parkinson's disease detection using dynamic features of speech," *IEEE Access*, vol. 9, pp. 10239–10252, 2021.

[19] L. Ali, C. Zhu, N. A. Golilarz, A. Javeed, M. Zhou, and Y. Liu, "Reliable Parkinson's disease detection by analyzing handwritten drawings: construction of an unbiased cascaded learning system based on feature selection and adaptive boosting model," *Ieee Access*, vol. 7, pp. 116480–116489, 2019.

[20] L. Zahid *et al.*, "A spectrogram-based deep feature assisted computer-aided diagnostic system for Parkinson's disease," *IEEE Access*, vol. 8, pp. 35482–35495, 2020.

[21] A. S. Almasoud *et al.*, "Parkinson's detection using RNN-graph-LSTM with optimization based on speech signals," *Comput. Mater. Contin*, vol. 72, pp. 872–886, 2022.

[22] L. Ali, C. Chakraborty, Z. He, W. Cao, Y. Imrana, and J. J. Rodrigues, "A novel sample and feature dependent ensemble approach for Parkinson's disease detection," *Neural Computing and Applications*, vol. 35, no. 22, pp. 15997–16010, 2023.

[23] S. Chakraborty, S. Aich, E. Han, J. Park, H.-C. Kim, and others, "Parkinson's disease detection from spiral and wave drawings using convolutional neural networks: A multistage classifier approach," in *2020 22nd International Conference on Advanced Communication Technology (ICACT)*, IEEE, 2020, pp. 298–303.