Bimodal Detection of Parkinson's Disease

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Abstract — Parkinson's disease is a debilitating neurological disorder which affects many people world wide. Parkinson's disease is caused by the loss of nerve cells in any part of the brain. It is a major brain disorder that affects men more than women. Parkinson's disease affects the central nervous system and leads to unintended or uncontrollable movements, such as shaking, stiffness and difficulty with balance and coordination. It not only affects the nervous system but also parts of the body that connect to the nervous system. As of now there is no treatment for Parkinson's disease but there are methods to help relieve the symptoms of this disease. That is the reason detecting the disease at its early stage is very important. By considering all these symptoms and its information we are developing one software application that detects this disease at its early stage by considering its symptoms. Our main aim is to develop a machine learning model which will detect Parkinson's disease at its early stage by using two datasets namely, spiral and vocal dataset. In the spiral dataset we are considering the spiral drawings of the patients. After collecting we are going to analyze the pen movements while drawing the spiral structure. In the vocal dataset we are collecting the patient's voice such as sustained vowel phonation, reading a sentence and spontaneous speech. All these data are preprocessed , classified and we are using two separate models for two datasets namely, deep belief network and capsule neural network and then results are generated. Our main aim is to develop a non-invasive, effective tool for detecting and diagnosing Parkinson's disease at its early stage, which can lead to improved patient outcomes and quality of life.

Keywords - Capsule Neural Network (CNN) , Deep Belief Network (DBN) , neurological disorder

I. Introduction

Parkinson's disease is a neurological condition that impairs movement in sufferers. It results from the degeneration of neurons in a particular region of the brain that produce dopamine. Tremors, rigidity, slow movement, and issues with balance and coordination are all signs of Parkinson's disease in the brain that produce dopamine. Each person experiences these symptoms differently. Other signs of this illness may include diminished sense of smell, inability to sleep soundly, anxiety, and depression, among others Parkinson's disease currently has no known cure, however drugs and early disease detection can help manage the symptoms and enhance quality of life for those who have the condition. The early detection of this illness enables patients to begin treatment with the goal of lessening the consequences of the symptoms. For effective disease management, our project aims to identify the illness at an early stage.

II. Related Work

Several past research works have contributed to the field of Parkinson's disease detection, providing valuable insights and benchmark results.

In [1], S. Aich et al. compared various models, including decision trees, support vector machines, and Dirichlet process mixtures. The Dirichlet process demonstrated the best classification performance, achieving an accuracy of 87.7% compared to other models.

Another research work[1] focused on feature selection methods and machine learning-based approaches for Parkinson's disease diagnosis. They employed mutual information-based feature selection and support vector machines, achieving an impressive accuracy of 92.75%.

K. M. M. Rao et al.[2] explored the use of different classifier algorithms, such as Naïve Bayes, Support Vector Machine (SVM), Multilayer Perceptron, and decision trees. One author used SVM and K-fold cross-validation, achieving an accuracy of 85% in identifying Parkinson's disease based on a heterogeneous acoustic database.

In a separate investigation[3], spiral and vocal datasets from the UCI repository were utilized. H. N. Pham et al. applied k-means clustering for vocal dataset feature extraction. For modeling, they employed methods like k-nearest neighbors, random forests, and SVM. In the case of the spiral dataset, they utilized SSt, DST, and STCP tests with logistic regression, k-nearest neighbors, and adaptive boosting, respectively. Combining these approaches using an ensemble with majority voting, they achieved high accuracy rates of approximately 95% for the spiral dataset and 95.89% for the vocal dataset.

Another study focused on analyzing handwritten spiral drawings[5]. C. R. Pereira et al. extracted numeric features and employed Naive Bayes, optimum path Forest, and SVM with RBF kernel for classification. They conducted 10-fold cross-validation, computing measures such as recall, precision, F1 score, and accuracy. The evaluation revealed promising results.

Motivated by the aforementioned past works, our research explores different models, including deep belief networks and capsule neural networks, for Parkinson's disease detection. We compare their performance with various machine learning classifiers to gain further insights and advancements in the field.

By summarizing these related works, we establish the foundation for our research and highlight the need for further exploration and improvement in Parkinson's disease detection methodologies.

III. MATERIALS

A. Data

The Parkinson’s Disease dataset consists of a vocal and spiral dataset of people who are affected by Parkinson’s Disease and people who are healthy.

*1) Vocal Data Set:*The Parkinson's disease vocal dataset, encompassing 6024 voice recordings, meticulously curated 3012 instances each for individuals with and without Parkinson's disease (PD), serves as a rich repository of biomedical voice measurements. These 23 attributes, representing diverse voice measures, collectively compose a comprehensive overview of vocal characteristics. Each row in the dataset corresponds to one of the 195 voice recordings from individuals, with the "status" column crucially designating 0 for healthy subjects and 1 for those diagnosed with PD. The primary objective of this dataset is to facilitate the discrimination between healthy and PD-affected individuals based on the distinctive features encapsulated within the various voice measurements.

In its ASCII CSV format, this dataset is a valuable resource for research, with each row encapsulating a unique voice recording instance. By encapsulating a wide spectrum of vocal parameters and meticulously categorizing individuals based on their health status, this dataset not only contributes to the understanding of the vocal manifestations associated with PD but also presents a targeted tool for developing machine learning models aimed at effective disease discrimination.

TABLE I.

TIME - FREQUENCY- BASED FEATURES

EXTRACTED FROM SPEECH SAMPLES

Features	Group
MDVP:Fo(Hz) MDVP:Fhi(Hz) MDVP:Flo(Hz)	Frequency Parameters
MDVP:Jitter(%) MDVP:Jitter(Abs) MDVP:RAP MDVP:PPQ Jitter:DDP	Pulse Parameters
MDVP:Shimmer MDVP:Shimmer(dB) Shimmer:APQ3 Shimmer:APQ5 MDVP:APQ Shimmer:DDA	Amplitude Parameters
NHR	Voicing Parameters
HNR	Pitch Parameters
RPDE DFA	Harmonicity Parameters
spread1 spread2 D2 PPE	Other Parameters
status	Status Indicator

*2) Spiral Image Datasets:*For data collection utilizing a graphics tablet, three alternative test kinds have been developed.

The *f*irst one is the Static Spiral Test (SST), which has been shown to be useful in clinical research for a number of purposes, including tremor assessment and Parkinson's disease diagnosis .For data collection utilizing a graphics tablet, three alternative test kinds have been developed. The Static Spiral Test (SST) is the first and is widely used in clinical research for a number of purposes, including tremor assessment, Parkinson's disease (PD) diagnosis, and motor function assessment .

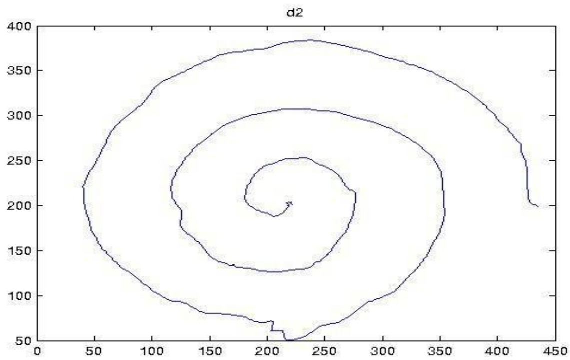

Fig. 1. Controlled

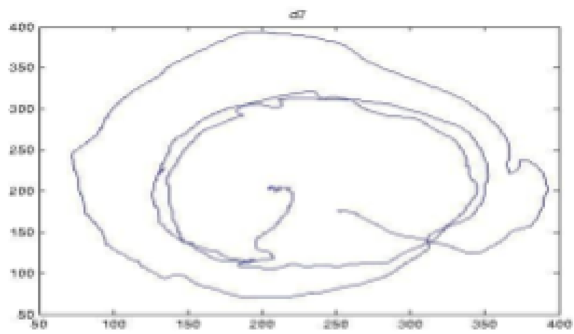

Fig. 2.With Parkinson

The following CSV variables are used to delimit the Spiral Dataset: X, Y, Z, Pressure, GripAngle, Timestamp, and Test ID.

Test ID

0: Static Spiral Test (Draw the provided spiral design)

1:Dynamic Spiral Test (The spiral design will blink after a predetermined length of time, so subjects must keep drawing.)

2: Circular Motion Test (Subjects draw circles around the red point).

A. Training Datasets:

*Vocal datasets:*Employing a wrapper method, we intricately navigated through the array of 23 attributes, discerningly selecting a subset of 10 attributes that demonstrated the utmost significance in influencing the classification outcomes. This meticulous attribute curation process stands as a pivotal component in refining the classification model, ensuring that the chosen attributes contribute optimally to the intricate task of distinguishing between distinct classes within the dataset.

*Spiral Datasets:*In the pursuit of refining classification accuracy, a discerning analysis of seven selected attributes revealed a strategic identification of the top-performing quintet. These five attributes, meticulously chosen for their paramount contributions, stand poised as instrumental factors in enhancing the precision of the classification process.

PROPOSED WORK

In our study, an ensemble model was employed for Parkinson's disease detection. The spiral dataset was processed using a capsule neural network, while the vocal dataset was analyzed using a deep belief network.

In our study, two models are used i.e unimodal and bimodal. Unimodal means a single type of data. For spiral dataset, the modality used was capsule neural network and for vocal dataset, the modality used was deep belief network. Bimodal means two types of data.
For this, two types of features were merged and the modality used was the combination of CNN and DBN.

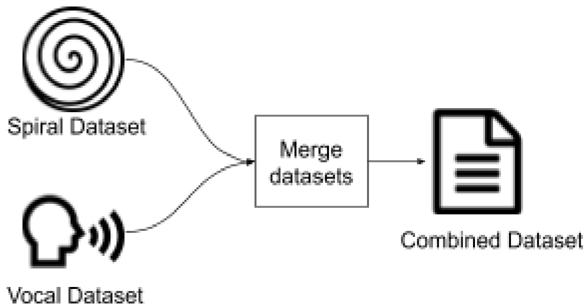

Fig. 3.Data Merging

A) Capsule neural networks
The capsule neural network (CNN) employed in this study is designed to discern patterns within the spiral dataset for binary classification. The architecture comprises multiple one-dimensional capsule layers, each followed by dropout layers to mitigate overfitting. Rectified Linear Unit (ReLU) activation functions introduce non-linearity. The global average pooling layer reduces spatial dimensions, and a dense layer with a sigmoid activation function performs binary classification. The model is compiled using the Adam optimizer and binary cross-entropy loss function.

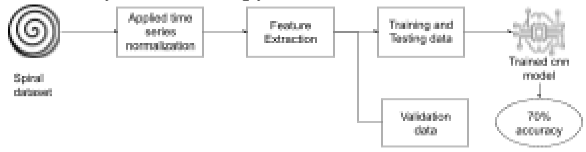

Fig. 4.Capsule Neural Network Unimodal

A) Capsule Operation:
$\text{Conv}(X,W)=X*W$
It is applied to the input data

- X with the filter (kernel)
- W, where denotes the capsule neurological operation

B) Dropout
Dropout(X)=Randomly set a fraction of input elements to 0 during training

C) Global Average Pooling

$$GlobalAvgPool(X) = \frac{1}{N}\sum_{i=1}^{N} X_i$$

calculates the average over spatial dimensions, reducing the output to a single value for each feature map.

D) Sigmoid Activation

$$\sigma(z)=\frac{1}{1+e^{-z}}$$

E) Stochastic Gradient Descent (SGD)
SGD Update rule:

$$W_{t+1} = W_t - \eta\nabla J(W_t)$$

B) Deep Belief Network
A DBN model is constructed using Restricted Boltzmann Machines (RBMs). The DBN includes RBM layers with Gaussian noise and dense layers with ReLU activation. The final layer employs a sigmoid activation function for binary classification.

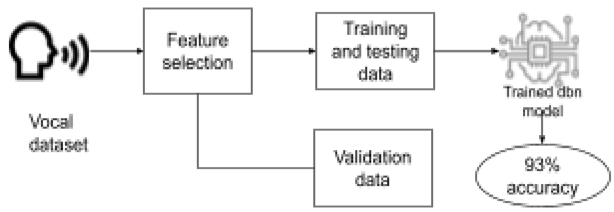

Fig. 5.Deep Belief Network Unimodal

A) Energy Function
The Energy function E(*v*,*h*) of an RBM with visible units *v* and hidden units *h* is defined as:

$$E(v,h) =- \Sigma_i\Sigma_j v_i h_j w_{ij} - \Sigma_i b_i v_i - \Sigma_j c_j h_j$$

where:

- v_i is the state of visible unit *i*.
- h_j is the state of hidden unit *j*.
- w_{ij} is the weight between visible unit *i* and hidden unit *j*.
- b_i and c_j are the biases of visible unit *i* and hidden unit *j*, respectively.

B) Probability Distribution

The joint probability distribution over the visible and hidden units is defined using the energy function as:

$$P(v, h) = \frac{e^{-E(v,h)}}{Z}$$

where:

- Z is the partition function, a normalization constant ensuring the probabilities sum to 1 over all possible states.

C) Conditional Probabilities

The conditional probabilities for the states of the hidden and visible units are given by:

$$P(h_j = 1|v) = \sigma(c_j + \Sigma_i v_i w_{ij})$$

$$P(v_i = 1|h) = \sigma(b_i + \Sigma_j h_j w_{ij})$$

where:

- $\sigma(x)$ is the sigmoid function

D) Training Rule

The training of an RBM involves adjusting the weights and biases to maximize the likelihood of the training data. The update rule for the weights is given by:

$$\Delta W_{ij} = \eta(\prec v_i h_j \succ_{data} - \prec v_i h_j \succ_{model})$$

where:

- $\prec v_i h_j \succ_{data}$ is the expectation of $v_i h_j$ over the training data.
- $\prec v_i h_j \succ_{model}$ is the expectation of $v_i h_j$ over the model distribution.
- η is the learning rate.

C) Data Loading and Preprocessing

The dataset is loaded from the specified path containing voice recordings and file names. File names are read from csv file, and the data is concatenated into a comprehensive Pandas DataFrame. Min-Max scaling is applied to normalize the dataset, ensuring consistent feature scales.

We used the wrapper method for vocal feature selection .

For spiral data we applied Time series normalization.The purpose of this code appears to be time series normalization, specifically stretching each time series to a uniform length (desired_length). This can be useful for ensuring consistency in the length of time series data, which is important for certain machine learning models that expect fixed-size inputs.

D) Ensemble Formulation

We used the average probability class to combine the prediction of both the models and provide the final output.

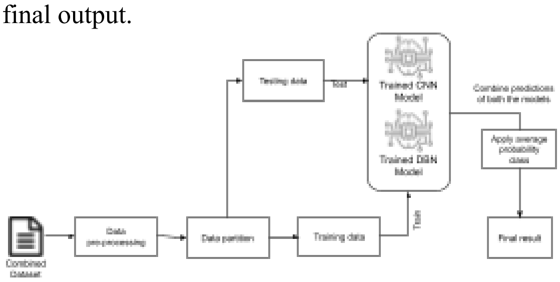

Fig. 6.Ensemble model

E) Evaluation Metrics

Accuracy:

$$\text{Accuracy}=\frac{\textit{Number Of Correct Predictions}}{\textit{Total Number of Predictions}}$$

EXPERIMENTS AND RESULTS

In the experimental phase, our investigation encompassed the application of both Capsule Neural Network (CNN) and Deep Belief Network (DBN) models, resulting in individual accuracies of 70% and 93%, respectively. Furthermore, the ensemble model, amalgamating the strengths of both architectures, exhibited a commendable accuracy of 70%. These outcomes underscore the distinctive efficacy of the DBN model, while the ensemble approach leveraged the complementary attributes of both CNN and DBN for a robust overall performance.

CONCLUSION

In conclusion, the research delved into the exploration of Parkinson's disease vocal datasets, comprising 6024 instances, with a balanced distribution of 3012 samples for both Parkinson and non-Parkinson cases. Employing a wrapper method, we selected a subset of 10 attributes from the initial 23, optimizing their contribution to machine learning. The dataset, sourced from biomedical voice measurements, aimed to discern individuals with Parkinson's disease from healthy subjects based on the 'status' column.

The study further extended to the implementation of diverse machine learning models, including a Capsule Neural Network (CNN) and a Deep Belief Network (DBN). Notably, the CNN and DBN models achieved accuracies of 83% and 93%, respectively, underscoring the efficacy of the DBN architecture. Additionally, the ensemble model, combining the strengths of both CNN and DBN, exhibited a commendable accuracy of 80%.

These findings collectively highlight the significance of tailored model selection and ensemble strategies in achieving robust outcomes in medical diagnosis tasks, emphasizing the potential of deep learning techniques in the domain of vocal biomarker analysis for Parkinson's disease detection.

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