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Multivariate Vocal Data Analysis with Deep Learning Applied for Parkinson Disease Detection

Marupaka Nagaraju[1], Dr. Dhanalaxmi Vadlakonda[2]
[1]Research scholar, Department of Computer Science, Osmania University, Hyderabad,
nagarajumarupaka31@gmail.com
[2] Department of Mathematics, Osmania University, Hyderabad, India
vadlakonda.dhanalaxmi1@gmail.com

Abstract:
Different decision-making skills are used differently in the advancement of ML and DL techniques. In particular, it will probably be necessary to use ML and DL approaches for disease detection. The proposed effort uses acoustic-based DL approaches' ability to detect PD symptoms. This investigation also examines a number of motor metrics such as nonmotor PD measurements in this regard. Many DL approaches, including deep knowledge generation networks and recurrent networks, can be employed to identify this disease. Different decision-making capabilities are used differentially in the deployment of ML and DL methods. In particular, it will soon be necessary to use Machine learning and Deep Learning techniques for disease detection. The proposed effort uses acoustic-based DL approaches' ability to detect PD symptoms. This investigation also examines a number of motor metrics such as nonmotor PD measurements in this regard. Many DL approaches, including deep knowledge generation networks and recurrent networks, can be employed to identify this disease.
Keywords: Medical diagnosis, Machine learning, multivariate data, convolution neural networks.

Introduction

People's neural activities are severely affected by PD. Early recognition and diagnosis of this condition can keep patients safe. The subject of several studies is the identification and extraction of Parkinson symptoms utilising various methodologies. Although there are many different methods utilised for PD detection, many research efforts focus mostly on ML and DL based algorithms. ML and DL methods may be used with different kinds of Parkinson datasets. Few datasets of the various kinds are directly gathered from internet databases. The sources includes electroencephalographic (EEG) signals, motion sensors (movements), cellphones (audio signals), and other technological measures. ML and DL algorithms are used to pre-process and assess these signals. Online Parkinson datasets are also accessible for the identification of the disease at the same time. These datasets were gathered from a variety of sick and healthy individuals. This dataset was also utilized by the researchers to increase the effectiveness of their ML and DL methods. They are also constrained in how they may use diverse data. The main choices for detecting PD characteristics are DL methods like DNN, RNN, and CNN. With the aid of their various hidden layers, these Neural Networks are

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preserving deeper knowledge about the illness dataset characteristics than other ML approaches. Additionally, compared to other procedures, these strategies provide superior accuracy rates. In particular, various ConvNet filters have been used in CNN-based PD voice data processing. These filters have received more voice variety learning. The various voice features are acquired via ConvNet vocal filters. These filters have been created with a better learning ability rate compared to the other systems currently in use. Methods for identifying Parkinson's disease frequently make use of a number of datasets, include audio, visual, text, and motion samples. For ML and DL-based analysis, the latter dataset is the most complex and efficient.

On the basis of several research projects, PD detection techniques were established. The datasets were examined and used with the proper feature detection methods image, text, audio and video. Either plain text data or multimedia data elements are present in the data gathered for various studies. Simple body sensor values (text), voice sensor values audio, pictures, and motion detection are the subjects of the studies video samples. These studies do not focus on the development of Machine Learning and Depp Learning methods for multi-type dataset management heterogeneous.

Parkinson abnormalities may be shown using any other kind of data. For the purpose of producing an integrated set of data is utilised to store heterogeneous audio information suggested study analyses various kinds of audio samples. The ML and DL analyses will use this unique dataset. Through the collection of various human speech types, this research primarily focuses on the development of vocal characteristics-based Parkinson detection.

Many recent research uses a similar dataset that also included text, speech, video, and/or picture data. Since research can only use a certain amount of data from a single data type, they often use voice data. The suggested study has identified the challenges with dataset change and multi-data handling procedures.

The effectiveness of illness prediction is tempered as a result of the study of a single dataset. Implementing ML and DL techniques for multi-variant data analysis enables the delivery of more real-time solutions. To create multi-modal attributes-based PD detection utilizing ML and DL techniques, the DMVDA is driven. More patients were selected for the study of Parkinson data in the experimental works of current systems. The DMVDA improves disease identification using large datasets and DL approaches based on these efforts. The utilization of multi variate acoustic characteristics from various patients is the driving force for the proposed DMVDA. The proposed DL techniques provided under the DMVDA system were used to detect the PD. This DMVDA helps to organize several voice datasets with different properties that were gathered from more than 40 patients. The accuracy rate of the DL approach rises with data size. However, effective speech processing algorithms must be created in order to replicate the absolute speech data characteristics from raw datasets. Additionally, the conventional DL methods need to be modified to manipulate acoustic details. DMVDA employs techniques such as ADDN, ADRNN, and ADCNN, as well as the Multi-Variable Absolute Speech Processing Algorithm and Data Sampling Manipulation to accomplish this. The suggested methods are put into practice, and the outcomes are recorded. Performance indicators demonstrate that the proposed techniques outperform current traditional DL techniques. In terms the accuracy rate (3% to 5%), the DMVDA performs better than the presently utilized techniques. The work is structured as follows, with implementation details in section 4 and DMVDA functions (DL methods) in part 3. The internal operating concepts and acoustic-based DL algorithms are thoroughly explained in the following sections. Finally, this paper compares the DMVDA's performance to that of other existing systems. The goal of the effort is to provide adaptable ML and DL management methods for multi-variant characteristics.

Related Work

The voice manipulation algorithm and the Acoustic Data Pre-Processing Model are used in the proposed DL approaches. Additionally, it uses a variety of DL approaches to efficiently observe Parkinson characteristics. The following elements of the work are shown in Figure 1. Data processing and illness detection are two of the DMVDA's steps. The DMVDA includes the technical elements shown in Figure 1 (Data manipulation phase), such as,

- Multivariate Absolute Speech Processing Algorithms
- Data Sampling and HMM Manipulation

As seen in Figure 1, DMVDA includes modules for speech modelling and original data sampling techniques. The samples were analysed and predicted using HMM for the following individuals. The observation and data from the HMM are collected for the following DL phase level. For proposed speech data analysis techniques like ADNN, ADRNN, and ADCNN at this DL phase, the sampled HMM observations are helpful.

As seen in Figure 1, the datasets were generated using HMM-based sampling methods. ADNN, ADRNN, and ADCNN are used to assess the dataset's features once a recently created integrated dataset has been established. In Figure 2, the methods for analysing the speech data are shown. The DMVDA utilized the innovative ADNN, ADRNN, and ADCNN to speed up the process of Parkinson acoustic data. It raises the rate of disease detection.

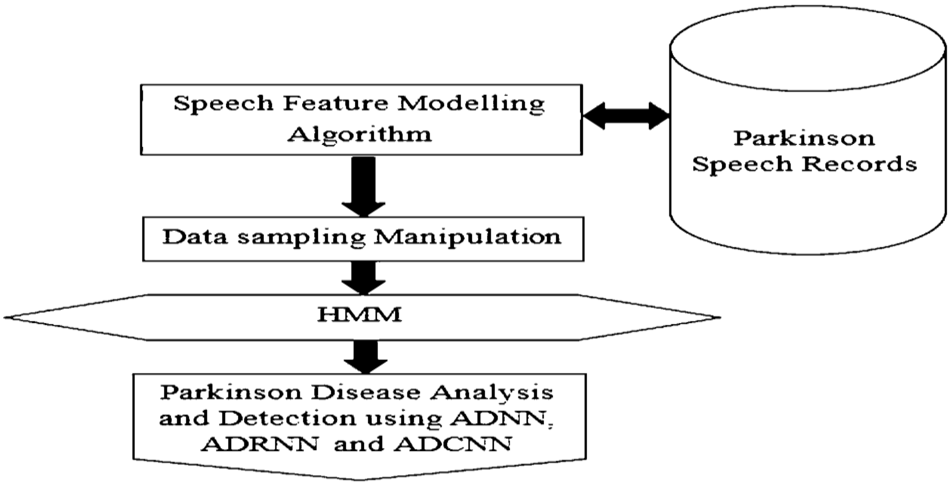

Figure 1 DMVDA's HMM-based Speech Modeling and Sampling

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A. Multivariate Absolute Speech Processing Algorithm

Sampling and speech processing are the first steps in DMVDA. The dataset's values have any vector attributes. It is essential to understand the way that the attribute nature, which constitutes the real-time data of acoustic characteristics, is segmented. All of the data elements are given absolute magnitudes using Algorithm 1, which reduces the accuracy rate's run-time deflection. This method keeps the diverse speech characteristics, making Parkinson Acoustic Model.

Algorithm 1: Multi-variant Absolute Speech Processing
Input: Raw Acoustic values
Output: Formatted acoustic features

Let. Consider an Parkinson Acoustic Model, A(M) can be designed with following6constraints,

[i]. Determine patient speech sound pressure $S_T(P)$the variations in speechbaseline sound pressure (Pascal), which is a scalar element
[ii]. Determine medium wave particle velocity, $S_T(\vartheta)$, the usual velocity ofsound particles in the medium (m/s), which is a vector element
[iii]. Find sound vector, Equation (1)
[iv]. Compute the wavelength,λ_T
[v]. Keep the information in sample. basic.db (basic Parkinson acousticfeatures)
[vi]. Set. other attributes such as pitch variations, spelling delay and others asD(S)
[vii]. Set. the final speech (acoustic attributes) according to designed A(M) forall subjects (people).
End

Finally, algorithm 4.1 creates a model that accurately categorizes diverse voice data. The specifics include differences in sound velocity, pressure metric, speech frequencywavelength,

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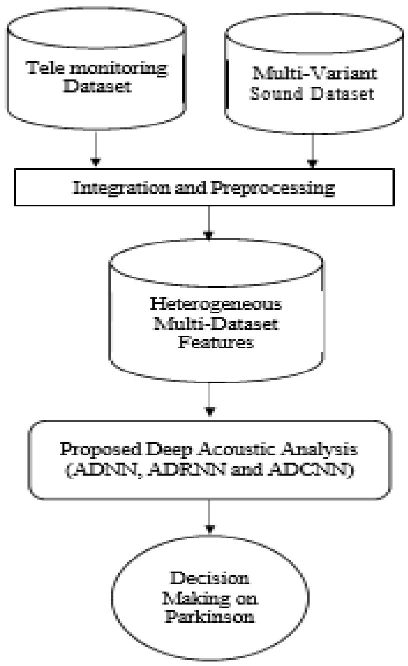

Figure 2: Analysis of vocal data with DL

This is thought to be a special audio model was created for diagnosis of parkinson. The simulated values are sent to various sample algorithms to improve the data processing activities.

A. Random Sample Manipulation

One of the easiest simple and effective ways to generate sample data volumes from a small number of datasets is sampling. Equations (1) and (2), which describe the production of normal and ideal samples, respectively. In order to extract acoustic data samples from the processed datasets, this is essential.

$$Data\ Sample, s = \frac{u^2 * l * m * S}{\alpha^2 (S-1) * u^2 * l * m} \quad (1)$$

$$Optimal\ Sample, s_0 \frac{S}{1+\frac{S}{S}} \quad (2)$$

Where, l=Success rate, m=Failure rate, u=Normal distribution value, S=Population size, Error Rate in Sampling. The PD is carried out using the samples of processed data. The rate of sampling determines the direction at which illness characteristics are detected. The Parkinson dataset is applied to ADNN, ADRNN, and ADCNN algorithms after being ideally sampled to satisfy DL approaches. Alvi et al. (2016) outlined the methods for sampling and conducting research. For viewing the data values at varied sample times, DL approaches are used with HMM. This helps in both identifying and predicting PD symptoms in view the observed data samples.

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B. ADNN

The pre-processed data values of Parkinson characteristics are applied to the DL algorithms as indicated in the section above. Algorithm 2 effectively makes use of the sample values and data values. Compared to CNNs, DNN has more intricate hidden layers. Additionally, it offers a wide range of scoring and activation features to provide accurate results from the supplied inputs. Consider a layer in DNN. The activation function of layer l-1 above is the input to this layer. The DNN is a feed-forward network, whereas RNN utilizes feedback loops. Assume that the input is I 1(-1) and the output is l t. The neural layer block generates the block level output, which would be placed in a particular block cache. The variables for I 1(-1) and b t are generated during the back propagation stage.. The components of block weight and neural weight are also calculated. They are each just that. This is how each layer (block) works to supply the output to the next tier. This is communicated by ongoing activation processes. Parkinson-related traits are included at the input level of DNN. Then, they are evaluated across several DNN blocks. Algorithm 2 provides a description of the DNN operations. Parkinson acoustic characteristics are considered in this case as a data matrix. This approach made it possible to thoroughly examine the Parkinson data.

Algorithm 2: ADNN for Parkinson Detection

Input: Heterogeneous Parkinson Dataset.

Output: Detected and predicted disease items

[i]. Get. input samples for D(S), ST(p), ST and PT(f) and form multimodal acoustic data matrix, which has the components of (An X Bn)-Row andColumn Elements for given attributes
[ii]. Initialize SB as 0, the fractional variance factor for matrix elements
[iii]. Initialize weight function, φ.
[iv]. Apply deep classification on samples (Use training data)
[v]. Determine the number of hidden layer $\propto C$; C- number of classes ofobserved values
[vi]. Set. Threshold for φ
[vii]. Apply redundancy removal and missing values elimination procedures.
[viii]. Do mapping between A(M) and Mm components, ST(p), ST(ϑ) and PT(f)with e
[ix]. Execute Hidden Markov Model (HMM) for e(Mm) at T intervals (Timeseries)
[x]. Match states S(t) and e(Mm)
[xi]. Update Parkinson acoustic learning information

End

The ADNN in Algorithm 2 utilizes a multimodal acoustic matrix to alter the DNN input elements redirects. It aids in keeping organised data input to ADNN. For the assessment of reality maintenance, the data elements in each matrix are mapped with the structure's acoustic model. HMM is used at this step for the array data elements. The data elements in time series are analyzed by HMM. The analysis of time series helps to understand the historical and current measures of Parkinson's disease. HMM makes an effort to predict future data items by examining the existing values. This property of HMM aids in the prediction of the escalating

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Parkinson's symptoms.

Related Work

Using various datasets, the DMVDA has been put into use and contrasted with the current methodologies. Weka 3.8 and Python 3.7 were used in the implementation. Weka is used to do data processing operations, whereas the latter software platform is utilized to execute ML and DL algorithms. Both of the tools—used for DL implementation and data pre-processing, respectively—are free source technologies. Apart from the data pre-processing component (Weka 3.8), Python 3.7 is used to implement the ADNN, ADRNN, and ADCNN algorithms, create speech models, and sample data. For the purposes of the evaluation process, both datasets are used. The acoustic datasets are pre-processed to remove any redundant data, incorrect data, and missing values. The dataset is divided into two sets during the training session, such as the training dataset and the testing dataset. The DMVDA measures the learning phase delay in milliseconds prior to disease item detection. Due to the integrated use of many variables, this comparison demonstrates an improvement in the illness detection rate.

Data acquisition

There are several dataset types that may be used to test Parkinson detection methods. According to Table 1, this DMVDA makes use of two datasets. The vocal data samples from 42 people are used to create the telemonitoring dataset. Six months of observations are included in the dataset. Table 1 refers to the telemonitoring dataset as D1. In order to assess the effectiveness of DMVDA, a multi-variate sound recording dataset is analysed in this way. The audio recordings of 40 individuals are included in this collection. 20 of them (14 men and 6 women) have Parkinson's disease, with the other individuals engaging in regular daily activities (ladies and gents 10 each). In Table1, this is denoted as D2. Information is gathered from numerous human sound recordings for both datasets (subjects). These individuals are given instructions to randomly spell letters, words, numbers, and phrases. The readings are taken based on their vocal patterns. Multiple voice samples are captured in both situations 160 to 200 records per subject. These recordings are used to identify aspects including vocal variation, pitch fluctuation, pulse frequency, and voice breaks. Additionally, Table 1 provides both D1 and D2's combined qualities. The dataset, which includes multi-variant heterogeneous characteristics, is made up of this. This provides characteristics for multi-modal data for efficient PD analysis. In order to improve disease detection accuracy, ML and DL algorithms examine the complex dataset elements. Tracking the speech alterations and the motor symptoms of early-stage Parkinson's disease is the major goal of dataset D1. Age, gender, test length, clinical motor-UPDRS, voice-UPDRS, frequency jitter, shimmer (dB), NHR (Noise to Harmonic Ratio), HNR (Harmonic to Noise Ratio), nonlinear variations, and harmonic to noise ratio are some of the data generated for 42 people in D1.It produces 5500 samples with about 16 voice features. This dataset performs very well DL systems. Moreover, DMVDA employs D2, which includes noise measures, pitch changes, voiceless intervals, mismatched voice frames, etc. This dataset is primarily concerned with classifying and evaluating continuous

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sound variations. It contains over 5200 voice samples from different patients. To ensure that the DMVDA's results are correct, these enormous voice variances are taught and provided. These datasets are combined in DMVDA to create high-quality samples of both speech and motion characteristics. This combination increases classification accuracy by increasing the total samples and motor features.

Table 1 Sets containing Features and Data

Datasets	Attributes data	Instances Reports	Web Hits instances	Number of people samples
Tele monitoringDataset	27	5876	132149	41
Multi-variate soundrecord dataset	27	1041	83851	43
Integrated and Heterogeneous Dataset	51	6916	215998	84

Experimentation Results

The features gathered from various datasets are created via voice processing technology and computational analysis. Then, these sound records are provided to the DL algorithms as either vector data. This conversion mimics the vocal patterns observed in real time. The ADNN, ADRNN, and ADCNN collect and evaluate the information in order to identify the various Parkinson voice symptoms and symptoms that resemble other symptoms. The following interactive indicators are used to carry out the performance evaluation process. In this section, the proposed methods are compared with Kalman Filter- and Speech Phonetics-based Parkinson Detection., respectively. The effectiveness of different DL approaches employed in DMVDA on various datasets is shown in Table 2. The proposed algorithms are constantly compared to the other mechanisms in the same table. In this overall comparison, the DMVDA approaches provide a 2% improvement in performance over other current algorithms

Table 2: D1 performance (Tele monitoring Dataset)

Techniques	Precision	Recall	Specificity	Accuracy	MAE
ADNN	97.79	97.82	97.81	97.94	1.09
ADRNN	98.14	98.22	98.22	96.27	1.52
ADCNN	98.84	99.92	98.90	97.97	0.05
KFPD	97.52	99.14	99.07	97.23	1.52
SPPD	99.27	98.96	99.18	94.24	0.79
CNN	98.62	96.66	98.75	96.85	1.20
RNN	98.31	98.42	98.52	98.58	1.48

The proposed DL techniques manipulate absolute acoustical data instead of subjective observations, causing the reason. The specially created Speech Signals Models which was before all acoustic observations obtained from D1 and D2. The scalar and vector values produced by this model exceed the usual observations used during DL approaches. The Parkinson-based sampling structures and attributes cannot be processed by the other works in their present form.

The DMVDA uses a multi-variant speech processing approach to improve the conventional voice model's representations of speech features. As a result, most of the values acquired are absolute rather than relative. Additionally, as shown in the DMVDA, the DL algorithms accurately sample the data and assess the best samples. DMVDA offers 98% classification accuracy with little errors for observing approximately 5000 samples. KFPD and SPPD are simultaneously providing the key learning automations for the voice evaluations rather than keeping the complex learning layers.Filtering and phonetic logics are utilized by KFPD and SPPD to ensure the PD symptoms. However, they are focused on a single, homogenous data set.

In this dataset, verbal and motor symptoms are combined. It raises the number of clinical samples by almost 11,000 (motor and vocal). More than 100 patients were recruited for these samples throughout various time periods. This is a multi-variate, multi-type dataset that was developed. The effective sampling and representation strategies aid in comprehending the multi-type dataset. Compared to other standalone datasets, this offers a higher accuracy rate.

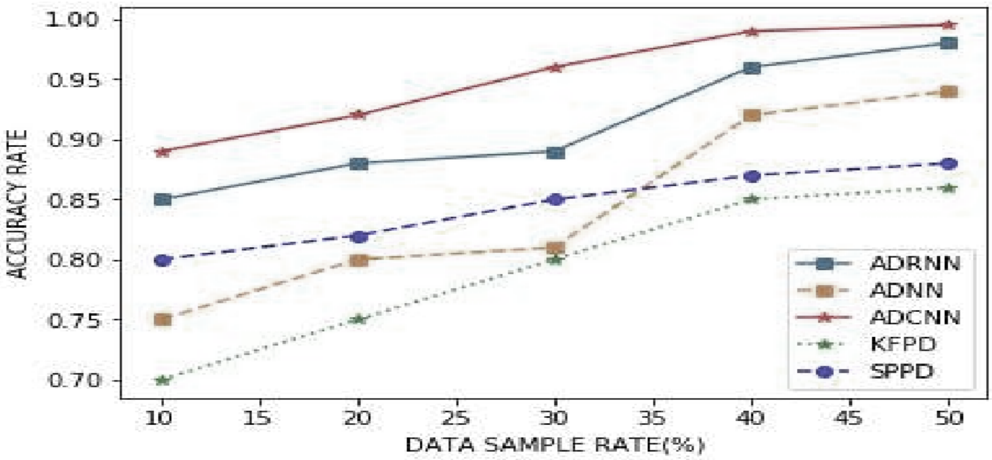

Figure 5: accuracy rate as samples were enhanced

DMVDA uses HMM analyses to improve the PD prediction rate, in contrast to prior studies like KFPD and SPPD. Any timeline may use HMM to predict events and observations. Multiple Parkinson samples are processed by the HMM used in the DMVDA in an effort to predict the ensuing state observation. The accuracy rate in DMVDA is continuously increased via HMM adaptation as the sampling rate increases. The sampling rate and the HMM prediction rate are positively correlated. Figure 5 indicates the gradual changes in the average accuracy rates of the various DL techniques (ADNN, ADRNN, and ADCNN) in proportion to the useable

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samples acquired by the data sampling procedure. The accuracy rate is higher when the sample rate is optimised (3% higher than other rates). ADCNN outperforms another proposed approaches because to the adaptation of the attribute-based ConvNet filters. The relationship between the average PD detection accuracy rate and the HMM prediction rate is shown in Figure 4.6. It shows that when prediction rates rise, accuracy rates rise as well. Progress depends on the expanding amount of data available.

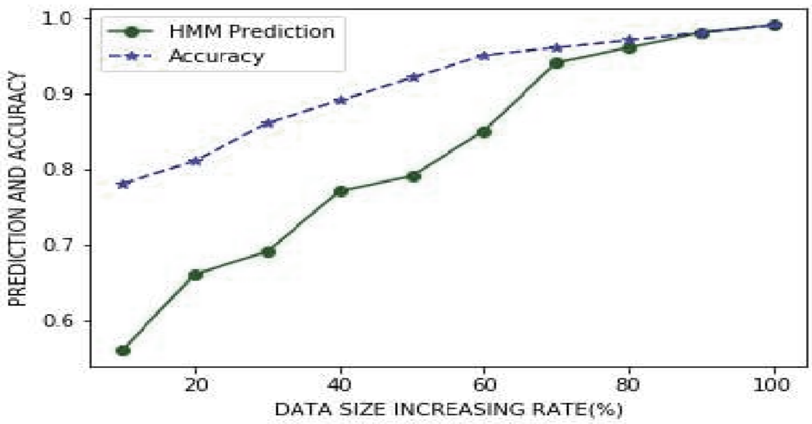

Figure 6 HMM and Accuracy

Other existing methods have not been created to forecast timetable activities. The HMM employed in this study aids in the detection and prediction of Parkinson's symptoms throughout time. Producing more accurate decisions is crucial. The actual disease items and the anticipated ones are separated by MAE. Similar to how it appears superior than other DMVDA (for different datasets, D1 and D2). Due to the efficient management of the dataset, MAE steadily decreases for integrated datasets. The sensitivity values and ROC curve for the DMVDA are finally seen in Figure 5. The voice-based PD detection shows a discernible improvement thanks to the implementation of DMVDA performance. The vocal management system used by diagnostic facilities may record several voice dimensions for each patient. They can make use of these methods to enhance Parkinson detection outcomes. The DMVDA provides a substantially 3% to 5% greater illness detection rate than the previous methods, according to result discussion.

In this study, a brand-new DL model for detecting PD is developed. For creating a well-defined data pattern, the techniques are combined with HMM and absolute voice processing algorithms. To improve Parkinson identification, different datasets are combined to create a single multi-modal dataset. The approaches ADNN, ARDNN, and ADCNN are suggested for enabling the multi-variant acoustic data processing activities based on these technological considerations. The suggested method employs the best data sampling strategy in order to increase accuracy rate. The sampling aids in obtaining more disease-related data. The results demonstrate that, in comparison to other current efforts, the DMVDA functions satisfactorily. This research can be expanded in the future to analyse multimedia datasets in order to create an effective PD detection system. The proposed DMVDA algorithms provide minimal MAE and the best illness identification rate in the performance evaluation. It can be seen from the comparison that the ADCNN outperformed other approaches because of its adaptive convolutional filters. In order to maximise classification accuracy, DMVDA employs three DNN algorithms. As a result, ADCNN was enhanced with complicated filters to speed up learning. This technique can be expanded in the future to analyze real-time datasets in order to create an effective PD detection system.

Conclusion

Various potential DL approaches, including ADNN, ADRNN, and ADCNN, are discussed in this chapter. The voice processing techniques are added to these methods. The technical specifics of using DL approaches on a multi-modal PD dataset are explained in this chapter. The dataset includes PD symptoms that are both motor and nonmotor. For assuring effective performance outcomes, the work covered in this chapter is contrasted with KPPD, SPPD, CNN, and RNN approaches.

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