Causes, Diagnosis And Prediction of Parkinson Diesease: A Review

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Abstract

In this review paper an introduction to Parkinson disease, stages in Parkinson disease, causes and the types of Parkinson disease has been discussed. Wearable devices or sensors that can be used for detection of Parkinson disease, checking the accuracy of the results or data provided by the wearable/portable sensors with clinical recorded data has also been discussed. Classifiers that can be used in machine learning for the detection of Parkinson disease have also been discussed. Methods by which Parkinson disease can be detected by medical lab tests have also been discussed. Also, we have discussed the prediction model of Parkinson disease using CNN in machine learning. All results are finally tabulated for comparison.

Keywords— Parkinson disease, wearable devices, machine learning, deep learning, machine learning classifiers.

INTRODUCTION

Parkinson's disease is a neurological ailment that deteriorates over time and impairs motor function. It results in shaking in the hands, arms, legs, jaw, and face as well as rigidity or stiffness in the limbs or trunk, slowness in bodily motions, an unsteady gait, and trembling in the affected areas. Early symptoms develop gradually and are modest. It takes place when the brain's natural dopamine-producing neurons (nerve cells) slowly degenerate. Dopamine, a substance that aids in message transmission across regions of the brain that regulate movement, is unusually low as a result of the loss of these cells. Dopamine deficiency makes it challenging to manage muscular tension and movement, both at rest and during times of activity[1], [2].

Parkinson's affects about:

- 0.4% of adults over 40.
- 1% of individuals over 65.
- 10% of persons are above 80.

- About 57 years old on average is the onset age.

Most cases of Parkinson's disease are idiopathic. Parkinson disease is generally found to occur in old age. But some rare cases are reported in early age too. Some of these cases are discussed in preceding sections.

A. Juvenile Parkinsonism:

Rarely starting in infancy or teenage and lasting up to 20 years is juvenile parkinsonism. Parkinson disease with young or early onset refers to cases that begin between the ages of 21 and 40. Juvenile and early-onset Parkinson disease may be different from later-onset Parkinson disease in that genetic reasons are more likely to be involved [1], [3].

- They advance more slowly[1], [3].
- They are quite susceptible to dopaminergic therapies[1].
- Most disabilities are caused by non-motor symptoms including pain, sadness, and worry [1].

B. Secondary Parkinsonism:

Similar to Parkinson disease and defined by basal ganglia dopaminergic blocking, secondary Parkinsonism is brain dysfunction that is brought on by a different condition than Parkinson disease (eg, drugs, cerebrovascular disease, trauma, post encephalitic changes) [4].

C. Atypical Parkinsonism:

A group of neurodegenerative disorders known as "atypical parkinsonism" share some characteristics with Parkinson disease but differ in their clinical presentation, prognosis, response to levodopa, and pathology (eg, neurodegenerative disorders such as multiple system atrophy, progressive supranuclear palsy, dementia with Lewy bodies, and corticobasal ganglionic degeneration) [5].

WEARABLE DEVICES USED FOR PARKINSON DISEASE

For quantitative assessment of Parkinson disease, some wearable devices have been developed to monitor PD patient’s health. These are such as:

A. Multi sensor wearable system for the quantitative assessment of Parkinson disease

As given in Table no. 1, according to the first wearable device used to measure for the quantitative assessment of the patients suffering from Parkinson disease. This device is a wearable portable device that can be mounted on the body of a patient. It has been developed for the simultaneous measurement of motion and neurophysiological signals in Parkinson disease patients. In this wearable device, it consists of total of 8 sensors in which 5 sensors are motion sensors and the other three sensors are electrophysiology sensors which are used to measure the following signals motion signals of the body, electroencephalogram, electrocardiogram and electromyography. For motion sensors the signals collected are the hand motion, the gait speed etc. For neurophysiological sensors the data collected are EEG, EKG, EMG signals. In this

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device, a Wi-Fi module has also been used to continuously obtain the data by the sensors and upload the data on a cloud-based server for the continuous monitoring of the PD patients[6].

B.Wearable EEG device

In this study, they have compared the EEG (Electroencephalography) signals from mEEG devices (commercially available wearable) to vEEG device (a recorded clinical video EEG). This study was conducted on twenty-two adult patients. Nowadays wearable EEG headsets are being developed as gaming hardware or other consumer products. The available consumer grade mEEG devices are low in price and have moderate quality as compared to clinical available EEG measuring devices. The wearable EEG measuring device has less channels (14 channels) as compared to clinical EEG (21 channels). So, here the main work conducted is to check and compare the mEEG data against the clinical standard used in healthcare. In this study the Emotiv EPOC EEG Headwear has been used which is actually a gaming Headwear this Headwear is connected to a Tablet by a 2.4 GHz band Bluetooth and the EEG signals are recorded continuously and monitored [7].

C. Efficient and compressive IOT based health care system for Parkinson's disease patient

In this research a device was designed which is IOT-based healthcare solution for patients with Parkinson's disease that is effective and compact. This is a wearable device which continuously collects EEG signals data from the PD patients. This data collection of the patients is monitored by the health care Centre. If there is any emergency a particular action can be taken by the help of monitoring and collection of the EEG data signals by the IOT technology with the compressive sensing (CS) method. In this wearable device system, the data is collected compressed and finally the EEG signals are encrypted using the compressive sensing method. The compressed collected data is then decompressed and also decrypted the data is examined and a particular decision is taken. In this wearable device system, the hardware comprises of an Electroencephalography EEG sensor which has to be wear on the patient's head, Arduino microcontroller, Bluetooth device, a cloud server[8].

D. Skin surface mounted sensor wearable device

In this research there were 13 Parkinson disease patient that wore skin surfaced mounted sensor which was BiostampRC sensor to collect tri-axial accelerometer and gyroscope data and they also wore a commercially available smart watch which was apple watch series 2 also for collecting tri-axial accelerometer data on the hand that has been most seriously affected. The participants were made to perform specific type of motor tasks in this process, monitored by the clinician and stored severity of tremor and bradykinesia in that specified limb. Machine learning model random forest model was used to classify PD symptoms the models were built using a population-based, leave-one-participant-out (LOPO) approach in this applying the training data from all participants but one to classify tremor and bradykinesia in the left-out patients. The two RF models were used binary and multiclass were used for each symptom like tremor and bradykinesia. Binary model classifies the presence or absence of the PD symptoms, and a multiclass model scores the PD symptoms on the scale of zero to four. This research tells that if we pair wearable sensors or wearable devices such as smart watches. With machine learning, it can provide us efficient, accurate and real time monitoring of the PD patients[9].

E. Detecting fluctuations in Parkinson disease patients by using wearable technology

Parkinson's disease (PD) patient's subjective self-assessments are being used to track changes in their motor symptoms. To enable accurate treatment rescheduling and dose modification, clinicians need accurate information regarding the incidence of a fluctuation. In this research, authors looked at how sensors were used to identify motor fluctuations in PD patients and how machine learning approaches were used to spot fluctuations. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) standards were followed during the review procedure. Ten studies between January 2010 and March 2021 were included, and their key traits and outcomes were evaluated and recorded. Four research employed actual scenarios that carried out specified tasks to collect data, five studies used daily activities, and only one study combined the two methods. The criterion for diagnosing PD is based on a neurologist's clinical evaluation of the patient. The patient is given activities to do, and the severity of the patient's PD symptoms is often assessed using the Unified Parkinson's Disease Rating Scale (UPDRS) or the MDS-UPDRS, a modification of the UPDRS sponsored by the Movement Disorder Society. The Hoehn and Yahr scale (HY) is used to assess disease progression. An antiparkinsonian treatment plan is modified and adjusted by a doctor to meet the specific needs of each patient based on the evaluation and modifications of these scaled scores. The assessment is based on the time a patient was checked in relation to the last dose of medication and is thus subjective. Doctors rely on patients' assessments of the severity because of the symptoms' alleged shifting nature[10].

Table 1: Comparison of various wearable devices or technology that can be used to monitor PD patient's

S.NO.	Title	Technology used	Applications	Sensors or hardware used
1	Multi sensor wearable system for the quantitative assessment of Parkinson disease [6]	8 sensors in which 5 sensors are motion sensors and the other three sensors are electrophysiology sensors	It is has been used for the quantitative assessment of the Parkinson patient	CC3220 MCU, MPU9250 chip, ADS1299 chip,
2	Can commercially available wearable EEG devices be used for diagnostic purposes [7]	EEG signals, comparing EEG signal data tracked from the wearable devices that are recorded with the clinical EEG devices used	To check the whether the commercial EEG detecting devices that are available are accurate with results or not	EEG sensor headwear, Emotiv Epoc, video EEG
3	Efficient and compressive IOT based health care system for Parkinson's disease patient [8]	Making a wearable EEG detecting device using EEG sensors	A cost efficient and more over a wearable and portable EEG device	EEG headwear, Arduino, Bluetooth device, cloud server
4	Role of data measurement characteristics in the accurate detection of Parkinson's disease symptoms using wearable sensors [9]	Wearable device used to measure tri-axial, accelerometer, gyroscope, apple ML classifiers used Random Forest.	Making of a wearable Device for detecting Parkinson symptoms.	Biostamp RC, apple watch series 2
5	Wearable technology to detect motor fluctuations in Parkinson's disease patients: current state and challenge[10]	PRISMA technology has been used in it.		

VARIOUS MACHINE LEARNING TECHNIQUES FOR CLASSIFICATION

Machine learning and deep learning techniques can be used to detect and predict Parkinson disease from the EEG signal, audio signal or MRI signals. Some of those techniques with their accuracy score is discussed in preceding subsections.

A. IB1 classifier:

An instance-based machine learning method called the IB1 classifier categorizes incoming instances based on how closely they resemble examples that have already been observed and are kept in memory. It operates by determining the closest match between the new instance and each stored instance using a given measure. The class labels of the nearby stored instances are then used to anticipate the new instance. Although the IB1 classifier is regarded as being straightforward and effective, it can be memory-intensive and prone to overfitting, particularly when the training data comprises noisy or irrelevant samples. A study was conducted on 31 male and female individuals in which 23 were diagnosed with Parkinson disease. IB1 classifier was used on speech signals dataset and found out the accuracy of 96.4103 percent when the IB1 classifier is used [11], [12].

B. Rotation Forest:

The Rotation Forest is an ensemble machine learning approach that enhances the performance and stability of the model by combining decision trees with feature subspace rotations. To create the final forecast, several decision trees are combined and trained on rotated copies of the feature subspace. A more reliable and accurate model result from the rotation of the feature subspace, which decreases overfitting and increases tree variety. The Rotation Forest is regarded as a very straightforward and effective algorithm since it has been demonstrated to work effectively in a range of applications and domains. A study was conducted on 31 male and female individuals in which 23 were diagnosed with Parkinson disease. Rotation forest classifier was used on speech signals dataset and found out the accuracy of 92.3077 percent when the Rotation forest classifier is used [12], [13].

C. Random forest:

Random Forest is a well-liked ensemble machine learning approach that blends different decision trees to provide predictions. To get the final forecast, the predictions of many decision trees are combined after they have been trained on a set of training data and features that is randomly selected. A more robust and accurate model is produced as a result of the training data and feature randomization, which also helps to decrease overfitting and boost tree variety. The technique known as Random Forest is thought to be both straightforward and efficient. A study was conducted in which the features were extracted from the speech signals. Random forest classifier was used and got an accuracy of 91.28 percent, specificity of 93.21 percent and sensitivity of 88.33 percent on using Random forest classifier [14] [15].

D. Multilayer Perceptron:

A sort of artificial neural network called a multilayer perceptron (MLP) is employed for supervised learning tasks including classification and regression. It is made up of several layers of linked nodes, commonly referred to as neurons that process and send data from the input layer to the output layer. Each neuron in an MLP gets inputs from the layer above, performs a weighted sum of the inputs, and then applies an activation function to create an output. The kind of MLP network, such as a feedforward or recurrent network, is determined by the activation function, which can be either linear or non-linear. A study was conducted in which the dataset is made up of biomedical voice measurements derived from the 31 people in which 23 people are diagnosed with Parkinson’s disease. Multilayer perceptron classifier was used for the following dataset and an accuracy of 93.2203 percent was obtained on using Multilayer perceptron classifier [16], [17].

E. Bagging:

A machine learning ensemble approach called bagging (also known as bootstrapping aggregation) can be used to improve a model's stability and minimize variation. The method involves training many instances of the same base model on various randomly picked subsets of the training data, then combining their predictions to arrive at the final prediction. A more robust and accurate model is produced as a result of the random sampling, which also increases model variety and reduces overfitting. Bagging has been found to be effective in a wide range of applications, including classification, regression, and anomaly detection. It may be applied to a number of base models, including decision trees, neural networks, and support vector machines. A study was conducted in which Parkinson's dataset of UCI Repository was used which had data of the measurement of the voices which had data of 31 individuals out of which 23 of them were PD patients and rest were healthy people. While using Bagging classifier an accuracy of 81.11 percent was obtained[18]–[20].

F. Sequential minimal optimization:

A method for handling complicated linear Support Vector Machines problems is called sequential minimal optimization (SMO) (SVMs). It is a quick and effective method of optimizing a problem that involves repeatedly changing two variables that have a significant bearing on the optimization issue. The SMO technique addresses this issue by decomposing the optimization problem into more manageable sub-problems that may be handled quickly. The optimization problem in an SVM is addressed by identifying the hyperplane that best divides the data into several classes. A study was conducted in which Parkinson's dataset of UCI Repository was used which had data of the measurement of the voices which had data of 31 individuals out of which 23 of them were PD patients and rest were healthy people. While using sequential minimal optimization classifier an accuracy of 0.76 and sensitivity of 0.97 was obtained in that study [21], [22].

G. Decision Table:

A Decision Table classifier is a straightforward rule-based machine learning model that employs if-then statements to produce predictions. It operates by defining a set of guidelines that outline the circumstances under which a specific result should materialize. The most likely result is then determined by comparing the input data to these guidelines. Decision Table classifiers are most helpful in fields where the correlations between input features and outputs are well understood and can be simply expressed in a set of rules. They can handle continuous and categorical data and are simple to comprehend. However, when there are intricate connections between input characteristics and outputs, their accuracy could be constrained. A study was conducted in which the dataset is made up of biomedical voice measurements derived from the 31 people in which 23 people are diagnosed with Parkinson's disease. Decision table classifier was used and an overall accuracy of 85.6 percent was obtained in this study[23], [24].

H. J48:

The C4.5 method is implemented by J48 in the WEKA machine learning toolbox. The C4.5 method creates a tree structure to express a set of if-then rules for categorizing cases. It is a decision tree-based classifier. At each internal node of the tree, the J48 classifier chooses the appropriate feature to split the data on based on information gain. The tree keeps growing until either a stopping requirement is achieved or all instances at a leaf node belong to the same class. J48 is regarded as one of the most precise decision tree-based classifiers and has received extensive application in many different fields. A study was conducted using LSVT dataset UCI ML repository. The main function of the dataset is to categorize dysphonia features of the Parkinson dataset. While using the J48 classifier an accuracy of 92.18 percent was achieved [25], [26].

I. Bayes Net:

The Bayes Net classifier, commonly referred to as the Bayesian network, is a probabilistic graphical model that depicts associations between variables as a directed acyclic graph (DAG). To determine the likelihood of various outcomes based on the connections between variables and their prior probabilities, the model applies Bayes' theorem. The graph's nodes in a Bayes Net classifier represent variables, while its edges show how variables are dependent on one another. Depending on the size and complexity of the network, it is possible to compute the probability of certain occurrences using precise or approximatively inference procedures. A study was conducted in which the data was obtained from the Parkinson’s Progression Markers Initiative database. Data of 184 normal patients and 402 early PD patients was used. The features used by the author are from University of Pennsylvania Smell Identification Test, RBD screening questionnaire, CSF Markers of Aβ1-42,α- syn, P-tau181, Ttau, T-tau/Aβ1-42, P-tau181/Aβ1-42 and P-tau181/T tau, and SPECT measurements of striatal binding ratio (SBR) data. While using Bayes net classifier an accuracy of 96.5854 percent was obtained [27], [28].

J. Naive Bayes classifiers:

The Naive Bayes classifiers are a series of Bayes' theorem-based probabilistic algorithms that are often employed in machine learning for classification applications. The fundamental tenet of Naive Bayes classifiers is that every feature independently contributes to the prediction of the class label. It is possible to calculate probabilities effectively and efficiently because to this independence presumption, which is also known as the "naive" element of the algorithm. Naive Bayes classifiers come in a variety of forms, each of which is appropriate for a certain kind of data, such as Gaussian, Multinomial, and Bernoulli Naive Bayes. A study was conducted in which the dataset is made up of biomedical voice measurements derived from the 31 people in which 23 people are diagnosed with Parkinson’s disease. In which each column in the table depicts particular voice measure and each row depicts one from the 195 voice recordings. The most important objective is to discriminate the healthy individuals from the Parkinson disease patients in which the status column is set to zero for healthy individual and one for PD patient. While using Naïve Bayes classifier an accuracy of 98.50 percent, precession of 99.75 percent, and recall of 99.24 percent [29], [30].

Table 2: Accuracy of Each Classification Technique on Each Parkinson's Disease Dataset

S. No	Algorithm	Accuracy (%)
1	IB1 classifier	96.41
2	Rotation forest	92.30
3	Random forest	91.28
4	Multilayer perceptron	93.22
5	Bagging	81.11
6	Sequential minimal optimization	76.00
7	Decision table	85.6
8	J48	92.18
9	Bayes net	98.58
10	Naïve Bayes	98.50

PARKINSON DISEASE DETECTION USING CONVOLUTIONAL NEURAL NETWORK

In this a CNN model is used and MRI images of the brain are used as input to detect Parkinson disease and make tell the difference between a healthy citizen and a Parkinson patient. It is primarily a data-driven strategy created exclusively to handle two-dimensional data. It is tough to put it anyway, but CNN discovers hidden characteristics. CNN-based methods are biologically inspired techniques that outperform other methods in many ways. It aids in the visualization of these spatially acquired properties. It significantly minimizes the number of hyper-parameters that need to be taught because of its spatial nature[33].In this model a method called image registration is used to align particular slices of a subject's MRI data. The Free Hand Region of Interest (ROI) approach is also used to crop the mid-brain region from each chosen slice. Three sets—training, testing, and validation—are created from the resulting photographs. The training, validation, and testing sets are used to train, respectively, validate, and test the CNN. A system diagram for the suggested model is shown below[33].

- Parkinson disease in MRI is identified using a unique 2D- CNN based method[33].
- We remove certain patches from the MRI to save computational expense[33].

These are the steps that are listed below in the table in the sequential order of the steps that are executed one by one in the current CNN model:

Input taken is MRI data of patients. ↓
Pre-processing is done. ↓
Division ratio is set. ↓
CNN model ↓
Prediction of network

The MR images that are entered into this system are finally identified as PD or HC. There are eight primary layers in all in the model. These layers are in the following order: dense layer 1, dense layer 2, convolution 1, max-pool 1, convolution 2, max-pool 2, convolution 3, and an output layer. All convolutional layers (Convt 1, Convt 2, and Convt 3) and Max-pooling layers

(Max pool 1, Max pool 2) have a 3x3 kernel size that results in the generation of 32 feature maps. These feature maps, which the CNN learns, give it the ability to distinguish between PD and HC in MR images. And after using this CNN model with the data set of MRI images an accuracy of 96 percent was achieved[31].

CONCLUSION:

In this review article, an overview of Parkinson disease has been provided, along with information on its stages, its causes, and the many forms of the illness. Sensors or wearable devices that can be used to identify Parkinson's disease and verify the accuracy of the information supplied by the wearable or portable sensors against clinically recorded data. There have been discussions on classifiers that can be used in machine learning to identify Parkinson disease. There have also been discussions on how to identify Parkinson's disease using medical lab testing. Additionally, we spoke about the CNN model for machine learning's use in Parkinson disease identification.

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