A REVIEW ON DIAGNOSTIC SYSTEM FOR EARLY DETECTION OF PARKINSON'S DISEASES USING MACHINE LEARNING ALGORITHMS

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ABSTRACT

Medical observations and assessments of clinical signals, such as the characterisation of a variety of motor symptoms, are widely used to diagnose Parkinson's disease (PD). Traditional diagnostic procedures, on the other hand, may be vulnerable to subjectivity because they rely on the interpretation of motions that are sometimes subtle to human sight and hence difficult to define, potentially leading to misdiagnosis. Meanwhile, early non-motor symptoms of Parkinson's disease might be moderate and be caused by a variety of diseases. As a result, these signs and symptoms are frequently missed, making early PD diagnosis difficult. Machine learning algorithms have been applied for the classification of PD and healthy controls or patients with comparable clinical presentations to solve these issues and to refine the diagnosis and assessment procedures for PD (e.g., movement disorders or other Parkinsonian syndromes). The term "early detection" refers to a method of detecting a problem early enough to start treatment. The study's goal is to provide insight into Biosignals diagnostic parameters for detecting brain and muscle abnormalities in Parkinson's disease (PD) patients. Because Parkinson's disease is caused by a decrease in dopamine synthesis in the substantia nigra of the brain, electroencephalogram and electromyogram-based GUI models would be an effective tool and true rationale for early identification of the disease. Biophysical recording device was used to gather EEG and EMG from early stage PD and healthy patients. Artificial Neural Networks were used to extract and categorise EEG and EMG features. A unique strategy to distinguishing PD from non-PD and tracking illness development is the designed model. There are a variety of models available, however the work described here combines biosignals interpretations with other factors such as those of radiological techniques to aid in disease diagnosis.

***Keywords: Parkinson's disease (PD), Electroencephalogram (EEG), Graphical User Interface (GUI), Machine Learning, Electromyogram (EMG), Neurodegenerative Disorder*.**

INTRODUCTION

Parkinson's disease is a chronic neurodegenerative brain ailment that impairs a person's ability to carry out daily tasks. The Parkinson's Foundation (PF) in the United States estimates that 8-10 million individuals worldwide are affected by Parkinson's disease, which is the second most common neurological ailment after Alzheimer's disease. Arvid Carlsson, a Swedish neuroscientist who won the Nobel Prize in Physiology in 2000, discovered that the primary cause of Parkinson's disease is a lack of Dopamine, a chemical messenger in the brain. Dopamine, which is found in the substantia nigra area of the brain, is a neurotransmitter that not only controls motor activity but also coordinates muscle functions. Many non-motor symptoms of Parkinson's disease appear before the motor symptoms. The term "neurodegenerative disease" refers to how the symptoms of the disease worsen as the disease progresses. Parkinson's disease is one such brain disorder caused by a lack of dopamine production in the substantia nigra of the brain. It is a neurotransmitter that causes humans to move [1].

PD can also be caused by a variety of environmental and genetic factors. Patients with Parkinson's disease frequently lose the connection between the brain and the muscles, resulting in erratic limb movement. It is most common in people over the age of 50. The following are some of the symptoms: Tremor, Bradykinesia, Postural

Instability, Rigidity, Sleep Disorder, Neuropsychiatric, and Autonomic Dysfunction [2]. The electroencephalogram (EEG) is a technique for detecting different brain functions. In their study, C.J Stam et al. [3] demonstrated that continuous EEG reflects post-synaptic opportunities in the brain. A wide range of neural events can be identified in real time with high time resolution. J.N Cavinees et al. [4] discovered that EEG is used in a resting phase as an indicator of unexpected neural background data as well as specific brain behaviour relationships.

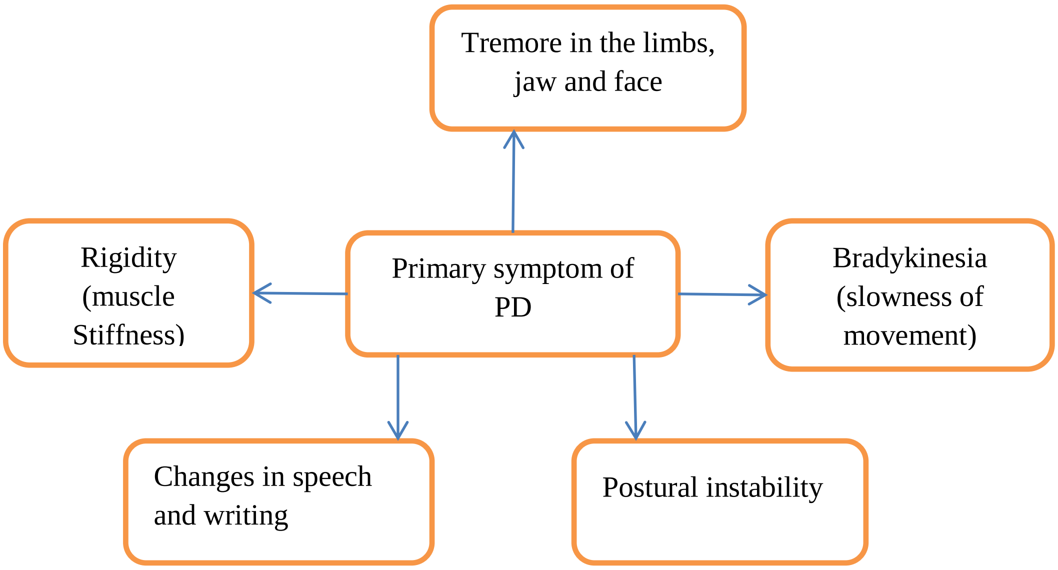

Figure 1: Primary symptom of PD

EMG is used to diagnose a PD patient and test various motor functions. Tremor in the limbs, as well as postural instability and bradykinesia, are all symptoms of Parkinson's disease, which can be detected by analysing and examining the various EMG patterns. Clinical and electromyography approaches to detect parkinsonian tremor were reported by I. Milanov [5]. The changes in EMG in PD, according to Y.Z Huang et colleagues [5,] are attributable to increased tonic background activity and an alternating pattern of EMG burst. The patient's muscle strength deteriorates, causing him or her to walk slowly. The graphic user interface (GUI) is a method of interacting with electronic devices. For illness diagnosis, a GUI is a very user-friendly tool. Many disorders, such as lung tumours and brain tumours, can be detected utilising various computer-based technologies that are user-friendly. P. Maziewski et al. [6] created a graphical user interface (GUI) that allowed patients with Parkinson's disease to keep track of their diaries, self-assessments, and prescription confirmations. Qi Wei Oung et al. [7] developed a tool for self-evaluation of patient self-reports, diaries, and other documents. Abdulwahab Sahyoun et al [6] created an illness symptom evaluation tool that uses an android-based phone application to evaluate the symptoms of patients.

Machine learning is currently one of the most used methods for diagnosing diseases. In comparison to other traditional procedures, it is a very effective tool with excellent precision. Shu Lih Oh et al developed a convolution neural network-based automatic PD detection system with classification rates of 88.25% accuracy, 84.7% sensitivity, and 91.77 percent specificity. Sinziani et al. [?] developed a machine-learning-based approach for detecting freezing of gait (FoG) in Parkinson's disease. With a sensitivity of more than 95%, the designed system detected FoG events.

The loss of dopaminergic neurons in the substantia nigra and basal ganglia causes Parkinson's disease. Tremor, postural instability, muscle rigidity, and slowness of movements are the four major symptoms.

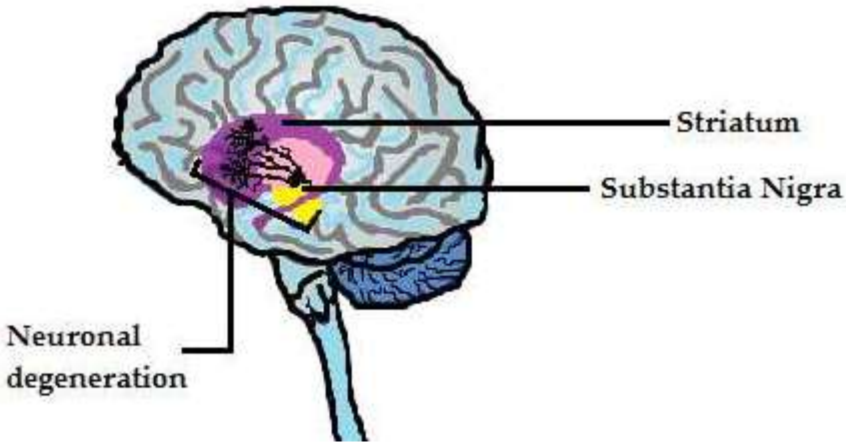

Figure 2: Release of dopaminergic neurons to striatum caused due to its degeneration in the substantia nigra, adapted from

Artificial neural networks are a type of machine learning approach that can be used to classify diseases. ANN is a type of artificial neuron that looks like a biological neuron. In 2013, Farhad Soleimanian et al. [8] used ANN to classify PD from non-PD participants. The back-propagation learning approach was used to classify the data with MultiLayer Perceptron (MLP). With a 93.22 percent accuracy rate, MLP was determined to be the best classifier. Some of the healthcare applications of ANNs are:

- Patient Diagnose Systems.
- Bio-chemical analysis
- Analysis of Medical Imaging
- Drug Development

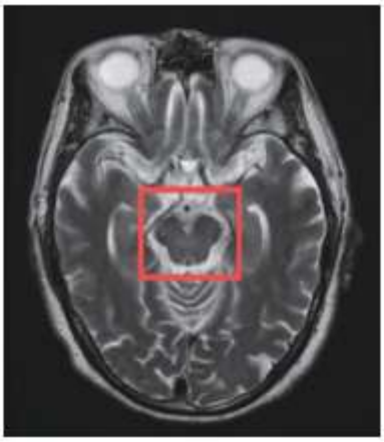

Figure 3: Brain map of PD patients

Although medical technology is rapidly evolving, the majority of Parkinson's disease diagnoses can be confirmed by patients' clinical symptoms; however, domestic and international experts have demonstrated through a large number of clinical experiences and experiments that the main pathological change of Parkinson's disease is the progressive nature of nigrostriatal cells loss and Degeneration of the nigra and striatum results in the accumulation of intracellular Lewis bodies. The loss of DA neurons causes clinical symptoms after a long preclinical process of about 5 years, and niger DA neurons are lost 50 percent of the time. In percent of patients, clinical symptoms are not obvious. DA energy neurons in the brain are lost by 70% to 80% in patients with PD symptoms. [5].

Routine MRI tests can reveal: 1 Brain atrophy: Extrapyramidal atrophy causes the third ventricle to enlarge, while widespread atrophy of the cerebral cortex causes the cerebral sulcus to widen. 2 Dense substantia nigra atrophy, based on T2-weighted images / proton density On the image, the sound of the thick band with a low iron concentration exhibited a local signal; the presence of high-concentration iron in the reticular zone and red nucleus of the nevus of normal brain tissue showed a low signal, and so on. Furthermore, degeneration and necrosis of melanocytes can be found in PD patients. Narrowing dense bands, blurring edges, and other manifestations have all contributed to iron metabolism. For the diagnosis of PD, the morphology and signal changes of the substantia nigra are observed, as well as the width of the substantia nigra and the ratio of the width of the substantia nigra to the midbrain. The distinction between PD and vascular Parkinson's syndrome gives an objective foundation. 3 The striatum area on the T2-weighted image reveals a poor signal due to low iron deposition in the putamen's posterolateral nucleus. [7].

Table 1: Degrees of PD progression and their symptoms

Degree of Progression	Symptoms
Mild	▪ Movement symptoms on one side of the body ▪ Changes in the body posture and facial expression ▪ Slight difficulty in walking
Moderate	▪ Movement symptoms on both sides of the body ▪ Impaired balance and coordination ▪ Freezing episodes are evident
Advanced	▪ Impaired cognition with visual hallucinations and delusions ▪ A significant difficulty in walking ▪ Dependent on others and assistance required

MACHINE LEARNING METHODS

1. ARTIFICIAL NEURAL NETWORKS (ANN):

Artificial neural networks (ANNs) are a class of statistical learning algorithms based on biological neural networks that are used in machine learning. A neural network is a collection of artificial neurons that can detect patterns. Neural networks learn by scouring a space of network weights for patterns. It's used to approximate or estimate functions that have a lot of inputs and aren't well understood. Artificial neural networks are commonly depicted as systems of interconnected "neurons" that can compute values from inputs/outputs and perform machine learning and pattern recognition.

2. K-NEAREST NEIGHBOURS CLASSIFIER (K-NN):

Learning analogy, or comparing a given test tuple with comparable training tuples, is used to classify nearest neighbours. Each tuple is an n-dimensional point. In a ndimensional pattern space, all training tuples are stored. It's a tuple-based classifier that can simply find the nearest neighbour in tuple space and label the unknown tuple with the same class label as the known one. The k-nearest neighbour classifier looks for the k-training tuple that is closest to the unknown tuple in the pattern space. These tuples are used to train the unknown tuple's closest neighbour classifier. Any distance metric, such Euclidean distance, can be used to determine proximity. Distance-based comparisons, such as nearest neighbour classifiers, provide equal weight to each attribute. As a result, if an attribute is noisy or unimportant, they may suffer from poor accuracy.

3. SUPPORT VECTOR MACHINES (SVM):

The Support Vector Machine (SVM) is a next-generation learning system based on recent developments in statistical learning theory. It's a non-linear and linear data algorithm. It transforms the original data into a higher-dimensional format, from which it may discover a hyper plane for data separation using support vectors, which are crucial training tuples. A Support Vector Machine (SVM) is a discriminative classifier using a separating hyper plane as its formal definition. To put it another way, given labelled training In a high or infinite-dimensional space, a support vector machine creates a hyper plane or group of hyper planes that can be used for classification, regression, or other tasks. Intuitively, the hyper plane with the greatest distance to the nearest training data point of any class, known as the functional margin, achieves a decent separation, because the larger the margin, the lower the classifier's generalisation error.

4. NAÏVE BAYESIAN CLASSIFIER:

Because it presupposes class condition independence, nave Bayesian classification is named nave. That is, the effect of a given class's attribute value is independent of the values of other attributes. This assumption is intended to save time and money, hence it is deemed naive. A Nave Bayesian model is simple to construct and does not require iterative parameter estimate, making it ideal for huge datasets. The main principle underlying naive Bayesian classification is to try to categorise data by maximising the number of possible classifications.

5. RANDOM FOREST:

Leo Breiman's (2001) random forest is a collection of decision tree-based classifiers. A bootstrap sample of the data is used to build each tree, which uses a candidate set of features chosen at random. For tree construction, it employs both bagging and random variable selection. After the forest has been created, test cases are percolated down each tree, and the trees make their class predictions. A random forest's error rate is determined by the strength of each tree and the correlation between any two trees. In a regression or classification problem, it can be used to rank the relevance of variables in a natural way.

6. BAGGING:

Bootstrap aggregation, often known as bagging, is a machine learning ensemble meta-algorithm that aims to increase the accuracy and stability of machine learning algorithms used in statistical classification and regression. It also helps to avoid over-fitting by reducing variance. It is most commonly associated with decision tree approaches, but it can be applied to any method. Bagging is a type of model averaging. Noise, bias, and variation are the main causes of learning errors. Noise is the result of the target function's error, Bias occurs when the algorithm is unable to learn the target, and Variance is how sampling impacts the learning method. Bagging helps to reduce these errors. In the case of unstable classifiers, averaging over bootstrap samples helps reduce error from variance.

7. BOOSTING:

Boosting is a machine learning ensemble metaalgorithm for decreasing bias and variance in supervised learning, as well as a family of machine learning algorithms for turning weak learners into strong ones. Boosting is based on Kearns and Valiant's (1988, 1989) question: Can a group of weak learners create a single strong learner? A weak learner is a classifier that has only a sliver of correlation with the correct categorization (it can label examples better than random guessing). A strong learner, on the other hand, is a classification that is arbitrarily well correlated with the correct classification.

Table 2: Summary of machine learning based methods for Parkinson disease prediction

Authors Name	Machine Learning Methods	Data Description	Performance
Indira R. (2014)	fuzzy C- means	Speech signal dataset	68.04% accuracy, 75.34% sensitivity and 45.83% specificity
Indira R. (2014)	ANN	Speech signal dataset	Recognition rate of 92 %.
R. Geeta (2012)	Classification	Speech dataset as high or low	Random tree classification 100% accuracy
Rubén A. (2013)	Wrapper feat- ure selection	non-motor symptoms	72% to 92% accuracy
Betalu E. (2014)	SVM	Age, gender, voice recording	76%accuracy 34% sensitivity
A.Tsans (2011)	Regression & Classification	Speech signal dataset	5–95 percentile
Sharma A(2014)	SVM	Speech signal dataset	85.29% accuracy
Bocklet (2011)	SVM	Speech dataset	79% result
Das R. (2010)	NN classifier	Speech signal dataset	92.9%accuracy
Cam M. (2008)	PNN	Voice recording dataset	92.9% accuracy
Caglar (2010)	ANN	PD dataset	96.77% accuracy, 87.5% sensitivity and 100% specificity
Ali Saad (2013)	Bayesian Naive Classifier (BNC)	video recorded	74.31% accuracy
Cho, C. (2009)	Linear discriminant analysis (LDA)	gait patterns	95% accuracy
Can, M.	ANN	Recording data	92.9% accuracy
Kapoor (2009)	Vector Quantization	Audio Input	95% accuracy
Wu, S (2011)	Decision Tree and Neural Network	recorded the speech signals	95% accuracy
Sellam V. (2014)	Radial Basis Functional Neural Network (RBFNN)	Voice and unvoiced speech signals	91% accuracy
Chen, H. (2013)	fuzzy k-nearest neighbour (FKNN)	PD data set	96.07% accuracy
Salvatore (2014)	SVM	Magnetic resonance imaging (MRI)	> 90% accuracy ,sensitivity and specificity
PrzybysZ. (2014)	Reflexive saccades measurements	Magnetic resonance imaging (MRI)	70% accuracy
Kihel, B. (2011)	Euclidean	Voice data	94.44% accuracy

CONCLUSION

This research provided a comprehensive assessment of machine learning-based techniques for Parkinson disease prediction. A brief overview of several computational intelligence techniques-based approaches for Parkinson disease prediction is offered. There is also a summary of the results achieved by various researchers in the literature to forecast Parkinson's disease.

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