Comprehensive Review of Parkinson's disorder Disease: From Diagnostics and Medication to Perspectives

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Abstract: Millions of people worldwide suffer from Parkinson's disease (PD), a long-term, degenerative neurological condition that significantly impairs both motor and non-motor abilities. This comprehensive review aims to offer a thorough examination of the current state of Parkinson's Disease, including its diagnosis, treatment options, and future research prospects. The analysis explores the symptomatic manifestations and diagnostic hurdles associated with PD, highlighting the importance of cutting-edge imaging techniques and biomarker discovery in enhancing early detection. Furthermore, it investigates conventional and novel treatment approaches, encompassing pharmaceutical interventions, surgical procedures, and innovative therapies such as deep brain stimulation and genetic manipulation. The use of artificial intelligence and machine learning to increase diagnosis accuracy and customize treatment regimens is also taken into account in this study. By consolidating recent breakthroughs and ongoing investigations, this review seeks to identify gaps in existing knowledge and suggest future avenues for enhancing the well-being and life quality of individuals affected by Parkinson's Disease.

Keywords: Parkinson’s Disease; Machine Learning; Support Vector Machine; Deep Learning; Artificial Neural Network

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Introduction

Parkinson's disease is a chronic neurological disorder that progressively impairs motor function and can eventually affect cognitive abilities and behavior. The condition was officially documented in 1817 by James Parkinson, an English medical practitioner, in his groundbreaking publication, "An Essay on the Shaking Palsy." Parkinson detailed the primary motor symptoms of the disease, including resting tremors, muscle stiffness, slow movement (bradykinesia), and balance issues, based on his observations of six patients in his practice and on London streets. He dubbed the condition "Shaking Palsy," highlighting its most noticeable symptom: involuntary trembling. Prior to Parkinson's formal description, similar symptoms were noted in ancient medical literature. Ayurvedic texts mentioned a condition called "Kampavata," characterized by tremors, rigidity, and slow movements. The Greek physician Galen (129–216 CE) also documented tremors and motor dysfunction, though he did not classify them as a

distinct illness. These historical references indicate that the disease has existed throughout human history, albeit unrecognized and misunderstood. Jean-Martin Charcot, a French neurologist, built on Parkinson's research in the late 1800s. He further distinguished Parkinson's disease from other neurological disorders, enhancing clinical understanding of the condition. Notably, Charcot introduced the term "Parkinson's disease" to honor James Parkinson, solidifying its place in medical nomenclature. Despite these early contributions, the underlying biological mechanisms of Parkinson's disease remained elusive for over a century. Researchers made a major discovery in the middle of the 20th century when they determined that the main pathological characteristic of the illness was the loss of neurons that produce dopamine in the substantia nigra. This discovery linked the motor symptoms of Parkinson's disease directly to dopamine deficiency, a crucial neurotransmitter involved in movement control. This insight led to the development of dopamine-based treatments, such as levodopa (L-DOPA), which remains a standard therapy today.

The early history of Parkinson's disease, from James Parkinson's initial observations to Charcot's refinements and subsequent biological discoveries, laid the foundation for understanding and managing this complex disorder. These advancements not only propelled the field of neurology forward but also underscored the value of meticulous observation and clinical research in deciphering the intricacies of human diseases. Parkinson's disease (PD) has emerged as the most rapidly expanding neurodegenerative condition globally, impacting over 8.5 million people, as reported by the WHO. The WHO notes that the prevalence of PD has seen a twofold increase in the past quarter-century. Symptoms of the condition might be both motor and non-motor. The former includes the characteristic triad of tremor, rigidity, and bradykinesia, while the latter encompasses cognitive deterioration and sleep disruptions, significantly diminishing patients' quality of life. In nations like India, the PD burden is escalating, with 771,000 cases documented in 2019. Notably, the average age of onset in India is approximately ten years earlier than global norms. Despite advancements in treatments such as levodopa/carbidopa and deep brain stimulation, accessing care remains problematic, particularly in low- and middle-income countries. The WHO underscores the importance of early detection, comprehensive management, and rehabilitative therapies to enhance patient outcomes. In 2022, the WHO released a technical brief titled "Parkinson Disease: A Public Health Approach," which outlines strategies for prevention, treatment, and care accessibility worldwide. The growing impact of PD necessitates increased awareness, improved treatment access, and ongoing research into disease-modifying interventions. As of 2024, PD continues to pose a significant and expanding global health challenge. The WHO emphasizes that early diagnosis, rehabilitation, and comprehensive care are crucial for improving patient outcomes. To address this growing concern, the WHO's 2022 technical brief highlights the importance of prevention, equitable care, and measures to combat the rising burden through enhanced awareness, accessibility, and sustained research into disease-modifying treatments.

Figure 1 illustrates how cellular dysfunction, including Lewy bodies, dopamine neuron loss in the substantia nigra, and motor symptoms are all part of Parkinson's disease. The synthesis of important neurotransmitters like acetylcholine and serotonin is impacted by Parkinson's disease (PD), a chronic, degenerative neurological illness marked by the slow loss of nerves in the substantia nigra [1]. These Neurotransmitter substances are crucial for movement control, leading to PD's primary impact on motor functions. The disease typically progresses through five stages. Initially, symptoms are not too severe. It presents with minimal tremors and limited mobility without impairing daily activity. Significant tremors

and muscular stiffness that make daily chores hard to complete are characteristics of stage 2. During stage 3, balance and fine motor activity decrease, with patients falling constantly, although they become accustomed to this condition. Stage 4 has more serious symptoms. Patients may lose the ability to walk and stand during final stages, and patients may become prone to hallucinations, and sometimes they need a wheelchair [2]. In addition to impairing motor function, Parkinson's disease (PD) has a significant negative influence on quality of life and raises the chance of developing a number of chronic illnesses.

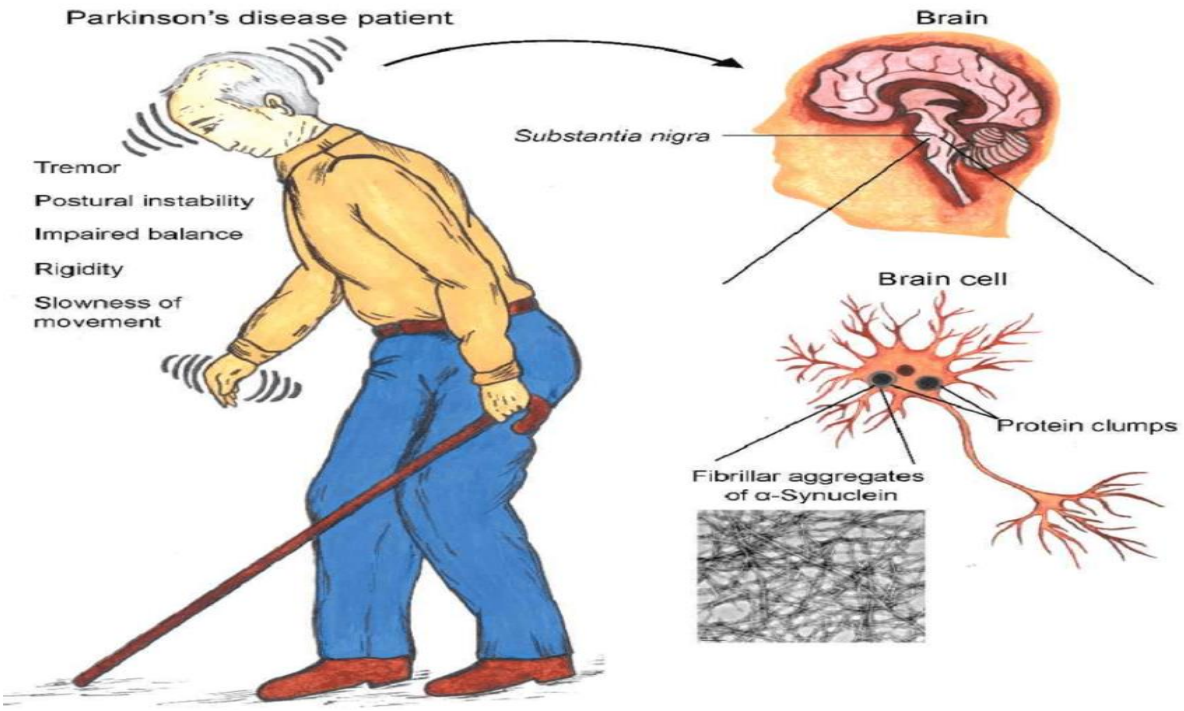

Figure : 1 Picture of Parkinson's Disease: Signs, Alterations in the Brain, and Cellular Processes

Diagnosis of PD is essentially made on the basis of identification of the motor and non-motor symptoms, as depicted in Fig. 1. The limiting factor for the diagnosis of PD compared to other neurodegenerative disorders having similar features is that 75% of cases are idiopathic. With this aim in view, to enhance diagnostic precision and support clinicians, usage of machine learning (ML) and DL techniques is increasing lately. These methods are considerably promising to improve diagnostic performance for PD and related conditions [3].

Dataset:

The UCI Machine Learning Repository's Parkinson's Telemonitoring Dataset, which had 5,875 records with 26 characteristics, was employed in the study. It includes biological speech features from 42 individuals with early-stage Parkinson's disease, recorded over 60 days using a telemonitoring device. The dataset was designed to predict UPDRS measures (Total and Motor) using machine learning techniques. Speech signal characteristics from 31 people at the National Centre for Voice and Speech in Denver, Colorado, are included in the dataset. It contains 147 PD phonetics and 48 healthy phonetics from the same individuals. There are 195 biomedical voice measures in the collection, including 8 people

in the control group and 23 people with PD diagnoses. People are categorized as either 0 (healthy) or 1 (PD) in the status column. In order to diagnose Parkinson's disease, the study used phonetic elements that were taken from speech signals.

Table 1 tabularizes that Patient demographics, motor symptoms, handwriting and speech metrics, cognitive scores, neurological biomarkers, and lifestyle variables are all included in the feature set for a machine learning model for Parkinson's disease.

Table : 1 Feature Set for Parkinson's Disease Machine Learning Model

Feature Name	Description	Data Type
Patient_ID	Unique identifier for each patient	Integer
Age	Patient's age	Integer
Gender	Male (1), Female (0)	Binary
Tremor_at_rest	Presence of resting tremors (Yes=1, No=0)	Binary
Bradykinesia	Slowness of movement (Yes=1, No=0)	Binary
Rigidity	Muscle stiffness (Yes=1, No=0)	Binary
Postural_instability	Difficulty maintaining balance (Yes=1, No=0)	Binary
Gait_disturbances	Abnormal walking patterns (Yes=1, No=0)	Binary
Jitter(%)	Variation in voice frequency	Float
Shimmer(dB)	Variation in voice amplitude	Float
HNR (Harmonics-to-noise ratio)	Hoarseness in voice	Float
Pitch_variation	Changes in voice frequency	Float
Dysphonia_measure	Measures vocal cord dysfunction	Float
Handwriting_speed	Time taken to write a sample sentence (sec)	Float
Spiral_test_score	Deviation in spiral drawing (0-1, higher = worse)	Float
Writing_pressure	Average pressure while writing (g)	Float
Cognitive_score	Cognitive test score (0-30, higher = better)	Integer
Reaction_time (ms)	Time taken to respond to stimulus (ms)	Float
Dopamine_scan	Dopamine levels in brain imaging	Float
MRI_abnormality	Structural brain changes (Yes=1, No=0)	Binary
CSF_Alpha_Synuclein	Alpha-synuclein protein level in cerebrospinal fluid	Float
Family_history	Family history of Parkinson's (Yes=1, No=0)	Binary
Pesticide_exposure	History of pesticide exposure (Yes=1, No=0)	Binary
Smoking_status	Smoker (Yes=1, No=0)	Binary

Caffeine_intake	Daily caffeine consumption (mg)	Integer

Preliminaries:

Support vector Machine:

Encouragement One effective class of supervised machine learning techniques for classification applications is the vector machine. SVM is useful for high-dimensional spaces, which are typical for data sets with features such as speech patterns, handwriting, or medical images. The SVM algorithm is based on the idea of finding the optimal hyperplane that separates different classes (e.g., Parkinson's disease vs. healthy individuals) with the maximum margin. Feature extraction is the first step in the process, wherein several physiological signals or clinical assessments are used as input data. Voice characteristics like pitch, jitter, shimmer, and Mel-frequency cepstral coefficients (MFCCs) are used to predict Parkinson's disease, as are handwriting characteristics including pen pressure, stroke length, and tremor analysis. Using kernel functions like linear, polynomial, or radial basis functions, these features 5which are usually noisy and nonlinear are translated onto a higher-dimensional feature space. This transformation enables SVM to find a separating hyperplane that may not be possible in the original feature space. For nonlinear data, SVM uses a trick called kernel trick, which can transform the data into a higher-dimensional space implicitly without explicitly calculating the coordinates, making it possible to separate data points that are not linearly separable in the original space. The SVM model attempts to maximize the margin, which is the distance between the closest points, called support vectors, of each class to the hyperplane, because a larger margin is said to lead to better generalization to unseen data. SVM works by minimizing a cost function that penalizes misclassification errors. The model also has a regularization parameter (C) that controls the trade-off between achieving a larger margin and minimizing misclassification. A higher value of C reduces the margin but allows fewer misclassifications, while a lower value of C allows for a wider margin but potentially at the cost of more misclassifications. The SVM model's efficacy is assessed using performance measures such as accuracy, precision, recall, F1-score, and Area Under the Curve (AUC). These metrics are used in the prediction of Parkinson's disease to assess the model's ability to differentiate between PD patients and healthy controls or between the illness's various phases. Early Parkinson's disease has been proven by SVMs as it is sensitive to differences between patient data and cannot be recognized by conventional diagnosis methods. Besides that, the algorithm has robustness on high-dimensional noisy data, hence it can suitably work for any data which includes wide-range features like voice and handwriting characteristics. However, SVM's performance can be sensitive to the choice of kernel, the quality of the feature selection, and the tuning of hyperparameters. Additionally, large datasets may require more computational resources, which can be a limitation in real-time or large-scale clinical applications. SVM offers a comprehensive, strong, and efficient framework to predict Parkinson's disease with the utilization of high-dimensional and nonlinear data and assists the medical fraternity to provide an early detection and diagnosis, leading to early intervention for improved patient outcomes with personalized treatment and improving the general health care delivery of a person affected with Parkinson's disease. The steps involved in the SVM process data preparation, kernel selection, hyperplane building, support vector identification, and optimization are depicted in Figure 2.

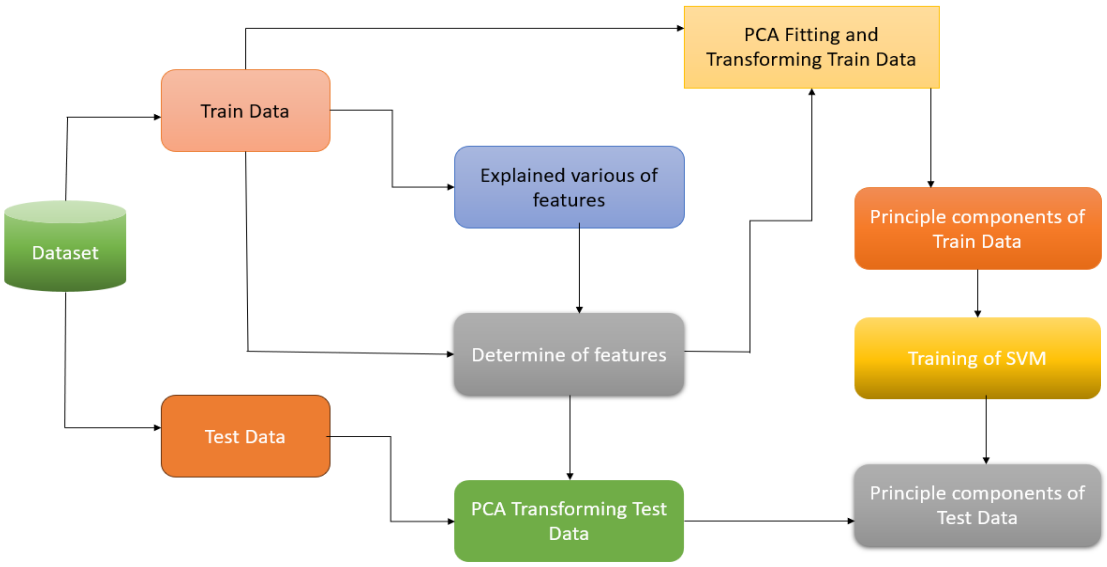

Figure : 2 Working Procedure for Support Vector Machine

Logistic Regression:

Logistic Regression is used in supervised binary classification, in which it gives the prediction output in terms of probabilities for yes or no values, thus finding a perfect solution to predict if the person possesses Parkinson's disease or not: the usual kind of classification required in the classification of Parkinson's disease is a yes (the patient exists) or a no (is healthy). Basically, logistic regression is excellent for cases like modelling the probability based on input attributes, and logistic regression handles numerals and variables. The first step, in the context of PD prediction, is gathering and preparing the dataset. These features include voice characteristics such as jitter, shimmer, and pitch; motor assessment such as tremors and bradykinesia; and handwriting patterns, among others. These features, usually obtained from a variety of sources such as clinical exams, speech analysis, or wearable devices, are fed to the logistic regression model. Modelling the link between the input data and the likelihood of the target class whether or not Parkinson's disease is present is how logistic regression operates. The logistic function, commonly known as the sigmoid function, is the essential element of logistic regression. It converts any input into a value between 0 and 1, which indicates the likelihood that a particular observation is a member of the positive group (in this example, PD).

The logistic function is expressed as:

$$P(y = 1|x)\ \frac{1}{1+e^{-z}} \qquad \text{..... (1)}$$

where $P(y = 1|x)$ is the probability of having Parkinson's disease, z is the linear combination of the input features (i.e., $z = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n$, and $X_1, X_2, \ldots X_n$ are the features used for prediction. It's trained so as to come up with best possible values for parameters $\beta_0, \beta_1, \ldots \beta_n$, minimizing difference between predicted labels and actual using an approach named Maximum Likelihood Estimation, which in effect uses coefficients β to identify contributions of various features to make that prediction-positive sign suggests feature makes the contribution more likely, given presence of PD and vice versa if negative. The decision boundary of logistic regression is set using the threshold for the predicted probability. When it exceeds 0.5, it classifies as positive or that there is PD; and below 0.5 is classified as negative, that there is no PD. It is sensitive to application since when the costs for

false positives and false negatives differ (like in medical diagnosis), it will change the threshold. One of the biggest advantages of logistic regression for PD prediction is that it is straightforward and easy to interpret. Coefficients for the model are indicative of the most influencing features in the model that will determine the presence of PD. For instance, greater values of voice features like jitter and shimmer can be related to a higher possibility of PD and thus assist the clinicians in reaching a proper decision. However, logistic regression also has some limitations. It assumes a linear relationship between the features and the log-odds of the outcome, which may not always be the case in complex datasets. Parkinson's disease involves various subtle, nonlinear relationships in the data, and logistic regression may struggle to capture these without proper feature engineering. To address this, polynomial features or interaction terms can be added to capture nonlinearity, but this increases model complexity. Furthermore, when input characteristics are highly correlated, logistic regression experiences multicollinearity; hence, regularization approaches like L1 (Lasso) or L2 (Ridge) are required to avoid overfitting and enhance generalization. The performance metrics are accuracy, precision, recall, F1-score, and Area Under the Curve (AUC), all of which determine how well the logistic regression model performs in the task of predicting Parkinson's disease. These will help to assess whether the model could be useful in clinical settings or not. In conclusion, logistic regression is a valuable tool in the prediction of Parkinson's disease, especially for applications where interpretability and simplicity are essential. It is effective in modeling linear relationships in the data but may not be as effective in capturing complex, nonlinear relationships without additional preprocessing. Nonetheless, logistic regression remains an accessible and useful approach for early PD detection, which can aid in timely interventions and personalized treatment plans for patients. Data preparation, sigmoid function application, gradient descent optimization, and probability threshold-based classification are all steps in the logistic regression process shows in Figure 3.

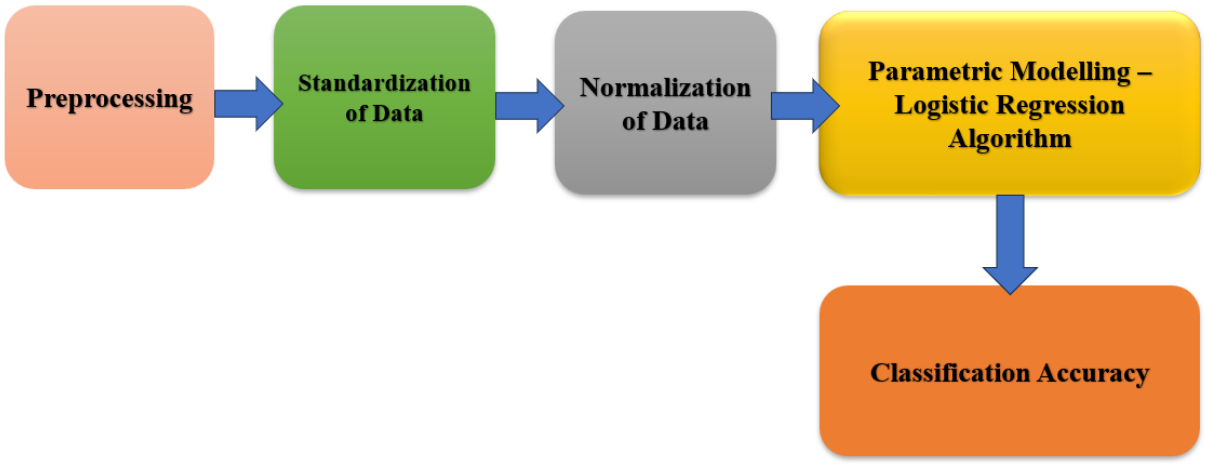

Figure : 3 Working Procedure for Logistic Regression

Naïve Bayes:

Naïve Bayes is a probabilistic classifier based on the application of Bayes' theorem with the "naïve" assumption of independence between features. In predicting Parkinson's disease, Naïve Bayes can be applied by treating the various symptoms or characteristics (such as speech patterns, motor

symptoms, and demographic data) as independent features. The model then calculates the likelihood of an individual having Parkinson's disease given the observed features, which is based on prior probabilities obtained from training data. For example, it takes historical data about patients with and without Parkinson's and then estimates the probability distribution for every feature in both classes: Parkinson's and non-Parkinson's. At prediction time, it multiplies the likelihoods for the observed features and combines these with prior probabilities to get a final classification probability. Although the assumption of independence may be unrealistic for real-world medical data, the simplicity of the Naïve Bayes, its computational efficiency, and ability to handle categorical and continuous data make it effective even in such complex scenarios. It is particularly useful when there are limited training data or when a quick, interpretable prediction is needed, despite potential limitations in capturing feature interactions. Naïve Bayes finds use in medical diagnosis, fraud detection, document categorization, spam filtering, sentiment analysis, and recommendation systems shows in Figure 4.

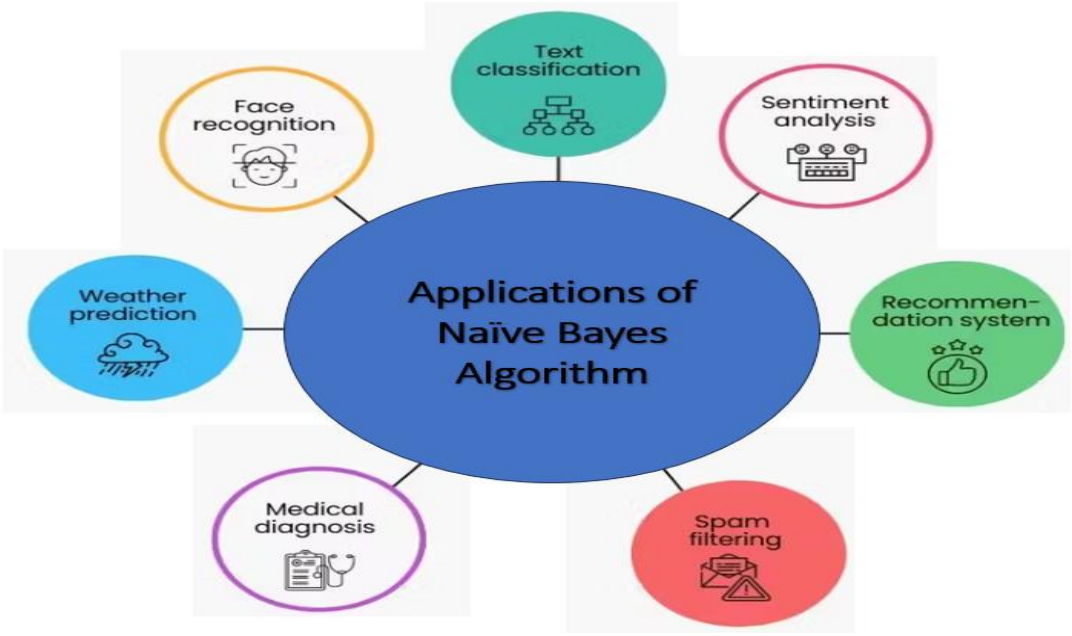

Figure : 4 Applications of Naïve Bayes Algorithm

Artificial Neural Network:

Computational models modeled after the human brain are called artificial neural networks. They process and learn from data via layers of networked nodes, or neurons. In predicting Parkinson's disease, ANNs can model complex, non-linear relationships between the features of motor symptoms, speech patterns, cognitive abilities, and demographic data. Input Patient data, in the form of age, strength of tremors, voice attributes, etc, is fed to the input layer of the network. The one or more layers of hidden layer neurons apply the activation functions, which detect any intricate patterns and correlations in this data. By adjusting the weight between neurons at training time through algorithms such as backpropagation, the goal is to try to minimize these prediction errors. Once trained, this network can then predict the risk for new patients about Parkinson's disease. ANNs are useful because they naturally have the capability of handling very high-dimensional data that may take on the format of time series for medical record-keeping purposes or speech signal representations. End. They, however require huge amounts of data and computational resources for training and may be less interpretable

than simpler models although recent developments have aimed at increasing their transparency. Data preprocessing, input layer activation, weight modifications through forward and backpropagation, gradient descent optimization, and final prediction based on learnt patterns are all steps in the operation of an artificial neural network (ANN) shown in the Figure 5.

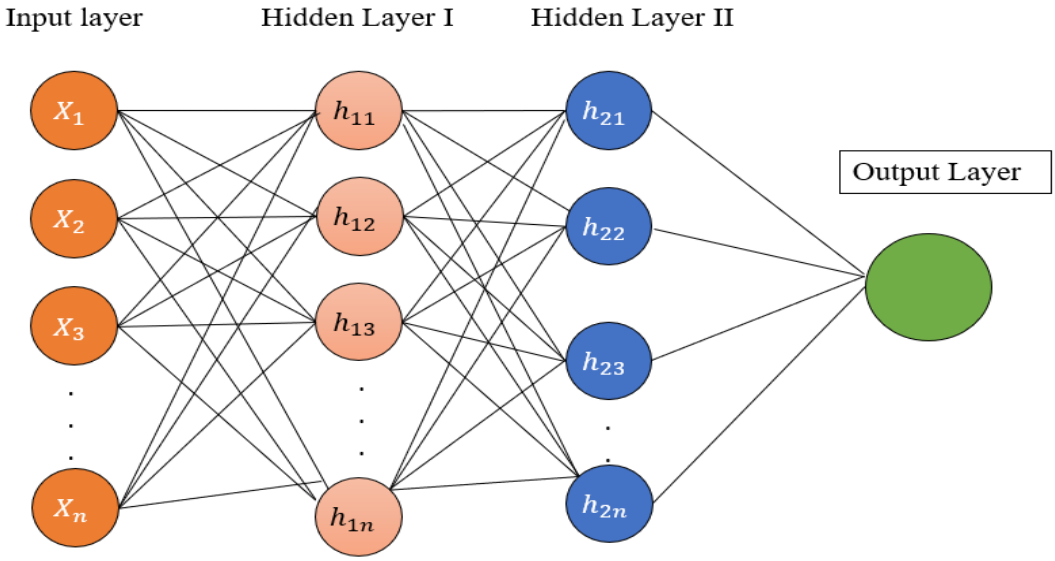

Figure: 5 Working Procedure for Artificial Neural Network

Literature Review:

A hybrid method for using speech analysis to diagnose Parkinson's disease (PD) was proposed by Lamba et al. (2022) [4]. Alongside classifiers like Naïve Bayes, KNN, and RF, the study experimented with a variety of feature selection techniques, such as mutual information gain, additional trees, and evolutionary algorithms. The dataset used is obtained from the machine learning repository at UCI. The class imbalance is corrected using the Synthetic Minority Oversampling Technique (SMOTE). The integration of genetic algorithms with the RF classifier resulted in 95.58% accuracy. The smaller feature subsets enhance performance for all classifiers. In the genetic algorithm, the best improvement was recorded, which is about 21.70%. Future work will consider testing this method with larger speech datasets that acknowledge the influence of early symptoms of PD on hand-writing. Srieam et al. (2015) [5] analyzed the dimensionality of PD data sets and found that the data set is full of parallel dimensions. On comparing their different methods with majority voting and kNN, the highest accuracy of 88.9 was achieved using SVM. As a result, RF achieved an accuracy rate of 90.26%, whilst NB had the lowest score of 69.23%.

Using hierarchical clustering and self-organizing maps, more clusters can be found in a healthy dataset rather than in the diseased. By adding olfactory loss and rapid eye movement sleep behavior disturbance as indicators for the diagnosis of Parkinson's disease, Nayan et al. (2016) [6] have expanded on earlier research. MLP, BayesNet, RF, and boosted Logistic Regression (LR) were among the machine learning models tested in the study. Of these, the boosted LR model achieved the greatest accuracy at 97.159% with an impressive ROC score of 98.9%, suggesting that it may be a potential model for the early prediction of Parkinson's disease. Senturk et al. (2020) [7] suggested machine learning-based methods for diagnosing Parkinson's disease (PD) by employing feature selection techniques such

recursive feature removal and feature significance. SVM, decision trees, and neural networks have all been employed and evaluated; the best combination, SVM/RFE, produced the highest accuracy, 93.84%, once more focusing on voice features. Polat et al. (2012) [8] suggested using speech signals to diagnose PD. They used SMOTE for preprocessing the dataset and achieved an excellent accuracy of 94.8% using an RF classifier. Mostafa et al. (2020) [9] studied vocal problems to diagnose PD. Feature selection techniques were used to design a multiple-feature evaluation method, and the highest accuracy of 99.49% was achieved by RF. Vowel analysis was the main emphasis of Tuncer et al. (2020) [10], who employed relief-based techniques, SVD-based feature selection, and Minimum Average Maximum (MAMa) tree preprocessing to identify PD. Out of the eight classifiers used, kNN had the highest classification accuracy, 92.46%. Genetic algorithms (GA) and other optimization approaches were used by Soumaya et al. (2019) [11] to enhance SVM's performance for PD detection. Their proposed classification model used a variety of features, including Linear Predictive Coding (LPC), energy, zero-crossing rate (ZCR), Mel-frequency cepstral coefficients (MFCC), and wavelet Shannon entropy, and achieved an accuracy of 91.18% with GA and SVM. Nilashi et al. proposed a predictive model for the UPDRS scale by incremental SVM (2016) [12]. This model predicted both total-UPDRS and motor-UPDRS, results showing MAEs equal to 0.4656 and 0.4967, respectively, which have healthcare application. Using classifiers like SVM, KNN, and LR, Shamrat et al. (2019) [13] applied AI approaches to identify PD using a variety of datasets. Whereas LR attained 97% accuracy, SVM attained 100%. The efficiency of SVM in PD dataset analysis was highlighted in the study. Lahmiri et al. (2019) [14] concentrated on using speech patterns to diagnose Parkinson's disease. They achieved a 92.21% accuracy rate by using a nonlinear SVM classifier and eight pattern-ranking methods.

Employing smartphones and acoustical cardioid sensors, Almeida et al. (2019) [15] demonstrated a system for PD detection by speech signals and pronunciation. The results achieved higher accuracy through pronunciation tasks in comparison to the speech tasks as it achieved the accuracies of 94.55% using acoustic cardioid channels and 92.94% using the smartphone channels. By creating the Ant Lion Optimizer Algorithm, Sharma et al. (2019) [16] created a PD prediction model. They then supplied the reduced feature subset data to classifiers such as kNN, Decision Trees (DT), and RF. The accuracy level of the model that was provided was 95.91%. By enhancing feature selection with an upgraded Grey-Wolf algorithm, Sundaram et al. (2019) [17] demonstrated a PD detection system based on datasets from the UCI machine learning library. Using a voice dataset, the system's accuracy was 93.87%. Using metrics like equal error rate (EER), area under the ROC curve (AUC), accuracy, specificity, and sensitivity, Almeida et al. (2019) [15] further tested their methodology and showed that phonation was more successful than speech in detecting Parkinson's disease (PD), with an accuracy of 94.55% and an AUC of 0.92. A big data-based multi-classifier system was presented by Shamli et al. (2016) [18] in order to improve prediction performance and shorten time to action. They used the PD voice dataset from UCI and obtained the best results using C4.5, SVM, and ANN classifiers. In 2013, Azad et al. [19] presented a decision tree (DT)-based approach for PD prediction. Using a dataset of 197 cases, the study applied classification approaches such ID3 and decision stumps. The outcomes demonstrated that decision trees were more accurate than alternative techniques. Using speech recordings from 80 people, Naranjo et al. (2019) [20] created a clinical expert system for PD diagnosis. Through cross-validation, the Bayesian classification approach yielded a 75.2% accuracy rate. Speech, voice, and HandPD datasets were utilized by Gupta et al. (2018) [21] to diagnose Parkinson's disease. They

achieved an accuracy of 92.19% by refining the Cuttlefish algorithm and lowering the characteristics. Sarkar et al. (2019) [22] used algorithms of speech processing and proposed an ML classification with SVM-RBF and mRMR having a classification accuracy of 86%.

Tuncer et al. (2020) [23] discussed a new octopus-based approach in diagnosis of PD by obtaining highly accurate classification results both in gender recognition and PD, thus bringing a combination of accuracy as 97.62%. With an accuracy of 95.39%, Nissar et al. (2021) [24] presented a voice-based PD detection system that combined Extreme Gradient Boosting with feature selection techniques like mRMR and RFE. Using UCI voice data, Gunduz et al. (2019) [25] developed a CNN PD classification method that produced an accuracy of 86.9%. Using the Bat Algorithm (BAT), Olivares et al. (2012) [26] demonstrated a PD diagnostic system that had a 96.74% accuracy rate and a 3.27% loss. A vocal-based pre-diagnosis technique for Parkinson's

disease was described by Solana et al. (2021) [27], with 94.7% accuracy achieved by the SVM-RBF classifier. Vowels were employed by Yaman et al. (2020) [28] to identify PD, and the SVM classifier achieved an accuracy of 91.25%. Using RFE and SVM, Senturk et al. (2020) [7] used machine learning approaches to diagnose PD with 93.8% accuracy. Aich et al. (2019) [29] classified PD using PCA and online feature selection based on regression, with RF and PCA yielding a 96.83% accuracy rate. Fuzzy c-means clustering and pattern recognition were employed by Rustempasic et al. (2013) [30] to predict PD with 68.04% accuracy and 75.34% sensitivity. Olfactory tests for PD detection were examined by Silveira et al. (2008) [31], who found that they had an 89.0% specificity and an 81.1% sensitivity. Prashanth et al. (2014) [32] employed SVMs and classification trees for PD detection with 85.4% accuracy and 90.5% sensitivity. Anju et al. (2020) [33] showed the possibility of PD detection using smartphone data, including voice and movement data, by reviewing 17 ML-based studies.

In their comparison of NB, RF, LR, and SVM for PD identification, Tarigoppula et al. (2018) [34] found that SVM had an accuracy of 88.9%. A fuzzy-based KNN model was proposed by Chen et al. (2005) [35], and it achieved an accuracy of 96.07%. A hybrid model for PD detection was created by Jiang et al. (2016) [36], and it achieved an overall accuracy of 95.97%. According to Hariharan et al. (2014) [37], feature preprocessing can diagnose Parkinson's disease with 100% classification accuracy. [51] The study used 48 characteristics and machine learning to reach a 98.04% classification accuracy for Parkinson's illness. SVM and NB showed the quickest execution durations (~10 ns) for real-time applications, while Naïve Bayes (NB) and Multi-Layer Perceptron (MLP) offered the greatest accuracy. To increase prediction accuracy, extensive data preparation is advised. Deep learning-based techniques and automated feature selection should be investigated in future studies. The study used a free database with more than 9 million records for feature extraction and emphasizes the need of huge datasets for efficient categorization. Figure 6 illustrates the comparison of the different models.

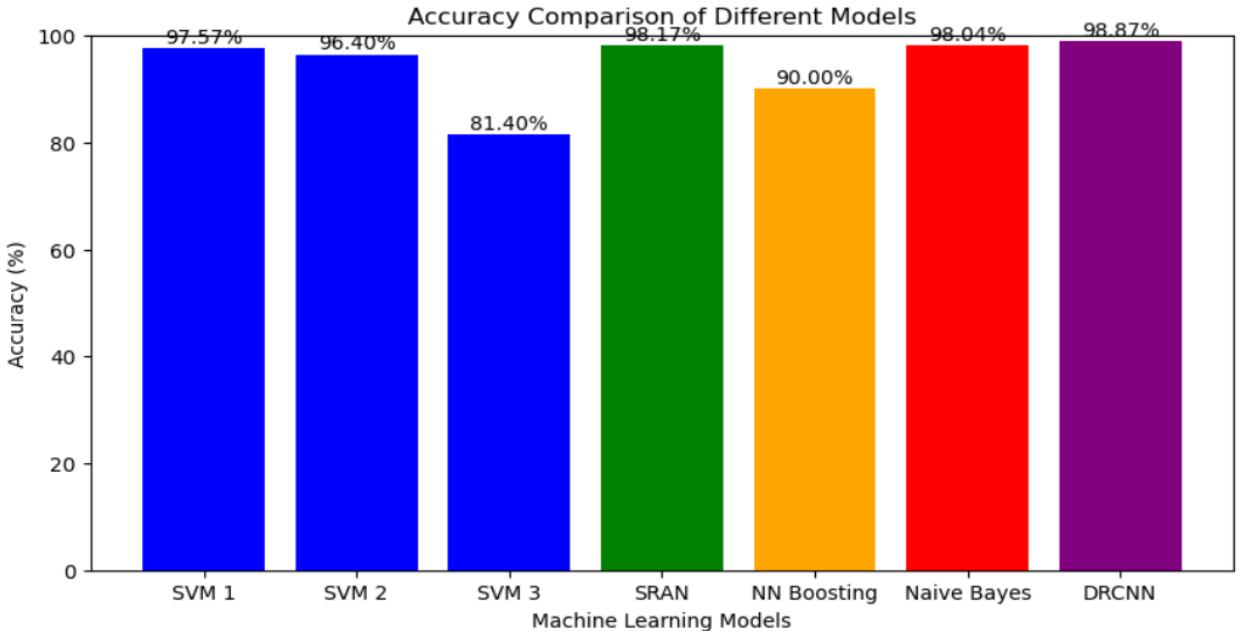

Figure : 6 Accuracy for Different Models

Challenges:

[38] The necessity of better early Parkinson's disease identification is emphasized in the paper. Large, heterogeneous datasets provide difficulties for current models. An updated version of the UPDRS might be added to the suggested approach to improve forecast accuracy. It's still difficult to diagnose Parkinson's disease accurately and early. Large, varied datasets are difficult for current models to handle, and the UPDRS's constraints affect prediction accuracy. The study emphasizes that in order to improve early-stage PD detection, more speech characteristics and the integration of different machine learning techniques are required. [48] It is difficult to recognize Parkinson's disease in its early stages since standard diagnosis ignores complicated non-motor symptoms in favor of motor symptoms. Diagnosing these symptoms is challenging due to their variety. Machine learning applications have been limited by prior research that mostly focused on motor and kinematic data. Finding pertinent traits is necessary for an early diagnosis of Parkinson's disease. [57] The accuracy of Parkinson's disease detection algorithms is influenced by a number of factors. Bias is introduced when the effects of age and medicine on speech are disregarded. Inconsistencies are further exacerbated by differences in corpora between PD patients and controls. Results from classifiers that lack cross-validation techniques may be erroneous. Assessments are made more difficult by patient variations that cause variation in UPDRS readings, and a typical problem is the absence of information regarding the intervals between UPDRS evaluations and recordings. Additionally, many studies do not mention demographic variations, which affects results, and phonatory characteristics in running speech may be deceptive. [54] Shivakoti.et.al identified a number of difficulties in categorizing the development of tremors in Parkinson's disease. Classifier accuracy was poor, particularly in the first few seconds after tremor initiation, and false negatives might delay necessary DBS stimulation and make patients uncomfortable. While inductive battery recharging is still impracticable due to its size and patient discomfort, the significant computing power needed for training may have an influence on battery life in real-world applications. The difficult circumstances in which the classifiers performed highlighted how difficult it is to decipher PD signals.

Table 2: An overview table that compares the performance of the proposed technique to previous work.

S.No	Author	Year	Algorithm	Accuracy (%)
1	Nutan Singh.et.al [47]	2024	EFSA Algorithm	90.2%
2	Syed Nisar H.et.al [42]	2024	AdaBoost	96%
3	Magesh.et.al [49]	2024	XGB, RF	97.5%
4	Mohammed.et.al [50]	2024	HM	96.6%
5	Kadhim.et.al [45]	2024	Gower Distance	98.3%
6	Arafe.et.al [38]	2023	Decision Tree, Naïve Bayes, KNN, SVM	68.5%
7	Camacho.et.al [39]	2023	CNN	79.3%
8	Praneeth.et.al [55]	2023	Proposed DRCNN	98.87%
9	Alalayah.et.al [41]	2023	MLP	98%
10	Ahmadi.et.al [60]	2023	AdaBoost	96.30%
11	Mithun Shivakoti.et.al [54]	2023	CatBoost	95.1%
11	Elshewey.et.al [58]	2023	SVM	92.3%
12	Lamba.et.al [4]	2022	RF, KNN, NB	95.58%
13	Hawi.et.al [59]	2022	RF	88.84%
14	Rohit.et.al [56]	2022	RF & XGBoost	93.88%
15	Wang.et.al [2]	2020	Applied CA-Net, AG,SE,ResNext50,VGG16	98.7%
16	Senturk.et.al [7]	2020	ANN, SVM, CART	93.84%
17	Pahuja.et.al [53]	2018	SRAN Classifier	98.17%

Furthermore, it is still very difficult to accurately forecast tremors by analyzing LFP signals in real time. [52] The symptoms of Parkinson's disease and depression sometimes overlap, making diagnosis difficult. To enhance patient outcomes, precise early detection techniques are required. To improve accuracy, future studies should evaluate the suggested method on bigger datasets. Improving early PD detection methods requires including pertinent clinical data. [48] Kamble.et.al pointed to a number of difficulties in making a Parkinson's disease diagnosis. Accuracy is impacted by the complexity of voice feature extraction and normalization. Algorithms for machine learning are susceptible to overfitting and computational load. Outliers in spiral drawing tests can result in errors, while Fourier processing has trouble picking up on minute frequency changes in scanned pictures. Furthermore, the requirement to preprocess scanned pictures makes analysis more difficult, underscoring the shortcomings of conventional diagnostic techniques. [46] Wang.et.al identified the main obstacles to diagnosing Parkinson's disease with CNNs. Their interpretability is limited by their nonlinear nature, which influences clinician acceptability. While there are limitations due to the small testing population and the restricted data from two locations, inaccurate brain nuclei segmentation may affect classification accuracy. Delineating zones of interest by hand is expensive and time-consuming. The performance of the suggested approach may be enhanced by adding anatomical attention and improving segmentation models. [40] Abiyev.et.al comes to the conclusion that Parkinson's disease may be accurately diagnosed using fuzzy brain architecture. Through simulations using UCI data, it highlights the structure and learning algorithms of the suggested system and shows enhanced recognition rates. A comparative investigation demonstrates the combination of fuzzy systems with neural networks for improved diagnosis and validates improved classification performance. [43] Mei.et.al discussed the first to assess machine learning techniques for Parkinson's disease diagnosis. Through the use of clinical, behavioral, and biometric data, machine learning improves accuracy in clinical decision-making and early diagnosis. Studies with a variety of data formats have found high diagnosis accuracy. On the other hand, reporting methods and outcomes need to be more transparent. Because of current limitations, clinicians should use caution when interpreting machine learning results. Early PD diagnosis may be further facilitated by the use of new biomarkers. [44] Using clinical evaluations and MRI data from the PPMI database, the study used machine learning and transfer learning to examine Parkinson's disease. The most effective technique for dealing with unbalanced data was determined to be a combination of SMOTE and ENN. Using explainable AI approaches, the Extra Tree classifier obtained the best accuracy of 98.44%. The best pretrained models for MRI analysis were DenseNet169 and InceptionV3, which had respective accuracies of 85.08% and 50.24%. The goal of future research is to enhance model performance and create apps that are easy for medical practitioners to utilize. [57] Shivakoti.et.al examines cutting-edge techniques for diagnosing and assessing Parkinson's disease using voice analysis. It recognizes important contributions to the discipline and offers suggestions for further study. Although the majority of automatic detection techniques reach accuracy rates between 80% and 95%, there is disagreement over the optimal diagnostic component for early-stage Parkinson's disease. The study highlights the necessity of larger datasets and more reliable approaches. Although no standard approach has been clinically confirmed yet, it suggests that articulatory and phonatory elements are critical for PD identification.

Conclusions:

The research offers a thorough examination of Parkinson's disease (PD), including information on diagnosis, management, and potential future developments. While recognizing issues including data

asymmetry, a lack of standardized procedures, and computational costs, it emphasizes the value of machine learning, voice analysis, and clinical evaluations in the diagnosis of Parkinson's disease. The importance of articulatory and phonatory features in PD detection, the high classification accuracy attained by different ML models, and the demand for reliable techniques and bigger datasets are some of the main conclusions. Future studies should concentrate on creating real-time, clinician-friendly diagnostic tools, enhancing model transparency, and incorporating new biomarkers. Table 2 illustrates the compares the performance of the proposed technique to previous work.

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