Overview of machine learning-based detection methods for Parkinson's disease

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Abstract

The Parkinson's disease (PD) is one of the most common diseases, especially in elderly people,it is a neurodegenerative disorder that affects nervous system and the root cause of it is falling rates of dopamine levels in the forebrain.and diagnosis of Parkinson's disease (PD) is commonly based on medical observations and assessment of clinical signs, including the characterization of a variety of motor symptoms. However, traditional diagnostic approaches may suffer from subjectivity as they rely on the evaluation of movements that are sometimes subtle to human eyes and therefore difficult to classify, leading to possible misclassification.

To address these difficulties and to refine the diagnosis and assessment procedures of PD, machine learning methods have been implemented for the classification of PD.To provide a comprehensive overview of Various machine learning methods that have been used , developed, proposed, and analyzed to detect the Parkinson disease, given the required data. This paper is a survey on the efficiency of voice based Parkinson disease detection using machine learning algorithms, various new technologies applied, and their accuracies achieved. and these studies demonstrate a high potential for adaptation of machine learning methods and novel biomarkers in clinical decision making, leading to increasingly systematic, informed diagnosis of PD.

Keywords: Parkinson's disease, voice impairment, speech signals, machine learning, classification, feature selection.

1. Introduction

Two hundred years ago at the age of 62, James Parkinson wrote a 66 page treatise entitled An Essay on the Shaking Palsy. Parkinson defined the shaking palsy as a nervous disorder characterized by a trembling of the limbs at rest, lessened muscular power and a stooped posture associated with a propulsive, festinant gait.(1) Parkinson's disease is the second most common neurodegenerative disorder worldwide with increasing incidence as the general population ages. Parkinson's disease is a progressive neurodegenerative disorder of unknown etiology that affects over 1 million people in north America only(3). the symptoms of this malady do not become noticeably until between the ages of 50 and 69 years and occurs in 1 -2 of people over the age of 60 years, rising to 3.5% of the age 85-89 years(21). about 0.3% of the general population is affected, and the prevelance is higher among men than women with a ratio of 1.5 to 1.0 (2).

the hallmark clinical symptoms of parkinson's disease are largely motoric in nature and include resting tremor, muscular rigidity, bradykinesia, , and postural abnormalties. (2).

by the time Parkinson's disease becomes clinically apparent more than 50 of dopaminergic neurons in substantia nigra have been lost, with a corresponding 80 decline in striatal dopamine levels. thus, early identification of the disease is essential if neuroprotective therapies are to be implemented. that's why diagnosis of Parkinson's disease is very important.currently the diagnosis relies on clinical examination. the current gold standard is based on motor signs and symptoms (bradykinesia, resting tremor, rigidity, postural reflex impairment) and response to dopaminergic drugs. in addition to the classical motor signs and symptoms. Parkinson's disease is well recognized to also affect non-motor neural circuits.however, the accuracy of Parkinson's disease diagnosis in practice is only around 80%, implying that a large population with Parkinson's disease is undiagnosed or misdiagnosed(46). hence, identification of novel motor or non-motor markers of Parkinson's disease or improving the accuracy of currently available diagnostic tools is important particularly in early disease. therefore, noninvasive speech tests have been explored as a marker of the disease, since deterioration of speech is consistently observed in patients with Parkinson's disease.(6)

Speech motor approach has been considered by a number of investigators, for tracking Parkinson's disease severity with sufficient sensitivity,and the quantitative analysis of speech motor changes that have been associated with the disease.(4)

hypokinetic dysartha, a speech disorder characterized by indistinctness of articulation, weakness of voice, and

lack of inflection, burst speech, and hesitations and stoppages, is an integral part of the motoric changes in Parkinson's disease.it is generally believed that hypokinetic dysartha occurs in at least half of all patients with Parkinson's Disease. in speech pathology clinics 98% of all cases of hypokinetic dysartha are the results of Parkinson's disease. thus, hypokinetic dysartha occurs often enough to serve a confirmatory evidence for the neurological diagnosis and is sometimes the first sign of the disease.the reason for thins association between voice changes and onset of Parkinson's disease is probably due to the fact that speech is arguably one of the most complicated motor actions under volitional control, and may therefore be susceptible to slight degenerative changes in basal ganglia circuitry affected in the pathophysiology.

2. Background

before listing the available studies related to Detecting Parkinson's disease using machine learning .it is necessary to have a background knowledge about machine learning and its different kind of algorithms.

Therefore,machine learning is the field of study that gives computers the ability to learn without being explicitly programmed.Machine learning systems can be classified according to the amount type of supervision they get during training.

Machine learning algorithms can be divided into categories according to their purpose, and the main categories are the following : supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning(25).

2.0.1. Supervised learning

In supervised learning, the training set you feed to the algorithm includes the desired solutions, called *labels*(33).A typical supervised learning task is classification, and Classification uses an algorithm to accurately assign test data into specific categories. It recognizes specific entities within the dataset and attempts to draw some conclusions on how those entities should be labeled or defined. another typical task is to predict a target numeric value.this sort of task is called *regression*.Here are some of the most important supervised learning algorithms :

- K-Nearest Neighbors
- Linear Regression
- Logistic Regression
- Support Vector Machines (SVMs)
- Decision trees and random Forests
- Neural networks

3. Summary of research methods

for detecting Parkinson's disease, the proposed approaches are based on motor symptoms explicitly related to voice. and for that, most studies have used popular machine learning models for binary classification, the reasons why they chose classical machine learning models as opposed to the newer, deep learning models are the limited training data available and the emphasis on clinical application.besides, the mechanism of traditional machine learning models are well understood(44),

3.1. Neural Network

convolutional neural network (CNN) is the go-to classifier method for most papers.(17) in this study an easy-to-apply, sensitive, and effective transfer learning based deep CNN model was proposed for diagnosis of PD. It was investigated how voice dataset from one large dataset using fine-tuning approaches of transfer learning model could enhance the identification of PD,and the results revealed that the proposed CNN model based on transfer learning with a fine-tuning approach provides an acceptable detection of PD with a high accuracy.for Resul Das (39) In this study, various classification methods were used for diagnosing of the Parkinson's disease by using SAS base software. Implementations were carried out on the PD dataset to diagnose Parkinson's disease in a fully automatic manner. Four independent classification models were used. These are Neural Network, Regression ,DMNeural, and Decision tree respectively.David Sztaho et al (42) they have used for classification artificial feed-forward neural network (ANN with neurons in hidden layers : 10, 10) and deep neural network with rectifier activation function (DNN with neurons in hidden layers : 20, 20).

3.2. Gradient boosting

Gradient boosting algorithm can be used for predicting not only continuous target variable (as a Regressor) but also categorical target variable (as a Classifier).There has been numerous studies focused on extreme gradien boost.Iqra Nissar et al (19) ,have evaluated the performance of nine machine learning based models including naive Bayes, k-nearest neighbor, logistic regression, multilayer perceptron, random forest, support vector machines (linear and RBF kernel), decision tree, and Extreme Gradient Boost (XGBoost) with RFE (Recursive Feature Elimination) and mRMR(minimum-Redundancy and Maximum-Relevance) feature selection techniques.Among all the models, the XGBoost achieved the highest accuracy besides the mRMR feature selection technique has performed better in making a decision for detection.

WU WANG et al (43) found that the boosting methods provide superior detection performance compared to the twelve considered machine learning models in discriminating normal people with patients who have Parkinson's disease.The literature on Ibrahim Karabayir et al paper (15)found that the Light Gradient Boosting model presented here outperformed the statistical approach in all metrics (AUC,sensitivity, specificity,precision and accuracy)

3.3. Support Vector Machines

SVM works by mapping data to a high-dimensional feature space so that data points can be categorized.therefore the supervised ML-based algorithm alone (SVM) could detect early PD with 89.6% and 86.9% overall classification performance (38) .for Salim Lahmiri et al (40) they have selected SVM for classification due to its ability to map original patterns from a high dimensional space to eventually construct an optimal boundary hyper-plane in this space by using nonlinear kernel functions. In addition, it achieves the global optimum and is robust even when the original data sample is small.Maryam Pishgar et al (35) found that a conventional SVM model performed better than an LSTM model across sensitivity and specificity metrics on a small dataset comprised of voice features from the 2018 FEMH Voice Disorder challenge, and their proposed model perform similarly and in a case outperformed more complicated models, such as XGBoost and LSTM-FCN.

A comparative study (34) found only slight performance gains from using a DNN over a SVM model on dataset of 406 voice samples from the MEEI voice disorder database. and in (41) they have Selected features by chi-square from the histogram that was formed by the feature discriminant ratio method from the short-time Fourier transform of the gait signals selected features from histogram were classified by support vector machines.

3.4. Fuzzy Neural System

Fuzzy c-means clustering was described in the paper of Indira Rustempasic et al (18), as the algorithm that works as follows. Initially a random selection of fuzzy partition matrix U is chosen, and centers are calculated. The centers v(i) and the membership strengths are calculated through the use of equations. in this paper presents a diagnostic fuzzy cluster means and pattern recognition systems to help in diagnosis of Parkinson's disease using a set of speech signals.Rahib H. Abiyev et al (38) in their paper they have presented the diagnosis of Parkinson's diseases using fuzzy neural structures.The structure and learning algorithms of FNS are presented.Fuzzy clustering and gradient descent learning algorithms are applied for the development of the FNS. Learning is performed using 10-fold cross validation data set.

3.5. Logistic Regression

Logistic regression is a statistical analysis method to predict a binary outcome.John M. Tracy et al (34) have chosen tree classic machine learning models : L2-regularized logistic regression, random forest, and gradient boosted decision trees .they've found that AUC scores remain high with the best score of 0.85. With the Logistic Regression model.comparative study have been done by Resul Das (40) , In this study, various classification methods were used for diagnosing of the Parkinson's disease by using SAS base software. Implementations were carried out on the PD dataset to diagnose Parkinson's disease in a fully automatic manner. Four independent classification models were used. These are DMNeural,Neural Network, Regression, and Decision tree respectively.in Andrius Vabalas et al (41) they have used Logistic Regression as a classifier.It uses logistic function to predict binary classes based on linear combinations between class and features. Logistic regression was implemented using Scikit-learn library.

4. Dateset

4.1. data Source

4.1.1. independent recruitment of human participants

In order to truly advance Parkinson's disease research and clinical care, innovative recruitment strategies are required to attract large numbers of research participants, as well as to accurately capture patient-reported outcomes (PROs) from diverse.segments of the PD community (45).43.06% of the studies that have used independent recruitment of human participants as their data source .the subjects historically underrepresented in PD research were recruited in higher numbers as a function of digital outreach than baseline recruitment practices. For example, digital strategies successfully attracted women, as well as participants who were older, non-white (African-American, Asian, American Indian, Multi-racial), Hispanic, lower income,less educated, and in worse physical health. This may be because traditional recruitment strategies over-sample those with regular access to specialized PD care and time to participate in research. Social media also may be accessible and appealing to more diverse segments of the PD community than movement disorder specialty centers, or even traditional, in-person support groups.

4.1.2. UCI Machine Learning Repository

The publicly available data that have been used in 44 studies for Parkinson's disease detection is the "Parkinson Dataset with Replicated Acoustic Features Data Set" that was donated to University of California Irvine Machine learning repository by Naranjo, et al .(11)the dataset includes patients with early-stage Parkinson's disease not taking medication.A follow up study (11) reported that parkinson's disease duration was 5 years or less for all subjects, with a mean Unified Parkinson's Disease Rating Scale (UPDRS) score of 19.6 (SD=8.1). The dataset available (11) included 44 acoustic features extracted from voice recordings of 40 patients with Parkinson's disease and 40 controls.Recordings od a sustained phonation of vowel /a/ for 5s were repeated three times (three runs). Digital recordings were implemented at a 44.1 KHz sampling rate and 16 bits/sample (11).

The 44 acoustic features extracted from voice recordings comprised five categories :pitch and amplitude local perturbation, noise, special envelope, and nonlinear measures. Four pitch local features (jitter relative, jitter absolute, jitter RAP (relative absolute perturbation)), jit-

ter PPQ (pitch perturbation quotient), and five amplitude perturbation measures (shimmer local, shimmer dB, APQ3 (3 point Amplitude Perturbation Quotient), APQ5 (5 pint Amplitude Perturbation Quotient), and APQ11(11-point Amplitude Perturbation Quotient)) were extracted using a waveform matching algorithm. As measures of relative level of noise in speech (11). five different variants of harmonic-to-noise ratio (HNR) corresponding to different frequency bandwidths (HNR05 [0–500 Hz], HNR15 [0–1500 Hz], HNR25 [0–2500 Hz], HNR35 [0–3500 Hz], HNR38 [0–3800 Hz]).(13) Glottal-to-Noise Excitation Ratio (GNE), which quantifies the amount of voice excitation, was also calculated. Since PD is known to affect articulation (14), 13 Mel Frequency Cepstral Coefficients (MFCCs) associated with articular position and 13 Delta Coefficients as time dependent derivatives of MFCCs were also extracted. In addition, Recurrence Period Density Entropy (RPDE), Detrended Fluctuation Analysis (DFA), and Pitch Period Density Entropy (PPE) were also extracted as non-linear measures of voice recordings. Further details of the dataset can be found in Naranjo et al.(11)

4.1.3. PPMI database

15.28% of the studies have used PPMI database. Parkinson's Progression Markers Initiative (PPMI) Clinical enrolls prodromal, recently diagnosed Parkinson's participants and healthy controls. This cohort description section covers eligibility criteria at enrollment for PPMI Clinical.

All PPMI participants are also assigned to cohorts and subgroups in an analytic dataset based on a central review of the most recent longitudinal PPMI data. The analytic cohort reflects new PPMI data that may modify the enrollment cohort designation. The analytic data set cohort assignments should be used rather than the enrollment cohort assignments for all data analysis. PPMI began initial recruitment in 2010. After an enrollment hiatus, the study expanded and reinitiated recruitment in 2020. There are some differences in the protocol, eligibility criteria, and schedule of activities between these two phases. All PPMI data has been harmonized in the current data structure. PPMI is recruiting people with and without Parkinson's disease.At PPMI's 33 clinical sites in 11 countries, 1,400 participants have contributed data and biosamples to the most robust Parkinson's database and specimen bank ever created. The study has applied deep molecular profiling techniques to generate data from whole genome and epigenome sequencing and transcriptomics, for example.

4.1.4. PhysioNet

PhysioBank is a large and growing archive of physiological data.Data from critical care clinical settings that may include demographics, vital sign measurements made at the bedside, laboratory test results, procedures, medications, caregiver notes, images and imaging reports, and mortality (both in and out of hospital).and 6.94% of the studies have used PhysioNet as their dataset. To achieve this, we can try to implement artificial neural network with different number of hidden layers and number of nodes in future and compare all the accuracies.

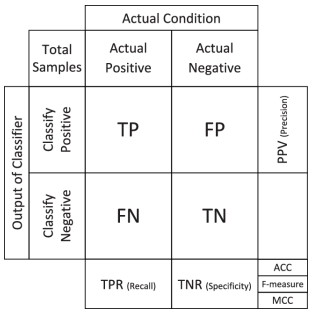

Figure 1: Confusion matrix

4.2. Features

Speech deterioration is one of the motor symptoms of PD.Patients have reduced pitch variability compared to controls as well as reduced intra-individual variability As described above, each acoustic feature was calculated three times for different runs of the speech test. Thus, in addition to testing the diagnostic accuracy of our analytic approach, it does also help to be able to investigate intra-individual changes in response from different runs of the test. acoustic features are considered calculated for all three runs as individual predictors. Moreover, for a given acoustic feature, three artificial variables were created representing the change from one run to another.Therefore, the feature set included 264 acoustic features and sex for 80 subjects.

5. Evaluation

After the feature selection, the model is implemented and output is produced in the form of probability or class. the next step is to find how efficient the model is using test dataset based on some metrics.therefore, to assess the classification performance different metrics like accuracy, recall, precision, F-1 score and AUC-ROC curve have been used.Choosing the correct metrics to evaluate the machine learning model is very important as it influences how the performance is measured and compared.

5.1. Confusion matrix

A confusion matrix is the most intuitive matrix that is used to find the accuracy and correctness of the models. It is used for the binary class and multi class classification problems. It describes the performance of classification models in which the truth values are already known. A confusion matrix is a table with two dimensions, one for the actual target value and one for the predicted value. To explain the concept of the confusion matrix, assume the binary classification problem in which classes are 1 and 0 which is shown in figure 1.

The actual labels are represented by rows and the predicted labels are represented by columns. The basic terms of confusion Matrix are discussed as follows :

— True positive (TP) : It can be defined as a systems ability to correctly classify the instances as positive, which means that if the actual label is 1, then predicted label is also 1. In terms of percentage, it is expressed as the True Positive Rate (TPR), also called sensitivity is the proportion of correctly predicted positive examples. It is given by :
— True negative (TN) : It is also called as specificity and is defined as the ability of a system to correctly classify the examples as negative, which means that if the actual label is 0 then predicted label is also 0. It is represented as True Negative Rate (TNR) in terms of the fraction of correctly predicted negative samples by the model.
— False Positive (FP) : In this case, the model incorrectly classifies the instances as positive. That is, the model predicts the class label as 1 whose label was originally 0. False Positive Rate (FPR) is represented as the fraction of negative cases which are predicted as the positive ones and is given by :
— False Negative (FN) : It is the system's ability to incorrectly classify the examples as negative which means that for the actual label 1, the predicted label for a class is 0. False Negative Rate (FNR) is the fraction of positive samples that were predicted as negative instances and is given by :
— Precision : It is defined as the ratio of true positive relevant instances to the total number of retrieved instances. It is given by :

$$Precision(\%) = \frac{TP}{TP + FP} \tag{1}$$

— Recall : It is also called as the sensitivity and is defined as the fraction of correct positive examples predicted to the total number of positive occurrences.

$$Sensitivity(\%) = \frac{TP}{TP + FN} \tag{2}$$

— F1-score : Precision and recall are summarized into another metric which is called as F1- score. It represents a harmonic mean of recall and precision.

$$F1 = 2\frac{Precision.Sensitivity}{Precision + Sensitivity} \tag{3}$$

It may also represented as :

$$F1 = \frac{2TP}{2TP + FP + FN} \tag{4}$$

— Accuracy : It is the fraction of the number of correct predicted examples to the total number of instances present in the dataset. It is given by :

$$Accuracy(\%) = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

5.2. AUC-ROC

It is a probability curve and a performance measurement that is widely used for binary classification problems. This curve tells how much the classification model is able to distinguish one class from the other class. In the ROC curve, the y-axis represents the true positive rate and the x-axis represents the false positive rate. The value of AUC ranges from 0 to 1. The model which has AUC close to 1 has an excellent classification performance, whereas the model which has AUC close to 0 has the worst measure of separability, and when AUC of the model is 0.5, the model does not have separation capacity.

6. Discussion and future direction

Machine Learning techniques has got prominent role as they are applied in variety of domains especially in the healthcare. Unlike traditional methods, the models generated by applying ML techniques show dynamic outputs as data is fed into it. One shall make note that significant and narrow research is needed to obtain knowledge in diagnosing the disease. Various machine learning algorithms and techniques are being proposed rapidly, out of which some are observed to be promising with the results and few demonstrated their usage in different fields. Advantage with the ML generated models is that when more data is used, the precision values gets increased and the much accuracy in predictions can be gained.

Despite the fact that fairly high accuracies has already been reached, the presented results still allow for some improvements. for future use we can try to implement artificial neural network with different number of hidden layers and number of nodes.pursuing this further we can employ an nontraditional set of algorithms (e.g. StreamKM (**?**), ClusTree (**?**) and LogLog algorithm (**?**)).Hence, to evaluate whether these approaches can these approaches can perform on a similar lever of accuracy or maybe even outperform the other methods.

7. Conclusion

This paper has provided a comprehensive overview of the machine learning methods to the diagnosis of Parkinson's disease.Here, we presented included studies in a high-level summary, providing access to information including machine learning methods that have been used in the diagnosis of Parkinson's disease and associated outcomes, types of clinical, behavioral and biometric data that could be used for rendering more accurate diagnoses,other highly relevant information, including databases that could be used to enlarge and enrich smaller datasets.In summary, It can be identified that maximum of all ML techniques used by various authors worked better but developing a very faster classifier using novel architecture of neural network fuzzy neural network.or else,to use the novel architecture of neural network combined with specific approach may work better.

Table 1: Studies that applied machine learning models to voice recordings to diagnose parkinson's disease

Objectives	Source of data	Number of subjects (n)	Machine learning method(s), splitting strategy and cross validation	Outcomes	Year	References
Classification of PD from HC	UCI machine learning repository	31 ; 8 HC + 23 PD	Light and Extreme Gradient Boosting	F1= 0.839 [0.831–0.847] AUC= 0.898 [0.892–0.905] Accuracy= 0.841 [0.833–0.849] sensitivity= 0.839 [0.827–0.850] specificity= 0.844 [0.832–0.855] PPV= 0.853 [0.843–0.863]	2020	Ibrahim Karabayir et al
Classification of PD from HC	UCI machine learning repository	31 ; 8 HC + 23 PD	Random Forest	F1= 0.810 [0.800–0.819] AUC= 0.884 [0.876–0.892] Accuracy= 0.818 [0.810–0.826] sensitivity= 0.795 [0.782–0.808] specificity= 0.841 [0.831–0.852] PPV= 0.844 [0.834–0.854]	2020	Ibrahim Karabayir et al

Objectives	Source of data	Number of subjects (n)	Machine learning method(s), splitting strategy and cross validation	Outcomes	Year	References
Classification of PD from HC	UCI machine learning repository	31 ; 8 HC + 23 PD	Support Vector Machines	F1= 0.730 [0.721–0.739] AUC= 0.838 [0.830–0.846] Accuracy= 0.744 [0.735–0.752] sensitivity= 0.704 [0.691–0.716] specificity= 0.784 [0.771–0.798] PPV= 0.780 [0.769–0.791]	2020	Ibrahim Karabayir et al
Classification of PD from HC	UCI machine learning repository	31 ; 8 HC + 23 PD	K-nearest neighborhood	F1= 0.744 [0.735–0.753] AUC= 0.841 [0.834–0.848] Accuracy= 0.760 [0.752–0.768] sensitivity= 0.712 [0.699–0.725] specificity= 0.807 [0.796–0.818] PPV= 0.796 [0.786–0.806]	2020	Ibrahim Karabayir et al

Objectives	Source of data	Number of subjects (n)	Machine learning method(s), splitting strategy and cross validation	Outcomes	Year	References
Classification of PD from HC	UCI machine learning repository	40 ; 20 HC + 20 PD	Linear regression, LDA, Gaussian naïve Bayes, decision tree, KNN, SVM-linear, SVM-RBF with leave-one-subject-out cross validation	Logistic regression or SVM-linear accuracy = 70	2020	Ibrahim Karabayir et al
Classification of PD from HC	UCI machine learning repository	31 ; 8 HC + 23 PD	Logistic regression, KNN, naïve Bayes, SVM, decision tree, random forest, DNN with 10-fold cross validation	KNN accuracy = 95.513	2020	Ibrahim Karabayir et al
Classification of PD from HC	UCI machine learning repository	40 ; 20 HC + 20 PD	SVM, logistic regression, ET, gradient boosting, random forest with train-test split ratio = 80 :20	Logistic regression accuracy = 76.03%	2020	Ibrahim Karabayir et al
Classification of PD from HC	UCI machine learning repository	40 ; 20 HC + 20 PD	S Fuzzy classifier with 10-fold cross validation, leave-one-out cross validation or a train-test ratio of 70 :30	Accuracy = 100%	2020	Ibrahim Karabayir et al

Objectives	Source of data	Number of subjects (n)	Machine learning method(s), splitting strategy and cross validation	Outcomes	Year	References
Classification of PD from HC	UCI machine learning repository	40 ; 20 HC + 20 PD	Least Absolute Shrinkage and Selection Operator Regression	Logistic regression accuracy = 76.03%	2019	Ibrahim Karabayir et al
Classification of PD from HC	UCI machine learning repository	40 ; 20 PD + 9 MSA + 5 FND + 1somatization + 1 dystonia + 2 CD + 1ET + 1 GPD	logistic regression	F1= = 85%	2016	Ibrahim Karabayir et al
Classification of PD from HC	UCI machine learning repository	31 ; 8 HC + 23 PD	SVM-linear with 5-fold cross validation	Error rate 0.13	2019	Ibrahim Karabayir et al
Classification of PD from HC	UCI machine learning repository	108 ; 56 HC + 52 PD	Least Absolute Shrinkage and Selection Operator Regression	Logistic regression accuracy = 1.9%	2019	Ibrahim Karabayir et al
Classification of PD from HC	UCI machine learning repository	31 ; 8 HC + 23 PD	CART, SVM, ANN	SVM accuracy = 93.84%	2020	Ibrahim Karabayir et al
Classification of PD from HC	UCI machine learning repository	40 ; 20 HC + 20 PD	Stacked generalization with CMTNN with 10-fold cross validation	SAccuracy = 70%	2015	Kraipeerapun and Amornsamankul

Objectives	Source of data	Number of subjects (n)	Machine learning method(s), splitting strategy and cross validation	Outcomes	Year	References
Classification of PD from HC	UCI machine learning repository	31 ; 8 HC + 23 PD	Least Absolute Shrinkage and Selection Operator Regression	F1= 0.763 [0.755–0.7723] AUC= 0.870 [0.863–0.877] Accuracy= 0.761 [0.753–0.769] sensitivity= 0.782 [0.769–0.794] specificity= 0.741 [0.729–0.754] PPV= 0.762 [0.753–0.772]	2020	Ibrahim Karabayir et al
Classification of PD from HC	UCI machine learning repository	31 ; 8 HC + 23 PD	logistic regression	F1= 0.771 [0.762–0.780] AUC= 0.839 [0.830–0.847 Accuracy= 0.771 [0.762–0.780] sensitivity= 0.777 [0.765–0.790] specificity= 0.764 [0.750–0.778] PPV= 0.780 [0.769–0.791]	2020	Ibrahim Karabayir et al

Objectives	Source of data	Number of subjects (n)	Machine learning method(s), splitting strategy and cross validation	Outcomes	Year	References
Classification of PD from HC	UCI machine learning repository	31 ; 8 HC + 23 PD	resNet 18 layers	F1= 0.92 Recall= 0.92 Accuracy= 0.917 Precision=0.92	2018	Marek Wodzinski
Classification of PD from HC	UCI machine learning repository	31 ; 8 HC + 23 PD	Naive Bayes	F1= 0.85 Recall= 0.84 Accuracy= 84.21 Precision=0.89	2019	Iqra nissar et al
Classification of PD from HC	UCI machine learning repository	31 ; 8 HC + 23 PD	Logistic regression	F1= 0.85 Recall= 0.86 Accuracy= 86.18 Precision= 0.85	2019	Iqra nissar et al
Classification of PD from HC	UCI machine learning repository	31 ; 8 HC + 23 PD	k-NN	F1= 0.83 Recall= 0.86 Accuracy= 85.53 Precision= 0.83	2019	Iqra nissar et al
Classification of PD from HC	UCI machine learning repository	31 ; 8 HC + 23 PD	Multilayer Perceptron	F1=0.85 Recall= 0.84 Accuracy= 84.86 Precision= 0.85	2019	Iqra nissar et al

Objectives	Source of data	Number of subjects (n)	Machine learning method(s), splitting strategy and cross validation	Outcomes	Year	References
Classification of PD from HC	UCI machine learning repository	31 ; 8 HC + 23 PD	Random forest	F1= 0.86 Recall= 0.92 Accuracy= 0.917 Precision=0.92	2019	Iqra nissar et al
Classification of PD from HC	UCI machine learning repository	31 ; 8 HC + 23 PD	SVM (linear)	F1= 0.83 Recall= 0.84 Accuracy= 84.21 Precision= 0.83	2019	Iqra nissar et al
Classification of PD from HC	UCI machine learning repository	31 ; 8 HC + 23 PD	SVM (RBF)	F1= 0.89 Recall= 0.88 Accuracy= 88.15 Precision=0.89	2019	Iqra nissar et al
Classification of PD from HC	UCI machine learning repository	31 ; 8 HC + 23 PD	Decision Tree	F1= 0.89 Recall= 0.89 Accuracy= 88.81 Precision= 0.89	2019	Iqra nissar et al
Classification of PD from HC	UCI machine learning repository	31 ; 8 HC + 23 PD	XGBoost	F1= 0.92 Recall=0.93 Accuracy= 92.76 Precision= 0.93	2019	Iqra nissar et al

Objectives	Source of data	Number of subjects (n)	Machine learning method(s), splitting strategy and cross validation	Outcomes	Year	References
Classification of PD from HC	UCI machine learning repository	31 ; 8 HC + 23 PD	Classification	Recall= 92.86 Accuracy= 94.97 Precision= 96.30	2017	David Sztaho et al
Classification of PD from HC	UCI machine learning repository	31 ; 8 HC + 23 PD	Regression	RMSE= 1.085 Pearson= 0.741 Spearman= 0.748	2017	David Sztaho et al
Classification of PD from HC	UCI machine learning repository	31 ; 8 HC + 23 PD	Fuzzy neural system with 16 hidden neural	RSME training= 0.232154 RSME evaluation= 0.291636 RSME testing= 0.283590 Accuracy= 100	2015	Rahib H.Abiyev et al

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