Review of early and accurate detection of Parkinson's disease

Soly Mathew Biju, Obada Al-Khatib, Hock Chuan Lim, Suzanne Malt, Hashir Zahid Sheikh
Faculty of Engineering and Information Sciences, University of Wollongong, Dubai, United Arab Emirates

Article Info

Article history:

Received Jul 3, 2023
Revised Nov 6, 2023
Accepted Jan 30, 2024

Keywords:

Early detection
Feature selection
Machine learning
Parkinson's disease
Performance metrics

ABSTRACT

Parkinson's disease (PD) is a central sensory system-based progressive illness with no cure. The origin of this illness is unknown. According to various research, it has been found that it is caused due to genetics or environmental factors. It is usually found in older people. However, there is no accurate treatment for this disease. So, the patient must be monitored periodically. It usually starts with deterioration in speech performance. The major problem with this disease is that it's very costly to treat. The paper aims to report details of numerous aspects of detection of PD published in recent years based on the focus and benefits of the study, the methodology being used, accuracy of the system, and future research suggested for the study. A systematic study was done based on a search of the literature. A total of 50 articles were discovered.

Corresponding Author:

Soly Mathew Biju
Faculty of Engineering and Information Sciences, University of Wollongong in Dubai
Office 201, Block 15, Knowledge Park, PO Box 20183, Dubai, UAE
Email: solymathewbiju@uowdubai.ac.ae

1. INTRODUCTION

Parkinson is a disease that progress over time. As it progresses, the symptoms become increasing debilitating. It is a neurodegenerative disease that can present at any age, most commonly in people above the age of 60. It can pose as a severe threat to aged people [1]. Early diagnosis of parkinson's disease (PD) is crucial in hospitals. According to the World Health Organization (WHO), it is estimated that more than 80% of the people who are over the age of 60 will die due to these chronic non-communicable diseases [2]. Early signs and symptoms often remain unnoticed. Early detection and treatment however are critical in determining the individual's long-term quality of life. Whilst there are multiple theories about the causes of Parkinson, the theory that has received the greatest attention and therefore research is the deterioration of dopaminergic neurons in the substantia nigra, which advances to dyskinesia, cognitive impairment, and emotional problems [3].

Given the presentation of symptoms being predominately neurological in nature, the research has tended to focus on identifying changes in the brain in individuals diagnosed with PD [4]. However, as evident in the brain images presented in Figure 1 which shows a normal persons brain Figure 1(a) and a person with PD Figure 1(b), it's challenging for doctors to rely on brain imaging alone to diagnose PD. Moreover, symptoms such as bradykinesia, rigidity gait and balance impairment can present as signs and symptoms in a variety of other neurological disorders. However, to date, efforts to diagnose PD are skewed, as it relies on symptoms and signs in the patient. There is no proper test to identify PD which makes it hard to detect the disease early [5]. There are various ways to recognize PD by observing the difference in handwriting [6] and speech [7].

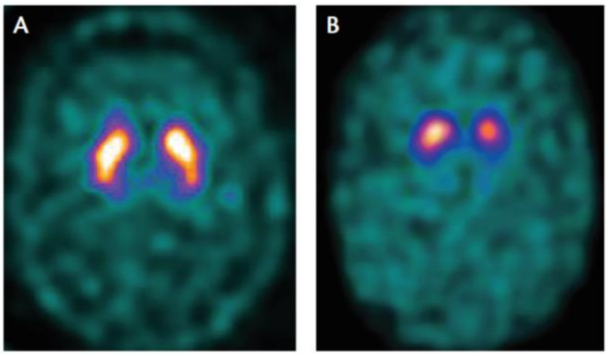


Figure 1. Brain imaging (a) normal person (b) person with PD [8]

The voice data can be applied through a machine learning program to identify PD patients. Speech recordings can be further analyzed using mel-frequency cepstral coefficients (MFCC), perceptual linear prediction (PLP) and relative spectral perceptual linear prediction (RASTA-PLP) [9], [10]. These features help in determining whether the patient has PD or not by providing better performance when compared with raw voice data. MFCC is now commonly used to assess the voice quality in hospitals [11]. This has also been used in recognition and identification of the person speaking.

Other ways to detect PD is using hypokinetic dysarthria (HKD). HKD decreases the movement of voice generating muscles [12]. This could have an impact on respiration, phonation, resonation, and articulation while speaking [13]. PD influences the periodicity of the speech which can cause the sound of their voice, like shaking or unevenness (jitter and shimmer) and how well their voice sounds together (harmonicity). This is generally due to the limited movement of the face muscles. Figure 2 shows a view of neural circuit related to HKD. However, the detection of these auxiliary symptoms depends on the experience of the clinician [14]. Hence, an effective method is required to detect the PD.

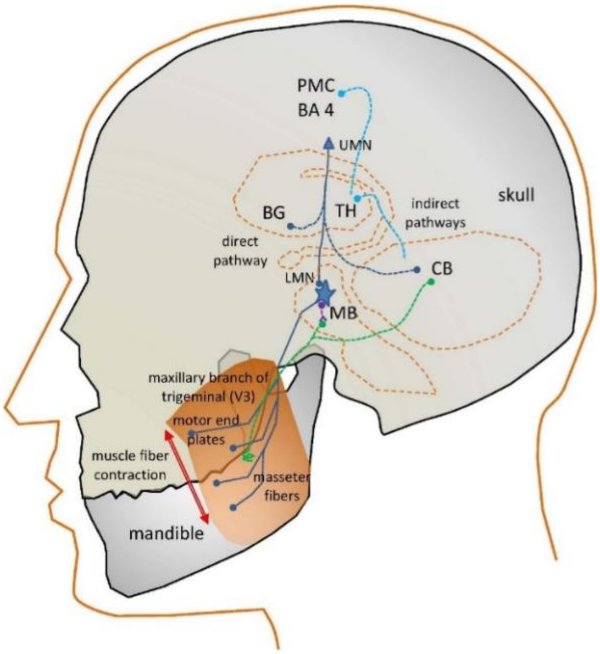


Figure 2. View of neural circuits engaged in the activity of the masseter neruomotor units [15]

There are other ways to detect PD like gait analysis [16]. Patients that have PD could have abnormal gait patterns. To analyze this, various gait features need to be studied. The gait features could be the average value of whole joint position of hip, knee, and ankle. Figure 3 shows how gait can be scored to evaluate PD.

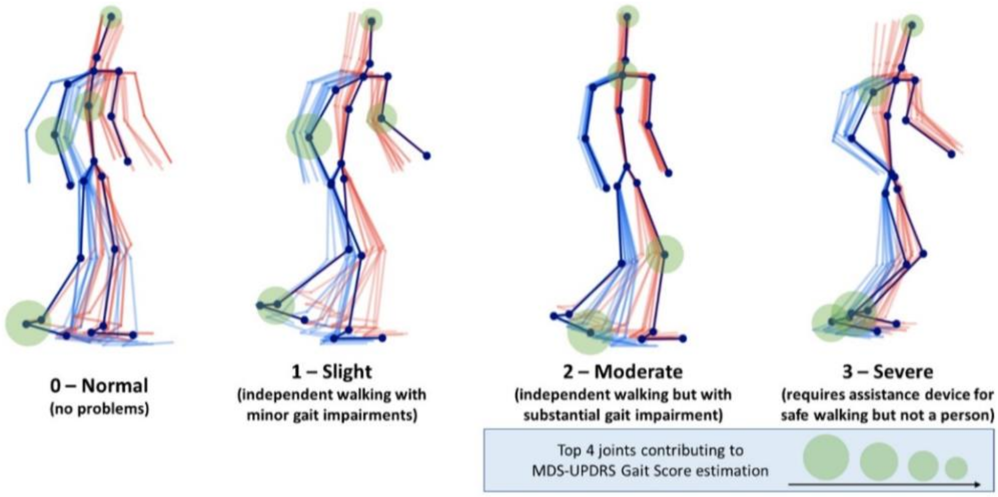


Figure 3. Gait scoing system [17]

The use of gyroscopes and accelerometer can aid in the detection of PD [18]. This could be done by collecting the data when the patient moves and analyzing it later using machine learning to evaluate the condition of the patient. This can be done using unified Parkinson's disease rating scale (UPDRS) [19]. This scoring method can help in determining the severity of the symptoms and help in the diagnosis of PD. The UPDRS is shown in Table 1.

Table 1. UPDRS scale [20]

UPDRS	Clinical severity
0	Absent
1	Slight and infrequently present
2	Mild and persistent
3	Moderate and present most of the time
4	Marked and present most of the time

Machine learning can be used to help in detection of PD. This can be done by getting data of different symptoms like voice and gait. These chunks of data can be used to train a model, that can be helpful in predicting if the patient has PD or not [9]. This paper tries to assess the early detection of PD by doing a thorough review and assessment based on a broad mixture of early detection of PD papers. We exhibit this detailed review that emphasizes the critical accomplishments, accuracy, limitations, methodology used, and emphasize the challenges and prospects for this emerging area of study.

2. METHOD

This literature review centered on a critical analysis of the existing research on the early detection of PD. Various ideas have been studied to get an understanding of the developments made on this vital problem. This analysis attempts to link this inconsistency in the literature by performing a thorough review and evaluation based on a complete fusion of early detection of PD associated research published. The following are a summary of the key beliefs developing from this literature review: i) algorithms used, ii) software or hardware or both, ii) accuracy and efficiency of the system, iii) methodology used, iv) benefits of the study, and v) future improvements.

This paper grouped relevant papers by using a method known as keyword search. Numerous keywords were discovered on IEEE explore. The keywords were "detection", "Parkinson disease" and "classification". The primary objective of this study is to recognize the existing research level on early detection of PD. After searching through IEEE explore, 50 articles were obtained that met the standards for this evaluation. All the papers were meticulously evaluated by the authors to uncover common aspects. These factors were linked to discover the discrepancies in each paper. The main objective of the paper was also unearthed when administering these papers. The results section is split into 3 sections that are aim of articles, accuracy, and methodology used.

3. RESULTS AND DISCUSSION

Chatterjee *et al.* [1] propose a methodology that can be used to detect PD. This is done with the help of a special algorithm that processes the brain computerized tomography (CT) scans. These scans are used to differentiate between normal patients and patients with PD. The algorithm takes the scan and converts it to grey scale to process the image to be used for anisotropic filtering. After filtering the image is segmented and passed through bounding box. After this the final image is evaluated to determine PD. This algorithm was able to achieve an accuracy of 87.5%. Juanjuan *et al.* [2] used an inertial sensor to collect data of upper body movement. This was used to extract features that could be used to detect PD. These sensors were placed on wrist and fingers. After extracting multiple features, the data was passed through a multilayer perceptron (MLP) model to detect PD. The system was able to achieve an accuracy of 95.70%. Xu *et al.* [3] used a brain network construction method to differentiate between healthy and PD patients. This is done by using resting state functional magnetic resonance imaging (rsfMRI). The brain networks were constructed and compared to identify the features. This proposed method was able to achieve an accuracy of 95.6%. Zhang *et al.* [4] used a machine learning system consisting of principal component analysis (PCA) and machine learning. PCA is used to detect discriminative characteristics from magnetic resonance imaging (MRI) scans. After that and support vector machines (SVM) model is applied to determine PD. This system was able to achieve an accuracy of 93.75%. Bourouhou *et al.* [5] applied 3 different types of classifiers to determine which one is the most efficient one. Voice recordings were used as data in this experiment. These voice recordings were used to extract features that would be passed to those classifiers. The classifiers used were k-nearest neighbors (KNN), naïve Bayes (NB), SVM. The SVM was able to outperform other classifiers by achieving an accuracy of 80%. Nalini *et al.* [6] devised an experiment that uses two modalities that are voice and handwriting to detect PD. This is done by applying machine learning techniques in MATLAB on the audio data. While data for handwriting is obtained by using a gyroscope. The classifier used in audio data is SVM. Both systems are integrated together to get the results.

Vikas and Sharma [7] used the voice features to detect whether a person has PD or not. The audio recording is processed through pre-emphasis block to compensate with high-frequency values. After that the data is split into frames and hamming window is applied on them. Then it's passed through fast fourier transform (FFT). Finally, it passed through discrete cosine transform, after normalizing it using logarithm. The output generated consisted of MFCC values like formant, pitch, jitter, and shimmer. Rusz *et al.* [9] used the same approach used by Benba *et al.* to detect PD. It was concluded that the method used by Benba *et al.* might not be appropriate for people with different kind of neurological disorders. Moreover, the cepstral analysis could have been influenced by age and gender. The system was able to achieve an accuracy of 96% using SVM classifier. Benba *et al.* [11] use MFCC to aid in detection of PD. Various coefficients were extracted from MFCC by doing voice analysis on the data. After obtaining the data it is passed through a machine learning model. The machine learning model used is SVM in this experiment. The model was able to achieve an accuracy of 91.17% when 12 coefficients were used. Chandrayan *et al.* [13] use factor analysis to determine which features could be helpful in detection of PD. After selecting the important factors that could help in prediction, the system is passed through a machine learning model. The machine learning model used in this experiment is SVM. The system was able to achieve an accuracy of 90%. Fang [14] evaluate different classifiers. Moreover, an improved version of KNN is also suggested. The classifiers used in this experiment are KNN, NB, and random forest (RF). The improved KNN algorithm uses entropy weight method to increase the efficiency of KNN. The dataset used in this experiment was from the University of California Irvine machine learning repository (UCI). The improved KNN algorithm was able to achieve an accuracy of 93.88% which is 2% more than other algorithms used in this experiment.

Soubra *et al.* [16] used gait analysis to determine PD in patients. The data of vertical ground reaction force (VGRF) was obtained from Physionet. This data was normalized, and features were obtained from it like mean, standard deviation, skewness, power and mean power. Receiver operating characteristics (ROC) curves were used to detect PD using these features. Chen and Lin [18] introduce a novel method to detect PD using Wi-Fi. The method tracks the daily movement and changes in posture which could be helpful in detecting tremors. This is done by tracking the influences made in Wi-Fi signal fields. After the data is collected, it is trained using a convolutional neural network (CNN) machine learning model. This model was able to achieve an accuracy of 100%. Exley *et al.* [19] analyzed the possibility of predicting sub scores using the movement disorder society (MDS)-UPDRS motor examination. Various motor related symptoms were assessed such as body bradykinesia and hypokinesia, postural stability, rigidity, and tremor at rest. Root means square error (RMSE) was used to evaluate the features extracted across each UPDRS. Machine learning models that were implemented in this system were ridge and lasso logistic regression, RF, decision tree (DT), SVM, nearest neighbors, and extreme gradient boosting (XGBoost). The system achieved an accuracy of 77.6%

Polat [21] took dataset from University of California Irvine (UCI) machine learning database. The dataset consists of 756 samples and 753 features. The dataset was divided into two categories, healthy patient and patients with PD. The healthy patient had around 192 sample while the PD patients had 564 samples. The

PD patients consisted of 107 men and 81 women with ages varying from 33 to 87. The authors proposed a procedure that combines synthetic minority over-sampling technique (SMOTE) and forest classifier. This procedure applies SMOTE to the PD dataset to manage the unfair class allocation. After the data is balanced, it is passed through a forest classifier to differentiate between healthy and PD patients. The hybrid model was passed through various test to determine its accuracy. For the first test, the authors used a holdout method that used half of the data to train a forest classifier and other half to test it. This experiment had an accuracy of 81.74%. For the second test, 10-fold cross validation was done on the data and then passed through the forest classifier. This experiment had an accuracy of 87.03%. In the next experiment, the hold out method was used on the hybrid model consisting of SMOTE and forest classifier. This experiment yielded an accuracy of 92.34%. In the last experiment, 10-fold cross validation method was used on the hybrid model consisting of SMOTE and forest classifier. This experiment yielded an accuracy of 94.89%. These results look promising and shows that SMOTE has a great impact in the determination of PD patients in class-imbalanced problem.

While Masood *et al.* [22] proposed a framework in which features are identified and ranked from the dataset. The dataset is passed through recursive feature elimination with cross-validation (RFECV) and three classifiers to acquire feature record. The output is combined using “optimal feature combiner”. The aim of the assembled classifiers in the framework is to complete the feature set generated by RFECV, with FFECV being the baseline. After the feature selection is done, the output data is passed through multiple classifiers like MLP, DT, KNN, SVM, and NB. The results of these classifiers are then compared. The experiment had three test datasets. The first dataset [23] achieved an accuracy of 98.3% compared to 92.4% without the use of feature selection. The second dataset [24] achieved an accuracy of 95.1% compared to 90% without the use of feature selection. The last dataset [25] achieved an accuracy of 100% compared to 90.1% without the use of feature selection. MLP produced the highest accuracy among all the classifiers. This framework surpasses the chi-square-based feature selection approach too.

Sivaranjini and Sujatha [26] analyze the single photon emission computed tomography (SPECT) images using geometric measures and orthogonal moment in PD patient. SPECT images of healthy control and PD patients with a tally of 10 pictures each. The left and right striatum are separated by image binarization procedure. The difference in concentration level in the images is employed here. The geometric characteristics observed in the pictures are area, convex area, filled area, solidity, extent, tortuosity, perimeter, major axis length, minor axis length, form factor, compactness, and circularity. It was found that there was a reduction in area, convex area, filled area, perimeter, major axis length, minor axis length and tortuosity in PD patients when compared to the others. While there was an increase in solidity, extent, form factor, compactness, and circularity. This shows the decreased dopamine transporter levels in PD when associated with HC by using the shape-based analysis.

Markose *et al.* [27] designed a prototype which is based on Arduino uno and ADXL335 tri-axial accelerometer. This device will be worn by the PD patient to monitor them. The acceleration readings will be taken from various parts of the arm like fingertips, wrist, and the forearm. The accelerations were obtained for three axes. The data was uploaded to MATLAB program to analyze it using the aid of graphs. For the fingertip the highest amplitude was in 0.13 m/s^2 – 0.2 m/s^2. The power spectral density in this range was 40 dB/Hz to 80 dB/Hz. For the wrist, the highest amplitude was in 0.14 m/s^2 – 0.17 m/s^2. The power spectral density in this range was 50 dB/Hz – 80 dB/Hz. Finally for the forearm, the highest amplitude was in 0.12 m/s^2 to 0.13 m/s^2. The power spectral density in this range was 60 dB/Hz – 80 dB/Hz. These results don’t signify what is expected from them. It would be hard to interpret whether the person has PD or not. Nevertheless, this prototype has some constraints. It would be difficult to wear this without the help of a professional. Moreover, it could cause issues if worn during daily activities due to the size and impracticability.

Brewer *et al.* [28] conducted an experiment that consisted of thirty participants. The participants were not allowed to consume the PD medication for at least 12 hours before testing. A custom-made mount was made with two Nano 17 6-axis force/torque sensor. The participants had to use index finger and thumb to exert pressure on the instruments. The data of force applied on the sensors was recorded for three minutes. The data was analyzed with three variables that were tremor integral, RMSE and lag among the target waveform and participant’s force reaction. These variables were correlated together so that it could be compared to UPDRS. The outcome demonstrated that this framework has distinct scores for people with deviating clinical result and that it can be effective in assessing the development of PD symptoms. This procedure will have improved performance when associated with UPDRS in spaces like fine motor control in the initial periods of disease development.

While Banita [29] proposed a rating scale that could be used to identify the stage in PD. The scale must be precise and exact so there isn’t any ambiguity amongst the stages. This scale is called ABHITA rating scale. This will be done with the aid of questionnaires, which will be filled by PD patients. The main aim is to get which stage the patient is in, using a time effective approach. It might even be used to detect early-stage PD. Prashanth and Roy [30] use machine learning techniques to classify early PD patients from the healthy ones. These techniques include logistic regression, RF, boosted trees and SVM. Wilcoxon rank sum test was used to determine the features. These features would be used to train the machine learning models. These methods produced an accuracy of more than 95% with logistic regression being the most accurate in determining who has PD. Aličković and Subasi [31] use machine learning to determine PD and scans without evidence of dopaminergic deficit (SWEDD). SWEDD and PD have similar symptoms so it could be hard to differentiate between the two. SMOTE was used to tackle with disparity in the dataset. The classification methods used are NB, SVM, logistic regression, artificial neural networks (ANN), DT, RF, and rotational forest. Two experiments were done to determine PD and discrimination of SWEDDs from PD. SMOTE was combined with RF along with rotational forest. This stacking of classifier along with SMOTE yielded better results than using the classifier separately. Moreover, the use of SMOTE had a significant impact on the accuracy.

Adams [32] was to determine PD using the attributes of finger movement through the utilization of machine learning on it. This method doesn't involve the use of dedicated gear or medical care. This procedure consisted of using a Tappy application which record the keystroke data and their timing. This data was generated from the participants and preprocessing was done on it. The classifiers used were SVM, multi-level perception, RF, nu-support vector classification, DT classifier, KNN, and quadratic discriminant analysis (QDA). The results of this experiment were that sensitivity was in the range of 92% to 100%, specificity was in the range of 95% to 100% and the maximum area under the curve (AUC) was in the range of 0.97 to 1.0. These findings were much more precise than that accomplished by Human computer interaction (HCI). According to LeMoyne *et al.* [33], iPhone is used as an accelerometer system to determine PD tremors. The iPhone was placed on the participants hand with the aid of a glove. The application was able to capture the readings from the participant in 10 second increments. This was done 10 times to get more accurate data. The participants with PD had obvious and calculated tremor variations. Their mean time average acceleration was 2.4 times more than normal participants. The coefficient of variation was 4.1 times more in PD participants.

He *et al.* [34] used an innovative method using video to determine PD in participants using skeleton-based technique. The system is first trained using PD gait dataset. This is done by skilled specialists. Extensive trials were performed in numerous environments to demonstrate the practicality of the solution. The system was able to reach an accuracy of 84.1%. Brewer *et al.* [35] use force tracking to quantify motor control deficits in PD patients. To measure the force, two 6 axis force NANO 17 sensors were used. The sensor was placed in a custom hardware setup. The participants had to exert pressure on the sensors using thumb and index fingers. After collecting the data, it was preprocessed to be used by a machine learning model. The machine learning model used in this experiment was SVM. The framework was able to reach an accuracy of 85%. Patnaik *et al.* [36] used rapid eye movement (REM) sleep behavior disorder to predict the chances of developing PD. Charles University in Prague was used to collect data from 130 participants. A logit model was used in analyzing the data. After using the logit model, significant variables were discovered. Then the dataset was trained using DT along with Catboost. The system was able to achieve an accuracy of 71% in determining people who don't have Parkinson and 100% in people who have PD. Salarian *et al.* [37] propose two algorithms, one to detect tremors and other to detect bradykinesia. To detect tremors, a measurement system was devised which consisted of sensors that were attached on the forearms. Each sensor had 3 gyroscopes to measure the roll, yaw, and pitch. To identify tremors, the angular velocity from every axis were examined. To identify bradykinesia, the period of movement was crucial along with any factor linked to the movement. The authors were able to find great overall sensitivity and specificity which were 99.5% and 94.2%. Significant correlations were made with UPDRS as well.

Kraipeerapun and Amornsamankul [38] suggest the incorporation among stacked generalization and complementary neural networks to determine PD in patients. This solved the regression problems. PD speech dataset was used in training and testing the framework. This framework was compared with the traditional neural networks, stacked generalization and complementary neural networks. This framework was able to reach an accuracy of around 70% which was more than the previous methods. Stamford *et al.* [39] focuses on the soft signs of PD which are usually neglected. These soft signs are nonlocomotory symptoms and nonmotor symptoms.

The other issue is that when patients visit the doctor, they may not be showing the symptoms as they may have taken medications that could have masked them for the time being. Moreover, the quality of life in PD patients could be improved by focusing on three areas that are medication monitoring, symptom logging, and cognitive assessment. The solution to these problems could be purposeful exercise and sleep quantification. Moreover, problems like fatigue, mood disorders, psychosis, cognitive impairment, and dementia needs to be considered as well. Systems should be designed to tackle with these issues. To overcome these issues, these need to be logged, so it could be assessed by a specialist. To do that a monitoring device needs to be devised that could log this data and provide feedback. Furthermore, this data can be used later in machine learning to optimize the detection of PD. Aich *et al.* [40] used a nonlinear classifier with DT to identify PD. PCA is done on original feature set (OFS). The authors used classifiers like RPART, PART, C4.5, PART, Bagging classification and regression tree (Bagging CART), Boosted C5.0, and RF. These classifiers are applied to both data set that consists of PCA and OFS. The results showed that PCA with RF achieved an accuracy of 96.83%. It also had highest sensitivity, specificity, positive predictive value (PPV) and negative predative value (NPV). Wu *et al.* [41] introduce a gait sensing platform to determine PD. This platform consists of force sensitive pressure sensors. After getting the data, features were extracted from this platform. The data collected consisted of 386 volunteers, 218 healthy participants and 168 with PD. This data was passed through various classifier to get the best results possible. The classifier used are NB, KNN with k=3, SVM with linear kernel, DT (C4.5), linear discriminant analysis (LDA), QDA, adaboost (ADA), subspace technique (SUB), RF with 50 trees. RF model was able to achieve an accuracy of 92.49%.

Kumar *et al.* [42] use the voice dataset to identify the PD. Each patient takes various tests, and the results are collected. After the data is collected, machine learning algorithm is applied to it to identify the effectiveness of the model. It is done for all the models to determine the best one using a singular code. The classification methods used are DT, NB, and neural network. The authors focused on the problems of machine learning programs in accepting PD as a classification problem. A model is devised instead of using machine learning algorithms separately. Ranjan and Swetapadma [43] used various machine learning algorithms on a dataset. These algorithms consisted of SVM, KNN, and ANN. The system was able to achieve an accuracy of 100% for ANN and KNN. Even though both have 100% accuracy, ANN has higher misclassified data and takes more time to process. So eventually, KNN seems to perform better among these algorithms. Zhang *et al.* [44] used two classifiers to test the new features devised by them with convoluted neural networks. The two classifiers used are RF and MLP. The features are adapted from speech processing fields and are obtained using accelerometer. These feature sets were evaluated using the two classifiers. The results showed that MLP had better AUC than the other classifier. While Joshi *et al.* [45] propose a new architecture for the classification of Alzheimer's and PD by using most influencing risk factors. Classification methods used include DT, bagging, BF tree, RF, radial basis function (RBF) networks, MLP, and neural network. The results showed that the risk factors for PD include stroke, diabetes, genes, and age are a very influential factor in the growth of PD symptoms. The RF tree and MLP achieved an accuracy of 99.25%. Bakar *et al.* [46] use two training algorithms called leven-marquardt (LM) and scaled conjugate gradient (SCG) to evaluate the PD voice dataset. Then both datasets are evaluated based on their accuracy rate, mean square error (MSE), and iteration. The classification of LM is better than SCG in terms of accuracy rate, and lower MSE. This can be used to assist medical team in determining PD using MLPs neural network. Eskidere *et al.* [47] use a random subspace KNN classifier ensemble to detect PD. This ensemble was also evaluated against single KNN. Ensemble of KNN improves the precision of detection of PD. This was proven by this experiment. The random subspace ensemble surpassed the traditional single KNN in the classification of PD. It was also concluded that these results are promising and can be used in diagnosis of PD.

Su and Chuang [48] use a fuzzy entropy measure to dynamically select features that aids in detecting PD. It would evaluate the overall variation from ordinary sets. To evaluate the system, the accuracy was determined for all features. It was noticed that overall accuracy was low when compared with some of the features. After removing certain features, the program was able to reach an accuracy of 97.5%. While Shahbakhti *et al.* [49] use genetic algorithm and adaptive neuro fuzzy classifier (ANFC) with SVM to determine PD in patients. A voice dataset was used and from that 22 linear and non-linear features were extracted. SVM was applied to both genetic algorithm and ANFC to evaluate their performance. ANFC had a combination of linear and non-linear features while genetic algorithm had linear features only. ANFC achieved an accuracy of 95.7%. Hussain and Sharma [50] evaluate the effects of stacking classifiers in detection of PD. The stacking consisted of NB, logistic regression, KNN, SVM, and DT. This stacking classifier was compared against, SVM, logistic regression, KNN, RF, and adaptive boosting. Among these classifiers SVM performed the best by getting an accuracy of 92%. However, the stacked classifier was able to beat SVM by achieving an accuracy of 93%. Jahan *et al.* [51] used a system which uses spiral or wave sketches to determine PD in patient. This is done using a deep leaning approach called CNN. Two CNN models were tested with transfer learning method. However, there was a limitation that was the lack of dataset. The model was able to achieve an accuracy of 96.67%. Agarwal *et al.* [52] use extreme machine learning to evaluate PD patients. Speech samples from patients are used to evaluate them. The testing of this method proved to be quite successful with training data. It was able to surpass SVM and neural network significantly. However, when it was tested with independent set of data, it achieved an accuracy of 81.55%. this This was far better than neural network but was closer to SVM. Ogawa and Yang [53] use residual-network-based deep learning to identify PD in patients. A 10 layer 1-d CNN is introduced that will help with the classification. The dataset used to train and evaluate the patient consisted of vocal features. These two networks were evaluated, and the residual-network-based approach had a significant improvement in the accuracy in the detection of PD. It was able to achieve an accuracy of 88.8%.

Nithya *et al.* [54] developed an automated system that could diagnose PD using machine learning. The data used in this experiment are the MRI scans of brain which is preprocessed to normalize the intensity and unshaped masking errors. The classifier used in this experiment is a hybrid which consists of SVM and RF. The system was able to achieve an accuracy of 93%. Aversano *et al.* [55] use a combination of MLP with echo state network to detect PD. To balance the dataset, SMOTE was used during the preprocessing stage. To substantiate this methodology, various classification algorithms were used like boosting DT. The system was able to achieve an accuracy of 96.9%. Laganas *et al.* [56] use speech data that was obtained from phone calls to detect PD. The data is captured passively over calls to protect the privacy of the patient. Four different languages are used that are English, German, Greek, and Portuguese. For each language a separate model is used. Various features were extracted from voice recordings, so that it can be utilized later. The model used in this experiment are generated using multiple instance SVM and logistic regression. Dixit *et al.* [57] use MRI scans of the brain to detect PD, anxiety detection, and stress detection in PD patients. Various different machine learning models are used that are logistic regression, KNN, DT, RF, adaboost, and auto variant interpretable machine learning (ViML). The system was able to achieve an accuracy of 92%. Yang *et al.* [58] proposed a novel method that utilizes inertial measurement to assess the performance of gait while walking or running. Five sensors are attached in multiple places on the body, that would be used to obtain the gait data. Data was obtained by asking PD patient and healthy patient to walk on the traced path. The algorithm designed is able to assess the gait detection, turning detection and stride length. This program was able to achieve an accuracy of 98%. Mamun *et al.* [59] use machine learning to detect PD. Features from voice data are used to train the model. Multiple machine learning models are used such as XGBoost, LightGBM, RF, Bagging, AdaBoost, DT, logistic regression, SVM, KNN, and NB classifiers. The system was able to achieve an accuracy of 95%. The Table 2 in appendix summarizes all the articles presented in this review.

4. CONCLUSION

This paper was focused on the early detection of PD. It discovered various concepts and methods being used by the authors these days. 72% of the papers studied used software analysis in their paper, while 6% did not use any software or hardware in their paper. The software analysis usually consists of machine learning algorithms being applied on the open-source data. Moreover, 12% of the papers used both hardware and software. The remaining 10% used hardware. The most common hardware used was inertial sensor. The difference in these papers is the classifiers used and the features used to detect PD. Around 38% of these papers used stacked classifier to improve the performance of the overall system or used multiple classifiers to find the best one. Some used selective features to show how features impact the detection of PD. Moreover, 8% of these papers used SMOTE to overcome the inconsistencies in the data. Almost 28% of the articles reviewed did not provide any accuracy for their systems. However, 80% of the systems that provided accuracy, were able to achieve an accuracy of 90% or more.

ACKNOWLEGMENTS

This research work was supported by Abu Dhabi National Oil Company (ADNOC), Emirates NBD and Sharjah Electricity Water & Gas Authority (SEWA), Dubai Electricity and Water Authority R& D Center as the sponsors of the 3rd Forum for Women in Research (QUWA): Women Empowerment for Global Impact at University of Sharjah. It is also supported by UOWD research grant.

APPENDIX

Table 2. Paper comparison (*continue*...)

Paper	Aim of study	Hardware/ software	Benefits of the study	Devices used	Algorithms	Accuracy (%)	Accuracy method used	Data base	Future study proposed
1	detect PD using brain CT scans	Software	Use of brain scans to detect Parkinson by applying various preprocessing techniques	-	Anisotropic filtering, image segmentation, bounding box, grey scale conversion	87.50	Precision, Accuracy, F-Measure	UCI	To use in labs and hospital in real time
2	detect PD using upper limb movement	Both	Use of inertial sensor to detect PD, use of machine learning to optimize results	Inertial sensor	MLP	95.70	Accuracy, AUC	-	Can be used as a reference in future studies

Table 2. Paper comparison

Paper	Aim of study	Hardware/ software	Benefits of the study	Devices used	Algorithms	Accuracy (%)	Accuracy method used	Data base	Future study proposed
3	Use of rsfMRI to detect PD	Software	Anovel method of brain construction to help in detection of PD	-	SVM	95.60	Accuracy, AUC	Huashan Hospital Shanghai	Multicenter data studies to be done to verify the results of this study.
4	Detect PD using PCA and SVM	Software	Use of PCA to extract features from MRI	-	SVM	93.75	Accuracy	-	Can be helpful as a clinical tool
5	Comparison of different classifiers	Software	Use of multiple classifiers to determine the most accurate one	-	KNN, NB, SVM	80	Accuracy	UCI	Increase the efficiency and implement other classifiers.
6	Use of audio and handwriting to detect PD	Both	Use of two different data sources to determine PD	Gyroscope	SVM	-	-	-	-
7	Provide an efficient method to detect PD	Software	Use of voice features to detect PD	-	FFT, Mel-Filter bank, DCT	-	-	-	-
9	Using voice cepstral analysis to verify Benba *et al*'s finding	Software	Cepstral analysis can be influenced by age and gender and other neurological conditions	-	SVM	96	Accuracy	[23]	Use of standardized procedure, meticulously chosen speaker groups neutral with respect to gender and age
11	Evaluate voiceprint using MFCC and SVM	Software	Does a comparison using MFCC and SVM	-	SVM	91.17	Accuracy	-	-
13	To determine important voice features	Software	Uses essential features of voice, uses machine learning to optimize the accuracy	-	SVM	90	Accuracy, AUC	[25]	Add more features and extend it to other fields
14	To improve KNN algorithm with information entropy to aid in detection of PD	Software	Use of multiple classifiers to determine if the improved KNN is effective or not	-	KNN, NB, RF	93.88	Accuracy	UCI	-
16	To identify abnormal gait patterns to detect PD	Software	Use of VGRF data to detect gait abnormalities	-	ROC	-	ROC	PhysioNet	-
18	To determine PD using daily movement and motor symptoms	Both	Uses a novel method to detect PD, use of Wi-Fi which is easy to implement	Router, laptop	CNN	100	Accuracy	-	Localize movements better
19	To predict UPDRS motor system using machine learning	Software	Evaluates various motor symptoms to help in detection of PD, comparison with UPDRS score	-	ridge and lasso logistic regression, RF, DT, SVM, nearest neighbors, and XGBoost	77.60	Accuracy, AUC	-	Include patient with multiple motor symptoms and single symptoms to improve the efficiency of the program

Table 2. Paper comparison

Paper	Aim of study	Hardware/ software	Benefits of the study	Devices used	Algorithms	Accuracy (%)	Accuracy method used	Database	Future study proposed
21	Hybrid method (the combination of SMOTE and RF)	Software	Solves the class-imbalance problem in machine learning	-	SMOTE, Forest Classifier	94.89	Precision, accuracy, F-Measure	UCI	Could be used in other medical real-world class-imbalanced classification problems
22	Uses RFECV to generate features and pass-through multiple classifiers	Software	Feature selection framework to help in identifying an optimal set of features	-	MLP, NB, SVM, KNN, DT	100	Precision, accuracy, F-Measure	[23]-[25]	Can be applied to other problems of a similar domain to look more closely at certain attributes and identify patterns.
26	Comparison of SPECT images between PD and healthy participants	-	Geometric features such as area, axis length, extent and PD significant changes differentiating between normal and circularity measures show	-	-	-	p-value	Parkinson’s Progression Markers Initiative (PPMI)	-
27	Prototype was designed to observe and quantify the tremor signal from PD patients	Hardware	Acceleration readings from different parts of arm to determine tremor	Arduino UNO, ADXL 335 tri-axial accelerometer	MATLAB code	-	waveform	-	Could be used to study tremor from PD patients
28	(ASAP) to obtain a quantitative and reliable measure of motor impairment in early to moderate PD	Hardware	Use of custom-made device to determine the tremor in PD patients	Two Nano 17 6-axis force/torque sensor	-	-	Lasso Regression	-	Recruited larger samples and through investigation of other methods of feature selection to reduce the number of predictor variables.
29	Use of questionnaires to detect PD using ABHITA rating scale	-	There isn't ambiguity amongst the stages	-	-	-	-	-	Use of different image processing using ABHITA rating scale
30	Use of machine learning to classify PD patients from healthy ones	Software	Use of multiple machine learning classifier to get best outcome. Wilcoxon rank sum test to determine the features.	-	Logistic regression, RF, Boosted Trees, SVM	95	Accuracy, AUC	PPMI	It can be helpful in clinical setting to physicians without the need of PD experts.
31	Use of machine learning to determine PD and SWEDD.	Software	Uses SMOTE to tackle disparity in the dataset.	-	NB, SVM, logistic regression, ANN, DT, RF, rotational forest	99.55%	Accuracy, AUC	PPMI	Can help physician in making an accurate diagnosis for PD

Table 2. Paper comparison

Paper	Aim of study	Hardware/ software	Benefits of the study	Devices used	Algorithms	Accuracy (%)	Accuracy method used	Database	Future study proposed
32	To determine PD using the attributes of finger movement by utilizing machine learning	Software	Use of tappy application to get data, without using dedicated gear or medical assistance	Windows device	SVM, multi-level perception, RF, nu-support vector classification, DT, KNN, QDA.	100	Accuracy, AUC	PPMI	Increase number of participants to enhance the reliability of the technique
33	Use of iPhone's accelerometer to determine PD tremors	Hardware	Gets data 10 times to improve the precision of the framework	Iphone	-	-	-	-	more tests are required to quantify the application of PD tremor detection
34	Use of video and skeleton-based technique to identify PD in participants	Both	the method has been implemented in hospital and it can achieve real-time performance	Atlas200DK	SVM	84.10%	Accuracy, F1-Measure	Physio Net	-
35	Use of force sensor to get data from patients and then apply SVM to get results	Both	Conducted various experiment each minute to quantify the data.	Two 6 axis force NANO 17 sensors	SVM	85%	Accuracy	-	Recruit more individuals to determine reliability of the experiment and follow individuals' longevity to validate the assessment
36	Use of REM sleep behavior disorder to predict chances of developing PD	Software	use of logit model to analyze the data and perform machine learning on it	-	DT, Catboost	71%	Accuracy, F1-Measure	Charles University	-
37	Proposed two algorithms, one to detect tremors and other to detect bradykinesia	Hardware	Use of gyroscope to get roll, yaw, and pitch to identify tremors	Three miniature uniaxial gyroscopes	-	-	-	-	-
38	Use of stacked generalization and complementary neural networks to determine PD in patients	Software	This framework was compared with the traditional neural networks, stacked generalization, and complementary neural networks	-	Stacked generalization, complementary neural networks	70%	Average Accuracy	UCI	Consider uncertainty conditions occurred in both truth and falsity neural networks
39	Focuses on the soft signs of PD which are usually neglected	-	Nonlocomotory symptoms and nonmotor symptoms could be helpful in determining PD	-	-	-	-	-	-
40	A nonlinear DT based classification approach to predict the PD using different feature sets of voice data	Software	Use of PCA to identify features, use of nonlinear classifier with DT to classify PD	-	PCA, Bagging Cart, RF, Boosted C5.0, RPART, C4.5, C5.0	96.87%	Accuracy	[25]	Use other feature reduction technique to compare the performance

Table 2. Paper comparison

Paper	Aim of study	Hardware/ software	Benefits of the study	Devices used	Algorithms	Accuracy (%)	Accuracy method used	Database	Future study proposed
41	A study on gait-based PD detection using a force sensitive platform	Both	Use of u-shaped walkway to extract gait feature, use of multiple classifiers to find the best	U-shaped electronic Walkway	NB, KNN, SVM with linear kernel, DT (C4.5), LDA, QDA, adaboost (ADA), SUB, RF.	92.49	Accuracy, F1-Measure	-	-
42	Advanced and effective classification of PD using enhanced neural networks	Software	Use of effective machine learning algorithm based on parameters, classification using different algorithm without appending different machine learning algorithm	-	DT, NB, neural networks	-	-	UCI	Classifying Parkinson’s telemonitoring dataset
43	An intelligent computing based approach for PD detection	Software	Use of various machine learning algorithm to determine the accuracy	-	SVM, KNN, ANN	100	Accuracy	UCI	Implement the method in hospitals to evaluate the accuracy of the system
44	To evaluate the performance of handcrafted features and compare it to CNN	Both	use of different classifiers, compared with conventional features to differentiate the performance	-	MLP, RF	-	AUC	-	To analyze the learning framework and the effect of dataset, whether handcrafted features have an advantage over conventional features
45	Selecting most influencing factors with the help of different attribute evaluation scheme	Software	Use of genetic factors in the determination of PD using ML and neural network	-	DT, bagging, BF tree, RF, RBF networks, MLP, neural network	99.25	Accuracy	ADRC	-
46	Analysis of two training algorithm with PD voice dataset	Software	Use of two classifiers on voice dataset	-	LM, SCG	92.95	Accuracy	Parkinson disease data set (PDD)	-
47	Use of random subspace KNN classifier to evaluate its performance with single KNN	Software	Use of random subspace method to evaluate the PD,	-	KNN	-	Classification error	PDD	-
48	Use of different feature set for different voice data to detect PD	Software	Use of dynamic feature selection using fuzzy entropy for speech pattern	-	LDA	97.50	Accuracy	[24]	Use different classifier to test the feature selection algorithm, analyze voice with higher discrimination for PD
49	Evaluate the difference of ANFC and GA with SVM	Software	Use of linear and non-linear features to evaluate the performance of SVM	-	SVM	95.70	Accuracy	[25]	-
50	Effects of stacking on the outcome of PD patient classification	Software	Use of stacking to get better accuracy	-	Logistic regression, RF, KNN, SVM, stacking, adaptive boosting	93	Accuracy, F1-Measure	UCI	Refine results by refining feature selection, implementation of feature vectors, deploying hybrid model

Table 2. Paper comparison

Paper	Aim of study	Hardware/ software	Benefits of the study	Devices used	Algorithms	Accuracy (%)	Accuracy method used	Database	Future study proposed
51	Detecting PD using spiral and wave sketching	Software	Handle limited dataset using transfer learning	-	CNN	96.67	Accuracy	Kaggle	Use of new architecture that uses transfer learning
52	Advanced and effective classification of PD using enhanced neural networks	Software	Use of effective machine learning algorithm based on parameters, classification using different algorithm without appending different machine learning algorithm	-	DT, NB, Neural Networks	-			Classifying Parkinson's telemonitoring dataset
53	Use of extreme learning machine to evaluate speech signals	Software	ELM shows promising results against neural networks and is comparable to the SVM	-	ELM	81.55	Average Accuracy, MCC	UCI	Explore the capabilities of this method by adding more features
54	Detect PD using CNN	Software	10 layer 1-d residual network type CNN is used,	-	CNN	88.80	Accuracy, F1-Measure, MCC	UCI	Hyperparameter should be considered
55	Diagnose PD using a hybrid technique	Software	Using a hybrid approach, data is preprocessed for more accurate results	-	Logistic regression, RF, SVM, DT, KNN	100	Accuracy, Precision	PPMI	Improve the system to handle large and complex data sets
56	Detect PD using spiral test with the help of echo state networks	Software	uses ESN based configuration to detect PD, uses MLP and SMOTE	-	SMOTE, MLP	96.90	Precision, accuracy, F-Measure	UCI	Increase the dataset by adding more features and to implement it in clinical trials
57	Uses speech data from phone calls to detect PD	Software	Uses different languages to test for PD, use of multiple ML models	-	Multiple instance SVM, logistic regression	-	AUC	-	Increase the dataset
58	Detection of PD using various machine learning algorithms	Software	Use of multiple ML models, can also be used for anxiety disorder and stress prediction	-	Logistic regression, KNN, DT, RF, Adaboost, Auto ViML	92	Accuracy, Precision	Kaggle	-
59	Detection of PD using gait	Hardware	Use of a novel method, uses gait to determine PD while running and walking	Inertial sensor	spatiotemporal gait model	98	Accuracy	-	Investigate the characteristics of patients on and off meds
60	Detection of PD using machine learning	Software	Use of multiple machine learning classifier to get best outcome, use of SMOTE	-	XGBoost, LightGBM, RF, Bagging, AdaBoost, DT, logistic regression, SVM, KNN, and NB classifiers	95	Accuracy, AUC	[25]	-

REFERENCES

[1] J. Chatterjee, A. Saxena, G. Vyas, and A. Mehra, "A computer vision approach to diagnose Parkinson disease using brain CT images," in *2018 Second International Conference on Computing Methodologies and Communication (ICCMC)*, IEEE, Feb. 2018, pp. 463–467, doi: 10.1109/iccmc.2018.8488034.

[2] H. Juanjuan, Y. Zhiming, W. Jianguo, L. Bochen, and Y. Xianjun, "An automatic detection method for bradykinesia in Parkinson's disease based on inertial sensor," in *2020 IEEE 3rd International Conference on Electronics Technology, ICET 2020*, IEEE, May 2020, pp. 166–169, doi: 10.1109/ICET49382.2020.9119604.

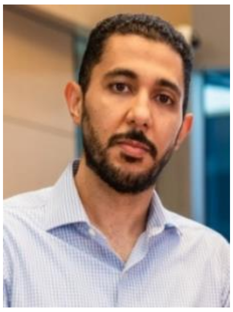
[3] H. Xu, L. Wang, C. Zuo, and J. Jiang, "Brain network analysis between Parkinson's disease and health control based on edge functional connectivity," in *2022 44th Annual International Conference of the IEEE Engineering in Medicine & Biology Society*

(EMBC), IEEE, Jul. 2022, pp. 4805–4808, doi: 10.1109/EMBC48229.2022.9871613.
[4] L. Zhang, C. Liu, X. Zhang, and Y. Y. Tang, "Classification of Parkinson's disease and essential tremor based on structural MRI," in *Proceedings - 2016 7th International Conference on Cloud Computing and Big Data, CCBD 2016*, IEEE, Nov. 2017, pp. 353–356, doi: 10.1109/CCBD.2016.075.
[5] A. Bourouhou, A. Jilbab, C. Nacir, and A. Hammouch, "Comparison of classification methods to detect the Parkinson disease," in *2016 International Conference on Electrical and Information Technologies (ICEIT)*, 2016, pp. 421–424, doi: 10.1109/EITech.2016.7519634.
[6] M. Nalini, R. Gayathiri, R. Srimathi, R. Vidyathmikaa, and S. Jenifer, "Detection of Parkinson's Disease using voice changes and hand-tremor," in *2022 International Conference on Communication, Computing and Internet of Things (IC3IoT)*, IEEE, Mar. 2022, pp. 1–4, doi: 10.1109/IC3IOT53935.2022.9767979.
[7] Vikas and R. K. Sharma, "Early detection of Parkinson's disease through Voice," in *2014 International Conference on Advances in Engineering and Technology (ICAET)*, IEEE, May 2014, pp. 1–5, doi: 10.1109/ICAET.2014.7105237.
[8] C. L. Gallagher, "Imaging in Parkinson's disease," *Practical Neurology*. [Online]. Available: https://practicalneurology.com/articles/2019-sept/imaging-in-parkinsons-disease
[9] J. Rusz, M. Novotny, J. Hlavnicka, T. Tykalova, and E. Ruzicka, "High-accuracy voice-based classification between patients with Parkinson's disease and other neurological diseases may be an easy task with inappropriate experimental design," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 25, no. 8, pp. 1319–1321, Aug. 2017, doi: 10.1109/TNSRE.2016.2621885.
[10] M. R. Maruf, M. O. Faruque, S. Mahmood, N. N. Nelima, M. G. Muhtasim, and M. J. A. Pervez, "Effects of Noise on RASTA-PLP and MFCC based Bangla ASR Using CNN," in *2020 IEEE Region 10 Symposium (TENSYMP)*, IEEE, 2020, pp. 1564–1567, doi: 10.1109/TENSYMP50017.2020.9231034.
[11] A. Benba, A. Jilbab, A. Hammouch, and S. Sandabad, "Voiceprints analysis using MFCC and SVM for detecting patients with Parkinson's disease," in *2015 International Conference on Electrical and Information Technologies (ICEIT)*, IEEE, Mar. 2015, pp. 300–304, doi: 10.1109/EITech.2015.7163000.
[12] J. Rusz *et al.*, "Smartphone allows capture of speech abnormalities associated with high risk of developing Parkinson's disease," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 26, no. 8, pp. 1495–1507, Aug. 2018, doi: 10.1109/TNSRE.2018.2851787.
[13] S. Chandrayan, A. Agarwal, M. Arif, and S. S. Sahu, "Selection of dominant voice features for accurate detection of Parkinson's disease," in *2017 Third International Conference on Biosignals, Images and Instrumentation (ICBSII)*, IEEE, Mar. 2017, pp. 1–4, doi: 10.1109/ICBSII.2017.8082297.
[14] Z. Fang, "Improved KNN algorithm with information entropy for the diagnosis of Parkinson's disease," in *2022 International Conference on Machine Learning and Knowledge Engineering (MLKE)*, 2022, pp. 98–101, doi: 10.1109/MLKE55170.2022.00024.
[15] A. Gómez *et al.*, "A Neuromotor to Acoustical jaw-tongue projection model with application in Parkinson's disease hypokinetic dysarthria," *Frontiers in Human Neuroscience*, vol. 15, Mar. 2021, doi: 10.3389/fnhum.2021.622825.
[16] R. Soubra, M. O. Diab, and B. Moslem, "Identification of Parkinson's disease by using multichannel vertical ground reaction force signals," in *2016 International Conference on Bio-engineering for Smart Technologies (BioSMART)*, IEEE, Dec. 2016, pp. 1–4, doi: 10.1109/BIOSMART.2016.7835604.
[17] M. Kocabas, N. Athanasiou, and M. J. Black, "VIBE: Video inference for human body pose and shape estimation," in *2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 2020, pp. 5252–5262, doi: 10.1109/CVPR42600.2020.00530.
[18] S. Y. Chen and C. L. Lin, "Subtle motion detection using Wi-Fi for hand rest tremor in Parkinson's disease," in *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, IEEE, Jul. 2022, pp. 1774–1777, doi: 10.1109/EMBC48229.2022.9871540.
[19] T. Exley, S. Moudy, R. M. Patterson, J. Kim, and M. V. Albert, "Predicting UPDRS motor symptoms in individuals with Parkinson's disease from force plates using machine learning," *IEEE Journal of Biomedical and Health Informatics*, vol. 26, no. 7, pp. 3486–3494, Jul. 2022, doi: 10.1109/JBHI.2022.3157518.
[20] O. Bazgir, S. H. Habibi, L. Palma, P. Pierleoni, and S. Nafees, "A classification system for assessment and home monitoring of tremor in patients with Parkinson's disease," *Journal of Medical Signals and Sensors*, vol. 8, no. 2, 2018, doi: 10.4103/2228-7477.232088.
[21] K. Polat, "A hybrid approach to Parkinson disease classification using speech signal: The combination of SMOTE and random forests," in *2019 Scientific Meeting on Electrical-Electronics and Biomedical Engineering and Computer Science, EBBT 2019*, IEEE, Apr. 2019, pp. 1–3, doi: 10.1109/EBBT.2019.8741725.
[22] S. Masood, K. W. Maqsood, O. Pal, and C. Kumar, "An ensemble-based feature selection framework for early detection of Parkinson's disease based on feature correlation analysis," *Mathematical Methods in the Applied Sciences*, Nov. 2021, doi: 10.1002/mma.7835.
[23] A. Benba, A. Jilbab, and A. Hammouch, "Discriminating between patients with Parkinson's and neurological diseases using cepstral analysis," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 24, no. 10, pp. 1100-1108, Oct. 2016, doi: 10.1109/TNSRE.2016.2533582.
[24] B. E. Sakar *et al.*, "Collection and analysis of a Parkinson speech dataset with multiple types of sound recordings," *IEEE Journal of Biomedical and Health Informatics*, vol. 17, no. 4, pp. 828-834, July 2013, doi: 10.1109/JBHI.2013.2245674.
[25] "Parkinsons data set," *UCI Machine Learning Repository*, 2022, doi: 10.24432/C59C74
[26] S. Sivaranjini and C. M. Sujatha, "Analysis of Parkinson's disease SPECT images using geometric measures and orthogonal moments," in *2018 Fourth International Conference on Biosignals, Images and Instrumentation (ICBSII)*, IEEE, Mar. 2018, pp. 206–212, doi: 10.1109/ICBSII.2018.8524601.
[27] N. R. Markose, P. D. Moyya, and M. Asaithambi, "Analysis of tremors in Parkinson's disease using accelerometer," in *2021 IEEE 7th International Conference on Bio Signals, Images and Instrumentation*, 2021, pp. 1–5, doi: 10.1109/ICBSII51839.2021.9445140.
[28] B. R. Brewer, S. Pradhan, G. Carvell, and A. Delitto, "Application of modified regression techniques to a quantitative assessment for the motor signs of Parkinson's disease," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 17, no. 6, pp. 568–575, Dec. 2009, doi: 10.1109/TNSRE.2009.2034461.
[29] Banita, "Detection of Parkinson's disease using rating scale," in *2020 International Conference on Computational Performance Evaluation (ComPE)*, IEEE, Jul. 2020, pp. 121–125, doi: 10.1109/ComPE49325.2020.9200071.
[30] R. Prashanth and S. D. Roy, "Early detection of Parkinson's disease through patient questionnaire and predictive modelling," *International Journal of Medical Informatics*, vol. 119, pp. 75–87, Nov. 2018, doi: 10.1016/j.ijmedinf.2018.09.008.
[31] E. Aličković and A. Subasi, "Early detection of Parkinson's disease and SWEDD using SMOTE and ensemble classifier," in *Computer-aided Design and Diagnosis Methods for Biomedical Applications*, Boca Raton: CRC Press, 2021, pp. 113–136, doi: 10.1201/9781003121152-5.
[32] W. R. Adams, "High-accuracy detection of early Parkinson's disease using multiple characteristics of finger movement while

typing," *PLOS ONE*, vol. 12, no. 11, Nov. 2017, doi: 10.1371/journal.pone.0188226.
[33] R. LeMoyne, T. Mastroianni, M. Cozza, C. Coroian, and W. Grundfest, "Implementation of an iPhone for characterizing Parkinson's disease tremor through a wireless accelerometer application," in *2010 Annual International Conference of the IEEE Engineering in Medicine and Biology*, IEEE, Aug. 2010, pp. 4954–4958, doi: 10.1109/IEMBS.2010.5627240.
[34] Y. He, T. Yang, C. Yang, and H. Zhou, "Integrated equipment for Parkinson's disease early detection using graph convolution network," *Electronics*, vol. 11, no. 7, Apr. 2022, doi: 10.3390/electronics11071154.
[35] B. R. Brewer, S. Pradhan, G. Carvell, and A. Delitto, "Feature selection for classification based on fine motor signs of parkinson's disease," in *2009 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, IEEE, Sep. 2009, pp. 214–217, doi: 10.1109/IEMBS.2009.5333129.
[36] D. Patnaik, M. Henriques, and A. Laurel, "Prediction of Parkinson's disorder: A machine learning approach," in *2022 Interdisciplinary Research in Technology and Management (IRTM)*, Feb. 2022, pp. 1–3, doi: 10.1109/IRTM54583.2022.9791490.
[37] A. Salarian, H. Russmann, C. Wider, P. R. Burkhard, F. J. G. Vingerhoets, and K. Aminian, "Quantification of tremor and Bradykinesia in Parkinson's disease using a novel ambulatory monitoring system," *IEEE Transactions on Biomedical Engineering*, vol. 54, no. 2, pp. 313–322, Feb. 2007, doi: 10.1109/TBME.2006.886670.
[38] P. Kraipeerapun and S. Amornsamankul, "Using stacked generalization and complementary neural networks to predict Parkinson's disease," in *2015 11th International Conference on Natural Computation (ICNC)*, 2015, pp. 1290–1294, doi: 10.1109/ICNC.2015.7378178.
[39] J. A. Stamford, P. N. Schmidt, and K. E. Friedl, "What engineering technology could do for quality of life in Parkinson's disease: A review of current needs and opportunities," *IEEE Journal of Biomedical and Health Informatics*, vol. 19, no. 6, pp. 1862–1872, Nov. 2015, doi: 10.1109/JBHI.2015.2464354.
[40] S. Aich, K. Younga, K. L. Hui, A. A. Al-Absi, and M. Sain, "A nonlinear decision tree based classification approach to predict the Parkinson's disease using different feature sets of voice data," in *2018 20th International Conference on Advanced Communication Technology (ICACT)*, IEEE, Feb. 2018, pp. 1–2, doi: 10.23919/icact.2018.8323863.
[41] X. Wu, X. Chen, Y. Duan, S. Xu, N. Cheng, and N. An, "A study on gait-based Parkinson's disease detection using a force sensitive platform," in *2017 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*, 2017, pp. 2330–2332, doi: 10.1109/BIBM.2017.8218048.
[42] K. K. Kumar, P. V. Babu, S. C. Gopi, and Z. Arfa, "Advanced and Effective classification of Parkinson's disease using enhanced neural networks," in *2020 4th International Conference on Intelligent Computing and Control Systems (ICICCS)*, IEEE, 2020, pp. 801–807, doi: 10.1109/ICICCS48265.2020.9120970.
[43] A. Ranjan and A. Swetapadma, "An intelligent computing based approach for Parkinson disease detection," in *2018 Second International Conference on Advances in Electronics, Computers and Communications (ICAECC)*, 2018, pp. 1–3, doi: 10.1109/ICAECC.2018.8479490.
[44] A. Zhang *et al.*, "Automated tremor detection in Parkinson's disease using accelerometer signals," in *Proceedings of the 2018 IEEE/ACM International Conference on Connected Health: Applications, Systems and Engineering Technologies*, New York, USA: ACM, Sep. 2018, pp. 13–14, doi: 10.1145/3278576.3278582.
[45] S. Joshi, D. Shenoy, G. G. V. Simha, P. L. Rrashmi, K. R. Venugopal, and L. M. Patnaik, "Classification of Alzheimer's disease and Parkinson's disease by using machine learning and neural network methods," in *2010 Second International Conference on Machine Learning and Computing*, IEEE, Feb. 2010, pp. 218–222, doi: 10.1109/ICMLC.2010.45.
[46] Z. A. Bakar, N. M. Tahir, and I. M. Yassin, "Optimal location of property in United Arab Emirates using geographical information system," in *2010 6th International Colloquium on Signal Processing & its Applications*, 2010, pp. 1–4, doi: 10.1109/CSPA.2010.5545301.
[47] O. Eskidere, A. Karatutlu, and C. Unal, "Detection of Parkinson's disease from vocal features using random subspace classifier ensemble," in *2015 Twelve International Conference on Electronics Computer and Computation (ICECCO)*, IEEE, Sep. 2015, pp. 1–4, doi: 10.1109/ICECCO.2015.7416886.
[48] M. Su and K. S. Chuang, "Dynamic feature selection for detecting Parkinson's disease through voice signal," in *2015 IEEE MTT-S International Microwave Workshop Series on RF and Wireless Technologies for Biomedical and Healthcare Applications, IMWS-BIO 2015 - Proceedings*, IEEE, Sep. 2015, pp. 148–149, doi: 10.1109/IMWS-BIO.2015.7303822.
[49] M. Shahbakhti, D. Taherifar, and A. Sorouri, "Linear and non-linear speech features for detection of Parkinson's disease," in *The 6th 2013 Biomedical Engineering International Conference*, IEEE, Oct. 2013, pp. 1–3, doi: 10.1109/BMEiCon.2013.6687667.
[50] A. Hussain and A. Sharma, "Machine learning techniques for voice-based early detection of Parkinson's disease," in *2022 2nd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE)*, IEEE, Apr. 2022, pp. 1436–1439, doi: 10.1109/ICACITE53722.2022.9823467.
[51] N. Jahan, A. Nesa, and M. A. Layek, "Parkinson's disease detection using CNN architectures with transfer learning," in *2021 International Conference on Innovative Computing, Intelligent Communication and Smart Electrical Systems (ICSES)*, IEEE, Sep. 2021, pp. 1–5, doi: 10.1109/ICSES52305.2021.9633872.
[52] A. Agarwal, S. Chandrayan, and S. S. Sahu, "Prediction of Parkinson's disease using speech signal with extreme learning machine," in *2016 International Conference on Electrical, Electronics, and Optimization Techniques (ICEEOT)*, IEEE, Mar. 2016, pp. 3776–3779, doi: 10.1109/ICEEOT.2016.7755419.
[53] M. Ogawa and Y. Yang, "Residual-network-based deep learning for Parkinson's disease classification using vocal datasets," *2021 IEEE 3rd Global Conference on Life Sciences and Technologies*, pp. 275–277, 2021, doi: 10.1109/LifeTech52111.2021.9391925.
[54] M. Nithya, V. Lalitha, K. Paveethra, and S. Kumari, "early detection of Parkinson's disease using machine learning image processing," in *2022 International Conference on Computer Communication and Informatics (ICCCI)*, 2022, pp. 1–4, doi: 10.1109/ICCCI54379.2022.9740961.
[55] L. Aversano, M. L. Bernardi, M. Cimitile, M. Iammarino, and C. Verdone, "Early detection of Parkinson's disease using spiral test and echo state networks," in *2022 International Joint Conference on Neural Networks (IJCNN)*, 2022, pp. 1–8, doi: 10.1109/IJCNN55064.2022.9891917.
[56] C. Laganas *et al.*, "Parkinson's disease detection based on running speech data from phone calls," *IEEE Transactions on Biomedical Engineering*, vol. 69, no. 5, pp. 1573–1584, May 2022, doi: 10.1109/TBME.2021.3116935.
[57] S. Dixit, A. Gaikwad, V. Vyas, M. Shindikar, and K. Kamble, "United neurological study of disorders: Alzheimer's disease, Parkinson's disease detection, anxiety detection, and stress detection using various machine learning algorithms," in *2022 International Conference on Signal and Information Processing (IConSIP)*, Aug. 2022, pp. 1–6, doi: 10.1109/ICoNSIP49665.2022.10007434.
[58] Y. Yang, L. Chen, J. Pang, X. Huang, L. Meng, and D. Ming, "Validation of a spatiotemporal gait model using inertial measurement units for early-stage Parkinson's disease detection during turns," *IEEE Transactions on Biomedical Engineering*, vol. 69, no. 12, pp. 3591–3600, Dec. 2022, doi: 10.1109/TBME.2022.3172725.
[59] M. Mamun, M. I. Mahmud, M. I. Hossain, A. M. Islam, M. S. Ahammed, and M. M. Uddin, "Vocal feature guided detection of Parkinson's disease using machine learning algorithms," in *2022 IEEE 13th Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON)*, IEEE, Oct. 2022, pp. 566–572, doi: 10.1109/UEMCON54665.2022.9965732.

BIOGRAPHY OF AUTHOR

Dr. Soly Mathew Biju CEng MBCS CITP FHEA is an Associate Professor at the University of Wollongong in Dubai. She is the discipline leader for Computer Science and has over 24 years of work experience in academia and IT industry. Her research interests are in machine learning, sensors applications, IoT, and AI application in designing systems. She is a chartered engineer and also Fellow Higher Education Academy. She is an author of a book recently published titled ‘Advanced interdisciplinary applications of machine learning python libraries for data science’. She is also holding mastery in IBM certified IBM AI analyst, IBM IoT cloud developer, security intelligence engineer, and IBM cloud application developer. She can be contacted at email: solymathewbiju@uowdubai.ac.ae



Dr. Obada Al-Khatib received the B.Sc. degree (Hons.) in electrical engineering from Qatar University, Qatar, in 2006, the M.Eng. degree (Hons.) in communication and computer from the National University of Malaysia, Bangi, Malaysia, in 2010, and the Ph.D. degree in electrical and information engineering from The University of Sydney, Sydney, Australia, in 2015. From 2006 to 2009, he was an Electrical Engineer with Consolidated Contractors International Company, Qatar. In 2015, he joined the Centre for IoT and Telecommunications, The University of Sydney, as a Research Associate. Since 2016, he has been an Assistant Professor with the Faculty of Engineering and Information Sciences, University of Wollongong in Dubai, UAE. His current research interests include wireless communications and networking with current emphasis on signal processing, IoT, machine learning for next-generation wireless networks, unmanned aerial vehicles, cloud and edge computing, and smart cities. He can be contacted at email: ObadaAlkhatib@uowdubai.ac.ae

Dr. Hock Chuan Lim, Ph.D. is a University Professor at University of Wollongong Dubai. He received his PhD in Computer Science (CS) from the University of New South Wales (UNSW) Australia. He has a strong background in Computational Science, with a particular focus and interests in games development and immersive technologies. He has published articles in peer-reviewed journals and have presented his research at international conferences such as IEEE Serious Games and Application for Health (SeGAH). He is committed to advancing knowledge in the field of computational sciences and health and is currently involved in research project on the use of augmented reality to support healthcare & education. He can be contacted at email: hclim@uowdubai.ac.ae for further inquiries.

Dr Suzanne Robertson-Malt is Associate Professor at the University of Wollongong in Dubai (UOWD) and is the Discipline Leader for the Bachelor of Nursing (Bridging) and the Master of Nursing programs. She has a keen interest in leadership, clinical research, evidence implementation, and shared governance. She is an advocate of the ‘flipped classroom/learning’ pedagogy proposed by flipped learning network (FLN) that is defined by four principles: flexible environment, learning culture, intentional content, and professional educator. Prior to joining UOWD, she has a successful track record as an industry specialist with a work history that includes both senior position in clinical and academic environments, such as Director of Implementation Science, Joanna Briggs Institute, University Adelaide; Director of Nursing Practice & Research and Clinical Director of the Heart Institute at the King Faisal Specialist Hospital & Research Centre, Riyadh, Saudi Arabia and Clinical Manager, Coronary Care Unit – John Flynn Private Hospital, Gold Coast, Australia. She can be contacted at email: SuzanneRMalt@uowdubai.ac.ae.

Hashir Zahid Sheikh is a Robotics Engineer at Appspro. Current research interests’ robotic systems, machine learning, and communication. Previously worked on implementation of a sustainable and scalable vertical micro-farm. He can be contacted at email: hashir9581@hotmail.com.