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Detecting Early Parkinson's Disease via Computer Keyboard Interaction by Using Machine Learning

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Abstract

One of the most popular progressive neuro-degenerative motor diseases in the world that has influence on more than 6.3 million people is Parkinson's disease (PD). Currently there is no reliable test for detecting PD by non-specialist physicians, particularly in the early stage of the disease in which the signs might be poor and subtly characterized. This leads to misdiagnose the disease by non-physicians up to 25%. In both motor and non-motor symptoms lack of neurons that produce dopamine will occur and individuals might be the holder of the disease for couple of years before diagnosis. There is a high demand for an objective and more accurate of detecting early PD, especially the ones that could be used personally at home or office. Timing information of keystroke from 85 individuals (that consist of 42 with PD and 43 controls) were taken in this investigation as they have been typed on a keyboard of computer with an extended period and displayed that PD has impact on many characteristics of finger and hand movements. When this done to two participants groups, our proposed bagging ensemble model were capable to differentiate the early PD from the others successfully with 82% accuracy and 0.86 AUC. The approach does not depend on the skill or experience of the specialist and does not need any medical supervision and specialized equipment. For more general applications, PD cannot be distinguished from similar related disorders because the symptoms of the second underlying disorder are not currently incorporated.

Keyword: *Parkinson's disease, Machine Learning, Feature Extraction, Classification, Human Computer Interaction*

1. Introduction

Parkinson's disease or simply (PD) is the most common occurring neuro-degenerative disease in older people (which comes after Alzheimer's Disease), that has effect on more than 6.3 million people in the worldwide, which is nearly 2% of people at the age of 65. In both motor and non-motor signs, losing of neurons that produce dopamine will occur in PD individuals. Presently there are no any solutions to slow the progression of the disease, no mechanism of prevention and no cure. Parkinson's disease is one of the most serious of all chronic disease from the viewpoint of suffers [1].

Presently, diagnosing of PD depend on the consideration of a combination of noticeable symptom by a physician (commonly a neurologist). In generally diagnosing PD is missed totally or misdiagnosed. Pogan in his study [2] discovered that, "based on a UK autopsy research", there were a misdiagnosis rate up to 24% and which is greatly depended on: whether or not they were applying criteria's of diagnostic of clinical instructions and who was doing the diagnosis process. Diagnosing by main care doctors had a correct diagnosis of only 53% and experts who were not movement disorder specialist had a correct diagnosis rate of just 75%. In contrast, the movement disorder experts have diagnosed mistakenly by only 6% to 8% that leads to raise a clear issue to be referred on to a movement expert, the practitioner of the patient's primary

health firstly should observe and diagnose the symptoms of the disease. Besides that, an individual may be the disease holder for five up to 10 years before it is diagnosed, and then when it diagnosed. Already 70% of the neurons in the brain that affected by PD have been lost [3].

Regarding of diagnosing the disease in generally, there are many functional and physical biomarker that may be used to get both predictive and diagnostic information (such as predicting response to drug and therapy). Human Computer Interactions "HCI" studies the interface between computer and people, delivering markers that may be utilized to quantify the condition of the users, such as mental, cognitive and physiological conditions. On a fundamental level, any devices that user interface with, as well producing an output that may be store and measure, could be used as a major aspect of HCI gadgets, for example: Computer, tablet PCs, wearable device, cell phones and gaming platform. In any cases, technology-based appraisals should likewise give accurate and valid outcomes, permit repetitive and simple use, and be free of rater's preparation [4].

Parkinson's disease results in a scope of both motors and non-motors symptom that make impact on movement such as tremor, jerkiness, slowness and sidedness. The theory of this examination study was that by changing the characteristics of fingers movement in individuals while they are typing on computer keyboard, PD can be identified in its beginning periods and such kind of changes might be utilized to differentiate and classify individual's status either with early PD or control subject[1].

In diagnosing Parkinson's disease, previously many researches have been examined such as finger and hand movements, finger tapping tests, handwriting, lifting and gripping task, speech analysis, feature of movements and gaits. Until this point of time, such examinations have all indicated limitations in or more aspects in the specificities and sensitivities of result, the level of mediation and expert supervision required, or the necessity for specific equipment that have forestalled their application more by and large as apparatuses to identify or analyze PD.

In generally when Parkinson's disease is diagnosed, already the disease been advanced, important neurons has been damaged or lost, and any plausibility of deferring further progression of the disease or giving neuroprotection is improbable. The objective must be to analyze and treat the disease a long time before the irreversible damaging changes have occurred [2], preferably minimum 5 years sooner than it becomes PD. Moreover, the most extreme signs of the disease will happen in the advanced phases, because of that early treatment and detection will have the most advantage for the individuals [5].

The goal of this examination was to recognize those attributes of fingers movement that are influenced by Parkinson's disease, and then capable to accurately classify the status of disease of the individuals in the examination by using machine learning "ML" application.

The main Parkinson's disease features are postural instability, bradykinesia, tremor, motor block and muscle rigidities, in addition there a wide scope of other motors and non-motors symptom. Typically, rest tremor is the most popular and simply identified symptom of the disease that is available in 70% to 75% of the PD individuals. Tremor happen at a frequency of "4 to 6 Hz" and are noticeable at the distal part of a furthest point, for example the hands and likewise include chin, leg and chin. Usually rest tremors vanish while sleeping and doing an action. Another Parkinson's disease most characteristic feature is Bradykinesia, in which characterized by a slowness of starting voluntary movement and in supporting dull movement with reduction in progressive of amplitude and speed, as well it is symptomatic of all disorders of basal ganglia and is exemplified by trouble with doing simultaneous and sequential task [6]. As indicated by Jahanshahi et al. [7], Parkinson's disease's initial manifestation is usually slowness in doing the typical tasks of day by day life, particularly those activities that need fine motor controls.

The complications with diagnosing Parkinson Disease emerge because there are no definitive tests and presently diagnosing the PD only based on observational and clinical criteria. Most PD's symptoms are uncertain and regular to different disease, both in neurodegenerative and non-neurodegenerative. Evaluation of the disease can be done by "Unified Parkinson's disease Rating Scale" or simply UPDRS [8], which is scale dependent on a score taken from the evaluation of the neurological which is done by a clinician, although it is a subjective scale that leads to absence of sensitivity, repeatability and objectivity in the scale. Typically, PD is preceded by a pre-motor stage that may keep going for length of time or even

for decades, among the beginning of neuro-degeneration and manifestations of the classic clinical motor symptom. Tremor is one of the most widely pre-diagnostic sign of PD that will start to happen 2 years before diagnosing the disease, 41% of subjects informing symptom to their medicinal professional and less than 1% of controls do, and already occurrence of the tremor become higher at five up to 10 years before diagnosing the disease. Pre-motor symptoms hold promise for the early detection of Parkinson's disease and recently considerable progress has been made in building up pre-motor symptoms as a method for diagnosing the PD in earlier stages, regardless of the dependence on the motor symptoms for the standard of diagnosing the disease. Biomarkers shows high potential for dependable early detecting PD, while sonography and neuro-imaging show high potential in early detecting the disease for high scale of specificity and sensitivity [2].

There is long history of identifying the users by using keystroke. In the study [9] , by using biomarkers dynamic, with the accuracy of 90% to 99%, during the time of writing the login of a computer to identify clients. In their method, they used key latency and hold time by utilizing a neural network and Gaussian mixture model. This and many other examples, show that keystroke dynamics may be used accurately to classification of the features of the user. Features of keystroke dynamics may be extracted by utilizing the timing information of the key been pressed and key been released. The key hold time and the latency among keys "which means time interval between pressing one key and a succeeding key" are normally been exploited [10]. Additionally, to ordered pairs "two successive keystrokes", n-tuple of a sequence of keystrokes also have been examined and keystroke dynamics investigation has used various ML and classifications algorithms.

In our study, we show the ability to differentiate the individuals either in early stages of Parkinson's disease or healthy controls. Natural interactions with computer keyboard of the participants have been monitored, and then key timing recorded which occur between pressing and releasing a key when the users are writing with standard keyboard. The framework naturally learns by examples the "PD" typing designs by comparing the PD holders with the healthy cohort with comparable typing education and skill. In our study, there is no need to obtain information about the text being typed. Later a methodology has been utilized to classification process for detecting individual's status either with early stages of PD or healthy ones, by using the combination of numerous keystroke features that was analyzed by an ensemble machine learning classification algorithms, Random forest and Bagging have been used. At the point of applying to two separate cohort, this methodology had the chance to successfully differentiate among early PD individuals and healthy individual controls with 82% accuracy, 83% sensitivity, 0.81% specificity and an AUC of 0.86 in the use of bagging ensemble classifier. In this system medical supervision or specialized equipment is not required, as well does not rely on the skill and experience of practitioner.

1.1 Related work

Parkinson's disease biomarkers can be studied and evaluated through different ways like speech analysis, gait and movement analysis, lift and grip tests, handwriting and as well as different types of Human computer interactions "HCI" like finger and hand movement, finger tapping tests.

One of the technologies or tools that has been used in the past to find, monitor, and detect severity of symptom's in Parkinson disease was machine learning techniques through speech data as mentioned in [11]. Different indoor systems and equipment are developed to monitor Parkinson's disease at home using accelerometer data [12] and gyroscope data to sense upper part of body activities. Mobile equipment and tools like wearable sensor data has been utilized to predict and find the severity of PD symptoms, like bradykinesia, dyskinesia and tremor by using data acquired from accelerometer [13]. Since most of the wearable devices that has been used to sense and monitor PD was done by checking upper body of patient and shoe worn sensors have been utilized to evaluate locomotion for early stages of diagnosis. In his study Bachlinet al. [14] has been used wearable technology to find and get more information about gait, especially freezing of gait by using accelerometer sensor which are fixed to the lower part of body and belt.

In normal subjects, by getting older the frequency of finger tapping decreases, the speed of the tapping in men is faster compared to women and using the dominant finger for tapping makes it faster than non-dominant fingers. The sequence of movements and sequential movement are facilitated by basal ganglia, though finger tapping tests can be used in those subjects with PD to assess bradykinesia and disturbances of rhythm formation [15]. Yokoe et al. measured 14 parameters of finger tapping test movement using touch sensor and accelerometer, to show visible differences between PD and non-PD subjects. They reached to a result that by maximum opening velocity was the most sensitive measure and most closely aligned with the UPDRS finger tapping tests score through categorizing these into amplitude, velocity and rhythm parameters [16].
Subjects with no PD has faster reaction times than those with PD with similar age and this could be analyzed in respect to the order of mental steps that happens among the subsequent physical response and the time that a stimulus is presented. The times of reaction could be differentiated into either a simple response (like pressing on 1 key) or it can be a confusing and complex response (such as pressing several keys) [17]. In [18] they realized that, especially when complex responses are needed, the reaction frequency of subjects with PD were slower, both in the delayed onset of premotor process and the motor response themselves. Giancardo et al. [19], used keyboard typing of people on computer as a source for observation and quantifying motor impairments for patients with PD and prompted using keyboard typing characteristics in biometrics.By using Support Vector Machine "SVM" and a time series analysis of keystroke hold time, it's been observed that critical differences among controls and patients with PD, but a related research of characteristics of typing with a larger set of patients only obtained an accuracy of 78%.
As a result, from researches done before is that Parkinson's disease affects many aspects of finger and hand movements and that many of these can be analyzed (both in combination and singly) via changes in the response characteristics as people write a sequence of texts with keyboard of computer.

2. Dataset

"neuroQWERTY MIT-Csxpd" database have been used in this study that comprises the keystroke logs of 85 subjects with Parkinson's disease and without. The dataset has been gathered and analyzed for the aim of indicating that the normal interactions of keyboard computer might be used to recognize the motor symptoms of early stages of Parkinson's disease. At the time of sessions of typing of subjects by using standard word processor, timing information has been taken. Individuals were educated to type as they ordinarily do at their home, as well they had the authority to correct mistake in their typing sessions if they needed [19].
From 2 groups of experiments 2 dataset have been gathered [19]:
1- PD_MIT-CS1PD (Early-PD dataset): 31 subjects. 18 PD cases and 13 normal cases. This group have visited the disorder units twice to accomplish the study.
2- PD_MIT-CS2PD (De-novo dataset): 54 subjects. 24 PD cases and 30 normal cases. This group have visited the disorder units once to accomplish the study.
Beside the raw typing data, clinical tests have been done on each subject, including finger tapping tests and UPDRS. For each subject data also involves gt (ground truth) that tell us either has PD or not and typing speed. As well at each case for each key stroke data there are four columns (the key been pressed, the hold durations in second, the key release time in second from time 0 and the key press time in second from time 0) [19].

3. Methodology

Keyboard is in fact, one of the first input devices used for human-computer interaction (HCI). In this interaction type, the movement of body and limbs is inescapable. In consequence, our predictive models, which are based on the machine learning are emerged from the psychomotor behavior or, simply, motor

control of typists. Proposed classifier models aim to discover behavioral biometrics such as typing patterns and rhythms, which are generated by the computer users while they are typing. Those behavioral biometrics can be explored from keystroke dynamics (so-called keystroke biometrics) and make us able to capture the footprints left behind persons with the Parkinson diseases without undertaking expensive and time-consuming clinical test, which are required supervision and interpretation of physicians or expert medical staff.

3.1 Keystroke Dynamics

We can categorize methods to obtain the keystroke dynamics into two main groups: acquired keystroke dynamics (illustrated in black color in Figure 1) and calculated keystroke dynamics (illustrated in gray color in Figure 1). We can acquire the timing information of key-down and key-up events when a person pressed and released each key while typing at a computer keyboard. Then, other keyboard dynamics such as hold duration, flight duration, press latency and release latency could be computed from the acquired keyboard dynamics, which are illustrated in Figure 1 and explained in Table 1 in details.

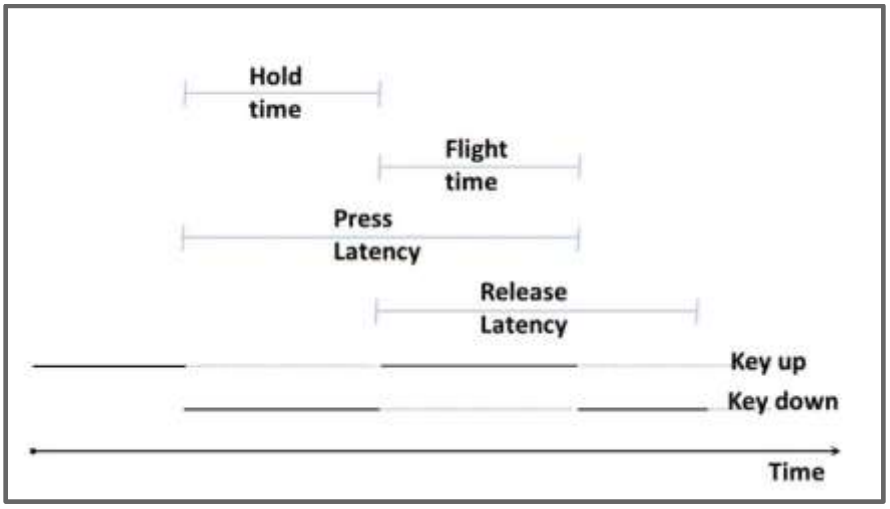

Figure 1: Illustration of keystroke timings while typing [20].

Table 1: Keystroke proceedings while successive keys are pressed and released.

Key stroke data	*Definition*	*Comments*
Timestamp	The time of day (hh:mm:ss.sss).	The time at which each keystroke began.
Hold Time	The elapsed time (ms) between the Key Down and Key Up events when pressing and releasing a key.	Hold Time is a measure of how quickly the finger is tapped and can also indicate the relative force of tapping. Hold Times are typically in the range of 60 to 140 ms [15].
Flight Time	The elapsed time (ms) among releasing a key and pressing the subsequent key.	Flight Time = Latency − Hold Time

Latency	The elapsed time (ms) from the Key Down or Key Up of one key until the Key Down or Key Up of the subsequent key.	Latency is typically anywhere in the range of 50 to 800 ms (anything greater than that was considered to be a pause in typing) [15].

Concerning diagnosing PD, there is a variety of features existing during typing on computer keyboard, through many motor symptoms such as [15]:

- Variability of sign and movement of finger and hand tremors.
- Degradation of typing of sequence of letters (n-tuple) and in repetitive movements.
- Slowness of movements (in both keystroke events hold time and latency time among sequential keys).
- Changing over time while the progression of the disease is occurred.
- Changing throughout the day times (tiredness during daytime).
- Reaction of the speed (comparable of a finger tapping tests).
- Jerkiness of motions (pause and hesitation).
-

In this approach, the keystroke biometrics of individuals typing has been taken while they normally do at the keyboard of computer. This was the importance of the study, that means no outside supervisions were included, the keystroke observing were totally un-intrusive upon their typical daily activities, and no limitations for typing tasks of the individuals. The way of timings happens while typing the sequences of letter are illustrated in Figure 1 and the events of keystroke timing that have been taken are explained in Table 1.

3.2 A general framework of our methodology

The block diagram of our study has been illustrated in Figure 2.

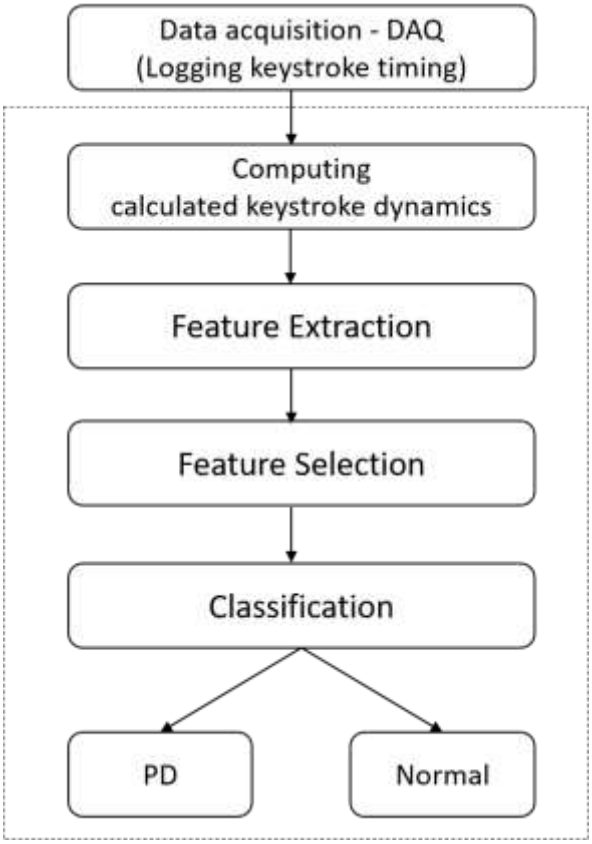

Figure 2: A general framework of our methodology

The keystroke timings acquisition stage involves logging of key-down and key-up time, which is done by [19] and recorded in the neuroQWERTY MIT-CSXPD datasets of DeNova-PD and Early-PD. By using those acquired keyboard dynamics of key-down and key-up time, we have computed the keyboard dynamics of hold durations, flight durations, press latency and release latency. Then we have captured typing biometrics of a person through several different features extracted from the calculated keyboard dynamics. We did our feature extraction only for space keys for all subjects for the aim of speeding up the operation and it is the most used keys among others. Finally, we have presented the extracted features to the machine learning classifiers to identify ones with Parkinson's disease.

In terms of classification, we obtained the highest accuracy rate by Random forest and Bagging ensemble classifiers among other classifiers. We applied Random forest algorithm by assigning Early-PD dataset as training set and assigning De-novo dataset as testing set, vice versa. Then we applied Bagging Ensemble algorithm by assigning Early-PD dataset as training set and assigning De-novo dataset as testing set, vice versa as illustrated in Figure 4.

3.3 Feature Extraction and Feature Selection

For each computed keyboard dynamics of hold durations, flight durations, press latency and release latency, we have extracted means, standard deviation, variance, kurtosis and skewness features, which are all 21 including the typing speed feature.

Machine learning models experiencing overfitting if the number of the feature become larger or even identical than the number of observations kept in a dataset. To get rid such kind of problems, it is important to apply dimensionality reduction or feature selection. In the use of feature selection techniques, there are many advantages that we face, like: reducing the risk of overfitting, improving the rate of accuracy, speeding up in training, increasing the explain-ability of the models, and improving data visualizations [21]. The aim of feature selection for a classifier model is to decrease the quantity of features that are available in the original dataset by making new subset for the sake of selecting the most relevant features with discriminative power.

By running an exhausted search, all combinations of the data set are applied the random forest and bagging machine-learning classifiers. The best performing subset of the "hold time variance", "hold time standard deviation", "hold time mean", "flight duration standard deviation", "flight duration means", "flight duration variance", "typing speed" features are selected. Altogether, there were seven features in total we worked on.

3.4. Machine learning Classifiers

3.4.1. Random Forest:

Random forest classifier made up of several decision trees and this proofs that this learning algorithm was initially proposed by Breiman [22]. In random forest classifier, trees available can be regarded and treated as a single classifier. So, the output of the classifier is product of all the decision trees that make up the classifier as its structure is further explained in Figure 3.

In order to generate a random forest classifier which made up of several T trees, we summarized the growth rule of each decision tree as follow [23] :

(1) In the training set we will assume that N defines the total number of cases, then all the N samples in a random manner will be selected from the training set, in which every single sample is replaced during the process of every sample and N training samples acquired. It is not necessary or required to use all the training data. Usage of data available in the training data can be used for single process or more than once in the other hand some of these data is not used at all.

(2) Let's propose that M is the declared as input features' dimension, and for dimension of randomly chosen sub-features from the original feature vectors we will put m (m < M). After that from the M features, m feature variables are selected randomly. And the process of splitting the nodes of the m-dimensional features are done by the best split.

(3) The process of growing tree will continue until the separation of all training samples are done without pruning.

As mentioned, there are two aspects that affects the forest error rate [23] :

(1) The first aspect is correlation of the forests any two trees. The error rate is directly proportional with the correlation, the higher error rate, makes the error rate more and conversely, the smaller error rate means the less correlation.

(2) Each individual tree's strength in the forest. The forest rate error decreases when the strength increases. In the random forest algorithm, production of random vectors like θ_k, is not depending on the previous random vectors in which distributed to all trees, and grow of each tree is done using random vector θ_k and set of training data, which produces collection of tree - structured classifiers $\{h(x, \theta_k), k = 1,...\}$ at input vector x. Generalization error of random forest algorithm is shown in the equation below [23] :

$$PE^* = PX,Y\ (mg(X < Y) \quad (1)$$

where subscripts X and Y represents random vectors which indicates the probability is over the X,Y space and mg represents margin function that measures the extent to which the average number of votes at

random vectors for the right output exceeds the average vote for any other output. Margin function is represented by

$$mg\ (X,Y) = av_k I\ (h_k(X) = Y) - \ max_{j \neq y} av_k I\ (h_k(X) = J) \quad (2)$$

since $I\ (\cdot)$ represents indicator function.

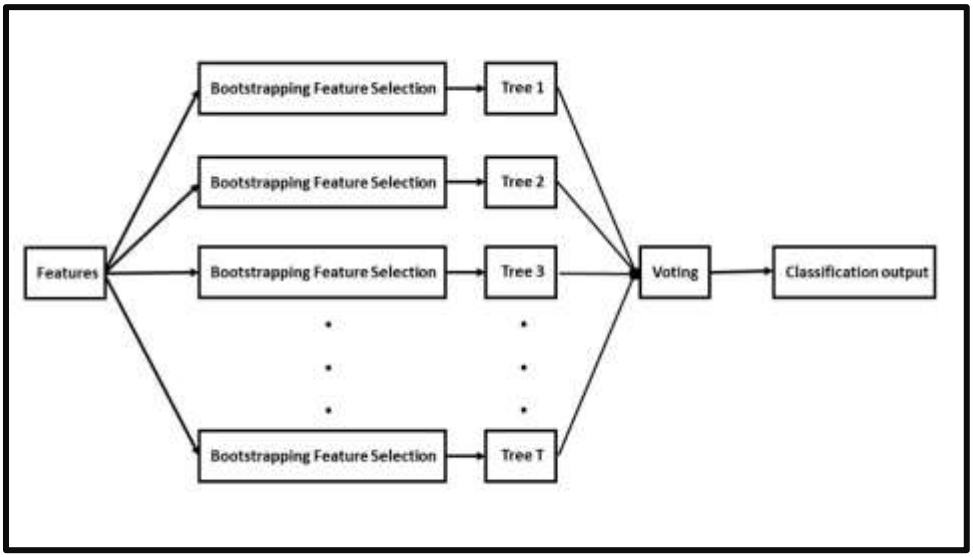

Figure 3: Scheme of Random forest classifier.

3.4.2. Bagging Ensemble Classifier:

The direct algorithm for ensemble modelling that combines the aggregation with the basic methods of base model formation is known as bootstrap aggregation or Bagging. When creating a model, bootstrap samples of the training set are used to form the first base model, and then the unweighted voting is applied after the combination of the formed base to make up the classification task. This process may not have extreme predictive power, but it can improve performance if the algorithm is unstable compared to a single model formed using the same basic algorithm. Stable algorithms are not much different at the base model, Because of that the performance of the classifier cannot be improved or even slightly reduced. Ensemble modeling eliminates the overfitting problem of the base model by the aggregation model which eliminates the overfitting successfully. Similarly, more attributes will create more possibilities for generating several different models without the need for attribute selection. Bagging's final model is at least as efficient as single model in the optimistic situation, and it may improve it. To improve the Bagging ensemble, the number of the base models should be increased. Bootstrap samples can be used to find the limit of the model diversity [24]. In this study, we have constructed the bagging ensemble based on the C4.5 decision tree classifier.

3.5. Performance Evaluation

Various approaches have been used to determine the performance of machine learning classifiers. Dividing the entire dataset in to two parts such as: testing and training subsets is a general way to estimate the performance. The mentioned sets should be selected free from each other. Then, we use the training set to

train classifier in order to find the optimized classifier parameters and at last, to find the error rate of optimized classifier, test data is used [25].
We use two additional terms during the evaluation of the classifier's performance, which are specificity and sensitivity. The property of how the classifier is recognizing the positive samples is known as Sensitivity, which can be defined as by [26]:

$$\text{Sensitivity} = \frac{TP}{TP+FN} \text{ x } 100 \quad (3)$$

where the number of positive samples which are true is TP and number of false negative samples are FN. Here the number of people who have positive result tests on having Parkinson's disease is known as Sensitivity. The task of showing how good the classifier is recognizing the negative samples is belonging to Specificity as well, and it is defined by [26]:

$$\text{Specificity} = \frac{TN}{TN+FP} \text{ x } 100 \quad (4)$$

where the number of negative samples which are true is TN and number of false positive samples are FP. Here the number of people who have negative result tests and having no Parkinson's disease is known as Specificity. The equation of Accuracy is defined by [26]:

$$\text{Accuracy} = \frac{Sensitivity+Specificity}{2} \quad (5)$$

Receiver Operating Characteristics (ROC) curve is another index of statistics, It's used to predict the difference of something from different results which are the outcome of different statistical methods [26]. ROC curve is formed by showing the plot for the true positive values and the false positive values on vertical axis (sensitivity) and horizontal axis (1- specificity) respectively. The calculations of false positive and true positive are done and shown as plotted points on the ROC axes. Then, to estimate the performance of the classification, mean area under the curve (AUC) will be applied which is a classifiers advantageous metric. Classifier is directly proportional to the area, the bigger the area, the better is the classifier model [26].

4. Result and Discussions

There are limitations in the compound clinical scores such as the subjectivity of assessments and the frequency of the measurements. Thence, for reliable and quantitative test there is unmet medical needs, that could accomplish clinical scales for numerous applications for example evaluating drug responses and identifying cohorts at risk, among others. By using the un-constrained use of digital devices in a setting that represent our daily activities, our envisioned method could accomplish these standards and permit for a frequent and objective assessment of Parkinson's disease motor signs. Our approach shows assurance and could accurately differentiate an early stage of Parkinson's disease with mild parkinsonian symptoms from normal cohort.

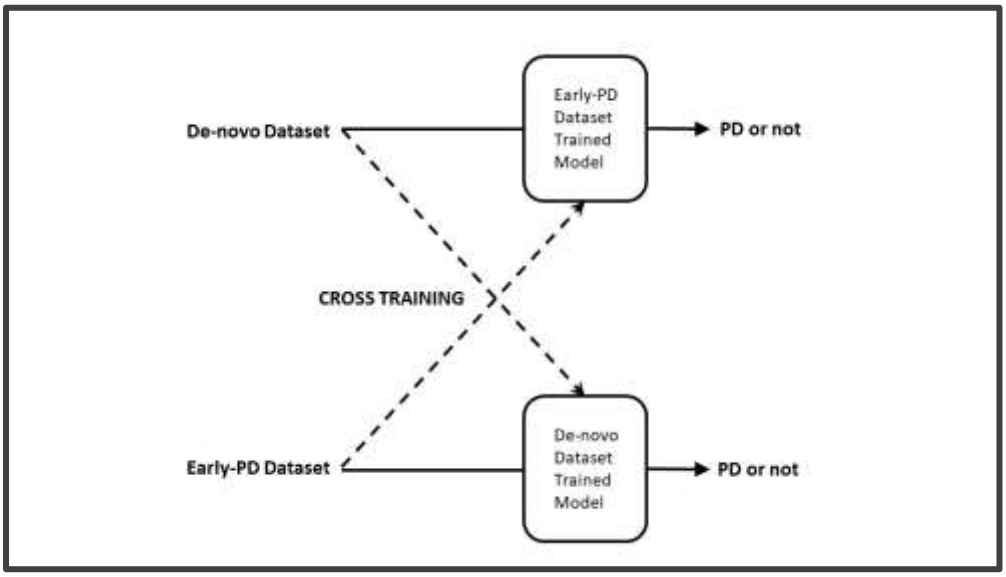

Figure 4: Cross validation strategy used in this paper.

To make able to compare our model with previously proposed models, we have utilized the same evaluation methodology as Ref. [2], which is training the classifier model on the De-novo dataset and evaluate it on Early-PD dataset and vice-versa as illustrated in Figure 4. In Table 2 and Table 3, the discriminate performance of the bagging ensemble and the Random forest ensemble models are reported and shown in Figure 5. We found the following AUC: 0.94 for the Early-PD dataset, 0.77 for the De-novo dataset and 0.86 for the average of both. The Area Under Curve (AUC) allowed us to get reliable metrics even in the presence of un-balanced number of individuals in the independent dataset.

Table 2: Performance of Bagging ensemble model for the cross validation of the Early-PD and De-novo Datasets.

Model #	Test Dataset	Train Dataset	Area Under the ROC curve (AUC)	Accuracy
II	Early-PD	De-novo	0.94	94%
I	De-novo	Early-PD	0.77	70%
	Average		0.86	82%

Table 3: Performance of Random forest ensemble model for the cross validation of the Early-PD and De-novo Datasets.

Model #	Test Dataset	Train Dataset	Area Under the ROC curve (AUC)	Accuracy
II	Early-PD	De-novo	0.93	90%
I	De-novo	Early-PD	0.77	76%
	Average		0.85	83%

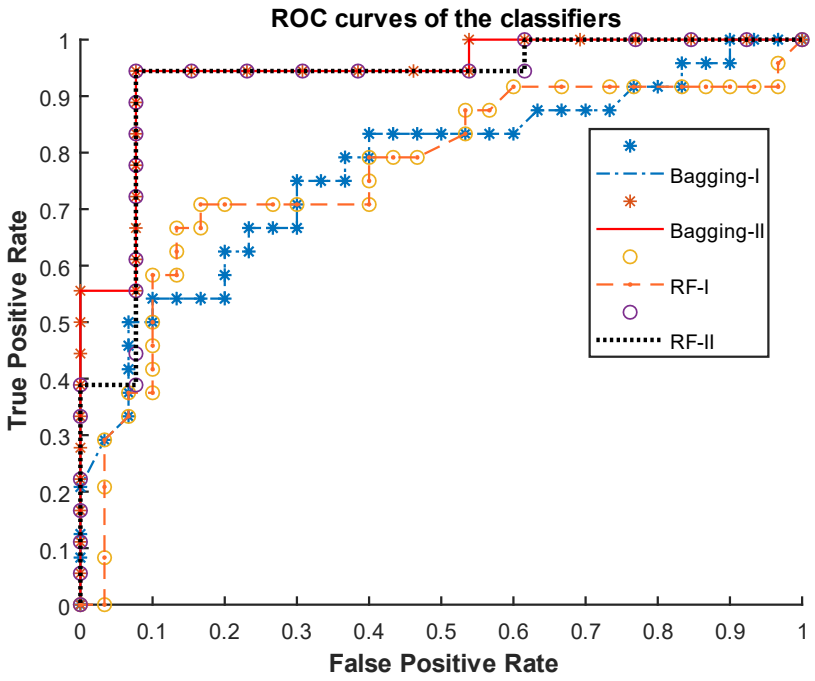

Figure 5: The ROC curves for the evaluated models

Among previous studies, our results show comparable or even higher in the performance of distinguishing early stage of Parkinson's disease from the others. Table 4 shows the average performance of 2-fold cross-validation and involves our model including all previously proposed models that employed the same dataset and the same validation strategy.

Table 4: Performance of all the models that used the same cross-validation strategy and quantitative clinical test. (* No Data Available)

Study	Diagnostic Type	Accuracy	AUC
Single key tapping [17]	Clinical quantitative motor performance test	NDA*	0.61
Alternating finger tapping [17]	Clinical quantitative motor performance test	NDA*	0.75
nQi [17]	Statistical model	0.76%	0.81
Stdev [27]	ML model	0.75%	0.82
FRESH [27]	ML model	0.73%	0.80
MACD [27]	ML model	0.81%	0.85
Our Study	ML model	0.82%	0.86

5. Conclusion

In our approach, keystroke timing information has been taken from individuals while they were typing at the computer keyboard, individuals were 85, that comprised 42 with PD and the rest were normal. It displayed that Parkinson's disease has impact on many characteristics of finger and hand movements, that may be obtained from features of keystrokes. For classifying either the individual has early PD or normal a novel approach has been used, by applying a combination of various features of keystroke that were learned by Random forest and Bagging ensemble of machine learning classification models.

In our technique, identification of the early stage of Parkinson's disease individuals was able with an accuracy of 82%, and an AUC of 0.86. It was the principal strategy to exceed the symptomatic accuracy rate of non-expert physicians and the achieved results are significantly more accurate than that produced by previous Human-computer interaction researches, which suggests it might be an accurate, objective detection of the Parkinson's disease, particularly in its early levels in which motor symptoms like tremor and bradykinesia cannot be observable yet. At this time the approach does not incorporate a second cardinal Parkinson's disease motor symptoms such as rigidity and postural instability, which means by itself, cannot distinguish between Parkinson's disease and other movement related disorders.

The approach does not need any medical supervision, does not require any specialized attachments and equipment, does not rely on the skills and experiences of the practitioner, and it may be set up in the subject's office or home as they regularly type on the keyboard of computer.

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