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A Comparative Study of Early Detection of Parkinson's Disease using Machine Learning Techniques

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***Abstract*— Parkinson's Disease (PD) is considered a malison for mankind for several decades. Its detection with the help of an automated system is a subject undergoing intense study. This entails a need for incorporating a machine learning model for the early detection of PD. For discovering a full proof model, the cardinal prerequisite is to study the existing computational intelligent techniques in the field of research used for PD detection. Many existing models focus on singular modality or have a cursory analysis of multiple modalities. This encouraged us to provide a comparative literature study of four main modalities signifying major symptoms used for early detection of PD, namely, tremor at rest, bradykinesia, rigidity, and, voice impairment. State- of-the-art machine learning implementations namely Logistic Regression (LR), Support Vector Machine (SVM), Decision Tree (DT), K-nearest neighbors (KNN), Stochastic Gradient Descent (SGD) and Gaussian Naive Bayes (GNB) are executed in these modalities with their respective datasets. Furthermore, ensemble approaches such as Random Forest Classifier (RF), Adaptive Boosting (AB) and Hard Voting (HV) are implemented. Our results are compared with those obtained with their respective researches. Among all the tests, applying Random Forest (RF) on Static Spiral Test (for detecting tremor) gave us the most significant result, i.e. the highest accuracy of 99.79%. This leads to the conclusion that the multi-modal approach with the help of the ensemble method should be used to get better and accurate results.**

Keywords*— *Parkinson's Disease, Machine Learning, Multi-modal, Ensemble Approach and Bioinformatics.

I. INTRODUCTION

Parkinson's disease (PD) is a long-termed, neurological disorder that causes a person to lose control over several body functions including speech. It is the second most common neurodegenerative disease after Alzheimer's disease [1]. Dr. James Parkinson was the first to describe this condition called 'paralysis agitation' or 'the shaking palsy' [2]. In the 21st century, PD is a ubiquitous issue. In 2015, PD affected 6.2 million people and resulted in about 1,17,400 deaths globally. This accounts for various researches [3] [4] [5] to be undertaken to study and eventually cure the disease.

The loss of nerve cells in the part of the brain called the substantia nigra causes PD. These nerve cells or neurons create an organic chemical named dopamine which acts as a neurotransmitter between the parts of the brain and central nervous system that helps to control and co-ordinate body movements. Although this disease can be diagnosed at an early stage [6], its long term treatment is not yet discovered. The clinical diagnosis of the patient by the doctor was focused on his/her sense and experience, based on his/her knowledge and studying previous cases of PD from large databases in the hospitals. But with the advent of strong tools like Artificial Intelligence and Machine Learning, this took a subtle turn [7], various state-of-the-art machine learning tools and techniques analyzed the high dimensions of data in the datasets which made the work of prediction simple.

The primary symptoms of PD were the motor dysfunctions, which involved tremors of limbs, hand, legs, and jaws, bradykinesia or slowness of movement, rigidity in limbs which is observable in the PD affected patient's gait and postural instability [8] [9]. Furthermore, there are several other symptoms like loss of memory and depression which are termed as non-motor symptoms [10] [11]. PD can be diagnosed, but its effective treatment is a challenging task. There is no definitive cure discovered for PD or either to show its progression, but there are various rating methods like Unified Parkinson's Disease Rating Scale (UPDRS) and MDS-UPDRS [12], which helps to estimate the severity of the disease. Sometimes there is a possibility that patients do not cooperate with the doctors while examination [13] which causes imprecise and inaccurate results. So, the usage of automated tools like machine learning would ease the task of clinicians and would improve the diagnosis accuracy.

II. OBJECTIVES

The cardinal objectives of this paper are

1. To manifest an overarching survey of research papers in different modalities to detect PD.
2. To provide an array of various comparisons between different techniques of data pre-processing, feature extraction and classifiers.

3. To implement various machine learning algorithms and compare them to conclude which one gives the best results.
4. The scope to implement an ensemble approach for better prediction of PD.

III. LITERATURE REVIEW

Researches done for the detection of PD includes all the aspects such as biological, chemical and genetics. Gradually some of them evolved by applying machine learning and artificial intelligence, which contributed as a major tool for the early detection of this disease. PD is a diagnostic disease and there is no confirm symptom or guaranteed detection technique, there are many people who have given their best shot for the detection and prevention of this disease. As machine learning depends on predictive standards, it is highly preferred for such researches. There are many symptoms encountered in PD, which leads to various findings like, detection by analyzing a single symptom or by analyzing more than one symptoms. Detection using a single symptom at a time is given higher priority for this review work. Common symptoms for PD are shown in Fig. 1.

Various sensors are used for the detection of motor symptoms nowadays, but because sensors may not be available in every corner of the world and even data sets are limited, may hinder the accuracy of the result. The major focus of this review work is towards the detection mechanism which is discussed thoroughly. An array of research papers is discussed with their implementations and have also implemented some of the techniques which are compared with the original ones. It is to be noted that all the publications are not involved, especially those which include MRI scans.

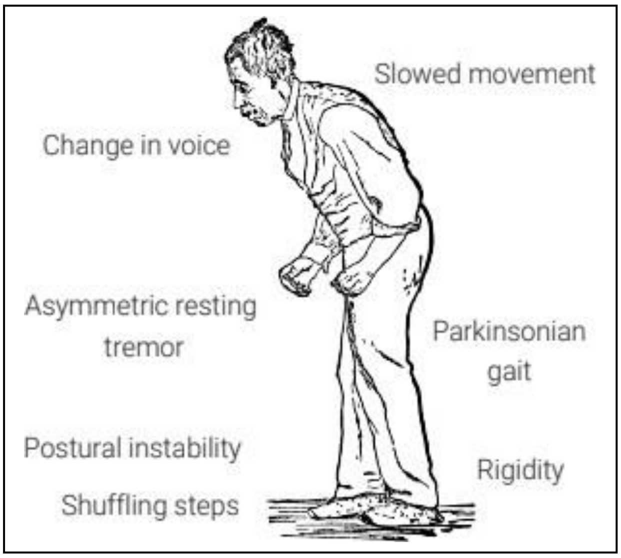


Fig. 1. Symptoms

A. Bradykinesia

Bradykinesia or slowness of movement is one of the major symptoms of PD. It results from a failure of basal ganglia output to reinforce the cortical mechanisms that develop and execute the motor system commands which results in motion [14][15]. The reduced dopaminergic substances to the striatum may result in increased neuronal firing which serves as a hindrance to the basal ganglia output [16][17]. Due to this deficiency, the person starts to experience abnormal movement activities [18], which results in difficulty with self-paced motions. The person is not able to react normally or is suffering from dyskinesia and uncontrolled involuntary muscle movement, which eventually results in tremors. Bradykinesia is often referred to as akinesia or hypokinesia. These words are analogous, but with a slight difference [19]. Akinesia refers to the paucity of voluntary movements (for example, countenance) and hypokinesia refers to the fact that the movements are slow (bradykinesia) at the same time they are smaller than desired (for example, handwriting). These terms refine the fact that PD patients are clumsy.

Bradykinesia can be detected by various techniques and its analysis [20][21]. Data Mining techniques and its applications are widely used to adhere to this cause [22][23]. Along with it, a new technology 'Leap Motion' aimed at detecting bradykinesia with ease. It is a smart device that tracks the patient's behavior on an everyday basis [24]. It notes that various types of human-computer interaction analyze many PD biomarkers. Our primary focus on detecting bradykinesia is by analyzing the typing criterion of the patient [20]. The Tappy application is used efficiently to generate keystroke data which enabled system-wide real-time recording. PD causes rigor movement in the phalanges and limbs. In analyzing the Tappy Keystroke data, it was observed that various characteristics of hand and finger movement of the PD affected patient were different than the normal person. Along with the Tappy software, many other techniques were studied to note the typing characteristic of the patient. Mobile technology opened a different stratum for this detection [26]. The typing activity on smartphones was noted and the results were examined. Both the typing on the keyboard and the touchscreen of the smartphone indicated the same outcome, but the data pre-processing, feature extraction and analysis of parameters were different. The speed by which the patient types became a new branch in this research [27] which gave astounding reviews. Typing bolstered the multi- modal research approach for PD detection, as along with bradykinesia it helped to detect tremors.

B. Tremor at rest

Tremor is a rhythmical and involuntary oscillatory movement of the body parts. It is a symptom diagnosed in various diseases [28]. There are some peculiar characteristics by which PD affected tremors are identified. PD patients have a high effect of tremors in hands compared to other body parts. It is mainly when a person is more at rest rather than having tremors in any kinetic movements. This characteristic was listed in the medical consensus statement of the Movement Disorder Society (MDS) in 1998 and it is prevailing for two decades. A case study of 100 pathological patients contends that 68% of cases were at the onset of the disease, 75% were suffering from the disease, and in 9%, tremors pacified lately [29]. The tremor at rest was noted in one patient among 47 PD diagnosed patients [30], which refers to a 4 to 6 Hz pill- rolling tremor [31]. In extreme cases, tremor at rest can also occur in oral organs, but it rarely occurs in the head. There are other types of tremors like a kinetic or postural tremor which also occurs to PD patients, but not so dominant as the tremor at rest. One of the major diagnostic features is the suppression of rest tremor during movement initiation [32]. These studies prove that tremor dominant PD is a distinct subtype that can help in the early detection of PD. Tremor at rest is itself a wide field of research and various techniques help in its detection. Wearable sensors are the new approach to detect tremor at rest in PD patients [33]. The sensors are easily manipulated and can calibrate the results with finesse. With the advent of sensors, new theories on detecting a different type of tremor came into existence. Re- emergent tremor, a type of postural tremor known to be prevalent in PD affected patients was seen at large [34]. Levodopa, a dopamine alternative agent influences the tremor by diminishing the magnitude. This drug affects the resting time of the tremor and is observed to be effective. An acoustic study of tremors paved its way as a newly emerging branch in the study of tremors [35]. Using acoustic analysis, a study detected tremor in PD affected patients. Results found that voice disability did not correlate with the acoustic voice tremor measures. The motor symptoms of the patients were examined too for a better relationship with the voice tremor. Along with voice tremor, limb tremor and cerebellar tremor detection is an important step for detection of the tremor in PD patients. Reference [36] poses the solution to it by detecting the tremor automatically and remotely. Adaptive deep brain stimulation (aDBS) came to light for detecting precise control over motor symptoms [37]. It aims at improving the results of DBS by executing a closed-loop approach. In a DBS, the state of tremor is dynamically captured for a better perspective and accurate results [38].

C. Rigidity

It is one of the four major symptoms for the detection of PD. It refers to the abnormal stiffness in the limbs or other body parts, which prevents muscles from stretching or relaxing [39]. It can occur to one or both sides of the body. Characteristics of Rigidity are stiffness in muscles, like facial muscles. Disability to display countenance and not able to enunciate fluently paved way for speech therapy. It is administered by speech pathologists who teaches facial exercises and helps the patient to speak and communicate. Rigidity causes difficulty in doing the day to day work like walking or getting up [40]. The affected patient can barely stretch or relax. Rigidity affects both the extensor muscles and the flexor muscles, but the significant changes are noted in the latter one. It is examined scrupulously during slow stretching. Fast stretching provides us visible evidence for spasticity. It is treated with various medications like levodopa and various inhibitors, namely, catechol-O-methyltransferase (COMT) inhibitors, and monoamine oxidase-B (MAO-B) inhibitors. Physiotherapy is also administered to pacify the excruciating effects of the disease. As the disease progresses the day to day tasks become more difficult. Hence, specialists perform occupational therapy to ameliorate their effects. For some exceptions, these exercises do not work, and the patient continues to suffer from the effect. Here comes the concept of deep brain stimulation, which initiates electrical impulses into the targeted regions of the brain.

In general, clinical diagnosis provides a concrete analysis of rigidity. Doctors test the patient's muscles by flexing and extending them and then look for endured rigidity. With the advent of artificial intelligence, various methods have been developed which assist doctors. Advanced technologies have improved the stratum of research for detecting rigidity like, Dynamic Bayesian Networks (DBN) [41] tracked the motor functions of the patients with clinical scores. The parameters of various scales were compared with clinical probabilities which helped to determine the impact of it on the patient. Another one is the Gait Analysis [42] [43]. Furthermore, there are various ways to detect rigidity, by using sensors and accelerometers [44] [45]. Wearable sensors and feedback devices brought or opened a new dimension in detecting motor symptoms for PD [49]. An amalgamation of accelerometers, gyroscopes, and goniometers are one of the most widely used devices. With gait assessment, feedback contributed as an alternative for surgical intervention. Wearable haptic and auditory feedback noted various parameters namely - progression angle [50] and mediolateral trunk tilt. Many applications of this new approach are prevalent in society. Identifying movement disorders and assessing surgical outcomes [48] is the most common amongst them.

D. Voice Impairment

To consider voice impairment in the early detection of PD or not is a debate going on for many years. Many renowned neurologists do not consider this symptom as an early sign of PD. Whereas, some adamantly quote that vocal symptoms are the most prominent ones at an early stage along with tremor and rigidity [51] [52]. An intermittent solution is provided in [53] that voice impairment can be described at an early stage of PD and there is conclusive evidence of the late appearance of dysarthria in PD patients. Dysarthria is a speech disorder associated with the improper functioning of muscles required for speech. There are many other types of speech disorders associated with PD like hypophonia and tachyphemia [54]. These disorders have a common effect on the patient as it affects their speech in various ways. It gets slurred, the person may face difficulty to find the right words as the speech gets slower and many more. This brings changes in their behavioral traits and makes the patient mentally unstable [55]. PD causes damage in the nerves which affects the central nervous system simultaneously deteriorating the substantia nigra pars compacta. This results in limiting the secretion of dopamine, which helps to produce smooth muscle movement hence affecting the facial muscles and the countenance of the affected person [52].

IV. Implementations

A. Bradykinesia

According to studies, finger tapping frequency reduces as the age increases. There is also a difference among men and women and a small difference in dominant and other fingers. Using an accelerometer and touch sensor, 14 parameters of Finger Tapping Tests (FTT) movement were detected which shows the clear difference between PD affected patients and healthy subjects [20]. PD patients tend to have slower reactions compared to non-PD patients. By considering all the points, the early diagnosis of PD is possible by detecting slowness using typing. The dataset was collected in two different ways i.e. Tappy software on the computer and an application on Android smartphone. Tappy dataset of 217 participants was gathered, however, only some of them were included in the subsequent analysis. In computers, the data is collected by running Tappy software as the background process which focuses on five columns of right-hand fingers and five columns of left-hand fingers. This software makes use of the" SetwindowsHookEx" API to note down the keyboard timing events. The individual keystroke timing data was saved on the individual's computer and then uploaded to the server once a day via FTP. The individual having at least 2000 keystrokes data and having mild severity was considered for the early detection of the disease. This cut-short the data to 53 participants including both PD and non-PD patients. In the pre-processing stage, the data was formatted into n x m matrix (n denoting the number of subjects and m denoting the number of features). The missing values were treated with mean imputations and the data was normalized in the range of 0 to 1.

The features involved (27 features) were relatively large compared to 53 subjects. For preventing the over-fitting, the dataset was divided into two groups of features i.e. hold with 9 features and latency with 18 features. Furthermore, the dimensionality reduction (Linear Discriminant Analysis) was implemented as the last step of pre-processing. The dataset was randomly separated into 'train' and 'test' set combining with k-fold cross-validation (where k=10) to confirm that all the data was included. Rather than considering the data as a time series of events, they were considered as a sequence of ordered pairs in this study, i.e. in the form of n tuples. All the machine learning models as shown in the figure were implemented on the training dataset to have maximum accuracy in classifying PD or non-PD patients. The specificity (the minimum number of false positives) was also an important criterion for maximizing the area under the curve (AUC). Further, after getting the results, it was considered that individual features were not able to deliver desired results, so a combination of multiple features was used for the classification which uses the ensemble approach. For each hold and latency group, the predicted probabilities were averaged, and the final step combined the weighted average of the predicted probabilities of individual groups with their respective classification accuracy. This study was able to detect early PD subjects with a specificity of 95 to 100%, sensitivity of 92 to 100%, and AUC ranging between 0.97 and 1.00.

As mobile technology is dominant and having wide range opportunities nowadays, the study has also been undertaken for early detection of PD through mobile touchscreen typing [25]. In this study, the data of 51 subjects were taken from which 24 people were diagnosed with PD and 27 were healthy subjects. A custom screen keyboard is developed, which is based on the open-source software "AnySoftKeyboard" (github.com/AnySoftKeyboard) which is working with the Android smartphone. Three major steps are involved in this process i.e. the minimization of noise and artifacts, feature extraction, and evaluation of feature vector to determine the adaptability of classification. These techniques of detection through typing are very helpful as they neither include any medical supervision nor do they need any experienced practitioner.

B. Tremor at rest

On comparing PD patients with healthy subjects, they exhibit difficulties in performing skills such as handwriting. Minute hesitations and pauses are often seen while performing actions and that can be categorized as a form of tremor. As the tremor at rest is seen in the early diagnosis, the detection of tremor is done to obtain insights into motor disruption aspects of PD. The spiral test was used most of the time for the assessment of the impact on this movement disorder. The handwriting dataset of 75 persons was taken into account (37 PD affected patients and 38 healthy subjects). This study was carried out in eight different tasks. Drawing Archimedean spirals was the first task and writing letters and words in cursive were distributed in the rest of the tasks. The handwriting signals were obtained using a digitizing tablet of Wacom technology in the x-y plane and the third axis was taken as the pressure axis. All the feature vectors were pre-processed and the SVM classifier was implemented for classification. The accuracy of 79.4% was obtained after considering all the features along with very similar values of specificity and sensitivity.

Another approach for detecting tremors was implemented and then concatenated with the detection of the change in voice to obtain more accurate results. This research suggests the multi-modal approach to combine the reliability of two separate studies. The tremor was detected using the spiral test in which the dataset of a total of 77 persons (62 PD affected patients and 15 healthy subjects) was included. Furthermore, the spiral test was divided into three different tests viz. Static Spiral Test (SST), Dynamic Spiral Test (DST) and Stability Test on Certain Point (STCP). In the pre-processing step, the attributes were calculated according to the min-max scaling and correlation was applied on the attribute which ruled out one feature. The dataset was then split into three different tests.

C. Rigidity

Gait analysis provided an effective measure to detect rigidity. Wearable body-worn sensors prevailed in a new direction for the detection of balance and gait impairments. As [50] [63] shows recent advancements in the body-worn sensor technology which gave rise to an affordable and convenient way to measure it. Reference [63] showed various neural control systems and their respective impairments. The patients were asked to perform tasks accordingly and their metrics were duly noted. To measure postural instability the parameter postural sway was measured. Sensorimotor control loop was used for its measurement and various features like velocity, jerk, sway, and frequency were extracted. Examination of stance (quiet stance) was plotted on the graph showing mediolateral and anteroposterior as x and y-axis. The postural responses showed the reflex factor of normal people was more prominent than the PD affected ones. They were not able to adapt to the movement changes efficiently. The freezing of gait proposed by freezing ratio (freezing frequencies divided by the power of gait frequencies of horizontal shank acceleration). Reference [50] also proposed a similar implementation of wearable sensors that collected datasets from healthy and osteoarthritis affected patients walking on the ground surface. Gait parameters like joint kinematics, segment orientation, and joint forces were noted. The paper reviewed researches on different body parts which affected the gait of the patient. It showed fewer articles were involved in feedback than sensing. Hip, Thigh, and Pelvis were the least noted body parts for both sensing and feedback gait parameters.

D. Voice Impairment

In recent years, there is a tough competition between researchers to determine accurate and efficient methods for detecting PD acoustically. With the advent of Artificial Intelligence, this competition has evolved and is progressing steadily. As multiple Artificial Neural Networks have been configured and tuned accordingly (improved feature extraction) for providing better classification techniques [56]. Traditionally, Speech-Language Pathologists (SLPs) diagnose the speech impairment and prescribe medications and exercises accordingly. With the advent of new technology, methods of assisting patients evolved. One of its examples is EchoWear [57], a smartwatch technology that remotely monitors patient's activities. This technology is very useful and removes the cons of in-person SLP treatment. Other state-of-the-art machine learning techniques like KNN solve the classification problem of PD [58]. Where the features are extracted aiming for maximum optimization. Several acoustic, prosodic and vocal analyses helped in detecting PD [59]. It extracted features and applied correlation between them to get the most important features out of all followed by SVM implementation for classification. Speech disorders also affect other activities of the human body like inhaling, exhaling, prosody, and articulation [60]. Through an instant vocal test, they were able to identify the speech disorders. By conducting a standard speech examination protocol, they were able to conduct vocal analysis on two PD affected patients for 10 years [61]. Automated analytical methods were implemented to identify the speech rate and articulation factors. PD affected patients would show a lower rate which would mean their vocal muscles are compromised [62].

V. Results and Discussion

All the Machine learning algorithms are compared based on Specificity and Sensitivity. The ability to predict the probability of actual positive trials and the ability to predict the probability of actual negative trails are denoted by the terms Sensitivity and Specificity respectively. These two terms are evident in all the results (Fig. 2, Fig. 3, Fig. 4, Fig. 5, Fig. 6 and Fig. 7).

Along with the algorithms, three ensemble approaches are implemented namely, RF (Bagging method), AB (Boosting method) and HV (Voting method) in all four modalities to increase the proposed accuracy. The fundamental meaning of an ensemble approach is to concatenate multiple machine learning models into one predictive model. In the case of RF, it will create the sub-samples which are utilized by the algorithm to produce aggregated results to increase the accuracy. In the case of AB, it will allocate higher weights to weak classifiers which would eventually increase their accuracy as this will combine multiple weak classifiers into one strong classifier. In the case of HV, it will unite all the algorithms and makes the final prediction by a simple majority vote. In general, all the algorithms having accuracy greater than some threshold should be included in hard voting to get a better result.

A. Bradykinesia

To understand the symptoms and extract useful features from the data, various machine learning algorithms have been implemented. The dataset used is taken from the UCI repository. The results of all the algorithms are enlisted in Fig 2. The highest accuracy of 97.5% is obtained by implementing RF and HV.

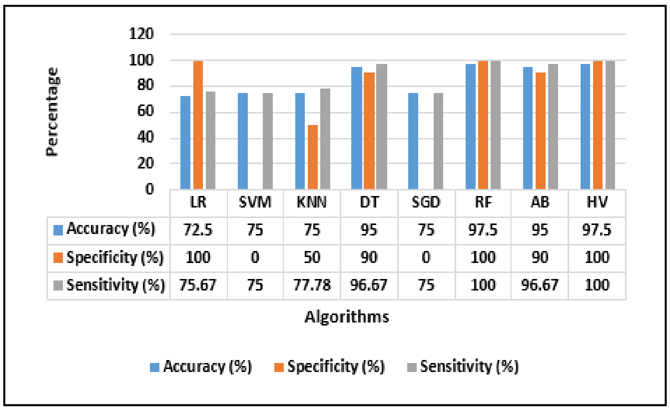
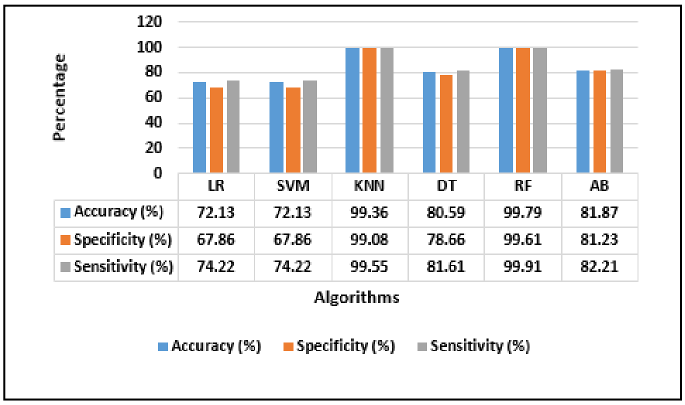


Fig. 2. Results of Bradyknesia

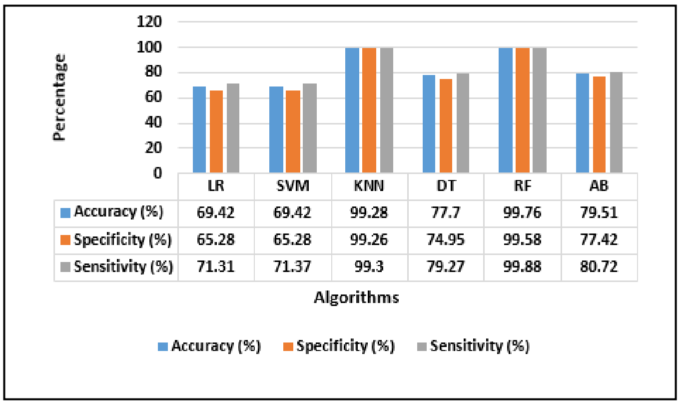
B. Tremor at rest

Various machine learning models shown in the figure are applied and many of them resulted in higher accuracy compared to previous studies and have used the dataset from the UCI repository. The highest accuracy of 99.79%, 99.76% and 99.71% was obtained by RF in SST, DST, and STCP respectively as shown in Fig. 3, Fig. 4, and Fig. 5.



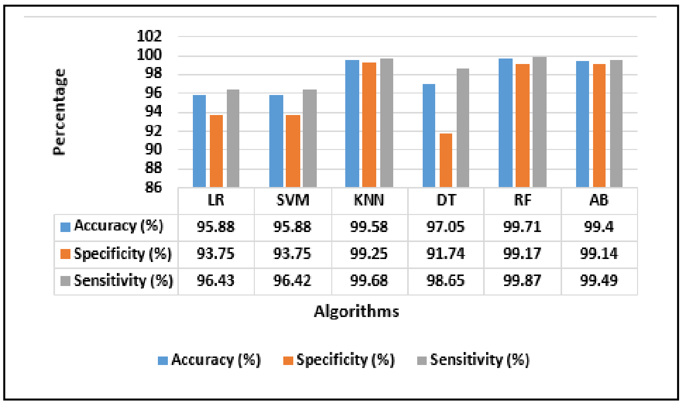
	LR	SVM	KNN	DT	RF	AB
Accuracy (%)	72.13	72.13	99.36	80.59	99.79	81.87
Specificity (%)	67.86	67.86	99.08	78.66	99.61	81.23
Sensitivity (%)	74.22	74.22	99.55	81.61	99.91	82.21

Fig. 3. Results of SST



	LR	SVM	KNN	DT	RF	AB
Accuracy (%)	69.42	69.42	99.28	77.7	99.76	79.51
Specificity (%)	65.28	65.28	99.26	74.95	99.58	77.42
Sensitivity (%)	71.31	71.37	99.3	79.27	99.88	80.72

Fig. 4. Results of DST

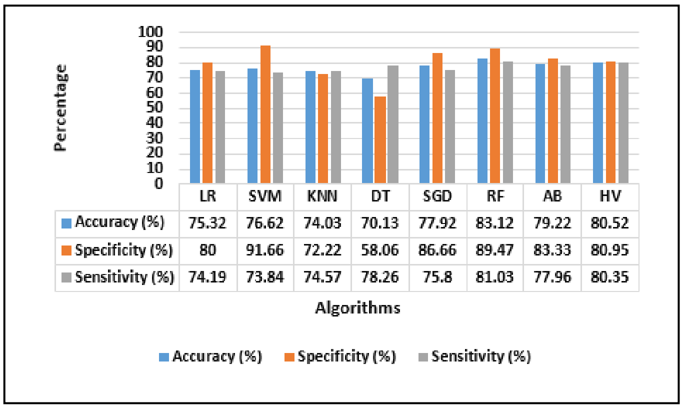


	LR	SVM	KNN	DT	RF	AB
Accuracy (%)	95.88	95.88	99.58	97.05	99.71	99.4
Specificity (%)	93.75	93.75	99.25	91.74	99.17	99.14
Sensitivity (%)	96.43	96.42	99.68	98.65	99.87	99.49

Fig. 5. Results of STCP

C. Rigidity

To understand the significance of gait analysis for rigidity detection, Physionet's Gait Database is implemented. Preprocessed the data, extracted the features and implemented various state-of-the-art machine learning algorithms. The highest accuracy was noted to be 83.12% in Random Forest Classifier and Adaptive Boosting as shown in Fig. 6.

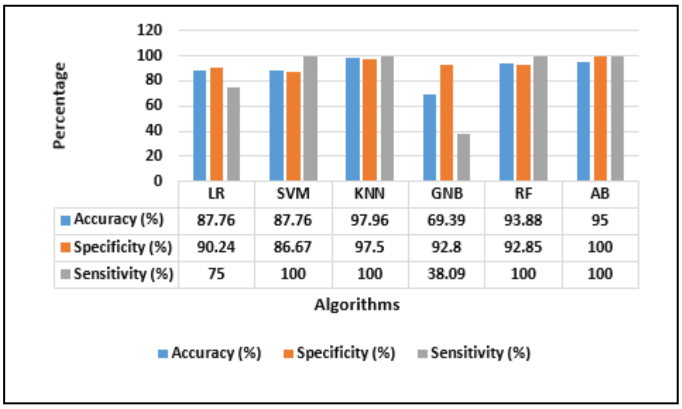


	LR	SVM	KNN	DT	SGD	RF	AB	HV
Accuracy (%)	75.32	76.62	74.03	70.13	77.92	83.12	79.22	80.52
Specificity (%)	80	91.66	72.22	58.06	86.66	89.47	83.33	80.95
Sensitivity (%)	74.19	73.84	74.57	78.26	75.8	81.03	77.96	80.35

Fig. 6. Results of Rigidity

D. Voice Impairment

The dataset of the UCI repository is used which consists the data of 31 people (23 PD affected patients and 8 healthy subjects). Various machine learning algorithms are implemented for the classification of the disease and the results are shown in fig. 7, got a maximum accuracy of 97.96% by implementing KNN on the same dataset.



	LR	SVM	KNN	GNB	RF	AB
Accuracy (%)	87.76	87.76	97.96	69.39	93.88	95
Specificity (%)	90.24	86.67	97.5	92.8	92.85	100
Sensitivity (%)	75	100	100	38.09	100	100

Fig. 7. Results of Voice Impairment

VI. Conclusion

Artificial Intelligence and medical sciences have developed a relationship that helps to cure pervasive diseases like PD. Various symptoms like Bradykinesia, Tremor at rest, Rigidity and Voice Impairment can be detected for early detection of PD. There is no definite medical procedure/diagnosis to cure parkinsonism of a person, which even applies to bioinformatics. But, strong tools like Machine Learning have abridged the process of detecting PD by making it economically viable and effective. Based on the researches discussed in this paper, machine learning can assist doctors in detecting PD. Simple electronic devices, like a mobile phone for voice recording, using software like Tappy for detecting slowness in movement, and many more can be utilized for detection. According to the results shown in section V, the detection of bradykinesia and tremor leads to the concrete results for the early detection of this disease. Moreover, noticed the accuracy of detection could be increased in two ways, by implementing ensemble approaches like bagging, boosting, voting, and by increasing the size of the dataset.

REFERENCES

[1] D. B. Calne "Is idiopathic parkinsonism the consequence of an event or a process" Neurology, Vol. 44, no. 15, pp. 5–5, 1994.

[2] J. Parkinson "An Essay on Shaking Palsy. London: Whittingham and Rowland Printing 1817".

[3] Surathi, P., Jhunjhunwala, K., Yadav, R., Pal, P. K. "Research in Parkinson's disease in India: A review : Annals of Indian Academy of Neurology" 19(1), 9–20. doi:10.4103/0972-2327.167713, 2016.

[4] Muthane UB, Chickabasaviah YT, Henderson J, Kingsbury AE, Kilford L, Shankar SK, et al. "Melanized nigral neuronal numbers in Nigerian and British individuals" Mov Disord. 2006;21:123941.

[5] Baldereschi M, Di Carlo A, Rocca WA, Vanni P, Maggi S, Perissinotto E, et al. "Parkinson's disease and parkinsonism in a longitudinal study: Two-fold higher incidence in men. ILSA Working Group. Italian Lon- gitudinal Study on Aging." Neurology. 2000;55:135863.

[6] Steven T. DeKosky, Kenneth Marek "Looking Backward to Move For- ward: Early Detection of Neurodegenerative Disorders" The American Association for the Advancement of Science Vol. 302, Issue 5646, pp. 830-834 DOI: 10.1126/science.1090349, 2003.

[7] Farhad Soleimanian Gharehchopogh, Peyman Mohammadi and Parvin Hakimi "Application of Decision Tree Algorithm for Data Mining in Healthcare Operations: A Case Study." International Journal of Com- puter Applications, Vol: 52, No:6, PP:21-26, 2012.

[8] A. Schrag, C. D. Good, K. Miszkiel, H. R. Morris, C. J. Mathias, A. J. Lees, and N. P. Quinn "Differentiation of atypical parkinsonian syndromes with routine MRI." Neurology, Vol. 54, pp. 697–702, 2000.

[9] R. Angel, W. Alston, and J. R. Higgins. "Control of movement in Parkinson's disease." Brain, Vol. 93, no. 1, pp. 1–14, 1970.

[10] S. L. Wu, R. M. Liscic, S. Kim, S. Sorbi, and Y. H. Yang "Non-motor symptoms of Parkinson's disease." Parkinson's Dis., 2017. DOI:10.1155/2017/4382518, 2017.

[11] T. Yousaf, H. Wilson, and M. Politis "Imaging the nonmotor symptoms in Parkinson's disease." Int. Rev. Neurobiol., Vol. 133, pp. 179–257, 2017.

[12] C. G. Goetz, et al. "Movement disorder society-sponsored revision of the unified Parkinson's disease rating scale (MDS-UPDRS): Scale presentation and clinimetric testing results." Mov. Disord., Vol. 23, no. 15, pp. 2129–70, 2008.

[13] B. Post, M. P. Merkus, R. M. de Bie, R. J. de Haan, and J. D. Speelman "Unified Parkinson's disease rating scale motor examination: Are ratings of nurses, residents in neurology, and movement disorders specialists interchangeable?" Movement Dis., Vol. 20, pp. 1577–84, 2005.

[14] R.L. Albin, A.B. Young and J.B. Penney, "The functional anatomy of basal ganglia disorders." Trends Neurosci 1989; 12: 366–75, 1989.

[15] M.R. DeLong "Primate models of movement disorders of basal ganglia origin." Trends Neurosci. 1990 Jul;13(7):281-5, 1990.

[16] R. Levy, W.D. Hutchison, A.M. Lozano and J.O. Dostrovsky "Synchro- nized neuronal discharge in the basal ganglia of parkinsonian patients is limited to oscillatory activity." Neurosci 2002; 22: 2855–61, 2002.

[17] P. Brown "Oscillatory nature of human basal ganglia activity: relation- ship to the pathophysiology of Parkinson's disease." Mov Disord 2003; 18: 357–63, 2003.

[18] A. Berardelli, J. C. Rothwell, P. D. Thompson, M. Hallett, "Pathophysi- ology of bradykinesia in Parkinson's disease." Brain, Volume 124, Issue 11, November 2001, Pages 2131–2146, 2001.

[19] Schilder JC, Overmars SS, Marinus J, van Hilten JJ, Koehler PJ, "The terminology of akinesia, bradykinesia and hypokinesia: Past, present and future." Parkinsonism Relat Disord. 2017;37:2735. doi: 10.1016/j.parkreldis.2017.01.010., 2017.

[20] Adams, Warwick R. "High-accuracy detection of early Parkin- son's Disease using multiple characteristics of finger movement while typing." PloS one vol. 12,11 e0188226. 30 Nov. 2017, doi:10.1371/journal.pone. 0188226, 2017.

[21] Dunnewold, Rob J. W.; Hoff, Jorrit I.; van Pelt, Hans C. J.; Fredrikze, Pauline Q.; Wagemans, Erik A. H.; van Hilten, Bob J. J "Ambulatory Quantitative Assessment of Body Position, Bradykinesia, and Hypokine- sia in Parkinson's Disease." Journal of Clinical Neurophysiology: May 1998 - Volume 15 - Issue 3 - p 235-242, 1998.

[22] Suganya, P., and C. P. Sumathi, "A Novel Metaheuristic Data Mining Algorithm for the Detection and Classification of Parkinson Disease." Indian Journal of Science and Technology 8.14, 2015.

[23] Verma A, Kaur I, Singh I, "Comparative analysis of data mining tools and techniques for information retrieval." Indian Journal of Science and Technology. 2016; 9(11), 2016.

[24] Çakmak, Y. Ö; Ö lçek, S.C.; Ö zsoy, B.; Gökçay, D." Quantitative Measurement of Bradykinesia in Parkinson's Disease Using Commercially Available Leap Motion." Biosignals, Proceedings of the 11th International Joint Conference on Biomedical Engineering Systems and Technologies; Funchal: Madeira, Portugal, 2018; Volume 3, pp. 227–232. 2018.

[25] T. Arroyo-Gallego et al., "Detection of Motor Impairment in Parkin- son's Disease Via Mobile Touchscreen Typing." IEEE Transactions on Biomedical Engineering, vol. 64, no. 9, pp. 1994-2002, Sept. 2017. doi: 10.1109/TBME.2017.2664802, 2017.

[26] Thompson, A. "The speed you type on a keyboard could reveal if you are in the early stages of Parkinson's disease." Published online August 30, 2018.

[27] Adams, WR. "The detection of hand tremor through the characteristics of finger movements while typing." Posted August 5, 2018. bioRxiv 385286; doi:https://doi.org/10.1101/385286. Accessed online September 17, 2018., 2018.

[28] Chen W, Hopfner F, Becktepe JS, Deuschl G. "Rest tremor revis- ited: Parkinson's disease and other disorders." Transl Neurodegener. 2017;6:16. Published 2017 Jun 16. doi:10.1186/s40035-017-0086-4., 2017.

[29] Hughes AJ, Daniel SE, Blankson S, Lees AJ. "A clinicopathologic study of 100 cases of Parkinson's disease." Arch Neurol. 1993;50:140–8. doi: 10.1001/archneur.1993.00540020018011., 1993.

[30] Rajput AH, Rozdilsky B, Ang L. "Occurrence of resting tremor in Parkinson's disease." Neurology. 1991;41:1298–9. doi: 10.1212/WNL.41.8.1298., 1991.

[31] Deuschl G, Papengut F, Hellriegel H. "The phenomenology of parkin- sonian tremor." Parkinsonism Relat Disord. 2012;18(Suppl 1):S87–89. doi: 10.1016/S1353-8020(11)70028-1., 2012.

[32] Papengut F, Raethjen J, Binder A, Deuschl G. "Rest tremor suppression may separate essential from parkinsonian rest tremor.' Parkinsonism Re- lat Disord. 2013;19:693–7. doi: 10.1016/j.parkreldis.2013.03.013, 2013.

[33] Lonini, L., Dai, A., Shawen, N. et al. "Wearable sensors for Parkinson's disease: which data are worth collecting for training symptom detection models." npj Digital Med 1, 64 (2018) doi:10.1038/s41746-018-0071-z., 2018.

[34] Wiken, M., Rossi, M. D., Rivero, A. D., Hallett, M., & Merello, M. "Latency of re-emergent tremor in Parkinson's disease is influenced by levodopa." Parkinsonism & Related Disorders.' doi:10.1016/j.parkreldis.2018.10.019., 2018.

[35] Gillivan-Murphy, P., Miller, N., & Carding, P. "Voice Tremor in Parkinson's Disease: An Acoustic Study. Journal of Voice." doi:10.1016/j.jvoice.2017.12.010., 2017.

[36] Alper, M. A., Morris, D.,& Tran, L. "Remote detection and measurement of limb tremors. 2018 5th International Conference on Electrical and Electronic Engineering (ICEEE)." doi:10.1109/iceee2.2018.8391329., 2018.

[37] M. Arlotti, L. Rossi, M. Rosa, S. Marceglia, and A. Priori "An external portable device for adaptive deep brain stimulation (aDBS) clinical research in advanced Parkinson's disease." Med Eng Phys, vol. 38, pp. 498-505, May 2016., 2016.

[38] Yao, L., Brown, P., Shoaran, M., "Resting Tremor Detection in Parkinson's Disease with Machine Learning and Kalman Filtering.", 2018 IEEE Biomedical Circuits and Systems Conference (BioCAS). doi:10.1109/biocas.2018.8584721, 2018.

[39] Endo, T., Okuno, R., Yokoe, M., Akazawa, K., Sakoda, S. "A novel method for systematic analysis of rigidity in Parkinson's disease. Move- ment Disorders.", 24(15), 2218–2224. doi:10.1002/mds.22752., 2009.

[40] Di Biase, Lazzaro et al., "Quantitative Analysis of Bradykinesia and Rigidity in Parkinson's Disease.", Frontiers in neurology vol. 9 121. doi:10.3389/fneur.2018.00121, 2018.

[41] Baradaran, N., Tan, S. N., Liu, A., Ashoori, A., Palmer, S. J., Wang, Z. J., Oishi M. M. K., McKeown, M. J., "Parkinson's Disease Rigidity: Relation to Brain Connectivity and Motor Performance." Frontiers in Neurology, 4. doi:10.3389/fneur.2013.00067, 2013.

[42] Opara J, Malecki A, Malecka E, Socha T., "Motor assessment in Parkinson's disease.", Ann Agric Environ Med 24:411–415. https://doi.org/10.5604/12321966.1232774, 2017.

[43] Ossig, C., Antonini, A., Buhmann, C., Classen, J., Csoti, I., Falken- burger, B., . . . Storch, A., "Wearable sensor-based objective assessment of motor symptoms in Parkinson's disease.", Journal of Neural Trans- mission, 123(1), 57–64. doi:10.1007/s00702-015-1439-8, 2015.

[44] S. Aghanavesi, J. Westin., "A review of Parkinson's disease cardinal and dyskinetic motor symptoms assessment methods using sensor systems.", pp. 52–57, 2016.

[45] Yeung, L.F., et al., "Evaluation of the Microsoft Kinect as a clinical assessment tool of body sway.", Gait Posture 40(4), 532–538, 2014.

[46] Shetty, S., & Rao, Y. S., "Estimate and replace: A novel approach to integrating deep neural networks with existing applications.SVM based machine learning approach to identify Parkinson's disease using gait analysis.", 2016 International Conference on Inventive Computation Technologies (ICICT). doi:10.1109/inventive.2016.7824836, 2016.

[47] Morris JR., "Accelerometry – a technique for the measurement of human body movements.", J Biomech 1973;6:729–36, 1973.

[48] Shull PB, Shultz R, Silder A, Dragoo JL, Besier TF, Cutkosky MR, et al., "Toe-in gait reduces the first peak knee adduction moment in patients with medial compartment knee osteoarthritis.", J Biomech 2013;46:122–8, 2013.

[49] Rouhani H, Favre J, Crevoisier X, Aminian K., "Measurement of multi- segment foot joint angles during gait using a wearable system.", J Biomech Eng 2012;134:061006, 2012.

[50] Pete B. Shull, Wisit Jirattigalachote, Michael A. Hunt, Mark R. Cutkosky, Scott L. Delp., "Quantified self and human move- ment: A review on the clinical impact of wearable sensing and feedback for gait analysis and intervention, Gait & Pos- ture.", Volume 40, Issue 1, 2014, Pages 11-19, ISSN0966-6362 https://doi.org/10.1016/j.gaitpost.2014.03.189, 2014.

[51] Löhle M, Storch A, Reichmann H, "Beyond tremor and rigidity: non- motor features of Parkinson's disease.", J Neural Transm (Vienna) 116: 1483-1492., 2009.

[52] Schalling E, Johansson K, Hartelius L, "Speech and Communication Changes Reported by People with Parkinson's Disease", Folia Phoniatr Logop 69: 131-141, 2017.

[53] Defazio G, Guerrieri M, Liuzzi D, "Assessment of voice and speech symptoms in early Parkinson's disease by the Robertson dysarthria profile.", 2015.

[54] Goberman AM, Blomgren M, Metzger E, "Characteristics of speech disfluency in Parkinson disease.", Journal of Neurolinguistics 23: 470- 478, 2010.

[55] Cohen H, "Disorders of Speech and Language in Parkinson's Disease. Mental and Behavioral Dysfunction in Movement Disorders.", Humana Press pp.125-134., 2003.

[56] Berus, L., Klancnik, S., Brezocnik, M., & Ficko, M., "Classifying Parkinson's Disease Based on Acoustic Measures Using Artificial Neural Networks.', Sensors, 19(1), 16. doi:10.3390/s19010016, 2018.

[57] Dubey H, Goldberg JC, Abtahi M, "EchoWear: smartwatch technology for voice and speech treatments of patients with Parkinson's disease.", in Proceedings of the conference on Wireless Health, Bethesda, Maryland pp.1-8, 2015.

[58] Shirvan, R. A., & Tahami, E., "Voice analysis for detecting Parkin- son's disease using genetic algorithm and KNN classification method.", 2011 18th Iranian Conference of Biomedical Engineering (ICBME). doi:10.1109/icbme.2011.6168572, 2011.

[59] Bocklet, T., Noth, E., Stemmer, G., Ruzickova, H., & Rusz, J., "Detec- tion of persons with Parkinson's disease by acoustic, vocal, and prosodic analysis.", 2011 IEEE Workshop on Automatic Speech Recognition & Understanding. doi:10.1109/asru.2011.6163978, 2011.

[60] Rusz, J., Čmejla, R., Růžičková, H., Klempíř, J., Majerová, V., Pic- mausová, J., . . . Růžička, E., "Acoustic assessment of voice and speech disorders in Parkinson's disease through quick vocal test.", Movement Disorders, 26(10), 1951–1952. doi:10.1002/mds.23680, 2011.

[61] Harel, B. T., Cannizzaro, M. S., Cohen, H., Reilly, N., & Snyder, P. J., "Acoustic characteristics of Parkinsonian speech: a potential biomarker of early disease progression and treatment.", Journal of Neurolinguistics, 17(6), 439–453. doi:10.1016/j.jneuroling.2004.06.001, 2004.

[62] Martínez-Sánchez F, Meilán JJG, Carro J, Gómez Íñiguez C, Millian- Morell L, et al., "Speech rate in Parkinson's disease: A controlled study.", Neurolog´ıa (English Edition) 31: 466-472, 2016.

[63] Horak, F. B. and Mancini, M., "Objective biomarkers of balance and gait for Parkinson's disease using body-worn sensors.", Mov Disord., 28: 1544-1551. doi:10.1002/mds.25684, 2013.

[64] Sriram T.V.S., Rao M.V., Narayana G.V.S., Kaladhar D.S.V.G.K., "Di- agnosis of Parkinson Disease Using Machine Learning and Data Mining Systems from Voice Dataset.", Proceedings of the 3rd International Con- ference on Frontiers of Intelligent Computing: Theory and Applications (FICTA) 2014, 151–157. doi:10.1007/978-3-319-11933-517, 2015.

[65] Sriram, Tarigoppula & Rao, M. & Narayana, G & Vital, T. & Dowluru, Kaladhar SVGK., "Intelligent Parkinson Disease Prediction Using Ma- chine Learning Algorithms.", IJEIT. 3. 212-215, 2013.