

Multimodal Machine Learning Framework for Early Detection of Parkinson's Disease Using Hand Drawings, Vocal Features, ECG, and Gait Analysis

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ABSTRACT

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This work discusses multi-modal detection of Parkinson's disease through advanced machine learning techniques applied on handwriting, voice, ECG patterns, and gait patterns. Early diagnosis is important since the progression of PD is bound to negatively influence even non-motor functions besides motor functions, thus severely affecting the quality of life. The motor symptoms are further emphasized in handwriting analysis in the form of variations in spirals' drawing angles and the amplitudes of wave drawings, which are compromised of fine control. Among the deep learning models tested, DenseNet-121 was exceptional, with an accuracy of 85.17%, which was more than other architectures such as ResNet, AlexNet, and VGG16. Voice analysis is more on non-motor symptoms, which focus on speech disturbances due to tremors and rigidity. Through different machine learning classifiers such as Support Vector Machines, K-Nearest Neighbors, XGBoost, among others, the slight vocal characteristics related to PD were well-detected. The SVM proved to be the most efficient model with 89.74% accuracy, where both precision and recall were well-balanced, thereby demonstrating its efficiency in this area. The scope was widened beyond handwriting and speech by bringing in ECG data analysis, which could possibly provide further diagnostics. Gradient Boosting, Logistic Regression, and Random Forest were evaluated for the dataset, with Gradient Boosting having shown the highest accuracy at 89.57%. Similarly, with gait analysis through chest-mounted MPU sensor data, new perspectives about motor symptoms arose. In the area of gait analysis, AdaBoost model proved to be better to study gait patterns, showing an accuracy of 85.71%, proving the detection of such minor gait abnormalities that most of the classical assessment tends to miss. Integrating handwriting, voice, ECG, and gait analysis in a study brings a holistic framework that goes beyond clinical approaches in conventional methods of diagnosis. Different use of machine learning models enables the early and accurate detection of Parkinson's disease, making interventions at the right time possible.

Keywords: — Multi-modal detection, Parkinson's disease, machine learning, handwriting analysis, speech analysis, ECG patterns, gait patterns, early diagnosis, DenseNet-121, Support Vector Machines, Gradient Boosting, AdaBoost, tremors, fine motor control, holistic framework, deep learning, spiral drawing analysis, wave drawing analysis, vocal disturbances, neurodegenerative disorder

I. INTRODUCTION

Parkinson's disease (PD) is a neurodegenerative disease with progressive loss of dopaminergic neurons in the substantia nigra of the brain. Dopamine deficiency causes imbalances in the system of motor control, giving way to such well-known features of the disease as tremors, muscle rigidity, bradykinesia, and postural instability. Although Parkinson's disease most frequently occurs in the elderly, early-onset Parkinson's can occur in younger people, usually younger than 50. Through the progression of the disease, the symptoms commonly worsen, severely impairing both physical and emotional well-being. Beyond the motor symptoms, common non-motor symptoms such as sleep disorders, decline in cognitive functions, depression, anxiety, and autonomic dysfunction are also widespread and often present before the motor symptoms appear. These non-motor features make it a little challenging to diagnose Parkinson's disease early. The complexity of such features gave birth to the need to develop new diagnostic tools and therapeutic strategies to combat the multifaceted nature of the disease and improve patient outcomes.

Parkinson's disease is the most common neurodegenerative disorder in the world, with a steady rise in prevalence. The increase is more pronounced in countries with a high proportion of elderly people. With increased life expectancy and proportion of elderly population, Parkinson's disease has become a major public health problem. It is estimated that there are approximately 10 million patients living with Parkinson's disease at present, and the prevalence will double by 2040 in high-income countries with aging populations. There will be a large increase in Parkinson's cases within the United States. This will further add stress to the health care systems in the country. Other than health care, the Socio-Economic implications of more cases of Parkinson's are very severe since patients often need long-term care and support. The caregivers also suffer greatly both physically, emotionally, and financially due to the progressive nature of the disease. This has brought into limelight the great need for early diagnosis and efficient management strategies to reduce the effect of Parkinson's in individuals, families, and the healthcare system at large.

Molecularly, Parkinson's is mainly caused by the aggregation of alpha-synuclein proteins, which causes toxic clumping that forms Lewy bodies within the neurons. These Lewy bodies disrupt normal cellular function and the death of dopaminergic neurons leads to a variety of both motor and non-motor symptoms. This disease pathology is further made complex by contributing factors of mitochondrial dysfunction, oxidative stress, and neuroinflammation that causes degeneration in neurons. Such molecular mechanisms for understanding will provide the basis in developing targeted therapy that may result in arresting the progression of such a disease, or at best, slowing its progression. Current research studies would focus on finding drugs or the intervention that, hopefully can possibly prevent accumulation of alpha-synuclein or protect neurons against oxidative damage to improve dopaminergic neuronal generation. Yet up to date still, no actual cure was produced for this disease as the science behind molecular biology and biotechnology would open up various prospects that seemed more fitting that maybe someday be able to produce hope in one of the afflicted patients.

The risk factors in Parkinson's are a combination of genetic, environmental, and lifestyle factors. Most genetic predispositions involved in the Parkinson's disease arise from mutations on the LRRK2 gene, PARK7, and a few other linked genes. Most of these mutations produce abnormal protein folding, mitochondrial impairment, and neuroinflammation, which are all potential causes of onset. Exposure to pesticides, herbicides, and other neurotoxin has been considered a likely environmental risk factor. Occupational exposure seems to be linked in an age- and industry-adjusted fashion to higher rates of Parkinson's in workers in agriculture and industry. Head trauma is another lifestyle factor that could contribute to the risk. Low levels of physical activity and poor dietary practices have also been associated with higher risks. The prevention of risk factors of Parkinson's disease is being considered as prevention of head injuries, diet, and regular exercise. The coming together of genetics and environment provides proof of the complexities in Parkinson's and leads the researchers to recommend more personalized forms of prevention and treatment.

The wide variety of symptoms that present with Parkinson's disease makes diagnosis and treatment especially tricky. The typical motor symptoms related to the condition include tremor, rigidity, and bradykinesia, but these can also be more recognizable in later stages. However, the early onset of non-motor symptoms such as cognitive decline, depression, sleep disturbances, and autonomic dysfunction often makes diagnosis problematic, because these symptoms might coexist with other diseases. The majority of these non-motor symptoms go unnoticed or are misdiagnosed, causing a delay in diagnosis and exacerbating the quality of life of the patients. Cognitive impairments include loss of memory and difficulties with executive function, common in the later stages of Parkinson's disease, while depression is common in patients even before the emergence of motor symptoms. Therefore, it emphasizes the need for a more holistic approach to diagnosis, encompassing both motor and non-motor symptoms, and alerts clinicians to subtle early signs that may precede the classic motor symptoms.

Early diagnosis of Parkinson's will improve the results of the patient since early intervention may retard the rate of disease progress and sometimes the symptoms disappear. At the moment, there is no single specific test that one can apply for the diagnosis of Parkinson's disease. Mostly it is diagnosed from clinical assessment involving evaluation of some motor symptoms in patients and patients' histories besides family histories. Among new diagnostic techniques for Parkinson's include handwriting and voice analysis, potentially able to capture the early phases of the disease. Patients with Parkinson's usually manifest micrographia (small and cramped handwriting), as well as changes in quality and pitch that can be evaluated and measured digitally with the assistance of machine learning algorithms. If monitored closely enough, such variations may help a clinician notice Parkinson's far earlier than he or she otherwise could. This early detection is crucial for initiating treatments that may help to slow down disease progression and improve the patient's quality of life. With the integration of advanced diagnostic technologies, early diagnosis and intervention for Parkinson's disease are becoming more achievable, offering hope for improved management of the disease.

Current issues in Parkinson's management include a lack of an absolute biomarker for its diagnosis and a failure to treat the non-motor symptoms that severely affect patients. While therapies such as levodopa and dopamine agonists have been created, they target primarily the motor symptoms and do not halt the progression of the disease. A final therapy option is DBS, where some patients experience relief of their motor symptoms. However, this is not a treatment. The hardest to treat and most debilitating quality of life issues in these patients are non-motor symptoms such as depression, cognitive impairment, and disturbances in sleep. Treatment would have to be an integration of pharmacologic and nonpharmacologic strategies. Researchers have been working intensively to look for new therapies that could make non-motor symptoms decrease with improvement in patients' well-being. Diagnostic techniques, such as blood tests, imaging techniques, and genetic testing, will further be used to advance early detection and patient outcomes. Therapies will continue to be the area of research interest for Parkinson's disease management.

Handwriting analysis has been developed as a vital tool for the early detection of Parkinson's disease. It provides a non-invasive, cost-effective method for tracking the progression of the disease. Patients suffering from Parkinson's show micrographia, in which their handwriting is smaller, cramped, and irregular in shape, as the disease progresses. Now, with digital platforms, the changes in the handwriting patterns can be tracked over time, which will enable health care professionals to assess the severity of the disease. In particular, spiral and wave drawings have been used to assess motor control and can reveal early signs of Parkinson's. Machine learning algorithms applied to these handwriting patterns can provide quantitative insights, making it easier to monitor disease progression and track treatment efficacy. Because handwriting analysis is easy, accessible, and inexpensive, it has tremendous potential for use in both clinical and home settings, thus making it possible to monitor patients continuously and diagnose Parkinson's disease at an early stage.

Voice analysis is another promising technique for early detection of Parkinson's disease. Speech patterns even change before other overt motor symptoms, such as hypophonia (low speech volume), monotonic speech, and limited pitch variation. The reason for these changes is that the vocal muscles are weakened because of the depletion of dopamine in the brain. Researchers have successfully devised ways of using machine learning algorithms to assess acoustic features, including jitter, shimmer, and pitch variation, in the evaluation of subtle changes in the voice, which often mark the very early stages of Parkinson's disease. Similar to handwriting analysis, voice analysis allows for a non-invasive method for early detection and is thus a potential approach that can monitor the patient in real time with continuity. This makes it a highly scalable solution for large populations, and it could serve as a valuable addition to a multi-modal diagnostic approach for Parkinson's disease.

It is now increasingly acknowledged that ECG analysis may be used to understand autonomic dysfunction that typically occurs in patients with Parkinson's disease. It is now understood that this condition can sometimes manifest as alterations in heart rate variability, detectable through measurements in an electrocardiogram. Heart rate variability is essentially the balance between the sympathetic and parasympathetic nervous systems, which in Parkinson's disease is disrupted. From ECG data, the researchers can deduce the extent of autonomic dysfunction that plays a role in the progression of Parkinson's disease. Analysis of ECG in combination with other diagnostic methods like voice and handwriting analysis may be used to have a better view of the disease's progression. In addition, wearable ECG sensors enable continuous monitoring, which is useful for both clinical assessment and research purposes. This can improve the understanding of the impact of the disease on the autonomic nervous system and contribute to better diagnostic and therapeutic strategies.

Another very critical tool for the early detection and monitoring of Parkinson's disease is gait analysis. In early disease stages, alterations in the patterns of walking are detectable as reduced stride length, slowing down of the gait, and changes in gait rhythm. Wearable sensors, particularly IMUs, make it possible to track the movement with very high precision, enabling the precise recording of the aforementioned early motor changes. Advances in 3D motion analysis technology further improve the gait analysis, allowing one to capture much more detailed insights into motor performance. Gait changes are, in fact often among the very first noticeable indicators of Parkinson's disease; this is why analysis of gait is such a crucial tool in early detection of the disease. Continuous monitoring of patients' gaits helps to detect the subtlety in motor changes and intervene before patients become critically aware of these motor changes. This approach is also scalable, as wearable sensors can be used in clinical settings or at home, enabling patients to monitor their symptoms in real-time.

Besides the classical detection methods, research has led to the introduction of alternative techniques in the very early identification of Parkinson's disease. They include testing through the sense of smell, tracking of eye movement, and examination of cerebrospinal fluid biomarkers. Olfactory dysfunction includes a loss or diminishment of smell sensation and is one of the most common presenting symptoms years before the onset of motor features. Olfactory testing can, thus, identify individuals who are

liable to suffer the consequences of the disease since it is closely related with the progression. Eye movement abnormalities, including hypoblink rates and defective saccadic movements, are early findings that may potentially place a patient at risk for Parkinson's. The abnormal eye movements reflect pathology in movement-related brain areas and can be detected without intrusiveness using eye-tracking technology. Alpha-synuclein, a protein that aggregates into Lewy bodies in Parkinson's patients, is another kind of CSF biomarker. These samples give direct pathological evidence. However, CSF analysis requires procedures such as lumbar puncture, which can limit its use generally. Despite these disadvantages, olfactory testing, eye movement tracking, and CSF biomarker analyses can become additional useful tools along with others; diagnostic practices such as handwriting analysis or voice biomarkers can more effectively provide a better accuracy of diagnosis for a better overall portrayal of Parkinson in the early times.

The modern age of diagnosing Parkinson's completely overhauls its landscape via AI and the application of related machine learning capabilities. AI and ML algorithms can now process and analyze multimodal data from sources, such as handwriting, voice, gait, and ECG, that can uncover subtle patterns the human clinician cannot identify on his own. It can contribute to improved both diagnostic accuracy and early intervention as it can indicate subtle biomarkers of disease progression. For example, AI models can now discern the changes in handwriting, from being smaller and more variable in size, or voice changes, such as pitch and tremor, to a degree of precision never before possible. AI-powered wearable devices are part of the daily lives of patients, providing continuous streams of data through constant, real-time monitoring and thus allowing for continuous evaluation of the progression of the disease. These devices, equipped with sensors for gait analysis, voice monitoring, and ECG, offer insights into the state of the disease and help in the personalization of treatment plans. Scalability in AI-driven solutions could monitor larger numbers of patients while incrementally allowing changes in symptomatology, suggesting an earlier time to identify that conditions are getting worse and a much more proactive role in patient care. A variety of diagnostic approaches, including handwriting, voice, ECG, and gait analysis, through a single platform can be connected to allow medical professionals and scientists to better realize Parkinson's early on.

This novel approach to Parkinson's disease diagnosis uses AI and machine learning along with non-invasive technologies to make early, accurate, and personalized diagnoses. It analyzes biomarkers in voice, gait, tremors, and other variables to create a complete disease profile that allows timely interventions. It equips patients and their caregivers with precious information for proper treatment and lifestyle choices, but real-time monitoring eliminates uncertainty and enhances patient control while providing a caregiver with actionable daily management. It is hoped that widespread use of this integrated system can improve quality of life, slow down the progression of the disease, and reduce health burdens. There is hope now for patients and families in this transformational shift in the management of Parkinson's disease with the use of AI and machine learning when coupled with respective hardware systems.

II. RELATED WORKS

Several studies have been conducted on the early detection and progression analysis of Parkinson's disease using different methodologies with the assistance of ever-evolving technologies and data-driven approaches. Literature highlights that a considerable number of factors such as vocal attributes, handwriting analysis, gait patterns, and biometric indicators like SpO2 and ECG can help in the early identification of the disease. This survey attempts to highlight current research on the use of integrated multi-modal data and machine learning techniques for Parkinson's disease detection and severity assessment in terms of important advancements, challenges, and gaps in the current state of research.

Studies investigate advanced speech processing techniques to apply them to the clinical assessment of motor phenomena in individuals with Parkinson's disease, with special interest in voice as a rich source of motor biomarkers. Personalized Convolutional Recurrent Neural Networks and Phone Attribute Codebooks are applied for the analysis of voice recordings of 14 patients with Parkinson's disease who had their ON and OFF motor states before and after dopaminergic medication assessed. The p-CRNN model achieved a very high classification accuracy of 82.35% with sensitivity and specificity rates at 0.86 and 0.78, respectively, whereas the PAC-based approach achieved an accuracy of about 73.08% with a sensitivity and specificity of 0.69 and 0.77, respectively. Although the performance of the PAC is lower, it offers a better interpretability of computational biomarkers, which are valuable for clinical applications. Both approaches have highlighted the features of speech affected by dopaminergic treatment: phonetic and prosodic ones, thus bringing to light separate components of speech that are specifically linked to the states of PD. ^[1]

In order to detect these conditions, there are ML analyses applied with voices from 432 patients out of which 278 had Parkinson's Disease in different datasets acquired here such as three: from UCI ML Respository. Four ML models—ANN, RF, GB, and SVM—are combined with two ensemble methods, namely, soft voting classifier - EVC and stacking method - ESM. These are trained and tested through 50 iterations of analysis using different data splits and 10-fold cross-validation. Results showed that the ESM, SVM, and GB models had a strong consistency in outperforming others on key metrics: accuracy, sensitivity, specificity, precision, F1 score, and ROC AUC. The models still delivered high performance, thus upholding the strength of this approach. In brief, the findings seem to suggest promising ML-driven voice analysis in PD early diagnosis and especially with models such as the ESM, SVM, and GB. Its use of varieties of datasets combined with large samples will further empower the reliability and validity and thereby boost generalizability. Such findings have high clinical relevance for the speech-language pathologists, and they now boast more sophisticated tools to sharpen diagnosis, enhance the process of intervention, and progress the improvement in patients. ^[2]

The current study addresses the challenge of distinguishing Parkinson's disease (PD) from essential tremor (ET), two of the most common movement disorders that have overlapping clinical features, using automated speech analysis. Both conditions manifest distinct speech patterns—hypokinetic dysarthria in PD and hyper kinetic dysarthria in ET—but speech assessment has been less explored for the purpose of differentiation. The authors note that phonetic variability across languages is one of the primary barriers to the development of a universal diagnostic framework. For this purpose, Gaussian mixture models were applied in order to assess domain adaptation across languages for the classification of PD and ET patients in Czech using models trained in German and Spanish. Speech was analyzed across three dimensions: articulation, phonation, and prosody. The performance is evaluated on a bi-class setting, which deals with PD against ET and the Tri-class PD, ET, and healthy control. It demonstrates that if all speech dimensions are put together, binary classification's peak accuracy was seen to be attained at 81.4% and 86.2% for monologue and /pa-ta-ka/ tasks. In the case of Tri-class, healthy signal integration provided a result of achieving accuracies to be at 63.3% and 71.6% for those tasks. The findings show that the integration of machine learning into automated speech analysis is an effective and adaptable tool in distinguishing between PD and ET, especially across languages, which could enable early diagnosis and ongoing monitoring of patients. ^[3]

Handwriting, especially spiral drawing, is essential for early stages of Parkinson's disease diagnosis. Most AI techniques currently used are based on equipment that, in most circumstances, cannot be used at home. A possible diagnostic approach should be based on visual features inherent in hand drawing. An archimedes dataset was developed; it captures certain characteristics of drawing, such as tremor and spacing, suitable for a different scenario. Hand drawing-based visual information was more informative of PD traits than dynamic information in ablation studies. The new Continuous Convolution Network called CC-Net was proposed which reduced the pooling layers to draw diverse features from images and maintained critical image information. CC-Net showed very robust performance at 89.3% classification accuracy, 0.733 MCC, and average AUC at 0.934. It shows that analysis of hand-drawing has the potential to provide accessible accurate diagnostic solutions for Parkinson's disease. ^[4]

To improve the spiral drawing test for detecting the motor symptoms of Parkinson's disease (PD), a new smart ink pen equipped with motion and force sensors was developed. Compared to other traditional digitizers, this smart ink pen still holds the natural gesture and user-friendliness of standard handwriting tools, thus appropriate for clinical use. There were 29 patients with PD and 29 age-matched controls included in the study. Spiral drawings were analyzed based on 45 indicators. Key findings included reduced fluency, variable applied force, and kinematic spectral peaks in the 4–7 Hz band among PD patients. These indicators captured disease-related motor impairments that clinical scales could only moderately correlate with. Machine learning models demonstrated a high classification accuracy of 94.38%, highlighting fluency and power distribution as crucial discriminators. This smart-pen approach serves as a quantitative, time-saving supplement to a clinician's more traditional tests to detect the symptoms of this disease and keep track of those symptoms. ^[5]

This study used tablet technology to support the medical diagnosis of Parkinson's disease through machine learning for handwriting abnormalities, a common symptom of Parkinson's disease. In contrast to previous studies conducted on isolated words or sentences, this study tested handwriting as a sequence of sentences so that the progression in writing characteristics over time could be captured. The study comprised handwriting samples from 24 patients with Parkinson's disease and from 24 healthy controls. Feature selection was carried out by exhaustive search, and binary classification was done using an SVM algorithm. The model had an overall accuracy of 91.67%, thus outperforming previous studies in the fact that it achieved superior results using fewer features. This methodology brings out the potential of analyzing temporal handwriting changes for effective PD diagnosis using advanced tablet-based tools and machine learning techniques. ^[6]

This review aims at summarizing, in detail, the key technologies and algorithms involved in the assessment of gait features in patients with Parkinson's disease (PD) with special attention to diagnosis and symptom monitoring. The present review considered published articles between January 1, 2005, and August 30, 2019, retrieved from PubMed, addressing gait analysis in PD. Only studies that utilized technologies to differentiate between PD patients and healthy controls or stratify them according to motor status or stages of the disease and reported at least 80% sensitivity and specificity were included. The algorithms for diagnosis in gait analysis showed a balanced accuracy range of 83.5–100%, with sensitivity and specificity between 83.3–100% and 82–100%, respectively. The accuracy for motor status discrimination ranged from 90.8–100%, sensitivity ranged between 92.5–100%, and specificity between 88–100%. These results establish promising applications for gait analysis algorithms in the clinical arena as providing an accurate and reliable measurement of diagnosing PD and the progression of its symptoms. Despite the huge volume of studies on objective gait analysis for PD, only a few have reported algorithms with adequate accuracy to be clinically useful. [7]

The objective was to observe a six-year journey of PD within the disease stage, making necessary distinctions between whether the change should be accredited or attributed to mere aging, changes due to pharmacological influences like medication, and changes purely driven by pathology through the pathology involved in PD itself. Gait disturbance is quite an early presentation of Parkinson's disease. An early indication which often manifests within the pathology process is usually attributed to falls in patients. If optimal dopaminergic medication can occur, gait impairments actually progress, further underlining its importance. The study included 109 newly diagnosed PD participants and 130 control subjects, who all underwent at least two gait assessments within a period of up to six years. Gait was assessed every 18 months by using an instrumented walkway to measure sixteen spatiotemporal gait characteristics. The progression of the characteristics was estimated using linear mixed-effects models. Results indicated that ten gait features significantly deteriorated in patients with PD, with four of these deteriorations being caused directly by the progression of disease. Two others contributed to the deterioration due to aging, so these reflect the interplay between aging and disease progression. Gait impairment remains progressive for all features except for step width variability regardless of dopaminergic medication adjustments. The findings are suggestive of gait impairments in PD progression over time both by disease-specific mechanisms and by age-related factors, with little correlation to adjustments in dopaminergic therapy. [8]

This study looks at the effects of DBS using directional current steering on gait in advanced patients suffering from Parkinson's Disease. The effectiveness of DBS is an important benefit, but this is often at a cost; PD patients with active DBS develop gait problems. Therefore, this study is to establish if the gait side effects would be improved and even reversed when directional current steering is employed during DBS treatment. Eleven PD patients that received an implanted directional lead took part in the study. The direction of the pyramidal tract identified during directional mode screening was set to 0°. Patients conducted two tests—the six-meter-walk test and the time-up-and-go (TUG) test—while a three-dimensional motion capture system captured a range of gait parameters. The study measured gait under different conditions, including baseline, directional steering at eight angles (0°, 45°, 90°, 135°, 180°, 225°, 270°, and 315°), conventional ring mode, and placebo stimulation (0 mA), with pulse width and frequency kept constant. The results showed that there were no significant differences in gait parameters during the six-meter-walk test between the directional, baseline, placebo, or ring modes ($p > 0.05$). However, during the TUG test, stride length was significantly different at 0° compared to other directions ($p < 0.001$), though no significant differences were found for other gait parameters. A slight narrowing of stride width was observed in the 0° direction but was not statistically significant. Conclusion. The study has shown that directional current steering in DBS may allow for improvement in gait performance in PD patients without harmful side effects of pyramidal tract stimulation. [9]

The current study is concerned with the clinical features and ECG parameters relationship in patients suffering from Parkinson's disease. The clinical features among 156 enrolled patients with Parkinson's disease included BMI, age, disease duration, and stage, and ECG parameters involved RR, PR, QRS, and QT intervals as well as heart rate-corrected QT. The findings were such that BMI had a positive correlation with both PR and QRS intervals in patients with PD. Furthermore, QRS interval showed a positive correlation with disease duration and Hoehn and Yahr stage. Age was found to be positively correlated with both QT interval and QTc. These results suggest that several clinical features and ECG parameters are interrelated, and some ECG measures reflect autonomic dysfunction or disease progression in PD patients. The study points out the relevance of monitoring ECG parameters in the treatment of PD, which may provide significant insights into the progression of the disease and inform clinical decision-making. [10]

This study looks into the possibility of using cardiac electrical activity in determining individuals who are at high risk of developing Parkinson's disease, especially through involvement of the autonomic nervous system, which usually precedes the motor symptoms of PD. The analysis was conducted on 10-second electrocardiogram (ECG) recordings from 60 subjects: 10

subjects with prevalent PD, 25 with prodromal PD, and 25 controls without the development of PD. For extracting features from ECGs, techniques such as the heart rate variability (HRV) metrics and common signal processing techniques were implemented, along with a Probabilistic Symbolic Pattern Recognition method. The latter was then classified using stepwise logistic regression that distinguished between the prodromal PD cases and controls. The regression model found four features of the PSPR method that predict PD; the final model had an AUC curve of 0.90 [0.80, 0.99], signifying strong performance. Five-fold cross-validation had an average AUC of 0.835 [0.831, 0.839]. The study concludes that cardiac electrical activity, especially as analyzed with the help of machine learning techniques, has significant potential for identifying at-risk individuals in terms of high risk of developing prodromal PD, providing insights not captured by traditional HRV metrics. ^[11]

It analyses the electrocardiogram features in various forms of motor symptoms, related to Parkinson's disease (PD). The PIGD group compared with the TD group was matched. The source of data comes from 118 patients affected by PD and were classified under the PIGD group totaling to 74 participants and under the TD group tallying to 44 participants. Clinical features comprise age, duration of the disease, classification and ECG features like PR interval, QRS, QT, and QTC. The study findings indicate that the QT interval in PD patients correlates positively with disease duration and Hoehn–Yahr stage, suggesting that the QT interval lengthens as the disease progresses. Furthermore, the QT interval was significantly longer in the PIGD group than in the TD group. The study concludes that a prolonged QT interval may be an indicator of a longer course of disease and a more severe condition, which may be useful in monitoring disease progression in PD patients. ^[12]

The objective of this paper was to evaluate whether smartphone-based accelerometer and gyroscope signals can classify Parkinson's disease patients from controls with a 20-step walking test. Comparing three different methods of feature selection, which included Minimum Redundancy Maximum Relevance (mRMR), Sequential Forward Selection (SFS), and Sequential Backward Selection (SBS), were utilized along with nine different classification algorithms. It could reduce the number of total features from 201 to 4–15 features. Highest accuracy achieved on single step classification was with SFS 7 using the Naive Bayes classifier, which produced an accuracy of 75.3%. The second best was obtained using SFS 4 and k-NN, which had an accuracy of 75.1%. Overall classification was based on the majority vote of the classified steps, and the accuracy achieved by K-NN was 84.5% with a corresponding error rate of 15.5%. This study demonstrates the feasibility of using smartphone sensors for PD monitoring, demonstrating the effectiveness of feature selection techniques and classifiers. Results are promising for long-term, real-life monitoring systems for PD patients, opening possibilities for more personalized treatment adjustments and improved patient care. ^[13]

This paper introduces a novel magnetic tracking system for the reliable diagnosis of early-stage Parkinson's disease, an important condition that calls for timely intervention and slows down the progression of the disease. The system uses a low-power, cost-effective, and highly accurate technology to monitor translational and vibrational movements in a spatial cubic domain, which makes it a good solution for portable monitoring in both home settings and general practices. This method can help ease the burden on big neurological centers and also helps the emerging field of telemedicine. The validation of this system was done by using three main tests. These tests included movement trajectory tracking, rest tremor, and finger tapping tests, which are based on the Unified Parkinson's Disease Rating Scale. All of these experiments were created based on the idea of mimicking human activity by a robotic arm. The system successfully followed and captured tremor frequencies. With regard to the finger tapping test, an initial classification approach that relies on the k-Nearest Neighbors algorithm yields an encouraging classification rate of 93%. The system also correctly detected tremor frequencies in both the rest tremor and movement trajectory tests. This breakthrough technology would promise much more for the early detection and ongoing monitoring of PD, thus ensuring more accessible, efficient, and less invasive diagnostics. ^[14]

The highly variable and unpredictable nature of PD symptoms among individuals and even within the same patient emphasizes the requirement for new monitoring tools to be used by physicians and patients in the home setting, so the physician can immediately make appropriate changes in treatment. BWS sensors have become precious in the study of clinical features related to PD, such as motor fluctuations, dyskinesia, tremor, bradykinesia, and freezing of gait (FoG) with other gait disturbances. In this regard, these sensors are not only beneficial for patient care but also form the basis for many research studies. This study provides a comprehensive summary of the most widely used BWS for PD patients in Europe, focusing on their role in enhancing treatment management. While BWSs may provide exciting possibilities for improving the management of PD, the range of their applications in everyday clinical practice remains to be more fully delineated. Their use will likely require a critical appraisal of how these devices contribute to the assessment of not only motor features but also the various non-motor features of PD, including

its cognitive and emotional manifestations. By providing continuous, real-time data, BWS can empower both clinicians and patients, offering a more personalized and dynamic approach to managing PD. ^[15]

Hypoxia is a condition where tissues are not provided with enough oxygen, and this results in impaired oxidative energy production. Cells stabilize hypoxia-inducible factor α (HIF-1 α), a critical regulator of the molecular response to hypoxia, which helps maintain cellular homeostasis and promotes adaptation through gene expression modulation under low oxygen conditions. Being the most energy-demanding organ, the brain is especially sensitive to oxygen deprivation, and hypoxic injury often results in considerable metabolic changes in neural cells that are typically associated with neurodegeneration. It has been hypothesized that neurodegenerative diseases may be mitigated by the manipulation of levels of HIF-1 α . In particular, the hypoxia/HIF-1 α signaling pathway was found to relate to many relevant factors for PD, such as gene mutations and risk factors in molecular processes related to mitochondrial dysfunction, oxidative stress, and inefficient protein degradation. This review therefore attempts to trace the role that hypoxia and HIF-1 α signaling play within the molecular pathways contributing to PD development. It will further discuss novel emerging neuroprotective strategies targeted towards stabilizing HIF-1 α , that may provide the much-needed direction for novel therapy to retard disease progression and optimize patient outcome. ^[16]

This study assessed exercise tolerance and oxygen saturation levels in PD patients to determine rehabilitative needs. In 55 inpatient PD patients in the "ON" phase, clinical assessments were conducted focusing on motor function, respiratory capacity, and oxygen saturation during exercise and sleep. Results revealed that 96% had decreased exercise tolerance, 21.8% exhibited exercise-induced desaturation, and 12.7% had nocturnal desaturation. Regression analysis indicated significant relationships between low exercise tolerance and indices of motor and respiratory dysfunction: oxygen saturation. On this basis, an integration of motor and respiratory rehabilitation becomes increasingly critical at advanced stages of the disease. ^[17]

PD is a neurodegenerative disorder that affects over 6 million people worldwide and is characterized by the loss of dopamine-producing neurons, leading to motor and non-motor symptoms. In the early stages of PD, up to 25% of patients are misdiagnosed by non-specialist clinicians. The current study examined keystroke timing data from 103 participants: 32 with mild Parkinson's and the remainder were non-PD controls. Novel: This method utilizes a combination of multiple keystroke features and machine learning classifiers, achieving 96% sensitivity, 97% specificity, and an AUC of 0.98 in discriminating early-stage PD from controls. The procedure itself is non-invasive and does not involve specialized equipment or the need to visit a facility, but could be performed from home. In its current version, it addresses only some of the cardinal PD symptoms, which diminishes the differential diagnostic capability. ^[18]

Current research focuses on the application of Multimodal Deep Learning and detection of a prodromal stage of Parkinson's Disease employing the novel and exciting 3D architectures enhanced by Explainable Artificial Intelligence (XAI) methods. Lately, leveraging data from the Parkinson's Progression Markers Initiative, a joint co-learning approach for multimodal fusion was introduced. This enabled the end-to-end training of deep neural networks to learn complementary information from imaging and clinical data. DenseNet with EN outperformed other models and achieved significant accuracy improvements when supplemented with clinical data. XAI techniques, including Integrated Gradients for ResNet and DenseNet and Attention Heatmaps for Vision Transformer (ViT), demonstrated that DenseNet paid more attention to areas in the brain deemed critical for pathophysiology during prodromal stages such as the right temporal and left pre-frontal regions. The same was true with ViT; it focused more on the lateral ventricles, which is linked with cognitive decline, supporting their involvement in the prodromal stage. These findings highlight these regions as significant early biomarkers for PD, demonstrating the potency of this framework in predicting the subtypes of PD and thereby helping in earlier diagnosis, making a way forward for advanced diagnostics and precision medicine. ^[19]

The symptoms of Parkinson's disease (PD), which include tremors, rigidity, akinesia, and balance, overlap with those of other diseases, thereby necessitating early detection for effective treatment. This paper provides a multimodal machine learning architecture that aims to use EEG and MRI data to assist in the diagnosis of PD. The approach will improve the accuracy in diagnosis based on the complementary nature of the datasets obtained through EEG and MRI. The methodology consists of preprocessing and feature extraction for both EEG and MRI, with PCA for data fusion and reduction of dimensions. Fused data analysis was carried out using a LightGBM model validated using 10-fold cross-validation and further tested on independent datasets to make the results more robust for all kinds of patients' demographics. The model reached a remarkable accuracy of 97.17% and a sensitivity of 96.58% along with a specificity of 96.82%, beating the traditional diagnostic approach. Incorporation of EEG along with MRI led to an overall overview of the neurophysiological and neuroanatomical changes in PD, and advanced

machine learning techniques helped them detect subtle patterns suggestive of early stages of PD, thus promising an early diagnosis tool. ^[20]

This survey has established that there is great potential for the early detection, diagnosis, and management of health problems with sensor technology integrated with machine learning. Since it leverages real-time data collection and analysis, continuous monitoring, and personal intervention become possible and accurate disease tracking can occur. As machine learning continues to evolve to include diverse sets of data, it will offer even more sophisticated clinical decision-making for the development of scalable, non-invasive tools for diagnosis. This research provides further groundwork for truly efficient, pro-active healthcare that will lead towards better patient outcome and quality-of-life for widespread conditions.

III. PROBLEM STATEMENT

The immense and escalating need for the accurate, noninvasive and scalable solutions for early detection of Parkinson's disease underlines the major flaws of many traditional ways of diagnosis that are often done in a very subjective manner. These methods are not frequent to be timely and therefore their delays exacerbate the patient's situation. To this end, the research plans to introduce an integrated and advanced detection system, which integrates several data sources like voice analysis, handwriting analysis using wave and spiral patterns, gait evaluation, and ECG signal processing, all this being powered by machine learning algorithms. The system is designed to be a reliable and timely diagnostic solution that can improve the quality of life of patients at risk of Parkinson's disease through early interventions and accurate diagnosis. Moreover, the approach also intends to include hardware such as wearable sensors and diagnostic devices for real-time data collection, thereby, to boost the overall functionality and scalability of the system. By surpassing the limits of traditional methods, this system proposes a more objective, efficient and extensive approach to early detection and intervention.

IV. OBJECTIVES

The primary objective of this research is the development of an efficient, accurate, non-invasive, and scalable method for early detection and grading of Parkinson's disease (PD). This shall be accessible, reliable, and adaptable to the diversity of health care environments that range from clinics to home settings. The method will be non-invasive and reduce the requirement for expensive diagnostic tools that are complex, hence cost-effective and suitable for wide use. In addition, the system will monitor continuously to detect PD early, track the progression of the disease, which is essential for timely intervention and personalized care. Such is a multi-modal approach based on many data sources derived from both physiological and behavioral measurement techniques: starting with voice and handwriting patterns that range from simple spiral waves through complex hand-pattern drawing, through gait, up to and including ECG signal processing. Each of those offers fantastic detail regarding various sides of motor performance and multiplicity itself offers further depth in detailing the disease. Voice analysis can detect submicroscopic alterations in speech features. Handwriting and drawing analyses can indicate an impairment in the fine motor movement. Gait monitoring is a useful tool to assess the walk pattern, while ECG signal analysis provides valuable information about autonomic dysfunction, one of the more common features associated with PD.

Feature extraction and voice analysis are core components of this diagnosis process. The system extracts pitch, frequency, speech rate, and tremor characteristics from voice recordings. Such features let the assessment of motor functions as well as detection in early stages of PD be made. Machine learning techniques applied to this feature extraction can help detect anomalies such as dysphonia and tremor in subtle voice disturbances, common in patients with Parkinson's disease. This voice analysis would provide a non-invasive and real-time disease detection.

Assessment of the spiral and wave drawings has been another method to diagnose PD. In these spiral and wave patterns drawn by people with PD, irregularities often occur due to reduced size and difficulty maintaining fluid motion as observed in other signs of motor dysfunction. This system can gauge the degree to which these effects occur and assess how significant impairments in these movements are and provide valuable details about the patients' condition. Similarly, this detailed handwriting examination evaluates parameters, such as slowness in writing, illetriteness, or variability in paper size, contributing more information in the effect caused by PD about fine motor functioning, including impact of bradykinesia and micrographia.

This evaluation of motor impairment associated with Parkinson's disease will highly rely on extracting data from gait through wearable sensors. For instance, one can extract such parameters as stride length, walking speed, and body movement by using a sensor such as an accelerometer or a gyroscope. All these parameters tend to be abnormally low in PD patients and are useful

indicators of the progression of disease Gait analysis aims to monitor early changes in walking patterns like freezing of gait (FOG) and follow them along with time, so as to understand the evolution of the disease.

The research also covers aspects of ECG signal extraction and processing. The particular heart rate variability (HRV) is also known to indicate dysfunction in the autonomic nervous system, a characteristic commonly seen in patients suffering from Parkinson's disease. Thus, it will be able to monitor autonomic changes in the patient and provide insights into progression with the abstraction and processing of relevant ECG features. Interpretation of HRV and other ECG parameters on analysis will help to understand how Parkinson's disease has an impact on the cardiovascular system and aid in the assessment of the degree of autonomic dysfunction.

The hardware design for this system should be easy to collect data from multiple sources, such as voice recordings, gait monitoring sensors, and ECG devices. The hardware should be easy to use, portable, and comfortable for the patient so that continuous monitoring is possible without interference in their daily life. As much as the wearable sensors are for gait analysis, it should be minimally invasive as possible. As for voice recording and ECG devices, these should be very user-friendly to allow the reading of real-time data for analysis. Most essentially, it covers the integration and fusion of multi-modal data acquired. Through establishing advanced algorithms integrating voice, hand writings, gait patterns, and even electrocardiographic data stream from the very same set into a common portal, an optimal analysis of leading towards the particular patient condition might be carried with the accuracy in combination and incompleteness it could manage with. Integration can help blend up insights generated via one modality and supplement towards better interpreting any other data obtained for gaining knowledge of how and at what velocity the disease moves. Data fusion will ensure that the analysis exploits the strength of each modality and compensates for the individual weakness.

Another important feature of this is a real-time monitoring system. This system shall give instant feedback to both the patient and healthcare providers. It has to have a user-friendly interface, showing clinicians all the analyzed data, allowing constant review of the motor and autonomic functions of the patient. In the case of wearable devices, for example, integration with real-time monitoring systems will alert the patients and providers concerning abnormal readings or deteriorations in the condition. This leads to early interventions and more-informed decision-making. In addition to the main goals listed above, our study also aims at scalability and access for a broader population. It is important that the system is adaptable to diverse users, as well as having different levels of access to technology. This calls for affordability, simplicity, and ease of use, especially in the case of patients who may not be technological. It will be a system that, in itself will be able to accommodate the variety of healthcare infrastructure. Thus, the system will grow in popularity based on different aspects-from well-set hospitals to low-scale healthcare units.

Moreover, ethical issues regarding data privacy. In our proposed research, concerns for ethical reasoning and data privacies are one of the mainstream issues. That is because such a system captures and analyzes vital health information data. Thus patient information privacy issues are major among the security elements. Strong data security, best ethical standards followed, and very well-defined procedure for informed consent will be taken. The entire system will be designed in strict adherence to healthcare laws and data protection acts so as to protect patients' rights while maintaining the confidentiality of the data throughout the process.

Clinical validation and testing are the last steps of our research. The system will be passed through strict clinical trials and investigations to check upon its accuracy and reliability as well as overall working in the context of real world clinical settings. This validation step is very necessary for making a practical and usable system. We will test the system rigorously to ensure readiness for clinical use and meaningful contributions toward early detection and management of Parkinson's disease. The additional objectives in attaining our research will be factored in according to the larger context of accessibility, ethics, and clinical viability.

The present research is focused on the development of an integrated non-invasive, scalable system with an early stage and grading ability of Parkinson's disease through the multi-modal analysis supporting approach. The proposed system is designed for analyzing multiple sources of physiological and behavioral data-voice, handwriting, gait, and ECG. What's more, focusing on scalabilities, ethically concerns along with data confidentiality and clinical validations will ensure this solution is efficacious and safe and ready to be applied within a diversified real healthcare environment.

V. METHODOLOGY

Algorithms utilized in solving varied problems that lie in machine learning, starting from classification to regression as well as for dimensionality reduction and feature selection. It mainly depends on a variety of different underlying principles of either statistical methods or decision trees and other ensemble methods plus optimization techniques with the intent to make a prediction or draw an inference. Machine learning techniques most applied throughout the domain. The enlisted methods are -

1. Logistic Regression
2. Support Vector Machine (SVM)
3. K-Nearest Neighbors (KNN)
4. Decision Tree
5. Random Forest
6. Naive Bayes
7. XGBoost
8. AdaBoost
9. Gradient Boosting
10. Linear Discriminant Analysis (LDA)
11. Quadratic Discriminant Analysis (QDA)
12. LightGBM
13. ResNet - 34
14. DenseNet - 121
15. AlexNet

Each of these techniques offers some specific advantage according to the problem, and what is to be used is mainly a function of characteristics of the data, the complexity of the problem, and performance requirements.

01] Logistic Regression

Logistic Regression is one of the most straightforward algorithms for binary classification models. It determines the probability of event occurrence by using data that feeds into a logistic or sigmoid function mapping any real number to a probability in the range 0 to 1. It assumes a linear relationship between input variables and the log-odds of the dependent variable. Logistically speaking, logistic regression is used on problems of binary outcome types: "Yes" or "No," "Success" or "Failure," and so on. It is very simplistic yet can be pretty effective if classes are linearly separable. It also works well on small to medium-sized sets with no too complicated data and is known for interpretability. It suffers, from the very dangerous phenomenon of overfitting since it cannot capture nonlinear relationships, and outliers can severely affect it.

$$P(y = 1 | X) = \frac{1}{1 + e^{-(w^T x + b)}}$$

Equation 1 - Mathematical Expression of Logistic Regression.

The logistic regression models the probability $P(y=1|X)$ for a binary output using the sigmoid function applied on a linear combination of the features X . The weights are given by w ; b is a bias term. T denotes transpose of vector w , and e is the base of the natural logarithm. The sigmoid ensures that the outcome is between 0 and 1.

02] Support Vector Machine (SVM)

Support Vector Machine is a robust algorithm in supervised learning and is predominantly applied for classification problems but also in regression problems. SVM aims at finding an optimal hyperplane, which maximizes the margin of separation of two classes within a feature space. The decision boundary is considered the best when the data points are maximally separated on both

sides. When data are not linearly separable, SVM employs the use of kernel functions (e.g., polynomial, radial basis function) in mapping data to a higher dimensionality where there can be possible linear separation. SVM performs quite well in a high-dimensional space and has extensive applications in text classification, image recognition, and bio informatics. SVM can address both linear and non-linear problems. It can, however, be computationally costly when working with large datasets, and may also fail in noising data and overlapping classes.

$$f(x) = \text{sign}(w^T x + b)$$

Equation 2 - Mathematical Expression of Support Vector Machine.

SVM identifies a hyperplane specified by w and b to classify the data points in two classes, the decision boundary maximizes the margin between these two classes. The sign determines the class of a point based on which side of the hyperplane it falls.

03] K-Nearest Neighbors (KNN)

K-Nearest Neighbors is a non-parametric, instance-based learning algorithm, used primarily for classification and regression tasks. In KNN, the output of a data point is based on the majority vote (classification) or average (regression) of its 'K' nearest neighbors in the feature space. The method of operation includes the calculation of the distance of a test point to the training points (the Euclidean distance being common). It picks out the closest points. KNN is simple and intuitive and has applications in cases of small dataset sizes or noisiness of data. It is computationally expensive at inference time because for each test point, it requires computing the distance to all the training samples. KNN also can be not so effective on high-dimensional data (curse of dimensionality) and depends on careful choice of the 'K' parameter to avoid overfitting or under fitting.

$$f(x) = \text{argmax} \sum_{i=N_k}^k I(y_i = k)$$

Equation 3 - Mathematical Expression of K-Nearest Neighbors.

KNN classifies a data point X based on the most-frequent label k of its k -nearest neighbors. N_k denotes the neighbors set, and $I(y_i = k)$ is an indicator function for class k .

04] Decision Tree

A decision tree is a flowchart-like structure used for both classification and regression. The process of division into subsets based on feature values can form a tree with decision nodes and leaf nodes. Root node starts off the entire dataset and each decision node represents a feature by further splits, while the leaves represent the output or the predicted values. The main reasons why decision trees are so appealing to use in business decision-making and in cases where interpretability is important is because they are easy to interpret, visualize, and understand. They are also vulnerable to overfitting, particularly when the tree becomes too deep. This has led to several techniques like pruning, in which one cuts off branches that do not improve the model much, and ensemble methods such as Random Forest. Although they are very simple, Decision Trees can be used for both categorical and numerical data and are applied in a lot of customer segmentation and loan approval decision systems.

$$f(x) = \sum_{j=1}^J p_j I(X \in R_j)$$

Equation 4 - Mathematical Expression of Decision Tree.

A decision tree partitions the feature space X into J regions R_j , where each region R_j is associated with a predicted class probability p_j . The tree chooses the splits that maximize information gain or minimize impurity.

05] Random Forest

Random Forest is a method of an ensemble approach combining multiple decision trees to enhance model accuracy and robustness. This method builds a collection of decision trees by training one on a random subset of data with a random selection

of features at each split. The final prediction would be made by averaging over the predictions for regression and majority vote over all the trees for classification. Random Forest reduces overfitting with individual decision trees because it increases diversity through using random sampling and bootstrapping. It also is less susceptible to outliers in that the combined effect of a number of decision trees can effectively dampen an outlier's effect. Random Forests are really good for dealing with large datasets as well as dealing with complex problems, and can handle both continuous and categorical attributes. However, they are computationally intensive, especially when the number of trees is large, and they lack interpretability compared to a single decision tree.

$$f(x) = \frac{1}{T} \sum_{t=1}^T f_t(X)$$

Equation 5 - Mathematical Expression of Random Forest.

The Random forest is the average prediction from T decision trees $f_t(X)$. Each of these trees was constructed on a randomly sampled subset of data and features, hence reducing variance, but improving the accuracy. Overfitting also reduces because multiple trees are involved, and an average of these trees' predictions would be obtained.

06] Naive Bayes

A Naive Bayes is a probabilistic classifier derived based on Bayes' theorem assuming that all the features within the data set are conditionally independent given the class. And amazingly, though such an "impractical" assumption would bring about naive, Naive Bayes seems to work astonishingly well even with high dimensional input data for certain applications of text classification. These include applications in spam detection, sentiment analysis, and much more. Various kinds of Naive Bayes classifiers exist like Gaussian, Multinomial, Bernoulli. The algorithm works based on the computation of the posterior probability of every class given input features and the selection of the class with the highest probability. Naive Bayes is very efficient, needing relatively little training data to estimate the parameters and working well for categorical features and large numbers of features in a dataset. However, its assumption of feature independence is often unrealistic, which can limit its performance in certain cases where features are strongly correlated.

$$P(y|X) = \frac{P(X|y) P(y)}{P(X)}$$

Equation 6 - Mathematical Expression of Naive Bayes.

Bayes' theorem is used in Naive Bayes to approximate the posterior probability of class y given features X . The likelihood $P(X|y)$, the prior $P(y)$, and evidence $P(X)$ are used.

07] XGBoost

XGBoost is an optimized, highly efficient version of the gradient boosting algorithm. It constructs an ensemble of decision trees sequentially, where every new tree focuses on the residuals of the previous trees to correct their errors. XGBoost includes regularization terms (L1 and L2) to prevent overfitting and is well-suited for handling missing values, large datasets, and noisy data. The big strength of the XGBoost algorithm is related to speed, scalability for high-dimensional problems especially with huge volumes of data and complexity. For structured or tabular data, it's well known to be one of the most powerful algorithms, which ranked top of nearly all competitions conducted in the sphere of machine learning. The bad news, it is hyper-parameter sensitive; when it has proven to offer extreme accuracy, but it doesn't explain anything easily.

$$f(x) = \sum_{t=1}^T \eta f_t(X), f_t \in F$$

Equation 7 - Mathematical Expression of XGBoost.

XGBoost is an ensemble method that combines weak learners f_i iteratively. The learner minimizes the loss function, where η is the learning rate. The space of possible trees is defined by the set F . It uses gradient boosting to optimize the model by adjusting the weights of weak learners based on the gradient of the loss function to improve the accuracy of predictions.

08] AdaBoost

AdaBoost is the name of another ensemble technique that relies on the combination of multiple weak classifiers, typically decision trees, to form a good strong classifier. It works well by sequentially training the classifiers one after another, focusing on misclassified samples from the previous classifier through their addition of higher weights. The final prediction from the combination of all individual classifiers is made via weighted majority voting or averaging. AdaBoosting is known for improving the strength of weak models without requiring huge computational power and is good on binary classification. It can make a weak classifier less biased than the original set of data provided. However, it is relatively sensitive to outliers and noisy values, which tends to over-fit if not accurately tuned.

$$f(x) = \text{sign} \sum_{t=1}^T (\alpha_t f_t(X))$$

Equation 8 - Mathematical Expression of AdaBoost.

AdaBoost is the combination of weak classifiers $f_i(X)$, weighted by α_i , which depend on their accuracy. It is concentrated on misclassified examples; this improves overall performance. It decreases bias by iteratively adjusting the weights of misclassified samples to enhance the ability of the model to correctly classify difficult instances.

09] Gradient Boosting

Gradient boosting is the machine learning technique that iteratively builds an ensemble of weak models while focusing on the error difference made by preceding models. Each new model tries to predict the residuals or the errors of the existing ensemble. Models are mainly decision trees, and the output is a weighted sum of all predictions. Gradient Boosting is an optimization technique for minimizing a specific loss function, which is mean squared error for regression and log loss for classification. It adds new models iteratively. Its strength lies in its applicability to complex, non-linear data for regression as well as classification with very high accuracy. It is computationally expensive and very sensitive to overfitting because of the large number of trees, which need careful tuning of hyperparameters like the learning rate.

$$f(x) = \sum_{t=1}^T \eta h_t(X)$$

Equation 9 - Mathematical Expression of XGBoost.

Gradient Boosting constructs trees h_t to minimize the gradient of the loss function, sequentially correcting errors made by prior models. It controls the learning rate. This is the process that allows refining the model on residuals to continue improving predictive accuracy and eliminate bias.

10] Linear Discriminant Analysis (LDA)

Linear Discriminant Analysis is a statistical method for dimensionality reduction and classification where LDA finds the linear combination of features that best separates two or more classes with maximum class-to-within-class variance ratio. In contrast to PCA, unsupervised and merely picking directions hoping to end up with the maximum variance in data, LDA is supervised where the search for directions will end up maximizing class separability. LDA becomes efficient when classes are well-distinguishable with data normally distributed, having a constant covariance in the classes under consideration. These algorithms are employed to recognize pattern like face identification and medical diagnostic analysis.

$$\delta_k(X) = X^T \sum^{-1} \mu_k - \frac{1}{2} \mu_k^T \sum^{-1} \mu_k + \ln P(y = k)$$

Equation 10 - Mathematical Expression of LDA.

LDA assumes a Gaussian distribution over each class, finding linear decision boundaries by maximizing class separation based on means μ_k , shared covariance Σ , and prior $P(y=k)$. It projects the data onto a lower-dimensional space, maximizing class separability, hence useful for linearly separable classification tasks.

11] Quadratic Discriminant Analysis (QDA)

Although QDA is similar to LDA, QDA does not have the assumption of a common covariance matrix for each class. This makes QDA allow quadratic decision boundaries rather than linear ones; hence it becomes more beneficial for problems if one finds violations in the assumption of equal covariance matrices as in the case of LDA. For examples where the aforementioned situation prevails, QDA would be better at such situations although prone to more overfitting than LDA in case of high dimensional or few training examples and due to requirement of estimating larger parameters QDA is more sample-size and assumption about normality sensitive.

$$\delta_k(X) = -\frac{1}{2} \ln |\Sigma_k| - \frac{1}{2} (X - \mu_k)^T \Sigma_k^{-1} (X - \mu_k) + \ln P(y = k)$$

Equation 11 - Mathematical Expression of QDA.

QDA relaxes LDA's shared covariance assumption, allowing class specific co-variances Σ_k . This results in quadratic decision boundaries. QDA is particularly effective for datasets where the class distributions have distinct shapes or orientations, thus enabling more flexible decision boundaries.

12] LightGBM

LightGBM is one of the lightest gradient boosting frameworks, made for large-scale machine learning, optimized for both speed and memory efficiency, supporting massive datasets, millions of rows, and hundreds of features, unlike traditional gradient boosting methods which use a leaf-wise growth strategy instead of the level-wise approach. This often results in a more accurate model with fewer trees, because the algorithm tends to grow the most informative leaves first. LightGBM natively supports categorical features, eliminating the need for preprocessing. Its high performance and scalability come with the price of careful tuning, especially when handling imbalanced datasets, to prevent overfitting.

$$f(x) = \sum_{t=1}^T \eta h_t(x), \quad h_t \in F$$

Equation 12 - Mathematical Expression of LightGBM.

LightGBM is a gradient-boosting framework optimized for speed and memory. It constructs trees h_t iteratively, emphasizing data points that have higher loss. It uses the histogram-based approach and leaf-wise tree growth and is very efficient in handling big data with high dimensionality.

13] ResNet34

ResNet34 is a deep residual network of 34 layers that overcomes the difficulties associated with training very deep neural networks. The residual connections enable layers to learn residual mappings rather than direct transformations, thus helping to overcome the vanishing gradient problem that arises in deep architectures. This allows deeper networks and increases further optimization as well as accuracy. Therefore, the architecture of ResNet34 is somewhat flexible, which can be used successfully for tasks such as image classification and object detection along with many more feature extraction techniques that take place within the computer vision context.

$$y = F(x, \{W_i\}) + x$$

Equation 13 - Mathematical Expression of ResNet34.

It introduces residual learning wherein the output y is the sum of the input x and a learned residual function $F(x, \{W_i\})$. It eases the training for deep networks. This effectively addresses the vanishing gradient problem, which has been a hurdle to train very deep architectures.

14] DenseNet121

DenseNet121 is a member of the family DenseNet, which connects each layer to every subsequent layer in the same dense block. Dense connection supports the feature reuse and gradient flow very well and, thus, gives better performance with a reduced number of parameters. DenseNet121 aims to achieve the highest accuracy with efficiency in computation by reducing the redundancy and information sharing. It has been widely used in tasks requiring detailed feature extraction, and some examples include medical imaging or object segmentation.

$$x_l = H_l([x_0, x_1, \dots, x_{l-1}])$$

Equation 14 - Mathematical Expression of DenseNet121.

DenseNet121 concatenates all the feature maps $x_0, x_1, \dots, x_{l-1}$ from earlier layers to determine the output for layer l based on function H_l promoting feature reuse. This connectivity pattern decreases redundancy, encourages effective use of parameters, and fortifies the gradient flow during backpropagation.

15] AlexNet

AlexNet changed the computer vision game in 2012 by winning the ImageNet Large Scale Visual Recognition Challenge. Some of the innovation in this architecture were stacked convolutional layers, ReLU activation functions, and max pooling. All these innovations soon found their way into the subsequent wave of deep learning architecture.. Although by modern standards rather shallow, AlexNet proved that deep neural networks are indeed a good tool for large-scale image classification and brought deep learning to the center of interest in both research and applications. Its historic importance lies in demonstrating that deep learning could be accurate in very complex visual tasks.

$$f(x) = W_5 \cdot \text{ReLU}(W_4 \cdot \text{ReLU}(\dots W_1 \cdot X))$$

Equation 15 - Mathematical Expression of AlexNet.

AlexNet is a type of convolutional neural network that stacked layers of convolutions with ReLU activation's. AlexNet was actually the first of its kind in introducing dropout, GPU training, and even augmenting data. It was augmented through translations and reflections of images.

Logistic Regression, LDA, QDA machine learning models do a good job for features in Parkinson's that are linearly separable, whereas SVM would do well if the data of voice and gait patterns go to a large number of features. Tree-based models such as Decision Trees, Random Forest, XGBoost, AdaBoost, Gradient Boosting, and LightGBM captures non-linear interaction and does very well in case of ensemble learning. KNN provides proximity-based classification useful to identify fine motor impairments in handwriting. Deep learning architectures such as ResNet-34, DenseNet-121, and AlexNet are competent in the recognition of spiral and wave patterns. Collectively, these models allow for a good early detection based on the diversity of multimodal data.

All of these algorithms have strengths and weaknesses, so they are applied especially to specific applications in machine learning. Their basic principles are also very different from one another, which varies from a more statistical approach like logistic regression and Naive Bayes to complex ensemble methods like Random Forest and XGBoost. Besides data type and problem complexity, an algorithm can be suitable with other aspects of interpretability, scalability, and the performance that it shows against overfitting or under fitting. Mastery of such methods includes understanding when to use which, considering requirements and possibly dealing with large-scale datasets or requiring high accuracy or explained models. The most careful selection of the most appropriate algorithm is critical in optimizing the model's effectiveness so that it can capture relevant patterns in the data and produce reliable predictions or classifications.

VI. IMPLEMENTATION

Parkinson's disease is a degenerative disorder affecting primarily the motor function regulation and can never be cured. Its symptoms include shaking, stiffness, and loss of balance that worsen gradually over time. Traditionally, the diagnosis of PD relied on clinical evaluations and scanning techniques, which are largely subjective and, hence, failed to detect early onset of the disease. With the development of technology, it is now possible to make a more precise and efficient diagnosis and monitoring of PD.

This study uses deep learning models for the analysis of both motor and non-motor parameters. It can be said that the analysis has been made deeper by using more parameters of the disease. Specifically, motor parameters, such as hand drawing the spiral and wave drawings tasks, have been analyzed by using state of the art deep architectures, which include ResNet-34, ResNet-50, DenseNet-121, DenseNet-169, VGG-16, and AlexNet. These models are trained to be able to extract the subtle aspects of motor control in both diseased and non-diseased subjects. It is through such analysis of the motor impairments that our system provides a fair and objective way for distinguishing PD patients from healthy persons, thus being able to conduct continuous and proper monitoring of their motor symptoms through time.

Furthermore, this framework includes the study of voice signals to address non-motor PD symptoms. It draws features from patterns of speech and tremor through voice recordings that are applied for classification purposes into affected and unaffected patients using the following machine learning classifiers: logistic regression, K-nearest neighbors, support vector machines, random forests, XGBoost, and Neural Network MLP.

In addition, the framework includes gait and ECG analysis to further enhance the understanding of PD. Gait analysis focuses on detecting abnormal walking patterns, such as stride length and cadence irregularities, which are often observed in PD patients. Similarly, ECG data analysis captures subtle variations in heart rate variability and autonomic function that may indicate the presence of the disease. Both gait and ECG data are processed through a variety of machine learning models, including Logistic Regression, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Decision Tree, Random Forest, Naive Bayes, XGBoost, AdaBoost, Gradient Boosting, Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), and LightGBM. These models were chosen for their robustness in handling diverse data types and for the ability to unveil complex patterns that differentiate PD patients from healthy controls.

For data acquisition and real time processing, the system uses a Raspberry Pi as the central processing unit to interface with microphones, camera unit, accelerometers, gyroscopes, and ECG electrodes. These sensors can capture the relevant motor and physiological parameters efficiently to allow seamless collection and analysis in an integrated, compact hardware setup.

A. DATA COLLECTION

01] Hand Drawing Data

Spiral and wave hand drawings were utilized as the first-level task of this research for assessing Parkinson's Disease symptoms. It had asked healthy subjects or affected patients to draw respective spiral and wave patterns on the trace sheet. The reason for selecting these drawing tasks was that, they tend to reveal motor impairments such as tremors, rigidity, and bradykinesia, which are characteristic of PD. The shape and symmetry of the spiral in the spiral drawing task were scrutinized for any irregularities or distortions in the pattern. As such, PD patients tend to lose the smooth and constant curves, and the size of the spiral as well as the consistency of the spacing between the turns were also evaluated, since inconsistent spirals with varied sizes may suggest a problem in motor control. Presence of tremors was also documented as involuntary shaking is one of the common symptoms of PD. Moreover, changes in stroke speed and force exerted by the stylus on the task were taken into account, as in PD patients the movements are often slower and stiffer.

Similarly, in wave drawing, continuity and smoothness were assessed in a wave pattern that often appeared to be jagged or broken, due to the inability to maintain smooth and continuous curves of the wave form. The amplitude and uniformity of the waves were also measured for any form of abnormality that could alert one to problems with motor functions. The speed of drawing was also checked, as slowing or uneven speed can suggest bradykinesia - a symptom of PD. The data from such spiral and wave drawing tasks are then analyzed so that relevant features like stroke consistency, speed, and variation of drawing might be extracted; these features tend to differentiate patients affected by Parkinson's disease and healthy individuals while providing an objective, quantifiable approach to evaluating motor impairments in Parkinson disease. Figure 1. showcases the obtained data for handwriting analysis.

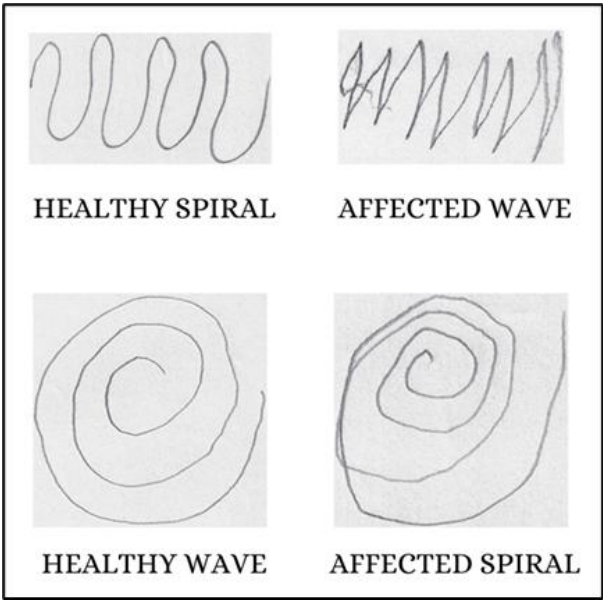


Figure 1 - Spiral and Wave Hand drawing Dataset.

02] Voice Data

Voice data was recorded by having the participants repeat a prolonged sound, following which the speech features such as pitch, jitter, shimmer, and speech rate were recorded. All these are vital in assessing PD because PD patients often exhibit a reduced pitch range, increased jitter and shimmer, and a reduced speech rate as a result of their motor impairment. Vocal intensity and volume were also measured since hypophonia is a common finding in PD patients where speech volume is reduced. The features were assessed by the extracted machine learning models for discrimination purposes between the diseased PD cases and the controls, contributing towards the non-motor symptom assessment of the disease. The table below shows the list of Voice features which were assessed to detect the disease.

FEATURES	FULL FORM
Name	Name of the subject
MDVP:Fo(Hz)	Fundamental Frequency in Hertz
MDVP:Fhi(Hz)	Maximum Fundamental Frequency
MDVP:Flo(Hz)	in Hertz
MDVP:Jitter(%)	Minimum Fundamental Frequency
MDVP:Jitter(Abs)	in Hertz
MDVP:RAP	Jitter Percentage
MDVP:PPQ	Jitter Absolute
Jitter:DDP	Relative Amplitude Perturbation
MDVP:Shimmer	Pitch Period Perturbation Quotient
MDVP:Shimmer (dB)	Difference of Distance Perturbation
Shimmer:APQ3	Shimmer (Amplitude Perturbation)
Shimmer:APQ5	Shimmer in Decibels
MDVP:APQ	3-point Amplitude Perturbation
Shimmer:DDA	Quotient
NHR	5-point Amplitude Perturbation
HNR	Quotient
RPDE	Amplitude Perturbation Quotient
DFA	Difference of Distance Amplitude
spread1	Noise to Harmonics Ratio
spread2	Harmonics to Noise Ratio
D2	Recurrence Period Density Entropy
PPE	Detrended Fluctuation Analysis
	First Fundamental Frequency
	Spread
	Second Fundamental Frequency
	Spread
	Correlation Dimension
	Pitch Period Entropy

Table 1 - List of features extracted for voice analysis from the collected dataset.

03] ECG Data

A standard ECG sensor was used to obtain the ECG data. Patients were required to rest for as long as possible and maintain minimal heart activity for some time while undergoing observation. Their interest in getting the physiological markers of Parkinson's Disease often involved heart rate variability alterations. Most of the alterations involving autonomic dysfunction, often accompanying the disease in patients, relate to HRV. The ECG signals were processed in order to extract features such as the QT interval, R-R intervals, and other parameters from the time and frequency domains. Analyzing these features would perhaps facilitate subtle identification of cardiac abnormalities potentially capable of better distinguishing PD patients from healthy controls for a more comprehensive assessment of the disease. The table below shows the list of ECG Signal features which were assessed to detect the disease.

Table 2 - List of features extracted for ECG Signal analysis from the collected dataset.

FEATURES	IMPORTANCE
RR_Interval	Indicates heart rate variability (HRV); reduced HRV suggests autonomic dysfunction in PD.
PR_Interval	Prolonged interval may indicate conduction disturbances, common in PD due to autonomic issues.
QT_Interval	Prolonged QT interval can signal cardiac autonomic dysfunction, often observed in PD.
T_Flattened	Flattening of T-wave suggests autonomic dysfunction, a typical PD-related cardiovascular change.
QRS_Duration	Prolonged QRS duration linked to cardiac conduction abnormalities in PD patients.
Heart_Rate	Fluctuations in heart rate due to impaired autonomic regulation are common in PD.

04] Gait Data

To collect gait data, the patient's chest was fitted with a 3-degree accelerometer sensor that captured dynamics during walking movement. The recorded motion is that of acceleration on the x, y, and z axes for this accelerometer and detailed information related to the stride pattern of a patient as shown in Figure 2.

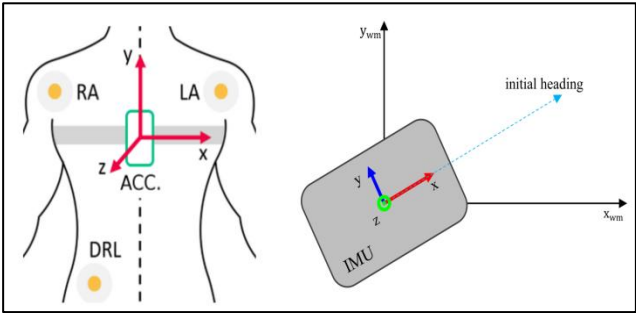


Figure 2 - Gait Dataset Collection using MPU Sensor.

Some recorded features include the length of a stride, cadence, walking speed with step symmetry, and body sway. Accelerometer data is processed and analyzed to identify the abnormal gait characteristics that would be used in classification. It employs machine learning algorithms to classify patients with Parkinson's Disease and normal subjects through gait characteristics. This facilitates the early diagnosis and monitoring of the disease. Real-time data captured by the system allow continuous evaluation and timely intervention. It is a non-invasive means to monitor PD, providing evidence about the mobility status of a patient.

For the spiral and wave drawings, feature extraction concentrates on the behavior of the subjects' motor control while performing the writing strokes thereby providing clues of actual motor control impairments that PD patients suffer from. In spiral drawing, important features include the number of rotations, curvature, and the time taken to complete the drawing. For wave drawings, parameters such as consistency of tilt, amplitude, and symmetry of the wave shape are significant. These features come from time-series analysis and image processing like edge detection and Fourier transforms. The extracted data helps contain representative characteristics about the irregularities like tremors or inconsistent pressure and speed of stroke that are associated with motor dysfunctions in PD. The goal is an objective and continuous measurement of motor symptoms to capture fine motor control problems that might differentiate such patients from healthy controls.

For voice data, description emphasis is on the vocal folds, because PD tends to alter speech patterns in terms of pitch, volume, and articulation. It extract crucial features, such as jitter (frequency variation), shimmer (amplitude variation), and speech rate, from Audi-recorded speech samples made with the Librosa Module. These are also Mel-frequency cepstral coefficients-they serve to extract the power spectrum of the voice and are sensitive to the extremely subtle changes that could occur in the voice of PD patients. It also serves to refer to the non-motor symptoms of dysarthria (slurred speech) and tremor-related voice disturbances. Machine learning classifiers then use this feature extraction to tell the difference between PD patients and healthy individuals.

For ECG data, feature extraction would involve an assessment of the electrical activity of the heart, which is known to be affected by autonomic dysfunctions commonly occurring in patients suffering from Parkinson's Disease. Some examples of the key features taken to extract out from the ECG signals include the HRV, RR interval, PR interval, QT interval, T-wave flattening suggestive of potential abnormality due to cardiac disease, and QRS duration. These features provide indications of changing cardiovascular activity in PD patients because dysfunction of autonomic nervous system has the ability to disrupt the heart's normal rhythm, altering cardiac activity. These features can be used to delineate beginning changes in cardiac function in veterans with Parkinson's Disease early enough for prompt intervention whereby a conventional diagnostic procedure may have missed such signs.

For gait data, the feature extraction extracts information concerning the motion captured by the 3-degree-of-freedom accelerometer sensor mounted on the patient's chest. The accelerometer measures acceleration along the x, y, and z axes, which presents information describing body motion throughout the gait. Their most important gait features, here list some of them, include etc., stride length, cadence, walking speed, and symmetry between the left and right legs. The sway or body oscillation has also been quantified. These characteristics are important in identifying motor disturbances, such as bradykinesia (slowness of movement), rigidity, and postural instability, which are typical in patients with PD. Using algorithms, the gait parameters that have been extracted will provide a basis for distinguishing PD patients from counterpart healthy controls based on the detected abnormalities depicted in their respective walking patterns. It offers a low-cost and continuous approach to monitor the execution of Parkinson's disease in real-time.

B. SELECTION OF MODELS AND TRAINING

For the purpose of classification of Parkinson's Disease (PD) based on the features extracted from voice, spiral and wave handwriting, ECG, and gait data, a robust machine learning pipeline was laid out, including the selection of appropriate models, data preprocessing, feature extraction, and model training. The goal was to implement both traditional models of machine learning and deep learning on the data acquired from each modality to learn the complex patterns associated with PD. This would ensure that any model processed multiple facets of the data efficiently, and the progress and presence of PD were well classified.

Using voice data, scores of machine learning models were evaluated, including Logistic Regression (LR), Support Vector Machines (SVM), K-Nearest Neighbors (KNN), Random Forest (RF), and XGBoost. The baseline model of LR was set up to measure simple linear relationships across voice features, including pitch, jitter, shimmer, MFCCs, and so on. Due to the complex relationships anticipated in high-dimensional spaces, SVM was used because of its strong performance, while KNN used proximity-based classification relying on effective character feature similarities. The ensemble methods, RF and XGBoost,

granted higher accuracy by aggregating the outcome of multiple decision trees, making them well suited for high variance and complex data. Furthermore, however, an MLP deep learning model got incorporated to ascertain the non - linearities embedded in the voice features as well as interactions thereof. Preprocessing in these vocal data had been done in order to extract appropriate features of speech before partitioning into 80-20 training-test datasets. Finally, a search to retrieve the best parameters of the model was conducted on 10-fold cross-validation, and consequently, aided in the perfect functioning of the model without risking overfitting.

Deep-learning models were implemented to identify subtle motor impairments caused by PD in the case of spiral and wave handwriting. This manifests in such irregularities as differing stroke pressure, direction, speed, and consistency. ResNet-34, ResNet-50, DenseNet-121, VGG-16, and AlexNet were chosen, given their proven ability to capture complex spatial patterns in images and time-series data. These models specifically created for visual data processing were trained to detect deviations in handwriting that are often associated with the early signs of PD. Handwriting data augmentation, including rotation, scaling, and noise addition, was performed to improve the robustness of the models and generalize better on unseen data. More so, this 80%-20% training/testing split was applied in order to ensure effective model validation. The deep learning models automatically learned hierarchical features that proved vital for identifying variations in the spiral and wave drawings.

For ECG data, machine learning models such as Logistic Regression, Random Forest, SVM, Gradient Boosting (XGBoost and LightGBM), and Naive Bayes were tested for their ability to classify PD according to features extracted from the ECG signal such as the RR interval, PR interval, QT interval, and heart rate variability. These features provide insight into autonomic dysfunction typically observed in PD patients. The models were trained to characterize the change in heart rate variability and QRS duration as characteristic patterns of PD. Such methodologies as RFE and various feature selection techniques were applied in order to justify model performance based on solely the most relevant features. Hyper parameter optimization was performed by cross-validation, and model training was performed with the same training/testing split. These resulting classification models enabled the identification of PD based on abnormal cardiac markers and autonomic dysfunction, commonly observed during disease progression.

A 3-degree accelerometer was mounted on the patient's chest to collect information on gait parameters such as stride length, cadence, walking speed, and left-right foot symmetry for the gait analysis. These gait features were captured and classified in a model under one of Logistic Regression, K-Nearest Neighbors (KNN), SVM, Random Forest, XGBoost, and Gradient Boosting. This was aimed at recognizing gait irregularities, such as reduced stride length or asymmetric walking, the typical hallmarks for Parkinson's disease. These foot accelerometer data were pre-processed, normalized, and segmented into specified time intervals to capture fluctuations in the gait features properly. The models were developed using cross-validation while taking special care to set hyperparameters for best performance. Time-series analysis and feature extraction using parametric algorithms for calculating mean and variance of stride length and cadence performance were also used to detect abnormal patterns. The models generated would be able to facilitate in the detection of early-stage PD through gait disturbance owing to the problems or impairments of motor systems due to the disease.

A multi-modal fusion approach was, therefore, employed to further improve PD detection, by combining the features from all four modalities of data collection, namely, voice, handwriting, ECG, and gait: hence from each mode deep perception into the course of the disease. Early fusion consists of syncretizing the features of all modalities into a unique feature vector, which was then used as input to the machine models for training purposes. Late fusion was also introduced, where single models were trained for each modality whose predictions were merged into standard predictions by a weighted voting scheme, or planar using a meta-classifier, integrating different realizations of the same sample. The fusing model would permit such devices the opportunity to learn numerous types of features, giving them an edge of resilience and power for assessment.

During the training and evaluation, the accuracy, precision, recall, F1-score, and ROC AUC were computed as performance metrics to assess their contribution in diagnosing PD. The 10-fold cross-validation-cum-cross-evaluation was conducted, and grid search and random search techniques for hyper parameter optimization were employed. This comprehensive approach enabled the implementation of a most effective multi-modal system that allows for early PD detection by providing a reliable and scalable tool for clinical and patient follow-up.

C. MODEL EVALUATION AND TESTING

Model evaluation is one of the most important steps in machine learning and gives insight into how well the trained model generalizes to data totally unseen during training. A variety of performance metrics were utilized throughout this study to evaluate the performance of the machine learning models for detecting Parkinson's Disease (PD). These metrics include accuracy, precision, log loss, F1 score, Mean squared error (MSE), recall, and confusion matrix. Each of the metrics will be explained in detail, including their respective mathematical formulations.

1. Accuracy

Accuracy is the measure of how many predictions were correct over all instances in question. It presents a general overview of the performance of the model. In the research, accuracy is pivotal in assessing how well the model can distinguish between healthy individuals and PD patients. But since this computation provides an overview, it might not altogether suffice due to the model's failures to show good performance on imbalanced datasets in which one of the classes is underrepresented. In spite of this setback, accuracy has remained among the most telling metrics for gauging the model's overall reliability.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Equation 16 - Mathematical Expression to calculate accuracy.

Here, TP represents True Positive, TN represents True Negative, FP represents False Positive and FN represents False Negative values respectively.

2. Precision

Precision is critical in this research in terms of how many of the positive cases predicted actually are correct. A greater precision value indicates a lower false positive rate, which is very huge in any medical diagnosis. For instance, if the model grossly misidentifies a healthy individual as suffering from PD, that may lead to prolonged unnecessary treatment and create panic in the patient. Precision is key in ensuring positive predictions by the model are actual PD cases. Within the realm of Parkinson's Disease, avoiding false-positive misdiagnoses is essential.

$$Precision = \frac{TP}{TP + FP}$$

Equation 17 - Mathematical Expression to calculate precision.

where, TP represents True Positive and FP represents False Positive values respectively.

3. Log Loss

Log loss is significant in this study because it penalizes models that assign high probabilities but are wrong, i.e., probabilities that are too close to either 0 or 1. Since all predictions regarding PD detection are knowledge probabilities, e.g., "likelihood" of a person having PD, log loss provides more detailed feedback on how good the prediction is. The metric prevents the model from being overconfident in the wrong predictions. This penalty is useful, especially when pressing health-care decisions must be made based on the outcome of the model. A reduction in log loss indicates that the model's probability predictions come closer to the true outcomes.

$$Log Loss = -\frac{1}{N} \sum_{i=1}^N [y_i \cdot \log(p_i) + (1 - y_i) \cdot \log(1 - p_i)]$$

Equation 18 - Mathematical Expression to calculate log loss.

In this case, N denotes number of samples, y_i denotes true label (0 or 1) and p_i denotes predicted probability of the positive class (0 to 1)

4. Recall

Recall is critical in this study, as it measures the ability of the model to correctly identify all positive cases, PD patients, to which the dire consequences of not being diagnosed with PD outweigh the costs associated with it (false negatives). Being a very important parameter for good detection of Parkinson's Disease, as this is a medical application, the cost of a few false selections can often be borne, as long as the diseased people get further investigation. Therefore, the higher the recall, the lower the probability that some potential cases of Parkinson's Disease would be overlooked.

$$Recall = \frac{TP}{TP + FN}$$

Equation 19 - Mathematical Expression to calculate recall.

5. F1 Score

The F1 score gives a special importance to this study due to possible class imbalance in PD detection. The assumption of a PD patient being lower in number in comparison to a healthy individual hobbles the representation of the model performance when evaluated only on the accuracy score. The F1 score, being the harmonic mean of precision and recall, creates a balance and provides a great perspective on these important metrics. F1 gives insights into the model's performance regarding positive class prediction, as well as negative class prediction, in this instance, indicating that one of the two classes is underrepresented.

$$F1\ Score = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}$$

Equation 20 - Mathematical Expression to calculate F1 Score.

6. Mean Squared Error

Although MSE is normally used in regression tasks, it is also important for classification models with a continuous outcome (usually a probability). In this research, MSE assesses how far the predicted probability of the model is from the actual label. If the MSE is small, it suggests that the predicted probability by a decoder is close to the actual one. MSE thus indicates the quality of the predictions in terms of the accuracy of the model's estimated confidence levels that may impact a clinician's decision in diagnosing Parkinson's Disease.

$$MSE = \frac{1}{N} \sum_{i=1}^N [(y_i - p_i)^2]$$

Equation 21 - Mathematical Expression to calculate MSE.

Here, N denotes number of samples, y_i denotes true value and p_i denotes predicted value.

7. Confusion Matrix

Understanding the performance of a model at a granular level is only possible with the aid of the confusion matrix, which provides insight on how many true positives, true negatives, false positives, and false negatives a model produces. This indicates a much better understanding of the mistakes the model lives under and then refines the model to improve it. For example, if the confusion matrix has a higher number of false negatives, it indicates that the model needs to be refined to increase recall.

		Actual Values	
		Positive (1)	Negative (0)
Predicted Values	Positive (1)	TP	FP
	Negative (0)	FN	TN

Figure 3 - Representation of Confusion Matrix.

Evaluation metrics help one in developing an insight into the model performance and play a vital role in establishing how well or satisfactory a given model is at diagnosing Parkinson's Disease. Accuracy serves generally as a gauge of correctness, while precision, recall, and F1 give an in-depth understanding of the trade-off between sensitivity to PD patients and specificity to avoid false positives. Log loss penalizes wrong predictions, especially those made with higher confidence. MSE is more appropriate for regression applications, but still offers useful insights regarding the classification cases where the output prediction is probability-based. The ultimate conclusion of the evaluation metrics, along with the confusion matrix, gives a very clear picture of the model of a model's prediction behavior, which is very much needed for further optimization and models' perfections. Considering all of these metrics allows one to be confident that the developed models for detecting PD are reliable, accurate, and can be used in the clinical setting.

D. INTEGRATION OF MULTIPLE DATA MODALITIES

The association of different data modalities of PD detection has the potential to cover a broad area by improving the sensitivity and specificity of different parameters. Each modality, namely hand drawing, voice, ECG, and gait, gives some understanding regarding the nature of the symptoms in PD. Multi-model data analysis thus gives a comprehensive view of the condition of expressions related to symptoms of the disease. To accomplish this, a multi-modal machine learning (ML) framework was constructed using early and late fusion techniques able to integrate these features for effective classification.

According to this method, the features were extracted from different modalities and stacked all together into one large feature vector through early fusion. Such a model learned the dependence and correlations between different modalities. For example, for wave or spiral drawings, tremors are combined with the variations in pitch for voice and regularities of gait patterns. In turn, the model makes use of the combined feature vector to train a supervised ML model. Early Fusion was helpful in such cases due to its ability to provide a holistic pattern, especially when the modalities had complementary characteristics.

According to the late fusion concept, for each modality, there were different models trained independently. For example, decoding the handwriting was executed with the help of DenseNet121; processing vocal features employed a SVM, because speech data requires a sequential arrangement. Likewise, time-series classifiers worked on ECG features, and spatiotemporal models evaluated gait data. The outputs of these individual models were aggregated using algorithms like weighted voting, majority voting, or meta-classifier to make the final prediction. This clearly shows that individual modalities would have their advantages in contributing to the prediction while minimizing the possibility of one noisy modality affecting overall model performance.

Feature engineering for integration faced challenges related to scale differences among features and overall dimensionality. When normalization techniques were used, each modality could contribute equally to the model, irrespective of the value scales of different modes. More common techniques in preprocessing such as PCA were suggested for effective elimination of redundant or less informative features, oriented toward extremely efficient computation and immediate interpretability.

An integrated model was trained on a diverse dataset in which healthy controls and PD patients were in balanced representation. An MLP was used to effect the non-linear integration of modalities including to model their interaction. Hyper parameter tuning was carried out using grid search and random search, with parameters such as learning rate, regularization strength, and feature weights of modalities by this method. Cross-validation was carried out in order to validate model generalizability and diminish the possibility of overfitting.

Integration of multiple modalities significantly improved detection accuracy compared to single-modality models. Exploiting complementary information, the model lowered false negatives, which are dangerous in medical applications where undiagnosed cases can be dire. For example, handwriting data provided motor irregularity information, and voice and ECG features supplied insights into associated non-motor symptoms thereby greatly enhancing the capability of diagnosis.

In conclusion, the integration of various data modalities for the diagnosis of PD improved the accuracy and reliability in the diagnosis: the assembling of early and late fusion techniques with a robust feature engineering approach and optimization of ML had shown a glimpse into the possibility of multi-modality frameworks to solve very difficult medical problems. This very model leaves many ideas for future progress in the area of automated diagnosis and personalized health care.

E. HAWDWARE SYSTEM

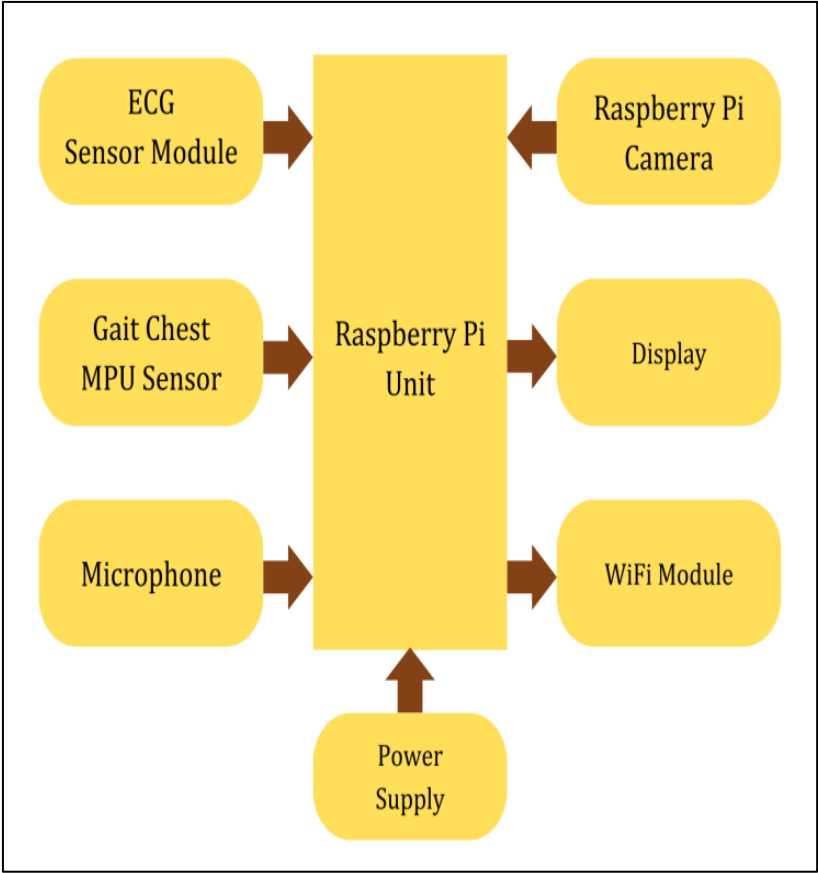


Figure 4 - Block Diagram of Hardware System.

The hardware implementation adopted the use of various sensors and modules to allow for the breadth of data collection and analysis to be done for the detection of Parkinson's Disease (PD). At the heart of the system was the Raspberry Pi, taking the position of the Embedded Control Unit (ECU). The Raspberry Pi was chosen for its compact size, low power demand, and compatibility with different sensors, essential for effective data acquisition, preprocessing, and integration. Since it had GPIO pins with a Linux operating system, it interfaced smoothly with peripherals and is thus an appropriate solution for portable multi-sensor applications. This project used the Raspberry Pi 4B, having 4GB of RAM, with the addition of a Wi-Fi module to allow timely data transfer and a 5V power bank to help carry out continuous operations.

Voice data was recorded using a sensitive USB microphone, which performed sustained phonation tasks, like sustaining the sound . Analysis of the voice tremors and their instabilities, which are significant signs of PD, was possible. A unidirectional condenser microphone was chosen to further reduce background noise while picking the complete audio about it clearly. Using the PyAudio library, the microphone was interfaced with the Raspberry Pi to take voice data in real-time, and the feature extraction was conducted using the Librosa library in the analysis of frequency and time-domain characteristics of the voice samples. To analyze

the drawing patterns of the hand, the draw-a-spiral-and-wave assignments were photographed in high resolution by the Raspberry Pi camera module on a ready-made template. This component was correctly mounted at an optimum height with intensively bright illumination to allow capturing of even the subtlest tremors contained in such drawings. Preprocessing techniques, including noise suppression and edge detection with the use of OpenCV Principal Components Analysis, were used to extract features indicative of motor dysfunction.

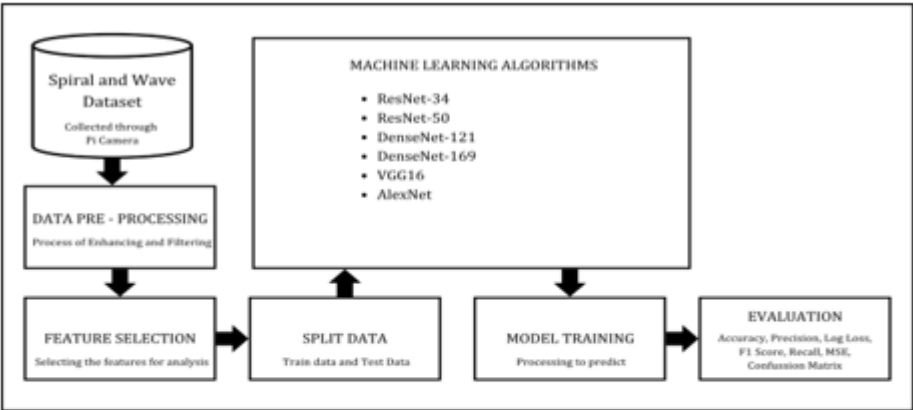


Figure 5 - Block Diagram of Hand Drawing Analysis.

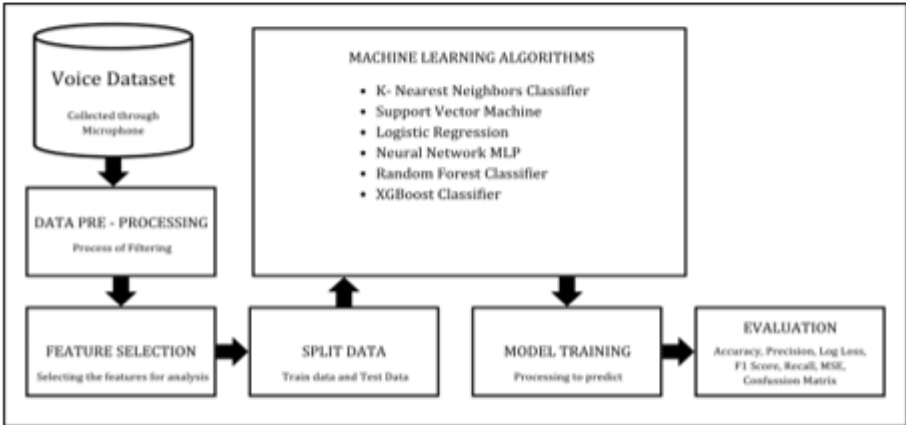


Figure 6 - Block Diagram of Voice Analysis.

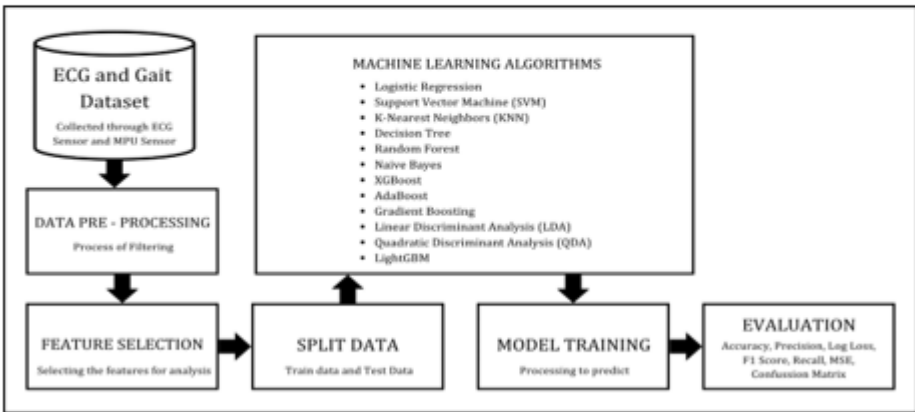


Figure 7 - Block Diagram of ECG and Gait Analysis.

The multimedia accelerometer with inertial measurement unit sensor (MPU6050) would be attached to the patient's upper chest in order to capture gait parameters related to spatio-temporal parameters. This 3-axis accelerometer provides real-time data for acceleration and angular velocity, which allows appraisal of gait disturbances and postural instability. Connection with the Raspberry Pi would be established via the I2C protocol for smooth transfer of data. Furthermore, pre-processing steps include calibration and noise filtering of parameters such as step cadence and stride chop to define stride regularity. A high-sensitivity realizable ECG module was used for the acquisition of electrocardiographic data and some observations regarding autonomic dysfunction using the parameters such as RR Interval, QT Interval, and QRS Duration. Used a low-cost ECG module that had dry electrodes for user comfort during extended use. The real-time display of processed data will be displayed on the interface allowing for showing results. Thus, the system should be modular, portable, and scalable. All sensors were synchronized for data acquisition; preprocessing was done locally using a Raspberry Pi to minimize storage capacity. In fact, different models of machine learning for multi-modal data analysis were used to classify PD patients and healthy subjects.

VII. RESULTS AND DISCUSSION

The Results and Discussion chapter presents a relatively broad analysis of what the system has given back regarding its working and functionality for detecting Parkinson’s disease. The performance of machine learning models was evaluated against several metrics, including accuracy, precision, recall, F1 score, log loss, and confusion matrices, to assess their success in recognizing Parkinson's disease. The potential of separate modalities of spiral and wave handwriting analysis, voice analysis, ECG signals, and gait information is explored in such a suggestion, laying stress on their contribution towards the entire system. Also, the effect of combining multiple data modalities on their accuracy of detection is discussed. The chapter also goes into the practicality of implementing the operation and how it would work in reality, including the importance of definitive, cost-effective solutions for the early and accurate detection of Parkinson’s disease.

A] Spiral and Wave - Hand Drawing Analysis

1. RESNET-34

Table 3 - Result table of Model ResNet - 34.

EPOCH	TRAIN LOSS	VALID LOSS	ACCURACY	TIME
0	1.655003	0.854319	0.500000	00:41
1	1.399725	0.661609	0.800000	00:27
2	1.071367	0.638107	0.750000	00:29
3	0.969734	0.942346	0.700000	00:25
4	0.847144	1.020449	0.733333	00:30
5	0.861470	0.918422	0.800000	00:24
6	0.819885	0.867286	0.783333	00:25
7	0.757911	0.878943	0.816667	00:29
8	0.758251	0.895106	0.816667	00:24
9	0.717758	0.809857	0.816667	00:26

It demonstrates outstanding performance in analysis of hand-drawn data where the accuracy becomes 81.67% on the 7th epoch; training loss continually decreases, and validation loss showed fluctuation behavior and seems like it has gone into a stall at the very end. Epoch time is consistent therefore training is consistent, but divergence in loss suggests that it really needs more probing. As a means to enhance performance, regularizing, adjusting the learning rate, data augmentation, and early stopping, along with hyper parameter tuning, can improve generalization and reduce validation loss.

2. RESNET-50

The ResNet-50 model is quite good in dealing with hand-drawing data, and its highest accuracy reaches 76.67% in the 6th epoch. The training loss tends to decrease with new epochs; however, the validation loss is sporadic, indicating overfitting or under-generalization. It is observable that the model's performance is not stable, showing that the accuracy is decreasing as validation loss is increasing, which denotes the model's inability to adapt to the validation data. The stable time of the training results reveals the high quality of training that has been achieved, but in order to prevent later and greater validation loss fluctuations and to achieve the highest accuracy possible, generalization has to be improved by doing regularization, data augmentation, or fine-tuning the architecture.

Table 4 - Result table of Model ResNet - 50.

EPOCH	TRAIN LOSS	VALID LOSS	ACCURACY	TIME
0	0.916377	0.636152	0.683333	00:36
1	1.056380	0.656015	0.700000	00:32
2	1.157664	0.843288	0.700000	00:35
3	1.158303	1.030600	0.733333	00:32
4	1.044749	0.711210	0.750000	00:34
5	0.995304	0.806717	0.716667	00:33
6	0.985888	0.680070	0.766667	00:32
7	0.981679	0.773015	0.700000	00:35
8	0.933008	0.956950	0.700000	00:32
9	0.850253	0.782971	0.666667	00:35

3. DENSENET-121

Table 5 - Result table of Model DenseNet - 121.

EPOCH	TRAIN LOSS	VALID LOSS	ACCURACY	TIME
0	0.985671	0.694144	0.733333	00:29
1	0.754824	0.484870	0.733333	00:29
2	0.678787	0.607804	0.750000	00:31
3	0.763258	0.969738	0.800000	00:31
4	0.735078	0.797341	0.816667	00:32
5	0.694312	0.628933	0.800000	00:28
6	0.662225	0.690574	0.851700	00:29
7	0.647854	0.712517	0.851700	00:31
8	0.626096	0.776893	0.851700	00:30
9	0.565133	0.800234	0.851700	00:32

The DenseNet-121 model showed excellent results for hand-drawing data; peak accuracy ranged between 85.17% from the 6th epoch. It showed a slow reduction in the training loss; the validation loss has some variation, but in general, remains fairly stable. Good generalization can be ascertained based on the gradually increasing accuracy along with controlled variations in validation loss; slight changes during later epochs would require further fine-tuning. With stable training times and promising results, further optimizations such as regularization, data augmentation, and learning rate scheduling could be applied to enhance performance further. Overall, the model seems robust for this task.

4. DENSENET - 169

The DenseNet-169 model performs decently while analyzing the hand-drawn data; the peak accuracy achieved during training is 76.67% at the 6th epoch, and it continues to do so. The training loss is steadily decreasing and hence is learning perfectly but, having spikes in validation loss, means challenging generalization. The stability in accuracy of the model with the noise fluctuations reflects its potential to be robust; however, the fact that validation loss becomes higher sometimes hints at regularization and data-preprocessing improvements being in order. The training time was consistent with this experiment; therefore, if optimized and fine-tuned with sufficient training and a proper optimizer, this model can go really well on this task.

Table 6 - Result table of Model DenseNet - 169.

EPOCH	TRAIN LOSS	VALID LOSS	ACCURACY	TIME
0	1.228958	0.906763	0.616667	00:35
1	1.051276	0.599612	0.700000	00:38
2	0.969538	1.124437	0.616667	00:34
3	0.895675	1.049062	0.700000	00:37
4	0.855953	0.915649	0.750000	00:36
5	0.763573	1.179581	0.716667	00:35
6	0.702714	0.689903	0.766667	00:37
7	0.679061	0.748759	0.766667	00:34
8	0.612276	0.801563	0.766667	00:37
9	0.568734	0.816435	0.766667	00:35

5. VGG - 16

Table 7 - Result table of Model VGG16.

EPOCH	TRAIN LOSS	VALID LOSS	ACCURACY	TIME
0	1.233069	0.557125	0.766667	01:31
1	1.057547	0.424269	0.883333	01:25
2	1.024386	0.565602	0.850000	01:24
3	0.937139	0.651897	0.816667	01:26
4	0.898746	0.466686	0.883333	01:25
5	0.860076	0.561753	0.833333	01:25
6	0.760136	0.663044	0.816667	01:25
7	0.758178	0.634949	0.833333	01:28
8	0.661982	0.644653	0.833333	01:25
9	0.655634	0.663215	0.833333	01:24

The VGG-16 model shows robust early performance on the hand-drawing data set with peak accuracy of 88.33% in several epochs, mostly during the initial epochs. The training loss reduces steadily, while validation loss shows fluctuations, particularly in the latter epochs, and thus could face some issues of generalization. However, even with such fluctuations, the model still keeps up a good level of accuracy, thereby proving its strength. The constant training times depict steady processing. Further improvements, perhaps regularization or even data augmentation, will help stabilize validation loss and maybe improve performance, but overall VGG-16 performs well at this task.

6. ALEXNET

In case of hand-drawn data analysis, the model AlexNet achieves a peak value of 81.67% accuracy at epoch 6. It sustains this value into subsequent epochs, while training loss decreases steadily as an indicator of effective learning; however, it fluctuates through validation loss. The accuracy improvements indicate that it is well adaptable to the task, but this is somewhat threatened by the spikes in validation loss at times; it might just be overfitting or validation set sensitivity. The short, consistent training times show efficient processing of the network. AlexNet becomes a good contender for this particular task with considerable room for fine-tuning or regularization-based optimization.

Table 8 - Result table of Model AlexNet.

EPOCH	TRAIN LOSS	VALID LOSS	ACCURACY	TIME
0	1.360816	0.882201	0.600000	00:06
1	1.202358	0.555810	0.750000	00:05
2	1.062525	0.589067	0.766667	00:07
3	0.884177	0.800327	0.733333	00:06
4	0.900412	0.877342	0.750000	00:04
5	0.859992	0.841593	0.766667	00:05
6	0.793817	0.562621	0.816667	00:06
7	0.781968	0.594367	0.816667	00:04
8	0.790172	0.677045	0.800000	00:05
9	0.797909	0.756086	0.800000	00:06

According to the results obtained, DenseNet-121 has proved to be the best performing of the six, with consistent peak accuracy of 85.17% and relatively stable training and validation loss trends, thus proving strong generalization and robust learning. The other models like VGG-16 and DenseNet-169 had promising accuracy of up to 88.33% and 76.67%, respectively, but had larger fluctuations in the validation loss, thus generalization was an issue. AlexNet and ResNet-50 had moderate performance; AlexNet was efficient but not that stable. DenseNet-121 is the best model to analyze hand-drawing data, as it has high accuracy, stable learning, and constant training times. Further fine-tuning and data augmentation could enhance its performance further.

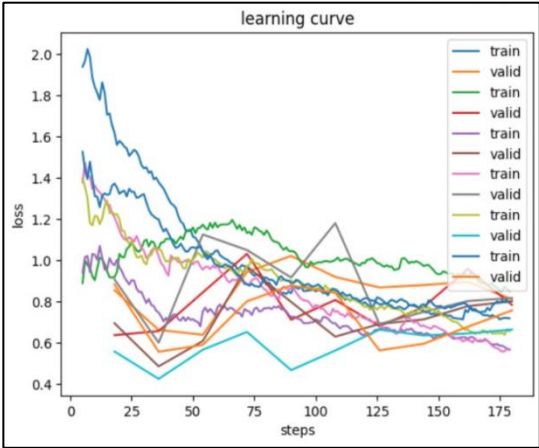


Figure 8 - Hand Drawing Analysis learning curve.

B] Voice Analysis

The Voice Analysis section in this study examines the performance of various models based on the ability of those models to extract relevant features from voice data and how effective the model is in its prediction. An extensive analysis is also conducted regarding the training and validation metrics, which are loss and accuracy, thereby indicating the generalization capabilities and efficiency of the respective models. From the comparison of these models, the strengths and weaknesses of each architecture are determined, and the most appropriate approach can be selected for voice data analysis. The findings of this study contribute in establishing a baseline for future research as well as provide necessary insights to improve methodologies in voice-based applications.

Table 9 - Result table of Voice Analysis.

MODEL	ACCURACY	F1 SCORE	PRECISION	LOG LOSS	RECALL SCORE
Logistic Regression	0.82051	0.88524	0.9	6.46937	0.87096
K-Neighbor Classifier	0.79487	0.85185	1.0	7.39356	0.74193
Support Vector Machine	0.89743	0.93939	0.88571	3.69678	0.96125
XG Boost Classifier	0.74358	0.81481	0.95652	9.24196	0.70967
Neural Network MLP	0.82051	0.88135	0.92857	6.46937	0.83870
Random Forest Classifier	0.84615	0.9	0.93103	5.54517	0.87096

1. Logistic Regression

Logistic Regression performs well with the performance metrics: it gets an accuracy of 82.05%, F1 score of 88.52%, and precision of 90%. Its recall is 87.10%, showing that it has a great capability to correctly identify true positives and, hence, can be used for tasks in which failure to predict the positive class would lead to some disastrous consequences. A log loss value of 6.46937 indicates moderate confidence level in probabilities of predictions and hints that the model is fairly well-calibrated but would require additional regularization for better optimization. Therefore, this model will be best suited for those scenarios where interpretability and simplicity is the utmost importance.

2. KNN Classifier

The KNN Classifier gives an accuracy of 79.49% and an F1 score of 85.19% with perfect precision at 100%. However, its recall score drops to 74.19%, which means that though it avoids false positives, it fails to detect all true positives effectively. The high log loss value of 7.39356 points to less confident probability estimates, suggesting sensitivity to variations in data distribution. KNN may perform better with additional hyper parameter tuning or increased dataset size and is better suited for applications emphasizing precision over recall.

3. Support Vector Machine (SVM)

SVM surpasses the rest, having an accuracy of 89.74% with an F1 score at 93.94% and a recall at 96.12%. The fact that it yields a precision of 88.57% puts forward the equilibrium predictive abilities with the relatively small log loss standing at 3.69678 in relation to high accuracy and its generalization to other datasets is strong. Thus, SVM best deals with such tasks requiring large amounts of dimensionality and hard decision boundaries. Its performance shows good aptness for voice analysis tasks that demands precision and recall.

4. XGBoost Classifier

The XGBoost Classifier has an accuracy of 74.36% and an F1 score of 81.48%, which is moderate. Its high precision of 95.65% indicates a good ability to avoid false positives, but a recall score of 70.97% indicates that it fails to identify all true positives. The log loss of 9.24196 is the highest among the models, which means reduced confidence in probability estimates. Although XGBoost can be very effective in tasks involving structured data, its performance in this context suggests that it may require further hyper parameter optimization to achieve comparable results.

5. Neural Network MLP

Accuracy-82.05%, F1 score-88.13%, Precision-92.86%; this model of Neural Network works great in achieving true positives without any error; but the sensitivity is a little low compared with a few other models as it obtained a recall of 83.87%. A log loss of 6.46937 reveals that the predictions have almost similar confidence as with Logistic Regression. The performance of the MLP will show scope for improvements with further tuning, for instance with architecture or a learning rate setting, and is suitable for applications that demand flexible and adaptive solutions.

6. Random Forest Classifier

The Random Forest Classifier achieves an accuracy of 84.61%, F1 score of 90%, and precision of 93.10%. The recall score of this model is 87.10% and log loss is 5.54517, indicating that it is a good overall performer with well-calibrated probability estimates. It has an ensemble nature that benefits from its robust predictions and prevents overfitting. Its balanced performance metrics and robustness with noisy data make it a good candidate for voice analysis tasks where precision and recall are both important.

The SVM model is the strongest, with the maximum accuracy (89.74%), F1 score (93.94%), and recall (96.12%), meaning it can learn very fast, does not make many false negatives, and consequently gives confident predictions and reliable outcomes, as evident from precision (88.57%) and log loss (3.69678). Other notable runners include Logistic Regression with 82.05% and Random Forest at 84.61%, each yielding solid F1 scores, although a bit weaker at recall compared to SVM. Hence, if it is to perform, the SVM is best. However, the Logistic Regression and Random Forest work better if interpretation is an aim.

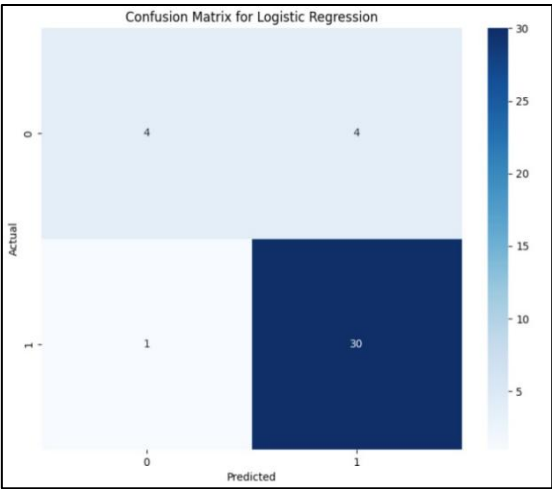


Figure 9 - Confusion Matrix of Logistic Regressor - Voice.

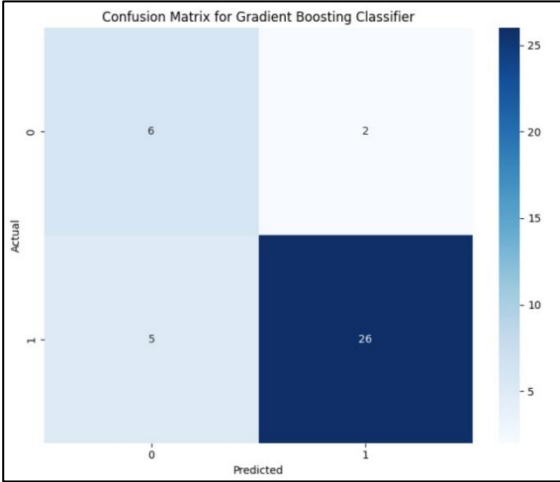


Figure 10 - Confusion Matrix of XG Boost - Voice.

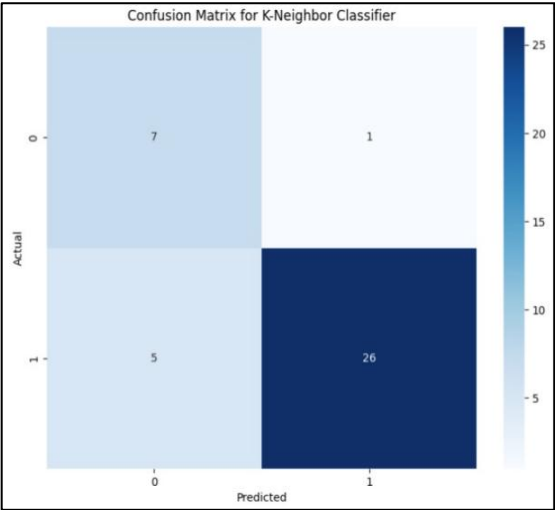


Figure 11 - Confusion Matrix of KN-Neighbor - Voice.

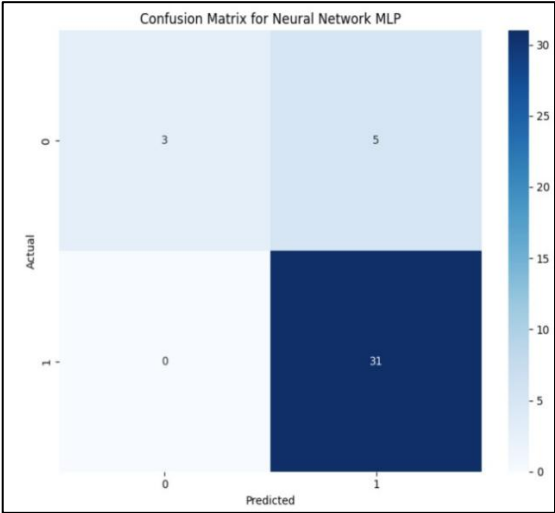


Figure 12 - Confusion Matrix of Neural Network - Voice.

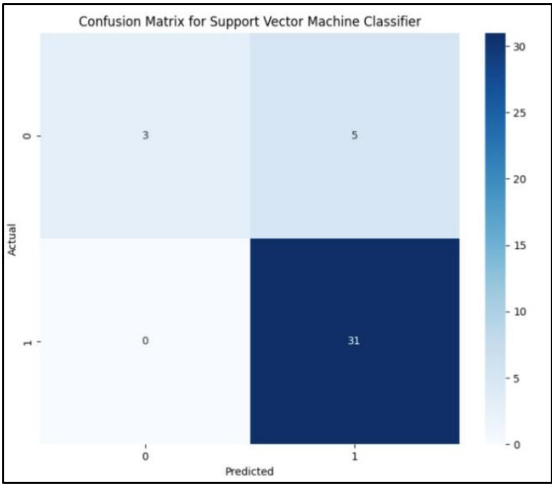


Figure 13 - Confusion Matrix of Support Vector - Voice.

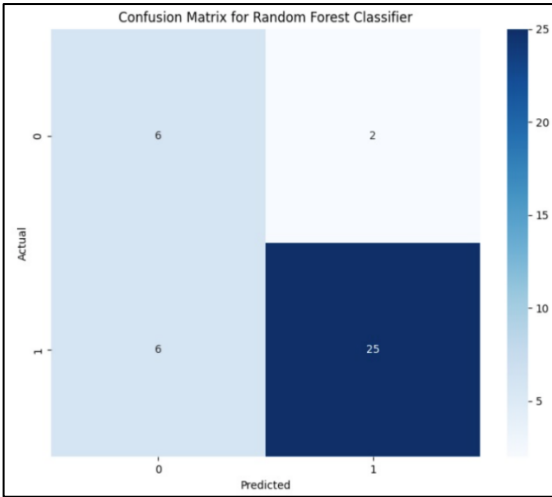


Figure 14 - Confusion Matrix of Random Forest - Voice.

03] ECG Signal Analysis

In this section, we present our analysis results with ECG signals for the detection of Parkinson's disease (PD). The goal of this analysis is to pick up subtle variations in heart rate variability (HRV) and other electrical patterns of the ECG that may suggest the presence of PD. We were studying such vital signs that impact cardiac regulation to ascertain any characteristics and differences like RR interval and variability, variations in PQRST waveforms as classifiable in indicating PD disease. In summary, these features help ascertain ECG analysis's use for detecting early-onset PD at lower cost through a non-invasive technique with respect to further PD progress that enables intervention to happen well before complications.

Table 10 - Result table of ECG Signal Analysis.

Model	Accuracy	Precision	Recall	F1-Score	Log Loss
Logistic Regression	0.704421	0.7228098	0.7239789	0.7229385	0.4424002
SVM	0.842105	0.8480565	0.8478945	0.8479512	0.2129963
KNN	0.848632	0.8545338	0.8537688	0.8539155	0.8055685
Decision Tree	0.852	0.8567604	0.8568	0.856773	1.9031045
Random Forest	0.875579	0.8792118	0.8780211	0.8781174	0.1256046
Naive Bayes	0.733474	0.7493067	0.7501266	0.7491204	0.3655971
XGBoost	0.874316	0.8781624	0.8768844	0.8769879	0.1166473
AdaBoost	0.875579	0.8792118	0.8780211	0.8781174	0.5287293
Gradient Boosting	0.895789	0.8894197	0.8882101	0.8983064	0.1010335
LDA	0.701895	0.7209972	0.7217055	0.7212591	0.4428919
QDA	0.752211	0.7667082	0.7669899	0.7657344	0.3420483
LightGBM	0.873263	0.8771247	0.8759367	0.8760411	0.1101155

Various performance metrics have been evaluated on different machine learning models used for the analysis of ECG signals in Parkinson's disease detection, including accuracy, precision, recall, F1 score, and log loss. Such a combination of metrics would be necessary to depict each model's performance for ECG signal classification as accurate and having confident predictions, without causing any confusion with a lot of false positives or false negatives.

1. Logistic Regression

Logistic Regression performed at a moderate level with an accuracy of 70.44%. Although its precision, recall, and F1 score are nearly identical at around 72%, the model's relatively high log loss of 44.24% suggests that it is not very confident in its predictions. This might be indicating that Logistic Regression is not the appropriate model to pick up slight changes in ECG signals as far as Parkinson's disease is concerned.

2. Support Vector Machine

SVM was pretty impressive with 84.21% accuracy. SVM had very good precision of 84.81%, recall of 84.79%, and F1 score of 84.80%. It was therefore picking up very well both the true positives and the true negatives. Moreover, the low log loss of 21.30% shows that it is confident about its predictions. These metrics make SVM an ideal tool for detecting patterns that are not necessarily obvious but may be crucial for the detection of Parkinson's disease in ECG signals.

3. K-Nearest Neighbors

KNN had a similar accuracy of 84.86%. The model has good precision and recall, with 85.45% and 85.38%, respectively, which means the model is very good at both positive and negative instances. But the higher log loss of 80.56% indicates that the model does not have the confidence to make strong predictions. Lack of confidence makes KNN less reliable than SVM and other models like Random Forest or Gradient Boosting.

4. Decision Tree Classifier

Decision Tree has a score of 85.20%, with precision and recall close to each other, around 85.68%. However, though these scores are great, the Decision Tree model is associated with high log loss at 1.9031, which can suggest overfitting and lack of confidence in prediction. This overfitting would not help the model decide subtle differences between ECG signals due to Parkinson's disease. Therefore, it does not qualify well for this case where generalization is key.

5. Random Forest Classifier

Again, Random Forest had an impressive accuracy of 87.56%. Precision and recall were similar to each other at 87.92% and 87.80%, respectively. The F1 score was 87.81. The log loss of the model was as low as 12.56%, which meant that it was prone to giving reliable predictions with confidence. Therefore, Random Forest represents a great option for the analysis of ECG signals in the detection of Parkinson's disease due to its high-dimension tolerance and its ability to generalize on different features.

6. Naive Bayes

Naive Bayes showed a relatively weaker performance, with accuracy of 73.35%, low precision at 74.93%, and recall at 75.01% as compared to other models. Though the F1 score is fair at 74.91%, the higher log loss of 36.56% indicates that the model lacks confidence in its predictions. As such, Naive Bayes is not the best choice for analyzing ECG signals in this context.

7. XG Boost

XGBoost, another very powerful model, has an accuracy of 87.43% with precision and recall that are nearly equal at 87.82% and 87.69%, respectively, showing a very balanced performance. Low log loss of 11.66% indicates confident and reliable predictions. XGBoost is another strong contender for pattern detection in ECG signals and can offer competitive performance alongside Random Forest.

8. AdaBoost

AdaBoost's performance was great as well: accuracy of 87.56%, precision is 87.92%, recall is 87.80% with very minor differences. Although its log loss was higher at 52.87%, this reveals that, in fact, despite being good for predictions, perhaps AdaBoost just isn't as decisive in its classification as the latter models are XGBoost and Random Forest would be.

9. Gradient Boosting Algorithm

Gradient Boosting has the best accuracy at 89.57%, precision at 88.94%, and recall at 88.82%. Its F1 score was also the highest of all models at 89.83%, with a log loss that was also the lowest (10.10%). This signifies that Gradient Boosting is more confident and reliable with its predictions. It has therefore become the model best suited for the analysis of ECG signals in the diagnosis of Parkinson's disease.

10. Linear Discriminant Analysis

Linear Discriminant Analysis performed averagely with an accuracy of 70.19% and is among the lower accuracies for all models. The precision, recall, and F1 score are moderate at 72.10%, 72.17%, and 72.13%, respectively. With this being said, a higher log loss of 44.29% shows that LDA has a lack of confidence in its predictions. It implies LDA isn't the best tool in diagnostic intention for an analysis of ECG signals that could point to a patient with Parkinson's disease, as other models such as Gradient Boosting, Random Forest, and XGBoost were much relatively better.

11. Quadratic Discriminant Analysis

QDA is better than LDA since it achieved the accuracy with precision 75.22% while the rest was slightly low with respect to precision, recall, and F1 scores at 76.67%, 76.70%, and 76.57% respectively, compared to the rest of the models. This value of log loss is 34.20% lower than that for LDA, thus slightly better in confidence of prediction, but is still higher than the leading models like Gradient Boosting and Random Forest. Hence, though QDA performs better than LDA, it still is less apt for ECG signal analysis in the detection of Parkinson's disease due to the overall moderate results.

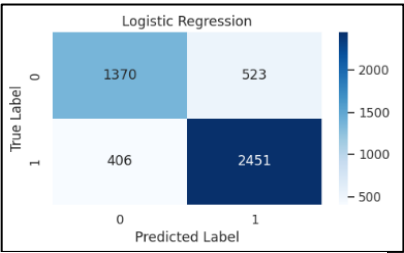


Figure 15 - Confusion Matrix of Logistic

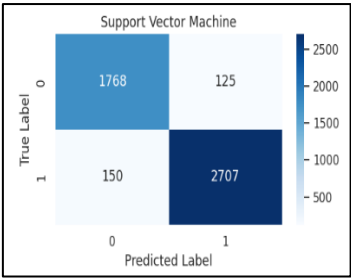


Figure 16 - Confusion Matrix of SVM -

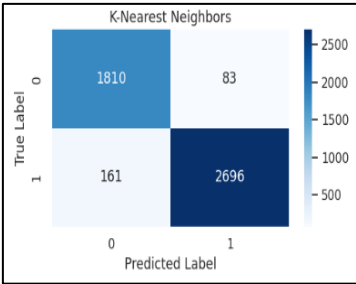


Figure 17 - Confusion Matrix of KNN -

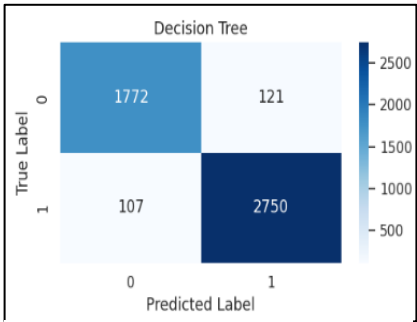


Figure 18 - Confusion Matrix of Decision

12. LightGBM

LightGBM performed very well, achieving 87.33% accuracy with precision at 87.71%, recall at 87.59%, and F1 score at 87.60%. Log loss of 11.01% was a good indication that the model predicts reliably and confidently, hence LightGBM can be a viable alternative for ECG signal analysis. Its high values of precision and recall reflect that the model identifies both positive and negative cases well. Gradient Boosting comes out as the best model for ECG signal analysis for the detection of Parkinson's disease. With the highest accuracy of 89.57%, precision of 88.94%, recall of 88.82%, and F1 score of 89.83%, along with the lowest log loss of 10.10%, Gradient Boosting proved its ability to make accurate predictions with confidence. Models like Random Forest, XGBoost, and LightGBM also worked out well as alternative options. Although, because of the overall superior performance, Gradient Boosting is the model of choice recommended for reliable and effective ECG signal analysis in the detection of Parkinson's disease.

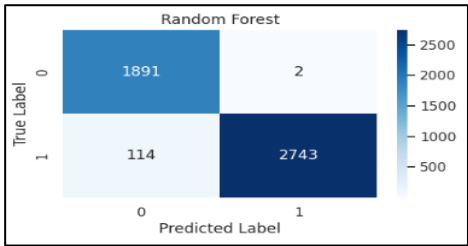


Figure 19 - Confusion Matrix of Random Forest - ECG.

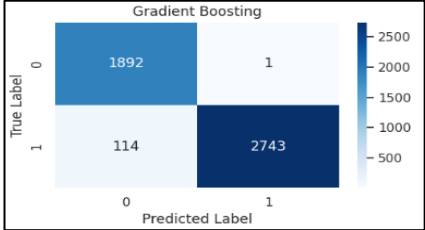


Figure 23 - Confusion Matrix of Gradient Boosting - ECG.

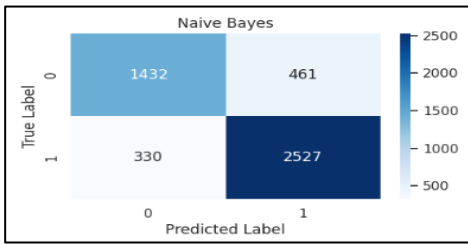


Figure 20- Confusion Matrix of Naive Bayes - ECG.

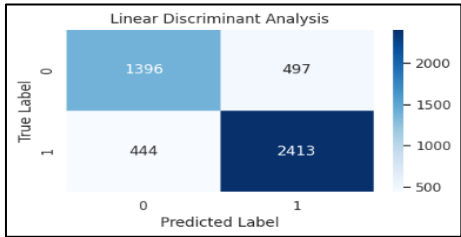


Figure 24 - Confusion Matrix of LDA - ECG.

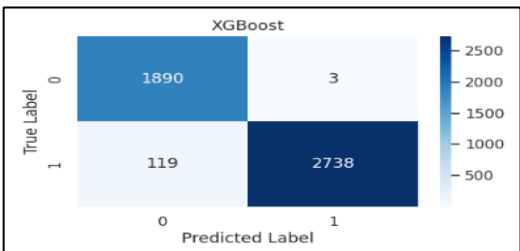


Figure 21- Confusion Matrix of XGBoost - ECG.

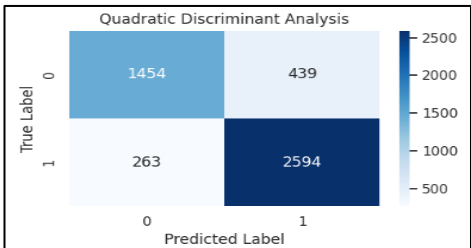


Figure 25- Confusion Matrix of QDA - ECG.

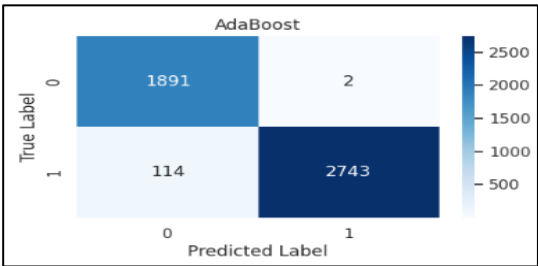


Figure 22 - Confusion Matrix of AdaBoost - ECG.

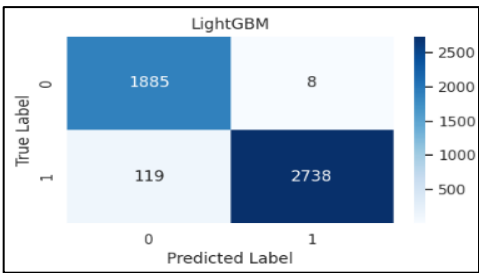


Figure 26 - Confusion Matrix of LightGBM - ECG.

04] Gait Analysis

The gait analysis in this study is the most important component in evaluating motor control and identifying possible signs of the progression of Parkinson's disease (PD). Utilizing different gaits, including stride length, gait velocity, and accelerometer data, we might establish relationships between these factors. The results presented here show the connection between gait abnormalities and PD symptom severity; this allows them to be successfully used as biomarkers. Here, different types of machine learning algorithms were used in an attempt to accurately classify gait signals and then apply them for a prediction of the severity of the subject's condition based on motor abilities. The results provide a thorough assessment of how gait analysis can be utilized as a non-invasive means of monitoring the progression of diseases, thus enabling early detection and more effective management strategies.

Table 11 - Result table of Gait Analysis.

Model	Accuracy	F1 Score	Precision	Recall	MSE	Log Loss
Logistic Regression	0.4285	0.5000	0.5000	0.5	0.5714	1.2833
SVM	0.4285	0.5000	0.5000	0.5	0.5714	0.6246
KNN	0.4285	0.600	0.5000	0.75	0.5714	5.7196
Decision Tree	0.7142	0.7500	0.7500	0.75	0.2857	10.2981
Random Forest	0.4285	0.5000	0.500	0.5	0.5714	0.7249
Naive Bayes	0.7142	0.7500	0.7500	0.75	0.2857	8.8716
XGBoost	0.5714	0.5714	0.6666	0.5	0.4285	0.7971
AdaBoost	0.8571	0.8571	0.9888	0.75	0.1428	0.7134
Gradient Boosting	0.5714	0.5714	0.666667	0.5	0.4285	4.5114
LDA	0.4285	0.5000	0.5000	0.5	0.5714	0.7420
QDA	0.5714	0.5714	0.6666	0.5	0.4285	15.447
LightGBM	0.4285	0.5000	0.5000	0.5	0.5714	0.6991

1. Logistic Regression

Logistic Regression had an accuracy of 42.85%, indicating poor discrimination ability within the classes and the gait analysis dataset it was applied upon. Its F1 score, as well as precision, amounts to 0.5; this means the model performs an average job - neither better than the rest, nor worse off. The same is with a recall value amounting to 0.5, meaning positive and negative classes are equally correctly identified. However, the model suffers in terms of the prediction accuracy and generalization due to its high MSE of 0.5714 and log loss of 1.2833.

2. Support Vector Machine

The SVM model behaves exactly the same as Logistic Regression with the same accuracy at 42.85%. F1 score, precision, and recall are all 0.5, so the SVM model is showing the same kind of behavior as Logistic Regression when classifying instances. With moderate metrics like this, however, the MSE for the SVM model at 0.5714 and the log loss at 0.6246 demonstrate that the SVM model maintains a moderate level of accuracy

3. K-Nearest Neighbors (KNN)

The KNN got the same accuracy as both Logistic Regression and SVM, at 42.85%, however, its F1 score of 0.600, precision of 0.5, and recall of 0.75 present a different kind of balance in its performance. KNN seems to do well in recall, so it seems it is better in identifying positive instances. But still, the high MSE of 0.5714 and log loss at a significantly high 5.7196 unveil that this model suffers from inefficiencies about error minimization.

4. Decision Tree

The accuracy is highly improved to a level of 71.42% with Decision Tree model. Its F1 score, precision, and recall of 0.75 indicate a balanced performance with a solid ability to correctly classify both positive and negative instances. However, its high MSE of 0.2857 and log loss of 10.2981 indicate that, although the model is effective in fitting the data, it could overfit sometimes, resulting in poor generalization and predictive accuracy.

5. Random Forest

Random Forest's accuracy was as same as the other two; that is 42.85% while the F1 score, precision, and recall are all equal to 0.5. As it's an ensemble-based model, but it's not showing more or significantly different than Logistic Regression or SVM, for instance, its MSE was around 0.5714 with log loss as 0.7249 which is a piece of evidence indicating the moderate model's generalization capability.

6. Naive Bayes

Naive Bayes showed a tremendous increase compared to the other models by obtaining an accuracy of 71.42%. Naive Bayes obtained the same F1 score, precision, and recall of 0.75 like the Decision Tree model. It clearly states that Naive Bayes has been able to classify instances properly with a balanced approach. Its MSE of 0.2857 and log loss of 8.8716 show that, while it performs better than models like Logistic Regression and Random Forest, it still struggles with error minimization and generalization.

7. XGBoost

The accuracy of XGBoost is 0.5714 with an F1 score of 0.5714, precision of 0.6666, and recall of 0.5. This indicates that XGBoost performs pretty well, especially regarding precision. Still, the recall is relatively low, which means that the model is not able to identify all the positive instances properly. MSE 0.4285 and log loss 0.7971 show that, though better than most simpler models, there is still a place for improvement with error and generalization.

8. AdaBoost

The AdaBoost algorithm resulted in the best accuracy, at 0.8571, so it's the best algorithm out of all of these in this comparison. With an impressive F1 score of 0.8571, precision of 0.9888, and recall of 0.75, AdaBoost outperforms all other models in the correct identification of both positive and negative instances. The MSE of 0.1428 and log loss of 0.7134 for the model show its superior predictive accuracy and generalization, outperforming all other models tested in this study. These results make AdaBoost the most reliable model for gait analysis based on the provided dataset.

9. Gradient Boosting

Gradient Boosting had an accuracy of 0.5714 with an F1 score and precision also at 0.5714 while having a recall at 0.5. This model also compares closely with XGBoost in terms of performance in the field since the difference for precision and recall is somewhat reasonable. However, an MSE of 0.4285 and log loss at 4.5114 would indicate that the model can be improved further since the model fails to accurately minimize errors to generalize better than the best models in this comparison.

10. Linear Discriminant Analysis (LDA)

LDA was almost as good as Logistic Regression, SVM, and Random Forest with an accuracy of 0.4285, F1 score of 0.5, and precision and recall also at 0.5. This means that LDA has no significant improvement over the simpler models, so it may not be a good fit for the gait analysis task. The MSE of 0.5714 and log loss of 0.7420 will further prove the fact that error reduction and generalization capability by LDA are limited.

11. Quadratic Discriminant Analysis (QDA)

QDA model has achieved the accuracy of 0.5714 with the F1 score, precision and recall of 0.5714, 0.6666, 0.5 respectively. Its precision is better but recall does not go beyond the mark. With the MSE of 0.4285 and a log loss of 15.447, it's clear that although QDA holds some promise regarding precision, the model generalizes poorly, hence its high error metrics. Thus, it cannot be relied on as much as other models like AdaBoost and Naive Bayes.

12. LightGBM

LightGBM, a gradient boosting framework, reported an accuracy of 0.4285, in line with Logistic Regression, SVM, and Random Forest. The F1 score, precision, and recall for LightGBM were all 0.5, indicating average performance in classifying the instances. Although these results indicate that the model can identify both positive and negative instances with a reasonable level of balance, its performance does not exceed the simpler models in the comparison. The MSE is 0.5714 and log loss is 0.6991 with this model. That is to say, LightGBM does not rise to a really significant level in terms of predictive accuracy. The best model for gait analysis based on the performance of all the tested models is AdaBoost with an accuracy of 85.71%, F1 score of 0.8571, precision of 0.9888, and recall of 0.75. It also shows the lowest MSE of 0.1428 and log loss of 0.7134, which reflects its high predictive accuracy and generalization capabilities. The consistent high performance across all metrics makes AdaBoost the most effective and reliable model for this task, offering the best balance between precision, recall, and error minimization. Hence, AdaBoost is recommended as the optimal choice for gait analysis in this study.

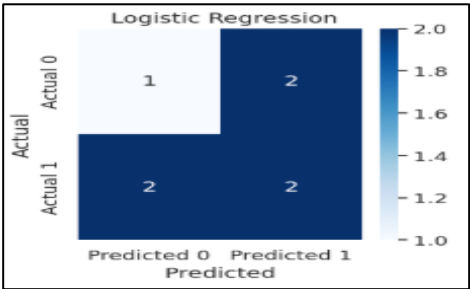


Figure 27 - Confusion Matrix of Logistic Regression -

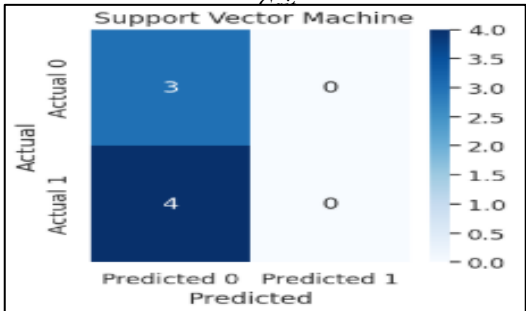


Figure 28 - Confusion Matrix of SVM - Gait.

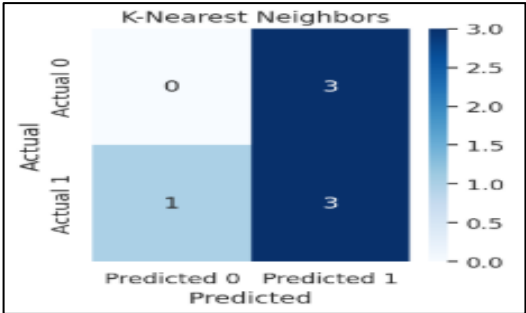


Figure 29 - Confusion Matrix of KNN - Gait.

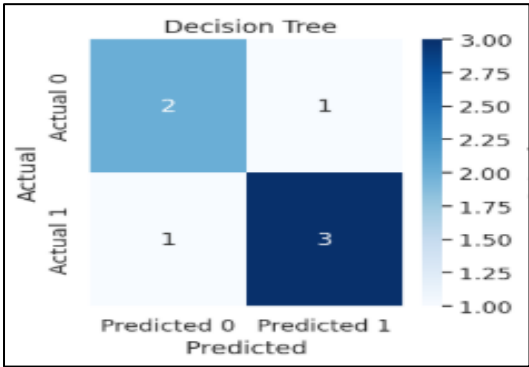


Figure 30 - Confusion Matrix of Decision Tree -
Gait

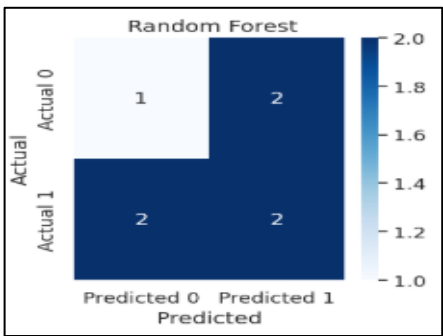


Figure 31 - Confusion Matrix of Random Forest - Gait.

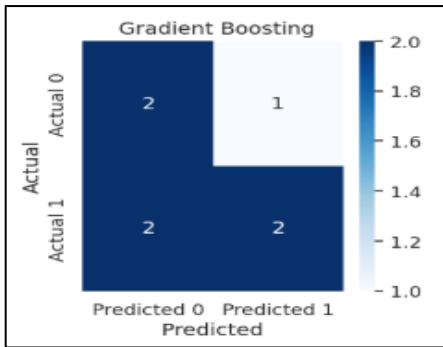


Figure 35 - Confusion Matrix of Gradient Boosting - Gait.

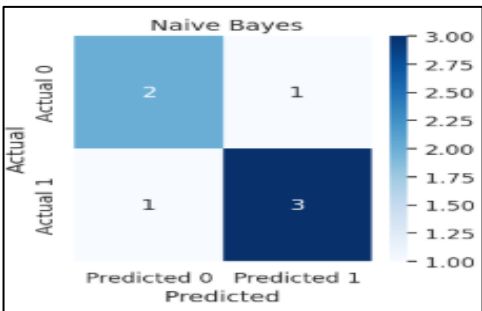


Figure 32 - Confusion Matrix of Naive Bayes - Gait.

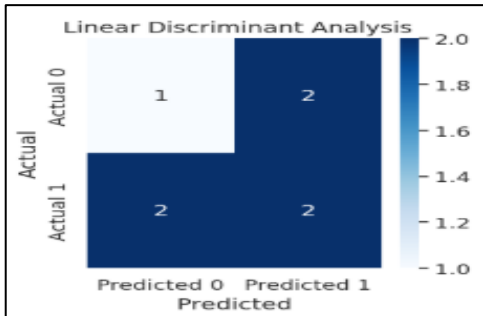


Figure 36 - Confusion Matrix of LDA - Gait.

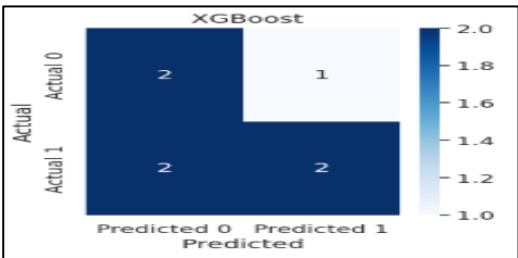


Figure 33 - Confusion Matrix of XGBoost - Gait.

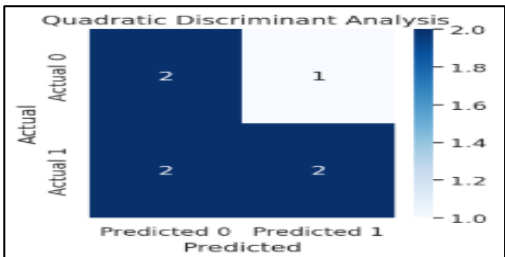


Figure 37 - Confusion Matrix of QDA - Gait.

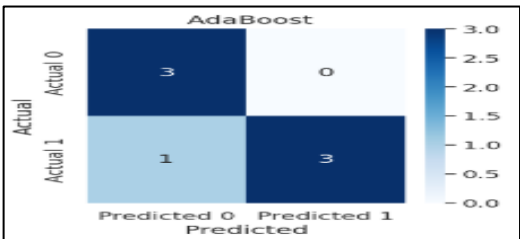


Figure 34 - Confusion Matrix of AdaBoost - Gait.

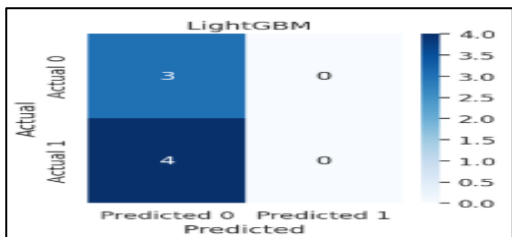


Figure 38 - Confusion Matrix of LightGBM - Gait.

Hardware implementation of Parkinson's Disease (PD) detection using a central Embedded Control Unit, which was designed to integrate several sensors for real-time data acquisition using a Raspberry Pi. This model of the Raspberry Pi 4B is selected because it has a small size, low power consumption, and various modules of sensor integration that would help in efficient preprocessing, data acquisition, and smooth integration. It was coupled with a Wi-Fi module and a 5V power bank, which permitted uninterrupted functioning, thus timely data transfer and real-time monitoring.

Voice analysis was carried out with a sensitive USB microphone attached to the Raspberry Pi. The microphone together with the PyAudio library permit uninterrupted real-time voice recording during prolonged phonation, a key activity for the diagnosis of tremors and vocal instability, which are hallmarks of PD. Utilizing the feature extraction by Librosa, it analyzed both the time-domain and the frequency-domain characteristics of the voice samples. It succeeded in finding higher jitter and shimmer in the

patient's voices who have PD because they possess tremors of their voices. By choosing a unidirectional condenser microphone, the background noise could be reduced, thus accurately capturing voice data.

Aside from this voice evaluation, the "draw-a-spiral-and-wave" hand motor task was implemented to measure impaired fine motor capability. This motor skill evaluation method has been typically taken by digital camera high resolution, as a feature of Raspberry Pi Camera module, where photos taken have further processing steps done via OpenCV, especially at the edges with Principal Components Analysis feature extraction for each captured wave pattern. The results showed that the hand-drawing patterns of PD patients were irregular, such as having uneven stroke widths and failing to maintain a consistent motion. These results are in agreement with the known motor dysfunctions in PD, which include tremors and rigidity that impair fine motor control. The system captured even the subtlest tremors during drawing.

The gait analysis component used an MPU6050 sensor, an inertial measurement unit with 3-axis accelerometer and gyroscope capabilities. This was mounted on the upper chest region of the patient so that spatio-temporal parameters of gait such as cadence, step length, and angular velocity are captured. Real-time processing happened through the transmission of data using the I2C protocol towards the Raspberry Pi. The results showed that, in PD patients, there was a significant gait disturbance, which included reduced step length, slower cadence, and irregular stride pattern. These gait abnormalities rightly correlate with the major hallmark symptoms associated with PD - bradykinesia and postural instability. The MPU6050 sensor effectively captured these gait parameters, thus offering valuable insights into motor dysfunction related to PD.

A low-cost ECG module with dry electrodes was used to obtain electrocardiographic data. This module is user-friendly for extended use. Parameters such as RR Interval, QT Interval, and QRS Duration were measured. These are essential parameters in assessing autonomic dysfunction, which is a common feature in PD patients. Analysis of the ECG data revealed abnormal autonomic responses in PD patients, including reduced heart rate variability and prolonged QT intervals. These results are well in line with previously published literature linking autonomic dysfunction with PD.

VII. CONCLUSION

This research is a very important step in the direction of a multi-modal framework for the diagnosis of Parkinson's disease, which can allow for early detection and management by integrating handwriting, voice, gait, and ECG data. The combination of these modalities with machine learning techniques will provide a holistic approach for the identification and monitoring of motor and non-motor symptoms of PD. It has eliminated the disadvantages associated with the use of traditional methods by offering an effective, non-invasive, and inexpensive method to be applied conveniently across all healthcare systems. This is the innovation that promises to revolutionize the neurodegenerative diseases management. The systems ensure high accuracy across multiple modalities due to their utilization of the most advanced algorithms, including DenseNet-121 for handwriting, SVM for voice data, Gradient Boosting for ECG signal processing, and AdaBoost for gait analysis. This would thus allow early disease detection and continuous monitoring of the progression of the diseases, with timely interventions and tailored care. Further, wearable sensors and user-friendly hardware designs that are used can ensure that it is a system that collects real-time, practical data and thus make it available for patients and providers. With such patient-centric design, the system also enhances usability, especially to elderly and the physically challenged.

Future updates might be on incorporating high-tech wearable technology with additional sensors, including accelerometers, gyroscopes, and electromyographic (EMG) sensors, in order to record a more significant amount of physiological and behavioral data. AI-powered predictive analytics, based on the historical data of the patient, may provide a deeper understanding of disease progression and the efficacy of treatments. Secure, seamless data sharing among healthcare professionals will be made possible through cloud-based data management solutions. It will ensure collaborative decision-making in compliance with privacy regulations. Broader clinical validation will include diverse demographic groups to ascertain the reliability and applicability of the system across varied healthcare contexts. These would include integration of the system with telemedicine platforms, adaptive algorithms tailored to the individual patient profiles, and expanded modalities such as retinal imaging and olfactory tests, which will deepen diagnostic precision and accessibility. The proposed framework has profound health ramifications when applied to the unmet challenges of neurodegenerative diseases. Its ability to reduce long-term treatment costs, alleviate caregiver burden, and improve patient outcomes underscores its transformative impact. By filling the gaps of healthcare accessibility and equity, this system would guarantee its utility both in developed clinical settings and in resource-poor areas. Moreover, this research now offers potential means of diagnosis and management for other neurological disorders; multi-modal analysis and machine learning power revolutionizes healthcare.

This work thus gives a strong basis to early detection and management of Parkinson's disease. In further advancements and clinical validation, this proposed system shall be of greater use in fighting neurodegenerative disorders by improving the quality of life of the patients and families. It is a building block for personalized medicine, monitoring, and assessment, and therapeutic testing, setting new and innovative landmarks that will contribute significantly to making life better, healthier, and more balanced.

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