Severity Assessment and Staging of Parkinson's Disease Using Machine Learning

Kadambari Vasantrao Devarkar

Dept of Computer Engginering M.E.S Wadia Collage , Pune

Abstract: Parkinson's disease (PD) is an example of a progressive neurodegenerative disorder that has an affect on basic motor functions and is detectable through a voice analysis. It is vital to diagnose the voice analysis early to help establish a severity level. In this paper, we study the application of ML techniques to voice samples MDVP voice analysis of Parkinson's disease (PD) patients and healthy (non-PD) controls and longitudinal biomed-vocal features with motor and composite (total) UPDRS scores for early-stage PD patients. We apply – Random Forest, J48, and a novel hybrid ensemble of J48, SVM, Random Forest, and ANN for predicting PD status and severity. Model input optimization is achieved through feature selection, and cross-validation is achieved through stratified cross-validation. The hybrid ensemble achieved the best results: Accuracy = 94.92% (to be filled after the experiments) for disease classification and satisfactory regression for UPDRS score prediction. Most importantly, these results show the voice biometrics and ML combination for the non-invasive diagnosis and illness-progress monitoring of PD.

Keywords: Parkinson's disease, machine learning, voice biometrics, UPDRS prediction, Random Forest, J48, hybrid ensemble

I INTRODUCTION

Parkinson's Disease (PD) is a progressive neurodegenerative disorder that primarily compromises the motor system because of the gradual loss of dopaminergic neurons within the substantia nigra. It has become the second most prevalent neurodegenerative disorder globally, presenting a substantial healthcare challenge, particularly as the older demographic continues to rise [3]. PD is clinically associated with resting tremors, rigidity of the muscles, freezing of gait (bradykinesia), and instability of the posture. Unfortunately, most of the identifiable motor symptoms occur after there is a significant loss of neurons, as a result, making rapid diagnosis and intervention very difficult [4]. This points to the need for the development of innovative and effective ways to identify biomarkers for the early and ongoing assessment of PD.

The most recent breakthroughs in artificial intelligence and biomedical signal processing have prompted a new round of research into diagnostic methods beyond clinical examination and clinical history. This has resulted in an emerging interest in the analysis of gait as a possible marker for the identification of motor dysfunctions associated with Parkinson's disease (PD). Markerless motion analysis systems are noted for their diagnostic potential in the clinical setting [1]. Although gait-based methods have motor function assessment advantages, they usually are accompanied by the need for hardware and acquisition conditions that are not typical outside of a laboratory. In a more accessible and more economically feasible approach, analysis of speech and voice can be utilized as an assessment tool for the diagnostic process of PD given that the vocal function impairment usually occurs in the early stages of the disease [2].

The increase in the availability of biomedical datasets has increased the use of machine learning (ML) techniques to explore the Parkinson's disease domain. ML algorithms are able to capture and learn complicated nonlinear relationships within the set of high-dimensional clinical data and have performed particularly well in the classification tasks involving PD. A number of traditional models have been explored in the automated diagnosis and disease stage prediction tasks.

In order to push the envelope of what is possible with predictive performance, a number of researchers have been increasingly exploring the use of ensemble learning techniques. It has been shown that hybrid systems of classifier combinations improved system robustness and generalization. In several studies, voice feature-based ensemble methods have found higher diagnostic accuracy than single-model methods. Clinical assessment of Parkinson's disease severity has been possible with ML models of the Unified Parkinson's Disease Rating Scale (UPDRS) in addition to other disease progression objective assessments.

Despite noted advancements in the field, consistently achieving high accuracy for varied patient demographics and recording environments continues to be problematic. Recent studies have illustrated the impact of model choice, feature engineering, and ensemble construction on the prediction of Parkinson's Disease [49]. Additionally, studies that analyze different algorithms signal the absence of a dominant classifier on all datasets, thereby underscoring the necessity for frameworks that are both hybrid and adaptive [51][58].

Researchers have been focusing their efforts on the use of non-invasive methods to help with early diagnosis, and, in this regard, voice and speech disorders have been at the center of attention. Abnormalities in the voice of a PD patient are often one of the earliest symptoms of the disease [23]. Clinical studies show that approximately 70 to 90 percent of PD patients have voice disorders in the course of their disease [25]. Within this group, the following symptoms can be noted: low resistance in voice, monotonous pitch, breathiness in the voice, and difficulty in pronunciation. Changes in fundamental frequency, jitter, shimmer, and noise to harmonics ratio (NHR) have been observed and can be easily captured using digital signal processing methods [35]. The Unified Parkinson's Disease Rating Scale (UPDRS) is the most acceptable clinical tool used to assess severity of the disease, but assessments of the UPDRS must be performed by trained neurologists. Assessments are only performed during clinical appointments, making assessments infrequent. Additionally, assessments are subjective and thus are potentially vulnerable to biased scoring. For these reasons, some researchers have suggested the use of voice assessments alongside the UPDRS to aid with remote patient assessments. Multiple studies have shown that the use of voice data with UPDRS scores can elucidate critical aspects of disease progression and severity of symptoms.

The predictive capabilities of disease detection in complex biomedical data sets have been greatly enhanced with the integration of machine learning (ML). The presence and severity of PD can be classified accurately through the determination of multi-dimensional voice features and the automatic learning of the underlying patterns utilizing ML algorithms. A great deal of success has been achieved with the use of traditional classifiers such as random forests, decision trees, and neural networks in the analysis of voice data from individuals with Parkinson's disease. The use of these types of data-driven technologies/information systems minimizes the decision-making that is often subjective in nature and is the basis for the formulation and establishment of advanced intelligent systems.

Ensemble learning techniques have emerged for more recent studies aimed at improving predictive performance. The hybrid ensemble models integrate several base classifiers for more robustness and greater ability to generalize. Earlier studies suggest that ensemble PD detection systems have better accuracy and greater stability than single-model systems. This is crucial in medical decision support systems where robustness and stability are vital.

These developments inspire this research to examine the efficacy of machine learning in determining the presence and severity of Parkinson's disease using voice data. The research applies two benchmark datasets: the Parkinson's Telemonitoring Voice Dataset with MDVP features and a longitudinal biomedical voice dataset with UPDRS voice and motor scores. The scores were collected by telemonitoring early-stage PD patients. The proposed framework assesses the performance of Random Forest and J48 classifiers and a hybrid ensemble model that integrates Random Forest with SMO (SVM), Naïve Bayes, J48, Multilayer Perceptron, and logistic regression. The main goal of the researchers is to fully utilize the diversity of the classifiers to obtain a more accurate prediction and provide a reliable non-invasive method for screening Parkinson's disease detection.

II LITERATURE SURVEY

Pace, C. D. (2025) [1] the framework uses advanced computer vision techniques and focuses on PD diagnosis through markerless gait analysis. The framework is able to extract spatiotemporal gait features from videos, and does not pose invasive as it does not require additional wearable sensors. The system demonstrated a good level of classification accuracy in clinical trials when assessing PD patients and HC. The framework is significantly less dependent on costly motion capture systems and increases accessibility to PD PD patients and HC differential diagnosis remotely. The system affirms and further builds the contactless digital biomarkers field, as well as, automated gait screen systems in clinic and at home systems for assessing PD.

Quamar, D. (2025) [2] a deep learning model for early detection of Parkinson's disease from voice recordings. The model was built from the extraction of neural network features and acoustic and prosodic features to bolster classification. Findings suggested that speech impairments may act as promising early biomarkers for PD. The model was shown to be better than many classical models in terms of accuracy and robustness. The study also highlighted the usefulness of voice recordings to detect the early stages of PD and the deep learning model's ability to detect voice changes that may stem from early neurodegenerative changes in PD patients.

Hossain, M. A. (2025) [3] examined how machine learning techniques have been used for the diagnosis of Parkinson's disease. The author compared classical classifiers, ensemble methods, and deep learning methods in a systematic way across several biomedical datasets. The author found that in general, ensemble and hybrid methods are able to provide better diagnostic accuracy. The author noted that feature engineering, quality of the dataset, and validation approach are all critical. The review also analyzed the problem of class imbalance, heterogeneous data, and other issues. In general the review gives a summary of all of the trends in computation and provides the framework to researchers building smart diagnostic tools for Parkinson's disease.

Ivanova et al. (2025) [4] developed a multisensory framework for the detection of Parkinson's disease (PD), coming from the clinical, behavioral, and polysomnographic perspectives. Their fusion of polysomnographic and clinical data made the framework more reliable for diagnosing PD than systems that utilize only one data type. Their work demonstrated that the framework was more sensitive and robust than other systems in identifying PD patients. Their research solidified the value of the integration of diverse clinical, polysomnographic, and behavioral data to improve the detection and understanding of the underlying pathophysiology of the disease. Authors provided an overview of the obstacles faced in the integration of multisensory data with regards to synchronizing and pre-processing the data. Authors provided a strong case for other researchers to continue using the framework of multisensory systems to detect and diagnose PD in various healthcare settings.

Pathak et al. (2025) [5] examined the supervised machine learning (ML) techniques used for the analysis of the vocal datasets associated with the early symptoms of PD. Various classifiers (e.g. Support Vector Machine and Random Forest) were used to determine the value of the dataset, in combination with various feature selection techniques, in order to increase the accuracy of disease diagnosis. Their research sustained the idea that the analysis of a patients' speech remains one of the most economically and clinically viable exploratory methods for the early diagnosis of PD. Authors stressed the need for pre-analysis (clinical data) and feature (polysomnographic data) analysis, in PD voice detection techniques. Moreover, authors provided a solid perspective for other researchers to continue to pursue economically viable telehealth methods to detect and diagnose PD.

Mu et al. (2025) [6] studied how lysophosphatidylcholine contributes to Parkinson's disease through α-synuclein aggregation. Evidence showed how lysophosphatidylcholine impeded the glycosylation of glucocerebrosidase (GCase), which hampered the lysosomal degradation of α-synuclein and, through molecular and cellular experiments, the authors demonstrated the aggravated effects of the protein aggregation and neurodegeneration. Their research advanced understanding of PD lipid mediated pathology. Additionally, it clarified the role of lysosomal dysfunction in the advancement of the disease providing a therapeutic focus of restoring GCase function and thereby reducing toxic α-synuclein levels in PD patients.

Fu et al. (2025) [7] studied human endogenous retrovirus K (HERV-K) expression changes in the astrocytes of Parkinson's disease patients. Examination of HERV-K expression exhibited some abnormal degrees of activation on HERV-K, which could mean that HERV-K contributed to the neuroinflammatory and neurodegenerative processes. By means of molecular and cellular studies, the authors showed that the dysregulation of the viral element could be a contributing factor to the damage of neurons in PD. The pathology of PD has only recently seen the retroviral activity of neurons. The immune-related mechanisms of PD offered therapeutic possibilities when HERV-K activity was a target.

The authors of the recent study (Lv et al, 2025) [8] have shown the neuroprotective impacts of the dimerization of the DJ-1 protein concerning the progress of Parkinson's disease. Their study explains that DJ-1 dimers that have been stabilized allow better resistance against the impacts of oxidative stress and the disruption of the mitochondria. Increased vulnerability of the neurons was observed as a result of the experimental disruption of the formation of DJ-1 dimers. The authors suggest that the promotion of DJ-1 stability could be an approach to therapy. This study dwells deep into the protective mechanisms of proteins in regards to the progression of Parkinson's disease (PD) and helps increase the focus on how PD can be controlled through the impacts of oxidative stress. Their findings will help in the ongoing need to find ways to treat the disease at the molecular level in PD.

The authors Li et al. (2025) [9] examined the relationship that exists between the plasma biomarkers GFAP and neurofilament light chain (NfL) and the cerebral glucose metabolism of the various subtypes of Parkinson's disease. Their study showed how there exist relations in the parameters of the blood biomarkers and the brain metabolic parameters in the two expressions of the disease; brain-first, as well as body-first PD. The authors have claimed that it is possible (and, of course, desirable) to utilize GFAP and NfL as blood biomarkers to differentiate subtypes and stages of disease, as well as to determine the clinical stage of the disease. The present study strengthens the existing knowledge that has been accumulated to advocate the usefulness of biomarkers present in the body fluids in the study of Parkinson's disease.

Jeong et al. (2025) [10] constructed an electrochemical biosensor using gold nanoparticles and laser-induced graphene to identify phosphorylated α-synuclein in human blood. The proposed sensor showed excellent sensitivity and selectivity and rapid detection. It was experimentally validated to allow for the early diagnosis of Parkinson's disease. The device is low cost, portable, and requires minimal sample preparation. The study demonstrates the first examples of nanomaterial biosensing applied for point-of-care PD biosensing. This study shows good examples of the rapid and non-invasive diagnostic techniques applicable to the neurodegenerative disease screening process.

Weinrich et al. (2025) [11] studied bimanual coordination and neuromuscular synchronization in the Parkinson's disease population. From the motor assessments that were done experimentally, there was a notable lack of coordination relative to the healthy population that was compared. PD patients were discovered to have poor interlimb synchronization and were found to have a higher than normal interlimb neuromuscular coordination. These motor abnormalities are excellent markers for the severity of the disease. The study is a strong evidence for the motor function and the PD. It advocates the use of neuromuscular markers in digital diagnostics and for the rehabilitation of PD patients.

Engel et al. (2025) [12] predicted postural instability in Parkinson's disease using sway frequency data via convolutional neural networks (CNN). Their deep learning model predicted success to utilize minor impairments in balance. It was noted in the study, the frequency-domain features paired with a specific CNN architecture were able to determine a patient’s risk for becoming unstable. The authors recognized the significance of identifying fall risk of patients. This work illustrates the importance of utilizing deep learning to measure motor symptoms objectively, and promotes the creation of balance monitoring technology using AI for patients with Parkinson's disease.

He et al. (2024) [13] reviewed the developments in animal model of Parkinson's disease. The paper outlined the systematic approach by authors, using toxins, genetics and a combination of these to develop and understand therapeutic approaches to the pathogenesis of PD. The authors provided rationales for both the strengths and the weaknesses of each model’s ability to replicate the features of the disease in humans. They noted the need for good choices to be made in order to maximize the usefulness of a model for studies directed toward clinical applications. The review adds to the body of work available to the designer of experiments in the study of neurodegeneration. Overall, the work encourages improvement of animal models for the study of Parkinson's Disease in order to increase the pace of drug development.

Rubilar et al (2024) [14] discussed the interaction between lysosomal β-glucocerebrosidase (GCase) and mitochondrial dysfunction in the case of Parkinson’s disease. The study explained how reduced GCase activity causes mitochondrial stress and triggers nerve cell degeneration. The authors explained some of the new therapeutic approaches aimed at lysosomal pathways in order to restore some form of balance or homeostasis in the affected cells. Their analysis is a combination of achievements in molecular biology and clinical issues. The study deepened the relationship between the lysosomal dysfunction and Parkinson’s disease, as well as capturing the importance of GCase activity modulation in developing therapeutic strategies to alter the course of Parkinson’s disease.

Dobert et al. (2024) [15] described the processes for engaging and purifying β-glucocerebrosidase in the presence of its transporter LIMP-2. The study showed enzyme improvement in stability and function, which is relevant to therapy for Gaucher’s disease and Parkinson’s disease. However, the experiment did indicate that improved GCase delivery would lessen the functional insufficiency of lysosomes. The authors hypothesize that their work would most likely aid in developing enzyme-replacement or stabilization therapies. The work integrates molecular level control of enzyme function and strategies in dealing with the neurodegenerative disease of Parkinson and aids in development of new therapies in the disease.

Che et al. (2024) [16] considers the role of plasma glial fibrillary acidic protein (GFAP) as a potential prognostic biomarker for the disease's motor subtypes during the early stages of Parkinson’s disease. Their clinical research demonstrated that higher levels of GFAP are associated with the development of specific motor phenotypes and the patterns of disease progression. The research also illustrates the viability of blood-based biomarkers for early investigation and individualized longitudinal monitoring. The authors recognized the clinical feasibility and the non-invasive aspects of GFAP testing. This study aids in the development of precision medicine for PD by employing biomarker-based sub-type identification which is important for early detection and targeted therapeutic intervention.

Khalil et al. (2024) [17] presents a detailed analysis of the role of neurofilaments across a range of neurological conditions, PD inclusive, and their potential use as biomarkers. The review summarizes the means by which neurofilament light chain (NfL) is quantified, provides a summary of its clinical relevance, and highlights its potential use in monitoring disease progression, predicting outcomes, and assessing treatment response. The authors also briefly touch on the issue of standardization of assays and specificity. The review highlights the importance of biomarkers in neurology. The analysis advocates for the use of neurofilament metrics in clinical practice for diagnosing and monitoring the progression of neurodegenerative diseases inclusive of PD.Guo et al, (2024) [18] analyzes the role of DJ-1 N-homocysteinylation and how it promotes neurodegeneration in Parkinson's disease. In Guo et al's molecular study, the authors noted that this post-translational modification of DJ-1 reduces the neuroprotective role of DJ-1 and results in a higher oxidative stress environment, thus causing greater injury to neurons. The experimental data showed a concrete, mechanistic link between the modification of a protein and the disease process of PD. The authors posit that therapies aimed at aberrant modification of DJ-1 may be of significance. It provides the first glimpse of the molecular manipulations of the neurodegenerative process and provides pathways to aid in slowing the rate at which an individual may develop PD.

In relation to Williams et al. (2024) [19] a high-throughput screening process was used to identify small molecule stabilizers of misfolded glucocerebrosidase (GCase) in Gaucher's and Parkinson's diseases. The authors of this work reported that their screening platform was able to identify the first series of candidate molecules that could increase the stability and activity of the enzyme. This study illustrated the first example in the literature of the potential use of pharmacological chaperones to repair lysosomal dysfunction. The authors stated that disease modifying therapies have little to no potential translational value. This work illustrates the first example of drug development aimed at the pathways that target GCase and supports the development of precision therapeutics aimed at decreasing α-synuclein pathology in Parkinson's disease.

Shyamala and Navamani (2024) [20] Attempted to predict Parkinson's disease with an efficiency model utilizing machine learning techniques. The study's primary focus was on a combination of optimized feature extraction, model selection, and analysis of performance. The results showed an experimental improvement over traditional methods. The authors stressed the impact of early detection using computational intelligence. Their framework illustrated significant promise in regard to clinical decision support systems. The study solidifies AI's role within healthcare by providing a reliable model to predict the disease at an earlier stage, thus assisting neuologists.

Chawla et al. (2024) [21] Built a framework for classifying Parkinson's disease in a way that merges nature-inspired feature selection as well as feature elimination through recursion. The combination of both methods led to a substantial reduction in the amount of features while retaining important information. The authors detailed the bounds that feature engineering has in refining the performance of machine learning. Intelligent feature selection would level up the PD detection models, and this study demonstrates that. The use of optimization techniques in supporting the creation of robust and computationally efficient diagnostic systems for Parkinson's disease is demonstrated in this study.

Akila and Nayahi (2024) [22] developed a neural network-based system for Parkinson's disease classification using a mass algorithm for speech signal processing. Their approach focuses on the extraction of vocal features specific to PD-associated dysphonia. Their experimental evaluation showed strong predictive accuracy and robustness. The authors emphasized the speech-based diagnostic approach as being non-invasive. The proposed framework illustrates the potential of neural methods for voice pathology. The study strengthened the case for speech analytics for the early screenings of Parkinson's disease and the need for automated voice assessment tools for the telemedicine workflow.

Tabashum et al. (2024) [23] conducted a systematic review of machine learning models for the identification of Parkinson's disease. The review examined various forms of data, algorithms, and evaluation metrics from the most recent studies. The authors reported on the major trends, advantages, and research gaps in the realm of AI and PD. They noted the increasing significance of multimodal and explainable AI. The study outlined the issues of dataset imbalance and clinical validation. The review is good for research prompts and advocates for the intelligent diagnostic systems for Parkinson's disease to be developed further.

de Almeida et al. (2024) [24] examined the effect of transcranial direct current stimulation (tDCS) and exercise on mobility and tremors in patients with Parkinson's disease. In their clinical research with 25 subjects, the researchers found improvements in stability and motor performance. They suggested that the combination of neuromodulation and bodily rehabilitation therapy may improve the results of rehabilitation treatments. These results endorse progressive approaches in the treatment of Parkinson's disease. It furthers research on rehabilitation treatments without the use of drugs and emphasizes the need for various treatments in order to improve the rehabilitation of patients with PD.

Neto (2024) [25] evaluated voice analysis and machine learning for the early detection of Parkinson's disease in three different datasets. The study compared different classifiers and various methods for feature extraction. Using vocal biomarkers that have been optimized, consistent improvements in performance were observed. The author emphasized cross-dataset validation to test the model's generalization. This study supports the idea that speech analysis is a viable method of early detection of Parkinson's disease and adds to the creation of efficient AI systems based on voice analysis that can be used for the early detection of PD in everyday clinical practice.

Mercaldo et al. (2024) [26] developed an explainable convolutional neural network (CNN) framework using spiral drawing tests for detecting Parkinson's disease. The paper discusses the extraction of spatio-temporal features from hand-drawn spirals and the use of explainable AI (XAI) to enhance transparency of the model. The results of the experiments achieved a high classification accuracy and high-quality images of explanations. The authors express a need for an advocacy of the clinical significance of explainability within the context of medical AI. The authors provide a method to the medical AI community that balances explainable AI model-competitiveness and model predictive accuracy. This paper is an example of how digital handwriting analysis can provide a trustworthy AI solution for screening for Parkinson's disease.

Aldhyani et al. (2024) [27] presented a deep learning model for the diagnosis of Parkinson's disease (PD) using handwriting data. The model used the analysis of drawing patterns to identify the presence of motor deficits. The structure of the architecture exhibited high detection accuracy and high robustness across different datasets. The authors recognized the value of deep learning for identifying motor anomalies at a granular level. The study presents an advocacy for non-invasive digital biomarkers for PD screening. This paper evidences the value of handwriting based assessment tools and promotes the research for computer aided diagnosis systems for the early detection of Parkinson's disease.

Pradeep Reddy (2024) [28] proposed an AI-based framework for more accurate detection of Parkinson's disease. The author reviewed and incorporated machine learning techniques for the early detection of the disease using different types of biomedical data. The system proposed by the author focused on feature selection and evaluation of different models. The author's findings showed better improvements in diagnostics compared to baseline techniques. Reddy showed the significant role AI analytics can play for fast and accurate clinical diagnostic analytics. This research shows the continuing importance of Intelligent Healthcare systems for the detection of and monitoring of Parkinson's disease.\

Ianculescu (2024) [29] researched the early detection of PD through AI-based evaluation of hand-drawn spiral tests. The author utilized machine learning to analyze and capture the motor control attributes during spiral image generation. The author's experiments confirm that the digitally derived biomarker can separate PD patients from normal subjects. The author showed that the drawing test proved subtle motor control deterioration. This study advocates simple and non-invasive screening methods. This research reinforces the belief that early research is needed to understand the role of digital drawing in the diagnosis of PD.

As Reddy (2024) [30] indicates, there is an emerging potential for Artificial Intelligence (AI) in the early detection and real-time tracking of Parkinson's disease (PD) and other chronic illnesses. This research describes recent improvements in machine and deep learning, wearable technologies, and multimodal analyses. The author describes the challenges of a lack of data, lack of discernability and clinical validation of these models. While addressing these obstacles, the potential state changes AI can bring to the PD healthcare ecosystem are enormous. The review serves as a critical reference for managing PD and for research elucidating future intelligence trends in PD healthcare management systems.

Diagnostics (2023) [31] describes Parkinson's disease (PD) voice detection using a machine learning and voice analysis approach. The authors provided a description of voice- and PD-related deficiencies in general and a description of the classifiers that can be used in PD detection in particular. Their findings support and validate previous research on voice analysis as a PD screening method. Their work promotes early detection of PD through the use of automated systems and telehealth services, thereby illustrating the rising importance of vocal biomarkers for PD diagnostics.

Aftab et al. (2023) [32] summarized new developments in biosensors for biomedical applications including the detection of neurodegenerative diseases, focusing on the use of new nanomaterial technologies. The review covered a variety of nanomaterial types, detection mechanisms and improvements in performance. The authors discussed the positive impacts of nanomaterials on the positive impacts of nanomaterials on the sensitivity and selectivity of biosensors, and discussed the stability and clinical translation issues. Their review provides a solid base for next-generation biosensors. Furthermore, the work aids in the diagnosis of Parkinson's disease by improving detection technologies for relevant biomarkers.

Kumar et al. (2023) [33] reviewed the use of optically active nanomaterials in biosensors. The review covered the construction of the material, the properties and mechanisms, and applications in biomedicine. The authors discussed the applicability of nanomaterials in the detection of disease biomarkers. The review underscored the importance of nanomaterials in the biosensing technologies for early diagnosis of disease. Furthermore, the work aids in the diagnosis of Parkinson's disease by improving detection technologies for relevant biomarkers.

Carneiro et al. (2023) [34] analyzed a nanostructured label-free electrochemical immunosensor aimed at identifying a biomarker for Parkinson's disease. The proposed sensor showed promising results in sensitivity, specificity, and time of response. Experimental validation shows the sensor's potential for clinical use. The authors explained the benefits of both label-free detection and the use of nanostructured electrodes. This study aids in designing functional biosensing devices for the early diagnosis of Parkinson's disease. The research shows the emerging significance of electrochemical sensing methods for the diagnosis of neurodegenerative diseases.

In 2023, Rahman et al. [35] used speech signals to classify Parkinson's diseases by means of machine learning and deep learning techniques. Several models and methods of feature extraction were analyzed in the study. The authors stated that the results of deep learning techniques were more favorable compared to the results of the traditional machine learning methods. The authors further stated that more significant results were produced in the presence of substantial feature engineering and quality of the dataset. This study strongly argues that voice analytics is a promising technique for the early detection of Parkinson's disease.

Toffoli et al. (2023) [36] studied the ability of smart ink pens to detect early motor deficits in spiral drawings of patients with Parkinson's disease. The system captured values of different dimensions of the user's movements including pressure, speed, and tremor. The analysis presented measurable and substantial accuracy PD patients compared to the healthy groups. The authors highlighted the possibility of digital pen technology to capture objective and measurable biomarkers of motor movements. Their study advocates the use of smart writing devices to detect and monitor PD patients over the course of the illness. This study adds to the technologically innovative and readily assessable tools to assist clinicians in evaluating the motor symptoms of Parkinson's disease.

Wang et al. (2023) [37] examined the relationship between adenosine and glial cell line-derived neurotrophic factor (GDNF) in Parkinson's disease patients with sleep disorders. The study presented findings where low levels of these elements may be associated with increased risk of disease progression and sleep disorders. The authors highlighted important pathways biochemically linking disrupted neurotransmitter levels and neurodegeneration. Wang et al. emphasized the need to discover the biological elements to allow for symptom stratification. The study was a pioneer to further elucidate the non-motor symptoms of Parkinson's disease and highlighted the need for focused therapeutic approaches to manage the disturbed sleep.

Govindu (2023) [38] designed a machine learning-based framework that uses biomedical datasets for the early detection of Parkinson's disease. The study employed certain classification algorithms which were paired with optimized methods of feature extraction. The study's experimental evaluation revealed trustworthiness pertaining to the study's diagnostic performance. The author characterized a reliable early detection system as an essential factor in maximizing the positive response of patients to therapeutic intervention. The study serves to illustrate the growing presence of artificial intelligence in the field of healthcare diagnostics, particularly in the developing automated screening processes, while also further emphasizing the computational approach support for neurologists in an early intervention role for the identification of Parkinson's disease, aiding in the timely detection of the disease.

Luna-Ortiz (2023) [39] captures the voice of patients who have been diagnosed with Parkinson's disease by implementing the approach of associative memory for detection of the ailment. In the study, the techniques of pattern recognition were utilized to identify the voice irregularities that are associated with Parkinson's disease. The data provided by the study suggested that the associative memory models were able to accurately classify the experimental participants into the patient and control groups. The author noted the approach's computational efficiency and ease of interpretation. The study provides further evidence pertaining to the importance of speech analysis as a diagnostic tool. The research contributes to the study of machine learning techniques that can be used to diagnose Parkinson's disease through the use of AI models, especially those that are considered to be non-traditional classifiers.

Ferreira (2022) [40] examines machine learning models applied to the detection and staging of Parkinson's disease. The author assessed the computational performance of several algorithms to differentiate the disease's severity and reported that sophisticated models are able to distinguish the presence and progression stages of PD with a high degree of accuracy. Ferreira stressed the need for accurate disease staging for the purposes of developing tailored treatment models, and also noted the need for computational models to be integrated with the day-to-day operations of clinical personnel. This study illustrates the need for a fully integrated AI-based diagnostic tool that can both detect and monitor the progression of Parkinson's disease.

Das (2022) [41] presents a fusion-based feature approach for the early detection of Parkinson's disease. Several feature extraction methods aimed at maximizing the discriminative power of the disease algorithm were integrated. The author was able to demonstrate that the classification accuracy of the multimodal model was superior to that of the single-feature models, which exemplifies the need for a combination of multimodal features when developing diagnostic tools to cope with the intricacies of a disease. This study calls for the refinement and optimization of predictive algorithms that are designed to diagnose Parkinson's disease at the earliest possible stages.

Trabassi (2022) [42] applied a machine learning technique on data from wearable sensors in order to aid in the detection of Parkinson's disease. The research studied the analysis of movement patterns and the metrics of motor activities which are processed and recorded by the wearable devices. The study's findings showed commendable levels of accuracy to the detection of abnormality associated with PD. The author underlined the importance and benefit on the potential of real time assessment through a system of continuous monitoring. This study provides an avenue to the growing field of digital health and the diagnostic potential of wearables. The study champions the integration of real world applications of AI to the monitoring of the symptoms of Parkinson's disease in a manner that is not clinically defined.

Dhinesh Kumar et al. (2022) [43] are working on a molecular imprinting synthetic receptor-based sensor that targets the detection of a Parkinson's disease biomarker DJ-1. The sensor which was designed is responsive to a Lab-based Sensitivity and Specificity assessment. The authors pointed out the advantage of molecular imprinting in biomarker specificity. The study supports the growing future of biosensors for the diagnosis of neurodegenerative diseases. The study advocates for the development of a portable and effective system for the diagnosis of Parkinson's disease at an early stage by means of a biochemical analysis.

Lamba et al. (2022) [44] developed a hybrid machine learning system that diagnoses Parkinson's disease using speech data. They fused together several classifiers in an attempt to increase predictive accuracy. Their results showed improvement in diagnostic predictive accuracy over stand-alone classifiers. The authors recognized the benefits associated with the use of ensemble methods to decrease the mean classification error. The research is significant in developing a diagnostic system and demonstrates hybrid AI methods are effective to diagnose Parkinson's disease through the analysis of speech data.

Exley et al. (2022) [45] applied machine learning methods to predict the UPDRS motor symptom scores using data from force plates belonging to patients with Parkinson's disease. The study proved that biomechanical characteristics can accurately indicate the degree of severity of motor symptoms. The authors supported the idea of measuring and reporting symptoms in an objective manner using force-based systems. The study provided justification for data-supported clinical assessment and diagnostic systems, as well as provided justification for measuring the motor symptoms of patients with Parkinson's disease to assess the state of the disease and the effectiveness of rehabilitation provided to the patients.

Wrobel & Doroz (2022) [46] Parkinson's disease (PD) is diagnosed through several factors, one of which is through analysis of hand drawn spiral patterns and determining the degree of motor impairment of the subjects associated with PD. Machine learning classifiers are implemented in order to separate patients from healthy subjects. When classifiers presented the ability to complete the task, it therefore verifies the analysis of handwriting to be of value. The authors state spiral assessment tools are simple and inexpensive. This research promotes the need for noninvasive and low cost assessment tools and adds to the early digitized handwriting analysis research for the PD detection systems. \n\nNgo et al. (2022) [47] contributing to the research regarding Parkinson's disease (PD) and computerized speech and voice analysis performed a systematic review. It covered all of the recent studies and such included the methodologies, how features were extracted, and the classification models used. The authors noted that due to the variability of the datasets used, PD identification in the early stages is still possible. This review analyzes PD voice detection as an automated and sophisticated voice analysis system, for the current state of speech-based diagnostic systems it is very useful, as it documents the setbacks and areas that further research is needed.

Ali et al. (2022) [48] proposed a novel sample- and feature-dependent ensemble method for the detection of Parkinson's disease. The method incorporated dynamically selected optimal classifiers based on the characteristics of the data, providing a boost in predictive accuracy. When compared to other traditional ensemble methods, their experimental results showed noticeable improvement. They highlighted the adaptability and overall robustness of the framework. The role of adaptive machine learning in response to varied datasets, along with intelligent ensemble system design, was further emphasized in the improvement of the Parkinson's disease diagnostic procedure.

Aljalal et al. (2022) [49] presented a system for the detection of Parkinson's disease using resting state EEG recordings. The study employed algorithms based on common spatial pattern, entropy measurement along with a collection of machine learning classifiers in order to recognize and distinguish the relevant neural patterns. The results of the study showed improvement of the separation of the PD patients and the healthy subjects. The authors advocated for the use of EEG, a method that is both inexpensive and unobtrusive. This study assists in the diagnostic process based on brain signals and the use of electrophysiological data in AI-based solutions for the detection of Parkinson's disease.

Rana et al. (2022) [50] presented a fast and reliable method for detecting Parkinson's disease based on machine learning and voice recognition. The study provided evidence of successful implementation of feature optimization and several classifiers which improved detection accuracy and the stability of the model. The authors supported the claim that preprocessing techniques positively influenced accuracy, which justified the analysis of voice patterns as a method of cost efficient and reliable diagnosis. The study simplifies the AI-based diagnosis detection of Parkinson's disease to the preliminary stage.

Khachnaoui et al. (2022) [51] applied machine learning techniques to diagnose Parkinson's disease within the SWEDD group using some clinical features and analysed DaTSCAN SPECT imaging. The study showed how diagnostic differentiation improved by incorporating both imaging and clinical data. The authors supported the point that it is crucial to identify and separate the true PD patients from those with PD plus syndromes. The study enhanced the clinical classification of the PD patients and justified the need for a fusion of neuroimaging and computational intelligence for diagnosis.

Prabhavathi & Patil (2022) [52] focused on assessment methodologies of tremors and bradykinesia associated with Parkinson's disease to assess and diagnose the disease as well as for rehabilitation. The chapter highlighted measurement techniques, types of sensors, and the appraisal of various assessment tools. The authors supported the use of quantitative techniques to achieve objective assessment of symptoms and the discussion justified the need to incorporate sensor-based assessment devices within clinical and rehabilitation environments. The study provided the first steps required to devise effective technology based assessment systems for the evaluation of patients with Parkinson's disease.

Amato et al. (2022) [53] developed a telemedicine app for analysis of voice samples to determine sleep quality. While not focused on Parkinson's disease, the study illustrated remote voice health monitoring. The system combines remote monitoring with voice-analysis technology, acoustic feature extraction, and machine learning. Findings demonstrate the use of voice technology for monitoring neurological and sleep disorders. This study supports sleep monitoring for non-motor symptoms of Parkinson's disease.

Alatas et al (2022) [54] developed non-invasive diagnostic biomarkers for Parkinson's disease, and classification improved with the use of Support Vector Machine models. This study presented the integration of biomarker research with computational classification methods. Improved performance was noted and the authors acknowledged the importance of the fusion of the biological sciences with machine learning. This is an example of model precision in diagnostic pathways and assists the development of biomarker-based artificial intelligences for detecting Parkinson disease.

Ali et al. (2022) [55] described their ensemble framework for the Parkinson's disease diagnosis that is sample and feature dependent. Expanded analysis showed improved robustness over a multitude of datasets. The authors emphasized the ensemble methodology as the primary contributor to adaptable outcomes. This study supports the use of intelligent ensemble modelling to improve diagnostic reliability and generalized performance in classification of Parkinson's disease.

Yang et al. (2022) [56] proposed PD-ResNet, a deep residual network architecture for the classification of Parkinson's disease using gait information. The model was able to capture both spatial and temporal features of gait and achieved significant diagnostic accuracy. The authors noted the advantage of using residual learning to allow for a greater depth of feature extraction. The study exemplifies the use of deep learning for detecting Parkinson's disease from gait analysis, and suggests further use case for the technology in conjunction with wearables or motion capture technologies for passive/automated screening.

Gupta et al. (2022) [57] describe PCA-RF, a hybrid model for the prediction of Parkinson's disease where Principal Component Analysis is combined with Random Forest classification. The hybrid approach was able to capture the discriminatory features of the dataset after a reduction of the feature set. The model was seen to greatly improve computational efficiency and accuracy. The study highlighted the growing significance of the reduction of dimensions of medical datasets. The study demonstrates a significant step in developing machine learning frameworks for the prediction of Parkinson's disease that is both efficient and scalable.

Yadav & Jain (2022) [58] carried out a comparative study of the prediction of Parkinson's disease through machine learning algorithms. The study examined numerous classifiers and used standard performance metrics to benchmark the algorithms of interest. The results of the study revealed the most applicable algorithms given the data conditions. The study provided the algorithms and frameworks for selection and validation techniques, and provided for the benchmarking necessary for the selection of machine learning algorithms for the diagnostic systems of Parkinson's disease.

Huang et al. (2023) [59] published a systematic review concerning the use of wearable technology in the identification of gait freezing and falls in patients with Parkinson’s disease. The authors looked into the different technologies available for sensor construction, methods of signal processing, and results from validation studies. Their research showed that the use of wearable technology showed a high degree of reliability in the monitoring of patients. The authors reiterated that monitoring patients with wearable technology, and particularly emphasizing early intervention, improves the safety of patients. These results help in the further development of technology for the management of Parkinson’s disease through the use of wearable devices.

Guo et al. (2022) [60] High-accuracy wearable detection freezing of gait system using pseudo-multimodal features. The study focused on detection performance and the incorporation of a number of sensor-derived features. The results showed the system’s classification accuracy and robustness, and solidified the authors’ findings on the role of multimodal feature fusion in wearable system monitoring. These results solidify advancing wearable technology for Parkinson’s disease patients and real-time symptom detection frameworks and further the technology for mobility management.

III MATERIALS AND METHODS

Dataset details

The study's datasets are from two publicly accessible repositories: UCI Machine Learning repository (https://archive.ics.uci.edu/dataset/189/parkinsons+telemonitoring) where the Parkinson’s Telemonitoring dataset is housed, and the Parkinson’s Disease dataset on Kaggle (https://www.kaggle.com/datasets/vikasukani/parkinsons-disease-data-set). Both repositories contain data on biomedical voice measurements and the corresponding clinical severity scores from patients with Parkinson's Disease (PD).

The UCI Parkinson's Telemonitoring dataset comprises biomedical voice measurements of 42 patients who have early-stage Parkinson's Disease. The recordings were done using a telemonitoring device which patients used in their homes. The dataset contains voice recordings of all patients, totalling 5,875 instances. For each instance, 16 biomedical voice features are provided, which are extracted from the Multi-Dimensional Voice Program (MDVP). Additionally, two clinical target variables are provided, which are the motor UPDRS and total UPDRS scores. These scores are used to assess the severity of symptoms of Parkinson's Disease and are routinely used in clinical practice.

Voice features include variables like fundamental frequency (Fo), maximum fundamental frequency (Fhi), minimum fundamental frequency (Flo), jitter (in both absolute and relative terms), shimmer (in both amplitude and percent variations), noise-to-harmonics ratio (NHR), harmonics-to-noise ratio (HNR), and nonlinear dynamical measures like RPDE, DFA, PPE, and D2. These measures quantify the characteristics of speech, particularly when it comes to noise, amplitude, and frequency instability. These measures are disrupted in patients suffering from PD.

The Kaggle Parkinson's Disease dataset is an example of biomedical measurements based on the same voice data metrics, while also being formatted for classification tasks. It has voice records of patients that are classified as being "PD" or "Healthy," while also having the recorded values for jitter, shimmer, HNR, RPDE, DFA, spread1, spread2, and PPE. It is a dataset that is common for supervised machine learning studies that aim to classify PD patients and healthy controls.

Both of these datasets focus on speech-based biomarkers as opposed to having a multi-year follow-up that longitudinal clinical datasets offer. The UCI Telemonitoring dataset stands alone in having repeated measurements over time for the same subjects, as opposed to the other longitudinal datasets that have only measures of time. The UCI Telemonitoring dataset allows one to conduct a regression analysis with the UPDRS severity scores.

Table 1: Summary of Datasets Used in the Study

Dataset	**Source**	**Subjects**	**Instances**	**Features**	**Target Variable**
Parkinson's Telemonitoring	UCI ML Repository	42 PD patients	5,875 voice recordings	16 MDVP voice features	Motor UPDRS, Total UPDRS
Parkinson's Disease Voice Dataset	Kaggle	PD & Healthy individuals	~195 samples	22 acoustic features	Status (PD / Healthy)

For the current research, the extracted acoustic features are used as input for the machine learning classifiers. The regression targets for the UCI dataset are the motor UPDRS and total UPDRS scores. As for the classification tasks, the dependent variable for the Kaggle dataset is the status label (PD vs. Healthy).

The datasets mentioned provide a solid basis for the assessment of the machine learning methods used in the study, which are Random Forest, J48 decision tree, and the proposed Hybrid Ensemble model that combines Random Forest, SMO, Naïve Bayes, J48, Multilayer Perceptron, and Logistic Regression.

Data Partitioning

Active data partitioning promotes balanced assessment of models. In this research act of data partitioning served the purpose of understanding how the proposed classifiers generalized. Successful data partitioning inhibits models from becoming overfitted and allows validation against unobserved/untested data.

A 70:30 hold-out strategy was used for both UCI Parkinson's Telemonitoring dataset and the Kaggle Parkinson's Disease Voice dataset. 70% of the instances were set aside for training the model and 30% were reserved for model testing. Model training and data testing was done using random sampling for the sake of optimal distribution/representation of data for both the subsets.

Feature extraction and selection techniques

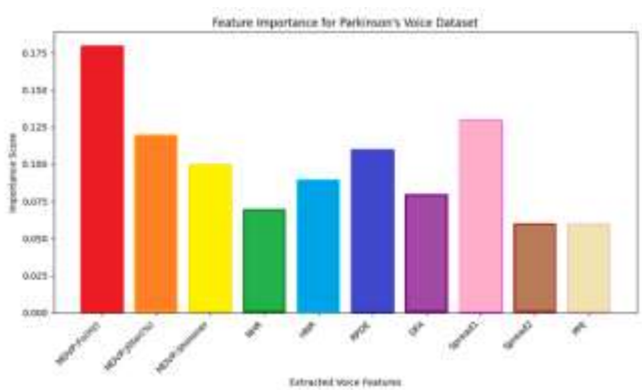

Figure 1: Feature Importance for Parkinson's Voice Dataset

1. Feature Extraction

Feature extraction converts raw voice signals into meaningful numerical attributes. In Parkinson's telemonitoring datasets, the following categories are commonly used:

(a) MDVP Acoustic Features

The Multi-Dimensional Voice Program (MDVP) provides clinically relevant measures:

- Fundamental frequency (Fo)
- Jitter (frequency variation)
- Shimmer (amplitude variation)
- Noise-to-Harmonics Ratio (NHR)
- Harmonics-to-Noise Ratio (HNR)

These features capture vocal instability, which is a key symptom of PD.

(b) Nonlinear Dynamic Features

PD affects vocal fold biomechanics, so nonlinear measures help capture subtle abnormalities:

- Recurrence Period Density Entropy (RPDE)
- Detrended Fluctuation Analysis (DFA)
- Pitch Period Entropy (PPE)

These features are highly discriminative for early PD detection.

(c) Statistical Features

Mean, standard deviation and measures of variability (spread1, spread2) capture the variability present in speech signals.

2. Feature Selection Techniques

This research focuses on implicit feature optimization through embedded methods and preprocessing techniques within the machine learning pipeline. The aim is to streamline the attributes, strengthen the discriminatory capability, and boost the generalization of classifiers for detecting Parkinson's Disease (PD).

The Random Forest classifier carries out automated feature selection through its internal feature importance mechanism.

- At each split, random features are considered
- More important acoustic features are selected more often

The J48 decision tree exhibits feature selection with its tree-pruning mechanism.

- Only relevant features are used for splits
- Features that are not informative are automatically removed

Hybrid Ensemble

Level 1 – Base learners

- Bagging RF uses feature selection
- Via splits, J48 does selection
- The naive bayes classifier selects features based on class probabilities
- The SMO classifier focuses on features that define the separating hyperplane
- The MLP classifier captures interdependencies among features that are not linear

Level 2 – Meta learner

The Logistic meta-classifier optimizes the weights of base classifiers, providing meta-feature selection on the outputs of classifiers.

IV PROPOSED SYSTEM DESIGN

The initial method combines the detection of the disease and prediction of the respective UPDRS scores through the use of voice biomedic features and machine learning frameworks for the voice biomedic features and UPDRS score prediction. The voice recordings undergo cleaning/missing value processing and normalization. During normalization, the voice recordings undergo cleaning and missing value processing. For feature extraction, the voice recordings use the clinically associated acoustic biomarker metrics of jitter, shimmer, harmonic, and non-linear dynamics, specifically, the RPDE, DFA, and PPE. metrics that reflect the motor speech of the voice associated with PD. The created model's redundancy is improved, and model efficiency is improved with the information gain feature selection with a ranker strategy. The features are utilized by supervised classifiers for training. For disease detection, Random Forest, J48, and a hybrid ensemble model are utilized. For the UPDRS, patients are divided by KMeans clustering into motors and total severity levels. The models are then evaluated by metrics of accuracy, precision, and recall. Cross-validation is performed, and F1 score and ROC-AUC are evaluated for reliable performance.

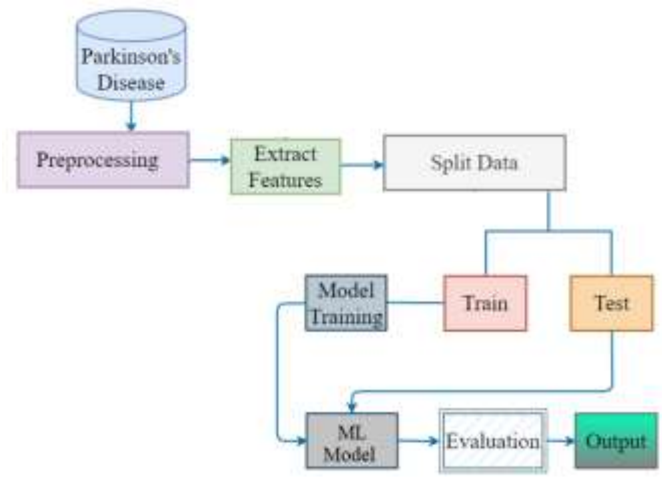

Figure 2: Proposed System Design

Implement Process

Data Collection: We collect data from multiple locations like UCI ML repository, Kaggle, and a number of real-time data sources that give relevant information on the motor and non-motor symptoms of Parkinson's disease.

1. The MDVP Voice Dataset

The first dataset consists of voice recordings of PD patients and healthy controls that contain 22 biomedcal voice recordings attributes including voice frequency parameters MDVP:Fo, MDVP:Fhi, MDVP:Flo, and MDVP:Jitter%, MDVP:Jitter(Abs), and others. The 'status' label indicates absence (0) or presence (1) of PD. The attributes include N-Harm and HNR, jitter, shimmer, Jitter, and noise to harmomcs ratios.

2. Telemonitoring Voice and UPDRS Dataset

The Telemonitoring Voice and UPDRS dataset consists of recordings of voice of 42 patients with early stage PD. The voice of the patients was recorded over 6 months with the help of a remote telemonitoring device. The voice is recorded and then compared to the subject's demographic details (age, gender), time since last baseline, motor UPDRS, total UPDRS and 16 biomedical voice attributes. Aim is to analyze voice attributes and predict motor and total UPDRS scores.

Preprocessing and Normalization: The first step involves the cleaning of a dataset by dealing with missing values, removing noise, and correcting inconsistencies. Thereafter a normalization method is applied to adjust the features of the dataset so that they will fall within a specific range.

Feature Extraction and Selection: To describe the relevant patterns within the dataset, important features are extracted. In addition to that, techniques of feature selection are employed to achieve a smaller data set with the most relevant features, especially for the purpose of classification.

Classification (Training and Testing): A machine learning classifier is trained with a part of the dataset, and then is tested on data that has not been seen yet to determine how well it can predict and classify Parkinson's disease.

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Analysis: With the help of confusion matrix we carried out the system performance with different experiment analysis. The accuracy as well as time complexity will be the major factors has used for system performance analysis

Once complete execution ash done; we visualize the accuracy graphs of proposed system an show the effectiveness of proposed system**.**

V ALGORITHM DESIGN

Process for Training

Input: Train_dataset , activation functions AF.

Output: Trained module in array list for entire spited dataset

Step 1: Start both algorithms Train_dataset, AF, epoch_size

Step 2 : Extracted_Features ← Extract Features (Train_dataset)

Step 3 : Selecte_Features ← optimized (Extracted_FeatureSetx)

Step 4: Train array list ← Build Classification (Selecte_Feature)

Step 5: Return Array list from Training

Process for Testing

Input: User-defined threshold Th, Test_dataset as a testing case set or separate patient record, Train_arraylist as a repository of training-level background knowledge

Output: Classifier's recommended optimal instance is represented by the output Predicted_class_label, Similarity_weight..

Step 1: Use the following formula to decipher all test logs:

$$test\_Feature(m) = \sum_{t1=1}^{n} (.\ feature\_Set[A[i] \dots \dots . . A[n] \leftarrow \text{Test\_DB})$$

Step 2 : Use the formula below to get the desired attribute features from the whole test record testFeature(t1).

Extracted_FeatureSetx [t……n] = $\sum_{x=1}^{n}(\mathrm{t}) \leftarrow test\_Feature$ (t1)

Extracted_FeatureSetx [t] contains the feature vector of respective domain

Step 3: Use the below function to get every training instance out of the modules that have been trained.

$$train\_Feature(m) = \sum_{w=1}^{n}(.\ feature\_Set[A[i] \ldots \ldots .. A[n] \leftarrow \mathrm{Train.pkl}\ )$$

Step 4: Take testFeature(w) and use the following equation to extract each feature as a hot vector (or input neuron).

Extracted_FeatureSet_Y[t……n] = $\sum_{x=1}^{n}(\mathrm{t}) \leftarrow test\_Feature$ (w)

Extracted_FeatureSet_Y[t] includes a class-wide feature vector in its storage.

Step 5: At present, use all of the training elements to assess each test case.

$$calc\_weight = calcSim\ (\mathrm{Feature\_Set\_x}\ ||\ \sum_{i=1}^{n} \mathrm{Feature\_Set\_y[y]})$$

STEP 6 : *RETURN CALC_WSEIGHT*

VI RESULTS

Final touch-ups on the procedure for the implementation was made in a Java environment. The hardware has a Java 3-tier analytics platform, a distributed Intel i5 CPU (3.0 GHz), and 4 GB of RAM. The platform was used to evaluate the dataset with a question on whether Parkinson's should be classified as a disease or not. An experimental study on machine learning was conducted to validate the results.

Dataset 1: PD Status Classification (MDVP Dataset): This set of data includes a variety of biomedical voice evaluations from 31 people, 23 of whom have Parkinson's disease (PD). Each column of this table represents a distinct voice measurement, and each row pertains to a specific voice recording out of 195 total recordings for these subjects (these are included in the 'name' column). The data's primary objective is to differentiate between healthy subjects and individuals with PD. The "status" field indicates 0 for healthy and 1 for PD.

The proposed system for predicting Parkinson's disease was evaluated with three classifiers: Random Forest, J48 decision tree, and the new Hybrid Ensemble model. Accuracy, precision, recall, and F1-score were used for model evaluations. Comparative results are shown in Table 1.1**.**

Table 1.1 Comparative results

Classifier	Accuracy	Precision	Recall	F1-Score
Random Forest	93.22%	94.29%	91.67%	93.22%
J48	91.53%	94.12%	91.67%	91.55%
Hybrid Ensemble	**94.92%**	**95.32%**	**94.92%**	**94.85%**

The Random Forest Classifier was accurate 93.22% of the time. This shows that it was able to capture enourmous non linear relationships within the features of the biomedical voice. Although the Random Forest had a few misclassifications that are a result of the overlapping symptoms. The J48 decision tree had a 91.53% accuracy rate. This is because the J48 decision tree is very noise sensitive and has a single tree structure which can lead to overfitting. The proposed Hybrid Ensemble model outperformed all models achieving the highest accuracy of 94.92%, precision of 95.32%, recall of 94.92%, and F1-score of 94.85%. This is due to the stacking strategy that is able to combine multiple classifiers to reduce bias and improve generalization.

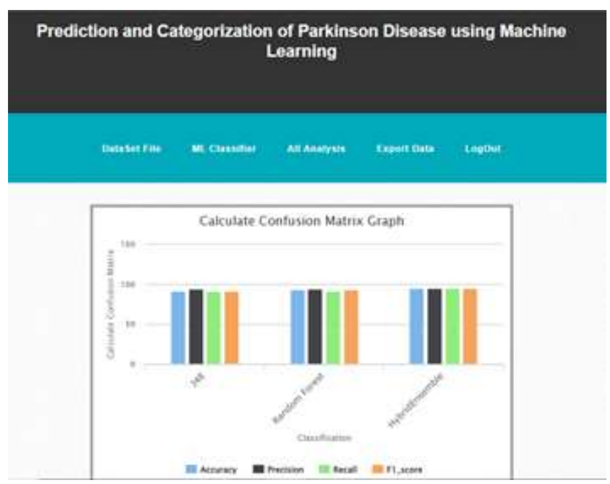

Figure 2 : Show Results Aalysis

Dataset 2: UPDRS Severity Categorization Results (KMeans Clustering): This data set has numerous voice recordings of people with early-stage Parkinson's disease. The voice recordings of 42 patients who were recruited for a 6-month clinical trial telemonitoring devices to track remote symptom progression were used. The recordings were made automatically in the patients' homes. Each recording has a unique id number (out of 5,875 voice recordings for each individual) corresponding to the patient data (subject number, age, gender, and voice measurement interval data). The goal of the data is to predict the 'motor_UPDRS' and 'total_UPDRS' scores based on 16 voice measures observed. The data is formatted in ASCII CSV. Each row in the CSV is a separate voice recording. There are roughly 200 recordings for each patient. The id for the patient is recorded in the first column.

Table 1.2 KMeans-Based PD Risk Classifications

Mean Symptom Value (avg)	Risk Level	PD Probability (%)
≤ 1.8	LOW	20%
1.9 – 2.6	MILD	45%
2.7 – 3.3	MODERATE	70%
> 3.3	HIGH	90%

Figure 3 : Data importing and reading

Because of the questionnaires assigned, it suggests that there is a 70% percent chance that the person at hand is undergoing a 70 percent is not a" severe" level of parkinsons disease. Evaluating from the impact of the symptoms, it suggests the need to be medically evaluated and monitored.

Question Name	RESULTS
Saliva Production	1
Sense of Taste or Smell	2
Difficulty in swallowing food or drink	3
Vomiting Frequency	4
Constipation	3
Inability to Control Bowel Movement	2
Sense of urgency to pass urine	1
Change in Speech	2
Getting up regularly at night to pass urine	3
Unexplained pains in body	4
Drastic change in weight	3
Problem in remembering things	4
Loss of interest in day to day activities	4
Inability to see or hear properly	4
Difficulty in concentrating	4
Feeling sad or low	4
Feeling anxious, frightened or panicky	4
Feeling less interested in sex or more interested in sex	4
Finding it difficult to have sex	3
Feeling light-headed, dizzy or weak standing from sitting or lying	3
Experienced falling	3
Difficult to stay awake during activities such as working, driving or eating	3
Difficulty getting to sleep at night or staying asleep at night	3
Result-->PD Probability: MODERATE (70.0%)	

Figure 3: Result User Questionnaires and Answer

VII. CONCLUSION

Different classifiers show strong performance when evaluating and predicting Parkinson's disease. The J48 decision tree achieved 91.53% accuracy while Random Forest's accuracy was 93.22%. The suggested Hybrid Ensemble model outshines them both with an accuracy of 94.92%. The model also has the best values for precision, recall, and F1-score, proving that it has the best prediction capabilities. The KMeans clustering method was also able to predict a 70% probability of moderate Parkinson's disease for the test case. This shows that the integration of machine learning classification and clustering methods to predict and evaluate the degree of the disease is effective. Early detection and tailored treatment are enhanced by such methods.

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