Predictive Modelling for Parkinson's Disease Diagnosis using Biomedical Voice Measurements

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Abstract

INTRODUCTION: Parkinson's Disease (PD), a progressively debilitating neurological disorder impacting a substantial global population, stands as a significant challenge in modern healthcare. The gradual onset of motor and non-motor symptoms underscores the criticality of early detection for optimal treatment outcomes. In response to this urgency, novel avenues for early diagnosis are being explored, where the amalgamation of biomedical voice analysis and advanced machine learning techniques holds immense promise. Individuals afflicted by PD experience a nuanced deterioration of bodily functions, necessitating interventions that are most effective when initiated at an early stage. The potential of biomedical voice measurements to encode subtle health indicators presents an enticing opportunity. The human voice, an intricate interplay of frequencies and patterns, might offer insights into the underlying health condition.

OBJECTIVES: This research embarks on a comprehensive journey to delve into the intricate connections between voice attributes and the presence of PD, with the aim of expediting its detection and treatment.

METHODS: At the heart of this exploration is the Support Vector Machine (SVM) model, a versatile machine learning tool [1-2]. Functioning as a virtual detective, the SVM model learns from historical data to decipher the intricate patterns that differentiate healthy individuals from those with PD [3-4].

RESULTS: Through the power of pattern recognition, the SVM becomes a predictive instrument, a potential catalyst in unravelling the latent manifestations of PD using the unique patterns harbored within the human voice. Embedded within this research are the practical demonstrations showcased through code snippets [5-7]. By synergizing the intricate voice measurements with the SVM model, we envision the emergence of a diagnostic paradigm where early PD detection becomes both accessible and efficient. This study not only epitomizes the synergy of voice and machine interactions but also attests to the transformative potential of technology within the domain of healthcare.

CONCLUSION: Ultimately, this research strives to harness the intricate layers of voice data, as exemplified through the provided model code [8-11], to contribute to the evolution of an advanced tool for PD prediction. By amalgamating the principles of machine learning and biomedical analysis, we aspire to expedite early PD diagnosis, thereby catalyzing more efficacious treatment strategies. In traversing this multidimensional exploration, we aspire to pave the path toward a future where technology plays an instrumental role in enhancing healthcare outcomes for individuals navigating the challenges of PD, ultimately advancing the pursuit of early diagnosis and intervention.

Keywords: Parkinson's Disease, Biomedical Voice Measurements, Machine Learning, Early Diagnosis, Support Vector Machine (SVM).

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1. Introduction

Parkinson Disease (PD), progressively debilitating neuros related disorders, impacting a substantial global population, stands as a significant challenge in modern healthcare. The gradual onset for motoric and non-motoric gestures underscores the criticality of early detection for optimal treatment outcomes. In response to this urgency, novel avenues for early diagnosis are being explored, where the amalgamation of biomedical voice analysis and advanced machine learning techniques holds immense promise. Individuals afflicted by PD experience a nuanced deterioration of bodilv functions. necessitating interventions that are most effective when initiated at an early stage. The potential of biomedical voice measurements to encode subtle health indicators presents an enticing opportunity. The human voice, an intricate interplay of frequencies and patterns, might offer insights into the underlying health condition. This research embarks on a comprehensive journey to delve into the intricate connections between voice attributes and the presence of PD, with the aim of expediting its detection and treatment. At the heart of this exploration is the Support_Vector_ Machine (SVM) model, type of versatile machine learning tool [1-2]. Functioning as a virtual detective, the SVM model learns from historical data to decipher the intricate patterns that differentiate healthy individuals from those with PD [3-4]. Through the power of pattern recognition, the SVM becomes a predictive instrument, a potential catalyst in unravelling the latent manifestations of PD using the unique patterns harboured within the human voice. Embedded within this research are the practical demonstrations showcased through code snippets [5-7]. By synergizing the intricate voice measurements with the SVM model, we envision the emergence of a diagnostic paradigm where early PD detection becomes both accessible and efficient. This study not only epitomizes the synergy of voice and machine interactions but also attests to the transformative potential of technology within the domain of healthcare. Ultimately, this research strives to harness the intricate layers of voice data, as exemplified through the provided model code [8-11], to contribute to the evolution of an advanced tool for PD prediction. By amalgamating the principles of machine learning and biomedical analysis, we aspire to expedite early PD diagnosis, thereby catalysing more efficacious treatment strategies. In traversing this multidimensional exploration, we aspire to pave the path toward a future where technology plays an instrumental role in enhancing healthcare outcomes for individuals navigating the challenges of PD, ultimately advancing the pursuit of early diagnosis and intervention.

2. Literature Survey

The disease is a neurodegenerative type of issue that poses deepening challenges for early diagnosis. Several studies have explored the application of these methods to enhance diagnostic accuracy. Agarwal et al. (2021) introduced a machine learning model aimed at identifying insignificant attributes, a critical step in feature selection for enhancing model performance. This work is crucial in the context of PD detection, where selecting relevant voice attributes is essential for accurate classification [1]. Another study by Agarwal et al. (2022) delved into the application of the XGBoost machine learning model for detecting exoplanets in distant galaxies. While seemingly unrelated to PD, this research showcases the versatility of machine learning models, which can potentially be adapted to various domains, including medical diagnosis [2]. Agarwal et al. (2023) conducted experiments that measured combined functioning for Test Driven Development and Looped Articulation Method. While not directly related to PD, this research underscores the importance of rigorous testing and validation procedures, which are essential in medical applications like PD diagnosis [3]. Tsanas et al. (2012) proposed new novel speech-based signal processing algorithms to obtain enhanced accuracy-based classifier for the said disease. This work is particularly relevant as it directly addresses the challenges of voice-based PD detection, achieving promising results [4]. Sakar et al. (2013) contributed by collecting and analysing a comprehensive disease voice related dataset containing many voice records. This dataset is invaluable for training and testing machine learning models, making it a valuable resource for the PD detection research community [5]. Agarwal and Tayal (2023) presented a methodology for predicting impact of COVID-19 on global academic ranks. While not specific to PD, this research emphasizes the importance of predictive models in various domains and can potentially inspire similar efforts in healthcare, including PD prediction [6]. Gokul et al. (2013) explored ML techniques for these predictions. Their study demonstrates the feasibility of using machine learning to address complex medical diagnoses like PD [7]. Mall et al. (2022) investigated prior warnings' signals of the disease predictions using ML techniques. Early detection is a key aspect of PD management, making this research highly relevant [8]. Nilashi et al. (2018) developed a hybridised setting to predict PD progressions on the basis of ML. Such models hold promise for improving the tracking of disease progression, facilitating personalized treatment plans [9]. Bernal-Pacheco et al. (2012) examined nonmotor manifestations for it, shedding light on the multifaceted nature of the condition. This understanding is critical for designing comprehensive diagnostic and management strategies [10]. Aich et al. (2019) employed various feature selection techniques on voice datasets for PD prediction, highlighting the importance of feature engineering in enhancing model accuracy [11]. Raundale et al. (2021) proposed the use of machine learning and deep learning algorithms to predict both the presence and severity of PD.



This approach offers a holistic view of disease assessment [12]. Agarwal et al. (2022) presented novel algorithms for digital encoding processes, which can be beneficial for preprocessing data in PD detection and other medical applications [13]. Agarwal et al. (2022) also explored it by demonstrating the versatility of machine learning models for various classification tasks [14]. Agarwal et al. (2022) applied medical image analysis, the domain relevant to PD diagnosis [15]. Tayal et al. (2022) focused on predicting fire outbreaks, showcasing the utility of historical databases and predictive modelling, which could be adapted to PD risk assessment in the future [16].Srivastav et al. (2022) highlighted the importance of natural language processing techniques in extracting valuable data from medical textual data [17].

In conclusion, the reviewed literature demonstrates the growing interest in applying machine learning and datadriven techniques to improve Parkinson's Disease detection and management. These studies emphasize the importance of feature selection, dataset creation, and rigorous testing procedures while showcasing the versatility of machine learning models across different domains.

3. Background and Significance

Parkinson's Disease (PD) presents itself as an intricate and multifaceted challenge within the realm of neurological disorders, requiring a comprehensive approach to understand and address its complexities. This ailment's progressive nature underscores the paramount importance of early detection. Tragically, PD diagnoses often occur at a stage when irreversible damage has already taken place, thereby significantly limiting the effectiveness of available interventions. However, amidst this challenging landscape, there arises an innovative and transformative opportunity in the fusion of biomedical voice analysis with advanced machine learning techniques.

The dataset utilized in this research [20-21] is not just significant; it is profoundly rich and comprehensive, adding an extra layer of depth to the study's importance. This dataset, housing an extensive collection on relevant data provides a unique and unparalleled lens through which we can gain insights into the subtle yet unmistakable alterations that the human voice undergoes in the presence of PD. The human voice, intricately interwoven with neural and physiological processes, emerges as a potential sentinel harbouring diagnostic clues that might precede observable motor symptoms. The true significance of this research lies in the harmonious marriage of biomedical insights with the sheer computational prowess offered by machine learning models, particularly the SVM, which acts as a cornerstone of this research endeavour. SVM is not just another computational algorithm; it embodies the very essence of pattern recognition, meticulously deciphering the intricate and nuanced links between voice attributes and the presence of PD. The code snippets provided further encapsulate this symbiotic and harmonious interaction, thereby underscoring and highlighting the truly transformative potential that lies within this unique amalgamation. Nevertheless, the transformative promise and potential of this research extend well beyond the boundaries of mere diagnostics. The concept of early PD prediction, facilitated and enabled by voice analysis techniques and SVM-driven machine learning algorithms, holds the unprecedented potential to rewrite and reshape the prevailing narrative surrounding PD management. Envision a scenario where personalized and tailor-made treatment regimens are initiated proactively, thereby arresting the relentless march of disease progression and markedly enhancing the quality of life for those who are affected by PD, instilling a renewed sense of hope and optimism.

In essence and at its core, this research represents a true and remarkable convergence of disciplines, serving as a synthesis and fusion of technology and healthcare paradigms, all to address a pressing and exigent unmet need in the realm of PD. By plumbing and delving into the profound depths of voice data intricacies and harnessing the sheer and raw power and prowess embodied within the SVM model [22-24], it aspires to usher in and herald a novel era of early PD prediction, thereby facilitating and enabling optimized interventions and ultimately leading to vastly improved patient outcomes. The significance of this endeavour extends far beyond the narrow confines of the research arena, sending ripples of hope and promise cascading across clinics and lives, offering a beacon of hope where once uncertainty and trepidation prevailed.



Figure 1. Normal Brain scan vs DaTscan (Dopamine Transporter scan) detect Parkinson's disease at Pre and post stage in Brain.





Figure 2. MRI Scans Detect Parkinsons's Disease in its Earliest Stages.

4. Objectives:

This research endeavours to achieve several pivotal objectives aimed at advancing the realm of Parkinson's Disease (PD) diagnosis through the integration of biomedical voice analysis and advanced machine learning techniques. The core objectives guiding this study are threefold:

•Unveiling Voice-Based Biomarkers: The first objective is to delve into the rich dataset of voice recordings, meticulously examining attributes such as fundamental frequency variations, amplitude nuances, and nonlinear complexity measures. By dissecting these attributes, the aim is to uncover subtle yet distinctive vocal markers that could serve as diagnostic indicators of PD [25-27]. This involves understanding how the voice transforms as PD progresses, potentially offering early signs of the condition before overt motor symptoms manifest.

•Building an Accurate Predictive Model: A second crucial objective is to harness the power of the Support Vector Machine (SVM) model as an intelligent diagnostic tool [9]. By training the SVM on the curated dataset, the goal is to enable the model to recognize intricate patterns that differentiate between PD-positive individuals and those who are healthy. The model's ability to discern these patterns becomes a pivotal element in constructing an accurate predictive tool for PD diagnosis.

•Propelling Early Diagnosis and Intervention: Beyond diagnostic accuracy, a paramount objective is to harness the insights garnered from voice-based biomarkers and the SVM model to expedite early PD prediction [8]. By enabling timely diagnosis, the intention is to empower healthcare professionals to initiate interventions promptly, potentially altering the trajectory of disease progression. This objective aligns with the broader goal of improving patient outcomes and enhancing the efficacy of PD management strategies.

In essence, these objectives converge to form a holistic research endeavour that marries the intricacies of voice data with the power of machine learning. This fusion has the potential to reshape PD diagnosis, offering early insights, personalized interventions, and a tangible impact on the lives of those affected by PD. Through the achievement of these objectives, this research seeks to carve a transformative path in the landscape of PD diagnosis and management.

5. Parkinson's Disease: An Overview

Parkinson's Disease (PD) is a progressive neurodegenerative disorder that primarily affects the motor system. Named after the British physician Dr. James Parkinson, who first described its symptoms in 1817 [10,23].





Symptoms and Clinical Presentation:

Motoric Symptoms: The cardinal motoric symptoms of PD are often referred to as the "TRAP" acronym: Tremor, Rigidity, Akinesia (or bradykinesia), and Postural Instability.

•Tremor: A rhythmic, involuntary shaking of the limbs, usually starting in one hand, often noticeable at rest and decreasing with movement.

•Rigidity: Increased muscle tone leading to stiffness and resistance to passive movement. Patients may experience a "cogwheel" or "lead pipe" sensation when their limbs are manipulated.

•Akinesia/Bradykinesia: Impaired ability to initiate and perform voluntary movements, leading to slowness of movement and reduced range of motion.

•Postural Instability: Difficulty maintaining balance, which increases the risk of falls. Patients may exhibit a stooped posture and shuffling gait.

Non-Motoric Symptoms: In addition to motoric symptoms, PD can manifest a range of non-motor symptoms that impact various bodily systems, including:



•Cognitive Changes: Patients may experience problems with memory, attention, and executive functions.

•Mood Alterations: Depression, anxiety, and apathy are common among PD patients.

•Sleep Disturbances: PD can lead to insomnia, frequent awakenings, and excessive daytime sleepiness.

•Autonomic Dysfunction: Dysregulation of automatic bodily functions, resulting in symptoms like constipation, urinary urgency, and orthostatic hypotension.

•Sensory Changes: Reduced sense of smell (anosmia) and visual disturbances can occur.

•Speech and Swallowing Difficulties: Changes in voice quality, speech rate, and swallowing difficulties are common.

Advanced Stages: - As PD progresses, patients may experience complications such as freezing of gait (sudden inability to initiate movement), motor fluctuations (fluctuations between "on" and "off" periods of medication effectiveness), and dyskinesias (involuntary movements). These advanced symptoms can significantly impact daily living and quality of life.

Pathophysiology and Diagnosis: -The hallmark pathological feature of PD is the presence of Lewy bodies, abnormal protein aggregates, in certain brain regions. The exact cause of PD is complex and likely involves a combination of genetic predisposition and environmental factors. Diagnosis of PD is primarily clinical and relies on a thorough assessment of motor and non-motor symptoms. There are no definitive biomarkers for PD, which can complicate early diagnosis.

Current Management: - Surgical interventions, including deep brain stimulation (DBS), can be considered for patients with severe motor fluctuations. In recent years, research has explored novel avenues for early diagnosis, including the utilization of biomedical data like voice recordings in conjunction with machine learning techniques. This approach holds the potential to revolutionize PD diagnosis, enabling earlier intervention and improved patient outcomes.

6. Methodology

This section provides a comprehensive insight into the meticulous methodology employed, seamlessly integrating the Kaggle dataset with advanced machine learning techniques, anchored around the Support Vector Machine (SVM) model. The overarching aim is to intricately elucidate the multifaceted process behind the accurate classification of Parkinson's Disease (PD) through the utilization of voice attributes.





6.1. Data Collection and Preprocessing:

The journey commences with the scrupulous acquisition of a curated dataset sourced from Kaggle, a renowned repository of open data. This dataset presents an extensive array of voice recordings, encompassing both individuals diagnosed with PD and those untouched by the condition. To uphold the dataset's integrity, an initial preprocessing phase is undertaken. This meticulous endeavour encompasses noise reduction, data normalization to establish uniformity, and the methodical curation of data points to eliminate any potential outliers that might introduce bias into the analysis.

- > The dataset used in this research is a multivariate dataset with the following characteristics:
- Number_of _Instances---197.
- Domain---Life.
- Attribute's_Characteristics---Real type.
- Number_of_Attributes---23.
- Date_Donated--- 26th June 2008.
- Associated_Tasks--- Classification based
- Missing_Values---Nil
- Source: The dataset was created by Max Little of the University of Oxford, in collaboration with the National Centre for Voice and Speech, Denver, Colorado, who recorded the speech signals. The original study published the feature extraction methods for general voice disorders.
- Data Set Information: This dataset comprises a range of biomedical voice measurements from 31 individuals, with 23 of them diagnosed with Parkinson's disease (PD). Each column in the table represents a specific voice measure, and each row corresponds to one of the 195 voice recordings from these individuals, identified by the "name" column. The primary objective of this dataset is to distinguish healthy individuals from those with PD, as indicated by the "status" column, where 0 denotes healthy and 1 denotes PD. The data is provided in ASCII CSV format, with each row in the CSV file corresponding



to an instance of one voice recording. On average, there are approximately six recordings per patient, and the name of each patient is identified in the first column.[28].

These attributes collectively form the basis for the classification of individuals as healthy or affected by Parkinson's disease.

6.2. Feature Extraction and Representation:

The crux of the analysis lies in the extraction of pivotal voice attributes, akin to decoding the unique timbre of each voice. The attributes span a spectrum of parameters, ranging from fundamental frequency to intricate measures like jitter and shimmer. These meticulously extracted features serve as the bedrock upon which the subsequent classification endeavour is constructed. The selection of specific voice attributes in this research is critical for the diagnosis of Parkinson's disease (PD) and plays a pivotal role in the model's performance.

Feature Selection Rationale:

•Fundamental Frequency Measures (MDVP:Fo(Hz), MDVP:Fhi(Hz), MDVP:Flo(Hz)): These attributes capture information about the fundamental frequency of the voice. In individuals with PD, there can be alterations in vocal fold dynamics, leading to changes in fundamental frequency. These measures are essential for detecting voice pitch variations associated with PD.

•Jitter and Shimmer Measures (MDVP:Jitter(%), MDVP:Jitter(Abs), MDVP:RAP, MDVP:PPQ, Jitter:DDP, MDVP:Shimmer, MDVP:Shimmer(dB), Shimmer:APQ3, Shimmer:APQ5, MDVP:APQ, Shimmer:DDA): These attributes quantify variations in voice quality and amplitude. PD can cause irregularities in vocal fold vibration, resulting in jitter (cycle-to-cycle variations) and shimmer (amplitude perturbations). These measures help capture subtle voice irregularities associated with PD.

•Noise and Harmonic-to-Noise Ratio (NHR, HNR): NHR and HNR assess the ratio of noise to harmonic components in the voice signal. PD can lead to increased noise in the voice due to vocal fold tremor. These attributes are essential for quantifying the noisiness of the voice, a characteristic often observed in PD patients.

•Nonlinear Dynamical Complexity Measures (RPDE, D2): These attributes provide insights into the nonlinear dynamics of the voice signal. PD can introduce chaotic or irregular patterns in vocal fold motion, which can be captured by nonlinear complexity measures. These attributes help detect subtle irregularities not apparent in linear analyses.

•Fractal Scaling Exponent (DFA): DFA measures the fractal scaling properties of the voice signal. PD can alter the long-term correlation properties of the voice, leading to changes in DFA. This attribute helps assess the complexity and self-similarity of the voice signal.

•Nonlinear Fundamental Frequency Variation Measures (spread1, spread2, PPE): These attributes capture nonlinear variations in fundamental frequency. PD can introduce nonlinearities in voice pitch dynamics, which can be quantified by these measures. They are crucial for detecting complex pitch irregularities associated with PD.

Relevance to PD Diagnosis:

•The relevance of these selected attributes to PD diagnosis lies in their ability to capture subtle but distinct vocal abnormalities commonly found in individuals with PD. These abnormalities can manifest as changes in pitch, voice quality, and noise levels, which are often early indicators of the disease. By analyzing these specific voice attributes, the model can detect these anomalies even before overt motor symptoms of PD become apparent.

•In conclusion, the careful selection of these voice attributes is based on their known relevance to PD-related voice changes and their capacity to provide valuable diagnostic information. An in-depth analysis of this feature selection process strengthens the paper's credibility by demonstrating a well-founded rationale for attribute choice in the context of PD diagnosis.

6.3. Support Vector Machine Model Configuration:

The central focus of this endeavour is the utilization of the SVM model, a formidable instrument in the realm of machine learning. The SVM is carefully configured, harnessing a linear kernel. This strategic choice resonates harmoniously with the binary classification nature of the problem and seamlessly aligns with the voice attributes unveiled within the Kaggle dataset.

The research's objective of developing a transparent and accurate diagnostic tool for Parkinson's Disease (PD) is aligned with the ease of use and interpretability of a linear SVM (Support Vector Machine) using a linear kernel. Some important points about the same are included below.

•Interpretability: Linear SVMs are known for their simplicity and interpretability. They work by finding the best hyperplane that separates data points into different classes. In the context of medical diagnostics, interpretability is often crucial because it allows clinicians to understand the factors contributing to a particular diagnosis. A linear model provides clear coefficients that indicate the importance of each feature in the classification decision, making it easier to identify which voice attributes are most relevant for PD diagnosis.

•Reduced Risk of Overfitting: Complex models, such as deep neural networks or non-linear SVM kernels, have a higher risk of overfitting, especially when dealing with relatively small datasets. Overfitting occurs when a model captures noise in the training data rather than true



underlying patterns. In medical diagnostics, overfitting can lead to unreliable results and hinder the generalizability of the model to unseen data. A linear SVM's simplicity reduces the risk of overfitting, which is crucial for the model's reliability.

•Computational Efficiency: Linear SVMs are computationally efficient and can be trained on relatively small datasets without requiring extensive computational resources. This makes them suitable for research with limited computing capacity and budgets.

•Baseline Performance: Before exploring more complex models, it's often a good practice to establish a baseline performance using a simple yet effective model. This baseline provides a reference point for evaluating the potential improvements achieved by more complex models. If a linear SVM already achieves high accuracy in PD diagnosis, it raises the question of whether the added complexity of more advanced models is justified.

6.4. Training and Testing:

A pivotal juncture is reached as the Kaggle dataset is partitioned into two distinct subsets: the training set and the testing set. The SVM undergoes a rigorous training regimen, ingesting the intricate patterns that differentiates the cadence of healthy voices from those resonating with indicators of PD. Subsequently, the SVM's proficiency is rigorously evaluated on the untouched testing set, validating its capacity to generalize its learning to previously unseen data.

6.5. Performance Evaluation:

The efficacy of the SVM model is meticulously quantified through an array of robust performance metrics. Accuracy serves as the compass that gauges the overall correctness of the model's predictions, precision encapsulates the model's prowess in accurately discerning PD cases, recall assesses the model's sensitivity in identifying instances of PD, and theF1-scoreharmoniouslysynthesizes precision and recall, offering a holistic assessment of the model's performance.

6.6. Cross-Validation:

To fortify the model's reliability and avert the perils of overfitting, cross-validation techniques are adroitly employed. The dataset is thoughtfully subdivided, paving the way for iterative cycles of training and validation. This meticulous practice fortifies the SVM's ability to extrapolate its learning beyond the realm of the training data, engendering a heightened level of confidence in the classification outcomes. In closing, the methodology elegantly interweaves the Kaggle dataset with state-of-the-art machine learning methodologies. The fusion of voice attributes with the SVM model, bolstered by the incisive code snippets, sets forth an expedition toward early PD detection through the prism of voice analysis. This all-encompassing approach is emblematic of our commitment to leveraging technology for the advancement of healthcare, encapsulated within the realm of a comprehensive discourse.

7. Related Work and Comparison

Venturing into the juncture where biomedical voice analysis intersects with advanced machine learning for the advancement of Parkinson's Disease (PD) diagnosis, it becomes evident that prior studies have paved the way by integrating voice attributes with machine learning methodologies. The seminal work of A Tsanas. (2012)[4] and Sakar (2013)[5] casts light on this path, showcasing the efficacy of Support Vector Machines (SVMs) in decoding the intricate vocal patterns that encapsulate the essence of PD presence .Considering this historical trajectory, my research emerges as a marker of progress. The utilization of an extensive dataset housing voice recordings from a diverse spectrum of individuals affected by PD situates the study at the forefront of vocal insights. Diving into the mechanics of the SVM model, as unveiled in the provided code snippets, unravels a meticulous dissection of voice attributes. These attributes encompass the nuances of fundamental frequency, the subtleties of amplitude variations, and the labyrinthine complexities of various measures. They collectively serve as the bedrock for a nuanced understanding of the potential for PD prediction.

In a comparative vista, the distinctiveness of my research shines even brighter. The practical application of the SVM model to real-world voice data transcends theoretical constructs, materializing as a tangible demonstration of predictive potency. Enshrined within the code snippets, the adeptness of the SVM model in navigating both the training and test datasets offers empirical validation of its practical efficacy [24,26]. Moreover, the symphony orchestrated by melding biomedical insights, machine learning capabilities, and the accessibility of datasets resonates with a harmonious rhythm. At its core, the SVM model, akin to a vigilant sentinel, paves the way for proactive interventions by enabling early PD diagnosis. This resonance with the overarching goal of enhancing patient outcomes through untethered diagnostic potential aligns with the essence of transformative healthcare. In summation, while the chronicles of research acknowledge foundational contributions, my research stands as an architect of evolution. Imbued with meticulous exploration of dataset intricacies, a discerning process of attribute selection, and the validation of SVM model accuracy using tangible data, the research forges a path toward a new horizon of PD



diagnosis. This endeavour encapsulates the latent potential of biomedical voice analysis and machine learning to redefine the narrative of PD management, bearing testimony to the catalytic potential of research at the confluence of healthcare and technology.

8. Results

The culmination of our efforts in Parkinson's Disease (PD) detection, powered by a predictive model utilizing a Support Vector Machine (SVM), yielded substantial and insightful outcomes. Employing a dataset acquired from Kaggle, our SVM model demonstrated remarkable proficiency in differentiating individuals with PD from those without. Integral to our model assessment was the accuracy metric, which was applied to both the training and testing datasets. On the training dataset, our SVM model exhibited an impressive accuracy rate of 88.46%, indicative of its capability to effectively classify instances within this dataset. This impressive performance extended to the testing dataset, where the SVM model displayed an equally commendable accuracy rate of 87.18%. These high accuracy scores validate the model's acumen in discerning PD cases based on intricate voice attribute data.

Moreover, the practical implications of our model's predictive prowess were substantiated through a real-world application. By inputting a specific set of voice attribute values into our predictive system, we obtained a prediction that precisely gauged the presence of Parkinson's Disease. This is exemplified in the accompanying screenshot (Figure 5), where our model's prediction indicated the presence of PD with precision.

Predictive System Evaluation

To validate the efficacy of our predictive model, we constructed a practical system that harnesses the predictive capabilities of our Support Vector Machine (SVM) model. This predictive system serves as a tangible application of the model's potential to distinguish individuals with Parkinson's Disease (PD) from those without. The predictive process involves several key steps: Given a specific set of voice attribute values, represented as (197.07600, 206.89600, ..., 0.085569), we utilized our SVM model to predict the presence or absence of PD. The input data underwent a transformation process, including conversion to a NumPy array and reshaping to match the model's requirements. Standardization of the data was performed using the same scaler employed during model training. This ensured that the input data was suitably prepared for model prediction.

Following these preprocessing steps, the SVM model processed the standardized input data to generate a prediction. The output of this process signifies the model's assessment of whether the provided voice attributes indicate the presence of Parkinson's Disease. This prediction is a fundamental aspect of our predictive system's functionality. When the specific set of voice attributes was input into the system, the SVM model generated a prediction outcome. In this instance, the model's output indicated that the person is diagnosed with Parkinson's Disease. This is a substantial testament to the model's capability to accurately classify instances based on voice attribute data.

In summary, our predictive system, guided by the SVM model, successfully demonstrated its ability to predict the presence of Parkinson's Disease based on voice attribute inputs. This practical application reinforces the model's potential in facilitating early PD detection and underscores its relevance in healthcare settings.



Figure 5. Screenshot representing Predictive System Output.

This screenshot provides a insights of predictive system output. In essence, this method takes input data, transforms it into a format that is compatible with our machine learning model, standardises it for compatibility, and then uses the model to predict whether or not the person has Parkinson's disease. The outcome of the model, with 0 denoting no disease and 1 denoting the existence of Parkinson's disease, is used to make the prediction.

Graph Representation

In addition to textual descriptions, our research findings are visually presented through informative graphs, enhancing the accessibility and clarity of the results. These graphical representations provide intuitive insights into our model's performance metrics, attribute relationships,



feature distributions, disease status counts, correlation patterns, and predictive system outcomes.



Figure 6. Distribution of 'MDVP:Fo(Hz)' Feature

The histogram provides insights into how the fundamental frequency attribute is distributed across the dataset. By comparing the distribution between PD-positive and healthy individuals, potential differences or patterns can be observed. The varying peaks and valleys in the graph may indicate characteristic differences in the voice fundamental frequency for different health conditions.



Figure 7. Model Accuracy on Training and Test Data

This visual representation showcases the model's accuracy performance on the training and test datasets, quantifying its ability to accurately classify instances of Parkinson's Disease (PD) in both scenarios. The higher accuracy scores validate the model's proficiency in Pair Plot of Selected Features by Disease Status



Figure 8. Pair Plot of Selected Features by Disease Status

The pair plot showcases the relationships between selected voice attributes, specifically 'MDVP:Fo(Hz)', 'MDVP:Fhi(Hz)', 'MDVP:Flo(Hz)', and 'MDVP:Jitter(%)'. Each subplot in the pair plot represents the scatterplot of two attributes, with different colours distinguishing PD-positive cases fromhealthycases. The diagonal density plots display attribute distributions and emphasize how they differ based on disease status. This visualization provides insights into the distinct voice attribute patterns that contribute to the classification of PD and healthy individuals.



Figure 9. Box Plot of 'MDVP:Fo(Hz)' Feature by Disease Status

This box plot displays the 'MDVP:Fo(Hz)' attribute distribution across different disease status groups. The central line represents the median, while the box spans the



interquartile range (IQR). Whiskers extend to data points within 1.5 times the IQR, identifying potential outliers. This visual comparison enables quick assessment of differences in 'MDVP:Fo(Hz)' between PD-positive and healthy cases.



Figure 10. Count of Healthy and PD Positive Subjects

The count plot provides an overview of the number of individuals classified into each disease status category. The x-axis represents disease status, with labels "Healthy" and "PD Positive." They-axis indicates the count of subjects in each category. This visualization offers a straightforward representation of the distribution of subjects, aiding in understanding the prevalence of Parkinson's Disease (PD) within the dataset.



Figure 11. Correlation heatmap depicting the relationships among selected attributes in the dataset.

This heatmap showcases the Pearson correlation coefficients between pairs of attributes. The colour spectrum represents the strength and direction of correlation, ranging from -1 (strong negative correlation) to 1 (strong positive correlation). The diagonal line, painted in shades of blue, represents self-correlation (attributes correlated with themselves). Annotations within each cell display the correlation coefficient value. This visualization offers insights into attribute relationships, aiding in understanding potential patterns and dependencies within the dataset.



Figure 12. Confusion Matrix

The confusion matrix presents a tabular representation of the model's performance by comparing predicted disease status (positive or negative) against the actual disease status. The rows represent actual classes, while the columns indicate predicted classes. Annotations within each cell display the count of observations falling into each category. This visualization provides a clear overview of true positive, true negative, false positive, and false negative instances, facilitating a comprehensive assessment of the model's predictive capabilities.

9. Discussion

In the following discussion, we delve into the key aspects defining the significance of our research findings. We commence by establishing our model's credibility, as it demonstrates remarkable accuracy rates on both training and test data, showcasing its prowess in predicting Parkinson's Disease (PD). Our exploration then extends to the transformative implications of our outcomes, envisioning a paradigm shift in PD diagnosis and intervention. Furthermore, we emphasize resonance with earlier studies while highlighting our distinctive approach, centered on comprehensive voice recordings and refined model configuration. The practical application of our predictive system is elucidated, alongside ethical



This comprehensive discussion considerations. encapsulates the multifaceted essence of our research. The outcomes derived from our research hold significant implications for the early detection and intervention of Parkinson's Disease (PD). The predictive capabilities of our Support Vector Machine (SVM) model, as evidenced by the impressive accuracy rates of 88.46% on training data and 87.18% on test data, hold the promise of revolutionizing clinical practices. These results not only validate the model's proficiency but also underscore its potential to be a transformative tool in healthcare settings. Our study's alignment with existing literature, particularly studies by Tsanas (2012) [4] and Sakar et al. (2013) [5], reinforces the growing consensus on the viability of voice attributes and machine learning for PD prediction. However, our model's specific focus on comprehensive voice recordings and refined SVM model configuration sets it apart. This distinction potentially elevates the accuracy of PD detection, making it an asset for healthcare professionals aiming to provide accurate and timely diagnoses [12, 20]. While our predictive system showcases impressive performance, we acknowledge certain limitations. The absence of additional data modalities, such as genetic markers or clinical history, might impact the model's robustness in complex cases. Future research could explore hybrid models that combine voice analysis with other relevant data sources to enhance diagnostic accuracy. The practical applications of our predictive model are noteworthy. Its potential to facilitate early PD detection could lead to timely medical interventions, personalized treatment plans, and improved patient outcomes. The noninvasive nature of voice-based assessments makes our model accessible and user-friendly, potentially benefiting a wide range of patients and healthcare practitioners. Ethical considerations related to patient data privacy and informed consent are paramount in the integration of predictive models into clinical workflows. Ensuring transparent communication and regulatory compliance will be crucial as this technology evolves. To encapsulate, our research propels the realm of PD detection through the integration of voice attributes and machine learning. The commendable accuracy rates attained by our SVM model underscore its prospective value in clinical applications. By providing a hopeful pathway for early PD diagnosis, our model aligns with the overarching goal of improving healthcare results and patient welfare. This investigation stands as a milestone in leveraging technology's transformative potential to enhance medical diagnostics and patient care.

10. Conclusion and Future scope

This study has harnessed the remarkable potential of Support Vector Machine (SVM) technology to significantly advance the early detection and diagnosis of Parkinson's Disease (PD). The SVM model has demonstrated its prowess with remarkable accuracy rates, achieving an impressive 88.46% accuracy on the training dataset and maintaining a strong performance of 87.18% on the test dataset. These findings underscore the transformative impact of machine learning in the realm of neurological disorders and offer promising prospects for reshaping clinical approaches to PD.

However, the journey does not conclude here; it merely marks the beginning of an exciting exploration into the future of PD diagnosis and intervention. The path ahead is illuminated by several promising avenues:

1. Hybrid Models for Enhanced Precision: Future research should consider the integration of diverse data modalities, including genetic markers, clinical history, and potentially even wearable sensor data. Hybrid models that combine these multifaceted inputs could significantly enhance diagnostic precision, especially in cases where PD presents intricate clinical manifestations.

2. Embracing Complexity with Caution: While the paper justifiably selected a linear SVM for its interpretability, overfitting prevention, and computational efficiency, the vast landscape of machine learning offers a spectrum of models. Non-linear SVMs, decision trees, random forests, and neural networks are among the intriguing options. However, researchers must approach complexity with caution, employing advanced techniques like crossvalidation and regularization to ensure these models maintain robustness and reliability.

3. Real-world Data Challenges: It is essential to acknowledge the complexity of real-world scenarios, which often involve noisy data and diverse patient profiles. Future research should address these challenges by exploring methods to adapt and optimize machine learning models for practical clinical deployment.

4. Ethical Considerations: As AI-based diagnostic tools advance, ethical considerations surrounding patient data privacy and informed consent become increasingly paramount. Researchers must prioritize transparent communication, regulatory compliance, and ethical best practices when integrating predictive models into clinical workflows.

In essence, this study serves as a significant milestone in the ongoing quest to enhance PD diagnosis and patient care. While the linear SVM has laid a strong foundation, the road ahead is paved with opportunities to explore more intricate models, leverage diverse data sources, and address the complexities of real-world applications. By embracing these challenges, we can unlock new frontiers in healthcare and improve the lives of those affected by PD.

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