**Title: *Parkinson’s Predictor: AI-Powered Early Detection Platform*: A Literature Review**

# Introduction

* + **Purpose of the Review**

The Parkinson's Predictor is an advanced AI-powered platform designed for the early detection and monitoring of Parkinson's disease. This innovative technology leverages machine learning algorithms and data from various sources, such as wearable devices, voice analysis, and patient health records, to identify early signs and symptoms associated with Parkinson's. By analyzing subtle changes in motor function, speech, and other physiological markers, the platform can identify risk patterns long before clinical symptoms become pronounced.

* + **Scope and Project:**

**Early Detection of Parkinson's Disease (PD):**

Develop an AI-powered platform that can detect Parkinson's disease in the early stages before when clinical symptoms are fully manifested.

Machine learning models use medical data comprising motor functions, speech, and handwriting to predict the likelihood of PD.

**Non-invasive diagnostics**

Design a system that does not require expensive or invasive medical procedures but instead utilizes data from non-invasive sources such as speech patterns, gait analysis, and movement-related sensors.

It is able to collect real-time information from its users through wearables and mobile applications on cell phones.

**Multiple Sources Integration :**  
  
This will combine data feeds from wearable sensors, questionnaires from the users themselves, medical history, or any other kind of biomarker-like voice analysis.  
Combine such data sources with dataanalyticsand artificial intelligence to really know in more depth.  
An interface that is easy to use, so that the patient can access and understand the predictions of the system in the same manner as a healthcare provider.  
Make it easy to access and use through a mobile application or web-based portal for a non-technical person.

**AI and Machine Learning Algorithms:**

Implement machine learning and deep learning algorithms (e.g., Support Vector Machines, Random Forest, Neural Networks) to identify patterns in data that indicate early signs of PD.

Optimize models to improve prediction accuracy over time using feedback and new data.

**Risk Assessment and Monitoring:**

Provide real-time monitoring of users’ health metrics and offer a risk assessment that can guide clinicians in their decision-making process.

Monitor the progression of symptoms and update recommendations accordingly to help healthcare providers manage treatment.

**Accessibility and Scalability:**

Ensure the platform is accessible to a wide demographic by being available on smartphones and devices with low cost, facilitating use in diverse healthcare settings globally.

Design the platform to be scalable for use across different regions, considering varying healthcare infrastructure.

# Background and Context

* + **Foundational Concepts**

Definition: In Parkinson's disease, the neuron population in the substantia nigra that produces the neurotransmitter dopamine is continuously destroyed.

Symptoms: PD presents with a mix of motor symptoms such as tremors, rigidity, and bradykinesia and non-motor symptoms such as cognitive impairment and sleep disorders.

Early diagnosis might result in PD being treated before the appearance of any motor symptoms, and even before the disease appears.Thus the patients' condition can be well-managed and their quality of life will be good.

**Biomarkers for Parkinson's Disease:**

Biomarkers Definition: Biological markers, or biomarkers, are measurable indicators of the presence or severity of a disease.

Relevant Biomarkers in PD: For Parkinson's, some biomarkers include gait patterns, voice changes, hand tremors, and changes in handwriting. Emerging biomarkers also include olfactory loss and specific proteins in cerebrospinal fluid.

Implication in Predictive Value: Biomarkers can indicate the earliest stages of abnormalities that form a basis for AI models to predict the onset of PD before full manifestation of its symptoms.

**Artificial Intelligence and Machine Learning**

Artificial Intelligence Artificial Intelligence can be defined as the ability of machines to mimic human intelligence. The capabilities enable machines to perform tasks that are normally undertaken by human cognitive functions such as learning and problem-solving.

Machine Learning: This is a subset of AI that deals with developing algorithms which enable computers to learn from data and make suitable decisions. The major categories are supervised and unsupervised learning in which supervised learning is based on labeled data, while unsupervised learning discovers patterns in unlabeled data.

Deep Learning: ML with the usage of neural networks, that is, having more than one layer. In these, CNNs, RNNs, the learning of complex patterns becomes highly useful in the medical field for high-dimensional data analysis.

Predictive Modeling:

Definition: Predictive modeling involves using statistical techniques and machine learning to forecast outcomes based on historical data.

Role in PD Detection: By training models on datasets from diagnosed PD patients, AI can learn to predict the risk of Parkinson's onset in new patients based on similar patterns, supporting earlier diagnosis.

Non-Invasive Data Collection Technologies:

Wearable Devices: Devices like smartwatches and fitness trackers can continuously monitor motor function metrics like gait, tremors, and activity levels.

Smartphone Applications: Mobile apps can monitor users’ speech, movements, and other relevant metrics passively or through user interaction.

Impact: These technologies offer accessible, non-intrusive ways to gather continuous data for AI analysis, essential for real-world application.

* + **Historical Overview:**

**Early Understanding of Parkinson’s Disease (PD):**

1817: Dr. James Parkinson first described Parkinson's disease in his essay An Essay on the Shaking Palsy, identifying key symptoms like tremors, muscle rigidity, and bradykinesia (slowed movement). At the time, diagnosis was solely based on clinical observations, often leading to late-stage identification.

1950s: The discovery that Parkinson's disease is linked to dopamine deficiency in the brain led to the development of treatments like Levodopa, which remains a cornerstone of PD management today. However, these treatments manage symptoms rather than cure or prevent the disease.

Advancements in Neuroimaging and Biomarkers (1970s–2000s):

1970s: The introduction of neuroimaging techniques, such as MRI and PET scans, provided more objective tools for studying PD and its effects on the brain, helping to identify structural changes associated with neurodegenerative diseases.

1990s–2000s: Researchers began to identify potential biomarkers (e.g., motor symptoms, speech patterns, and biochemical changes) that could indicate early PD. While promising, these techniques were often invasive, costly, or accessible only in advanced clinical settings.

Emergence of AI in Medical Diagnostics (2000s):

2000s: As computational power grew, researchers began exploring artificial intelligence (AI) and machine learning (ML) as tools to analyze complex data in healthcare. Early AI-based diagnostic tools were developed for diseases with structured datasets, like cancer, due to easier data availability.

Late 2000s: AI interest in neurodegenerative diseases like Parkinson’s grew as researchers realized the potential of AI to detect early, subtle patterns within diverse data sources. However, significant challenges remained in data collection, model accuracy, and interpretability.

Integration of Wearable Devices and Smartphone Applications (2010s):

2010s: Wearable technology and smartphone sensors became more advanced, offering a new method for continuous, non-invasive monitoring of patients. Devices like smartwatches began to track health metrics (e.g., heart rate, movement, sleep patterns), which researchers recognized as useful for detecting PD-related motor symptoms.

Studies emerged using these devices to monitor gait, tremors, and speech, and combining this data with AI models to predict PD risk and progression. These advancements significantly boosted AI's feasibility in early PD detection.

**Development of AI-Powered Early Detection Platforms for PD (Late 2010s–2020s):**

Late 2010s: Researchers started using deep learning and advanced ML algorithms for PD prediction. These models could handle large amounts of data from diverse sources, like voice recordings, facial expression analyses, and motor patterns. This allowed for preliminary successes in non-invasive, early PD prediction.

2020s: With improvements in algorithm accuracy and the increasing availability of health data, the focus shifted to developing comprehensive AI-powered platforms specifically aimed at early detection. Major research institutions and tech companies began investing in predictive tools for PD, often combining data from wearable devices, speech analysis, and sensor data with robust AI algorithms.

Ethical and Clinical Integration: Around this time, there was also a growing focus on making these AI systems interpretable and ensuring they met ethical standards in healthcare, facilitating integration into clinical settings and real-world use.

Current and Future Directions:

2020s and Beyond: Today, AI-powered early detection platforms for PD are being refined to provide highly accurate, accessible, and real-time predictions. Current research focuses on improving model transparency, validating predictions in clinical trials, and expanding the types of data used for diagnosis. The future direction includes expanding AI-based early detection to other neurodegenerative diseases and personalizing predictions to individual risk profiles.

# Key Themes in the Literature

1. **Theme 1**:

The Use of Gait and Vocal Patterns in Early Detection of Parkinson's Disease

Summary of Findings: Studies have shown that both gait and vocal patterns are significant early indicators of Parkinson’s disease (PD).

Gait Analysis: Changes in gait, such as reduced stride length, decreased arm swing, and shuffling steps, are commonly observed in PD patients even before motor symptoms become fully apparent. Various studies highlight that subtle gait abnormalities may manifest years before diagnosis. AI models analyzing data from wearable devices (e.g., smartwatches, fitness bands) have been effective in detecting these early changes. For instance, gait features extracted through accelerometers and gyroscopes in wearables have enabled machine learning models to achieve reasonable accuracy in distinguishing between individuals with early PD symptoms and healthy controls.

Vocal Patterns: Alterations in voice, such as reduced vocal strength, monotone speech, and changes in articulation, are also significant indicators. Vocal impairments in PD patients arise from motor control issues affecting the vocal cords and respiratory muscles. Studies using acoustic analysis have shown that machine learning models can identify these subtle vocal changes before noticeable motor symptoms develop. Some research has reported success in distinguishing PD patients from healthy individuals based on parameters like pitch, volume variability, and pause frequency.

Key Debates:

Predictive Accuracy: There is debate over which of these two indicators—gait or vocal patterns—provides more accurate and reliable early detection. Some studies suggest gait abnormalities are stronger indicators due to the physical progression of PD, while others argue vocal pattern changes can be detected sooner and are less influenced by external factors like terrain.

Data Quality and Consistency: Another debate centers on the variability in data quality across different devices and environments. For example, gait data may vary significantly based on device positioning and user activity levels, whereas vocal data can be affected by background noise or the quality of the microphone used. This raises questions about the standardization and reliability of data sources.

Generalizability Across Populations: Vocal changes and gait abnormalities may vary across demographic groups (e.g., age, gender, language), which can impact model generalizability. Researchers debate the need for region-specific or population-specific models to improve accuracy.

Methodologies:

Wearable Sensor Analysis for Gait: Most gait studies use wearable sensors like accelerometers and gyroscopes embedded in smart devices or specialized wearable devices. Machine learning algorithms, such as Support Vector Machines (SVM), Random Forest, and Convolutional Neural Networks (CNNs), are commonly used to analyze features like step frequency, cadence, and posture.

Speech Signal Processing for Vocal Patterns: Speech data is typically gathered via smartphone applications or recording devices, capturing vocal samples in controlled or semi-controlled settings. These studies often employ feature extraction techniques (e.g., Mel-frequency cepstral coefficients, pitch, jitter, and shimmer) and algorithms like SVM, k-Nearest Neighbors (k-NN), and Recurrent Neural Networks (RNNs) for analysis. Researchers frequently use acoustic analysis tools to refine data, ensuring that vocal biomarkers are accurately isolated for model input.

Overall, gait and vocal patterns are valuable yet distinct data sources in early PD detection, each with specific strengths and challenges. Addressing debates around accuracy, data variability, and generalizability will be crucial to further improve AI-powered early detection platforms for Parkinson’s.

# Methodological Approaches

AI-Powered Early Detection Platform (Focused on Gait and Vocal Patterns)

Common Methodologies

Observational Studies Using Wearable Sensors for Gait Analysis:

Approach: These studies collect gait data in real-world or semi-controlled environments using wearable devices (e.g., accelerometers, gyroscopes in smartwatches or smartphones). The data includes metrics such as stride length, cadence, and step regularity, which are then processed to detect early PD-related abnormalities.

Data Analysis: Machine learning algorithms, including Support Vector Machines (SVM), Decision Trees, and Convolutional Neural Networks (CNNs), are commonly used to classify gait patterns and identify PD-related changes.

Speech Signal Processing for Vocal Patterns:

Approach: Vocal data is usually collected through smartphone applications, recording devices, or even remotely via phone calls. Studies often focus on features like pitch, volume, articulation rate, jitter, and shimmer.

Data Analysis: Algorithms such as SVM, k-Nearest Neighbors (k-NN), and Recurrent Neural Networks (RNNs) are used to process and classify these vocal features, aiming to distinguish subtle changes indicative of PD.

Quantitative Machine Learning and Deep Learning Models:

Approach: A range of machine learning and deep learning techniques are used to analyze both gait and vocal data quantitatively. These models are trained on datasets labeled by medical professionals to identify PD patterns in healthy individuals versus those with early PD symptoms.

Examples: Random Forest, Decision Trees, and Long Short-Term Memory (LSTM) networks are popular, as they are effective in recognizing sequential patterns in gait or vocal data over time.

Experimental Validation with Control Groups:

Approach: Some studies employ experimental designs where PD patients and healthy controls are assessed under similar conditions to compare gait and vocal patterns. These are often conducted in controlled environments like gait labs or acoustic rooms.

Objective: The goal is to validate whether specific biomarkers detected in PD patients are consistently absent or minimal in control subjects, enhancing the reliability of prediction models.

**Strengths and Weaknesses**

Wearable Sensor Studies (Gait Analysis):

Strengths: Wearable sensors allow continuous, real-time data collection in natural environments, providing high-quality insights into daily gait patterns. They are also non-invasive and widely accessible.

Weaknesses: Data can be inconsistent due to variations in user activities, device positioning, and the surrounding environment. External factors, like the type of surface walked on, can influence gait patterns, complicating model accuracy.

Speech Signal Processing (Vocal Patterns):

Strengths: Vocal analysis is cost-effective and accessible, as smartphones or standard recording devices can capture speech. Vocal biomarkers may reveal PD changes earlier than motor symptoms, making them valuable for early diagnosis.

Weaknesses: Vocal data quality can be affected by environmental noise, microphone quality, and user compliance. Additionally, differences in language and accent can influence vocal features, which may affect model generalizability across diverse populations.

Quantitative Machine Learning and Deep Learning Models:

Strengths: ML and DL models can process large, complex datasets, effectively identifying subtle patterns in both gait and vocal data. They also enable feature extraction, enhancing the model’s predictive capability for early PD signs.

Weaknesses: These models require extensive training data, which can be difficult to obtain for early PD. Furthermore, ML/DL models are often “black boxes,” making it challenging to interpret specific predictions, a limitation in clinical applications.

Experimental Validation with Control Groups:

Strengths: Using control groups enables a baseline comparison, improving the accuracy of findings and providing a clearer view of PD-related changes.

Weaknesses: Experimental setups can lack ecological validity, as results obtained in controlled environments may not generalize to everyday scenarios. Recruiting and controlling for matched demographics is also resource-intensive.

Trends in Methodology

Increased Use of Deep Learning Techniques: Recently, there has been a shift from traditional ML algorithms (e.g., SVM, Decision Trees) to more advanced deep learning methods like Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, which are better suited for handling complex, high-dimensional data and sequential patterns, especially in gait and vocal analyses.

Remote Data Collection via Smartphones and Wearables: With the rise of IoT and telemedicine, researchers are increasingly leveraging remote data collection methods, enabling continuous monitoring without needing frequent clinic visits. This trend is especially useful in studying PD, where real-time, longitudinal data is essential for early detection.

Hybrid Models Combining Multiple Data Sources: There is a growing interest in multimodal models that integrate both gait and vocal data, as well as other biometrics, to enhance prediction accuracy. Hybrid approaches can leverage the strengths of each data source, providing a more comprehensive view of early PD indicators.

# Gaps and Limitations in the Literature

* **Identify Gaps**:

Limited Longitudinal Studies:

Current research often relies on cross-sectional data rather than longitudinal studies, which track patients over time. Since Parkinson's disease (PD) is progressive, capturing changes in gait and vocal patterns longitudinally could improve the ability to predict disease onset and progression.

Lack of Standardization in Data Collection:

There is no universally accepted standard for capturing and processing gait and vocal data. Variability in wearable devices, smartphone models, and recording conditions makes it difficult to compare results across studies, leading to inconsistencies.

Underrepresentation of Diverse Populations:

Many studies focus on specific age, gender, or ethnic groups, potentially limiting the generalizability of findings. Vocal and gait patterns vary naturally across demographics, and underrepresentation can bias predictive models, reducing their effectiveness in broader applications.

Integration of Multimodal Data:

Most studies either focus solely on gait or vocal patterns. While recent research has explored multimodal data approaches, there is still limited work that combines these two factors with other biomarkers (e.g., facial expressions, handwriting analysis) for a holistic early detection model.

Limitations

Sample Size:

Many studies have small sample sizes, especially when distinguishing between early PD patients and healthy controls. This limitation affects the robustness and generalizability of findings, making it difficult to develop reliable AI models.

Environmental and Contextual Variability:

Gait data can be significantly influenced by environmental factors (e.g., surface type, walking speed) and vocal data by context (e.g., background noise, microphone quality). These factors can introduce noise, reducing model accuracy and making it harder to apply findings in real-world settings.

Reliance on High-Quality Equipment for Data Collection:

Some studies rely on high-quality lab equipment or specialized recording devices that may not be practical or affordable for widespread use. This limits the applicability of findings to real-world, lower-cost setups like smartphones or standard wearables, which are essential for scalable early detection.

Model Interpretability:

Many AI and machine learning models used for early PD detection are complex and function as "black boxes," making it difficult to understand why a specific prediction was made. This lack of interpretability presents challenges in clinical adoption, as healthcare providers need transparent models to make informed decisions.

Opportunities for Further Research

Longitudinal and Real-World Studies:

Future studies should prioritize longitudinal research, tracking gait and vocal patterns over extended periods. Real-world studies that capture data continuously in natural settings can provide valuable insights into early PD changes, enhancing predictive accuracy.

Development of Standardized Protocols:

Establishing standardized protocols for data collection and processing would improve the consistency and comparability of findings across studies. This could involve creating guidelines for wearable sensor placement, gait and vocal data capture conditions, and preprocessing steps.

Inclusion of Diverse Demographics:

Expanding study populations to include diverse demographics (e.g., different ages, ethnicities, languages) would allow for more generalized models. Including diverse groups could help researchers understand how gait and vocal biomarkers vary and improve model accuracy across different populations.

# Applications and Implications

* **Practical Applications**:

Early Diagnosis and Intervention:

By identifying early indicators of Parkinson’s disease (PD) through gait and vocal patterns, AI-powered platforms enable healthcare providers to diagnose the condition earlier than traditional clinical methods allow. This early detection facilitates timely interventions, such as lifestyle adjustments, medication, and physical therapy, potentially slowing disease progression.

Remote Monitoring and Telemedicine:

Using smartphones and wearable devices to monitor gait and vocal changes enables continuous, remote patient monitoring. This is especially beneficial for patients in rural or underserved areas who may have limited access to in-person healthcare. Telemedicine platforms could integrate this technology to provide consistent updates to healthcare providers, allowing for proactive care adjustments based on real-time data.

Personalized Treatment Plans:

AI-based early detection systems can inform more personalized treatment approaches by tracking each patient’s unique symptom progression. For example, gait and vocal monitoring could guide physical therapy intensity or speech therapy exercises tailored to a patient's specific needs, improving the overall management of PD symptoms.

Screening Tool in General Practice:

Primary care providers could use these platforms as a screening tool during routine check-ups. Integrating gait and vocal analysis into general practice would allow for early PD detection in a broader population, beyond those already experiencing noticeable symptoms, increasing early intervention opportunities.

Support for Clinical Trials and Drug Development:

These AI-powered tools can also be valuable in clinical trials, where accurate early-stage diagnosis is essential. Researchers can use continuous gait and vocal monitoring to identify subtle improvements or declines in response to new medications or therapies, aiding in the assessment of treatment efficacy and accelerating drug development.

Theoretical Implications

Advancement of Neurodegenerative Disease Models:

Findings on gait and vocal biomarkers for early PD detection support the concept that neurodegenerative diseases like PD manifest in subtle, non-motor ways long before clinical diagnosis. This challenges and expands traditional models, which often emphasize later-stage motor symptoms, suggesting that early non-motor changes should be a focal point in PD research and theory.

Integration with Multimodal Diagnostic Models:

The literature on gait and vocal patterns emphasizes the potential of multimodal diagnostic approaches, which combine various biomarkers (e.g., gait, voice, facial expressions). This holistic approach shifts the theoretical framework for neurodegenerative disease diagnostics from single-symptom analysis to a more complex, integrated model, recognizing the value of combining different early indicators for enhanced accuracy.

Influence on AI and Healthcare Model Theory:

Findings highlight the role of artificial intelligence in transforming early diagnostic models, especially in chronic diseases. The integration of AI in early detection tools for PD could pave the way for similar methodologies in other neurodegenerative diseases, suggesting that AI-powered diagnostic tools will play a larger role in the future healthcare model. This shift introduces a theoretical framework where AI is not just an aid but a core diagnostic element.

Reevaluation of Gait and Vocal Patterns in Neurodegenerative Theory:

The research supports theories that gait and vocal biomarkers, long associated with motor control issues, may hold predictive value for cognitive decline as well. This reevaluation could influence broader theories about the progression of neurodegenerative diseases, suggesting that cognitive and motor symptoms may be interconnected earlier in the disease’s development.

By incorporating findings from gait and vocal analysis into both practical applications and theoretical models, researchers and practitioners can refine early PD detection strategies, ultimately enhancing patient care and expanding our understanding of neurodegenerative diseases.

# Conclusion

* **Summary of Key Points**:

The review of literature on AI-powered early detection for Parkinson's disease (PD) reveals that gait and vocal patterns are valuable early indicators of the disease. Gait analysis, using wearable sensors, captures subtle abnormalities like reduced stride length and shuffling, which often appear before motor symptoms are evident. Similarly, vocal pattern changes, such as monotone speech, reduced volume, and altered articulation, provide key insights into early-stage PD. Machine learning models, especially deep learning, have been effective in analyzing these biomarkers, allowing for predictive accuracy when these data sources are applied independently or in combination. However, challenges remain, including standardization of data collection, model interpretability, and the need for diverse and longitudinal studies.

* **Implications for Future Work**:

The findings underscore several directions for advancing PD research and early detection technology:

Focus on Longitudinal Studies:

Future research should prioritize longitudinal studies to track the progression of gait and vocal changes over time. Continuous data collection in real-world settings will better capture the nuanced progression of PD, improving prediction accuracy and model reliability.

Standardization and Generalizability:

Establishing standardized protocols for gait and vocal data collection would enhance consistency across studies. Additionally, research should include diverse demographic groups to ensure that AI models are robust and applicable to a wide population, addressing variations in gait and vocal characteristics due to age, ethnicity, and language.

Advancing Multimodal Approaches:

Integrating gait, vocal patterns, and additional biomarkers (e.g., facial expressions, handwriting) could yield a more comprehensive early detection platform. Multimodal approaches may increase sensitivity to early PD indicators, supporting more accurate and holistic assessments.

Promoting Explainable AI:

Researchers should explore Explainable AI techniques to increase model interpretability, a critical factor for clinical adoption. By making model predictions transparent, healthcare providers will have more confidence in using AI for early PD diagnosis and can better explain findings to patients.

Utilizing Low-Cost, Scalable Technologies:

Validating these models on affordable, widely available devices like smartphones and smartwatches could make early detection accessible on a larger scale. This focus on scalability would support early intervention in underserved or remote areas, maximizing the platform’s impact.

In summary, advancements in AI and machine learning for analyzing gait and vocal biomarkers hold promising potential for early PD detection. Addressing existing gaps and limitations through longitudinal studies, standardization, and multimodal approaches will drive future research, ultimately improving patient outcomes and expanding our understanding of Parkinson’s disease.

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