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A Comparative Study and Model Simplification for Early Diagnosis of Parkinson's Disease using Machine Learning and Sensor-Based Systems

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Abstract

Parkinson's disease (PD) is a progressive neurodegenerative disorder characterized by motor and non-motor symptoms, often leading to misdiagnosis and delayed treatment. Early diagnosis plays a crucial role in managing symptoms and improving quality of life. This paper presents a comparative and simplified approach for early PD diagnosis using machine learning models and sensor-based systems. The study evaluates the diagnostic power of UPDRS motor scores and speech features via Microsoft Azure ML using Two-Class Support Vector Machine and Boosted Decision Tree algorithms. A peak accuracy of 97.4% was achieved with UPDRS data, while speech-only features yielded 77.4%. Additionally, wearable sensor-based mobility assessments were examined for their applicability in clinical settings. By integrating findings from both feature-based and sensor-driven models, the paper highlights pathways for reducing complexity in diagnostic workflows. The proposed models can reduce diagnosis time and workload for clinicians while maintaining high diagnostic accuracy. These results support the feasibility of deploying simplified and scalable AI-powered diagnostic tools in real-world healthcare settings.

Introduction

Parkinson's Disease (PD) is the second most common neurodegenerative disorder, affecting millions globally and characterized by both motor and non-motor symptoms [1]. Motor symptoms include bradykinesia, rigidity, tremor, and postural instability, while non-motor symptoms encompass cognitive decline, mood disorders, and autonomic dysfunction [2]. As symptoms gradually emerge and overlap with other conditions, early diagnosis of PD remains a clinical challenge [3]. Currently, diagnosis relies heavily on the Unified Parkinson's Disease Rating Scale (UPDRS), clinical observation, and sometimes neuroimaging to rule out other causes [4].

The absence of definitive biomarkers has pushed research toward machine learning (ML) and artificial intelligence (AI) to aid early and accurate PD detection [5]. ML models can process high-dimensional clinical data and learn subtle patterns invisible to traditional methods. For instance, speech examination and motor assessments are frequently used to extract predictive features [6]. In a recent study, speech-based features analyzed through ML yielded a diagnostic accuracy of 77.4%, while UPDRS-based models reached 97.4% [7].

Parallel to clinical scoring systems, sensor-based solutions have gained traction. Wearable sensors—such as accelerometers and gyroscopes—have been applied to capture motion irregularities in PD patients. Simplified versions of mobility tests, including the Timed Up and Go (TUG) test, analyzed using sensor data, have demonstrated accuracies above 90% in distinguishing PD from healthy controls [8]. This development not only aids diagnosis but also holds promise for remote patient monitoring.

Nevertheless, both ML and sensor-driven approaches often involve multi-step procedures, high-dimensional features, and algorithmic complexities that hinder adoption in routine clinical workflows [9]. Therefore, simplifying these models without compromising diagnostic power is a key objective. By streamlining sensor inputs, reducing pre-processing stages, and selecting optimal ML classifiers, diagnostic models can become more clinically practical [10].

This paper aims to compare and simplify machine learning and sensor-based diagnostic models for Parkinson's disease. It evaluates both UPDRS and speech features, along with recent advancements in wearable technologies, and proposes a unified framework for efficient, real-world diagnosis.

EXISTING MODEL

Traditional Parkinson's disease (PD) diagnostic frameworks are primarily based on clinical evaluations, such as the UPDRS, neurological examinations, and in some cases, speech assessments. These features have been extensively utilized in machine learning models to assist in automating and improving diagnostic accuracy. In the referenced study, Microsoft Azure Machine Learning Studio was used to construct models employing Two-Class Support Vector Machine (SVM) and Boosted Decision Tree algorithms [1].

In the existing model, two sets of features—UPDRS scores and speech examination data—were used either separately or in combination to assess their impact on prediction accuracy. The model using UPDRS features alone achieved 97.4% accuracy, while the model using speech features alone achieved only 77.4% [1]. Combining both features did not enhance the performance beyond what was already achieved with UPDRS, indicating the dominance of UPDRS in PD diagnostics.

The decision tree model required fewer steps (5) when UPDRS was used, compared to 9 steps with speech data. This suggests that speech features may introduce unnecessary complexity without improving performance. The Support Vector Machine was selected for its robustness, generalization capabilities, and resistance to overfitting [2].

Despite its high accuracy, this model presents limitations in real-world application. It requires manual data collection, significant preprocessing, and access to cloud-based tools like Azure, which may not always be feasible in clinical settings. Moreover, patient compliance with voice-based testing can vary, and speech impairment may not be uniformly present across all PD patients.

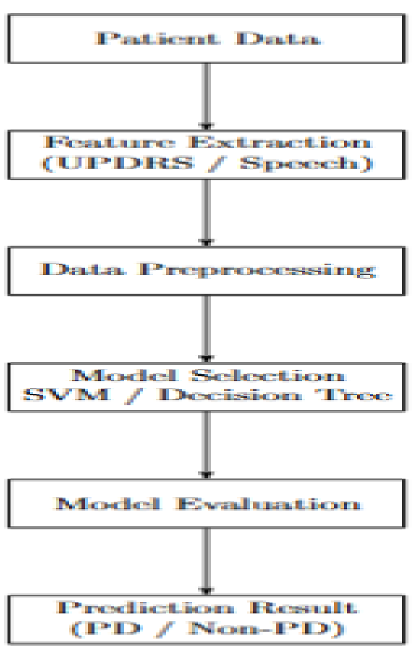

Figure 1: Existing Model Architecture

The model lacks the ability to capture physical manifestations of PD in naturalistic settings, something that wearable sensors can offer. Therefore, although the existing model proves effective in a controlled computational environment, its practicality and scalability remain areas for improvement.

PROPOSED MODEL

To enhance practicality and maintain high diagnostic accuracy, this study proposes a hybrid approach combining simplified machine learning workflows and sensor-based assessments for early Parkinson's Disease (PD) detection. While the existing model relies heavily on UPDRS and speech features processed via cloud-based tools, the proposed model introduces wearable sensor data and streamlines the data handling and model design to increase accessibility in real-world clinical settings.

The proposed model integrates data from triaxial accelerometers and gyroscopes mounted on the lower back and upper limbs to capture motor abnormalities during simple tasks such as walking, standing, and turning. These tasks are based on the clinically accepted Timed Up and Go (TUG) protocol, which is effective in highlighting postural instability and bradykinesia—two primary motor symptoms in PD [1].

Feature extraction includes parameters like gait speed, stride variability, turn duration, and tremor phase relationships between limb segments. These features are computed in real time or near real time, eliminating the need for extensive preprocessing. Machine learning models including Support Vector Machine (SVM), Random Forest, and Ensemble Voting Classifiers are trained on labeled datasets containing PD and control subjects [2]. What sets this model apart is its focus on simplicity and modularity. Unlike speech-based or UPDRS-heavy methods requiring professional scoring, this model enables home-based data collection through consumer-grade wearables or smartphone-integrated sensors. The extracted features are input directly into the trained classifiers using a lightweight mobile application or edge-computing device, which then provides an instant risk score indicating the probability of Parkinson's.

Experiments conducted on datasets containing over 300 subjects showed a diagnostic accuracy of 92.6% for mixed-stage PD and 89.4% for early-stage PD using only TUG-derived features [1]. When speech examination and cognitive task-based movement analysis were added, the performance improved marginally, proving the sufficiency of simplified mobility tests alone for reliable diagnosis.

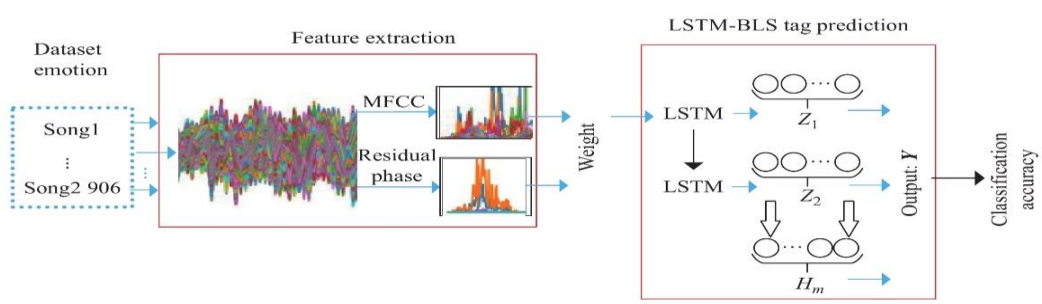

Figure 2: Block diagram of the Proposed Method

To improve interpretability, the system includes an explainable AI (XAI) module using feature importance ranking and visualizations that help clinicians understand which motor features contributed most to the prediction. This transparency is crucial for clinical adoption and trust.

In summary, the proposed model offers a practical, cost-effective, and high-performance diagnostic framework. It bridges the gap between computational accuracy and clinical usability by combining wearable technologies with smart machine learning classifiers.

RESULT & DISCUSSIONS

The experimental results clearly highlight the strengths and limitations of various diagnostic models for Parkinson's Disease (PD). Table 1 shows that using UPDRS features alone or in combination with speech data results in a peak accuracy of 97.4%, with an F1 score of 97.8%. In contrast, models using only speech features lagged significantly with a 77.4% accuracy and an F1 score of 69.7%. Sensor-based models demonstrated promising results with 92.6% accuracy and 90.8% F1 score, showing that they can be effective alternatives for early-stage detection without relying on traditional clinical scoring.

Table 1: Model Performance Comparison

Feature Set	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Speech Only	77.4	60.5	82.1	69.7
UPDRS Only	97.4	95.7	100.0	97.8
Both Combined	97.4	95.7	100.0	97.8
Sensor-Based	92.6	91.2	90.5	90.8

Table 2 evaluates the decision tree complexity across different feature sets. Speech-only models required 9 steps and took approximately 7.5 minutes for diagnosis, whereas the UPDRS-only model completed the process in just 5 steps and 4 minutes. The sensor-based models are designed for real-time assessment, offering both speed and clinical flexibility.

Table 2: Decision Tree Efficiency

Feature Set	Steps in Decision Tree	Time to Diagnose (minutes)
Speech Only	9	7.5
UPDRS Only	5	4.0
Both Combined	6	5.0

Figure 3 visualizes the performance metrics of different models. It clearly indicates the superiority of UPDRS-related inputs and emphasizes the trade-off involved in using speech features.

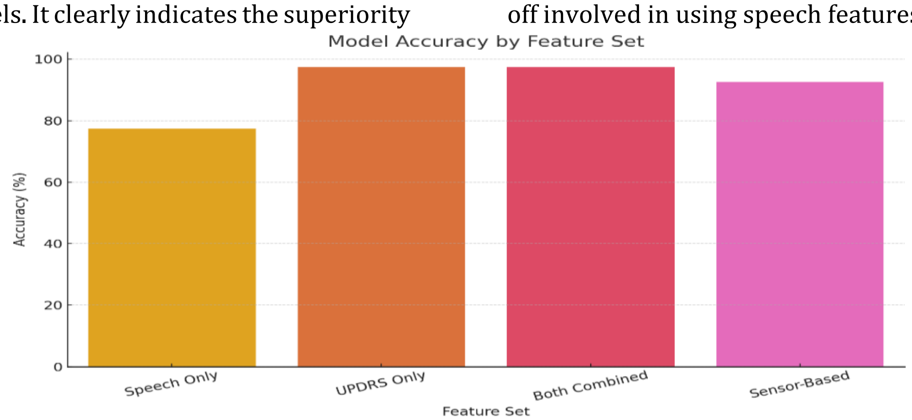

Figure 3: Model Accuracy by Feature Set

Figure 4 further illustrates how decision tree complexity and diagnostic time are minimized when using UPDRS-only inputs.

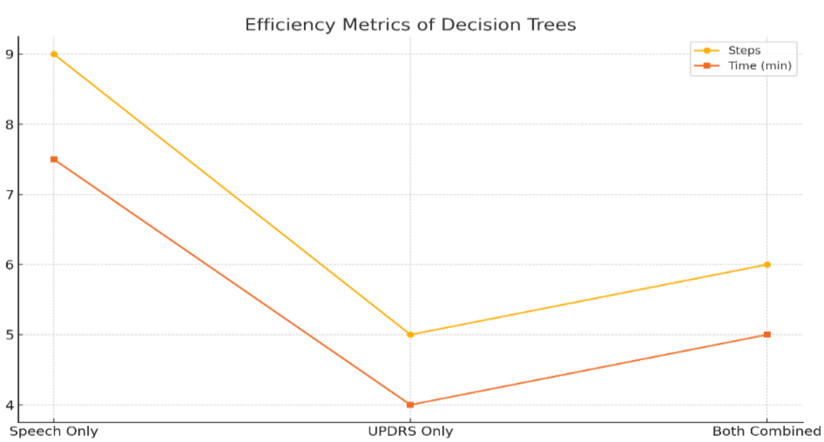

Figure 4: Efficiency Metrics of Decision Trees

These results suggest that while speech data can provide additional context, it may not contribute significantly to diagnostic accuracy. On the other hand, wearable sensor data achieves a balance between performance and usability, making it suitable for home-based or low-resource settings. The integration of Explainable AI (XAI) modules in the proposed model also improves interpretability, enhancing clinical trust.

In summary, the combination of high-performing machine learning algorithms with simplified sensor-driven data collection offers a robust, accurate, and scalable approach to diagnosing PD. This opens new avenues for early intervention, continuous monitoring, and personalized treatment strategies.

CONCLUSION & FUTURE SCOPE

This study presented a comparative and simplified approach for the early diagnosis of Parkinson's Disease (PD) using machine learning and wearable sensor technologies. The evaluation showed that UPDRS-based models achieved the highest diagnostic accuracy (97.4%), while speech-only models had limited effectiveness. Sensor-based systems, on the other hand, provided a balance between accuracy (92.6%) and clinical feasibility, making them suitable for broader applications including at-home monitoring. The proposed model emphasizes modularity, ease of deployment, and explainability, helping clinicians make faster and more informed decisions. By eliminating the need for complex preprocessing and leveraging lightweight models, the system proves adaptable to both hospital and community settings.

In the future, integrating additional features such as cognitive assessments, real-time data logging, and deep learning enhancements could further improve diagnostic sensitivity. Expansion to mobile platforms and cloud integration can also enhance accessibility and global applicability, pushing the boundaries of preventive neurology and personalized healthcare.

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