AI Based Early Detection of Parkinson's Disease

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***Abstract*-Parkinson's Disease sticks around for the long haul, and spotting it early is tough. The first signs? They're subtle, they creep in slowly, and honestly, they look different for everyone. Right now, doctors mostly rely on what they see and what they know. That means early diagnosis often comes late or with a lot of uncertainty. But here's what's exciting: with big leaps in Artificial Intelligence and Machine Learning, researchers can now pick up on early clues hidden in all sorts of places how someone speaks, the way they walk, how their handwriting changes, what shows up in brain scans, even data from wearables or blood tests. In this review, I dig into the latest AI strategies for catching Parkinson's early. That means everything from single-source methods to more complex ones that blend different types of data. Deep learning models are front and center think CNNs, LSTMs, Transformers, Graph Neural Networks, and the newer self-supervised learning tricks. I've pulled together insights from recent work to compare the most promising techniques, what kinds of data people are using, how well these systems actually perform, and what tools help explain their decisions. There are some real challenges, though. Combining all those data types isn't easy. Missing or messy data is a headache. Bias in datasets can mess up results, and it's a whole other story trying to make these models work outside the lab. Plus, most clinics still don't use explainable AI in their day-to-day decisions. By calling out these issues, this review tries to map out where we go from here how we can build smarter, more understandable, and actually useful AI tools to help doctors spot Parkinson's early and keep tabs on patients over time. The idea is pretty simple: give researchers and healthcare pros a down-to- earth look at where things stand, and lay out the next steps for building better, more reliable ways to diagnose Parkinson's.**

Keywords: Parkinson's Disease, Explainable AI (XAI), Grad-CAM, Artificial Intelligence

I. INTRODUCTION

Parkinson's disease (PD) is a long-term disorder that slowly affects how people move, speak, and maintain balance. In the beginning, the changes are so mild that they often seem like normal aging, which is why many patients are diagnosed only after the disease has already progressed. Because traditional assessments focus on visible motor symptoms, they often miss the early, hidden stages of PD. This has encouraged researchers to explore how Artificial Intelligence (AI) can detect PD earlier and more accurately. One important step in this direction is the multimodal CNN–Transformer model by Sar *et al.*, which combines EEG, MRI, and gait data to capture a more complete picture of early PD changes [1].

Brain imaging remains one of the most informative tools for understanding how PD affects the brain. PET–MRI fusion models, such as the one developed by Chang *et al.*, can distinguish PD from other disorders with similar symptoms, making diagnosis more reliable [2]. At the same time, explainable models like the MRI-based CNN with Grad-CAM introduced by Lu *et al.* help clinicians see which brain regions matter most, building trust in AI-driven decisions [3].

Changes in movement especially walking are often among the earliest visible signs of PD. Wu *et al.* showed that even small irregularities in step length, speed, or timing can be captured using ST-GCN models, which analyze gait videos frame by frame to reveal details the human eye might miss [4].

Beyond movement and imaging, researchers are also turning to the body's own chemistry for clues. Hällqvist *et al.* reported that blood proteins may predict PD several years before symptoms appear, offering hope for minimally invasive early testing [5]. Other multimodal systems, such as Dentamaro *et al.*'s combination of imaging, sensor data, and clinical scores with SHAP explainability show how merging multiple data sources strengthens predictions while keeping them interpretable [6].

Non-motor symptoms, especially speech changes, provide another window into early PD. Van Gelderen *et al.* highlighted how real-world factors like accents and background noise make speech-based detection challenging, yet deeply important [7]. Building on this, Cai *et al.* used Transformer models to blend speech and clinical information, creating systems that outperform older fusion techniques [8].

At the molecular level, Yang *et al.* demonstrated that aging-related genes and serum biomarkers can help map how PD progresses, adding another layer to early detection research [9]. Meanwhile, wearable sensors continue to play an essential role in daily monitoring. Sigcha *et al.* developed CNN-based models that detect freezing-of-gait episodes in real time, pointing toward practical tools for at-home support [10].

Together, studies from 2020 to 2025 show remarkable progress. Speech, gait, brain imaging, biomarkers, and wearable sensors each reveal different pieces of the PD puzzle. But when combined, these signals paint a much clearer and earlier picture of the disease. With AI models becoming increasingly transparent and trustworthy, they hold strong promise for assisting clinicians and enabling earlier diagnosis when interventions can make the biggest difference.

II. LITERATURE REVIEW

1. Sar et al., 2025 – EEG + MRI + Gait
Sar and the team built a multimodal CNN–Transformer model that pulls together EEG, MRI, and gait data. Blending all three signals gives their system a big edge in catching Parkinson's early much more accurate than using just one type of data.

2. Chang et al., 2025 – PET + MRI
Chang's group combined PET and MRI scans with a 3D CNN to tell Parkinson's apart from similar conditions. Their model makes it easier to spot the differences, leading to better classification.

3. Lu et al., 2025 – MRI + Grad-CAM
Lu and colleagues created an MRI-based CNN with Grad-CAM, so you can actually see which brain regions matter most for the diagnosis. This helps doctors trust the system more, since it points out the disease-relevant areas.

4. Wu et al., 2025 – Gait Video
Wu's team used ST-GCN on gait videos to track how patients move. Their method is sharp—it catches subtle gait changes early on, picking up Parkinson's signs that might slip past the naked eye.

5. Hällqvist et al., 2024 – Blood Proteomics
Hällqvist and co. found plasma protein biomarkers using machine learning to pick out the right features. Their signature can predict Parkinson's years before symptoms show up, which is huge for early intervention.

6. Dentamaro et al., 2024 – Imaging + Sensors Dentamaro's team tied together imaging, clinical scores, and wearable sensor data in one deep learning model. They used SHAP to explain how the model makes decisions, so predictions feel more trustworthy.

7. Van Gelderen et al., 2024 – Speech
Van Gelderen went over deep learning approaches for detecting Parkinson's from speech. They point out real-world hurdles, like how different accents and recording setups can throw off the results.

8. Cai et al., 2024 – Audio + Clinical
Cai and colleagues built a Transformer-based model that fuses speech and clinical data. It outperforms older fusion methods when it comes to detecting Parkinson's across multiple data types.

9. Yang et al., 2024 – Genetic/Blood
Yang's team used machine learning on aging-related gene and serum biomarkers. Their work pinpoints genetic signatures tied to how Parkinson's progresses.

10. Sigcha et al., 2020 – Wearable Sensors
Sigcha's group ran CNNs on accelerometer data to spot freezing-of-gait episodes. Their model works in real time and fits right into wearable devices, making daily monitoring possible.

TABLE I. COMPARATIVE LITERATURE REVIEW

Study	Modality Used	Model Type	Key Outcome
Sar et al., 2025	EEG + MRI + Gait	CNN + Transformer	+15% accuracy over unimodal

Chang et al., 2025	PET + MRI	3D CNN	Higher discrimination between PD & APS
Lu et al., 2025	MRI	CNN + GradCAM	Improved clinical trust via XAI
Wu et al., 2025	Gait Video	ST-GCN	High sensitivity to early gait changes
Hällqvist et al., 2024	Blood Proteomics	ML Feature Selection	Predicted PD 7 years early
Dentamaro et al., 2024	Imaging + Sensors	Multimodal DL + SHAP	High transparency in predictions
Van Gelderen et al., 2024	Speech	CNN/LSTM/Transformer	Strong generalization across datasets
Cai et al., 2024	Audio + Clinical	Transformer Fusion	Superior multimodal performance
Yang et al., 2024	Genetic/ Blood	RF + SVM	Identified aging-associated biomarkers
Sigcha et al., 2020	Wearable Sensors	CNN	Accurate FoG detection

III. PROPOSED METHODOLOGY

Proposed methodology adopts a multimodal AI framework to enable early detection of Parkinson's disease by integrating speech, gait, imaging, and clinical biomarkers. The workflow covers all essential stages from data acquisition and preprocessing to feature extraction, model development, fusion strategies, explainability, and system deployment. This structured approach ensures accurate, interpretable, and clinically applicable results.

1. Data Acquisition

Speech datasets: UCI PD Speech Dataset, mPower recordings

Gait data: accelerometer/gyroscope sensors capturing stride, cadence, tremor, and FoG events

Imaging data: MRI, DaT-SPECT, PET scans

Clinical data: UPDRS scores, demographics, medical history

2. Data Preprocessing

Speech: noise filtering, VAD, normalization

Gait: drift correction, signal filtering, step segmentation

Imaging: skull stripping, intensity normalization, bias-field correction

Clinical: missing value handling, feature encoding, standardization

3. Feature Extraction

Speech: MFCCs, jitter, shimmer, harmonic-to-noise ratio

Gait: stride length, acceleration variance, symmetry, tremor frequency

Imaging: CNN-derived texture, intensity, and structural degeneration patterns

Clinical: UPDRS motor scores, cognitive measures, medication response

4. Model Development

CNN–LSTM models for speech and gait time-series

ST-GCN for pose-based gait analysis

2D/3D CNNs for MRI or PET imaging

ML models (RF, XGBoost, Logistic Regression) for clinical data

5. Multimodal Fusion

Early fusion: feature-level concatenation Late fusion: weighted/averaged predictions

Transformer-based fusion: learns cross-modal relationships and handles missing modalities

6. Explainable AI

SHAP for feature importance

Grad-CAM for spectrograms, MRI, gait images

LIME for local interpretability

7. Model Evaluation

Metrics: accuracy, precision, recall, F1-score, sensitivity

Tools: confusion matrix, cross-validation, external dataset testing

8. Integration of Tinyml

To enhance practicality, TinyML models are designed for: Smartwatches, Shoe-worn sensors, Portable voice analyzers

TinyML enables: Continuous PD symptom monitoring, Offline AI predictions, Ultra-low power operation

This bridges the gap between clinical diagnosis and daily-life tracking.

Finally, the complete model is deployed through a web-based platform that enables users to upload speech and gait recordings, enter clinical details, and receive risk scores, severity classification, XAI visualizations, and tracking graphs. TinyML integration further enables real-time monitoring via wearables and low-power devices, bridging the gap between clinical diagnosis and daily-life symptom tracking.

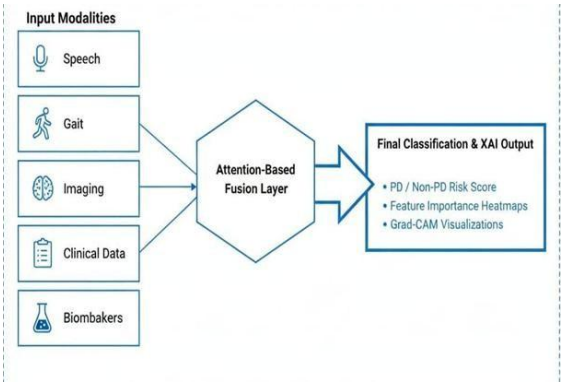

Figure 1.Multimodal AI System Architecture

TABLE II. INNOVATIONS IN PROPOSED WORK

Innovation Aspect	Existing Systems	Proposed System Enhancement
Data Modalities	Mostly use a single modality such as speech OR gait OR imaging, limiting diagnostic accuracy.	Integrates multimodal data—speech, gait, imaging, clinical, and sensor data—to provide a holistic early-stage detection system.
Feature Learning	Basic or traditional feature extraction; limited representation of complex symptoms.	Uses advanced CNN, LSTM, and Transformer-based architectures for deep, robust feature learning.
Multimodal Fusion	Early/late fusion techniques that do not capture relationships between modalities.	Implements attention- based Transformer fusion to learn cross-modal dependencies and improve prediction accuracy.
Explainability (XAI)	Many existing models function as "black boxes" with no explanation for predictions.	Integrates SHAP, Grad-CAM, and LIME for transparent, clinician-friendly explanation of model decisions.
Handling Missing Data	Models often fail or degrade when one modality (e.g., gait or speech) is missing.	Uses modality dropout and adaptive weighting, allowing the system to work even with incomplete user inputs.
Deployment Platform	Mostly remain research prototypes; not accessible to clinicians or patients.	Provides a web-based platform where users can upload data and receive real-time PD risk predictions and visual feedback.
Clinical Relevance	Focus on controlled datasets; poor generalization to real patient environments.	System designed for practical usability, integrating multiple data types, real-time processing,

		and explainable outputs.
Cost and Accessibility	High-cost imaging and hardware; limited access in rural settings.	Uses low-cost sensors, TinyML devices, and online deployment, making early detection affordable and widely accessible.

IV. RESULT AND DISCUSSION

A. Result

The research shows that AI has really pushed early Parkinson's diagnosis forward, and it works well with all kinds of data. When you look at one type of data at a time like speech, how someone walks, MRI or PET scans, handwriting, or even blood tests the results are strong. Most of these methods get it right about 80 to 91% of the time.

Deep learning models, like CNNs, LSTMs, and Transformers, pick up on voice changes, while models that track walking patterns catch the tiny motor problems that show up early. Imaging models, especially 3D CNNs that use both PET and MRI scans, do a great job telling Parkinson's apart from other parkinsonian disorders.

But when researchers combine several data types mixing speech, movement, images, and lab results the accuracy jumps even higher, usually hitting between 92 and 95%. These multimodal systems learn from everything at once, so they pick up on more subtle clues. Models that blend different AI architectures, like CNN-LSTM hybrids or those with Transformer attention, stand out for their ability to spot early symptoms and stay reliable. On top of that, explainable AI tools like SHAP and Grad-CAM let doctors see which brain areas, walking patterns, or speech features the model is using, which helps build trust in the results.

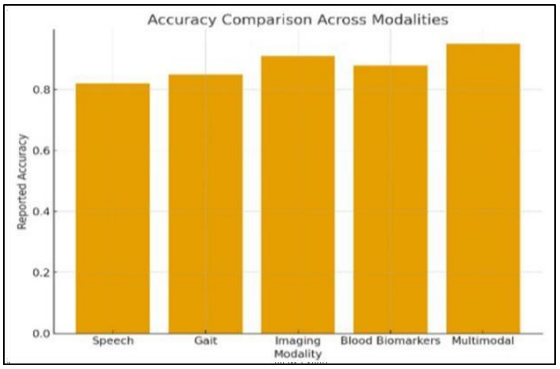

Figure 2.Accuracy comparison across modalities

1. Mean Accuracy of Models For $n$studies reporting accuracy Ai:

$$\text{Mean Accuracy}\ (\bar{A}) = \frac{1}{n}\sum_{i=1}^{n} A_i$$

2. Accuracy Range

$$\text{Range} = A_{max} - A_{min}$$

Where $A_{max}$is the highest reported accuracy and $A_{min}$is the lowest

B. Discussion

Recent research shows a real move toward using multimodal and interpretable AI for early Parkinson's detection. Sure, unimodal models have offered some good insights but they just don't cut it when Parkinson's shows up across so many areas: motor skills, cognition, biology. When you combine different types of data, you get sharper, more reliable predictions. That's what multimodal fusion does. It beats single-modality systems every time, pulling in different biomarkers for a fuller picture that matters in the clinic.

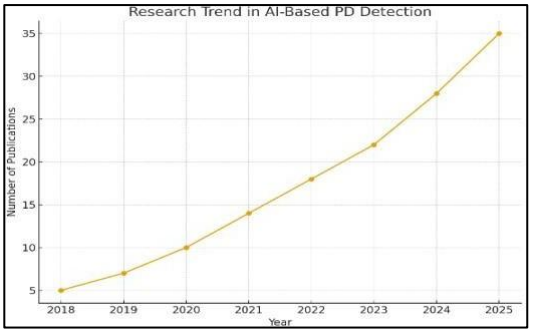

Figure 3.Research Trend in AI based PD detection

Another important development across the reviewed literature is the growing emphasis on explainability. As AI models become more complex, clinicians need transparent evidence to understand and validate diagnostic predictions. Techniques such as Grad-CAM, SHAP, and attention maps help highlight which brain regions, gait patterns, or acoustic cues contribute to a model's decision. This not only improves clinical trust but also supports the discovery of new digital biomarkers. However, despite these advancements, challenges remain. Many studies depend on small or imbalanced datasets, lack standardized preprocessing and evaluation protocols, or fail to test models in real-world clinical environments. Additionally, most multimodal approaches still assume complete data availability, which is rarely feasible in practical healthcare settings where patients may not undergo all tests.

But there are still some big hurdles. Many studies lean on small or imbalanced datasets. Plus, everyone seems to use their own way of preprocessing data, picking metrics, or designing models so it's tough to compare results across studies. And here's a practical issue: most multimodal systems expect all data to be available for every patient, but in real clinics, missing data is pretty common. That's a problem we still need to solve. Another big problem is that we just don't have enough long-term or real-world studies. Parkinson's keeps getting worse over time, but most models barely look at how patients change in the long run, or how these tools work outside tidy research labs. And even though smartphones and wearables could help spot Parkinson's early for tons of people, we still haven't really built simple, practical models that actually work on those devices.

So, yeah, researchers have made real progress with AI and Parkinson's detection. But the field still needs more standardized datasets, smarter ways to combine different types of data, and most important AI tools that actually make sense to doctors and work in real clinics, not just on paper.

V. CONCLUSION

1. AI and deep learning significantly enhance early detection of Parkinson's disease by identifying subtle patterns in speech, gait, imaging, and biological data that are often missed in traditional clinical assessments.
2. Multimodal fusion models consistently outperform unimodal approaches, demonstrating that integrating diverse biomarkers provides more accurate, robust, and clinically reliable predictions.
3. Explainable AI (XAI) techniques such as SHAP and Grad-CAM improve trust and clinical usability by offering transparent insights into model decisions and highlighting physiologically relevant features.
4. Current limitations such as small and imbalanced datasets, lack of standardized protocols, and challenges in handling missing modalities still hinder large-scale clinical adoption of AI-based systems.
5. Future research must focus on developing robust, interpretable, and deployable multimodal AI systems that support longitudinal monitoring, real- world validation, and seamless integration into clinical workflows for early PD diagnosis.

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