

Review on Quantum AI-Based Parkinson's Disease Diagnosis Optimiser

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Abstract –

Parkinson's disease is a progressive neurological disorder. Speech, gait, and handwriting often change before a specialist can confirm the diagnosis. Clinics still depend heavily on observation, which takes time and can vary between doctors. Recent papers combine machine learning with quantum and hybrid quantum-classical models to improve screening from multimodal data. This review covers eight studies (2023–2026) that use Quantum LSTM, variational quantum circuits, quantum neural networks, quantum-inspired SVM, and metaheuristic feature selection for PD detection. We note which biomarkers each work uses, the accuracy or AUC reported, and repeated limits: simulation-only runs, public datasets, and weak clinical follow-up. A shared pipeline is summarised. Quantum AI may help earlier detection, but surveyed systems are not yet ready for routine hospital use without hardware noise tests and longer patient studies.

Key Words: *Parkinson's Disease, Quantum Machine Learning, Hybrid Quantum-Classical Models, Quantum LSTM, Variational Quantum Circuits, Speech Biomarkers, Gait Analysis, Medical Diagnosis, Review Paper.*

I. INTRODUCTION

Parkinson's disease (PD) affects millions of people worldwide. Loss of dopamine-producing neurons leads to tremor, muscle stiffness, slow movement, and speech changes. Early diagnosis allows earlier treatment, but many patients are identified only after symptoms become clear in clinic.

Classical diagnosis relies on clinical observation, which can vary between hospitals. Machine learning already helps by analysing voice, handwriting spirals, and wearable gait signals. Quantum machine learning (QML) is a newer option: patient features are encoded into quantum states and processed with variational circuits or quantum-inspired optimisers alongside standard deep learning.

This review examines eight papers (2023–2026) on quantum AI optimisers for PD diagnosis. Section 2 summarises each study. Section 3 describes the common pipeline. Section 4 discusses results and limits. Section 5 outlines future work. Section 6 concludes.

II. LITERATURE SURVEY

A. Quantum and Hybrid Models

Quantum LSTM (2024). Arepalli et al. [1] present a Quantum LSTM for early PD detection. They report better accuracy, precision, and recall than a classical LSTM with

shorter training time. Results are based on public datasets; deployment on hospital systems is not described.

Hybrid quantum-classical framework (2025). Swarna et al. [2] combine deep learning with variational quantum circuits (VQC) using speech, gait, and EEG data. The hybrid model outperforms classical baselines in their tests, but all quantum steps run on simulators rather than physical quantum hardware.

Dual-track explainable network (2026). Jenish et al. [3] use quantum circuits for clinical features and a CNN for medical images, with Grad-CAM maps for explainability. Reported accuracy is about 97%, but the method needs rich multimodal records that many clinics do not collect together.

Quantum-inspired screening (2025). Vatsavai et al. [4] apply a quantum-inspired support vector machine to voice, gait, and demographic data. AUC near 0.98 indicates strong ranking of cases versus controls. The approach is not fully gate-based quantum computing and still depends on feature engineering.

B. Optimisation, Voice, and Gait

QMFOFS-HCNN (2024). Mansour [5] uses Quantum Mayfly Optimisation for feature selection with a CNN-LSTM classifier. Accuracy between 96% and 100% is reported; without external validation on diverse patients, overfitting is a concern. Model interpretability is limited.

QNN on voice (2023). Batra et al. [6] apply a quantum neural network to voice biomarkers only. They report better accuracy and faster training than classical models on a small dataset. Voice-only screening cannot reflect gait or cognitive decline. QML gait analysis (2024). Hashmi et al. [7] classify gait features from wearables using QML and outperform several classical methods. Practical use requires patients to wear sensors consistently, and results are not reported on noisy real quantum processors.

Hybrid speech-clinical model (2025). Kumar et al. [8] merge speech and clinical variables in a hybrid quantum-classical model with improved robustness over baselines. The authors note that long-term clinical trials and high compute cost remain open issues.

C. Datasets

Common datasets include UCI Parkinson's Telemonitoring, HandPD, mPower, and the Parkinson's Progression Markers Initiative (PPMI). Voice-focused work often uses standard dysphonia corpora. Public data aids comparison between papers but may not represent diverse medication states, ages, and recording devices. Evaluation should use patient-independent train-test splits. Accuracy, F1-score, and AUC-ROC are widely reported; for screening tasks, AUC often describes performance better than a single accuracy at one threshold.

III. METHODOLOGY OVERVIEW

Although implementations differ, most papers follow a similar optimizer pipeline from raw data to diagnostic output.

A. Preprocessing and Encoding

Raw voice recordings, handwriting traces, gait sequences, and electronic health records are cleaned, normalised, and sometimes augmented (for example with DCGAN-based synthesis in QSVM pipelines). Missing values are handled by imputation or removal. Classical feature vectors are then mapped to qubits using angle encoding or amplitude encoding so variational quantum layers can model non-linear links between symptoms.

B. Feature Selection and Classification

Classical filters and quantum-inspired optimisers (Mayfly search, Bayesian chaotic optimisation) reduce feature dimension before training. Classifiers include quantum SVM, variational quantum circuits, quantum neural networks, and quantum LSTM. Some systems add a second stage for disease severity (for example Hoehn-Yahr or UPDRS-style scores). Threshold optimisers balance false positives against missed cases.

C. Reporting

Several frameworks output structured reports, charts, or heatmaps for clinicians. End-to-end latency is often dominated by audio preprocessing and gait windowing rather than the quantum circuit itself.

IV. OBSERVATIONS AND INSIGHTS

Hybrid models tend to perform best when modalities differ in nature, such as combining audio with tabular laboratory results. Quantum LSTM and QNN studies argue for advantages on sequential or high-dimensional biomarkers. Explainability tools like Grad-CAM respond to a real clinical need for trust in automated suggestions.

Reported performance varies by dataset: Arepalli et al. [1] emphasise training speed and precision-recall gains; Swarna et al. [2] show multimodal VQC fusion helps; Jenish et al. [3] and Vatsavai et al. [4] reach high-90s accuracy or AUC; Mansour [5] reports the highest raw accuracy range; Batra [6] and Hashmi [7] demonstrate gains on voice and gait respectively; Kumar [8] highlights robustness when speech and clinical data are combined.

Recurring limitations include reliance on simulators, limited cohort size, absence of multi-hospital replication, lack of longitudinal follow-up, and no discussion of regulatory approval. Quantum-inspired methods may still be useful before fault-tolerant hardware matures, provided evaluation standards improve. Many current studies rely on public datasets with limited samples. The high dimensionality of quantum states can lead the model to memorize dataset noise rather than learning generalized biological markers. Future research must prioritize cross-dataset validation and longitudinal trials to ensure that the 99% accuracy rates translate to clinical environments.

TABLE I. COMPARISON OF SURVEYED QUANTUM AI PD DIAGNOSIS STUDIES

	Study Year	Inputs	Result	Limitation
Arepalli [1]	2024	Clinical series	High acc./F1	Public dataset
Swarna [2]	2025	Speech, gait, EEG	Beats classical ML	Simulator only
Jenish [3]	2026	Clinical + imaging	~97% acc.	Multimodal data
Vatsavai [4]	2025	Voice, gait, demo.	AUC ~0.98	Quantum-inspired
Mansour [5]	2024	Multimodal	96-100% acc.	Overfitting risk
Batra [6]	2023	Voice	QNN > classical	Small sample
Hashmi [7]	2024	Wearable gait	QML > ML	Needs sensors
Kumar [8]	2025	Speech + clinical	Robust hybrid	No long-term trial

V. FUTURE DIRECTIONS

Near-term research should expand cohorts across sites, compare simulator and cloud quantum processor results, and publish preprocessing scripts for reproducibility. Explainability should be a default requirement. Medium-term work could add facial expression and posture cues to voice and gait. Long-term integration with hospital electronic health records and multi-year patient tracking remains essential for clinical adoption.

VI. CONCLUSION

Quantum AI optimisers for Parkinson's disease diagnosis are an active research area. The eight studies reviewed here show progress in accuracy, feature selection, and in some cases interpretability when quantum or hybrid layers complement classical deep learning. Voice and gait remain the most accessible biomarkers; multimodal fusion offers the highest ceiling if data collection can be standardised.

No reviewed system is ready for unsupervised clinical deployment. Noise on current quantum hardware, hospital IT integration, and ethics of recording vulnerable patients need further work. With patient-independent validation and neurologist-led pilots, quantum-enhanced screening could support earlier PD care without replacing expert clinical judgement.

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