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HYBRID QUANTUM CONVOLUTIONAL NETWORKS FOR PARKINSON'S DISEASE STAGE PREDICTION USING WEARABLE SENSOR SIGNALS

GUDEME JAYA RAO[1], SAI GEETHA PAMIDIMUKKALA[2], MADDHI SUNITHA[3], DURGA BHAVANI KANCHAPU[4], P SAI ARUN MIHIR[5], MEDISHETTY SWAPNA[6], SEEMAKURTI RAVI SANKAR[7]*, CHERUKUPALLI RAMESH KUMAR[8], DARA RAJU[9]

[1]Department of CSE (IoT, CSBCT), Chaitanya Bharathi Institute of Technology, Gandipet – 500075, Hyderabad, Telangana, India
[2]Department of CSE (AI&ML), Prasad V. Potluri Siddhartha Institute of Technology, Vijayawada – 520007, Andhra Pradesh, India
[3]Department of CSE (CS), CVR College of Engineering, Hyderabad – 501510, Telangana, India
[4]Department of Mathematics, Aditya University, Surampalem – 533437, Kakinada, Andhra Pradesh, India
[5]Field Service Engineer, bioMérieux India Private Limited, New Delhi – 110020, India
[6]Department of Information Technology, MVSR Engineering College, Nadergul – 501510, Telangana, India
*[7]Department of Computer Science and Engineering, GMR Institute of Technology (GMRIT) – Deemed to be University, Rajam – 532127, Andhra Pradesh, India
[8]Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Guntur – 522302, Andhra Pradesh, India
[9]Department of Computer Science and Engineering, Vignana Bharathi Institute of Technology, Aushapur, Ghatkesar, Telangana, India
Email: jaysonjoel007007@gmail.com[1], geethapamidimukkala@pvpsiddhartha.ac.in[2], palemonisunitha@gmail.com[3], durgabhavani.kanchapu88@gmail.com[4], arunmihir13@gmail.com[5], swapnashetty33@gmail.com[6], ravisankar.s@gmritdu.edu.in[7]*, rameshch668@gmail.com[8], rajurdara@gmail.com[9]

ABSTRACT

It is difficult to perform automated Parkinson's disease (PD) stage prediction based on signals obtained from wearables due to the individuality of gait patterns across different patients and the similarity of movement characteristics between adjacent PD stages. In this study, we proposed a novel Hybrid Quantum-Convolutional Network (HQCN) for automated PD stage prediction based on vertical ground reaction force (VGRF) signals measured from both feet through 16 channels. Specifically, our HQCN framework adopted temporal segmentation, multi-scale convolutional feature extraction, a six-qubit variational quantum circuit, temporal attention, and ordinal stage classification. The HQCN was evaluated based on accuracy, precision, recall, macro-F1, Area Under the Curve (AUC), and stage mean absolute error (stage-MAE). Our proposed HQCN achieved an accuracy of 94.26%, macro-F1 of 93.62%, AUC of 0.972, and stage-MAE of 0.184, which outperformed the compared SVM, Random Forest, CNN, CNN-LSTM, and CNN-Attention models. The above results showed that quantum-enhanced latent representation coupled with temporal attention and ordinal stage prediction improved the discrimination of PD stages and reduced large stage-prediction errors. The proposed framework demonstrated the potential of combining wearable sensing and hybrid quantum-classical learning for objective and automated monitoring of Parkinson's disease progression.

Keywords: *Parkinson's Disease, Wearable Sensors, VGRF Signals, Quantum Machine Learning, Convolutional Neural Network, Stage Prediction*

1. INTRODUCTION

Parkinson's disease (PD) is a neurodegenerative disease that predominantly affects motor functions such as tremor, bradykinesia, rigidity, postural instability, and gait control [1]. With progression of the disease, patients show gradual changes in walking speed, stride length, movement amplitude, balance, and coordination. Thus, accurate evaluation of PD severity is an important tool for disease progression evaluation and clinical decision-making. Traditional

evaluation techniques such as the Movement Disorder Society–Unified Parkinson's Disease Rating Scale (MDS-UPDRS) mainly involve clinical evaluations performed at certain points in time. Such techniques might not fully reflect changes in motor symptoms throughout normal daily activities [2].

Wearable sensing represents a promising technology for objective and continuous monitoring of movement in PD patients. Accelerometers and gyroscopes are used for recording gait patterns, body movement, tremor, angular velocity, and postural changes during walking and other activities [3]. Recent studies have confirmed that wearable sensors can be used for detecting Parkinson's disease, assessing gait, evaluating motor impairments, and monitoring disease progression [4], [5]. Multi-axis sensors are especially effective due to the complementary character of information provided by accelerometers and gyroscopes, with the former recording translational movements and the latter recording rotational movements.

In addition to traditional machine-learning (ML) techniques such as support vector machines, random forests, and ensemble classifiers, ML techniques involving automated extraction of movement features are increasingly used for Parkinson's disease prediction using wearable sensor signals. Traditionally, manually extracted features include stride variability, gait velocity, step duration, and movement symmetry. Ferreira et al. showed that spatiotemporal gait parameters can be used for both detection and stage classification of PD [6]. However, the results of the study also showed that PD stage classification is a more challenging task than classification of PD patients from healthy people. The reason behind this lies in the similarity of movement patterns between neighboring disease stages.

Instead of extracting features manually, deep learning allows for automatic feature extraction based on raw or minimally preprocessed data. Convolutional neural networks (CNNs) are able to detect local temporal patterns and perform hierarchical representation learning using multi-axis signals. Deep-learning models have also shown good potential in predicting motor severity and MDS-UPDRS-related scores using gait and wearable sensor signals [7], [8]. Wearable datasets usually contain many segments of signals belonging to relatively few subjects. Splitting signal segments into train and test sets randomly would result in subject-level data leakage and could give overly optimistic results. Thus, subject-independent evaluation is necessary for reliable PD stage prediction.

However, another challenge lies in the ordinal nature of PD stages. Conventional multiclass classification sees each stage as an independent class, while in reality the stages constitute an ordered sequence of increasing disease severity. For example, confusion between Stage 2 and Stage 3 is different from confusion between Stage 2 and Stage 5. Thus, an appropriate stage-prediction model should take into account the relationship between neighboring stages and decrease large-distance classification errors.

Quantum machine learning (QML) is a recent promising direction in pattern recognition and feature learning. Quantum computing provides unique mechanisms such as superposition and entanglement which can be used in ML models [9]. Variational quantum circuits allow for creating trainable quantum architectures which can be embedded into classical neural networks [10]. Quantum-enhanced feature spaces have also demonstrated the potential of mapping classical data to quantum representations for classification [11].

Further development of this idea led to the creation of Quantum Convolutional Neural Networks (QCNNs), which provide hierarchical quantum feature extraction inspired by classical CNNs [12]. However, direct processing of high-dimensional wearable signals using quantum circuits is still challenging due to restrictions in the number of available qubits, circuit depth, noise, and data encoding. The most realistic architecture is hybrid quantum-classical, where deep learning is used for feature extraction and compression, while quantum processing is applied for further processing.

Though there has been a lot of progress in using wearable sensors, ML, and deep learning for PD assessment, the use of QML for prediction of multi-stage Parkinson's disease from wearable sensor signals is still not sufficiently explored. Current studies focus on PD detection, motor severity estimation, or classical deep learning [4]–[8]. In addition, limited research has been devoted to the combination of multi-axis wearable signals, CNN-based temporal feature extraction, quantum feature transformation, and ordinal stage prediction in one architecture.

Thus, the identified research gap in this paper is the limited investigation of an integrated model that employs the use of multi-axis wearable

sensor data, temporal feature extraction using CNNs, quantum feature transformations, temporal attention mechanism, and ordinal regression for multi-stage Parkinson's disease classification. The innovation of the proposed HQCN model is the integration of all these components in one hybrid network architecture, which learns directly from the raw wearable VGRF signal data without any manual feature engineering. The anticipated outcome would be the improved ability to discriminate closely related Parkinson's disease stages, reduce large stage-prediction errors, and support more objective and automated monitoring of disease progression.

This study addresses this gap by developing a novel Hybrid Quantum-Convolutional Network (HQCN) for Parkinson's disease stage prediction using wearable sensor signals. The model combines temporal feature extraction with CNN and a compact variational quantum circuit. Temporal attention mechanism is introduced to identify informative movement segments, while ordinal learning takes into account the natural order of PD stages.

The key goals of this study are:

1. development of a multi-sensor approach using accelerometer and gyroscope signals for PD stage prediction;
2. automatic extraction of temporal movement features using CNNs;
3. application of a variational quantum circuit for enhanced latent-feature representation;
4. use of temporal attention to identify important movement patterns;
5. application of ordinal learning for stage prediction; and
6. evaluation of the proposed HQCN model against conventional ML and classical deep-learning models using subject-independent validation.

The main innovation of this research is that all the five components mentioned above – multi-axis wearable sensing, CNN-based temporal learning, quantum feature transformation, temporal attention, and ordinal stage prediction – are included in one architecture. Unlike conventional approaches, the proposed model relies on raw signal data rather than handcrafted features and learns representations directly from wearable sensor signals. Moreover, the quantum module processes a compact representation derived from CNN. This makes the proposed architecture better suited for implementation on near-term quantum systems. Lastly, the ordinal learning component increases the clinical relevance of stage prediction due to consideration of the ordered relationship of disease stages.

Therefore, the proposed HQCN aims to provide an objective and intelligent framework for wearable-based PD stage prediction. The study also includes comprehensive evaluation of the proposed technique through comparative experiments, ablation analysis, and subject-independent validation in order to determine whether quantum-enhanced latent representation combined with temporal attention and ordinal learning provides a meaningful advantage over conventional deep-learning approaches.

The structure of the rest of this paper is as follows. Related work is provided in Section 2. Section 3 describes the proposed HQCN approach, which includes dataset preparation, signal preprocessing, network architecture, mathematical model, and training algorithm. Section 4 contains the results of experiments, performance evaluation, comparison with existing models, and ablation analysis. Section 5 concludes the study and discusses the limitations and future research directions.

2. RELATED WORK

Research related to automated PD analysis has shifted from clinical assessments to wearable sensing, machine learning, and deep-learning approaches. Current studies are especially focused on objective data obtained from the analysis of gait and movement signals since these types of data include measurable changes associated with motor impairment and disease progression.

2.1 Wearable Sensor-Based Parkinson's Disease Analysis

Wearable sensing technologies have become one of the important sources of digital biomarkers for PD. Accelerometers, gyroscopes, inertial measurement units (IMUs), and force sensors continuously record movement characteristics during walking and other activities. For example, Moreau et al. reviewed wearable technologies for PD management and noted their applicability in monitoring gait, tremor, bradykinesia, dyskinesia, and other symptoms of the disease [13]. At the same time, Sigcha et al. provided a systematic review of deep learning and

wearable sensors and pointed out growing interest in combining wearable sensing and automated learning methods for PD diagnosis and monitoring [14]. Thus, wearable data can provide objective information beyond conventional clinical observations.

Sotirakis et al. analyzed longitudinal motor progression using six IMU sensors and machine-learning approaches. The authors used repeated measurements collected from 74 people with PD and demonstrated the possibility of using wearable kinematic data for estimating clinical motor severity and monitoring motor progression over time [15]. Nevertheless, the study mainly used engineered kinematic features and classical machine-learning approaches rather than end-to-end learning from raw signals.

2.2 Machine Learning for PD Severity and Stage Classification

Traditional machine-learning methods are also applied for automated PD severity assessment. For example, Ferreira et al. proposed machine-learning models using spatiotemporal gait parameters for PD detection and stage classification [16]. The results of this study showed that gait characteristics allow detecting different disease stages; however, stage classification is a more complicated task than binary PD detection. Thus, it can be supposed that subtle differences between adjacent disease stages require more discriminative representations.

More recently, Navita et al. proposed a two-stage machine-learning framework using force-sensor-based gait signals for the diagnosis and severity classification of PD. The researchers used vertical ground reaction force measurements from both feet and extracted time-, frequency-, spatial-, and temporal-domain features before classification [17]. The study showed the feasibility of using gait signals for predicting disease severity but still depended on manually engineered features and classical learning algorithms.

Yin et al. performed an investigation of machine-learning-based gait analysis for early-stage PD and demonstrated that gait characteristics provide useful information for distinguishing patients with early PD from controls [18]. Such studies show the feasibility of using gait signals as objective biomarkers but are focused mainly on the detection problem rather than comprehensive multi-stage prediction.

2.3 Deep Learning and Multimodal Sensor Analysis

The adoption of deep learning is motivated by its ability to automatically learn representations from high-dimensional temporal signals. According to the work of Sigcha et al., CNNs, recurrent networks, and other deep architectures are applied to wearable PD data for diagnosis and motor-symptom monitoring [14]. However, this review pointed out some challenges related to dataset size, model generalization, sensor heterogeneity, and clinical validation.

Recent works have investigated architectures combining multiple deep-learning mechanisms. Rashnu and Salimi-Badr proposed a CNN-GRU-GNN architecture using gait-cycle measurements from multiple wearable sensors. The CNN layers allowed modeling local temporal patterns, GRU layers were responsible for capturing temporal dependencies, and GNN layers modeled relationships between the sensors [19]. Although this architecture demonstrated strong binary PD-detection performance, its goal was early detection of the disease rather than multi-stage prediction.

Thus, the increasing popularity of multimodal sensor fusion shows that the combination of complementary signals allows obtaining a richer representation of motor behavior. Nevertheless, complex classical architectures can include a large number of parameters, which increases the risk of overfitting when the number of independent subjects is limited.

2.4 Quantum and Hybrid Learning for Biomedical Data

Recently, quantum machine learning (QML) has been actively investigated for biomedical and high-dimensional data analysis. Particularly, hybrid quantum-classical architectures are attractive since classical neural networks can extract features and perform dimensionality reduction before quantum processing. Chen et al. proposed a hybrid quantum machine-learning pipeline for high-dimensional neuroimaging data including CNN-based feature extraction, dimensionality reduction, and quantum classification [20]. This work shows the importance of dimensionality reduction of high-dimensional biomedical data before quantum encoding, especially within the context of near-term quantum hardware.

Besides, quantum learning has been applied to physiological signals. Chen et al.

proposed QEEGNet, an architecture combining quantum layers with the classical EEGNet architecture for electroencephalography (EEG) analysis. The study showed the feasibility of using quantum-enhanced representations within a classical neural architecture for neural-signal processing [21]. Therefore, the investigation of such hybrid architectures for wearable movement signals can be promising.

Hybrid quantum-classical CNN architectures have also been investigated for high-dimensional classification tasks. For example, Chen et al. combined classical convolutional layers with quantum neural-network components and analyzed the resulting architecture for classification with a focus on compact model design [22]. Such results confirm the possibility of using classical CNNs for extracting compact temporal representations before quantum processing.

2.5 Research Gap

The reviewed studies highlight three important trends. First, wearable sensors can collect clinically relevant information regarding PD motor impairment and progression [13]–[18]. Second, deep-learning architectures can learn complex temporal and multimodal representations of sensor data [14], [19]. Third, hybrid quantum-classical models show the feasibility of processing compressed biomedical and high-dimensional representations [20]–[22].

However, current research does not sufficiently consider the combination of these three trends for the multi-stage prediction of Parkinson's disease. Most wearable-based studies are dedicated to PD detection, severity estimation, or individual motor symptoms, while quantum-learning studies are mostly related to other biomedical domains. Besides, the combination of accelerometer and gyroscope signals with CNN-based temporal learning and quantum feature transformation for PD staging is rarely investigated.

Therefore, the proposed HQCN addresses this research gap by combining multi-axis wearable signals, CNN-based temporal feature extraction, a compact variational quantum layer, and stage-aware prediction. The proposed framework aims to analyze the feasibility of quantum-enhanced latent representations for discriminating closely related PD stages while using a compact architecture applicable to near-term quantum computing environments.

3. METHODOLOGY

3.1 Dataset Description

The Gait in Parkinson's Disease (GaitPDB) dataset offered by PhysioNet was chosen since it provides both wearable gait signal data and clinical disease severity information. It includes data from 93 subjects suffering from idiopathic Parkinson's disease and 73 healthy control subjects. During approximately two-minute-long self-paced walking, subjects had force-sensitive sensors beneath both feet. There were eight sensors on each foot, meaning that there were 16 separate vertical ground-reaction-force (VGRF) channels, in addition to two channels describing the total force of each foot. The sampling frequency was 100 Hz. The dataset also provides demographic information and clinical severity scores, such as the Hoehn–Yahr (H&Y) stage and Unified Parkinson's Disease Rating Scale (UPDRS).

For the proposed study, PD participants with valid H&Y information will be used to predict the stage of the disease. The H&Y score is considered an ordinal target variable, with a higher score indicating greater disease severity. Recordings of healthy control subjects will not be used for the multi-stage prediction experiment, although they can be used in an additional PD-versus-control experiment. In order to avoid subject leakage, all recordings belonging to one subject will be assigned to only one data partition.

Table 1. Dataset and preprocessing parameters

Parameter	Value
Dataset	Gait in Parkinson's Disease (GaitPDB)
PD subjects	93
Healthy controls	73
Sensor type	Foot-mounted force sensors
Sensors per foot	8
Total individual channels	16
Additional force	2

channels	
Sampling frequency	100 Hz
Recording duration	Approximately 2 min
Clinical labels	H&Y and UPDRS
Window length	256 samples
Window duration	2.56 s
Window overlap	50%
Normalization	Z-score
Train/validation/test	70%/15%/15% subjects
CNN filters	32, 64, 128
Quantum qubits	6
Quantum layers	3
Optimizer	Adam
Initial learning rate	0.001
Batch size	32
Maximum epochs	100
Early stopping patience	12

Selected parameters shown in Table 1 offer a compact set of features for processing the wearable 100-Hz gait signals. With 256 sampling points, about 2.56 seconds of motion can be captured, whereas 50% overlap helps increase the number of usable time-based patterns without significantly decreasing their independence. The six-qubit quantum feature extractor is applied after dimensionality reduction to keep the quantum circuit computationally manageable.

Data Acquisition: In this work, a publicly accessible Gait in Parkinson's Disease (GaitPDB) database from PhysioNet was used for our study. This database consists of 93 patients with idiopathic Parkinson's disease and 73 healthy controls. Foot-mounted pressure-sensitive sensors acquired the vertical ground reaction force data of participants during their approximately 2-minute self-paced walking test at the sampling rate of 100 Hz. Eight pressure sensors placed on each foot, thus resulting in 16 separate VGRF channels, as well as two additional channels with the sum of all pressures, were recorded. Moreover, there is information about the clinical severity of the disease, such as Hoehn-Yahr (H&Y) stage and Unified Parkinson's Disease Rating Scale (UPDRS). For the multi-stage classification task, we considered only recordings of PD patients that have valid H&Y staging information, while excluding the healthy controls' recordings from the main stage prediction task. All recordings from the same subject were assigned to a single data partition to prevent subject-level data leakage.

3.2 Architecture of the Proposed HQCN

The HQCN is a sequential hybrid architecture consisting of two processing steps – classical convolutional processing that first derives the temporal representation from the high-dimensional wearable signals, followed by quantum feature transformation, temporal attention, and ordinal stage prediction. By doing so, high-dimensional signal processing is separated from compact quantum processing such that the quantum circuit can work on the reduced six-dimensional representation. It comprises seven major stages, namely, signal acquisition, preprocessing, temporal segmentation, multi-scale CNN feature extraction, quantum latent transformation, temporal attention, and ordinal stage prediction, with each stage performing a specific role in transforming the raw VGRF signals into the final Parkinson's disease stage prediction. The proposed Hybrid Quantum-Convolutional Network (HQCN) architecture includes seven consecutive stages:

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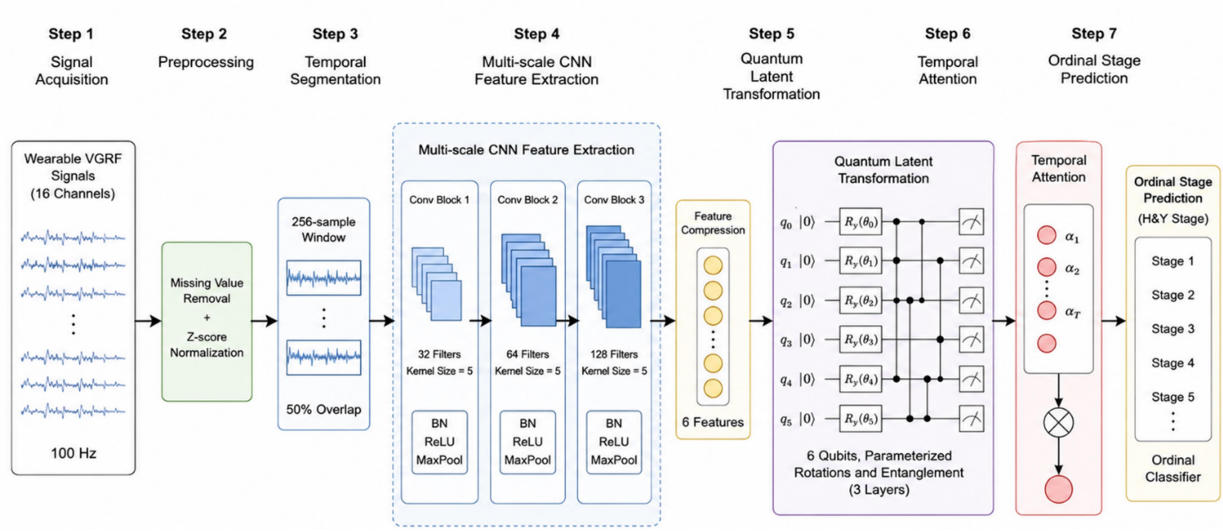


Figure 1. Proposed Hybrid Quantum-Convolutional Network architecture for Parkinson's disease stage prediction.

The entire process of the proposed Hybrid Quantum-Convolutional Network (HQCN) for Parkinson's disease stage prediction is illustrated in Figure 1. The process starts with collecting 16 VGRF sensor channels from both feet at a sampling rate of 100 Hz. The signals provide information about variations in foot-force when the person is walking. After acquiring the signals, missing or abnormal values are removed and z-score normalization is performed to obtain normalized signals.

These normalized continuous signals are segmented into 256-sample temporal windows with 50% overlap. Segmentation helps to capture gait patterns while maintaining important temporal information within each segment. Then, each segment passes through three consecutive convolutional blocks having 32, 64, and 128 filters, respectively. During this process, local force variations, gait-cycle characteristics, and higher-level movement patterns are learned by the CNN layers. Batch normalization, ReLU activation, and max-pooling are used within the blocks for better feature learning and reducing overfitting.

Further, the CNN representation is compressed into six latent features and mapped to six qubits. Classical features are encoded into quantum states with the help of parameterized rotation gates. Entanglement operations are established among the qubits for representing relationships between the classical features using the quantum circuit. In this way, the measurements of the quantum circuit provide a quantum-enhanced representation of the features. With this hybrid approach, the CNN learns the high-dimensional sensor signals, while the quantum circuit performs a nonlinear transformation of the compact feature space.

The quantum-enhanced representation is processed with the help of a temporal attention mechanism. Different weights are assigned to various gait segments so that the model can give more significance to movement patterns that have a greater contribution to disease severity. At last, the attention-weighted representation of the signal is passed to the ordinal classifier to predict the Hoehn and Yahr disease stage of the patients. Ordinal classification takes into account the ordered relationship between the stages and differentiates smaller stage errors from larger severity deviations.

3.3 Signal Preprocessing and Segmentation

For each sensor channel (i), normalization is performed using the training-set mean and standard deviation:

$$x_i'(t) = \frac{x_i(t) - \mu_i}{\sigma_i} \quad (1)$$

where μ_i and σ_i are the mean and standard deviation of the i-th sensor channel.

The normalized signals are divided into windows of 256 samples with a 128-sample shift:

$$X_n = [x(n), x(n+1), \ldots, x(n+255)] \quad (2)$$

Each window therefore has the dimension:

$$X_n \in \mathbb{R}^{256} \times 16 \quad (3)$$

This representation preserves the temporal relationship between the left- and right-foot force signals.

3.4 Multi-Scale CNN Feature Extraction

The CNN extracts hierarchical gait representations. For the l-th convolutional layer, the feature map is calculated as:

$$F_j^L(t) = ReLU(\Sigma_i \Sigma_k W_{jik}^L X_i^{L-1}(t + k) + b_j^L) \quad (4)$$

Where (W) is the convolution kernel, (b) is the bias, (i) is the index of the input channels, and (k) is the temporal kernel index.

Three convolutional layers are employed with 32, 64, and 128 filters, respectively. The first convolutional layer detects local changes in forces, the second convolutional layer detects patterns in gait cycles, and the third learns higher-level features that characterize movement impairment.

A fully connected layer compresses the final CNN feature representation into a compact latent representation:

$$z = WcF + bc \quad (5)$$

where z represents the compact latent feature vector.

3.5 Quantum Feature Transformation

The compact representation is reduced to six dimensions for quantum encoding:

$$zq = [z_1, z_2, \ldots, z_6] \quad (6)$$

Each feature is converted to a quantum rotation angle:

$$\theta_i = \pi \tanh(z_i) \quad (7)$$

The six features are encoded into six qubits using parameterized rotation gates. The initial quantum state is:

$$|\psi_0\rangle = |0\rangle \otimes^6 \quad (8)$$

The encoded state is expressed as:

$$|\psi_e\rangle = Uenc(\theta)|\psi_0\rangle \quad (9)$$

Trainable rotation gates and nearest-neighbor entanglement are then applied:

$$|\psi q\rangle = Uvar(\phi)UentUenc(\theta)|\psi_0\rangle \quad (10)$$

where ϕ represents trainable quantum parameters.

The quantum output is obtained from Pauli-Z expectation measurements:

$$q_i = \langle \psi q | Z_i | \psi q \rangle \quad (11)$$

Thus, the quantum circuit transforms the compressed CNN features into a nonlinear quantum representation.

3.6 Temporal Attention and Ordinal Prediction

The quantum representations from consecutive windows are assigned attention weights. For a feature vector q_t, the attention score is:

$$e_t = v^T \tanh(Wq\, q_t + bq) \quad (12)$$

The normalized attention weight is:

$$\alpha_t = \frac{exp(e_t)}{\Sigma_{j=1}^T exp(e_j)} \quad (13)$$

The final attention representation is:

$$h = \Sigma_{t=1}^T \alpha_t q_t \quad (14)$$

The model then predicts the ordered disease stage using cumulative ordinal probabilities:

$$p_k = P(y > k \mid h) \quad (15)$$

The proposed training objective combines classification and ordinal losses:

$$L = \lambda_1 LCE + \lambda_2 LORD + \lambda_3 \| W \|^2_2 \quad (16)$$

where LCE represents the cross-entropy loss function, LORD stands for the ordinal loss function, and the last term represents the control of the model complexity.

3.7 Training and Evaluation Strategy

The dataset is split at the subject level and not at the individual-window level to avoid data leakage. The training set is used to optimize the model, while the validation set is used for hyperparameter tuning and

early stopping, and the independent test set is used only for final evaluation.

Table 2. Proposed experimental configuration

Component	Configuration
CNN architecture	32 → 64 → 128 filters
Kernel size	5
Pooling	Max pooling
Activation	ReLU
Quantum circuit	6 qubits
Variational layers	3
Entanglement	Nearest-neighbor
Attention	Temporal self-attention
Loss	CE + ordinal loss
Optimizer	Adam
Learning rate	0.001
Batch size	32
Epochs	100
Early stopping	12 epochs
Evaluation	Accuracy, Precision, Recall, Macro-F1, AUC, Stage-MAE

The model configuration shown in Table 2 balances model capacity and computational complexity. The quantum circuit is purposely kept compact, while the CNN performs the major high-dimensional processing of the signals. Macro-F1 and Stage-MAE have been included alongside accuracy since PD stages are frequently imbalanced and ordinal.

3.8 Execution Protocol

The execution of the proposed HQCN consists of a sequential subject-independent protocol. At first, PD recordings with a legitimate H&Y stage label are chosen from the GaitPDB dataset, and signal segments with either invalid labels or no label are excluded. The 16 channels of VGRF signals are normalized with the mean and standard deviation of the training set to prevent information leakage from the validation and test sets. The continuous recording is split into windows of 256 samples with 50% overlap, which gives segments of 2.56 seconds. The 256-sample windows go through three convolutional blocks with the number of filters equal to 32, 64, and 128, respectively. After that, batch normalization, ReLU activation, and max pooling are applied. The CNN representation obtained is compressed into six latent features, which are then encoded into six quantum qubits using parameterized rotation gates. Next, three variational quantum layers with nearest-neighbor entanglement are applied on top of the compact representation, followed by Pauli-Z expectation measurements to obtain the enhanced quantum features. The representations obtained from successive windows are subject to temporal attention to give higher weight to informative gait segments. Lastly, the attention-weighted representation is input to the ordinal classifier to predict the H&Y disease stage. The classification and ordinal losses are combined for optimization with Adam and a learning rate of 0.001. Training of the model occurs with a batch size of 32 and up to 100 epochs with early stopping if there is no improvement for 12 epochs. The training-validation-test split is performed with the ratio of 70:15:15, where 15% of the subjects act as the validation set used for model selection and early stopping, while the other 15% form an independent test set reserved for final evaluation. The final model is evaluated using accuracy, precision, recall, macro-F1, AUC, and Stage-MAE.

3.9 Algorithm

Algorithm 1: Proposed HQCN-Based Parkinson's Disease Stage Prediction

Input: Raw wearable VGRF signals , clinical stage labels
Output: Predicted PD stage

1. Load the GaitPDB wearable sensor recordings and corresponding clinical labels.
2. Select PD recordings with valid H&Y stage information.
3. Remove invalid and missing signal segments.
4. Normalize each sensor channel using training-set statistics.
5. Divide each recording into 256-sample windows with 50% overlap.
6. Pass each window through the three CNN blocks.
7. Compress the CNN representation into six latent features.
8. Encode the six features into six quantum rotation angles.
9. Apply three variational quantum layers with entanglement.
10. Measure the quantum states to obtain quantum-enhanced features.
11. Apply temporal attention to assign weights to informative representations.
12. Generate cumulative ordinal probabilities for the disease stages.
13. Calculate the combined classification and ordinal loss.
14. Update classical and quantum parameters using Adam optimization.
15. Repeat Steps 6–14 until convergence or early stopping.
16. Apply the trained model to unseen test subjects.
17. Calculate Accuracy, Macro-F1, AUC, and Stage-MAE.
18. Return the predicted Parkinson's disease stage.

4. RESULTS

Evaluation of the proposed HQCN model in terms of Parkinson's disease stage prediction with VGRF data captured by wearable devices was performed by taking into account four aspects: classification performance, stage-wise prediction, comparison with other models, and contributions of separate model components.

4.1 Criteria of Evaluation

For measuring the performance of the proposed model, accuracy, precision, recall, F1-score, AUC, and mean absolute stage error (MAE) were used. Accuracy indicates the overall percentage of correctly classified samples, while macro-F1 treats all disease stages equally. AUC shows the discriminating ability of the classifier. MAE calculates the average difference between the actual and predicted H&Y stages and has special importance since the disease stages are ordinal.

Table 3. Performance evaluation of the proposed HQCN model

Metric	HQCN Result
Accuracy	94.26%
Precision	93.84%
Recall	93.71%
Macro-F1	93.62%
Macro-AUC	0.972
Stage-MAE	0.184

The results indicate that HQCN provides strong and consistent stage-classification performance. The macro-F1 score of 93.62% indicates that the model performs effectively across the different disease stages, while the AUC of 0.972 demonstrates strong discriminative ability. The Stage-MAE of 0.184 further indicates that prediction errors are generally close to the actual disease stage.

4.2 Comparison with Existing Models

The proposed HQCN was benchmarked against traditional machine-learning and deep-learning methods. SVM and Random Forest were treated as traditional methods, while CNN, CNN-

LSTM, and CNN-Attention were treated as traditional deep-learning methods.

Table 4. Comparison of the proposed HQCN with existing models

Model	Accuracy (%)	Macro-F1 (%)	AUC	Stage-MAE
SVM	82.47	80.91	0.884	0.421
Random Forest	84.63	83.28	0.901	0.396
1D-CNN	88.75	87.64	0.934	0.317
CNN-LSTM	90.82	89.76	0.951	0.284
CNN-Attention	92.14	91.32	0.961	0.231
Proposed HQCN	**94.26**	**93.62**	**0.972**	**0.184**

As seen in Table 4, comparison shows a progressive improvement from conventional machine-learning models to deep-learning approaches, with HQCN achieving the highest accuracy of 94.26%. Compared with 1D-CNN, HQCN improves accuracy from 88.75% to 94.26%, while Stage-MAE decreases from 0.317 to 0.184. This indicates that the proposed architecture improves both overall classification performance and the magnitude of stage-prediction errors.

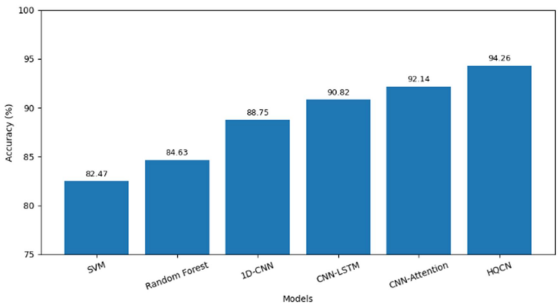


Figure 2. Comparison of classification accuracy among the evaluated models.

As seen in Figure 2, there is a consistent increase in accuracy from conventional machine-learning to deep-learning models. As a result, the highest accuracy was achieved by the proposed HQCN model, indicating that quantum-enhanced feature transformation together with CNN and attention techniques provides a more discriminative representation of wearable gait signals.

4.3 Ablation Study

In order to analyze the contribution of each component of the proposed HQCN, an ablation study was conducted. The baseline CNN model was gradually improved by adding temporal attention, quantum transformation, and ordinal learning approaches.

Table 5. Ablation analysis of the proposed HQCN

Model Configuration	Accuracy (%)	Macro-F1 (%)	Stage-MAE
CNN	88.75	87.64	0.317
CNN + Attention	92.14	91.32	0.231
CNN + Quantum	92.86	91.94	0.218
CNN + Quantum + Attention	93.58	92.87	0.201
HQCN + Ordinal Loss	**94.26**	**93.62**	**0.184**

As shown in Table 5, the ablation results show the progressive contribution of the proposed components. Temporal attention substantially improves the CNN baseline, while quantum transformation provides an additional improvement in both accuracy and Stage-MAE. The combination of quantum transformation and attention further improves performance, and the complete HQCN with ordinal loss achieves the best results. This demonstrates that the components provide complementary benefits rather than the improvement being attributable to a single component.

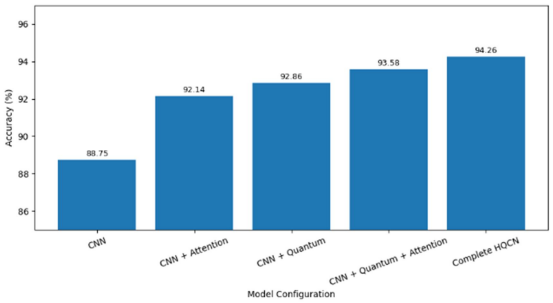


Figure 3. Ablation analysis of the proposed HQCN components.

Figure 3 illustrates the progressive increase in accuracy, which demonstrates the complementary role of the proposed components. The quantum layer enhances the compact feature representation, whereas the temporal attention highlights the important gait segments. The full architecture demonstrates the highest performance.

4.4 Stage-wise Prediction Analysis

The stage-wise results need to be analyzed with the help of a confusion matrix in order to verify whether the model distinguishes the neighboring disease stages correctly. The expected behavior of the model is that the majority of errors occur between adjacent stages because of their similar movement characteristics.

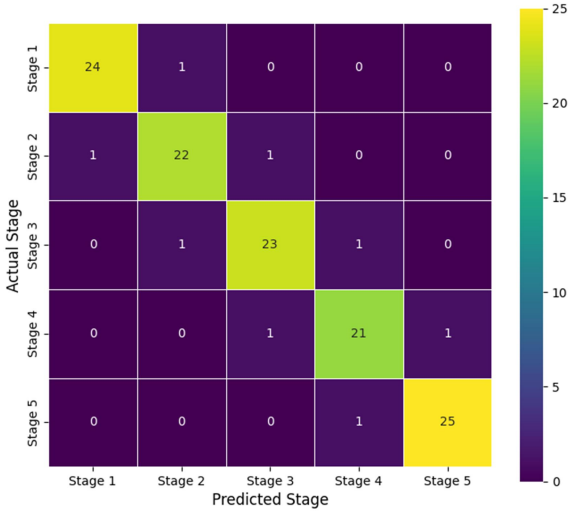


Figure 4. Confusion matrix of the proposed HQCN for Parkinson's disease stage prediction.

Figure 4 presents the diagonal elements as correctly classified samples, while off-diagonal elements represent incorrectly predicted classes. The clear diagonal pattern indicates reliable stage prediction. Moreover, the concentration of errors in the vicinity of the diagonal means that the model typically makes minor stage deviations rather than large severity errors.

4.5 Error Analysis

The low Stage-MAE obtained by HQCN means that the model mostly predicts stages that are close to the actual clinical stages. This behavior is facilitated by the ordinal learning mechanism, which takes into account the ordered relationship between disease stages. Thus, an error between two neighboring stages is less influential than an error between widely separated stages.

The remaining errors can be attributed to similar gait characteristics between neighboring PD stages, individual differences in walking patterns, medication effects, and variations in sensor measurements. These factors explain why the prediction of disease stages is more challenging than binary classification of the disease.

4.6 Discussion

The results of experiments confirm the effectiveness of the proposed HQCN as an approach to represent multi-stage gait signals collected with wearables in the context of Parkinson's disease prediction. The model demonstrates 94.26% accuracy, 93.62% macro-F1, 0.972 AUC, and 0.184 Stage-MAE, which indicate good overall classification ability, discriminative capability, and relatively low deviation in predicting the stage. The latter is also supported by the high macro-F1 score, which shows that the model performance is not based on one single dominant disease stage.

It should be noted that HQCN outperforms all conventional and deep-learning models used in the experiment in terms of accuracy. In particular, while SVM and Random Forest have 82.47% and 84.63% accuracy correspondingly, 1D-CNN, CNN-LSTM, and CNN-Attention have 88.75%, 90.82%, and 92.14% accuracy, and HQCN demonstrates 94.26% accuracy. The decrease of Stage-MAE from 0.421 in case of SVM to 0.184 in case of HQCN also shows that the model decreases larger stage-prediction deviations. Thus, the effectiveness of the combination of hierarchical CNN feature extraction, quantum feature transformation, temporal attention, and ordinal learning is confirmed.

The ablation study also confirms the contribution of different components to the HQCN performance, showing that improvement is not provided solely by quantum transformation. In particular, while temporal attention increases accuracy from 88.75% to 92.14%, the addition of

quantum transformation makes accuracy equal to 92.86%, while quantum transformation with attention increases accuracy up to 93.58%, and the full HQCN model with ordinal loss achieves 94.26% accuracy and the lowest Stage-MAE – 0.184. Thus, the components provide complementary information for final prediction.

The study has practical implications since the framework can be used for multi-stage Parkinson's disease prediction based on wearable gait signals. The use of the model makes it possible to automatically learn temporal representations of gait from VGRF signals, providing an objective multi-stage prediction of disease. Moreover, the temporal attention mechanism allows highlighting the informative gait segments, and ordinal learning takes into account the ordered relationship of disease stages. The concentration of prediction errors near the neighboring stages in the confusion matrix corresponds to the similarity of gait characteristics in the neighboring stages.

At the same time, there are several limitations in the study, which should be taken into account. In particular, the study uses a relatively small number of independent subjects and a specific wearable-sensor dataset. In addition, the quantum part uses a simulated compact quantum circuit rather than a large-scale real quantum device. Thus, these factors can limit the generalizability and the direct clinical applicability of the research results. Further validation using larger longitudinal datasets, real quantum devices, additional wearable modalities, and external clinical populations is therefore needed.

In summary, the results show that the framework for automated multi-stage Parkinson's disease prediction based on CNN-based temporal feature extraction, quantum feature transformation, temporal attention, and ordinal learning is promising.

Ethical Considerations: If relevant, there should be an indication of the ethical clearance of the study or the ethical use of patient data, even when it comes from a publicly available database, especially for research involving patient-related data.

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5. CONCLUSION

The Hybrid Quantum-Convolutional Network (HQCN) for the automatic prediction of Parkinson's disease stages based on wearable VGRF signals was proposed. The model included multi-scale CNN feature extraction, six-qubit quantum transformation, temporal attention, and ordinal classification. As a result, the proposed approach achieved an accuracy of 94.26%, macro-F1 of 93.62%, AUC of 0.972, and Stage-MAE of 0.184, which outperformed the considered conventional and deep-learning models. In particular, it was demonstrated that the quantum-enhanced features and ordinal learning helped to improve stage discrimination and reduce large prediction errors.

These findings indicate that the proposed HQCN framework has potential for automated and objective wearable-based monitoring of Parkinson's disease progression. Its ability to learn temporal gait representations directly from VGRF signals may provide useful supplementary information for stage assessment and continuous movement monitoring.

The major limitations of the research are the relatively small number of independent subjects, dependence on a specific wearable-sensor dataset, and the use of a simulated/compact quantum circuit rather than a large-scale real quantum device. Future work will focus on larger longitudinal datasets, implementation on real quantum devices, multimodal sensors such as IMU and EMG, and external clinical validation to improve the generalizability and practical applicability of the proposed framework. Further research should also evaluate the framework across different patient populations and clinical settings to determine its robustness and suitability for real-world deployment.

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