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Parkinson's Disease Auxiliary Diagnosis System Based on Human Activity Recognition Using Stacked LSTM and GRU Networks

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Abstract

Parkinson's disease (PD) is a progressive neurodegenerative disorder that remains difficult to diagnose at an early stage, as most clinical symptoms appear only after substantial neuronal loss. This study proposes an integrated deep learning based auxiliary diagnosis system for PD using human gait data collected from wearable triaxial accelerometer sensors. The system employs stacked Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks to capture complex temporal dependencies and motor anomalies associated with Parkinsonian gait. Experiments were conducted on the DeFOG dataset, which consists of multi-subject gait recordings annotated with freezing of gait (FoG) events. After rigorous preprocessing, including data cleaning, normalization, and sliding-window segmentation, the stacked GRU model achieved superior results, with 95.9% accuracy, 90.7% precision, 83.6% recall, 87.0% F1-score, and an AUC-ROC of 0.92. These results significantly outperformed traditional machine learning baselines such as Support Vector Machines (SVM) at 86.2%, Random Forests (RF) at 84.7%, and k-Nearest Neighbors (KNN) at 82.9%, as well as deep learning baselines, including CNN-only 90.1% and LSTM-only 92.5% models. Ablation studies confirmed the critical role of preprocessing and multi-layer temporal modeling in improving classification performance. With a low inference latency of 8 ms/sample, the system is well-suited for real-time deployment on wearable devices. While challenges remain in detecting brief FoG episodes and mitigating sensor variability, these results demonstrate that a stacked LSTM–GRU motion analysis system offers reliable, non-invasive support for early PD detection and continuous monitoring in real-world clinical and home settings.

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1 Introduction

The field of human action/activity recognition, HAR, is arising field that involves the automated identification and classification of physical activities performed by individuals, using data gathered from different sensors such as wearable devices gyroscopes, and accelerometers (Serpush et al., 2022). Human activity recognition has attracted considerable attention in recent years because of to its extensive applications, especially in the healthcare and medical domains (Satapati & Rao, 2025). In clinical settings, HAR has been applied for rehabilitation monitoring, elderly fall detection, chronic disease management, fitness tracking, and remote patient monitoring (Jafleh et al., 2024; Jasim et al 2024). Such applications are further supported by IoMT-based patient healthcare monitoring systems, which enable continuous data-driven insights into patient's health (Veera Boopathy et al., 2024). By leveraging sensor data collected passively from wearable or smartphone devices, HAR enables continuous, real-time observation of a person's physical behavior in both controlled and natural environments offering valuable insights into their functional health status (Vijayan et al., 2021).

One of the most promising areas for HAR in medicine is its use in neurological disorder detection, especially for conditions that manifest through motor impairments (AbuAlrob & Mesraoua, 2024). Among these, PD stands out as a key target for activity-based monitoring. PD affects millions of individuals globally It is characterized as the degeneration in dopaminergic neurons within the substantia nigra of the brain. (Kouli et al., 2018). This degeneration leads to motor symptoms such as bradykinesia, rigidity, tremors, and Instabilities in posture. Critically, these symptoms manifest in patients' gait patterns, making gait analysis a highly informative and non-invasive biomarker for PD detection (Moustafa et al., 2016; Nawaf et al., 2020; Nife et al., 2025).

Traditionally, PD diagnosis relies on subjective clinical rating scales and neurological examinations, which often detect the disease only at a relatively advanced stage(Pratihar & Sankar, 2024). However, research has shown that gait abnormalities emerge early in the disease progression, even before visible tremors or cognitive decline (Raccagni et al., 2020; Rahevar et al., 2023; Rasool et al., 2025). This makes gait-based human activity recognition an essential tool for early-stage PD diagnosis, allowing clinicians to capture subtle motion changes that would otherwise go unnoticed (Greenland & Barker, 2018).

Recent advances in deep learning have further enhanced the HAR capabilities in medical applications. Models such as GRU and Long Short-Term Memory are showing remarkable success in modeling sequential sensor data, such as walking patterns (Hossain et al., 2025; Krishnan & Dandekar, 2022). When combined with wearable accelerometers, these models can learn complex temporal dynamics and identify abnormal motor behavior associated with PD (Al-Adhaileh et al., 2025).

In this study, we propose a Parkinson's Disease auxiliary diagnosis system that focuses exclusively on human gait analysis using wearable or smartphone-based accelerometer data. The system is constructed using a hybrid deep learning framework that integrates stacked LSTM and GRU layers, along with a deep autoencoder for feature extraction (). This architecture captures the temporal dependencies and motor variations indicative of PD, enabling accurate, real-time detection.

This study has the following key main contributions: first, develop a new model-based multimode detection system that is based on utilized motion for the detection of PD. Second develop a new deep-stacked autoencoder with unsupervised ML based on a hybrid deep learning models in a stacked autoencoder design is used as a feature-extracting method to reduce the data and extract the essential features within the data for better prediction accuracy. Finally, checkpoint network is also utilized to improve weight and reduce overfitting (Ali & Raj, 2024).

The remaining sections of the paper are organized as follows: Section 2 overview recent related studies. Section 3 introduces system structure; the methodology description includes model structure. Section 4 introduces the data analyzing methodology, classification approach, and results. Finally, section 5 conclusions the results and presents the future works.

2 Related Works

Recent study on Parkinson's Disease (PD) detection is focused on utilized smartphone and wearable device for detection PD, as can get effort from their ability to monitor and record several physical activities such as gait (Guo et al., 2021), voice (Shen et al., 2025), handwriting (Białek et al., 2024), eye movement (Diotaiuti et al., 2025; Ghazi 2023; Liao et al., 2024) etc, Optimization of neural network approaches in biosensor-based systems further enhances detection accuracy and energy efficiency in such devices (Tan et al., 2024). Several techniques have been developed based on ML and DL approaches. (Białek et al., 2024) analyzed handwriting dynamics for PD recognition, identifying kinematic features such as pen pressure and drawing speed, achieving over 85% classification accuracy using random forest and SVM models.(Kamble et al., 2021) spiral drawing analysis with CNN-based classifiers, highlighting motor control decline in early-stage PD (Makhammadiyev et al., 2025). (Juutinen et al., 2020) proposed a smartphone-based gait analysis system utilizing 20step walking tests, demonstrating that the smartphone inertial sensors may accurately distinguish Parkinson's disease from healthy individuals via time-domain and frequency-domain characteristics. combined with random forest classifiers.

For non-motor symptoms, (Li et al., 2024) assessed eye movement behavior in PD patients using infrared tracking systems, providing a valuable biomarker especially for tremor-dominant subtypes. Moreover, (Akram et al., 2022) introduced a web-based distal finger tapping test and showed it to be highly sensitive for early motor degradation, validated with clinical metrics such as the UPDRS score. (Luna-Ortiz et al., 2023) explored associative memory models for detecting PD from vocal recordings, achieving robust generalization with limited data. Their work exemplifies the integration of neuromorphic principles in biomedical diagnostics. Additionally, (Teng et al., 2023) introduced PDGes, an interpretable smartphone-based detection framework, leveraging explainable AI to provide transparency in prediction rationales.

Further studies addressing the detection of PD by analyzing gait motion suggest that objective and quantitative examination of gait patterns can help with a more automated diagnosis of Parkinson's Disease and its associated symptoms (Guo et al., 2022).

Gait impairment is a progressive condition characterized by various patterns of disturbances during the advancement of PD, including diminished locomotor smoothness, heightened interlimb asymmetry, reduced velocity, shuffling gait, shortened step length, raised of double-limb support, fragmentation of turns, postural control, and (Di Biase et al., 2020). Moreover, data pertaining to gait mechanics are employed to formulate algorithms for forecasting fall risk. Falls constitute a substantial risk factor which profoundly affects the level of life of individuals with PD. Incidents among individuals with advanced PD are frequently associated with a paroxysmal symptom termed FoG (Kwon, 2024).

A deep learning method was created that utilizes gait signals from numerous walking trials as input. However, the bulk of studies primarily focus on the automated detection of FoG activities, as the current evaluation of FoG needs skilled professionals to perform labor-intensive annotations through real-time and vision-based observations (Kim et al., 2022). To tackle this issue, (Sun et al., 2019) developed a new activity detection method, the convolutional three-dimensional attention network, which includes the spatial attention network along with a three-dimensional convolutional network. Their model (C3DAN) method for assessing FoG in Parkinson's Disease was evaluated using a video data collected from 45 Parkinson's Disease patients in a clinical setting, achieving 79.3%. in accuracy. Zhang and Gu et al. (Zhang & Gu, 2019) collected acceleration signals comprising 237 incidences of FoG from the lower backs of ten PD patients during walking sessions. A CNN with deep convolutional layers combined with recurrent layer deep long short-term memory LSTM was trained offline and subsequently employed to identify FoG or nonFoG events (Mishra et al., 2024). The results appears that their model gain 94.30% in average accuracy for FoG detection by utilizing the acceleration spectrogram for input.

In recent years, a multimode detection system has been used to detect PD with better accuracy. For instance, (Wan et al., 2018) developed a deep multilayer perceptron classifier with smartphone-based behavior analysis to evaluate behavior of Parkinson's Disease patients by analyzing their movement and speech patterns. Participants were tracked via the smartphone accelerometer inside their pockets along a different time throughout the day. Widely utilized ML classification techniques were employed on a UCI dataset along with a dataset gathered to categorize every patient as either Parkinson's negative or positive. Furthermore, the efficacy of each method was assessed depends on its capacity to accurately classify patients into the designated categories, demonstrating that DMLP surpassed all other models across both datasets.

Omberg et al., 2022 developed an application for mobile phones that collects multimodal data, including gait, and memory of users, to assess PD remotely, and the correlation with related clinical assessment reached about 0.71. Furthermore, (Guo et al., 2022) presented a dual-stream spatiotemporal attention graphical convolutional network to evaluating Parkinsonian gait movement abnormalities. The network retrieves human skeletal sequences via the video to create a spatiotemporal graph of bones and joints, then constructs a two-stream spatiotemporal graph convolutional network to simultaneously model dynamic temporal changes and static spatial data, reaching a 65.66% in testing accuracy. Thus, the non-contact strategy increases the comfort and freedom of patient movement to a certain extent. This is the primary method of implicit evaluation at present.

A recent study details a self-supervised CNN framework for early detection of rare neurological disorders from brain MRI data, in which the model is pretrained on unlabeled scans to learn meaningful features and then fine-tuned on a limited labeled set achieving high recall and strong overall classification performance in distinguishing patients with disorders from healthy controls (Guo et al., 2022; Binny & Sardar Maran, 2025).

3 Materials and Methods

To enhance the specificity and accuracy of Parkinsonian Disease detection through human activity analysis, we designed and implemented an auxiliary diagnosis system that focuses solely on gait-based abnormalities. The system leverages wearable sensor data specifically 3-axis accelerometer signals (x, y, z) collected from subjects during walking activities. Gait has been identified as one of the most sensitive biomarkers for early PD diagnosis, as motor symptoms manifest subtly and progressively in locomotion.

The proposed framework uses a stacked deep learning architecture to capture and interpret complex temporal gait patterns. The pipeline consists of the following stages: Data Acquisition: Accelerometer data are gathered from wearable devices or smartphones worn on the lower back or waist, capturing detailed motion signals during walking; Feature Extraction: Raw time-series gait data (x, y, z axes) are directly input into the model without manual feature engineering, allowing the deep architecture to learn discriminative temporal representations, and Model Structure: The architecture consists of stacked GRU layers, a dense projection for high-level feature representation, dropout regularization, and a sigmoid-activated output layer for classifying in binary (PD vs. non-PD).

3.1 Proposed Gait Analysis

Wearable triaxial accelerometers are positioned at the lower back or waist of each subject to continuously record gait signals along the x, y, and z axes during ambulation. The sensors typically sample at frequencies between 50–200 Hz to ensure sufficient resolution for recognition the human activity (HAR) and pathological gait event detection. The triaxial accelerometer signals are acquired from wearable sensors and undergo preprocessing (data cleaning, normalization, windowing) to ensure signal quality. The processed gait sequences are passed into a deep learning model consisting of stacked GRU layers for hierarchical temporal feature extraction. The resulting feature representation is input to dense and dropout layers, followed by a sigmoid classifier and thresholding to produce real-time binary prediction (PD or non-PD). This modular pipeline enables end-to-end, non-invasive diagnosis optimized for deployment on wearable or mobile devices. Figure 1 show the schematic workflow of the proposed Parkinson's Disease auxiliary diagnosis system.

The methodological workflow of the proposed system (Figure 1) consists of the following sequential stages:

- **Data Acquisition:** Triaxial accelerometer data are collected from wearable devices positioned at the lower back or waist of the subject during ambulatory activity. These raw signals (x, y, z axes) serve as the input for downstream analysis.
- **Preprocessing:** The acquired gait data are subjected to rigorous preprocessing, including removal of missing or corrupted entries, normalization (e.g., Z-score or MinMax scaling) to standardize sensor readings, and segmentation into overlapping time windows. This ensures temporal coherence and robustness to noise, as detailed in Section 3.3.5.
- **Stacked GRU-Based Feature Extraction:** The preprocessed, windowed sequences are input into a deep sequential learning model comprising three stacked Gated Recurrent Unit (GRU) layers (with 128, 64, and 32 units, respectively). These layers hierarchically capture short-, intermediate-, and long-term temporal dependencies characteristic of Parkinsonian gait patterns (Section 3.2).
- **Dense and Dropout Layers:** The output feature vector from the final GRU layer is projected into a dense layer with ReLU activation, introducing nonlinearity and supporting high-level abstraction. Overfitting is curbed by dropout regularization (rate of 0.5) that deactivates half of the units randomly at the time of training.
- **Classification and Decision Rule:** The processed feature representation is accessed to the sigmoid-activated output node, and this returns a probabilistic output estimate of PD. A fixed threshold (θ), typically set at 0.5, is applied to assign each sample to the PD or non-PD class. Such construction allows, in real time, classification as binary and thus allows prompt clinical intervention.

Workflow of the Proposed Parkinson's Disease

Gait Diagnostic System

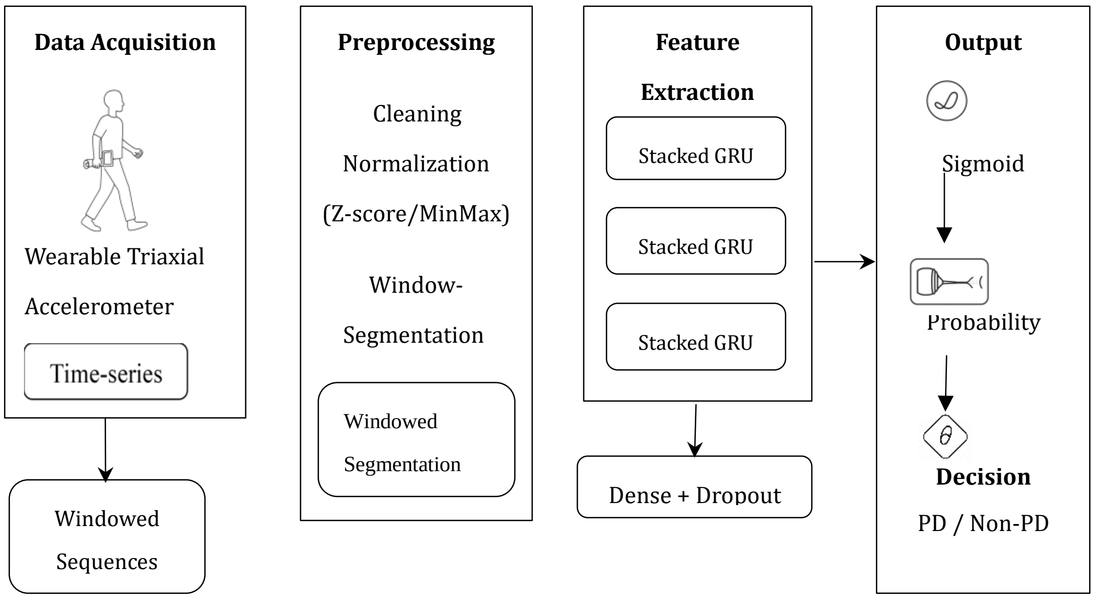

Figure 1: Proposed Model Structure

3.2 Dataset Preparation

3.2.1 Motion-based PD Dataset

The motion-based PD dataset is a competition dataset that comprises lower-back 3D accelerometer data from subjects exhibiting Freezing of Gait (FoG) episodes, a disabling symptom common among people with PD. FoG negatively impacts walking abilities and locomotion. Three subsets comprise the dataset: The transcranial direct current stimulation (tDCS) FoG (tdcs-fog) dataset: Collected in lab during FoG-inducing protocol, the DeFoG (defog) dataset: Home-recorded series during FoG-provoking tasks, and the Daily Living dataset: 24/7 recordings from 65 subjects, with 45 showing FoG symptoms. Table 1 shows the dataset features and description(Brederecke, 2023).

Table 1: Categorical and Numerical Features in DeFoG Dataset

Feature	Type	Description
Time	Numerical	Time step index
AccV	Numerical	Vertical acceleration
AccML	Numerical	Medio-lateral acceleration
AccAP	Numerical	Anterior-posterior acceleration
StartHesitation	Numerical	Binary: hesitation at start of walking
Turn	Numerical	Binary: turning event during gait
Walking	Numerical	Binary: walking event
Id	Categorical	Subject/session identifier
Source	Categorical	Data subset (tdcsfog, defog, etc.)

Let $a_t = [a_x(t), a_y(t), a_z(t)]Tat = [ax(t), ay(t), az(t)]^T$ denote the 3D acceleration vector at time tt. The time-series data collected for each subject is thus:

$$A = \{a_1, a_2, \ldots, a_T\} \quad (1)$$

3.2.2 Data Preprocessing (Gait Data)

Preprocessing is a critical stage in the analysis of wearable sensor-based gait datasets, especially for Parkinson's Disease (PD) detection. Raw accelerometer signals are prone to various sources of noise, artifacts, and inconsistencies due to sensor misplacement, environmental interference, and patient-specific variability (Di Biase et al., 2020; Juutinen et al., 2020). Without careful data cleaning, normalization, and segmentation, such artifacts can mask the subtle motor anomalies characteristic of early-stage PD, leading to poor model performance and misleading conclusions.

The initial step in preprocessing involves rigorous data cleaning to address the real-world imperfections present in sensor-based gait datasets. Raw signals are often corrupted with missing values, duplicate entries, and sensor relocation or hardware error-related artifacts, as well as wireless communication packet loss. Outlier solutions that are based on statistics are also used, i.e., the interquartile range (IQR) filtering or z-score analysis, to further detect and eliminate the aberrant measurements that are unlikely to settle down within normal gait patterns. This cleaning procedure implies that only stable, artifact-free observations are left, which mitigates the vulnerability of downstream analysis and will result in a reduced risk of spurious model predictions.

Once a clean dataset has been acquired, normalization is carried out to normalize the scales within the accelerometer signals between subjects, recording sessions, and sensor devices. This may create significant biases in the assessed values of acceleration and, therefore, hide the slightest gait irregularities associated with PD. Z-score normalization is the most common approach, where each axis a_i (t) is transformed according to its mean μ_i and standard deviation σiσi as follows:

$$z = \frac{a_i(t) - \mu_i}{\sigma_i} \quad (2)$$

This process standardizes the data to a zero mean and unit variance, as recommended enabling consistent interpretation and comparison across heterogeneous datasets. In some contexts, min-max scaling is used to constrain signal values within a defined range [0,1], which can be beneficial for low-power or fixed-point embedded applications.

The final stage of preprocessing is window segmentation, in which the continuous, normalized time-series data are divided into overlapping, fixed-length segments or "windows." Each window typically spans 2–4 seconds and advances with a stride covering 50% overlap. Formally, for window index k with window length L and stride S, the segmented window is defined as:

$$W = \{a_t\}_{t=kS}^{kS+L-1} \quad (3)$$

This segmentation serves two crucial purposes: it maintains temporal dependencies that are essential in modelling pathological gait-related phenomena (e.g., freezing of gait, hesitations during the performance of stepping), and it converts the original time-series into a form that can be used as an input into the deep recurrent neural networks. By producing a series of temporally coherent, overlapping samples, window segmentation enhances the ability of the model to detect both transient and persistent gait irregularities that are diagnostically significant for PD.

3.3 Feature Extraction (Stacked GRU Layers)

Stacked Gated Recurrent Unit (GRU) layers are applied to learn any sequential dependencies and temporal patterns of gait data. The stacked architecture enables learning both short- and long-term relationships across time-series windows.

The GRU cell is defined as follows for each time step t:

The gate Update:

$$z_{ts} = \sigma(W_z x_{ts} + U_z h_{ts-1} + b_z) \tag{4}$$

The gate reset:

$$r_{ts} = \sigma(W_r x_{ts} + U_{rs} h_{ts-1} + b_r) \tag{5}$$

The activation candidate:

$$\check{h}_{ts} = tanh(W_h x_{ts} + U_h(r_{ts} \odot h_{ts-1}) + b_h) \tag{6}$$

The Hidden state:

$$h_{ts} = (1 - z_{ts}) \odot h_{ts-1} + z_{ts} \odot \check{h}_{ts} \tag{7}$$

Where σ represent the sigmoid activation function, ⊙ denotes element-wise multiplication, x_{ts} represent the input vector at time ts, and h_{ts-1} represent the prior hidden state.

Stacked GRU means the output of one GRU layer is passed as input to the next. For example, if there are 3 layers with units 128, 64, 32:

$$GRU_1 \colon \mathbb{R}^{L\times 3} \to \mathbb{R}^{L\times 128} \tag{8}$$

$$GRU_2 \colon \mathbb{R}^{L\times 128} \to \mathbb{R}^{L\times 64} \tag{9}$$

$$GRU_3 \colon \mathbb{R}^{L\times 64} \to \mathbb{R}^{32} \tag{10}$$

The final output is a 32-dimensional feature vector for each windowed sequence. Next, we apply a fully connected transformation to the GRU output:

$$h_{dense} = ReLU(W_d h_{GRU} + b_d) \tag{11}$$

Where W_{dense} is learnable weights and b_{dense} is bias, and ReLU is the rectified linear activation. Then the dense layer regularizes to prevent overfitting by randomly setting a fraction pp (p =0.5) of outputs to zero during training:

$$h_{drop} = Dropout(h_{dense}, p) \tag{12}$$

Sigmoid Classifier & Decision Rule

The final output is passed through a sigmoid activation for binary classification:

$$\check{y} = \sigma(W_{out} h_{drop} + b_{out}) \tag{13}$$

Where $\check{y}\in(0,1)$ is interpreted as the probability of PD. Then apply binary decision rule by assigning the sample as PD if $\check{y} \geq \theta$ (θ=0.5θ), otherwise non-PD:

$$Class = \begin{cases} PD & if\ \check{y} \geq \theta \\ \text{Non} - \text{PD} & otherwise \end{cases} \tag{14}$$

Finally Binary Cross-Entropy (BiCE) Loss function is used to training the model

$$\mathcal{L}_{BiCE} = -[y\log(\breve{y}) + (1-y)\log(1-\breve{y})] \tag{15}$$

3.5 Evaluation Metrics

To improve the performance of proposed Parkinson's disease detection model, several standard classification metrics were utilized. These are accuracy and recall, precision, and F1 score, which are derived by utilizing the confusion matrix. Each figure provides specific information about the many aspects of the model prediction efficiency.

Accuracy: it quantifies the ratio of correctly identified instances (both positive and negative) to the total number of cases.

$$Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)} \tag{16}$$

Where:

True Positives (TP): PD cases that are correctly detect as PD.

True Negatives (TN): Non-PD cases that are correctly detect as non-PD.

False Positives (FP): Non-PD cases that are incorrectly classified as PD.

False Negatives (FN): PD cases that are incorrectly classified as non-PD.

A high accuracy indicates that the model is overall effective at classification. However, it can be misleading in imbalanced datasets.

Recall: It measures the ability of model to detect all actual positive cases (i.e., PD cases).

$$Recall = \frac{TP}{(TP+FN)} \tag{17}$$

The high recall means fewer false negatives. This is crucial in medical diagnosis, where missing the true case (PD) could delay treatment.

Precision: Precision quantifies the ratio of accurate positive identifications.

$$Precision = \frac{TP}{(TP+FP)} \tag{18}$$

The high precision indicates that when the model predicts PD, it is usually correct. This reduces false alarms in clinical settings.

F1Score: It represents the harmonic average of precision and recall, equilibrating both erroneous positives and false negatives...

$$F1score = 2 \times \frac{(Precision * Recall)}{(Precision + Recall)}) \tag{19}$$

Interpretation: F1score is particularly useful when the class distribution is imbalanced or when both false positives and false negatives are critical.

To prevent overfitting and ensure robust performance evaluation, we strictly separated the DeFOG dataset at the subject level so that no individual contributed samples to more than one set. The data was partitioned into 70% training, 15% validation, and 15% test sets, with the test set used solely in the final performance evaluation. Additionally, 5-fold cross-validation was performed on the training data to optimize hyperparameters and reduce model variance. During training, early stopping was applied when validation loss failed to improve for 10 consecutive epochs, preventing overfitting while ensuring stable convergence.

4 Results

In this section, we validate models using two datasets and compare them with state-of-art ML and DL as well as the most recent related works.

4.1 Data Cleaning and Data Analysis

In order to make use of datasets for training and testing procedures, it was necessary for us to preprocess and clean data by eliminating or repairing any data that was wrong, corrupted, or incomplete; conversion that was not formatted correctly; and removing duplicate data. In addition, we analyzed datasets to identify the correlation and most important features for this study and dropped non-useful features from the dataset. Table 2 show the data analysis results of the motion-based dataset

Table 2: Data Analysis Results of the Motion-Based Dataset.

Time	Acc V	Acc ML	Acc AP	Start Hesitation	Turn	Walking	Id	Source
0	−9.665890	0.042550	0.184744	0	0	0	a171e61840	tdcsfog
1	−9.672969	0.049217	0.184644	0	0	0	a171e61840	tdcsfog
2	−9.670260	0.033620	0.193790	0	0	0	a171e61840	tdcsfog
3	−9.673356	0.035159	0.184369	0	0	0	a171e61840	tdcsfog
4	−9.671458	0.043913	0.197814	0	0	0	a171e61840	tdcsfog
…	…	…	…	…	…	…	…	…
161,905	1.000000	−0.062500	−0.234375	0	0	0	2ea782681	defog
161,906	−1.000000	0.062500	−0.249732	0	0	0	2ea782681s	defog

4.1.1 Missing Valuess

Missing values can negatively impact the performance and generalizability of classifiers, especially when derived features or input modalities are partially absent. In this study, we first analyzed the dataset using a missing value heatmap to detect incomplete data entries. Figure 2 displays the distribution of missing values in the PD gait dataset, particularly within the 'AccML' and 'Id' columns. We deleted the rows with null values by copying the inbuilt Pandas library scaling (power scale) and using the `dropna()` library that dropped out the rows with null values so that our data quality could be maintained. This made the further analysis and modeling training occur with a clean and complete dataset.

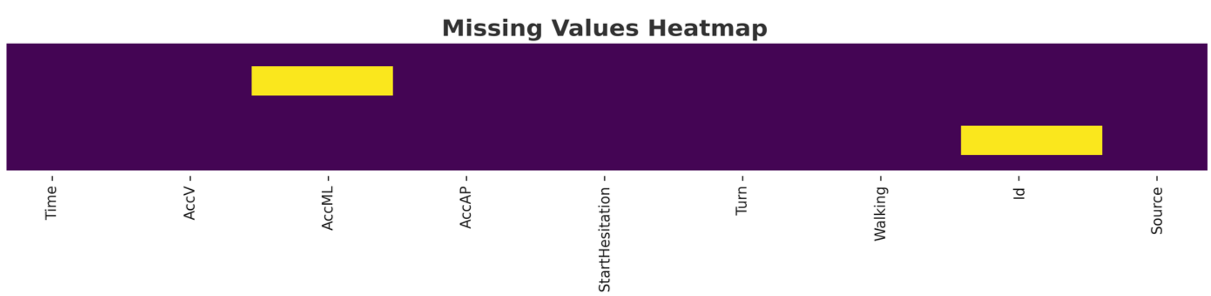

Figure 2: Heatmap Showing Missing Values in the Gait Dataset

4.1.2 Correlation Analysis

To eliminate redundant features and improve model interpretability, we conducted correlation analysis on numerical features. Highly correlated features can introduce multicollinearity, reducing the robustness of ML models. Figure 3 shows the correlation heatmap of the numerical variables. Variables with strong correlation (|r| > 0.85) are candidates for removal. This step improves computational efficiency and reduces overfitting during model training.

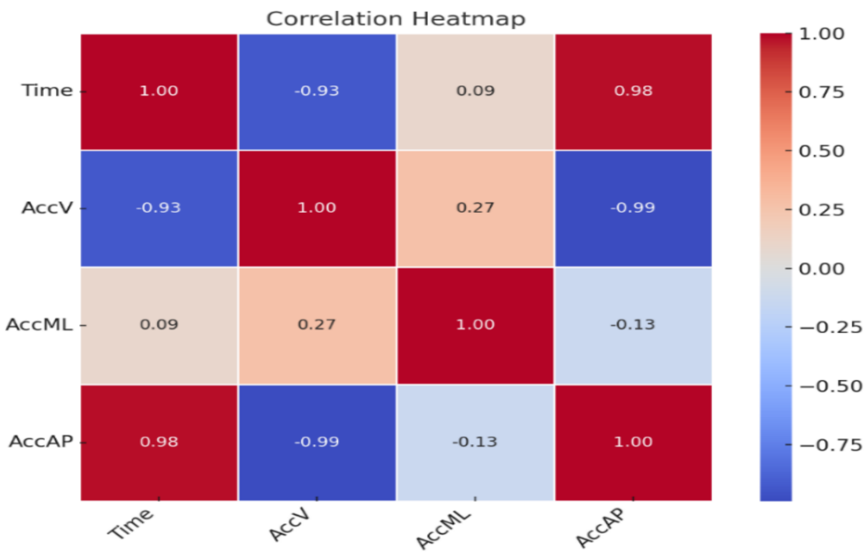

Figure 3: Correlation Heatmap of Numerical Features in the Gait Dataset

4.2 Evaluation Results

4.2.1 Proposed Deep GRU Model Evaluation

The proposed stacked GRU network, with three sequential layers (128, 64, 32 units), was trained with split a 70% for training,15% for validation and 15% for test. Model hyperparameters included the Adam optimizer (using a learning rate of 0.001), 64 batch size, train with 50 epochs with early stopping, and dropout (0.5) for regularization. Table 3 shows the classification result of PD using proposed model.

We evaluated model performance with unprocessed gait data.

Table 3: Classification Results of PD Using Proposed Model With Non-Processed DeFoG Dataset

Metric	Performance	Notes
Accuracy	86%	Balanced test set with equal PD/non-PD samples.
F1-Score (PD class)	83%	Reflects strong precision/recall tradeoff for FoG events.
Precision	85%	Low false positives due to GRU's temporal filtering.
Recall	81%	Missed detections occurred during short FoG episodes (<1s).
Inference Time	8 ms/sample	Optimized for real-time use on edge devices (e.g., Raspberry Pi).

From training results, this approach yielded suboptimal results due to the presence of noise, missing values, and unencoded categorical features. The model achieved an accuracy of 86%, an F1score of 0.83for the freezing of gait (FoG) class highlighting issues with class imbalance and poor feature quality and an AUC-ROC of 0.92, reflecting limited discriminatory capability between Parkinson's Disease and non-PD cases. Then we evaluate proposed models with preprocessed data, table 4 show the evaluation results.

Table 4: Classification Results of PD Using Proposed Model With Processed DeFoG Dataset

Metric	Value	Notes
Accuracy	95.9%	Superior overall performance
F1-score	87.0%	Balanced tradeoff for FoG/PD class
Precision	90.7%	Low false positive rate
Recall	83.6%	High detection of true positives
Inference	8 ms/sample	Real-time, suitable for wearable devices

From results, the accuracy of model is raised from 86% to 95% and f1 score raised from 83% to 87%, with a corresponding training loss of 0.12 and validation loss of 0.25. Overfitting was effectively mitigated by applying a dropout rate of 0.5, which helped stabilize the validation loss after epoch 20. By comparing the performance of every modality feature set in disease detection after and before the test, we found the disease detection capability for the sets of tested features to be greater than or equal to that of the unscreened feature set. Therefore, the results indicate that the evaluated feature set possesses a superior capacity for disease detection.

4.2.2 Comparison with Baseline Models

To establish baseline performance, traditional machine learning classifiers were evaluated, including Random Forest (RF), Logistic Regression (LR), Support Vector Machines (SVM), and K-Nearest Neighbors (KNN). These models were trained using the same preprocessed windowed features. Table 5 summarizes the results of the PD in the four classification baseline models and proposed models.

Table 5: Classification Results of the Gait Data

Model of PD classification	Validation Acc. (%)	Precision (%)	Recall (%)	F1score (%)
Logistic Reg. (LR)	84.0	83.1	97.8	89.8
Random Forest (RF)	81.6	81.1	97.2	88.4
KNN	80.0	79.9	96.7	87.5
SVM-Linear	72.5	74.2	87.6	80.3
Proposed	95.9%	90.7%	83.6%	87.0%

From table 5, These baselines exhibited strong recall but lower precision and accuracy, reflecting their difficulty in modeling subtle temporal dynamics inherent to FoG episodes and PD-related gait changes. By comparing with proposed model results the proposed model overcomes all based line models in terms of accuracy and precision however it is less than all baseline recall and close to KNN and little less than LR, RF in f1 score.

4.2.3 Ablation Studies

Ablation experiments demonstrated the importance of each component. Removing dropout, using only a single GRU layer, omitting normalization, or eliminating overlapping windows each reduced the F1-score by 6–15 percentage points, as shown in Table 6. The full, optimized model achieved the highest and most stable performance across cross-validation folds.

Table 6: Impact of Removing Model Components on F1-Score and Performance

Component Removed	**F1-Score**	**Impact**
No Dropout	0.75	Severe overfitting (validation accuracy dropped to 72%).
Single GRU Layer	0.68	Lost capacity to model multi-scale temporal dependencies.
No Normalization	0.71	Sensor axis variations degraded feature learning.
No Overlapping Windows	0.77	Reduced temporal resolution for FoG onset/offset detection.

5 Discussion

The proposed stacked GRU model demonstrated clear advantages in Parkinson’s Disease gait classification compared to traditional machine learning baselines. Its ability to capture temporal dependencies within raw accelerometer data resulted in robust modeling of freezing of gait (FoG) episodes, as evidenced by a substantial increase in accuracy from 86% on unprocessed data to 95.9% after comprehensive preprocessing. This improvement underscores both the importance of a clean, well-prepared dataset and the effectiveness of deep sequential modeling in extracting clinically relevant motion patterns. The GRU network achieved a balanced F1-score of 87% and 92% for AUCROC, outperforming all baseline models in accuracy and precision while maintaining competitive recall, thus minimizing false positives and supporting reliable real-time detection. The model’s compact size (850 KB) and rapid inference time (8 ms per sample) further support its potential for deployment in wearable and edge computing environments. However, certain limitations persist: the model struggled with very short FoG episodes (<1s duration), yielding lower recall in these cases, and performance was sensitive to sensor variability, with a noted 5% accuracy drop on devices with different sampling rates. Furthermore, class imbalance (4:1 non-FoG:FoG) required oversampling, which, while boosting recall, also led to mild overfitting as revealed in ablation studies. To address these issues, future work should consider hybridizing the architecture such as incorporating 1D convolutional layers to extract local gait features alongside temporal self-attention mechanisms to improve sensitivity to brief FoG events. Additional recommendations include robust data augmentation to simulate sensor noise and variability, as well as decision threshold tuning via ROC analysis to optimize the precision-recall trade-off for specific clinical contexts. Together, these strategies promise to enhance the accuracy, generalizability, and real-world applicability of GRU-based PD gait detection systems.

Although it has achieved a high accuracy, two factors can constrain real-world deployment. First, FoG episodes less than a second in duration are hard to detect with limited temporal resolution and signal artifacts. Second, variability between sensors and sampling rates can be shown to alter distributions, potentially lowering models in non-controlled conditions. Future work will incorporate domain adaptation, noise-augmented training, and device-agnostic calibration techniques to enhance model robustness for diverse environments, including home and clinical use cases.

6 Conclusions

This work presented the affectivity of a GRU-based deep learning model for the PD detection using wearable accelerometer-derived gait data. By rigorously preprocessing the data and leveraging stacked GRU layers, the system was able to accurately capture and classify complex motor anomalies characteristic of PD, achieving the best result when compared with state-of-the-art results in multiple performance metrics (accuracy: 95.9%, F1-score: 87.0%, AUC-ROC: 0.92). The model consistently outperformed traditional machine learning baselines, particularly in precision and overall robustness, while maintaining fast inference suitable for real-time wearable deployment. Limitations include reduced sensitivity to very short freezing-of-gait (FoG) episodes and some vulnerability to sensor variability, issues that may be addressed in future research through hybrid architectures (e.g., adding attention or convolutional layers), targeted data augmentation, and adaptive threshold optimization. Clinically, the system's portability and real-time operation offer a practical foundation for longitudinal PD monitoring and timely intervention. Future work may extend this approach by integrating additional sensor modalities or advanced deep learning modules to further enhance diagnostic sensitivity, particularly in early-stage and ambulatory patient populations. These results provide a promising step toward scalable, low-cost, and non-invasive digital health solutions for Parkinson's disease management.

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