Real-Time Freezing of Gait Prediction in Parkinson's Disease Using Multimodal Sensor Fusion And IoT-Enabled Deep-Learning

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Abstract:

Freezing of Gait (FoG) is a debilitating symptom of Parkinson's Disease (PD) that severely impacts mobility and quality of life. Early prediction of FoG can facilitate timely interventions, improving patient outcomes. This study proposes a multimodal sensor fusion approach combined with deep learning and Internet of Things (IoT) technology for real-time FoG prediction. The system integrates data from inertial measurement units (IMU), electromyography (EMG), electroencephalography (EEG), and foot pressure sensors. Pre-processing includes Noise removing window design method using a sliding window approach. Feature extraction in time, frequency, and nonlinear domains is followed by feature selection using Linear Discriminant Analysis (LDA) and Mutual Information (MI) a hybrid CNN-LSTM deep learning model is employed to capture spatial and temporal patterns in gait data.This approach paves the way for intelligent, real-time wearable monitoring systems, enhancing mobility, safety, and quality of life for PD patients.

Keywords: Freezing of Gait, Parkinson's Disease, Multimodal Sensor Fusion, , Electromyography, Electroencephalography, Foot Pressure Sensors, Linear Discriminant Analysis.

1) Introduction

The episodic lower extremity movement condition known as FOG poses a significant risk of impairment and is particularly prone to falls. FOG monitoring can help in FOG diagnosis and therapy. The frequency and length of freezing episodes can be decreased by monitoring and providing suitable gait direction.This work aims to employ multimodal fusion. techniques to increase the monitoring model's resilience.[1] The force-sensitive insole (FSI) and inertial measurement unit (IMU) concurrently gather

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the 32 FOG sufferers' gait data. In order to create a multimodal fused FOG monitoring model, complementary features were extracted from IMU and FSI inputs, respectively, using deep neural networks.

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[1] Li, Bochen, Yan Li, Yining Sun, Xianjun Yang, Xu Zhou, and Zhiming Yao, "A monitoring method of freezing of gait based on multimodal fusion", Biomedical Signal Processing and Control, Vol.82 ,2023.

It is essential to have a precise and timely FoG forecast in order to create such an assessment setting. Additionally, anticipating the FoG advance in time for prompt patient cueing is crucial for the practical deployment of these cueing modalities [2]. Approaches for data reduction and feature extraction that have been presented recently for a variety of uses. ML and DL algorithms are the foundation of many of these applications. Numerous research has been conducted that provide insight into how incoming signals are discriminated in gait motions. The discovery of FoGs using ML approaches has presented significant problems for academics. In this procedure, features are extracted using both conventional and novel techniques using handmade and deep structures. Techniques for feature extraction and data reduction are employed to improve the efficiency of general data analysis procedures by either reducing computing complexity or increasing feature description. Since there are several approaches to signal or data analysis, we look at bottleneck attention inside the recently created and extremely promising DL framework [3]. Though they frequently encounter difficulties because they require handmade and structural information, classical ML algorithms have demonstrated promising results in identifying Parkinson's disease (PD) in comparison to time-consuming and costly approaches like neurological scanning (e.g., MRI,). On the other hand, the capacity of DL and CNN approaches to automatically extract noteworthy visual characteristics from datasets in many fields has attracted interest. DL architectures are a focus of medical and image processing research since they used a range of data sources, including facial traits, handwriting samples, audio signals, and gait patterns, to identify Parkinson's disease (PD) early in recent years [4]. Physicians merely use accessible measures to grade Parkinson's disease (PD) and recommend drugs to reduce its symptoms. The subjective assessment used throughout the whole study may be flawed if it is not carried out by professionals. Therefore, the creation of an automated gait parameter analysis system is required to precisely identify both healthy and PD people and treat them skilfully [5].

- To Integrate multiple sensor data sources (e.g., IMUs, EEG, EMG, force sensors) to enhance predictive accuracy.

2 Bajpai, Rishabh, Suyash Khare, and Deepak Joshi, “A multimodal model-fusion approach for improved prediction of freezing of gait in parkinson’s disease”, IEEE Sensors Journal, Vol.23, no. 14 ,2023.

3 Abbasi, Sara, and Khosro Rezaee, “Deep Learning–Based Prediction of Freezing of Gait in Parkinson's Disease with the Ensemble Channel Selection Approach”, Brain and Behavior,Vol, 15, no. 1, 2025.

4 Benredjem, Sabrina, Tahar Mekhaznia, Rawad Abdulghafor, Sherzod Turaev, Akram Bennour, Bourmatte Sofiane, Abdulaziz Aborujilah, and Mohamed Al Sarem. "Parkinson’s Disease Prediction: An Attention-Based Multimodal Fusion Framework Using Handwriting and Clinical Data”, Diagnostics, Vol. 15, no. 1 (2024): 4.

5 Kour, Navleen, Sunanda Gupta, and Sakshi Arora. "Sensor technology with gait as a diagnostic tool for assessment of Parkinson’s disease: a survey." Multimedia Tools and Applications, Vol. 82, no. 7, 2023.

- To Utilize advanced deep learning architectures (e.g., CNNs, LSTMs, Transformers) to capture spatial and temporal patterns in movement data.
- To Apply preprocessing techniques like filtering, Noise removing window design, and feature extraction to enhance signal quality.
- To Develop Internet of Things based system for real-time FoG monitoring and prediction.

This remainder of the paper is organized into important sections that are explained as follows: Section II lists the current research works in DL Model for Early Prediction of Freezing of Gait in Parkinson’s Disease that have been completed by different authors. Section III outlines the workflow of the proposed method. The comparison results of proposed model with traditional model for DL Model for Early Prediction of Freezing of Gait in Parkinson’s Disease shown in Section IV. In Section V, together with references, is the conclusion of the suggested work that will be undertaken in a future scope.

2) Related work

Gupta et al., (2024) [6] The proposed study developed and assessed deep learning models using Inertial Measurement Unit, Electromyography, and Electroencephalography inputs from individuals with Parkinson's disease. Other classifiers were examined with the CNN+LSTM architecture. With stratified ten-fold cross-validation, the model's accuracy was assessed. We examined inter-subject performance and the noise-resistant nature of IMU+EMG and IMU+EMG+EEG combinations. In order to highlight the significance of temporal dynamics in the multimodal method, pre-FOG detection skills were also examined. Findings: The CNN+LSTM model predicted FoG events with a high accuracy of 94.45%.

Rishabh Bajpai et al., (2023) [7] This study offers a thorough examination of inertial measuring units and EEG to forecast FoG advance over time. Two neural networks, EEGFoGNet and IMUFoGNet, were combined to create an ensemble model that was evaluated at various ensemble weights and PHs. Additionally, the model is evaluated for two real-world situations: personal applications and clinical or research settings. With stratified ten-fold cross-validation, the model's accuracy was assessed. We examined inter-subject performance and the noise-resistant nature of IMU+EMG and IMU+EMG+EEG combinations, a transfer learning approach was employed. At 1 second's PH, the model's accuracy was at its highest of 92.1%, while at 5 seconds' PH, it was at its lowest of 86.2%.

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[6] Gupta, Rohit, Amit Bhongade, and Tapan Kumar Gandhi, "Multimodal Sensor Fusion Deep Learning Model for Early Prediction of Freezing of Gait in Parkinson's Disease", 2024.

[7] Bajpai, Rishabh, Suyash Khare, and Deepak Joshi, "A multimodal model-fusion approach for improved prediction of freezing of gait in parkinson's disease", IEEE Sensors Journal, Vol. 23, no. 14, 2023.

Guo et al., (2022) [8] This study suggests a wearable FoG detection technique that avoids the collection of actual EEG data by combining EEG and acceleration data in many modes. Methodologies: An very wearable inertial sensor for detecting fog may be used to extract pseudo-multimodal characteristics, such as pseudo-EEG and acceleration, and a EEG characteristic from accelerations were measured using Long-short-term memory networks serve as the foundation for this proxy assessment methodology. Results: A self-collected FoG dataset was used to analyze the performance of several feature combinations in both subject-dependent and cross-subject scenarios.

Wang et al., (2024) [9] Four crucial tactics are included in the model architecture: (1) Using large convolutional kernels to detect progressive motion changes; (2) Using multi-dimensional and multi-scale convolution to unravel the intricacy of motion coordination and gait dynamics; (3) Using twin-tower structure to capture gait self-similarity and asymmetry; and (4) Encouraging cross-domain information exchange with multi-domain attention. In addition, we provide a knowledge distillation (KD)-based architecture that makes predictions more accurate while lowering the model's reliance on numerous sensors. Findings: The model's Area Under the Curve for FOG prediction is 85.8%.

Kun Hu et al., (2021) [10] This paper offers a Graph fusion NN for multimodal learning-based FoG identification, a new end-to-end deep architectureby the integration of footstep pressure maps and video recording. In order to reduce representation redundancy among various modalities, GFN builds in multimodal graphs, complementary FoG representations are produced by measuring the adjacency patterns of the encoded properties of each modality, which are treated as vertex-level inputs. Moreover, in contrast to the previous unimodal strategies, GFN is anticipated to perform better with inputs that have missing modalities since it is designed to handle multimodal graphs of arbitrary shapes.

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[8] Guo, Yuzhu, Debin Huang, Wei Zhang, Lipeng Wang, Yang Li, Gabriella Olmo, Qiao Wang, Fangang Meng, and Piu Chan, "High-accuracy wearable detection of freezing of gait in Parkinson's disease based on pseudo-multimodal features", Computers in Biology and Medicine, Vol.146 ,2022.

[9] Wang, Wenan, Jingfeng Lin, Xinning Le, Yaru Li, Tao Liu, Lunxin Pan, Min Li, Dezhong Yao, and Peng Ren. "Addressing Multiple Challenges in Early Gait Freezing Prediction for Parkinson's Disease: A Practical Deep Learning Approach." IEEE Journal of Biomedical and Health Informatics, 2024.

[10] Hu, Kun, Zhiyong Wang, Kaylena A. Ehgoetz Martens, Markus Hagenbuchner, Mohammed Bennamoun, Ah Chung Tsoi, and Simon JG Lewis, "Graph fusion network-based multimodal learning for freezing of gait detection", IEEE Transactions on Neural Networks and Learning System,Vol. 34, no. 3, 2021.

Sun et al., (2024) [11] In order to Enhance learning of the discriminative class-specific gait characteristics by incorporating the hand-picked features into a DNN known as ResNeXt. We conduct our experiments utilizing the publicly available Daphnet dataset, which consists of gait recordings from 10 PD patients and eight subjects displaying FoG epochs. Adjusting the segment length to 5 s and the pre-FoG duration to 1 s, respectively, produced the best results. We tested a range of pre-FoG durations and segment lengths. With an MF1 score of 0.89 and a Kappa coefficient of 0.87, the highest prediction accuracy is 95.40%.

Elbatanouny et al., (2024) [12] A thorough This article presents a meta-analysis of FOG prediction and detection methods, focusing on the integration of wearable sensor technologies and Ml techniques. The use of cueing devices is also examined in the investigation. One notable gap in FOG prediction research is the minimal use of explainable AI (XAI) techniques. Understanding the reasoning behind algorithm predictions is necessary to increase user acceptance and comprehension. The presentation identifies some limitations of current research on FOG detection and prediction.

Bochen Li et al., (2023) [13] Using multimodal fusion approaches this study is intended to increase the monitoring model's robustness. The FSI and IMU gather the gait data of 32 FOG patients at the same time. The two modalities were combined at the feature level to produce a multimodal fused FOG monitoring model using an adaptive weighting technique. Complementary characteristics from the FSI and IMU inputs were extracted, respectively, using deep neural networks. Experimental results show that in the FOG detection task, the proposed multimodal fusion strategy outperforms the unimodal model by improving the F1 value by 0.029.

Ghayvat et al., (2024) [14] In order to This proposed technique uses a The Kaiser-Meyer-Olkin test, Kalman Filter, and Weighted Fuzzy Logic Controller are used to measure gait characteristics throughout the standing, walking, and resting phases.

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[11] Sun, Hua, Qiang Ye, and Yi Xia, "Predicting freezing of gait in patients with Parkinson's disease by combination of Manually-Selected and deep learning features", Biomedical Signal Processing and Control,Vol. 88, 2024.

[12] Elbatanouny, Hagar, Natasa Kleanthous, Hayssam Dahrouj, Sundus Alusi, Eqab Almajali, Soliman Mahmoud, and Abir Hussain, "Insights into Parkinson's Disease-Related Freezing of Gait Detection and Prediction Approaches: A Meta-Analysis", Sensors,Vol. 24, no. 12, 2024.

[13] Li, Bochen, Yan Li, Yining Sun, Xianjun Yang, Xu Zhou, and Zhiming Yao, "A monitoring method of freezing of gait based on multimodal fusion", Biomedical Signal Processing and Control, Vol. 82 ,2023.

[14] Ghayvat, Hemant, Muhammad Awais, Rebakah Geddam, Muhammad Ahmed Khan, Lewis Nkenyereye, Giancarlo Fortino, and Kapal Dev, "AiCarePWP: Deep learning-based novel research for Freezing of Gait forecasting in Parkinson", Computer Methods and Programs in Biomedicine, Vol.254, 2024.

Neuromodulator format, intensity, frequency, duration, and velocity are among the variables that are calculated in advance to prevent freezing episodes. CNN's ability to identify FoG during a variety of activities is validated by this investigation. It presents a brand-new electrical stimulation cueing technique that enhances gait function and lowers the incidence of FoG in PD patients.

Wang et al., (2024) [15] Suggest a new Using to alert patients before the start of FOG symptoms, multi-channel gait characteristics may be included into a comprehensive prediction framework using a multi-channel time-series neural network technique. The causal distributed convolution in MCT-Net makes it a real-time approach that might deliver the best prediction sooner and be utilized in remote devices. A single deep learning model is also created by combining and extracting several sensor location data using MCT-Net's intra-channel and inter-channel transformers. With a 96.21% accuracy rate and an F1-score, the proposed MCT-Net beats four state-of-the-art FOG prediction baselines. of 80.46% on average two seconds before to FOG on set.

Riyadh M. Al-Tam et al., (2024) [16] This study uses well-known machine-learning methods to increase the precision of the diagnosis. Numerous individual and ensemble artificial intelligence models, such as RF, DT, LR, GB, SVM, Stacking, and Bagging Ensemble classifiers, have been presented. On two common benchmark datasets, three scenarios are used. The greatest results are obtained when the Stacking Ensemble classifier is used, where Parkinson's disease is classified using logistic regression, and features are extracted using support vector machines and gradient boosting. Stacking Ensemble classifier results for the first dataset show 94.87% accuracy and 90.00% AUC, while the results for the second dataset show 96.18% accuracy and 96.27% AUC.

Yuhan Hou et al., (2023) [17] In order to assist avoid falls, our effort creates wearable, flexible sensors that can identify FoG and notify partners and patients. With the use of a DL model and multimodal sensory data collected from scattered wireless sensors, FoG is identified on the sensors. We have developed There are two types of wireless sensors in use:

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15 Wang, Boyan, Xuegang Hu, Rongjun Ge, Chenchu Xu, Jinglin Zhang, Zhifan Gao, Shu Zhao, and Kemal Polat, “Prediction of Freezing of Gait in Parkinson’s disease based on multi-channel time-series neural network”, Artificial Intelligence in Medicine, Vol. 154 ,2024.

16 R. M. Al-Tam, F. A. Hashim, S. Maqsood, L. Abualigah and R. M. Alwhaibi, "Enhancing Parkinson’s Disease Diagnosis Through Stacking Ensemble-Based Machine Learning Approach," in *IEEE Access*, vol. 12, pp. 79549-79567, 2024

17 Hou, Yuhan, Jack Ji, Yi Zhu, Thomas Dell, and Xilin Liu. "Flexible gel-free multi-modal wireless sensors with edge deep learning for detecting and alerting freezing of gait symptom." IEEE Transactions on Biomedical Circuits and Systems,Vol. 17, no. 5 (2023): 1010-1021.

1) An elastic patch is fastened to the patient's legs to gather movement data from accelerometers and EMG; 2) a C-shaped central node is positioned around the patient's ears to gather an EEG, identify FoG using an on-device DL model, and provide auditory alarms when FoG is found. Using low-power ultra-wideband transceivers, the patch-type sensors wirelessly transmit the collected data to the central node.

Pratihar et al., (2024) [18] This study offers a thorough analysis of current biomarker research, improvements in healthcare infrastructure, and technology developments for objective evaluation. Using machine learning algorithms, it provides a thorough evaluation of many biomarkers' use in diagnosing Parkinson's disease across numerous datasets. Tables summarizing recent research outcmes highlight important methodology such feature selection, data preparation, and classification algorithms. The performance, advantages, and drawbacks of several diagnostic techniques are also examined in this study, offering important new information on how well they diagnose Parkinson's disease. Additionally, the paper discusses disease monitoring, integrating data from several sources to improve diagnosis accuracy, and multimodal biomarker integration.

Franco et al., (2024) [19] Using Systematic Reviews and Meta-Analyses with the Preferred Reporting Items criteria, the authors of this study present a systematic evaluation of new DL approaches that have been recently presented for the analysis of PD. A six-year period (from 2018, when the first paper was published, until 2023) was used to search the databases Web of Science, PubMed, and Scopus. This research comprises 25 publications that examine the movement analysis of individuals with Parkinson's disease (PD) utilizing sensors that are both capable of being worn and not. Additionally, several studies employed DL networks for surveillance, diagnosis, and categorization.

Kour et al., (2023) [20] This article provides a concise synopsis of Parkinson's disease (PD), outlining its effects on human gait, and discussing related ideas. We also go into great detail about SB technology and how different sensors work in PD gait identification. In conclusion, we look at the machine learning paradigms and how well they do in PD analysis. Analysis of prior and ongoing research on sensor-based diagnosis of PD motor symptoms is the aim of this study.

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[18] Pratihar, Ruchira, and Ravi Sankar. "Advancements in Parkinson’s Disease Diagnosis: A Comprehensive Survey on Biomarker Integration and Machine Learning." *Computers* 13, no. 11 (2024): 293.

[19] Franco, Alessandra, Michela Russo, Marianna Amboni, Alfonso Maria Ponsiglione, Federico Di Filippo, Maria Romano, Francesco Amato, and Carlo

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Ricciardi. "The Role of Deep Learning and Gait Analysis in Parkinson's Disease: A Systematic Review." *Sensors* 24, no. 18,2024.

[20] Kour, Navleen, Sunanda Gupta, and Sakshi Arora. "Sensor technology with gait as a diagnostic tool for assessment of Parkinson's disease: a survey." Multimedia Tools and Applications 82, no. 7 (2023): 10211-10247.

Ref.No	Dataset used	Algorithm used	Result achieved
21	UCI dataset	Convolutional neural networks (CNNs) algorithm, Machine learning	Achieving 99.88% accuracy
22	FoG dataset	ML Algorithm	The DL model attains a high specificity of 0.88 and a detection sensitivity of 0.81.
23	University of California Irvine (UCI)	ML Algorithm	Achieved an accuracy of 96.46%
24	PD data set	Machine learning (ML) algorithms	0.70 ± 0.28 accuracy and 0.74 ± 0.39 area under the ROC curve
25	Daphnet Dataset, Multimodal Dataset	ML and DL algorithms	Achieving F1 scores of 0.994 using 29.9 times fewer parameters

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[21] Abbasi, Sara, and Khosro Rezaee, "Deep Learning–Based Prediction of Freezing of Gait in Parkinson's Disease with the Ensemble Channel Selection Approach", Brain and Behavior, Vol.15, no. 1 ,2025.

[22] Hou, Yuhan, Jack Ji, Yi Zhu, Thomas Dell, and Xilin Liu, "Multi-Modal Wireless Flexible Gel-Free Sensors with Edge Deep Learning for Detecting and Alerting Freezing of Gait in Parkinson's Patient", arXiv preprint,2023.

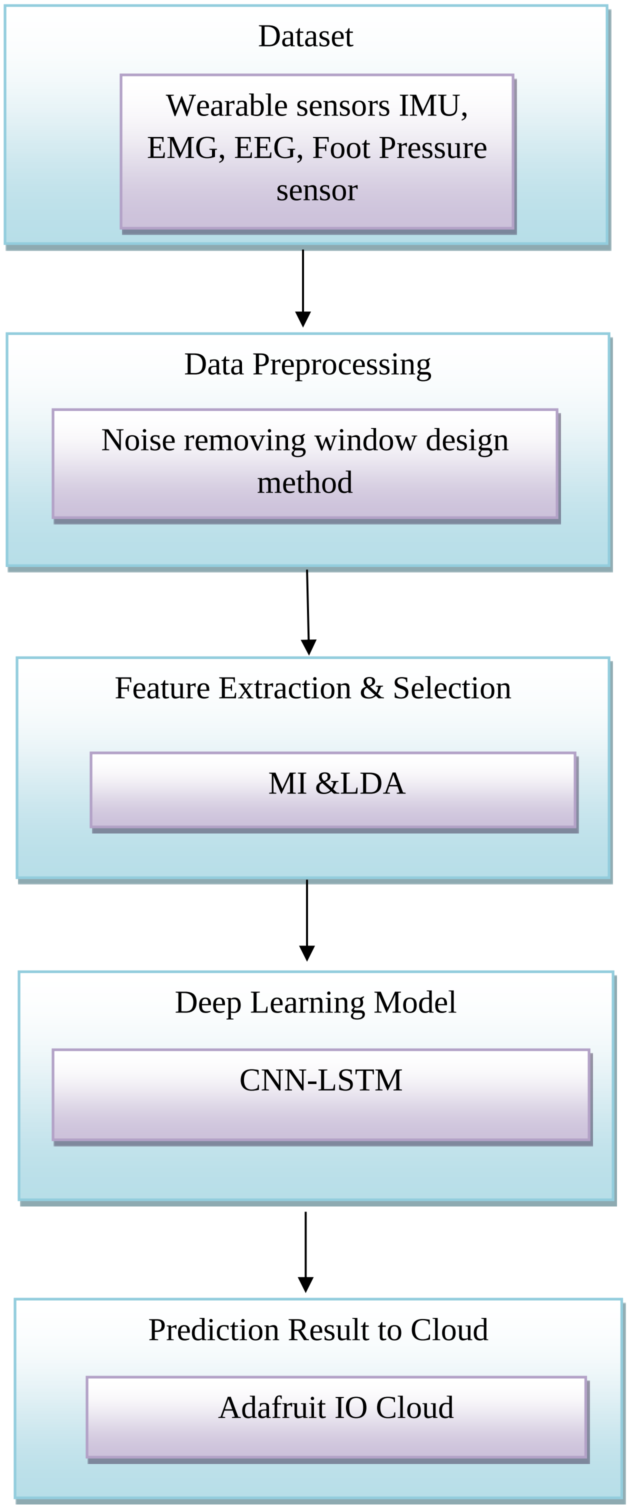
[23] K. Velu and N. Jaisankar, "Design of an Early Prediction Model for Parkinson's Disease Using Machine Learning", IEEE Access, vol. 13, 2025.

24 Magni, Stefano, Rene Peter Bremm, Konstantinos Verros, Xin He, Sylvie Lecossois, Finn Jelke, Andreas Husch, Jorge Goncalves, and Frank Hertel. "Machine learning differentiation of Parkinson's disease and normal pressure hydrocephalus using wearable sensors capturing gait impairments." medRxiv (2025): 2025-01.

25 Yi, Myung-Kyu, and Seong Oun Hwang. "Detection of Freezing of Gait in Parkinson's Disease Using a Lightweight Attention-Based Deep Learning Model with Pruning and Dynamic Quantization Techniques on Wearable Devices",2024.

3) Proposed Methodology

The proposed methodology integrates multimodal sensor fusion, deep learning, and IoT-based real-time monitoring to predict FoG in PD patients shown in figure 1. This first step involves data acquisition, where wearable sensors continuously collect gait data from Inertial Measurement Units (IMU), Electromyography (EMG), Electroencephalography (EEG), and Foot Pressure Sensors. IMU captures motion dynamics, EMG monitors muscle activity, EEG records brain signals, and foot pressure sensors analyse walking stability. The collected data is labeled to differentiate normal gait from FoG episodes. To ensure high-quality input, data preprocessing is performed, including noise filtering using Butterworth filtering to remove artifacts, normalization to standardize sensor readings, and segmentation using a sliding window approach to divide data into fixed-length sequences. Next, feature extraction and selection are applied, where time, frequency, and nonlinear features, such as statistical measures, wavelet transforms, and entropy-based metrics, are computed. LDA and MI are used to enhance model efficiency and decrease dimensionality. The hybrid CNN-LSTM deep learning model is used for categorization. From sensor data, the CNN extracts spatial information, while the LSTM records temporal relationships. in gait patterns. To enable real-time monitoring, wearable sensors transmit data to a cloud or edge-computing platform, allowing continuous analysis and remote healthcare provider access. Finally, the accuracy of the model is used to assess its performance., F1-score, and AUC-ROC, demonstrating superior results compared to traditional machine learning models.


Dataset
Wearable sensors IMU, EMG, EEG, Foot Pressure sensor
Data Preprocessing
Noise removing window design method
Feature Extraction & Selection
MI &LDA
Deep Learning Model
CNN-LSTM
Prediction Result to Cloud
Adafruit IO Cloud

3.1) Dataset

Predicting FoG episodes in PD patients is the primary goal of this study. Thus, it was essential to choose a dataset with a sufficient number of FoG episodes. The dataset includes skin conductance, EEG, EMG, and IMU recordings from 12 people with Parkinson's disease (6 men and 6 women). STMicroelectronics STM32 CPU, gyro, and TDK MPU6050 6-DoF accelerometer were utilized as specific hardware subsystems to record SC and IMU data. Four Inertial sensors were positioned at the lateral tibia of both legs, the fifth lumbar spine (L5) at the waist, and the left arm. This left arm's inertial sensor was modified to include the SC acquisition. A TF memory card was used to store the data, and the SC and ACC sampling rates were set at 500 Hz.

The distal phalanges of the middle and left index fingers were used to take the SC measurement. Information from three main signals IMU, EMG, and EEG is integrated during the procedure. Specifically, EMG signals from three muscles, EEG signals from 21 channels, and signals from two IMU sensors (left and right legs) were used. Every signal modality has unique sampling frequencies and properties. As a result, each signal is pre-processed independently. A sequence of operations carried out in a particular order comprised the dataset collection experiment. These exercises included starting and finishing a gait, walking in an arena while doing quarter turns and U-turns, for additional analysis, the current study uses EEG, EMG, and IMU sensor data from ten patients who have had a sufficient number of FoG episodes.

3.2) Data Pre-processing

EEG is a crucial instrument for assessing brain activity and behavior. The processing of the EEG, EMG, and IMU data is constantly impacted by artifacts in the electrical activity that was recorded. Thus, it is necessary to develop methods for precisely identifying and obtaining clean EEG data from EEG recordings. the FIR filter to make EEG easier, less noisy, less expensive, and less power-hungry. It prevents blending in other biological signals and occupies less space on the chip than earlier digital filters. One essential step in digital signal processing is filtering. High FIR filtering passband ripples may be the cause of low stop band attenuation. Therefore, windowing techniques are used at the filtering stage to overcome the issue. The impulse response of the actual filter may be expressed as:

$$h(n) = h_d(n) * w(\mathrm{n}) \tag{1}$$

Were

- The optimal filter's impulse response is hd (n).
- A particular window function w(n).

The filters are referred to as transition bandwidth, cut off frequency, and stopband attenuation. Therefore, it is preferable to employ to minimize the distortion of the attenuation signal, a filter with a cutoff frequency outside the transition bandwidth and the distortion generated by attenuation. The original single's maximum frequency is more than twice the sampling rate. There are several ways to filter using the windowing technique is capable of extracting the EEG, ECG, and IMU input's Signals with alpha, beta, gamma, theta, and delta frequencies. Several windowing strategies include the following.

The rectangular window is the most fundamental kind, also known as the Dirichlet or Boxer window. Equation provides the function for the rectangular window (2).

$$W_{Rec}(n) = \begin{Bmatrix} 1, for\ |n| \leq \frac{M-1}{2} \\ 0, otherwise \end{Bmatrix} \quad (2)$$

Where M is the window's length in samples:

Another kind of cosine window is the hamming window, sometimes called an improved raised cosine window. Equation (3) may be used to find the Hamming function.

$$W_{Hann}(n) = \begin{Bmatrix} 0.55 - 0.46cos\left(\frac{2\pi n}{M-1}\right), for\ 0 \leq |n| \leq M-1 \\ 0, otherwise \end{Bmatrix} \quad (3)$$

Following the Hamming window is the hanging window. Another name for it is the Cosine BellTo to avoid confusion with the extremely similar Hamming window, some authors prefer to call it a henning window. In equation (4), the hanning function is expressed.

$$W_{Hann}(n) = \begin{Bmatrix} 0.55 - 0.5cos\left(\frac{2\pi n}{M-1}\right), for\ 0 \leq |n| \leq M-1 \\ 0, otherwise \end{Bmatrix} \quad (4)$$

With the exception of the endpoints, which are at zero, the Bartlett function may be expressed using Eq. (5).

$$W_{Bar}(n) = \begin{cases} 1 + n\, for - \frac{M-1}{2} < n < 1 \\ 1 - n\, for\ < n < 1\frac{M-1}{2} \end{cases} \quad (5)$$

The Kaiser window, often referred to called the Kaiser-Bessel window was developed by Bell Laboratories' James Kaiser. It is a parameter from the window function family that is used to create finite impulse response filters and perform spectral analysis.Equation (6) is used to express the Kaiser window function.

$$W_{Kaiser}(n) = \begin{cases} \frac{I_0(\beta)}{I_0(\alpha)}, for\ |n| \leq \frac{M-1}{2} \\ 0, otherwise \end{cases} \quad (6)$$

3.3) Feature Extraction (Mutual information)

MI is a nonparametric way to gauge how relevant two variables are to one another. A good framework for quantifying these ideas is offered by Shannon's theory of information [20]. Assume that the class labels are represented by a discrete-valued random variable C, whereas a continuously-valued random feature vector is represented by a random variable X. According to Shannon's information theory, entropy H(C) may be used to quantify the uncertainty of class label C as

$$H(C) = -\sum_{c\epsilon C} P(c)\, log\, P(c) \quad (7)$$

A discrete random variable C's probability is represented as p(c). The uncertainty of C is quantified by the conditional entropy as s, given a feature vector X.

$$H(C|X) = -\int P(x)(\sum_{c\epsilon C} P(c|x) \log P(c|x))dx \quad (8)$$

Where P (c x) represents the conditional probability for variable C given X. The conditional entropy frequently equals or surpasses the initial entropy. When variables X and C are not related, the conditional entropy is equal. By definition, the MI is the amount that reduces the class uncertainty. Consequently, H(C) − H (C X) = I (X; C). Following the application of p (c, x) = p (c x) p(x) and ∫ = x You may write p(c) p (c, x) dx, I as

$$I(X;C) = \sum_{c\epsilon C} \int x\ \ p(c,x) log \frac{P(c,x)}{p(c)p(x)} dx \quad (9)$$

There is a strong correlation between two random variables if their MI is high. Only in the event that the two random variables are completely independent, the MI is zero Features having a larger quantity of MI relative to classes are considered useful in classification issues. Two Bayes error constraints support the usage of MI for feature extractions. Raviv and Hellman's upper limit, p (H(C) I (X; C)) 2 e ≤ −, is the first bound.

3.4) Feature Selection (Linear Discriminant Analysis)

Using the Fisher criterion below, LDA seeks to determine the ideal projection matrix $W_{opt} \in R^{n \times p}$ in in order to calculate the maximum proportion of the anticipated samples within-class scatter SW to between-class scatter SB:

$$J(W_{opt} = argmax \frac{||W^T S_B W||}{||W^T S_W W})$$ (10)

Where SB and SW are defined as the between and within class covariance:

$$S_B = \sum_{i=1}^{N} p_i(\overline{x_\iota} - \bar{x})\,(\overline{x_\iota} - \bar{x})^T$$ (11)

$$S_W = \frac{1}{m}\sum_{i=1}^{N}\sum_{x \in C_i}(\overline{x_\iota} - \bar{x})\,(\overline{x_\iota} - \bar{x})^T$$ (12)

Where x is the overall mean vector, i x is the ith class mean, mi is the number of training samples for the ith class, and (x_i) m is the priori probability of each class. The eigenvectors linked to the greatest eigenvalues of the extended eigenvalue problem below are the ideal W_{opt} in order to maximize.

$$S_B W_i = \lambda_i S_W W_i$$ (13)

This important eigen vectors of -1 B W S S that correlate to this eigenvalue λi can be solved to calculate the solution. The transformation matrix W's row vectors are then column vectors wi. It should be mentioned that only eigenvectors that match eigenvalues carrying the majority of the energy that is, the whole dispersion should be chosen. The fact The fact that this transform decor links the SB and SW matrices is another intriguing feature. No more features may be added than this since SB's rank is at a maximum of N-1.

3.5) Deep Learning Model (CNN-LSDM)

CNN's capacity to concentrate on the most pronounced components inside the field of vision makes it a popular choice for feature engineering. In time series, LSTM is widely used because to its capacity to grow in accordance with the temporal sequence. A CNN-LSTM-based stock forecasting model is created based on the traits of CNN and LSTM. The input layer, pooling layer, LSTM hidden layer, one-dimensional convolution layer, and complete connection layer are all included in the structural diagram of the CNN and LSTM models, which is displayed in Figure

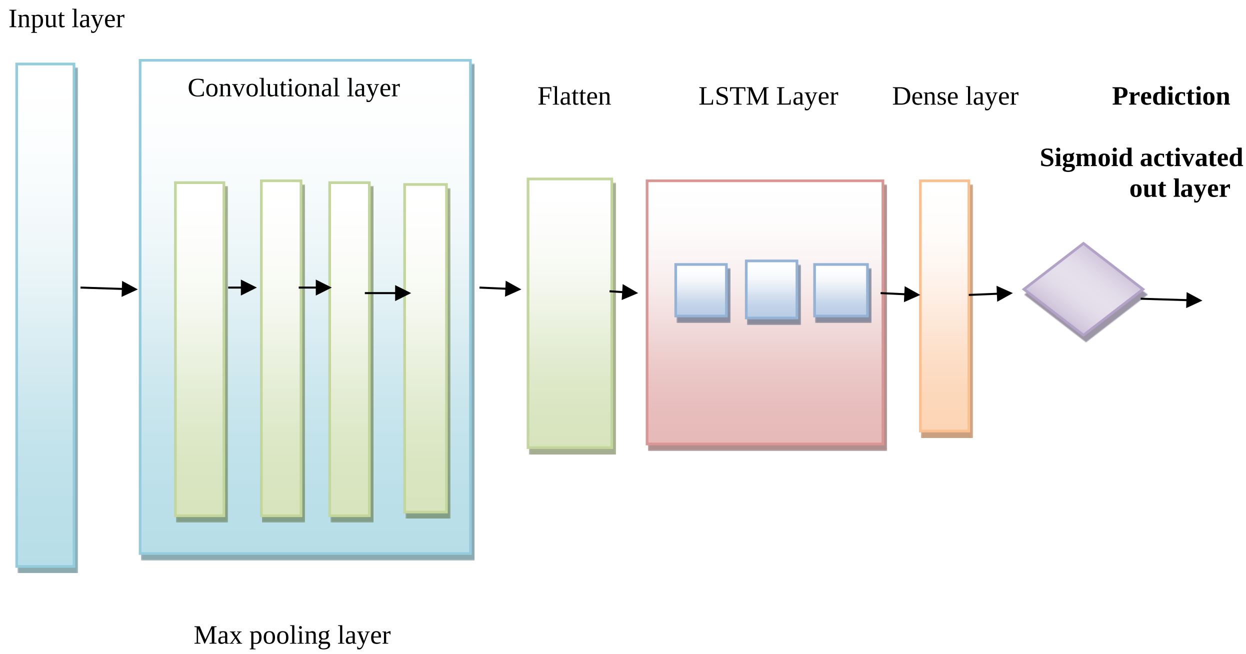


Figure 2 CNN –LSDM architecture

The problem is solved and the network training cost is reduced by adding following the convolution layer with a pooling layer to lower the feature dimension. Although the convolution layer collects the properties of the input, the retrieved feature dimensions are extremely high.

$$l_t = tanh(x_t * k_t + b_t) \quad (14)$$

Where xt is the input vector, the convolution kernel's weight is kt, the bias is bt, the activation function is tanh, and the output value following convolution is lt.

The LSTM network model was created to address the persistent issues of disappearance and gradient explosion in RNN. Text analysis, speech recognition, and emotional analysis have all made substantial use of it due to its ability to provide very accurate predictions and its own memory. Forecasting the stock market has also made use of it. A typical RNN has a single repeating module with a straightforward internal structure.

The forget gate receives both the output value from the previous instant and the input value from the current instant. Calculating the forget gate's output value is the next step, as indicated by the formula below.

$$f_t = \sigma(W_f.[h_{t-1}, X_t] + b_f) \tag{15}$$

Where xt is Wf is ht−1 is the output value from the previous instant, bf is the bias, the weight of the forget gate, and the present time is the input value. The range of foot values is 0 to 1. The input gate receives both the present time's input value and the previous time's output value. Following computation, the following formula indicates the output value of the input gate and the candidate cell's state.

$$i_t = \sigma(W_{i.}[h_{t-1}, x_t] + b_i) \tag{16}$$

$$\widetilde{C_t} = \tanh(W_c.[h_{t-1}, x_t] + b_c) \tag{17}$$

When Wi stands for the input gate's weight, bi for its bias, Wc for its weight, and bc for its candidate input g's bias; the numbers range from 0 to 1. Update the current cell status as follows:

$$C_t = f_t * C_{t-1} + i_t * \widetilde{C_t} \tag{18}$$

When the output gate receives -e output ht−1 and input xt as input values at time t, the output is generated as follows.

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \tag{19}$$

Where Wo ot has a range of values between 0 and 1, bo is the output bias, and is the weight of the output gate. The following illustrates how the LSTM's output value is determined by calculating the output of the output gate and the state of the cell.

$$h_t = o_t * \tan(C_t) \tag{20}$$

4) Result and discussion

Five metrics have been utilized to percentage classification accuracy, sensitivity, specificity, precision, and F1-score are used to assess The effectiveness of the proposed FoG prediction models. The percentage of successfully categorized cases among all instances is known as classification accuracy. It is preferred to have high precision. But for datasets that are unbalanced, it might not be enough. The distribution of successfully and erroneously categorized examples across classes is not revealed by it. By dividing the overall number of positive forecasts by the number of real positive predictions, precision is computed. When false positive costs are substantial, it is essential. The precision of the model aids in evaluating its capacity to prevent false positives. Conversely, the proportion of actual positive projections to all actual positive instances is known as sensitivity. When the cost of false negatives is high, it is essential. Sensitivity aids in assessing the model's ability to detect positive examples. Specificity is defined as the ratio of actual negative events to actual negative projections. It assesses the model's ability to identify negative cases. The harmonic mean of sensitivity and accuracy is known as the F1-score. It is a helpful indicator of an unequal distribution of classes. It provides a balance between accuracy and sensitivity. All performance measures were based on the confusion matrix (Equation 1–5).

$$\text{Classification Accuracy}=\frac{TP+TN}{TP+TN+FP+FN} \tag{21}$$

$$\text{Precision} = \frac{TP}{TP+FP} \tag{22}$$

$$\text{Sensitivity} = \frac{TP}{TP+FN} \tag{23}$$

$$\text{Specificity} = \frac{TN}{TN+FP} \tag{24}$$

$$F1 = \frac{2\times Precision \times Recall}{Precision+Recall} \tag{25}$$

Here TP, TN, FP, and FN are, in order, false positive, true negative, true positive, and true negative.

The mean value of the gait characteristics, as determined by the 3D motion capture system and wearable accelerometer data, is displayed in Table 1The wearable accelerometer-based approach and the five gait parameters obtained from the 3D motion capture technology exhibit a good connection. The suggested method's estimated walking speed, stride length, step time, and stride length demonstrated a robust association with the equivalents obtained from the 3D motion capture system. displays the outcomes of the four classifiers that were used. The following computer specifications are used to implement the Google Colab environment's categorization algorithms: Windows 10, an Intel Core i7-7700 CPU running at 3.6 GHz 64-Bit, and 8 GB of RAM.

Table 1 Gait parameter mean value derived from 3D motion capture and wearable accelerometer-based estimate.

S. No	Step time	Stride time	Step length	Stride length	Walking time
Left Leg	7.21	6.58	6.85	7.23	7.20
Right leg	7.35	7.21	6.53	6.80	6.98

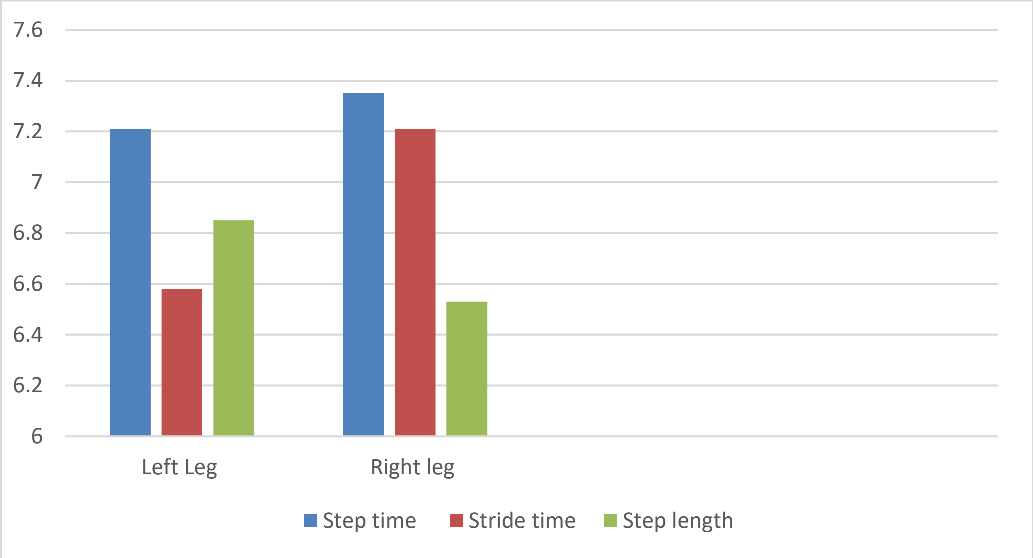


Figure 3 The average gait parameter error rate for the left and right legs was determined using a 3D motion capture system and a worn accelerometer.

The figure 3 presents a comparison between the left and right legs during a walking cycle, showing key walking metrics, including walking duration, stride length, step length, and stride time. The left leg has a slightly shorter step time (7.21 seconds) compared to the right leg (7.35 seconds), indicating that the left leg is completing its step faster. Additionally, the stride time for the left leg (6.58 seconds) is shorter than that of the right leg (7.21 seconds), suggesting a quicker overall cycle for the left leg. In terms of distance, the left leg also covers a longer step length (6.85 meters) and stride length (7.23 meters) compared to the right leg, which has a step length of 6.53 meters and a stride length of 6.80 meters. Finally, the walking time for the left leg (7.20 seconds) is slightly longer than for the right leg 6.98 seconds.

Table 2 Hybrid CNN-LSDM Classifier

Simulation	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Mean**
Accuracy	85.71	88.57	88.57	91.42	88.57	88.57	91.42	88.57	88.57	91.42	89.139
Sensitivity	85.11	87.91	87.91	90.89	87.91	87.91	90.89	87.91	90.89	88.524	88.524
Specificity	85.34	88.12	88.12	91.21	88.12	88.12	91.21	88.12	88.12	91.21	88.769

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The table 2 average mistake rate was less than 10%. At 91.42%, the CNN-LSDM The highest accuracy is provided by a classifier using a radial basis function. It shows that we were able to correctly predict 46 patients out of 15 patients that included both classes. Additionally, it provides the highest specificity and sensitivity, 91.21% and 90.89%, respectively.

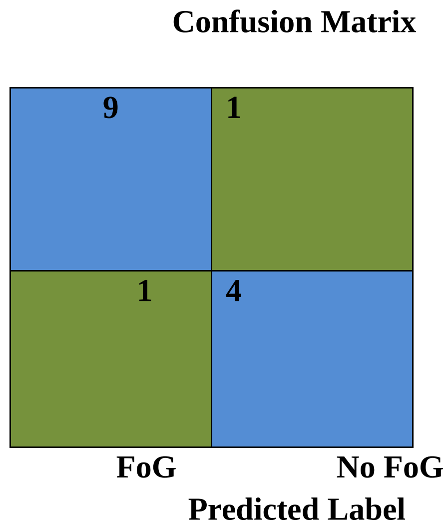

Figure 4 Confusion matrix for the proposed approach

This result shows that the system accurately classified 32 of the 36 FoG patients as FoG and 14 of the 15 no FoG patients as no FoG. Figure 4 displays the FoG classification confusion matrix.

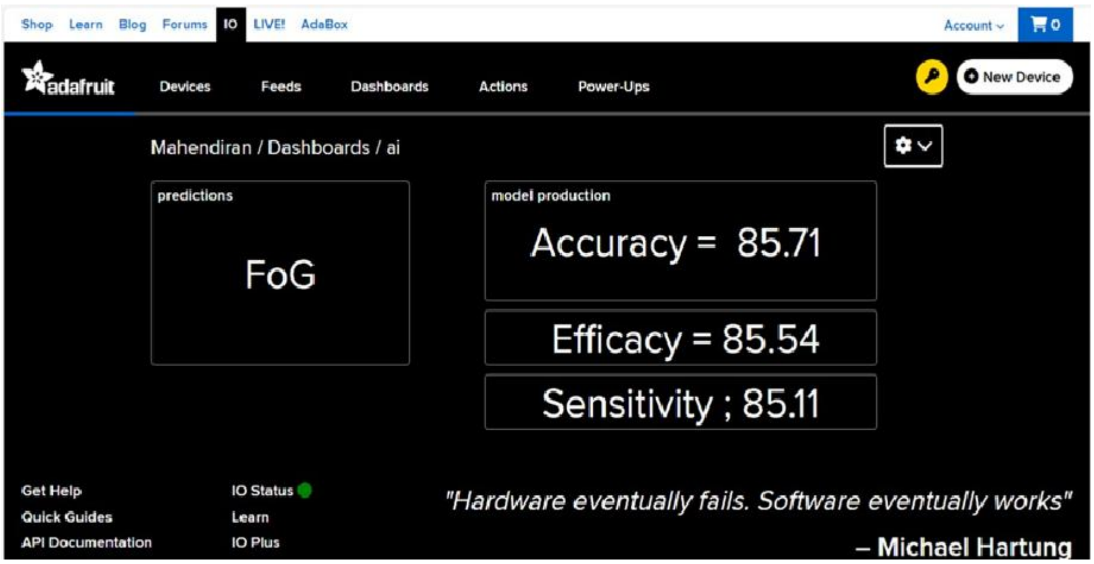

Figure 5 Adafruit IO Cloud

The Figure 5 shows the values of accuracy 85.71%, Efficiency 85.54%, and Sensitivity 85.11% provide key insights into this performance of a DL model related to FoG likely in the context of Fo Computing or IoT data analysis. Accuracy refers to the overall proportion of correct predictions made by the model, with 85.71% of its predictions being accurate. Efficiency measures how well the model utilizes computational resources, and an efficiency score of 85.54% indicates that the model achieves good results while maintaining effective use of resources such as processing time or memory. Sensitivity, also known as recall, measures how effectively the model identifies actual positive cases, and with a value of 85.11%, the model is capable of correctly identifying 85.11% of all the positive instances. These three metrics together give a clear picture of how well the model performs in terms of prediction accuracy, resource efficiency, and its ability to detect relevant outcomes, making it a balanced and reliable model for practical use.

5) Conclusion

In conclusion, the proposed multimodal sensor fusion approach combined with deep learning and IoT technology provided an innovative and effective solution for real-time prediction of FoG in PD patients. By integrating data from various sensors (IMU, EMG, EEG, and foot pressure sensors) and leveraging advanced techniques like feature extraction, feature selection, and a hybrid CNN-LSTM model, the system successfully captured both spatial and temporal patterns in gait data. The real-time nature of the IoT-based platform allowed for continuous monitoring and timely interventions, such as cueing strategies or medication adjustments, which significantly improved patient outcomes. The experimental results highlighted the superiority of the proposed model over traditional machine learning approaches, suggesting its potential for enhancing mobility, safety, and the overall quality of life for PD patients. This approach represented a significant step toward the development of intelligent, wearable monitoring systems capable of providing continuous, remote healthcare support.