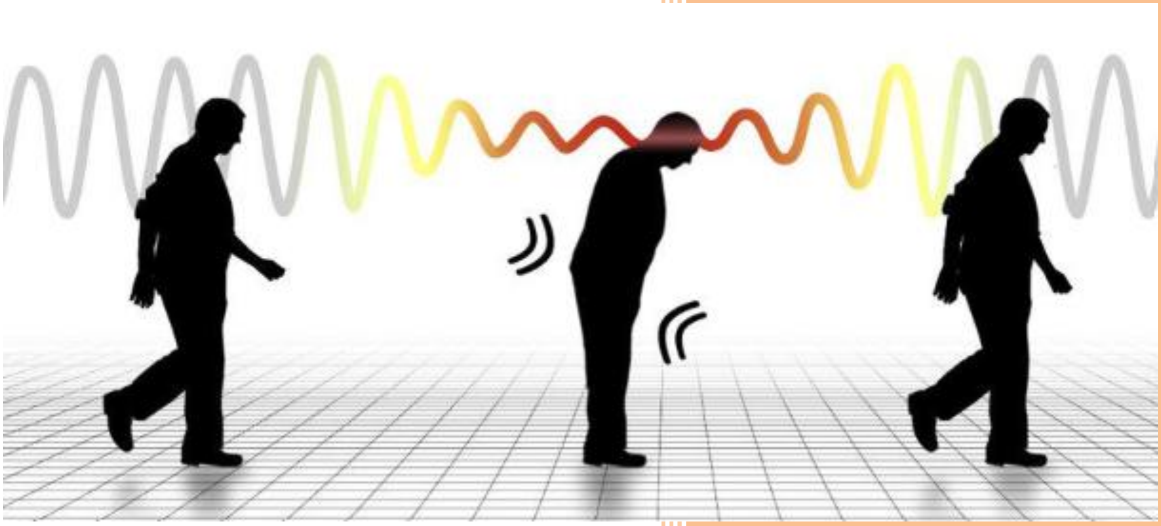
2025

Detecting Freezing of Gait in Parkison’s Patients Using AI and IMU sensors



Rick Steenhorst, Jelmar Riedeman & Lotte Lampe
Master Applied Artificial Intelligence
11-4-2025

Content

Introduction

Parkinson's disease is the second most common progressive neurological disorder. Its prevalence has been projected to double over the next 30 years. Parkinson's symptoms typically appear years before clinical diagnosis, but by the time they are recognized, significant dopaminergic neuron loss has already occurred [1]. One of the most disabling yet poorly understood motor symptoms of Parkinson's disease is Freezing of Gait (FoG), a sudden and temporary inability to move the feet forward despite the intention to walk [2]. Freezing episodes increase the risk of falls, reduce mobility, and severely impact the quality of life of patients. Comprehensive detection of FoG could enable timely interventions, improving patient outcomes through personalized therapy and medication adjustments. Traditional diagnostic methods rely on clinical assessments and subjective observations [3], which may fail to capture subtle gait changes leading up to freezing episodes. AI-driven motion analysis using Inertial Measurement Units (IMUs) offers an approach for objective, real-time detection of freezing patterns, potentially allowing for earlier diagnosis, timely intervention, and a comprehensive tracking of occurrences.

Problem

Despite advancements in Parkinson's disease research [4], accurately detecting FoG remains a challenge. Freezing episodes can be unpredictable and brief, making them difficult to assess during clinical visits. Patients may not always recall or accurately describe these episodes, leading to underreporting and delayed intervention. According to the DEEP FOG study, FoG affects 54.8% of Parkinson's patients [5]. Among these, 61.6% experience FoG only in the "off" state, when medication is not active, while 36.6% experience it in both "on" and "off" states. This highlights the widespread impact of FoG and the need for reliable detection methods.

Wearable sensor-based approaches provide a solution to detect and analyze FoG episodes objectively, by using IMUs to measure acceleration and gyroscopic movements. AI-powered models can help in identifying FoG patterns and predicting upcoming episodes, potentially allowing for earlier diagnosis, timely intervention, and consistent monitoring.
To realize such a system in a practical, everyday setting, the hardware must be compact, low-power, and capable of real-time data processing. The ESP32 microcontroller is well-suited for this task due to its small form factor, integrated wireless communication (Bluetooth and Wi-Fi), dual-core processor, and sufficient memory to support lightweight machine learning models. Its low energy consumption makes it ideal for wearable applications, while its affordability and open-source ecosystem allow for rapid development and deployment. However, deploying AI models on such embedded devices also presents challenges, including memory constraints, limited computational power, and the need for efficient feature extraction methods.

Objective

The objective of this research is to develop a lightweight, AI-powered system capable of detecting Freezing of Gait episodes in real time using data from Inertial Measurement Units, processed on an embedded device such as the ESP32. By enabling accurate and timely detection of FoG events, the system aims to support early intervention strategies, such as adaptive medication scheduling, real-time feedback to the patient, or alerts to caregivers. Ultimately, this approach could contribute to reducing fall risk, enhancing mobility, and improving the overall quality of life for individuals living with Parkinson’s disease.

Research Questions

The goal of this study is to detect FoG in individuals with Parkinson's disease using artificial intelligence (AI) in combination with data from Inertial Measurement Units (IMUs). IMUs provide an objective, continuous, and non-invasive way to monitor gait patterns, making them highly suitable for applications in movement disorder detection. However, implementing AI-based solutions on low-power embedded hardware such as the ESP32 microcontroller introduces several technical constraints. These include limitations in memory, processing power, and energy consumption, which must all be addressed to achieve reliable real-time detection.

To guide this research and address both the opportunities and challenges of using AI in a resource-constrained embedded system, the following main research question was formulated:

Main Question: How can an AI model be optimized and deployed on an ESP module for real-time detection of freezing of gait in Parkinson's patients?

To support and answer the main research question, a number of sub-questions were developed. These help break down the problem into manageable components, each addressing a key aspect of the overall system:

Sub Questions:
- What type of data is needed to analyze step patterns effectively?
- What are suitable open-access datasets?
- What types of AI models are suitable for detecting freezing episodes based on gait data?
- How can the model be optimized for efficient processing on embedded hardware, such as the ESP32? ESP
- What are the challenges of deploying AI models on devices like the ESP32 for real time FoG detection?
- How can an ESP32 module process and analyze gait data in real-time to detect freezing episodes?

These questions structure the investigation and ensure that all relevant technical, practical, and scientific elements are considered during the design, development, and evaluation of the proposed solution.

Dataset

Overview

To effectively analyze step patterns and detect FoG in Parkinson's patients, this study uses time-series motion data collected from IMUs. Specifically, the MPU6050 accelerometer-gyroscope module is used to measure gait characteristics. The required data types include:

- Accelerometer Data (3-axis) – Measures linear acceleration in mediolateral (ML), anteroposterior (AP), and vertical (SI) directions.
- Gyroscope Data (3-axis) – Captures angular velocity across the same three directions.
- Sampling Rate – A high-frequency sampling rate (e.g. 128 Hz) ensures detailed motion capture.
- Annotated FoG Episodes – Labeled events indicating the presence of freezing, used as ground truth during model training and evaluation.

Dataset Description

This project uses the publicly available dataset by Boari et al. (2021) [6], which was specifically designed to study FoG during turning movements, a known trigger for freezing episodes. The dataset contains IMU sensor data, synchronized video recordings, and expert-annotated freezing events.

Key characteristics:

- 35 Parkinson's patients with FoG (16 females, 19 males)
- Age range: 44–84 years; diverse body types
- Activity: Participants performed a turning-in-place task (alternating 360° turns left and right for 2 minutes)
- Sampling frequency: 128 Hz
- Data format: Each session is stored in a separate CSV file (15,360 rows = 120 seconds × 128 Hz)
- Labeling: Expert-reviewed freezing events are marked with a binary flag (FoG = 1, no FoG = 0)

Each CSV file contains 9 columns:

1. Frame number
2. Time (s)
3. ACC ML (g)
4. ACC AP (g)
5. ACC SI (g)
6. GYR ML (°/s)
7. GYR AP (°/s)
8. GYR SI (°/s)
9. FoG flag

This standardized dataset accelerates development by removing the need for data collection, while still offering high-quality, consistent, and annotated recordings.

Why This Dataset is Suitable for This Project

The dataset selected for this project is particularly well-suited for the development and evaluation of a real-time FoG detection system, for several key reasons:

High Relevance to FoG Scenarios
The dataset focuses specifically on the turning-in-place task a common trigger for FoG in Parkinson's patients. Unlike straight-line walking, turning often induces freezing episodes, making this dataset highly relevant for training models that need to detect such events in real-world settings.

Expert-Annotated Freezing Events
Each FoG episode in the dataset is manually annotated by clinical experts using synchronized video recordings. These high-quality, human-verified labels provide reliable ground truth for supervised machine learning, enhancing model accuracy and validity.

High-Resolution IMU Data
With a sampling rate of 128 Hz and six key sensor streams (accelerometer and gyroscope on three axes), the dataset offers fine-grained motion detail. This level of resolution allows the model to pick up subtle movement patterns associated with early or brief freezing episodes.

Diverse Patient Population
The dataset includes recordings from 35 individuals diagnosed with Parkinson's disease, with a broad age range (44–84 years) and varying physical characteristics. This diversity helps improve the model's ability to generalize across different patient profiles.

Ethical and Practical Accessibility
The dataset is publicly available, ethically approved, and shared under open-access terms. This makes it not only accessible for academic use but also ethically aligned with the standards required for working with sensitive medical data.

Standardized Protocol
Data was collected in a consistent and controlled manner across all participants, ensuring that variability is due to the subjects' condition rather than inconsistent measurement. This improves comparability between sessions and patients.

Together, these factors make the Boari et al. (2021) dataset a robust and efficient choice for building and testing a lightweight, embedded AI model for real-time FoG detection using wearable sensors.

How to Access and Use the Dataset

Other researchers and developers can easily access and work with this dataset using the following links:

Dataset article (Boari et al., 2021):
https://www.frontiersin.org/articles/10.3389/fnins.2022.832463/full

Dataset download (Figshare):
https://figshare.com/articles/dataset/A_public_dataset_of_video_acceleration_and_angular_velocity_in_individuals_with_Parkinson_s_disease_during_the_turning-in-place_task/14984667/7

To use the data:

1. Download the file IMU.zip from Figshare.
2. Extract and use only the CSV files corresponding to the turning task, exclude files labeled with standing still, as they are not relevant for FoG detection.
3. Use columns 3 to 8 (acceleration and angular velocity) along with the FoG flag (column 9) for model training.

The structured layout and expert annotations make this dataset highly suitable for training and evaluating machine learning models for real-time FoG detection.

Machine learning models

The task of detecting Freezing of Gait (FoG) in individuals with Parkinson's disease was formulated as a binary classification problem, where the input consists of time-series data collected from a wearable IMU sensor. To identify appropriate machine learning models for this task, the Scikit-learn model selection cheatsheet was used as a reference (see Appendix I). Given that the data was structured, labeled, tabular, and of modest size, the guidelines pointed toward lightweight, supervised classification algorithms. Based on this, four models were selected and evaluated:

- Linear Support Vector Classifier (Linear SVC)
- k-Nearest Neighbors (KNN) Classifier
- Decision Tree Classifier
- Random Forest Classifier (ensemble method)

These models were chosen due to their relatively low computational complexity, their effectiveness on structured datasets, and most importantly, their compatibility with embedded deployment environments, such as the ESP32 microcontroller. More complex deep learning models (e.g., CNNs or LSTMs) were not considered, as they require significantly more memory and processing power, which is not feasible without external AI acceleration.

Model optimization

To analyse large amounts of time series data on a small device, the amount of data needs to be reduced.
A really slow Parkinson's patient walks at a speed of one step every 3.56 seconds A. Contreras (2022). The data points are collected at a speed of 128 hz. To put these number into data points, 3.56 * 128 = 456. The dataset we have contains 3 values every datapoint. This means that for real time data processing 456 * 3 = 1368 data points need to be processed. To choose a method of reducing the data, first is looked at the symptoms of Parkingson walking.
There are many Parkinson related walking deviations:

- Smaller steps
- Slower speed
- Less trunk movement (especially rotation)
- A narrow base of support (feet too close together)
- Less or absent arm swing (on one side of the body or both)
- Trouble turning
- The feet land flat on the floor with each step instead of on the heel (can lead to shuffling and falls)
- Festination or shuffling (quick, small, involuntary steps forward; often accompanied by stooped posture)
- Retropulsion (quick, small, involuntary steps backward)

The main trend in these symptoms are either unnecessary movement or stillness during walking. To reduce the dimensions and give these core symptoms to the model, instead of

456 data points we give the total and absolute movements of these 456 data points combined. This way the model will be able to see unnecessary movements, quick steps, balance adjustments or just any unnecessary movements or stillness. The amount of data points needed is also reduced from 456 * 3 to 3 (total movement) + 3 (absolute movement). With 6 data points instead of 1368 the computing power will be significantly reduced, increasing the prediction refresh rate and decreasing the delay.

Model Performance Comparison

Each model was trained and evaluated using the same preprocessed dataset and cross-validated with a 70/15/15 train-test-validation split. Performance was assessed using standard classification metrics: accuracy, precision, recall, F1-score, ROC AUC, and confusion matrices. Details about these metrics and performance for each model can be found in appendix III.

Linear SVC (test)

- Accuracy: 86.2%
- Precision: 86.2%
- Recall: 86.2%

The Linear SVC model demonstrated solid performance in detecting FoG events, achieving a test accuracy of 86.2%. Both the precision and recall for the FoG class were 86.2%, indicating that the model is equally capable of correctly identifying true freezing episodes and avoiding false alarms. The confusion matrix confirms this balanced performance, with 73 true positives and 71 true negatives, and relatively few misclassifications: 12 false positives and 11 false negatives. This consistent detection capability makes Linear SVC a reliable candidate for real-time FoG classification in wearable applications.

KNN Classifier

- Accuracy: 83.8%
- Precision: 83.9%
- Recall: 83.8%

The K-Nearest Neighbours (KNN) model achieved an overall test accuracy of 83.8%, with a precision of 83.9% and a recall of 83.8% for detecting Freezing of Gait (FoG). These results indicate that the model performs consistently across both FoG and non-FoG classifications. According to the confusion matrix, the model correctly identified 68 true positives and 72 true negatives, while making 11 false positive and 16 false negative predictions. This balance between sensitivity and specificity suggests that KNN is a dependable option for FoG detection, with only a modest number of missed or misclassified events.

Decision Tree

- Accuracy: 84.4%
- Precision: 84.5%
- Recall: 84.4%

The Decision Tree classifier achieved a test accuracy of 84.4%, with a precision of 84.5% and a recall of 84.4% for the FoG class, indicating balanced performance in detecting freezing episodes. The confusion matrix shows that the model correctly classified 72 non-freezing events and 69 freezing events, while making 11 false positive and 15 false negative predictions. These results demonstrate that the Decision Tree model is capable of distinguishing between FoG and non-FoG with reasonable accuracy, though it may miss a small portion of actual freezing episodes.

Random Forest Classifier

- Accuracy: 86.8%
- Precision: 87.2%
- Recall: 86.9%

The Random Forest classifier demonstrated strong and reliable performance, achieving a test accuracy of 86.8%, with a precision of 87.2% and a recall of 86.9% for detecting Freezing of Gait (FoG). According to the confusion matrix, the model correctly predicted 76 non-freezing events and 69 freezing episodes, while making only 7 false positive and 15 false negative classifications. This indicates that the Random Forest model maintains a strong balance between detecting true FoG events and minimizing false alarms, making it one of the most effective candidates for real-world deployment in wearable FoG detection systems.

Final Selection

All models were trained and evaluated on the same dataset using a consistent 70/15/15 train-test-validation split, and assessed with standard classification metrics. Among the four models tested, the Random Forest Classifier delivered the most balanced and robust performance.

- It achieved the highest accuracy (86.8%), slightly outperforming Linear SVC (86.2%), Decision Tree (84.4%), and KNN (83.8%).
- It also had the highest precision (87.2%) and recall (86.9%) for the FoG class, indicating that it was the most capable of correctly identifying true freezing episodes while minimizing false positives.
- The confusion matrix further supports this, showing the lowest number of false positives (7), which is especially valuable in real-world applications where false alarms could reduce user trust or lead to unnecessary interventions.

While Linear SVC and Decision Tree also demonstrated strong and balanced results, the Random Forest model consistently outperformed them across nearly all key metrics, including the ability to generalize well to unseen data. Its ensemble structure contributes to increased stability and robustness, reducing the risk of overfitting.

Challenges deploying AI on ESP32

Now that the model is trained we focus on deploying the model on the ESP32. The ESP32 is a compact, low-power microcontroller suitable for wearable applications. Deploying AI models on embedded systems such as the ESP32 for real-time FoG detection poses several technical and practical challenges. These can be broadly categorized into hardware limitations, energy efficiency, model optimization, and real-time processing constraints.

Hardware and Resource Constraints

The ESP32, while powerful for its size and cost, is a resource-constrained device with limited RAM (512 KB), flash memory (typically 4 MB), and processing power (dual-core 240 MHz CPU). These limitations restrict the complexity and size of machine learning models that can be deployed.

- Memory bottleneck: Large models (e.g., deep neural networks) exceed the available memory, leading to instability or failure during inference.
- Processing speed: Real-time detection requires fast inference. A delay in prediction could render the detection ineffective in clinical or assistive settings.

This is corroborated by the study by Fanariotis et al. (2023) [7], which emphasizes that edge IoT devices struggle with running computationally intensive models due to their limited resources. The authors highlight that even widely-used models like Support Vector Machines (SVMs) and k-NNs need heavy optimization or cannot be used at all without significant pruning or quantization

Model Optimization and Compression

To deploy an ML model on ESP32, it must often be simplified or compressed. Techniques such as model pruning, quantization, and feature reduction are vital to reduce the footprint and computation time.

- For our project, we selected Random Forests due to their balance between accuracy and simplicity. Though not as compact as linear models, they can be transformed into static decision trees and exported as plain C code, making them ideal for embedded deployment.
- This approach aligns with the TinyML methodology highlighted by Chua Kiang Hong et al. (2023) [8] , which discusses porting AI models like Multiple Linear Regression and ANN onto the ESP32 for weather prediction. The success of these simpler models on ESP32 supports our model choice for FoG detection.

Real-Time Data Handling

Real-time FoG detection requires continuous data acquisition from IMU sensors, preprocessing, and inference all with minimal latency.

- The ESP32 must balance sensor data collection, buffering, and model inference, which can lead to bottlenecks.
- Incorrect buffer handling or slow inference may result in missed freeze events or false positives.

Power Efficiency and Autonomy

A crucial challenge is maintaining energy efficiency, especially if the ESP32 is to be used as a wearable device powered by a battery. According to Fanariotis et al. (2023) [7] , energy consumption during inference is often overlooked, yet it's vital for long-term, real-world deployment of embedded ML systems. Models that are not optimized for inference speed can drain batteries quickly, reducing the system's usability

Real-Time Gait Data Processing and Prediction on ESP32

In this project, the ESP32 is used as an on-body device worn by Parkinson’s patients to detect Freezing of Gait (FoG) episodes in real time. To ensure timely warnings and effective intervention, it is critical that predictions occur with minimal delay after a freezing event.

To facilitate its use as a wearable system, a custom 3D-printed enclosure was designed to house the ESP32, IMU sensor, and wiring. This enclosure ensures the components are securely positioned, while allowing access to the USB port and power supply. Further details regarding the enclosure design and fabrication process are provided in Appendix IV.

To replicate the conditions of the dataset and enable real-time processing, the following steps were implemented on the ESP32:

IMU Sensor Integration

- An IMU sensor is attached to the patient's ankle and connected to the ESP32 to capture continuous gait data.
- The sensor records acceleration, rotation, and orientation in real time across three axes.

Data Compression and Feature Relativization

- For slow-walking patients (one step every ~3.56 seconds), each step consists of approximately 456 data points at a 128 Hz sampling rate.
- To reduce computational load, these data points are transformed into six core features: total and absolute movement along the three axes.
- This approach significantly reduces data volume while preserving key movement characteristics.

Feature Extraction and Analysis

- The ESP32 processes the compressed data to extract relevant features that capture indicators of FoG, such as abrupt stillness, irregular motion, or compensatory shifts in balance.
- These features serve as inputs to the prediction model.

Prediction and Classification

- The processed features are evaluated by a pre-trained Random Forest classifier deployed on the ESP32.
- The system updates its predictions every 0.5 seconds, ensuring rapid detection of freezing episodes with minimal latency.

Communication and Output

- Prediction results are transmitted via Bluetooth or USB to a connected device (e.g., smartphone or laptop), allowing users or caregivers to receive real-time alerts.

During testing, the ESP32 successfully handled real-time data acquisition, preprocessing, and classification within its hardware constraints. The feature engineering approach enabled the system to maintain a refresh rate of 0.5 seconds per step, ensuring timely response and continuous monitoring in a wearable format (see Appendix III for performance details).

Next Steps

As a next step the model could be optimised by tuning the hyperparameters. We recommend doing this with a grid search. The main parameters to tune when using a random forest model are n_estimators and max_feautures [9]. N_estimators is the number of trees in the forest. The larger this value, the better the performance tends to be up to a certain point. However, training time also increases with more trees, and beyond a certain number of trees, the improvement becomes marginal. The max_features parameter controls the size of the random subset of features considered when splitting a node. Lower values reduce variance but can increase bias. Empirical good defaults for classification tasks are "SQRT' (a random subset of size √n_features) for classification tasks. Using smaller values like 0.3 introduces more randomness and is often used in the literature. Other parameters to consider are max_depth and min_samples_split , which allow trees to fully develop, though this can result in high memory usage. Further and more in depth explanation can be found in [10] and [9].

The model showed promising results on the used dataset, however the current preprocessing pipeline may not generalize well to real-world scenarios. In practice, patients walk at different speeds, may freeze more or less frequently, and exhibit varied gait patterns in uncontrolled environments. These variations can influence how well the model detects Parkinson-related symptoms. As a result, an important next step would be to fine-tune the model to recognize Parkinson-related patterns across a broader range of walking speeds and real-life scenarios. This could include dynamic adjustment of step segmentation, collecting more diverse data, and validating the model in uncontrolled environments to improve robustness and generalizability.

Conclusion

This research presents the development of an AI-powered system for real-time detection of Freezing of Gait (FoG) in Parkinson's patients, using an Inertial Measurement Unit (IMU) and a Random Forest model optimized for deployment on a low-power embedded device (ESP32). FoG is a debilitating symptom that significantly impacts patients' mobility and quality of life. The results demonstrate that it is feasible to achieve accurate detection using resource-constrained hardware, making the system suitable for wearable applications.

Among the tested models, the Random Forest classifier achieved the best performance, with an accuracy of 86.8%, precision of 87.2%, and recall of 86.9%. By applying efficient feature extraction, reducing raw sensor data from 1368 to just 6 key features per step, the model was able to operate within the ESP32's limitations while providing predictions every 0.5 seconds. This fast response is essential for timely intervention and user feedback in real-world use.

Despite the promising results, some challenges remain. The current preprocessing pipeline is based on a controlled dataset and may not generalize well to real-life walking conditions, which vary in speed, movement patterns, and environmental context. Future work should focus on improving model generalization, collecting more diverse data, and fine-tuning hyperparameters to further boost performance.

In conclusion, this project shows that with smart optimization and efficient use of hardware resources, a reliable, real-time FoG detection system can be developed. Such a system has the potential to improve the safety, independence, and quality of life for people living with Parkinson's disease.

Discussion - Ethical Considerations

The integration of AI and wearable technology in healthcare offers promising avenues for improving the diagnosis and monitoring of complex conditions like Parkinson's disease. However, such innovations also raise important ethical questions that must be addressed to ensure responsible development and deployment.

Data Privacy and Patient Consent

The use of Inertial Measurement Units (IMUs) to monitor gait involves continuous collection of personal and sensitive movement data. Although the dataset used in this project was publicly available and anonymized, real-world deployment would require strict adherence to data protection laws such as the General Data Protection Regulation (GDPR). Patients must be fully informed about how their data will be collected, processed, and stored, and must give informed consent. Even seemingly harmless sensor data, when combined with timestamps or location data, could potentially be re-identified.

False Positives and Psychological Impact

A wearable FoG detection system aims to provide real-time feedback or warnings to patients. However, false positives where the system incorrectly flags a freezing event can cause unnecessary anxiety or frustration for users. This could lead to reduced trust in the system and non-compliance. On the other hand, false negatives failing to detect a real freezing event could result in missed interventions and increased fall risk. Striking a balance between sensitivity and specificity is not only a technical challenge but also an ethical one, as it directly impacts patient safety and well-being.

Responsible Innovation

Finally, deploying AI in healthcare settings requires ongoing evaluation and iteration. The model should be transparent, explainable, and subject to regular audits, especially as it encounters new data in real-world environments. Additionally, collaboration with clinicians, patients, and ethicists is essential to ensure that the technology aligns with the values and needs of its users.

In conclusion, while the technical implementation of a wearable FoG detection system shows great promise, its success in practice depends equally on how ethical challenges are addressed. Privacy, fairness, reliability, and user impact must be considered from the outset to ensure that the technology truly benefits Parkinson's patients in a safe, respectful, and inclusive manner.

Sources

[1] E. Tolosa, A. Garrido, S. W. Scholz, and W. Poewe, ‘Challenges in the diagnosis of Parkinson’s disease - PubMed’. Accessed: Apr. 09, 2025. [Online]. Available: https://pubmed.ncbi.nlm.nih.gov/33894193/

[2] S. Rahimpour *et al.*, ‘Freezing of Gait in Parkinson’s Disease: Invasive and Noninvasive Neuromodulation’, *Neuromodulation J. Int. Neuromodulation Soc.*, vol. 24, no. 5, pp. 829–842, Jul. 2021, doi: 10.1111/ner.13347.

[3] J. Opara, A. Małecki, E. Małecka, and T. Socha, ‘Motor assessment in Parkinson`s disease’, *Ann. Agric. Environ. Med. AAEM*, vol. 24, no. 3, pp. 411–415, Sep. 2017, doi: 10.5604/12321966.1232774.

[4] J. D. Elsworth, ‘Parkinson’s disease treatment: past, present, and future’, *J. Neural Transm. Vienna Austria 1996*, vol. 127, no. 5, pp. 785–791, May 2020, doi: 10.1007/s00702-020-02167-1.

[5] M. Amboni *et al.*, ‘Prevalence and associated features of self-reported freezing of gait in Parkinson disease: The DEEP FOG study’, *Parkinsonism Relat. Disord.*, vol. 21, no. 6, pp. 644–649, Jun. 2015, doi: 10.1016/j.parkreldis.2015.03.028.

[6] C. Ribeiro De Souza *et al.*, ‘A Public Data Set of Videos, Inertial Measurement Unit, and Clinical Scales of Freezing of Gait in Individuals With Parkinson’s Disease During a Turning-In-Place Task’, *Front. Neurosci.*, vol. 16, Feb. 2022, doi: 10.3389/fnins.2022.832463.

[7] A. Fanariotis, ‘Power Efficient Machine Learning Models Deployment on Edge IoT Devices’. Accessed: Apr. 09, 2025. [Online]. Available: https://www.mdpi.com/1424-8220/23/3/1595

[8] C. K. Hong, M. A. Abu, M. I. Shapiai, M. F. Haniff, R. S. Mohamad, and A. Abu, ‘Analysis of Wind Speed Prediction using Artificial Neural Network and Multiple Linear Regression Model using Tinyml on Esp32’, *J. Adv. Res. Fluid Mech. Therm. Sci.*, vol. 107, no. 1, pp. 29–44, Jul. 2023, doi: 10.37934/arfmts.107.1.2944.

[9] ‘RandomForestClassifier’, scikit-learn. Accessed: Apr. 09, 2025. [Online]. Available: https://scikit-learn/stable/modules/generated/sklearn.ensemble.RandomForestClassifier.html

[10] ‘1.11. Ensembles: Gradient boosting, random forests, bagging, voting, stacking’, scikit-learn. Accessed: Apr. 09, 2025. [Online]. Available: https://scikit-learn/stable/modules/ensemble.html