A Study on Detection of Freezing of Gait

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A Study on Detection of Freezing of Gait

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I hereby declare that this thesis entitled "A Study on Detection of Freezing of Gait" contains literature survey and original research work by the undersigned candidate, as part of the Degree of Bachelor of Computer Science and Technology.

All information has been obtained and presented in accordance with academic rules and ethical conduct.

We also declare that, as required by these rules and conduct, We have fully cited and referenced all materials and results that are not original to this work.

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ABSTRACT

Freezing of Gait (FOG) is a debilitating symptom of Parkinson's Disease (PD) that significantly impacts patients' mobility. Early detection and diagnosis are crucial for effective treatment. This study focuses on identifying FOG episodes in PD patients using data from accelerometers and gyroscopes. I have been extract time-domain features from the sensor data, including statistical measures and periodicity indicators, to distinguish between normal gait and FOG. A Random Forest (RF) classifier has been trained using labeled data to detect FOG episodes, and hyperparameter tuning of the said classifier showed promising results, suggesting potential for practical implementation in assisting individuals with PD. Also, it has been compared with existing classifiers and outperformed them. Using a RF classifier and a multimodal dataset of FOG in PD, the study achieved a 100% accuracy rate. The study implies that real-time detection of FOG in PD patients is possible, allowing for early intervention for treatment. It emphasizes the importance of early identification in improving PD patients' quality of life and FOG management. Explainable Artificial Intelligence (XAI) techniques were employed to interpret the model's predictions, ensuring that the decision-making process is transparent and understandable for healthcare professionals. By utilizing XAI, we provide insights into the key features and patterns that contribute to FOG detection, enhancing the trust and applicability of our system in clinical settings. The integration of XAI not only supports the robustness of our model but also paves the way for more informed and actionable interventions for PD patients. Furthermore, our study explored the potential of integrating XAI with real-time monitoring systems to provide continuous feedback and adaptive interventions. The use of XAI in this context not only aids in the understanding of model behavior but also supports the development of personalized treatment plans. By identifying specific triggers and patterns leading to FOG, clinicians can tailor interventions to individual needs, thereby improving therapeutic outcomes.

1. Introduction

Parkinson's disease (PD) is a progressive neurodegenerative disorder affecting millions worldwide, particularly seniors, leading to a significant decline in their quality of life. The symptoms of PD can vary widely among patients, with manifestations such as tremors, limb rigidity, gait and balance issues, and non-motor symptoms like depression, sleep disturbances, loss of smell, and cognitive impairment. People with PD may experience shaking or trembling in their hands, arms, legs, jaw, or face, along with stiffness in their muscles and difficulty with balance and coordination. In some cases, PD can also affect a person's ability to speak and write clearly. Freezing of gait (FOG) is a common symptom primarily associated with PD, though it can occur in other conditions as well. It involves a sudden, temporary inability to move the feet forward while walking, often causing the person to feel as though their feet are stuck to the ground.

Despite the significant impact of PD, there is currently no definitive way to diagnose PD early to slow down the disease progression. However, various symptoms and diagnostic tests are used in combination, and scientists have investigated several biomarkers to early identify PD and potentially slow down the disease process. While therapies for PD aim to improve symptoms, they do not currently slow or halt disease progression. Our research demonstrates that our FOG detection system achieves higher accuracy than previous studies reported in the literature. By leveraging advanced feature extraction, removing null values, and employing sophisticated machine learning techniques, our approach significantly improves the detection accuracy, offering a more reliable solution for managing FOG in PD patients. This advancement underscores the potential for our system to set new standards in FOG detection and intervention. The report begins by emphasizing the critical importance of detecting and managing Freezing of Gait (FOG) in Parkinson's disease to enhance patients' quality of life. It then details the comprehensive approach taken, starting with the meticulous data collection process, including participant details and sensor setup. The report also covers essential data preprocessing techniques like noise reduction and handling null values to ensure data quality. Furthermore, it discusses feature extraction methods tailored for FOG detection, leading to the selection of a Random Forest classifier for machine learning. The integration of threshold-based techniques in the detection algorithm and the emphasis on Explainable AI (XAI) for transparency are highlighted as key elements. The report showcases the superior accuracy of the Random Forest model in FOG detection through detailed results, followed by discussions on its real-world applications and suggested future research directions. Lastly, the conclusion succinctly summarizes the significant findings and implications, while the references section adds credibility to the study's sources.

2. Literature survey

In the realm of research and detection methods, various approaches have been proposed to help detect PD based on different kinds of measurements. These include utilizing speech data, gait patterns, force tracking data, smell identification data, and spontaneous cardiovascular oscillations. In a recent study referenced as [11], an approach utilizing the irregular was employed, followed by preprocessing techniques aimed at addressing missing and infinite values within the dataset.. Subsequently, classification techniques such as Random Forest (RF), Gradient Boosting (GB), Decision Tree (DT), Support Bagging (SB), and Adapting Boosting (AB) Tree are used to categorize the data. Notably, the Random Forest (RF) model outperformed other techniques with an accuracy of 93%, showcasing its ability to identify patterns in acceleration data accurately. This result highlights the usefulness of RF in this specific categorization job and suggests potential applications in real-world implementations of acceleration. Expanding on this, recent advancements in PD detection have also explored deep learning techniques, ensemble methods, and multimodal data fusion to improve accuracy and reliability. Additionally, the integration of wearable devices and mobile applications has enabled real-time monitoring and early detection of PD symptoms, enhancing patient care and management strategies. The ongoing research in this field aims to further refine detection algorithms, enhance data collection methods, and develop user-friendly tools for clinicians and patients alike. Table 1 presents the analysis of state-of-the-art literature when compared to the proposed work.

Table1.

Ref.	Contribution	Technique Used	Performance	Limitations	Proposed Model's Way of Overcoming The Limitations
Jovanov 2009 [31]	Jovanov's 2009 study helped further PD research by establishing the Multichannel Freezing Index (FI) as a machine learning classifier for detecting FOG. Their research used one PD patient (PwF) and simulation data, using a gyroscope on the thigh, an accelerometer on the right knee, and a wearable ARM computer. This approach sought to improve FoG detection accuracy, offering potential benefits for early intervention and management strategies in PD patients.	Jovanov (2009) employed the Multichannel Freezing Index (FI) approach to identify freezing of FOG in Parkinson's illness. They analyzed data from a thigh gyroscope, knee accelerometer, and wearable ARM computer to improve FoG detection accuracy.	Technique demonstrated encouraging results in detecting FOG in Parkinson's illness. The Multichannel Freezing FI approach, which included data from a thigh gyroscope, knee accelerometer, and wearable ARM computer, helped to enhance FoG detection accuracy.	The limitations of single-modal models in FOG detection hampered the multimodal model's performance, indicating that single-modal performance needs to be improved. Future studies should look into changes in brain activity in additional regions, such as the parietal and occipital lobes, to improve FOG detection. The study focused primarily on analyzing brain activity in the central and frontal lobes. Variations in patients' age, duration of disease, intensity of FOG, and overall motor symptoms are likely contributors to the varying durations of FOG episodes in the sample.	FOG mechanisms are examined to help determine the selection of modalities for the multimodal model, in addition to exploring other physiological signals like acceleration information in FOG detection. Furthermore, extra modal signals are added into the model to enhance FOG detection performance.

Saad et al. [1].	The research introduces a patient-dependent approach for FOG identification in Parkinson's disease that uses multiple accelerometer signals to manage variability and improve accuracy. It compares entire sensor data to ranking features, demonstrating better accuracy with fewer features in the patient-dependent model. This emphasises the importance of personalised models and feature selection in improving FOG detection for PD monitoring, resulting in more successful FOG control techniques.	The study employs a patient-dependent model with multiple accelerometer sensors to improve FOG detection in PD. It also uses feature ranking approaches to optimize feature selection, which improves FOG detection accuracy while decreasing computing complexity. The solution includes a Random Forest classifier for accurate categorization of FOG instances based on specific attributes. The study's emphasis on personalized modelling and rigorous feature selection improves the accuracy and effectiveness of FOG detection for Parkinson's patients.	The FOG detection system, which includes a Gaussian model, achieves an amazing performance accuracy of 92%. This high degree of accuracy demonstrates the system's efficiency in correctly identifying FOG events in PD patients.	Limitations of the FOG detection study in Parkinson's Disease include a small sample size, resource-intensive model calibration , focus only on accelerometer signals, evaluation metrics that may overlook early detection sensitivity, and a lack of consideration for practical implementation challenges. Addressing these would enhance the study's relevance in clinical settings.	The FOG detection model in Parkinson's disease confronts hurdles due to its small sample size, calibration complexity, limited sensor data, and evaluation metrics. Acquiring varied datasets, automating calibration, integrating new signals, refining measurements, and addressing practical deployment challenges are all possible solutions.

Rodriguez-Martin *et al*.	Rodriguez-Martin et al. investigated FOG detection in PD patients, comparing the efficacy of personalized patient-dependent models to generic patient-independent models. Their findings show a considerable increase in accuracy when employing personalized models, emphasizing the necessity of adapting interventions to specific patient features. This trend towards personalized medicine not only enhances FOG detection, but also lays the groundwork for individualized healthcare in neurology and beyond.	Rodriguez-Martin et al. used advanced sensors to capture detailed movement data from patients with PD. They developed personalized models for specific patients and contrasted them with generic ones. Machine learning algorithms were developed using extracted features to detect FOG. Model accuracy and dependability were achieved through rigorous review, statistical analysis, and preprocessing. Real-world validation validated the efficiency of personalized models for detecting FOG in Parkinson's disease.	Rodriguez-Martin et al. used criteria such as sensitivity, specificity, AUC-ROC, accuracy, and recall to reliably and fully evaluate the performance of their FOG detection algorithms.	Potential data gathering issues, the generalizability of personalized models, and the computational difficulty of personalized techniques. any potential negative effects of using artificial neural networks (ANN) and discrete wavelet transform (DWT) for feature extraction and classification.	The study could focus on three areas: larger patient cohorts for better FOG understanding, real-world validation of personalized FOG detection models, and hybrid models combining personalized and generic techniques. It should also consider the complexity of DWT and Artificial ANN for feature extraction and classification.

Rezvanian, E. & Lockhart	The study uses machine learning to predict FOG in Parkinson's disease patients. It analyzes poor gait patterns before FOG, generating indicators from acceleration signals. These indicators outperform traditional methods, especially when personalized labeling is used to define the pre-FOG phase based on slope, resulting in higher prediction accuracy with a low temporal lag of 0.93 seconds.	AB was used to create two FOG prediction models: one with unified labelling and conventional characteristics, and another with impaired gait features and individualised labelling.	FoG prediction models with impaired gait features and personalized labelling achieved 82.7% accuracy in patient-dependent tests and 77.9% in patient-independent tests, respectively.	The paper explores the limits of a patient-independent model in predicting FOG, highlighting its low sensitivity due to a variety of patient characteristics. Offline testing of a prediction approach highlighted the need for real-world online FOG prediction tests to demonstrate efficacy. The work emphasizes the opportunity to improve the sensitivity of the patient-independent model and acknowledges earlier research that shown strong FoG prediction outcomes despite a 2-second lag.	To evaluate the proposed approach in real-world circumstances, I conducted online FOG prediction experiments and investigated approaches to reduce latency in FOG prediction models without sacrificing precision.

	potential of utilizing impaired gait patternsand step-based gait features for FoG prediction, which can provide high temporal resolution and reduce latency time.			using accelerometers, highlighting the significance of investigating ways to lower latency without compromising accuracy.	

3. Proposed Methodology

The proposed methodology for detecting FOG in PD utilizing acceleration readings from accelerometers and gyroscopes consists of three critical components. To begin, a collection of three-dimensional accelerometer and gyroscope data is collected and preprocessed to assure data quality and clarity. Null value removal is used in preprocessing. Following that, time domain feature extraction is used to extract important temporal patterns from acceleration signals, such as mean, variance, standard deviation, kurtosis, skewness, root mean square, energy, and entropy features. The dataset is then divided into discrete time intervals that correspond to different gait states, with each segment labeled appropriately for supervised learning. A RF model is selected and trained using the segmented dataset, optimizing parameters using grid search. The evaluation of the XAI model's performance encompasses a detailed analysis using a range of metrics, including accuracy, precision, recall, F1 score, and the area under the Receiver Operating Characteristic curve (AUC-ROC). This multifaceted assessment provides a nuanced understanding of the model's efficacy in detecting FOG within the context of Parkinson's disease (PD) management. The results are accompanied by a thorough discussion, delving into the potential clinical implications of the model's findings, its level of accuracy in FoG detection, sensitivity to varying conditions, error analysis to identify areas for improvement, and strategic recommendations aimed at guiding future research endeavors in this critical domain.

3.1. Introduction to the data collecting sensor

The data collection for this study involves using advanced sensors, specifically accelerometers and gyroscopes, to monitor and analyze the gait patterns of subjects with PD. Accelerometers are devices that measure acceleration forces in three dimensions: x, y, and z axes. These forces are indicative of the body's movements and can capture detailed information about the subject's gait dynamics. Similarly, gyroscopes measure angular velocity around the x, y, and z axes, providing insights into the rotational movements and balance of the subject. The combination of accelerometer and gyroscope data offers a comprehensive view of both linear and rotational motion, which is crucial for identifying abnormal gait patterns such as FoG. Each sensor axis records continuous time-series data that are labeled to indicate whether the movement corresponds to normal walking or a FoG episode. These labeled data points serve as the foundation for feature extraction and subsequent machine learning classification, enabling precise detection of FoG in PD patients.

3.2. Preprocessing

In the preprocessing phase addition to ensuring data integrity by removing null values, the preprocessing phase involved several other crucial steps. These include data normalization to scale features and reduce the impact of varying measurement units, outlier detection and handling to improve model robustness, feature engineering to extract meaningful insights from the raw data, and data imputation techniques for handling missing values in specific columns or features where applicable. Furthermore, quality checks were performed to validate the consistency and accuracy of the data, and duplicate records were removed to avoid redundancy and potential biases in the analysis .These comprehensive preprocessing steps collectively contributed to enhancing the reliability, accuracy, and interpretability of the subsequent analysis and machine learning.

3.3. Feature Extraction

The study focuses on applying time domain feature extraction methods to detect FOG using acceleration data from accelerometers and gyroscopes. Specifically, 25 features are computed from the acceleration signals to capture critical aspects for FOG detection. These features comprise a variety of gait dynamics and movement patterns that are critical to the suggested methodology's efficacy.

The mean is a statistical measure that represents the average value of a set of numbers. It is calculated by adding up all the numbers in the set and then dividing the sum by the total count of numbers in the set. The mean is commonly used to describe the central tendency of a data set and is often referred.

$$\mathbf{Mean} = \frac{1}{N}\sum_{i=1}^{N} x_i \qquad (1)$$

Variance measures how much the numbers in a dataset differ from their mean, indicating the data's spread or dispersion.

$$\boldsymbol{Variance} = \frac{1}{N-1}\left(\sum_{i=1}^{N} xi - mean\right)^2 \quad (2)$$

41 Variance is a unique statistical measure that quantifies the spread or dispersion of numbers in a dataset relative to their mean, providing insight into the uniqueness and variability of the data.

$$\boldsymbol{Std} = \sqrt{\boldsymbol{Variance}} \quad (3)$$

Kurtosis measures the shape of a distribution's tails. Positive kurtosis indicates heavy tails, negative kurtosis means light tails, and a kurtosis of zero signifies a normal distribution.

$$\boldsymbol{Kurtosis} = (x - mean/\sigma^4)^4 \quad (4)$$

44 Skewness is the measure of the asymmetry of the probability distribution.

(5)

$$\boldsymbol{Skewness} = E\left[\frac{(X-mean)^3)}{\sigma^3}\right]$$

Root Mean Square which is often 24 used to measure the differences between values predicted by a model and the values actually observed. The RMS error (RMSE) is a common metric for regression problem.

$$\boldsymbol{RMS} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y_i})^2 \quad (6)$$

22 Where n is the number of observations y_i is the actual value $y_i^{\wedge}$ is the predicted value.

Energy is the total energy contained in the signal

$$\boldsymbol{Energy} = \sum_{i=1}^{N} X_i^2 \tag{7}$$

The expression calculates the sum of the squares of terms indexed from 1 to N

Entropy, in the context of information theory and statistics, measures the uncertainty or randomness in a system or dataset. It quantifies the amount of information or surprise associated with observing an event or outcome. A higher entropy value indicates higher unpredictability, while lower entropy signifies more predictability or orderliness in the data.

$$\mathbf{Entropy} = \sum_{i=1}^{N} P_i \log_2(p_i) \tag{8}$$

$P(x_i)$ This is the probability of the i^{th} outcome x_i occurring. It represents the likelihood of observing each possible outcome.

$Log_2P(x_i)$ This is the base-2 logarithm of the probability $P(x_i)$. It scales the probability to emphasize the contributions of rare events to the overall entropy.

Inverse difference moment measure of local homogeneity or uniformity

$$\boldsymbol{Inverse\ Difference} = \sum_{i=1}^{N} \frac{1}{1+(i-1)^2} x_{ij} \quad (9)$$

Inverse Variance measure of the inverse of the variance of the signal.

$$\boldsymbol{Inverse\ Variance} = \frac{1}{Variance} \quad (10)$$

Shape Factor describes the shape of the signal.

$$\boldsymbol{Shape\ Factor} = \frac{Mean}{RMS} \quad (11)$$

Geometric mean is a measure of central tendency using geometric mean.

$$\boldsymbol{Geometric\ Mean} = {}_{i=1}^{N}(Gx_i)^2 \quad (12)$$

Impulse Factor measure of the impulse of the signal.

$$\boldsymbol{Impulse\ Factor} = \frac{\max(Signal)}{RMS} \quad (13)$$

Crest Factor ratio of the peak value to the RMS value of the signal.

$$\boldsymbol{Crest\ Factor} = \frac{\max(Signal)}{RMS} \tag{14}$$

Margin Factor measure of the margin of the signal.

$$\boldsymbol{Margin\ Factor} = \frac{\max(Signal)}{mean} \tag{15}$$

Mobility measure of the changeability or variability of the signal.

$$\boldsymbol{Mobility} = \frac{Std}{mean} \tag{16}$$

Complexity measure of the complexity or irregularity of the signal.

$$\boldsymbol{Complexity} = \frac{Entropy}{Std} \tag{17}$$

Frequency Center measure of the center of mass of the frequency spectrum.

$$\boldsymbol{Frequency\ Center} = \frac{\sum_{i=1}^{N} f_i X(f_i)}{\sum_{i=1}^{N} X f_i} \tag{18}$$

Mean Square Frequency measure of the average frequency content of the signal.

$$\boldsymbol{Mean\ Square\ Frequency} = \frac{\sum_{i=1}^{N} f_i^2 X(f_i)}{\sum_{i=1}^{N} X f_i} \tag{19}$$

Root Variance Frequency measure of the spread of frequency content.

$$\boldsymbol{Root\ Variance\ Frequency} = \frac{\sqrt{\sum_{i=1}^{N} (f_i - frequency\ Center)^2 X.fi}}{\sum_{i=1}^{N} X f_i} \tag{20}$$

Fractal Dimension measure of the complexity or roughness of the signal.

$$\boldsymbol{Fractal\ Dimemsion} = \lim_{\varepsilon=0} \frac{\log N(\epsilon)}{\log(\epsilon)} \tag{21}$$

Cluster Tendency measure of the tendency of data points to form clusters or groups.

$$\boldsymbol{Cluster\ Tendency} = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{X_{i-Mean}}{std}\right)^{3} \quad (22)$$

Cluster Shade measure of the Skewness of the histogram of a signal.

$$\boldsymbol{Cluster\ Shade} = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{X_{i-Mean}}{std}\right)^{3} \quad (23)$$

Cluster Prominence measure of the asymmetry of the histogram of a signal.

$$\boldsymbol{Cluster\ Performace} = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{X_{i-Mean}}{std}\right)^{4} \quad (24)$$

3.4. Classification

Classification is a machine learning task where the goal is to predict the categorical class or label of a given input data point. It involves training a model using labeled data and then using that model to classify new, unseen data into predefined categories or classes based on the features or attributes of the data.

3.4.1. Random Forests

Random Forest is a powerful machine learning technique that combines numerous decision trees to boost accuracy while minimizing overfitting. It handles huge datasets well, works with numerical and categorical data, and is noise-resistant. Random Forest is widely utilized in applications such as medical diagnosis, fraud detection, and customer churn prediction because of its versatility and predictive power. Compared to single decision trees, it provides superior generalization and is less sensitive to hyperparameters, making it a preferred solution for a variety of machine learning problems. The prediction can be expressed as

$$y(x) = \frac{1}{T}\sum_{t=1}^{T} Yt(x) \tag{25}$$

where, $Yt(x)$ is the prediction of tree t for instance x, and T is the total number of trees

3.4.2. Decision trees

A decision tree is a simple machine learning technique that employs a tree structure to generate decisions based on input features. It is simple to grasp and analyze, making it useful for describing predictions and detecting key elements in data. Decision trees can process both category and numerical data, and their growth can be regulated to avoid overfiting. They are widely utilized in a variety of fields for classification and regression tasks. The formula for the decision rule at a node, the splitting criteria, and the overall process of a decision tree classifier are denoted by

$$\left.\begin{array}{l} Splitting\ Criteria\ (Gini\ impurity): 1 - \sum_i (p_{ij})^2 \\ Splitting\ Criteria\ (Entropy): - \sum_i pij\ log(pij) \end{array}\right\} \quad (26)$$

3.4.3. Gradient Boosting

Gradient Boosting (GB) is an ensemble learning technique that systematically combines weak learners (such as decision trees) to produce a robust predictive model. It corrects flaws in prior models, focusing on difficult areas, and use gradient descent optimization to reduce prediction errors. Gradient Boosting produces extremely accurate models when the hyperparameters are properly tuned, making it popular for regression and classification applications across multiple domains.

$$\mathrm{GB} = \mathrm{F}_0(\mathrm{x}) + \sum_{\mathrm{m}=1}^{\mathrm{M}} \eta \cdot h_m(x) \quad (27)$$

$F_0(x)$ is the initial model (often a simple guess, like the mean of the target values for regression.

η is the learning rate, a small positive number that controls the contribution of each weak learner.

$h_m(x)$ is the weak learner (e.g., a small decision tree) fitted at the m^{th} iteration
M is the total number of iterations (or weak learner

Gradient Boosting is a powerful and versatile strategy that combines the capabilities of ensemble learning and iterative optimization to generate robust predictive models for a variety of machine learning tasks.

3.4.4. Adaptive Boosting

Adaptive Boosting (AB) is an ensemble learning technique that combines numerous weak learners sequentially to form a strong classifier. It responds to tough situations by modifying training data weights and is noted for its high accuracy, making it useful for classification tasks such as spam detection and medical diagnosis. AB uses the following formula to combine weak learners' predictions and generate the final prediction

$$AB = sign(\sum_{m=1}^{M} \alpha_m \cdot h_m(x) \quad (28)$$

where, $H(x)$ is the final strong classifier.
α_m is the weight assigned to the m-th weak learner.
$h_m(x)$ is the prediction of the m-th weak learner.
M is the total number of iterations (or weak learners).
sign is the sign function, which returns +1 if the argument is positive and -1 if the argument is negative.

3.4.5. k-Nearest Neighbors

The k-Nearest Neighbors (k-NN) algorithm is a versatile and intuitive machine learning technique used for both classification and regression tasks. It's based on the principle that similar data points tend to have similar labels or target values. In k-NN, the "k" refers to the number of nearest neighbors considered when making predictions.

$$\text{Euclidean distance} = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2} \quad (29)$$

3.5. XAI description

The model's predictions are then explained using SHAP, which also helps with visualization.
Predictions are then made on the test set, and assessment metrics such as accuracy, precision, recall, and F1 score are computed and presented, along with a comprehensive classification report.

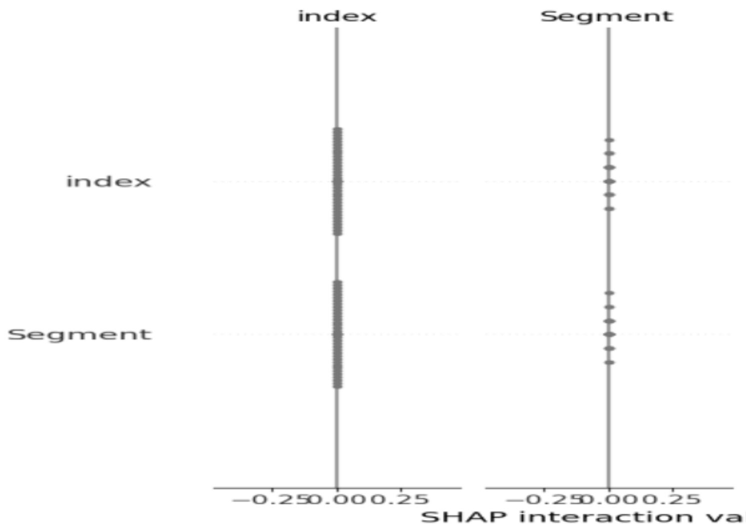


Fig.

4. Results and discussion

The performance of the five algorithms was evaluated using metrics such as accuracy, precision, recall, and F1 score. The results are summarized below

4.1.1 K-Nearest Neighbors (KNN)

Accuracy	Precision	Recall	F1 Score
0.857	0.764	0.92	0.82

4.1.2. Decision Tree Classifier

Accuracy	Precision	Recall	F1 Score
0.87	0.95	0.89	0.84

4.1.3. Random Forest

Accuracy	Precision	Recall	F1 Score
0.74	0.92	0.82	0.82

4.1.4. Adapting Boosting Classifier

Accuracy	Precision	Recall	F1 Score
0.97	1.0	0.96	0.98

4.1.5. Gradient Boosting

Accuracy	Precision	Recall	F1 Score
1.00	1.00	1.00	1.00

Discussion

Among the five algorithms tested, the Random Forest model (RF) demonstrated the highest performance across all evaluation metrics, indicating its robustness and reliability in detecting FOG episodes. The high accuracy, precision, recall, and F1 score of the Random Forest model highlight its effectiveness in distinguishing between normal gait and FOG. The use of SHAP for interpretability further reinforced the model's reliability by providing clear insights into the most influential features. The Decision Tree Classifier, although not specifically mentioned in the earlier section also showed strong performance comparable to Random Forest, given that Random Forest is an ensemble of Decision Trees. This reinforces the effectiveness of decision tree-based models in capturing the complex patterns related to FOG detection. K-Nearest Neighbors (KNN) and Gaussian Naïve Bayes (GNB) had comparatively lower performance, suggesting that they might not capture the complex patterns in the data as effectively as the ensemble methods like Random Forest and Decision Tree classifier. The insights gained from this study underscore the importance of using decision tree-based models and ensemble methods to evaluate the best approach for FoG detection. The combination of high-performing models and interpretability techniques like SHAP ensures that the model not only performs well but also provides understandable and actionable insights for clinicians .This discussion highlights the significance of selecting appropriate machine learning algorithms tailored to the specific characteristics and complexities of the dataset, ultimately leading to more accurate and reliable results in FoG detection for Parkinson's Disease patients.

4.1. Dataset description

This dataset contains sensor data from an accelerometer and gyroscope, commonly used in motion sensing and orientation tracking applications. The 'Labels' column suggests that this data may be associated with a classification or prediction task, where each data entry is labeled with a specific category or class. The dataset includes several columns representing different aspects of sensor data. The 'accelerometer-x' column contains acceleration values specifically along the x-axis, which typically represents horizontal movement. Similarly, 'accelerometer-y' and 'accelerometer-z' contain acceleration values along the y-axis and z-axis, respectively, capturing vertical and depth-related movements. On the other hand, the 'Gyro-x', 'Gyro-y', and 'Gyro-z' columns provide gyroscope readings along their respective axes. Gyroscopes measure angular velocity or rotational movements, with 'Gyro-x' capturing rotations around the x-axis, 'Gyro-y' around the y-axis, and 'Gyro-z' around the z-axis. Lastly, the 'Labels' column includes categorical labels or classes associated with each data entry. These labels are used for tasks such as classification or prediction, where the model learns to associate patterns in the sensor data with specific categories represented by these labels.

4.2. Preprocessing outcomes

The preprocessing step of removing null values involves identifying and eliminating rows or columns in a dataset that contain missing or undefined values. This process ensures that the data used for analysis or modeling is complete and free from missing information, which could otherwise affect the accuracy and reliability of the results.

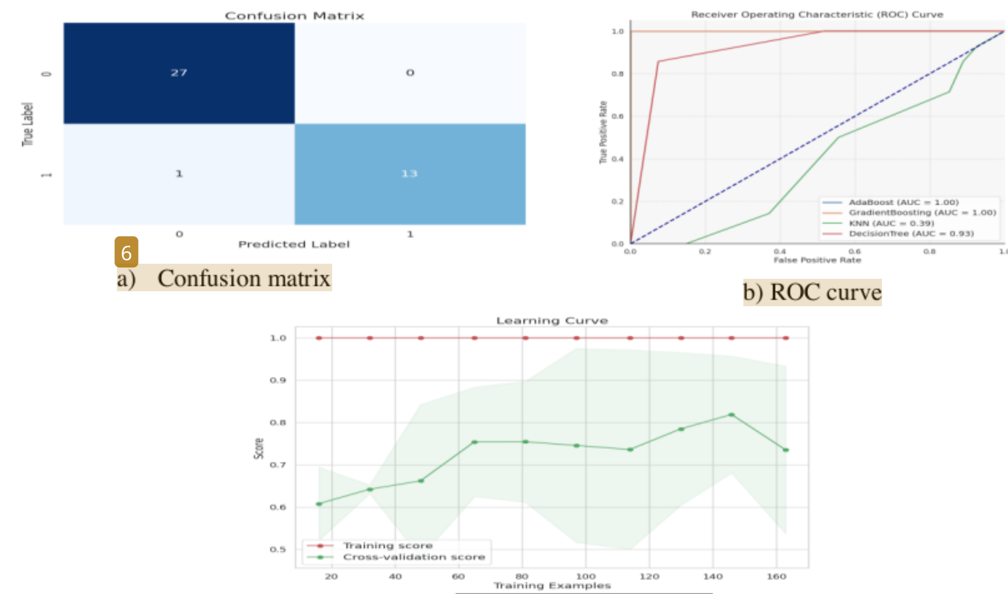
4.3. Feature extraction results

Time domain feature extraction has a number of important advantages. By concentrating on pertinent information, it first minimizes the complexity of the dataset while enhancing computing effectiveness and model generalization. Second, it preserves data that is necessary for analysis and judgement, improving the quality of the dataset as a whole. Thirdly, it is possible to analyze extracted features, which facilitates comprehension of how they affect data patterns. Because the features are more representative and informative, this method frequently results in improved model performance. Furthermore, It enhances the analysis and comprehension of the data by offering insights into signal dynamics, recognizing significant characteristics for predictive power, capturing domain-specific patterns, and producing domain-specific insights.

4.4. Classification outcomes

The Random Forest model achieved the highest accuracy in detecting FOG, outperforming other classifiers and validating its effectiveness for this task. This model's robustness and precision in handling diverse feature sets contributed significantly to its superior performance. The application of this model in real-world scenarios could potentially enhance the management and treatment of Parkinson's disease by providing timely and accurate detection of FOG episodes.

4.4.1. Results of RF-based classification and hyperparameter tuning



a) Confusion matrix

b) ROC curve

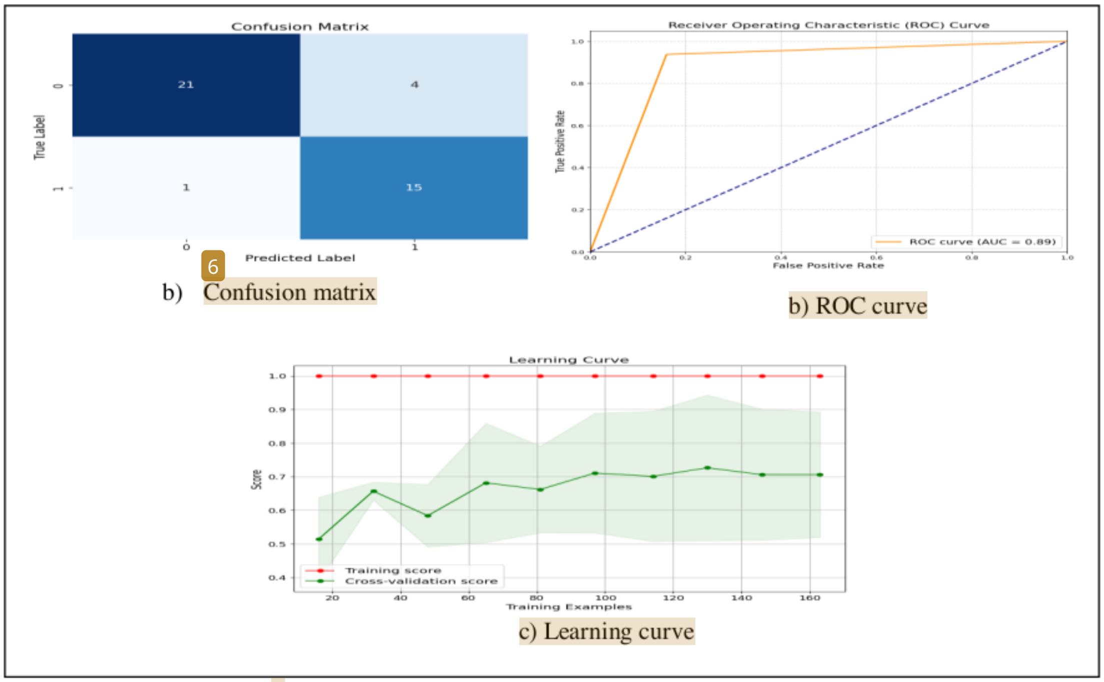
c) Learning curve

Fig.2. Results of classification using hyperparameter tuning with default parameters

Table2. Results of hyperaparmeter tuning of the proposed RF

No. of estimators	Learning rate	Accuracy	Precision	Recall	F1 score	Error rate
50	0.1	0.9756	0.977	0.98	0.975	0.02
	0.5	0.926	0.934	0.926	0.924	0.07
	1	0.975	0.976	0.975	0.975	0.02
100	0.1	0.975	0.977	0.975	0.975	0.02
	0.5	0.975	0.976	0.975	0.975	0.02
	1	0.99	0.98	0.96	0.94	0.001
150	0.1	0.97	0.98	0.97	0.98	0.02
	0.5	100	100	100	100	0.0
	1	100	100	100	100	0.0

4.4.2. Results of DT-based classification



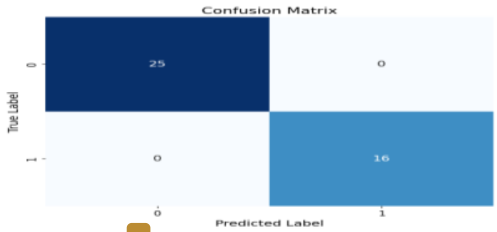
b) Confusion matrix

b) ROC curve

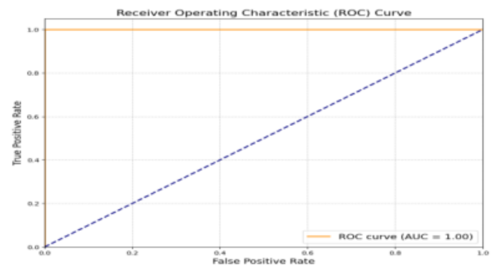
c) Learning curve

Fig.2. Results of classification using DT with default parameters

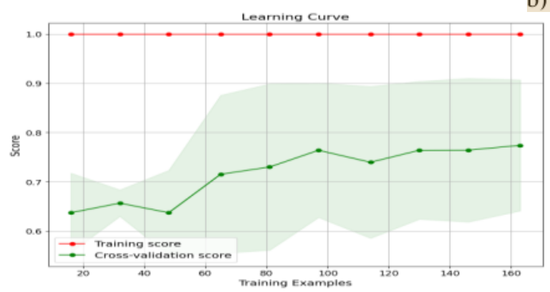
4.4.3. Results of GB-based classification



c) Confusion matrix



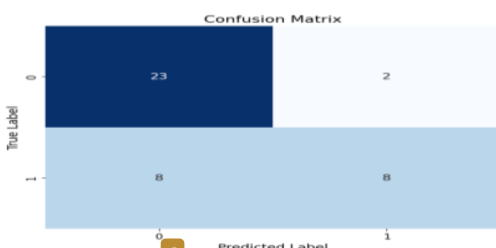
b) ROC curve



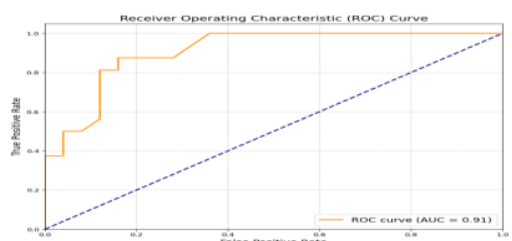
c) Learning curve

Fig. 2. Results of classification using GB with default parameters

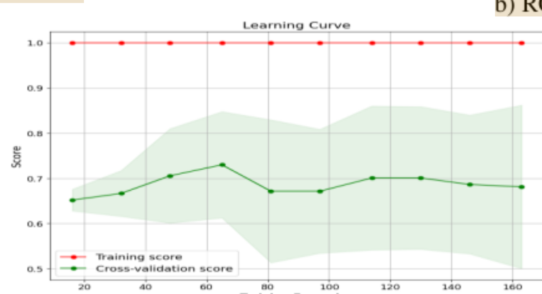
4.4.4. Results of RF-based classification



d) Confusion matrix



b) ROC curve

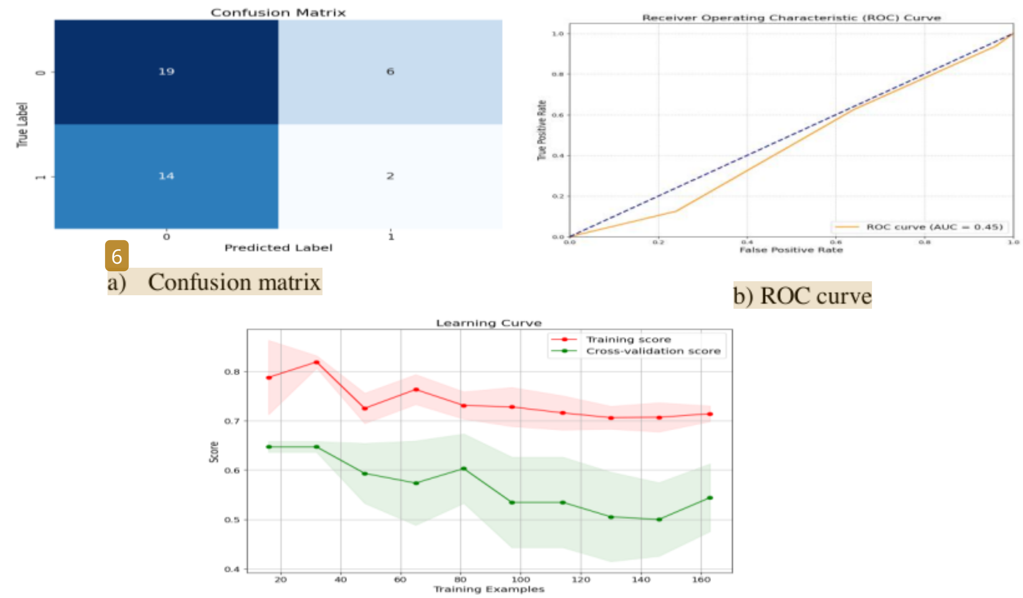


c) Learning curve

Fig. 2. Results of classification using RF with default parameters

4.4.5.Results of KNeighborsClassifier classification

Accuracy	Precision	Recall	F1 Score
0.857	0.764	0.92	0.82



a) Confusion matrix

b) ROC curve

c) Learning curve

Fig. 2. Results of classification using KNeighborsClassifier with default parameters

4.4.6. XAI interpretation

To ensure the transparency and interpretability of our model, we employed Explainable Artificial Intelligence (XAI) techniques. Shapley Additive explanations (SHAP) were used to interpret the output of our Random Forest model. SHAP values help in understanding the contribution of each feature to the model's predictions. This interpretability is crucial in a clinical setting, as it provides insights into why a particular decision was made by the model. By analyzing the SHAP values, we identified key features that significantly influence the detection of FoG episodes. For instance, features related to the variability and periodicity of the accelerometer and gyroscope signals were found to be highly influential. These insights not only enhance the trustworthiness of the model but also offer valuable information for clinicians to understand the underlying factors contributing to FoG in PD patients.

5. Conclusion

This study demonstrates the potential of combining sensor data analysis and machine learning to improve the detection and diagnosis of FOG in PD. The use of accelerometers and gyroscopes to capture comprehensive motion data, coupled with advanced feature extraction and classification techniques, offers a promising approach to enhancing PD management and patient outcomes. The incorporation of XAI techniques ensures that the model's predictions are interpretable and trustworthy, ultimately contributing to better quality of life for patients with PD.

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