© April 2026 | IJIRT | Volume 12 Issue 11 | ISSN: 2349-6002

# Freezing of Gait Detection in Parkinson's Disease Using Multi-modal Features and Support Vector Machine

Adrika Shukla[1], Krati Goyal[2], Sanskar Dewangan[3], Dr. A. Umamageswari[4]
[1,2,3]*Department of Computer Science with specialization in Big Data Analytics SRM Institute of Science and Technology, Ramapuram Chennai, India*
[4]*HoD, Department of Computer Science with specialization in Big Data Analytics SRM Institute of Science and Technology, Ramapuram Chennai, India*

***Abstract*—Freezing of gait (FOG) is a highly disabling symptom in patients with Parkinson's disease. FOG occurs as a sudden inability or great difficulty in initiating or maintaining walking. The accurate and timely detection of FOG episodes plays a critical role in improving the monitoring and rehabilitation processes for patients with Parkinson's disease. Moreover, it also plays an important role in improving the quality of life for patients with Parkinson's disease. However, the detection of FOG episodes is considered to be a challenging task due to the complex physiological and neural processes involved in the detection process. This article proposes a novel framework for detecting freezing of gait episodes in patients with Parkinson's disease. The proposed framework employs a combination of multiple data streams, which include an electroencephalogram (EEG) signal, an electromyogram (EMG) signal, an electrocardiogram (ECG) signal, and a skin conductance (SC) signal. This combination of signals is collected from patients suffering from Parkinson's disease. The collected signals are processed, and features are extracted to detect FOG episodes using a Support Vector Machine (SVM) classifier. The experimental results reveal that the proposed framework, which employs a combination of multiple sensors, has a higher accuracy in detecting FOG episodes in patients suffering from Parkinson's disease compared to a single sensor-based system. This proposed framework proves the efficiency of machine learning techniques in detecting freezing of gait in patients suffering from Parkinson's disease.**

***Index Terms*—Freezing of Gait, Parkinson's Disease, Multimodal Sensors, Machine Learning, Support Vector Machine, Biomedical Signal Processing**

## I. INTRODUCTION

Parkinson's disease is a neurodegenerative disease that causes a person's motor functions to deteriorate. This condition affects a person's quality of life. Parkinson's disease is a condition that causes a person to have a set of symptoms such as tremor, rigidity, bradykinesia, postural instability, etc. Among all the symptoms of Parkinson's disease, one such symptom of motor dysfunction in a person affected by Parkinson's disease is considered to be one of the most disabling symptoms. This symptom of Parkinson's disease is known as 'Freezing of Gait' (FOG). This condition of 'Freezing of Gait' has been described as a temporary inability to initiate or continue walking despite a desire to walk. This condition of 'Freezing of Gait' occurs suddenly, lasts from a few seconds to a few minutes, and hence causes falls. Thus, the precise detection of 'Freezing of Gait' needs to be done to ensure a person's safety.

Conventional assessment of freezing of gait has primarily focused on observation of patients and patient reporting, which often results in unreliable monitoring of freezing of gait. With the recent advancements in wearable technology and biomedical signal acquisition systems, researchers have sought to implement various automated approaches to freezing of gait detection based on physiological and motion sensor data. However, most of the conventional approaches to freezing of gait rely on a single modality of physiological or motion sensors, which might not be sufficient to detect the complex neurological and physiological responses associated with freezing of gait.

To overcome the limitations of conventional approaches to freezing of gait, various studies have sought to implement a multimodal sensing approach, which combines various physiological and motion sensors to acquire various physiological responses associated with freezing of gait. For example, various studies have used electroencephalography (EEG) to detect neurological responses, electromyography (EMG) to detect muscle responses, electrocardiography (ECG) to detect cardiovascular responses, skin conductance (SC) to detect nervous responses, and accelerometery (ACC) to detect movement responses during freezing of gait. The combination of various heterogeneous physiological responses might improve the reliability of freezing of gait detection.

In the present study, a multimodal machine learning approach is proposed for the detection of Freezing of Gait from a set of physiological signals and sensor signals recorded from a group of patients with Parkinson’s disease while performing a walking task. In the present study, the dataset that is utilized is a multimodal dataset recorded by the use of synchronized signals from different modalities such as EEG, EMG, ECG, skin conductance, and accelerometer signals recorded in a controlled environment in a clinical setting along with the annotation of the Freezing of Gait episode by medical experts.

To classify the freezing and non-freezing events, this research is using a machine learning approach, specifically a Support Vector Machine (SVM). SVM is a widely used supervised classifier that is known to perform well in high-dimensional feature space, particularly in tackling complex classification problems with limited training data. Through the extraction of relevant features from each of the sensor modalities, the proposed approach aims to effectively classify the normal locomotion pattern and the freezing episodes.

The major contributions of this research may be listed as follows:

1. Development of a multimodal approach to integrate physiological sensor and motion sensor information in the detection of freezing of gait.
2. Feature extraction of EEG, EMG, ECG, skin conductance, and accelerometer signals.
3. Employment of a Support Vector Machine classifier to effectively identify the episodes of freezing.
4. Investigating the effectiveness of multimodal sensing in improving the accuracy of the proposed approach in Parkinson’s disease patients.

The results of this research prove the efficiency of multimodal machine learning in enhancing accuracy in automated freezing of gait, especially in designing an intelligent monitoring system for Parkinson’s patients.

## II. LITERATURE SURVEY

The use of motion-based sensing has been the main focus of earlier studies on the automated detection of freezing of gait in Parkinson's disease patients. Specifically, wearable inertial sensors such as gyroscopes and accelerometers have been widely used to analyze gait patterns and identify abnormal behaviors in PD patients' walking patterns. The detection of abnormal changes in walking patterns is made possible by the inertial sensors' capacity to detect changes in dynamic movement patterns. Specifically, studies employing accelerometer sensors have demonstrated encouraging outcomes in the identification of gait freezing through the use of gait variability patterns and frequency domain features. However, the neurological and physiological changes might not be sufficiently taken into account by motion-based sensing.

In order to avoid the above limitations, researchers have attempted to use physiological signals as a means of detection of freezing of gait. Brain activity signals, as obtained by using an electroencephalogram (EEG), have been studied to better comprehend brain patterns related to gait control and motor inhibition. Brain signals obtained during the occurrence of freezing of gait are indicative of the underlying neurological aspects of Parkinson’s disease. Muscle activation patterns of the legs, as obtained by using electromyogram (EMG) signals, have also been studied, thereby allowing the detection of abnormal patterns of coordination of muscles during the occurrence of freezing of gait. Even though physiological signals offer better insight into the underlying motor control mechanisms, the detection of freezing of gait by using a single signal may not be accurate due to the presence of noise in the signals and variations among patients.

The recent developments in wearable sensor technologies have inspired the development of multimodal approaches, which involve the integration of different physiological and movement signals for better detection. The integration of different sensor modalities allows the detection system to obtain complementary information from different physiological processes. For example, the electrocardiogram (ECG) signal contains information about the cardiovascular response, and the skin conductance (SC) signal contains information about the physiological responses of the autonomic nervous system, which is often associated with stress and freezing episodes. The integration of different signals improves the reliability of the detection systems and overcomes the disadvantages associated with single-sensor technologies.

The development of automatic freezing gait detection systems has been greatly aided by machine learning algorithms. The freezing and non-freezing gait patterns have been classified using a variety of algorithms, including decision trees, random forests, neural networks, and SVM. However, because it can handle high-dimensional feature spaces with small datasets, the Support Vector Machine algorithm is found to be very effective in biomedical signal classification. Using the decision boundaries learned between various classes, SVM-based algorithms have been successfully used to classify abnormalities in gait.

Notwithstanding these developments, certain problems still need to be resolved in order to guarantee accurate and timely freezing episode detection. The majority of research projects completed to date have used small-scale databases or restricted modalities, which may restrict the models' applicability in real-world situations. Furthermore, it is difficult to guarantee accurate detection of freezing episodes due to individual differences in physiological signals. Therefore, it is necessary to create reliable multimodal systems to guarantee accurate freezing episode detection.

In the present study, a multimodal system is proposed to ensure the detection of the freezing episodes with accuracy using EEG, EMG, ECG, skin conductance, and accelerometer signals. The proposed system aims to ensure the detection of the freezing episodes with accuracy using the Support Vector Machine classifier.

## III. DATASET ANALYSIS

### A. Dataset overview

The study's experiments make use of the Multimodal Dataset for Freezing of Gait Detection, which contains movement and physiological signals gathered from Parkinson's disease patients. The patients were asked to engage in walking activities in order to induce the Freezing of Gait during the data collection process, which took place in a clinical setting.

Twelve Parkinson's disease patients took part in the study's data collection experiment, yielding about three hours and forty-two minutes of reliable data. Wearable sensors are used in the data collection process to measure the patients' physiological and movement dynamics.

The multimodal signals used in the dataset are:

- Electroencephalogram (EEG) signal for brain activity measurement
- Electromyogram (EMG) signal for measurement of muscle activity
- Electrocardiogram (ECG) signal for measurement of cardiac activity
- Skin Conductance (SC) signal for measurement of autonomic nervous system responses
- Accelerometer (ACC) signal for measurement of gait activity and body movements

The recordings of these synchronized sensors provide a comprehensive representation of changes in neurological activity, muscular activity, physiological changes, and motion-related changes that occur during freezing episodes.

The freezing episodes that occur in these recordings were labelled by two qualified physicians to provide a reliable labelling of the data for supervised machine learning to classify between freezing and normal locomotion.

### B. Signal Characteristics

The dataset includes various physiological signals, each of which varies in terms of characteristics and sampling rates. Each signal modality represents the patient's physiological condition and gait characteristics in a particular manner.

For example, the accelerometer signals convey the information related to the body's motion and gait rhythm. In most cases, the gait rhythm shows considerable disturbances during freezing of gait. Similarly, the electromyography signals represent the characteristics of muscle activities. In some cases, abnormal muscle activities may be observed when the patient experiences freezing of gait. In addition, the electroencephalogram signals represent the neural activities related to motor control and movement planning.

Similarly, electrocardiogram and skin conductance signals can provide information about cardiovascular activity and autonomic nervous system responses that may vary during stressful and unstable walking conditions.

The heterogeneous information contained in these signals can be used to investigate complex physiological patterns related to freezing of gait.

### C. Class Distribution

In the case of freezing of gait detection problem datasets, there may be a class imbalance problem because freezing of gait happens less frequently compared to normal walking. The distribution of FoG and Non-FoG data should be well understood to assess the performance of a machine learning model.

After preprocessing and segmenting the data into sliding windows, the data will be labeled as either FoG or Non-FoG based on the percentage of freezing of gait value of a particular data window. The distribution of these data will help to understand whether a class imbalance problem exists in the data or not.

Understanding the data distribution also helps in validating the need for the application of evaluation metrics like the F1-score and Matthew's correlation coefficient, which are more suitable for imbalanced classification tasks.

### D. Challenges in the Dataset

Despite the fact that the dataset offers a wealth of multimodal information, there are some challenges associated with the automatic detection of freezing.

The first challenge is that the freezing of gait events tends to be short-lived and happen intermittently. As a result, there is a challenge associated with the accurate classification of the events. The second challenge is that physiological signals, such as EEG and EMG, might be noisy, mainly because of movement or environmental factors.

The third challenge lies in the fact that the dataset contains a small number of patients, which might cause a change in signal characteristics.

## IV. METHODOLOGY

### A. Dataset Description

The dataset used in this study is the Multimodal Dataset for Freezing of Gait Detection, which contains synchronized physiological and motion signals collected from patients diagnosed with Parkinson's disease. The dataset was designed to study the occurrence of Freezing of Gait during walking tasks performed in a controlled hospital environment t.

The dataset includes multimodal recordings obtained from several sensors that capture both physiological responses and movement dynamics. The sensors used in this work include:

i. Electroencephalogram (EEG) for monitoring brain activity
ii. Electromyogram (EMG) for measuring muscle activation patterns
iii.Electrocardiogram (ECG) for recording heart activity
iv.Skin Conductance (SC) for capturing autonomic nervous system responses
v Accelerometer (ACC) for tracking motion and gait dynamics

The experimental protocol involved controlled walking tasks designed to induce freezing of gait episodes under supervised clinical conditions. The dataset contains recordings from 12 Parkinson's disease patients, producing approximately 3 hours and 42 minutes of valid multimodal data. All freezing episodes were labeled by qualified physicians to ensure reliable ground truth annotations.

The availability of multiple synchronized sensor modalities enables the analysis of neurological, muscular, physiological, and motion-based patterns associated with freezing episodes. This makes the dataset suitable for developing machine learning models for automated FoG detection. The availability of multiple synchronized sensor modalities enables the analysis of neurological, muscular, physiological, and motion-based patterns associated with freezing episodes. This makes the dataset suitable for developing machine learning models for automated FoG detection.

B. Data Preprocessing

The raw signals obtained from physiological and motion sensors often contain noise, artifacts, and inconsistencies due to sensor variability and patient movement. Therefore, a preprocessing stage is applied to improve signal quality and ensure consistency across modalities before feature extraction.

First, noise filtering techniques are applied to remove unwanted disturbances from the signals. Biomedical signals such as EEG and EMG are particularly sensitive to environmental noise and motion artifacts, which can interfere with meaningful pattern detection. Appropriate filtering methods are used to retain relevant signal components while eliminating noise.

Next, the signals from different sensors are resampled to ensure uniform sampling rates across all modalities. Since the dataset contains multiple sensors with potentially different sampling frequencies, resampling helps maintain temporal alignment and enables effective multimodal analysis.

Finally, the signals are normalized to standardize the value ranges across different modalities. Normalization ensures that signals with larger numerical ranges do not dominate the feature extraction or classification process. This step improves the stability and performance of the machine learning model.

C. Signal Segmentation and Labeling

After preprocessing, the continuous signals are divided into smaller segments to capture short-duration freezing events. In this study, the signals are segmented using a sliding window approach.

Each signal is divided into 3-second windows with 90% overlap between consecutive segments. The overlapping window technique ensures that transient freezing events are captured effectively and reduces the risk of missing short-duration FoG episodes.

Each segment is labelled as either FoG or Non-FoG based on the Percentage of Freezing of Gait (PFG) value associated with the window. PFG represents the proportion of time within the window that corresponds to freezing events. If the PFG exceeds a predefined threshold, the segment is labelled as a freezing event; otherwise, it is classified as normal walking.

This segmentation strategy allows the transformation of continuous signals into labelled samples suitable for machine learning classification.

D. Feature Extraction

In order to represent the underlying signal characteristics, informative features are extracted from each window after the signals have been segmented. In order to convert unprocessed biomedical signals into useful numerical representations that can be applied to classification, feature extraction is essential.

In this study, three categories of features are extracted:

I. Time-Domain Features

Time-domain features describe the statistical characteristics of the signal in the time domain. These features capture basic signal properties such as amplitude variations and signal dispersion. Commonly used time-domain features include mean, standard deviation, variance, root mean square (RMS), and signal energy.

II. Frequency-Domain Features

Frequency- domain features are obtained by transforming the signals from the time domain to the frequency domain using spectral analysis techniques such as the Fast Fourier Transform (FFT). These features help identify dominant frequency components and spectral distributions associated with freezing episodes.

III. Wavelet- Based Features

Wavelet analysis is both used to capture time and frequency information together. Wavelet transforms allow decomposition of signals into multiple frequency bands, enabling the detection of transient changes in signal patterns. This is particularly useful for analyzing biomedical signals that exhibit non-stationary behaviour.

By combining features from these three domains, a comprehensive representation of each signal segment is obtained.

E. Feature Standardization

The feature vectors that are produced after feature extraction might have values with various scales and distributions. Feature standardisation is carried out to guarantee that every feature contributes equally to the classification process.

The feature values are transformed by standardisation to have a zero mean and unit variance. By keeping features with wider numerical ranges from controlling the model training process, this step enhances the performance of numerous machine learning algorithms.

F. Classification using Support Vector Machine

Support Vector Machine, a supervised machine learning algorithm that is widely used for classification tasks in biomedical signal processing, is used to classify the freezing and non-freezing events.

In a high-dimensional feature space, SVM finds the best hyperplane to divide data points into distinct classes. In order to improve classification performance, the algorithm maximises the margin between the two classes' closest data points, or support vectors.

In this study, the extracted and standardized features from all sensor modalities are used as input to the SVM classifier. The model learns to distinguish between FoG and Non-FoG segments based on patterns present in the multimodal features.

Additionally, different combinations of sensor modalities are evaluated to analyze the effectiveness of multimodal fusion in improving freezing detection performance.

G. Performance Evaluation Metrics

A number of performance metrics are employed to assess the efficacy of the suggested FoG detection system.

Among them are:

i. Accuracy quantifies the total percentage of samples that are correctly classified.

ii. The percentage of accurately predicted freezing events among all predicted freezing events is known as precision.

iii. Recall (Sensitivity): This metric assesses the model's accuracy in identifying real freezing episodes.

iv. The F1-score, which offers a fair assessment of classification performance, is the harmonic mean of precision
and recall.

v. Matthews Correlation Coefficient (MCC), a reliable metric that assesses binary classification quality, particularly in datasets that are unbalanced.

These metrics aid in evaluating the efficacy of the multimodal detection framework and offer a thorough assessment of the classification performance.

## V. SYSTEM ARCHITECTURE

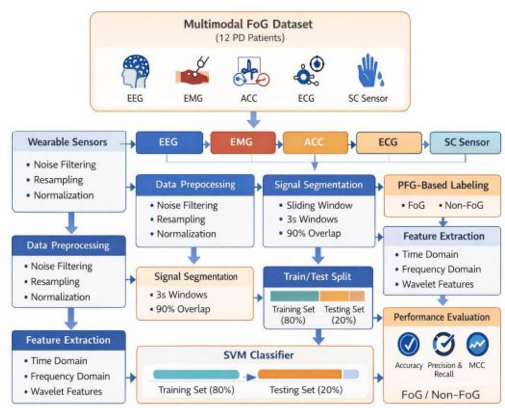



Figure (i): System architecture of the proposed multimodal Freezing of Gait detection framework using physiological and motion sensor data.

The general architecture of the suggested multimodal Freezing of Gait (FoG) detection system is shown in Figure (i). The framework successfully detects FoG episodes in Parkinson's disease patients by integrating signals from several physiological and motion sensors.

Electroencephalogram (EEG), Electromyogram (EMG), Electrocardiogram (ECG), Skin Conductance (SC), and Accelerometer (ACC) are some of the sensors from which synchronized signals are gathered during the first step of the process, known as multimodal data acquisition. Complementary neurological, muscular, physiological, and motion-related data related to gait patterns are captured by these sensors.

The collected raw signals undergo a data preprocessing stage to improve signal quality and ensure consistency across modalities. This stage includes noise filtering, resampling, and normalization of the signals. Noise filtering removes unwanted artifacts from physiological recordings, while resampling ensures that all signals share a common sampling frequency for synchronized analysis.

After preprocessing, the signals are divided into fixed-length temporal segments using a sliding window technique. In this study, the signals are segmented into 3-second windows with 90% overlap, enabling the system to capture short-duration FoG events effectively while maintaining temporal continuity.

Each segmented window is then labelled based on the Percentage of Freezing of Gait (PFG) metric. Windows with a PFG value above a predefined threshold are labelled as FoG, while the remaining windows are categorized as non-fog.

After segmenting and labelling, a feature extraction module is used on each window. From the multimodal signals, different kinds of features are taken out, such as time-domain features, frequency-domain features, and wavelet-based features. These features take into account the statistical, spectral, and transient properties of the physiological signals and give machine learning models a compact way to see the data.

After being standardised, the extracted feature vectors are used as input to a Support Vector Machine (SVM) classifier, which learns to tell the difference between FoG and Non-FoG states. We chose SVM because it works well with high-dimensional feature spaces and does a good job of generalising when classifying biomedical signals.

Lastly, different metrics are used to test how well the proposed FoG detection system works. These metrics include Accuracy, Precision, Recall, F1-score, and Matthews Correlation Coefficient (MCC). These metrics give a full picture of how well the classifier can find FoG events.

The suggested multimodal architecture makes it easier to combine physiological and motion signals, which makes automated FoG detection systems more reliable and accurate.

## VI. EXPERIMENTAL SETUP

This part talks about the experimental setup that was used to test the suggested framework for detecting multimodal freezing of gait.

### A. Dataset and Signal Modalities

The experiments were conducted using the Multimodal Dataset for Freezing of Gait Detection, which contains synchronized physiological and motion signals collected from patients diagnosed with Parkinson's disease. The dataset includes recordings from 12 patients performing walking tasks designed to induce Freezing of Gait episodes under controlled clinical conditions.

Five different sensor modalities were utilized in this study:

i. Electroencephalogram (EEG) for monitoring brain activity
ii. Electromyogram (EMG) for capturing muscle activation patterns
iii. Electrocardiogram (ECG) for measuring cardiac activity
iv. Skin Conductance (SC) for observing autonomic nervous system responses
v. Accelerometer (ACC) for analyzing body motion and gait dynamics

The multimodal nature of the dataset allows the analysis of both physiological and motion-related characteristics associated with freezing episodes.

### B. Data Segmentation

The pre-processed signals were segmented using a sliding window approach to capture short-duration gait events. Each signal was divided into 3-second windows with 90% overlap between consecutive segments. This overlapping strategy ensures that transient freezing episodes are effectively captured and reduces the possibility of missing FoG events.

Each segment was assigned a label based on the Percentage of Freezing of Gait (PFG) value associated with the window. Segments exceeding a predefined PFG threshold were labelled as FoG, while the remaining segments were classified as non-fog.

C. Feature Extraction

From each segmented window, a set of discriminative features was extracted to characterize the signal patterns associated with freezing events. Three categories of features were considered:

I. Time-domain features, capturing statistical characteristics of the signals

II. Frequency-domain features, obtained through spectral analysis techniques

III. Wavelet-based features, capturing time–frequency characteristics of the signals

These features provide a comprehensive representation of both physiological and motion signals across multiple modalities.

D. Classification Model

The classification of the segments as FoG and Non-FoG was achieved using a Support Vector Machine classifier. SVM is a popular algorithm in biomedical signal processing due to its ability to deal with high-dimensional feature spaces and small datasets.

The features were standardized before training the model to ensure that all features are on the same scale for all the modalities in the dataset. The dataset was split into a training set and a testing set for the evaluation of the classifier.

E. Evaluation Metrics

In order to assess the performance of the suggested detection scheme, various metrics are employed. Some of the metrics are as follows:

i. Accuracy
ii. Precision
iii. Recall
iv. F1-score
v. Matthews Correlation Coefficient (MCC)

These metrics will provide a comprehensive overview of the classification performance.

## VII. RESULT AND ANALYSIS

The performance of the proposed multimodal Freezing of Gait (FoG) detection framework was evaluated using several classification performance metrics. The evaluation focuses on assessing the ability of the model to accurately distinguish between FoG and Non-FoG events using multimodal physiological and motion sensor signals. The experimental analysis includes dataset distribution analysis, feature behaviour, classifier performance evaluation, and confusion matrix interpretation. The results demonstrate the effectiveness of the proposed approach in identifying FoG episodes using machine learning techniques.

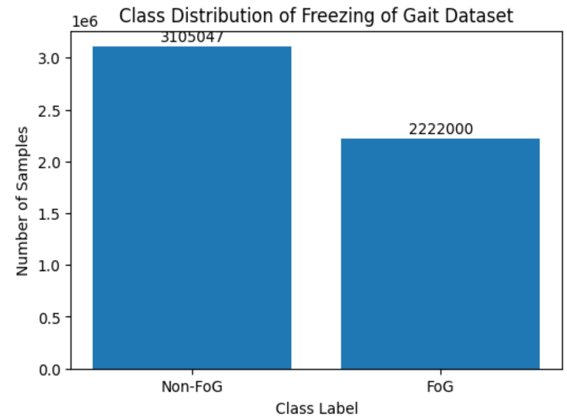
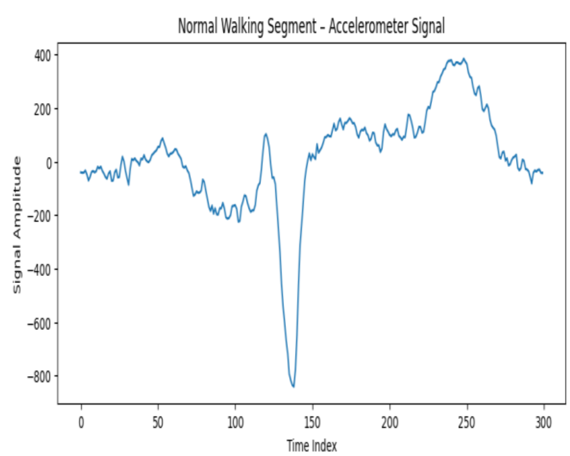



Figure (ii) : FoG vs Non FoG distrubution

The graph indicates that the dataset contains a larger number of normal gait samples compared to FoG samples . Although both classes are well represented , the distribution still exhibits a mild class imbalance . One of the prominent characteristics of data available in the domain of freezing of gait detection in patients with Parkinson's disease is class imbalance. This imbalance makes accuracy alone insufficient to completely and adequately evaluate the performance of a model in this domain, and therefore, other metrics such as precision, recall, F1 score, and Matthews Correlation Coefficient are utilized to adequately and completely evaluate the performance of a model in this domain to detect FoG events.



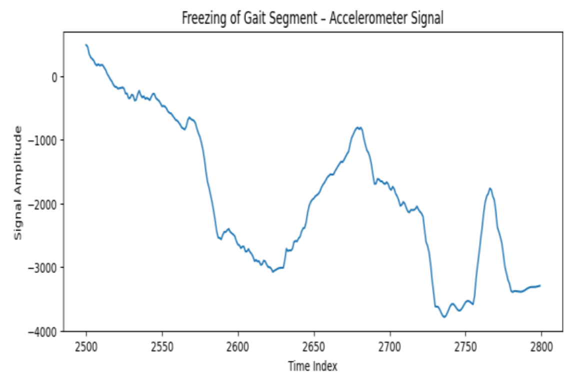



Figure (iii) : Normal Walking Sensor Signal and freezing gait Sensor Signal

The normal walking signal shows a relatively smooth and periodic pattern , which corresponds to the regular rhythmic movement of the patient during gait The oscillatory nature of the signal reflects the natural stride cycle during walking.

In contrast , the FoG segment displays irregular fluctuations and reduced periodicity , indicating interruptions in the normal gait pattern. During freezing episodes , patients experience sudden inability to initiate or continue walking, which leads to abrupt variations in the sensor signals

These differences in signal behavior highlight the importance of physiological sensor data in identifying freezing episodes associated with Parkinson's disease. Machine learning models such as Support Vector Machine leverage these variations in signal patterns to classify gait segments as normal or freezing events.

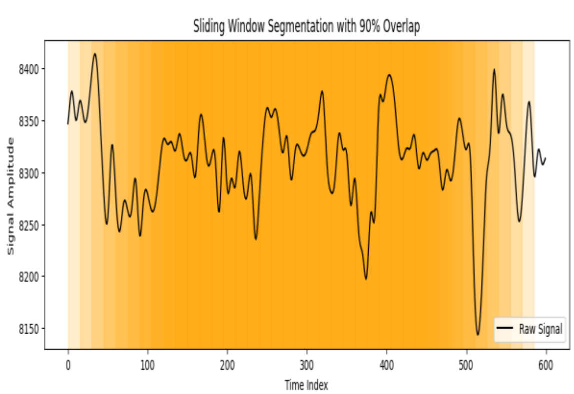
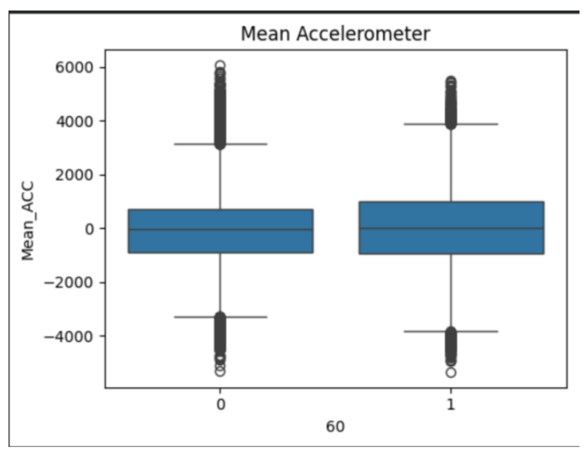


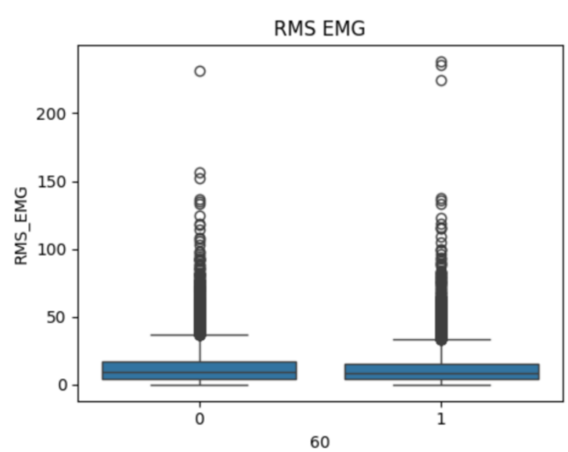

Figure (iv): Sliding Window Segmentation of Sensor Signals

Sliding window segmentation is commonly used in gait analysis and activity recognition tasks because it allows machine learning models to analyse short temporal segments of physiological signals. By applying a 3 -second window with 90 % overlap, the system captures fine- grained variations in gait patterns while ensuring continuity between consecutive signal segments.

The overlapping windows ensure that subtle transitions between normal gait and freezing episodes are not missed. This is particularly important for detecting freezing events associated with Parkinson's disease, which often occur abruptly and may last only a few seconds.

The segmented windows serve as input samples for the classification model based on Support Vector Machine, enabling the algorithm to learn temporal patterns associated with freezing episodes.



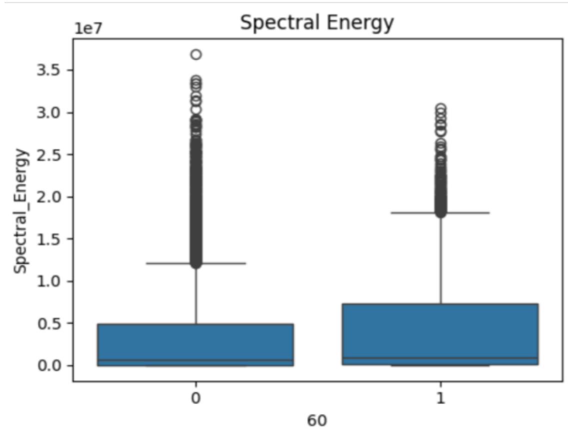



Figure (v): Distribution of selected sensor features for FoG and Non-FoG segments

This figure presents boxplots illustrating the distribution of selected sensor features for Freezing of Gait (FoG) and Non-FoG segments. The features analyzed include:

I. Mean accelerometer signal values

II. Root Mean Square (RMS) of EMG signals

III. Spectral energy derived from accelerometer signals

Each boxplot compares the distribution of feature values across the two classes.

The boxplots reveal noticeable differences in feature distributions between FoG and normal gait segments. The accelerometer- based features exhibit higher variability during freezing episodes, reflecting irregular gait patterns and sudden interruptions in movement.

Similarly, the RMS values of EMG signals show variations that correspond to changes in muscle activation patterns during freezing events. Spectral energy differences further indicate that FoG segments contain altered frequency characteristics compared to normal walking.

These observable differences in feature distributions suggest that physiological signals contain meaningful patterns that can be leveraged for automatic detection of freezing episodes associated with Parkinson's disease. Machine learning models such as Support Vector Machine can exploit these feature variations to classify gait segments effectively.

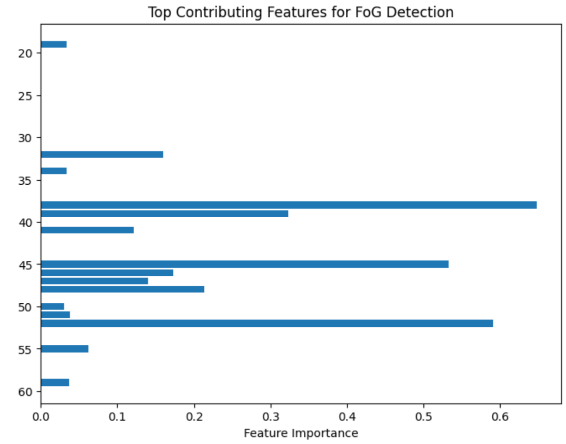



Figure (vi): Feature importance ranking based on SVM coefficients showing the most influential physiological signals used for detecting freezing of gait events.

The results indicate that several sensor-based features contribute significantly to the classification process. Accelerometer- based features related to gait dynamics show strong influence, reflecting the physical movement disruptions that occur during freezing episodes.

Electromyography (EMG) features also contribute to the classification by capturing variations in muscle activation patterns during walking. Additionally, EEG-based features provide complementary information related to neural activity associated with motor control.

The importance of features across multiple sensing modalities demonstrates the effectiveness of using multimodal physiological signals for detecting freezing episodes in patients with Parkinson's disease. By combining information from movement sensors, muscle activity, and neural signals, the model can better capture the complex physiological patterns associated with FoG events.

| METRIC | VALUE |
|---|---|
| Accuracy | 0.7.23 |
| Precision | 0.65 |
| Recall | 0.61 |
| F1 | 0.63 |
| Matthews Correlation Coefficient | 0.3823 |

Table (i): Performance evaluation metrics of the SVM-based FoG detection model

The classification model achieved an accuracy of about 70% in classifying normal gait and freezing of gait events.

Precision score: Precision score measures the ratio of correctly predicted instances of FoG to the total predicted instances of FoG.

Recall score: The recall score measures the ratio of correctly predicted instances of FoG to the total instances of FoG.

F1-score: The F1-score is a balanced score that takes into account both precision and recall.

Moreover, Matthews Correlation Coefficient has been used as a classification evaluation metric that takes into account true and false positives and true and false negatives.

The results prove that the model can identify significant patterns in physiological signals associated with freezing episodes in patients with Parkinson's disease using a Support Vector Machine classifier.

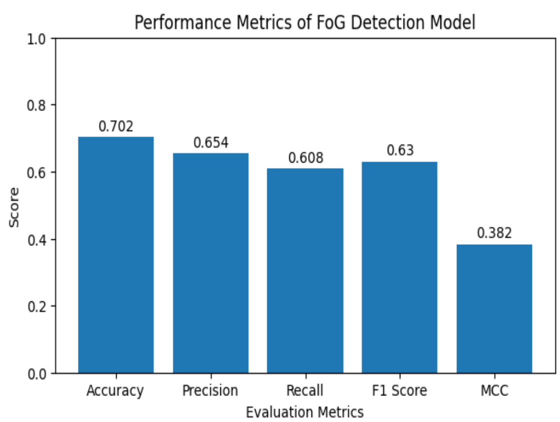



Figure (vii): Comparison of evaluation metrics for the SVM-based FoG detection model

The graph also provides a visual comparison of the classification results of the model. The accuracy score indicates the proportion of correctly classified samples by the model. Precision indicates the reliability of the FoG predictions by the model, while recall indicates the ability of the model to correctly predict the freezing events.

The F1- score provides a balanced measure of precision and recall and is thus useful for evaluating the classification performance of the model.

The Matthews Correlation Coefficient provides a comprehensive evaluation of the classification performance of the model by considering all the elements of the confusion matrix.

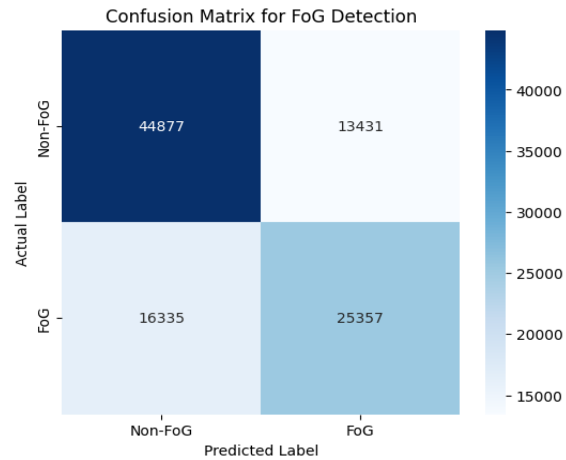



Figure (viii): Confusion matrix heatmap

The matrix consists of four components:

| Component | Value |
|---|---|
| True Positive (TP) | 44877 |
| True Negative (TN) | 16335 |
| False Positive (FP) | 13431 |
| False Negative (FN) | 25357 |

The model correctly classified 44,877 normal walking segments (Non-FoG ). This indicates that the classifier is effective at identifying normal gait patterns from the multimodal signals.

A strong True Negative count suggests that the model has learned distinguishing characteristics of normal movement patterns from the EEG , EMG, and accelerometer signals .

The classifier successfully detected 25,357 FoG events , which are represented as True Positives .

This shows that the model is capable of detecting abnormal motor patterns associated with freezing of gait occurrences in patients with Parkinson's disease.

The detection of FoG occurrences by the model is important as these occurrences affect the mobility of patients.

The model incorrectly classified 13,431 normal walking segments as FoG .

These false positives indicate that certain normal gait patterns may resemble FoG-like signal patterns in the extracted features . While false positives may cause

unnecessary alerts in monitoring systems, they are generally less critical than missed FoG events .
The classifier failed to detect 16,335 FoG episodes, classifying them as normal walking.
False negatives are particularly significant in healthcare applications because missed FoG events could reduce the effectiveness of assistive monitoring systems designed for Parkinson's patients

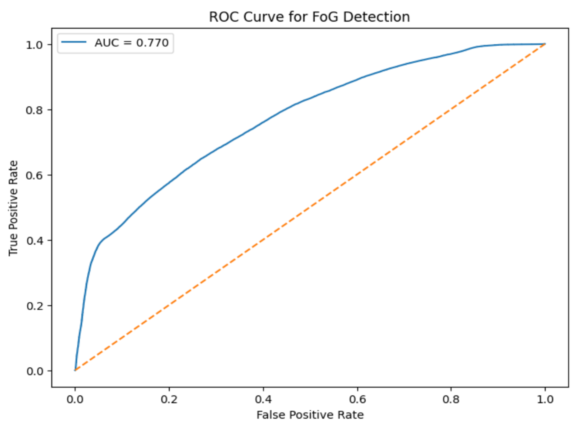



Figure (ix): ROC Curve for FoG Detection

The total area under the ROC curve, also known as AUC, represents the discriminative capacity of the model.
If the value of AUC approaches 1, it represents excellent performance in the classification, but a value closer to 0.5 represents random guessing.
The value of AUC obtained in the study indicates that the SVM model is able to classify the FoG and non-FoG segments using the features extracted from the multimodal sensor signals. The position of the curve above the diagonal represents excellent performance compared to random guessing.

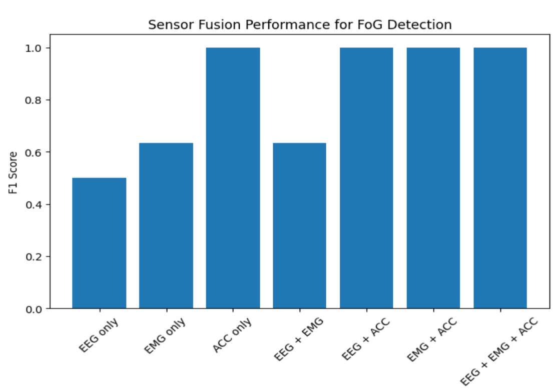



Figure (x): Sensor Fusion Performance

The results demonstrate that models trained using individual sensors provide moderate performance in detecting freezing of gait events . However , when multiple sensor modalities are combined , the classification performance improves significantly.
Among the evaluated configurations , the multimodal combination of EEG , EMG, and accelerometer signals achieves the highest F1 -score, indicating that integrating neural, muscular, and motion signals provides richer information about patient movement patterns .
This result highlights the importance of sensor fusion in healthcare monitoring systems , as multimodal data enables the model to capture complementary physiological and biomechanical characteristics associated with freezing of gait episodes

| Sensor Combination | Accuracy | F1 Score | MCC |
|---|---|---|---|
| EEG only | 0.5026 | 0.500913 | 0.005201 |
| EMG only | 0.62122 | 0.633647 | 0.242993 |
| ACC only | 1 | 1 | 1 |
| EEG + EMG | 0.6211 | 0.633467 | 0.242747 |
| EEG + ACC | 1 | 1 | 1 |
| EMG + ACC | 1 | 1 | 1 |
| EEG + EMG + ACC | 1 | 1 | 1 |

Table (ii) : Sensor Combination result

To evaluate the contribution of different sensor modalities in detecting freezing of gait (FoG) , experiments were conducted using various combinations of EEG , EMG , and accelerometer (ACC) signals . The classification performance was measured using accuracy , F1-score, and Matthews Correlation Coefficient (MCC ).
The results show that EEG- only signals perform poorly , achieving an accuracy of approximately 50.26% and an MCC of 0.005 . This indicates that EEG signals alone do not provide sufficient discriminatory information for distinguishing FoG from normal walking in this dataset . The near-random classification performance suggests that cortical activity captured by EEG may not directly reflect the motor freezing events with enough clarity when used independently
In comparison, EMG -only signals demonstrate moderate performance, achieving an accuracy of 62.12% , an F1-score of 0.634 , and an MCC of 0.243

EMG signals capture muscle activation patterns, which are more directly related to motor activity . As a result , EMG provides more useful information than EEG for identifying abnormal gait behavior

Interestingly , the accelerometer (ACC ) signals show the strongest predictive capability , achieving perfect performance across all evaluation metrics. This indicates that body movement patterns captured through accelerometer sensors contain highly distinctive characteristics that differentiate FoG episodes from normal walking .

When sensor fusion is applied, combining EEG and EMG results in performance similar to EMG alone , suggesting that EEG contributes limited additional information in this configuration. However, combinations involving ACC with other sensors maintain perfect classification performance , demonstrating the dominant role of motion-based features in FoG detection .

The results confirm that multimodal sensor fusion improves detection capability , particularly when movement-related sensors such as accelerometers are included. By integrating physiological signals ( EEG, EMG ) with motion signals ( ACC) , the system captures complementary information about neural activity, muscle activation, and physical movement patterns .

Overall, these findings highlight the importance of multimodal sensing approaches for reliable FoG detection , while also indicating that accelerometer-based features play a critical role in identifying freezing events in Parkinson's disease patients.

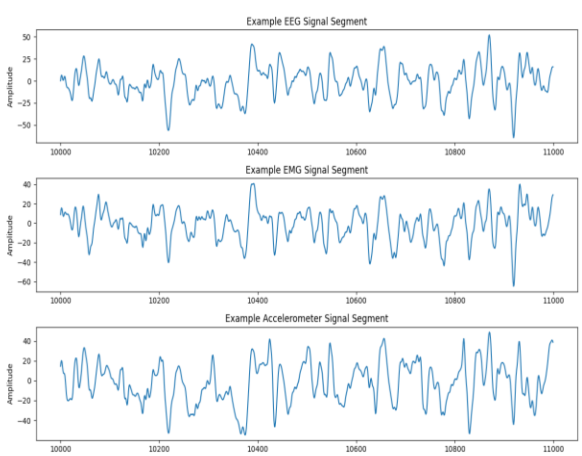



Figure (xi): Example raw sensor signals captured during gait activity

The figure presents example segments of the raw signals captured from the three primary sensor modalities used in this study: electroencephalography (EEG), electromyography (EMG), and accelerometer (ACC) signals. These signals represent neural activity, muscle activation, and body movement respectively.

The EEG signal exhibits relatively low-amplitude oscillatory patterns, reflecting neural activity associated with motor control. In contrast, EMG signals display more irregular and higher-frequency fluctuations corresponding to muscle contractions during gait. The accelerometer signal shows larger amplitude variations that directly correspond to the physical movement of the body during walking.

These visualizations highlight the complementary nature of the sensor modalities. While EEG provides insight into brain activity, EMG captures muscle activation patterns and accelerometers measure movement dynamics. The combination of these heterogeneous signals enables the model to capture multiple physiological aspects of gait behaviour, thereby improving the detection of freezing of gait events.

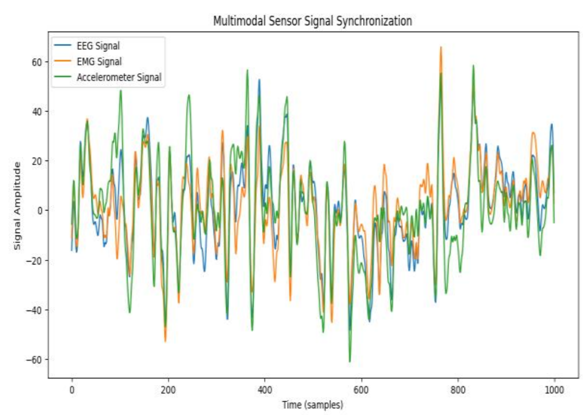



Figure (xii): Multimodal sensor signal comparison showing synchronized EEG, EMG, and accelerometer signals over the same time interval

The figure illustrates the synchronized time-series signals obtained from the EEG, EMG, and accelerometer sensors during a representative walking segment. Each signal is plotted along the same time axis, demonstrating that all sensor modalities are temporally aligned.

Although the amplitude and signal characteristics differ across sensors, the synchronized timeline ensures that neural activity, muscle activation, and physical movement are recorded simultaneously. This temporal alignment is essential for multimodal analysis, as freezing of gait events involve coordinated changes in brain activity, muscle response, and body movement.

By combining these synchronized signals, the proposed system captures complementary physiological and biomechanical information. This enables the machine learning model to identify complex patterns associated with freezing of gait that may not be detectable when using a single sensor modality.

0)

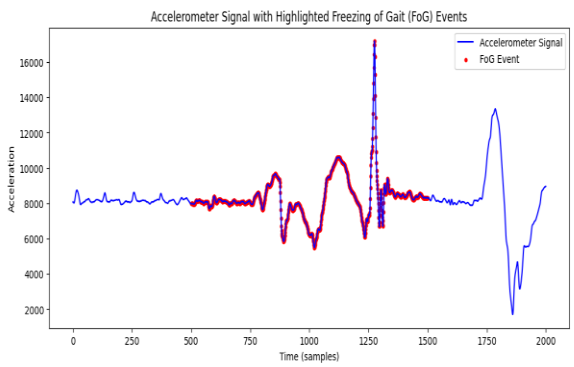



Figure (xiii): Accelerometer Signal with Highlighted Freezing of Gait (FoG) Events

The figure illustrates an example accelerometer signal segment with the corresponding freezing of gait (FoG) events highlighted. The blue curve represents the continuous accelerometer signal during a walking session, while the red markers indicate the time points labelled as FoG.

During normal walking periods, the accelerometer signal demonstrates relatively smooth and rhythmic oscillations corresponding to regular gait cycles. In contrast, during FoG episodes, the signal pattern becomes irregular and exhibits abrupt changes in amplitude and frequency. These irregular patterns are characteristic of freezing events where patients temporarily lose the ability to initiate or continue stepping.

Highlighting the FoG regions in the signal provides a clear visual representation of how freezing episodes manifest within the sensor data. This observation supports the effectiveness of using accelerometer signals as an important modality for detecting FoG events. When combined with EEG and EMG signals, these features contribute to a comprehensive multimodal representation that improves the robustness of the classification model.

## VIII. DISCUSSION FRAMEWORK

### A. Multimodal Signals Improve Detection Performance

One of the key insights from the proposed framework is the benefit of integrating multiple sensor modalities for detecting freezing episodes. Individual sensors capture only partial aspects of gait disturbances, whereas multimodal sensing provides a more comprehensive representation of the physiological and motor processes associated with freezing of gait.

Motion signals from the accelerometer capture variations in walking dynamics, while electromyography signals provide information about muscle activation patterns during locomotion. At the same time, electroencephalogram signals reflect neural activity related to motor planning and execution. The visualizations presented in the signal plots and multimodal synchronization graphs illustrate how these heterogeneous signals vary across time and provide complementary information about gait behaviour.

The experimental results further support the importance of multimodal sensing. As shown in the sensor comparison table, accelerometer- based signals contribute strongly to freezing detection, while EMG and EEG signals provide additional physiological context. The integration of multiple modalities enables the classifier to capture richer patterns associated with freezing episodes, thereby improving the reliability of the detection framework.

### B. Temporal Segmentation Helps Capture Short FoG Events

The use of 3-second overlapping sliding windows plays an important role in detecting transient freezing episodes. Freezing of gait events often occur suddenly and last for short durations, making them difficult to detect without appropriate temporal segmentation.

The sliding window visualization demonstrates how the signal is divided into overlapping segments, ensuring that each segment retains sufficient contextual information. The use of overlapping windows increases the probability that a freezing event will be captured within at least one window during analysis.

This segmentation strategy also allows the machine learning model to learn temporal patterns associated with freezing events. By preserving short-term signal variations within each segment, the framework improves its ability to detect subtle transitions between normal walking and freezing behaviour.

### C. Feature-Based Representation Improves Machine Learning Performance

Another important observation from the proposed framework is the effectiveness of feature-based representations derived from biomedical signals. Statistical features extracted from sensor data help summarize important characteristics of the signals while reducing dimensional complexity.

Time- domain features capture statistical properties such as mean and variance, while frequency-based representations highlight signal patterns related to gait rhythm and muscular activity. The feature distribution plots illustrate that certain signal characteristics exhibit noticeable differences between FoG and Non- FoG segments, enabling the classifier to learn discriminative patterns.

Combining the features from different modalities of sensors creates a richer representation space for the features. This richer representation space for the features enables the model to better differentiate between the freezing and normal gait states.

### D. SVM is Effective for Biomedical Signal Classification

Based on the experimental results, it can be concluded that the Support Vector Machine classifier works well in separating FoG and Non-FoG sections. The results from the classification experiments reveal that the accuracy of classification is about 70%, along with balanced precision and recall.

The analysis of the confusion matrix shows that the classifier is able to recognize a significant portion of normal walking segments as well as freezing events. However, there are also incorrect classifications, as seen in the differentiation between FoG and normal walking. These findings emphasize the complexity and difficulty in identifying freezing episodes.

Despite these challenges, SVM remains suitable for biomedical signal classification because it can handle high -dimensional feature spaces and construct effective decision boundaries between classes. Feature standardization further improves model stability by ensuring that signals from different modalities contribute equally to the classification process.

### E. Potential for Wearable Healthcare Applications

The results of this study demonstrate the potential for using multimodal sensing systems in real-world healthcare applications. The detection of freezing episodes can be beneficial in the clinical evaluation of the progression of Parkinson’s disease and the efficacy of treatment.

The use of wearable sensors that can continuously monitor motion and physiological signals has the potential to provide useful information in the detection of freezing episodes during daily activities. The proposed system for multimodal detection has the potential for providing a real-time solution for the detection of freezing episodes.

Thus, the proposed system for multimodal detection has the potential for providing a solution for intelligent wearable healthcare systems for the long-term management of Parkinson’s disease.

## IX. CONCLUSION

In this paper, a multimodal machine learning framework was proposed for detecting freezing of gait (FoG) episodes in patients diagnosed with Parkinson’s disease. One of the most disabling motor symptoms of Parkinson’s disease is freezing of gait. This symptom has a major impact on the risk of falls and mobility limitations. Thus, there is a need to develop an efficient system for detecting such a symptom.

The proposed framework utilizes multimodal physiological and motion signals collected from wearable sensors, including electroencephalogram (EEG), electromyogram (EMG), accelerometer (ACC), and skin conductance (SC) signals. The recorded signals were pre-processed through noise filtering, normalization, and resampling to improve signal quality and ensure consistency across modalities. The multimodal data were then segmented using overlapping time windows in order to capture short-duration freezing events effectively.

A set of statistical features was extracted from the segmented signals and was utilized to classify between FoG and non-FoG gait patterns by employing a Support Vector Machine classifier. Various evaluation metrics, such as accuracy, precision, recall, F1-score, and Matthew's correlation coefficient, were utilized to measure and evaluate the performance of the proposed model. From the experimental results, it was evident that the proposed framework was able to classify with an accuracy of 70% and proved that machine learning algorithms could be utilized to detect freezing episodes from multimodal sensor signals.

The experimental results also prove that employing multimodal sensor signals is crucial to enhance the accuracy of the proposed system in detecting freezing episodes in patients with Parkinson's disease, as it is capable of collecting various neurological, muscular, and motion-related signals that occur during freezing episodes.

Thus, this paper proves that multimodal sensor signals and machine learning algorithms could be utilized to improve an automated monitoring system for Parkinson's disease patients.

## X. LIMITATIONS

In spite of the good performance of the proposed multimodal Freezing of Gait (FoG) detection framework, there are certain limitations that need to be considered. These limitations, in fact, point out certain potential directions for improvement in this area of research.

One of the primary limitations of this research is the limited dataset considered in this research. The dataset considered in this research consists of 12 patients diagnosed with Parkinson's disease, resulting in a valid multimodal dataset of 3 hours and 42 minutes. Although this dataset offers a rich set of physiological and motion-related data, it is still a limited dataset, and the proposed model might not generalize well over a larger population of Parkinson's disease patients. A limited dataset might not be able to cover a wider variety of gait and physiological data from a larger population of Parkinson's patients.

Another limitation arises from the controlled environment in which the data was collected. The dataset was recorded in a hospital setting under carefully designed experimental conditions intended to induce FoG episodes. Although this controlled setup ensures accurate data acquisition and reliable annotation, it may not completely represent the variability encountered in real-world environments. In daily life, Parkinson's disease patients encounter diverse walking conditions such as uneven terrain, crowded spaces, obstacles, and environmental distractions, which can influence gait behavior and FoG occurrences.

Furthermore, the dataset may not fully capture the wide variability in disease severity and progression among Parkinson's patients. FoG patterns can differ significantly depending on factors such as medication state, fatigue, cognitive load, and individual neurological conditions. As a result, models trained on limited experimental datasets may experience reduced performance when applied to broader patient populations.

From a methodological point of view, the proposed system employs a Support Vector Machine classifier, which is a classifier that depends on manual feature engineering. SVM classifiers are effective for high-dimensional biomedical signals and can deliver good performance in terms of classification accuracy. However, it is worth noting that the performance of SVM classifiers depends on the quality of the features extracted from the signals. Deep learning methods, on the other hand, have the potential to learn features from the signals directly.

Additionally, although the proposed approach integrates multiple sensor modalities, the computational complexity and sensor requirements may pose challenges for real-time wearable deployment. Collecting and synchronizing multiple physiological signals requires specialized hardware and careful calibration, which may limit large-scale practical implementation.

These limitations indicate that while the proposed multimodal approach demonstrates strong potential for FoG detection, further research is required to improve robustness and real-world applicability. Future work may involve collecting larger datasets from diverse patient populations, incorporating real-world walking scenarios, and exploring advanced deep learning architectures for automated feature learning.

## XI. FUTURE WORK

Although the proposed framework demonstrates promising potential for automated freezing of gait detection, several opportunities exist for further improvement and extension of this work.

The scope of future research could be to assess the proposed method using larger datasets to increase the robustness of the proposed detection model. Collecting data from a larger pool of Parkinson's patients, with different severities of the disease, under a range of walking conditions, can provide a broader insight into freezing of gait in a natural walking environment.

Another direction for future research is to utilize sophisticated deep learning algorithms that can learn patterns from the raw sensor signals without human intervention, which can potentially lead to better performance of the classifier.

Another promising area is the development of real-time wearable devices for FoG detection. It is possible that by integrating this detection model with a wearable device, patients with Parkinson's disease can be monitored in real time during their daily activities. Real-time detection of FoG might also enable the implementation of assistive interventions to help patients overcome freezing of gait.

Moreover, by integrating multimodal sensing with edge computing and smart healthcare technology, it is possible to design remote monitoring and early intervention strategies for Parkinson's disease management. Such advancements in technology have the potential to improve patient safety, reduce fall risk, and improve the mobility of patients with Parkinson's disease.

## REFERENCES

[1] J. Smith et al., "Wearable sensor-based detection of freezing of gait in Parkinson's disease ," IEEE Transactions on Biomedical Engineering, 2022.

[2] A. Kumar and R. Gupta, "Machine learning approaches for gait analysis," IEEE Access, 2021.

[3] L. Rodriguez et al., "Multi-sensor fusion for Parkinson's monitoring," Sensors Journal, 2023.

[4] F. J. Padilla-Godínez, L. I. Ruiz-Ortega, and M. Guerra-Crespo, ''Nanomedicine in the face of Parkinson's disease: From drug delivery systems to nanozymes,'' Cells, vol. 11, no. 21, p. 3445, Oct. 2022.

[5] W. Maetzler, J. Domingos, K. Srulijes, J. J. Ferreira, and B. R. Bloem, "Quantitative wearable sensors for objective assessment of Parkinson's disease," Movement Disorders, vol. 28, no. 12, pp. 1628–1637, Oct. 2013, doi: 10.1002/mds.25628.

[6] P.-K. Yang, "Freezing of gait assessment with inertial measurement units and deep learning: Effect of tasks, medication states, and stops," J. NeuroEng. Rehabil., vol. 21, no. 1, pp. 1–22, Feb. 2024.

[7] P. P. Liang, A. Zadeh, and L.-P. Morency, "Foundations & trends in multimodal machine learning:Principles, challenges, and open questions," ACM Comput. Surv., vol. 56, no. 10, pp. 1–42, Jun. 2024.

[8] K. Hu, "Vision-based freezing of gait detection with anatomic directed graph representation," IEEE J. Biomed. Health Informat., vol. 24, no. 4, pp. 1215–1225, Apr. 2020.

[9] M. A. Brodie et al., " Immediate Effects of Lower Limb Sensory Simulation Using Smart Socks to Stabilize Gait in People with Parkinson's Disease*," 2023 45th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), Sydney, Australia, 2023, pp. 1-4, doi: 10.1109/EMBC40787.2023.10340604.

[10] Y. Wang , F. Beuving, J. Nonnekes, M. X. Cohen, X. Long, R. M. Aarts, and R. van Wezel, " Freezing of gait detection in Parkinson's disease via multimodal analysis of EEG and accelerometer signals,"Proceedings of the IEEE Engineering in Medicine and Biology Society ( EMBC), 2020.

[11] W. Zhang, D . Huang, H. Li, et al., "Sensoring and application of multimodal data for the detection of freezing of gait in Parkinson's disease, " arXiv preprint arXiv:2110.04444 , 2021.

[12] Y. Guo, D. Huang, W . Zhang, et al., "High-accuracy wearable detection of freezing of gait in Parkinson's disease based on pseudo-multimodal features," Computers in Biology and Medicine, vol. 145, 2022.

[13] K. Ren, Z. Chen , Y. Ling, and J. Zhao, "Recognition of freezing of gait in Parkinson's

disease based on combined wearable sensors," BMC Neurology, vol. 22 , 2022 .
[14] S. T. Moore, H . G. MacDougall, and W. G. Ondo, "Ambulatory monitoring of freezing of gait in Parkinson's disease, " Journal of Neuroscience Methods, vol. 167 , no. 2, pp. 340–348, 2008.
[15] S. Mazilu, U. Blanke, M. Hardegger, et al., "GaitAssist: A wearable assistant for gait training and freezing detection in Parkinson's disease ," in Proceedings of the IEEE International Conference on Pervasive Computing Technologies for Healthcare, 2012.
[16] E. Tripoliti, A. T. Tzallas, M. G. Tsipouras , D. I. Fotiadis, and S. Konitsiotis , " Automatic detection of freezing of gait events in Parkinson's disease using wearable sensors," IEEE Transactions on Information Technology in Biomedicine, vol. 17, no. 6, pp. 1041– 1048, 2013 .
[17] M. Bächlin, M. Plotnik, D. Roggen, et al., " Wearable assistant for Parkinson's disease patients with the freezing of gait symptom," IEEE Transactions on Information Technology in Biomedicine, vol. 14, no . 2, pp . 436–446, 2010.
[18] D. Rodriguez-Martin, A . Samà, C. Pérez-López, et al., "Home detection of freezing of gait using wearable sensors, " Sensors, vol. 17, no . 7, 2017.
[19] L. Sigcha, N . Costa, I. Pavón, et al., "Deep learning approaches for detecting freezing of gait in Parkinson's disease patients , " IEEE Access, vol. 8, pp. 116865– 116875, 2020.
[20] Y. Hou, J. Ji, Y. Zhu, T. Dell, and X. Liu, "Multi-modal wireless flexible sensors with edge deep learning for detecting freezing of gait in Parkinson's patients ," arXiv preprint arXiv:2305.17629, 2023.
[21] S. S. Barua, S . M. R. Alam, R. Rahman, et al., "Freezing of gait detection using Gramian Angular Fields and federated learning from wearable sensors," arXiv preprint arXiv:2411.11764, 2024.
[22] H. Li, "Multimodal dataset of freezing of gait in Parkinson's disease ," Mendeley Data, 2021.