Predictive Analysis of Freezing of Gait Events in Parkinson's Disease Using Accelerometer Data and LGBM Modeling: A Precision-Centric Approach

Rishi Doshi, Hardik Gupta, Praniket Walavalkar, Dyuti Vartak, and Narendra Shekokar

Abstract The human body is prone to numerous neurological abnormalities that deteriorate movement and coordination. One such condition is Parkinson's disease (PD), which primarily attacks the older masses and causes them discomfort in the latter phases of their lives. Freezing of Gait (FOG), being a special symptom of PD, deteriorates mobility and degenerates quality of life. This study analyzed three phenomena known as FOG events, namely, Start Hesitation, Turn, and Walking. The gaps in existing research highlighting the scarcity of understanding of the mechanisms and factors leading to FOG events have been addressed and eliminated. This research aims to predict which of the three movements will most likely be affected. A four-step sequential approach is proposed that is initiated by the exploration of patients' accelerometer tests. The preprocessed, evenly sampled, and outlier-free data is then subjected to feature engineering. Following metadata integration, the feature-engineered dataset is fed to the Light Gradient Boosting Machine (LGBM) due to its ability to handle extensive datasets. The suggested model computes the probability of each of the three FOG events being impaired in a patient diagnosed with Parkinson's disease. Precision was evaluated in the presence and absence of outliers for a comparative analysis. In the absence of outliers, LGBM gave a superior precision of 0.7354, 0.8225, and 0.2689 for start hesitation, turning, and walking, respectively.

R. Doshi · H. Gupta (✉) · P. Walavalkar · D. Vartak · N. Shekokar
Dwarkadas J, Sanghvi College of Engineering, Mumbai, India
e-mail: ghardik5902@gmail.com

R. Doshi
e-mail: rishidoshi2002@gmail.com

P. Walavalkar
e-mail: praniketwalavalkar01@gmail.com

D. Vartak
e-mail: vartakdyuti@gmail.com

N. Shekokar
e-mail: narendra.shekokar@djsce.ac.in

S. Kumar et al. (eds.), *Proceedings of International Conference on Communication and Computational Technologies*, Lecture Notes in Networks and Systems 1122,
https://doi.org/10.1007/978-981-97-7426-5_16

Keywords Parkinson's disease · Freezing of gait · LGBM · Accelerometer data · Movement impairments · Machine learning

1 Introduction

Parkinson's disease (PD) is a significant neurological disorder that presents considerable difficulties for healthcare professionals. This chronic condition, which hampers motor function, affects many individuals globally. Despite extensive research conducted on the biological aspects of Parkinson's disease, there are still numerous aspects of this condition that remain elusive. Hence, further investigation is warranted to comprehend and develop remedies for the issue at hand comprehensively. A characteristic feature of Parkinson's disease (PD) is the gradual degeneration of dopaminergic neurons within the basal ganglia region of the brain. Motor symptoms, including bradykinesia, tremors, rigidity, and postural instability, can be attributed to a dopamine deficiency. The causes of these symptoms can be attributed to an imbalance in neurotransmitter levels. Parkinson's disease has been associated with autonomic dysfunction, affective abnormalities, sleep disturbances, cognitive impairment, and motor dysfunction.

Freezing of gait (FOG) is a puzzling and frustrating symptom of Parkinson's disease (PD) and other Parkinsonian disorders. It creates frustration and immobility, making it difficult to start or sustain rhythmic, forward walking. FOG impairs mobility and independence, and falls, reducing quality of life. FOG can be caused or made worse by a variety of factors, both motor and non-motor. Problems with gait initiation, tight spaces, twisting motions, and interference from performing two tasks simultaneously are classic examples of FOG triggers. The majority of FOG evaluation strategies call for the use of FOG-provoking protocols. Patients diagnosed with FOG are observed engaging in activities that may make their condition worse. Wearable technology has the potential to make FOG testing more effective. Adding more sensors can increase FOG detection, but this comes at the expense of compliance and overall usefulness. Therefore, combining these two approaches can prove to be the most effective option. Accelerometers located in the lower back combined with machine learning may accurately diagnose FOG, as incorporated and further discussed in this study. These algorithms are trained and evaluated using relatively small datasets, severely restricting their generalizability. However, this research closes this gap by considering a large dataset of more than <no. of records>.

The primary objectives of this research are:

- To evaluate the probability of each of the three movements incorporated in this study: Turn, Start hesitation, and Walking leading to FOG episodes. This contribution would improve the diagnosis, comprehension, and treatment of FOG in order to better the lives of the many people who experience this debilitating Parkinson's disease symptom.

- Enhancing personalized therapy will lessen the burden of age-related movement, cognitive, and mobility impairments.
- To demonstrate the attempts to gain a fresh understanding of the physiological and pathophysiologic mechanisms underlying cognitive and motor function, the variables affecting these functions, and how they alter with age and illness, providing new tools and methods for detecting and tracking cognitive and motor aging early on.

The paper is organized by the introduction in Sect. 1, including the background on Parkinson's disease, Freezing of Gait, and the scope and objective of this study. The literature review in Sect. 2, which consists of the methods and gaps in the existing research, is followed by the methodology in Sect. 3, which elucidates the proposed workflow. The results of the proposed implementation are discussed in Sect. 4, followed by the conclusion, which includes the summary and future scope of the study in Sects. 5 and 6, respectively.

2 Literature Survey

Numerous studies examined the use of deep learning and machine learning approaches to diagnose Parkinson's disease (PD) and identify episodes of freezing of gait (FoG), a prominent symptom in PD patients. Random forest classifiers and KNN proved to be the most effective approaches for illness identification. Some research centered on identifying the illness using EEG and EMG signals. Techniques like support vector machines and AdaBoost achieved higher accuracy than other models.

Srikanth [1] compares several Machine Learning classifier algorithms implemented on a clinical images dataset, including XGBoost, Random Forest, KNN, and SVM, and proposes Random Forest as the best model since it offers superior performance with an accuracy of 90%.

The major goal of Nissar et al. [2] is to evaluate the research on deep learning and machine learning methods used for the detection of Parkinson's disease. For classification purposes, a variety of models, including naive bayes, SVM, deep neural networks, decision trees, and random forests are successfully implemented. The deep neural network attained the greatest accuracy of 99.49% among deep learning techniques.

In order to identify PD at an early stage, Wang et al. [3] present a unique deep-learning approach that takes into account a number of indicators, including Rapid Eye Movement and olfactory loss, cerebrospinal fluid data, and dopaminergic imaging markers. A comparison of the suggested deep learning model with twelve machine learning and ensemble learning techniques using only a small amount of data demonstrates the created model's better detection ability, which has the greatest accuracy of 96.45%.

Using their respective datasets, Raval et al. [4] implement machine learning algorithms such as Logistic Regression, SVM, Decision Tree, KNN, Stochastic Gradient

Descent, and Gaussian Naive Bayes, as well as ensemble approaches like RF, Adaptive Boosting, and Hard Voting. The most significant result, with maximum accuracy of 99.79%, was obtained by RF on the Static Spiral Test (for detecting tremor).

Tadse et al. [5] employ and compare four machine learning algorithms: Decision Tree, Logistic Regression, K-nearest neighbours, and Support vector machines for the early prediction of PD. Decision Tree, yielding the highest accuracy of 94.87%, is suggested to be the model fit for predicting PD early and efficiently.

In their study, Kamoji et al. [6] employed various machine learning algorithms, including Logistic Regression, Naive Bayes, K-NN, RF, and Decision Tree Classifier. They applied the Decision Tree Classifier on three different feature sets: the Freezing of Gait dataset, which was utilized to predict the presence of symptoms related to the patient's legs and trunk by analyzing their gait; the Parkinson Clinical speech dataset, which aimed to detect deviations in audio frequency; and the Parkinson Disease wave analyzable dataset. It is suggested that employing a Decision Tree classifier on the FOG dataset, yielding an accuracy rate of 96.06%, represents the optimal and pragmatic approach.

SVM, Logistic Regression, Discriminant Analysis, KNN, Decision tree, Random Forest, Bagging tree, Naive Bayes, and AdaBoost are the nine Machine Learning Algorithms (MLA) that are the subject of examination and assessment of Ouhmida et al. [7]. The most effective algorithm is suggested to be KNN, which produces a maximum accuracy of 97.22%.

Anand et al. [8] incorporate Principal Component Analysis (PCA) and Kernel Principal Component Analysis as two dimensionality reduction (DR) techniques that are used along with a variety of classification-based machine learning and deep learning algorithms. These algorithms are implemented and compared based on time complexity as a contributing factor. Using just 10 characteristics, it was found that KNN achieved the greatest accuracy, up to 95%.

Celik et al. [9] conducted a comparative analysis of various classification algorithms, including Logistic regression, SVM, Extra Trees, Gradient Boosting, and RF, to predict Parkinson's disease. The dataset's feature space was expanded due to correlation maps that were generated using Principal Component Analysis (PCA) and Information Gain (IG). The incorporation of expanded feature sets resulted in enhanced accuracy in the classification of Parkinson's disease.

Saikia et al. [10] are of the opinion that an electroencephalogram (EEG) and electromyogram (EMG)-based GUI model would be a useful tool and genuine explanation for the early identification of PD. Artificial neural networks extracted and classified EEG and EMG feature data.

In their research, Kumar et al. [11] propose a deep-learning model to identify Parkinson's disease (PD). When applied to spiral photos, the model achieves high detection and validation accuracies of 99.89% and 99.01%, respectively. Similarly, when applied to wave images, the model achieves detection and validation accuracies of 99.54% and 97.96%, respectively.

Djuri-Jovii et al. [12] established an expert system for the automated categorization of various gait patterns. The method uses Pearson's correlation to distinguish between normal and pathological gaits and characterizes each step by its time, shank displacement, and spectral components. Strides that tremble or have a full motor block are considered abnormal. In comparison to normal strides, abnormal strides were found in 100% of the 12 patient datasets examined.

Mekruksavanich et al. [13] created the SE-DeepConvNet. It is a small, deep convolutional neural network with squeeze-and-excite parts that are specially designed for fog identification. To test how well the SE-DeepConvNet works, the authors use the Daphnet dataset. The model's impressive 95.66% accuracy rate in their test demonstrates that it is more effective than other deep learning models.

An automated approach for detecting freezing of gait is introduced by Abdallah et al. [14], which utilizes convolutional neural networks (CNNs) to autonomously acquire and develop features and differentiate between instances of freezing occurrences and regular gait. The suggested technique obviates the necessity of human feature extraction and feature selection. With over 95% accuracy, specificity, and sensitivity, the architecture described could tell the difference between freezing events and normal walking.

According to Khan et al. [15], wearable accelerometer sensors measured acceleration in three dimensions. They were used to do three different activities: walking along a straight line, walking at random, and walking as usual. Following this, characteristics with significant discriminatory power were fed into a classifier to differentiate between regular accelerometer readings and instances of Freezing of Gait (FoG) identified using accelerometer data. Bagged Trees exhibited the highest degree of accuracy, attaining a classification accuracy of 90.4%.

Following the feature extraction process utilizing the Fast Fourier Transform (FFT) algorithm, Polat et al. [16] employed the logistic regression modelling for the detection of freezing of gait (FoG) instances within the dataset. Remarkably, the achieved classification accuracy for FoG cases related to Parkinson's Disease (PD) using acceleration signals was 81.3%. Along with logistic regression, this study also looked at how well four different classifiers—(SVM), Quadratic SVM, Cubic SVM, and k-Nearest Neighbors (kNN)—could sort FoG cases.

Tahafchi et al. [17] introduce an innovative approach in their research paper to detect halting of gait (FoG). This method categorizes occurrences of paralyzing episodes by employing a support-vector-machine algorithm and temporal, spatial, and physiological variables. By utilizing a more extensive range of characteristics, the methodology improves its ability to identify precise occurrences of Freezing of Gait (FoG). Based on the findings, it can be inferred that the recently suggested approach demonstrates enhanced efficacy when the traditional energy-based method fails to produce desirable results (as indicated by an approximate area under the receiver operator curve of 0.5). The receiver operator curve achieves an area of 0.96.

Zhang et al. [18] used strange walking patterns that happen before episodes of Freezing of Gait (FoG) to make a machine-learning model that could predict FoG episodes. The purpose of making two prediction models with AdaBoost was to find out if adding compromised gait variables makes predicting Freezing of Gait (FoG) episodes easier. According to the study's results, the proposed model showed a 5.7%

improvement in accuracy, giving it an overall accuracy rate of 82.7% during patient-dependent testing. Similarly, a significant improvement of 9.8% in accuracy was observed, leading to an accuracy rate of 77.9% during patient-independent testing.

Even though many studies have looked at different parts of Parkinson's disease, we still don't know much about how to predict and treat cognitive damage, especially in the form of FOG, in people who have the disease. Much of the existing research has concentrated on motor symptoms and traditional therapies, leaving a considerable gap in our understanding of the mechanisms that contribute to FOG episodes and effective measures for prediction and mitigation. The UCI dataset has limitations in terms of complexity; however, the utilization of deep learning techniques has the potential to enhance accuracy by implementing ensemble approaches and expanding the dataset size. The FOG and speech datasets exhibited satisfactory performance, although the wave and spiral data can be readily acquired. Traditional machine learning methods have trouble capturing the complex relationships between sensor data and freezing of gait (FOG) in people with Parkinson's disease (PD). Previous research has exhibited a deficiency in conducting a thorough comparative examination of existing approaches for detecting Freezing of Gait (FoG), largely emphasizing offline analysis of accelerometer data.

3 Methodology

The proposed workflow commences with the inaugural step of data collection and exploration. Results of the 3D lower back accelerometer tests incorporating four attributes: subject, visit, test and medical condition were gathered and visualized. Following the successful collection of raw data, four preprocessing techniques were utilized to enhance the data's quality and accuracy. Statistical methods were employed to forecast and address missing values, categorical variables were transformed into actual numeric values, data was standardized using min–max scaling, and possible outliers were identified and removed through the utilization of box plots for visualization purposes. Following that, the process of integrating metadata was conducted to enhance the data further, and the obtained feature-engineered data was prepared to be utilized for training the model. LGBM was selected as the regression model used to compute the probability of impairment of the three FOG events. The overview of the methodology has been mapped in Fig. 1.

3.1 Dataset Description and Exploration

This study gathered data from reports of lower back 3D accelerometer tests of patients who were considered subjects. Two types of experiments were conducted to assess the data of the subjects. For instance, the TDCSFOG dataset was formulated from a data series collected in a lab where subjects completed a FOG-provoking

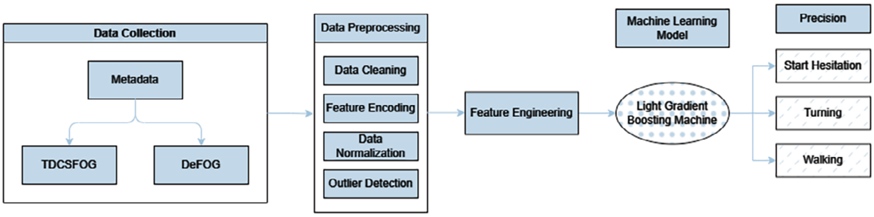


Fig. 1 System architecture

protocol. Each series of the TDCSFOG dataset was uniquely identified based on four attributes: subject, visit, test, and medical condition. The DeFOG dataset, on the other hand, consists of data series collected at home, where the subject completed a FOG-provoking protocol. The series of this dataset incorporated three attributes: subject, visit, and medical condition. Since the metadata for TDCSFOG is six times larger than the DeFOG metadata, both are merged in order to analyze the information of all 107 patients. Another daily living dataset was incorporated, consisting of one week of continuous recordings of 65 subjects, of which 45 exhibited FOG symptoms. The tdcsfog metadata identified each series in the TDCSFOG dataset by unique Subject, Visit, Test and Medication conditions, whereas the DeFOG metadata identified the DeFOG dataset records by unique Subject, Visit, and Medication conditions. The test set used for evaluation contained about 250 data series, of which TDCSFOG and DeFOG cases were in the same proportion as the training set.

After careful and in-depth visualization of the combined dataset, certain trends were deduced, as illustrated in Fig. 2. Approximately 80% of the participants are men. More than 66% of the participants are 65–75 years old. Around 60% of the participants were diagnosed 5–15 years ago. Among participants aged between 80 and 85, the majority are women.

The features correlation was also plotted to see how strongly or weakly they are related to each other as depicted in Fig. 3.

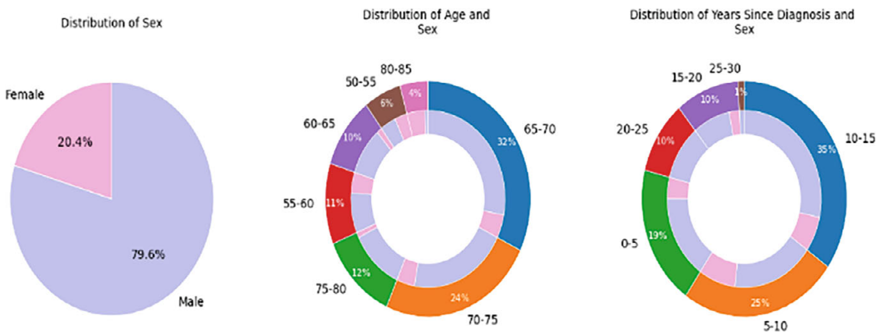
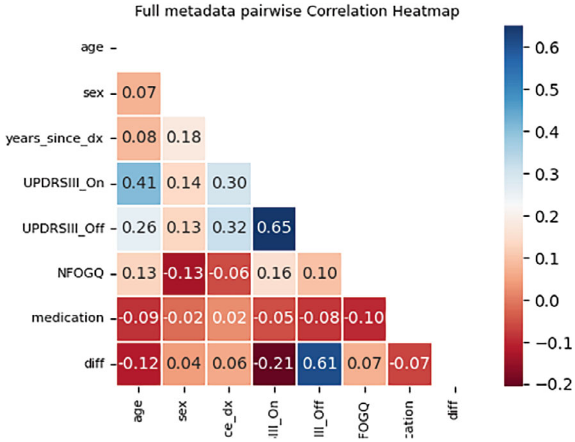


Fig. 2 Distribution of sex with respect to age and diagnosis

Fig. 3 Correlation between features



3.2 Data Preprocessing

Preprocessing research data is crucial for producing reliable and informative results. The method commences with addressing the matter of missing data, with specific focus on the 'UPDRSIII_Off' field. This stage is crucial for avoiding information gaps and assuring the data's completeness. Multivariate Imputation by Chained Equations (MICE) is crucial in this situation. The model considers complex relationships between variables, enhancing the dataset's accuracy and representativeness for further analysis. Additionally, it is critical to convert categorical attributes into standardized numeric values in order to ensure that the dataset is properly organized and compatible with a wide range of analytical methods and algorithms. This standardization facilitates the analysis process by ensuring consistency. Combining these preprocessing steps makes the dataset more dependable in preparation for statistical analysis, machine learning, and modelling.

Handling missing data: The process starts with a thorough dataset integrity assessment. Each column is carefully checked for missing or "null" numbers. Computing the total count of null values in each column provides a complete picture of missing data. This first evaluation makes it possible to discuss and fix these data gaps.

The UPDRSIIIOn/UPDRSIIIOff (Unified Parkinson's Disease Rating Scale) represent scores when on and off medication, respectively. A lot of attention is paid to the 'full_metadata' entry called 'UPDRSIII_Off.' This column is important because it shows important things about the 'UPDRSIII_Off' results. The goal is to figure out how much data is missing from this area and how that fits into the whole data set. The null percentage in this column allows the algorithm to calculate the proportion of missing values relative to the dataset's size.

A strong correlation between 'UPDRSIII_Off' scores and the 'UPDRSIII_On' scores is identified in Fig. 4. Also, there are some connections that aren't as strong but can still be seen with attributes like age, gender, and the number of years since

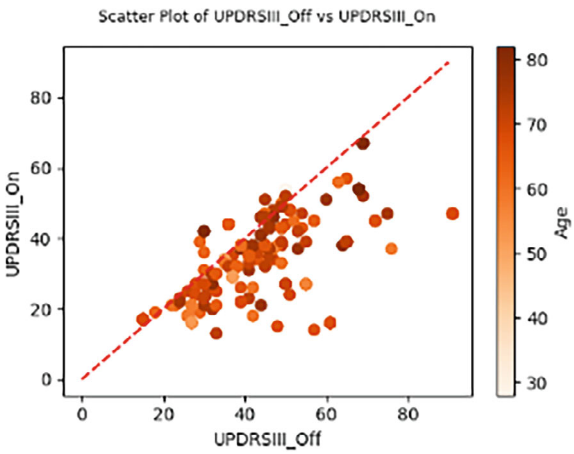


Fig. 4 Relation between UPDRSII_OFF versus UPDRSIII_On

the diagnosis. This correlation shows how important it is to fill in missing values, especially in the above stated columns, where scores seem to be linked to other key variables.

Imputation is seen as a good way to deal with the problem of filling in the missing numbers in these two columns. Imputation is figuring out what the missing values should be based on the already known data and the relationships between the variables. Multivariate Imputation by Chained Equations (MICE) was the imputation method in this case. MICE is liked because it can deal with complex interdependencies between variables. This makes it a good choice for cases in which variables affect each other. This model uses statistical methods to predict missing values in the columns given. Importantly, the imputation process is done slowly and uses the links and relationships between the different factors in the dataset to make more accurate estimates.

Once the missing values in the 'UPDRSIII_Off' and 'UPDRSIII_On' columns have been guessed, the next step is to put these estimated values back into the dataset displayed in Fig. 5.

Converting categorical features: This section fully explains how the categorical variables in the research dataset were preprocessed. The focus is changing the categorical variables in the 'defog_metadata_subjects' and 'tdcsfog_metadata_subjects' datasets. This step is very important because it turns categorical data into a standard format that can be used for further research. It is important to understand the structure of these datasets.

Specifically, mapping changes are made to two factors. First, the 'sex' variable is changed, which stands for the biological and social construction of gender. The values 'F' for females and 'M' for males are 0 and 1, respectively. In the same way, mapping changes are made to the 'medication' variable, which shows the state of medicine. The numerical numbers for "on" and "off" are 0 and 1, respectively. This change ensures that the representations of medication state are all the same, making it easier to do consistent and reliable analysis across the dataset. In order to ensure

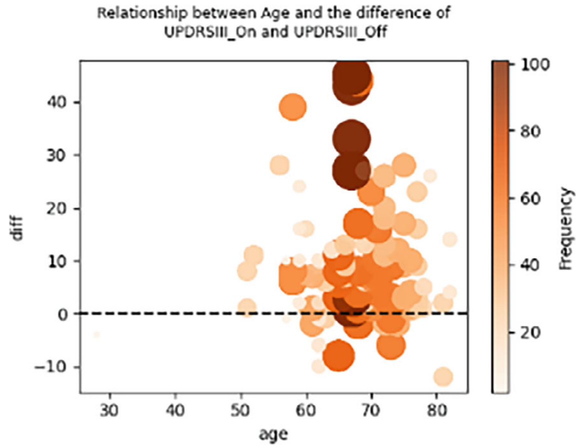


Fig. 5 Relationship between age and difference of UPDRSIII_OFF and UPDRSIII_On

the future usability of the 'subject' and 'Id' variables, it is necessary to turn them into real values at a later stage.

Normalizing data: Normalization is a valuable preprocessing stage to ensure that all variables are subjected to identical treatment in subsequent analyses. This prevents certain factors with larger values from dominating the analysis simply by virtue of their magnitude. In order to execute this approach, a function is developed with the explicit purpose of applying Min–Max scaling to designated columns inside a DataFrame.

The minimum and maximum values for the selected columns must be computed to implement the Min–Max scale method. These values are required by the Min–Max scaling method, which attempts to transform the data into a consistent range from 0 to 1. This alteration guarantees the dimensions of all the data contained within the chosen columns. The marginalized value can be obtained by subtracting the minimum value from the original data point. The result is subsequently divided by the discrepancy between the greatest and lowest values. The result is then divided by the minimum and utmost values. Individual execution of this procedure occurs for every cell in the designated columns. The final output is a data frame, where each integer has been normalized.

Utilizing a normalized data frame as the outcome is crucial since it greatly enhances the accuracy and comparability of subsequent research. Normalizing data facilitates the process of comparing and interpreting information by taking into consideration the varying scales of the items. This guarantees that every variable has an equitable influence on the analysis. This stage is crucial for data preparation for data-driven tasks such as machine learning and statistical analysis.

Outliers: The dataset includes a wide variety of event types, and the analysis's accuracy depends on the ability to distinguish between them. After the dataset is completely built and prepared for analysis, any occurrences of NaN (missing) values are removed. A box plot, as illustrated in Fig. 6, is utilized to represent the duration

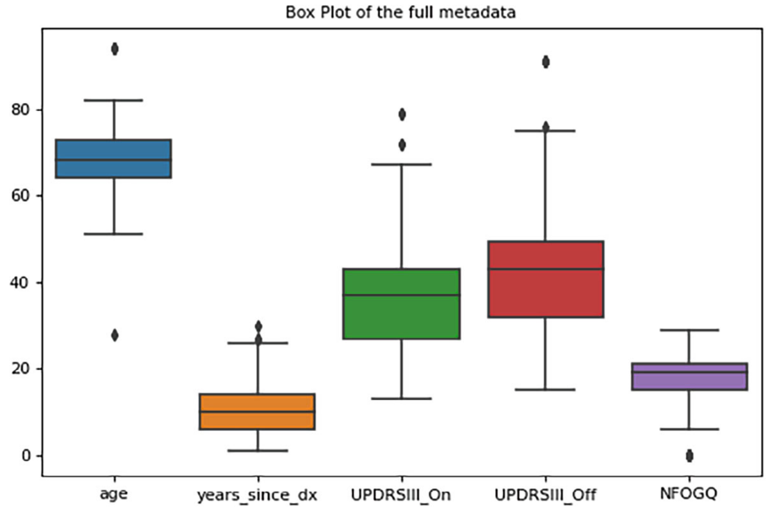


Fig. 6 Box plot of features for checking outliers

of occurrences across different event types visually. The graph illustrates the classification of events on the horizontal axis, while the vertical axis represents the time of each event. Box plots are an invaluable tool for finding outliers since they visually reflect data's spread and central tendency. Annotations improve the box plot, especially by drawing attention to the highest values, which show where the whiskers end for each event category.

An integral aspect of the research process is the identification of outliers, which refer to data points that deviate significantly from the expected range. A temporal threshold of 200 s is established in order to identify and isolate outliers. Possible outliers are data points that exceed this level. It is crucial to acknowledge that the selection of this level holds significant importance, as it is typically selected carefully to enhance the model's performance during subsequent fine-tuning stages. The subsequent stage of the procedure involves eliminating any data points that deviate significantly from the rest of the dataset. The box plot provides a distinct frame of reference for this task since it visually represents the maximum value for each occurrence category. Rows in the 'events_df' data frame that exceed the maximum threshold by a margin greater than 200 s are eliminated, hence eliminating any potential outliers. The dataset "events_filtered" contains the processed data, which have been effectively cleansed of potential outliers. Additionally, adding this revised dataset is important for ensuring that future analyses or modelling work is accurate and reliable because it shows event durations more clearly and accurately.

3.3 Feature Engineering

Feature engineering involves loading data, integrating metadata, normalizing accelerometer readings, and creating a range of features to augment the dataset. A reader function is designed to process files containing sensor data and execute a sequence of operations to preprocess the data for analysis. The function has the capability to accept arguments, such as ‘file’, ‘module’, and ‘pre_type’, which can be utilized to modify its behaviour based on the specific circumstances. The function uses the ‘pd.read_csv’ method to retrieve data from the designated file. The identity, sometimes referred to as “Id,” is extracted from the file path and subsequently assigned to a new column in the dataframe. The ‘module’ argument is used to select ‘defog_metadata_subjects’ or ‘tdcsfog_metadata_subjects’ as methods for incorporating metadata into the data. Various feature engineering techniques are applied to the accelerometer data. The columns of accelerometer data called “AccV,” “AccML,” and “AccAP” are changed in different ways so that their properties can be studied. Accelerometer data for corresponding FOG events like “AccV,” “AccML,” and “AccAP” is shown in Fig. 7.

These changes include normalization, cumulative summation, and calculating moving statistics like sum, minimum, maximum, mean, standard deviation, and delta. Also, exponentially weighted moving averages (EWMA) are calculated to show how the data behaves differently. We can figure out other things about the object from facts about time. If events are found, the function will give a return value of “None,” which means that the information linked with this “Id” is not good for training. The processed data is put into two different data frames. Adopting this full approach ensures that the data is well-prepared, standardized, and has many different features, making it more suitable for the research question.

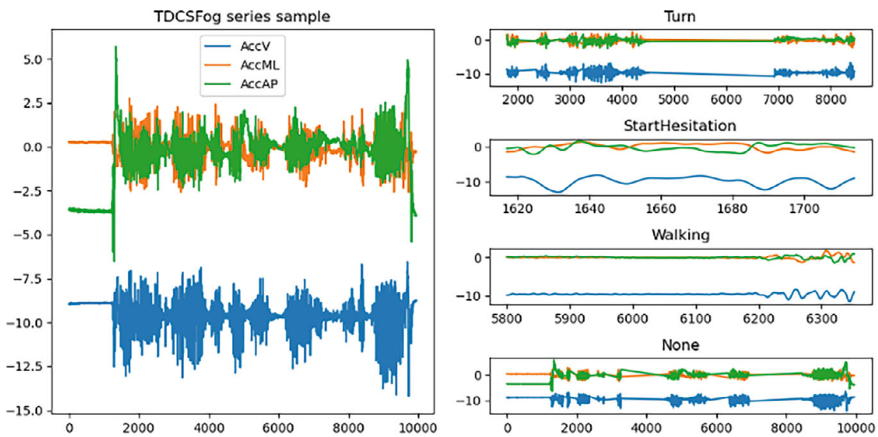


Fig. 7 Effect of accelerometer data on various episodes

3.4 Model Selection and Training

Within this particular section, we aim to provide a comprehensive explanation for the decision to employ the Light Gradient Boosting Machine (LGBM) as the primary predictive model for our research endeavour. In this discussion, we will explore the prominent characteristics that make LGBM a noteworthy selection and examine its operational mechanism, providing a clear understanding of how it aligns with the goals of this research.

The selection of LGBM as the major predictive model for our research is based on several convincing factors, including its efficiency and scalability, utilization of regularization techniques, capacity to handle categorical data, and strong performance on big datasets [19]. Due to its remarkable computational efficiency, the LGBM approach is an excellent option for managing massive datasets and feature spaces with high-dimensionalities. The memory-optimized architecture and ability to effectively handle substantial volumes of data align nicely with our research goals. Due to the presence of continuous 3D accelerometer readings in the dataset, there is a substantial volume of data. To effectively manage this, it is necessary to build a memory-optimized architecture.

Including many regularization techniques and early stopping mechanisms in LGBM [20] supports our choice of this model as the main prediction model for our study. L1 (Lasso) and L2 (Ridge) regularization are two of the regularization methods that the model provides. Overfitting can be reduced using these techniques by adding penalty terms to the loss function (1). Additionally, the strategy includes the early stopping method. This crucial component assesses the model's performance on a separate validation dataset throughout the training phase and immediately halts the training if overfitting is detected. These complementary techniques ensure the resilience and optimal generalization performance of the model. They are a fantastic fit for the goals of our investigation.

$$L(\theta) = \sum_{i=1}^{N} L(y_i, F(x_i, \theta)) + \lambda\Omega(\theta) \tag{1}$$

where, $L(\theta)$ represents loss function, λ is the regularization parameter, and $\Omega(\theta)$ is the regularization term.

Because of its high pace and scalability, LGBM is a perfect fit for our research [20]. This is perfect for circumstances where obtaining high anticipated accuracy and efficiency are equally crucial. Without the need for preprocessing, the model can handle both numerical and categorical features with efficiency. The LGBM algorithm contains a number of adjustable parameters that let you manage the model's complexity and lower the risk of overfitting. Given the dataset's label targets, a supervised learning approach was employed to address the problem. This task can be categorized as a multi-class classification problem due to the inclusion of various objectives, such as turning, walking, and starting. The vast dataset must be classified utilizing a robust and efficient methodology. Employing a model like LightGBM

(LGBM) is necessary to tackle the problem of imbalanced datasets in multi-class situations.

A gradient boosting algorithm called the Light Gradient Boosting Machine (LGBM) repeatedly generates a set of decision trees. The model can progressively learn and modify its predictions when this ensemble methodology is used. Every additional tree in the ensemble is created to fix any mistakes or incorrect classifications made by the trees that came before it. This algorithm's usage of a leaf-wise tree expansion technique is one of its key features. In contrast to the conventional approach, which first expands a tree from depth, LGBM employs a strategy that involves choosing the leaf node that provides the greatest loss reduction for expansion [21]. This process often produces more fair and deep trees, enabling the model to depict complex relationships in our data accurately. Moreover, it optimizes the procedure by gradually converging towards the best solution using the gradient descent technique. A regulated method to obtain the optimal model is made possible by the learning rate parameter, which controls the size of each step taken during optimization.

In order to determine the optimal parameters for the LightGBM method, a GridSearchCV procedure is conducted using the specified parameter grid. The parameter grid consists of three hyperparameters: max_depth, learning_rate, and n_estimators. For the max_depth hyperparameter, the values 6, 8, and 10 are considered. The learning_rate hyperparameter is evaluated using the values 0.15, 0.1, and 0.01. Lastly, the n_estimators hyperparameter is explored with the values 50, 70, and 90. The optimal parameter values used for this study are as follows: max_depth = 8, learning_rate = 0.1, and n_estimators = 70. Furthermore, as part of the fine-tuning procedure, the variables UPDRSIII_On and UPDRSIII_Off were excluded from the tdcsfog dataframe.

The key components that make LGBM exceptionally appropriate have been identified and highlighted. Furthermore, an extensive understanding of its working mechanism and pertinent mathematical notations and formulas have been clarified. The convergence of these characteristics provides us with a robust modelling and forecasting tool and successfully synchronizes the LGBM model with our study goals.

4 Results and Discussion

The accelerometer data used to train the LGBM (Light Gradient Boosting Machine) regression model was the most important part of this study. The model's performance was comprehensively evaluated using various metrics on a testbed consisting of 4682 instances and 46 features. The evaluation metrics were employed to evaluate the effectiveness and accuracy of the proposed methodology. The model outputs three probabilities, each pertaining to an FOG event, an instance listed in Table 1.

K-fold cross-validation, a resampling method involving the division of the dataset into k subsets, was utilized in this study to assess the performance of the LGBM

Table 1 A small sample of the output of test cases

Instance ID	Start hesitation	Turn	Walking
003f117e14_867	0.0169633	0.0186592	0.0001075
003f117e14_874	0.0169633	0.0183729	0.0001246
003f117e14_876	0.0149632	0.0183729	0.0001192
003f117e14_1828	0.0012843	0.2931558	0.0003868
003f117e14_1953	0.0012843	0.2877404	0.0004175
003f117e14_2163	0.0015811	0.227426	0.000382
003f117e14_2244	0.0010171	0.1939136	0.0003706
003f117e14_2375	0.0013712	0.206998	0.0004054
003f117e14_2616	0.0009333	0.204171	0.0004077

regression model. In order to guarantee the attainment of unbiased results, a validation set was constructed from each fold, with the remaining folds being utilized for training intentions. Group-based cross-validation with the "Id" column for partitioning was chosen to deal with data dependencies and reduce the chance of overfitting. The method mentioned above included an analysis of the built-in group structures. This made the model better at predicting different situations and allowed for a more accurate evaluation of its performance.

The evaluation criterion utilized in this study is the mean average precision (MAP), which is a metric that quantifies the average precision of predictions made for each event class. Hence, placing greater importance on accurately predicting event categories is more significant than attaining complete precision in forecasting all events. According to Table 2, the inclusion of outliers impacts the precision of the results, but not significantly, given that healthcare scenarios often involve atypical cases.

The primary causes of a FOG (Fog of War) incident are hesitation and turning. There are big differences between what was observed and what was evaluated on the test, which suggests that the evaluation might not have been accurate if the above data were used.

Table 2 Precision of FOG event contribution in the presence and absence of outliers

FOG event	Precision with outliers	Precision without outliers
Start hesitation	0.7138	0.7354
Turning	0.8231	0.8225
Walking	0.253	0.2689
Overall	0.5967	0.6111

5 Conclusion

Freezing of gait (FOG) refers to the abrupt impairment in the capacity to execute turning movements, commence walking, or maintain locomotion in individuals who have Parkinson's disease. The above phenomenon exerts detrimental effects on individuals' mental and physical well-being, making them susceptible to increased likelihood of falls and diminished autonomy. Among the several approaches for assessing FOG, the most effective technique entails employing wearable devices to conduct FOG-inducing tests. This study employs machine learning models to compute the probability of each of the three FOG movements described above being hampered in a patient diagnosed with Parkinson's. These probabilities are derived from data collected via a lower back accelerometer worn by individuals with Parkinson's disease. The LightGBM algorithm is employed as a regressor to evaluate probability. Upon testing the algorithm in the presence and absence of outliers, it was deduced that LGBM performed better, yielding a precision of 61.11% overall. The low precision for walking suggests that it is a rare FOG event with a low probability of occurrence. Therefore, the need for prediction of impairment in FOG patients has been addressed in this study to enhance medical attention to such patients, especially seniors who desperately need mitigation in such disturbing conditions.

References

1. Srikanth R (2022) Parkinson disease detection using various machine learning algorithms. In: 2022 international conference on advanced computing technologies and applications (ICACTA). IEEE
2. Nissar I, Mir WA, Shaikh TA (2021) Machine learning approaches for detection and diagnosis of Parkinson's disease-a review. In: 2021 7th international conference on advanced computing and communication systems (ICACCS), vol 1. IEEE
3. Wang W et al (2020) Early detection of Parkinson's disease using deep learning and machine learning. IEEE Access 8:147635–147646
4. Raval S, Balar R, Patel V (2020) A comparative study of early detection of Parkinson's disease using machine learning techniques. In: 2020 4th international conference on trends in electronics and informatics (ICOEI)(48184). IEEE
5. Tadse S, Jain M, Chandankhede P (2021) Parkinson's detection using machine learning. In: 2021 5th international conference on intelligent computing and control systems (ICICCS). IEEE
6. Kamoji S et al (2021) Prediction of Parkinson's disease using machine learning and deep transfer learning from different feature sets. In: 2021 6th international conference on communication and electronics systems (ICCES). IEEE
7. Ouhmida A et al (2022) Parkinson's disease classification using machine learning algorithms: performance analysis and comparison. In: 2022 2nd international conference on innovative research in applied science, engineering and technology (IRASET). IEEE
8. Anand A et al (2018) Evaluation of machine learning and deep learning algorithms combined with dimensionality reduction techniques for classification of Parkinson's disease. In: 2018 IEEE international symposium on signal processing and information technology (ISSPIT). IEEE

9. Celik E, Omurca SI (2019) Improving Parkinson's disease diagnosis with machine learning methods. In: 2019 scientific meeting on electrical-electronics & biomedical engineering and computer science (EBBT). Ieee
10. Saikia A et al (2020) Machine learning based diagnostic system for early detection of Parkinson's disease. In: 2020 international conference on computational performance evaluation (ComPE). IEEE
11. Kumar T, Tiwari A, Yadav V (2022) Early detection of parkinson's disease using convolutional neural network. In: 2022 fifth international conference on computational intelligence and communication technologies (CCICT). IEEE
12. Djurić-Jovičić MD, Jovičić NS, Radovanović SM, Stanković ID, Popović MB, Kostić VS (2013) Automatic identification and classification of freezing of gait episodes in parkinson's disease patients. IEEE Trans Neural Syst Rehabil Eng 22(3):685–694
13. Mekruksavanich S, Jitpattanakul A (2021) Detection of freezing of gait in parkinson's disease by squeeze-and-excitation convolutional neural network with wearable sensors. In: 2021 15th international conference on open source systems and technologies (ICOSST). IEEE, pp 1–5
14. Abdallah M, Saad A, Ayache M (2019) Freezing of gait detection: deep learning approach. In: 2019 international arab conference on information technology (ACIT). IEEE, pp 259–261
15. Khan AZ, Aamir F, Kafeel A, Khan MU, Aziz S (2021) Freezing of gait detection in parkinson's disease from accelerometer readings. In: 2021 Mohammad Ali Jinnah University international conference on computing (MAJICC). IEEE, pp 1–5
16. Polat K (2019) Freezing of gait (fog) detection using logistic regression in parkinson's disease from acceleration signals. In: 2019 scientific meeting on electrical-electronics & biomedical engineering and computer science (EBBT). Ieee, pp 1–4
17. Tahafchi P, Molina R, Roper JA, Sowalsky K, Hass CJ, Gunduz A, Judy JW (2017) Freezing-of-gait detection using temporal, spatial, and physiological features with a support-vector-machine classifier. In: 2017 39th annual international conference of the IEEE engineering in medicine and biology society (EMBC). IEEE, pp 2867–2870
18. Zhang Y, Yan W, Yao Y, Bint Ahmed J, Tan Y, Gu D (2020) Prediction of freezing of gait in patients with Parkinson's disease by identifying impaired gait patterns. IEEE Trans Neural Syst Rehabil Eng 28(3):591–600
19. Łoś H, Mendes GS, Cordeiro D, Grosso N, Costa H, Benevides P, Caetano M (2021) Evaluation of XGBoost and LGBM performance in tree species classification with sentinel-2 data. In: 2021 IEEE international geoscience and remote sensing symposium IGARSS. IEEE, pp 5803–5806
20. Lin M, Ma L (2021) Research on setting voltage of electrolyzer based on LGBM-LSTM algorithm. In: 2021 IEEE 4th international conference on computer and communication engineering technology (CCET). IEEE, pp 414–419
21. Shukla A, Chettiar G, Choudhary A, Thakur A, Kumar S (2022) Integrating comparison of malware detection classification using LGBM and XGB machine learning algorithms. In: 2022 IEEE international conference on blockchain and distributed systems security (ICBDS). IEEE, pp 1–7