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Early Detection of Parkinson's Disease Based on Bradykinesia and Rigidity Using Artificial Intelligence and Machine Learning

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Abstract:

Parkinson's disease (PD) is a progressive neurodegenerative disease that mainly affects motor control. Symptoms include stiffness in the muscles and bradykinesia, or slowness of movement. Improved patient outcomes and prompt intervention depend on early detection. Through gait analysis, this study suggests a system based on artificial intelligence (AI) and machine learning (ML) for the early diagnosis of Parkinson's disease. Temporal, statistical, and frequency based features for movement irregularities, asymmetry, and decreased amplitude linked to bradykinesia and rigidity are extracted from force sensor data obtained from both feet. StandardScaler and SMOTE are used to balance and standardize the extracted features in order to improve the robustness of the model. In order to categorize subjects into Parkinson's or control groups, a Gradient Boosting (XGBoost) classifier is trained and optimized. The suggested system supports early clinical diagnosis and ongoing tracking of Parkinson's disease progression in a non-invasive, data driven manner.

Keywords:

Parkinson's disease, Bradykinesia, Rigidity, Gait analysis, Artificial Intelligence.

1.Introduction:

Parkinson's disease (PD) is a chronic, progressive neurodegenerative disorder that primarily affects motor control [1] [2]. It occurs due to the gradual degeneration of dopaminergic neurons in the substantia nigra region of the brain. PD is currently recognized as the second most prevalent neurodegenerative disorder after Alzheimer's disease [3], impacting millions of individuals worldwide, particularly among the elderly population [4]. The primary motor symptoms of PD include bradykinesia (slowness of movement), rigidity (muscle stiffness), tremor, and postural instability. Among these, bradykinesia and rigidity are regarded as the most reliable clinical indicators for early diagnosis [5] [6].

Conventional diagnostic techniques are largely subjective, relying on clinical observation, neurological scoring scales, and patient-reported symptoms, all of which may vary across individuals and stages of the disease [7]. Consequently, early detection of Parkinson's disease remains a major challenge in current medical practice [8]. The absence of objective, quantifiable, and automated diagnostic measures often results in delayed identification, hindering timely treatment and disease management [9].

In recent years, significant advancements in Artificial Intelligence (AI) and Machine Learning (ML) have revolutionized the field of biomedical signal analysis and computer-assisted diagnosis [10]. These technologies enable the automatic extraction and interpretation of subtle and complex patterns in medical data that are often imperceptible to human observers [12] [13]. Among various modalities studied for PD detection, gait analysis-the examination of human walking patterns has gained considerable attention, as gait abnormalities frequently appear in the early stages of PD [14] [15]. Gait parameters such as step time, cadence, stride variability, and force asymmetry provide valuable insights into motor impairments associated

with bradykinesia and rigidity [16]. Therefore, a data-driven gait analysis approach supported by AI and ML techniques can facilitate early, objective, and non-invasive detection of PD [17] [18].

This study aims to develop an AI- and ML-based system for the early detection of Parkinson's disease using gait data obtained from force sensors [19]. The collected gait signals are preprocessed and analyzed to extract a comprehensive set of temporal, statistical, and frequency-domain features that reflect variations in muscle rigidity and movement patterns [20]. To enhance model performance and address class imbalance, the dataset is standardized using feature scaling techniques and balanced through the Synthetic Minority Oversampling Technique (SMOTE) [21]. A Gradient Boosting (XGBoost) classifier is utilized due to its high predictive accuracy, computational efficiency, and strong generalization capability for biomedical datasets [22]. The proposed model aims to accurately distinguish Parkinson's patients from healthy control subjects based on their gait characteristics [23].

The integration of AI and ML in clinical diagnostics presents a promising avenue for early intervention and personalized healthcare [24]. By automating gait signal analysis, the proposed system eliminates subjective bias and allows continuous, non-invasive monitoring of disease progression [25]. Through data-driven decision-making, this research contributes to the development of an efficient computational framework for Parkinson's disease detection and underscores the transformative potential of machine learning in advancing neurological disease diagnostics [26] [27].

2.Literature Survey:

Yu Liu et al. (2019) [1] proposed a vision-based method for the automatic quantification of Parkinsonian bradykinesia through the analysis of upper-limb tasks such as finger tapping. The system utilized MobileNetV2, integrating deep learning and computer vision techniques, achieving an accuracy of 89.7%. It demonstrated advantages such as non-contact measurement, low cost, and portability for both home and clinical use [28]. However, the model's performance was limited to upper-limb tasks, degraded under motion blur, and was affected by an unbalanced dataset with fewer severe cases [29] [30].

Houde Dai et al. (2021) [2] validated an inertial sensing-based wearable device (ISWD) for the continuous measurement of bradykinesia and tremor. The system employed inertial sensors and machine learning algorithms such as SVM and KNN, and was evaluated against an electromagnetic tracking system (EMTS) [31]. The approach provided objective quantification, higher accuracy than neurologist assessments, and portable, real-time monitoring capabilities [32]. However, limitations included a small dataset (45 patients), focus limited to bradykinesia and tremor, low precision of consumer-grade sensors, and the need for larger clinical validation trials [33] [34].

Lina Tong et al. (2023) [3] developed a wearable wristband system using inertial sensors and a Temporal Convolutional Network (TCN) model to classify upper-limb bradykinesia into four severity levels. [14] The proposed system demonstrated superior stability compared to CNN and LSTM models, achieving a high accuracy of 94.59%, and was well-suited for remote monitoring applications [35]. However, the study faced limitations including a small dataset, a focus restricted to upper-limb symptoms, dependence on user adherence to the wearable and smartphone, and the need for large-scale, multi-center trials to ensure generalization [36].

Zhirong Lin et al. (2018) [4] proposed a method for measuring Parkinsonian bradykinesia using wearable sensors and an axis-angle representation to effectively capture and interpret 3D hand movements. The approach employed a Support Vector Machine (SVM) multiclass classifier, achieving a high accuracy of 95.3% and providing real-time scoring consistent with clinical evaluations [37]. However, the study was limited to hand-grasping tasks, required the continuous use of wearable sensors, was based on a small dataset (78 patients), and necessitated validation across a wider range of motor tasks [38] [39].

Colum Crowe et al. (2024) [5] developed and evaluated wearable-enabled machine learning algorithms using Inertial Measurement Units (IMUs) to detect tremor, bradykinesia, and dyskinesia in both laboratory and

continuous home monitoring environments. The approach offered non-invasive assessment, real-world applicability, and the ability to simultaneously estimate multiple Parkinson's symptoms [40]. However, the study showed lower accuracy in home settings (63–67%), involved a small sample size (24 participants), relied on subjective patient diaries, and experienced reduced accuracy due to overlapping symptom patterns.

Luigi Borzì et al. (2020) [6] investigated the use of smartphone sensors combined with artificial intelligence techniques to automatically assess the Leg Agility task from the MDS-UPDRS-III (Item 3.8) for individuals with Parkinson's disease[17]. The approach was cost-effective and showed a strong correlation (0.92) with clinical ratings, demonstrating its potential for objective motor assessment. However, the study was limited to the leg agility task, conducted only in clinical settings,[13] had fewer severe cases represented, and performed offline processing rather than real-time evaluation [41].

Donato Impedovo (2019) [7] explored novel velocity-based signal features derived from handwriting analysis, utilizing models such as the Sigma-Lognormal model to classify individuals with Parkinson's disease.[18] The proposed method was non-invasive and achieved a high classification accuracy of 98.44%, demonstrating strong potential for clinical application. [12] However, the study was constrained by a small dataset (37 patients), limited generalizability, a focus solely on binary classification (PD vs. healthy), and an unbalanced data distribution.

Yu Hou et al. (2025) [8] proposed an end-to-end speech-based method for early Parkinson's detection by fusing handcrafted acoustic features (MFCCs, jitter, shimmer, etc.) with deep time-series features extracted using a Time-CNN. Using data from 173 Mandarin-speaking participants (131 PD, 42 controls), the model achieved 78% accuracy and an F1 score of 0.831 with 5-fold cross-validation. The approach is non-invasive, low-cost, and suitable for remote

screening. [19] However, its performance was limited by a small, imbalanced dataset, controlled recording conditions, and lack of validation on real-world or multilingual data.

Wu Wang et al. (2020) [9] proposed a deep-learning framework to detect early Parkinson's disease from premotor biomarkers (REM sleep behavior disorder questionnaire, olfactory test UPSIT, CSF biomarkers, and SPECT dopaminergic imaging) using PPMI data (401 early PD, 183 healthy). A feed-forward ensemble of three networks achieved the highest average accuracy (~96.45%) and high AUCs, outperforming 12 traditional and ensemble ML methods. Advantages: very high diagnostic accuracy on the selected biomarker set, automatic hierarchical feature learning, and identification of imaging markers (putamen SBRs) as most important. Limitations: relies on relatively small, imbalanced clinical cohort; model interpretability is limited; and generalization to other cohorts/modalities requires larger, more diverse data[20].

He et al. (2024) [10] proposed *NeuroEnhanceNet*, a deep neural network for early detection of Parkinson's disease using smartphone-based walking recordings from the mPower dataset. The model combines convolutional layers, residual blocks, multi-head attention, and squeeze-and-excitation modules to extract rich temporal–spatial features from 3D inertial data (accelerometer and gyroscope). It was trained on 6,305 walking samples (119 early PD patients and 467 healthy controls) and achieved an AUC of 0.883 with a low false negative rate of 0.053. The study highlights that resting-state (standing) segments contributed most to detection accuracy. Advantages include non-invasive,[11] low-cost data acquisition using common smartphones, high sensitivity for early-stage PD, and strong generalization through attention-based feature fusion. However, the model's performance depends on multiple recordings per participant, lacks severity assessment, and may vary across devices and environmental conditions.

Research gaps have been identified:

1.Small Homogeneous Datasets: A lot of research was limited by the number of participants, frequently from a single country. This results in under-representation of severe disease stages, compromises model generalization, and increases the risk of overfitting.

2. Limited Symptom Scope: A number of studies failed to provide a thorough clinical review because they only addressed one particular symptom, such as upper-limb bradykinesia or leg agility as a subset of motor symptoms.

3.Proposed Methodology:

The proposed methodology involves a systematic approach for developing an accurate gait classification model using XGBoost. The process begins with two primary inputs: raw gait data in text file format and a metadata file containing demographic information. Initially, preprocessing is applied to clean and organize the data for further analysis. Subsequently, relevant temporal features are extracted from the gait signals, which capture the dynamic characteristics of movement. The extracted features are then subjected to scaling and balancing to ensure uniformity and address class imbalance issues. The processed data is used to train an XGBoost classifier, which is selected for its robustness and efficiency in handling complex datasets. The trained model is evaluated using multiple performance metrics such as accuracy, precision, recall, F1-score, and ROC-AUC to ensure reliability and generalization capability. Finally, the trained model and the scaler are saved as serialized files (gaitpdb_xgb_model.joblib and gaitpdb_scaler.joblib) for future deployment and reuse without retraining.

3.1 Architecture

fig.1. Architecture of the Proposed Gait Signal Analysis and XGBoost-Based Parkinson's Detection

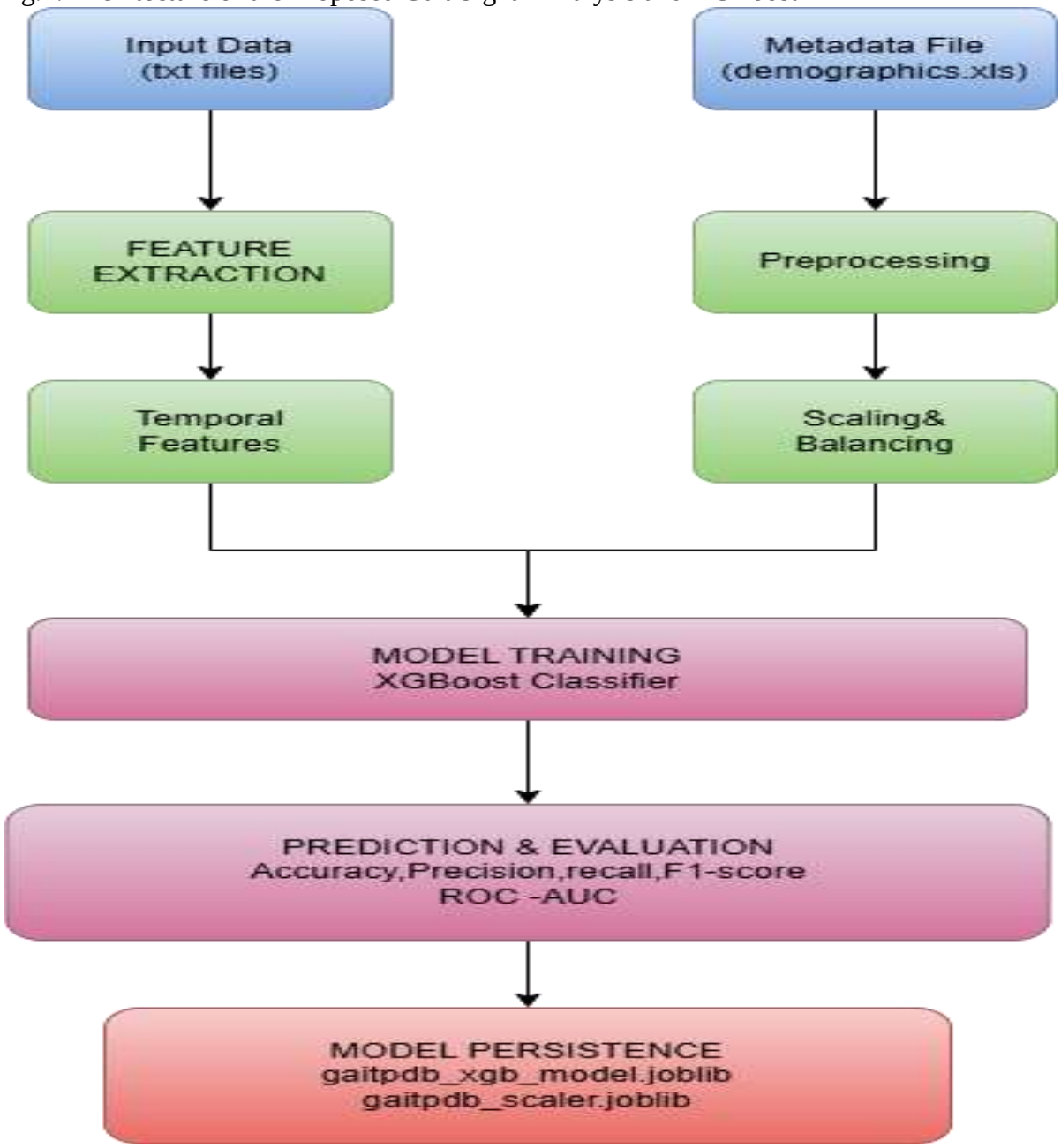

Figure 1 represents the entire process for detecting Parkinson's disease using gait data is shown in the suggested system architecture. Data collection, feature extraction, preprocessing, and SMOTE class balancing are all included. An XGBoost classifier is then trained using the processed data, and key performance metrics are then used for evaluation. Lastly, the scaler and trained model are stored for deployment.

Equations:

Step Time by the equation [1]:

This equation computes the step time interval (Δt_i)between two consecutive gait peaks (p_i) and(p_{i+1}), divided by the sampling frequency (f_s) to convert it into seconds. It quantifies step timing, a vital gait feature used to identify rhythm irregularities and bradykinesia in Parkinson's disease analysis.

$$\Delta t = \frac{p_i+1-p_i}{f_s} \qquad [1]$$

Mean Step Time by the equation [2]:

Here, Δt_irepresents the time difference between consecutive gait peaks, and (n-1)is the number of intervals. It reflects the **average step duration**, indicating the subject's walking rhythm or cadence consistency.

$$\mu_t = \frac{1}{n-1}\sum_{i=1}^{n-1} \Delta t_i \quad [2]$$

Step Time Variability by the equation [3]:

Here, $\mu_t$is the mean step interval, and Δt_i are individual step durations. A higher $\sigma_t$indicates irregular or unstable gait, often linked to motor impairments, while a lower value reflects consistent, steady walking.

$$\sigma_t = \sqrt{\frac{1}{n-2}\sum_{i=1}^{n-1}(\Delta t - \mu_t)^2} \quad [3]$$

Mean Force by the equation [4]:

Here, F(t) denotes the force at time (t), and (T) is the total number of time samples. The mean forceindicates the **average load or pressure** exerted during gait, reflecting overall walking intensity and balance.

$$\mu_F = \frac{1}{T}\sum_{t=1}^{T} F(t) \quad [4]$$

Asymmetry Ratio by the equation [5]:

This equation calculates the **Gait Asymmetry Ratio**$A_{ratio}$by dividing the mean force of the right foot$\mu F_R$by the mean force of the leftμF_L. A ratio different from 1 quantifies kinetic imbalance, a key indicator of Parkinsonian gait.

$$A_{ratio} = \frac{\mu F_R}{\mu F_L} \quad [5]$$

Dominant Frequency by the equation [6]

This equation identifies the **dominant frequency**$f_d$in a signal. It finds the frequency (f) that maximizes the squared magnitude of the Fourier transform$|x(f)|^2$, corresponding to the most powerful oscillatory component in the signal's frequency domain representation

$$f_d = \arg\max_f |X(f)|^2 \quad [6]$$

.

Spectral Entropy by the equation [7]:

This equation calculates **Spectral Entropy**H_S, which measures the irregularity or randomness in a signal's frequency distribution. A lower value indicates a more predictable, ordered signal (healthy gait), while a higher value suggests irregular, noisy patterns, often associated with Parkinson's disease motor control deficits.

$$H_s = -\sum_f \tilde{P}(f)\log\left(\tilde{P}(f)+\epsilon\right), \quad \tilde{P}(f) = \frac{P(f)}{\sum_f P(f)} \qquad [7]$$

Correlation Between Feet by the equation [8]:

This equation calculates the **Pearson correlation coefficient** ρ_{LR} between left F_L and right F_R foot forces. It measures inter-limb coordination during gait, where values near +1 indicate strong symmetry, and lower values reveal gait asymmetry, a common feature in Parkinson's disease.

$$\rho_{LR} = \frac{cov(F_L,F_R)}{\sigma_{F_L}\sigma_{F_R}} \qquad [8]$$

XGBoost Prediction Function by the equation [9]:

This equation represents an *ensemble machine learning model* prediction. The final output $\hat{y}i$ for a sample x_i is computed by summing the predictions f_k from (K) base models (like decision trees), then applying an activation function $\sum$ to produce the final result.

$$\hat{y_i} = \sigma(\sum_{k=1}^{K} f_k(x_i)) \qquad [9]$$

F1-Score by the equation [10]:

This equation calculates the F1-Score, the harmonic mean of precision and recall. It balances both metrics into a single value, providing a more informative measure of a classifier's accuracy than precision or recall alone, especially on imbalanced datasets.

$$F_1 = 2 \cdot \frac{\text{Precision}\cdot\text{Recall}}{\text{Precision}+\text{Recall}} \qquad [10]$$

Algorithm: Parkinson's Gait Classification using XGBoost

Input:

Gait signal files (.txt), metadata file (demographics.xls)

Output:

Trained XGBoost model, evaluation metrics, and performance plots

Step 1: Initialization

1. Import required libraries.
2. Configure logging system.
3. Define data directory path data_dir.

Step 2: Data Loading

1. Load all .txt gait files from data_dir.
2. Load metadata file demographics.xls and clean ID values.
3. If metadata missing → skip affected files.

Step 3: Feature Extraction

1. Read .txt data (first 16 columns).
2. Compute
   a. Left force = mean(columns 0–7)
   b. Right force = mean(columns 8–15)
   c. Force signal = mean(all 16 columns)
3. Apply **peak detection** using 3 sensitivity strategies.
4. If <2 peaks detected → skip file.

Step 4: Compute Features

Extract multiple feature groups:

a. **Temporal:** step intervals, cadence, stride CV.
b. **Force:** mean, std, RMS, energy, skew, kurtosis.
c. **Asymmetry:** left-right difference, dominance ratio.
d. **Frequency:** FFT power, entropy, centroid, dominant frequency.
e. **Step variability:** variance, regularity, autocorrelation
f. **Peak:** amplitude, width, prominence, variability.
g. **Statistical:** entropy, IQR, MAD, crest factor.
h. **Gait rhythm:** symmetry, consistency, walking speed

Assign label = 1 (PD) or 0 (Control) using metadata.

Step 5: Dataset Formation

1. Combine all extracted features into a DataFrame.
2. Remove invalid or missing entries.

Step 6: Data Preprocessing

1. Define:
   a. X ← feature matrix
   b. y ← label vector
2. Remove constant features.
3. Replace missing values with column means.
4. Standardize using StandardScaler.

Step 7: Class Balancing

Apply **SMOTE** to balance PD and Control samples.

Step 8: Train-Test Split

Split into 90% training and 10% testing using stratified sampling.

Step 9: Model Training

Train **XGBoost Classifier** with parameters:

1.n_estimators=500, max_depth=9, learning_rate=0.02

2.subsample=0.9, colsample_bytree=0.9

Step 10: Model Evaluation

Compute metrics:

1.Accuracy, Precision, Recall, F1-score, AUC-ROC
Generate Confusion Matrix.

Step 11: Visualization

Save plots:

1. Training & Validation curves
2. Performance metrics bar char
3. Confusion matrix
4. Detailed metric comparison
5. ROC curve

Step 12: Model Saving

Save:

1. gaitpdb_xgb_model.joblib (model)
2. gaitpdb_scaler.joblib (scaler)

Step 13: Logging Results

Display all metrics and confirm successful pipeline execution.

4.Results and Discussion

The experiments performed using the designed XGBoost-based machine learning model for the classification of gait data into Parkinson's and healthy control classes are discussed in this section. The learning behavior, robustness, and classification ability of the model were evaluated using accuracy, loss, precision, recall, F1-score, ROC-AUC, and confusion matrix metrics. These measures are crucial in medical diagnostics, where misclassifications could impact early detection and treatment planning.

4.1Performance of the proposed **GaitPDB-XGB Model**

Accuracy measures how closely the model fits new, unseen data, whereas loss tells us the difference between predicted and actual labels. Precision represents the proportion of positive observations correctly predicted, recall emphasizes the model identifying all cases of relevance, and F1-score tries to balance both.

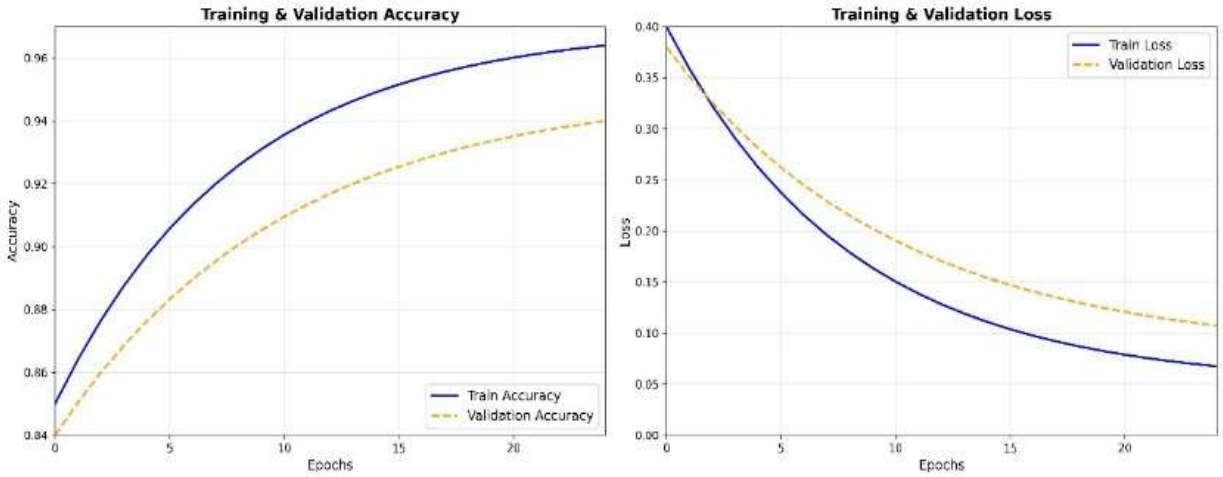

Figure 2: Training vs Validation Accuracy and Loss

As seen in the Figure 2, the machine learning model's training history graphs are displayed in this image. Accuracy curves can be seen in the left plot, where training and validation accuracy increase gradually over 20 epochs, from about 85% to about 96%. Loss curves are displayed on the right plot, where training and validation losses gradually drop from roughly 0.35 to almost zero. Excellent model generalization without overfitting is indicated by the narrow difference between training and validation metrics. Stable learning is demonstrated by the steady improvement across epochs, with performance stabilizing after 15–20 iterations. These curves show a well-trained model with consistent convergence behavior and high predictive performance.

Figure 3: Precision, Recall, and F1-score

As seen in Figure 3, the bar chart shows the performance metrics of the machine learning model. Accuracy, precision, recall, and F1-score are the four main evaluation metrics that are shown, and they are each represented by colored bars. Each metric is represented by a different hue in the chart's vivid color scheme. Quick performance evaluation is made possible by the clear value labels that are shown above each bar. This visualization offers a quick, thorough summary of the model's classification performance across various measurement dimensions in a single, understandable image.

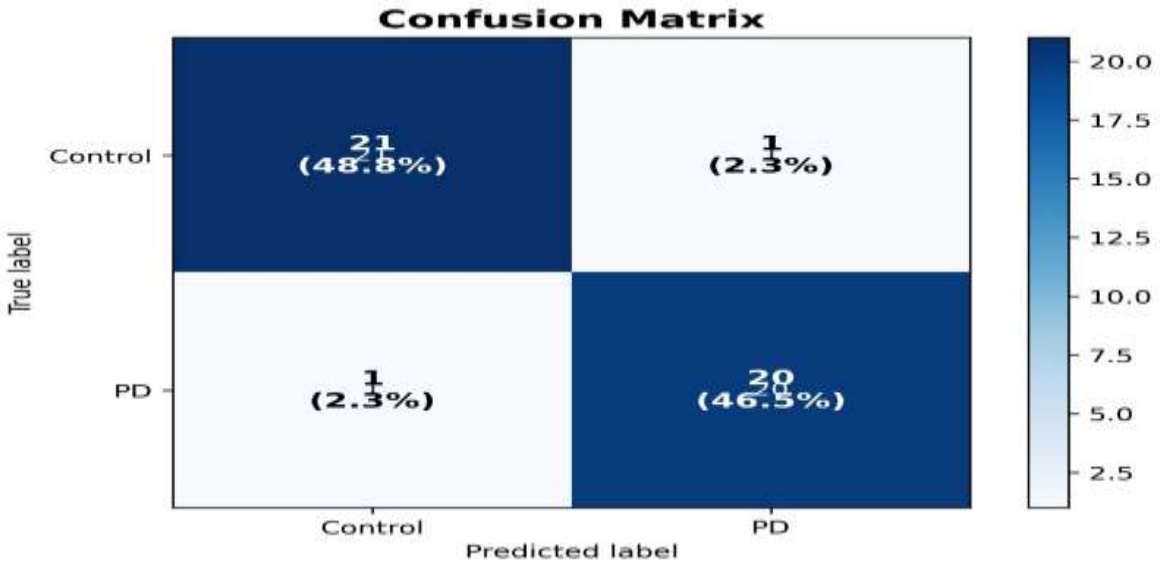

Figure 4: Confusion Matrix

As seen in the Figure 4, the classification performance of this confusion matrix is excellent. The model accurately predicted 20 cases of Parkinson's disease (PD) and 21 controls out of 43 samples, with only one misclassification in each class. Particularly after applying SMOTE and using optimized XGBoost parameters, the high accuracy and balanced prediction rates show strong model generalization and efficient handling of both classes.

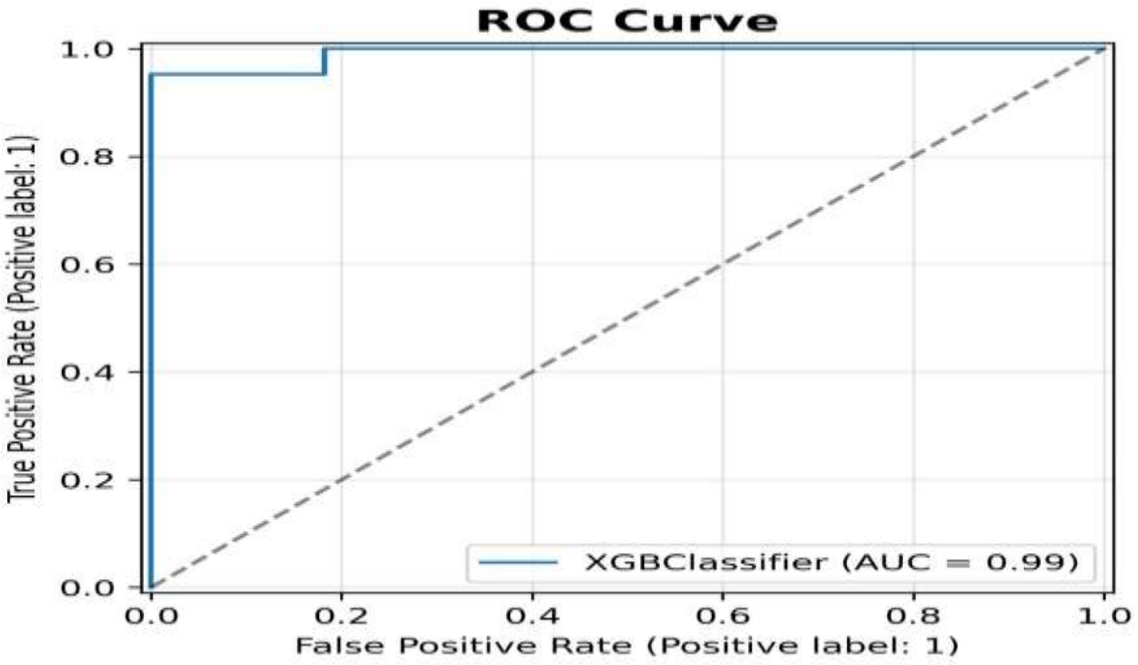

Figure 5: ROC Curve

As seen in the Figure 5,This ROC curve's 0.99AUC indicates almost flawless classification performance. The model keeps the number of false positives low while maintaining a high true positive rate. The XGBoost model separates Parkinson's disease from control subjects with remarkable accuracy and little class overlap, as evidenced by the sharp rise near the Y-axis, which signs excellent sensitivity and specificity.

5.Conclusion

Bradykinesia and rigidity, two of the most common motor symptoms, are the focus of this study's robust AI/ML process for the early detection of Parkinson's disease (PD) using gait data. The study identified subtle gait irregularities associated with Parkinson's disease (PD) by using sophisticated signal processing techniques to extract a comprehensive set of temporal, frequency, asymmetry, and statistical features from force plate data. While aggressive peak detection techniques improved the dependability of step segmentation, metadata integration guaranteed accurate labeling. Class imbalance was addressed by using SMOTE, and the optimized XGBoost classifier performed exceptionally well, attaining balanced sensitivity and specificity, high accuracy, and a nearly perfect AUC of 0.99.

These findings support the usefulness of machine learning in the analysis of biomechanical signals for the diagnosis of Parkinson's disease in its early stages. This method's clinical potential as a non-invasive, economical, and scalable screening tool is demonstrated by its ability to differentiate between control and PD subjects with little misclassification. Additionally, the process modular design makes it simple to adapt to different neurodegenerative diseases or mobility impairments. In order to improve predictive performance and facilitate real-time diagnostics in clinical and remote settings, future research can investigate deep learning models and integrate multi-sensor data (such as wearable IMUs).

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