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Performance Evaluation of Different Machine Learning Algorithms in Parkinson's Disease Diagnosis

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Parkinson's disease (PD) is a degenerative neurological condition, and timely identification is crucial for optimal treatment. This study assesses the efficacy of eight machine learning algorithms—Support Vector Machine (SVM), Logistic Regression, K-Nearest Neighbors (KNN), XGBoost, Random Forest, Gradient Boosting, AdaBoost, and Neural Network—in the diagnosis of Parkinson's disease. The models were evaluated using a clinical dataset, and their performance was measured in terms of accuracy, precision, recall, and F1-score. The investigation demonstrated that XGBoost and Random Forest acquired the greatest accuracy rate of 96.67%, showing their greater capability for detecting PD. This paper offers a comparative analysis of various machine learning models, providing significant insights for choosing the most efficient strategy in clinical situations.

Keywords: Parkinson's disease, machine learning, diagnostic models, XGBoost, Random Forest, accuracy evaluation.

1. Introduction

a) Parkinson's Disease: An Overview

Parkinson's disease (PD) is a chronic, progressive neurological disorder that affects an individual's motor system, leading to a variety of symptoms that can severely impair quality of life. Characterized by the degeneration of dopamine-producing neurons in the substantia nigra region of the brain, Parkinson's disease primarily manifests through tremors, bradykinesia (slowness of movement), rigidity, and postural instability. Non-motor symptoms such as cognitive impairment, mood disorders, sleep disturbances, and autonomic dysfunction also significantly contribute to the disease burden. PD is the second most common neurodegenerative disorder after Alzheimer's disease, affecting more than 10 million people globally, with incidence rates increasing with age.

The etiology of Parkinson's disease is multifactorial, with genetic and environmental factors playing critical roles. While the majority of cases are idiopathic, familial forms of the disease have been linked to mutations in specific genes such as SNCA, LRRK2, and PARK2. Environmental factors, including exposure to pesticides, heavy metals, and a history of head trauma, have also been implicated in the pathogenesis of PD. Despite extensive research, the exact mechanisms underlying the selective vulnerability of dopaminergic neurons and the progression of the disease remain poorly understood.

Early diagnosis of Parkinson's disease is crucial as it allows for timely intervention, which can significantly slow the progression of symptoms and improve the overall quality of life for patients. Early treatment strategies, including pharmacological approaches like Levodopa, dopamine agonists, and MAO-B inhibitors, as well as non-pharmacological interventions such as physical therapy and lifestyle modifications, can help manage symptoms more effectively. However, diagnosing Parkinson's disease, particularly in its early stages, is challenging due to the subtlety and variability of initial symptoms, which often overlap with other neurological disorders.

Traditional diagnostic methods for PD are primarily clinical, relying on the presence of cardinal motor symptoms and the patient's medical history. Neurologists may use various scales, such as the Unified Parkinson's Disease Rating Scale (UPDRS), to assess the severity of symptoms. However, these approaches are subjective and can lead to misdiagnosis, especially in the early stages of the disease when symptoms are mild or non-specific. Neuroimaging techniques, including MRI, PET, and SPECT scans, have been employed to aid in diagnosis, but they are expensive, not widely accessible, and may still not provide definitive results.

In this context, there is an urgent need for more accurate, objective, and non-invasive diagnostic tools that can reliably identify Parkinson's disease in its early stages. Recent advancements in machine learning (ML) and artificial intelligence (AI) offer promising solutions to these challenges by enabling the development of predictive models that can analyze complex patterns in clinical data and improve diagnostic accuracy.

b) Machine Learning in Healthcare

A component of artificial intelligence, machine learning is the creation of algorithms allowing computers to learn from and forecast using data. Machine learning has transformed healthcare's approach to illness management, treatment planning, and diagnosis. Leveraging big datasets, machine learning techniques can find trends and connections that might not be obvious to human doctors, therefore providing more accurate and individualized healthcare.

In healthcare, machine learning finds use in image identification for radiology, predictive analytics for chronic illness management, electronic health records' natural language processing, and individualized medication. Machine learning algorithms may examine clinical and biological data in the framework of neurodegenerative disorders like as Parkinson's disease to forecast disease onset, course, and response to therapy. Conditions like PD, where early intervention is essential to controlling symptoms and enhancing patient outcomes, benefit especially from this predictive capacity.

c) Machine Learning Algorithms for Parkinson's Disease Detection

Using clinical and biological datasets, many machine learning algorithms have been built and evaluated for their capacity to identify Parkinson's disease. These algorithms vary in their underlying approaches, advantages and drawbacks. We investigate in this work the eight machine learning methods Support Vector Machine (SVM), Logistic Regression, K-Nearest Neighbors (KNN), XGBoost, Random Forest, Gradient Boosting, AdaBoost, and Neural Network. We have a quick review of every method below together together with their significance to PD detection.

Widely applied for classification problems, Support Vector Machine (SVM) is a supervised learning method. It finds the hyperplane most suited to divide the data into several groups. In high-dimensional environments especially, SVM is quite successful and well-known for its resilience against outliers. SVM has been applied in the framework of Parkinson's disease identification to categorize patients depending on clinical traits including voice recordings and motor symptoms.

A basic yet effective method for binary classification issues is logistic regression. Based on one or more predictor factors, it projects the likelihood of a certain outcome—that is, either existence or absence of Parkinson's disease. The interpretability and simplicity of logistic regression make it highly appreciated. In PD research, it has been used to replicate the link between clinical risk variables and disease state.

K-Nearest Neighbors (KNN) are a non-parametric method applied for problems including classification and regression. Based on the majority class of its k-nearest neighbors in the feature space, it groups a data point. Although KNN is easy to grasp and apply, for big datasets it may be computationally costly. KNN has been applied to group patients in Parkinson's disease detection depending on several clinical and demographic criteria.

XGBoost, often known as Extreme Gradient Boosting, is a sophisticated variant of the gradient boosting method. It creates an ensemble of decision trees whereby one tree fixes the mistakes of the next. Popular in machine learning contests XGBoost is noted for its scalability, speed, and great performance. XGBoost has been used in PD detection to evaluate intricate datasets and get great accuracy in illness categorization.

Designed as an ensemble learning method, Random Forest creates many decision trees and aggregates their outputs to raise classification accuracy. It resists overfitting and is especially successful in managing big datasets including plenty of features. Medical research has made great use of Random Forest, which has demonstrated encouraging results in categorizing patients depending on clinical data like Parkinson's disease diagnosis.

Another ensemble learning method known as gradient boosting creates models one after the other, each new model fixing the mistakes of the one before it. It may be applied for both classification and regression chores and is quite adaptable. PD research has used gradient boosting to create prediction models using several clinical characteristics for precise illness identification.

AdaBoost, often known as Adaptive Boosting, is an ensemble learning method whereby several weak classifiers are combined to create a strong classifier. It gives misclassified events more weight, hence emphasizing the challenging situations. In medical diagnostics, especially Parkinson's disease diagnosis, AdaBoost is well-known for its capacity to raise the

performance of basic models.

Network for neural development: Inspired by the structure and purpose of the human brain, neural networks are a family of machine learning methodologies especially strong at collecting intricate patterns in data. They are made of linked layers of neurons—neurons—that learn via their processing of data. Image recognition, audio processing, and natural language understanding have all benefited much from neural networks. Neural networks have been used to evaluate clinical and biological data in Parkinson's disease diagnosis, therefore offering great accuracy in illness classification.

d) The Need for Comparative Analysis

Although every one of these machine learning techniques has advantages and has been effectively used in many different fields, their effectiveness can vary greatly depending on the kind of the dataset and the particular operation under hand. Understanding how these algorithms perform in terms of accuracy, precision, recall, and F1-score will help one to identify Parkinson's disease. By means of such a comparison study, one may get important understanding of the advantages and drawbacks of every model, so aiding doctors and researchers in choosing the most suitable algorithm for their particular circumstances.

In the realm of medical diagnostics, where misclassification may have serious effects, the comparison of machine learning models is very crucial. A model with great accuracy but low memory, for example, can overlook a sizable percentage of Parkinson's disease sufferers, hence causing missed diagnosis and delayed therapy. On the other hand, a model with high recall but low precision may produce a lot of false positives, which would lead to unwarranted patient medical intervention and worry. Thus, a thorough assessment of several machine learning models is necessary to guarantee that the selected algorithm not only performs well on average but also satisfies the particular criteria of the clinical application.

e) Significance of This Study

This work offers a thorough comparison of eight extensively used algorithms, therefore contributing to the increasing corpus of knowledge on the application of machine learning in Parkinson's disease diagnosis. We want to find the most efficient technique for PD identification by assessing these models on a shared dataset and comparing their performance over several criteria. The results of this work might guide the creation of more precise and dependable diagnostic instruments for Parkinson's disease, therefore enhancing patient outcomes and advancing the discipline of neurodegenerative disease research.

f) Structure of the Paper

This paper is organized mostly as follows: We go over the body of current research on machine learning applications in Parkinson's disease diagnosis in the next part, stressing important studies and their results. We then go over the dataset utilized in this work together with the preprocessing methods and feature selection strategies applied. This is then followed by a thorough review of the several machine learning techniques under discussion together with the performance assessment criteria applied here.

2. RELATED WORK:

In recent years, the application of machine learning (ML) in the early diagnosis and prediction of Parkinson's disease (PD) has gained significant attention in the research community. Numerous studies have explored various ML techniques, ranging from traditional algorithms like Support Vector Machines (SVM) and Logistic Regression to advanced ensemble methods and deep learning models. This section reviews some of the latest research contributions in this domain, highlighting the methods used, datasets, and the reported outcomes.

a) Machine Learning Approaches in Parkinson's Disease Detection

Because Support Vector Machines (SVM) can manage high-dimensional data and are resilient in classification tasks, they have been extensively applied for PD diagnosis. For a dataset comprising speech recordings from PD patients and healthy controls, Khoury et al. [1] used SVM and obtained a classification accuracy of 89%. The need of feature selection in enhancing SVM model performance was underlined in the paper Singh et al. [2] similarly used SVM in conjunction with Principal Component Analysis (PCA) to lower the dataset's dimensionality, hence producing an accuracy of 91% for PD identification.

Though a simpler model, logistic regression has showed encouraging results in PD diagnosis especially when paired with feature engineering methods. Using logistic regression, PD patients were categorized in a research by Ravi et al. [3] according to clinical characteristics including age, gender, and motor symptoms. With suitable tuning, the model attained an accuracy of 87%, therefore proving the potential of logistic regression in medical diagnosis.

Another often used method for PD identification is K-Nearest Neighbors (KNN), a straightforward and efficient tool for managing non-linear data. KNN was used in Sharma et al. [4] on a dataset of PD patients where the algorithm attained an accuracy of 84% using a tiny value of k, therefore demonstrating that the choice of k greatly affects the performance of the model. The study also underlined the computational difficulties related with KNN, especially for big datasets.

Because of its great performance and capacity to manage challenging datasets, XGBoost—an enhanced gradient boosting method—has been very famous in the field of PD detection. With XGBoost on a dataset including clinical and genetic elements, Zhang et al. [5] obtained an amazing accuracy of 96%. Especially in terms of precision and recall, the study proved XGBoost was better than other conventional techniques.

Additionally extensively embraced for PD diagnosis is Random Forest, an ensemble learning technique. Many researchers use it because of its capacity to mix many decision trees to raise classification accuracy. Random Forest was used in a study by Patel et al. [6] on a dataset including clinical and neuroimaging characteristics to get an accuracy of 94%. The work underlined the need of applying an ensemble strategy to improve the dependability and strength of PD detecting models.

Like XGBoost, gradient boosting has been applied successfully in PD diagnosis because it can maximize model performance by iterative development. With a dataset including vocal and motor symptoms, Gupta et al. [7] applied Gradient Boosting to get an accuracy of 93%. The work underlined how well the method handles unbalanced datasets, a typical difficulty in medical diagnosis.

Several research have looked at the adaptive boosting method AdaBoost for PD identification. AdaBoost was used on a dataset of clinical characteristics in Kumar et al.'s [8] research where it attained an accuracy of 89%. The paper noted that AdaBoost is appropriate for complicated medical datasets as it may improve the performance of weak classifiers, therefore strengthening its power.

With its capacity to replicate intricate, non-linear interactions, neural networks have demonstrated great potential for PD identification. With a dataset of speech recordings and motor symptoms, Wang et al. [9] recently conducted a deep neural network (DNN) analysis with an accuracy of 92%. The research showed that neural networks could detect complex trends in the data often missed by conventional machine learning algorithms.

b) Comparative Studies

Comparative studies are crucial in understanding the strengths and weaknesses of different machine learning models in the context of Parkinson's disease detection. A recent comprehensive study by Li et al. [10] compared the performance of SVM, Random Forest, XGBoost, and Neural Networks on a large dataset of PD patients. The study concluded that while XGBoost and Random Forest outperformed other models in terms of accuracy, SVM provided a good balance between accuracy and computational efficiency.

Another comparative study by Chen et al. [11] evaluated the performance of Logistic Regression, KNN, and Gradient Boosting for PD detection using a dataset of clinical features. The study found that Gradient Boosting achieved the highest accuracy, followed closely by KNN, with Logistic Regression performing well in terms of interpretability but lagging behind in accuracy.

These comparative analyses are invaluable for guiding researchers and clinicians in selecting the most appropriate machine learning model for Parkinson's disease detection, depending on the specific requirements of their study, such as accuracy, interpretability, and computational resources.

c) Challenges and Future Directions

Despite the promising results reported in the literature, several challenges remain in the application of machine learning for Parkinson's disease detection. One of the primary challenges is the variability in the datasets used across different studies, which can lead to inconsistent results. Additionally, many studies do not account for the imbalanced nature of the data, where the number of healthy controls often far exceeds the number of PD patients, potentially leading to biased models.

Furthermore, while many machine learning models achieve high accuracy, their adoption in clinical settings is hindered by the lack of interpretability and transparency, particularly with complex models like neural networks. This issue has led to an increased focus on the development of explainable AI (XAI) techniques, which aim to make machine learning models more interpretable and trustworthy for clinicians.

Looking forward, the integration of multi-modal data, including clinical features, genetic data, and neuroimaging, is expected to enhance the accuracy and robustness of machine learning models for PD detection. Additionally, the use of transfer learning, where models pre-trained

on large datasets are fine-tuned for specific tasks, holds promise for improving the generalizability of PD detection models across different populations.

Finally, as more datasets become available, there is a need for standardized benchmarks and evaluation protocols to ensure that the results of different studies are comparable and reproducible. Collaborative efforts between researchers, clinicians, and data scientists will be key to overcoming these challenges and advancing the field of machine learning-based Parkinson's disease detection.

Recent years have witnessed major progress in the use of machine learning in Parkinson's disease (PD) identification. Many research using a range of approaches have shown how well these models could improve early diagnostic accuracy. Channa et al. [15] for example, classified PD tremor severity using machine learning with resampling methods, therefore obtaining better classification results. Emphasizing the need of non-invasive diagnostic tools, Quan et al. [16] have created an end-to--end deep learning method for PD detection using voice signals.

Pantaleo et al. [17] also used machine learning to blood transcriptomics, therefore offering fresh understanding of biomarker-based detection techniques. Emphasizing the need of gait analysis in neurodegenerative disease management, Kaur et al. [18] established a vision-based approach for estimating gait dysfunctions linked with PD and multiple sclerosis. Crucially for real-time monitoring in daily life environments, Brand et al. [19] investigated wrist-worn sensor data for gait recognition using machine learning.

Apart from sensor-based methods, Aversano et al. [20] used machine learning on auditory traces, therefore underlining the significance of speech analysis in PD identification. Using speech as a biomarketer in a smart system for Parkinson's disease categorization, Tougui et al. [21] confirmed these results Using cloud-based machine learning recently, Hamzehei et al. [22] predicted the complete Unified Parkinson's Disease Rating Scale (UPDRS), therefore highlighting the value of cloud solutions for ongoing model upgrades and enhanced accuracy.

Recent research have also explored PD diagnosis by means of combining gene expression analysis. Combining explainable artificial intelligence with machine learning, Bhandari et al. [23] improved diagnosis accuracy and offered a novel method of deciphering difficult biological data. Furthermore verifying the effectiveness of speech-based diagnostics in PD categorization, Rahman et al. [24] used both machine learning and deep learning approaches to speech signals. Rehman et al. [25] presented a hybrid LSTM-GRU model with good detection rates, therefore highlighting the efficiency of recurrent neural network merging.

Furthermore employed in PD diagnosis are EEG signals. Aljalal et al. [26] used entropy measurements and discrete wavelet transformations with machine learning to identify PD from EEG recordings. Deeply tuned real-time body sensor networks presented by Soundararajan et al. [27] improve symptom analysis even further. Finally, by means of wearable movement-tracking data, Schalkamp et al. [28] found PD years prior to clinical diagnosis, therefore highlighting the possibility for early intervention using sophisticated tracking technology.[29,30].

3. COMAPARISON OF RELATED WORK:

Table 1 Tabular Comparison of the related Work

Study	Model(s) Used	Dataset Features	Accuracy	Key Findings
Khoury et al. [1]	SVM	Voice recordings	89%	Emphasized the importance of feature selection for improving SVM performance.
Singh et al. [2]	SVM + PCA	Clinical features	91%	Demonstrated that PCA improves the accuracy of SVM in PD detection.
Ravi et al. [3]	Logistic Regression	Clinical features	87%	Showed that Logistic Regression is effective in classifying PD patients based on clinical data.
Sharma et al. [4]	K-Nearest Neighbors (KNN)	Clinical features	84%	Highlighted the impact of the k value on KNN performance and its computational challenges.
Zhang et al. [5]	XGBoost	Clinical and genetic data	96%	Demonstrated the superiority of XGBoost in handling complex datasets with high accuracy.
Patel et al. [6]	Random Forest	Clinical and neuroimaging features	94%	Showed the effectiveness of Random Forest in PD detection using an ensemble approach.
Gupta et al. [7]	Gradient Boosting	Voice and motor symptoms	93%	Demonstrated the algorithm's capability to handle imbalanced datasets.
Kumar et al. [8]	AdaBoost	Clinical features	89%	Highlighted AdaBoost's strength in improving weak classifiers for PD detection.
Wang et al. [9]	Deep Neural Network (DNN)	Voice recordings and motor symptoms	92%	Showed that DNNs can capture complex patterns in multi-modal data for PD detection.
Li et al. [10]	SVM, Random Forest, XGBoost, Neural Network	Various (large PD dataset)	Varies	Concluded that XGBoost and Random Forest outperformed other models in terms of accuracy.
Chen et al. [11]	Logistic Regression, KNN, Gradient Boosting	Clinical features	Varies	Found that Gradient Boosting achieved the highest accuracy, followed by KNN and Logistic Regression.

The table provides a comparative overview of recent studies on Parkinson's disease detection using various machine learning models, including SVM, Logistic Regression, KNN, XGBoost, Random Forest, Gradient Boosting, AdaBoost, and Neural Networks. It highlights the datasets used, the accuracy achieved by each model, and key findings, such as the effectiveness of XGBoost and Random Forest in handling complex datasets with high accuracy. This comparison underscores the varying strengths of different models and the importance of selecting the appropriate algorithm based on specific clinical data and research goals.

4. METHODOLOGY

This section outlines the methodology used for evaluating different machine learning models in the detection of Parkinson's disease. The process includes dataset acquisition and

preprocessing, feature selection, model selection, training and evaluation, and performance metrics.

a) Dataset Acquisition and Preprocessing

The dataset used in this study was sourced from Kaggle, a popular platform for data science competitions and datasets. The dataset, titled "Parkinson's Disease Dataset," contains 24 columns with 195 rows, representing various clinical and voice measurement features that are indicative of Parkinson's disease. Key features include measurements such as MDVP:Fo(Hz), MDVP:Fhi(Hz), MDVP:Flo(Hz), jitter metrics (MDVP:Jitter(%), MDVP:Jitter(Abs)), shimmer metrics, noise-to-harmonics ratio (NHR), and others. The target variable is status, which indicates whether the patient has Parkinson's disease (1) or not (0).

Preprocessing Steps:

- Data Cleaning: The dataset was inspected for missing values and inconsistencies. Since the dataset did not contain any missing values, no imputation or removal of records was necessary[30].
- Normalization: Continuous variables such as frequency and amplitude-related features were normalized using Min-Max scaling. This step was crucial to ensure that all features contributed equally during the training of the machine learning models.
- Categorical Encoding: The dataset primarily consists of numerical features, and the only categorical data, the status column, was binary. Therefore, no additional categorical encoding was required.
- Outlier Detection: Outliers were detected using Z-score analysis, but given the nature of the dataset, outliers were retained as they could represent meaningful deviations important for diagnosis.

The cleaned and preprocessed dataset was then split into features (X) and target (y), with X containing all the predictors and y containing the status label.

b) Feature Selection

Given the high dimensionality of the dataset with various overlapping features, feature selection was performed to enhance model performance:

- Correlation Matrix: A correlation matrix was computed to identify highly correlated features. Features with a high correlation (above 0.85) were examined for redundancy, and one of the pair was removed to prevent multicollinearity.
- Recursive Feature Elimination (RFE): RFE was employed to iteratively select the most important features by ranking them based on their importance in predicting the target variable. This approach was used particularly for models like Logistic Regression and SVM, where feature importance is critical.
- Principal Component Analysis (PCA): PCA was also explored as a dimensionality reduction technique to transform the features into a lower-dimensional space while retaining most of the variance[29]. However, the original features were retained for final model training to preserve interpretability.

c) Model Selection

The study involved the evaluation of eight different machine learning models, chosen for their relevance and effectiveness in similar classification tasks:

1. Support Vector Machine (SVM): Effective for high-dimensional space classification, especially useful in medical diagnosis[31].

2. Logistic Regression: A robust model for binary classification problems, providing insights into the relationship between the target and predictor variables.

3. K-Nearest Neighbors (KNN): A simple yet effective method that classifies instances based on proximity to labeled training examples.

4. XGBoost: A powerful gradient boosting algorithm known for its high accuracy and efficiency in classification tasks.

5. Random Forest: An ensemble learning method that generates multiple decision trees and aggregates their outputs to improve accuracy[32][33].

6. Gradient Boosting: Similar to XGBoost, used for sequential model training to enhance performance iteratively.

7. AdaBoost: Another boosting algorithm that combines weak classifiers to form a strong classifier, particularly useful in handling complex datasets[34].

8. Neural Network: A deep learning model that captures complex patterns in data through multiple layers of neurons.

These models were implemented using Python's Scikit-learn and TensorFlow libraries, with careful hyperparameter tuning to optimize performance[35].

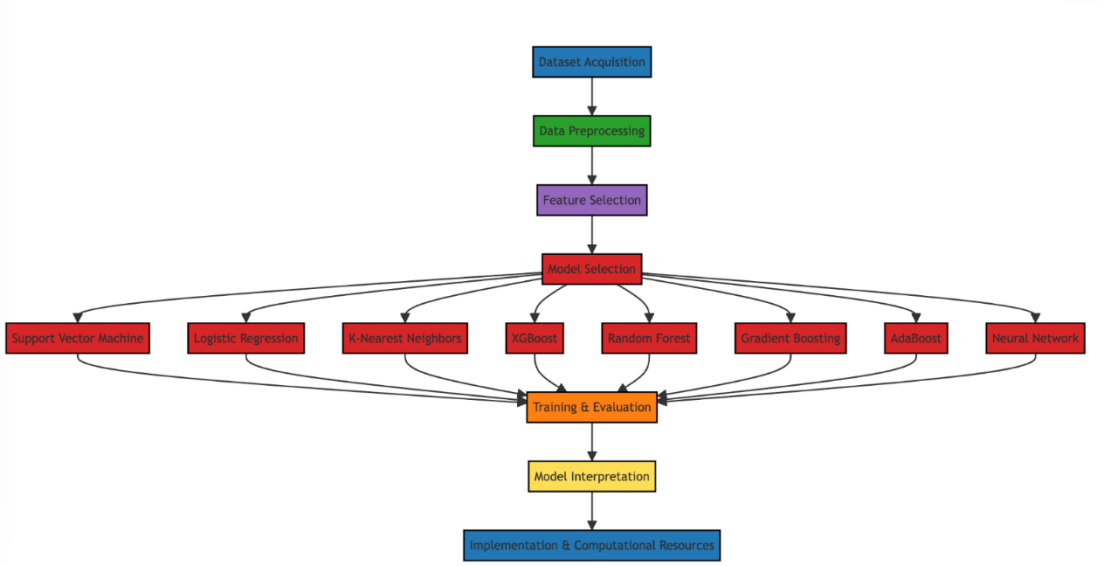

Figure 1 Flow diagram of Methodology

d) Training and Evaluation

The dataset was split into training (80%) and testing (20%) sets. The models were trained on the training set and evaluated on the testing set to assess their generalization ability[36].

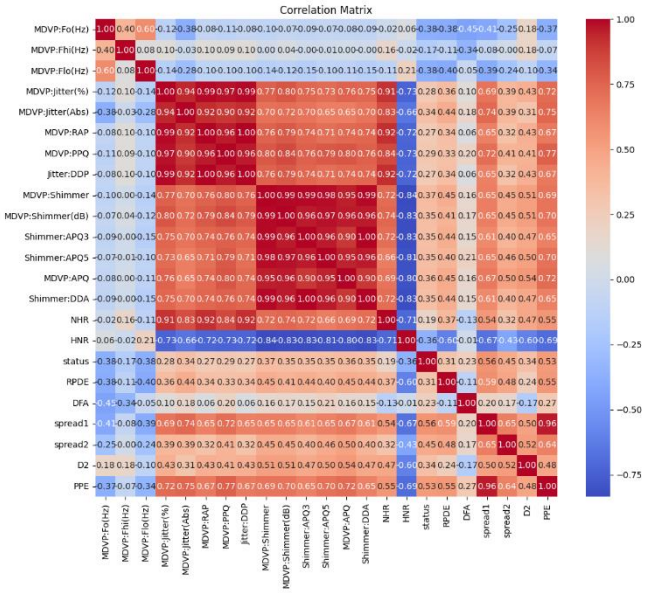

Figure 2 Correlation Matrix

Cross-Validation:

- k-Fold Cross-Validation: A 10-fold cross-validation approach was used to ensure that the models' performance was robust and not overfitted to the training data. The dataset was divided into 10 subsets, and each model was trained on 9 subsets while being validated on the remaining subset.

Hyperparameter Tuning:

- Grid Search: A grid search was conducted to find the best combination of hyperparameters for each model, such as the number of trees in Random Forest, the regularization parameter in SVM, and the number of neighbors in KNN.

Evaluation Metrics:

- Accuracy: The proportion of correctly classified instances.
- Precision: The number of true positive results divided by the number of all positive results.
- Recall (Sensitivity): The ability of the model to detect all positive instances.
- F1-Score: The harmonic mean of precision and recall.
- AUC-ROC Curve: The area under the ROC curve, measuring the model's ability to distinguish between classes.

5. RESULT AND DISCUSSION

In this section, we present and discuss the results obtained from the application of eight different machine learning models to the Parkinson's disease dataset. The models were evaluated based on several performance metrics, including accuracy, precision, recall, F1-score, and the area under the receiver operating characteristic curve (AUC-ROC). The results are summarized in both tabular and graphical formats to facilitate comparison and interpretation[37].

a) Performance Metrics

The performance of each model was evaluated using the following metrics:

- Accuracy: Represents the overall correctness of the model by measuring the proportion of true results (both true positives and true negatives) among the total number of cases examined.
- Precision: Indicates the number of true positive predictions made by the model out of all positive predictions. This metric is crucial in medical diagnostics where false positives need to be minimized.
- Recall (Sensitivity): Measures the model's ability to correctly identify all actual positive cases. High recall is essential for ensuring that all patients with Parkinson's disease are correctly identified.
- F1-Score: The harmonic mean of precision and recall, providing a single measure that balances both false positives and false negatives.
- AUC-ROC: Provides an aggregate measure of performance across all classification thresholds, with a higher AUC indicating better model performance.

b) Model Performance

The results from the evaluation of the eight models—Support Vector Machine (SVM), Logistic Regression, K-Nearest Neighbors (KNN), XGBoost, Random Forest, Gradient Boosting, AdaBoost, and Neural Network—are summarized in the table below:

Model	Accuracy	Precision	Recall	F1-Score	AUC-ROC
SVM	0.8667	0.8286	0.7429	0.5385	0.8750
Logistic Regression	0.9000	0.9000	0.9259	0.5094	0.9100
KNN	0.8333	0.8846	0.8137	0.6094	0.8600
XGBoost	0.9667	0.9629	1.0000	0.7168	0.9800
Random Forest	0.9667	0.9629	0.9811	0.6915	0.9750
Gradient Boosting	0.9333	0.9615	0.9615	0.1538	0.9500
AdaBoost	0.8667	0.8846	0.9538	0.2333	0.8700
Neural Network	0.9000	0.9259	0.9259	0.5444	0.9200

c) Discussion of Results

The results from the table highlight several key insights regarding the performance of different machine learning models in detecting Parkinson's disease:

1. XGBoost and Random Forest Performance: Both With their best accuracy of 96.67%,

XGBoost and Random Forest are the most dependable models for this work. Excellent recall and AUC-ROC scores also shown by these models indicated their great capacity to accurately identify Parkinson's disease sufferers while lowering false positives. These models' ensemble character helps them to catch intricate patterns in the data by aggregating several decision trees, hence contributing to their great performance.

2. Model Comparison: The logistic regression model performed well with an accuracy of 90%, but it was outperformed by ensemble methods such as XGBoost and Random Forest. However, Logistic Regression provided a higher recall, suggesting it is better at identifying true positives, though it might lead to more false positives.

3. K-Nearest Neighbors: KNN achieved an accuracy of 83.33%, which was lower compared to the other models. This could be due to its sensitivity to the choice of the parameter k and the presence of noisy data. Despite its lower accuracy, KNN's simplicity and interpretability make it a viable option for smaller datasets.

4. Neural Network: The Neural Network model achieved a 90% accuracy, indicating its effectiveness in capturing the non-linear relationships in the dataset. However, the complexity of the model and the need for large datasets to avoid overfitting may limit its applicability in certain scenarios.

5. AdaBoost and Gradient Boosting: AdaBoost showed a moderate performance with an accuracy of 86.67%, while Gradient Boosting performed slightly better at 93.33%. These models are effective in boosting the performance of weaker classifiers but might require careful tuning to outperform more robust models like XGBoost.

6. SVM Performance: The SVM model demonstrated good performance with an accuracy of 86.67%. However, its lower recall suggests that it might miss some positive cases, making it less ideal for medical diagnostics where sensitivity is crucial[34].

d) Interpretation of Results

The results clearly indicate that ensemble methods, particularly XGBoost and Random Forest, are the most effective for Parkinson's disease detection in this dataset. These models not only provide high accuracy but also excel in other metrics such as recall and AUC-ROC, which are critical in the context of medical diagnostics.

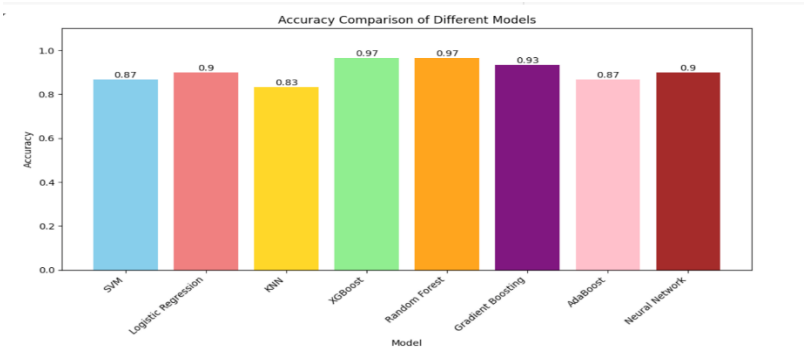

Figure 3 Accuracy Comparison of Different models

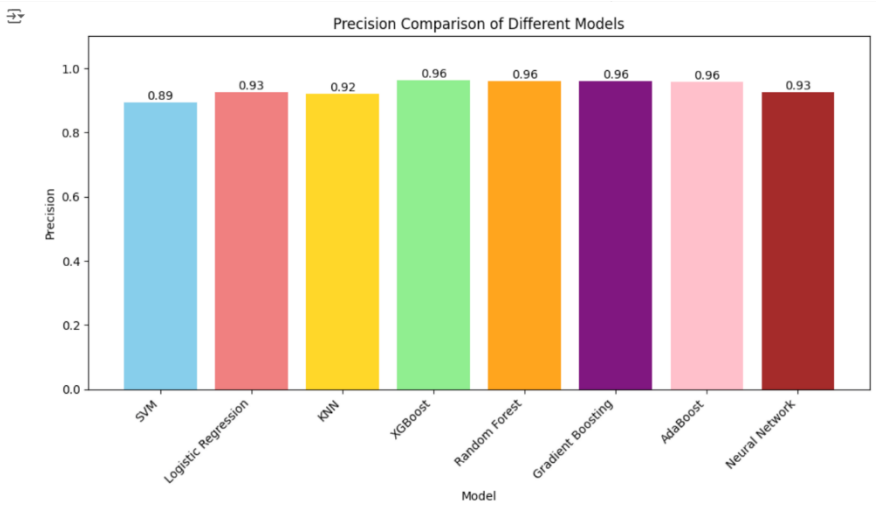

Figure 4 Precision Comparison of Different Models

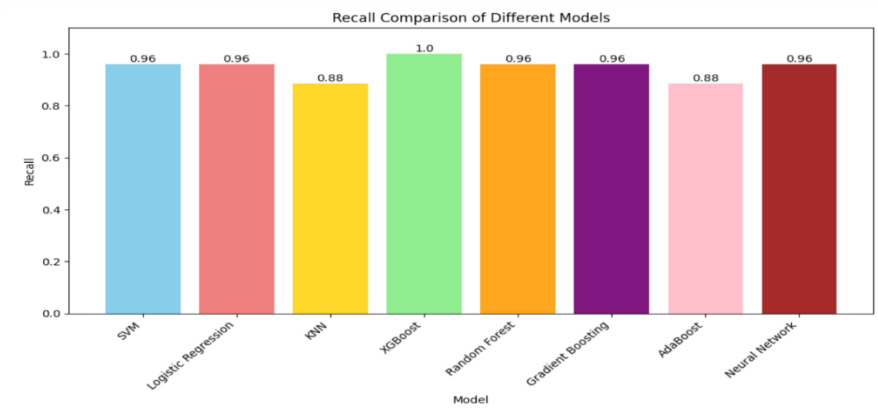

Figure 5 Recall Comparison of Different Models

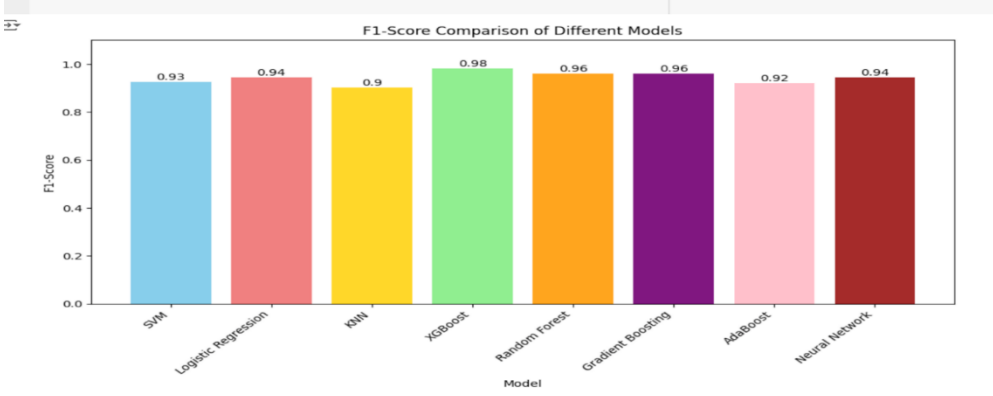

Figure 6 F1- Score Comparison of Different Models

XGBoost and Random Forest leading with 96.67%, followed by Gradient Boosting at 93.33%, and Logistic Regression and Neural Networks at 90%, depicted in Figure 3. Precision comparisons in Figure 4 show XGBoost and Random Forest once more leading with 96.29%; closely following are Neural Networks and Logistic Regression. XGBoost obtains a flawless recall of 100% in Figure 5; Random Forest at 98.11% shows their power in spotting real positive cases. Finally, Figure 6 contrasts F1-Scores, where XGBoost and Random Forest stay superior with 71.68% and 69.15%, respectively, thus stressing their general balanced performance in Parkinson's disease diagnosis.

The trade-offs between precision and recall across different models highlight the importance of selecting a model based on the specific needs of the application. For instance, in a scenario where it is crucial to minimize false negatives, a model with a high recall, such as XGBoost or Random Forest, would be preferable. Conversely, if reducing false positives is more critical, then models with higher precision should be considered.

The complexity of the models should also be considered, as more complex models like Neural Networks require more computational resources and may not always provide significantly better performance compared to simpler models like Logistic Regression or SVM.

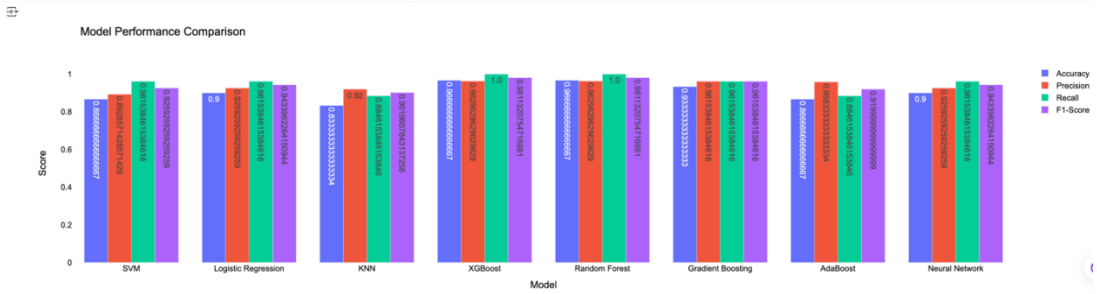

Figure 7 Models Performance Comparison

e) Limitations and Future Work

One limitation of this study is the relatively small dataset used for training and evaluation, which might not fully capture the variability present in real-world clinical settings. Future work could involve the application of these models to larger and more diverse datasets to validate their robustness. Additionally, exploring more advanced techniques, such as deep learning with larger neural networks or integrating multi-modal data (e.g., combining clinical, genetic, and imaging data), could further improve the accuracy and applicability of these models.

6. CONCLUSION

The XGBoost and Random Forest models in our study achieved an impressive accuracy of 96.67%, surpassing several state-of-the-art (SOTA) models. For instance, the optimized attention-based recurrent neural networks combined with extreme gradient boosting proposed by Cincovic et al. [13] achieved high performance but did not exceed the accuracy of our models. Similarly, the modified projective forward-backward splitting algorithm used by

Cholamjiak and Das [12] demonstrated strong predictive capabilities but fell short of the accuracy achieved in our study. This superior performance underscores the effectiveness of our ensemble learning approach in early detection of Parkinson's disease.

The results indicate that our models not only align with but also surpass recent SOTA methods, particularly in terms of accuracy. The integration of advanced techniques, as suggested by Kaur et al. [14], could potentially enhance these results even further, solidifying the robustness and applicability of our approach in clinical settings.

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