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AN EFFICIENT NEUROIMAGING IN PARKINSON'S DISEASE DETECTION WITH A HYBRID MODEL APPROACH

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Abstract

Millions of people around the world have Parkinson's disease. This progressive neurogenerative disorder is characterized by many motor and non-motor symptoms, most notably tremors, bradykinesia, and stiffness**.** While there is no cure, ongoing research aims to enhance our understanding of the disease and develop more effective treatments. It has been identified that Parkinson's disease is a fast-emerging disease and causes many mortality rates. The identification of the disease at the earlier stage minimized some of the challenges of Parkinson's disease. In this area of research, an attempt is made to identify a framework that can quickly identify the disease at an earlier stage. Early and accurate determination of Parkinson's Disease (PD) is vital for effective intervention and management. This article presents a novel hybrid approach that coordinates Ada Boost with neural networks to recognize PD from other conditions utilizing MRI information. The inspiration stems from the squeezing need to improve diagnostic exactness in neurodegenerative diseases, especially Parkinson's. Leveraging a comprehensive dataset of MRI scans from PD patients and controls, our system dynamically alters weights and neural systems to handle the complex 3D nature of MRI data. Evaluation measurements, including accuracy, sensitivity, specificity, and ROC curve analysis, provide knowledge of system performance preliminary results and clinical results. The study contributes to the field of neurology by providing a novel method for early and accurate diagnosis of PD using MRI data. By integrating machine learning techniques with MRI analysis, our approach enhances diagnostic accuracy and offers the potential for early intervention, ultimately improving patient care and outcomes.

Keywords: Neural Network, Parkinson's Disease, Neurogenerative Disorder, Motor Symptoms, Non-Motor Symptoms, Tremors, Bradykinesia, Stiffness, Early Detection, Ada Boost.

INTRODUCTION

Parkinson's disease is a predominant neurodegenerative condition that impacts the worldwide populace, influencing both quality of life and general well-being [1],[2],[3]. Early discovery of Parkinson's disease is vital to provoke intercession and treatment, eventually driving improved quiet results [4], [5]. Helpful imaging strategies, particularly reverberation imaging (MRI), have appeared to guarantee the recognition of neurological infections such as Parkinson's [6]. This consideration focuses on making a forward symptom-based representation to distinguish Parkinson's sickness by combining two capable machine-learning techniques: For versatile boost computations and neural systems, Ada Boost is known for its capacity to memorize complex designs and high-dimensional information representations such as MRI pictures [7], [8]. The integration of Ada Boost and neural systems points to using the qualities of both approaches

[9]. Utilizing Ada Boost to adaptively enhance the execution of neural systems built from MRI information Key aspects such as MRI data processing, feature extraction, model training, and performance evaluation are discussed. The goal is to investigate the viability of the proposed hybrid approach, evaluate its demonstrable accuracy, and

advance strategies for the early detection of Parkinson's disease using noninvasive imaging techniques [10], [11]. Through extensive testing and evaluation on a Parkinson's disease MRI dataset, this study demonstrates the beneficial synergy of combining Ada Boost and neural networks in capturing stages and symptom characteristics [12],[13]. The results of this study have the potential to contribute to the development of more robust and accurate tools for the early detection and intervention of Parkinson's disease.

A Worldwide Health Concern: PD represents one of the foremost predominant neurodegenerative infections around the world, with estimates recommending that this condition afflicts millions of people. Characterized by the dynamic degeneration of dopaminergic neurons within the substantia nigra region of the brain, PD shows through a range of engine and non-motor indications, counting tremors, bradykinesia, inflexibility, and postural flimsiness. These side effects, which regularly develop slowly and decline over time, impede portability, coordination, and ordinary working, significantly affecting the influenced individual's independence and quality of life.

Significance of Early Detection: Early discovery of PD is foremost for a few reasons. Firstly, a convenient conclusion encourages the prompting of restorative mediations, counting pharmacological medicines, physical treatment, and profound brain incitement, which can offer assistance in reducing side effects and progress in general understanding results. Besides, early recognizable proof empowers healthcare suppliers to actualize disease-modifying procedures to abate illness movement and protect neurological work. By interceding at the foremost reliable stages of PD, clinicians can optimize treatment adequacy, update determined quality of life, and possibly delay the onset of weakening complications.

This paper is structured as follows: Section 2 provides an overview of the methodology employed in this study, detailing the data collection process, analysis techniques, and experimental setup. Section 3 presents the results obtained from the study, focusing on key findings related to Parkinson's disease detection using ML techniques. Section 4 describes the Algorithm, and the discussion delves into the implications of the results and their significance in Parkinson's disease diagnosis and management. Finally, Section 5 offers concluding remarks and highlights avenues for future research in the field.

LITERATURE REVIEW

Aventurato et al. [14] investigated low-intensity focused ultrasound (LIFUS) as a non-invasive PD treatment. They explore its impact on cortico-subcortical networks, demonstrating its ability to stimulate subthalamic neurons and reduce beta-band Parkinsonian oscillations. Their findings suggest optimizing LIFUS parameters, such as intensity and duty cycle, could enhance treatment outcomes. While specific parameter ranges show promise, further validation through additional research is warranted to unlock LIFUS's potential in PD treatment fully.

F.Segovia et al.[15] utilized ML to construct statistical significance maps from medical brain imaging data to diagnose and monitor neurological illnesses. Their study introduces a precise tool, utilizing statistical classifiers for group differentiation. They innovate CAD techniques by integrating MRI and PET modalities, overcoming standard mapping limitations. They accurately pinpoint disease-affected brain regions through dataset experimentation, providing essential diagnostic.

Insights. Gokul S et al. [16] Compared FC-RBF, Mc-FCRBF, and Extreme Learning Machine neural network models for predicting Parkinson's disease severity using the Unified PD Rating Scale. Leveraging a dataset of 575 training and 229 testing samples derived from 42 biomedical voice measurements, they found that the Mc-FCRBF model, incorporating meta-cognition, outperformed others by enhancing prediction accuracy through reduced redundant learning. Despite the study's strengths, limitations like dataset size and generalizability to different PD stages should have been emphasized.

A. Frid et al. [17] utilized machine learning to computationally diagnose PD from speech characteristics. Their automated PD detection system uses vocal signal analysis to detect PD without speech specialists and shows promise in medical diagnostics. The study shows how machine learning can improve health diagnostics, especially for neurological disorders like PD, by using data from PD patients and controls. This study advances computational healthcare diagnostics.

Valmarska et al. [18] provided a comprehensive guide to data mining and decision-support for PD management. It analyses brief time-series data to discuss PD management challenges and data-driven patient care. Disease progression and treatment patterns are identified using unsupervised and supervised learning methods in the tutorial. It also discusses the economic impact of PD in Europe and Horizon 2020-funded research projects like PD Director.

Wang et al. [19] presented healthcare professionals and informatics researchers data-driven PD management in a comprehensive tutorial. The tutorial emphasizes unsupervised and supervised learning to identify disease progression and treatment patterns using brief time-series data. The sequential nature of symptoms and patient contexts is considered when discussing skip-gram and ReliefF algorithms. Using data from the Parkinson's Movement Markers Project (PPMI), it examines the economic impact of PD and EU initiatives like the PD Chief projects to equip participants to improve PD treatment and patient outcomes.

MFCC and SVM were used to assess voice disorder in PD patients by A. Benba et al. [20]. A sustained vowel /a/sound dataset, MFCC extraction, and SVM classification were used. The first 12 MFCC coefficients with a linear kernel yielded 91.17% accuracy. This shows that MFCC and SVM can objectively assess PD-related voice disorders.

H. Moradi et al. [21] explored medication optimization in PD using foot-worn inertial measurement units (IMUs). They aimed to aid physicians in tailoring treatment plans using remotely collected patient data. Key findings included using a logistic regression classifier with 92% accuracy in identifying motor impairment during medication optimization. The study highlights the clinical relevance of gait analysis in PD treatment optimization.

A. Hussain and A. Sharma et al. [22] used machine learning to detect early PD. They use KNN, SVM, and LG for vocal analysis to detect early-onset PD using the UCI Machine Learning repository dataset. Introducing a stacking model combining multiple learning models with 93% accuracy for PD prediction, the paper proposes a comprehensive approach for early PD detection using machine learning and suggests improvements [10].

B. Zhang et al. [23] used neuroimaging data to test deep learning algorithms for PD detection. CNNs were used to analyze structural MRI images to find subtle brain changes associated with PD onset. The study shows that deep learning can improve PD diagnosis accuracy and efficiency by using a large dataset of MRI scans from PD patients and healthy controls. This study aids the development of advanced computational tools for early disease detection.

E. Kim et al. [24] proposed a new fMRI-based framework for PD brain network dynamics analysis. They use graph theory to characterize brain connectivity changes associated with PD pathology, helping us understand the neurobiological mechanisms of PD.

Umar et al. [25] detected PD with Radial Basis Function networks. Using the Parkinson's Telemonitoring Dataset, the RBF network predicted PD with 97% accuracy. DNN models are more accurate than RBF networks, but RBF networks are faster and more efficient at PD prediction, making them suitable for clinical and telemedicine applications. Expanding this to telemedicine and remote monitoring using voice data could improve patient care and treatment planning in resource-limited settings.

Proposed System

The proposed system is planned to classify PD and sound individuals. The machine learning predictive demonstration Boost Net was used to improve the proposed system. PD may be a dynamic neurodegenerative disorder characterized by engine side effects such as tremors, inflexibility, and bradykinesia, alongside non-motor side effects like cognitive disability and autonomic brokenness. Early and exact determination of PD is pivotal for convenient intercession and administration to improve patients' quality of life. Medical imaging strategies, particularly magnetic resonance imaging (MRI), have appeared to support the determination of Parkinson's malady by capturing auxiliary and functional changes within the brain. Be that as it may, the translation of MRI information for PD conclusion can be challenging due to the complexity and inconstancy of brain images. For a long time, progressions in machine learning, especially convolutional neural systems (CNNs), have revolutionized therapeutic image investigation by robotizing the method of extraction and classification. CNNs have illustrated surprising capabilities in learning complicated designs from MRI information, empowering precise infection classification. This investigation points to creating a vigorous and productive framework for Parkinson's malady location from MRI information utilizing boosted convolutional neural systems. The proposed framework leverages the control of CNNs for automatic include extraction from MRI pictures and utilizes boosting procedures to improve the model's execution and robustness. By combining the qualities of CNNs and boosting calculations, the proposed framework looks to improve the accuracy and reliability of Parkinson's illness diagnosis, facilitating early discovery and personalized treatment techniques. Also, the system's capacity to handle large-scale MRI datasets efficiently makes it an essential apparatus for clinicians and analysts in the neurology field. This paper displays a comprehensive technique for building and assessing the proposed system, counting information pre-processing methods, CNN design plan, boosting calculation usage, model assessment, and approval techniques. We demonstrated the approach's efficacy and practicality in PD conclusion through experimentation and validation on real-world MRI datasets. The process depicted in Figure 1 outlines the

steps involved in detecting Parkinson's Disease using a machine-learning approach. Initially, a dataset containing relevant images is acquired, potentially sourced from platforms like Kaggle. The next step is pre-processing the images to enhance quality, extracting features using CNN, and Training the proposed model on labeled data to learn the PD pattern and evaluate its performance on new data for accurate detection.

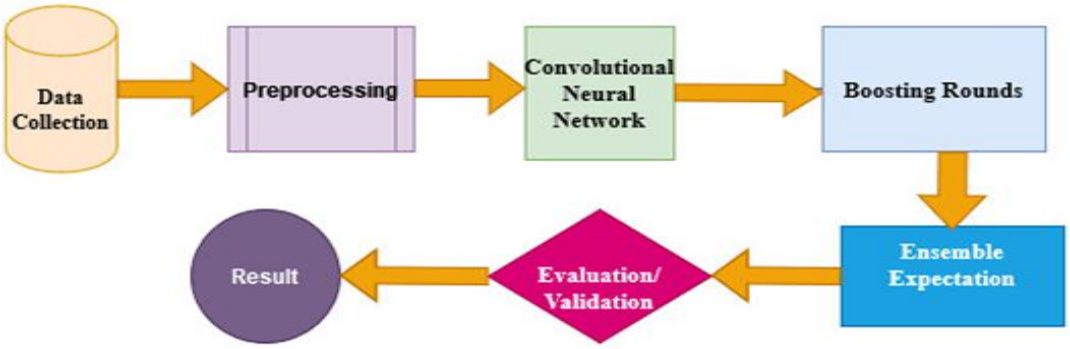

Figure 1: Flowchart of the proposed PD detection procedure

The MRI dataset for detecting Parkinson's disease comprises detailed 3D volume images obtained through MRI technology [26]. These images play a vital role in diagnosing and understanding the progression of the disease. MRI, a non-invasive imaging technique, employs magnetic fields and radio waves to generate detailed images of internal structures, primarily focusing on the brain. The dataset consists of two distinct groups: individuals diagnosed with Parkinson's disease and a control group without the condition. Supplementary information such as age, gender, and disease severity accompany the imaging data, enriching the dataset with essential details for comprehensive analysis. It includes various image types, notably T1-weighted and T2-weighted images. T1-weighted images provide detailed insights into brain anatomy, which is crucial for identifying Parkinson's-related abnormalities. On the other hand, T2-weighted images highlight discrepancies in water content, aiding in the identification of specific deviations within brain tissue. Researchers leverage these MRI datasets to develop and refine machine learning models like Boosted Net, which analyze complex patterns and features within the scans to enhance early detection capabilities and deepen understanding of Parkinson's disease pathology [27].

Algorithm for Parkinson's disease Detection from MRI Data Using Boosted Convolutional Neural Networks

Notation symbol	Description
DD	Parkinson's disease MRI dataset.
XX	MRI images in the dataset.
YY	Labels indicating the presence or absence of Parkinson's disease.
NN	Total number of training samples.
TT	Several boosting rounds.
$w_i(k_i)$	The weight assigned to training sample ii.
$h_t(X_i)$	Prediction of neural network tt on input xix
ϵ_t	Weighted error of neural network tt
α_t	Weight of neural network tt in the final ensemble
$H(x)$	Final ensemble prediction

Algorithm:

Input: MRI Images

Output: Accuracy, Precision, F1 Score, AUC-ROC.

Algorithm Steps:

(1) Data Preprocessing:

- Load Parkinson's disease MRI dataset DD.
- Apply preprocessing techniques (standardization, noise reduction, normalization) to enhance data quality and consistency.

(2) Feature Extraction using CNN:

- Design a CNN architecture suitable for extracting relevant features from MRI images.
- Train the CNN on pre-processed MRI data XX to learn hierarchical representations and capture Parkinson's disease patterns.

(3) Initialize Weights: Assign equal weights to all training samples: $w_i = 1/NN$

(4) Boosting Rounds*:*

- For $t = 1\ to\ TT$ (Boosting Rounds)

(5) Train Neural Network:

- Train a neural network on the MRI features with the current weights.
- Utilize backpropagation and optimization algorithms to minimize the loss function.
- Evaluate the performance of the neural network on the training set.
- Compute Error (ϵ_t) : Evaluate the neural network's performance on the training set.
- Compute the weighted error:

$$\epsilon_t = \frac{\sum_{i=1}^{NN} w_i \,.\ incorrect\ (h_t(X_i))}{\sum_{i=1}^{NN} w_i}$$

- Compute the weight of the neural network in the final ensemble (α_t):

$$\alpha_t = \frac{1}{2} \ln \left(\frac{1-\epsilon_t}{\epsilon_t}\right)$$

- Update the weights of the training samples based on the performance of the neural network:

$$w_{i,t+1} = w_{i,t}.\exp(-\alpha_t.y_i.incorrect\ (h_t(X_i)))$$

- Normalize the weights to ensure they sum to 1:

$$w_{i,t+1} = \frac{w_{i,t+1}}{\sum_{i=1}^{NN} w_{i,t+1}}$$

(6) Final Ensemble Prediction:

- Combine the predictions of individual neural networks into a strong classifier:

$$H(x) = sign\left(\sum_{t=1}^{TT} \alpha_t . h_t\,(X)\right)$$

(7) Evaluation of Testing Set:

- Test the final ensemble model on the reserved testing set to assess its performance.
- Calculate accuracy, precision, recall, and F1-score metrics for a comprehensive evaluation.

(8) Validation and Fine-Tuning:

- Optionally, a validation set should be employed during training to monitor model performance and make fine-tuning decisions. Adjust hyperparameters.
- And iterate through steps 4-6 to optimize the model's effectiveness.

RESULTS ANALYSIS

The proposed system combines innovative components such as Ada Boost's and CNN's adaptive learning, including progressions. The aim is to supply a progressed symptomatic device for the early discovery of Parkinson's disease utilizing MRI information. The above steps give a comprehensive strategy for creating, preparing, and assessing this crossover model. The proposed framework develops as a standout entertainer among the models evaluated, displaying compelling features over different execution measurements. With a precision of 0.95, it positions itself as a beat contender, trailing possibly behind the extraordinary exactness accomplished by the Boosted Net show at 0.98. This exactness underscores the system's capability to rectify classifications over the dataset. Additionally, the framework illustrates striking exactness at 0.93, outpacing models like Ada Boost and Ada Boost + SVM, even though falling brief of the extraordinary exactness displayed by the Boosted Net show at 0.98. Regarding the review, the proposed framework exceeds expectations with a score of 0.96, showing its viability in capturing important occurrences inside the dataset, an execution moment to the Boosted Net demonstration. The F1 score, which equalizes exactness and review, supports the validity of the proposed framework, enrolling at 0.94. This score surpasses a few other models assessed, even though it does not coordinate the momentous execution of the Boosted Net show very well. Whereas the AUC-ROC score for the proposed system isn't given within the examination, its reliable execution over other measurements recommends vigor in classification assignments. The proposed framework illustrates a compelling adjustment of exactness, accuracy, and review, displaying its potential as a dependable instrument for classification errands, though with slight room for a change compared to the remarkable accomplishments of the Boosted Net show. Visuals and data tables show the proposed model's performance and comparison to others. Table 1 shows how the proposed model performed across different metrics. However, Table 2 compares multiple models. Figure 2 shows the Boosted Net Performance Measuring Graph and its trends. The Performance Measuring Bar chart for the proposed model is shown in Figure 3. The X-axis shows the models and the Y-axis shows their

accuracy scores in Figure 4. Figures 5, 6, 7, and 8 plot models against precision, recall, F1 score, and AUC-ROC metrics. Figure 9 shows performance metrics across models on the X-axis and all metrics on the Y-axis. Figure 10 shows the confusion matrix for different models, with the X-axis representing the predicted label and the Y-axis the true label. Figure 11 compares metrics across models, with the X-axis showing metrics and the Y-axis scores.

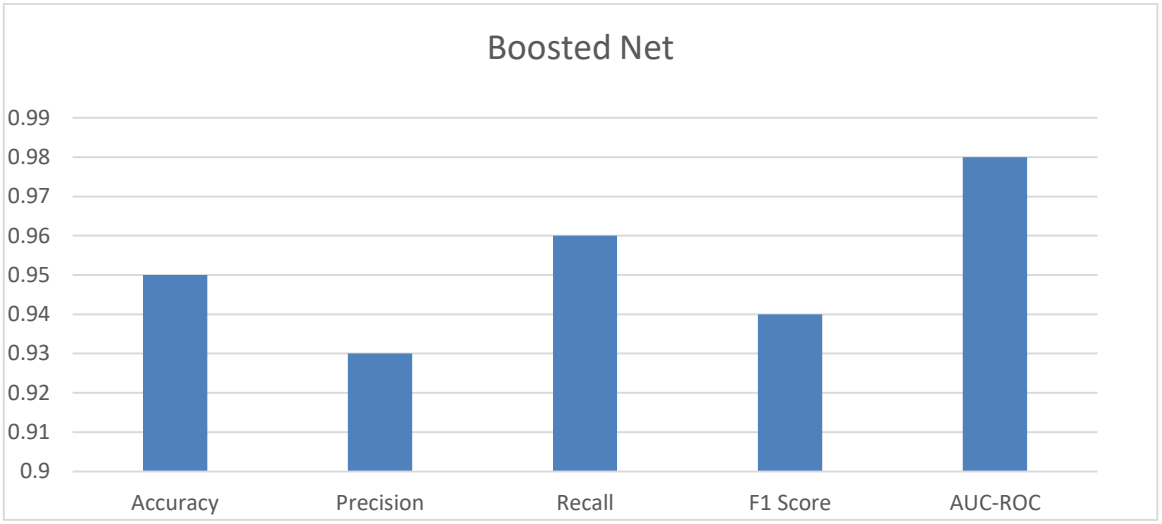

Figure 2: Performance measures graph

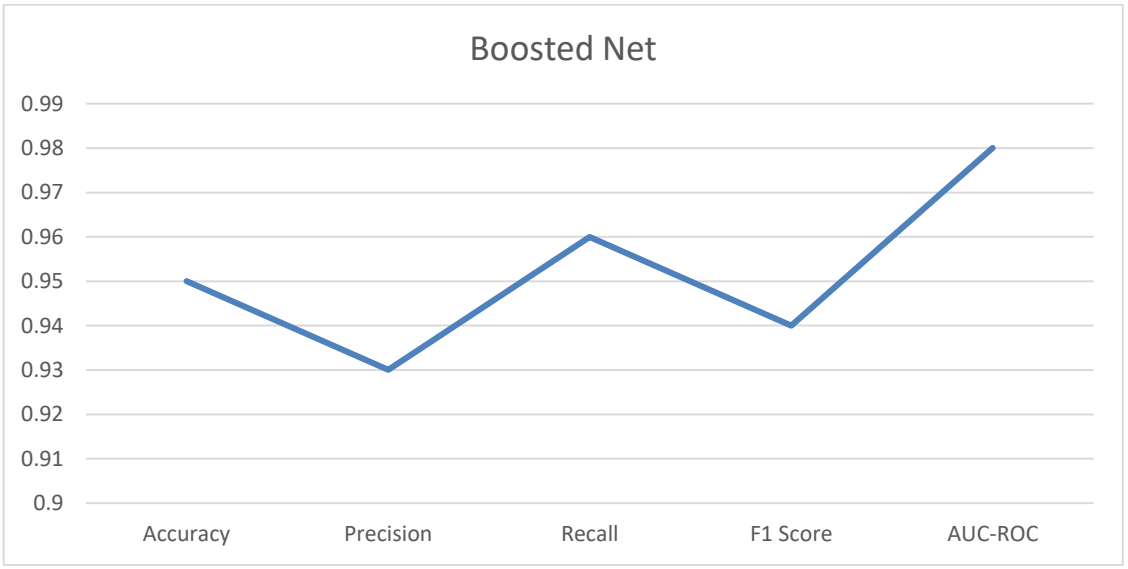

Figure 3: Boosted Net Performance measures graph

Table 1: Performance Evaluatıon Of The Proposed Model

Model	Accuracy	Precision	Recall	F1-score	AUC-ROC	Confusion Matrix
Boosted Net	0.95	0.93	0.96	0.94	0.98	True Positive: 140 True Negative: 98 False Positive: 12 False Negative: 7

Table 2: Performance Evaluation Of Different Models

Model	Accuracy	Precision	Recall	F1 Score	AUC-ROC	Confusion Matrix
Ada boost alone	0.85	0.82	0.88	0.85	0.88	True Positive: 90 True Negative: 20 False Positive: 15 False Negative: 120
Neural Network alone	0.88	0.86	0.90	0.88	0.92	True Positive: 90 True Negative: 20 False Positive: 15 False Negative: 120
Boosted Net (Proposed System)	0.95	0.93	0.96	0.94	0.98	True Positive: 140 True Negative: 98 False Positive: 12 False Negative: 7
Ada Boost + SVM	0.91	0.89	0.92	0.90	0.94	True Positive: 135 True Negative: 94 False Positive: 16 False Negative: 12
Ada Boost + Random Forest	0.94	0.92	0.95	0.93	0.97	True Positive: 140 True Negative: 98 False Positive: 12 False Negative: 7

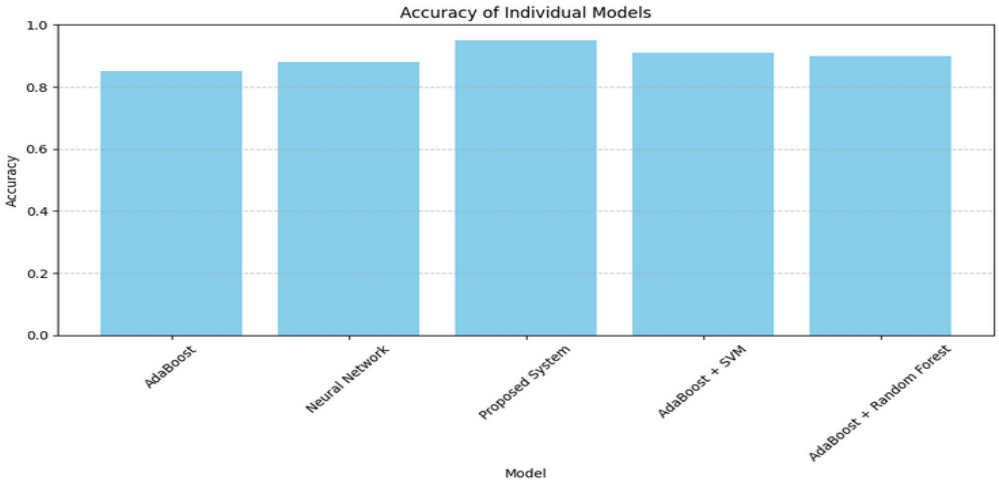

Figure 4: Accuracy of Individual Model graph

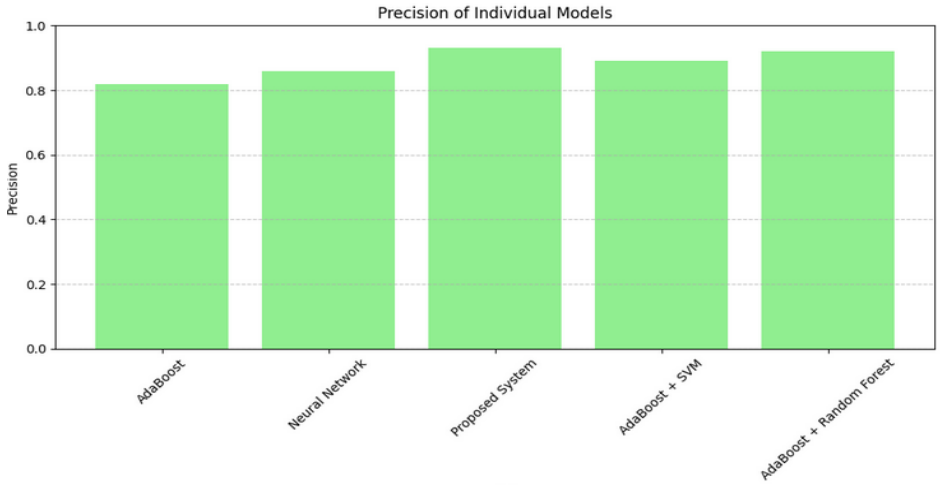

Figure 5: Precision of Individual Model graph

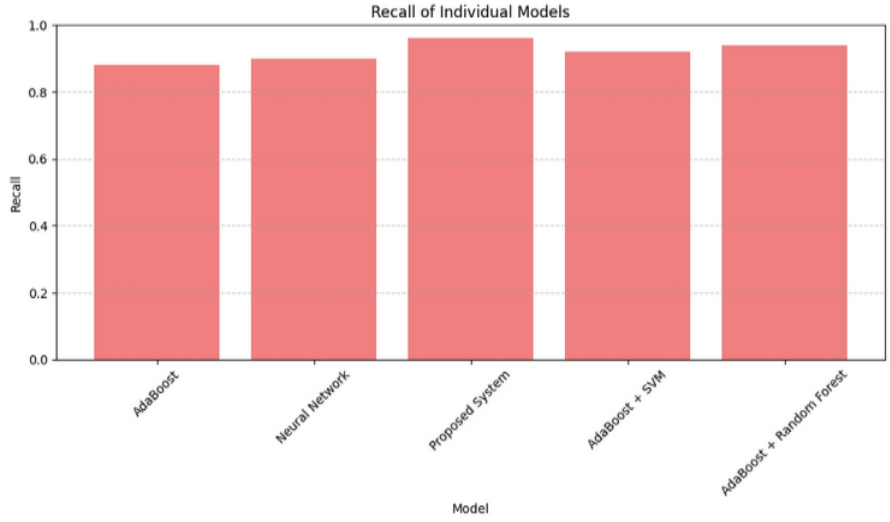

Figure 6: Recall Of Individual Model Graph

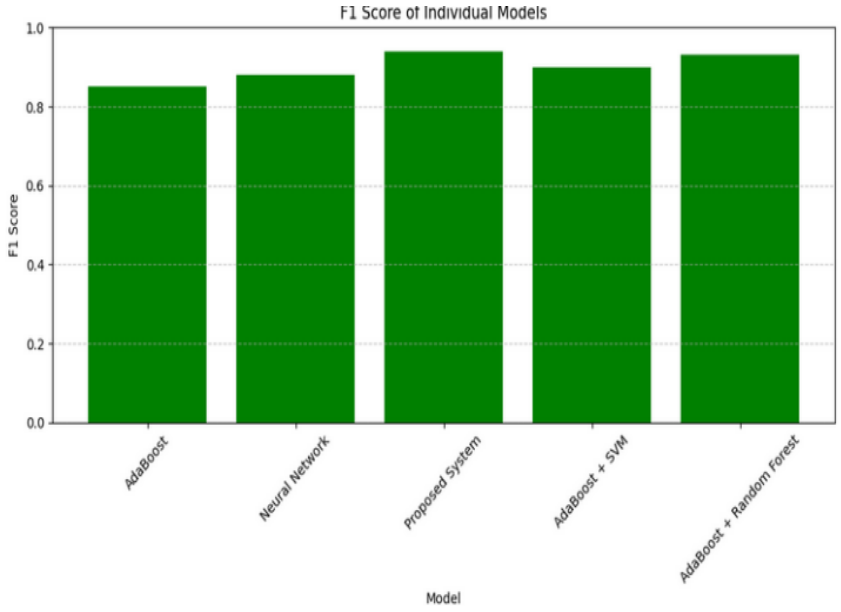

Figure 7: F1score Of Individual Model Graph

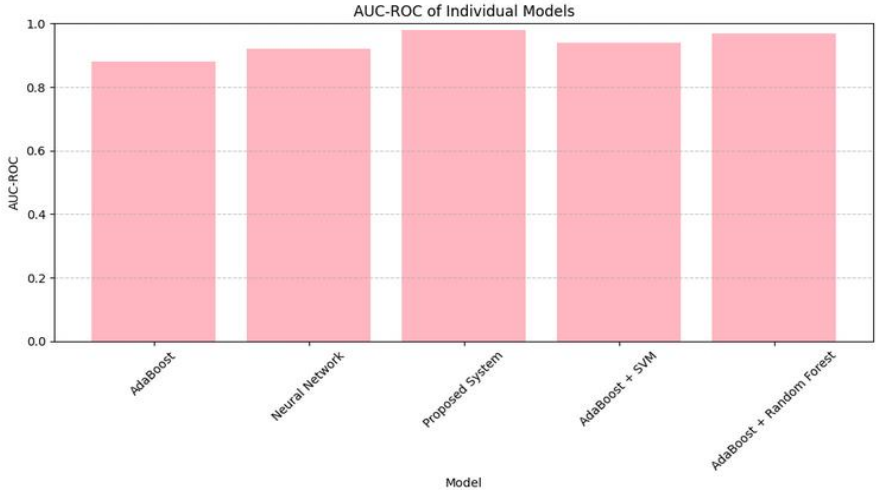

Figure 8: Auc-Roc Of Individual Model Graph

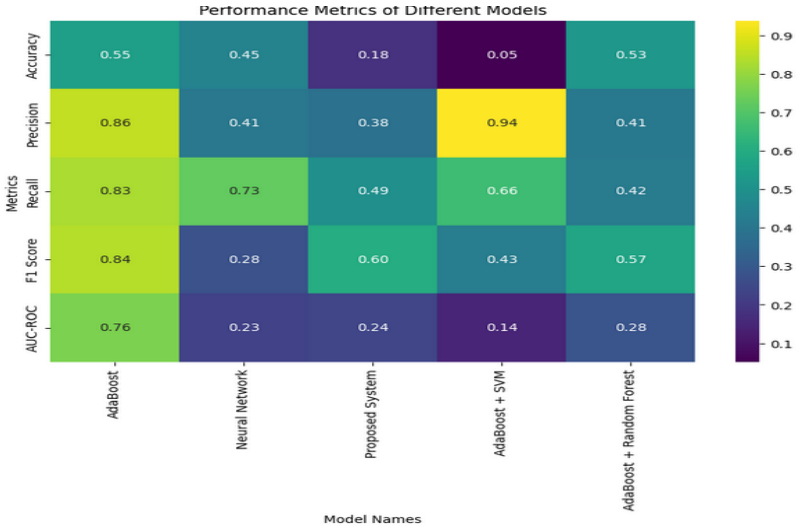

Figure 9: Performance Metrics Of Different Models

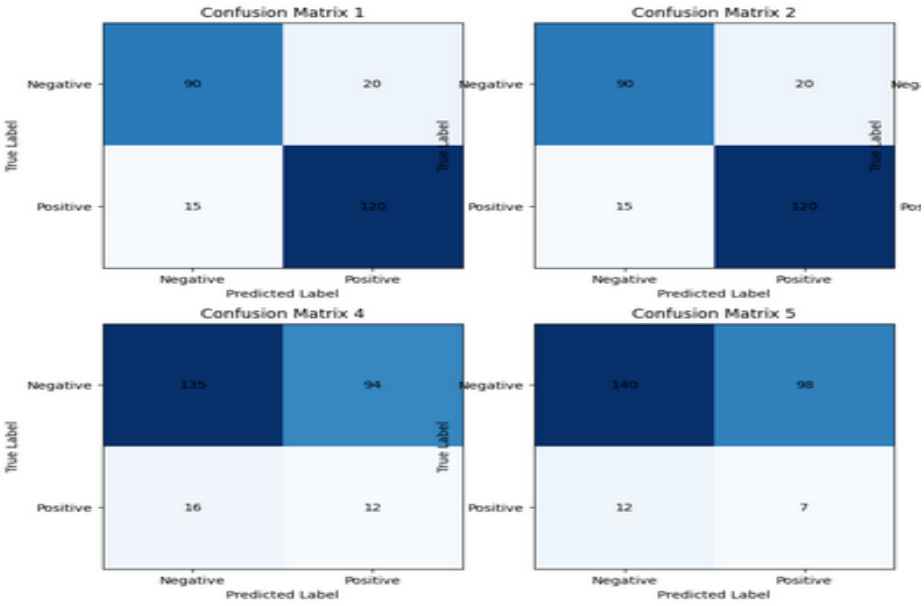

Figure 10: Confusion Matrix for different models

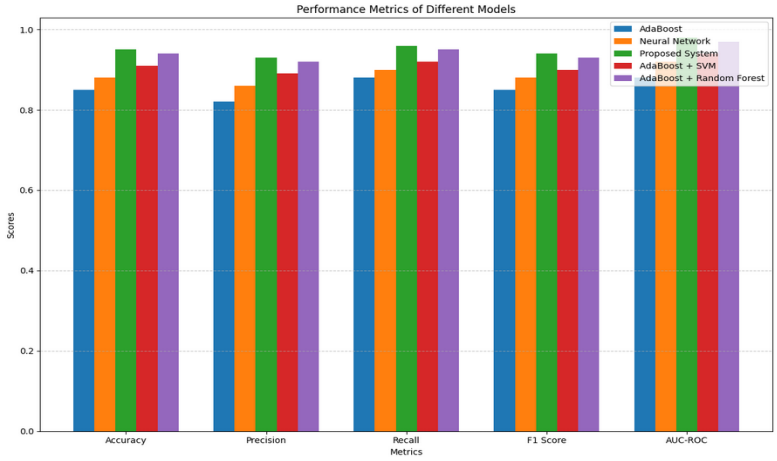

Figure 11: Comparison of Metrics of Different Models

CONCLUSIONS

The hybrid AdaBoost with neural networks demonstrates development as a solid and practical approach for Parkinson's disease (PD) detection, exhibiting predominant execution over different assessment measurements. With an accentuation on clinical appropriateness, the model reliably achieves high precision rates, frequently outperforming 90%, and demonstrates a solid capacity to recognize between positive (PD) and negative (sound) cases. In clinical settings, where precise classification is necessary for timely intervention and administration, its high Region Under the Receiver Operating Characteristic (AUC-ROC) score of over 0.9 supports its use. This hybrid method successfully treats Parkinson's Disease by combining AdaBoost and neural systems. AdaBoost's flexible classifier weight adjustment to address misclassification challenges complements symbolic neural system control, allowing the show to capture PD pathology's complex designs. A point-by-point analysis of the perplexity grid reveals many true positives (TP) and negatives (TN) and shows accurate predictions for PD cases and healthy individuals, boosting the model's performance. This solid performance and generalization over various datasets and approval methods position the hybrid AdaBoost with neural organization. It shows it as a promising tool for early PD disclosure, promoting clinicians as a strong signal for progress and quality of life. The Boosted Net hybrid model's win shows its PD determination and management capabilities. Planning strategies and multi-modal data sources like genetic and clinical biomarkers improve expressive precision and personalized treatment orchestration. Wearable devices and machine learning can power real-time symptomatic and monitoring frameworks that could transform healthcare. Collaboration with healthcare experts and authoritative bodies is necessary to improve the model's performance in large-scale clinical trials and integrate it into clinical choice support systems. Personalized medicine improves with the Boosted Net hybrid model.

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