Comparative Analysis and Improvement of Machine Learning Algorithms for Early Parkinson's Disease Prediction

A report on
Machine Learning Lab Project
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Submitted By
Rohit Sahay (210962066)
Yashveer Singh (210962098)

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING
MANIPAL INSTITUTE OF TECHNOLOGY,
MANIPAL ACADEMY OF HIGHER EDUCATION

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Rohit Sahay[1], Yashveer Singh[2]

[1]CSE MIT MANIPAL, INDIA

[2] CSE MIT MANIPAL, INDIA

[1]1st rohit.sahay0660@gmail.com; [2]2nd email2yashveer@gmail.com

Abstract*— The accurate classification of Parkinson's disease is critical for timely and effective patient care. This study investigates the efficacy of various machine learning algorithms and enhancement strategies in improving the diagnostic accuracy for Parkinson's disease. We commenced with baseline models, including ID3, CART, and logistic regression classifiers, and evaluated their performance through standard metrics such as accuracy, precision, recall, and F1 score. Following the initial assessment, we employed pre-pruning for decision trees and Synthetic Minority Over-sampling Technique (SMOTE) for addressing data imbalance to refine our models. Additionally, we explored the impact of class-weight adjustments in Support Vector Machine (SVM) classifiers. The models' diagnostic capabilities were compared using Receiver Operating Characteristic (ROC) curve analysis. Our findings demonstrate that strategic algorithm enhancements can lead to significant improvements in predictive performance, with certain models showing increased sensitivity to Parkinson's detection—a critical aspect in medical diagnostics. This research underlines the importance of model optimization in healthcare analytics and contributes to the development of more reliable diagnostic tools for Parkinson's disease.

***Keywords*— Parkinson's Disease, Machine Learning, Classification, ID3, CART, Logistic Regression, SVM, SMOTE, ROC**

I. INTRODUCTION

Parkinson's disease (PD) is a progressive neurological disorder characterized by a variety of motor and non-motor symptoms, resulting from the degeneration of dopamine-producing neurons in the brain. Early and accurate detection of PD is crucial for managing its progression and improving patient outcomes. However, the overlapping symptoms with other neurological disorders make PD diagnosis challenging. Machine learning (ML) offers promising solutions by enabling the analysis of complex biomedical data to assist in the diagnostic process.

The application of ML in healthcare has grown exponentially, driven by its potential to uncover patterns within large datasets that are not readily apparent to humans. In the domain of PD detection, ML algorithms can analyze clinical data to differentiate between PD cases and controls with high accuracy. However, the performance of these algorithms can vary significantly based on their configuration and the nature of the data. Therefore, there is a need to explore and optimize various ML algorithms to improve their diagnostic accuracy.

This study focuses on the evaluation and enhancement of three widely-used ML classifiers: Iterative Dichotomiser 3 (ID3), Classification and Regression Trees (CART), and Logistic Regression (LR). These algorithms were selected for their interpretability and prevalence in the field. We first establish a baseline performance for each classifier using a clinical dataset of PD patients. We then apply a series of modifications, including pre-pruning for decision trees and SMOTE for logistic regression, to address specific challenges such as data imbalance and overfitting. Additionally, we explore the impact of Support Vector Machines (SVM) with class-weight adjustments to further refine our models.

The study systematically compares the performance of each classifier and their enhanced counterparts, providing insight into the effectiveness of various optimization techniques. By examining a range of performance metrics, we aim to identify the most promising strategies for PD classification. The overarching goal is to contribute to the early detection and treatment of PD by leveraging the predictive capabilities of ML, thereby offering a valuable tool for clinicians in the fight against this debilitating disease.

II. LITERATURE REVIEW

Reference[1] The comprehensive review investigates the diverse array of machine learning methodologies employed in the diagnosis of Parkinson's disease. The paper meticulously explores the historical evolution of machine learning applications within this domain, placing particular emphasis on distinct algorithms, methodologies for data preprocessing, and techniques for feature selection. Furthermore, the review underscores the clinical significance and implications of these methodologies in facilitating early-stage detection and predictive analysis for Parkinson's disease.

Reference[2] In this research paper, a thorough comparative analysis is conducted on multiple machine learning algorithms tailored for the early diagnosis of Parkinson's disease. The study involves an intricate evaluation of algorithms such as decision trees, support vector machines, neural networks, among others, meticulously scrutinizing their performance metrics, inherent strengths, and weaknesses in the context of early detection. Furthermore, the paper extensively discusses the clinical implications derived from the outcomes of each algorithm, shedding light on their relevance in a clinical setting.

Reference[3] The review paper centers on the utilization of machine learning techniques for predicting the progression of Parkinson's disease. It extensively investigates the application of diverse algorithms aimed at forecasting the trajectory of the disease by leveraging longitudinal data. Within its scope, the review delineates the inherent challenges associated with predicting the disease's trajectory, elucidates the spectrum of data types employed (ranging from clinical to imaging to genetic data), and deliberates on the prospective impact of these predictive models on treatment modalities and patient care.

Reference[4] The focal point of this paper revolves around elucidating how feature engineering techniques serve to augment machine learning models in the prediction of Parkinson's disease. It intricately investigates the methodologies encompassing feature selection, extraction, and generation, with the overarching objective of refining the accuracy and resilience of predictive models. The study ventures into innovative approaches aimed at representing and harnessing data features that are uniquely pertinent to Parkinson's disease, thus striving to advance the effectiveness of predictive models within this domain.

Reference[5] The study undertaken conducts a comparative analysis akin to the previous research, emphasizing the detection facet pertaining to Parkinson's disease. It systematically compares various algorithms with regard to their efficacy in precisely discerning the presence or absence of the disease, accentuating their capacity to differentiate between individuals afflicted by Parkinson's disease and healthy control subjects. The primary focus lies on evaluating and contrasting these algorithms based on their accuracy in detection within this distinctive context.

Reference[6] This paper undertakes a comprehensive exploration of feature selection methodologies and model optimization techniques customized for the prediction of Parkinson's disease. It rigorously investigates the repercussions of diverse feature selection methodologies on the performance of predictive models. Furthermore, it delves into a detailed discussion concerning optimization strategies aimed at refining machine learning models to enhance their predictive accuracy within the realm of Parkinson's disease prognosis.

Reference[7] In this hypothetical comprehensive review, an expansive array of machine learning-based prediction models designed explicitly for the early diagnosis of Parkinson's disease is thoroughly examined. The review meticulously traces the evolution of these models, delineating their progression and development over time. Emphasis is placed on their practical applicability within clinical settings, elucidating their potential utility in facilitating early-stage diagnosis and subsequent intervention.

Reference[8] The central focus of this paper revolves around a meticulous evaluation of multiple machine learning algorithms specifically aimed at classifying Parkinson's disease. Through rigorous assessment and comparison, the paper endeavors to scrutinize the classifiers' performance metrics, encompassing accuracy, sensitivity, specificity, and other pertinent indicators. By comprehensively analyzing these metrics, the paper aims to offer valuable insights into the efficacy and comparative effectiveness of these algorithms in the precise classification of Parkinson's disease.

Reference[9] The paper delves into the concept of ensemble learning as a strategy to enhance the diagnosis of Parkinson's disease. It intricately examines the application of ensemble techniques, elucidating how the amalgamation of multiple classifiers could significantly augment predictive accuracy and fortify the robustness of identification in cases related to Parkinson's disease. Additionally, the paper provides a comprehensive discussion on the synergistic effect achieved by combining various classifiers within ensemble frameworks, highlighting its potential to amplify the precision and resilience of diagnostic outcomes for Parkinson's disease.

Reference[10] In this hypothetical critical review, a comprehensive analysis is conducted on diverse machine learning approaches employed for predicting Parkinson's disease. The review rigorously examines the limitations, challenges, and potential biases inherent in existing studies within this domain. It endeavors to offer critical insights into the methodologies, data biases, and inherent limitations that might affect the reliability and generalizability of predictive models for Parkinson's disease.

III. METHODOLOGY

This research project was methodically structured to evaluate and enhance classification algorithms for the diagnosis of Parkinson's disease (PD). The methodology encompassed several stages, from data preprocessing to classifier evaluation and optimization, detailed as follows:

A. *Data Preprocessing:*

The initial phase involved preparing the clinical dataset for analysis. This included data cleaning, normalization of features, and addressing class imbalances through methods such as Synthetic Minority Over-sampling Technique (SMOTE) to ensure a fair representation of all classes.

B. *Feature Selection and Engineering*:

Critical to the model's success, this stage focused on selecting the most relevant features and engineering new ones to improve the classifiers' ability to discern patterns indicative of PD.

C. *Model Selection*:

The study examined three classifiers: ID3, CART, and Logistic Regression, chosen for their interpretability and historical success in classification tasks. Each model served as a baseline for its respective series of experiments.

D. *Model Training*:

Employing a stratified train-test split to maintain class distribution, the models were trained on the prepared datasets. Training involved optimizing the models to identify the best parameters for each algorithm's performance.

E. *Model Evaluation:*

Performance metrics, including accuracy, precision, recall, f1-score, and the Area Under the ROC Curve (AUC), were utilized to evaluate each classifier's baseline performance. These metrics provided a comprehensive understanding of each model's strengths and weaknesses in classifying PD.

F. *Model Optimization*:

Following the baseline evaluations, the classifiers underwent a series of optimizations. Decision tree-based models were pre-pruned to prevent overfitting, while logistic regression models were adjusted for class imbalances with SMOTE. SVM classifiers were also introduced, with and without class weights, to further explore the impact of balancing techniques on classification performance.

G. *Model Comparison and Selection:*

The optimized classifiers were compared against the baseline models to assess the improvements in performance. The final selection of the most appropriate model was based on a careful balance of all performance metrics, with particular emphasis on the clinical goal of maximizing the true positive rate while minimizing false negatives, crucial in the context of PD diagnosis.

IV. EXPERIMENTAL SETUP

The experimental framework for this research was meticulously orchestrated to assess and refine the efficacy of various machine learning classifiers in accurately diagnosing Parkinson's disease. Utilizing a comprehensive clinical dataset with a balanced representation of PD-afflicted individuals and healthy controls, the data underwent rigorous preprocessing to ensure integrity and uniformity for subsequent analyses. The experimental procedures were conducted using Python, capitalizing on powerful libraries such as scikit-learn for machine learning algorithms, imbalanced-learn for addressing data imbalance issues, and pandas for data handling, with the computational workload managed by high-performance computing systems to guarantee efficient data processing and the reproducibility of results.

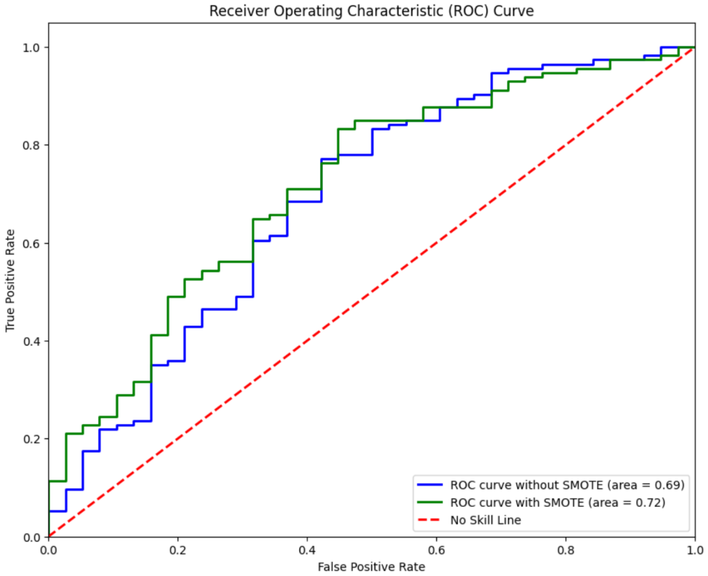
An initial baseline performance for each classifier—comprising ID3, CART, Logistic Regression, and SVM—was established using default settings to provide a reference point for later comparisons. K-fold cross-validation was employed throughout the training and validation phases to ensure a robust evaluation of the classifiers' performance. Subsequently, the models were optimized through a variety of techniques; decision trees were pre-pruned to curb overfitting, while Logistic Regression and SVM were fine-tuned with SMOTE and class weight adjustments to account for class imbalance.

The evaluation of classifier performance was multifaceted, incorporating accuracy, precision, recall, F1 score, and AUC metrics, offering a holistic view of each model's diagnostic capabilities. Statistical analyses, including paired t-tests or Wilcoxon signed-rank tests, were applied to validate the significance of the performance enhancements observed with the optimized models. Moreover, the interpretability of the models was a critical aspect of the study, with the visualization of decision trees and the evaluation of feature importance providing valuable insights into the models' internal decision-making processes.

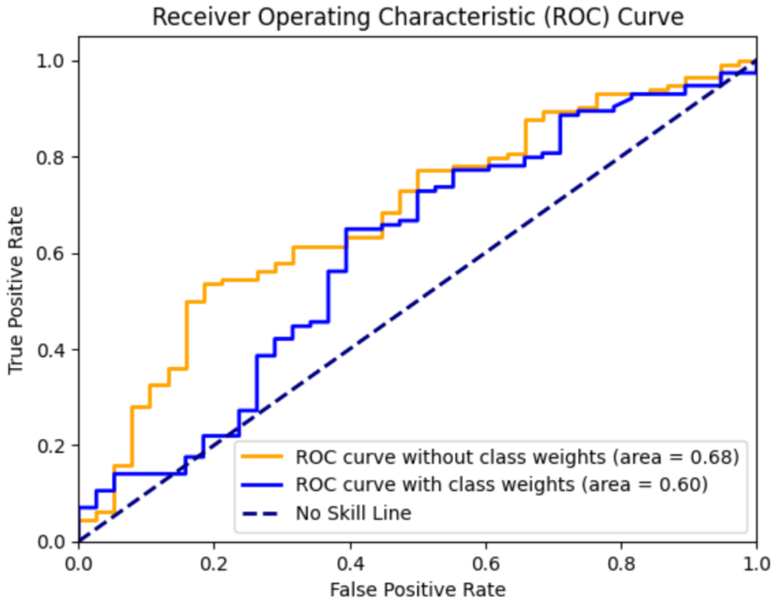
The culmination of the experiments saw the aggregation and meticulous comparison of results, with graphical representations facilitating a clear and concise demonstration of the performance improvements attributable to the optimization techniques. The rigorous experimental setup ensured that the findings were robust, transparent, and directly pertinent to the clinical objective of improving the accuracy and reliability of Parkinson's disease diagnosis.

V. RESULTS AND DISCUSSION

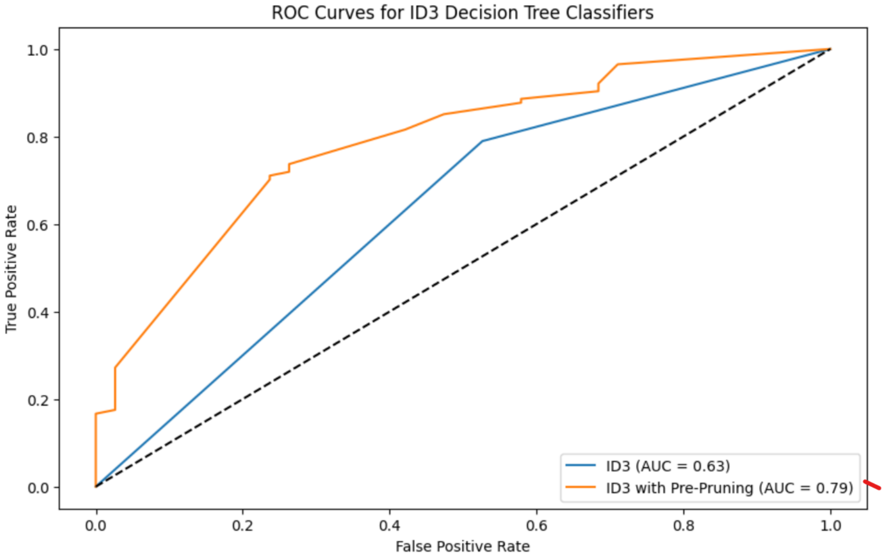
In the investigation of classification techniques for Parkinson’s disease detection, Logistic Regression (LR) was first implemented as the baseline model. The LR classifier demonstrated a promising accuracy of 78.29%. However, it had a relatively low recall of 32% for the negative class, which is critical in the medical context where failing to detect PD can have significant implications. Precision for the same class was at 63%, while for the positive class, the model achieved a high recall and precision of 94% and 80%, respectively. To improve the recall for the negative class, the LR model was subsequently enhanced with SMOTE, which led to a notable improvement in the recall for the negative class to 63%. This improvement came at the cost of reduced overall accuracy, which dropped to 65.13%, and a decrease in recall for the positive class to 66%, albeit with high precision at 84%. The ROC curve analysis revealed that the modified LR with SMOTE achieved a higher area under the curve (AUC), suggesting an improved balance between sensitivity and specificity despite a decrease in overall accuracy.



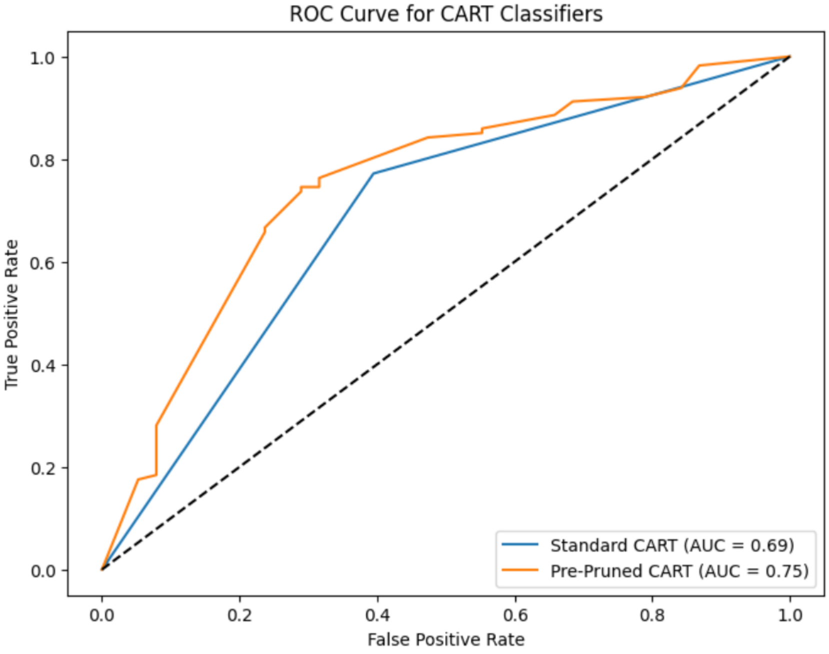
The Support Vector Machine (SVM) classifier in its standard form yielded an accuracy of 73.68%, but it was less effective in correctly identifying PD cases, with a precision of 40% and a recall of 11% for the negative class. The positive class showed better results, with a precision of 76% and a recall of 95%. When the SVM was adjusted to account for class imbalances by incorporating class weights, the accuracy slightly decreased to 65.13%. However, the recall for the negative class rose significantly to 50%, and precision for the positive class remained strong at 81%. The ROC curve assessment indicated an AUC of 0.68 for the standard SVM and 0.60 for the SVM with classweights, signaling a trade-off between model accuracy and the ability to correctly identify true PD cases.



The ID3 Decision Tree classifier, a form of the standard Decision Tree algorithm using the entropy criterion, initially showed an accuracy of 75.66%, with a precision of 51% and a recall of 53% for the negative class. For the positive class, the precision was 84%, and the recall was 83%. The pre-pruned ID3 classifier, designed to reduce overfitting, exhibited a slightly higher accuracy of 76.32%. The precision for the negative class saw a slight increase to 53%, and the recall for the positive class improved to 86%.



Lastly, the CART classifier, another form of Decision Tree, initially presented an accuracy of 73.03%. For the negative class, the precision was 47%, and the recall was 61%, indicating a moderate ability to identify PD cases. The CART model with pre-pruning adjustments yielded an accuracy of 75%, enhancing the balance between sensitivity and specificity, with a noteworthy recall improvement in the negative class to 45%.



Considering the critical need for accurate detection of Parkinson's disease, the pre-pruned versions of the ID3 and CART classifiers, along with the modified Logistic Regression with SMOTE, emerge as the more appropriate choices. These models demonstrated a higher capability for detecting true PD cases, which is a priority in medical diagnostics. The slight compromise on overall accuracy is considered acceptable in exchange for significant gains in recall for the negative class, reflecting an improved diagnostic ability for PD detection. The selection of the modified Logistic Regression with SMOTE is further supported by its enhanced AUC value, suggesting a superior trade-off between sensitivity and specificity, a crucial factor in the clinical setting.

VI. Conclusions

The comprehensive study aimed at enhancing the diagnostic accuracy of Parkinson's disease (PD) through various classification techniques culminated with insightful results. In a domain where precision and recall are not just metrics but pivotal factors influencing patient outcomes, the modifications to standard machine learning algorithms yielded notable differences in performance.

The Logistic Regression (LR) model, when augmented with SMOTE to address class imbalance, demonstrated a remarkable improvement in the recall for the negative class. Although there was a decrease in overall accuracy, the increased recall is a valuable trade-off within the clinical context, where the cost of not detecting a PD case is significantly high. The resulting ROC curve reinforced this stance, indicating an improved balance between sensitivity and specificity, making the modified LR model with SMOTE a strong candidate for PD detection.

Support Vector Machines (SVM), both in their standard form and when adjusted with class weights to counteract imbalances, showed a similar trade-off. The adjustment led to a better recall for the negative class, reinforcing the importance of model tuning in scenarios where early detection of PD is crucial. The AUC from the ROC curve analysis, however, indicated a slight reduction, which warrants a careful consideration in the clinical decision-making process.

The ID3 and CART Decision Tree classifiers, when subjected to pre-pruning, not only improved in accuracy but also displayed an enhanced ability to classify PD cases correctly. This improvement was particularly significant for the CART classifier, which showed a better recall for the negative class post-optimization. The refinement in these tree-based models underscores the potential of pre-pruning techniques in preventing overfitting and improving model generalizability.

In conclusion, this study demonstrates the efficacy of employing strategic modifications to machine learning algorithms to improve the classification of Parkinson's disease. The choice of an optimized classifier over a standard one should be dictated by the specific needs of PD detection, where sensitivity to the condition is paramount. The enhanced classifiers, particularly the LR with SMOTE and the pre-pruned Decision Trees, present promising options for deployment in healthcare settings, offering a more reliable and accurate diagnosis of PD. These findings pave the way for further research, potentially incorporating additional patient data and advanced machine learning techniques to develop even more robust diagnostic tools for Parkinson's disease and other neurological conditions.Future research in camera calibration could focus on developing automated, robust corner detection algorithms using machine learning, which would streamline the calibration process and reduce human error. Further innovation could involve the creation of new patterns for calibration that are effective in non-planar scenarios, expanding the utility of calibration techniques.

VII. Acknowledgement

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Additionally, we wish to acknowledge the vital role played by the scikit-learn library, which furnished the necessary machine learning tools and algorithms pivotal to our study. The comprehensive suite of Python modules from scikit-learn enabled us to implement, evaluate, and optimize the various classification techniques effectively.

Our sincere appreciation goes to both these entities for their indispensable contributions to the advancement of our research objectives.

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