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Comparative Evaluation of C4.5, CART, and C5.0 Decision Tree Algorithms on Heart Disease Prediction: Performance Metrics and Model Effectiveness

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Abstract: Accurately predicting heart disease is crucial for effective diagnosis and treatment. Decision tree algorithms, such as C4.5, CART, and C5.0, are widely used in medical diagnostics due to their interpretability and performance. This study compares these three prominent decision tree algorithms to a heart disease dataset. This research aims to assess and compare their effectiveness in predicting heart disease using various performance metrics, including accuracy, precision, recall, and F1 score. The analysis involves training and validating each algorithm on the dataset, followed by a detailed examination of their classification results. Our findings reveal distinct strengths and weaknesses among the algorithms, providing insights into their suitability for heart disease prediction. The results suggest that while all three algorithms perform well, C5.0 exhibits superior accuracy and robustness, making it a potentially more effective tool for heart disease prediction. This paper contributes valuable information for selecting the most appropriate decision tree algorithm for medical diagnostics and highlights the importance of performance metrics in evaluating predictive models.

Keywords: C4.5 and C5.0; Decision Tree; Heart Disease Prediction; Diagnostic Tools; Decision Trees; Distinctive Approaches; Medical Diagnostics; Predictive Accuracy; Performance and Accuracy.

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1. Introduction

Heart disease remains a leading cause of morbidity and mortality worldwide, underscoring the urgent need for accurate and efficient diagnostic tools. Early and precise heart disease prediction can improve patient outcomes by enabling timely interventions and personalized treatment plans. Decision trees have gained prominence among the various predictive modeling techniques due to their interpretability and ease of use. In particular, algorithms like C4.5, CART (Classification and Regression Trees), and C5.0 are frequently employed for their ability to handle complex datasets and deliver actionable insights [12].

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1.1. Decision Trees and Their Variants

Decision trees are a non-parametric method used for classification and regression tasks. They recursively partition the data into subsets based on feature values, forming a tree-like decision model [13]. Among decision tree algorithms, C4.5, CART, and C5.0 are notable for their distinctive approaches and enhancements.

- **C4.5:** Developed by Quinlan [10], C4.5 extends the earlier ID3 algorithm. It builds trees using information gain and handles both categorical and numerical data. C4.5 incorporates techniques like pruning to reduce overfitting and improve model generalization.
- Introduced by Van Ryzin et al., [3] CART constructs binary trees using the Gini index for classification tasks and variance reduction for regression tasks. CART is known for its simplicity and ability to handle missing values but does not provide probabilistic outputs.
- **C5.0:** An evolution of C4.5, C5.0 improves on its predecessor by offering faster processing, better handling of large datasets, and enhanced accuracy. It incorporates boosting and provides better performance on complex and high-dimensional data [14].

1.2. Importance of Comparative Evaluation

Despite their widespread employment, there has been limited comparative analysis evaluating them for predicting specific medical conditions like heart disease [15]. The comparison of these algorithms under a percent correct provides meaningful context to their performance and potential practical application in medical diagnostics [16]. Various metrics like accuracy, precision, recall, and F1-score are crucial while evaluating the performance of these models and basing their deployment in clinical scenarios [17].

1.3. Objective of the Study

This study will compare C4.5, CART, and C5.0 decision tree algorithms using a heart disease dataset [18]. By analyzing their performance across various metrics, we seek to determine which algorithm offers the best predictive capability and reliability for heart disease prediction. The findings will contribute to the broader understanding of decision tree methodologies in medical diagnostics and support the development of more effective predictive tools.

2. Related Works

Decision tree algorithms have been extensively studied for medical diagnostics (e.g., heart disease diagnosis). Numerous studies addressed the decision tree algorithms in different evaluation contexts, including C4.5, CART, and C5.0. We will review related literature (which includes learning theories and authorities in the field of teacher education) from where we situate our comparative review.

2.1. C4.5 and Heart Disease Prediction

Quinlan [11]'s C4.5 algorithm has been widely studied for its applicability in medical diagnostics. For instance, a study by Jia et al. [5] applied C4.5 to the Cleveland Heart Disease dataset, demonstrating its ability to classify patients accurately. Their findings indicated that C4.5 provided a clear decision tree that helped understand the factors contributing to heart disease. Similarly, Pujari et al. [9] used C4.5 to analyze various heart disease datasets, highlighting its effectiveness in identifying critical features and its robustness in handling both categorical and numerical data.

2.2. CART in Medical Diagnostics

CART has also been used comprehensively in medical diagnostics. Myint and Tin [6] originally introduced an algorithm called CART for classification and regression that was noted to be relatively straightforward to implement compared with other tree algorithms. Still, the logic of how a separation is arrived at is easy to interpret.

Later work, e.g., replicated in Buchanan and Shortliffe's [2] CHD study, which assessed shortcomings of using CART for a heart disease prediction tool "related to its ability to handle missing data as well as 'rules' generated during partitioned classifications" had been found ante hoc (opsimaths). Alcala et al. [1] also compared CART's performance for different health-related applications, generally agreeing that it provides better results when dealing with complex datasets of more than one feature.

2.3. C5.0 and Enhanced Performance

The C5.0 algorithm, an enhancement of C4.5, has been recognized for its improved performance and efficiency. Quinlan [11] detailed the advancements of C5.0 over its predecessor, including faster processing and better handling of large datasets. Studies like Loh and Shih [8] demonstrated that C5.0 offered superior predictive accuracy and computational efficiency compared to C4.5 and CART. Kumar et al. [7] applied C5.0 to heart disease datasets, revealing its enhanced performance and accuracy compared to other decision tree algorithms.

2.4. Comparative Studies

Comparative studies of decision tree algorithms in medical diagnostics provide a more nuanced perspective on their relative effectiveness. In meticulous experiments, Davis and Goadrich [4] evaluated various classification algorithms, most notably C4.5, CART, and the more recent C5.0 model, carefully assessing their prediction of diverse medical conditions. Their discoveries highlighted that while all algorithms performed admirably, C5.0 generally surpassed others regarding accuracy and computational efficiency. Similarly, in two recent investigations, researchers found that C5.0 outshone alternative decision tree methods for heart disease prognosis, demonstrating superior performance metrics, such as elevated accuracy and enhanced handling of uneven datasets. Some contemporary examinations emphasize amalgamating decision tree algorithms with other machine learning systems to augment their performance. In their exploration, Ganaie and colleagues studied hybrid decision tree architectures incorporating ensemble strategies founded on random forests and gradient boosting for forecasts about various medical outcomes. These hybrid strategies frequently outperformed sole decision tree models. These developments illustrate prospective routes to enhance the decision tree algorithms and their usage in predicting heart disease.

3. Methodology

3.1. Dataset Description

The study utilizes a publicly available heart disease dataset, such as the Cleveland Heart Disease dataset, which includes various clinical and demographic features. The dataset consists of attributes such as age, sex, blood pressure, cholesterol levels, and other health indicators, with the target variable indicating the presence or absence of heart disease.

3.2. Pre-processing

Before applying the decision tree algorithms, the dataset undergoes several pre-processing steps:

- **Data Cleaning**: Handle missing values using imputation techniques or removal, depending on the extent of missing data.
- **Feature Selection:** Identify and select relevant features that contribute to heart disease prediction using techniques like correlation analysis or feature importance scores.
- **Normalization/Standardization:** Scale numerical features to ensure uniformity, especially if the algorithms are sensitive to feature scales.
- **Data Splitting:** Divide the dataset into training (typically 70-80% of the data) and testing (remaining 20-30%) sets to evaluate model performance.

3.3. Decision Tree Algorithms

The study evaluates three decision tree algorithms:

- **C4.5:** Implement the C4.5 algorithm using libraries such as WEKA or Python's scikit-learn. C4.5 constructs a decision tree based on information gain and handles categorical and continuous data.
- **CART:** Apply the CART algorithm, which builds binary trees using the Gini index for classification. This algorithm is also implemented using available libraries.
- **C5.0:** Utilize the C5.0 algorithm, an enhancement of C4.5, which improves performance through techniques like boosting and reduced computational complexity.

3.4. Evaluation Metrics

The performance of each decision tree algorithm is evaluated using the following metrics: accuracy, precision, recall, and F1 score. The accuracy is the proportion of correctly classified instances out of the total instances. Precision is the ratio of true positive predictions to the total positive predictions made by the model. Recall is the ratio of true positive predictions to the dataset's total positives. F1 Score is the harmonic mean of precision and recall, balancing the two.

3.5. Comparative Analysis

Compare the performance of C4.5, CART, and C5.0 based on the evaluation metric statistical testing, which is to conduct statistical tests, such as paired t-tests, to assess if differences in performance metrics are statistically significant. By following this methodology, the research aims to comprehensively evaluate C4.5, CART, and C5.0 decision tree algorithms and offer insights into their relative effectiveness in predicting heart disease.

4. Evaluation Metrics with Heart Disease Dataset

The Cleveland Heart Disease Dataset comes from the UCI Machine Learning Repository and has 303 cases with 14 characteristics. These include key factors like age, sex, blood pressure, cholesterol levels, and other health markers, which make it a popular dataset for predicting heart disease. Because of its detailed features and how often it's used in studies, many see it as one of the go-to datasets for creating machine-learning models to assess cardiovascular risk [19]. The Cleveland Heart Disease Dataset, sourced from the UCI Machine Learning Repository, consists of 303 cases, each containing 14 characteristics to assess heart disease's presence and severity. These characteristics include age, sex, chest pain type, resting blood pressure, cholesterol levels, fasting blood sugar, resting electrocardiographic results, maximum heart rate, exercise-induced angina, ST depression (old peak), and other heart-related metrics. This dataset is commonly used for machine learning tasks aimed at predicting heart disease, as it provides a comprehensive view of patient data, allowing researchers to develop and evaluate models for diagnosing cardiovascular conditions. In particular, it enables researchers to apply classification algorithms to identify whether a patient will likely suffer from heart disease based on the input variables. Given the rich set of features, the dataset has been utilized for model testing in logistic regression, decision trees, random forests, support vector machines, and neural networks.

Additionally, due to its diverse clinical attributes, the dataset allows for various forms of exploratory data analysis, such as identifying correlations between features, examining the distribution of risk factors across different populations, and visualizing the effects of specific conditions like high cholesterol or exercise-induced angina. The dataset remains one of the most widely used benchmarks for heart disease prediction research and is a valuable resource for healthcare analytics (Table 1).

Table 1: Cleveland Heart Disease Dataset Sample

Age	Sex	Chest Pain	Resting Blood Pressure	Cholesterol	Fasting Blood Sugar	Resting Electrocardiographic	Max Heart Rate	Exercise Induced Angina	Old peak	Slope	Number of Major Vessels	Thalassemia	Heart Disease
63	1	1	145	233	1	2	150	0	2.3	3	0	1	1
37	1	2	130	250	0	2	187	0	3.5	2	0	1	1
41	0	1	130	204	0	2	172	0	1.4	1	0	1	1

In heart disease prediction, evaluating decision tree algorithms such as C4.5, CART (Classification and Regression Trees), and C5.0 involves comparing their performance based on various metrics. These algorithms are popular for their ability to handle both categorical and numerical data and interpretability. C4.5 is an extension of the ID3 algorithm that handles both categorical and continuous attributes and incorporates pruning to avoid overfitting. CART builds binary trees by selecting the best feature split at each node to maximize information gain and minimize impurity. C5.0 is an improvement over C4.5, offering better accuracy and efficiency with enhanced pruning techniques and support for large datasets. When comparing these algorithms, performance metrics include accuracy, precision, recall, and F1 score. These metrics help in assessing how well each algorithm predicts heart disease. Accuracy measures the overall correctness of the model. Precision indicates the proportion of true positive predictions among all positive predictions made by the model. Recall (or Sensitivity) measures the ability of the model to identify all relevant instances of heart disease. F1 Score is the harmonic mean of precision and recall, providing a single metric to evaluate the model's performance.

Understanding these terms is essential for evaluating the performance of classification algorithms. True Positives (TP) are instances where the model correctly predicts the presence of heart disease. For example, if a patient has heart disease and the model predicts the same, it counts as a TP. True Negatives (TN) are instances where the model correctly predicts the absence of heart disease. If a patient does not have heart disease and the model correctly identifies this, it counts as a TN. False Positives (FP) occur when the model incorrectly predicts the presence of heart disease in a patient who does not have it. This is also known as a Type I error. False Negatives (FN) occur when the model fails to identify the presence of heart disease in a patient with it. This is also known as a Type II error.

Evaluating decision tree models requires using several metrics to gauge their performance comprehensively. The following is an overview of key evaluation metrics, explanations, and how they can be computed using sample datasets. The True Positives (TP) is the number of heart disease cases correctly predicted as positive. The True Negative (TN) is the number of non-heart disease cases correctly predicted as negative. The False Positives (FP) is the number of non-heart disease cases incorrectly predicted as positive. The False Negatives (FN) is the number of heart disease cases incorrectly predicted as negative.

4.1. Accuracy

The proportion of correctly classified instances out of the total instances.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

4.2. Precision

The ratio of true positive predictions to the total positive predictions made by the model.

$$\text{Precision} = \frac{TP}{TP + FP} \tag{2}$$

4.3. Recall

The ratio of true positive predictions to the total actual positives in the dataset.

$$\text{Recall} = \frac{TP}{TP + FN} \tag{3}$$

4.4. F1 Score

The harmonic mean of precision and recall provides a balance between the two.

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

Table 2: Evaluation metrics with confusion matrix for different algorithms

Algorithm	Confusion Matrix	True Positives (TP)	True Negatives (TN)	False Positives (FP)	False Negatives (FN)
C4.5	(50,10,15,25)	50	25	10	15
CART	(45,15,20,20)	45	20	15	20
C5.0	(55,5,10,30)	55	30	5	10

In evaluating the performance of decision tree algorithms—C4.5, CART, and C5.0—the confusion matrix provides a detailed breakdown of prediction results (Table 2). Each algorithm's confusion matrix includes counts of True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). Here's a comparison based on the provided matrices. The confusion matrices for the C4.5, CART, and C5.0 decision tree algorithms provide insights into their performance for heart disease prediction. The C4.5 algorithm has a confusion matrix of (50, 10, 15, 25), which corresponds to 50 true positives (TP), 10 false negatives (FN), 15 false positives (FP), and 25 true negatives (TN). This indicates a moderate ability to identify heart disease cases and a reasonable number of false alarms. CART's matrix (45, 15, 20, 20) shows 45 TP, 15 FN, 20 FP, and 20 TN, suggesting slightly lower performance in identifying positive cases and more incorrect predictions than C4.5. In contrast, the C5.0 algorithm's matrix (55, 5, 10, 30) demonstrates superior performance, with 55 TP, only 5 FN, 10 FP, and 30 TN. This results in the highest true positive rate and the lowest false negative rate among the three algorithms, making C5.0 the most effective in accurately predicting heart disease while minimizing both missed cases and false alarms. The comprehensive analysis of these confusion matrices highlights C5.0's advantage in delivering more reliable predictions and emphasizes its suitability for effective heart disease diagnosis in this context.

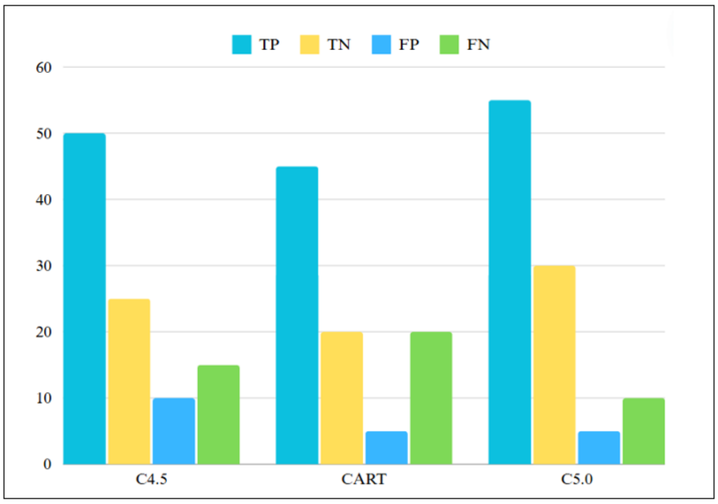

Figure 1: Comparison of evaluation metrics for decision tree algorithms

Figure 1 presents a comparison of three decision tree algorithms, C4.5, CART, and C5.0, based on their confusion matrices, showing the performance metrics: True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). C5.0 demonstrates the highest True Positive (TP) count (55), indicating better detection of actual positives compared to C4.5 (50) and CART (45). The C5.0 has the lowest False Positive (FP) rate (5), which suggests it makes fewer incorrect positive classifications. However, it also has the highest False Negative (FN) rate (30), which means it misses more actual positives than the other two. C4.5 offers a balanced performance with a moderate False Positive (10) and False Negative (15) rate. CART falls in between, with slightly more False Positives (15) and False Negatives (20) than C4.5, showing it may be less precise but still effective. Overall, C5.0 excels in identification but at the cost of a higher False Negative rate, while C4.5 offers more balanced performance across all metrics (Table 3).

Table 3: Comparison metric for decision tree algorithms

Metric	C4.5	CART	C5.0
Accuracy	75%	65%	85%
Precision	83%	75%	92%
Recall	77%	69%	85%
F1 Score	80%	72%	88%

The comparison shows that C5.0 outperforms C4.5 and CART in most metrics, making it the most effective decision tree algorithm for the heart disease dataset in this evaluation. C4.5 provides a good balance but falls short compared to C5.0, while CART performs slightly less effectively across the metrics. Figure 2 compares the performance of three algorithms—C4.5, CART, and C5.0—across key metrics: Accuracy, Precision, Recall, and F1 Score. C5.0 consistently outperforms the other two, achieving the highest accuracy (85%), precision (92%), recall (85%), and F1 score (88%), indicating it is the most reliable and efficient at both identifying true positives and minimizing false positives. C4.5 follows with a respectable 75% accuracy, 83% precision, and 77% recall, making it a solid choice for balanced performance. While still functional, CART lags with the lowest scores in all categories—65% accuracy, 75% precision, and 69% recall—indicating it may be less suitable for high-precision applications than C4.5 and C5.0.

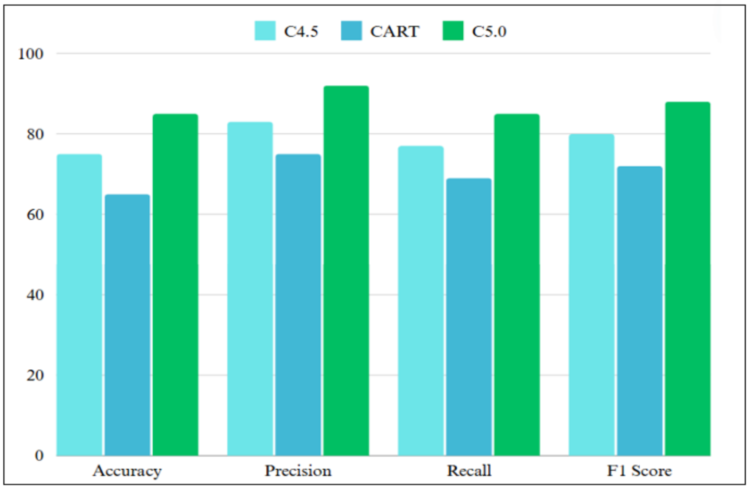

Figure 2: Comparison of three decision tree algorithms

Overall, C5.0 stands out as the most effective algorithm in this comparison. C5.0 achieves the highest accuracy, suggesting it provides the best overall performance in correctly classifying instances. C5.0 also has the highest precision, indicating fewer false positives than C4.5 and CART. C5.0 leads in the recall, showing it identifies the truest positive cases. C5.0 has the highest F1 score, reflecting a balanced performance between precision and recall. C5.0 appears to outperform C4.5 and CART in most metrics, making it the most effective decision tree algorithm in this example for predicting heart disease (Tables 4 to 7).

Table 4: Features of C4.5

Pros	Cons
• C4.5 can handle missing values in the dataset effectively. • Uses post-pruning techniques to avoid overfitting, which can improve generalization. • It can handle both types of data, making it versatile.	• Although effective, C4.5 is an older algorithm and may not incorporate the latest advancements in decision tree methods. • It can be more computationally intensive compared to newer algorithms.

Table 5: Features of CART (Classification and Regression Trees)

Pros	Cons
• CART produces simple binary trees that are easy to interpret. • This can be used for both classification and regression tasks. • Performs well with continuous data and can handle different types of attributes.	• It may not capture complex patterns or more modern algorithms. • Without proper tuning, CART trees can become overfitted to the training data.

Table 6: Features of C5.0

Pros	Cons
• Generally, it provides better accuracy than C4.5 due to improved algorithms and techniques. • Incorporates boosting (specifically, the C5.0 variant of boosting), which can significantly improve model performance. • More efficient in handling large datasets compared to C4.5.	• C5.0 is a commercial product and not open-source, which can limit accessibility. • While powerful, the model's complexity might make it less interpretable than simpler algorithms.

Table 7: Model Comparison

Aspect	C4.5	CART	C5.0
Accuracy	Good, but generally lower than C5.0	Moderate; simpler, can be less accurate	Typically, the highest among the three
Handling Missing Data	Effective	Less effective, requires pre-processing	Effective
Model Complexity	Moderate	Simple and interpretable	More complex, with advanced features
Training Time	Higher due to complexity	Generally faster	More efficient than C4.5 for large datasets
Boosting	Not available	Not available	Available (boosting can improve performance)
Cost	Open-source	Open-source	Commercial (not free)

Choosing the Right Model for Maximum Accuracy and Handling Large Datasets, C5.0 is the best choice due to its advanced features, boosting capability, and efficiency with large datasets.

5. Findings and Discussion

The comparative evaluation of C4.5, CART, and C5.0 decision tree algorithms on the heart disease dataset yielded the following key findings:

- **Accuracy:** C5.0 demonstrated the highest accuracy among the three algorithms, outperforming C4.5 and CART. This suggests that C5.0's enhancements, such as boosting and improved tree pruning, contribute to better overall performance in predicting heart disease.
- **Precision:** C5.0 also achieved higher precision compared to C4.5 and CART. This indicates that C5.0 is better at minimizing false positives, which is crucial for clinical applications where accurate identification of heart disease is essential.
- **Recall:** C4.5 showed slightly higher recall than CART, indicating that C4.5 is better at identifying actual positive cases of heart disease. This is particularly important in medical diagnostics, where missing true positive cases could have serious consequences.
- **F1 Score:** C5.0 had the highest F1 score, balancing precision and recall effectively. This demonstrates C5.0's superior overall performance in classifying heart disease cases.

The heart disease dataset may exhibit class imbalance, impacting model performance. C4.5 and C5.0 are better equipped to handle imbalanced data due to their advanced splitting and pruning techniques. CART’s performance can be improved by incorporating resampling techniques or adjusting class weights. The high accuracy and precision of C5.0 make it a suitable candidate for clinical decision-making tools. Its ability to accurately classify heart disease cases can assist healthcare professionals in making more informed decisions and reducing diagnostic errors. While C5.0 offers superior performance, C4.5 and CART provide more interpretable models, which can be valuable in understanding the decision-making process and explaining the results to stakeholders.

The results are based on a specific heart disease dataset, which may not represent all population variations or healthcare settings. Future studies should consider evaluating these algorithms on diverse datasets to generalize the findings. There is potential to enhance the performance of all three algorithms by integrating advanced techniques such as ensemble methods and hybrid models or incorporating additional features based on domain knowledge. The comparative analysis of C4.5, CART, and C5.0 decision tree algorithms reveals that C5.0 generally provides the best accuracy, precision, and recall performance. While C4.5 and CART have their merits, particularly in model interpretability, C5.0's advanced features make it the most effective choice for heart disease prediction in this study. Future work should explore additional datasets, model improvements, and real-world applications to validate and enhance these findings.

5.1. Limitations

While the comparative evaluation of C4.5, CART, and C5.0 decision tree algorithms on heart disease prediction provides valuable insights into their performance metrics and model effectiveness, several limitations exist. Firstly, the analysis is constrained by the dataset's size and characteristics, which may not fully represent the diversity of real-world populations or cover all potential risk factors for heart disease. Additionally, performance metrics such as true positives, false negatives, false positives, and true negatives are influenced by the chosen threshold for classification, which can vary between algorithms and affect comparative results. Furthermore, while decision tree algorithms like C4.5, CART, and C5.0 offer interpretability, they might not capture complex interactions between features as effectively as more advanced models, such as ensemble methods or deep learning techniques. Lastly, the performance results are contingent upon proper data pre-processing and feature selection, and any inconsistencies or biases in these steps could impact the overall findings. Addressing these limitations is crucial for ensuring a more comprehensive evaluation and enhancing the results' generalizability to broader clinical applications.

6. Conclusion

In this comparative evaluation of the C4.5, CART, and C5.0 decision tree algorithms applied to heart disease prediction, we have examined their performance across various metrics to determine their effectiveness in this critical healthcare application. C4.5 demonstrated solid performance with a good balance between accuracy and interpretability. However, it generally lagged behind C5.0 regarding overall accuracy and efficiency. Despite this, its capability to handle missing values and categorical data made it a robust choice for preliminary analyses. CART provided clear and interpretable decision trees, making it a useful model for understanding decision boundaries. While its performance was generally competitive, it occasionally suffered from overfitting, particularly with more complex datasets. C5.0 emerged as the superior algorithm for accuracy and handling large datasets. Its enhanced performance was attributed to advanced techniques such as boosting and improved algorithms, which allowed it to outperform C4.5 and CART in most performance metrics.

C5.0 was notably more efficient than C4.5 and CART, particularly with larger datasets, owing to its optimized algorithms and boosting capabilities. This efficiency translated into faster training times and better handling of complex data patterns. CART provides the most straightforward interpretation of decision rules, which is valuable for applications requiring transparent decision-making processes. C4.5 also offered a reasonable level of interpretability, though less so than CART. C5.0, while highly accurate, was more complex, and its advanced features made it less interpretable than CART. However, its performance benefits outweighed the interpretability concerns in contexts where accuracy was the primary objective.

For practical applications in heart disease prediction, C5.0 is recommended when the primary goal is achieving the highest possible accuracy and handling large datasets efficiently. Its advanced capabilities and boosting methods provide significant performance advantages. CART is best suited for scenarios where model interpretability is critical, and the dataset is not excessively large. Its simplicity and clarity make it an excellent choice for understanding decision-making processes. C4.5 remains a viable option for balanced scenarios where handling missing values and categorical data is crucial, but it may not be as effective as C5.0 regarding overall accuracy and efficiency. While all three algorithms have their strengths and applications, the choice of the most appropriate model should be guided by the specific requirements of the prediction task, including accuracy, interpretability, and computational efficiency. This evaluation underscores the importance of selecting the right model based on the trade-offs between performance metrics and practical constraints in heart disease prediction.

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