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Comparing Accuracy of Id3 and C45 Algorithm for Classifying Heart Disease

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ABSTRACT: The classification of heart disease remains a significant challenge in the healthcare domain due to the heterogeneity of patient data and the complex interplay of influencing factors. Accurate decision-making therefore requires the application of classification algorithms that are capable of effectively and efficiently identifying meaningful patterns within clinical datasets. This study aims to provide a recommendation for a more suitable classification algorithm for heart disease prediction by comparing two decision tree–based methods, namely ID3 and C4.5. Using a heart disease dataset obtained from IEEE DataPort comprising 1,190 patient records, the experiment was conducted with six selected attributes identified as the most relevant features. The performance of both algorithms was evaluated based on classification accuracy. The experimental results indicate that the C4.5 algorithm achieved a higher average accuracy of 0.847899, compared to 0.838655 obtained by the ID3 algorithm. These findings suggest that C4.5 demonstrates superior performance in classifying heart disease cases within the given dataset, making it a more effective choice for supporting clinical decision-making systems.

KEYWORDS: Heart disease, Data mining, Classification, Decision tree, ID3, C4.5

I. INTRODUCTION

Heart disease continues to be one of the world's most pressing health concerns, claiming millions of lives every year across both developed and developing nations. Conditions such as heart attacks and coronary artery disease account for a large share of global mortality, highlighting the urgent need for early detection and accurate diagnosis. Identifying heart problems at an early stage not only reduces complications but also allows physicians to design better treatment plans, improve survival rates, and enhance the overall quality of life for patients. However, traditional medical assessments—though clinically valuable—often struggle to recognize subtle and complex interactions hidden within large volumes of patient data. This limitation has led researchers and clinicians to explore the power of machine learning (ML), which can process multidimensional health data efficiently and reveal patterns that might otherwise go unnoticed. The use of ML-driven classification systems is rapidly transforming how healthcare professionals predict, diagnose, and manage heart disease.

Among various ML techniques, supervised learning has gained substantial attention in cardiology research because of its ability to learn predictive relationships from labelled patient records. A comprehensive review of supervised ML applications in heart disease diagnosis revealed that decision tree models are among the most popular and effective algorithms used for classification tasks. Other models such as logistic regression, Naive Bayes, and random forests are also widely applied, but decision trees stand out for their interpretability and clinical transparency—qualities that make them particularly valuable in healthcare settings, where explainable reasoning is essential for medical decision-making (Mao, Jimma, &Mihretie, 2025).

Decision trees function through a structured, step-by-step decision-making process, where data are divided according to specific conditions in a hierarchical "if–then" pattern. Two of the most well-known algorithms in this category are ID3 (Iterative Dichotomizer 3) and C4.5, both developed by Ross Quinlan. The ID3 algorithm chooses attributes that best reduce uncertainty, or entropy, in classification using a measure known as information gain. Building on this foundation, C4.5 introduces several improvements, including the ability to handle continuous variables (like blood pressure or cholesterol levels), deal with missing data, and employ pruning techniques to minimize overfitting. These refinements make C4.5 more

practical for analyzing real-world clinical datasets, which often contain complex and incomplete information.

When researchers compare these algorithms across different domains, results consistently show that **C4.5** tends to outperform **ID3**, particularly in datasets that contain continuous or noisy data. Its pruning process helps simplify overly complex models, improving accuracy and generalization (Abidin, 2025). Yet, there are cases where ID3 performs equally well—or even better—especially with smaller or simpler datasets that primarily use categorical attributes (Garwati et al., 2025). This variability suggests that the "best" algorithm is often context-dependent, and empirical testing on specific medical datasets, such as those related to heart disease, is crucial before deciding which approach to adopt.

In cardiovascular research, decision tree methods have consistently produced encouraging results. Studies applying tree-based algorithms have achieved moderate to high accuracy and have generated decision rules that are easily interpretable by clinicians. For instance, the C4.5 algorithm has classified heart disease data with accuracies exceeding 80%, accompanied by strong ROC-AUC scores, indicating reliable discrimination between healthy and at-risk patients (Gunawan, 2023). These findings underscore why decision trees remain an appealing choice for medical data analysis—they combine predictive power with transparency, a combination that is particularly important in clinical environments.

However, despite extensive use, direct comparisons between ID3 and C4.5 specifically in cardiovascular datasets remain scarce. Most prior studies evaluate decision trees in isolation or compare them to non-tree models such as support vector machines or neural networks. Few have systematically examined how ID3 and C4.5 perform side by side using the same dataset and evaluation criteria like accuracy, precision, recall, and F1-score. This lack of focused comparison creates a research gap that limits our understanding of which algorithm is most suitable for practical deployment in healthcare.

The IEEE DataPort heart attack dataset offers an excellent opportunity to address this gap. It contains a diverse range of features—including demographic, clinical, and lifestyle factors—that influence cardiovascular risk. Given C4.5's known strength in handling mixed data types and pruning, and ID3's simplicity and interpretability, a systematic evaluation using this dataset could yield valuable insights. Such a comparison would help determine which algorithm is more effective in supporting early diagnosis and risk prediction, particularly in clinical settings where speed, accuracy, and clarity are vital.

This research therefore seeks to perform a rigorous, side-by-side evaluation of ID3 and C4.5 algorithms using the IEEE DataPort heart attack dataset. By analyzing and comparing their performance across multiple metrics, the study aims to contribute to the development of data-driven tools that assist clinicians in diagnosing and managing heart disease. Ultimately, this investigation not only fills an existing gap in the literature but also provides practical guidance for future implementations of machine learning models in clinical decision support systems—bringing healthcare closer to faster, more accurate, and more explainable diagnostics.

II. BRIEF LITERATURE REVIEW

Decision tree algorithms have become fundamental tools in data-driven medical diagnostics, particularly for the classification and prediction of cardiovascular diseases. Among the most widely used variants are ID3 and C4.5, both introduced by Quinlan. Numerous comparative studies highlight the differences in structure, performance, and adaptability of these algorithms in various domains, with a growing body of work focusing on their applications in healthcare and heart disease prediction.

1. Evolution and Mechanism of ID3 and C4.5

The ID3 algorithm employs information gain as the splitting criterion to construct a tree model that best classifies data into target classes. While efficient, it handles only categorical data and tends to overfit when applied to noisy datasets. The C4.5 algorithm was developed as an extension to overcome these limitations, incorporating gain ratio to avoid bias toward attributes with many distinct values, as well as pruning techniques and support for continuous variables (Hssina et al., 2014). These enhancements have made C4.5 one of the most versatile decision tree algorithms in both academic and clinical applications (Hssina et al., 2014).

Comparative research confirms that C4.5 consistently outperforms ID3 on real-world datasets where missing or continuous values are common. In a recent applied analysis, Abidin et al. (2025) reaffirmed the superiority of C4.5 in classification accuracy and robustness, particularly when applied to medical data with varying feature scales (Abidin et al., 2025).

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2. Decision Tree Applications in Heart Disease Prediction

Heart disease remains a leading cause of mortality, and early diagnosis through computational methods has become essential. Decision tree-based classifiers have shown strong interpretability and ease of deployment, making them well-suited for medical decision support systems. Studies applying C4.5 and its derivatives to heart disease datasets report predictive accuracies ranging from 75% to over 90%, depending on data size and attribute selection.

For instance, Tin et al. (2024) conducted a comparative evaluation of C4.5, CART, and C5.0 using heart disease datasets and found C4.5 to achieve near-parity with newer variants, producing high classification accuracy and interpretability across performance metrics such as precision, recall, and F1-score (Tin et al., 2024). Similarly, Myint and Tin (2021) compared traditional and weighted decision trees, showing that while C4.5 performed consistently well, incorporating weight optimization improved overall predictive performance in clinical data classification (Myint & Tin, 2021).

Wiharto et al. (2016) implemented C4.5 for the interpretation of coronary heart disease clinical data, achieving strong results with an AUC of 84.2%, sensitivity of 74.7%, and specificity of 93.7%, emphasizing its suitability for clinical diagnostic systems (Wiharto et al., 2016). Similarly, Anugrah et al. (2023) compared C4.5 with SVM in classifying coronary heart disease, finding comparable performance (C4.5 accuracy: 64.30%), highlighting its interpretability advantage over black-box models (Anugrah et al., 2023).

3. Comparative Analysis and Optimization Approaches

While C4.5's modifications enhance performance, ID3 remains competitive in specific contexts. For instance, Sudrajat et al. (2017) reported ID3 achieving up to 99.83% accuracy with discrete datasets, outperforming C4.5 in certain structured cases due to its computational simplicity (Sudrajat et al., 2017). However, C4.5 generally shows superior adaptability when dealing with continuous data or mixed-type attributes.

Recent works have sought to further optimize decision trees through metaheuristic methods. Oktaviani and Abdulloh (2024) used Particle Swarm Optimization (PSO) and IWPSO to improve the accuracy of C4.5 in heart disease prediction, achieving 80.43% accuracy with base C4.5 and 84.23% after IWPSO enhancement (Oktaviani & Abdulloh, 2024). Similarly, Mia et al. (2022) demonstrated that applying oversampling techniques such as SMOTE improved classification balance and accuracy in decision tree-based heart disease prediction (Mia et al., 2022).

4. Hybrid and Ensemble Methods

Recent studies indicate that combining decision trees with other machine learning techniques can yield even better results. For example, Akila and Chandramathi (2015) integrated C4.5 with multilayer perceptron networks for coronary heart disease risk prediction, achieving 98.66% accuracy and improved diagnostic sensitivity (Akila & Chandramathi, 2015). Hybrid and ensemble approaches demonstrate the adaptability of decision tree frameworks.

III. RESEARCH METHOD

A. Data Gathering

The dataset used in this study was obtained from the IEEE DataPort public repository (https://ieee-dataport.org/open-access/heart-disease-dataset-comprehensive) and exported in CSV format for analysis. It contains clinical records from 1,190 patients, comprising 11 input attributes and one target variable representing the class label. Among these records, 629 instances correspond to patients diagnosed with heart disease, while 561 instances represent patients without heart disease. The detailed description of the dataset attributes is presented in Table 1.

The research workflow (Figure 1.) began with data acquisition, followed by a comprehensive preprocessing phase to ensure data quality and suitability for machine learning analysis. This preprocessing consisted of three main steps. First, data cleaning was performed to remove incomplete, duplicate, and inconsistent records. Second, relevant features were selected, and data transformation was applied to ensure that all attributes were formatted appropriately for the classification algorithms. Third, the dataset was partitioned using the K-Fold Cross-Validation technique, in which the data were divided into K subsets; in each iteration, one subset was used as the testing set, while the remaining subsets were used for training.

During each fold, two decision-tree-based algorithms, ID3 and C4.5, were applied to construct classification models. The resulting models were evaluated using standard performance metrics, including accuracy, precision, recall, and F1-score. This procedure was repeated until all K

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folds had been used as test data. Finally, the average performance across all folds was computed to determine which algorithm demonstrated superior effectiveness in classifying heart disease cases.

Table 1. List of Attributes

No	Attribute
1	Age
2	Sex
3	Chest Pain Type
4	Resting Blood Pressure
5	Cholesterol
6	Fasting Blood Sugar
7	Resting Electrocardiogram Results
8	Maximum Heart Rate Achieved
9	Exercise Induced Angina
10	Oldpeak =ST
11	The Slope Of The Peak Exercise ST Segment
12	Class

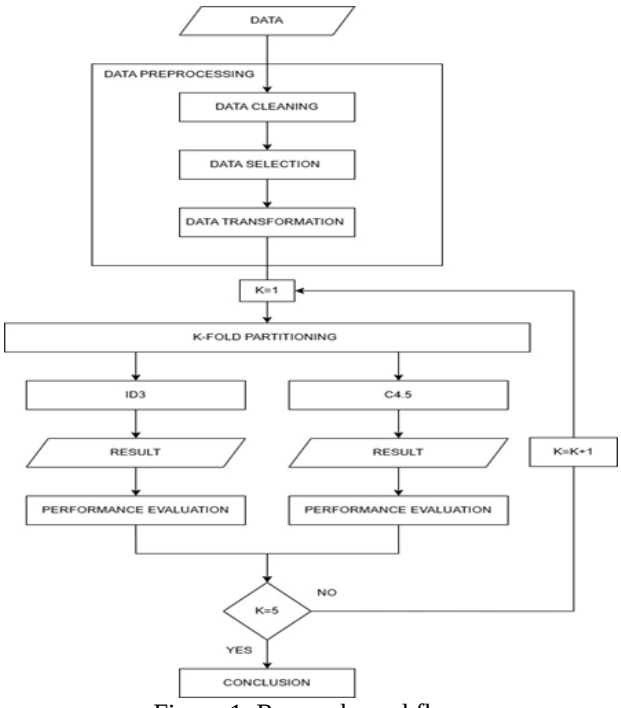

Figure 1. Research workflow

B. Data Preprocessing

a. Data Cleaning

The first stage of data preprocessing is data cleaning. This step is carried out to address missing values by either imputing or removing incomplete records. In addition, outliers (extreme

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values) that may distort the analysis are identified and handled appropriately. This stage also involves detecting and eliminating duplicate records to ensure the quality and consistency of the dataset before it is used for model training and evaluation.

b. Atribut Selection

After the data cleaning stage, a data selection process was carried out to reduce and eliminate attributes that were not relevant to the heart disease classification task. In this study, feature selection was performed using the Chi-Square method to identify the most significant attributes. The results of the Chi-Square feature selection are presented below.

Table 2. Selected Attribute

Attr.#	Feature	Chi-2 Score
9	oldpeak	179.109108
8	exercise angina	168.989554
10	ST slope	69.732959
2	chest pain type	68.144590
7	max heart rate	47.993316
5	fasting blood sugar	43.951531
0	age	36.521718
1	sex	27.225253
6	resting ecg	6.884583
3	resting bp s	4.599679
4	cholesterol	4.285759

c. Data Transformation

The next stage is data transformation, which is performed to facilitate the data mining process. Categorical attributes such as sex, chest pain type, resting ECG, exercise-induced angina, and ST slope were converted into numerical representations so that they could be processed effectively by the classification algorithms.

1. Age
0 :< 59
1 : 60 - 74
2 :> 75

2. Resting Blood Pressure
0 : ,120
1 : 121 - 139
2 : ≥ 140

3. Cholesterol
0 : < 200
1 : 200 - 239
2 : ≥ 240

4. Old Peak
0 : ≤ 0.0
1 : 0.1 – 1.0
2 : 1.1 – 2.0
3 : > 2.0

5. Max Heart Rate
0 : ≤ 100
1 : 101 - 140
2 : 141 - 180
3 : > 180

Next, a normalization process was applied to standardize the range of values across all attributes. Min–max normalization is a data preprocessing step that belongs to the data transformation stage. The purpose of normalization is to ensure that all variables share the same value range, so that no attribute dominates the analysis due to having significantly larger or smaller values. Having a uniform scale facilitates more accurate and efficient data analysis. Min–max normalization transforms the original values into a numerical range between 0 and 1 (Ambarwari et al., 2017).

One commonly used normalization method is the min–max function (Nurjanah et al., 2017), as shown in the following equation:

$$x_1^l = \frac{(x_1 - x_{min})}{(x_{max} - x_{min})}$$

Keterangan :
x_1^l = normalized value/ data
x = original data
x_{min}^1 = minimum value of the attribute
x_{max}^1 = maximum vaue of the attribute

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Table 3 provide a sample of 10 age data that have been normalized.

Table3. Normalized age data sample.

Atribut	Nilai Asli	Nilai Minimum	Nilai Maksimum	Nilai Setelah Normalisasi
Age	54	43	68	0,44
	55	43	68	0,48
	56	43	68	0,52
	60	43	68	0,68
	43	43	68	0
	46	43	68	0,12
	52	43	68	0,36
	60	43	68	0,68
	50	43	68	0,28
	64	43	68	0,84
	68	43	68	1
	50	43	68	0,28

C. Modelling ID3 Algorithm

The following are the steps used to construct a decision tree using the ID3 algorithm:

1. **Data preparation**

The dataset used to build the decision tree consists of 10 sample records with 11 attributes, as shown in Table 4.

2. **Calculation of initial entropy**

Based on the attributes selected from Chi-Square score in Table 2, the initial entropy of the entire dataset is calculated based on the number of instances belonging to the positive class (Normal = 0) and the negative class (Heart Disease = 1). The result of this entropy calculation is presented in Table 4.

Node		Category	Total cases	Heart Disease (1)	Normal (0)	Entropy	Gain
1	Total		10	6	4	0,97095	
	ST slope	1	3	1	2	0,9183	
		2	4	4	0	0	
		3	3	1	2	0,9183	0,419973
	chest pain type	1	1	1	0	0	
		2	2	1	1	1	
		3	3	0	3	0	

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		4	4	4	0	0	0,770951
	exercise angina	0	7	4	3	0,98523	
		1	3	3	0	0	0,281291
	oldpeak	0	6	3	3	1	
		1	1	1	0	0	
		2	3	2	1	0,9183	0,095462
	max heart rate	0	1	1	0	0	
		1	5	4	1	0,72193	
		2	2	1	1	1	
		3	2	0	2	0	0,409987
	Sex	0	3	1	2	0,9183	
		1	7	5	2	0,86312	0,091277

Table 4. Computation for Node 1using ID3

3. Entropy calculation for each attribute

The entropy for each attribute is calculated by dividing the data into subsets according to the values of that attribute. For example, the sex attribute has two possible values (female and male), so the dataset is divided into two groups based on these values.

4. Information gain calculation

Information gain is computed by subtracting the weighted average entropy of each attribute from the initial entropy. The results, shown in Table 4, indicate that the chest pain type attribute has the highest information gain (0.770951). Therefore, this attribute is selected as the root node of the decision tree, as illustrated in Figure 2.

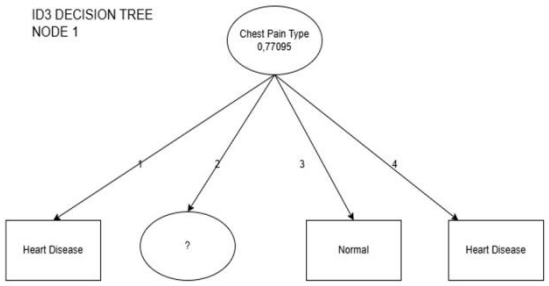

Figure2. Root Node of ID3

Table 5. Computation for Node 2 of ID3

		1	0	1	0	0	
		2	0	0	0	0	0
	max heart rate	0	1	0	1	0	
		1	1	1	0	0	
		2	0	0	0	0	
		3	0	0	0	0	1

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Node		Kategori	Total Cases	HeartsDisease(1)	Normal(0)	Entropy	Gain
2	chest pain type	2	2	1	1	1	
	ST slope	1	1	0	1	0	
		2	1	1	0	0	
		3	0	0	0	0	1
	exercise angina	0	2	1	1	1	
		1	0	3	0	0	0
	oldpeak	0	2	1	1	1	
	Sex	0	1	0	1	0	
		1	1	1	0	0	1

5. Node selection

Based on Table 4, after the chest pain type attribute was selected as the root node, the next step was to determine the nodes for each branch (partition). In Partition 1 and Partition 3, the entropy value is 0, indicating that all instances belong to the same class; therefore, these partitions were directly labeled as class 0 (normal). Partition 4 contains only heart disease cases, so it was directly labeled as class 1 (heart disease).In Partition 2, the data remain mixed, meaning the entropy is not zero. Therefore, this partition requires further splitting. The entropy and information gain for the remaining unused attributes were recalculated, as shown in Table 5. The attribute with the highest information gain was then selected as the next node in the decision tree, as illustrated in Figure 3.

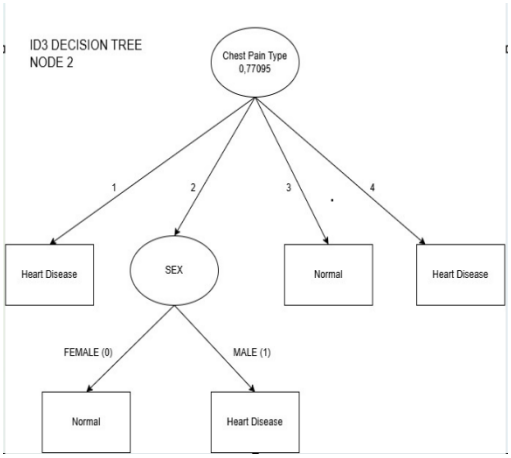

Figure 3. Decision Tree for ID3

The results of the calculations for Node 2 indicate that the **sex** attribute has the highest information gain. From this split, it is found that **Sex = 0 (female)** belongs to the **Normal** class, while **Sex = 1 (male)** belongs to the **Heart Disease** class. With this separation, all data are successfully classified into their respective target classes, and the decision tree construction process is completed..

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D. ModellingC4.5 Algorithm

The following are the steps and simulation for constructing a decision tree using the C4.5 algorithm:

1. **Data preparation**

The dataset used to build the decision tree consists of 10 sample records with 11 attributes, as shown in Table 6.

2. **Initial entropy calculation**

The initial entropy of the entire dataset is calculated based on the number of instances in the positive class (Normal = 0) and the negative class (Heart Disease = 1). The results of this entropy calculation are presented in Table 6.

3. **Entropy calculation for each attribute**

The entropy for each attribute is computed by dividing the dataset into subsets according to the values of that attribute. For example, the sex attribute has two possible values (female and male), so the data are divided into two corresponding groups.

4. **Information gain, split information, and gain ratio calculation**

Information gain is calculated by subtracting the weighted average entropy of each attribute from the initial entropy. The split information and gain ratio are then computed for each attribute. As shown in Table 6, the chest pain type attribute has the highest gain ratio (0.417534), and is therefore selected as the root node of the decision tree, as illustrated in Figure 5.

5. **Node and branch determination**

Based on Table 6, after chest pain type is selected as the root, the next step is to determine the nodes for each branch (partition). In Partition 1 and Partition 3, the entropy value is 0, so these partitions are directly labelled as class 0 (normal). Partition 4 contains only heart disease cases and is therefore labelled as class 1 (heart disease). In Partition 2, the data remain mixed, so further splitting is required using the remaining attributes. This process continues until all data are classified into their respective target classes, as shown in Table 7 and the decision tree in Figure 6.

Table 6. Computation for Node 1 using C4.5

Node		Category	Total Case	Heart Disease (1)	Normal (0)	Entropy	Gain	Split Info	Gain Ratio
1	Total		10	6	4	0,9709506			
	ST slope	1	3	1	2	0,9182958			
		2	4	4	0	0			
		3	3	1	2	0,9182958	0,419973	1,5709506	0,267337
	chest pain type	1	1	1	0	0			
		2	2	1	1	1			
		3	3	0	3	0			
		4	4	4	0	0	0,770951	1,8464393	0,417534
	exercise angina	0	7	4	3	0,9852281			
		1	3	3	0	0	0,281291	0,8812909	0,319181
	oldpeak	0	6	3	3	1			
		1	1	1	0	0			
		2	3	2	1	0,9182958	0,095462	1,2954618	0,073689
	max heart rate	0	1	1	0	0			
		1	5	4	1	0,7219281			
		2	2	1	1	1			
		3	2	0	2	0	0,409987	1,760964	0,232819
	Sex	0	3	1	2	0,9182958			

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		1	7	5	2	0,8631206	0,091277	0,8812909	0,103572

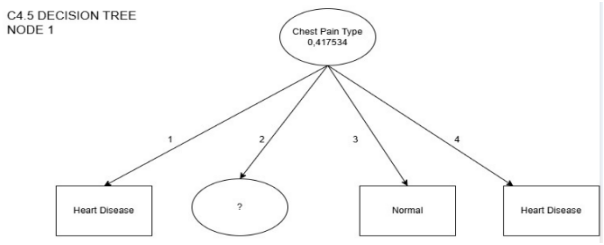

Figure 4. Root Node of C4.5

Table 7. Computation for Node 2 C4.5

Node		Category	Total Case	Heart Disease (1)	Normal (0)	Entropy	Gain	Split Info	Gain Ratio
2	chest pain type		2	2	1	1	1		
	ST slope	1	1	0	1	0			
		2	1	1	0	0			
		3	0	0	0	0	1	0	~
	exercise angina	0	2	1	1	1			
		1	0	3	0	0	0	0	0
	oldpeak	0	2	1	1	1			
		1	0	1	0	0			
		2	0	0	0	0	0	0	0
	max heart rate	0	1	0	1	0			
		1	1	1	0	0			
		2	0	0	0	0			
		3	0	0	0	0	1	0	~
	Sex	0	1	0	1	0			
		1	1	1	0	0	1	1	1

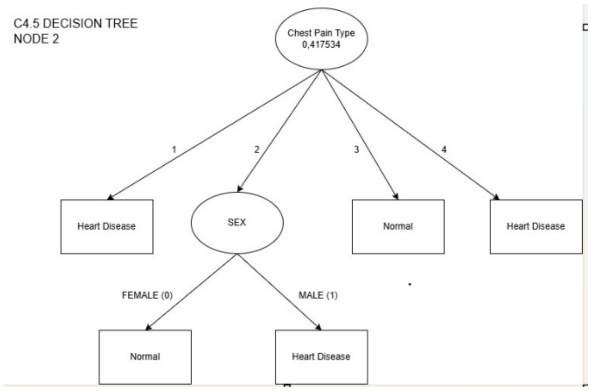

Figure 6. Decision Tree C4.5

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The results of the calculations for Node 2 indicate that the **sex** attribute has the highest gain. Based on this split, **Sex = 0 (female)** is classified into the **Normal** class, while **Sex = 1 (male)** is classified into the **Heart Disease** class. With this separation, all instances are successfully assigned to their respective target classes, and the decision tree construction process is completed.

IV. DISCUSSION

A. ID3 Performance

Model performance was evaluated using a confusion matrix to quantify classification accuracy. Accuracy was calculated as the ratio of correctly classified instances to the total number of observations, multiplied by 100%. To identify the optimal model configuration, multiple experiments were conducted by varying the proportion of training and testing datasets, and the resulting accuracy values were compared to determine the most effective data split.

Table8. Performance of ID3

Fold	Accuracy	Precision	Recall	F1
0	0,844538	0,844121	0,844779	0,844315
1	0,819328	0,819912	0,820933	0,819248
2	0,848739	0,849703	0,850694	0,848697
3	0,802521	0,802112	0,803075	0,802238
4	0,878151	0,878151	0,879464	0,878046

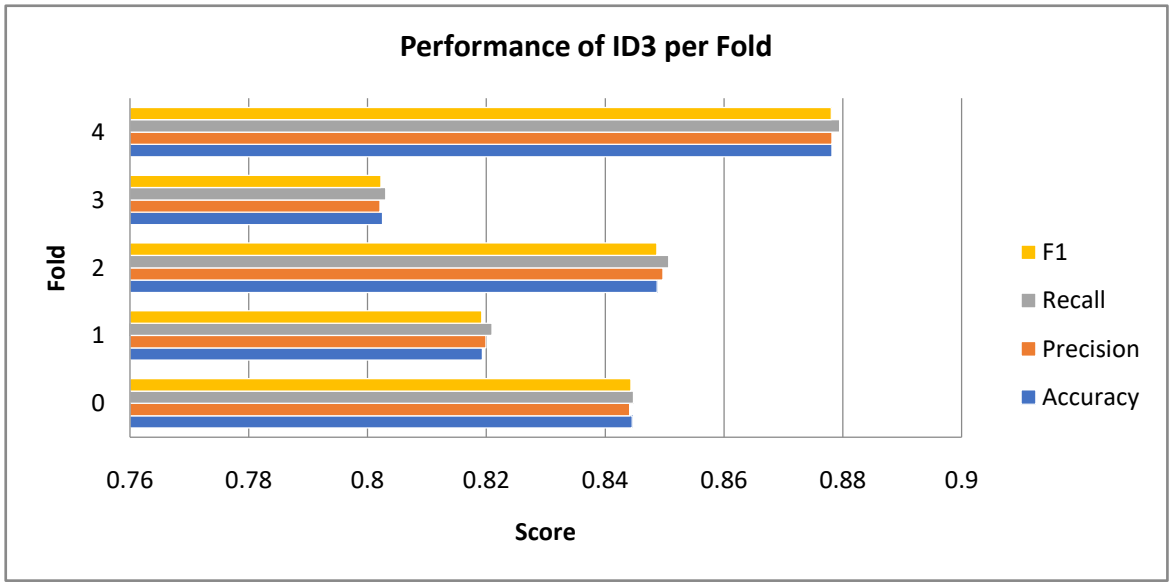

Figure 7. Performance Graph of ID3

As shown in Figure 7, the highest accuracy was obtained in the fourth fold, reaching a value of 0.878151, while the lowest accuracy occurred in the third fold with a value of 0.802521. The variation in accuracy across folds is relatively small, approximately 0.07, indicating that the ID3 model exhibits consistent performance during the training and testing processes. Overall, the accuracy, precision, recall, and F1-score fall within a narrow range, reflecting a balanced capability of the model in identifying both positive and negative classes. This stability suggests that the model does not suffer from significant overfitting or underfitting, as its performance remains steady across all folds. Therefore, it can be concluded that the ID3 model demonstrates reliable and robust classification performance on the test data.

B. C4.5 Performance

The validation of the results will be conducted using a confusion matrix to measure classification accuracy. The C4.5 algorithm is an

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extension of the ID3 algorithm. Accuracy is calculated by summing the number of correctly predicted instances, dividing this value by the total number of predictions, and multiplying the result by 100%. To achieve optimal accuracy, different proportions of training and testing data will be evaluated and compared.

Table 9. Performance of C45

Fold	Accuracy	Precision	Recall	F1
0	0,861345	0,861111	0,860779	0,86093
1	0,844538	0,843929	0,844246	0,844073
2	0,857143	0,856628	0,857639	0,85689
3	0,798319	0,797609	0,798115	0,797805
4	0,878151	0,877764	0,878968	0,877977

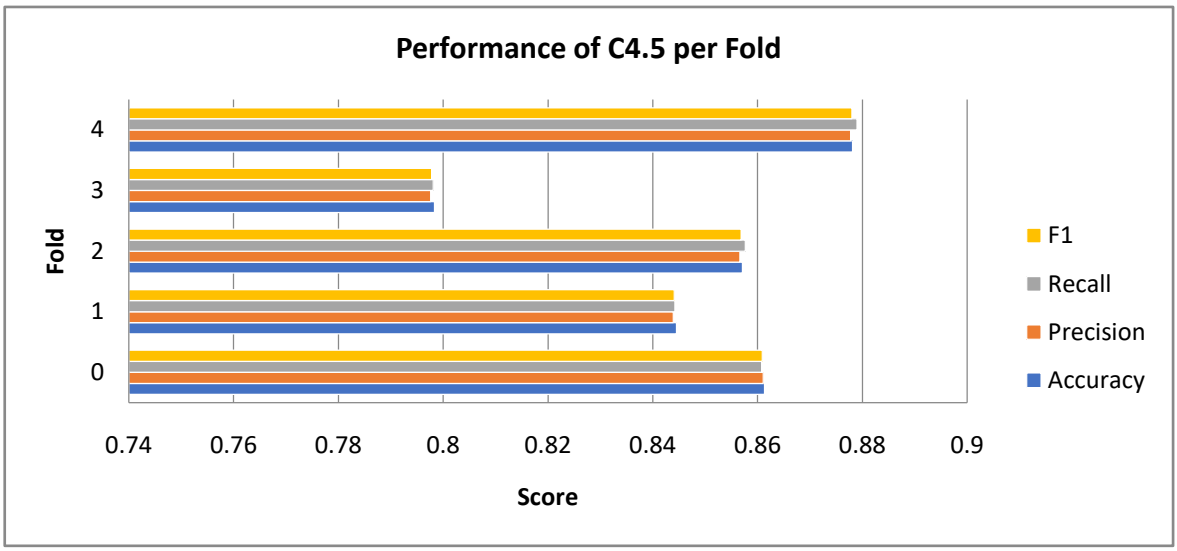

Figure 8. Performance of C4.5

As shown in Figure 8, the highest accuracy of the C4.5 algorithm was achieved in the fourth fold with a value of 0.878151, while the lowest accuracy occurred in the third fold at 0.798319. The difference in accuracy across folds (test partitions in the cross-validation process) is only about 0.08, which is still considered within a normal range. Overall, the accuracy, precision, recall, and F1-score of the C4.5 algorithm demonstrate good consistency across folds. This indicates that the C4.5 model performs reliably during testing. In other words, the model does not suffer from significant overfitting or underfitting, as its performance remains relatively balanced across all evaluations. This performance consistency highlights one of the strengths of the C4.5 algorithm, which applies a pruning process to simplify the decision tree. Through this approach, the model maintains high accuracy while preserving its ability to generalize and recognize patterns in new data.

C. Discussing Performance of ID3 and C4.5

The experimental results indicate that the C4.5 algorithm performs better than ID3 in classifying the dataset used in this study. The average accuracy achieved by C4.5 is 0.847899, while ID3 attains an average accuracy of 0.838655. In addition, C4.5 also demonstrates higher values across the evaluation metrics, with scores of 0.847408, 0.847949, and 0.847535, compared to ID3, which yields corresponding values of 0.838800, 0.839789, and 0.838509. Similar trends are observed for precision, recall, and F1-score, where C4.5 consistently outperforms ID3. This improvement suggests that the pruning mechanism and the use of gain ratio in the C4.5 algorithm contribute to greater model stability and enhanced pattern recognition. Pruning reduces tree complexity by eliminating irrelevant branches, thereby preventing the model from overfitting the training data. In contrast, ID3, which does not employ pruning, is more prone to generating overly complex trees and less stable performance across folds. Overall, the evaluation results demonstrate

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that the C4.5 algorithm provides superior and more balanced performance in classifying heart disease data, both in terms of accuracy and consistency across evaluation metrics as shown in Table 10 and its related histogram in Figure 9.

Table 10. Performance Comparation of ID# and C 45.

Metrik	ID3	C4.5
Accuracy	0.838655	0.847899
Precision	0.838800	0.847408
Recall	0.839789	0.847949
F1	0.838509	0.847535

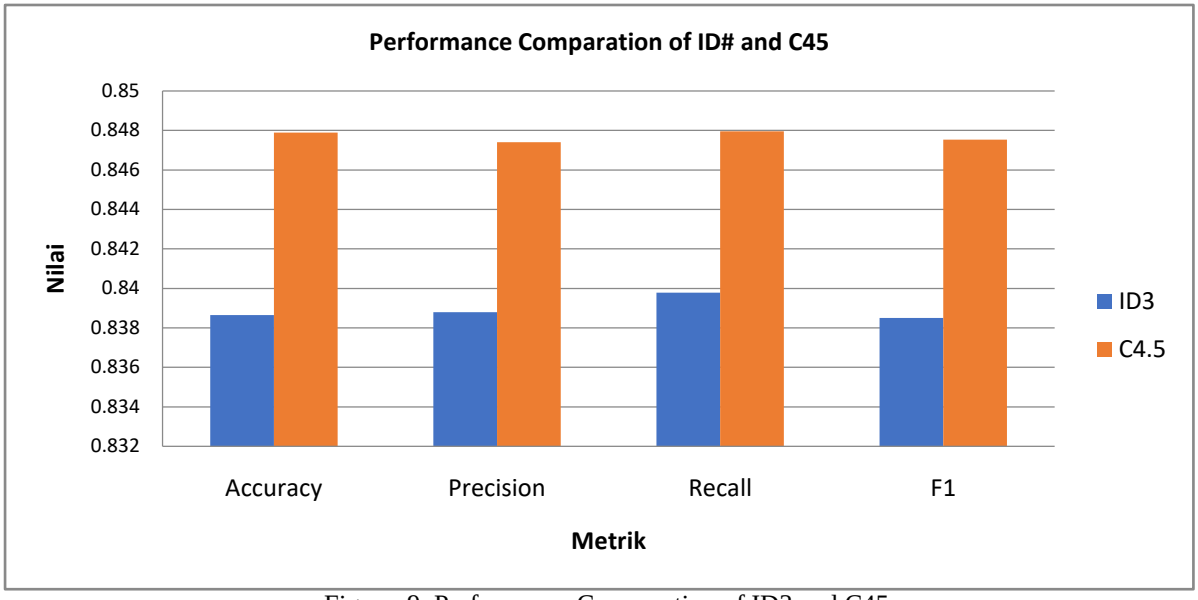

Figure 9. Performance Comparation of ID3 and C45

V. CONCLUSION

The following conclusions can be drawn from this study:

1. The C4.5 algorithm achieved the highest average accuracy of 0.847899, while the ID3 algorithm obtained an average accuracy of 0.838655. This indicates that C4.5 demonstrates superior overall performance compared to ID3.
2. Across all evaluation metrics—accuracy, precision, recall, and F1-score—the C4.5 algorithm consistently produced higher values than ID3.
3. Although the performance difference between the two algorithms is relatively small, as indicated by their closely comparable average scores, C4.5 still outperforms ID3 overall.
4. The superiority of C4.5 can be attributed to its ability to handle numerical attributes, manage missing values, and apply pruning techniques to reduce the risk of overfitting, resulting in a more stable and reliable classification model.

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