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Classification Of Customer Satisfaction Levels For Tring Application Services At Pegadaian Syariah Using The C4.5 Algorithm

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Abstract

Digital transformation in the financial sector encourages financial institutions to continuously improve the quality of digital services to meet customer needs and satisfaction. One of the digital services provided by PT Pegadaian Syariah is the Tring application, which offers various services such as pawn services, gold savings, financing, and online transactions. However, several issues are still encountered during its use, including feature maintenance and system instability, which may affect customer satisfaction. This study aims to develop a customer satisfaction classification model, identify the service factors that have the most significant influence, and measure the performance of the C4.5 algorithm in classifying customer satisfaction with the Tring application. A quantitative approach was employed using questionnaire data collected from 100 customers of the Plaza Taman Harapan Baru Branch of Pegadaian Syariah who had experience using the Tring application. The attributes considered consist of ease of use, service speed, feature completeness, application stability, information quality, and transaction quality. The classification process was performed using the C4.5 algorithm with the assistance of RapidMiner and evaluated using 10-Fold Cross Validation. The results show that Ease of Use (X1) was the most dominant factor, with the highest information gain value of 0.144965037, and was selected as the root node in the decision tree. The model achieved an accuracy of 83.00% and an Area Under the Curve (AUC) value of 0.931, which falls into the Excellent Classification category. These results indicate that the C4.5 algorithm provides good performance in classifying customer satisfaction into satisfied and dissatisfied categories.

Keywords: Tring Application, C4.5 Algorithm, Data Mining, Customer Satisfaction, Islamic Pawnshop

INTRODUCTION

Technological advancements are driving financial institutions to provide fast, easy, and efficient services. PT Pegadaian Syariah is responding to this development through the Tring app, which offers digital services such as pawning, gold savings, financing, and installments. This app makes it easy for customers to access services without having to visit a physical store.

However, the implementation of the Tring application still faces challenges, such as several features undergoing maintenance and suboptimal system performance. These conditions can hinder transactions, reduce convenience, and impact customer satisfaction. Therefore, an analysis of satisfaction levels based on ease of use, service speed, feature completeness, application stability, information quality, and transaction quality is necessary.

This study aims to develop a classification model of customer satisfaction with Tring app services using the Decision Tree C4.5 algorithm, identify influential service factors, and measure the classification accuracy. This research is important as material for evaluating the quality of Pegadaian Syariah's digital services. Its novelty lies in the application of the C4.5 algorithm to identify classification patterns and service factors that form the basis of Tring app customer satisfaction.

RESEARCH METHODS

This study uses a quantitative approach with a survey method through a questionnaire to Pegadaian Syariah customers who use the Tring application. The data obtained is used to



classify customer satisfaction levels using the C4.5 algorithm through entropy and gain calculations to determine the best attributes in forming a customer satisfaction profile.decision tree (Susi Fitryah Damanik & Anjar Wanto, 2022).

Figure 1. Research Stages

Source :(Napiun & Ruli, 2025)

Identification of problems

This study identified customer satisfaction issues with the Tring application, including ease of use, information quality, service speed, transaction quality, and convenience. The study was conducted at Pegadaian Syariah Plaza Taman Harapan Baru.

Literature study

Literature studies were conducted through journal, book, and scientific reference studies to strengthen the theoretical basis of the research, particularly regarding customer satisfaction, online services, data mining, decision trees, CART, and the C4.5 algorithm.

Customer Satisfaction

Customer satisfaction is a condition when customer needs, desires, and expectations are met (Aditama & Nur Latifah, 2025).

Online Services

Online services are internet-based services that allow various matters to be carried out easily, quickly, and in real time without face-to-face interaction (Lestar, 2022).

CART Algorithm

CART is a decision tree algorithm for predicting response variables based on one or more predictor variables (Ramadhan & Nugroho, 2025).

C4.5 Algorithm

C4.5 is a data mining classification method that produces decision trees based on training data for classification (Damanik & Wanto, 2022).

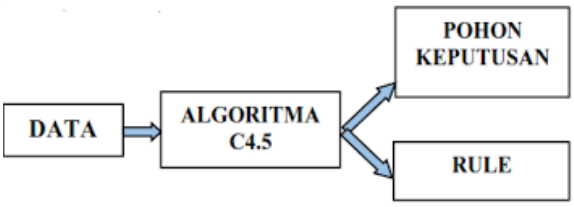


Figure 2. C4.5 Algorithm

Source :(Devinda Yulia, Abdi Pandu Kusuma, 2022)

Population and Sample

The study population consisted of 1,596 Tring app users at Pegadaian Syariah Plaza Taman Harapan Baru Branch. A sample of 100 respondents was selected using purposive sampling with the criteria being customers who have used the Tring app and have experience using its features or services. The research procedures included problem identification, literature review, sample determination, questionnaire preparation and distribution, data collection and processing, C4.5 model development, 10-Fold Cross Validation testing, model evaluation, and conclusion drawing.

Compilation of Questionnaires

The questionnaire was developed based on six factors: ease of use, service speed, feature completeness, application stability, information quality, and transaction quality. Each variable was developed into several indicators in the form of closed-ended statements to measure customer perceptions. The questionnaire data was then used as a dataset for classifying satisfaction levels using the C4.5 algorithm with the help of RapidMiner.

Data collection

Observation

Observations were conducted directly at the CPS Pegadaian Syariah Plaza Taman Harapan Baru to observe the service and use of the Tring application and identify research problems.

Interview

Interviews were conducted with customers using the Tring application to obtain information regarding their experiences, service quality, and obstacles in using the application.

Literature review

Literature study was conducted through journals, books, proceedings, and previous research as a theoretical basis related to data mining, classification, C4.5, decision trees, and RapidMiner.

Questionnaire

A questionnaire was distributed to 100 Tring app users using a purposive sampling technique. The obtained data was used as a dataset for classifying satisfaction levels using the C4.5 algorithm with RapidMiner.

Data analysis

The questionnaire data was analyzed using the C4.5 algorithm and compared with CART to form a decision tree and determine the differences in performance in classifying the level of customer satisfaction with the Tring application.

Conclusion of Report and Research

Testing was conducted using RapidMiner based on accuracy, precision, recall, and AUC values. The results of C4.5 and CART were compared to determine the algorithm's performance in classifying customer satisfaction.

RESULTS AND DISCUSSION

Data processing

Questionnaire Results

Table 1.Data Processing Results

No	Ease of Use	Service Speed	Complete Features	Application Stability	Information Quality	Transaction Quality	Satisfaction Level
1	4.33	5	4.67	5	5	5	Satisfied
2	5	5	5	5	5	5	Satisfied
3	4.33	4	4	4	4.33	4.33	Satisfied
4	4	4.33	3.00	3	3.67	3.67	Satisfied
5	5	4.67	5.00	5	5	5	Satisfied
6	5	5	5.00	5	5	5	Satisfied
7	4	4.33	3.67	4	4	4	Satisfied
8	5	5	5.00	5	5	5	Satisfied
9	4.67	4.67	4.67	4.67	5	5	Satisfied
10	5	5	5.00	4.33	4.33	5	Satisfied
11	3.33	3.33	3.33	4	3	3.67	Satisfied
12	4.33	4	4.33	4	4	4	Satisfied
13	3.67	3.67	3.67	3.33	4	4.33	Satisfied
14	4.33	5	4.67	5	5	5	Satisfied
...	...	...	...	...	...	...	...
100	4.33	3.67	2.33	3.33	3.00	3.67	Not satisfied

Source: 2026 Research

Data Transformation

Table 2. Data Transformation Table

No	Ease of Use	Service Speed	Complete Features	Application Stability	Information Quality	Transaction Quality	Satisfaction Level
1	Tall	Tall	Tall	Tall	Tall	Tall	Satisfied
2	Tall	Tall	Tall	Tall	Tall	Tall	Satisfied
3	Tall	Tall	Tall	Tall	Tall	Tall	Satisfied
4	Tall	Tall	Low	Low	Tall	Tall	Satisfied
5	Tall	Tall	Tall	Tall	Tall	Tall	Satisfied
6	Tall	Tall	Tall	Tall	Tall	Tall	Satisfied
7	Tall	Tall	Tall	Tall	Tall	Tall	Satisfied
8	Tall	Tall	Tall	Tall	Tall	Tall	Satisfied
9	Tall	Tall	Tall	Tall	Tall	Tall	Satisfied
10	Low	Tall	Tall	Tall	Tall	Tall	Satisfied
11	Tall	Low	Low	Tall	Low	Tall	Satisfied
12	Tall	Tall	Tall	Tall	Tall	Tall	Satisfied
13	Tall	Tall	Tall	Low	Tall	Tall	Satisfied
14	Tall	Tall	Tall	Tall	Tall	Tall	Satisfied
...	...	...	...	...	...	...	...
100	Low	Tall	Low	Low	Low	Tall	Not satisfied

Source:Research 2026

Calculation of Average Value

Table 3. Manual entropy and gain calculations in Excel

NODE	Attribute	Mark	Number of Questionnaires	Satisfied	Not satisfied	*Entropy*	*Gain*
	Ease of Use	Tall	76	72	4	0.297472249	0.144965037
		Low	24	13	11	0.994984828	
	Service Speed	Tall	82	72	10	0.534943699	0.017753539
		Low	18	13	5	0.852405179	
	Complete Features	Tall	70	67	3	0.255242113	0.139885647
		Low	30	18	12	0.970950594	
	Application Stability	Tall	67	62	5	0.382957672	0.061220664
		Low	33	23	10	0.884963636	
	Information Quality	Tall	77	71	6	0.394814846	0.083736563
		Low	23	14	9	0.965636133	
	Transaction Quality	Tall	84	74	10	0.526617066	0.024115852
		Low	16	11	5	0.896038233	

Source: 2026 Research

The manual calculation results of the C4.5 algorithm show that Ease of Use is the most ideal attribute as a root node because it has the highest information gain value of 0.144965037. This attribute is able to differentiate the level of customer satisfaction most effectively, with the high ease category dominated by satisfied respondents, namely 72 out of 76 respondents.

Other attributes have lower information gain values, namely Feature Completeness (0.139885647), Information Quality (0.083736563), Application Stability (0.061220664), Transaction Quality (0.024115852), and Service Speed (0.017753539). Thus, Ease of Use is the most dominant factor in the classification of customer satisfaction and is designated as the main root of the decision tree. These results are also consistent with modeling using RapidMiner, which places Ease of Use as the root node.

Preprocessing

Before proceeding further, the collected questionnaire data was checked to ensure there were no missing or incomplete data. The data was then prepared in a Microsoft Excel file and imported into RapidMiner software for analysis.

This study used the Cross Validation method to validate the model. This method is used to more fairly evaluate the performance of a classification model by dividing the data into several parts called folds. In each testing phase, some of the data is used for training and some for testing. This process is repeated continuously until all data has an equal chance of being used as training or testing data.

The implementation of Cross Validation aims to reduce the risk of overfitting and obtain more consistent assessment values. After the validation process is complete, the model's performance is assessed using several metrics such as Accuracy, Precision, Recall, and Confusion Matrix to determine how accurate the C4.5 algorithm is in classifying customer satisfaction levels towards the Tring application service at Pegadaian Syariah.

Classification Modeling
Implementation of C4.5 Algorithm
Data Input and Data Preprocessing

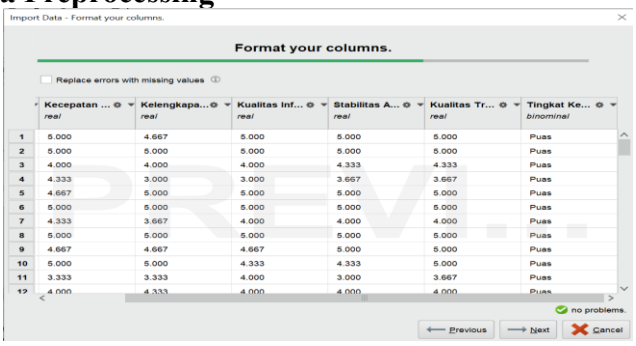


Figure 3. Dataset
Source: 2026 Research

The Data Preprocessing process begins by selecting the Import Data button on the RapidMiner Repository panel to upload an Excel file from your computer directory. Once the file directory is selected, the next step is to define the sheet and include all data cell areas containing the research variables. In the Format your columns stage, the role of the target attribute, "Satisfaction Level," is set to a label with a binomial data type, while the other predictor attributes are adjusted to real types. After all column parameters have been verified without any problems, the dataset is saved to the Local Repository under the name Dataset for use in the classification modeling stage.

Process

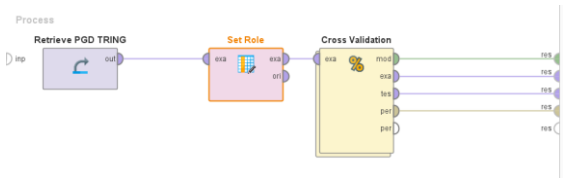


Figure 4. Process
Source: 2026 Research

***Retrieve*Data**

*Retrieve*is an operator used to retrieve datasets stored in the RapidMiner Repository. Before this process is carried out, the data from the questionnaire distribution to 100 respondents is imported into RapidMiner, then saved to the Repository under the name Tring. Storing the dataset in the Repository aims to ensure reusability without the need for re-importation. Next, the Tring dataset is added to the process area (Process View) using the Retrieve operator as the source.data that will be used in the next processing and analysis stages, such as forming a classification model using the C4.5 algorithm.

Set Role

*Set Role*is an operator used to determine the role of each attribute in the dataset before the classification process is carried out. In this study, the Set Role operator is used to set the Customer Satisfaction Level (Y) attribute as a label or target variable to be predicted by the C4.5 algorithm. Determining the Customer Satisfaction Level attribute as a label aims to enable RapidMiner to identify the relationship pattern between independent variables and the level of customer satisfaction with the Tring application service at Pegadaian Syariah.

Cross Validation

*Cross Validation*is an operator used to evaluate the performance of a classification model built using the C4.5 algorithm. In this study, the validation method used was 10-Fold Cross Validation, a validation technique that divides the dataset into 10 parts (folds). Each fold will be used alternately as test data (*testing*), while the other nine folds are used as

training data (*training*This process is repeated 10 times until each part of the dataset has had a chance to be tested once. The test results from all folds are then averaged to obtain a more accurate and objective model performance value.

Cross Validation Process

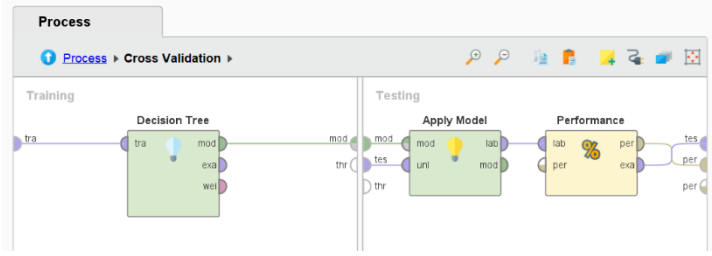


Figure 5. Process*Cross Validation*
Source: 2026 Research

***Decision Tree*On Training Data**

In the Training stage, the Decision Tree operator is used to build a classification model based on training data generated from the 10-Fold Cross Validation process. This operator processes the training data using attributes X1 (Ease of Use), X2 (Speed of Access and Service), X3 (Feature Completeness), X4 (Application Stability), X5 (Information Quality), and X6 (Transaction Quality) as predictor attributes and Customer Satisfaction Level (Y) as a label attribute. The result of this process is a decision tree model which is then used in the Apply Model stage to classify the test data.

In this study, the Decision Tree operator uses a criterion parameter with an information gain value. This parameter is used to determine the best attribute to be selected as the root node or the next node based on the highest Information Gain value. Furthermore, the maximum depth parameter is set at 10, meaning the maximum depth of the decision tree is limited to 10 levels. This setting aims to ensure the resulting model is not too complex and still able to perform the classification process optimally.

***Apply Model*and Performance Binominal Classification**

In the Testing phase, the process begins with the Apply Model operator, which applies the trained Decision Tree model to the test data, resulting in a predicted Customer Satisfaction Level. Next, the prediction results are evaluated using the Performance operator (Binominal Classification) by comparing the predicted values with the actual data. The evaluation is conducted using a Confusion Matrix, Accuracy, Precision, Recall, and Area Under Curve (AUC) to determine the performance of the resulting classification model.

RapidMiner Algorithm C4.5 Test Results

Confusion Matrix

*Confusion matrix*used to determine the number of data that the model successfully or unsuccessfully classifies into the appropriate class. Based on the test results, the following values were obtained:

Accuracy

accuracy: 83.00% +/- 9.49% (micro average: 83.00%)

	true Puas	true Tidak Puas	class precision
pred. Puas	75	7	91.46%
pred. Tidak Puas	10	8	44.44%
class recall	88.24%	53.33%	

Figure 6. Test Results*Accuracy*
Source: 2026 Research

The Accuracy value is used to determine the success level of the C4.5 algorithm in classifying the level of customer satisfaction with the Tring application service at Pegadaian Syariah.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100\%$$

Value substitution:

$$Accuracy = \frac{75 + 8}{75 + 8 + 7 + 10} \times 100\%$$
$$Accuracy = \frac{83}{100} \times 100\%$$
$$Accuracy = 83{,}00\%$$

Based on the test results using RapidMiner, the C4.5 algorithm classification model obtained an Accuracy value of 83.00% ± 9.49% with a micro average of 83.00%. This value indicates that the model has a good level of accuracy in classifying the level of customer satisfaction with the Tring application service at Pegadaian Syariah. The higher the Accuracy value obtained, the better the model's ability to provide predictions that match actual conditions. In this test, the similarity in the Accuracy and micro average values, which both reached 83.00%, indicates a balanced and consistent distribution of cross-validation data throughout the entire test in the confusion matrix.

Precision

precision: 44.44% (positive class: Tidak Puas)

	true Puas	true Tidak Puas	class precision
pred. Puas	75	7	91.46%
pred. Tidak Puas	10	8	44.44%
class recall	88.24%	53.33%	

Figure 7. Test Results*Precision*
Source: 2026 Research

Precision calculations are performed using the following formula:

$$Precision = \frac{TP}{TP + FP} \times 100\%$$

Value Substitution:

$$Precision = \frac{75}{75 + 7} \times 100\%$$
$$Precision = \frac{75}{82} \times 100\%$$
$$Precision = 91{,}46\%$$

The test results show that the model achieved a precision value of 44.44% with the positive class being "Dissatisfied." Precision is used to measure the accuracy of the model in predicting the positive class. This value indicates that of all data predicted as Dissatisfied, 44.44% were correct, while the remaining 55.56% were correct.This is data that actually falls into the Satisfied category. These results indicate that the model's ability to predict the Dissatisfied class is still suboptimal, resulting in misclassification within that class.

Recall

recall: 55.00% +/- 49.72% (micro average: 53.33%) (positive class: Tidak Puas)

	true Puas	true Tidak Puas	class precis
pred. Puas	75	7	91.46%
pred. Tidak Puas	10	8	44.44%
class recall	88.24%	53.33%	

Source: 2026 Research
Figure 8. Recall Test Results

Based on the Recall calculation, it is done using the following formula:

$$Recall = \frac{TP}{TP + FN} \times 100\%$$

Value Substitution:

$$Recall = \frac{75}{75 + 10} \times 100\%$$

$$Recall = \frac{75}{85} \times 100\%$$

$$Recall = 88{,}24\%$$

Based on the test results, the model obtained a Recall value of 55.00% ± 49.72% with a micro average of 53.33% in the positive class "Dissatisfied". This Recall Matrix is used to measure the model's ability to recognize all actual data that truly fall into the positive class.

The class recall value of 53.33% indicates that of the total actual data in the "Dissatisfied" category (15 samples), the new model was able to correctly identify 53.33% (8 data samples), while the remaining 46.67% (7 data samples) were still incorrectly classified into the "Satisfied" category (False Negative). This indicates that the model's ability to detect the "Dissatisfied" class is still at a moderate level. This condition is influenced by the imbalance in data distribution.(imbalanced data), where the number of samples in the "Satisfied" category is much more dominant compared to the "Dissatisfied" category.

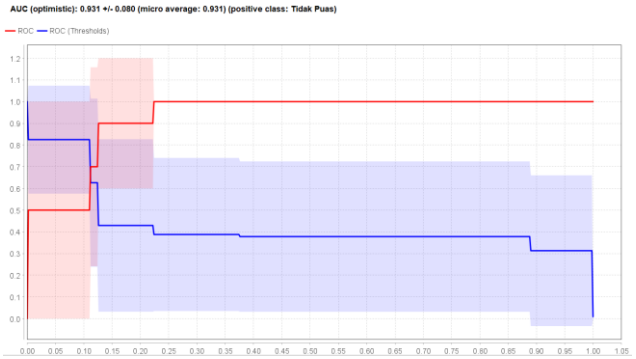
Decision Tree



Source: 2026 Research
Figure 9. Decision Tree

Next, data processing using RapidMiner was carried out to form a decision tree. The classification results showed that Ease of Use (X1) became the root node because it had the highest Information Gain value. Based on the decision tree formed, the rule was obtained that the value of X1 > 3,500 with Completeness of Features (X3) > 2,833 resulted in the Satisfied class, while X3 ≤ 2,833 resulted in Dissatisfaction. At X1 ≤ 3,500, the value of X1 ≤ 2,500 resulted in Dissatisfaction, while X1 > 2,500 was continued based on Speed of Service (X2). The value of X2 ≤ 3,833 resulted in Satisfaction, while X2 > 3,833 again considered X1, with a value > 3 resulting in Satisfaction and ≤ 3 resulting in Dissatisfaction.

AUC (Area Under Curve) Results



Source: AUC Performance Test Results

Figure 10. RapidMiner AUC results

*Area Under Curve (AUC)*used to measure the classification model's ability to distinguish between two classes: Satisfied and Dissatisfied. Based on the test results using RapidMiner, the AUC value was obtained at 0.931 with a positive class = Dissatisfied. This value indicates that the model has excellent ability to distinguish data belonging to the Satisfied and Dissatisfied classes. The closer the value is to 1.00, the better the model's classification ability, so this result indicates that the model is able to distinguish between the two classes with a high level of accuracy.

Based on the AUC value category, the value of 0.931 is in the range of 0.90–1.00, so it is included in the Excellent Classification category.Thus, the classification model built using the C4.5 algorithm demonstrated excellent performance in classifying customer satisfaction levels with the Tring application service at Pegadaian Syariah. These results demonstrate the model's ability to recognize data patterns effectively, effectively distinguishing between satisfied and dissatisfied customers.

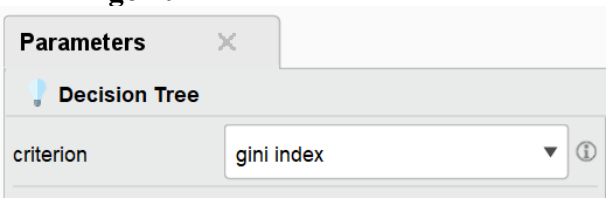
Table 4. AUC Value

AUC value	Category
0.90 - 1.00	*Excellent Classification*
0.80 - 0.90	*Good Classification*
0.70 - 0.80	*Fair Classification*
0.60 - 0.70	*Poor Classification*
0.50 - 0.60	*Failure*

Source :(Risk & Banking, 2023)

Based on the test results using RapidMiner, the AUC (Area Under Curve) value was obtained at 0.931 with a positive class = Dissatisfied. The interpretation of the AUC value refers to the categories presented in Table III.6, namely a value of 0.90–1.00 including Excellent Classification, 0.80–0.90 including Good Classification, 0.70–0.80 including Fair Classification, 0.60–0.70 including Poor Classification, and 0.50–0.60 including Failure. Based on these categories, the AUC value of 0.931 is in the range of 0.90–1.00, so it is included in the Excellent Classification category. This shows that the classification model built using the C4.5 algorithm has excellent capabilities in distinguishing Satisfied and Dissatisfied classes. Thus, the model has a high level of discrimination so that it is able to classify the level of customer satisfaction with the Tring application service at Pegadaian Syariah well.

Implementation of the CART Algorithm



Source: 2026 Research

Figure 11.*Criterion*on Operator*Decision tree*

In the CART algorithm, the Decision Tree operator uses the Gini Index as the criterion setting. This setting serves as the basis for determining the data separation at each branch of the decision tree. The Gini Index measures the level of impurity in the data groups formed from each separation. Using this criterion, the Decision Tree operator constructs a decision tree based on the patterns found in the research data.

In addition to setting these criteria, the CART implementation process is carried out using the same process as the C4.5 algorithm, including the use of Cross Validation, Apply Model, and Performance. The results of these processes are then used to obtain CART model evaluation scores, which will be compared with the results of the C4.5 algorithm in the next stage.

RapidMiner CART Algorithm Test Results

The performance evaluation of the Classification and Regression Trees (CART) model was tested using the 10-Fold Cross Validation method assisted by RapidMiner software. The test results showed that the CART algorithm was able to classify the level of customer satisfaction of Tring application users with an accuracy value of 88.00%. This model performance was supported by a precision value of 66.67% and a sensitivity level (Recall) of 60.00%. Measurement of the Receiver Operating Characteristic (ROC) performance curve produced an Area Under Curve (AUC) value of 0.881, which places the classification performance of the CART algorithm into the Good Classification qualification.

Comparison of C4.5 and Cart Algorithms

Table 5. Algorithm Comparison

Parameter	C4.5 Algorithm	CART Algorithm
Accuracy	83.00%	88.00%
Precision	44.44%	66.67%
Recall	53.33%	60.00%
AUC	0.931	0.881

Source: 2026 Research

Based on the comparative data in Table III.7, the CART-based classification model demonstrates superiority in most key performance indicators when compared to the C4.5 algorithm. In terms of prediction accuracy, CART recorded an accuracy value of 88.00%, 5.00% ahead of C4.5, which achieved 83.00%. This positive trend is in line with CART's precision achievement of 66.67% compared to C4.5's 44.44%, and its recall value of 60.00% compared to 53.33%.

However, the C4.5 algorithm excels in terms of class separation power through the Area Under Curve (AUC) parameter with a score of 0.931 which falls into the excellent classification category, while CART obtained an AUC score of 0.881 (good classification). In general, this comparison indicates that CART is more effective in suppressing the overall level of data prediction errors, while C4.5 has a slightly more optimal sharpness of inter-category boundary discrimination.

CONCLUSION

The application of the C4.5 algorithm successfully classifies the level of customer satisfaction of the Tring application into a decision tree model based on six main variables, including Ease of Use, Speed of Access and Service, Completeness of Features, Application Stability, Information Quality, and Transaction Quality. Based on entropy and information gain analysis, the Ease of Use attribute (X1) is the most dominant variable that influences customer satisfaction so that it is selected as the root node with the highest gain value of 0.144965037. Based on the 10-fold cross validation evaluation using RapidMiner, the C4.5 algorithm recorded an accuracy value of 83.00%, precision of 44.44%, recall of 53.33%, and AUC of 0.931 (excellent classification). As a comparison, the CART algorithm obtained an accuracy value of 88.00%, precision of 66.67%, recall of 60.00%, and AUC of 0.881 (good classification). The comparison results show that the CART algorithm has higher classification performance in accuracy, precision, and recall indicators, while the C4.5 algorithm is superior in AUC value.

This study is limited by the number of respondents, which only included 100 customers, and the use of six service attributes. Therefore, the classification results are still limited to the characteristics of the data and variables used in the study. Practically, the results of this study can be used as evaluation material for Pegadaian Syariah to improve the usability aspect of the Tring application through a simpler display, easy-to-understand service flow, and reduction of unnecessary steps. The results of the C4.5 model can also be used as supporting information in evaluating the quality of digital services and combined with direct evaluations from customers. Future research is recommended to use a larger number of respondents and add variables such as security, system quality, application display, and user experience so that the classification results can provide a broader picture.

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