Journal of Mathematics Instruction, Social Research and Opinion
Vol. 5, No. 3, September 2026, pp. 2417 – 2430, https://doi.org/10.58421/misro.v5i3.1953
ISSN 2962-7842

Application of the C4.5 Decision Tree for Classifying Furniture Product Sales Performance at CV Indowest Design Furniture

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Article Info

Article history:

Received 2026-07-31
Revised 2026-09-25
Accepted 2026-11-04

Keywords:

Data mining
Decision support system
Gain ratio
Leave-one-out cross-validation
Rattan products

ABSTRACT

Many rattan furniture producers, including CV Indowest Design Furniture, still judge product performance manually, so production, stocking, and promotion decisions rest on informal estimates. This study applied the C4.5 decision tree algorithm to classify the company's products by sales performance and embedded the model in a web-based decision support system. Sales records from August to November 2025 (99 transactions, 1,875 units) were aggregated into 17 product-level records. Each product was labelled best seller, moderate, or low seller from its average units per transaction using management-defined thresholds, and purchase frequency and unit selling price, each discretized into three levels, served as predictors. The tree was grown with the gain ratio criterion and implemented in a Laravel 10 and MySQL application. Unit selling price was selected as the root node (gain ratio 0.5585), and the final tree contains five rules. On the 17 training records the tree reached an accuracy of 76.47%, with macro-averaged precision, recall, and F1-score of 77.14%, and all five high-priced products were correctly identified as low sellers. Under leave-one-out cross-validation, however, accuracy fell to 47.06%, only slightly above the 41.18% majority-class baseline, because the two predictors could not reliably separate best sellers from moderate products. The tree therefore offers an interpretable profile of current sales performance, particularly for flagging high-priced slow movers, but it is not yet a dependable predictive tool; longer transaction histories and richer attributes are needed before it is used for forecasting.

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1. INTRODUCTION

Rattan furniture is one of Indonesia's established export-oriented craft industries, and Indonesian rattan furniture has been shown to remain competitive in several European import markets [1]. CV (Commanditaire Vennootschap) Indowest Design Furniture, a rattan furniture producer, operates in this competitive environment but does not yet have a

systematic mechanism for identifying which products perform best on the basis of actual transaction histories. Consequently, decisions on production scheduling, inventory replenishment, and promotional planning still depend largely on informal estimation, a practice that carries recurring operational risk.

This challenge is not unique to the furniture sector. Many small and medium-sized enterprises already hold substantial transaction data that remain unused because no structured analytical mechanism converts them into decision-relevant knowledge. In a pharmaceutical installation, for example, Adha and Widyastuti showed that a structured, criteria-based recommendation mechanism built on a fuzzy database can support drug and medical device procurement decisions [2].

A comparable pattern appears in small-scale retail and distribution. Diansyah and Exprada applied C4.5 to predict catfish sales at a recreational fishing pond, where fluctuating demand made stock levels difficult to plan [3], and Sari and Rifqo applied the same algorithm to Shell lubricant sales at CV Harapan Karya Mandiri, a distributor that needed a data-driven basis for anticipating demand and managing stock [4]. In both cases, the businesses had accumulated transaction records but lacked an analytical layer to translate them into stocking or promotional decisions.

Data mining offers a credible path toward resolving this class of problems. It applies statistical, mathematical, and machine learning techniques to discover useful patterns and knowledge in large data collections [5]. Classification, the assignment of instances to predefined categories on the basis of their attribute values, is particularly valuable in business settings because it converts raw records into structured, evidence-based insights. Related data mining tasks have already been applied to operational transaction logs, for example association-rule mining of consumer purchase lists in a building-materials store [6] and of library borrowing records [7], reinforcing the premise that historical transaction data, once properly mined, can inform operational decisions.

Among classification techniques, the C4.5 decision tree algorithm is one of the most widely adopted, largely because the trees it generates are transparent and easy to interpret, even for non-technical stakeholders. Developed by Quinlan as an extension of the earlier ID3 algorithm [8], [9], C4.5 can handle continuous-valued attributes and missing values and uses pruning to limit overfitting. Whereas ID3 selects splitting attributes by information gain alone, C4.5 normalizes that measure into a gain ratio, which curbs the bias toward attributes with many distinct values [9].

C4.5 has been applied widely outside the sales domain, particularly in healthcare and education, where interpretability matters as much as accuracy. Agesti, Dewanto, and Nada compared a CART-based decision tree with C4.5 for classifying blood donor eligibility at PMI Semarang City and obtained accuracies of 92.08% and 91.09%, respectively [10]. Setiawan combined C4.5 with forward selection and particle swarm optimization and raised heart disease classification accuracy from 77.11% to 84.73% [11]. Abidin et al. examined the computational steps of C4.5 by comparing a manual calculation with a Python implementation on the play tennis dataset [12]. Prakoso and Kurniawati built a C4.5 tree on three attributes of the UCI heart disease dataset (chest pain type, age, and cholesterol) and found chest pain type to be the root node [13], and Sartika and Yupianti used C4.5 to classify

thyroid disease at a regional hospital [14]. In education, Ulfa, Winarso, and Arribe built a C4.5 system that recommends study programmes to prospective students from school grades, test scores, and high-school major, but obtained only 12% accuracy, which they attributed to insufficient data and variables [15].

Within sales and inventory settings, C4.5 has been used to classify best-selling fast-food menu items [16], staple groceries [17], jewelry [18], cigarettes [19], springbeds [20], and promotional products [21]. To the best of our knowledge, however, no published study has applied C4.5 to product sales performance in Indonesia's rattan furniture sector. This study addresses that gap with three objectives: (i) to apply C4.5 to CV Indowest's August–November 2025 transaction data and classify each product as a best seller, moderate, or low seller; (ii) to evaluate the resulting model with accuracy, precision, recall, and F1-score, both on the training records and under leave-one-out cross-validation; and (iii) to embed the decision tree in a Laravel 10 and MySQL web application that serves as a decision support tool for company management.

2. METHOD

2.1 Data Collection

Data were collected through direct observation, structured interviews, and documentary review. On-site observation at CV Indowest Design Furniture traced the operational cycle from sales order receipt through invoice generation, warehouse dispatch, and report compilation, and revealed that sales records were managed informally, which limited their analytical use. Structured interviews with finance and warehouse personnel, the staff most directly involved in day-to-day transactions, clarified how records were kept, which product lines moved fastest, and what obstacles complicated data management. Comparable transaction-based classification has been applied at a regional distributor to predict internet card usage [22]. The documentary review drew on the company's official sales archive for August–November 2025. The archive contained 99 transactions covering 17 rattan furniture types (1,875 units in total), which formed the basis of all subsequent computations.

2.2 Stages of Data Mining

Han, Kamber, and Pei define data mining as the discovery of interesting patterns and knowledge from large amounts of data [5]; Berry and Linoff describe it as the exploration and analysis of large quantities of data to discover meaningful patterns and rules [23]; and Dunham frames it as finding hidden information in a database [24]. This study followed the knowledge discovery in databases (KDD) process [25], summarized in Figure 1, in five sequential stages.

https://doi.org/10.58421/misro.v5i3.1953

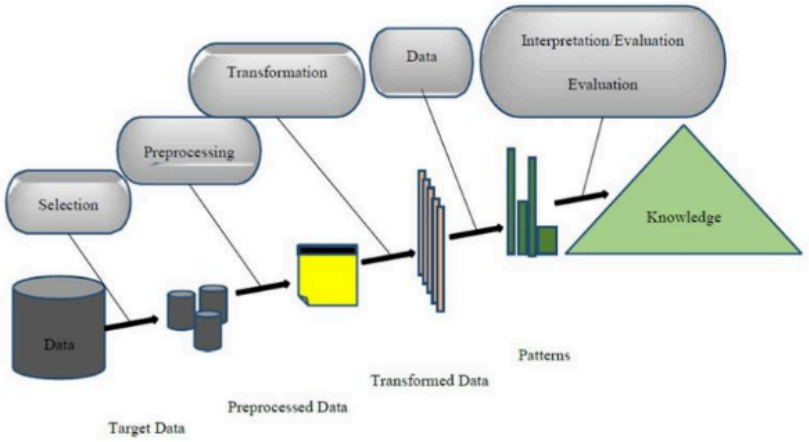


Figure 1. Stages of the knowledge discovery in databases (KDD) process (adapted from [25])

1) *Data selection*: relevant attributes and records were extracted from the operational database into a dedicated working file, separating the raw data from the analysis process.
2) *Preprocessing (cleaning)*: duplicate entries and records with missing values were removed, and inconsistencies were corrected.
3) *Transformation*: transactions were aggregated to product level, class labels were derived, and the numerical predictors were discretized (Section 2.3).
4) *Data mining*: the C4.5 algorithm was applied to the prepared data to construct the decision tree and extract classification rules (Section 2.4).
5) *Interpretation and evaluation*: the resulting patterns were evaluated for predictive performance (Section 2.5) and practical relevance and presented in a form that management could use.

2.3 Class Labelling and Attribute Discretization

Transactions were aggregated into one record per product. For each product, the purchase frequency (number of transactions), the total units sold, and the average number of units sold per transaction were computed, the last as

$$\bar{X} = \frac{\sum_{j=1}^{f} q_j}{f} \quad (1)$$

where q_j is the quantity in the j-th transaction of the product and f is its purchase frequency. For example, Rattan Lounge Chair (BRG-0001) appeared in 12 transactions with a total of 282 units, giving $\bar{X} = 282/12 = 23.50$ units per transaction. Class labels were assigned with fixed thresholds: *best seller* if $\bar{X} > 20$, *moderate* if $10 \leq \bar{X} \leq 20$, and *low seller* if $\bar{X} < 10$ units per transaction. These cut points are CV Indowest Design Furniture's internal standard for judging product performance and were not derived statistically. Because they are defined per transaction, they reward products bought in large batches rather than those with the largest total volume; this choice follows management practice and is revisited in Section 3.5.

Because the class label is a direct function of $\bar{X}$, the average quantity was excluded from the predictor set to avoid target leakage. The two remaining attributes, purchase frequency and unit selling price (Table 1), were used as predictors and discretized into three levels:

purchase frequency low (≤ 3 transactions), medium (4–7), and high (≥ 8); unit selling price low (≤ Rp 400,000), medium (Rp 400,001–900,000), and high (> Rp 900,000).

2.4 C4.5 Algorithm

The decision tree was grown with the C4.5 attribute selection procedure [9], which evaluates four quantities at each node. Saputra and Qoiriah applied the same procedure to stock inventory management in a small enterprise and reported 86.46% accuracy [26].

1) *Entropy*. Entropy measures the class heterogeneity of a set of records; it is zero for a pure set and maximal when all classes are equally represented [5], [8]:

$$\text{Entropy}(S) = -\sum_{i=1}^{k} p_i \log_2 p_i \tag{2}$$

where S is the set of records at the node, k is the number of classes (here three), and p_i is the proportion of records in S that belong to class i.

2) *Information gain*. Gain measures the reduction in entropy obtained by partitioning S on attribute A [5]:

$$\text{Gain}(S, A) = \text{Entropy}(S) - \sum_{v=1}^{m} \frac{|S_v|}{|S|} \text{Entropy}(S_v) \tag{3}$$

where m is the number of distinct values of A, S_v is the subset of S in which A takes its v-th value, and $|\cdot|$ denotes the number of records.

3) *Split information*. Because information gain favours attributes with many values, C4.5 penalizes the number and size of the partitions [9]:

$$\text{SplitInfo}(S, A) = -\sum_{v=1}^{m} \frac{|S_v|}{|S|} \log_2 \frac{|S_v|}{|S|} \tag{4}$$

4) *Gain ratio*. The splitting attribute is the one with the highest gain ratio:

$$\text{GainRatio}(S, A) = \frac{\text{Gain}(S,A)}{\text{SplitInfo}(S,A)} \tag{5}$$

Splitting is repeated recursively on each branch until a subset is pure or no attribute remains. Because both predictors were discretized beforehand, C4.5's handling of continuous attributes was not needed. A leaf is labelled with the majority class of its records; ties and empty branches take the majority class of the parent node. Following Quinlan's simplification principle [9], a subtree is collapsed into a single leaf when it does not reduce the number of misclassified training records. Muhidin and Suhenda used the same procedure for fast-food menu sales and found that quantity sold had the highest information gain (0.4634) and therefore formed the root node [16].

2.5 Model Evaluation

Model performance was summarized in a confusion matrix and the following measures, computed for each class c:

$$\text{Accuracy} = \frac{\text{number of correctly classified records}}{N} \tag{6}$$

$$\text{Precision}_c = \frac{TP_c}{TP_c + FP_c}, \qquad \text{Recall}_c = \frac{TP_c}{TP_c + FN_c} \tag{7}$$

$$F1_c = \frac{2 \times \text{Precision}_c \times \text{Recall}_c}{\text{Precision}_c + \text{Recall}_c} \tag{8}$$

where TP_c, FP_c, and FN_c are the true positives, false positives, and false negatives of class c and $N = 17$. Weighted averages weight each class by its number of records (support), whereas macro averages weight all classes equally and are therefore more sensitive to weak performance on a single class. Two evaluation schemes were used. *Resubstitution* applies the fitted tree to the same 17 records used to build it and therefore describes goodness of fit. *Leave-one-out cross-validation* (LOOCV) rebuilds the tree 17 times, each time on 16 records, and classifies the held-out record, giving a nearly unbiased but high-variance estimate of performance on unseen products. Both were compared with a majority-class baseline that always predicts the most frequent class. All computations were reproduced independently with a Python 3.13 script that uses only the standard library and is provided as a Supplementary File.

2.6 System Development Methodology

The decision support system was developed with the waterfall method, a sequential process model in which each phase is completed before the next begins and which suits projects whose requirements are well understood from the start [27]. This condition held here: the system requirements were fully specified at the outset, and the historical sales data did not require iterative reformulation during development. The same institution has previously applied multi-criteria decision-making methods to support criteria-based decisions, such as prioritizing free legal aid recipients [28]. Requirements analysis elicited functional and non-functional requirements, collected the sales data, selected the classification attributes, and defined input–output parameters. System design produced flowcharts, a data flow diagram (DFD), an entity relationship diagram (ERD), and user interface mock-ups. Implementation coded the C4.5 procedure as a core service in a Laravel 10 and MySQL web application. Testing validated all functional modules through black-box testing with the error guessing technique and assessed model performance with the measures in Section 2.5. Maintenance covers bug fixes, dataset updates, and feature adjustments as operational needs evolve.

3. RESULTS AND DISCUSSION

3.1 Dataset

Table 1 lists the 17 products in CV Indowest's catalogue, and Table 2 shows a sample of the transaction records. After aggregation, labelling, and discretization (Section 2.3), the product-level dataset in Table 3 was obtained. It contains 7 best sellers (41.18%), 5 moderate products (29.41%), and 5 low sellers (29.41%).

Table 1. CV Indowest Design Furniture product catalogue

No	Code	Product Name	Category	Stock	Selling Price	Cost Price	Unit
1	BRG-0004	Rattan Porch Swing	Accessory	276	Rp 870,000	Rp 512,000	pcs
2	BRG-0017	Queen Rattan Bed Frame	Bed Frame	190	Rp 2,000,000	Rp 1,500,000	pcs
3	BRG-0016	Single Rattan Bed Frame	Bed Frame	300	Rp 1,100,000	Rp 870,000	pcs
4	BRG-0014	Decorative Rattan Basket	Accessory	200	Rp 185,000	Rp 100,000	pcs
5	BRG-0003	Rattan Dining Chair	Chair	132	Rp 275,000	Rp 210,000	pcs
6	BRG-0001	Rattan Lounge Chair	Chair	78	Rp 320,000	Rp 250,000	pcs
7	BRG-0002	Rattan Porch Chair	Chair	100	Rp 310,000	Rp 250,000	pcs
8	BRG-0010	Rattan Display Cabinet	Cabinet	330	Rp 760,000	Rp 550,000	pcs

No	Code	Product Name	Category	Stock	Selling Price	Cost Price	Unit
9	BRG-0011	Rattan Wardrobe	Cabinet	500	Rp 940,000	Rp 780,000	pcs
10	BRG-0006	Rattan Dining Table	Table	267	Rp 630,000	Rp 412,000	pcs
11	BRG-0005	Rattan Coffee Table	Table	133	Rp 730,000	Rp 431,000	pcs
12	BRG-0008	Rattan Nightstand	Table	280	Rp 350,000	Rp 270,000	pcs
13	BRG-0015	Decorative Rattan Pot	Accessory	180	Rp 145,000	Rp 100,000	pcs
14	BRG-0013	Rattan Bookshelf	Shelf	130	Rp 415,000	Rp 350,000	pcs
15	BRG-0012	Rattan Wall Shelf	Shelf	210	Rp 295,000	Rp 180,000	pcs
16	BRG-0007	2-Seater Rattan Sofa	Sofa	80	Rp 1,250,000	Rp 900,000	pcs
17	BRG-0009	3-Seater Rattan Sofa	Sofa	60	Rp 1,480,000	Rp 1,100,000	pcs

Table 2. Sample of sales transaction records

Invoice_Number	Transaction_Date	Product_Code	Quantity	Description
INV-2025-001	2025-08-01	BRG-0005	18	Cash Purchase
INV-2025-002	2025-08-02	BRG-0009	1	Cash Purchase
INV-2025-003	2025-08-02	BRG-0006	7	Cash Purchase
INV-2025-004	2025-08-02	BRG-0003	9	Cash Purchase
INV-2025-005	2025-08-03	BRG-0002	5	Cash Purchase
INV-2025-006	2025-08-03	BRG-0010	20	Cash Purchase
INV-2025-007	2025-08-05	BRG-0002	7	Cash Purchase
INV-2025-008	2025-08-05	BRG-0001	7	Cash Purchase
INV-2025-009	2025-08-07	BRG-0008	24	Cash Purchase
INV-2025-010	2025-08-07	BRG-0005	7	Cash Purchase
INV-2025-011	2025-08-10	BRG-0012	39	Cash Purchase
INV-2025-012	2025-08-12	BRG-0012	35	Cash Purchase
INV-2025-013	2025-08-13	BRG-0002	7	Cash Purchase
INV-2025-014	2025-08-15	BRG-0011	41	Cash Purchase
INV-2025-015	2025-08-16	BRG-0006	14	Cash Purchase
INV-2025-016	2025-08-17	BRG-0004	40	Cash Purchase

Table 3. Product-level dataset after labelling and discretization

No	Product Name	Freq.	Avg Qty (X)	D.Freq.	D.Price	Class
1	Rattan Lounge Chair	12	23.50	High	Low	Best-Seller
2	Rattan Porch Chair	14	16.86	High	Low	Moderate
3	Rattan Dining Chair	9	17.67	High	Low	Moderate
4	Rattan Porch Swing	6	23.17	Medium	Medium	Best-Seller
5	Rattan Coffee Table	6	19.50	Medium	Medium	Moderate
6	Rattan Dining Table	7	11.00	Medium	Medium	Moderate
7	2-Seater Rattan Sofa	1	4.00	Low	High	Low-Seller
8	Rattan Nightstand	11	26.09	High	Low	Best-Seller
9	3-Seater Rattan Sofa	3	2.00	Low	High	Low-Seller
10	Rattan Display Cabinet	5	20.40	Medium	Medium	Best-Seller
11	Rattan Wardrobe	5	9.80	Medium	High	Low-Seller
12	Rattan Wall Shelf	4	35.25	Medium	Low	Best-Seller
13	Rattan Bookshelf	2	26.00	Low	Medium	Best-Seller
14	Decorative Rattan Basket	8	18.38	High	Low	Moderate
15	Decorative Rattan Pot	2	27.00	Low	Low	Best-Seller
16	Single Rattan Bed Frame	1	4.00	Low	High	Low-Seller
17	Queen Rattan Bed Frame	3	6.33	Low	High	Low-Seller

Three products lie close to a class threshold: Rattan Display Cabinet ($\bar{X}$ = 20.40) is a best seller by a margin of 0.40 units per transaction, Rattan Dining Table ($\bar{X}$ = 11.00) is a moderate product only 1.00 unit above the low-seller threshold, and Rattan Wardrobe ($\bar{X}$ =

9.80) is a low seller only 0.20 units below the moderate threshold. Their labels would change under slightly different cut points.

3.2 C4.5 Computation

Root node (iteration 1). With 7, 5, and 5 records in the three classes, the entropy of the full dataset is

$$\text{Entropy}(S) = -\frac{7}{17}\log_2\frac{7}{17} - \frac{5}{17}\log_2\frac{5}{17} - \frac{5}{17}\log_2\frac{5}{17}$$
$$= 0.5271 + 0.5193 + 0.5193 = 1.5657$$

Table 4 shows the class distribution in each subset produced by the two candidate attributes. For unit selling price, Equations (3)–(5) give

$$\text{Gain}(S, \text{Price}) = 1.5657 - \left(\frac{7}{17} \times 0.9852 + \frac{5}{17} \times 0.9710 + \frac{5}{17} \times 0\right) = 0.8744$$

$$\text{SplitInfo}(S, \text{Price}) = -\frac{7}{17}\log_2\frac{7}{17} - 2 \times \frac{5}{17}\log_2\frac{5}{17} = 1.5657$$

$$\text{GainRatio}(S, \text{Price}) = \frac{0.8744}{1.5657} = 0.5585$$

The same computation for purchase frequency gives an information gain of 0.4410, a split information of 1.5799, and a gain ratio of 0.2791 (Table 5). Unit selling price therefore becomes the root node. Its high-price branch is already pure: all five products priced above Rp 900,000 are low sellers.

Table 4. Class distribution per attribute value at the root node (iteration 1)

Attribute	Value	n	Best-Seller	Moderate	Low-Seller	Entropy
Purchase frequency	Low	6	2	0	4	0.9183
	Medium	6	3	2	1	1.4591
	High	5	2	3	0	0.9710
Unit selling price	Low	7	4	3	0	0.9852
	Medium	5	3	2	0	0.9710
	High	5	0	0	5	0.0000
Total (root)		**17**	**7**	**5**	**5**	**1.5657**

Table 5. Gain ratio summary for root node selection (iteration 1)

Attribute	Information Gain	Split Info	Gain Ratio	Remark
Purchase frequency	0.4410	1.5799	0.2791	–
Unit selling price	0.8744	1.5657	0.5585	Highest → root node

Second level (iteration 2). The low-price branch (n = 7; 4 best sellers and 3 moderate products; entropy 0.9852) was split by purchase frequency, the only remaining attribute (gain 0.2917, split information 1.1488, gain ratio 0.2539). Its low- and medium-frequency subsets each contain a single best seller, whereas the high-frequency subset holds 2 best sellers and 3 moderate products and, with no attribute left, becomes a leaf labelled moderate. The medium-price branch (n = 5; 3 best sellers and 2 moderate products; entropy 0.9710) would be split into a low-frequency subset with one best seller and a medium-frequency subset with 2 best sellers and 2 moderate products (gain 0.1710, split information 0.7219, gain ratio 0.2368). Because the tie in the medium-frequency subset resolves to the parent majority (best seller), this split does not reduce the number of training errors; it was therefore

collapsed, and the medium-price branch became a single leaf labelled best seller. Table 6 summarizes both branches.

Table 6. Class distribution in the second-level subsets (iteration 2)

Branch	Frequency	n	Best-Seller	Moderate	Low-Seller	Entropy
Price = Low	Low	1	1	0	0	0.0000
	Medium	1	1	0	0	0.0000
	High	5	2	3	0	0.9710
Price = Medium	Low	1	1	0	0	0.0000
	Medium	4	2	2	0	1.0000
	High	0	0	0	0	–

3.3 Decision Tree and Classification Rules

Figure 2 shows the final tree, which yields five classification rules:

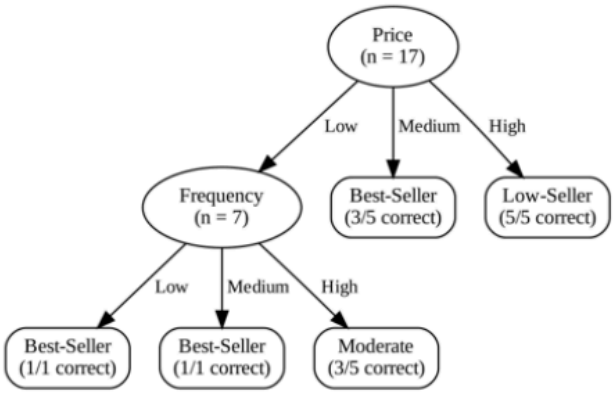


Figure 2. Final C4.5 decision tree; numbers in parentheses give the correctly classified training records and the records in each leaf

R1: IF Price = Low AND Frequency = Low THEN Class = best seller (1 of 1 training records correct)

R2: IF Price = Low AND Frequency = Medium THEN Class = best seller (1 of 1)

R3: IF Price = Low AND Frequency = High THEN Class = moderate (3 of 5)

R4: IF Price = Medium THEN Class = best seller (3 of 5)

R5: IF Price = High THEN Class = low seller (5 of 5)

Unit selling price is the dominant attribute: it isolates all low sellers in one pure leaf, and purchase frequency matters only among low-priced products. The prominence of price parallels the jewelry sales study of Syafputra et al., in which price thresholds appeared among the extracted classification rules [18].

3.4 Model Evaluation

Applying the five rules to the 17 records gives the predictions in Table 7 and the confusion matrix in Table 8. Thirteen products were classified correctly (accuracy 76.47%). The four errors are Rattan Lounge Chair and Rattan Nightstand, best sellers that fall in the moderate leaf of rule R3, and Rattan Coffee Table and Rattan Dining Table, moderate products that fall in the best-seller leaf of rule R4.

https://doi.org/10.58421/misro.v5i3.1953

Table 7. Decision tree predictions on the training records

No	Product Name	D.Freq.	D.Price	Actual	Predicted	Status
1	Rattan Lounge Chair	High	Low	Best-Seller	Moderate	Wrong
2	Rattan Porch Chair	High	Low	Moderate	Moderate	Correct
3	Rattan Dining Chair	High	Low	Moderate	Moderate	Correct
4	Rattan Porch Swing	Medium	Medium	Best-Seller	Best-Seller	Correct
5	Rattan Coffee Table	Medium	Medium	Moderate	Best-Seller	Wrong
6	Rattan Dining Table	Medium	Medium	Moderate	Best-Seller	Wrong
7	2-Seater Rattan Sofa	Low	High	Low-Seller	Low-Seller	Correct
8	Rattan Nightstand	High	Low	Best-Seller	Moderate	Wrong
9	3-Seater Rattan Sofa	Low	High	Low-Seller	Low-Seller	Correct
10	Rattan Display Cabinet	Medium	Medium	Best-Seller	Best-Seller	Correct
11	Rattan Wardrobe	Medium	High	Low-Seller	Low-Seller	Correct
12	Rattan Wall Shelf	Medium	Low	Best-Seller	Best-Seller	Correct
13	Rattan Bookshelf	Low	Medium	Best-Seller	Best-Seller	Correct
14	Decorative Rattan Basket	High	Low	Moderate	Moderate	Correct
15	Decorative Rattan Pot	Low	Low	Best-Seller	Best-Seller	Correct
16	Single Rattan Bed Frame	Low	High	Low-Seller	Low-Seller	Correct
17	Queen Rattan Bed Frame	Low	High	Low-Seller	Low-Seller	Correct

Table 8. Confusion matrix of the C4.5 decision tree (resubstitution)

Actual \ Predicted	Best-Seller	Moderate	Low-Seller
Best-Seller	5	2	0
Moderate	2	3	0
Low-Seller	0	0	5

Table 9 reports the per-class measures. Low sellers were identified with perfect precision and recall, whereas best sellers and moderate products were confused with each other. Because the three classes are of similar size, the weighted and macro averages are close (76.47% and 77.14%).

Table 9. Classification performance on the training records (resubstitution)

Class	Precision (%)	Recall (%)	F1-score (%)	Support
Best-Seller	71.43	71.43	71.43	7
Moderate	60.00	60.00	60.00	5
Low-Seller	100.00	100.00	100.00	5
Weighted average	76.47	76.47	76.47	17
Macro average	77.14	77.14	77.14	17

Table 10 compares resubstitution with LOOCV. Under LOOCV, accuracy fell to 47.06% (8 of 17 products), only 5.88 percentage points above the 41.18% majority-class baseline. All five low sellers were still classified correctly, but none of the five moderate products was recognized and four of the seven best sellers were labelled moderate, so the macro-averaged F1-score fell to 46.67%. Apart from the high-price rule, the tree therefore largely reproduces its training records: removing a single product is often enough to change the label of a small leaf.

Table 10. Resubstitution, leave-one-out cross-validation, and majority-class baseline

Evaluation scheme	Accuracy (%)	Macro P (%)	Macro R (%)	Macro F1 (%)
Resubstitution (training data)	76.47	77.14	77.14	77.14
Leave-one-out cross-validation	47.06	45.83	47.62	46.67
Majority-class baseline (Best-Seller)	41.18	13.73	33.33	19.44

3.5 Discussion

The results indicate that, in this dataset, unit selling price is the attribute most strongly associated with the per-transaction sales class. High-priced items, namely the sofas, bed frames, and wardrobe, are bought in small quantities per transaction and are consistently low sellers, whereas among lower-priced items purchase frequency does not separate best sellers from moderate products. Rattan Porch Chair (14 transactions, 236 units) and Rattan Lounge Chair (12 transactions, 282 units), for instance, differ in class only because their average quantities fall on either side of the 20-unit threshold (16.86 and 23.50), a distinction that neither predictor captures.

Comparable studies report higher accuracies, although differences in data, attributes, and evaluation design make direct comparison difficult. Ningsih et al. reached 96.15% accuracy in customer satisfaction classification, with one misclassified record among 26 test cases [29], and Leonardi et al. reported 92.11% accuracy for cigarette sales at a retail distributor, with product size as the most influential attribute [19]. Iswandaru and Indriyanti obtained 99.48% test accuracy and 96.77% five-fold cross-validation accuracy for promotional products, with unit price, product name, and month as the most discriminating attributes, but accuracy dropped to about 78% on external data from early 2025, which they attributed to shifts in consumer behaviour [21]. Melfia et al. reported 85% accuracy for best-selling staple groceries using product type, price, sales quantity, and sales time [17], and Sanjaya et al. used C4.5 to predict springbed sales patterns to support stock, production, and marketing decisions [20]. Two lessons follow for the present study. First, those studies used richer attribute sets or larger samples than the two predictors and 17 records available here. Second, the gap between internal and external accuracy reported by Iswandaru and Indriyanti mirrors the gap between resubstitution and LOOCV observed here, underscoring that in-sample accuracy overstates practical performance.

For management, the tree is best read as a descriptive profile of the August–November 2025 sales rather than as a forecasting model. Its most robust rule, R5, flags high-priced products as low sellers and remained correct for all five low sellers under LOOCV, which supports reviewing production quantities and promotion for those items. The rules that separate best sellers from moderate products are unstable and should not yet drive production or restocking decisions.

Beyond the classification model, the Laravel and MySQL application was verified by black-box testing with the error guessing technique. Table 11 summarizes the 16 scenarios, which cover authentication, product, stock, and transaction management, the C4.5 computation and visualization views, user management, and session handling; in every scenario the actual output matched the expected result.

https://doi.org/10.58421/misro.v5i3.1953

Table 11. Black-box testing summary (error guessing technique)

No	Function tested	Result
1	Login (valid and invalid credentials)	Pass
2	View product/stock data	Pass
3	Add product/stock data	Pass
4	Delete product/stock data	Pass
5	View transaction data	Pass
6	Add transaction data	Pass
7	Delete transaction data	Pass
8	View training dataset	Pass
9	View C4.5 computation results	Pass
10	View decision tree visualization	Pass
11	View classification results	Pass
12	View user data	Pass
13	Add user data	Pass
14	View change password form	Pass
15	Change password	Pass
16	Logout	Pass

Several limitations constrain these findings. First, the data cover only four months and yield 17 product-level records, which is small for a three-class problem; the LOOCV estimate is therefore highly variable, and seasonal effects could not be examined. Second, only two discretized predictors were available, and the discretization cut points, like the class thresholds, were set by judgement rather than optimized, and their sensitivity was not tested. Third, the class definition is based on average quantity per transaction, so a frequently purchased product with a high total volume can be labelled moderate; alternative definitions, such as total units or revenue, may better reflect commercial importance. Fourth, the tree was built with a manual, pre-discretized implementation of C4.5 without pessimistic-error pruning. Future work should extend the observation period, add attributes such as product category, seasonality, and promotional activity, and evaluate alternative class definitions and classifiers.

4. CONCLUSION

This study applied the C4.5 decision tree algorithm to classify the sales performance of rattan furniture products at CV Indowest Design Furniture and embedded the resulting model in a web-based decision support system. Using purchase frequency and unit selling price as predictors, the algorithm selected unit selling price as the most informative attribute and produced a compact tree of five rules. The tree describes the current sales data reasonably well and identifies high-priced products as low sellers without error, a pattern that remained stable when individual products were left out. It does not, however, reliably distinguish best sellers from moderate products: under leave-one-out cross-validation its accuracy was barely above that of always predicting the most common class. The model is therefore useful as an interpretable summary of which products move slowly, and the developed system provides the data management, computation, and visualization features needed to update that summary as new transactions arrive, but it should not yet be used to forecast product performance. Longer transaction histories, richer product attributes such as category, season, and promotion, alternative definitions of sales performance, and

comparison with other classifiers are needed before the system can support production and inventory planning with confidence.

REFERENCES

[1] M. F. Anwar, Harianto, and Suharno, "Dinamika daya saing ekspor furniture rotan Indonesia ke negara tujuan Eropa [Dynamics of the export competitiveness of Indonesian rattan furniture to European destination countries]," *J. Agribisnis Indones.*, vol. 8, no. 2, pp. 152–163, 2020, doi: 10.29244/jai.2020.8.2.152-163.

[2] K. M. Adha and S. Widyastuti, "Rekomendasi pengadaan obat dan alat kesehatan dengan fuzzy database (studi kasus: Instalasi Farmasi Klinik Utama Cideng Medical Center) [Recommendation for drug and medical device procurement using a fuzzy database (case study: Pharmacy Installation of Cideng Medical Center Main Clinic)]," *J. Ilm. Intech: Inf. Technol. J. UMUS*, vol. 1, no. 1, pp. 34–44, 2019, doi: 10.46772/intech.v1i01.36.

[3] T. M. Diansyah and Y. Exprada, "Penerapan algoritma C4.5 untuk memprediksi penjualan lele pada kolam pancing Galatama [Application of the C4.5 algorithm to predict catfish sales at the Galatama fishing pond]," *J. Sist. Komput. Inform.*, vol. 3, no. 4, pp. 567–574, 2022, doi: 10.30865/json.v3i4.4264.

[4] S. M. Sari and M. H. Rifqo, "Data mining analysis of Shell oil sales using the C4.5 algorithm at CV. Harapan Karya Mandiri," *J. Teknoif Tek. Inform. Inst. Teknol. Padang*, vol. 13, no. 2, pp. 48–56, 2025, doi: 10.21063/jtif.2025.V13.2.48-56.

[5] J. Han, M. Kamber, and J. Pei, *Data Mining: Concepts and Techniques*, 3rd ed. Waltham, MA, USA: Morgan Kaufmann, 2012, doi: 10.1016/C2009-0-61819-5.

[6] E. T. Naldy and A. Andri, "Penerapan data mining untuk analisis daftar pembelian konsumen menggunakan algoritma Apriori pada transaksi penjualan Toko Bangunan MDN [Application of data mining to analyze consumer purchase lists using the Apriori algorithm on sales transactions at the MDN building store]," *J. Nas. Ilmu Komput.*, vol. 2, no. 2, pp. 89–101, 2021, doi: 10.47747/jurnalnik.v2i2.525.

[7] S. Widyastuti, W. Ariandi, W. D. Putera, and R. R. Baratasena, "Using Apriori algorithm to analyze library borrowing patterns at SMK Negeri 1 Cirebon," *J. Gen. Educ. Humanit.*, vol. 4, no. 2, pp. 285–298, 2025, doi: 10.58421/gehu.v4i2.363.

[8] J. R. Quinlan, "Induction of decision trees," *Mach. Learn.*, vol. 1, no. 1, pp. 81–106, 1986, doi: 10.1007/BF00116251.

[9] J. R. Quinlan, *C4.5: Programs for Machine Learning*. San Mateo, CA, USA: Morgan Kaufmann, 1993.

[10] O. V. Agesti, F. M. Dewanto, and N. Q. Nada, "Perbandingan algoritma decision tree dan C4.5 untuk klasifikasi kelayakan calon pendonor darah di PMI Kota Semarang [Comparison of decision tree and C4.5 algorithms for classifying the eligibility of prospective blood donors at PMI Semarang City]," *J. Inform. Teknol. Sains*, vol. 7, no. 3, pp. 1149–1158, 2025, doi: 10.51401/jinteks.v7i3.6014.

[11] A. A. Setiawan, "C4.5 algorithm based on forward selection and particle swarm optimization for improving accuracy in heart disease patient classification," *J. Appl. Intell. Syst.*, vol. 9, no. 2, pp. 227–237, 2024, doi: 10.62411/jais.v9i2.11099.

[12] M. Abidin, M. H. Aufa, M. I. C. Saputra, B. B. Oyeyemi, and N. W. B. Grendis, "An analysis of the C4.5 decision tree algorithm method applied to the play tennis dataset and manual calculation approach," *Indones. J. Mod. Sci. Technol.*, vol. 1, no. 2, pp. 65–70, 2025, doi: 10.64021/ijmst.1.2.65-70.2025.

[13] A. Prakoso and Kurniawati, "Analisis model klasifikasi penyakit jantung dengan decision tree C4.5 berdasarkan pendekatan sentralisasi dan federated learning pada dataset UCI [Analysis of a C4.5 decision tree model for heart disease classification under centralized and federated learning approaches on the UCI dataset]," *J. Syst. Inf. Technol. Electron. Eng.*, vol. 5, no. 1, pp. 10–21, 2025.

[14] D. Sartika and Yupianti, "Klasifikasi penyakit tiroid menggunakan algoritma C4.5 (studi kasus: RSUD Hasanuddin Damrah Manna) [Thyroid disease classification using the C4.5 algorithm (case study: Hasanuddin Damrah Manna Regional Hospital)]," *Rekayasa*, vol. 13, no. 1, 2020, doi: 10.21107/rekayasa.v13i1.5912.

[15] A. Ulfa, D. Winarso, and E. Arribe, "Sistem rekomendasi jurusan kuliah bagi calon mahasiswa baru menggunakan algoritma C4.5 [Study programme recommendation system for prospective new students using the C4.5 algorithm]," *J. Fasilkom*, vol. 10, no. 1, pp. 61–65, 2020, doi: 10.37859/jf.v10i1.1511.

[16] A. Muhidin and E. Suhenda, "Klasifikasi penjualan makanan cepat saji menggunakan metode algoritma C4.5 (studi kasus: Ayam Penyet Nabila) [Classification of fast-food sales using the C4.5 algorithm (case study: Ayam Penyet Nabila)]," *SIGMA – J. Teknol. Pelita Bangsa*, vol. 11, no. 1, Mar. 2020.

[17] M. A. Melfia, K. A. Ramadhini, M. A. Maulana, A. L. Dasiva, A. A. Briantoro, and B. O. Lubis, "Penerapan data mining untuk klasifikasi data penjualan sembako terlaris dengan algoritma C4.5 [Application of data mining to classify best-selling staple grocery sales data with the C4.5 algorithm]," *J. Mhs. Tek. Inform.*, vol. 9, no. 3, pp. 4616–4621, 2025, doi: 10.36040/jati.v9i3.13450.

[18] H. Syafputra, H. L. Sari, and Khairil, "Klasifikasi penjualan perhiasan menggunakan metode decision tree algoritma C4.5 (studi kasus: Toko Emas Berkat Famili) [Jewelry sales classification using the C4.5 decision tree algorithm (case study: Berkat Famili gold shop)]," *J. Media Infotama*, vol. 20, no. 2, pp. 563–569, 2024, doi: 10.37676/jmi.v20i2.6517.

[19] M. Leonardi, R. Emilda, I. Katrin, and A. Yulianto, "Prediksi penjualan produk rokok pada PT. Indomarco Prismatama menggunakan algoritma C4.5 [Prediction of cigarette product sales at PT Indomarco Prismatama using the C4.5 algorithm]," *Paradigma*, vol. 23, no. 2, Sep. 2021.

[20] D. Sanjaya, A. Saleh, S. N. Sari, and S. R. Danur, "Algoritma data mining menggunakan metode decision tree untuk memprediksi pola penjualan produk springbed menggunakan algoritma C4.5 [Data mining with the C4.5 decision tree method to predict springbed sales patterns]," *Manag. Inf. Syst. J.*, vol. 4, no. 2, pp. 76–86, Mar. 2026, doi: 10.47065/mis.v4i2.2567.

[21] R. S. Iswandaru and A. D. Indriyanti, "Sales performance classification of promotional products using data mining," *J. Emerg. Inf. Syst. Bus. Intell.*, vol. 7, no. 2, pp. 213–220, 2026, doi: 10.26740/jeisbi.v7i2.75897.

[22] S. Widyastuti, Kosim, and N. R. Febrisya, "Algoritma naïve Bayes classifier untuk mengetahui prediksi penggunaan kartu internet Indosat pada PT. Sakalaguna Semesta [Naïve Bayes classifier for predicting Indosat internet card usage at PT Sakalaguna Semesta]," *J. Comput. Sci. Artif. Intell.*, vol. 2, no. 1, pp. 27–33, 2025, doi: 10.58468/tcp39749.

[23] M. J. A. Berry and G. S. Linoff, *Data Mining Techniques: For Marketing, Sales, and Customer Relationship Management*, 3rd ed. Indianapolis, IN, USA: Wiley, 2011.

[24] M. H. Dunham, *Data Mining: Introductory and Advanced Topics*. Upper Saddle River, NJ, USA: Prentice Hall, 2003.

[25] U. Fayyad, G. Piatetsky-Shapiro, and P. Smyth, "From data mining to knowledge discovery in databases," *AI Mag.*, vol. 17, no. 3, pp. 37–54, 1996, doi: 10.1609/aimag.v17i3.1230.

[26] A. D. Saputra and A. Qoiriah, "Penerapan algoritma C4.5 untuk mengatur persediaan stok barang berbasis website [Application of the C4.5 algorithm for web-based inventory stock management]," *J. Inform. Comput. Sci.*, vol. 3, no. 4, pp. 481–493, 2022, doi: 10.26740/jinacs.v3n04.p481-493.

[27] R. S. Pressman and B. R. Maxim, *Software Engineering: A Practitioner's Approach*, 9th ed. New York, NY, USA: McGraw-Hill Education, 2020.

[28] S. Widyastuti, W. Ariandi, M. Erwanto, and W. A. Pusriyanto, "Comparative analysis of the SMARTER and ELECTRE methods for determining priority recipients of free legal aid," *J. Gen. Educ. Humanit.*, vol. 5, no. 1, pp. 1679–1692, Feb. 2026, doi: 10.58421/gehu.v5i1.969.

[29] L. N. Ningsih, R. Septiani, A. Pramadjaya, and S. Nuralisah, "Implementing the C4.5 algorithm for customer satisfaction classification," *MALCOM: Indones. J. Mach. Learn. Comput. Sci.*, vol. 5, no. 4, pp. 1470–1480, Oct. 2025, doi: 10.57152/malcom.v5i4.2211.

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