**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, restocking, 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.

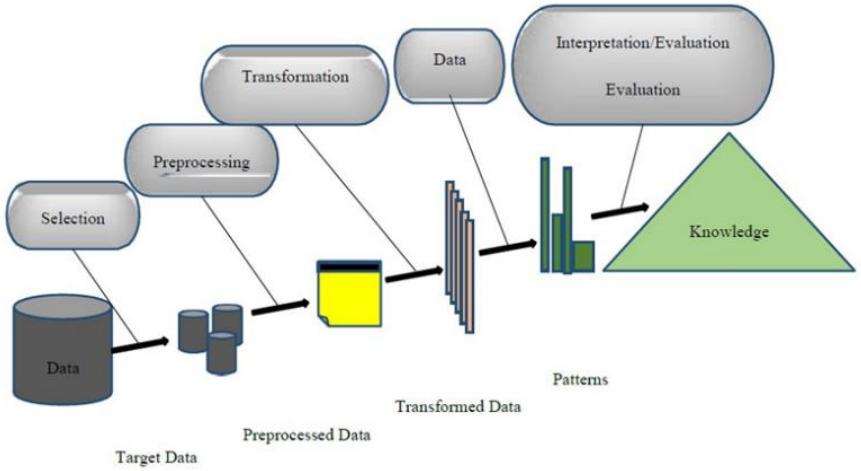



Figure 1. Stages of the knowledge discovery in databases (KDD) process (adapted from [25])

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

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

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 ($\bar{X}$) | 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:

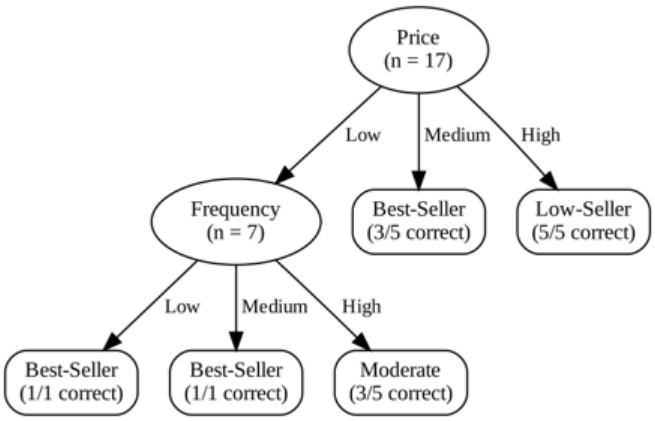



Figure 2. Final C4.5 decision tree; numbers in parentheses give the correctly classified training records and the records in each leaf

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.

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.

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.

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