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Analysis of Product Demand Prediction Using Decision Tree on Sales Data of Ceria Toys Store

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Article Info	ABSTRACT
Keywords: Data Mining, Decision Tree, Demand Prediction, Sales Analysis, Inventory Management.	Ceria Toys faces challenges in efficiently managing the inventory of electric bicycles, as product demand is influenced by factors such as market trends, seasons, and changing consumer preferences. To address this challenge, this research employs data mining techniques with the decision tree algorithm to predict product demand and assist in inventory management. The evaluation results of the predictive model show varying performance across product categories. The precision for the "Hot" category is 58.36%, while for the "Less Popular" category, it is 64.18%. The recall for the "Hot" category reaches 83.71%, but the recall for the "Less Popular" category is only 32.82%. Although the model performs better in predicting hot products, there is still room to improve the detection of less popular products. To enhance effectiveness, Ceria Toys can balance the dataset or adjust the model. With this information, the store can better prepare stock for hot products and optimize the management of less popular products. These steps are expected to maximize sales, reduce excess stock, and improve overall customer satisfaction.
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INTRODUCTION

The current development of the retail business is becoming increasingly competitive, requiring business operators to make more strategic decisions in product inventory management [1], [2]. Ceria Toys Store, as a provider of electric bicycles, faces significant challenges in meeting customer demand optimally without causing overstock. Product demand is influenced by various factors, such as market trends, seasons, and changing consumer preferences [3], [4]. Therefore, it is crucial for Ceria Toys Store to carefully analyze demand patterns to manage stock efficiently. To address challenges in product demand forecasting, Ceria Toys Store can utilize data mining methods, particularly the decision tree technique. Data mining is the process of collecting and processing data to extract valuable information using software and computational assistance from statistics, mathematics, or Artificial Intelligence (AI) technology. This process is also known as Knowledge Discovery in Database (KDD) [5], [6], [7], [8], [9], [10], [11], [12].

A decision tree is an effective data analysis tool for modeling the relationship between variables and the desired outcome, such as product demand. This technique utilizes a tree structure, where each path starting from the root follows a series of data splits until it reaches a final result in the form of a Boolean value at the leaf nodes [13], [14]. According to Dongdong Dong et al., a decision tree is a structure used in the ID3 algorithm to make decisions based on data partitioning. This structure is built by selecting attributes that provide the best information for dividing the data at each node, from top to bottom, until the data can no longer be separated. This decision tree functions to predict the category of new data based on classification rules derived from the analysis of the training set [15]. By identifying patterns in the data, this technique can help the store understand the factors influencing demand, such as seasons, market trends, and consumer preferences. Consequently, the store can make more accurate and precise decisions in planning product inventory, optimizing sales, and adjusting marketing strategies in response to changing market needs.

The research conducted by Muhamad Rizaludin and Farikatul Fikriah, titled "Predicting Customer Behavior on MSME Batik Products Using the Decision Tree Algorithm," demonstrated that the Decision Tree algorithm successfully identified customer behavior patterns in the demand data of MSME Batik Pieter Jackson, achieving an accuracy rate of 81.25% [16]. Meanwhile, the study by Demira Intan Suranda et al., titled "Sales Data Classification for Predicting Product Sales Levels Using the Decision Tree Method," found that the Decision Tree (ID3) algorithm was effective in analyzing sales data at Aruna Boutique, reaching an accuracy of 88.24%. This study also revealed that the best-selling products were Gamis 2 (Umama) and Veil 2 (DYN), whereas Gamis 1 (Mahdani) and Veil 3 (Azara) were less popular [17].

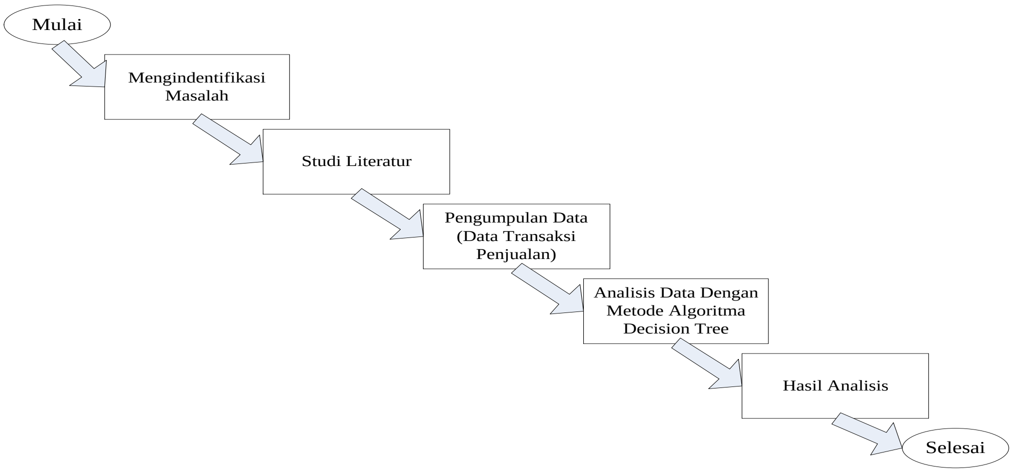
Other studies by Sinta Amanda Pratiwi et al., Syahbagus Radithya Haryo Santoso et al., and Dwita Elisa Sinaga et al. have shown that the use of the Decision Tree algorithm is an effective method for prediction across various fields, such as inventory management in pharmacies and automotive market targeting. With high accuracy rates achieved (80%, 91%, and up to 98.71%), this algorithm has proven capable of generating reliable predictive models based on available data. Furthermore, evaluations using metrics such as Precision, Recall, and F1-Score further reinforce the superiority of this method in delivering consistent and accurate results [18], [19], [20].

By applying Decision Tree analysis, Toko Ceria Toys will be able to manage inventory more effectively. The store can accurately predict product demand, helping to avoid unnecessary overstocking. This will enable the store to ensure smooth operations, maximize profits, and enhance customer satisfaction.

METHODS

Research Stages

The following are the research stages conducted:



Fifure 1. Research Stages

1. Identification of the Problem
   Ceria Toys faces challenges in predicting e-bike sales to optimize its business strategy and compete in an increasingly competitive market. One of the main issues is the effective and efficient management of inventory, which requires careful planning to ensure that stock levels remain optimal. Overstocking can lead to increased storage costs and the risk of product depreciation, while understocking may result in lost sales opportunities and reduced customer satisfaction. To address this issue, the company needs to leverage technology, data analysis, and appropriate forecasting strategies to align inventory levels with market demand optimally. If inventory management is not properly executed, it could negatively impact profitability and threaten business sustainability.
2. Literature Review
   The researcher will collect theoretical references from various relevant sources, including books and journals, to support this study. The selected literature will cover research on the decision tree algorithm, sales transaction patterns, and sales trends. These references will be utilized to understand the fundamental theories of data analysis, particularly in identifying customer purchasing patterns and sales trends. By studying this literature, the researcher can strengthen the theoretical foundation, build an appropriate analytical framework, and compare findings with previous studies. This process is expected to provide deeper insights, leading to effective and applicable solutions for Ceria Toys Retail Store.
3. Data Collection
   Sales transaction data for e-bike products from October 2023 to October 2024 will be collected as the primary sample for analysis. The data collection process involves direct interviews with the owner and employees, as well as extracting existing transaction records. Subsequently, data preprocessing will be conducted, including removing duplicates, correcting missing data, and normalizing the dataset to ensure its readiness for analysis and the validity of the extracted patterns.
4. Data Analysis

The process of analyzing e-bike sales patterns using the Decision Tree method begins with collecting sales data from October 2023 to October 2024, followed by data cleaning to eliminate errors or missing values. Next, relevant features such as date, price, and e-bike type are identified, and the target variable to be predicted—such as the number of units sold or revenue—is determined. The data is then split into a training set (80%) and a test set (20%) for model training and evaluation. The Decision Tree model is trained using the training data by setting appropriate splitting criteria and tree parameters. The model's performance is then evaluated using metrics such as accuracy or Mean Squared Error (MSE) on the test data. The resulting decision tree is analyzed to identify sales patterns, and sales strategy recommendations are formulated based on the findings. Finally, the model is applied for sales forecasting and monitored regularly to update it with new data.

Decision Tree

A Decision Tree is a flowchart-like tree structure where each internal node represents a test on an attribute, each branch indicates the outcome of the test, and each leaf node represents a class or class distribution. In general, the steps in the C4.5 algorithm are as follows.

Steps of the C4.5 Algorithm:

1. Select an attribute as the root.
2. Create branches for each value of the attribute.
3. Split the data into branches according to the attribute values.
4. Repeat the process for each branch until all data in a branch belong to the same class.

Steps in Building a Decision Tree Using the C4.5 Algorithm:

1. Prepare Training Data
   Prepare the training data derived from historical data. This data has already been categorized into specific classes.
2. Determine the Root Of the Tree
   Select an attribute as the root of the tree by calculating the gain value for each attribute. The attribute with the highest gain value will become the first root. Before calculating gain, first compute the entropy value using the formula:

$$H(S) = -\sum_{i=1}^{n} p_i \log_2 p_i \quad (1)$$

   Information:
   S : is the dataset
   n : is the number of classes
   pi : is the proportion of each class in the dataset
3. Calculate the Gain Value
   After obtaining the entropy value, calculate the gain value for each attribute using the formula:

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$$Gain(S,A) = Entropy(S) - \sum_{v \in Values(A)} \frac{|S_v|}{|S|} \times Entropy(S_v) \qquad (2)$$

Where:

S : is the entire dataset
A : is the attribute being evaluated
Values(A) : represents all possible values of attribute A
Sv : is the subset of S where attribute A has value v
|Sv| : is the number of instances in subset Sv
|S| : is the total number of instances in S
Entropy(Sv) : is the entropy of subset Sv

4. Repartitioning
   Repeat the second step for each branch until all records are perfectly partitioned.
5. Stopping Criteria
   a. All records in the node belong to the same class.
   b. There are no more attributes available for partitioning.
   c. No records are left in the branch.

Table 1. E-Bike Sales Transaction Dataset - Ceria Toys

No	Customer	Date	E-bike Type Category	Stock Price	Description
1	on-site	03/08/2023	pacific e-bike nimbuzz	0,150	laris
2	on-site	05/08/2023	pacific e-bike nimbuzz	0,155	laris
3	on-site	14/08/2023	revolve e-bike	0,140	kurang laris
4	on-site	16/08/2023	u-winfly e-bike rf7	0,197	kurang laris
5	on-site	24/08/2023	exotic e-bike veloce 1.5	0,155	kurang laris
6	on-site	26/08/2023	exotic e-bike fastron slx 5.0	0,197	laris
7	winda	30/08/2023	u-winfly e-bike rf7	0,166	kurang laris
8	on-site	10/09/2023	revolve e-bike	0,166	kurang laris
9	on-site	24/09/2023	revolve e-bike	0,166	kurang laris
10	on-site	24/09/2023	relicus e-bike	0,176	kurang laris
11	on-site	28/09/2023	cooltech e-bike 3.5	0,176	laris
12	on-site	02/10/2023	exotic e-bike fastron slx 5.0	0,150	laris
13	on-site	06/10/2023	exotic e-bike fastron slx 5.0	0,166	laris
14	on-site	17/10/2023	exotic e-bike veloce 1.5	0,176	kurang laris
15	on-site	19/10/2023	u-winfly motor t3s	0,176	kurang laris
16	on-site	20/10/2023	exotic e-bike 14x 250 explore sr	0,176	laris
17	on-site	22/10/2023	goda e-bike 147 ds	0,171	laris
18	on-site	22/10/2023	exotic e-bike groza 3.5	0,171	kurang laris
19	on-site	25/10/2023	goda e-bike 140 d	0,171	kurang laris
20	on-site	29/10/2023	exotic e-bike groza nx	0,176	kurang laris
21	on-site	30/10/2023	exotic e-bike blitz	0,176	laris

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No	Customer	Date	E-bike Type Category	Stock Price	Description
22	on-site	31/10/2023	cooltech e-bike ax	0,171	laris
23	on-site	01/11/2023	exotic e-bike 14x 250 explore sr	0,171	laris
24	on-site	02/11/2023	exotic e-bike fastron slx 5.0	0,171	laris
25	on-site	02/11/2023	syncross e-bike	0,166	kurang laris
26	on-site	05/11/2023	relicus e-bike	0,171	kurang laris
27	on-site	07/11/2023	cooltech e-bike 3.5	0,176	kurang laris
28	on-site	08/11/2023	exotic e-bike 14x 250 explore sr	0,176	kurang laris
29	on-site	09/11/2023	u-winfly e-bike r8s	0,135	kurang laris
30	on-site	12/11/2023	exotic e-bike groza nx	0,187	kurang laris
...	.....	.....	.....	.....	.....
831	ari bedagai	24/10/2024	cube e-bike rmb nc800	0,207	kurang laris
832	ari bedagai	24/10/2024	exotic e-bike veloce v3	0,207	kurang laris
833	on-site	24/10/2024	united e-bike genio vestra l2	0,207	kurang laris
834	on-site	24/10/2024	united e-bike genio vestra l1	0,202	kurang laris
835	on-site	25/10/2024	aviator e-bike at 225	0,207	kurang laris

Table 1 presents E-bike sales data from August 2023 to October 2024, covering a total of 835 transactions that have undergone data cleaning. This dataset has been preprocessed and includes key attributes such as customer information, transaction date, e-bike type category, stock price, and related descriptions. The objective of this analysis is to predict E-bike product demand using the decision tree algorithm. This approach will help identify sales patterns and forecast future demand, ultimately supporting strategic decision-making at Ceria Toys Store.

RESULTS AND DISCUSSION

This study utilizes E-bike sales data collected over a period of more than one year, from August 2023 to October 2024, encompassing a total of 835 transactions. The dataset includes various types of E-bikes and the quantities sold, stored in .xlsx (Excel) format. The research process involves a preprocessing stage to optimize the data, where the selected attributes include customer information, transaction date, E-bike type category, stock price, and related descriptions. The preprocessing stage aims to transform raw data into a more structured format by identifying and removing problematic or erroneous data, ensuring a high-quality dataset that is ready for further processing. From the total 835 transactions collected, a thorough validation process was conducted to eliminate errors, duplicates, or inconsistencies, ensuring that only valid data is used for subsequent analysis.

Decision Tree Method

RapidMiner is an open-source software used for data analysis, both descriptive and predictive, to generate insights that support more accurate decision-making. In its 2024 version 1.0, RapidMiner facilitates the implementation of the C4.5 algorithm to build

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classification models based on decision trees, allowing users to process data more efficiently and produce accurate predictions. The C4.5 algorithm is a method used for classification and predictive segmentation by constructing decision trees. It is widely recognized as a robust and easily interpretable approach, as it can transform complex data into a simplified set of rules. According to Kusrini, the general process of constructing a decision tree using the C4.5 algorithm involves several steps: selecting an attribute as the root of the tree, creating branches for each attribute value, splitting the data into these branches, and repeating this process for each branch until all data within a branch belong to the same class.

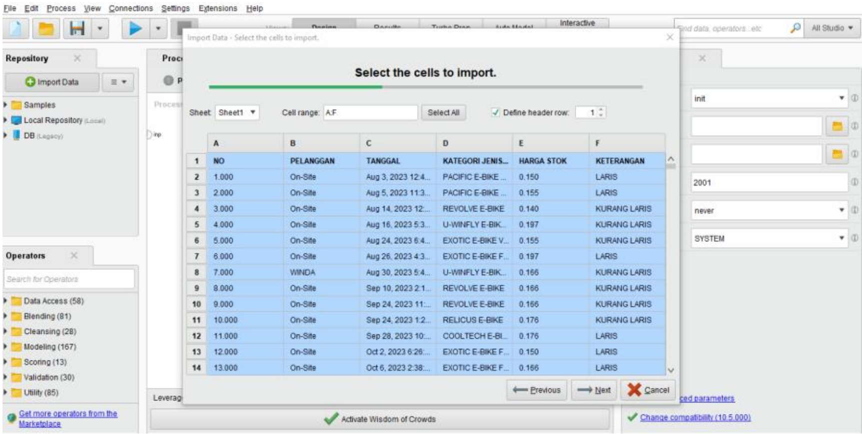

Figure 2. Import Data.

The dataset in Figure 2 consists of 835 records with four attributes and one label, imported from an Excel file for testing using RapidMiner. In this dataset, the "Keterangan" attribute serves as the label, which is the primary parameter for decision-making in the analysis process. Meanwhile, the other four attributes function as independent variables that support prediction or classification based on the label. Figure 3 displays the data types of each attribute, indicating whether the data is numerical, categorical, or of another type, which affects the subsequent data processing in RapidMiner.

Role	Name	Type
	Pelanggan	nominal
	TANGGAL	date_time
	KATEGORI JENIS E-BIKE	nominal
	HARGA STOK	real
label	KETERANGAN	binominal

Figure 3. Selection of Data Type.

Selection of Operator

In this process, the Cross Validation operator is used to objectively evaluate the model's performance and prevent data overfitting. This operator divides the dataset into two parts:

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training data (80%) and testing data (20%), to measure the performance of the model built using the C4.5 algorithm. In the decision tree construction process using the Decision Tree operator, the criterion for attribute selection is Information Gain, with the maximum tree depth set to 10 without applying a prepruning method. The Apply Model operator is connected to the Performance operator to evaluate the model's performance based on metrics such as accuracy, precision, and recall. Once all operators are correctly arranged, the model can be executed by clicking the Run button. The Performance operator specifically calculates the model's accuracy and provides a comprehensive evaluation of its success rate using the provided test data.3 illustrates the Cross-validation model, an evaluation technique that divides the dataset into multiple folds to ensure that each data point is alternately used as part of the training and testing data. This technique helps reduce bias in model performance evaluation and provides a more objective estimation of the model's performance on previously unseen data.

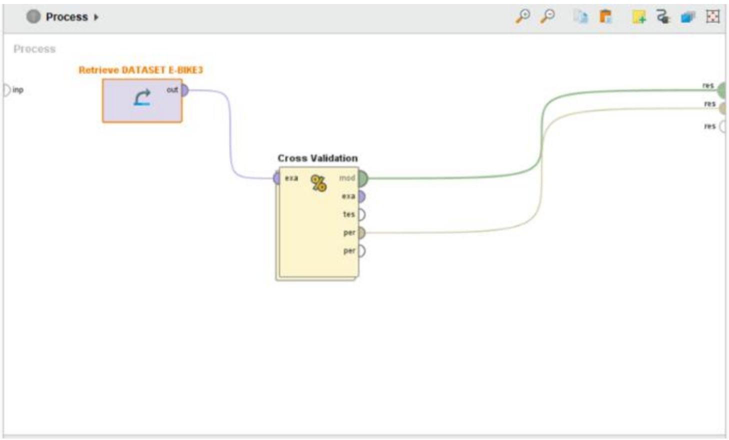

Figure 4. Model Process

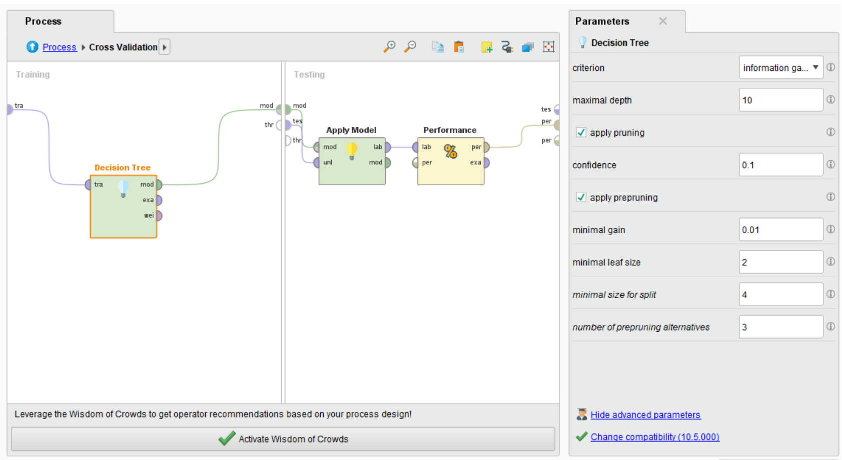

Figure 5. Validation Process

Decision Tree Results

The decision tree indicates that the primary attribute in classification is TANGGAL, where data after October 8, 2025, is always classified as KURANG LARIS. For data before this date, classification is determined based on more specific time ranges, HARGA STOK

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values, and customer categories. Customers such as DANIL TL and YANTO TL tend to be classified as LARIS, whereas On-Site is more frequently classified as KURANG LARIS. Decisions are made using Information Gain, revealing sales patterns based on time, price, and customer type.

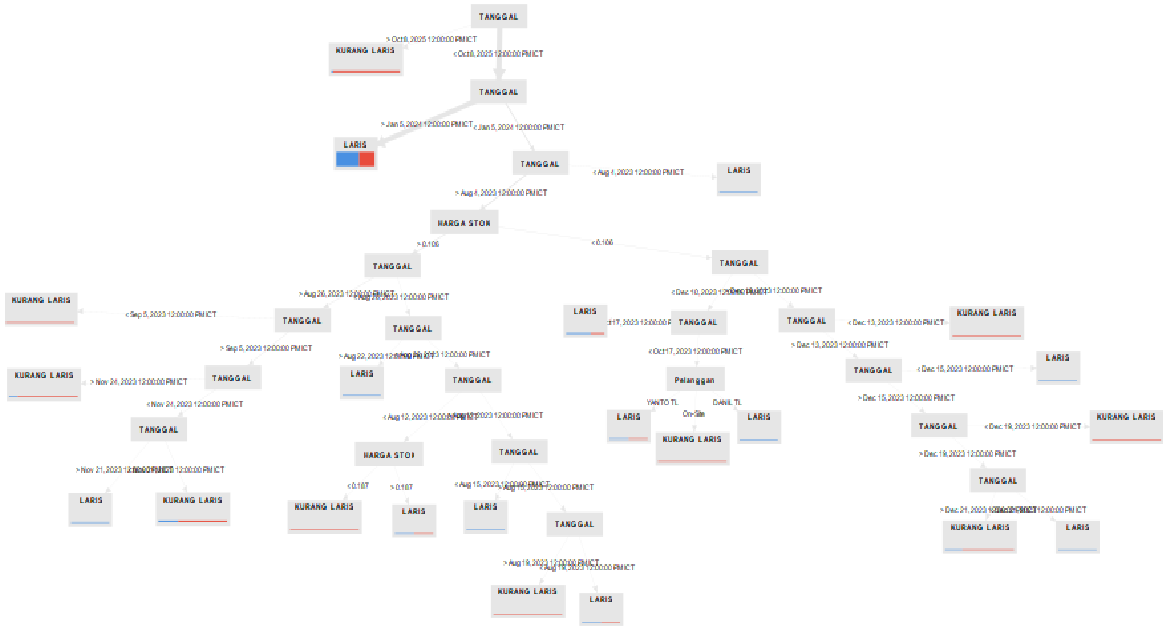

Figure 6. Decision Tree Result

Figure 6 represents the decision tree result from testing using RapidMiner. The following is a description of the decision tree outcome:

tanggal > oct 8, 2025 12:00:00 pm ict: kurang laris {laris=1, kurang laris=35}
tanggal ≤ oct 8, 2025 12:00:00 pm ict
| tanggal > jan 5, 2024 12:00:00 pm ict: laris {laris=384, kurang laris=259}
| tanggal ≤ jan 5, 2024 12:00:00 pm ict
| | tanggal > aug 4, 2023 12:00:00 pm ict
| | | harga stok > 0.106
| | | | tanggal > aug 26, 2023 12:00:00 pm ict
| | | | | tanggal > sep 5, 2023 12:00:00 pm ict
| | | | | | tanggal > nov 24, 2023 12:00:00 pm ict: kurang laris {laris=2, kurang laris=14}
| | | | | | tanggal ≤ nov 24, 2023 12:00:00 pm ict
| | | | | | | tanggal > nov 21, 2023 12:00:00 pm ict: laris {laris=3, kurang laris=0}
| | | | | | | tanggal ≤ nov 21, 2023 12:00:00 pm ict: kurang laris {laris=13, kurang laris=32}
| | | | | tanggal ≤ sep 5, 2023 12:00:00 pm ict: kurang laris {laris=0, kurang laris=10}
| | | | tanggal ≤ aug 26, 2023 12:00:00 pm ict
| | | | | tanggal > aug 22, 2023 12:00:00 pm ict: laris {laris=4, kurang laris=0}
| | | | | tanggal ≤ aug 22, 2023 12:00:00 pm ict
| | | | | | tanggal > aug 12, 2023 12:00:00 pm ict

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| | | | | | | tanggal > aug 15, 2023 12:00:00 pm ict
| | | | | | | | tanggal > aug 19, 2023 12:00:00 pm ict: kurang laris {laris=0, kurang laris=3}
| | | | | | | | tanggal ≤ aug 19, 2023 12:00:00 pm ict: laris {laris=2, kurang laris=2}
| | | | | | | tanggal ≤ aug 15, 2023 12:00:00 pm ict: laris {laris=3, kurang laris=0}
| | | | | | tanggal ≤ aug 12, 2023 12:00:00 pm ict
| | | | | | | harga stok > 0.187: laris {laris=1, kurang laris=1}
| | | | | | | harga stok ≤ 0.187: kurang laris {laris=0, kurang laris=6}
| | | harga stok ≤ 0.106
| | | | tanggal > dec 10, 2023 12:00:00 pm ict
| | | | | tanggal > dec 13, 2023 12:00:00 pm ict
| | | | | | tanggal > dec 15, 2023 12:00:00 pm ict
| | | | | | | tanggal > dec 19, 2023 12:00:00 pm ict
| | | | | | | | tanggal > dec 21, 2023 12:00:00 pm ict: kurang laris {laris=2, kurang laris=6}
| | | | | | | | tanggal ≤ dec 21, 2023 12:00:00 pm ict: laris {laris=2, kurang laris=0}
| | | | | | | tanggal ≤ dec 19, 2023 12:00:00 pm ict: kurang laris {laris=0, kurang laris=4}
| | | | | | tanggal ≤ dec 15, 2023 12:00:00 pm ict: laris {laris=2, kurang laris=0}
| | | | | tanggal ≤ dec 13, 2023 12:00:00 pm ict: kurang laris {laris=0, kurang laris=3}
| | | | tanggal ≤ dec 10, 2023 12:00:00 pm ict
| | | | | tanggal > oct 17, 2023 12:00:00 pm ict: laris {laris=18, kurang laris=10}
| | | | | tanggal ≤ oct 17, 2023 12:00:00 pm ict
| | | | | | pelanggan = danil tl: laris {laris=2, kurang laris=0}
| | | | | | pelanggan = on-site: kurang laris {laris=0, kurang laris=7}
| | | | | | pelanggan = yanto tl: laris {laris=1, kurang laris=1}
| | tanggal ≤ aug 4, 2023 12:00:00 pm ict: laris {laris=2, kurang laris=0}.

1. Sales Period and Product Trends:
   a. From October 8, 2025, to January 5, 2024, most products exhibited a trend of being less in demand, with fewer units sold compared to those classified as high demand.
   b. During the period from August 2023 to December 2023, the demand for both high and low-demand products was influenced by stock prices and specific customers.
2. The Impact of Price on Sales:
   a. A stock price higher than 0.106 indicates an increase in demand during certain periods, where products tend to be more in demand, although there are times when demand remains low.
   b. Conversely, products with a stock price lower than 0.106 tend to have lower sales and are often classified as less in demand.
3. Customers Influencing Sales:

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   a. Certain customers, such as DANIL TL and YANTO TL, show a tendency for products to be more in demand, with a significant number of units sold.
   b. Other customers, such as On-Site, have the opposite effect, with a higher number of products classified as less in demand.
4. Sales Time Patterns:
   a. There are variations in demand based on specific time periods, with a significant decline towards the end of the year, particularly in December 2023.
   b. Specific dates, such as December 19, 2023, to December 21, 2023, show a drastic drop in sales, with most products classified as less in demand.
5. Data-Driven Decision Making:
   a. Price and customer factors significantly influence product demand classification. Products with higher prices and those purchased by regular customers tend to be more in demand.
   b. Certain time periods, particularly the final months of the year, indicate an overall decline in demand.

accuracy: 59.77% +/- 4.32% (micro average: 59.76%)

	true LARIS	true KURANG LARIS	class precision
pred. LARIS	370	264	58.36%
pred. KURANG LARIS	72	129	64.18%
class recall	83.71%	32.82%	

Figure 7. Accuracy Results of the Decision Tree Method.

CONCLUSION

Based on the evaluation results of the product demand prediction model using a decision tree at Toko Ceria Toys, it was found that the model's performance varies across product categories. The precision for the Laris (high-demand) category is 58.36%, indicating that while most predictions for high-demand products are fairly accurate, there is still a margin of error. On the other hand, the precision for the Kurang Laris (low-demand) category is higher, at 64.18%, meaning the model is more effective in predicting low-demand products. However, the recall for the Laris category reaches 83.71%, demonstrating that the model is highly effective in identifying truly high-demand products. Conversely, the recall for the Kurang Laris category is only 32.82%, indicating that the model is not yet sufficiently effective in detecting low-demand products. Overall, while the model performs better in predicting high-demand products, there is still room for improvement in detecting low-demand products. This can be achieved by balancing the dataset or further adjusting the model. Based on this analysis, Toko Ceria Toys can consistently stock high-demand e-bike products to avoid stock shortages. Meanwhile, for low-demand products, optimization is necessary to prevent overstocking. One approach is to position high-demand products in more accessible locations for consumers, potentially increasing sales. By leveraging this information, the company can enhance the overall effectiveness of its inventory management and sales strategies.

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