Journal of Artificial Intelligence and Engineering Applications

Website: https://ioinformatic.org/

June 2026. Vol. 5. No. 3; e-ISSN: 2808-4519

Development of Web System for Sales Optimization at CV. CS Swalayan using Association Rule Method

Steven Imanuel Naibaho[1]*, Yulita Molliq Rangkuti[2]

[1,2]Department of Computer Science, Faculty of Mathematics and Natural Sciences, Universitas Negeri Medan, Indonesia
stevnuel@mhs.unimed.ac.id[1*], molliq22rangkuti@gmail.com [2]

Abstract

CV. CS Swalayan encounters challenges related to declining consumer purchasing power and the underutilization of transactional data for analyzing customer purchasing patterns. This study aims to develop a web-based system employing Association Rule methodology with the Apriori algorithm to optimize sales performance, identify top-selling products, and determine frequently co-purchased product combinations. The research methodology encompasses the collection of 296 sales transaction records for basic commodity products from CV.CS Swalayan during January 2025, followed by data preprocessing procedures. The Apriori algorithm is implemented with minimum support and confidence thresholds set at 0.01 and 0.3, respectively. The web-based system is developed using Python with the Flask framework for backend functionality, MySQL for database management, and validated through black-box testing methodology. The findings reveal the generation of 14 valid and robust association rules, notably "if Selai Srikaya Ngetop is purchased, then Roti Tawar Kupas Ngetop will be purchased" (confidence: 100%; lift ratio: 49.3) and "if Beras Sukaraya Cap Gurih 10KG is purchased, then Minyak Kita Minyak Goreng Sawit 1ltr will be purchased" (confidence: 100%; lift ratio: 16.4). The developed web system successfully passed black-box testing with a 100% success rate. This research contributes by providing a system that enables CV. CS Swalayan will make data-driven decisions to optimize sales strategies, marketing approaches, and inventory management practices.

Keywords: *Association Rule; Apriori Algorithm; Data Mining, Sales Optimizing; Purchase Patterns*

1. Introduction

The rapid development of information technology has significantly influenced various sectors, including the retail industry. According to data from the Indonesian Retail Entrepreneurs Association (APRINDO), the national retail industry recorded a growth of 3% in 2022, with the highest contribution coming from the minimarket and supermarket sectors [1]. One of the key strategies to enhance competitiveness in the retail sector is the utilization of sales transaction data to support more accurate decision-making processes. CS Swalayan is a supermarket located in Lau Bakeri Village, Kutalimbaru Sub-district, Deli Serdang Regency, North Sumatra Province, providing a wide range of essential goods, including groceries, household items, stationery, cosmetics, and other daily necessities. However, CS Swalayan is facing challenges in maintaining its competitiveness within an increasingly dynamic and competitive retail market environment. Currently, consumer purchasing power at CS Swalayan continues to decline due to the emergence of numerous competitors in the surrounding area, coupled with the absence of effective promotional strategies to attract customer interest. Consequently, CS Swalayan is losing opportunities to understand customer behavior and develop data-driven marketing strategies. One potential approach is analyzing sales transaction data stored in the supermarket information system to extract useful information that aids business decision-making [2].

The application of the association rule method using the Apriori algorithm has been proven effective in the retail sector across various studies. Research conducted by Prasad and Malik confirmed that the Apriori algorithm remains a primary method in market basket analysis due to its capability in identifying complex purchasing patterns [3] . Their study achieved an improvement of up to 35% in sales prediction accuracy compared to traditional methods. Meanwhile, Sari (2023) provided new insights into shifts in online consumer shopping behavior post-pandemic[4]. By utilizing e-commerce transaction data and implementing the Apriori algorithm, the study identified significant associations in product preferences, specifically increasing purchases of health and household products, and improved product recommendation accuracy by 32%, resulting in an 18% increase in sales within three months of implementation. Furthermore, research by Rahmi and Mikola (2021) demonstrated the effectiveness of the Apriori algorithm in analyzing consumer purchasing patterns at Toko Bakoel Sembako. From 30 transaction records with a minimum support of 3 and a minimum confidence of 70%, one significant association rule was obtained: “customers who purchase Sedap instant noodles tend also to buy eggs.” This finding confirms that transactional data—initially serving merely as operational records—can be transformed into valuable strategic information for business development, supporting decision-making in stock management, product placement, and promotional strategies[5]. Another study by Santoso (2021) indicated that the Apriori-based association method effectively identifies purchasing patterns and frequently co-purchased product combinations at Indomaret Tanjung Anom minimarket. Of the 22 association rules discovered, it was shown that customers frequently bought toothpaste and detergent together, with a minimum support of 40% and a minimum confidence of 80%. These results reinforce that the Apriori algorithm can support strategic improvements in sales optimization for minimarket operations[6].

Based on these prior studies, this research is conducted to bridge the existing gap by developing and implementing a web-based system utilizing the Apriori algorithm to analyze sales transaction data and generate actionable insights for sales optimization at CV. CS Swalayan. This study focuses on building a web-integrated Apriori analysis system to support continuous, real-time analytical capabilities tailored specifically to the operational context of CS Swalayan, ensuring that the system is not only academically relevant but also practically applicable in retail business operations.

2. Research Method

The research methodology consists of several stages and a structured workflow throughout the study. These stages are illustrated in Figure 1 below.

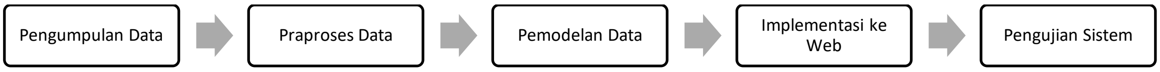

Fig. 1: Figure of research method

2.1. Data Collection

The type of data used in this study is secondary data. The data were obtained from sales transaction records at CS Swalayan for a period of one month, from January 1st, 2025 to January 31st, 2025. The collected data include transaction dates, transaction codes, and purchased product items. These data are used as the primary analytical source in this research. In addition, direct observations at the store were conducted to obtain deeper insights into customer behavior and store layout conditions that may influence purchasing patterns. This observation was complemented with staff interviews, enabling a more comprehensive contextual understanding of the quantitative data, thus improving the representativeness and accuracy of the analytical results.

2.2. Data Preprocessing

Data preprocessing is a crucial step to ensure that the transactional data are clean, relevant, and well-structured before being processed using the Apriori algorithm[7]. This stage aims to prepare the dataset optimally so that the generated association rules can be valid and meaningful. The preprocessing procedure includes three main phases: data selection, data normalization, and data transformation. In the data selection phase, only relevant attributes were retained, such as transaction ID, transaction date, and product items purchased. This ensures that the data fully align with the research objectives and exclude unnecessary attributes. The data normalization phase involves standardizing product names, removing duplicates, and correcting inconsistent or erroneous entries to ensure uniform database representation. This step reduces redundancy and enhances information accuracy. Finally, the data transformation phase converts the refined transactions into a market basket format, where each transaction is represented as a set of items purchased together. The dataset was then encoded into a binary matrix (1 = item purchased; 0 = item not purchased) using one-hot encoding. This structured format allows efficient frequent itemset identification and association rule generation using the Apriori algorithm[8][9].

2.3. Data Modeling

In this study, the association rule method with the Apriori algorithm is employed for data modeling. The fundamental principle of Apriori is to utilize *support* and *confidence* values to identify association rules that meet the defined threshold requirements[10]. Apriori operates iteratively to determine *frequent itemsets* from a transaction database. According to Rahmi & Mikola (2021), Apriori analyses items purchased together within multiple transactions to identify recurring patterns. The modeling steps include:

1. Pattern Identification
   Generating candidate item combinations (C1, C2, etc.) from transactional data and calculating support, confidence, and lift ratios to identify strong relationships between products.
2. Frequent Item Grouping
   Products with high frequency of co-occurrence are clustered based on the analysis results. This step provides insights into the most preferred product categories and supports promotional and inventory planning strategies.
3. Frequent Pattern Analysis
   Item combinations that satisfy the minimum *support* threshold are categorized as frequent itemsets. The support value of an itemset is calculated using Equation (1):
   $$\text{Support (A)} = \frac{\sum \text{transactions containing A}}{\sum \text{transactions}} \qquad (1)$$
   Meanwhile, for the support value of the two transactions, namely:
   $$\text{Support (A, B)} = \frac{\sum \text{transactions containings A , B}}{\sum \text{transactions}} \qquad (2)$$
   If a combination of items does not meet the minimum *support* threshold, the search for high-frequency patterns will be terminated to ensure computational efficiency.[11]

4. Confidence and Lift Analysis
   Once the item combinations that meet the minimum *support* value are obtained, the next step is to calculate the confidence value to determine the probability that the purchase of one item will be followed by the purchase of another. Confidence measures the strength of the correlation between items within a transaction and is calculated using Equation (3):
   $$\text{Confidence } A \rightarrow B = \frac{\text{Support } (A \cup B)}{\text{Support } A} \qquad (3)$$
   A high confidence value indicates a strong likelihood that customers who purchase product A will also purchase product B. Therefore, association rules with high confidence are considered more significant for supporting promotional decision-making and product arrangement strategies within the store. In addition to confidence, the analysis also incorporates the measurement of lift ratio, which determines the strength of product relationships relative to random independence between items. Lift is computed using Equation (4):
   $$\text{Lift } A \rightarrow B = \frac{\text{Confidence } (A \rightarrow B)}{\text{Support B}} = \frac{\text{Support } (A \cup B)}{\text{Support } (A) \times \text{Support } (B)} \qquad (4)$$

   A lift value greater than 1 indicates a positive association, meaning that the purchase of product A increases the probability of purchasing product B. Conversely, a lift value less than 1 suggests that the relationship between the products is weak or insignificant[12]. The results of confidence and lift analysis are used to filter out the most relevant and strongest association rules. These rules are then prioritized for strategic use in CS Swalayan, including improved product placement, cross-selling bundle promotions, and data-driven marketing approaches based on customer purchasing behavior[13].

2.4. System Implementation

The Apriori computation model developed using Python is integrated into a web-based system for implementation. Flask API is used as the backend framework to connect the Apriori calculation results with the website interface[14]. The database supporting this system is built using MySQL to store sales transaction data. Meanwhile, the front-end interface is designed to display system functionalities, including visual charts of best-selling products and the resulting association rules that highlight items frequently purchased together by customers.

2.5. System Testing

In this study, the system is evaluated using Black-Box Testing. Black-box testing is a software evaluation technique where the tester has no knowledge of the internal structure, design, or implementation of the system[15]. The testing focuses solely on input and output behavior to verify whether the system meets functional requirements.
The testing plan using the black-box method includes verification of key features, such as:

Table. 1: Blackbox Testing Scenario

Pernyataan	Hasil Pengujian			
	Prosedur Pengujian	Hasil Yang Diharapkan	Hasil Aktual	Status
Pengujian Akses Halaman Pengujian Hasil Analisis Data Pengujian Manajemen Data Transaksi Pengujian Kompabilitas Browser Pengujian Responsitivitas UI Pengujian Performa				

3. Result and Discussion

The implementation of the association rule method within the web-based system at CV. CS Swalayan has produced a set of informative and actionable findings that serve as the core of this analysis. This section presents and critically discusses the results obtained from the data mining process on sales transactions, focusing on the association rules that were successfully identified and demonstrate significant inter-product relationships. The discussion emphasizes evaluating the strength and reliability of the generated rules through the interpretation of key metrics such as support, confidence, and lift, as well as their implementation within the web-based system. The integration of these analytical results into the system enables users to directly access visualized insights and utilize them for more effective sales strategies, product placement decisions, and inventory management.

3.1. Data Collection and Preprocessing

The secondary data used in this study consist of 296 sales transaction records from the basic commodities (sembako) category at CV. CS Swalayan during January 2025. The category of transaction data collected includes sales of various products such as bread, instant noodles, milk, rice, cooking oil, and kitchen spices. The initial dataset contained eight attributes; however, after the preprocessing stage, only two attributes were retained for analytical purposes, namely transaction_number and item_name. The data were then transformed by grouping items based on their transaction numbers to create a market basket format, representing each transaction as a set of items purchased simultaneously. The transformation results show that there are 181 transactions with a single item, 93 transactions with two items, and 22 transactions with three items. Subsequently, the data were converted into a binary format using the *TransactionEncoder* library in Python to prepare the dataset for processing with the Apriori algorithm. The results of the data collection and preprocessing stages are presented in Table 2 below.

Table 2. List of Initial Transaction Data Following Data Preprocessing

Nomor_transaksi	Nama_barang
25010200000017	Beras sukaraya cap gurih 15kg
25010200000019	Indofood ketumbar bubuk 12,5g
25010200000021	Unibis bon bon biscuits 208g, sariwangi teh kotak 25 celup
25010200000035	Gula pasir 500g, minyak kita minyak goreng sawit 1ltr, beras sukaraya cap gurih 10 kg
25010200000046	Sariwangi teh kotak 25 celup, unibis bon bon biscuits 208g
…	...
25013100000522	Mie sedap instan rasa kari spesial 76g
25013100000556	Unibis bon bon biscuits 208g
25013100000587	Minyak kita minyak goreng sawit 1ltr
25013100000901	Unibis see hong puff malkist crackers 252g, Kg saltcheese coklat 190g

As shown in Table 2, transaction number 25010200000035 contains three purchased items: granulated sugar 500 g, Minyak Kita palm cooking oil 1 liter, and Sukaraya Cap Gurih rice 10 kg, and so on for the remaining transactions. The total number of transaction records obtained is 296. Based on these sales data, the overall number of products sold during the one-month period can be seen in Table 3 below:

Table 3. Total Results of Items Selling

Nama Barang	*Kategori*	*Frekuensi*
Sariwangi Teh Kotak 25 Celup	Susu, Teh & Kopi	35
Unibis Bon Bon Biscuits 208G	Roti	20
Gula Pasir 500G	Bumbu Dapur	19
Minyak Kita Minyak Goreng Sawit 1 ltr	Minyak Goreng	18
…	…	…
Roma Kelapa Cream Susu Vanila	Roti	3
Kecap Asin ABC 1Btl	Bumbu Dapur	2
Krim Kelapa Santan Siap Pakai 65ml	Bumbu Dapur	2
MS Soda Power 25G	Bumbu Dapur	1

As shown in Table 3, *Sariwangi Teh Kotak 25 Celup* is the most frequently purchased item, with a total of 35 purchases. Meanwhile, the least purchased product is *MS Soda Power 25 g*, which was bought only once. The table also serves as a reference for more in-depth analysis, specifically the formation of association rules and the Apriori process.

3.2. Itemset Formation

The itemset formation stage is the initial process in applying the Apriori algorithm, which aims to identify combinations of products that frequently appear together in the transaction dataset[16]. This process is carried out iteratively to generate *frequent itemsets* that meet the minimum support threshold. In this study, the minimum support threshold is set at 0.01 or 1% of the total transactions (296 transactions). The first stage is to generate candidate 1-itemset (C1), consisting of all unique products found in the transaction records of CV. CS Swalayan. The frequency of occurrence (support count) of each item is calculated to determine which products meet the minimum support requirement. Using Equation (1), the calculation example for the item *Sariwangi Teh Kotak 25 Celup* is as follows:

Support (Sariwangi teh kotak 25 celup)= (35)/296=0.1182

A complete result of the candidate 1-itemset calculation that fulfills the minimum support value is presented in Table 4 below.

Table 4. Results of C1 Itemset Calculation Meeting Minimum Support Threshold

Itemset	Total transaction	Support
Sariwangi teh kotak 25 celup	35	0.1182
Unibis bon bon biscuits 208g	20	0.0676
Gula pasir 500g	19	0.0642
Minyak kita minyak goreng sawit 1ltr	18	0.0608
Unibis see hong puff malkist crackers 252g	15	0.0507
Beras sukaraya cap gurih 10 kg	12	0.0405
Indofood sambal ekstra pedas botol 135ml	12	0.0405
Unibis butter cream biscuits 208g	12	0.0405
Frisian flag kental manis vanilla 1bks 38ml	11	0.0372
Garam cap ikan gabus 250g	8	0.0270
Roma sari gandum sandwich peanut butter 206g	8	0.0270
Indomie mie instan rasa kaldu ayam 75g	8	0.0270
Nestle milo rasa coklat sachet 22g	7	0.0236
Indomie mie instan goreng 75g	7	0.0236
Roti tawar kupas ngetop	6	0.0203
Unibis coco puff biscuits	6	0.0203
Unibis see hong puff kelapa 263g	5	0.0169
Blue band baking cake cookie 200g	5	0.0169
Mentega plastik	5	0.0169
Sarimi isi 2 mie instan goreng rasa ayam kremes 125g	5	0.0169
Popmie mie goreng	5	0.0169
Frisian flag kental manis coklat 1bks 38m	5	0.0169
Roma malkist creamy cappucino	5	0.0169
Unibis cream crackers 248g	5	0.0169
Segitiga biru tepung terigu 1kg	5	0.0169

Table 4 demonstrates the complete list of itemsets that possess support values in accordance with the predetermined minimum support threshold. Twenty-five items have support values that meet the established minimum support criteria. The itemset with the highest value is in Sariwangi teh kotak 25 celup, appearing 35 times across all transactions with a support value of 0.1182. This value indicates that this product is the most frequently purchased item in the grocery category or the best-selling product at CS Swalayan Lau Bakeri. If there are itemsets that do not meet the minimum support value, pruning will be performed, as these itemsets do not fall within the established minimum support criteria.

Next, the system generates the candidate 2-itemset (C2) by combining two different items from L1. Each combination is then calculated for its support value to determine whether the product pair meets the same minimum support threshold. Item combinations that pass this selection are categorized as frequent 2-itemsets (L2). Using Equation (2), the support calculation example for the item pair *Sariwangi Teh Kotak 25 Celup* and *Unibis Bon Bon Biscuits 252 g* is as follows:

Support (Sariwangi teh kotak 25 celup + Unibis Bon Bon Biscuits 252G) = (9) / 296 = 0.0304

From this calculation, there are 9 occurrences where the item combination *"Sariwangi Teh Kotak 25 Celup + Unibis Bon Bon Biscuits 252 g"* appears together within the transaction dataset, out of a total of 294 transactions. Based on the calculation, the support value for this item combination is obtained at 0.0304.
For the complete total calculation results of 2-itemset or C2 combinations that meet the established minimum support value, this can be observed in Table 5.

Table 5. Results of C2 Itemset Calculation Meeting Minimum Support Threshold

Combination of 2 Itemsets	Total Transactions	*Support*
{Sariwangi teh kotak 25 celup, unibis bon bon biscuits 252g}	9	0.0304
{Gula pasir 500g, minyak kita minyak goreng sawit 1ltr}	7	0.0236
{Selai srikaya ngetop, roti tawar kupas ngetop}	4	0.0135
{Mentega plastik 500g, gula pasir 500g}	4	0.0135
{Beras sukaraya cap gurih 10kg, minyak kita minyak goreng sawit 1ltr}	4	0.0135
{Sariwangi teh kotak 25 celup, unibis butter cream biscuits 208g}	4	0.0135
{Sariwangi teh kotak 25 celup, roma sari gandum sandwich peanut butter 206g}	3	0.0101
{Sariwangi the kotak 25 celup, unibis coco puff biscuits}	3	0.0101
{Indomie mie instan rasa kaldu ayam 75g, indofood sambal ekstra pedas botol 135ml}	3	0.0101
{Segitiga biru tepung terigu 1kg, gula pasir 500g}	3	0.0101

Based on Table 5 combinations of 2-itemsets meet the minimum support threshold (0.01). The combination with the highest support is {Sariwangi teh kotak 25 celup, Unibis bon bon biscuits 252g}, which appears 9 times with a support value of 0.0304, indicating that these two products are frequently purchased together. Conversely, the combination with the lowest support is {Segitiga Biru tepung terigu 1kg, gula pasir 500g} with 3 occurrences and a support value of 0.0101. High support values indicate a high frequency of simultaneous purchasing between products within those combinations.

After completing the calculations using the 2-itemset combinations, the next step is to examine whether the candidate 3-itemset can also be generated. The use of 3-itemset combinations allows the identification of purchasing patterns where three products are bought together within the same transaction. The support calculation formula for the 3-itemset is defined as follows:

Support (Gula Pasir 500G+Minyak Kita Minyak Goreng Sawit 1ltr+Beras Sukaraya Cap Gurih 10kg)= $\frac{2}{296}$ = 0.0135

Since there is only one 3-itemset combination that meets the minimum support threshold, the support calculation process is concluded at this stage. The next step is to compute the confidence and lift ratio values.

Based on the 2-itemset and 3-itemset combinations that have satisfied the predefined minimum support threshold, the subsequent step is to calculate the confidence value. Confidence is used to determine the probability level that multiple products are purchased together within the same transaction. By applying the minimum confidence value of **0.3** and using the formula provided in Equation (3), the results of the confidence calculation are obtained as follows.

Table 6. Confidence value of the 2-itemset candidate

Antecedent (A)	Consequent (B)	Support ($A \cup B$)	Support (A)	Nilai Confidence
Selai Srikaya Ngetop	Roti Tawar Kupas Ngetop	0.0135	0.0135	1.000
Roti Tawar Kupas	Selai Srikaya Ngetop	0.0135	0.0203	0.667
Beras Sukaraya Cap Gurih 10kg	Minyak Kita Minyak Goreng Sawit 1ltr	0.0135	0.0405	0.333
Mentega Plastik 500g	Gula Pasir 500g	0.0135	0.0169	0.800
Segitiga Biru Tepung Terigu 1kg	Gula Pasir 500g	0.0101	0.0169	0.598
Indomie Mie Instan Rasa Kaldu Ayam 75g	Indofood Sambal Ekstra Pedas Botol 135ml	0.0101	0.0270	0.375
Unibis Coco Puff Biscuits	Sariwangi The Kotak 25 Celup	0.0101	0.0203	0.500
Unibis Bon Bon Biscuits 252g	Sariwangi The Kotak 25 Celup	0.0304	0.0676	0.450
Roma Sari Gandum Sandwich Peanut Butter 206g	Sariwangi The Kotak 25 Celup	0.0101	0.0270	0.375
Unibis Butter Cream Biscuits 208g	Sariwangi The Kotak 25 Celup	0.0135	0.0405	0.333
Minyak Kita Minyak Goreng Sawit 1ltr	Gula Pasir 500g	0.0236	0.0642	0.388

Table 6 presents the confidence calculation results for the 2-itemset candidates. It can be observed that all identified candidates meet the minimum confidence threshold of 0.3. The next step is to calculate the confidence values for the 3-itemset candidates. Using Equation (3), the calculation results are presented in Table 7 below:

Table 7. Confidence value of the 2-itemset candidate

Antecedent (A, B)	Consequent (C)	Support ($A \cup B \cup C$)	Support (A, B)	Nilai Confidence
Gula Pasir 500g, Minyak Kita Minyak Goreng Sawit 1ltr	Beras Sukaraya Cap Gurih 10kg	0.0135	0.0236	0.572

From Table 7, it can be seen that for the confidence calculation of the 3-itemset candidates, only one itemset satisfies both the minimum support and minimum confidence thresholds. Based on the overall confidence analysis, a total of 13 association rules were identified as meeting the predefined minimum confidence requirement. The next step is to generate the final association rules by calculating the lift ratio, which serves as an indicator of how strong the relationship is between items within each association rule.

3.3. Association Rule Generation

After the confidence calculation is completed, the next step is to calculate the lift ratio. The lift ratio is used to measure the strength of the relationship between items within an association rule. Using Equation (4), the results of the lift ratio calculation are obtained as follows:

$$\text{Lift } A \rightarrow B = \frac{\text{Confidence } (A \rightarrow B)}{\text{Support } (B)} = \frac{\text{Support } (A \cup B)}{\text{Support } (A) \text{ Support } (B)} \quad (5)$$

For the rule derived from the following itemset:
BERAS SUKARAYA CAP GURIH 10KG + MINYAK KITA PALM COOKING OIL 10KG =
The lift ratio is calculated as follows:

$$\frac{0.0135}{(0.0405)(0.0608)} = 16.44$$

Based on the above result, the lift ratio value of the itemset Beras Sukaraya Cap Gurih 10KG and Minyak Kita Palm Cooking Oil 10KG is 16.44. This value exceeds the minimum lift threshold of 1, indicating a strong positive association between the two items. From the entirety of the calculations conducted, the complete set of discovered association rules is presented in the table below:

Table 8. Apriori Calculation Results for the Entire Dataset

Antecedents	Consequents	Support	Confidence	Lift Ratio
Selai Srikaya Ngetop	Roti Tawar Kupas Ngetop	0.0135	1	49.3
Roti Tawar Kupas Ngetop	Selai Srikaya Ngetop	0.0135	0.666	49.3
Beras Sukaraya Cap Gurih 10kg	Minyak Kita Minyak Goreng Sawit 1ltr	0.0135	1	16.4
Mentega Plastik	Gula Pasir 500g	0.0135	0.8	12.4
Segitiga Biru Tepung Terigu 1kg	Gula Pasir 500g	0.0101	0.6	9.3
Indomie Mie Instan Rasa Kaldu Ayam 75g	Indofood Sambal Ekstra Pedas Botol 135ml	0.0101	0.37	9.2
Beras Sukaraya Cap Gurih 10 Kg	Gula Pasir 500g	0.0168	0.41	6.4
Minyak Kita Minyak Goreng Sawit 1ltr	Gula Pasir 500g	0.0236	0.38	6
Gula Pasir 500g	Minyak Kita Minyak Goreng Sawit 1ltr	0.0236	0.36	6
Unibis Coco Puff Biscuits	Sariwangi Teh Kotak 25 Celup	0.0101	0.5	4.2
Unibis Bon Bon Biscuits 208g	Sariwangi Teh Kotak 25 Celup	0.0304	0.45	3.8
Roma Sari Gandum Sandwich Peanut Butter 206g	Sariwangi The Kotak 25 Celup	0.0101	0.37	3.1
Unibis Butter Cream Biscuits 208g	Sariwangi Teh Kotak 25 Celup	0.0135	0.33	2.8
Gula Pasir 500g, Minyak Kita Minyak Goreng Sawit 1ltr	Beras Sukaraya Cap Gurih 10 Kg	0.0135	0.57	14.9

Based on Table 8, the overall association rules generated in this study are as follows:

1. If purchasing **Selai Srikaya Ngetop**, then **Roti Tawar Kupas Ngetop** will also be purchased.
2. If purchasing **Roti Tawar Kupas Ngetop**, then **Selai Srikaya Ngetop** will also be purchased.
3. If purchasing **Beras Sukaraya Cap Gurih 10KG**, then **Minyak Kita Palm Cooking Oil 1L** will also be purchased.
4. If purchasing **Mentega Plastik**, then **Granulated Sugar 500g** will also be purchased.
5. If purchasing **Segitiga Biru Wheat Flour 1kg**, then **Granulated Sugar 500g** will also be purchased.
6. If purchasing **Indomie Instant Noodles Chicken Broth Flavor 75g**, then **Indofood Extra Spicy Chili Sauce 135ml** will also be purchased.
7. If purchasing **Beras Sukaraya Cap Gurih 10KG**, then **Granulated Sugar 500g** will also be purchased.
8. If purchasing **Minyak Kita Palm Cooking Oil 1L**, then **Granulated Sugar 500g** will also be purchased.
9. If purchasing **Granulated Sugar 500g**, then **Minyak Kita Palm Cooking Oil 1L** will also be purchased.
10. If purchasing **Unibis Coco Puff Biscuits**, then **Sariwangi Teabag Box (25 sachets)** will also be purchased.
11. If purchasing **Unibis Bon Bon Biscuits 208g**, then **Sariwangi Teabag Box (25 sachets)** will also be purchased.
12. If purchasing **Roma Sari Gandum Sandwich Peanut Butter 206g**, then **Sariwangi Teabag Box (25 sachets)** will also be purchased.
13. If purchasing **Unibis Butter Cream Biscuits 208g**, then **Sariwangi Teabag Box (25 sachets)** will also be purchased.
14. If purchasing **Granulated Sugar 500g** and **Minyak Kita Palm Cooking Oil 1L**, then **Beras Sukaraya Cap Gurih 10KG** will also be purchased.

3.6. System Design

For implementation purposes, a web-based system was developed using HTML and CSS for the user interface. To integrate the computational results generated in Python, the Flask API was utilized as the website backend to display the outcomes of the Apriori algorithm processing[17]. The resulting association rules are then used to group items that are potentially purchased together, as well as to provide visualizations such as charts of the most frequently sold products.

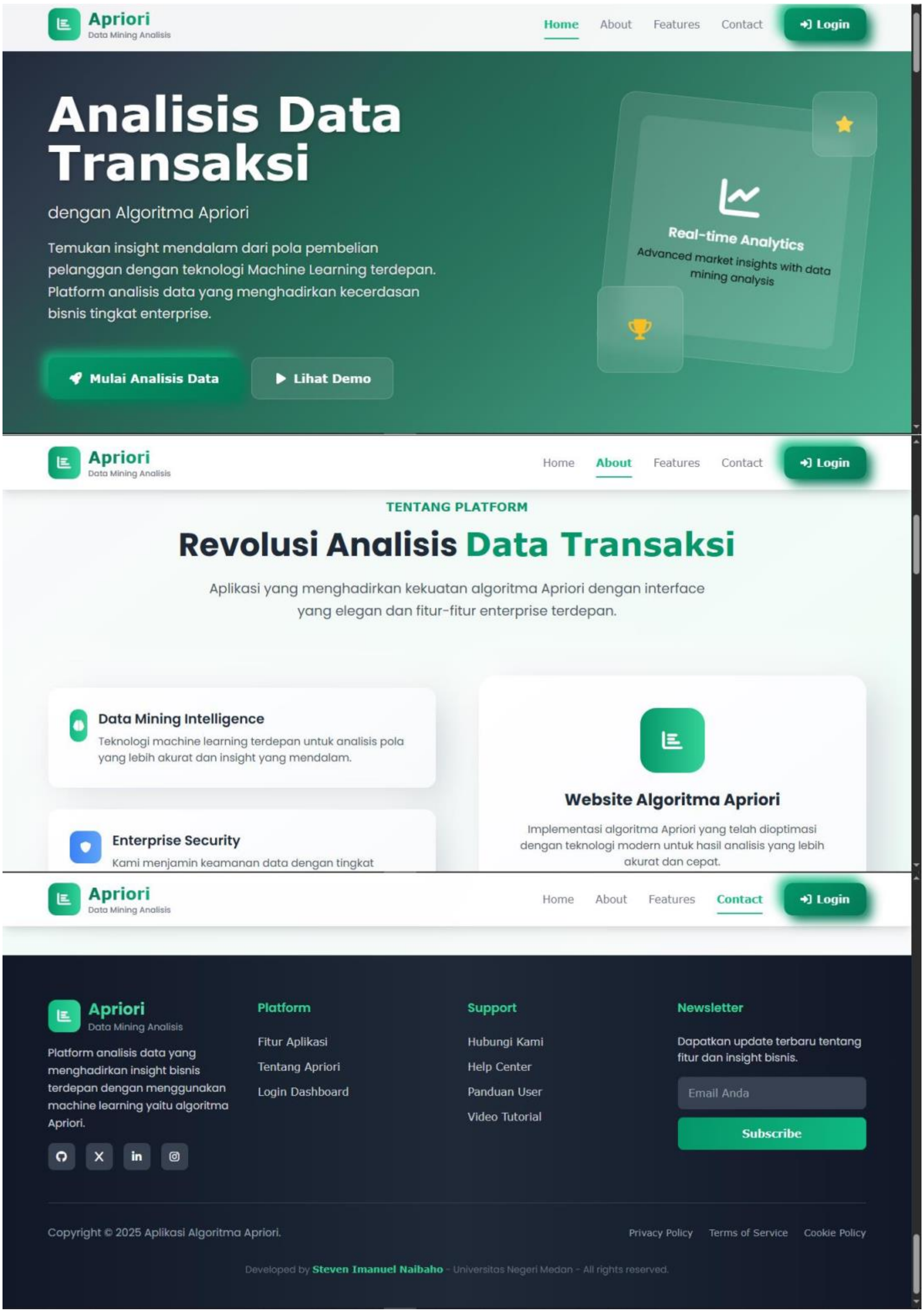

Fig. 2: Landing Page Website

Figure 2 displays the main page of the website, which includes an overview of the Apriori algorithm, a description of the available system features, and a login menu for accessing the system. Before accessing the website menus, users are required to log in first. If they do not have an account, users may register through the registration menu provided. The login and registration interfaces are shown in Figures 3 below.

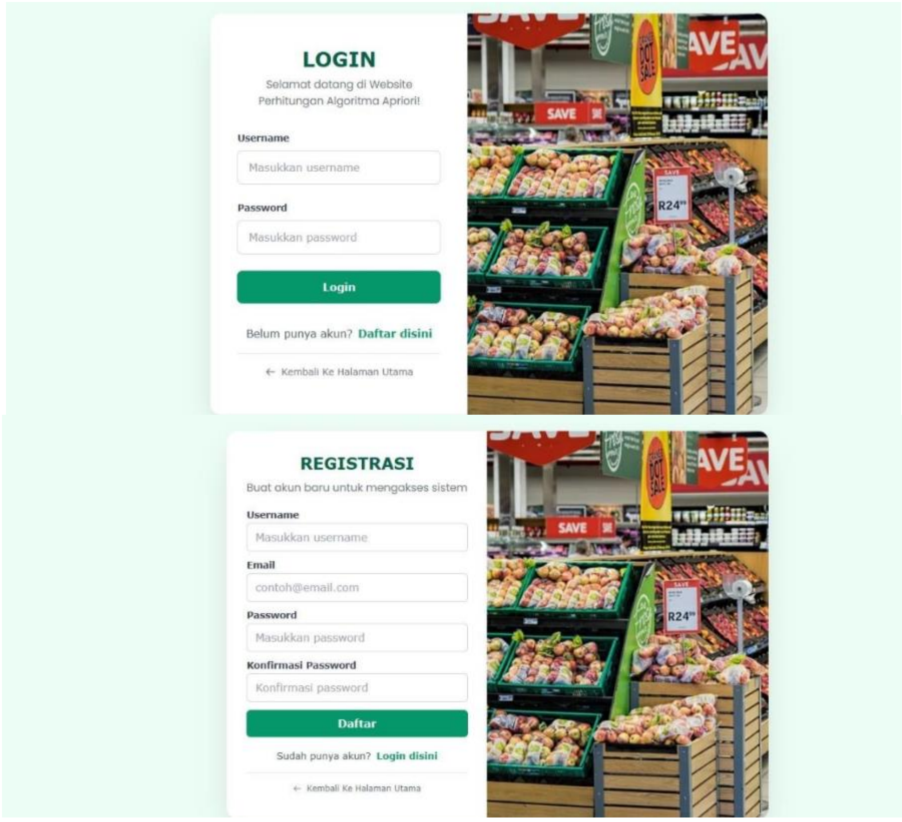

Fig. 3: Page of Login and Register

Users must successfully log in to gain access to the website features. The registered user data are stored in a MySQL database.

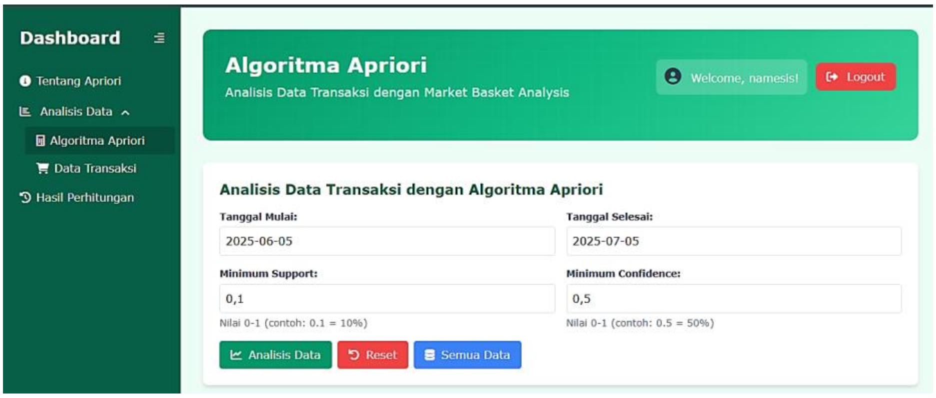

Fig. 4: Page of Analysis Data with Apriori Algorithm

Based from figure 4, users can input start and end dates for when transaction data will be processed. Subsequently, users can input minimum support and confidence values according to the available data quantity or as desired. The Data Analysis button initiates data analysis. The Reset button clears the contents of the data analysis form, and the All Data button analyses all data from the transaction data menu. After processing the data, the data analysis results appear in the Calculation Results menu. The following represents the display of calculation results that have been conducted in accordance with the criteria established in Figure 3 below.

Fig. 5: Result Apriori Algoritm

Figure 5 presents the dashboard interface displaying the outcomes of Apriori algorithm implementation in identifying association rules between products. The table summarizes the transaction period, the generated rules, and the respective support and confidence values that evaluate rule significance. For instance, one of the rules indicates that the purchase of Sukaraya Cap Gurih rice (10 kg) is frequently accompanied by the purchase of granulated sugar (500 g). Although the support value is relatively low (0.01), implying limited occurrence within the dataset, the confidence value is considerably high (0.7), reflecting a strong degree of reliability in this relationship. Furthermore, the action features, including detail, delete, and export to Excel, provide researchers with flexibility to examine, manage, and document the analytical results. Overall, this table not only reveals consumer purchasing patterns but also provides a strategic foundation for sales optimization, thereby reinforcing its practical implications for both academic research and retail business applications.

Fig. 6: Page of Results Apriori Algorithm

Figure 6 demonstrates the association rules results table previously calculated using the Apriori algorithm. From this table, combinatorial rules for items likely to be purchased together have been calculated using the predetermined support and confidence values. In the subsequent section, a bar chart is presented to illustrate the top ten items with the highest support values. The results depicted in the chart indicate that these itemsets correspond to products with the greatest purchase frequency. Consequently, these items may be identified as the best-selling products, which can serve as a strategic reference for sales optimization. This finding provides empirical evidence that the support value not only reflects purchase intensity but also functions as a determinant factor in identifying items with significant commercial potential within the scope of this study.

3.7. Blackbox Testing

The testing procedure applied in this research employed the black box method, which is designed to evaluate the operational efficiency and functional performance of the software. This section presents a detailed description of the system testing process as well as the feasibility assessment of the developed website, thereby ensuring that the application meets the required standards of usability, reliability, and effectiveness.

Table 9. Result of Blackbox Testing

Testing Parameters	Results	Percentage
Akses Halaman Utama	Berhasil	100%
Halaman Analisis Data	Berhasil	100%
Halaman Data Transaksi	Berhasil	100%
Halaman Hasil Perhitungan	Berhasil	100%
Hasil Analisis (Aturan Asosiasi)	Berhasil	100%
Detail Hasil Analisis	Berhasil	100%
Manajemen Data Transaksi	Berhasil	100%
Form Upload Data	Berhasil	100%
Kompatibilitas Chrome	Berhasil	100%
Kompatibilitas Edge	Berhasil	100%
Performa Loading (<3s)	Berhasil	100%
Responsivitas Mobile/Tablet	Berhasil	100%
Toggle Sidebar (Desktop)	Berhasil	100%
Toggle Menu (Mobile)	Berhasil	100%
Dropdown Menu	Berhasil	100%

As presented in Table 9, all test scenarios conducted through the Black Box Testing method achieved a 100% success rate. The evaluation encompassed multiple aspects, including access to the main interface, data analysis modules, transaction management features, and browser compatibility. Furthermore, the performance testing demonstrated that the homepage loading time was maintained under three seconds, thereby fulfilling operational efficiency standards. The responsiveness assessment confirmed that the system functioned properly across both tablet and mobile displays, with interactive elements such as the sidebar toggle and dropdown menus operating as expected. These results indicate that the developed website satisfies the essential criteria of functionality, compatibility, performance, and user interface responsiveness. Overall, the 100% success rate validated by a team of four evaluators highlights that the system is highly feasible for publication and practical utilization as a sales analysis platform based on the Apriori algorithm.

4. Conclusion

The study demonstrated the effective application of the Apriori algorithm to analyze customer purchasing patterns at CV. CS Swalayan using 296 transaction records from January 2025. By applying a minimum support threshold of 0.01 and a confidence threshold of 0.30, a total of 14 valid association rules were generated. Among the strongest rules identified were:
(1) Selai Srikaya Ngetop → Roti Tawar Kupas Ngetop (confidence: 100%, lift: 49.3), and
(2) Beras Sukaraya Cap Gurih 10kg → Minyak Kita Cooking Oil 1L (confidence: 100%, lift: 16.4).

A web-based analytical system was successfully developed, enabling users to upload data, configure analytical parameters, and visualise results through association rule tables and best-selling product charts. The findings reveal strong tendencies in product co-purchasing behaviour, providing a data-driven foundation for enhancing sales strategies, including product placement, bundling promotions, and inventory management. Although the results are promising, the system currently relies on a limited dataset from a single period, suggesting the need to incorporate larger and longitudinal datasets in future research. Further enhancements such as predictive analytics and recommendation mechanisms may also strengthen decision support for retail operations.

Acknowledgement

The author would like to express sincere gratitude to all those who contributed to this research, including the management of CS Swalayan, the employees of CS Swalayan who kindly provided the facilities for conducting the study, as well as the author's colleagues and academic supervisor, who have given valuable guidance and suggestions throughout the course of this research.

References

[1] Maria Cicilia Galuh Prayudhia, "Aprindo prediksi pertumbuhan ritel nasional capai 4,2 persen," ANTARA. Accessed: Sep. 27, 2024. [Online]. Available: https://www.antaranews.com/berita/3824925/aprindo-prediksi-pertumbuhan-ritel-nasional-capai-42-persen
[2] R. Hammad, V. C. Hardita, M. Zulfikri, and E. W. Sholeha, "Penerapan Metode Apriori Sebagai Sistem Pendukung Keputusan Pembentukan Paket Penjualan Bibit Buah," *J. SAINTEKOM*, vol. 12, no. 1, pp. 58–68, 2022, doi: 10.33020/saintekom.v12i1.240.
[3] L. G. Prasad, A., & Malik, "Application of Association Rule Mining in Market Basket Analysis: A Comprehensive Review," *Int. J. Inf. Technol. Comput. Sci.*, no. 14(3), pp. 51–62, 2022, doi: https://doi.org/10.5815/ijitcs.2022.03.05.
[4] A. Sari, D. P., Wicaksono, A. R., & Nurhalim, "Implementasi Algoritma Apriori untuk Analisis Pola Belanja Konsumen pada E-commerce di Era New Normal," *J. Teknol. Inf. dan Ilmu Komput.*, vol. 10, p. 3, 2023.
[5] A. N. Rahmi and Y. A. Mikola, "Implementasi Algoritma Apriori Untuk Menentukan Pola Pembelian Pada Customer (Studi Kasus : Toko Bakoel Sembako)," *Inf. Syst. J.*, vol. 4, no. 1, pp. 14–19, 2021, [Online]. Available: https://jurnal.amikom.ac.id/index.php/infos/article/view/561
[6] M. H. Santoso, "Application of Association Rule Method Using Apriori Algorithm to Find Sales Patterns Case Study of Indomaret Tanjung Anom," *Brill. Res. Artif. Intell.*, vol. 1, no. 2, pp. 54–66, 2021, doi: 10.47709/brilliance.v1i2.1228.
[7] Faris Syaifulloh, Eva Yulia Puspaningrum, and M. Muharram Al Haromainy, "Analisis Pola Pembelian Pelanggan Menggunakan Algoritma Squeezer, Apriori dan FP-Growth Pada Toko Bangunan," *Modem J. Inform. dan Sains Teknol.*, vol. 2, no. 3, pp. 134–147, 2024, doi: 10.62951/modem.v2i3.153.
[8] A. Adri, N. D. Rumlaklak, and D. R. Sina, "Implementasi Algoritma Apriori Untuk Analisa Data Penjualan (Studi Kasus: Toko Ud. Suryani)," *J. Komput. dan Inform.*, vol. 9, no. 2, pp. 182–188, 2021, doi: 10.35508/jicon.v9i2.5132.
[9] Sasonoputri Fauzia Safitrie and Wahyusarib Retno, "Penerapan Algoritma Apriori Untuk Menemukan Pola Peminjaman Buku Di Perpustakaan," *Simetris*, vol. 16, no. 1, pp. 17–23, 2022.
[10] A. Ibezato Zalukhu, D. Sartika, and S. Wahyuni, "Penerapan Algoritma Apriori untuk Optimasi Strategi Penjualan Berdasarkan Analisis Pola Pembelian di Torsa Cafe," *Bull. Inf. Technol.*, vol. 5, no. 4, pp. 295–304, 2024, doi: 10.47065/bit.v5i2.1715.
[11] D. Sitanggang, M. Kom, and A. Apriori, "Delima Sitanggang, M.Kom," 2023.
[12] N. A. Pradipta and R. D. H. Untari N, "Implementasi Algoritma Apriori Untuk Analisis Pola Pembelian Produk Donat Bolong," *Jutisi J. Ilm. Tek. Inform. dan Sist. Inf.*, vol. 13, no. 1, p. 268, 2024, doi: 10.35889/jutisi.v13i1.1778.
[13] Alwendi, A. S. Mandopa, and E. A. Hasibuan, "Aplikasi Data Mining Untuk Menentukan Masa Studi Mahasiswa Menggunakan Metode Association Rule Data Mining Application to Determine Student Study Period Using Association Rule Method," *J. Pendidik. Dewantara*, vol. 2, no. 1, pp. 1–6, 2023, [Online]. Available: https://jurnal.yagasi.or.id/index.php/dewantarahttp://dx.doi.org/10.58222/dewantara.v2i1.24
[14] D. F. Ningtyas and N. Setiyawati, "Implementasi Flask Framework pada Pembangunan Aplikasi Purchasing Approval Request," *J. Janitra Inform. dan Sist. Inf.*, vol. 1, no. 1, pp. 19–34, 2021, doi: 10.25008/janitra.v1i1.120.
[15] M. Afiksih, "Perancangan Aplikasi Pemesanan Makanan Berbasis Web di Kantin PT. Pegadaian Kanwil I Medan," *J. Comput. Sci. Informatics Eng.*, vol. 01, no. 2, pp. 66–77, 2022, doi: 10.55537/cosie.v1i2.61.
[16] Y. Kurnia, Y. Isharianto, Y. C. Giap, A. Hermawan, and Riki, "Study of application of data mining market basket analysis for knowing sales pattern (association of items) at the O! Fish restaurant using apriori algorithm," in *Journal of Physics: Conference Series*, 2019. doi: 10.1088/1742-6596/1175/1/012047.
[17] U. Syach and S. W. M. Edi, "Perancangan Aplikasi Web Manajemen Data Produk Bisnis Perhiasan Berbasis Flask Dan Mongodb," *IT-Explore J. Penerapan Teknol. Inf. dan Komun.*, vol. 3, no. 2, pp. 162–176, 2024, doi: 10.24246/itexplore.v3i2.2024.pp162-176.