Brilliance
Research of Artificial Intelligence

E-ISSN : 2807-9035
Volume 4, **Number** 2, November 2024
https://doi.org/10.47709/brilliance.v4i2.4981

Optimizing Customer Purchase Insights: Apriori Algorithm for Effective Product Bundle Recommendations

Ekinnisura kaban[1*], I Gede Mahendra Darmawiguna[2], Made Windu Antara Kesiman[3]
[1,2,3]Information System Study Program, Faculty of Engineering and Vocational, Ganesha Education University, Indonesia
[1]ekinnisura@undiksha.ac.id, [2]mahendra.darmawiguna@undiksha.ac.id, [3]antara.kesiman@undiksha.ac.id

open access

***Corresponding Author**

Article History:
Submitted: 19-11-2024
Accepted: 23-11-2024
Published: 30-11-2024

Keywords:
Apriori Algorithm; Data Mining; Minimum Confidence; Minimum Support; Purchase Pattern Analysis.

ABSTRACT

A retail store faces significant challenges in crafting effective sales strategies, particularly in designing promotional product bundles. To address this, the store leverages transaction data to analyze customer purchasing patterns, aiming to uncover products frequently bought together. This study employs data mining techniques, specifically the Apriori algorithm, to identify co-purchasing behaviors using 49,316 transaction records collected from January to June 2024. After thorough data cleaning and transformation, the Apriori algorithm identified 877 itemsets, spanning from frequent 1-itemsets to 4-itemsets. By setting a minimum support threshold of 0.003, the analysis narrowed down to 343 significant itemsets, including 325 frequent 1-itemsets and 18 frequent 2-itemsets, which served as the basis for generating association rules. Initially, 36 association rules were derived, highlighting various product relationships. To focus on impactful insights, the rules were filtered using a minimum confidence level of 0.5, yielding 3 highly relevant rules with lift ratios exceeding 1, indicating strong associations between antecedent and consequent products. These insights enable the store to design targeted promotional bundles, optimize product placement, and enhance overall sales performance. Additionally, this study demonstrates how data-driven strategies can provide a competitive edge by aligning with customer purchasing behaviors. To ensure continuous improvement, a Python-based system was developed, empowering the store to independently analyze transaction data and refine sales strategies in real time, adapting to evolving purchasing patterns as the dataset grows.

INTRODUCTION

The increasingly fierce competition in the retail sector demands businesses to develop effective sales strategies to attract and retain customers. One such strategy is selling product bundles as promotions, which has proven to boost purchase decisions, accelerate sales, and enhance customer satisfaction (Hakim, 2023; Mahardika, 2023). X store faces challenges in determining the right product combinations for promotional bundles, given the wide variety of available products and the lack of customer purchasing pattern analysis. Meanwhile, transaction data, which has so far been used merely as archives, holds great potential for processing to support sales strategies. Over one month, the store recorded 8,182 transactions, 57.98% of which involved purchases of more than one product. This indicates an opportunity to identify purchasing patterns using data mining techniques.

The data mining technique applied is association rule mining with the Apriori algorithm, an efficient method for discovering frequent itemsets and association rules from transactional data. The Apriori algorithm was chosen because it is more efficient than the FP-Growth algorithm in processing large datasets (Aquila et al., 2023; Prasetya et al., 2022). Previous studies have demonstrated the effectiveness of this algorithm in various cases. (Aisyah & Normah, 2019) applied it to the Koperasi Bappenas supermarket, generating three association rules with a minimum support of 20% and a confidence of 60%. (Ismasari et al., 2020) used it at Surya Mart Store to uncover customer purchasing patterns, producing four rules with 70% support and 80% confidence. (Robby Setiawan & Jananto, 2021) utilized this algorithm at PT. Pupuk Sriwidjaja to recommend fertilizer stock procurement, yielding nine association rules with 50% support and confidence. Other studies by (Aulia Miranda et al., 2022) at She Shop and (Juriyanto, 2023) at Asih Store also showed similar results, aiding decision-making in stock management and sales strategies.

This study presents a fundamental difference compared to previous research, particularly in terms of scale and scope. By utilizing a six-month dataset comprising 49,316 transactions, this research is able to uncover deeper and more comprehensive insights. Furthermore, it successfully developed a Python-based system designed to be independently operated by the store. This system enables the analysis of the latest transaction data on a periodic basis, ensuring that the patterns or rules generated remain relevant to current conditions. With this approach, the study makes a significant contribution to designing data-driven sales strategies that are not only accurate but also responsive to market dynamics and changes.

Brilliance
Research of Artificial Intelligence

E-ISSN : 2807-9035
Volume 4, **Number** 2, November 2024
https://doi.org/10.47709/brilliance.v4i2.4981

LITERATURE REVIEW

Association Rule

Association rule is a common technique in data mining used to discover patterns or relationships between items in a dataset (Qisman et al., 2021). This technique is often applied in Market Basket Analysis to identify items that frequently appear together. According to (Amsury et al., 2023), association rule helps in finding significant relationships between items in the data. This method utilizes several metrics to measure the strength and significance of item relationships, such as support, confidence, and lift (Takdirillah, 2020).

1. Support
   Support is the measure of how frequently an item appears in the entire set of transactions. It represents how often item X occurs across all transactions.
   $$\text{Support (X)} = \frac{\text{Number of Transactions Containing (X)}}{\text{Total Number of Transactions}}$$
   For the support value of 2 items, the formula is as follows:
   $$\text{Support (X, Y)} = \frac{\text{Number of Transactions Containing (X, Y)}}{\text{Total Number of Transactions}}$$
2. Confidence
   Confidence is the probability value of the relationship between the occurrence of one item given that another item has already appeared. Simply put, confidence indicates how likely item Y is purchased together when a customer also buys item X.
   $$\text{Confidence} = \frac{\text{Support (X, Y)}}{\text{Support (X)}}$$
3. Lift Ratio
   Lift ratio is the value of an association rule used to validate whether product X is truly purchased together with product Y. The lift ratio is considered valid if its value is greater than one.
   $$\text{Lift Ratio (X => Y)} = \frac{\text{Confidence (X => Y)}}{\text{Support (Y)}}$$

Algoritma Apriori

The Apriori algorithm was developed by Agrawal and Srikant in 1994 to find frequent itemsets in a dataset based on Boolean association rules (Qoniah & Priandika, 2020). This algorithm leverages information from previous itemsets to discover the next itemsets using a minimum support value as a candidate selection criterion (Fahrudin, 2019). The steps in the Apriori algorithm are as follows:

1. Determine minimum support
2. Scan the database to find candidate 1-itemsets (consisting of 1 itemset) and calculate the support value for each itemset. Itemsets that do not meet the minimum support value will be removed, and those that meet the minimum support will be included in the 1-itemset.
3. The itemsets that pass into the 1-itemset will be used for the next iteration. The 1-itemsets will perform a join operation between itemsets to generate candidate 2-itemsets (consisting of 2 itemsets). Then, calculate the support value, and itemsets that do not meet the minimum support value will be eliminated, while those that meet the support value will be included in the 2-itemset.
4. Repeat this step to find the next k-itemsets in the same manner as finding 1-itemsets and 2-itemsets until no more k-itemsets are formed.
5. Determine minimum confidence
6. For all k-itemsets that have been formed or meet the minimum support value, association rules will be constructed by calculating the confidence value. Itemsets that do not meet the minimum confidence value will be removed.

Cross Industry Standard Process for Data Mining (CRISP-DM)

The Cross Industry Standard Process for Data Mining (CRISP-DM) is a standard model for conducting data mining processes to ensure that data management is clear and structured. This model is used as a general problem-solving strategy for both business and research purposes. It consists of six phases: Business Understanding, Data Understanding, Data Preparation, Modelling, Evaluation, and Deployment (Arinal & Melani, 2023). Based on the mentioned CRISP-DM process phases, here is an explanation of each step:

1. Business Understanding
   In this phase, a strong understanding of the data mining research to be conducted from a business perspective is developed. Several aspects that need to be considered include the business problem at hand, clearly defining the business goals, determining the research objectives related to data mining, and planning the strategies to be executed.
2. Data Understanding

Brilliance
Research of Artificial Intelligence

E-ISSN : 2807-9035
Volume 4, **Number** 2, November 2024
https://doi.org/10.47709/brilliance.v4i2.4981

In the data understanding phase, the researcher will collect initial data to study and comprehend the data that will be used. The choice of appropriate data will determine the quality of the research results.

3. Data Preparation
During the data preparation phase, the data will be processed to align with the goals of analysis and modeling. Several steps will be carried out, including data cleaning, selecting relevant attributes, and performing data transformation to make it suitable for modeling.
4. Modelling
The modeling process involves selecting the appropriate data mining technique, algorithm, and tools for the research. Afterward, the chosen data mining techniques will be applied using the selected algorithms and tools.
5. Evaluation
The results of the data mining process from the modeling phase will be evaluated. This evaluation is performed on the model previously built to assess its performance and quality, determining if it meets the objectives set in the initial Business Understanding phase.
6. Deployment
In this phase, the knowledge or information obtained will be presented in a specific format for the users to benefit from. The deployment phase often includes preparing a simple report or implementing the data mining process in a repetitive manner.

METHOD

This research is a quantitative study that applies data mining using the association rule technique with the Apriori algorithm to discover patterns or relationships between items using sales transaction data from January to June 2024, obtained through observation at X store. The results are expected to assist the store in designing product bundle sales strategies that attract customer attention. This study follows the Cross Industry Standard Process for Data Mining (CRISP-DM) phases, which include Business Understanding, Data Understanding, Data Preparation, Modelling, Evaluation, and Deployment, to ensure a structured process. After the model is created, the system will be developed using the waterfall method, allowing the store to independently analyze the latest transaction data. The research flow can be seen in Figure 1.

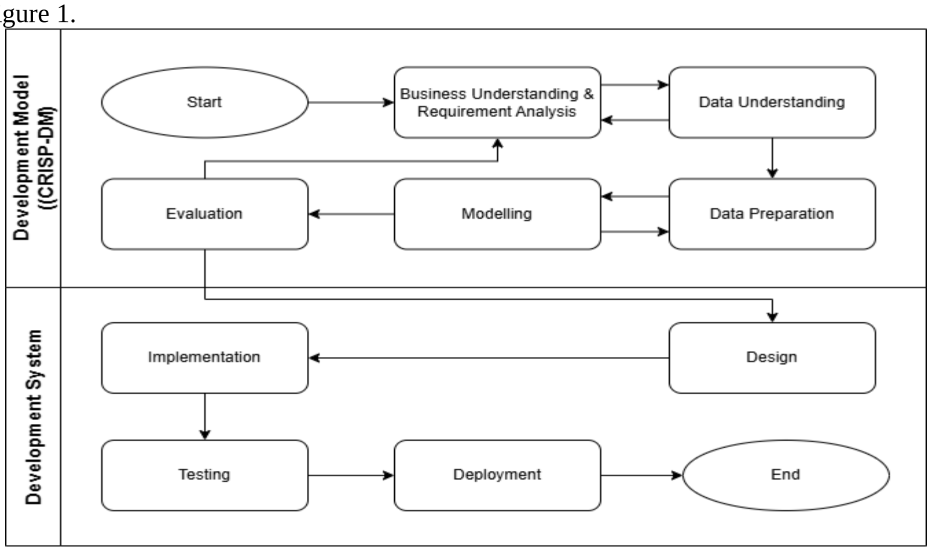

Figure 1. Research Flow

RESULT

Business Understanding

At this stage, direct observation is conducted to understand the business problems at X store. The store faces difficulties in designing product bundle sales strategies as promotions due to the large number of products, as well as wanting to anticipate competition from nearby stores. This strategy aims to prevent customers from switching to competitors and fulfill customer demand for product promotions. To address this issue, sales transaction data stored in the store's database will be processed using the association rule technique with the Apriori algorithm. This algorithm will identify customer purchase patterns through item combinations, helping the store determine which products can be bundled together for promotions. This stage also includes the analysis of system requirements, which consists of functional and non-functional requirements, to ensure that the developed system meets user needs.

Brilliance
Research of Artificial Intelligence

E-ISSN : 2807-9035
Volume 4, **Number** 2, November 2024
https://doi.org/10.47709/brilliance.v4i2.4981

Data Understanding

This stage involves the collection of sales transaction data from X store for the period of January–June 2024. The data was obtained from the store manager in Excel format, consisting of 49,316 transactions with an average of 273 transactions per day. Of the total, 29,259 transactions (59.33%) involved the purchase of more than one item, while 20,057 transactions (40.67%) involved the purchase of a single item. The majority of transactions that involved the purchase of more than one item indicate that the application of the association rule technique is appropriate for discovering purchasing patterns and providing product bundle recommendations. The transaction data is shown in Table 1.

Table 1. Data Transaction

	Date	**Transaction ID**	**Item Code**	**Item Name**	**Price**	**Quantity**	**Total**
0	2024-01-01	92268	552000	ACCECORIS 2000	2000	1	2000
1	2024-01-01	92268	8994231100016	KOPI BANYUATIS 250G	19500	1	19500
2	2024-01-01	92269	30001	GULA PASIR/KG	12500	1	12500
3	2024-01-01	92269	8998866200318	SEDAAP MIE AYAM BAWANG	2600	2	5200
4	2024-01-01	92269	8998866200325	SEDAAP MIE SOTO	2600	1	2600
...	…	…	…	…	…	...	…
101990	2024-06-30	141583	8999809700025	VICEE LEMON /2PCS	1500	2	3000

Data Preparation

In this stage, the sales transaction data obtained from X store will undergo data cleaning and transformation processes to make it ready for use by the Apriori algorithm. The data processing will be performed using the Python programming language due to its capability to handle large datasets and its provision of various analysis modules.

1. Data Cleaning

In the data cleaning process, transactions involving the purchase of only one item are removed, as the analysis requires transactions with more than one item. Irrelevant columns are also deleted, leaving the data with 29,259 transactions containing the columns Date, Transaction ID, and Product Name. The cleaned data can be seen in Table 2.

Table 2. Data Cleaning Results

	Date	**Transaction ID**	**Item Name**
0	2024-01-01	92268	ACCECORIS 2000
1	2024-01-01	92268	KOPI BANYUATIS 250G
2	2024-01-01	92269	GULA PASIR/KG
3	2024-01-01	92269	SEDAAP MIE AYAM BAWANG
4	2024-01-01	92269	SEDAAP MIE SOTO
...	…	…	…
101990	2024-06-30	141583	VICEE LEMON /2PCS

2. Data Transformation

In the data transformation process, the categorical data format will be converted into a boolean format so that it can be used during the modeling process with the Apriori algorithm. The result of the data transformation can be seen in Table 3.

Table 3. Data Transformation Results

Item Name	**ABC SUSU 30G SCH**	**ABC TERASI UDANG 84G**	**ACCECORIS 2000**	**ACCESORIS 1000**	**...**	**YUPI SWEET HEART 15G**
Transaction ID						
92268	False	False	True	False	...	False
92269	False	False	False	False	...	False
92270	False	False	False	False	...	False
92271	False	False	False	False	...	False
92272	False	False	False	False	...	False
…	…	…	…	…	...	…
141583	False	False	False	False	...	False

E-ISSN : 2807-9035
Volume 4, Number 2, November 2024
https://doi.org/10.47709/brilliance.v4i2.4981

In the result of the data transformation above, if an item is purchased in a transaction, it will be marked as True, and if no item is purchased in the transaction, it will be marked as False.

Modelling

In the modeling phase, an association technique is applied using the Apriori algorithm to discover customer purchasing patterns. This algorithm is used to find association rules between products in transaction data with the help of the mlxtend library. Several parameters are used, including the dataset, minimum support, max_len, and use_colnames. To find association rules, the mlxtend library is also utilized with the 'association_rules' import, which requires parameters such as the Apriori algorithm, metric (lift), and min_threshold. The application of the Apriori algorithm is divided into two stages: high-frequency pattern analysis and the formation of association rules.

1. High Frequency Pattern Analysis

In this stage, itemsets are combined and the support values are calculated, resulting in 877 itemsets consisting of 495 frequent 1-itemsets, 175 frequent 2-itemsets, 129 frequent 3-itemsets, and 78 frequent 4-itemsets. Next, the minimum support value is determined to generate the frequent itemsets that will be used in this research. The minimum support value is determined within the range of 0 to 1 to filter itemsets with frequencies exceeding the specified threshold. This research conducts three experiments to determine the minimum support parameter to be used. The results of the minimum support value experiments can be seen in Table 4.

Table 4. Experiment Results Minimum Support Value

Test	Minimum Support	Test Results
1	0.01	53 frequent 1-itemset & 2 frequent 2-itemset
2	0.005	151 frequent 1-itemset & 6 frequent 2-itemset
3	0.003	325 frequent 1-itemset & 18 frequent 2-itemset

Based on the three experiments with minimum support values of 0.01, 0.005, and 0.003, a support value of 0.003 was chosen for this research. The first experiment with a support of 0.01 resulted in very popular itemsets (53 frequent 1-itemsets and 2 frequent 2-itemsets). The second experiment with a support of 0.005 captured a broader pattern (151 frequent 1-itemsets and 6 frequent 2-itemsets), while the third experiment with a support of 0.003 identified less frequent but still relevant purchasing patterns (325 frequent 1-itemsets and 18 frequent 2-itemsets). The support value of 0.003 was chosen to explore a wider variety of products, including combinations of popular and less frequently purchased products.

2. Establishment of association rule

In this stage, association rules are formed from the frequent itemsets by calculating the confidence values. In association rules, the antecedents are items that trigger the appearance of items in the consequents, while the consequents are items that appear as a result of the antecedents. Association rules also involve itemset exchange, for example, Egg → Oil, which can be reversed to Oil → Egg. As a result, 36 association rules are formed. In this research, the minimum confidence value for the formed association rules is determined. The confidence value ranges from 0 to 1, where 0 indicates no relationship between items, and 1 indicates a very strong relationship. By setting a minimum confidence value, association rules with a relationship strength higher than the specified threshold can be filtered. Three experiments were conducted to determine the appropriate minimum confidence value, in accordance with the analysis goals. The results of the minimum confidence value experiments can be seen in Table 5.

Table 5. Experiment Results Minimum Confidence Value

Test	Minimum Confidence	Test Results
1	0.5	3 rules
2	0.3	8 rules
3	0.1	27 rules

Based on the three experiments, the minimum confidence values of 0.5, 0.3, and 0.1 were determined to observe their impact on the quality and quantity of association rules. The first experiment with a value of 0.5 resulted in 3 rules with strong relationships between products. The second experiment with 0.3 produced 8 rules, while the third experiment with 0.1 resulted in 27 rules. The minimum confidence value selected for this research is 0.5, as the focus is on rules with strong relationships between products for product bundle recommendations.

Evaluation

In the evaluation stage, the generated association rules will be tested for validity by calculating the lift ratio. Association rules are considered valid if they have a lift ratio greater than 1. The final results of the association rules can be seen in Table 6.

Brilliance
Research of Artificial Intelligence

E-ISSN : 2807-9035
Volume 4, **Number** 2, November 2024
https://doi.org/10.47709/brilliance.v4i2.4981

Table 6. The Final Result of The Association Rules

No	antecedents	consequents	support	confidence	lift
1	MINYAK SUNCO 500ML POUCH	TELUR AYAM/BUTIR	0.028333	0.804854	6.611239
2	AJINOMOTO 19G (20 / RTG) 1000	MASAKO AYAM 9G (12/RTG) 500	0.006562	0.662069	24.034089
3	SUKSES GORENG ISI 2 AYAM KREMES 133G	TELUR AYAM/BUTIR	0.004546	0.507634	4.169807

Based on the evaluation results of the association rules shown in Table 6, it can be seen that all the formed association rules have a lift ratio greater than 1. This indicates that the association rules are valid, meaning the antecedent items are truly purchased together with the consequent items.

Design

In this stage, a use case diagram and database are created to provide an overview of the system design. The use case diagram illustrates how the system will be used by the users. The design results of the use case diagram can be seen in Figure 2. The database functions to store the results processed by the users. The design results of the database can be seen in Figure 3.

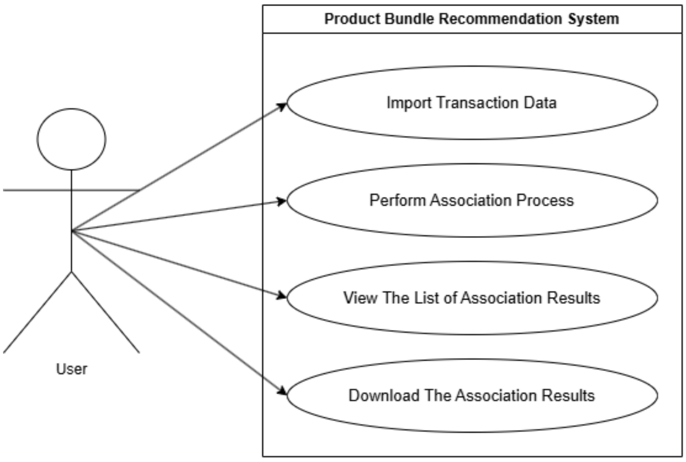

Figure 2. Use Case Diagram

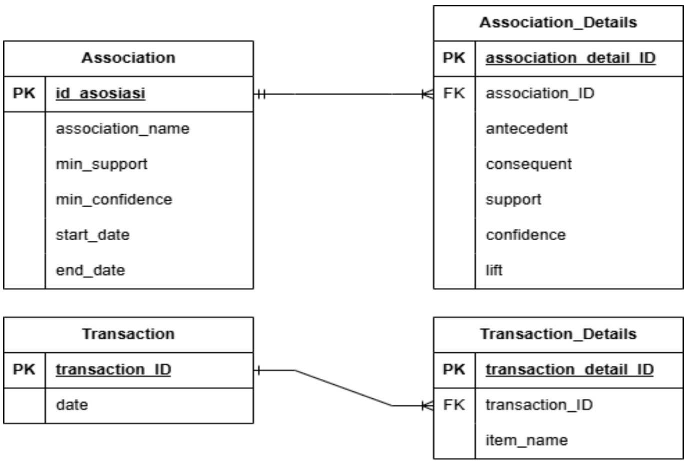

Figure 3. Database

System Implementation

In this stage, the system is developed according to the design that was created previously.

E-ISSN : 2807-9035
Volume 4, **Number** 2, November 2024
https://doi.org/10.47709/brilliance.v4i2.4981

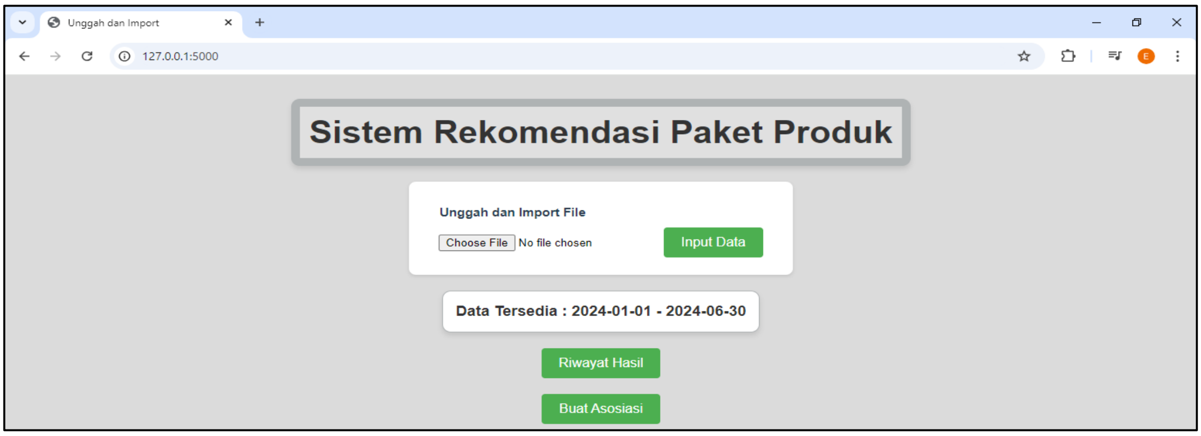

Figure 4. System Start Page

Figure 4 shows the result of the implementation of the system's home page as the dataset import feature, which functions to upload and import sales transaction data in Excel format. Next, there is a notification regarding the date range of the data available in the system. The "Input Data" button is used to input the uploaded transaction data into the database. The "History Results" button allows users to view the association analysis results that were previously conducted, while the "Create Association" button is used to generate a new Apriori analysis.

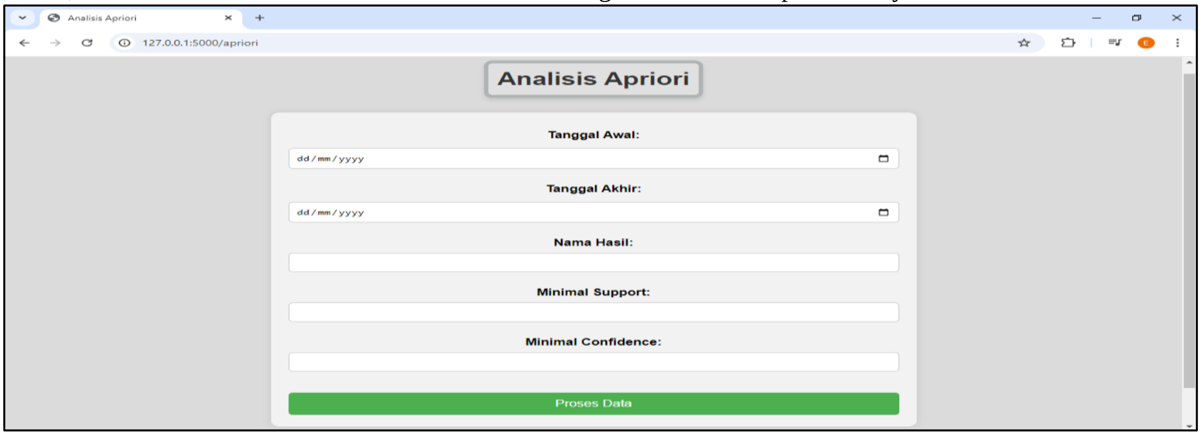

Figure 5. Association Process Page

Figure 5 shows the result of the implementation of the "Create Association" page, which is used to perform Apriori analysis. On this page, there are input fields such as "Start Date" and "End Date," which are used to record the start and end dates of the analysis, the "Result Name" field for recording the desired name of the association, and the "Minimal Support" and "Minimal Confidence" fields for entering the values used in the analysis. Additionally, there is a "Process Data" button, which is used to execute the Apriori analysis based on the input provided.

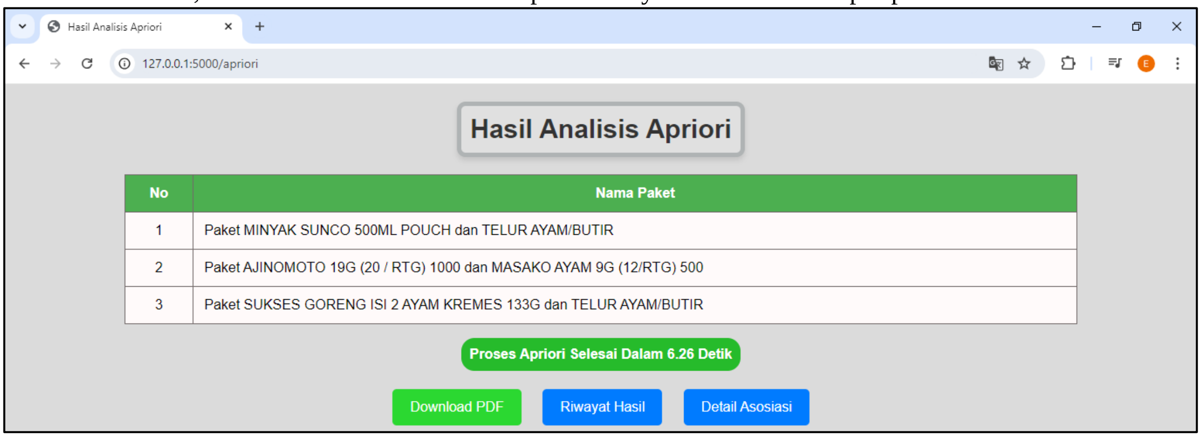

Figure 6. Association Results Page

Brilliance
Research of Artificial Intelligence

E-ISSN : 2807-9035
Volume 4, **Number** 2, November 2024
https://doi.org/10.47709/brilliance.v4i2.4981

Figure 6 shows the result of the implementation of the association process results page. This page contains product bundle recommendations that can serve as a reference for implementing product bundle sales strategies as promotions to attract customer attention. The page also displays the processing time for generating the product bundles. There are buttons such as "Download PDF," which allows users to print the Apriori analysis results in PDF format, "History Results," which enables users to view the list of Apriori analyses that have been performed, and "Association Details," which provides detailed information on the results of the Apriori analysis that has been conducted.

Figure 7. Association Details Page

Figure 7 shows the result of the implementation of the association details page. This page displays a table containing the columns "Antecedent" and "Consequent," which list the items involved in the association rule analysis. It also includes the columns "Support," "Confidence," and "Lift," which show the metric values for each association rule generated. Additionally, there are descriptions for each table header to help users understand the meaning of each table title displayed.

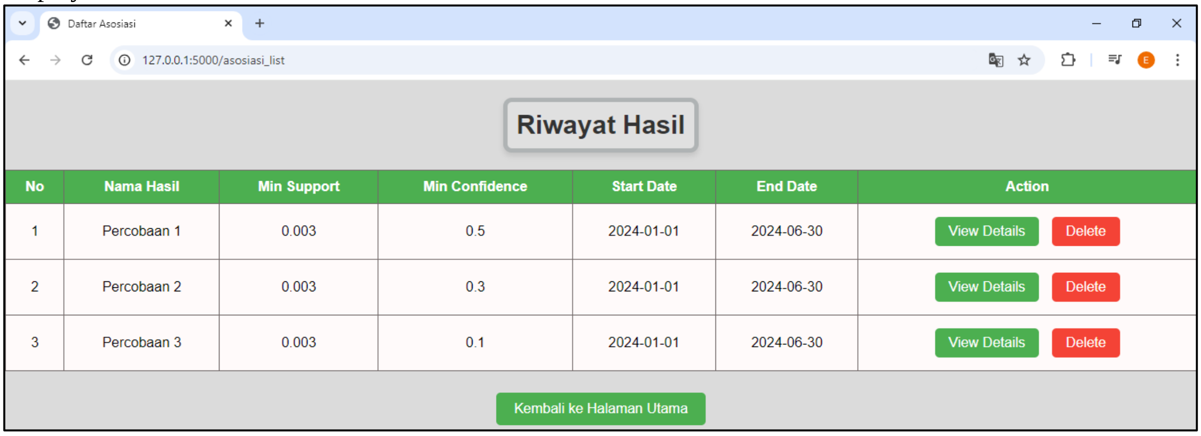

Figure 8. Association List Page

Figure 8 shows the result of the implementation of the association list page. This page displays a list of the Apriori analyses that have been previously conducted. It includes a "View Details" button, which allows users to view the details of the selected Apriori analysis, and a "Delete" button, which enables users to delete the desired Apriori analysis.

Testing

In this stage, functional testing is conducted on the system to ensure that the results meet the expected outcomes. The results of the functional testing can be seen in Table 7.

Table 7. Functional Testing Results

No	Test Description	Testing Steps	Expected Result	Test Result
1	Importing transaction data	1. Open the transaction data import page. 2. Upload the transaction data in Excel format.	Transaction data is successfully imported into the system.	Success
2	Running Apriori association process	1. Enter Start Date & End Date. 2. Enter the name of the association.	The association process is successfully completed and	Success

E-ISSN : 2807-9035
Volume 4, **Number** 2, November 2024
https://doi.org/10.47709/brilliance.v4i2.4981

		3. Enter the minimum support value. 4. Enter the minimum confidence value. 5. Click the "Process Data" button.	displayed on the system.	
3	Viewing association results	Click the "History Results" menu.	The system displays a list of association results.	Success
4	Downloading association results	1 Click the "History Results" menu. 2 Select the association result to download. 3 Click the "Export PDF" button to download the association result in PDF format.	The association results are successfully downloaded as a PDF.	Success

DISCUSSION

Comparison of Support Values

Based on three experiments with different support values, changes in support values significantly affect the number of itemsets generated. In the first experiment with a support value of 0.01, only 53 frequent 1-itemsets and 2 frequent 2-itemsets were detected, representing products with very high popularity. In the second experiment with a support value of 0.005, the number of itemsets increased to 151 frequent 1-itemsets and 6 frequent 2-itemsets, covering products with moderate popularity but still significant. In the third experiment with a support value of 0.003, the number of itemsets sharply increased to 325 frequent 1-itemsets and 18 frequent 2-itemsets, allowing the detection of products with less frequent purchases. Overall, the lower the support value, the more itemsets are identified. Determining the optimal support value should take into account the quality of the itemsets to obtain effective and relevant results in line with the desired objectives.

Comparison of Confidence Values

Based on three experiments with different minimum confidence values, changes in the confidence value significantly affect the number of association rules generated. In the first experiment, with a minimum confidence of 0.5, only 3 association rules were generated, reflecting very strong relationships between items. In the second experiment, with a minimum confidence of 0.3, the number of rules increased to 8, as the validity criteria for the rules became more relaxed. In the third experiment, with a minimum confidence of 0.1, the number of rules surged to 27, although the strength of the relationships between items in these rules weakened. Overall, the lower the confidence value, the more association rules can be identified, but with a potential decrease in the strength of the rules. Therefore, the selection of the optimal confidence value should be aligned with the analysis goals, whether for exploring hidden rules or focusing on rules with stronger relationships.

CONCLUSION

The results of the customer purchasing pattern analysis at X store using the Apriori algorithm demonstrate that the algorithm is effective in identifying purchasing patterns for product bundle recommendations. With a minimum support value of 0.003, 343 itemsets were obtained, consisting of 325 frequent 1-itemsets and 18 frequent 2-itemsets, which were used to explore hidden patterns in the transaction data. Association rules were formed with a minimum confidence value of 0.5, resulting in 3 association rules, which were then evaluated using lift ratio. The evaluation results show that all rules have a lift ratio greater than 1, indicating that products in the rules are frequently bought together. The generated rules are valid and can be used for product bundle recommendations. The design and implementation results of the customer purchasing pattern analysis system at X store using the Apriori algorithm show that the system was successfully designed and implemented to provide product bundle recommendations. This system can be effectively used as a data-driven decision-making basis for marketing and sales strategies.

REFERENCES

Aisyah, S., & Normah, N. (2019). Penerapan Algoritma Apriori Terhadap Data Penjualan Di Swalayan Koperasi Bappenas Jakarta Pusat. *Paradigma - Jurnal Komputer Dan Informatika*, *21*(2), 235–242. https://doi.org/10.31294/p.v21i2.6205

Amsury, F., Kurniawati, I., & Rizki Fahdia, M. (2023). Implementasi Association Rules Menentukan Pola Pemilihan Menu Di the Gade Coffee & Gold Menggunakan Algoritma Apriori. *INFOTECH Journal*, *9*(1), 279–286. https://doi.org/10.31949/infotech.v9i1.5357

Aquila, A., Pabendon, C., & Purnomo, H. D. (2023). *JURNAL MEDIA INFORMATIKA BUDIDARMA Penerapan Algoritma Apriori dan FP-Growth Untuk Market Basket Analisis Pada Data Transaksi NonPromo*. *7*, 975–984. https://doi.org/10.30865/mib.v7i3.6153

Arinal, V., & Melani, M. A. (2023). Penerapan Metode Asosiasi Pada Data Penjualan Transaksi Menggunakan

E-ISSN : 2807-9035
Volume 4, **Number** 2, November 2024
https://doi.org/10.47709/brilliance.v4i2.4981

Algoritma Apriori (Studi Kasus Circle'K Apartemen Marabella Jakarta Selatan). *Jurnal Sains Dan Teknologi*, *5*(1), 170–176. http://ejournal.sisfokomtek.org/index.php/saintek/article/view/1366%0Ahttp://ejournal.sisfokomtek.org/index.php/saintek/article/download/1366/1010

Aulia Miranda, S., Fahrullah, F., & Kurniawan, D. (2022). Implementasi Association Rule Dalam Menganalisis Data Penjualan Sheshop dengan Menggunakan Algoritma Apriori. *Metik Jurnal*, *6*(1), 30–36. https://doi.org/10.47002/metik.v6i1.342

Fahrudin, N. F. (2019). Penerapan Algoritma Apriori untuk Market Basket Analysis. *MIND Journal*, *1*(2), 13–23. https://doi.org/10.26760/mindjournal.v4i1.13-23

Hakim, A. R. (2023). Analisis Pola Pembelian Konsumen di Alfamart dengan Menggunakan Algoritma Apriori. *Jurnal Desain Dan Analisis Teknologi*, 193–199. http://journal.aptikomkepri.org/index.php/JDDAT/article/view/38%0Ahttp://journal.aptikomkepri.org/index.php/JDDAT/article/download/38/28

Ismasari, I., Ramadhan, M., & Hadikristanto, W. (2020). Analisis Tingkat Pembelian Konsumen dengan Algoritma Apriori. *Jurnal Ilmiah Intech : Information Technology Journal of UMUS*, *2*(02). https://doi.org/10.46772/intech.v2i02.292

Juriyanto, W. (2023). Penerapan Teknik Data Mining Menggunakan Algoritma Apriori pada Proses Penjualan di Toko Sembako. *EJECTS: Journal Computer, Technology and Informations System*, *3*(1), 8–14.

Mahardika, I. K. R. (2023). *Meningkatkan Keputusan Pembelian dengan Product Bundling , In Store Display , dan Diskon*. *3*(12), 2399–2412.

Prasetya, T., Yanti, J. E., Purnamasari, A. I., Dikananda, A. R., & Nurdiawan, O. (2022). Analisis Data Transaksi Terhadap Pola Pembelian Konsumen Menggunakan Metode Algoritma Apriori. *INFORMATICS FOR EDUCATORS AND PROFESSIONAL : Journal of Informatics*, *6*(1), 43. https://doi.org/10.51211/itbi.v6i1.1688

Qisman, M., Rosadi, R., & Abdullah, A. S. (2021). Market basket analysis using apriori algorithm to find consumer patterns in buying goods through transaction data (case study of Mizan computer retail stores). *Journal of Physics: Conference Series*, *1722*(1). https://doi.org/10.1088/1742-6596/1722/1/012020

Qoniah, I., & Priandika, A. T. (2020). Analisis Market Basket Untuk Menentukan Asossiasi Rule Dengan Algoritma Apriori (Studi Kasus: Tb.Menara). *Jurnal Teknologi Dan Sistem Informasi*, *1*(2), 26–33. https://doi.org/10.33365/jtsi.v1i2.368

Robby Setiawan, R., & Jananto, A. (2021). Implementasi Data Mining Untuk Rekomendasi Penyedia Pupuk Non Subsidi Dengan Menggunakan Metode Algoritma Apriori. *Jurnal TEKNO KOMPAK*, *17*(1), 13–24.

Takdirillah, R. (2020). Penerapan Data Mining Menggunakan Algoritma Apriori Terhadap Data Transaksi Sebagai Pendukung Informasi Strategi Penjualan. *Edumatic : Jurnal Pendidikan Informatika*, *4*(1), 37–46. https://doi.org/10.29408/edumatic.v4i1.2081