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Market basket analysis of fresh fruit retail using the apriori algorithm: identifying purchasing patterns and popular products

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ABSTRACT

The fruit retail sector continues to grow; however, most market basket analysis studies focus on non-perishable products, while fresh fruit retail remains underexplored despite its perishable and demand-volatile characteristics. This lack of empirical evidence often leads to inefficient stock management, inventory spoilage, and frequent stock-outs. This study addresses this research gap by applying the Apriori algorithm to analyze purchasing patterns and identify popular products in fresh fruit retail. The dataset consists of 50 sales transactions involving 25 fruit items collected from a single retail store. A minimum support threshold of 30% and a minimum confidence threshold of 60% were used to generate association rules. The results show that Citra Guava and Matoa are the most popular fruits, each with a support value of 62%. Several strong association rules, including Citra Guava–Matoa and Deli Guava–Matoa, exhibit confidence values above 80% and lift values greater than 1. These findings indicate that purchasing patterns in fresh fruit retail are relatively simple and concentrated. This study contributes by extending the application of market basket analysis to perishable product contexts and providing data-driven insights to support inventory planning and promotional strategies in fruit retail.

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1. INTRODUCTION

The fruit retail sector continues to grow alongside increasing public awareness of healthy consumption. In a competitive market environment, fruit retailers must understand consumer purchasing behavior to improve sales performance and design effective marketing strategies (Sari & Nasution, 2025). Transaction data recorded in point-of-sale systems provide an important source of information for this purpose.

Despite the availability of transaction data, fruit retailers frequently experience problems in stock management, product arrangement, and promotion, as reflected in inventory losses and frequent stock-outs. Overstocking of low-demand fruits often leads to spoilage due to the perishable nature of fresh fruit, while high-demand fruits are frequently unavailable, resulting in lost sales opportunities and inefficient inventory turnover caused by inaccurate demand estimation (Muharni & Andriyanto, 2024).

Data mining techniques enable the extraction of purchasing patterns from transaction data to support data-driven decision-making (Hidayat et al., 2023; Thariq, 2023). Association rule mining is widely used to identify products frequently purchased together and supports cross-selling, shelf arrangement, and bundling strategies (Irawan & Harlina, n.d.; Keputusan Pembentukan Paket Penjualan Bibit Buah et al., n.d.).

Previous studies have demonstrated the effectiveness of the Apriori algorithm in various non-perishable retail contexts (Purnama et al., 2025, Hibnastiar et al., 2025). However, empirical studies that specifically examine purchasing patterns in fresh fruit retail remain limited, despite its distinctive characteristics such as perishability, seasonality, and high demand variability. As a result, purchasing patterns derived from general retail contexts cannot be directly generalized to fresh fruit retail.

To address this research gap, this study applies the Apriori algorithm to fruit sales transaction data to identify popular products and stable purchasing associations under perishable conditions. The objective of this study is to provide empirical, data-driven insights that can support more accurate stock planning, product arrangement, and promotional decision-making in fresh fruit retail.

2. RESEARCH METHOD

This study employs a quantitative data mining approach using the Apriori algorithm to identify association relationships among fruit products and to classify product popularity based on support values. The dataset consists of 50 sales transactions involving 25 fruit items collected from a single fruit retail store. A total sampling technique was applied, in which all available transactions during the observation period were analyzed to represent actual purchasing conditions. (Irawan & Harlina, n.d.).

A minimum support threshold of 30% was applied to focus on frequently purchased items while avoiding the generation of excessive low-frequency patterns, considering the relatively small dataset size. Meanwhile, a minimum confidence threshold of 60% was used to ensure reliable and interpretable purchasing relationships. These threshold values were selected to balance the number and quality of association rules, resulting in a limited set of strong rules with confidence values above 60% and lift values greater than 1 (Fahmi Achmad et al., n.d.; Syahputra Sari & Wahyuni, 2024).

Although the Apriori algorithm involves repeated candidate generation and database scanning, its computational complexity remains manageable due to the limited dataset size of 50 transactions and 25 items, making it suitable for exploratory analysis. A preliminary threshold sensitivity test was conducted by applying lower support values, which generated numerous weak and less actionable rules. Therefore, the selected thresholds were considered optimal for this study. Compared to FP-Growth and Eclat, the Apriori algorithm was chosen for its transparency and ease of interpretation rather than computational efficiency, given the small-scale nature of the dataset.

Table 1. Transaction Data

No	Data Item Set
1	Citra Guava, Matoa, Orange, Apple, Avocado, Deli Guava.
2	Citra Guava, Green Guava, Passion Fruit, Avocado, June Plum.
3	Citra Guava, Matoa, June Plum, Watermelon, Orange.
4	Citra Guava, Matoa, Avocado, Apple, Orange, Deli Guava.
5	Citra Guava, Matoa, Apple, Orange, Avocado, June Plum.
6	Citra Guava, Matoa, June Plum,

	Orange, Deli Guava.
7	Citra Guava, Orange, June Plum, Matoa, Watermelon.
8	Matoa, Citra Guava, Deli Guava, June Plum.
9	Citra Guava, Deli Guava, Matoa, Mango.
...	...
50	Dragon Fruit, Strawberry, June Plum, Rambutan, Grape, Avocado, Matoa.

The data in Table 1 were then used to calculate the frequency of occurrence for each fruit item. To simplify the identification process, all analyzed items are summarized in Table 2, which includes 25 types of fruits. This list serves as a reference for mapping each item during the support calculation process.

Table 2. Item Name

No	Item Name
1	Citra Guava
2	Matoa
3	Green Guava
4	June Plum
5	Orange
6	Avocado
7	Apple
8	Mango
9	Watermelon
10	Deli Guava
11	Passion Fruit
12	Papaya
13	Melon
14	Pineapple
15	Starfruit
16	Sapodilla
17	Pear
18	Strawberry
19	Kiwi
20	Grape
21	Snake Fruit
22	Rambutan
23	Soursop
24	Lychee
25	Dragon Fruit

Next, product popularity levels were determined using the criteria in Table 3, which divides support values into five categories, ranging from Not Popular to Very Popular. These criteria were used as guidelines for popularity classification in the final stage of the study.

Table 3. Criteria table

Criteria Code	Criteria Name	Support Range
K1	Not Popular	< 20%
K2	Less Popular	20% – 39%
K3	Moderately Popular	40% – 59%
K4	Popular	60% – 79%
K5	Very Popular	> 80%

Before the computational stage, data preprocessing was conducted, including transaction restructuring and validation to ensure compatibility with the Apriori algorithm. Apriori has computational complexity that increases with the number of items and transactions due to repeated candidate generation and database scanning. However, given the relatively small dataset of 25 items and 50 transactions, the computational cost remains manageable, making Apriori suitable for this study. After the data were validated, the support value was calculated using the formula:

$$\text{Support} = \frac{Number\ of\ Transactions\ Containing\ A}{Total\ Transactions} \times 100\%$$

The support values of all items are presented in Table 4 and were used to identify products that meet the minimum support threshold of 30%. Compared to FP-Growth and Eclat, which are more efficient for large datasets, Apriori was selected for its simplicity, transparency, and suitability for exploratory analysis on small-scale fruit retail data (Fitriani & Malik, 2021; Noviana et al., 2023).

Table 4. Determining Support Value

No	Item Name	Transaction Frequency / Number of Transactions	Support	Description
1	Citra Guava	31	62%	Passed
2	Matoa	31	62%	Passed
3	Green Guava	21	42%	Passed
4	June Plum	23	46%	Passed
5	Orange	24	48%	Passed
6	Avocado	10	20%	Failed
7	Apple	11	22%	Failed
8	Mango	9	18%	Failed
9	Watermelon	13	26%	Failed
10	Deli Guava	17	34%	Passed
11	Passion Fruit	7	14%	Failed
12	Papaya	7	14%	Failed
13	Melon	3	6%	Failed
14	Pineapple	5	10%	Failed
15	Starfruit	3	6%	Failed
16	Sapodilla	5	10%	Failed
17	Pear	5	10%	Failed
18	Strawberry	3	6%	Failed
19	Kiwi	6	12%	Failed
20	Grape	9	18%	Failed
21	Snake Fruit	5	10%	Failed
22	Rambutan	6	12%	Failed
23	Soursop	5	10%	Failed
24	Lychee	6	12%	Failed
25	Dragon Fruit	6	12%	Failed
Total Transactions		50		

Based on Table 4, six products meet the minimum support threshold: Citra Guava, Matoa, Green Guava, June Plum, Orange, and Deli Guava. A preliminary threshold sensitivity test indicated that lower support values produced numerous weak rules, while higher thresholds significantly reduced the number of generated rules. Therefore, the thresholds of 30% support and 60% confidence were selected to balance rule relevance and practical applicability. These items are summarized in Table 5.

Table 5. Items That Passed

Item Code	Item Name	Transaction Frequency / Number of Transactions
1	Citra Guava	31
2	Matoa	31
3	Green Guava	21
4	June Plum	23
5	Orange	24
10	Deli Guava	17

After determining the items that passed (frequent 1-itemset), the study proceeded to the formation of two-item combinations. The results of the frequent 1-itemset calculations are shown in Table 6, which displays the support values of each item pair (Kurnia & Santoso, 2024).

Table 6. Determining Frequent 1-Itemset (L1)

No	Item Set	Citra Guava, Matoa	Citra Guava, Green Guava	Citra Guava, June Plum	Citra Guava, Orange	Citra Guava, Deli Guava	Matoa, Green Guava	...	Orange, Deli Guava
1	Transaction Frequency / Number of Transactions	27	15	19	16	13	13	...	7
2	Support	54%	30%	38%	32%	26%	26%	...	14%
3	Values Less Than 30%	-	15	-	-	13	13	...	7
4	Values Greater Than 30%	27	-	19	16	-	-	...	-
5	Description	Passed	Passed	Passed	Passed	Failed	Failed	...	Failed

From Table 6, item pairs that meet the minimum support value were obtained. These results were then summarized in Table 7, which presents the list of 2-itemset combinations that advanced to the association rule formation stage. Only combinations with minimum support ≥ 30% are listed in Table 7 for further analysis.

Table 7. Frequent 1-Itemset Results That Passed

Item Code	Item Name	Transaction Frequency / Number of Transactions	Description
1	Citra Guava, Matoa	27	Passed
3	Citra Guava, June Plum	19	Passed
4	Citra Guava, Orange	16	Passed
5	Matoa, June Plum	16	Passed
6	Citra Guava, Green Guava	17	Passed
7	Matoa, Deli Guava	17	Passed

Next, an attempt was made to form frequent 2-itemset (L2) consisting of three-item combinations. However, the results shown in Table 8 indicate that none of the combinations meet the predetermined minimum support value.

Table 8. Determining Frequent 2-Itemset (L2)

No	Item Set	Citra Guava, Matoa, June Plum	Citra Guava, Matoa,Orange	Citra Guava, Matoa, Green Guava	Citra Guava, June Plum, Orange	Citra Guava, Matoa, Green Guava	Citra Guava, Orange, Green Guava	Matoa, June Plum, Deli Guava
1	Transaction Frequency / Number of Transactions	15	13	12	10	8	6	3
2	Support	30%	26%	24%	20%	16%	12%	6%
3	Values Less Than 30%	15	13	12	10	8	6	3
4	Values Greater Than 30%	-	-	-	-	-	-	-
5	Description	Failed	Failed	Failed	Failed	Failed	Failed	Failed

Since no 3-itemset combinations met the minimum support criteria, the formation of association rules was conducted only on the 2-itemset combinations listed in Table 7. The confidence and lift calculations are presented in Table 9 as the basis for determining valid association rules. Confidence values were calculated using the formula:

$$\text{Confidence}(A \rightarrow B) = \frac{Support\ (A,B)}{\text{Support (A)}} \times 100\%$$

Meanwhile, lift values were calculated using the formula:

$$\text{Lift}(A \rightarrow B) = \frac{Support\ (A,B)}{\text{Support (A)} \times \text{Support (B)}} \times 100\%$$

The confidence and lift values for all rules are provided in Table 9.

Table 9. Formation of Association Rules

Item Code	Item Name – L2	Support	Item Name – L1	Support – L1	Confidence	Description	Lift
1	Citra Guava, Matoa	54%	Citra Guava	62	87	Passed	1.404786681
2	Citra Guava, Matoa	54%	Matoa	62	87	Passed	1.404786681
3	Citra Guava, June Plum	38%	Citra Guava	62	61	Passed	1.332398317
4	Citra Guava, June Plum	38%	June Plum	46	83	Passed	1.332398317
5	Citra Guava, Orange	32%	Citra Guava	62	52	Failed	1.075268817
6	Citra Guava, Orange	32%	Orange	48	67	Passed	1.075268817
7	Matoa, June Plum	32%	Matoa	62	52	Failed	1.22019635
8	Matoa, June Plum	32%	June Plum	46	70	Passed	1.22019635
9	Citra Guava, Green Guava	30%	Citra Guava	62	48	Failed	1.051893408
10	Citra Guava, Green Guava	30%	Green Guava	42	71	Passed	1.152073733
11	Matoa, Deli Guava	30%	Matoa	62	48	Failed	1.152073733
12	Matoa, Deli Guava	30%	Deli Guava	34	88	Passed	1.423149905

The rules that meet the requirements of minimum confidence ≥ 60% and lift > 1 are presented in Table 10 as the final association rules.

Table 10. Association Rules That Passed

Item Code	Item Name = L2	Confidence	Description	Lift
1	Citra Guava, Matoa	87%	Passed	1.404786681
1	Citra Guava, Matoa	87%	Passed	1.404786681
3	Citra Guava, June Plum	61%	Passed	1.332398317
3	Citra Guava, June Plum	83%	Passed	1.332398317
4	Citra Guava, Orange	67%	Passed	1.075268817
5	Matoa, June Plum	70%	Passed	1.122019635
6	Citra Guava, Green Guava	71%	Passed	1.051893408
7	Matoa, Deli Guava	88%	Passed	1.423149905

The final stage of the analysis is classifying all items based on their popularity levels using the criteria in Table 3. The complete results are shown in Table 11, which presents the popularity category of each fruit product, including the popularity status of each item (Hibnastiar et al., 2025; Nizaela F et al., 2022).

Table 11. Determining the Popular Product Table

No	Item Name	Transaction Frequency	Support	Criteria Name
1	Citra Guava	31	62%	Popular
2	Matoa	31	62%	Popular
3	Green Guava	21	42%	Moderately Popular
4	June Plum	23	46%	Moderately Popular
5	Orange	24	48%	Moderately Popular
6	Avocado	10	20%	Less Popular
7	Apple	11	22%	Less Popular
8	Mango	9	18%	Not Popular
9	Watermelon	13	26%	Less Popular
10	Deli Guava	17	34%	Less Popular
11	Passion Fruit	7	14%	Not Popular
12	Papaya	7	14%	Not Popular
13	Melon	3	6%	Not Popular
14	Pineapple	5	10%	Not Popular
15	Starfruit	3	6%	Not Popular
16	Sapodilla	5	10%	Not Popular
17	Pear	5	10%	Not Popular
18	Strawberry	3	6%	Not Popular
19	Kiwi	6	12%	Not Popular
20	Grape	9	18%	Not Popular
21	Snake Fruit	5	10%	Not Popular
22	Rambutan	6	12%	Not Popular
23	Soursop	5	10%	Not Popular
24	Lychee	6	12%	Not Popular
25	Dragon Fruit	6	12%	Not Popular

All these stages form a comprehensive analytical process using the Apriori algorithm to uncover consumer purchasing patterns and identify the most preferred products. Thus, the entire analysis using the Apriori algorithm was conducted systematically, from preprocessing to the formation of association rules (Saidah et al., n.d.).

3. RESULTS AND DISCUSSIONS

This section presents the results of purchasing pattern analysis using the Apriori algorithm and discusses the findings in comparison with previous studies in other retail contexts.

3.1 Support Analysis

Based on Table 4, six fruit items meet the minimum support threshold of ≥30%. Citra Guava and Matoa show the highest support values (62%), indicating strong consumer preference and high demand. Similar demand concentration has been reported in supermarkets and minimarkets, where a small number of products dominate sales volume (Purnama et al., 2025; Rokhmah & Bagoes Pakarti, 2024).

However, in fresh fruit retail, this concentration is more pronounced due to perishability, freshness perception, and daily consumption patterns, which limit consumer choices to a few frequently consumed fruits(Abidin et al., 2022; Muharni & Andriyanto, 2024).

3.2 Formation of Frequent Itemsets

The analysis of 2-itemsets (Table 6 and Table 7) reveals frequent combinations such as Citra Guava–Matoa (54%) and Citra Guava–June Plum (38%), suggesting complementary purchasing behavior influenced by taste compatibility and household consumption habits (Nawangsih & Purnamasari, 2023). In contrast, no 3-itemset combinations meet the minimum support threshold. This finding differs from general retail studies involving packaged goods, where multi-item combinations are more common due to longer shelf life and complementary usage (Anggraini et al., 2020; Keputusan Pembentukan Paket Penjualan Bibit Buah et al., n.d.; Thariq, 2023). In fruit retail, purchasing decisions tend to be simpler and driven by immediate consumption needs.

3.3 Formation of Association Rules

The strongest association rules include Citra Guava–Matoa (confidence 87%, lift 1.40) and Deli Guava–Matoa (confidence 88%, lift 1.42). Lift values greater than 1 indicate stable and non-random purchasing relationships. These rules implicitly form a simple association network centered on high-demand fruits, indicating rule stability despite the absence of complex multi-item combinations. From an economic perspective, such stable associations can be leveraged to optimize shelf arrangement, design bundling promotions, and support cross-selling strategies, which may reduce spoilage costs and improve inventory turnover in fresh fruit retail (Qoni'ah & Priandika, 2020) (Hibnastiar et al., 2025).

3.4 Product Popularity Analysis

Product popularity classification (Table 11) shows that only Citra Guava and Matoa fall into the "Popular" category, while Orange, June Plum, and Green Guava are classified as "Moderately Popular." Most other fruits exhibit low demand. This pattern highlights the importance of selective inventory allocation in fresh fruit retail to minimize losses from unsold perishable products and improve stock turnover (Sari & Nasution, 2025; Syahputra Sari & Wahyuni, 2024).

3.5 Research Gap and Contribution

Unlike most previous market basket analysis studies conducted in non-perishable retail contexts, which often identify complex multi-item purchasing patterns, this study demonstrates that purchasing behavior in fresh fruit retail is more concentrated and structurally simpler (Abidin et al., 2022; Adhinda et al., 2020; Nawangsih & Purnamasari, 2023). This difference can be attributed to the perishable nature of fresh fruits, short consumption cycles, and consumers' sensitivity to freshness, which limit the formation of large item combinations. These findings highlight the methodological limitation of directly generalizing association rules from packaged or durable goods retail to fresh produce contexts. Consequently, this study contributes by extending the application of the Apriori algorithm to perishable retail data and providing empirical evidence that domain-specific characteristics significantly influence the structure and stability of purchasing patterns. (Hidayat et al., 2023; Keputusan Pembentukan Paket Penjualan Bibit Buah et al., n.d.).

4. CONCLUSION

This study demonstrates that the Apriori algorithm can be effectively applied to analyze purchasing patterns and product popularity in fresh fruit retail. Beyond identifying frequently purchased fruits and association rules, the findings highlight that fruit purchasing behavior tends to be concentrated on a limited number of high-demand items, with relatively simple purchasing combinations. This characteristic distinguishes fresh fruit retail from other retail contexts involving packaged or durable goods (Herdiansyah, 2025; Keputusan Pembentukan Paket Penjualan Bibit Buah et al., n.d.).

Despite these contributions, this study has several limitations. First, the analysis is based on a relatively small number of transactions (50 transactions), which may limit the generalizability of the findings. Second, the data were collected from a single retail location, so the identified purchasing patterns may reflect local consumer preferences rather than broader market behavior. Third, this study does not consider seasonal variations and price factors, which are known to significantly influence fruit availability and consumer purchasing decisions (Prayogi et al., 2025; Qoni'ah & Priandika, 2020).

From a theoretical perspective, this study contributes to the literature on market basket analysis by demonstrating that association rule mining in perishable product contexts tends to produce simpler and more stable purchasing patterns compared to general retail products. Methodologically, the study shows that the Apriori algorithm remains suitable for small-scale datasets and exploratory analysis in fresh produce retail, where interpretability and transparency are prioritized over computational efficiency (Apriori Boby & Almaida Siregar, 2022).

From a practical standpoint, the findings provide evidence that data-driven analysis can support inventory planning, shelf arrangement, and promotional strategies aimed at reducing spoilage and stock inefficiencies in fruit retail. However, these implications should be interpreted cautiously due to the study's scope limitations (Anggraini et al., 2020; Hadinata et al., n.d.).

Future research is recommended to use larger and multi-location datasets to improve the robustness and generalizability of fruit purchasing patterns. Incorporating seasonal data, price variations, and promotional factors would also enhance analytical accuracy. Additionally, comparative studies involving alternative algorithms such as FP-Growth or Eclat could further evaluate methodological efficiency and pattern stability across different retail conditions.

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