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Analysis of Bread Sales Patterns at Queen Bakery Stores Using Algorithms *Fpgrowth*

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Abstract

The culinary industry, particularly the bakery business, is experiencing rapid growth with increasing competition. Changes in consumer trends, the rising number of market players, and fluctuating market dynamics pose significant challenges in maintaining stable sales. Queen Bakery, a bakery located in Medan, faces issues with fluctuating monthly sales, indicating that certain products are less in demand and that more effective marketing strategies are needed. To address this issue, the utilization of technology in data analysis is essential, particularly through the implementation of data mining techniques. Data mining enables the identification of consumer purchasing patterns more accurately and data driven. One of the most effective algorithms for sales pattern analysis is FPGrowth, which can identify frequently occurring itemsets in transactions. Unlike the Apriori algorithm, which requires extensive computations, FPGrowth is more efficient in discovering product associations frequently purchased together. This study aims to analyze sales patterns at Queen Bakery using the FPGrowth algorithm to provide strategic insights into inventory management and product marketing. The results of this research are expected to assist Queen Bakery in improving operational efficiency, optimizing product offerings, and formulating more competitive business strategies. By implementing data mining, the bakery can gain a deeper understanding of consumer preferences, ultimately enhancing sales performance and competitiveness in the dynamic culinary market.

Keywords: Data Mining, Sales Pattern Analysis, FPGrowth Algorithm, Marketing Strategy.

1. Introduction

In a period of rapid trade development, especially in the world of culinary sales, the passage of time has had a tremendous impact on changes and developments that cannot be avoided. As time goes by, it faces different challenges, such as increasingly tight industrial competition due to rising costs, expanding production volumes, and especially mechanics that know no boundaries [1][2]. This situation creates a dynamic trading environment, where competitiveness between businesses becomes a strength. The push in data innovation, especially in this advanced era, has had an important impact on various points of view of life [3]. The use of data innovation is not only limited to existence, but also extends to the world of commerce and companies, creating fun collaborations [4][5].

Ease of access to data innovation brings changes in trading standards and the way trade is conducted. Today, implementing data innovation is not an alternative, but a fundamental necessity to remain competitive and important. Businesses and entrepreneurship that are able to embrace data innovation remarkably have a preference in proficiency, faster choice making, and much better client engagement [6].

In the domain of commerce and business companies, consumer interest in buying is the most important determinant of victory [7]. Indeed, even though it is hidden within each buyer without clear rules, this buying interest is the key in describing the direction and sustainability of trading [8]. The rapid growth of bakeries in Indonesia reflects changes in consumer design and active advertising demand. Choosing a more up-to-date framework in bakery operations provides a focal point in bookkeeping skills and meets the growing needs of society [9].

In today's developing business world, many companies compete to increase sales turnover, such as bakeries. Bread made from wheat flour is popular among people and has become very popular. Bread can be a daily staple food, especially breakfast because of the abundance of

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nutrients in bread. The Queen Bakery bakery is one of the shops located on Jl. Durung No.97, Sidorejo Hilir, Medan Tembung, Medan City. Every day the Queen Bakery shop carries out activities such as sales transactions, receiving orders, providing bread stock and so on. However, this bakery experienced ups and downs in sales. One of the factors is that market competition in the bakery business is increasing, sales that fluctuate every month indicate that there are products that are not selling well, so proper analysis is needed. Therefore, methods are used that can produce information or marketing strategies in analyzing sales patterns to increase sales, namely the field of data science. *mining*.

Good business strategy techniques are really needed to gain profits in a good way and reduce losses to the bakery. To overcome this problem, you can use data mining techniques [10]. Data mining techniques require complex calculations, one of which is algorithm patterns *FPGrowth*, namely an algorithm that fixes the shortcomings of the Apriori algorithm [11]. *FPGrowth* can be used to determine the most frequently occurring data sets (*Frequent itemset*) in a data set [12][13]. Researchers will use algorithms *FPGrowth* against sales data at Queen's bakery to associate the number of bread products that consumers buy most. Data *Mining FPGrowth* useful in providing solutions for making decisions in improving successful business strategies in the midst of a competitive market [14]. FP-Growth was chosen because it has better efficiency than algorithms such as Apriori, especially for large datasets. Apriori uses a candidate generation approach, which means it must generate and evaluate many combinations of items before finding frequently occurring patterns. In contrast, FP-Growth uses the FP-Tree (Frequent Pattern Tree) structure to store transaction data in the form of a tree, which reduces the need to generate candidates explicitly and increases the efficiency of pattern search. In the case of bakery sales, if the dataset consists of many transactions with not too many items per transaction, FP-Growth is still superior because it is able to handle a lot of data quickly without having to store all candidate itemsets in memory. FP-Growth's main advantage over algorithms like Apriori is its efficiency in handling large datasets, as it only requires two scans of the data before building an FP-Tree. If the dataset is enlarged, FP-Growth is still relatively efficient compared to other algorithms, but there are still limitations in memory consumption. Therefore, research was carried out with the title sales pattern analysis using algorithms *FPGrowth*.

2. Research Methods

2.1. *Research Framework*

A research framework is a conceptual structure used to plan, design, and direct a study. So that when conducting research it becomes structured systematically and can be accepted by all parties [15]. The following is a framework for the research stages that will be carried out to solve the problems to be discussed:

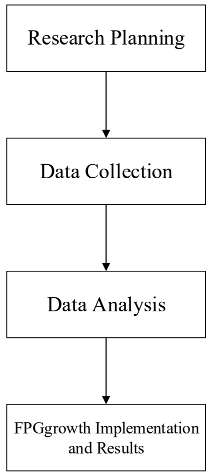

Figure 1. Research Framework

2.1.1 Research Planning: In general, planning is defined as an activity that examines what will be done, how to do it and when it will be done. Research planning or in various research textbooks is called research design, which means all the processes required in planning and implementing research. This research was carried out by applying the algorithm method *FPGrowth* in the analysis of bread sales patterns.

2.1.2 Data collection is a systematic process of collecting, organizing, and storing relevant and reliable information from various sources for analytical purposes [16]. In this research, the dataset used is the Queen Bakery bakery transaction dataset. The dataset obtained by this researcher is the data provided *manager* shop. So the data obtained amounts to 1010 *rows* data consisting of 7 variables and 45 menu types.

2.1.3 Data Analysis includes several steps, such as data cleaning and transformation, data exploration to extract initial information, application of analysis methods such as algorithms *FPGrowth* to find association patterns, as well as interpret the results and prepare reports to be presented to related parties. In this way, data analysis becomes a crucial stage in research that helps transform raw data into useful and actionable information. This analysis also shows how data can be used effectively to understand customer behavior and optimize business strategies.

2.1.4 Implementation and Results *FPGrowth* used to find frequency patterns that frequently appear in large data sets, such as in transaction data analysis. The aim is to meet the needs of researchers and present a clear picture and complete design. The stage begins with planning *flowchart* appropriate to this research process. *Flowchart* This will be used as a guide in carrying out the stages or processes in implementation by applying the algorithm method *FPGrowth*, this method is for finding frequently occurring items. The results obtained from *FPgrwoth* give *Frequent Itemset* that can be used is to find associations between items then suggest to customers who buy and also analyze customer purchasing patterns to understand their habits and improve marketing or sales strategies [17][18].

2.2. *Modeling*

In this research, modeling will be carried out using an algorithm *FPGrowth* for processing product data. Data engineering *mining* The one chosen in this research is the association technique [19]. Modeling aims to find association rules, where the association rules are then used as a reference for determining product stock [20]. The steps for forming a data model are: *mining* with algorithms *FPGrowth* below this.

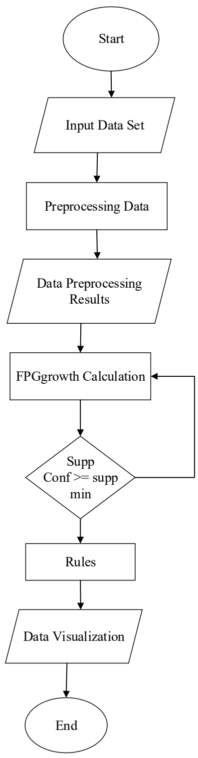

Figure 2. Flowchart Algoritma FPGrowth [21]

2.3. *Frequent Itemset Results*

Implementation is carried out by conducting trials on data that has been successfully collected. Where in this research uses language *python* And *google colaboratory* to run it and use *software rapidminer* as *tools* displays data visualization.

3. Results and Discussion

In this discussion, there are several discussions that must be resolved. The stages that will be discussed in this research are data collection, data analysis, and implementation and results *FPGrowth* as follows.

3.1. *Data Collection*

Product data on Queen Bakery is a collection of information that includes various types of bread sold by the shop. This data contains details about each product, such as transaction id, product name, quantity, and price. This information is critical for knowing customer preferences, managing inventory, and determining effective sales strategies. In addition, product data also records transactions involving each type of bread, such as the types of bread most frequently purchased, popular product combinations, as well as certain purchase times that indicate high demand. For example, holidays and seasonal changes can affect the demand for bread. For example, sales of tart bread or sweet bread may increase during holidays or weekends because they are used for celebrations. Meanwhile, on weekdays, plain bread or sandwiches are more popular as a practical breakfast. Food trends and the presence of competitors can also influence sales patterns. If the healthy food trend increases, customers may prefer whole wheat bread over sweet bread. In addition, if competitors offer attractive promotions, the store must adjust its sales strategy to remain competitive. External data such as weather, local events, or government policies (e.g. pandemic restrictions) can be integrated with transaction data to estimate sales trends. For example, cold weather might increase demand for bread with chocolate or cheese fillings. By using this data, Queen Bakery can analyze customer purchasing patterns, identify superior products, and optimize promotional strategies and stock management.\

Table 1. Product Data

Transaction Id	Product name	Quantity	Price
1	Vanilla	4	30.000
2	Hot Dog	4	20.000
3	Strawberry	4	15.000
4	Noodle Patties	5	20.000
5	Pasta Patties	5	20.000
6	Hello Kulcha	1	20.000
….	....	….	….
1010	Vanilla	3	30.000

3.2. *Data analysis*

This research aims to analyze bread sales patterns based on transaction data at the Queen Bakery Shop using an algorithm *FPGrowth*. This method was chosen because of its ability to discover significant purchasing patterns from large transaction data, thereby providing deep insight into customer preferences. Before analysis, data must go through a cleaning process, such as removing duplicate transactions, dealing with missing data, and ensuring date and price formats comply with standards. The data used includes 1,010 transactions recorded during a certain period, with a total of 43 types of bread available. At the data analysis flow stage, sales transaction data will be collected and then data analysis will be carried out using an algorithm. *FpGrowt*h so as to get the results of the data analysis.

Data preprocessing includes converting transaction data to a format suitable for the FP-Growth algorithm, such as grouping transactions by time, product category, and purchase amount. Data can also be encoded in binary form (e.g., 1 if the product was purchased in a transaction, 0 otherwise). The transformation data was obtained from the selection of sales data for 6 months consisting of 1010 transactions. At around 10,000 transactions, FP-Growth's execution time is still relatively fast, usually only seconds to minutes on computers with standard specifications. The FP-Tree structure can still be built efficiently as long as each transaction does not contain too many unique items. However, when the number of transactions increases to 100,000, FP-Growth can still work well, but the processing time can increase significantly, especially if the dataset has many different items or if the minimum support value is too low. A low minimum support value will result in more patterns that must be processed, thereby increasing the complexity of calculations and increasing memory consumption. Therefore, in scenarios with a large number of transactions, optimizations such as increasing the minimum support value or using parallel processing techniques are required to maintain algorithm efficiency. Available in Table 2 *Dataset* used is sample sales transaction data. Each row represents an item and each column represents a sales transaction. The values 0 and 1 have their own meanings, namely the value 1 indicates that the item was purchased in a particular transaction while the value 0 is the opposite.

Table 2. Sales Transaction Data in Binominal Format

Transaction ID	**Alloo Kulcha**	**Aloo Patties**	**BIF**	**UNTIL**	**Black Forest**	**Burger**	**Butter Scotch**	**Cassata**	**Cheese Chilly Roll**
1	1	0	0	0	1	0	0	0	0
2	0	0	0	0	0	0	0	0	1
3	0	0	0	1	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	1
7	0	0	0	1	0	0	0	0	0
8	0	0	0	1	0	0	0	0	0
9	0	0	0	0	0	0	0	1	0
10	0	0	0	0	0	0	0	0	0
…	…	…	…	…	…	…	…	…	…
1010	0	0	0	1	0	0	0	0	0

In the data presented, *Truffle* being the item with the highest frequency of 85, indicating its dominant popularity. Followed by *Small Pizza* with 81, *Pineapple* And *Chocolate 1P* 80 each, as well *Choco Pudding* as many as 77. Item combinations also have their own place, with *Pineapple*, *Truffle* being the most frequently appearing 12 times. Some other combinations such as *Chocolate 1P, Strawberry Pudding*, *Butter Scotch, Hot Dog*, And *Choco Pudding, Strawberry* each recorded 10 times. Other combinations, such as *Cheese Chilly Roll, Mango Pastry*, *Chocolate 1P, Mango Pastry*, And *Choc Roll, Tandoori Kulcha*, has a similar frequency, namely 9. Interestingly, there are also combinations that are very rarely found, such as *Burger, Noodle Patties, Onion Sandwich* And *Black Forest, Chocolate 1P, Cream Roll, Strawberry Pudding*, each only appearing once. This data provides insight into preferences for particular items and combinations, with a number of prominent patterns in individual items and favorite combinations.

From these data, it can be seen that the combination with medium frequencies, such as *Small Pizza, Truffle* which appeared 8 times, indicating a unique preference for certain items, although not as high as other popular items. On the other hand, combinations with low frequencies, such as *Burger, Noodle Patties, Onion Sandwich* And *Black Forest, Chocolate 1P, Cream Roll, Strawberry Pudding*, reflects tastes that consumers may rarely choose.

This shows the potential for offering packages *bundling* that combines these products, especially for customers looking for variety. Overall, this data provides insight into the popularity of individual products and purchasing patterns of product combinations. This information can be used to develop more effective marketing strategies, such as promotions on high-frequency product combinations or more efficient stock management for products that are frequently purchased together.

Table 3. Frequency of Appearance of Each Product

No	Product name	Frequency
1	Truffle	85
2	Small Pizza	81
3	Pineapple	80
4	Chocolate 1p	80
5	Choco Pudding	77
6	Pineapple, Truffle	12
7	Chocolate 1P, Strawberry Pudding	10
8	Butter Scotch, Hot Dog	10
9	Choco Pudding, Strawberry	10
10	Cheese Chilly Roll, Mango Pastry	9
11	Chocolate 1P, Mango Pastry	9
12	Choc Roll, Tandoori Kulcha	9
13	Butter Scotch, Club Sandwich	9
14	Small Pizza, Truffle	8
15	Burger, Noodle Patties, Onion Sandwich	1
16	Black Forest, Chocolate 1P, Cream Roll, Strawberry Pudding	1

Support is a measure that indicates how often an item or combination of items (*itemset*) appears in the overall transaction data. This value describes the level of existence of the item or *itemset* it's deep *dataset*. *Support* calculated by dividing the number of transactions containing the item or *itemset* certain amount of transactions.

For example, by using the formula *support*, we can calculate that:

$$Support\ (A) = \frac{Number\ of\ transactions\ containing\ item\ A}{Total\ Transactions} \times 100\% \quad (1)$$

$$Support\ (A, B) = \frac{Number\ of\ transactions\ containing\ items\ A\ and\ B}{Total\ Transactions} \times 100\% \quad (2)$$

$$Support(Truffle)\,\frac{85}{1010}x100\% = 8\%$$

$$Support(Small\ Pizza)\,\frac{81}{1010}x100\% = 8\%$$

$$Support(Pineapple)\,\frac{80}{1010}x100\% = 8\%$$

$$Support(Chocolate\ 1p)\,\frac{80}{1010}x100\% = 7\%$$

$$Support(Choco\ Pudding)\,\frac{77}{1010}x100\% = 7\%$$

$$Support(Pineapple, Truffle)\,\frac{12}{1010}x100\% = 1\%$$

$$Support(Chocolate\ 1P, Strawberry\ Pudding)\,\frac{10}{1010}x100\% = 0{,}9\%$$

$$Support(Butter\ Scotch, Hot\ Dog)\,\frac{10}{1010}x100\% = 0{,}9\%$$

$$Support(Choco\ Pudding, Strawberry)\,\frac{10}{1010}x100\% = 0{,}9\%$$

$$Support(Cheese\ Chilly\ Roll, Mango\ Pastry)\,\frac{9}{1010}x100\% = 0{,}8\%$$

$$Support(Chocolate\ 1P, Mango\ Pastry)\,\frac{9}{1010}x100\% = 0{,}8\%$$

$$Support(Choc\ Roll, Tandoori\ Kulcha)\,\frac{9}{1010}x100\% = 0{,}8\%$$

$$Support(Butter\ Scotch, Club\ Sandwich)\,\frac{9}{1010}x100\% = 0{,}8\%$$

$$Support(Small\ Pizza, Truffle)\,\frac{8}{1010}x100\% = 0{,}7\%$$

$$Support(Burger, Noodle\ Patties, Onion\ Sandwich)\,\frac{1}{1010}x100\% = 0{,}09\%$$

$$Support(BF, Chocolate1P, CR, SP)\,\frac{1}{1010}x100\% = 0{,}09\%$$

The following data shows the value *support* or the proportion of occurrences of various items and combinations of items in a whole *dataset*. *Truffle* has value *support* the highest was 0.084, followed by *Small Pizza* And *Pineapple* each with a value *support* 0.080, as well *Chocolate 1P* with 0.079. *Choco Pudding* is slightly below it in value *support* 0.076. Among the combinations, *Pineapple, Truffle* has value *support* the highest is 0.011, while other combinations such as *Chocolate 1P, Strawberry Pudding*, *Butter Scotch, Hot Dog,* And *Choco Pudding, Strawberry* has value *support* the same, namely 0.009. Combinations like *Cheese Chilly Roll, Mango Pastry, Chocolate 1P, Mango Pastry,* And *Choc Roll, Tandoori Kulcha* has value *support* of 0.008, which is also comparable to *Butter Scotch, Club Sandwich*. Meanwhile, combinations such as *Small Pizza, Truffle* has value *support* smaller, namely 0.007. Interestingly, the two least common combinations found, viz *Burger, Noodle Patties, Onion Sandwich* And *Black Forest, Chocolate 1P, Cream Roll, Strawberry Pudding,* only has value *support* of 0.0009. Mark *support* This provides insight into the level of popularity of items and combinations, so it can be used to determine more effective marketing strategies.

Table 4. Calculation of Support Values

No	Product name	Support
1	Truffle	0,084
2	Small Pizza	0,080
3	Pineapple	0,080
4	Chocolate 1p	0,079
5	Choco Pudding	0,076
6	Pineapple, Truffle	0,011
7	Chocolate 1P, Strawberry Pudding	0,009
8	Butter Scotch, Hot Dog	0,009
9	Choco Pudding, Strawberry	0,009
10	Cheese Chilly Roll, Mango Pastry	0,008

11	Chocolate 1P, Mango Pastry	0,008
12	Choc Roll, Tandoori Kulcha	0,008
13	Butter Scotch, Club Sandwich	0,008
14	Small Pizza, Truffle	0,007
15	Burger, Noodle Patties, Onion Sandwich	0,0009
16	Black Forest, Chocolate 1P, Cream Roll, Strawberry Pudding	0,0009

Confidence is an important measure in associative rule analysis that is used to evaluate the relationship between two items in transaction data. This measure shows how likely a customer is to purchase item B if they have purchased item A, thus providing an idea of the strength of the relationship between the two items. *Confidence* helps in determining relevant and frequently occurring customer purchasing patterns, which can be utilized for marketing strategies or stock management.*Confidence* calculated by dividing the values *support* from *itemset* combined (A and B) with *support* from the initial item (A). In other words, this formula describes the percentage of transactions containing item A and item B compared to the total transactions containing item A.

For example, by using the formula *confidence*, we can calculate that:

$$confidence\ (A, B) = \frac{Number\ of\ transactions\ containing\ items\ A\ and\ B}{Total\ Transaction\ A} \times 100 \tag{3}$$

$$Confidence(Truffle, Alloo\ Kulcha) = \frac{3}{85} x100\% = 0{,}03(3\%)$$

$$Confidence(Truffle, Vanilla) = \frac{6}{85} x100\% = 0{,}07(7\%)$$

$$Confidence(Small\ Pizza, Aloo\ Patties) = \frac{4}{81} x100\% = 0{,}05(5\%)$$

$$Confidence(Small\ Pizza, Strawberry) = \frac{8}{81} x100\% = 0{,}09(9\%)$$

$$Confidence(Pineapple, Truffle) = \frac{12}{81} x100\% = 0{,}14(14\%)$$

$$Confidence(Pineapple, Tutti\ Frutti) = \frac{8}{81} x100\% = 0{,}09(9\%)$$

$$Confidence(Chocolate\ 1p, Club\ Sandwich) = \frac{4}{80} x100\% = 0{,}05(5\%)$$

$$Confidence(Chocolate\ 1p, Cream\ Roll) = \frac{5}{80} x100\% = 0{,}06(6\%)$$

$$Confidence(Choco\ Pudding, BIS) = \frac{3}{77} x100\% = 0{,}03(3\%)$$

$$Confidence(Choco\ Pudding, BIF) = \frac{4}{77} x100\% = 0{,}05(5\%)$$

This means that there is a high probability that customers who buy item A will also buy item B. This value provides very useful insight, especially in determining promotional strategies, such as offering discounts for purchasing a combination of items or arranging the layout of products in the store so that items that are frequently purchased together are easier to reach. Thus, *confidence* not only provides a statistical picture, but also acts as a basis for decision making in increasing sales efficiency and customer satisfaction.

Based on available data, the bread products that are often purchased at the Queen Bakery bakery have several association rules produced *FPGrowth* shows the relationship between various items by level *confidence* certain in the form of a percentage. Items *Truffle* have an association with *Alloo Kulcha* with confidence of 4%**,** and with *Vanilla* by 7%. Meanwhile, *Small Pizza* have a relationship with *Aloo Patties* And *Strawberry*, respectively with 4% and 9% confidence. *Pineapple* showed stronger associations with *Truffle* by 14%, as well as with *Tutti Frutti* by 9%. Furthermore, *Chocolate 1p* have a relationship with *Club sandwich* 5% and *Cream Roll* 6%. Final, *Choco Pudding* indicates a relationship with *UNTIL* 5% and *BIF* 3%. These patterns provide valuable insight into customer purchasing habits. The pattern for combining goods and then deciding the price at which they will be sold can be used to improve marketing and sales strategies.

Table 5. Value Calculation *Confidence*

No	Premises	Conculsion	Confidence
1	Truffle	Alloo Kulcha	0,04
2	Truffle	Vanilla	0,07
3	Small Pizza	Aloo Patties	0,04
4	Small Pizza	Strawberry	0,09
5	Pineapple	Truffle	0,14
6	Pineapple	Tutti Frutti	0,09
7	Chocolate 1p	Club sandwich	0,05
8	Chocolate 1p	Cream Roll	0,06
9	Choco Pudding	UNTIL	0,03
10	Choco Pudding	BIF	0,05

3.3. *FPGrowth implementation*

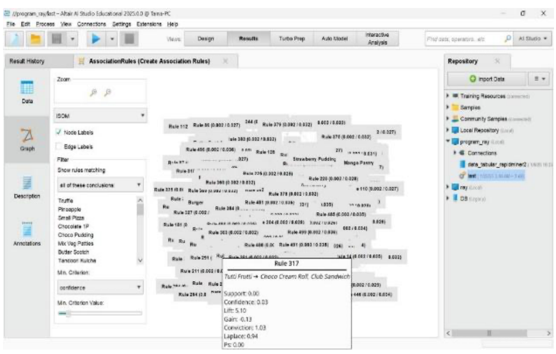

Figure 3. Formed FPTree

These results provide a clear picture of customer purchasing patterns at the Queen Bakery Store. The identified relationships between products can be utilized to improve business strategies, such as creating promotional packages or bundling offers based on combinations of products that are often purchased together. In addition, this information can also be used to organize product layouts in stores so that products that are often purchased together are more accessible to customers, which can ultimately improve their shopping experience.

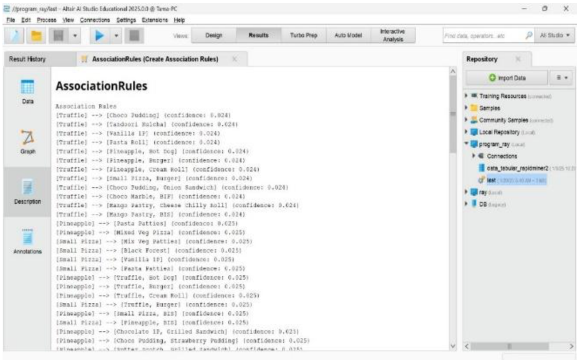

Figure 4. Association Rules

By understanding these patterns, stores can ensure the availability of products that are closely related to purchasing to avoid stock shortages that have the potential to reduce customer satisfaction. This analysis also opens up opportunities for developing more effective marketing strategies, such as offering discounts on certain products to encourage purchases of other product combinations.

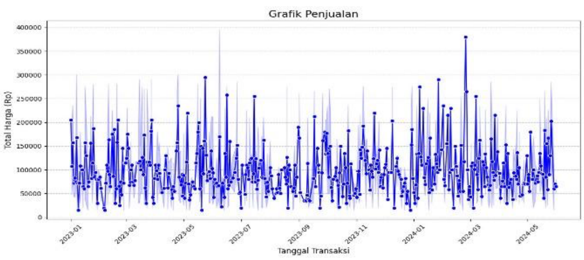

Figure 5. Sales Trend Graph

Next, the display of products sold within a certain period can be seen in the picture.

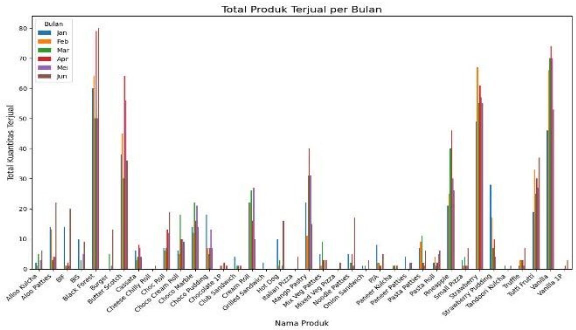

Figure 6. Product Trend Graph

The sales graph displayed depicts the dynamics of total daily revenue from transactions at the Queen Bakery Shop during the observed period. The horizontal axis shows the transaction date, while the vertical axis shows the total sales price in Rupiah (Rp). The fluctuation patterns in these charts provide important insight into sales variations over time. In general, sales show a pattern that fluctuates every day. Several significant spikes were seen, especially at certain times, for example around March 2024, when total sales reached more than IDR 300,000 in one day. This spike may be influenced by external factors such as promotions, national holidays, certain celebrations, or the launch of new products that attract customer interest. This spike indicates the potential for increased shopping activity at these strategic times. On the other hand, there are also periods with relatively low sales, where total daily revenue is below IDR 50,000.

This decline may reflect lower customer traffic on certain weekdays, inclement weather, or other factors that influence consumers' interest in shopping. Patterns like this provide an indication that there is an opportunity to increase sales activity through more aggressive marketing strategies in periods with low sales, such as offering discounts or product bundling packages. From this graph, it can be seen that sales are not constant but tend to have a certain cycle. This suggests that seasonal factors, specific days of the week, or special events play an important role in influencing sales volume. For example, higher sales on weekends or around major holidays can be exploited by stores to design specific promotions to attract more customers.

In addition, this data can also be the basis for managing inventory more effectively. By understanding peak and fall sales periods, stores can ensure sufficient product availability during busy periods and minimize excess stock during periods of low demand. This strategy not only improves operational efficiency but also helps maximize profits. Overall, this sales graph provides valuable insight into consumer behavior at the Queen Bakery Store. Queen Bakery can utilize the results of FP-Growth analysis to improve sales strategies by offering promos or bundling products that are often purchased together. In addition, recommendation-based marketing strategies can be implemented, for example by suggesting purchases of croissants and coffee based on customer shopping patterns. In stock management, this analysis helps stores optimize production quantities to match demand, reduce waste and prevent stock shortages. Additionally, loyalty programs can be tailored to customer preferences, such as offering exclusive discounts on their favorite products, thereby increasing customer satisfaction and retention. By properly utilizing this data, stores can identify opportunities to increase revenue and strengthen their position in the market.

4. Conclusion

Based on research analyzing bread sales patterns at Queen Bakery stores using the FP-Growth algorithm, several significant purchasing patterns were found. Some products such as *Pineapple* have a stronger relationship with *Truffle* (confidence 14%), and *Small Pizza* has a connection with *Strawberry* (confidence 9%). This shows that customers tend to buy certain products together, providing an idea of customer preferences. These patterns can be used to identify popular product combinations and prioritize products that contribute the most to sales. Products with a low level of confidence, such as *Choco Pudding* with *BIF* (3%), may indicate a weak relationship and may require promotional strategies to increase its popularity. Overall, the FP-Growth algorithm succeeded in uncovering associations between products that can be used to increase sales effectiveness and provide a more relevant shopping experience for customers.

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