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ANALYSIS OF THE SELECTION OF THE BEST ARABICA COFFEE BEANS USING APRIORI ALGORITHMS

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ABSTRACT

One of the coffee producers in North Sumatra is Karo Regency. Currently, the growth of coffee production in Indonesia is still hampered by the low quality of the coffee beans produced, which affects the development of the final coffee production. coffee, both in terms of selecting the best coffee beans and in terms of processing and benefits. To overcome this problem requires a system that can assist in making decisions regarding the selection of the best Arabica coffee beans with association pattern rules. As for applying associative rules to the selection of the best Arabica coffee beans in Tanah Karo between item combinations so as to form an itemset combination pattern and the Apriori Algorithm. Important association rules can be known with 2 parameters, namely, minimum support (the percentage of item combinations in the database) and minimum confidence (the strength of the relationship between items in the associative rules), both of which are determined by the user. The results of data mining calculations using the Apriori algorithm, data on the assessment of Mr. RM's coffee beans with a minimum support of 25% and a minimum confidence of 75%, form seven rules for Mr. RM's coffee beans. One of the best rules is that if the selection of Normal Bean Presentation is on the Andungsari 1, Andungsari 2, and Komasti coffee varieties, then with a 100% probability the selection on Leaf Rust Resistance will also be good for the selection of Andungsari 1, Andungsari 2, and Komasti coffee varieties. The best selection combination is {BN,B,KD,A} with a 100% confidence level and has the highest lift value, namely, 3.70.

Keywords: Apriori Algorithms, Association Rules, Coffee Bean Selection Decision Support Systems

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PRELIMINARY

Commodity products that have high economic value among other plantation crops and play an important role as a source of foreign exchange for the country, namely, coffee (Bertona, Faisal, & Handoko, 2020). One of the coffee producers in North Sumatra is Karo Regency. This is because the environment (soil, climate, altitude and temperature) is very good and supports the growth of coffee. Arabica coffee is a leading commodity in addition to horticultural production in Karo Regency (Ginting, Lubis, & Kesuma, 2022). There are

100 species included in the Coffee genus, but only three of them are cultivated by the people of Indonesia, namely Arabica, Robusta, and Liberica (Randriani & Dani, 2018).

Currently, the growth of coffee production in Indonesia is still hampered by the low quality of coffee beans produced, thus affecting the development of final coffee production according to (Supiyandi, Rizal, Siregar, Putra, & Saragih, 2022). Based on the author's observations and interviews with several coffee farmers in Karo, one of the causes of the non-development of coffee cultivation in Karo, because there are still many farmers who do not understand about coffee, both in terms of choosing the best coffee beans and in terms of processing and benefits. So many farmers prefer to grow fruits and vegetables rather than grow coffee. To solve this problem, a system is needed to help make decisions about the best Arabic coffee beans using association rules.

Apriori is part of the frequent itemset search algorithm using the associative rule method (association rules) (Alma'arif, Utami, & Wibowo, 2021). Apriori algorithm that aims to find frequent itemsets that run on a data set (Nasrah, Nasution, & Krianto Sulaiman, 2021). The Apriori method will generate Support, List, and Confident values. It is the values produced by Apriori that will determine the formation of a pattern. The formation of a pattern will make it interesting and a conclusion will be obtained (Dewayanti, 2018). On research (Manurung & Lubis, 2023) conducted research on the Effectiveness of Decision Support Systems for Selection of Hydroponic Plant Nutrients Using the Apriori Algorithm Method. The research aims to determine the pattern of fertilizer use in hydroponic plants. With a minimum support value of 20% and a minimum confidence of 70%, the final results show that the overall lift ratio test is more than 1.05 so that the strength of the association rule is large.

As for applying associative rules to the selection of the best arabica coffee beans in Tanah Karo between combinations of items so as to form a combination pattern of itemset and Aprriri Algorithm. The determination of association rules in the Apriori Algorithm is done iteratively, where to find the k-itemset (combination of itemset on k) can use k-1-itemset (combination of 1 itemset on k) (Rizaldi & Adnan, 2021). The advantages of association rule and Apriori are simpler and high frequency patterns. The advantages of the association rule and Apriori are simpler and high frequency patterns. Important association rules cannot be known with 2 parameters, namely, minimum support (the percentage of item combinations in the database) and minimum confidence (the strength of the relationship between items in the associative rules), both of which are determined by the user (Anggraini, Putri, & Utami, 2020).

METHODS

The Apriori algorithm is one of the algorithms that can be used in the application of market basket analysis to find association rules that meet the support and confidence limits (Qomariah, Basrie, & Pa'a, 2020) Two important benchmarks for whether or not an association are support and confidence. Support is a supporting value while confidence is a certainty value (Haidar, 2021) This algorithm is based on the fact that Apriori uses previous knowledge from an itemset with a frequent occurrence or is called a frequent itemset (Wardah, 2018). The main idea of the Apriori algorithm is: first, look for frequent itemsets (sets of items that meet the minimum support.) from the transaction database. Second, eliminating itemsets with low frequency based on a predetermined minimum support level (Sutrisno, 2020). The Apriori algorithm is the most famous algorithm for determining high frequency patterns. A high frequency pattern is a pattern of items in a database that has a frequency or support above a certain threshold which is called the minimum support term (Erfina, Melawati, & Destria Arianti, 2020) confidence (strength of relationships between elements in association rules). Both are user-defined (Anggraini et al., 2020). The importance or absence of an association can be known by two benchmarks, namely: support and confidence (Yani & Jusia, 2018)

The following are definitions to consider for the method of association rules:

Definition 1

The support for an item set A is the percentage of combined occurrences of all items in set A. It is expressed as follows (Asana, Ginantra, Parwita, Krismentari, & Meinarni, 2021):

$$S(A) = \frac{\text{itemset frequency (A)}}{\text{total transaksi}}$$

$$= \frac{1}{N}\sum_{i=1}^{N}\prod_{a\in\lambda} X_{ia} \geq \text{minimum support} \qquad (1)$$

Where

A = itemset

N = sum of total transactions

Xia = an i-th item on the a-th transaction

λ = integer on A

Definition 2

The support rule (A⇒B) is the proportion of events in which objects A and B occur simultaneously. We denote S(A⇒B). then it is formulated based on point 1 as follows:

$$S(A \Rightarrow B) = \frac{1}{N}\sum_{i=1}^{N} \prod_{p\in \lambda\cup\beta} X_{ip} \quad (2)$$

Where

S = support

A = itemset

N = sum of total transactions

X_{ip} = an i-th item on the p-th transaction

λ = integer on A

β = integer on B

Definition 3

The confidence rule (A⇒B) is a measure of the accuracy of association rules. Expressed as C(A⇒B). The formula for C(A⇒B) is:

$$C(A \Rightarrow B) = \frac{\sum_{i=1}^{N} \prod_{p\in \lambda\cup\beta} X_{ip}}{\sum_{i=1}^{N} \prod_{\in \lambda} X_{ia}} \quad (3)$$

Where

C = confidence

A = itemset

N = sum of total transactions

X_{ia} = an i-th item on the a-th transaction

X_{ip} = an i-th item on the p-th transaction

λ = integer on A

β = integer on B

(Jannah & Mansyur, 2021).

In this study, the information to be monitored was obtained from information on the selection of Pak RM coffee beans along with the results of the selection of the best coffee beans. the information is obtained directly from the research site, which is evaluating the selection of the best Arabica coffee beans in the Karo country.

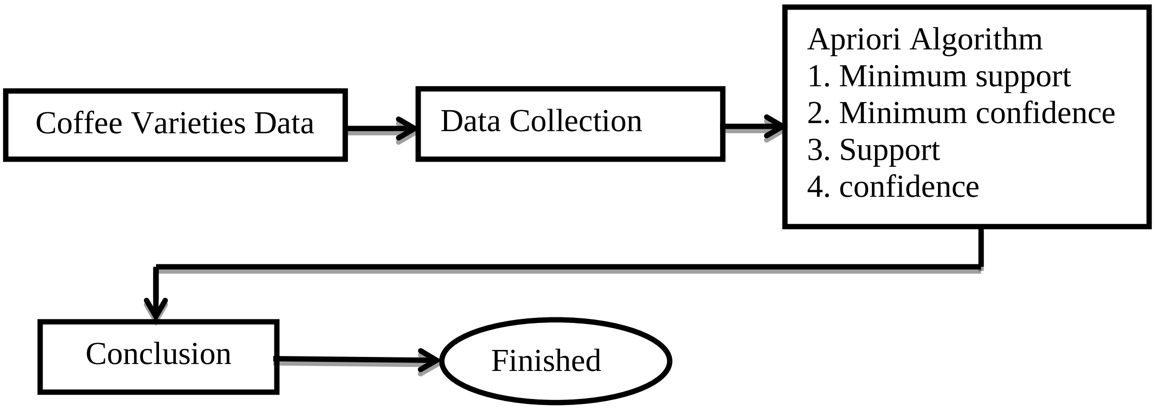

Figure 1. Research Flowchart

The information used in this study is based on Pak RM coffee assessment of the results of the selection of the best arabica coffee beans in Tanah Karo. The value used to write numbers is tens (up to 100) (Manurung & Lubis, 2023). Create a set of frequently used items with minimum support and minimum confidance (Andini, Hardinata, & Purba, 2022). Next, calculate the support value for the k-itemsset candidate. Confidence calculations are then performed on each k-itemset to determine whether the candidate can be used as the determinant of the association.

RESULT AND DISCUSSION

The numbers used to write down the value are tens, the assessment given by Mr. RM coffee is seen from the selection of Arabica coffee beans on coffee beans using 4 selections namely taste, normal bean presentation, resistance to leaf rust, production potential.

Table 1. Coffee Bean Selection Assessment

No.	Varieties of Kopi	Cita Rasa	Normal Seed Presentation	Resistanceto Kand Daun	Potential Production
1.	Kartika 1	87	70	72	95
2.	Kartika 2	85	75	81	94
3.	USDA 762	78	73	82	75
4.	S 795	79	94	87	79
5.	Abesinia 3	93	73	86	75
6.	Sigarar utang	92	91	85	92
7.	Andungsari 1	86	81	94	81
8.	Andungsari 2K	85	83	93	83
9.	Gayo 1	84	91	83	78
10.	Gayo 2	84	91	85	77
11.	Komasti	96	88	95	90

Apriori's algorithms do not recognize numerical data, so the collected numerical data are grouped based on the range derived from the mean and standard deviation of Arabica coffee bean evaluation data. The author divides the data into three classifications, which are A (high), B (medium), C (low). The table below was then decided using Microsoft Excel (Nasrah et al., 2021):

Table 2. Range of Assessment Data on Coffee Bean Selection

Range	Coffee Bean Selection			
	Taste	Normal Seeds	Leaf Resistance	Production Potential
A	≥89	≥89	≥89	≥89
B	80-89	80-89	80-89	80-89
C	≤80	≤80	≤ 80	≤ 80

The Apriori algorithm does not recognize numerical data, so the data values that have been collected are first viewed based on the group range values in table 2. Then a transformation is performed using Microsoft Excel, the results of which are shown in table 3.

Table 3. Assessment Data on Coffee Bean Selection After Data Transformation

Variety Name	Taste	Normal Seed Presentation	Resistance to leaf rust	Production Potential
Kartika 1	B	C	C	A
Kartika 2	B	C	B	A
USDA 762	C	C	B	C
S 795	C	A	B	C
Abesinia 3	A	C	B	C
Sigarar utang	A	A	B	A
Andungsari 1	B	B	A	B
Andungsari 2K	B	B	A	B
Gayo 1	B	A	B	C
Gayo 2	B	A	B	C
Komasti	A	B	A	A

Apriori algorithms must go through two steps, namely finding sets of repeated items and generating rules to combine these sets of repeated items. Carrying out these steps gives a minimum support value of 25% and a minimum confidence of 75%., which has been determined by the author and $X = \{X1, X2, \dots, X11\}$ is the coffee variety owned by Pak RM coffee or the set of all items.

Table 4. Calculation of Number of Items

Range	Coffee Bean Selection			
	Taste	Normal Seeds	Leaf Resistance	Production Potential
A	3	4	3	4
B	6	3	7	2
C	2	4	1	5

Apriori algorithmic methods then calculate the support of each 1-element set based on Equation 1 and compare it with the minimum support to obtain the frequent 1-element set (F1).

$F_1 = x_j \mid S(x_j) = \frac{1}{15}\sum_{i=1}^{15} X_{ij} \geq$ minimum support 25%}

Where

F_1 = frequent 1-*itemset*

S = support

X_j = j-th transaction

X_{ij} = an i-th item on the j-th transaction

Table 5. 1-Itemset and its Support

1.	Support CR A	$\frac{3}{11} = 0{,}27 = 27\%$
2.	Support CR B	$\frac{6}{11} = 0{,}54 = 54\%$
3.	Support CR C	$\frac{2}{11} = 0{,}18 = 18\%$
4.	Support BN A	$\frac{4}{11} = 0{,}36 = 36\%$
5.	Support BN B	$\frac{3}{11} = 0{,}27 = 27\%$
6.	Support BN C	$\frac{4}{11} = 0{,}36 = 36\%$
7.	Support KD A	$\frac{3}{11} = 0{,}27 = 27\%$
8.	Support KD B	$\frac{7}{11} = 0{,}63 = 63\%$
9.	Support KD C	$\frac{1}{11} = 0{,}09 = 9\%$

10.	Support PP A	$\frac{4}{11} = 0{,}36 = 36\%$
11.	Support PP B	$\frac{2}{11} = 0{,}18 = 18\%$
12.	Support PP C	$\frac{5}{11} = 0{,}45 = 45\%$

Based on Table 5 CR (Taste), BN (Normal Seeds), KD (Leaf Rust Resistance), PP (Production Potential). After trimming obtained the set of frequent 1-itemset (F1) namely: F1 = { CR A, CR B, BN A, BN B, BN C, KD A, KD B, PPA, PP C }.

The remaining items are then combined into a 2-part set and the allowance for those items is recalculated using Equation 2. The calculation result for 2 subsets is shown in Table 6.

Table 6. 2-Itemset And Support

No.	2-itemset	Support	100% Support
1.	CR A + BN A	1	$\frac{1}{11} = 0{,}09 = 9\%$
2.	CR A + BN B	1	$\frac{1}{11} = 0{,}09 = 9\%$
3.	CR A + BN C	1	$\frac{1}{11} = 0{,}09 = 9\%$
4.	CR A + KD A	1	$\frac{1}{11} = 0{,}09 = 9\%$
5.	CR A + KD B	2	$\frac{2}{11} = 0{,}18 = 18\%$
6.	CR A + PP A	2	$\frac{2}{11} = 0{,}18 = 18\%$
7.	CR A + PP C	1	$\frac{1}{11} = 0{,}09 = 9\%$
8.	CR B + BN A	2	$\frac{2}{11} = 0{,}18 = 18\%$
9.	CR B + BN B	2	$\frac{2}{11} = 0{,}18 = 18\%$
10.	CR B + BN C	2	$\frac{2}{11} = 0{,}18 = 18\%$
11.	CR B + KD A	2	$\frac{2}{11} = 0{,}18 = 18\%$
12.	CR B + KD B	3	$\frac{3}{11} = 0{,}27 = 27\%$
13.	CR B + PP A	2	$\frac{2}{11} = 0{,}18 = 18\%$
14.	CR B + PP C	2	$\frac{2}{11} = 0{,}18 = 18\%$

No.	2-itemset	Support	100% Support
15.	BN A + KD A	0	0
16.	BN A + KD B	4	$\frac{4}{11} = 0{,}36 = 36\%$
17.	BNA + PP A	1	$\frac{1}{11} = 0{,}09 = 9\%$
18.	BN A + PP C	3	$\frac{3}{11} = 0{,}27 = 27\%$
19.	BN B + KD A	3	$\frac{3}{11} = 0{,}27 = 27\%$
20.	BN B + KD B	0	0
21.	BN B + PP A	1	$\frac{1}{11} = 0{,}09 = 9\%$
22.	BN B + PP C	0	0
23.	BN C + KD A	0	0
24.	BN C + KD B	3	$\frac{3}{11} = 0{,}27 = 27\%$
25.	BN C + PP A	2	$\frac{2}{11} = 0{,}18 = 18\%$
26.	BN C + PP C	2	$\frac{2}{11} = 0{,}18 = 18\%$
27.	KD A + PP A	1	$\frac{1}{11} = 0{,}09 = 9\%$
28.	KD A + PP C	0	0
29.	KD B + PP A	2	$\frac{2}{11} = 0{,}18 = 18\%$
30.	KD B + PP C	5	$\frac{5}{11} = 0{,}45 = 45\%$

Based on Table 6 after pruning obtained the set of frequent 2-itemset (F2), namely: F2 = { CR B + KD B, BN A + KD B, BN A + PP C, BN B + KD A, BN C + KD B, KD B + PP C } The remaining items are then combined into 3-itemset, and the results of the 3-Itemset calculation can be seen in table 7.

Table 7. 3-Itemset and its support

No.	3-itemset	Support	100% Support
1.	CR B + KD B + PP C	2	$\frac{2}{11} = 0{,}18 = 18\%$
2.	BN A + KD B + PP C	3	$\frac{3}{11} = 0{,}27 = 27\%$
3.	BN C + KD B + PP C	2	$\frac{2}{11} = 0{,}18 = 18\%$
4.	CR B + BN C + KD B	1	$\frac{1}{11} = 0{,}9 = 9\%$

There were four candidates formed, namely CR B + KD B + PP C, BN A + KD B + PP C, BN C + KD B + PP C, and CR B + BN C + KD B. Since all candidates in a common 3-subset have a rare subset, there are no remaining candidates or the set of candidates in a common 3-subset = ∅. Determining an association rule determining the reliability of a common set of items based on Equation 3. However, this value can introduce errors, resulting in a high confidence value due to high support values, although the antecedents and consequences are independent of each other (Hikmawati, Maulidevi, & Surendro, 2021).

Table 8. Confidence Value Calculation

No.	Itemset	Confidence	Elevator
1.	CR C + KD B	$\frac{2}{2} = 1 = 100\%$	$\frac{100}{63} = 1{,}58$
2.	CR C + PP C	$\frac{2}{2} = 1 = 100\%$	$\frac{100}{45} = 2{,}22$
3.	BN A + KD B	$\frac{4}{4} = 1 = 100\%$	$\frac{100}{63} = 1{,}58$
4.	BN A + PP C	$\frac{3}{4} = 0{,}75 = 75\%$	$\frac{75}{45} = 1{,}66$
5.	BN B + KD A	$\frac{3}{3} = 1 = 100\%$	$\frac{100}{27} = 3{,}70$
6.	BN C + KD B	$\frac{3}{4} = 0{,}75 = 75\%$	$\frac{75}{63} = 1{,}19$
7.	KD C + PP A	$\frac{1}{1} = 1 = 100\%$	$\frac{100}{36} = 2{,}77$

With a minimum support value of 25% and a minimum confidence of 75%, there are seven rules. The best combination of selection is { BN B, KD A } with a confidence level of 100% and has the highest lift value of 3.70.

Once the rules of strong association are obtained, all the rules of this strong association are interpreted. This interpretation is useful for information on the best combination of Arabica coffee beans for Pak RM coffee.

1. Interpretation of rule 1: "If the selection of Flavor in USDA 762 and S795 coffee varieties, then with a 100% probability of selection Normal Bean Presentation will be well used in the selection of USDA 762 and S795 varieties.
2. Interpretation of rule 2: "If the selection of Flavors in USDA 762 and S795 coffee varieties, then with a 100% probability of Production Potential will be well used in the selection of USDA 762 and S795 varieties.
3. Interpretation of Rule 3: "If the selection of Normal Bean Presentation in coffee varieties S795, Sigarar utang, Gayo 1, and Gayo 2, then with a 100% chance of selection on Leaf Rust Resistance will be good also used in the selection of coffee varieties S795, Sigarar utang, Gayo 1, and Gayo 2.
4. Interpretation of Rule 4: "If the selection of Normal Bean Presentation in coffee varieties S795, Gayo 1, and Gayo 2, then with a 75% chance the selection on Leaf Rust Resistance will be well used also in the selection of coffee varieties S795, Gayo 1, and Gayo 2.
5. Interpretation of Rule 5: "If the selection of Normal Bean Presentation in Andungsari 1, Andungsari 2, and Komasti coffee varieties, then with a 100% chance of selection on Leaf Rust Resistance will be well used in the selection of Andungsari 1, Andungsari 2, and Komasti coffee varieties.
6. Interpretation of Rule 6: "If the selection of Normal Bean Presentation in Kartika 2, USDA 762, and Abesinia 3 coffee varieties, then with a 75% chance of selection on Leaf Rust Resistance will be well used in the selection of Kartika 2, USDA 762, and Abesinia 3 coffee varieties.
7. Interpretation of Rule 7: "If the selection of Normal Bean Presentation in Kartika 1 coffee varieties, then with a 75% chance of selection on Leaf Rust Resistance will be well used in the selection of Kartika 1 coffee varieties.

Based on the discussion above, it can be interpreted that with a minimum support value of 25% and a minimum confidence of 75%, there are seven rules that have been determined. The best selection combination with a 100% confidence level and has the highest lift value, namely, 3.70. So the selection of Normal Bean Presentation on Andungsari 1, Andungsari 2, and Komasti coffee varieties, with a 100% probability of selecting on Leaf Rust Resistance will also be good to use in the selection of Andungsari 1, Andungsari 2, and Komasti coffee varieties.

CONCLUSION

In this study there were 11 varieties of coffee in karo soil, namely Kartika 1, Kartika 2, USDA 762, S 795, Abesinia 3, Sigarar utang, Andungsari 1, Andungsari 2k, Gayo 1, Gayo 2, and Komasti. This research is only for karo land farmers. The final association rules obtained from applying the Apriori algorithm to the sample selection of coffee beans are "Taste, Normal Beans, Leaf Resistance, Production Potential" with a minimum support of 25% and a minimum confidence of 75%, forming seven rules. One of the best rules is that if the selection of Normal Bean Presentation is on the Andungsari 1, Andungsari 2, and Komasti coffee varieties, then with a 100% probability the selection on Leaf Rust Resistance will also be good for the selection of Andungsari 1, Andungsari 2, and Komasti coffee varieties.

The Apriori algorithm method has been successfully implemented on the coffee bean selection assessment data on Pak RM's coffee as a decision making. The determined support and confidence values will affect the accuracy in forming the rule, the higher the support and confidence values, the more accurate the rule will be. The association rule resulting from the frequent itemset can be used as a decision support in selecting coffee, and in accordance with.

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