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Application of the FP-Growth Method to Determine Drug Sales Patterns

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Abstract: Apotik is a shop that sells and mixes medicines based on a doctor's prescription and trades health goods. Apart from being a business actor, the pharmacy also provides health services that are easily accessible to the public. The problem that often occurs in pharmacies selling drugs is the need for optimal consumer service. The habit of consumers buying more than one type of drug makes pharmacists slow in providing the drug due to the inappropriate layout of the drug. The FP-Growth method in Data Mining is a method that can provide a solution in determining drug sales patterns in pharmacies. The FP-Growth method determines the data set that occurs most often simultaneously (Frequent Itemset). The research objective was to determine drug sales patterns based on drug sales transaction data so drug layouts could be determined. This research was conducted by taking drug sales transaction data samples from November 2021 to December 2021. The results of applying the FP-Growth method with a value of ≥ 15% as minimum support and a value of ≥ 15% as minimum trust pattern of drug sales in pairs. The application of Data Mining with the FP-Growth method has been implemented with the desired goal, with the final result in the form of a report on the results of determining drug sales patterns.

Keywords: Data Mining; FP-Growth; Frequent Itemset; Pharmacy; Sales Patterns

INTRODUCTION

Clinics are health service facilities that carry out health services in the form of basic medical and specialist individually. According to the type of service, the clinic is divided into Main Clinic and Primary Clinic. Main Clinic is a clinic that provides basic and specialist medical services (Indonesia, 2014). While the Primary Clinic is a clinic that provides essential medical services, namely general and special.

Klinik Pratama Sehati Husada is a health service center providing quality patient care. The clinic has several facilities that are almost the same as hospitals in general, so patients are comfortable in the clinic. One of the facilities available at the clinic is a pharmacy. A pharmacy is a pharmaceutical service facility for pharmacists to practice pharmacy. The Clinic Pharmacy is in charge of providing medicines for consumers. The drug sales system at the clinic is still running conventionally, using the manual method, so problems often occur in drug sales.

The problem that often occurs in drug sales at the clinic is an error in knowing the pattern of linkages of drugs that are often sold together, making it difficult to arrange the layout of drugs and determine which drugs to prioritize. Sold on the following date so that service to consumers is not optimal. The habit of consumers who want to buy more than one type of drug overwhelms the clinic from seeing drug sales patterns. To overcome the above problems, it is necessary to determine the pattern of drug sales so that the problem can be resolved. To determine drug sales patterns a Data Mining field is needed that can provide solutions to determine drug sales patterns.

According to (Chen et al., 2021; Miao et al., 2019; Sunarti et al., 2021) Data Mining is also called KDD (knowledge discovery in database). KDD is an activity that covers data collection, the use of data to find relationships or patterns in large data sets. One method in Data Mining that can be used to find patterns is the FP-Growth (Frequent Pattern Growth) method (Hasan & Zaman Mishu, 2018). The FP-Growth (Frequent Pattern Growth) method is a development of the Apriori method. The FP-Growth (Frequent Pattern Growth) method is a method used to determine the data set that occurs most frequently together (Frequent itemset).(Almira et al., 2021). The FP-Growth method uses the concept of forming a tree called the FP-Tree in finding frequent itemsets. By using the FP-Tree concept, the FP-Growth method becomes faster.

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LITERATURE REVIEW

The FP-Growth method is still being developed and discovered using (Ikhwan, 2018) "a Novelty of Data Mining for Fp-Growth Algorithm." Find Frequent Itemsets by searching. Improvement of RETECS method employing FP-Growth in continuous integration is the subject of (Wen et al., 2019) Research. We tested our test cases' re-prioritization using the RETECS approach and historical test data. According to laboratory findings, our strategy can increase mistake detection rates compared to the RETECS method.

Regarding (Ma et al., 2020) "Research on FP-Growth algorithm for agricultural major courses recommendation in China Open University system" resulted in Research on the professional course recommendation of one agriculture major in China's Open University system and the viability of the suggested method was confirmed. The FP-growth algorithm and the Apriori method are also compared in this study. While the FP-growth algorithm is known to have a quick processing time, its implementation is known to be somewhat tricky. Additional investigation by (Kaysar et al., 2019) In "Word Sense Disambiguation of Bengali Words using FP-Growth Algorithm," we suggested a system for the FP-Growth algorithm to disambiguate Bengali words based on their meanings. In order to demonstrate how the FP-Growth algorithm outperforms the Apriori strategy for Word Sense Bengali Disambiguation, we have also developed the Apriori algorithm and provided an analysis of both.

Additionally, we discovered during testing that our suggested strategy could capture the genuine meaning of the ambiguous word in 80% of the test sentences. The experiment results demonstrate that the optimization algorithm proposed in this paper can effectively solve the problem of parallel load imbalance and improve the cluster's overall efficiency by 5% to 15%. This is in line with earlier Research from (Zhang et al., 2017)entitled "Research and improvement of parallelization of FP-Growth algorithm based on spark."

METHOD

In this section, The steps of the research procedure are as follows since researchers used an R&D (Research and Development) approach to the study's findings(Bahar & Soegiarto, 2020):

1. Techniques for Data Collection (Data Collecting)

The following techniques are used to gather data for the study:

a. Observation

A method of acquiring data called observation entails personal visits to the pharmacy where the study will take place.

b. Interview

By employing this interviewing technique, it is possible to directly communicate with the system developed as a data source and obtain more information from those in positions of authority.

2. Literature Review (Library Research)

One of the elements serving as a theoretical foundation for researchers looking into the subjects given is a literature review. The researcher uses various library resources in this case, including books and regional, international, and other journals.

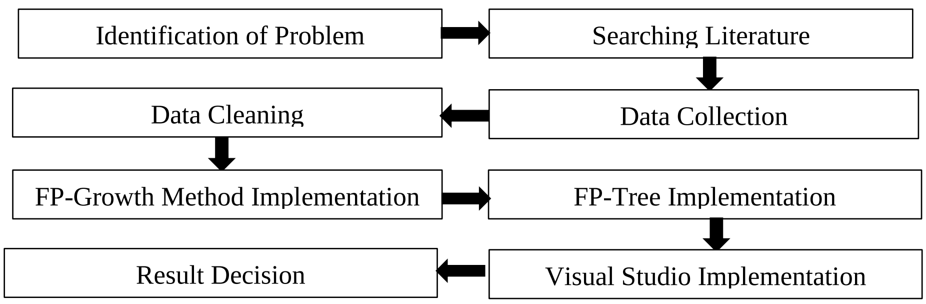

Figure 1 Research Design

3.1 FP-Growth Method

FP-Growth (Frequent Pattern Growth) is a method that can be used to determine the data set that appears most often (frequent item set) in a data set.(Xue et al., 2019) FP-Growth is an algorithmic method that reduces the size of datasets that represent frequent items into Frequent Pattern Trees (FP-Tree). The search for frequent itemsets using the FP-Growth method is carried out by generating a tree data structure (FP-Tree). The FP-Growth method is a development of the Apriori method.(Kalaskar & Barkade, 2018)

There are three main stages in the FP-Growth method, namely:

a. Generation of Conditional Pattern Base stage

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b. Conditional Pattern Tree generation stage
c. Frequent Itemset search stage

3.2 Association Rules

Association rule or association analysis is a technique for finding associative rules between a combination of items. Association analysis became famous because its application can analyze the contents of a customer's shopping cart. Association analysis is also called Market Basket Analysis. Association Rule or association analysis is defined as a process to find all associative rules that meet the minimum requirements for support (minimum support) and minimum requirements for confidence (minimum confidence).(Perangin-angin et al., 2017; Sibarani, 2020)
Association rule basic methodology is divided into two stages, namely:
a. High-frequency pattern analysis
This stage looks for item combinations with a support value in the database that meets the minimum requirements. The following formula obtains the support value of an item:

$$\textit{Support}\ (A) = \frac{\text{Number of Transactions Containing A}}{\text{Total Transactions}} \text{ X } 100\%$$

While the support value of the two items is obtained from the following formula:

$$\textit{Support}\ (A \cap B) = \frac{\text{Number of Transactions Containing A and B}}{\text{Total Transactions}} \text{ X } 100\%$$

b. Formation of associative rules
After all high-frequency patterns are found, then the associative rules that meet the minimum requirements for confidence are searched by calculating the confidence of the associative rules AB. The confidence value of the rules AB is obtained from the following formula:

$$\textit{Confidence} = P(B|A) = \frac{\text{Number of Transactions Containing A dan B}}{\text{Total Transactions A}} \text{ X } 100\%$$

RESULT

Application of the FP-Growth Method The application of the FP-Growth Method is a complete step regarding the Application of FP-Growth Method for Determine the Drug Sales Pattern following the references that have been used.

4.1 Transforming Drug Sales Transaction Data

The following is a sample of drug sales transaction data at the Sehati Husada Pratama Clinic, which will be transformed into a code item. At the data transformation stage, namely, changing the data to be shorter according to the data completion process. The transformation process is as follows:

Table 1 Item to Code Transformation

No	Date	Code	Medicine name
1	01 November 2021	A1	Dexa
		A2	Cefixime
		A3	Omz
		A4	Selkom C
		A5	Ambroxol
2	01 November 2021	A1	Dexa
		A6	Amoxicillin
		A7	Sanmol Syrup
		A8	B Complex
3	01 November 2021	A1	Dexa
		A9	Cetirizine
		A4	Selkom C
4	01 November 2021	A3	Omz
		A10	Domperidone

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		A8	B Complex
		A11	Magnidicon Syrup
5	02 November 2021	A3	Omz
		A10	Domperidone
		A12	Betahistine
		A13	Glyceryl Guaiacolate
....			
….			
165	31 Desember 2021	A10	Domperidone
		A32	Paracetamol
		A6	Amoxicillin
		A8	B Complex
		A16	Ranitidin

4.2 Determining Support 1 Itemset

In table 1, 165 datasets will be processed using FP-Growth. The following is the frequency of occurrence of each item from transaction data using the following formula:

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

Table 2. Frequency of Appearance of 1st and Support for Each Item

No	*Code*	Medicine name	*Frequency*	*Support*	*Support* (%)
1	A1	Dexa	81	81/165 = 0.4909	49,09%
2	A2	Cefixime	10	10/165 = 0.0606	6,06%
3	A3	Omz	50	50/165 = 0.3030	30,3%
4	A4	Selkom C	13	13/165 = 0.0787	7,88%
5	A5	Ambroxol	2	2/165 = 0.0121	1,21%
6	A6	Amoxicillin	34	34/165 = 0.2060	20,61%
7	A7	Sanmol Syrup	13	13/165 = 0.0787	7,88%
8	A8	B Complex	35	35/165 = 0.2121	21,21%
9	A9	Cetirizine	33	33/165 = 0.2	20%
10	A10	Domperidone	52	52/165 = 0.3151	31,52%
11	A11	Magnidicon Syrup	18	18/165 = 0.1090	10,91%
12	A12	Betahistine	5	5/165= 0.0303	3,03%
13	A13	Glyceryl Guaiacolate	11	11/165 = 0.0666	6,67%
14	A14	CTM	16	16/165 = 0.0969	9,7%
15	A15	Sanmol	7	7/165 = 0.0424	4,24%
16	A16	Ranitidin	23	23/165 = 0.1393	13,94%
17	A17	Ciprofloxacin	23	23/165 = 0.1393	13,94%
18	A18	Neurodex	9	9/165 = 0.0545	5,45%
19	A19	Cefadroxil	34	34/165 = 0.2060	20,61%
20	A20	Methylprednisolone	4	4/165 = 0.0242	2,42%
21	A21	Domperidone Syrup	6	6/165 = 0.0363	3,64%
22	A22	Omegdiar	10	10/165 = 0.0606	6,06%
23	A23	Metronidazole	4	4/165 = 0.0242	2,42%
24	A24	Zinkid	8	8/165 = 0.0484	4,85%
25	A25	Ferobion	3	3/165 = 0.0181	1,82%
26	A26	Dapyrin	9	9/165 = 0.0545	5,45%
27	A27	Antasida Syrup	1	1/165 = 0.0060	0,61%
28	A28	Curcuma	10	10/165 = 0.0606	6,06%
29	A29	Ambroxol Syrup	25	25/165 = 0.1515	15,15%
30	A30	Proris Syrup	4	4/165 = 0.0242	2,42%
31	A31	Amoxicillin Syrup	1	1/165 = 0.0060	0,61%

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32	A32	Paracetamol	68	68/165 = 0.4121	41,21%
33	A33	ATC Syrup	10	10/165 = 0.0606	6,06%
34	A34	Asam Mefenamat	5	5/165= 0.0303	3,03%
35	A35	Ventolin Nebule	1	1/165 = 0.0060	0,61%
36	A36	Amoxan drop	2	2/165 = 0.0121	1,21%
37	A37	Pacdin Cough	1	1/165 = 0.0060	0,61%
38	A38	ATC	15	15/165 = 0.0909	9,09%
39	A39	Doxycycline	1	1/165 = 0.0060	0,61%
40	A40	Gentamicin Zalf	2	2/165 = 0.0121	1,21%
41	A41	Sucralfat Syrup	9	9/165 = 0.0545	5,45%
42	A42	Omedom	1	1/165 = 0.0060	0,61%
43	A43	Cotrimoxazole Forte	13	13/165 = 0.0787	7,88%
44	A44	Meloxicam	6	6/165 = 0.0363	3,64%
45	A45	Chlorampenicol	1	1/165 = 0.0060	0,61%
46	A46	Lactas	3	3/165 = 0.0181	1,82%
47	A47	Amlodipine	4	4/165 = 0.0242	2,42%
48	A48	Vit C	6	6/165 = 0.0363	3,64%
49	A49	Metformin	4	4/165 = 0.0242	2,42%
50	A50	Glibenclamide	1	1/165 = 0.0060	0,61%
51	A51	OBP Syrup	2	2/165 = 0.0121	1,21%
52	A52	Simvastatin	5	5/165= 0.0303	3,03%
53	A53	Tempra drop	1	1/165 = 0.0060	0,61%
54	A54	Candesartan	2	2/165 = 0.0121	1,21%
55	A55	Vit K	1	1/165 = 0.0060	0,61%
56	A56	Zinc	5	5/165= 0.0303	3,03%
57	A57	Betamethasone	1	1/165 = 0.0060	0%.61
58	A58	Acyclovir Zalf	2	2/165 = 0.0121	1,21%
59	A59	Cotrimoxazole	2	2/165 = 0.0121	1,21%
60	A60	Allopurinol	1	1/165 = 0.0060	0,61%
61	A61	Cefixime Syrup	1	1/165 = 0.0060	0,61%
62	A62	Fasidol	3	3/165 = 0.0181	1,82%
63	A63	Chlorampenicol Zalf	1	1/165 = 0.0060	0,61%
64	A64	Acyclovir	1	1/165 = 0.0060	0,61%
65	A65	Prednisolone	2	2/165 = 0.0121	1,21%
66	A66	Salbutamol	1	1/165 = 0.0060	0,61%
67	A67	Bicnat	1	1/165 = 0.0060	0,61%
68	A68	Amoxicillin drop	1	1/165 = 0.0060	0,61%
69	A69	Hufabetamin	1	1/165 = 0.0060	0,61%

In Table 2 it can be seen the results of the frequency of drug items appearing, then determining support is carried out. In this study, the support count was taken ≥ 20%. The value of the support count will affect the items that are analyzed at the stage of making the FP-Tree, and the highest support value can be identified. Then the data that meets the support count will be sorted as follows:

Table 3 Frequency of the 2nd Appearance

No	Code	Medicine name	*Frequency*	*Support*	*Support* (%)
1	A1	Dexa	81	81/165 = 0.4909	49,09%
2	A32	Paracetamol	68	68/165 = 0.4121	41,21%
3	A10	Domperidone	52	52/165 = 0.3151	31,52%
4	A3	Omz	50	50/165 = 0.3030	30,3%
5	A8	B Complex	35	35/165 = 0.2121	21,21%
6	A6	Amoxicillin	34	34/165 = 0.2060	20,61%
7	A19	Cefadroxil	34	34/165 = 0.2060	20,61%
8	A9	Cetirizine	33	33/165 = 0.2	20%

4.3 Transferring Data Or Rearranging Data That Meets Minimum Support

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After sorting the data that meets the minimum support, the transaction data is rearranged based on the item values that meet the minimum support. The following data table contains minimum support:

Table 4 Transaction Data Containing Minimum Support

No	TID	Item
1	T1	A1, A3
2	T2	A1, A8, A6
3	T3	A1, A9
4	T4	A10, A3, A8
5	T5	A10, A3
6	T6	A8, A6, A9
7	T7	A1, A8, A6
8	T8	A3, A19, A9
9	T9	-
10	T10	A10
….		
….		
165	T165	A32,A10,A8,A6

4.4 Formation of FP-Tree (Frequent Pattern Tree)

The next step is to create an FP-Tree for each transaction. The image below illustrates the FP-Tree of each TID. The following is a tree structure of all existing transactions.

The following is the creation of a T1 tree starting with images A1, A3, namely:

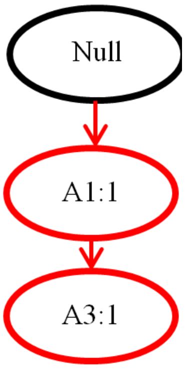

Figure 2 FP-Tree results starting from TID T1 namely { A1,A3 }

The following is the creation of a T2 tree starting with images A1, A8, A6, namely:

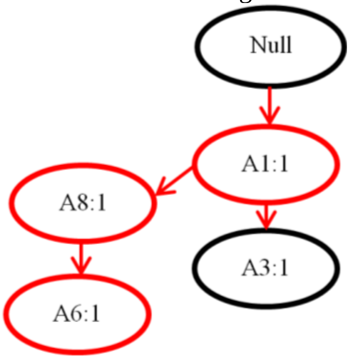

Figure 3 FP-Tree results starting from TID T2 namely { A1,A8,A6 }

The following is the creation of a T3 tree starting with pictures A1, A9 namely:

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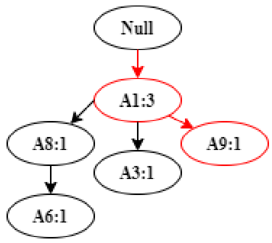

Figure 4 FP-Tree results starting from TID T3 namely {A1,A9}

The following is the creation of a T165 tree starting with images A32, A10, A8, A6 namely:

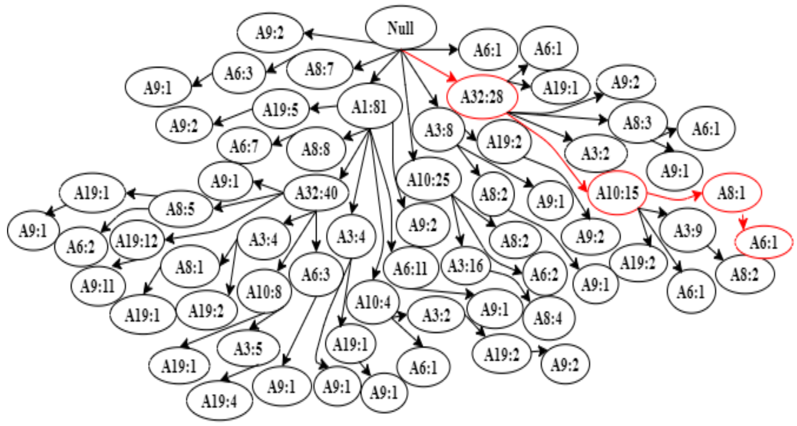

Figure 5 FP-Tree results starting from TID T165 namely { A32,A10,A8,A6 }

4.5 Application of FP-Growth

After forming the FP-Tree from a set of drug sales transaction data that has been done. In the next stage, FP-Growth is applied to find frequent item sets that meet the requirements. There are three main steps of FP-Growth which are as follows:

a. Generation of Conditional Pattern Base

The Conditional Pattern Base is obtained by reading each FP-Tree ending in a node.

Table 5 Conditional Pattern Base

Item	**Conditional Pattern Base**
A9	{A8,A6:1},{A1,A19:2},{A1,A32:1},{A1,A32,A8,A19:1},{A1,A32,A19:11},{A1,A32,A6:1},{A1,A3:1},{A1,A3,A19:1},{A1,A10,A3,A19:2},{A1,A6:1},{A1:2},{A3,A8:1},{A3:1},{A3,A19:2},{A32,A8:1},{A32:2}
A19	{A1:5},{A1,A32,A8:1},{A1,A32:12},{A1,A32,A3,A8:1},{A1,A32,A3:2},{A1,A32,A10:1},{A1,A32,A10,A3:4},{A1,A3:1},{A1,A10,A3:2},{A3:2},{A32,A10:2},{A32:1}
A8	{A1:8},{A1,A32:5},{A1,A32,A3:1},{A10,A3:4},{A10:2},{A3:2},{A32,A10,A3:2},{A32,A10:1},{A32:3}
A6	{A8:3},{A1,A8:7},{A1,A32,A8:2},{A1,A32:3},{A1,A10:1},{A1:11},{A10:2},{A32,A10:1},{A32,A10,A8:1},{A32,A8:1},{A32:1}
A3	{A1,A32:4},{A1,A32,A10:5},{A1:4},{A1,A10:2},{A10:16},{A32,A10:9},{A32:2}
A10	{A1,A32:8},{A1:4},{A32:15}
A32	{A1:40}
A1	-

b. FP-Tree Conditional Generation

After the conditional pattern base generation stage is carried out, the next stage is the FP-Tree conditional generation stage. This stage is carried out after the conditional pattern base is obtained, then the conditional FP-Tree is formed with a single item at the end of the node.

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Table 6 *Conditional FP-Tree*

Suffix	Conditional FP-Tree
A9	{A8:4},{A6:3},{A1:23},{A19:19},{A32:17},{A3:8},{A10:2}
A19	{A1:29},{A32:24},{A8:2},{A3:12},{A10:9}
A8	{A1:14},{A32:12},{A3:9},{A10:9}
A6	{A8:14},{A1:24},{A32:9},{A10:5}
A3	{A1:15},{A32:20},{A10:32}
A10	{A1:12},{A32:23}
A32	{A1:40}
A1	-

c. Frequent Itemset Search

Next, to get the frequent itemset, combine the items that will be conditional FP-Tree. Then the overall results are shown in the following table:

Table 7 Frequent Itemset Results

Suffix	Frequent Itemset
A9	{A8,A9:4},{A6,A9:3},{A1,A9:23},{A19,A9:19},{A32,A9:17},{A3,A9:8},{A10,A9:2}
A19	{A1,A19:29},{A32,A19:24},{A8,A19:2},{A3,A19:12},{A10,A19:9}
A8	{A1,A8:14},{A32,A8:12},{A3,A8:9},{A10,A8:9}
A6	{A8,A6:14},{A1,A6:24},{A32,A6:9},{A10,A6:5}
A3	{A1,A3:15},{A32,A3:20},{A10,A3:32}
A10	{A1,A10:12},{A32,A10:23}
A32	{A1,A32:40}
A1	-

4.6 Formation of Association Rules

From the results of the frequent itemset of the FP-Growth method, at this stage it is used to determine the value of support for each item set with the formula:

$$\text{Support }(A,B) = P(A\cap B) = \frac{\text{Number of Transactions Contains } A\cap B}{\text{Total Transactions}} \times 100\%$$

Table 8 Support Value in Suffix

No	Association Rule	*Count*	*Support*
1	A8,A9	4	4/165 x 100 % = 2,42%
2	A9.A8	4	4/165 x 100 % = 2,42%
3	A6,A9	3	3/165 x 100 % = 1,82%
4	A9,A6	3	3/165 x 100 % = 1,82%
5	A1,A9	23	23/165 x 100 % = 13,94%
6	A9,A1	23	23/165 x 100 % = 13,94%
7	A19,A9	19	19/165 x 100 % = 11,52%
8	A9,A19	19	19/165 x 100 % = 11,52%
9	A32,A9	17	17/165 x 100 % = 10,3%
10	A9,A32	17	17/165 x 100 % = 10,3%
….			
….			
51	A1,A32	40	40/165 x 100 % = 24,24%
52	A32,A1	40	40/165 x 100 % = 24,24%

After obtaining the association rules that determine support, the next step is to calculate confidence. To determine the confidence value for each item set, the formula is used:

$$\textit{Confidence }(A\rightarrow B) = \frac{\text{Number of Transactions Contains } A\cap B}{\text{Total Transactions } A} \times 100\%$$

Table 9 Confidence Value in Suffix

No	Association Rules	*Count*	*Confidence*
1	A8,A9	4	4/35 x 100 % = 11,43%

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2	A9.A8	4	4/33 x 100 % = 12,12%
3	A6,A9	3	3/34x 100 % = 8,82%
4	A9,A6	3	3/33 x 100 % = 9,09%
5	A1,A9	23	23/81 x 100 % = 28,4%
6	A9,A1	23	23/33 x 100 % = 69,7%
7	A19,A9	19	19/34 x 100 % = 55,88%
8	A9,A19	19	19/33 x 100 % = 57,58%
9	A32,A9	17	17/68 x 100 % = 25%
10	A9,A32	17	17/33 x 100 % = 51,52%
….			
….			
51	A1,A32	40	40/81 x 100 % = 49,38%
52	A32,A1	40	40/68 x 100 % = 58,82%

DISCUSSIONS

The results of the calculations are based on Select Itemset Pairs According to the Minimum Support and Minimum Confidence Values

If a value of ≥ 15% is taken as a minimum support and a value of ≥ 15% as a minimum confidence, then from the table above the conclusions are obtained, namely:

1. If Dexa (A1) is sold then Cefadroxil (A19) will also be sold, because support = 17.58% and 35.8% confidence.
2. If Dexa (A1) is sold then Paracetamol (A32) will also be sold, because support = 24.24% and confidence 49.38%.
3. If Omz (A3) is sold then Domperidone (A10) will also be sold, because support = 19.39% and 64% confidence.
4. If Cefadroxil (A19) is sold then Dexa (A1) will also be sold, because support = 17.58% and confidence 85.29%.
5. If Paracetamol (A32) is sold then Dexa (A1) will also be sold, because support = 24.24% and confidence 58.82%.
6. If Domperidone (A10) is sold then Omz (A3) will also be sold, because support = 19.39% and confidence 61.54%.

CONCLUSION

Based on the results of the analysis of the problems in the process of applying the FP-Growth method to determine sales patterns, the first step is to collect data through interviews to obtain drug sales data which will then be determined using the FP-Growth method. Based on the results of applying the FP-Growth method in determining drug sales patterns, the FP-Growth method issues the final result in the form of a report on determining drug sales patterns based on drug sales data. Based on the results of the implementation of the system that has been carried out, the calculation results for determining the pattern of drug sales in the system are the same as the results of manual calculations carried out using the FP-Growth method

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