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IMPLEMENTATION OF DATA MINING ASSOCIATION METHODS WITH APRIORI ALGORITHM FOR DETERMINING THE KEY PLAYERS OF FOOTBALL CLUB

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Abstract:

Persija *(Persatuan Sepak Bola Indonesia Jakarta)* is a professional football team that has been legendary in the history of football in Indonesia. The team, which is under the management of PT Persija Jaya Jakarta, has won eleven titles from the main divisions of the Indonesian league. The Persija Football Club has always evolved towards a modern team, although it is often not easy to defend a championship title. In fact, the composition of players and strategy is the primary key of each match that must be won. This study aims to find the rules of association between Persija FC players from matches that have been played. This research was completed using one data mining technique, namely the Apriori Algorithm. The results of the study have shown that there are 26 strong association rules in determining the composition of players to be revealed. Modeling results also show that using apriori algorithm at a minimum support value of 80% and a minimum confidence value of 95%, founded five-six key players. They have the most reliable association rules from the result of a match that ends in a draw or win. The association rules obtained can change according to the learning model of the new data changes that occur. Thus, the learning machine model that has been built always finds new rules in determining the key players for the next match.

Keywords **— Data Mining, Association Rules, Apriori Algorithm, Indonesian Football League, Football Player, Persija Football Club**

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I. INTRODUCTION

Football is one of the most popular sports in Indonesia. In the modern era like now, football is not only limited to matches or entertainment but also becomes one of the promising industries and sources of income for business people. The Government and the President have also given great attention to this sport. It has been proven that football is the only sport that is regulated in the Presidential Instruction No. 3/2019 concerning the Acceleration of Indonesian Football Development [1].

PT Persija Jaya Jakarta is a public company that regulates the management of the Persija Football Club (Persija FC). Persija FC was established on November 28, 1928, with the original name *Voetbalbond Indonesische Jacatra* (VIJ), which has won the domestic league 11 times and is the most successful club in the history of Indonesian football.

In his last season, the Shopee Liga 1 2019 competition, the Persija club had changed coaches three times, even though they still had to end the season with a not-so-good league position. This bad condition has happened because of the need to adjust the strategy and pattern of the game from the old coach to the new coach at a fast time [2].

Unsatisfactory results for the club Persija have drawn criticism from their supporters known as *The Jak Mania. The Jak Mania* demanded Persija always to achieve the best results and sometimes voiced pressure for the coaching team to be more severe in concocting strategies and the composition of the team of players. To find out the best arrangement of the team, of course, we need an in-depth analysis of the performance of each player, including analysis of the association relationships between players. Often a player plays less than optimal because the composition of the player does not fit into the team's strategy.

One method that can be used to solve these problems is the Data mining method. In general, the usefulness of data mining can be divided into descriptive and predictive. Descriptive means that data mining is used to look for patterns that can be understood by humans that explain the characteristics of the data. While predictive means that data mining is used to form a knowledge model that will be used to make predictions [3].

Data Mining using the association rules method has been known to be one of the methods for resolving the association pattern or relationship. The Apriori Algorithm has been known to be one of the methods for resolving the association pattern that worked effectively.

Several previous studies discussing data mining using the Apriori Algorithm have been carried out, for example, in the analysis of sales in the grocery store. This study aims to look for the rules of the association of goods that are usually purchased simultaneously with the highest frequency [4].

Other research related to the Association Rule and Apriori Algorithm discusses the Rain Prediction Simulation in the City of Bandung. This research was conducted in three main stages, namely analyzing high-frequency patterns, forming association rules, and testing the strength of the rules created by calculating lift ratios. The results of this study are to obtain the association rules in predicting rainy or not rainy weather in the coming day. The study resulted in 14 rules that were formed with the highest accuracy obtained at 75.89% and minimum confidence of 50% [5].

Previous studies also used data mining to rank players based on the value of the operands in a football match. This value is developed for the location of the feed and the chances of shots being produced. The research offered by this machine learning model uses data from the 2012-2013 La Liga Football competition [6].

Other previous studies also using the association method were also conducted to find valuable knowledge and discuss some patterns from the Europe Champions League football match data. This research also builds a visualization of the association rules found and integrates them with other data mining methods [7].

Based on previous literature, it is known that Data Mining using the Association Rule method is able to complete the data mining process from previous data. This study analyzes data from match summaries, so that the association relationship between players in each position is known, and what combination of the best players to win the match, both in defense and goal productivity. Another benefit of this research can be used by club management to determine which players are eligible for a contract extension for the following season.

This study aims to find the association rules of the composition of players who have been derived. The analysis is carried out on all results of matches in one 2019 competition season. The modeling process is carried out from match data that ends in a win or series. From the modeling done, found association rules that can be used for coaches in determining the composition of players for the next match.

II. RESEARCH METHODOLOGY

In this study, we used the Knowledge Discovery in Databases (KDD) model in previous studies [8], as shown in Figure 1.

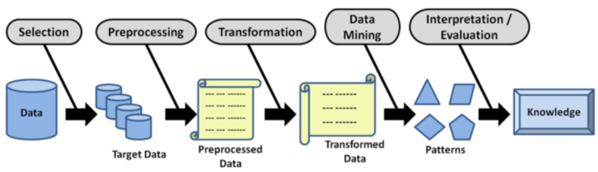

Fig. 1. Knowledge Discovery in Databases

Figure 1 has shown that the first stage of this research is data selection. The data used in this study is the result of matches from one full season played by Persija FC in 2019, as many as 34 matches.

The second step is processing the data that has been collected. At this stage, secondary data in the form of summary sheets of the results of the match are transferred to electronic worksheets in the form of .xls so that they can be read by the learning machine application that is built.

The next step is data transformation, which is the process of changing the value in the datasheet into a more meaningful form in the formation of the association model. The transformation includes changing data into an integrated database consisting of players, match statistics, and match results.

The main stage of this study is data mining to find patterns of relationships between players that have been obtained. The settlement is done using the Apriori algorithm, which is well known in the discovery of associative rules in data mining.

The final stage is to interpret the association patterns that are formed based on the desired Support and Confidence value limits. In this study, the evaluation of association rules is set at a minimum support value of 80% and a confidence value of at least 95%, based on the selection of match data analyzed in matches with winnings and draws. The interpretation is visualized in a prototype application that shows the strongest association relationship between players handed down in the match.

The limitation of this study is that it only uses data from one season, and only analyzes the association between players based on the history of the match with the winning and drawing results. In addition, the analysis was carried out using only one association method, the Apriori algorithm.

III. RESULT AND DISCUSSION

The data used in this study is the Persija match data at Shopee Liga 1 2019 in one season. The data attributes are seen in Table 1.

TABLE I. DATA ATTRIBUTES MATCH SUMMARY

Nbr.	Attribute Name	Description
1.	Date	Match Date
2.	Opponent	Opposing team
3.	Player	Line-up
4.	Position	Player position
5.	Yellow card	List of players who get a yellow card
6.	Red Card	List of players who get a red card
7.	Goal	List of players who scored
8.	Results	Match results

Based on the data attributes that have been seen in Table I, we begin to separate the types of data to be analyzed, which is a summary of the match, which has only the winning results and draws. This phase of separation is called data selection. The result of the data selection stage was the discovery of the team structure from 21 matches, as shown in Table II.

TABLE II. COMBINATION OF TEAM PLAYERS

Date	Initial Player Name	Result
20/05/19	AA,IS,RU,SP,TS,BM,NS,RS,RC,SS,MS	Draw
22/06/19	AA,AH,DS,MA,SP,TS,NS,RS,RC,FE,MS	Draw
10/07/19	SG,IS,MA,RU,TS,BM,NS,RS,RC,MS,YR	Draw
03/08/19	AA,IS,RH,RU,TS,BM,NS,RS,RC,SS,MS	Draw
10/08/19	SG,IS,RH,MA,RU,TS,NS,RS,RL,RC,MS	Draw
16/08/19	AA,DS,MA,TS,NS,RS,RL,RC,SS,HS,MS	Draw
20/08/19	AA,DS,RU,TS,NS,RS,RL,RC,SS,HS,MS	Win
24/08/19	SG,RH,MA,TS,NS,RS,RL,RC,SS,HS,MS	Draw
28/08/19	SG,IS,RH,MA,RU,TS,NS,RS,RL,RC,MS	Draw
15/09/19	AA,AL,RH,MA,TS,JT,NS,RS,RL,RC,MS	Win
23/09/19	AA,AL,FA,IS,TS,NS,RS,RL,RC,SS,MS	Win
20/10/19	AA,AL,FA,RH,NS,RS,RL,RC,SS,HS,MS	Win
24/10/19	AA,AL,FA,RH,NS,RS,RL,RC,SS,HS,MS	Draw
03/11/19	AA,AL,FA,RU,TS,JT,NS,RHD,RC,HS,MS	Win
07/11/19	AA,AL,FA,IS,RH,RU,NS,RC,SS,HS,MS	Draw
11/11/19	AA,AL,FA,IS,RU,TS,NS,RHD,RS,RC,MS	Win
15/11/19	SG,AL,FA,IS,TS,NS,RHD,RS,RC,SS,MS	Win
23/11/19	SG,AL,FA,RU,TS,NS,RHD,RS,SS,HS,MS	Draw
28/11/19	AA,AL,FA,RU,TS,NS,RS,RC,SS,HS,MS	Win
13/12/19	AA,IS,RU,TS,FR,NS,RS,RL,RC,SS,MS	Win
21/12/19	SG,AL,FA,IS,TS,FR,RHD,RC,SS,BP,HS	Win

Descriptions of each player's initials are as follows:

AA	: Andritany Ardhiyasa	(GK)
AH	: Al Hamra	(CB)
AL	: Alexandre Luiz	(CB)
BP	: Bambang Pamungkas	(FW)
BM	: Bruno Matos	(AMF)
DS	: Dany Saputra	(LB)
FA	: Fachrudin Aryanto	(CB)
FE	: Feby Eka	(LMF)
FR	: Fitra Ridwan	(CMF)
HS	: Heri Susanto	(FW)
IS	: Ismed Sofyan	(RB)
JT	: Joan Thomas	(AMF)
MA	: Maman Abdurrahman	(CB)
MS	: Marco Simic	(FW)
NS	: Novri Setiawan	(LMF)

RC	: Rohit Chand	(CMF)
RH	: Rezaldi Hehanusa	(LB)
RHD	: Rachmad Hidayat	(AMF)
RL	: Ramdani Lestaluhu	(AMF)
RS	: Riko Simanjuntak	(RMF)
RU	: Ryuji Utomo	(CB)
SG	: Shahar Ginanjar	(GK)
SP	: Steven Paulle	(CB)
SS	: Sandi Sute	(DMF)
TS	: Tony Sucipto	(R/LB)
YR	: Yogi Rahadian	(FW)

From Table II, it can be seen that there are ten winning games, and there are 11 draws. From 34 matches in one season, there are 13 matches with the result of losing and must be eliminated. This stage is the process of cleaning up data from forms of duplication, inconsistent data, and trimming data that is not needed for the mining process. At the transformation stage, there is no significant data change, and the data is ready to enter the next processing phase, the modeling process.

The main stage in this research is the modeling work using primary data. Modeling is intended to find patterns in the data in the form of association rules based on the application of the Apriori algorithm. The first pattern formation is the analysis of the highest playing frequency based on the determination of the minimum support value using Equation 3.

$$Support(A) = \frac{number\ of\ transactions\ containing\ A}{total\ number\ of\ transactions} \times 100\% \quad (3)$$

The calculation of the support value of the 2-itemset is solved using Equation 4.

$$Support(A, B) = \frac{number\ of\ transactions\ containing\ A\ and\ B}{total\ number\ of\ transactions} \quad (4)$$

In the process, the a priori algorithm finds frequent-itemset by iterating the data. An itemset is a set of items that are inside a set that is processed by the system, whereas frequent-itemset shows items that have a frequency of occurrence more than the specified minimum value (ɸ). In the k-iteration, all items set found that have k items are called k-itemset. Each iteration consists of two stages, namely the generation of candidates and the generation of rules [5].

To get the results of the association of key players, we chose ten matches with win status, with a minimum limit of ɸ = 80. Thus, the minimum value of support = 80%, and we also set a minimum confidence = 95% because the purpose of this study was to determine key players with a chance of winning from the association rules that are formed. After the minimum highest frequency rule has been defined, we look for a combination of k-itemset that meets the minimum support conditions using Equation 4.

From the results of calculating the Equation 3 and 4, the highest frequency pattern is obtained for seven players who have a support value of ɸ ≥ 80% as shown in Table III.

TABLE III. HIGHEST FREQUENCY PATTERN OF ITEMSET1

Nbr.	Player	Frequency	Support
1.	AA	8	80%
2.	AL	8	80%
3.	MS	9	90%
4.	NS	8	80%
5.	RC	10	100%
6.	RS	8	80%
7.	TS	9	90%

In Table III, it has been seen that found seven key players Itemset1 who always win from the highest playing frequency at the minimum support value of ɸ ≥ 80%. The next step is to start looking for the itemset2 player line-up as a combination of more than one player. The results of calculating the Itemset2 association are shown in Table IV.

TABLE IV. HIGHEST FREQUENCY PATTERN OF ITEMSET2

Nbr.	Player	Frequency	Support
1.	AA,MS	8	80%
2.	AA,NS	8	80%
3.	AA,RC	8	80%
4.	AL,RC	8	80%
5.	MS,NS	9	90%
6.	MS,RC	9	90%
7.	MS,RS	8	80%
8.	MS,TS	8	80%
9.	NS,RC	9	90%
10.	NS,RS	8	80%
11.	NS,TS	8	80%
12.	RC,RS	8	80%
13.	RC,TS	9	90%

Table IV shows that there are 13 players in the Itemset2 pattern that have the highest playing frequency at the minimum support value support

≥80%. When compared to Table III, 13 itemset player combinations have been won. Next, we look for support values for Itemset3 from the highest frequency pattern results, with the results shown in Table V.

TABLE V. THE CALCULATION RESULTS OF SUPPORT OF ITEMSET3

No.	Player	Frequency	Support	Result
1.	AA,NS,RC	8	80%	Passed
2.	AA,NS,MS	8	80%	Passed
3.	AA,TS,NS	7	70%	Failed
4.	AA,TS,RC	7	70%	Failed
5.	TS,NS,RC	8	80%	Passed
6.	AA,TS,MS	7	70%	Failed
7.	TS,NS,MS	8	80%	Passed
8.	AA,NS,RS	7	70%	Failed
9.	AA,RS,RC	7	70%	Failed
10.	RS,NS,RC	8	80%	Passed
11.	AA,RS,MS	7	70%	Failed
12.	RS,NS,MS	8	80%	Passed
13.	AA,RC,MS	8	80%	Passed
14.	RC,NS,MS	9	90%	Passed
15.	AA,RC,AL	6	60%	Failed
16.	AA,NS,AL	6	60%	Failed
17.	RC,NS,AL	7	70%	Failed
18.	TS,RC,MS	8	80%	Passed
19.	RS,RC,MS	8	80%	Passed
20.	AA,MS,AL	6	60%	Failed
21.	RC,MS,AL	7	70%	Failed
22.	TS,NS,RS	7	70%	Failed
23.	TS,RS,RC	7	70%	Failed
24.	TS,RS,MS	7	70%	Failed
25.	TS,RC,AL	7	70%	Failed
26.	TS,NS,AL	6	60%	Failed
27.	TS,MS,AL	6	60%	Failed
28.	NS,RS,AL	6	60%	Failed
29.	RC,RS,AL	6	60%	Failed
30.	NS,MS,AL	7	70%	Failed
31.	RS,MS,AL	6	60%	Failed

In Table V, it can be seen from the itemset3 pattern that there are only ten combinations for three players who meet the minimum support requirement ≥ 80%. After getting high-frequency patterns from itemset1, itemset2, and itemset3. Next, we enter into an association agreement that meets the minimum requirements using Equation 5.

$$Confidence = P(B|A) = \frac{\sum transaction\ containing\ A\ dan\ B}{\sum transaction\ containing\ A} \quad (5)$$

By calculating confidence A → B (if A, then B), the strongest association rules with minimum support are found ≥ 80% from key players for Itemset 2 and Itemset 3, as shown in Table VI.

TABLE VI. CALCULATION OF CONFIDENCE OF ITEMSETS

No.	A => B	Support A ∪ B	Support A	Conf.
1.	AA,NS=>RC	80	80	100%
2.	RC,AA,=>NS	80	80	100%
3.	AA=>RC,NS	80	80	100%
4.	AA,NS=>MS	80	80	100%
5.	MS,AA=>NS	80	80	100%
6.	AA=>MS,NS	80	80	100%
7.	TS,NS=>RC	80	80	100%
8.	TS,NS=>MS	80	80	100%
9.	MS,TS=>NS	80	80	100%
10.	RS,NS=>RC	80	80	100%
11.	RC,RS=>NS	80	80	100%
12.	RS=>RC,NS	80	80	100%
13.	RS,NS=>MS	80	80	100%
14.	MS,RS=>NS	80	80	100%
15.	RS=>MS,NS	80	80	100%
16.	AA,RC=>MS	80	80	100%
17.	MS,AA=>RC	80	80	100%
18.	AA=>MS,RC	80	80	100%
19.	RC,NS=>MS	90	90	100%
20.	NS,MS=>RC	90	90	100%
21.	MS,RC=>NS	90	90	100%
22.	NS=>RC,MS	90	90	100%
23.	MS=>NS,RC	90	90	100%
24.	MS,TS=>RC	80	80	100%
25.	RS,RC=>MS	80	80	100%
26.	MS,RS=>RC	80	80	100%
27.	RS=>MS,RC	80	80	100%
28.	AA => NS	80	80	100%
29.	AA => RC	80	80	100%
30.	AA => MS	80	80	100%
31.	TS => RC	90	90	100%
32.	RS => NS	80	80	100%
33.	NS => RC	90	90	100%
34.	NS => MS	90	90	100%
35.	MS => NS	90	90	100%
36.	RS => RC	80	80	100%
37.	RS => MS	80	80	100%
38.	MS => RC	90	90	100%
39.	AL => RC	80	80	100%

From the results of the Confidence calculation in Table VI, there is no value of 90% or 95%, and we only find a value of 100% for conditions that meet the minimum support requirement ≥ 80%. We also found a support value <80% for the results of the association but was eliminated because it did not comply with the minimum rules desired for the purpose of this study.

After the association rules are obtained that meet the minimum confidence requirements, then testing is done by calculating the value of the lift to determine whether the rules are valid or not. The association rule test will be checked using the lift ratio value in Equation 6.

$$Lift\ Ratio = \frac{Confidence\ (A,B)}{Benchmark\ Confidence\ (A,B)} \quad (6)$$

The Benchmark Confidence value can be found by the Equation 7.

$$Benchmark\ Confidence = \frac{Nc}{N} \quad (7)$$

Description:

N_c is the number of transactions with items that are consequent

N is the number of database transactions

From the test results using Equation 6, we founden that there are 26 of 39 rules with Lift test values that meet the requirements of> 1.00. This limit refers to previous studies [5]. All association rules obtained can be seen in Table VII.

TABLE VII. The Rules of Association Obtained

No.	A => B	Rules
1.	RC,AA,=>NS	If Rohit Chand and Andritany Ardhiyasa play, then Novri Setiawan must also play
2.	AA=>RC,NS	If Andritany Ardhiyasa plays, then Rohit Chand and Novri Setiawan must also play
3.	AA,NS=>MS	If Andritany Ardhiyasa and Novri Setiawan play, then Marco Simic must also play
4.	MS,AA=>NS	If Marco Simic and Andritany Ardhiyasa play, then Novri Setiawan must also play
5.	AA=>MS,NS	If Andritany Ardhiyasa plays, then Marco Simic and Novri Setiawan must also play
6.	TS,NS=>MS	If Tony Sucipto and Novri Setiawan play, then Marco Simic must also play
7.	MS,TS=>NS	If Marco Simic and Tony Sucipto play, then Novri Setiawan must also play
8.	RC,RS=>NS	If Rohit Chand and Riko Simanjuntak play, then Novri Setiawan must also play
9.	RS=>RC,NS	If Riko Simanjuntak plays, then Rohit Chand and Novri Setiawan must also play
10.	RS,NS=>MS	If Riko Simanjuntak and Novri Setiawan play, then Marco Simic must also play
11.	MS,RS=>NS	If Marco Simic and Riko Simanjuntak play, then Novri Setiawan must also play
12.	RS=>MS,NS	If Riko Simanjuntak plays, then Marco Simic and Novri Setiawan must also play
13.	AA,RC=>MS	If Andritany Ardhiyasa and Rohit Chand play, then Marco Simic must also play
14.	AA=>MS,RC	If Andritany Ardhiyasa plays, then Marco Simic and Rohit Chand must also play
15.	RC,NS=>MS	If Rohit Chand and Novri Setiawan play, then Marco Simic must also play
16.	MS,RC=>NS	If Marco Simic and Rohit Chand play, then Novri Setiawan must also play
17.	NS=>RC,MS	If Novri Setiawan plays, then Rohit Chand and Marco Simic must also play
18.	MS=>NS,RC	If Marco Simic plays, then Novri Setiawan and Rohit Chand must also play
19.	RS,RC=>MS	If Riko Simanjuntak and Rohit Chand play, then Marco Simic must also play
20.	RS=>MS,RC	If Riko Simanjuntak plays, then Marco Simic and Rohit Chand must also play
21.	AA => NS	If Andritany Ardhiyasa plays, then the team must also play Novri Setiawan
22.	AA => MS	If Andritany Ardhiyasa plays, then the team must also play Marko Simic
23.	RS => NS	If Riko Simanjuntak plays, then the team must also play Novri Setiawan
24.	NS => MS	If Novri Setiawan plays, then the team must also play Marko Simic
25.	MS => NS	If Marco Simic plays, then the team must also play Novri Setiawan
26.	RS => MS	If Riko Simanjuntak plays, then the team must also play Marco Simic

From the rules formed in Table VII, it is known that there are six key players from various positions to win, they are Andritany Ardhiyasa (GK), Tony Sucipto (RB), Rohit Chand (CMF), Riko Simanjuntak (RMF), Novri Setiawan (RK) LMF), and Marko Simic (FW). These key players always appear in every association rule obtained. The composition of the key players shown in Figure 2.

Fig. 2. The Key Players Obtained

If the rules are applied from match data that end in a draw, the same five key players are obtained. The difference is Andritany Ardhiyasa (GK) is not included in the category of key players. It can be concluded that the discovery of these key players has an accuracy of up to 83% based on modeling the association rules of matches that have both winning and drawing results. If all players are played together, then it is probable that Persija FC will get a win because each key player has a strong association relationship with the victory results in the previous matches.

We have also presented the association's interpretation into a prototype application for the determination of key players that are compiled based on the association rules that are formed. The prototype design is done using a web-desktop based programming language, which in the future will be developed into a mobile application.

Figure 3 through Figure 6 shows the interface of the prototype of the learning machine application that was built. The whole picture shows various processes ranging from uploading historical data to the summary of the results of the match, the process of forming association rules with the Apriori algorithm, and the visualization process of finding the association rules.

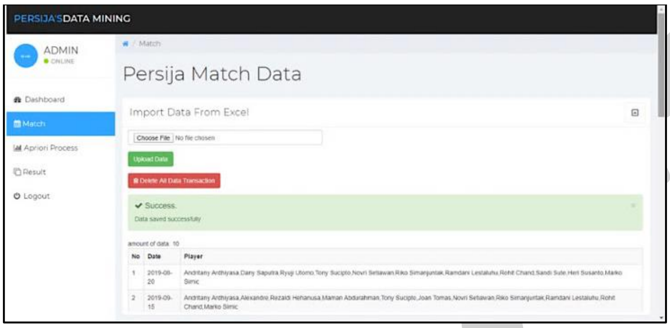

Fig. 3. Data Import Process

In Figure 3, it has been seen that the imported data will be processed with several iterations to get the high-frequency pattern of an itemset. The process of applying the Apriori algorithm is done, as shown in Figure 4.

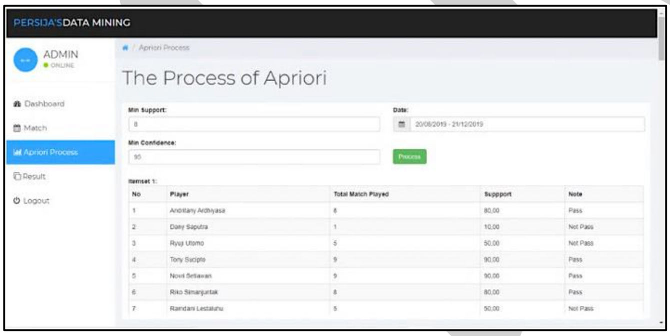

Fig. 4. The Process of Apriori

After all the iteration processes are completed, then from Figure 4 the support values for determining the rules of association between players are identified. The results of the association rules are tested in the lift test, as shown in Figure 5.

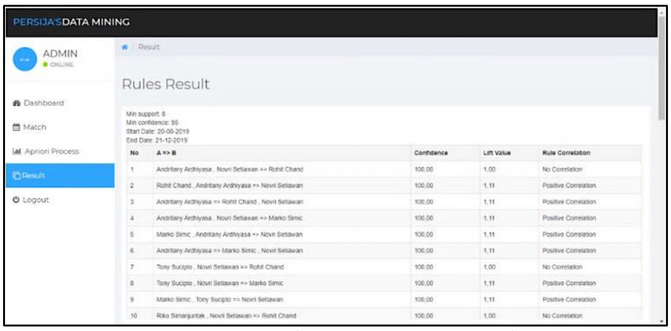

Fig. 5. Results of testing rules with the Lift test

At the test stage, a valid arrangement of rules has been obtained and meets the criteria for problem-solving. Visualization of the application of the formed association rules can be seen in Figure 6.

Fig. 6. The Formation of Key Players

It can be seen in Figure 6 that the application system built is able to visualize the association rules that are formed with validity reaching 100% or the same as the results of calculations on the application of the Apriori algorithm.

IV. CONCLUSION

From this study, it can be concluded that the Apriori method can be used well to determine the association of Persija FC players, based on a summary of the results of matches that have been played in a season. Determination of the association's relationship is set with a minimum value of 80% support and a minimum value of 95% Confidence from the summary of the results of the match with the winnings and draws.

The discovery of the association pattern has been validated by measuring the value of the elevator and can show that there are a number of key players who have the strongest association in the match that has been won. The association relationship pattern was also successfully visualized in a prototype that was built with validity reaching 100%.

This research can be developed in the future to find association rules for determining the line-up of eleven players. Besides, the research scope can also be expanded by involving the attributes of the accumulation of time played by each player in previous matches.

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