Analysis of sales levels of pharmaceutical products by using data mining algorithm C45

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ABSTRACT
This research was conducted to analyze the level of sales of pharmaceutical products at a Pharmacy. This is done to find out the types of products that have high and low sales levels. This study uses the C45 Data Mining Algorithm concept that will produce a conclusion on the prediction of sales of pharmaceutical products through data processing obtained from sales transactions at pharmacies. This C45 algorithm will form a decision tree that provides users with knowledge about products that are in great demand by consumers based on sales data and predetermined variables. The final result of the C45 algorithm produces a number of rules that can identify the inheritance of a type of medicinal product. C45 algorithm is able to produce 20 types of categories that will be labeled goals based on the number of pharmaceutical products, since it can be concluded that C45 successfully defines 55% of the existing objective categories.

Keywords:
Algorithm C45
Data mining
Knowledge
Pharmaceutical

1. INTRODUCTION
The sale of pharmaceutical products to Indonesians can be found in various places, one of which is a pharmacy. Pharmacy is one of the health service facilities in helping to achieve optimal health status for the community. Health services are all efforts made individually or collectively in an organization to maintain and improve their health, prevent and cure diseases, and restore the health of individuals, families, communities [1]. Good health services are supported by the availability of pharmaceutical products, which can meet consumer needs and understand consumer behavior [2]. As for things related to consumers, especially experiences with digital concepts are very necessary for now [3]. To find out the needs and behavior of consumers, we must analyze and process the data we have with various concepts such as data mining or big data [4].

Data mining is the process of mining data to generate new knowledge from very large data [5]. In data mining, there is a classification process, including classifying the promotion of private schools in order to have good branding [6]. Data mining is closely related to data, information and knowledge. A process in data mining that starts with a data extraction process which then produces information [2]. The information that will be generated will then be processed to produce a bias in the form of a pool (pattern). This pattern will be translated into knowledge that can produce decisions [3]. Data mining is part of the knowledge discovery in database (KDD) process, which in the KDD process consists of stages of data cleaning, data integration, data selection, data transformation, data mining, evaluation of patterns and presentation of knowledge, such us Figure 1. There are several algorithms commonly used in data processing and analysis,
including the K-nearest neighbor (KNN) with a global GINI diversity index for subsidized food classification in the city of Semarang, Indonesia in recent years many methods have been used for data classification [7]. For other classification processes, the c45 algorithm can be used [8]. To do predictions, you can also use this c45 algorithm [9].

The C45 algorithm which is one of the algorithms in machine learning can be used to diagnose various types of diseases in the medical world, supported by other algorithms in machine learning [10-12]. Besides the C45 algorithm can also be combined with the naïve Bayes algorithm to analyze a social, academic problem, [5, 13, 14]. Many researchers combine and compare the c45 algorithm with other algorithms such as the comparative analysis of Naive Bayes, K Nearest Neighbor and C.45 methods in weather forecasting that provide decision support [15]. In addition, c45 datamining can also be used to measure the level of customer satisfaction in an institution or organization [16]. The C45 algorithm can also measure the level of service quality in banking companies [17]. In managing product availability, several inventory management techniques can be used, one of which is data mining with the c45 algorithm, k means and others [18]. The c45 method can be used for various prediction processes and is compared with the Support Vector Machine algorithm for identification of pests and diseases in plants [19]. The c45 algorithm can also be used to diagnose covid 19 surveillance classifications which include PDP, ODP, and OTG [20]. The results showed that the COVID-19 surveillance diagnosis using the C4.5 algorithm was successfully modeled into a decision tree with the classification of PDP, ODP, and OTG. The testing process in the form of confusion matrix with 3 (three) classes produces an accuracy rate of 92.86% which is included in the very good classification category.

The implementation of the C45 data mining algorithm can be carried out in all aspects of life including in soil or civil science. With a data mining approach that uses the C4.5 Algorithm decision tree, a classification model will be created where the model functions as a classification of the causes of landslides in Purwakarta district [21]. Twenty-eight goals and thirty-six measures were used, and nine departments were involved to monitor the performance of the goals so that the company achieved the goals set. The research conducted data mining with the C4.5 algorithm [22]. The resulting rules are 11 rules and the level of accuracy achieved is 79.41%. In this study the authors apply the C45 algorithm to analyze customer loyalty. The variables used are based on price, attitude in serving consumers [23]. Based on the analysis of the use of data mining with the C4.5 algorithm, it can be used in customer data sets into strategic management activities so that it can accommodate customers as long as possible properly, this C4.5 algorithm application must be included in the data set. The C45 method is used to predict furniture sales, through this process the product items that are most in demand by customers are found [24, 25].

Figure 1. The process of knowledge discovery in database

2. RESEARCH METHOD

One of the decision tree induction algorithms is ID3 (iterative dichotomiser). ID3 was developed by J. Ross Quinlan. In the ID3 algorithm procedure, the input is in the form of training samples, training labels and attributes. C4.5 algorithm is the development of ID3. Algorithm C 4.5: Select attribute as root, create a branch for each value, for cases in the branch, repeat the process for each branch until all cases in the branch have the same class. To select the root attribute, based on the highest GAIN value of the attributes which exists. To get the GAIN value, you must first determine the ENTROPY value.
The research focuses on the process of analyzing the data of drug products entering pharmacies through suppliers with the C4.5 algorithm and using the Weka (tools data mining) program to obtain classification results. There are 6 attributes used in the study, namely: (1) IDs from 1 to 20; (2) names consist of supplier names, namely: A001, A002, A003, A004, A005, A006, A007, A008, A009, A010, A011, A012, A013, A014, A015, A016, A017, A018, A019, dan A020; (3) the number of drugs consisting of 1296, 896, 528, 8000, 180, 200, 132, 132, 144, 400, 340, 456, 200, 3000, 222, 6360, 362, 300, 144, 144; (4) types of drugs consists of generic drugs and patents; (5) Delivery consists of fast and late; (6) Prices consist of 1500, 2008, 3500, 210, 5400, 12400, 10500, 10500, 5700, 7300, 3600, 3200, 3000, 600, 3200, 950, 5200, 3570, 5500, 4700; The C4.5 algorithm starts from the process of selecting the attribute with the highest gain as the root of the tree, then makes a branch for each value, then divides the cases into branches, after that repeats the process for each branch until all cases in the branch have the same class. Flowchart can clearly illustrate the stages and steps in the classification using the C4.5 algorithm. It can be seen in the form of a flowchart in Figure 2. C4.5 Algorithm Classification Technique begins with data processing and transformation so that the raw data used for analysis is data with complete attributes and can produce decision trees. Supplier data that has been obtained is processed to process the C45 data mining process by searching for entropy, after the entropy value is obtained then look for the gain value. The entropy value and the existing gain then look for the highest gain value, because the highest gain value will determine the root node in the decision tree, then get a new node in the decision tree, such us Figure 2.

![Flowchart proses algoritma C45](image)

3. RESULTS AND ANALYSIS
3.1. Data analysis

Data analysis is the stage for analyzing the data needed for the design of the system to be made, in this case the authors take data through the literature relating to the research theme, to find information compile the theories related to the discussion so that there is a fusion complex between one and the other, such us Table 1.

The classification process for each Sales table field, such us Table 2.

1. Classification of Medicine Amounts
   a. \( \geq 1200 \): if the number of medicine is more than or equal to 1200, so the number of medicine is many
   b. \(< 1200 \): if the amount of medicine is less than 1200 then the number of medicine is few

2. Price Classification
   a. \( \geq 5000 \): If the price of the medicine is more than or equal to 5000 per pcs then the drug is expensive
   b. \(< 5000 \): If the price of medicine is less than 5000 per pcs, the medicine is cheap

3. Classification of types of medicines
   a. Generic: is a medicine whose patent has expired so that it can be produced by all pharmaceutical companies without the need to pay royalties
   b. Paten:a new medicine that is produced and marketed by a pharmaceutical company that has a patent
4. Delivery
   a. Fast: Is a supplier that is delivered on time or sooner than the agreed time
   b. Late: Delivery is made by the supplier later than the agreed time.

The entropy search processing formula is performed as follows:

\[
Ent(S) = \sum_{i=1}^{n} p_i \cdot \log_2 p_i
\]

Note:
- \( S \) : case set
- \( A \) : attribute
- \( n \) : Number of partitions \( S \)
- \( p_i \) : proportion from \( S_i \) to \( S \)

Gain search processing formula performed as follows:

\[
Gain(S, A) = Entropy(S) - \sum_{i=1}^{n} \frac{\left| S_i \right|}{\left| S \right|} \cdot \log_\left( \frac{\left| S_i \right|}{\left| S \right|} \right)
\]

\( Entropy(S) \)
- \( S \) : case set
- \( A \) : attribute
- \( n \) : number of partitions \( A \)
- \( \left| S_i \right| \) : the number of cases in the partition to \( i \)
- \( \left| S \right| \) : number of case in \( S \)

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Table 1. Medicine supplier search

| ID | Name   | Number of Medicine | Types of Medicine | Delivery | Price | Decision       |
|----|--------|--------------------|-------------------|----------|-------|----------------|
| 1  | A001   | 1296               | generic           | Fast     | 1500  | In Demand      |
| 2  | A002   | 1896               | generic           | Fast     | 2008  | In Demand      |
| 3  | A003   | 528                | patent            | Late     | 3500  | Not In Demand  |
| 4  | A004   | 8000               | generic           | Fast     | 210   | In Demand      |
| 5  | A005   | 180                | patent            | Fast     | 5400  | In Demand      |
| 6  | A006   | 200                | generic           | Fast     | 12400 | Not In Demand  |
| 7  | A007   | 132                | patent            | Late     | 10500 | Not In Demand  |
| 8  | A008   | 132                | generic           | Fast     | 10500 | Not In Demand  |
| 9  | A009   | 144                | patent            | Fast     | 5700  | In Demand      |
| 10 | A010   | 400                | generic           | Fast     | 7300  | Not In Demand  |
| 11 | A011   | 340                | patent            | Fast     | 3600  | In Demand      |
| 12 | A012   | 456                | generic           | Late     | 3200  | Not In Demand  |
| 13 | A013   | 200                | generic           | Late     | 3000  | Not In Demand  |
| 14 | A014   | 3000               | generic           | Late     | 600   | In Demand      |
| 15 | A015   | 222                | generic           | Fast     | 3200  | In Demand      |
| 16 | A016   | 6360               | patent            | Late     | 950   | In Demand      |
| 17 | A017   | 362                | generic           | Fast     | 5200  | Not In Demand  |
| 18 | A018   | 300                | generic           | Fast     | 3570  | In Demand      |
| 19 | A019   | 144                | patent            | Late     | 5500  | Not In Demand  |
| 20 | A020   | 144                | generic           | Fast     | 4700  | In Demand      |

Source: Arafah Pharmacy, Padang Panjang

Table 2. Data supplier pharmacies (Medicine) January 2017-January 2019

| ID | Name   | Number of Medicine | Types of Medicine | Delivery | Price | Decision       |
|----|--------|--------------------|-------------------|----------|-------|----------------|
| 1  | A001   | Many               | Generic           | Fast     | Cheap | In Demand      |
| 2  | A002   | Few                | Generic           | Fast     | Cheap | In Demand      |
| 3  | A003   |Few                 | Patent            | Late     | Cheap | Not In Demand  |
| 4  | A004   | Many               | Generic           | Fast     | Cheap | In Demand      |
| 5  | A005   | Few                | Patent            | Fast     | Expensive | In Demand  |
| 6  | A006   | Few                | Generic           | Fast     | Expensive | Not In Demand |
| 7  | A007   | Few                | Patent            | Late     | Expensive | Not In Demand |
| 8  | A008   | Few                | Generic           | Fast     | Expensive | Not In Demand |
| 9  | A009   | Few                | Patent            | Fast     | Expensive | In Demand      |
| 10 | A010   | Few                | Generic           | Fast     | Expensive | Not In Demand |
| 11 | A011   | Few                | Patent            | Fast     | Cheap   | In Demand      |
| 12 | A012   | Few                | Generic           | Late     | Cheap   | Not In Demand  |
| 13 | A013   | Few                | Generic           | Late     | Cheap   | Not In Demand  |
| 14 | A014   | Many               | Generic           | Late     | Cheap   | In Demand      |
| 15 | A015   | Few                | Generic           | Fast     | Cheap   | In Demand      |
| 16 | A016   | Many               | Patent            | Late     | Cheap   | In Demand      |
| 17 | A017   | Few                | Generic           | Fast     | Expensive | Not In Demand |
| 18 | A018   | Few                | Generic           | Fast     | Cheap   | In Demand      |
| 19 | A019   | Few                | Patent            | Late     | Expensive | Not In Demand |
| 20 | A020   | Few                | Generic           | Fast     | Cheap   | In Demand      |

Source: Arafah Pharmacy, Padang Panjang

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3.2. Process of analyze

Decision tree has two types of attribute data consisting of several input attributes of the target attribute and of course supporting the existing problem, its function as a comparison in calculating gain and ratio. In the training data set the sample size and must at least one target attribute whose value is a temporary conclusion of the problem of each instance (record), in this study the value of the target attribute is: bestsellers and less in demand. This data mining design writer uses the C4.5 algorithm. The process in the decision tree is to change the form of data (tables) into a tree model, change the tree model to a rule, and simplify the rule.

3.2.1. Node calculation 1

The process of finding total entropy and gain is done by grouping the data correctly, then calculating the data and using the entropy and gain search formula for each data attribute, such us Table 3. From the calculation results in the Table 3, it can be seen that the largest gain value is the attribute "Number of Medicine" of 0.2646. So that the attribute "Number of Medicine" becomes the root node. On the attribute "Number of Medicine" there are 2 attribute values, namely few and many, then further calculations need to be done. From this process, a temporary tree can be produced, such as Figure 3.

| NODE | Number of Case (S) | Less Loyal (S1) | Loyal (S2) | Entropy | Gain |
|------|-------------------|----------------|-----------|---------|------|
| 1    | Total             | 20             | 9         | 11      | 0.9710 |
|      | Number of Medicine |                |           |         |      |
|      | Many              | 5              | 0         | 5       | 0    | 0.2646 |
|      | Few               | 15             | 9         | 6       | 0.9710 |
|      | Type of Medicine  |                |           |         |      |
|      | Generic           | 13             | 6         | 7       | 0.9957 | 0.0008 |
|      | Patent            | 7              | 3         | 4       | 0.9852 |
|      | Delivery          |                |           |         |      |
|      | Fast              | 13             | 4         | 9       | 0.8905 | 0.1119 |
|      | Late              | 7              | 5         | 2       | 0.8631 |
|      | Price             |                |           |         |      |
|      | Expensive         | 8              | 6         | 2       | 0.8113 | 0.1815 |
|      | Cheap             | 12             | 3         | 9       | 0.8113 |

Figure 3. Temporary decision tree node 1

3.2.2. Node calculation 1.1

The process of finding total entropy and gain is done by grouping the data correctly, then calculating the data and using the entropy and gain search formula for each data attribute, such us Table 4. From the results of calculations in Table 4, it can be seen that the largest gain value is the attribute "Shipping" of 0.0637. So the attribute "Delivery" becomes the root node. At the "Delivery" attribute there are 2 attribute values, namely fast and Late, then further calculations need to be done. From this process, a temporary tree can be produced, such as Figure 4.

| NODE | Number of Case (S) | Less Loyal (S1) | Loyal (S2) | Entropy | Gain |
|------|-------------------|----------------|-----------|---------|------|
| 1.1  | Small Number of   |                |           |         |      |
|      | Medicine          | 15             | 9         | 6       | 0.9710 |
|      | Type of Medicine  |                |           |         |      |
|      | Generic           | 9              | 7         | 2       | 0.7642 | 0.145 |
|      | Patent            | 6              | 2         | 4       | 0.9183 | 2     |
|      | Delivery          |                |           |         |      |
|      | Fast              | 10             | 5         | 5       | 1     | 0.063 |
|      | Late              | 5              | 4         | 1       | 0.7219 | 7     |
|      | Price             |                |           |         |      |
|      | Expensive         | 9              | 6         | 3       | 0.9183 | 0.020 |
|      | Cheap             | 6              | 3         | 3       | 1     | 0     |

Figure 4. Temporary decision tree node 1.1
3.2.3. Node calculation 1.2

The process of finding total entropy and gain is done by grouping the data correctly, then calculating the data and using the entropy and gain search formula for each data attribute, such as Table 5. From the results of calculations in Table 5, it can be seen that the largest gain value is the attribute "Price" of 0.4200. So the attribute "Price" becomes the root node. At the "Price" attribute there are 2 attribute values, namely Expensive and Cheap, and then further calculations need to be done. From this process, a temporary tree can be produced, such as Figure 5.

Table 5. Calculation of the highest gain node 1.2

| NODE | Number of Case (S) | Less Loyal (S1) | Loyal (S2) | Entropy | Gain |
|------|--------------------|-----------------|------------|---------|------|
| 1.2  | Fast Delivery      | 10              | 4          | 6       | 0.9710|
|      | Type of Medicine   | Generic         | 7          | 4       | 3    | 0.9852| 0.2814|
|      | Patent             | 3               | 0          | 3       | 0    |
|      | Price              | Expensive       | 6          | 4       | 2    | 0.9183| 0.4200|
|      |                    | Cheap           | 4          | 0       | 4    | 0    |

3.2.4. Node calculation 1.3

The process of finding total entropy and gain is done by grouping the data correctly, then calculating the data and using the entropy and gain search formula for each data attribute, such as Table 6. The results in the decision tree in Table 6 can be concluded that it can be a decision tree, such as Figure 6.
Table 6. Highest gain calculation node 1.3

| NODE  | Jumlah Kasus (S) | Kurang Loyal (S1) | Loyal (S2) | Entropy | Gain |
|-------|------------------|-------------------|------------|---------|------|
| 1.3   | Cheap Price      | 6                 | 4          | 2       |      |
|       | Type of Medicine | 4                 | 4          | 0       |      |
|       | Patent           | 2                 | 0          | 2       |      |

For more details, the results in the decision tree can produce rules like the following:

| Rule  | IF Condition THEN Decision |
|-------|---------------------------|
| Rule 1| IF Number of Medicine = Many THEN Decision = Loyal |
| Rule 2| IF Number of Medicine = Few THEN Decision = Less Loyal |
| Rule 3| IF Number of Medicine = Few Delivery = Late THEN Decision = Kurang Loyal |
| Rule 4| IF Number of Medicine = Few Delivery = Fast THEN Decision = Loyal |
| Rule 5| IF Number of Medicine = Few Delivery = Fast Price = Cheap THEN Decision = Loyal |
| Rule 6| IF Number of Medicine = Few Delivery = Fast Price = Expensive THEN Decision = Less Loyal |
| Rule 7| IF Number of Medicine = Few Delivery = Fast Price = Expensive Type of Medicine = Patent THEN Decision = Loyal |
| Rule 8| IF Number of Medicine = Few Delivery = Fast Price = Expensive Type of Medicine = Generic THEN Decision = Less Loyal |

Figure 6. Temporary decision treenode 1.3

3.3. Result of analyze

The results of the analysis showed that the C4.5 algorithm succeeded in 21 types of categories which became the destination label based on the number of medicine, so it can be said that the C4.5 algorithm succeeded in defining 55% of the existing destination. Supplier A001 Loyal and Classified a leaf node(label), A002 Loyal (Classified a leaf node(label), A003 Less Loyal Cases that occur for the name of PT "A003" are very few, only occurred 9 times during January 2017 to January 2019, with a data presentation of 4.5%, A004 Classification is Loyal and Classified a leaf node(label), A005 Classification is Loyal and Classified...
a leaf node(label), A006 Less Loyal Cases that occur for the name of PT "A006" are very few, only occurred 8 times during January 2017 to January 2019, with data presentation of 4%, A007 Less Loyal Cases that occur for the name of PT "A007" are very few, only occurred 7 times during January 2017 to January 2019, with data presentation of 3.5%, A008 Less Loyal Cases that occur for the name of PT "A008" are very few, only occurred 6 times during January 2017 to January 2019, with data presentation of 3%., A009 Loyal Classified as a leaf node (label), A010 Less Loyal Cases that occur for the name of PT "A010" are very few, only occurred 5 times during January 2017 to January 2019, with data presentation of 2.5%, A011 Loyal Classified as a leaf node (label), A012 Less Loyal Cases that occur for the name of PT "A012" are very few, only occurring 4 times during January 2017 to January 2019, with data presentation of 2%, A013 Less Loyal Cases that occur for the name of PT "A013" are very few, only occurred 3 times during January 2017 to January 2019, with data presentation of 1.5%, A014 Loyal Classified as a leaf node (label), A015 Loyal Classified as a leaf node (label), A016 Loyal Classified as a leaf node (label), A017 Less Loyal Cases that occur for the name of PT "A017" are very few, only occurred 2 times during January 2017 to January 2019, with a data presentation of 1%, A018 Loyal Classified as a leaf node (label), A19 Less Loyal Cases that occur for the name of PT "A019" are very few, only occurred once during January 2017 to January 2019, with data presentation of 0.5%, A20 Loyal Classified as a leaf node (label).

From the report we have 11 Classification of Supplier Loyal and 9 Supplier Less Loyal, Loyal Supplier is A001, A002, A004, A005, A009, A011, A014, A015, A016, A018 and A020 and A003, A006, A007, A008, A010, A012, A013, A017, A019 is Less Loyal Supplier.

4. CONCLUSION
C45 algorithm helps the pharmacy to determine which medicine are in demand and those that are not in demand based on the number of medicine, types of medicine, delivery and price. The final result of the C45 algorithm produces a number of rules that can identify the inheritance of a type of medicinal product. This research is able to produce a classification of pharmaceutical product sales. The data that is processed is occurred once during January 2017 to January 2019, with data presentation of 0.5%, A20 Loyal Classified as a leaf node (label), A010 Less Loyal Cases that occur for the name of PT "A010" are very few, only occurred 5 times during January 2017 to January 2019, with data presentation of 2.5%, A011 Loyal Classified as a leaf node (label), A012 Less Loyal Cases that occur for the name of PT "A012" are very few, only occurring 4 times during January 2017 to January 2019, with data presentation of 2%, A013 Less Loyal Cases that occur for the name of PT "A013" are very few, only occurred 3 times during January 2017 to January 2019, with data presentation of 1.5%, A014 Loyal Classified as a leaf node (label), A015 Loyal Classified as a leaf node (label), A016 Loyal Classified as a leaf node (label), A017 Less Loyal Cases that occur for the name of PT "A017" are very few, only occurred 2 times during January 2017 to January 2019, with a data presentation of 1%, A018 Loyal Classified as a leaf node (label), A19 Less Loyal Cases that occur for the name of PT "A019" are very few, only occurred once during January 2017 to January 2019, with data presentation of 0.5%, A20 Loyal Classified as a leaf node (label).

From the report we have 11 Classification of Supplier Loyal and 9 Supplier Less Loyal, Loyal Supplier is A001, A002, A004, A005, A009, A011, A014, A015, A016, A018 and A020 and A003, A006, A007, A008, A010, A012, A013, A017, A019 is Less Loyal Supplier.

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