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Developing Data Mining Prediction System for Health Center Medicine Inventory using Naïve Bayes Classifier Algorithm

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Abstract

Public health centers mostly use conventional methods in managing drug supply, usage, and demand data, without a system that can predict the number of drug requests. This research aims to develop a data mining solution by implementing a prediction system using the Naïve Bayes Classifier algorithm to predict drug supplies from the Koni Health Center, Jambi, to the Health Office Pharmacy Installation. The method applied in this research is a quantitative approach through the experimental method. The research data includes inventory, usage, and remaining stock of various types of drugs from 2017 to 2021 which are divided into four quarters. The results of this study show that the classification system using the Naïve Bayes Classifier method is able to classify data quickly and efficiently according to drug supply. The system test results show an accuracy of 73.91%, recall of 85.71%, and precision of 54.54%. These findings can help Puskesmas in optimizing drug inventory management, reducing errors in inventory estimates, and increasing accuracy in meeting patient drug requests.

Keywords: Naïve Bayes Classifier Algorithm; Medicine Supply; Puskesmas; Prediction system

1. Introduction

Information systems have brought new changes in all aspects of the lives of their users (Hidayatullah et al., 2020; Jin et al., 2020; Tabsoba et al., 2023). The rapid development of information systems has created various media, especially in helping to improve data processing (Wardani et al., 2022). Data processing is converting data into more helpful information that can be obtained quickly, efficiently, and accurately compared to what is done manually (Saputra, 2020).

One of the businesses in the health sector that wants to implement information systems in its business activities is the Community Health Center (Pusat Kesehatan Masyarakat (Puskesmas)) (Kurniawan et al., 2017; Yogananda, 2021). Puskesmas is a health service facility that organizes public health activities and first-level individual health services in its working area by prioritizing efforts to prevent and cure diseases (promotive) (Mentang et al., 2018). Puskesmas is a health facility for them because the cost of treatment is cheap and easy to reach. In order to improve services to the community, health centers need to increase the need for medicines in type and quantity. Therefore, Puskesmas must always provide a stock of medicines used by patients who seek treatment according to the patient's illness. Medicine Inventory at Health Centres is essential for maintaining stock in a health facility's management and tracking system of drugs and medical supplies. The health center's medicine inventory system includes procuring, storing, distributing, and monitoring drug stocks to ensure availability and efficient use. The system involves grouping medicines based on factors such as type, dosage, expiry date, and frequency of use. The health center medicine inventory maintains adequate stock levels, prevents stock-outs or wastage, and optimizes supply chain management. It is also beneficial to ensure timely and uninterrupted health services for patients.

The Regional Technical Implementation Unit (Unit Pelaksana Teknis Dinas (UPTD)), Puskesmas Koni is one of Puskesmas required to keep a stock of medicines ready for patients. Patients who come to the Puskesmas Koni for treatment every day are numerous Sufficient to make the stock of medicines available at Puskesmas insufficient to meet the quota for medicine use. Therefore, the medicine supply at Puskesmas Koni must constantly be monitored appropriately so that there is sufficient supply and stock of medicines.

However, the current data collection of medicine supplies is still based on the estimates of health center officers. This causes frequent inaccuracies in the data collection of medicine supplies because some medicines are overstocked, and some are understocked. When the demand for medicines is excessive, the medicines will accumulate in the long term, so that the medicines will expire. If the demand for medicines is too low, it will not be good, and services to the community will not be optimal.

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Data on the amount of medicine supplies to be distributed to pharmaceutical installations is critical so that the health center can provide medicines according to the use of medicines needed at the health center (Abdianto et al., 2021; Danianty et al., 2020). Research with medicine demand prediction problems is a classification problem that can be solved using machine learning algorithms. Previous research predicting medicine supplies using the naïve Bayes algorithm is very accurate and effective, so it is beneficial for hospitals in predicting medicine supplies and making medicine purchases (Siregar et al., 2018; Tugiman et al., 2022).

Medicine demand prediction is a relatively low probability problem, using a small dataset, but neural networks require a number of training modalities, which may lead to the problem of inaccurate prediction accuracy. For problems with a small amount of data, the Naïve Bayes algorithm is relatively more suitable (Jaya and Yusman, 2021; Zheng et al., 2022). In addition, the main reason for using the Naïve Bayes method is because it uses a simple and easy algorithm to run and has a very accurate accuracy value compared to other methods (Sembiring and Tambunan, 2021; Siburian, 2021; Wahyuni and Marbun, 2020).

One way to solve the medicine demand problem is through data mining algorithm techniques. Data mining has two essential functions in its utilization. There are predictive (classification, prediction, and time-series analysis) and descriptive (association, clustering, and summarization). A prediction system is used to forecast the inventory levels of medicines at a health center. This prediction is based on historical data and input variables such as drug consumption rates, replenishment schedules, and seasonal demand patterns. Based on these data, the system can accurately predict future inventory needs. This prediction system is helpful to ensure that the health center maintains optimal stock levels to prevent shortages and overstock.

One type of data mining that has a function to predict the future is the Naïve Bayes Classifier algorithm (Barus, 2021). The Naïve Bayes Classifier algorithm is a statistical classifier algorithm where the classification process can predict the probability of class membership of data that will later fall into a particular class based on probability calculations.

Based on these problems, the researchers developed data mining by implementing a prediction system for medicine supply data from the UPTD Puskesmas Koni to the Health Office Pharmacy Installation using the Naïve Bayes algorithm to predict the amount of medicine supply that will be distributed to the Health Office Pharmacy Installation in the following month so that there is no excess or shortage of medicine stock. The dataset used is medicine supply data for 2017 - 2021, with four quarters each year.

2. Method

The method applied in this study is a quantitative approach through an experimental method. This study took data from the Koni Health Center and the Health Office Pharmacy Installation using several data collection methods. First, a literature study collected various sources such as journals, books, articles, and previous research. Furthermore, observations were made to observe the research location to obtain supporting data and an understanding of the system running at that location. Interviews were also conducted with relevant parties at the research location. The main data utilized in this research is primary data obtained directly from the source. The data includes inventory, usage, and remaining stock of various types of medicines from 2017 to 2021, divided into four quarters. Only relevant test data will be used in this study, which will be classified according to the needs of the analysis.

2.1. Research Procedures and Naïve Bayes Model Testing

This research was carried out using several interrelated research stages. First, the data-checking stage divides training and testing data with percentage variations in various scenarios.

Figure 1. shows the process flow of the Naïve Bayes algorithm, starting with reading the training data. Next, counts and probabilities are calculated by considering whether the data is numeric. The mean and standard deviation of each numeric parameter are calculated for numeric data. Then, the probability is calculated by dividing the number of data matching the same category by the total data in that category. After obtaining these values, a table of means, standard deviations, and probabilities is compiled.

The second stage involves a parameter correlation test with the Cosine Similarity method to determine the influence of parameters on requirements. After that, a data model is formed through Naïve Bayes Classifier using Backward Feature Selection. Data processing includes removing duplicates, handling inconsistencies, and correcting errors in the data. The system implementation stage includes software development with the Naïve Bayes algorithm using PHP and the XAMPP framework.

The evaluation stage also includes analyzing the results of the Naïve Bayes algorithm using Microsoft Excel, where if there are deficiencies, improvements can be made again until it meets the needs. Furthermore, in the testing stage, the system is tested to ensure its performance is as expected. The test uses medicine usage data from the previous month to compare the prediction results with the actual data from the Koni Health Center. The suitability of system results and manual calculations is a parameter of test success.

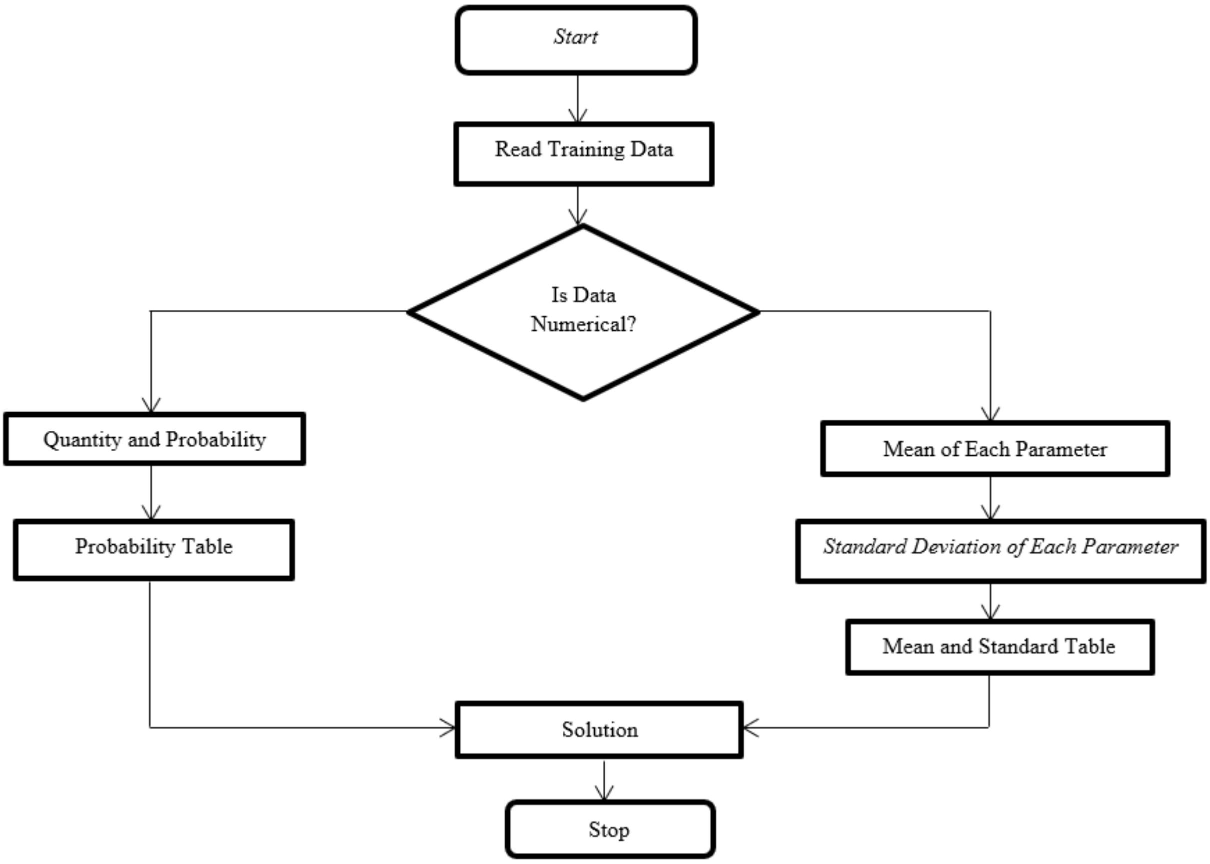

Figure 1. Process Flow of Naïve Bayes algorithm

2.2. Information System Framework

Figure 2. shows the software flow in an information system framework with three main phases: input, process, and output. The input phase involves LPLPO data from Puskesmas, including attributes such as quarter, medicine name, supply, usage, remaining stock, request, and description. After input, preprocessing is done to ensure the data is consistent, followed by calculation using the Naïve Bayes method, involving the prior and conditional probability search stages. The end result is a prediction or classification of medicine inventory, which is displayed on the website with the possibility of sufficient or insufficient and can be downloaded as a stock inventory prediction result.

System testing is carried out to test the results and analyze the results from calculations using Microsoft Excel with the Naïve method Data Mining Algorithm. The data processing results found by following the research work process will produce the results of predicting drug demand at the Koni Health Centre for the following month. It can also be seen whether the results obtained have the best similarity and accuracy level. The stages carried out in predicting drug supplies in this study are as follows: 1) Perform a conversion process that can be processed with the naïve Bayes process using several fields, including drug name, packaging, month, year, demand, usage, predicted amount of inventory, description (sufficient or insufficient); 2) Discarding the categories of inventory and usage data because the difference between average inventory and usage is too far. 3) The parameter used to determine the prediction of drug demand using the naïve Bayes method in the next period is the drug inventory parameter.

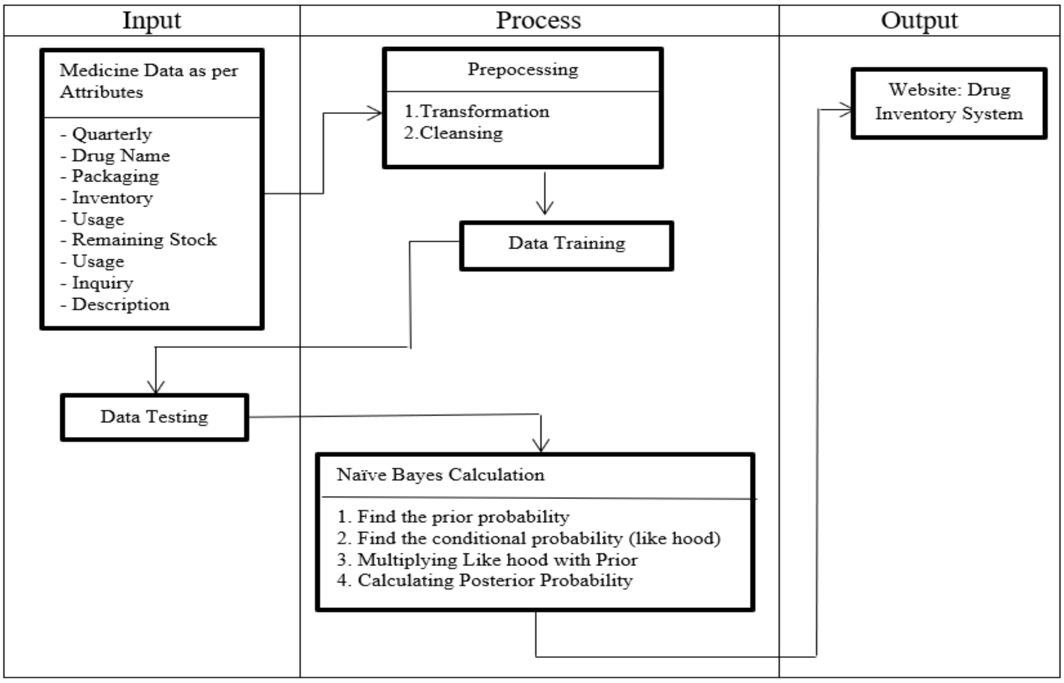

Figure 2. Information System Framework

3. Result & Discussion

3.1. System Interface Design

Interface design is an important part of the system, because the first thing seen when the system is run is the system interface.

Figure 3. shows the system interface. This design consists of various pages with different appearances. First, the login page has input forms for username and password. Then, the dashboard page displays menus such as dashboard, user data, import data, and data preprocessing (including transformation and cleaning). Next are attribute data pages, training data, testing data, and prediction results.

Each page has distinctive design elements; for example, there is an add data button on the user data page and a user data display with options to edit and delete data. The import data page has delete and import data buttons, displaying the successfully imported data. The preprocessing page, both transformation and cleaning, has a refresh button, delete data, and a button to run transformation or cleaning. For the attribute data page, attribute data is displayed with search options. The training data page has an add data button, an option to edit, and a data search option. Meanwhile, the testing data page provides data options and buttons to select testing data and displays a testing data form with options to edit and delete data. Finally, the prediction results page shows the calculation stages of the Naïve Bayes method from input to output results and a button to edit and delete data.

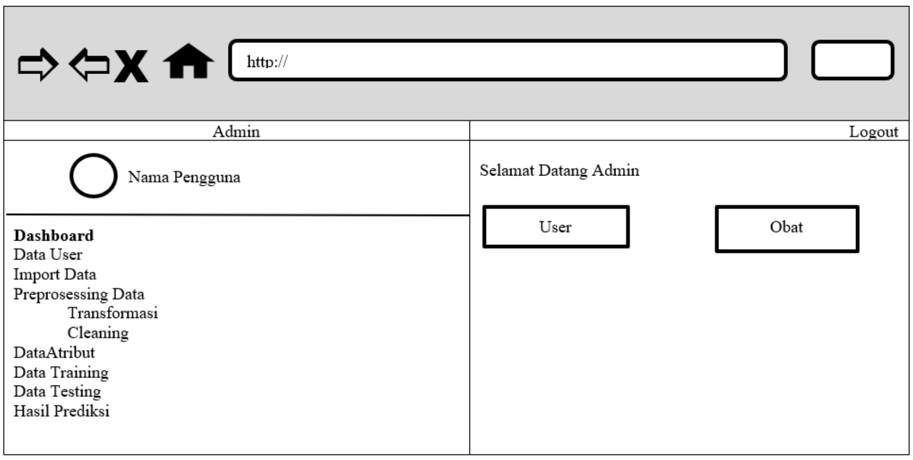

Figure 3. System Interface Design View

3.2. *Test Correlation of Data Modeling Parameters with Cosine Similarity*

From the number of parameters utilized, a correlation evaluation was first conducted by calculating the similarity value of each parameter to the requirement. The higher the similarity value, the lower the independence. This correlation evaluation uses the Cosine Similarity approach, and is organized in order of the most significant similarity values. Since Cosine Similarity does not have a standard limit for the correlation coefficient, the researcher has set a minimum limit of 0.4 as a measure of dependent parameters.

Based on the correlation evaluation results in Table 1., it can be observed that the usage parameter has the highest similarity value, which is 0.99333. This indicates that the usage parameter has a strong relationship with inventory. Meanwhile, the demand parameter shows the lowest similarity, with a value of 0.88979. Demand parameters are independent of inventory. The next step is to conduct a cross-parameter correlation test to explore these parameters' relationships.

Table 1. Inventory Correlation Test with All Parameters

Dependent Parameters	Independent Parameters	Similarity
Inventory	Usage	0.99333
Inventory	Stock	0.97072
Inventory	Demand	0.88979

3.3. *System Implementation Transformation*

The system implementation involves applying the Naïve Bayes method in several stages. It starts with retrieving the initial medicine usage data from the health center in Excel format, which is then customized into structured columns. The adjusted data is imported into a MySQL database, and through a transformation process, the medicine usage that was initially organized by year is converted into quarters of each year. The following process was data cleaning to remove duplicates. The ready data is then used as training data with the label "sufficient" or "insufficient" according to the supply, and this stage is displayed through the system interface.

This method calculates medicine usage per quarter to forecast medicine inventory. The attribute data contains information such as quarter, medicine name, package, inventory, usage, remaining stock, demand, and stock description for classification. The process involves converting the data to a format suitable for the Naïve Bayes method, enabling practical medicine prediction analysis. Table 2. will show the data based on medicine usage.

Table 2. Data based on the amount of medicine usage

No	TR	Medicine Name	Packaging	Inventory	Usage	Remaining Stock	Request	Description
1	1	Acyclovir cream 5 %	tube	76	50	26	10	Sufficient
2	2	Acyclovir cream 5 %	tube	42	30	12	40	Sufficient
3	3	Acyclovir cream 5 %	tube	146	82	64	100	Sufficient
4	4	Acyclovir cream 5 %	tube	58	28	30	55	Insufficient
5	1	Acyclovir cream 5 %	tube	7	6	1	7	Sufficient
6	2	Acyclovir cream 5 %	tube	80	10	70	88	Insufficient
7	3	Acyclovir cream 5 %	tube	308	73	235	300	Sufficient
8	4	Acyclovir cream 5 %	tube	141	56	85	130	Sufficient
9	1	Acyclovir cream 5 %	tube	52	0	52	50	Sufficient
10	2	Acyclovir cream 5 %	tube	91	31	60	100	Insufficient
11	3	Acyclovir cream 5 %	tube	54	4	50	54	Sufficient
12	4	Acyclovir cream 5 %	tube	50	25	25	50	Sufficient
13	1	Acyclovir cream 5 %	tube	25	0	25	24	Sufficient
14	2	Acyclovir cream 5 %	tube	15	15	0	25	Insufficient
15	3	Acyclovir cream 5 %	tube	50	20	30	60	Insufficient
16	4	Acyclovir cream 5 %	tube	10	10	0	9	Sufficient
17	1	Acyclovir cream 5 %	tube	50	20	30	60	Insufficient
18	2	Acyclovir cream 5 %	tube	70	60	10	80	Insufficient
19	3	Acyclovir cream 5 %	tube	100	0	100	100	Sufficient
20	4	Acyclovir cream 5 %	tube	68	1	67	78	Insufficient
21	1	Acyclovir cream 5 %	tube	146	15	131	100	Sufficient
22	2	Acyclovir cream 5 %	tube		28	113	200	Insufficient
23	3	Acyclovir cream 5 %	tube	100	82	18	80	Insufficient
24	4	Acyclovir cream 5 %	tube	76	28	48	80	Insufficient

Table 2. shows data based on the amount of medicine usage as well as various related factors. Each row represents a different medicine and includes information such as quarter (TR), medicine name, package type, initial stock, usage amount, remaining stock after usage, demand, and whether there is sufficient supply. This information illustrates the

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pattern of medicine usage across quarters and is helpful for medicine stock classification research.

3.4. Naïve Bayes Calculation

The calculation using the Naïve Bayes method involves calculating probabilities based on existing attributes and classes. In Table 3., there is a calculation of the probability P(Ci) for the classes "Sufficient" and "Insufficient" based on the value of the Description attribute.

Table 3. Calculation of P (Ci)

Attribute Value	emergence	Results
P (Description = Sufficient)	13/24	0.542
P (Description = Insufficient)	11/24	0.458

In Table 4., the class "Sufficient" appears 13 times out of 24 data, so the probability is 13/24 or about 0.542. Meanwhile, the "Insufficient" class appears 11 times, resulting in a probability of about 0.458.

Table 4. Calculation of P(X|Ci)

Attributes	Value	Sufficient (0.542)	Insufficient (0.458)
Quarterly	1	5/13 = 0.385	1/11 = 0.091
Medicine Name	Acyclovir cream 5 %	13/13 = 1	11/11 = 1
Packaging	tube	13/13 = 1	11/11 = 1
Inventory	50	1/13 = 0.077	2/11 = 0.182
Usage	20	0/13 = 0	2/11 = 0.182
Remaining Stock	30	0/13 = 0	3/11 = 0.273
Request	60	0/13 = 0	2/11 = 0.182

The probability stage in Table 5. is critical to understand the data properties used for prediction. The Nave Bayes method can categorize the test data into the correct class based on the quality determined by considering these probabilities.

Table 5. Calculation of testing data

Label (Sufficient)	Label (Not Sufficient)
Quarter (1) = 0.385	Quarter (1) = 0.091
Medicine Name (Acyclovir cream 5%) = 1	Medicine Name (Acyclovir cream 5%) = 1
Packaging (tube) = 1	Packaging (tube) = 1
Inventory (50) = 0.077	Inventory (50) = 0.182
Usage (20) = 0	Usage (20) = 0.182
Remaining stock (30) = 0	Remaining stock (30) = 0.273
Demand (60) = 0	Demand (60) = 0.182
Value (Sufficient) = 0.542 * 0.385 * 1 * 1 * 0.077 * 0 * 0 * 0 = 0	Value (Not Sufficient) = 0.458 * 0.091 * 1 * 1 * 0.182 * 0.182 * 0.273 * 0.182 = 8.1174101434608E-5

1) Calculating Probability Per Class.
   In Table 4.1, the probability for the "sufficient" category is 13/24 = 0.54, while for the "insufficient" category is 11/24 = 0.45. The numbers 13 and 11 are generated from the number of medicines in each category, with a total of 24 data used.
2) Calculating Probability/Likelihood Per Variable. For ease of understanding, data no.1 will be used (Inventory =50, Usage = 20, Remaining Stock = 30 and Demand = 60).
   Sufficient
   P (Inventory) = 1/13=0.07
   P (Usage) = 0/13=0
   P (Remaining Stock) = 0/13=0
   P (Demand) = 0/13=0

   Insufficient
   P (Inventory) = 2/11 = 0.182
   P (Usage) = 2/11 = 0.182
   P (Remaining Stock) = 3/11 = 0.273
   P (Demand) = 2/11 = 0.182
3) Multiplying all the probabilities of each class
   P (Sufficient) = 0.07*0*0*0 = 0
   P (Insufficient) = 0.182*0.182*0.273*0.182 = 8.11
4) Comparing results
   Based on all the values that have been accumulated, it can be categorized as insufficient inventory.

3.5. Algorithm Performance Testing

Accuracy testing and confusion matrix calculation are performed to identify the accuracy, precision, and recall of the test data. A confusion matrix is a table that represents the performance of a model or algorithm with specific details. Each row in this matrix represents the actual class of the data, while each column represents the predicted class of the data (or vice versa). Table 6. provides further explanation of the matrix.

Table 6. Conffusion Matrix Testing

	Predicted Negative	Predicted Positive	True	False
Actual Negative	True Negative (TN)	False Positive (FP)	24	0
Actual Positive	False Negative (FN)	True Positive (TP)	2	0

In this test, True Positive indicates data that is correctly recognized as positive by the model, while True Negative indicates data that is correctly identified as negative. False Positive reflects data that should be negative, but is predicted as positive by the model, and False Negative describes data that should be positive, but is predicted as negative. Therefore, the use of confusion matrix helps us understand the extent of the model's performance in classifying the data. In the example confusion matrix table, 24 True Positive, 2 False Negative, and 2 False Positive are generated.

Based on this information, other data can be generated that has significant value in measuring model performance, including calculations of accuracy, precision, and recall (Saputro and Bety, 2019).

Accuracy measures the overall effectiveness of the model. The formula is shown in equation (1).

$$\text{Accuracy Calculation} = \text{TP} + \text{TN} \times \frac{100}{\text{Total}} \quad (1)$$
$$= 12 + 22 \times \frac{100}{46}$$
$$= 73{,}913\%$$

The system has an accuracy of 74%

Precision measures the proportion of true positive results out of all positive predictions made by the model. The formula is shown in equation (2).

$$\text{Precision Calculation} = \frac{12}{10+12} \times 100 \quad (2)$$
$$= 54{,}54\%$$

The system has an accuracy of 55%

Recall (also known as sensitivity or true positive rate) measures the proportion of true positive results out of all actual positive instances. The formula is shown in equation (3).

$$\text{Recall Calculation} = \frac{12}{12+2} \times 100 \quad (3)$$
$$= 85{,}71\%$$

The system has an accuracy of 86%.

The algorithm performance test results show that the system has a reasonable level of accuracy. However, there is potential to improve categorization accuracy and precision. The algorithm correctly identified most of the relevant data (high recall), but its precision should be further improved to prevent false positives. So, although it gives reasonably good results, the performance of this algorithm still needs to be improved.

4. Conclusion

The implementation of the Medicine Inventory Prediction System at the Koni Health Center in Jambi using the Naïve Bayes method is effective in data mining classification with a small amount of data, allowing fast and efficient classification. The system test results show an accuracy of 73.91%, recall of 85.71%, and precision of 54.54%. With this, the probability value of the criteria can be increased to determine whether the medicine stock will be sufficient or insufficient for the next month based on the classification process performed by the Naïve Bayes method. This study's results can help Puskesmas optimize medicine inventory management, reduce errors in inventory estimates, and increase accuracy in meeting patient medicine demand. Therefore, further research is recommended to increase the amount of medicine supply data so that accuracy can be further improved. Furthermore, the development of this application can consider using other methods such as LSM, DECISION TREE, and Fuzzy Time Series for comparison. System configuration support and security enhancements must also be considered in future development.

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