Comparison of Decision Tree and Gaussian Naive Bayes Algorithms for Classification of Inpatients Based on Hematology Data

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ABSTRACT

Background: Hematology data analysis has an important role in supporting clinical decision-making, particularly in determining patient treatment status. However, manual analysis of laboratory data requires considerable time and may increase the risk of errors. Machine learning approaches can assist in identifying clinical patterns from hematology data. **Objective:** This study aims to compare the performance of Decision Tree and Gaussian Naive Bayes algorithms in classifying inpatient and outpatient status based on hematology laboratory data. **Methods:** This quantitative experimental study applied a Knowledge Discovery in Databases approach. The dataset consisted of 4,412 hematology examination records obtained from a public dataset. Data preprocessing included data cleansing, feature encoding, and data splitting into 80% training data and 20% testing data. Decision Tree and Gaussian Naive Bayes algorithms were implemented using Python and evaluated using accuracy, precision, recall, and F1-score metrics. **Results:** The Decision Tree algorithm achieved better performance than Gaussian Naive Bayes, with an accuracy of 73.61%, precision of 66.67%, recall of 69.47%, and F1-score of 68.04%. Meanwhile, Gaussian Naive Bayes obtained an accuracy of 68.63%, precision of 64.71%, recall of 49.30%, and F1-score of 55.96%. **Conclusion:** Decision Tree demonstrated superior performance in classifying patient treatment status based on hematology data. Its ability to generate interpretable clinical decision patterns makes it more suitable for supporting clinical decision support systems compared with Gaussian Naive Bayes.

Keywords decision tree; naïve bayes; hematologi; machine learning; patient

INTRODUCTION

Patient classification and triage management in healthcare facilities play a crucial role as a reference for the diagnostic process, medical resource allocation, and hospital bed availability (1). A complete blood count (CBC) is a basic examination used to determine a patient's clinical condition(2). Hematology parameters in routine blood tests are interrelated(3). The volume of laboratory data on blood tests is increasing day by day. Currently, pattern analysis of hematology data remains manual, requiring significant time and risking errors due to fatigue among medical staff.

A machine learning-based computational approach can provide a solution for extracting hidden clinical patterns (4) from hematology data as a basis for developing a clinical decision support system. Regarding the classification process, selecting the appropriate algorithm will impact the accuracy of the results(5).

This study focuses on a comparison of two classification algorithms: Decision Tree and Gaussian Naïve Bayes. Gaussian Naïve Bayes is known for its computational speed when handling large amounts of data, while Decision Tree is known for its ability to map non-linear relationships(6)(7).

Several previous studies have applied machine learning to disease classification techniques, including the K-Nearest Neighbor algorithm to classify heart disease with 94% accuracy(8), the Support Vector Machine algorithm to classify diabetes with 87% accuracy(9), the logistic regression algorithm to detect heart disease with 87% accuracy(10), the naive Bayes algorithm to classify diabetes mellitus with 90.20% accuracy (11) dan and the decision tree algorithm to classify children's nutritional status(12).

This study aims to compare the performance of the decision tree and Gaussian Naive Bayes algorithms in classifying patient care status and to identify the best classification model for predicting patient hospitalization status using hematology laboratory data. The experiment used the Python programming language within the Google Collaboratory environment. It is hoped that this research will provide recommendations for the best classification algorithm for application in clinical decision support systems.

METHODS

The research methods include research design, data collection, data preprocessing, classification algorithm implementation, and model testing and evaluation.

1. Research Design

   This research is a quantitative experiment using machine learning. The Knowledge Discovery In Databases scheme used compares the performance of two classification algorithms.
2. Data Collection

   The dataset was obtained through Kaggle using the Patient Treatment Classification dataset (13). The data are secondary data in the form of 4,412 routine hematologic laboratory test results. The data characteristics are as follows:
   a. Predictor Features: Consists of 10 features, divided into 9 numeric features (Haematocrit, Haematoglobin, Erythrocyte, Leucocyte, Thrombocyte, MCH, MCHC, MCV, and Age), and 1 textual feature (SEX).
   b. Target Variable (Source): A categorical binary class that determines the patient's final treatment status, whether outpatient or inpatient.
3. Data Preprocessing

   This stage is performed before entering the modeling process and includes:
   a. Data Cleansing

   This stage cleans the dataset. The dataset used has 100% completeness and no missing values were found.
   b. Feature encoding

   This stage transforms non-numerical categorical features into binary form. This aims to simplify algorithm execution by changing the SEX (F) column to 0, SEX (M) to 1, and the SOURCE (out) column to 0 and SOURCE (in) to 1.
   c. Data Splitting

   The dataset is divided into two parts: 80% training data and 20% testing data to validate performance.
4. Implementation of Classification Algorithms

   The algorithms tested are:
   a. Gaussian Naïve Bayes : This is one of the naïve Bayes algorithms used in this study because most of the predictor features in the dataset are numeric(14). This algorithm works by calculating the probability of an event based on Bayesian theory, assuming the numerical values of each feature are normally distributed (15).
   b. Decision tree: This is a decision tree algorithm capable of grouping data and repeatedly separating rules based on a threshold value for medical features with the lowest entropy level (16).
5. Model Testing and Evaluation

   Testing is conducted by predicting the test data with both models. The results are presented in a confusion matrix with four main evaluations:

a. Accuracy

$$\frac{True\ Positive+True\ Negative}{(True\ Positive+True\ Negative+False\ Positive+False\ Negative}\ldots\ldots(17)$$

b. Precision

$$\frac{True\ Positive}{(True\ Positive+False\ Positive)}\ldots\ldots(18)$$

c. Recall

$$\frac{True\ Positive}{(True\ Positive+False\ Negative)}\ldots\ldots(19)$$

d. F1 Score

$$2x\ \frac{(Precision\ x\ Recall)}{(Precision+Recall)}\ldots\ldots(20)$$

RESULTS

1. Dataset Characteristics

Tabel 1 presents the characteristics of the dataset in the form of the distribution of patient clinical data.

Table 1 Dataset Characteristics

Parameter	Minimum Value	Maximum Value	Mean	Standard Deviation
Haematocrit	13.7	69.0	38.20	5.97
Haemoglobins	3.8	18.9	12.74	2.08
Erythrocyte	1.48	7.86	4.54	0.78
Leucocyte	1.1	76.6	8.72	5.05
Thrombocyte	8.0	1183.0	257.52	113.97
Age	1.0	99.0	46.63	21.73

Table 1 shows that the dataset has a fairly dynamic range of variation, with the Leucocyte and Thrombocyte components having relatively high outlier values (maximum values of 76.6 and 1183.0, respectively). The medical numerical data generally follows a normal distribution, which is a strong reason for using Gaussian Naïve Bayes. Outpatient data consisted of 2,628 samples and inpatient data consisted of 1,784 samples.

2. Confusion Matrix Results

The model was trained using 80% of the training data (3,529 data) and 20% of the testing data (883 data). The results are presented in Table 2 and Figure 1

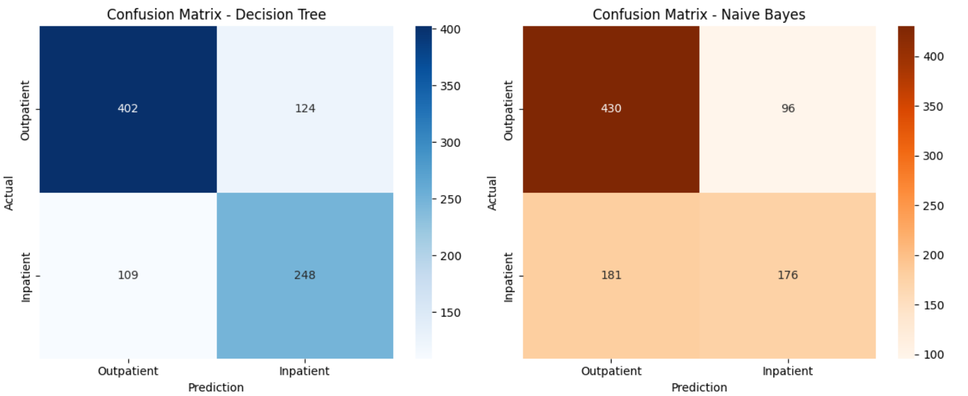

Figure 1. Confusion Matrix Decision Tree dan Naïve Bayes

Table 2: Confusion Matrix Results

Model	True Outpatient (TN)	False Inpatient (FP)	False Outpatient (FN)	True Inpatient (TP)
Decision Tree	402	124	109	248
Naive Bayes	430	96	181	176

3. Performance Comparison Matrix

The final performance comparison results for the data testing are presented in Table 3.

Table 3: Classification Algorithm Performance Comparison

Algorithm	Accuracy	Precision	Recall (Sensitivity)	F1-Score
Decision Tree	73,61%	66,67%	69,47%	68,04%
Naive Bayes	68,63%	64,71%	49,30%	55,96%

The accuracy and recall of the Decision Tree algorithm are higher than those of Naïve Bayes. In medical informatics, a high recall value is prioritized over accuracy(21), because health facilities must not incorrectly predict inpatients as outpatients, because of the risk of the patient not being treated and worsening the patient's health condition.

DISCUSSION

1. Decision Tree Performance Analysis

The results demonstrated the superiority of Decision Tree with an accuracy of 73.61% and a recall of 69.47%. This performance far surpasses Gaussian Naive Bayes due to Decision Tree's ability to perform node splitting based on non-linear relationships between features. The results of the decision tree are presented in Figure 2.

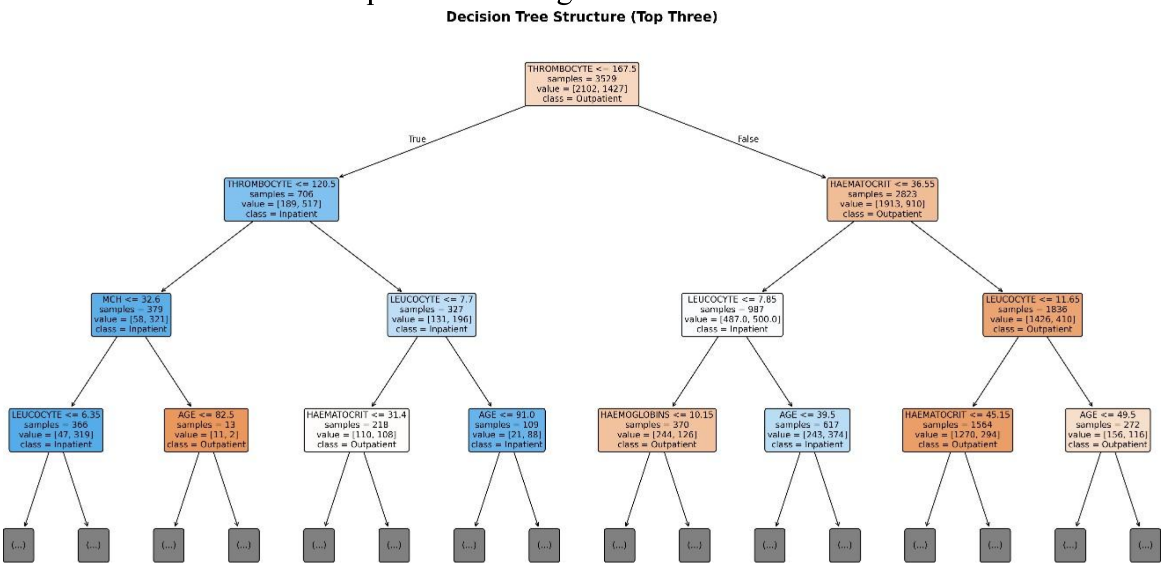

Figure 2 Research Results Decision Tree

From the resulting decision tree, several rules (IF-THEN rules) were extracted that reflect the patient's clinical condition. These include:

a. Rule 1: Detect Acute Infection or Systemic Inflammation (Combination of Leukocytes and Hemoglobin)

Rule: IF Leukocytes > 10.3 AND Hemoglobins < 11.4 Then Class = in (Inpatient)

This rule makes clinical sense because an increase in leukocytes indicates an active immune response, such as an acute bacterial infection, sepsis, or severe inflammation (22).

When this condition is accompanied by a decrease in hemoglobin levels (< 11.4 g/dL), which indicates anemia(23), the patient experiences decreased oxygen-carrying capacity in the tissues as the body fights the infection(24). This clinical combination places the patient at high risk for hemodynamic instability(25), making the algorithm's decision to hospitalize the patient appropriate for more intensive treatment.

b. Rule 2: Thrombocytopenic Crisis (Risk of Spontaneous Bleeding)

Rule: IF Thrombocyte < 100 Then Class = in (Inpatient)

The decision tree identifies low thrombocyte count as one of the critical thresholds. A thrombocyte count below 100×10^3 per microliter of blood (moderate thrombocytopenia) increases the risk of bleeding(26). If this number continues to fall below 50×10^3 per microliter of blood, the risk of spontaneous bleeding increases dramatically(27). The decision tree's decision to immediately classify the patient as in (hospitalization) regardless of other parameters in this sub-node demonstrates the algorithm's ability to recognize a medical emergency indicator based on a single, striking parameter.

c. Rule 3: Stable Patient Group (Outpatient)

Rule: If Leucocytes are in the Normal Range (5.6 - 10.3) and Hemoglobin > 12.9, then Class = Out (Outpatient

For patients with a normal hematological profile, white blood cells indicating no significant infection, and hemoglobin levels sufficient for oxygen transport to body tissues(28), the algorithm stably classifies them as outpatient. This indicates that the patient's physiological condition is likely stable and requires only outpatient care.

This explanatory power is the primary advantage of Decision Trees in the field of Health Informatics. Unlike Neural Network models, Decision Trees produce an open, rule-based system that mimics the thought process of a doctor triaging patients in the emergency department or laboratory.

An accuracy of 73% highlights that inpatient admission decisions are highly complex and cannot be determined by blood test results alone. Other critical factors, such as physical symptoms, vital signs (including blood pressure and temperature), and comorbidities, are not recorded in this dataset. The absence of these variables acts as a limiting factor, causing substantial data overlap in the model.

2. Gaussian Naive Bayes Performance Analysis

Research shows that the Gaussian Naive Bayes algorithm performed lower than the Decision Tree, with an accuracy rate of 68.63% and a significant decrease in recall to 49.30%. These figures demonstrate how Naive Bayes works when interacting with real patient clinical data. Gaussian Naive Bayes operates by assuming that the fluctuations in blood test results for patients, both inpatients and outpatients, have a normal or balanced distribution pattern (bell-shaped). This algorithm calculates the mean and variance of each laboratory result separately to estimate the probability of a patient requiring inpatient or outpatient care. This method saves time and effort. Gaussian Naive Bayes eliminates the need for complex iterative calculations or repeated data cutoffs, as with Decision Trees(29). All probability calculations are completed in a single pass, making this algorithm very fast and robust when processing large amounts of data(30).

The main weakness that reduces the performance of this model is its overly rigid rules (31). This model assumes all laboratory results are independent and have no influence whatsoever on whether a patient should be hospitalized or outpatient. This assumption is irrelevant when related to the medical world, for example:

a. Relationship between Red Blood Cells, Hemoglobin, and Hematocrit

Biologically, the levels of these three components are interconnected. If the number of red blood cells decreases, hemoglobin and hematocrit levels will automatically decrease(32),for example in anemia.

b. Blood Cell Indice (MCV, MCH, MCHC)

Blood cell indices are obtained from direct calculations of hemoglobin, hematocrit, and red blood cells(33).

When this model multiplies the probabilities of closely related features to make them appear unrelated, it creates unnecessary information overload. This results in a biased final probability calculation and distorts the decision-making process for determining patient status.

This inconsistency in the probability calculation directly impacts the low Recall score, which is only 49.30%. This model failed to detect more than half of patients who actually required hospitalization, instead mistakenly assuming outpatient care was sufficient (181 false negatives). The model lost sensitivity because it only looked at individual lab values. It failed to detect patterns in symptom combinations, such as a decrease in hemoglobin accompanied by a simultaneous spike in white blood cell counts. This condition, however, is a strong indication of a severe infection in the patient.

CONCLUSION

The Decision Tree algorithm demonstrated the best performance with 73.61% accuracy, 66.67% precision, 69.47% recall, and an F1-score of 68.04%. Decision Tree was able to extract easily understood and tested medical decision patterns, resulting in a safer model with a lower risk of false negatives. The Gaussian Naive Bayes algorithm boasts high computational efficiency, but its limitations in handling interconnected clinical features cause the Recall value to drop sharply to 49.30%.

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