Building of Informatics, Technology and Science (BITS)
Volume 7, No 3, December 2025 Page: 1684−1693
ISSN 2684-8910 (media cetak)
ISSN 2685-3310 (media online)
DOI 10.47065/bits.v7i3.8414

Decision Tree Classification for Reducing Alert Fatigue in Patient Monitoring Systems

Kheisya Talitha Herfiani[1], Aris Nurhindarto[1,*], Farrikh Alzami[1], Setyo Budi[1], Rama Aria Megantara[2], M Arief Soeleman[2], L Budi Handoko[2], Rofiani[3]

[1] Faculty of Computer Science, Information Systems Study Program, Universitas Dian Nuswantoro, Semarang, Indonesia
[2] Faculty of Computer Science, Informatics Engineering Studi Program, Universitas Dian Nuswantoro, Semarang, Indonesia
[3] Panti Pelayanan Sosial Anak Dharma Putera, Purworejo, Indonesia
Email: [1]tatakheisyatalitha@gmail.com, [2,*]arisnurhindarto@dsn.dinus.ac.id, [3]alzami@dsn.dinus.ac.id, [4]setyobudi@dsn.dinus.ac.id, [5]aria@dsn.dinus.ac.id, [6]m.arief.soeleman@dsn.dinus.ac.id, [7]handoko@dsn.dinus.ac.id, [8]rofiani206@gmail.com
Correspondence Author Email: arisnurhindarto@dsn.dinus.ac.id
Submitted: **25/09/2025**; Accepted: **06/12/2025**; Published**: 08/12/2025**

Abstract−The development of information technology in healthcare opens new opportunities to improve continuous patient monitoring. A major challenge is alert fatigue, where medical personnel are overwhelmed by excessive notifications, reducing concentration, work efficiency, and potentially compromising patient safety. This study presents a proof-of-concept application of the Decision Tree algorithm to analyze alert triggering factors in patient monitoring systems. The dataset is a synthetic health monitoring dataset from Kaggle, containing 10,000 entries with vital parameters including blood pressure, heart rate, oxygen saturation, and glucose levels, designed with deterministic logical relationships between threshold indicators and alert outcomes. The imbalanced dataset (73.67% alert triggered, 26.33% no alert) was intentionally not processed using imbalanced learning techniques to demonstrate Decision Tree's capability in processing structured health data and producing interpretable classifications. The research methodology included data preprocessing, exploratory data analysis, data splitting (90% training, 10% testing), GridSearchCV optimization, and performance evaluation. Results showed perfect metrics (100% accuracy, precision, recall, F1-score), reflecting the deterministic nature of the synthetic dataset rather than real-world clinical complexity. Feature importance analysis identified blood pressure as the most dominant variable, followed by heart rate and glucose levels. This study demonstrates Decision Tree's interpretability and feature importance analysis capabilities in health data contexts, establishing a methodological framework that requires validation on real clinical Electronic Health Record (EHR) data for practical application in reducing alert fatigue and supporting informed clinical decisions.

Keywords: Decision Tree; Alert Fatigue;Patient Monitoring; Health Data Classification; Model Accuracy

1. INTRODUCTION

Technological advances in healthcare have brought significant changes to the way patients are monitored. One key innovation is a real-time patient monitoring system integrated with various advanced sensors. This system is designed to detect even the slightest changes in vital parameters, such as blood pressure, heart rate, oxygen saturation, and glucose levels. The goal is to provide a rapid and accurate early warning system so that medical personnel can take necessary action [1]. This system is expected to improve patient safety, particularly in critical conditions that require close monitoring, such as patients in the intensive care unit (ICU), emergency department (ER), or patients with chronic diseases who require continuous monitoring at home. An effective monitoring system is crucial in the modern clinical environment to prevent deterioration of patient conditions and ensure timely response, ultimately saving lives.

Although monitoring systems have provided significant benefits, their implementation in the field often faces serious challenges. One major issue is alert fatigue, a condition where medical personnel are overwhelmed by receiving too many insignificant notifications [2]. This occurs because the system often triggers an alarm based on a single, simple anomaly, without considering the patient's overall condition. As a result, medical personnel can become less sensitive to alerts, potentially even ignoring important alarms that actually require a rapid response [2]. This phenomenon not only threatens patient safety but can also decrease the work efficiency of medical teams, increase stress, and ultimately reduce the overall quality of care. This alert fatigue phenomenon arises because the system frequently triggers irrelevant notifications, leaving medical personnel overwhelmed and less responsive to crucial alarms.

To overcome alert fatigue, a smarter approach to managing and analyzing patient data is needed. It's crucial to identify the combination of vital conditions that truly influence alert triggering, rather than relying solely on a single variable. One effective method for this is the Decision Tree algorithm. This algorithm's advantage lies in its ability to present clear, easily understood, and interpretable classification rules [3]. This capability is crucial in the clinical domain, where decisions must be based on solid understanding, rather than simply the results of an unexplained "black box." By identifying the most relevant combinations of vital parameters, we can build more selective and reliable alert models.

Previous research has demonstrated the reliability of Decision Trees in various classification applications. For example, the ID3 and C4.5 algorithms have demonstrated high, even near-perfect, accuracy on complex data [4]. The classification rules generated by these algorithms provide a strong foundation for decision-making. Furthermore, these algorithms are also capable of identifying dominant attributes that influence classification results [5]. The application of Decision Trees in healthcare has proven effective in identifying key factors that influence patient outcomes. For example, this algorithm has been utilized to analyze risk in heart disease cases, successfully providing robust and

Building of Informatics, Technology and Science (BITS)
Volume 7, No 3, December 2025 Page: 1684−1693
ISSN 2684-8910 (media cetak)
ISSN 2685-3310 (media online)
DOI 10.47065/bits.v7i3.8414

accurate insights, confirming its capabilities in this domain [6]. Its ability to produce interpretable models makes it an ideal choice for clinical applications, where transparency in decision-making is crucial.

Although numerous studies have utilized Decision Trees in the healthcare sector, the majority of these studies focus solely on disease detection or algorithm performance testing. However, no studies have specifically addressed the phenomenon of alert fatigue in patient monitoring systems, emphasizing the analysis of the combination of vital variables that trigger notifications. This gap represents a research gap and the primary contribution offered in this study. Although other methods exist [7], the crucial need for clinical transparency and explainability makes the Decision Tree's clear, understandable rules the ideal choice for this safety-critical application [8] and significantly improve accuracy on complex data [4]. Different from previous studies, this study is specifically directed to analyze in depth the relationship between several vital parameters simultaneously, such as heart rate, blood pressure, oxygen saturation, and glucose levels, to produce a more accurate and reliable warning pattern.

Thus, Decision Tree is a relevant classification method for application in data-driven health monitoring systems. This model not only helps predict patient conditions based on physiological parameters but can also be adapted to real-time monitoring systems and wearable devices. Its superior interpretability and classification capabilities make Decision Tree a primary choice in the development of data-driven health systems [9]. This finding is supported by other research that suggests Decision Tree is capable of providing accurate and relevant classification results in a health context [10].

To demonstrate the methodological approach, we utilize a synthetic health monitoring dataset that contains idealized logical relationships. While this allows clear demonstration of Decision Tree capabilities, validation on real clinical data is essential for practical deployment. Moreover, Based on the conditions and urgency, the research focuses on applying a Decision Tree algorithm to deeply analyze the factors that trigger alarms in patient health monitoring systems. This analysis is expected to yield a more accurate combination of vital conditions in determining when an alert should be issued. The goal is to create a more selective, effective, and reliable notification system, ultimately reducing alert fatigue and significantly improving patient safety.

2. RESEARCH METHODOLOGY

2.1 Research Stages

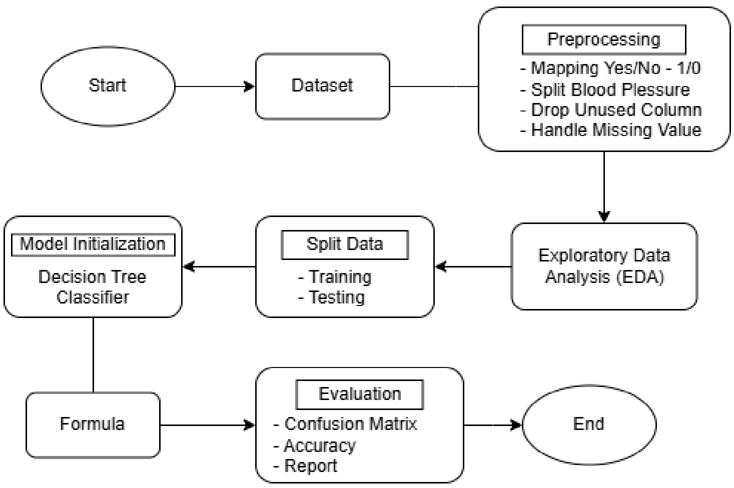

Figure 1. Flowchart of Research Method Steps

The research steps are shown in Figure 1. The research begins with data pre-processing. At this stage, several crucial steps are carried out, such as data mapping, which converts 'Yes'/'No' values to '1'/'0', data separation, which splits the blood pressure column, removes irrelevant columns, and handles missing values. After pre-processing, the data proceeds to the Exploratory Data Analysis (EDA) stage, where data patterns and characteristics are analyzed in depth. Next, the dataset is divided into two parts: testing data to objectively assess its performance and training data to train the model. In the Model Initialization stage, a Decision Tree Classifier is selected as the classification model to be trained with the prepared training data. Then, the model's performance is evaluated using the test data. The evaluation metrics include Confusion Matrix, Accuracy, and Report. This stage aims to measure the model's effectiveness in predicting classes on data not included in the training set. Finally, the research concludes after model evaluation.

2.2 Data Source

This study employs a synthetic health monitoring dataset (Elderly Care EDA Prediction) obtained from Kaggle [11] for methodological demonstration purposes. The dataset contains 10,000 monitoring entries with structured vital sign parameters and binary threshold indicators. Important Note, The dataset is designed with deterministic logical rules

Building of Informatics, Technology and Science (BITS)
Volume 7, No 3, December 2025 Page: 1684−1693
ISSN 2684-8910 (media cetak)
ISSN 2685-3310 (media online)
DOI 10.47065/bits.v7i3.8414

where alert outcomes are directly determined by threshold exceedances, representing an idealized scenario. While this enables clear demonstration of Decision Tree interpretability and feature importance analysis, it does not capture the complexity of real clinical environments including sensor noise, temporal dependencies, patient-specific variations, and clinical context that influence actual alert systems. Thus, the process begins with data collection and analysis, which includes pre-processing processes such as changing data types, separating combined columns, analyzing descriptive statistics and visualizing correlations between features.

2.3 Initial Processing

In the preprocessing stage, a series of data cleaning and transformations are performed to prepare the dataset for the modeling phase. The first step is mapping categorical values. Binary columns such as 'Heart Rate Below/Above Threshold (Yes/No)', 'Blood Pressure Below/Above Threshold (Yes/No)', and several others are converted from 'Yes' or 'No' to numeric values '1' and '0'. In addition to these features, this mapping process is also applied to the target variable (label) of the research, namely the 'alert triggered' column. This column is the dependent variable that will be predictively predict by the model. Specifically, the 'alert triggered' target variable is defined where class '1' (representing 'yes') is the condition when the system detects a health anomaly in the patient requiring an alert or intervention. This occurs when sensor data (such as heart rate or blood pressure) exceeds a predetermined safe threshold. Meanwhile class '0' (representing 'no') is defined as a normal condition, where the patient's sensor data is within a reasonable range and no warning is triggered. This process is crucial for transforming text data into a format understandable by machine learning models. Next, the 'Blood Pressure' column, which contains two values at once, systolic and diastolic, is split into two separate columns. This split separates the 'Blood Pressure' data, which was previously in the 'value1/value2' format, into two new numeric features: 'Systolic' and 'Diastolic'. This step ensures each feature has a single, relevant value. After this splitting process, the original 'Blood Pressure' column is no longer needed and is removed from the dataset. Additionally, several other columns deemed irrelevant to the analysis were removed, including 'Device-ID/User-ID', 'Timestamp', and 'Caregiver Notified (Yes/No)'. These columns were removed to simplify the dataset and eliminate features that did not significantly contribute to the model's predictions. Finally, the dataset also handled missing values. For each column, the model performed a check. If the column was categorical, the missing value was filled with the mode (the most frequently occurring value). For numeric columns, the missing value was filled with the median of that column. This approach was chosen to maintain data integrity and ensure the model could run smoothly due to incomplete data.

2.4 Exploratory Data Analysis (EDA)

This stage aims to study the structure, characteristics, and quality of the data. The Exploratory Data Analysis (EDA) process includes examining the data types in each column, identifying and handling missing data, and descriptive analysis to obtain statistical summaries of numeric features. Furthermore, the class distribution of the Alert Triggered (Yes/No) target variable is analyzed to determine whether the data used is balanced or imbalanced. Based on Table 1, it can be seen that the class ratio is 1:3, thus categorizing the data as an imbalanced dataset. However, the imbalanced data will not be processed further and will not be converted into imbalanced learning, because this study aims to observe the extent to which the Decision Tree algorithm is able to process the data to produce classifications. Through this EDA stage, important insights are obtained regarding the data that form the basis for subsequent pre-processing and modeling stages.

Table 1. Target Variables

1	0.7367
0	0.2633

2.5 Split Data

The next step after pre-processing is to divide the dataset into 9,000 training data sets and 1,000 testing data sets as seen in table 2. The training set is used to train the Decision Tree algorithm to recognize patterns and relationships between features that support the decision-making process. Meanwhile, the testing set is used to evaluate the model's performance when tested on data that has not yet been analyzed. This separation plays a crucial role in ensuring that the resulting model not only fits the training data but also has generalization capabilities when applied to new data.

Table 2. Split Data

Training set	9000 data
Testing set	1000 data

2.6 Model Intialization

In this study, the Decision Tree classification model is used as the primary method for predicting predetermined target variables. The implementation process of this model begins with the initialization phase, where the basic parameters of the algorithm are determined according to the research needs, such as the maximum tree depth, the minimum number of samples at each node, and the criteria for selecting the best attributes. After initialization, the model is then prepared for the training phase using previously cleaned and processed data. The Decision Tree algorithm was chosen

Building of Informatics, Technology and Science (BITS)
Volume 7, No 3, December 2025 Page: 1684−1693
ISSN 2684-8910 (media cetak)
ISSN 2685-3310 (media online)
DOI 10.47065/bits.v7i3.8414

for its excellent ability to form clear, systematic, and easy-to-understand decision rules. These rules are visualized in a tree structure, so that the relationships between variables and the decision-making process can be seen transparently. This makes Decision Trees highly relevant for application in the healthcare sector, where careful interpretation of analysis results requires understanding not only by researchers or data analysts, but also by medical personnel and other relevant parties. Therefore, the use of Decision Trees is expected to make a significant contribution to supporting the health data analysis process, particularly in assisting in monitoring, analyzing, and making decisions related to patient conditions more accurately and easily explained.

2.7 Formula

In the evaluation phase, Decision Tree performance is evaluated using a Confusion Matrix as seen in table 3, which provides a more detailed understanding of its classification accuracy. This matrix compares the model's predicted output with the actual labels of the data. The four main types of results displayed are False True Positive (TP), Positive (FP), True Negative (TN), and False Negative (FN). TP represents positive data that is correctly predicted, while TN represents negative data that is also correctly classified. Errors occur in FP when negative data is predicted as positive, and in FN when positive data is not detected successfully. Through these four indicators, the model evaluation measure is calculated using the relevant formula.

Table 3. Confusion Matrix

Confusion Matrix	Predictive Positive	Predictive Negative
Actual Positive	TP	FP
Actual Negative	TN	FN

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (1)$$

$$Precision = \frac{TP}{TP \pm FP} \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

$$F1 - score = 2 \times \frac{Precission \times Recall}{Precission \pm Recall} \quad (4)$$

These four formulas are fundamental metrics for evaluating how well a classification model performs. Accuracy (equation 1) is the most common metric and measures the overall performance of the model. Accuracy is calculated as the ratio of the number of correct predictions (either True Positive (TP) or True Negative (TN) divided by the total data set. Simply put, it describes the percentage of correct predictions the model makes. However, accuracy can be misleading, especially if the data is imbalanced (e.g., 90% of the data is 'Negative'). For this, we need more specific metrics like Precision and Recall. Precision (equation 2) focuses on the quality of the 'positive' predictions made by the model. This metric is calculated by dividing True Positives (TP) by the number of all positive predictions (TP + FP). Precision tells us what percentage of all 'positive' predictions the model makes are actually positive. High precision is important when the cost of False Positives (FP) is high (e.g., marking regular emails as spam). On the other hand, Recall (equation 3) focuses on the model's ability to find all existing 'positive' cases. This metric is calculated by dividing True Positives (TP) by the number of all cases that were actually positive (TP + FN). Recall describes how many of all the cases that were actually 'positive' were successfully found by the model. High recall is especially important when the cost of False Negatives (FN) is high (e.g., failing to detect a disease). Often, there's a trade-off between Precision and Recall; increasing one often decreases the other. This is where the F1-Score (equation 4) comes in. The F1-Score is the harmonic mean of Precision and Recall, providing a single number that balances both metrics. This is very useful for comparing overall model performance, especially when you care about False Positives and False Negatives equally.

2.8 Evaluation

The model evaluation aims to measure the effectiveness of the Decision Tree's performance after going through the training phase. Testing results using test data yielded perfect accuracy with a value of 1.0 (100%). This indicates that the model is capable of classifying the target Alert Triggered (Yes/No) class without error. Furthermore, the classification report and Confusion Matrix show F1-score, accuracy, recall, and precision values of 1.0 for both categories (0 and 1). This accuracy is further strengthened by the Confusion Matrix results, which indicate that all class 0 (2,633 data) and class 1 (7,367 data) data were correctly predicted without a single misclassification. Thus, the model proved highly reliable in finding patterns in the analyzed data.

3. RESULT AND DISCUSSION

This section presents the results and discussion of the Decision Tree method implementation, including the best parameter configurations in the training process, such as tree depth, minimum number of samples per node, and attribute selection criteria. The research results also include a classification report with accuracy, precision, recall, and F1-score metrics to assess the model's performance in predicting the target variable. Furthermore, a decision tree visualization is presented, showing the decision-making process from the root to the leaf nodes, thus facilitating the classification rules. This section also includes correlation and feature importance analyses, indicating the variables that most influence the prediction results. Overall, the combined results provide a comprehensive overview of Decision Tree performance while supporting clear and transparent interpretation, particularly in the context of applications in the healthcare sector.

3.1 Model Configuration and Classification Report

a. Best Parameters

Based on the results of parameter optimization as seen in table 4, the best configuration for the classification model was obtained using the Gini criterion, max depth None, min samples leaf of 1, and min samples split of 2. The selection of the Gini criterion indicates that the model is more optimal in measuring the level of data impurity at each split. The max depth None value means that the tree depth is not limited, so the model has full flexibility in forming a decision tree structure according to the complexity of the data. Furthermore, the min samples leaf value of 1 indicates that each leaf can contain at least one sample, allowing the model to capture data variations in detail. Meanwhile, the min samples split of 2 indicates that node splits can only be performed if there are at least two samples, thus preventing excessive overfitting. With this combination of parameters, the model is able to achieve good classification performance and can still be used effectively even without the application of imbalance learning techniques to the dataset.

Table 4. Best Parameters

Criterion	Gini
Max_Depth	None
Min_Samples_Leaf	1
Min_Samples_Split	2

b. Classification Report

The classification report in Table 5 shows that the model performed perfectly. The accuracy, precision, recall, and F1-score for both categories, namely Not Alert (class 0) and Yes Alert (class 1), each reached 1.0 (100%). This confirms that the model was able to correctly identify each class without any errors. The confusion matrix shows that all data were successfully predicted correctly, where 263 data in the Not Alert class were correctly classified as Not Alert (True Not Alert), and 737 data in the Yes Alert class were correctly classified as Yes Alert (True Yes Alert). There were no incorrect predictions, either in the form of False Positives or False Negatives. With an evaluation achievement of 1.0 (100%) across all metrics, it can be concluded that this model has very optimal and reliable performance in classification, and has high potential for application in real systems that require high accuracy.

Table 5. Classification Report

Accuracy: 100%	True Not Alert	True Yes Alert	Class Precision
Pred Yes Alert	263	0	100%
Pred Not Alert	0	737	100%
Class Recall	100%	100%	

3.1.1 Correlation Analysis, Decision Trees, and Feature Importance

a. Heatmap Analysis

The Figure 2 shows a correlation heatmap between physiological variables and clinical indicators used in a health monitoring system as seen in figure 2. Red indicates a positive correlation, while green indicates a negative correlation, with the intensity of the color representing the strength of the relationship between the variables. The correlation results show that the Oxygen Saturation (SpO_2) indicator has a fairly strong negative relationship with the SpO_2 Below Threshold (Yes/No) variable with a value of around -0.67, which means that the higher the oxygen level in the blood, the less likely the SpO_2 indicator is below the threshold. In addition, the blood pressure indicator also shows a fairly clear relationship, where Blood Pressure Below/Above Threshold has a moderate correlation with Systolic (0.56) and Diastolic (0.37), indicating that the blood pressure threshold status is directly influenced by the numerical blood pressure value. In the Alert Triggered (Yes/No) variable, there is a positive correlation with several factors, especially with Blood Pressure Threshold (0.45), Glucose Levels Below/Above Threshold (0.35), and Heart Rate (0.34). This indicates that the alert system is more frequently triggered when physiological conditions exceed certain thresholds, such as high blood pressure, abnormal sugar levels, and increased heart rate. A lower correlation was also observed between the alert and SpO_2 Below Threshold (0.28) and directly with

Building of Informatics, Technology and Science (BITS)
Volume 7, No 3, December 2025 Page: 1684−1693
ISSN 2684-8910 (media cetak)
ISSN 2685-3310 (media online)
DOI 10.47065/bits.v7i3.8414

numerical blood pressure. Meanwhile, the Glucose Levels variable in raw numerical form did not show a significant correlation with other variables, but its threshold status did influence alert triggering.

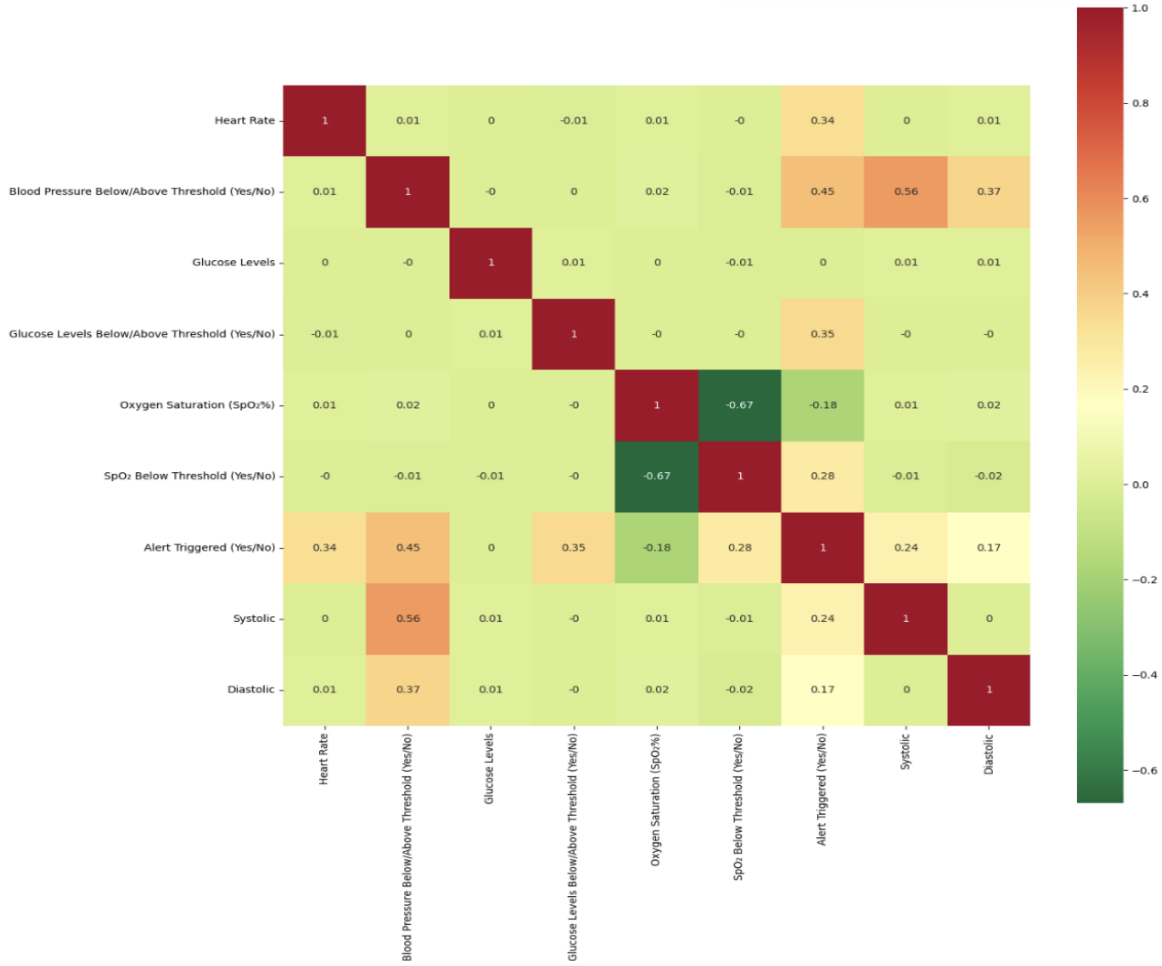

Figure 2. Heatmap Analysis

Overall, this heatmap indicates that the health alert system is more sensitive to threshold variables (binary) than to raw numerical values. Therefore, future analyses and predictive models should place more emphasis on threshold status while still considering potential redundancy between variables such as systolic with threshold blood pressure, or numerical SpO_2 with threshold SpO_2 indicators.

b. Decision Tree Analysis

Figure 3 is a visualization of a decision tree with a depth limited to level three. At the root of the tree, the first feature used to separate the data is Blood Pressure Below/AboveThreshold (Yes/No) ≤ 0.5. This node has a Gini value of 0.388 with a total of 9000 samples, consisting of 2370 class 0 data and 6630 class 1 data. Because the number of class 1 is more dominant, this root node is classified as class 1. If the condition on this blood pressure feature is False (more than 0.5), then the data directly enters the leaf node with a Gini value of 0, indicating that the pure data is entirely class 1 with a total of 3256 samples. This means, in a group with a certain blood pressure, all data can be directly predicted as class 1 without the need for other feature examination. If the condition at the root is True (≤ 0.5), then the branch continues to the Heart Rate ≤ 100.5 feature. In this path, if the heart rate value is greater than 100.5, the node formed is a pure node with a gini of 0 and a sample size of 1836, all of which are class 1. This means that this condition also immediately produces a class 1 prediction. However, if the heart rate value is less than or equal to 100.5, then the data still needs to be further separated based on the Glucose Levels Below/Above Threshold (Yes/No) feature less than or equal to 0.5. In this branch, if the glucose value is ≥ 0.5, the node returns to pure with a gini of 0, a sample size of 1026, and all of which are included in class 1. Conversely, if the glucose value is less than or equal to 0.5, the data of 2882 samples is continued with the Oxygen Saturation (SpO2%) ≤ 91.5 feature test. At this node, the gini value of 0.292 indicates that the data is not completely pure because there is a mixture of classes, namely 2370 samples of class 0 and 512 samples of class 1. However, the majority of samples belong to class 0, so this node is predicted as class 0. However, because the visualization is limited to a depth of three, further branching of this node is not shown and is replaced with the symbol "(…)"

Building of Informatics, Technology and Science (BITS)
Volume 7, No 3, December 2025 Page: 1684−1693
ISSN 2684-8910 (media cetak)
ISSN 2685-3310 (media online)
DOI 10.47065/bits.v7i3.8414

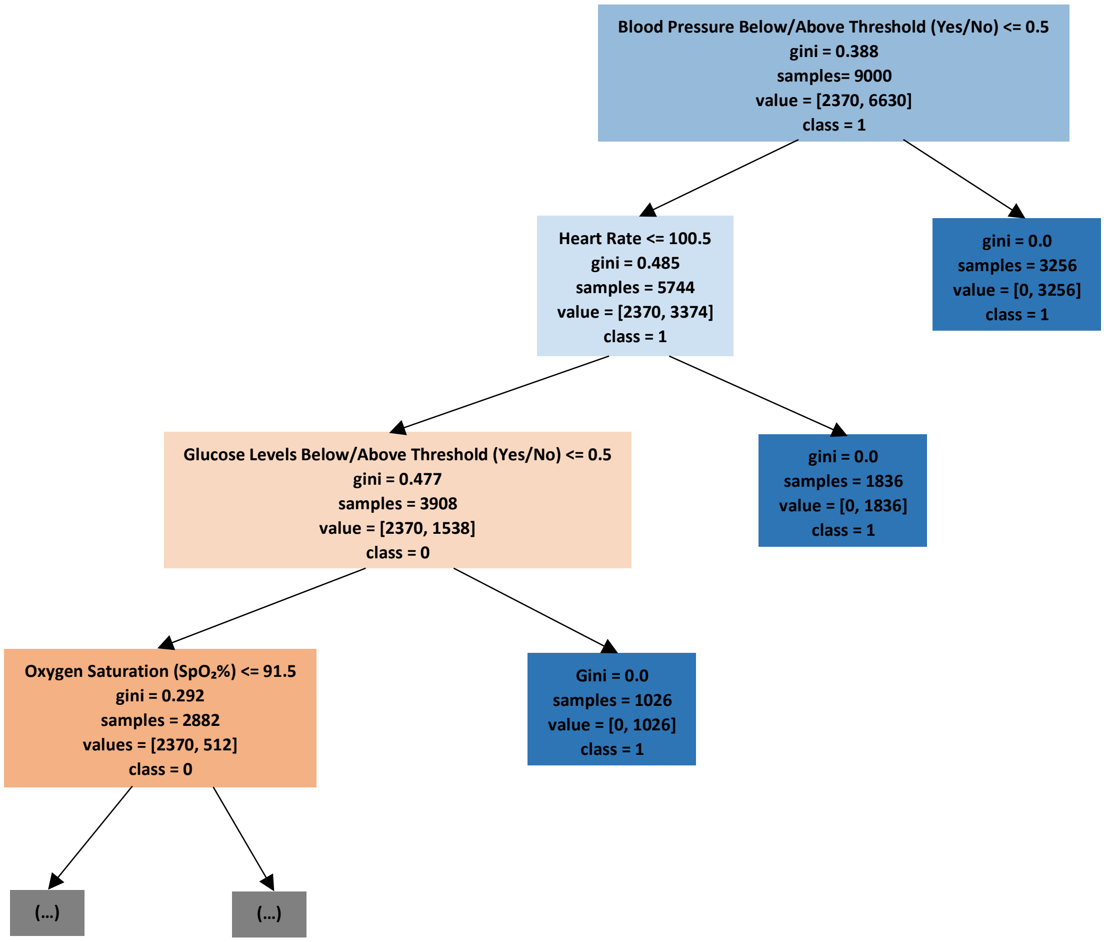

Figure 3. Decision Tree

Overall, this decision tree shows that Blood Pressure is the most significant separator at the root, followed by Heart Rate, then Glucose Levels, and finally Oxygen Saturation in the deeper branches. The majority of paths result in pure class 1 nodes, except for the combination of low Blood Pressure, low Heart Rate, low Glucose, and low SpO2, which tends towards class 0, although there is still a small amount of mixing. Thus, this tree structure hierarchically explains how physiological variables are used in determining classification results, while also showing the data distribution, purity level, and the majority of classes at each branch.

c. Feature Importance Analysis

The results of the feature importance analysis as seen in Figure 4 show that the variable with the greatest influence on the classification process is glucose levels below/above threshold, which occupies the top position with the highest contribution value compared to other variables. This indicates that the condition of glucose levels, whether below or above the threshold, plays a significant role in influencing the model's decision. The next variable with a high level of importance is heart rate, followed by oxygen saturation (SpO_2%), and blood pressure below/above threshold. These four variables provide a dominant contribution in determining the classification results, as seen from the graph which shows a quite striking difference in feature importance values compared to other variables such as absolute glucose levels, SpO_2 below the threshold, systolic blood pressure, and diastolic blood pressure, which show a relatively lower influence on the model. These findings align with the decision tree structure formed during the model training phase. The initial branching of the tree begins with blood pressure, demonstrating its role as a key separating factor in the classification process. Subsequently, the branching continues to heart rate, glucose levels, and oxygen saturation, which consistently support the results of the feature importance analysis. The agreement between the decision tree visualization and the feature importance values strongly indicates that these variables are indeed the primary determinants of classification performed by the Decision Tree algorithm. At first glance, these results indicate an inconsistency with the decision tree visualization in Figure 2, where 'blood pressure' is the splitter at the root node (most significant initially), while in the feature importance graph, 'glucose levels' has the highest contribution and 'blood pressure' is only ranked fourth. This conflict can be explained methodologically: the root node simply represents the best initial split that maximizes impurity reduction at a single point, while the feature importance graph measures the total cumulative Gini impurity reduction across the entire tree (all branches and depths). Therefore, the correct interpretation is that although 'blood pressure' is the best initial splitter for dividing the entire data, the 'glucose levels' feature in total provides the greatest cumulative predictive power when calculated across all subsequent branches in the tree structure.

Building of Informatics, Technology and Science (BITS)
Volume 7, No 3, December 2025 Page: 1684−1693
ISSN 2684-8910 (media cetak)
ISSN 2685-3310 (media online)
DOI 10.47065/bits.v7i3.8414

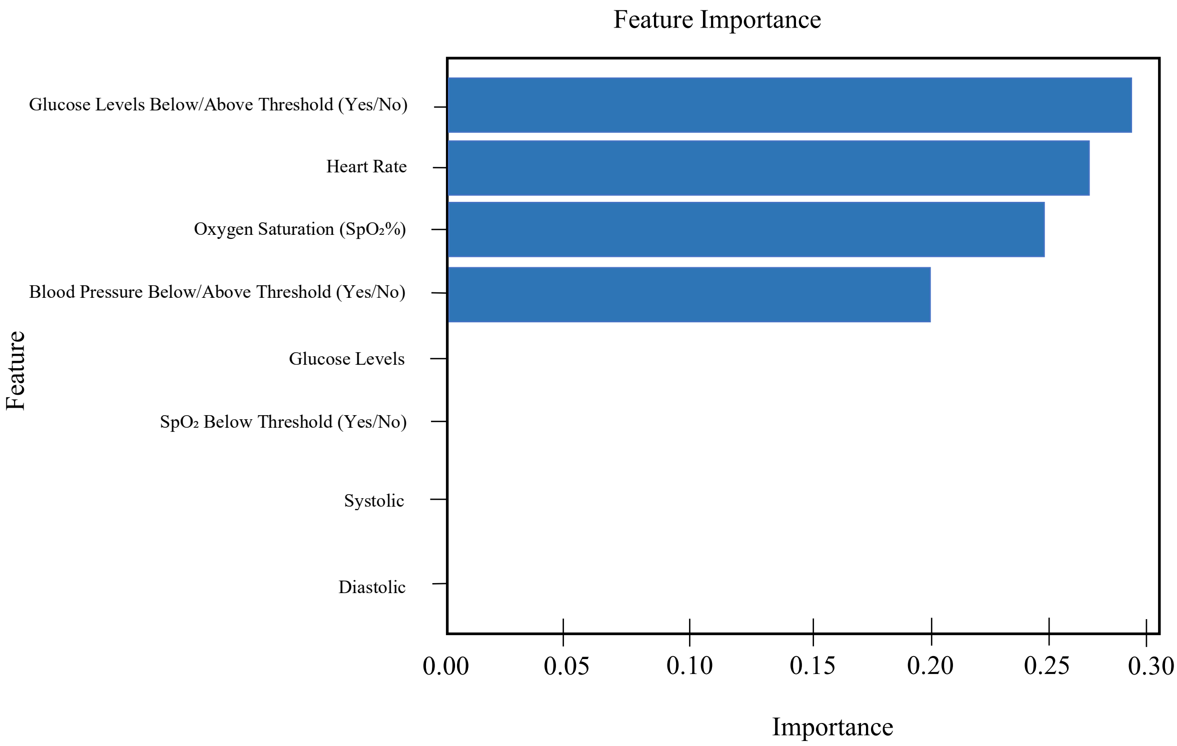

Figure 4. Feature Importance

Thus, the results of this analysis not only demonstrate the priority order of variables based on their contribution but also strengthen our understanding of how the model makes decisions systematically and transparently in the context of health data.

3.2 Discussion

The Decision Tree Classifier proved excellent at identifying patterns related to alert fatigue in healthcare monitoring systems. Evaluation using the F1-score, accuracy, recall, and precision metrics yielded a perfect score of 1.0 (100%). This demonstrates that the Decision Tree can consistently classify data without any misclassification [12]. This model not only perfectly predicts patient conditions but also fundamentally addresses the problem of alert fatigue. This phenomenon, where healthcare professionals are overwhelmed with irrelevant notifications, can compromise patient safety [13]. This model provides a solution by generating more selective and meaningful alerts, in line with other clinical studies that use similar methods to design more informative and actionable alarm messages, thereby reducing distraction in intensive care settings. One of the key advantages of the Decision Tree, demonstrated in this study, is its ability to generate clear and easily interpretable decision rules [14]. Unlike complex black-box models, the decision tree structure allows healthcare professionals to visually and hierarchically understand how each decision is made [15]. The resulting decision tree visualization shows that blood pressure is the most significant separating variable, followed by heart rate and glucose levels, respectively. This clear finding reinforces the relevance of decision trees in solving classification problems in healthcare, where decision transparency is crucial [16]. Furthermore, the results of the feature importance analysis indicate that key physiological variables contribute most significantly to the classification process [17]. Overall, glucose levels are the predictor with the greatest influence, followed by heart rate, oxygen saturation (SpO_2), and blood pressure. This sequence reflects an important nuance revealed by the model, where the initial branching begins with blood pressure, then continues with heart rate, glucose levels, and oxygen saturation. The explanation for this is that although blood pressure serves as the most significant initial delimiter for broadly segmenting the data, glucose levels and heart rate cumulatively provide the greatest predictive power across all branches of the tree. In other words, once patients are categorized by blood pressure, variations in glucose levels and heart rate become the primary determinants of the final classification. This finding not only strengthens the model's validity but also confirms its clinical relevance, given that these four variables are important indicators in monitoring a patient's health condition [18]. The clinical implications of these findings are crucial for mitigating alarm fatigue. Traditional systems that may rely too heavily on a single blood pressure threshold can generate numerous false alarms. Our approach demonstrates that by considering the interaction between blood pressure, glucose levels, and heart rate, the system can better distinguish between harmless transient fluctuations and truly critical conditions. For example, a blood pressure-triggered alarm may not activate if the patient's glucose levels and heart rate are stable, significantly reducing the number of unnecessary alarms and allowing healthcare providers to focus on alerts of high clinical significance. This highly accurate model performance is also consistent with other studies applying Decision Trees to medical classification, where the model achieved accuracy above 98%, demonstrating the potential for high

Building of Informatics, Technology and Science (BITS)
Volume 7, No 3, December 2025 Page: 1684−1693
ISSN 2684-8910 (media cetak)
ISSN 2685-3310 (media online)
DOI 10.47065/bits.v7i3.8414

accuracy in this sensitive domain [19]. It is important to compare these results with other literature that may achieve lower accuracy in predicting clinical alarms. Many studies struggle due to the complexity of physiological signals or reliance on more complex features. The success of this study's approach, which achieved 100% accuracy, is likely due to the use of clear and definitive threshold-based features, which closely align with the rule-based logic of the decision tree. However, as stated in the study's caveat, this 100% score should be interpreted with caution. These results demonstrate the model's high learning capacity on the given dataset, but further validation on larger and more diverse datasets is needed to ensure its generalizability, especially given the model configuration and imbalanced nature of the data. This study comprehensively underscores the role of Decision Trees as a robust and highly relevant classification approach for application to healthcare data [20]. The model's easy interpretation also aligns with findings from other studies. Decision Trees excel because their classification process is simple, easily understood by humans, and they are capable of delivering high levels of accuracy [21]. Decision tree analysis has also proven effective in modeling and decomposing complex decision-making processes, providing a robust framework for identifying key criteria influencing outcomes. These results are further supported by studies demonstrating that decision trees can provide accurate and relevant classification results, making them a versatile tool for a wide range of applications [8].Thus, the model developed in this study is not only technically successful but also makes a significant practical contribution to improving patient monitoring systems and supporting more effective decision-making.

It worth mention, the perfect classification metrics achieved in this study (100% accuracy, precision, recall, F1-score) must be interpreted within the context of the synthetic dataset's characteristics. Real-world patient monitoring systems face challenges absent in this data: (1) sensor measurement errors and noise, (2) temporal dynamics and alert fatigue patterns over time, (3) patient-specific physiological variations, (4) clinical context dependencies, and (5) false alarm rates that vary by clinical setting. Studies using real EHR data typically report classification accuracies of 75-90%. Therefore, while this study successfully demonstrates Decision Tree interpretability and establishes a methodological framework, clinical validation is imperative before deployment in healthcare settings.

4. CONCLUSION

This study concludes that the Decision Tree algorithm is an effective, relevant, and promising approach to address alert fatigue in patient monitoring systems. Test results show the model achieves very high performance, with a metric approaching 1.0 (100%). However, given the model configuration and imbalanced data characteristics, this excellent score should be interpreted with caution. It is more evidence of the model's high learning capacity on a given specific dataset (synthetic dataset), rather than a guarantee of real-world performance. Despite these performance scores, the primary clinical relevance of Decision Trees lies in their ability to generate simple, clear, and easily interpretable decision rules. This aspect is crucial in the clinical setting, where transparency in decision-making is crucial for maintaining patient trust and safety. The decision tree visualization in this study shows that blood pressure is the most dominant separating factor, followed by heart rate and glucose levels, confirming that the model successfully captured clinically relevant vital indicators. This study has several limitations that should be acknowledged. The use of a synthetic dataset and the decision not to apply imbalanced data handling techniques means that the model's performance on more complex and varied real-world clinical data remains untested. This was done to determine the extent to which the Decision Tree algorithm can process imbalanced data and still produce classification results. Therefore, generalizations of these findings should be made with caution. The implementation of Decision Trees not only demonstrates technical success in predicting patient outcomes but also offers significant practical implications. The practical implication of this study lies not in achieving a 100% score, but rather in its potential to support healthcare professionals in making faster, data-driven decisions through transparent rules. Focusing on the interpretability and clinical relevance of the decision rules generated by this model, further research is expected to lead to the development of Decision Tree-based clinical applications integrated with patient monitoring systems. The primary focus should be validation using real patient data in everyday medical workflows, and the implementation of more robust validation methods such as Stratified K-Fold Cross-Validation and hyperparameter tuning (such as limiting max_depth) is mandatory to ensure the resulting model is not only transparent but also generalizable and clinically reliable.

ACKNOWLEDGMENT

The author expresses her deepest gratitude to her mentors and supervising lecturers for their continuous guidance, direction, and support throughout the process of writing this paper. Their contributions of knowledge, experience, and input have been instrumental in the success of this work. She also expresses her gratitude to her beloved family for their prayers, moral support, and encouragement that have always accompanied her every step of the way. To her beloved one, she expresses her gratitude for the invaluable understanding, patience, and motivation, which have been the main driving force in completing this paper. She also extends her gratitude to her colleagues and various parties who have helped, both directly and indirectly, so that this writing can be completed well. All forms of support, attention, and cooperation have been an important part that is very meaningful to her.

Building of Informatics, Technology and Science (BITS)
Volume 7, No 3, December 2025 Page: 1684−1693
ISSN 2684-8910 (media cetak)
ISSN 2685-3310 (media online)
DOI 10.47065/bits.v7i3.8414

REFERENCES

[1] L. P. Astuti, Y. Trisyani, and R. Mirwanti, “Implementasi Early Warning System (Ews) dalam Mendeteksi Perburukan Akut pada Pasien Dewasa di Ruang Rawat Inap Rumah Sakit,” *J. Telenursing JOTING*, vol. 5, no. 2, pp. 1590–1603, Aug. 2023, doi: 10.31539/joting.v5i2.6356.

[2] E. A. M. Michels, S. Gilbert, I. Koval, and M. K. Wekenborg, “Alarm fatigue in healthcare: a scoping review of definitions, influencing factors, and mitigation strategies,” *BMC Nurs.*, vol. 24, no. 1, p. 664, Jun. 2025, doi: 10.1186/s12912-025-03369-2.

[3] Mifta Wilda Al -Aluf and Zaehol Fatah, “Klasifikasi Algoritma Decision Tree Untuk Tingkat Kemiskinan Di Indonesia,” *J. Comput. Sci. Technol. JOCSTEC*, vol. 3, no. 1, pp. 55–62, Jan. 2025, doi: 10.59435/jocstec.v3i1.440.

[4] P. A. Kristianti and S. Jatmiko, “Klasifikasi Pemilihan Produk Perbankan Dengan Algoritma Decision Tree Id3 Dan C4.5,” *JATI J. Mhs. Tek. Inform.*, vol. 9, no. 4, 2025, doi: 10.36040/jati.v9i4.13907.

[5] T. D. Yuliani *et al.*, “Penerapan Algoritma C4.5 dalam Klasifikasi Dominasi Jenis Kelamin pada Data Penduduk Kota Depok Berdasarkan Kelompok Usia di Tahun 2019–2023,” *JATI J. Mhs. Tek. Inform.*, vol. 9, no. 2, 2025, doi: 10.36040/jati.v9i2.12584.

[6] A. R. Raharja, Jayadi, A. Pramudianto, and Y. Muchsam, “Penerapan Algoritma Decision Tree dalam Klasifikasi Data ‘Framingham’ Untuk Menunjukkan Risiko Seseorang Terkena Penyakit Jantung dalam 10 Tahun Mendatang,” *Technol. J.*, vol. 1, no. 1, Feb. 2024, doi: 10.62872/cwgzp962.

[7] F. Alzami, E. D. Udayanti, D. P. Prabowo, and R. A. Megantara, “Document Preprocessing with TF-IDF to Improve the Polarity Classification Performance of Unstructured Sentiment Analysis,” *Kinet. Game Technol. Inf. Syst. Comput. Netw. Comput. Electron. Control*, vol. 5, no. 3, pp. 235–242, Aug. 2020, doi: 10.22219/kinetik.v5i3.1066.

[8] R. A. Saputra and A. Pratama, “Implementasi Decision Tree untuk Prediksi Harga Rumah di Daerah Tebet,” *J. Inf. Syst. Manag. JOISM*, vol. 6, no. 2, pp. 164–170, Jan. 2025, doi: 10.24076/joism.2025v6i2.1928.

[9] H. Mardivta, “Evaluasi Sistem Informasi Pencatatan Medis Menggunakan Decision Tree untuk Peningkatan Akurasi Diagnosis,” *J. Inf. Syst.*, vol. 2, no. 1, 2024.

[10] R. M. Caturkusuma, F. Alzami, A. Nurhindarto, M. T. Sulistiyono, C. Irawan, and Y. Kusumawati, “Predicting IT Incident Duration using Machine Learning: A Case Study in IT Service Management,” *sinkron*, vol. 9, no. 1, pp. 8–19, Jan. 2025, doi: 10.33395/sinkron.v9i1.14310.

[11] B. Risk, “Elderly Care EDA Prediction.” Kaggle, 2025. [Online]. Available: https://www.kaggle.com/code/devraai/elderly-care-eda-prediction/input?select=health_monitoring.csv

[12] A. H. Nasrullah, “Implementasi Algoritma Decision Tree untuk Klasifikasi Produk Laris,” *J. Ilm. ILMU Komput.*, vol. 7, no. 2, pp. 45–51, Sep. 2021, doi: 10.35329/jiik.v7i2.203.

[13] R. D. Widyastuti, S. P. Arso, and A. Suryoputro, “Keselamatan pasien sebagai pilar penting dalam mencegah kesalahan medis: Tinjauan sistematik,” *Holistik J. Kesehat.*, vol. 19, no. 2, pp. 277–285, May 2025, doi: 10.33024/hjk.v19i2.639.

[14] H. Z. Rahimi, S. Defit, and J. Veri, “Implementasi Decision Tree dalam Pengambilan Keputusan untuk Pemberian Beasiswa,” *JATI J. Mhs. T*, vol. 9, no. 3, 2025, doi: 10.36040/jati.v9i3.13580.

[15] A. Tholib, *Implementasi Algoritma Machine Learning Berbasis WEB dengan Framework Streamlit*, Cetakan 1. Probolinggo: Pustaka Nurja; LP3M Universitas Nurul Jadid, 2023. Accessed: Sep. 20, 2025. [Online]. Available: https://repository.unuja.ac.id/id/eprint/1666/1/Buku%20Implementasi%20Machine%20Learning%20berbasis%20Web%20dengan%20Framework%20Streamlit%20.pdf

[16] H. Purnomo, R. E. Pambudi, and R. Irawan, “Penerapan Decision Tree untuk Klasifikasi Penyakit Berdasarkan Data Rekam Medis,” *Aisyah J. Inform. Electical Eng.*, vol. 7, no. 1, 2025, doi: 10.30604/jti.v7i1.655.

[17] D. Aprilianto and E. Rizal, “Klasifikasi Penyakit Kanker Paru Menggunakan Algoritma Random Forest Berbasis Streamlit,” *METIK J.*, vol. 9, no. 2, 2025, doi: 10.47002/svz4r327.

[18] R. Irfannandhy, L. B. Handoko, and N. Ariyanto, “Analisis Performa Model Random Forest dan CatBoost dengan Teknik SMOTE dalam Prediksi Risiko Diabetes,” *Edumatic J. Pendidik. Inform.*, vol. 8, no. 2, pp. 714–723, Dec. 2024, doi: 10.29408/edumatic.v8i2.27990.

[19] A. Nurhidayat, W. A. Arrosyid, and R. Samsinar, “Prediksi Tumor Otak Menggunakan Metode Convolutional Neural Network (CNN) dan Algoritma Decision Tree,” *Semin. Nasioanl Teknol. Sains STAINS*, vol. 4, no. 1, 2025, doi: 10.29407/d3822f90.

[20] A. S. Biyantoro and B. Prasetiyo, “Application of Decision Tree for Health Status Classification, Compared to KNN and Naive Bayes,” *IJIRSE Indones. J. Inform. Res. Softw. Eng.*, vol. 4, no. 1, pp. 47–55, 2024, doi: 10.57152/ijirse.v4i1.1342.

[21] F. Endah, Encis Indah Suryaningsih, *Penerapan Data Mining Metode Decision Tree untuk Mengukur Penguasaan Bahasa Inggris Maritim*. Semarang: CV. Pustaka STIMART AMNI Semarang, 2021. Accessed: Sep. 20, 2025. [Online]. Available: https://penerbit.unimar-amni.ac.id/wp-content/uploads/2022/09/master-Monograf-Miss-Endah.pdf