

A Comparative Study of Decision Tree and Neural Network Algorithms for Stroke Risk Prediction

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ABSTRACT

Stroke is one of the leading non-communicable diseases that causes high mortality and long-term disability, making early risk prediction an important public health issue. In Indonesia, the increasing prevalence of stroke highlights the need for data-driven approaches to support early detection and prevention efforts. This study aims to compare the performance of Decision Tree and Neural Network algorithms in predicting stroke risk using health-related data. The research method employs a publicly available stroke prediction dataset obtained from Kaggle consisting of 5,111 records. Data preprocessing was conducted to handle missing values and prepare the dataset for modeling, followed by data splitting into training and testing sets using an 80:20 ratio. Model performance was evaluated using accuracy, precision, recall, and F1-score metrics. The results show that the Decision Tree model achieved higher overall accuracy of 80.72%, but demonstrated low recall for the stroke class. In contrast, the Neural Network model produced a lower accuracy of 69.37% but achieved a high recall of 82%, indicating better sensitivity in detecting stroke cases. These findings reveal a trade-off between overall accuracy and sensitivity in both models. It can be concluded that Neural Network is more suitable for stroke risk prediction when early detection is prioritized, while Decision Tree is preferable for achieving higher general classification accuracy.

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1. INTRODUCTION

Stroke is one of the most globally impactful non-communicable diseases in terms of mortality and long-term disability [9], [15]. The World Health Organization reports that more than 13 million new stroke cases occur worldwide each year, with millions of people dying or experiencing permanent disability as a result. Stroke not only imposes a substantial health burden but also generates significant social and economic impacts across countries [14]. This phenomenon is also evident in Indonesia, where stroke remains one of the leading causes of death and disability among adults. The 2023 Indonesian Health Survey (SKI) reported that the national prevalence of stroke reached approximately 8.3 per 1,000 population aged ≥ 15 years, meaning that more than 8 out of every 1,000 individuals were affected in that year. The prevalence is considerably higher in older age groups, particularly among those aged 75 years and above, reaching more than 41 per 1,000 population [3], [8]. These findings indicate an increasing burden of stroke associated with aging and comorbid conditions within the Indonesian population.

Historical data further demonstrate a rising trend in stroke prevalence. The Basic Health Research (Risikesdas) reported an increase from 7 per 1,000 population in 2013 to 10.9 per 1,000 population in 2018, indicating a substantial nationwide escalation in stroke cases. It is estimated that more than 1.7 million Indonesians have experienced stroke, making it a critical public health issue requiring cross-sectoral intervention [16]. Demographic transitions, unhealthy lifestyles, and inadequate early detection of risk factors such as hypertension, diabetes mellitus, dyslipidemia, and obesity contribute significantly to the growing number of stroke cases. The disease burden becomes more complex as stroke increasingly affects younger age groups, thereby impacting productivity and overall quality of life.

Machine learning offers significant potential to support early detection and prediction of stroke risk using healthcare data. Various algorithms can identify complex risk patterns that are difficult to detect using conventional statistical approaches. Among the commonly applied algorithms in disease prediction are Decision Tree and Artificial Neural Network (ANN) [12], [13]. Decision Trees are recognized for their interpretability, enabling healthcare professionals to understand decision rules more easily, while Neural Networks are capable of modeling complex nonlinear relationships among variables. Each method possesses distinct characteristics that may influence predictive performance on the same dataset [5]. Previous studies have shown that classification algorithms such as Decision Tree and Neural Network perform effectively when implemented in decision support systems for early detection of chronic diseases, particularly in healthcare applications [6].

Although several studies have applied machine learning techniques for disease prediction, comprehensive comparative analyses between Decision Tree and Neural Network models using consistent evaluation metrics remain limited. This gap highlights the need for an objective comparative study to assess the performance of both algorithms in predicting stroke risk. Therefore, this study aims to compare Decision Tree and Neural Network algorithms for stroke risk prediction in order to determine the most appropriate method for developing a health-related decision support system. The findings are expected to contribute to more accurate early detection strategies, thereby supporting effective stroke prevention and management in Indonesia.

2. METHOD

The research method is a systematic stage used to achieve research objectives in a structured and measurable manner. In this study, the method used was designed to compare the performance of Decision Tree and Neural Network algorithms in predicting stroke risk. The research stages included literature study, data collection and preprocessing, model development, and evaluation and analysis of results. This approach is expected to produce an accurate and scientifically accountable prediction model.

2.1 Data Collection

The data collection stage is a crucial initial step in this study, as data quality directly affects the performance of the developed models. This research employs two machine learning algorithms, namely Decision Tree and Neural Network, which are implemented using the Python programming language. The dataset used in this study is a stroke prediction dataset obtained from scientific research and publicly available through the Kaggle platform, consisting of a total of 5,111 data points. The dataset contains various attributes relevant to stroke risk factors and serves as the basis for the training and testing processes of the predictive models.

2.2 Decision Tree

Decision Tree is a supervised learning algorithm used for classification problems by forming a decision tree structure based on data attributes [7]. Each node represents an attribute, while the branches show the results of data separation to produce classes in the leaf nodes. This algorithm is widely used because it is easy to interpret and capable of clearly describing the decision-making process [11]. The decision tree is formed by selecting the best attribute at each node based on the measure of data uncertainty [1]. One of the commonly used measures is Entropy and Information Gain. Entropy is used to measure the level of data irregularity, which is formulated as.

$$Entropy(S) = \sum_{i=1}^c -p_i \log_2 p_i \quad (1)$$

Where :

$Entropy(S)$	= Entropy value of dataset set S
S	= Dataset
C	= Number of classes
p_i	= Frequency probability of class i in the dataset

$$Entropy(T, X) = \sum_{c \in X} P(c)E(c) \quad (2)$$

Where :

$Entropy(T, X)$ = Entropy after attribute T is split based on attribute X
 $P(c)$ = Probability of attribute class
 $E(c)$ = Entropy value of the attribute class

$$Gain(A) = Entropy(S) - \sum_{i=1}^k \frac{[S_i]}{[S]} \times Entropy(S_i) \quad (3)$$

Where :

$Gain(A)$ = Information Gain attribute A
 $Entropy(S)$ = Entropy value of dataset S
 $[S_i]$ = Number of samples for value i
 $[S]$ = Total number of data samples
 $Entropy(S_i)$ = Entropy of the i-th subset after separation

Using Entropy and Information Gain calculations, the Decision Tree algorithm is able to determine the most optimal attribute in separating data at each node. The attribute with the highest Information Gain value is selected as the separator, so that the resulting decision tree structure can produce an effective and easily interpretable stroke risk prediction model.

2.3 Neural Network

Neural Networks are supervised learning algorithms inspired by biological nervous systems and used for classification problems [4]. This algorithm consists of an input layer, hidden layer, and output layer that are interconnected through weights. Neural Networks have the ability to model complex nonlinear relationships between data attributes [10]. The computational process in a neural network is carried out by calculating the activation value of neurons using an activation function [2]. One of the commonly used activation functions is the sigmoid function, which is formulated as follows.

$$f(x) = \frac{1}{1 + e^{-x}} \quad (4)$$

Where:

$f(x)$ = Activation function output
 x = Sum of the product of the input and the weight
 e = Exponential number

The error value is calculated to measure the difference between the actual value and the predicted value, which is formulated as.

$$E = \frac{1}{2} (y - \hat{y})^2 \quad (5)$$

Where:

E = Error value
 y = Actual value
 \hat{y} = Predicted value

The weight update process is performed using the *backpropagation* algorithm to minimize the error value, with the following equation.

$$\omega_{new} = \omega_{old} - \eta \frac{\partial E}{\partial w} \quad (6)$$

Where:

ω_{new} = New weight
 ω_{old} = Old weight
 η = Learning rate

$\frac{\partial E}{\partial w}$ = Error derivative with respect to weight

With this mechanism, the Neural Network is able to perform iterative learning to produce an optimal stroke risk prediction model, the performance of which is then compared with the Decision Tree algorithm.

2.4 Research Flow

The research flow was designed to describe the stages of research implementation in a systematic and structured manner. The purpose of designing the research flow was to provide an overview of the series of research activities carried out and to ensure that each stage was carried out in a focused manner and was scientifically accountable. The research flow used in this study can be seen in Figure 1.

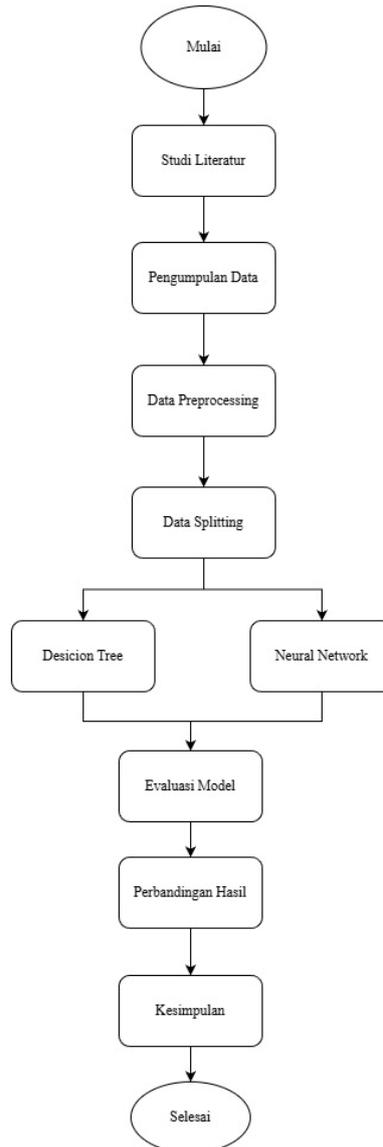


Figure 1. Research Flow

Figure 1 shows the research flow, which begins with a literature study to obtain a theoretical basis related to stroke risk prediction and machine learning algorithms, followed by data collection and pre-processing to clean and prepare the data for use in modeling. During the pre-processing stage, missing values in several numerical attributes were handled using a statistical mean approach, as this was considered effective in maintaining data distribution without reducing the sample size. Next, the dataset was divided into training data and test data using an 80:20 ratio, where the large proportion of training data was intended to allow the Decision Tree and Neural Network models to learn patterns optimally, while the test data was used to evaluate the model's performance objectively. This process ended with the evaluation and comparison of the

performance of the two algorithms to determine the best model, which then became the basis for drawing the final conclusions of the study.

3. RESULTS AND DISCUSSION

This chapter presents the results of the study obtained from the application of the Decision Tree and Neural Network algorithms in predicting the risk of stroke. The model testing results are analyzed and discussed based on the evaluation metrics used to assess the performance of each algorithm, so that the performance comparison and its implications for the research objectives can be determined.

3.1 Decision Tree Model Evaluation

The Decision Tree model was evaluated to determine the algorithm's performance in predicting stroke risk based on test data. The evaluation results were used to assess the model's ability to classify accurately according to the specified testing metrics. The evaluation of the decision tree model can be seen in Table 1.

Table 1. Evaluation of the Decision Tree Model

Class	Precision	Recall	F1-Score	Support
0	0.97	0.83	0.89	972
1	0.11	0.42	0.18	50
Accuracy			0.80	1022
Macro avg	0.54	0.62	0.53	1022
Weighted avg	0.92	0.81	0.86	1022

Table 1 shows the results of evaluating the performance of the Decision Tree model in predicting stroke risk. The model produced an accuracy value of 81% with excellent performance in class 0 (no stroke risk), as indicated by a precision value of 0.97, recall of 0.83, and F1-score of 0.89. However, the model's performance in class 1 (at risk of stroke) is still relatively low, with a precision value of 0.11, recall of 0.42, and F1-score of 0.18. This difference in performance indicates that the Decision Tree model tends to be more effective in classifying the majority class than the minority class. The macro average and weighted average values show the effect of data imbalance on the overall model performance, which can be visualized in Figure 2.

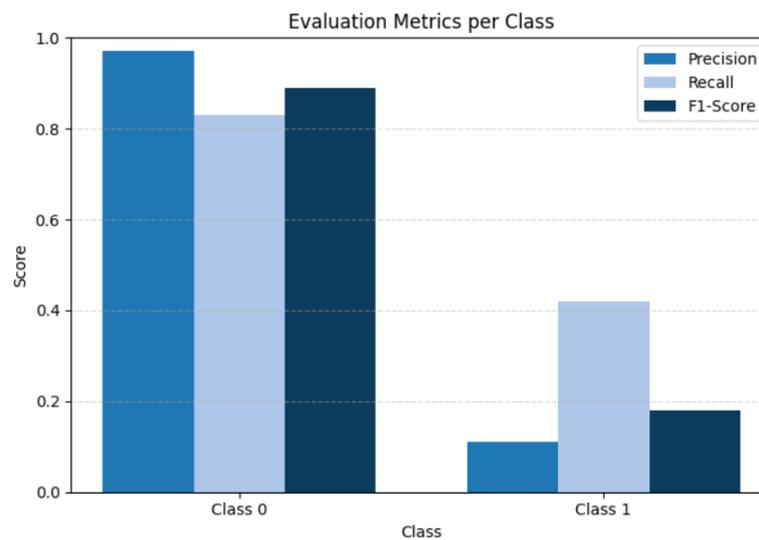


Figure 2. Comparison Chart of Decision Tree Classes

Figure 2 is a visualization of the results of evaluating the Decision Tree model in predicting stroke risk. The graph shows the difference in model performance in each class, where the model has better ability in classifying class 0 (no stroke risk) compared to class 1 (stroke risk). This can be seen from the dominance of correct predictions in the majority class, while in the minority class there are still significant classification errors. This visualization reinforces the numerical evaluation results in Table 1, while also showing the effect of data imbalance on the performance of the Decision Tree model in detecting stroke cases.

3.2 Neural Network Model Evaluation

The Neural Network model evaluation was conducted to measure the algorithm's performance in predicting stroke risk. The analysis of the evaluation results aims to determine the accuracy and effectiveness of the model in learning non-linear data patterns. The neural network model evaluation can be seen in Table 2.

Table 2. Neural Network Model Evaluation

Class	Precision	Recall	F1-Score	Support
0	0.99	0.69	0.81	972
1	0.12	0.82	0.21	50
Accuracy			0.69	1022
Macro avg	0.54	0.75	0.51	1022
Weighted avg	0.92	0.69	0.78	1022

Table 2 shows the results of evaluating the performance of the Neural Network model in predicting stroke risk. The model produced an accuracy value of 69%, with excellent performance in class 0 (no stroke risk), as indicated by a precision value of 0.99, a recall value of 0.69, and an F1-score of 0.81. In class 1 (at risk of stroke), the model shows a high recall value of 0.82, but with a low precision value of 0.12, resulting in an F1-score of 0.21. This condition indicates that the Neural Network model has high sensitivity in detecting stroke cases, but still produces quite a number of inaccurate positive predictions. The macro average and weighted average values show that data imbalance affects the overall performance of the model, which can be visualized in Figure 3.

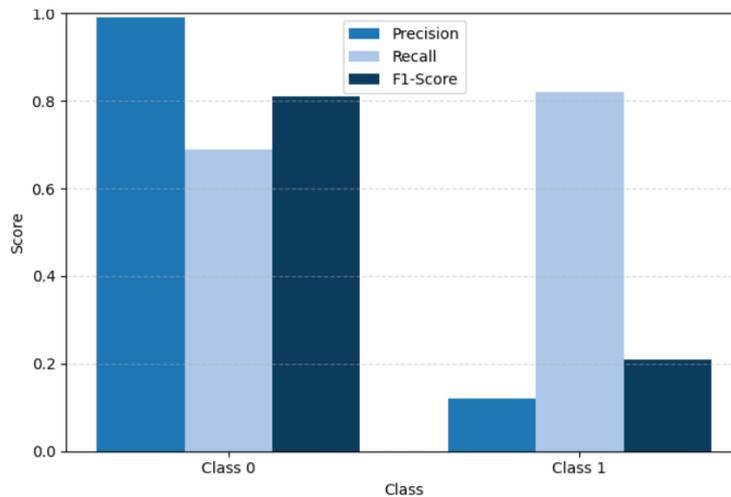


Figure 3. Neural Network Class Comparison Chart

Figure 3 is a graph of the Neural Network model evaluation results in predicting stroke risk. The graph shows the distribution of classification performance in each class, where the model demonstrates good ability in detecting the stroke risk class, as reflected in the high recall value in the class. 1. However, there are still a number of prediction errors in the form of false positives, resulting in low precision values for that class. This visualization clarifies the evaluation results in Table 2 and shows the effect of data imbalance on the performance of the Neural Network model in classifying stroke risk.

3.3 Comparison of Decision Tree and Neural Network

A comparison of the performance between the Decision Tree and Neural Network algorithms was conducted to determine the difference in the performance of the two models in predicting stroke risk. This comparative analysis was based on the evaluation results obtained from each model to identify the algorithm with the most optimal performance. The results of the comparison of the performance of the two algorithms can be seen in Figure 4.

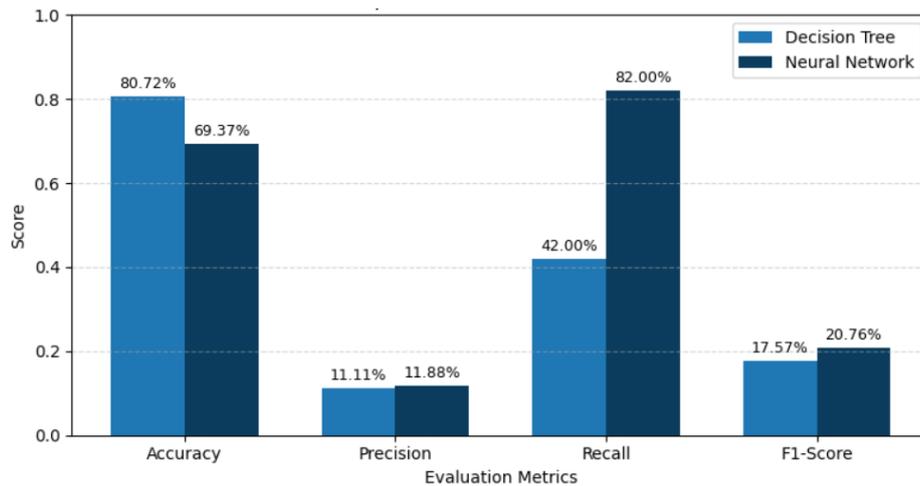


Figure 4. Decision Tree and Neural Network Chart

Figure 4 shows a comparison of the performance of the Decision Tree and Neural Network models based on the Accuracy, Precision, Recall, and F1-Score metrics. The evaluation results show that the Decision Tree model has a higher accuracy value of 80.72% compared to the Neural Network at 69.37%, indicating better overall classification capabilities. However, in terms of the recall metric, the Neural Network shows far superior performance with a value of 82%, while the Decision Tree only reaches 42%, indicating Neural Networks are more effective in detecting positive classes. In terms of precision metrics, both models have relatively low and nearly identical values, namely 11.11% for Decision Trees and 11.88% for Neural Networks, indicating a high rate of positive prediction errors. Furthermore, the F1-Score value shows that the Neural Network (20.76%) is slightly better than the Decision Tree (17.57%), reflecting a better balance between precision and recall in the Neural Network model. Overall, this difference indicates a trade-off in performance between models influenced by the characteristics and imbalance of the data used. Figure 4. Model Performance Comparison

3.4 Discussion

Based on the evaluation results, the Decision Tree model achieved an overall accuracy of 80.72%, surpassing the Neural Network model at 69.37%. This indicates that Decision Tree is better at global classification due to its ability to classify the majority class (no risk of stroke) very well. However, this model tends to be less sensitive in detecting stroke cases in the minority class. Conversely, the Neural Network model showed superior performance in recognizing nonlinear patterns associated with stroke risk, as reflected in a recall value of 82%. Although the false positive rate (low precision) is still quite high, this high sensitivity makes the Neural Network more effective in detecting positive cases than the Decision Tree. The difference in performance between the two models is directly influenced by the class distribution in the imbalanced dataset, where the amount of non-stroke data is much greater than stroke data. Because this study did not apply data balancing techniques such as oversampling (SMOTE), undersampling, or class weighting, the model still shows a bias towards the majority class. Nevertheless, this study on real-world data provides an objective picture of the challenges of classification in the health domain. There is a clear trade-off between global accuracy and minority class detection capability in this study. Practically, these findings have important implications for the national health system. The use of Neural Networks is highly recommended for community screening and early detection in community health centers due to their ability to minimize the risk of failure to detect stroke cases. Meanwhile, Decision Trees are more appropriate when the main priority is general classification accuracy. Strategically, the integration of this data-based technology can strengthen efforts to prevent non-communicable diseases. Addressing data imbalance presents an opportunity for further research to reduce the number of positive prediction errors and improve precision more optimally.

4. CONCLUSION

The test results show that the Decision Tree model produced an Accuracy value of 80.72%, Recall of 42%, Precision of 11.11%, and an F1-Score of 17.57%. The relatively high accuracy value indicates that this model is capable of classifying data well in general. However, the low precision and recall values for the stroke class indicate that Decision Tree is still not optimal in detecting actual stroke cases, because the model tends to focus more on recognizing the majority class (non-stroke), thus limiting its sensitivity to the minority class. The Neural Network model obtained an Accuracy value of 69.37%, Recall of 82%, Precision of 11.88%, and

an F1-Score of 20.76%. Although its accuracy value is lower than that of the Decision Tree, the Neural Network shows better ability in identifying patients at risk of stroke, as reflected in its high recall value. The ability to detect as many stroke cases as possible is a crucial aspect, because errors in the form of undetected patients at risk (false negatives) can have serious implications for patient safety. Therefore, the Neural Network is considered more relevant and efficient for the purposes of this study, given its ability to capture complex nonlinear patterns in medical data. Further research is recommended to apply data imbalance handling techniques and model parameter optimization to achieve more balanced prediction performance between sensitivity and prediction accuracy.

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