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APPLICATION OF ARTIFICIAL NEURAL NETWORK METHODS TO DETECT HEART ATTACKS

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Abstract*—A heart attack is a medical emergency caused by restricted blood flow to the heart, commonly leading to myocardial infarction due to blood clots or fat accumulation. Early detection of heart disease is crucial to support prevention efforts and assist healthcare professionals in timely diagnosis and treatment. This study applies the Backpropagation Neural Network (BPNN) algorithm as an intelligent computing method for heart attack detection. Experimental results demonstrate a prediction accuracy of 96.47%, confirming the effectiveness of artificial neural networks in identifying heart attacks in patients. These findings highlight the potential of BPNN as a reliable and precise early detection system, which can support more accurate clinical decision-making and improve the effectiveness of heart attack prevention and treatment.*

Keywords: *accurate diagnosis, artificial neural network, BPNN, early detection, heart attack.*

Abstrak*—Serangan jantung merupakan kondisi medis darurat akibat terhambatnya aliran darah ke jantung, yang umumnya menyebabkan infark miokard karena penggumpalan darah atau penumpukan lemak. Deteksi dini penyakit jantung sangat penting untuk mendukung upaya pencegahan serta membantu tenaga medis dalam proses diagnosis dan penanganan tepat waktu. Penelitian ini menerapkan algoritma Backpropagation Neural Network (BPNN) sebagai metode komputasi cerdas untuk mendeteksi serangan jantung. Hasil pengujian menunjukkan tingkat akurasi prediksi sebesar 96,47%, menegaskan efektivitas jaringan saraf tiruan dalam mengidentifikasi serangan jantung pada pasien. Temuan ini berimplikasi pada pemanfaatan BPNN sebagai sistem deteksi dini yang andal dan presisi, sehingga dapat mendukung pengambilan keputusan klinis yang lebih akurat serta meningkatkan efektivitas pencegahan dan penanganan serangan jantung.*

Kata Kunci*: diagnosis akurat, jaringan saraf tiruan, BPNN, deteksi dini, serangan jantung.*

INTRODUCTION

A heart attack refers to a medical condition where the heart's blood supply becomes obstructed. This life-threatening condition is typically triggered by blood clots or accumulations of fat, cholesterol, and other substances. Such blockages can hinder blood flow to the heart, potentially leading to damage or destruction of the heart muscle and posing a fatal risk. In medical terminology, this condition is known as myocardial infarction (Devi et al., 2023).

According to the 2014 Sample Registration System (SRS) survey in Indonesia, coronary heart disease ranked as the second leading cause of death across all age groups after stroke, accounting for 12.9% of total deaths. Additionally, data from the World Health Organization (WHO) in 2012 reported that 17.5 million people worldwide died from cardiovascular diseases, representing 31% of the 56.5 million global deaths that year. Notably, over three-quarters of these cardiovascular-related deaths occurred in developing countries with low to middle income levels (Muharram et al., 2024).

The escalating incidence of heart attack cases underscores the critical need for accurate, early predictions for preventive care. Traditional clinical decisions, often reliant on intuition or limited experience, are susceptible to inaccuracies, while manual or rule-based diagnoses struggle with complex, large datasets, necessitating robust data-driven tools. Leveraging patient data with intelligent computing techniques can establish heart attack patterns, improving diagnostic accuracy (Stonier et al., 2024).

Previous research has explored intelligent computing for heart attack detection. For example, Stonier et al. (2024) focused on broader cardiac disease risk prediction, and Dieste-Velasco (2021) applied pattern-recognition neural networks to different domains like electronic circuit faults. While these studies demonstrate general machine learning and neural network applicability, they often vary in algorithms, datasets, and specific conditions targeted. Our study distinguishes itself by specifically applying the Backpropagation Neural Network (BPNN) algorithm for the early detection of suspected heart attack symptoms, utilizing a comprehensive set of patient medical record data from Primaya Hospital Bekasi, thereby providing a targeted and highly accurate diagnostic tool for medical officers in Indonesia.

Research on the relationship between real phenomena is the primary goal of science. One approach commonly applied is the Artificial Neural Network (ANN), an information processing system designed to mimic the characteristics of biological neural networks. A key feature of ANN is its learning capability. This learning process typically relies on training data, with the Backpropagation method being one of the most widely used techniques (Li, 2024).

In this study, the focus will be on detecting heart attacks using the Artificial Neural Network (ANN) method, with the objective of evaluating the accuracy level in supporting early detection efforts. The dataset employed in this research consists of medical records of heart attack symptoms from patients at Primaya Hospital Bekasi.

MATERIALS AND METHODS

An artificial neural network is a type of artificial system that mimics the human brain, aiming to replicate the brain's learning process through simulation (M. Mijwil, 2021). According Qamar & Ali Zardari, (2023) it provides the limitation that, " Artificial neural networks (hereinafter referred to as neural networks) are an attempt at a very basic level to imitate the type of nonlinear learning that occurs in natural neuron networks."

Artificial neural networks are designed as mathematical models to mimic human cognition based on several assumptions (Mr. Dongare Sadanand & Dr. Sachin Bhosale, 2023). Information processing occurs through simple elements called neurons, which communicate via interconnected signals. Each connection has an assigned weight, and each neuron applies an activation function to the weighted sum of its inputs to determine its output signal.

In Artificial Neural Networks, several key terms are defined. Neurons, also known as nodes or units, are processing elements that receive input, process it, and generate an output (Kashimpure, 2023). A network consists of interconnected neurons forming layers, including hidden layers that enhance the model's ability to solve complex problems (I. Hilaiwah et al., 2021). Inputs are values processed to produce outputs, which serve as the final solution. Weights represent mathematical connections between neurons, while activation functions update weight values during iterations (Nokeri, 2022). A basic activation function involves multiplying inputs by their weights and summing them (summation sigma), which can be linear, non-linear, or sigmoid (Sharma, 2022). Lastly, the learning paradigm defines how the network learns, either through supervised or unsupervised learning (Emmert-Streib & Dehmer, 2022).

Training backpropagation covering three phase.

Phase 1: Forward Propagation

In the forward propagation phase, input signals (x_i) are passed through the network to the hidden layer using a specific activation function. The output from each hidden unit (z_j) is then propagated forward to the subsequent layer, again utilizing an activation function. This process continues until it reaches the output layer (y_k). The network output (y_k) is then compared to the target output (t_k). The difference between the target and the output (t_k - y_k) represents the error. If this error falls within the acceptable tolerance range, the iteration stops. However, if the error exceeds the defined limit, the network's weights are adjusted to minimize the error.

Phase 2: Backward Propagation

In the backward phase, the error (t_k - y_k) is used to calculate a δ_k factor (k = 1, 2, ..., m), which helps distribute the error from the output unit y_k to all connected hidden units. This δ_k value is also utilized to update the weights of the connections linked to the output layer. Using the same principle, δ values are calculated for each unit in the hidden layers to serve as the basis for adjusting the weights of all preceding connections from the lower layers.

Phase 3: Weight Adjustment

Once all δ values are determined, the weights of the connections throughout the network are updated simultaneously. The adjustment of each weight is influenced by the δ value of the neuron in the layer above. For example, the weight adjustment for connections leading to the output layer is guided by the δ_k associated with the output units. These three phases are repeatedly performed until a stopping criterion is met. Typically, the stopping conditions include either reaching the maximum number of iterations or achieving an error value smaller than the predetermined tolerance threshold (Angga Aditya Pratama et al., 2024).

The training process for a neural network that includes a single hidden layer and utilizes a binary sigmoid activation function follows the steps outlined below (Veenu, 2021):
Step 1: initialize the weights with value numbers small random.

Step 2: during condition stop wrong, do steps 3 to 8 of feed forward.

Step 3: each input unit (x i, i=1… n) receives input signal x i and forwarded to hidden units (hidden layers).

Step 4: each unit hidden (z j, z=1… p) add up weight input signal

$$z_{inj} = v_{j0} + \sum_{i=1}^{n} x_i v_{ji} \quad (1)$$

With apply function activation sigmoid binary.

$$z_j = f\left(z_{in_j}\right) = \frac{1}{1+e^{-z_{in_j}}} \quad (2)$$

Step 5: count all output network in unit y k (k=1, 2… m)

$$y_{in_k} = w_{k0} + \sum_{j=1}^{p} z_i w_{kj} \quad (3)$$

$$y_k = f\left(y_{in_j}\right) = \frac{1}{1+e^{-y_{in_k}}} \quad (4)$$

Step 6: count factor δ unit output based on error in each unit output y k (k=1, 2… m). δ k is the error unit that will be used in changing the weight of the layer below it (step 7).

$$\delta_k = (t_k - y_k) f'(y_{in_k}) = (t_y - y_k) y_k (1 - y_k) \quad (5)$$

Calculate the weight change term Δ w kj = αδ k z j; k=1, 2… m; j=0, 1… p)

Step 7: calculate the hidden unit factor δ based on the error at each hidden unit z j (j= 1, 2… p)

$$\delta_{in_j} = \sum_{k=1}^{m} \delta_k w_{kj} \quad (6)$$

Factor δ hidden unit

$$\delta_j = \delta_{in_j} f'\left(z_{in_j}\right) = \delta_{in_j} z_j (1 - z_j) \quad (7)$$

Calculate the weight change term v_{ji} (which is used later to change the weight of v_{ji}).

$$\Delta v_{ji} = \alpha \delta_j x_i; (j = 1,2, \ldots, p; i = 0,1, \ldots, n) \quad (8)$$

Step 8: calculate all weight changes
Changes weight line which going to unit output.

$$w_{kj}(baru) = w_{kj}(lama) + \Delta w_{kj}; (k = 1,2, \ldots, m; j = 0,1, \ldots, p) \quad (9)$$

Changes the weight of the line leading to the hidden unit.

$$v_{ji}(baru) = v_{ji}(lama) + \Delta v_{ji}; (j = 1, \ldots, p; i = 1,2, \ldots, n) \quad (10)$$

Once the training process is finished, the network can be utilized for recognizing patterns. At this stage, only the forward propagation process (steps 4 and 5) is applied to generate the network's output (Dieste-Velasco, 2021).

In this study, data and information were collected using several methods, including observation and literature review. The author conducted direct observations for one month at Primaya Hospital Bekasi, located at Jl. KH Noer Alie Kav 17-18, Kalimalang, Bekasi, utilizing patient medical record data with the diagnosis code "I" (suspected heart attack) from the hospital's Medical Records Unit. Additionally, a literature review was conducted to obtain theoretical references relevant to the study. The research process included several stages: data collection, initial data processing, model/method development, experimentation and testing, and evaluation and validation of results (Tabuena et al., 2021).

The dataset for this research comprises 170 patient medical records from Primaya Hospital Bekasi, with 110 patients identified as "sick" and 60 as "healthy". This comprehensive dataset includes attributes X1-X10, covering demographic details (age (X1), gender (X2)), physiological measurements (systolic (X3), diastolic (X4), low-density lipoprotein (X5), high-density lipoprotein (X6), total cholesterol (X7), triglycerides (X8)), and symptoms (chest pain (X9), weak condition (X10)), alongside the "Results" indicating health status. Recognizing initial inconsistencies and missing values, a preprocessing step was crucial: the 'replace missing operator' in RapidMiner Studio Free 8.0.001 was used to ensure data quality and integrity for subsequent analysis. A sample of this processed dataset is presented in Table 1.

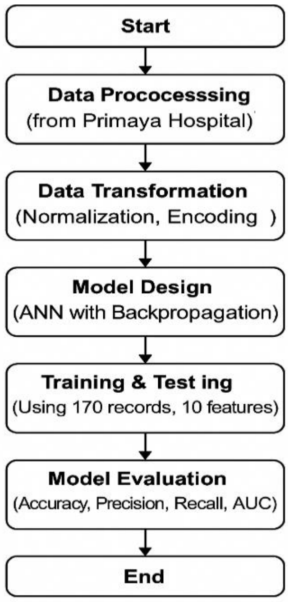
Table 1. Medical record data

No	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	Results
1	55	male	120	70	152	56	188	69	FALSE	FALSE	healthy
2	50	female	100	70	119	33	183	87	FALSE	FALSE	healthy
3	64	female	130	100	118	57	121	115	FALSE	FALSE	healthy
4	65	female	98	70	91	80	154	92	FALSE	FALSE	healthy
5	64	male	109	80	87	89	166	33	FALSE	FALSE	healthy
6	64	male	80	70	105	69	135	69	FALSE	FALSE	healthy
7	40	male	83	70	106	80	139	116	FALSE	FALSE	healthy
8	52	female	100	70	93	55	155	89	FALSE	FALSE	healthy
9	23	female	88	70	122	53	136	80	FALSE	FALSE	healthy
10	20	male	126	60	79	40	143	57	FALSE	FALSE	healthy
11	61	female	120	70	67	45	150	149	FALSE	FALSE	healthy
12	45	female	110	70	100	40	135	103	FALSE	FALSE	healthy
13	57	female	130	80	112	60	143	161	FALSE	FALSE	healthy
14	40	male	130	70	102	59	242	186	FALSE	FALSE	healthy
...	...	...	...	...	...	...	...	...	...	...	...
168	60	female	130	70	155	77	272	197	TRUE	TRUE	sick
169	73	male	130	80	128	82	289	169	TRUE	TRUE	sick

Source: (Research Results, 2024)

To ensure high-quality data for the training process, preprocessing was conducted using several techniques, as recommended by Joshi et al (2021). This involved data cleaning to address issues like the one initial record with missing attribute values, specifically by using RapidMiner's "Replace Missing Values" operator for estimation. Data integration was performed by consolidating relevant patient medical records retrieved from the hospital's archive system into a unified dataset. Finally, data reduction was applied through dimensionality reduction, selecting only the most significant attributes based on medical relevance and expert input to eliminate irrelevant features and improve model performance.

The entire research process is illustrated in Figure 1, which depicts the stages of data collection, preprocessing, model training, validation, and evaluation.



Source: (Research Results, 2024)
Figure 1. Research Flow

RESULTS AND DISCUSSION

This study was designed to predict whether someone is having a heart attack using artificial neural network backpropagation. The input layer consists of 10 nodes, namely age (X1), gender (X2), systolic blood pressure (X3), diastolic blood pressure (X4), LDL cholesterol levels (X5), HDL cholesterol levels (X6), total cholesterol (X7), level triglycerides (X8), type of chest pain (X9), pale/shortness of breath/weak condition (X10) along with one bias node. The output layer consists of two nodes, namely the health prediction results (Y1) and sick (Y2), amount layer hidden (hidden layer) is 9 pieces with 1 bias node. The values used in the calculation will vary depending on the measurement results. In the backpropagation design, 500 iterations are used with the desired error level initialized at 1.0×10^{-5}.

The data used in the study were taken randomly from the medical records of patients with heart disease and those without heart disease in Primaya Hospital Bekasi as many as 170 people. The data of the attributes experienced by the patient will then be processed by the network. So that the data can be recognized. By the network, the data must be represented in numerical form, both the variables and their contents which are input for heart attack symptoms along with categories. And output which is symptom prediction attack heart. Matter This because of network using the binary sigmoid activation function (logsig) which ranges from 0 to 1. The values used are obtained based on the category from each variable as well as to make it easier to remember the definition.

Definition Input

Heart attack symptoms are converted into variables/attributes whereas category from each of these symptoms is converted into numerical form.

Because the network is built using activation functions binary sigmoid where the range is from 0 to 1 then the numeric data is transformed into data in the range 0.1 to 0.9.

Determination Target

The desired result at this stage is the detection of a value to predict whether someone is having a heart attack or not. The intended result is as follows:

1. If the target is “healthy” it means that the person is not having a heart attack.
2. If the target is “sick” it means that the person is having a heart attack.

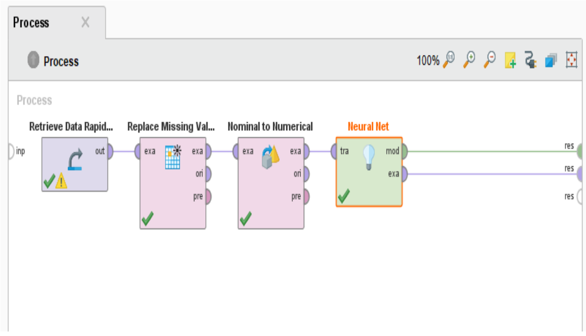
From the data obtained, training data was created And data target Which used as input data. Heart attack symptom data from the 10 attributes are used as training data while the result data is used as target data.

The network used to diagnose heart attack symptoms is an artificial neural network backpropagation, which is an algorithm for supervised training with multilayer feedforward learning steps. This network has several layers, namely the input layer, the output layer, and several hidden layers. These hidden layers help the network to be able to recognize more input patterns compared to networks that do not have layers. hidden. When a training pattern is provided as input, it is processed through the hidden layer units and subsequently propagated to the output layer.

Artificial neural network model undergoes a model training process by providing:

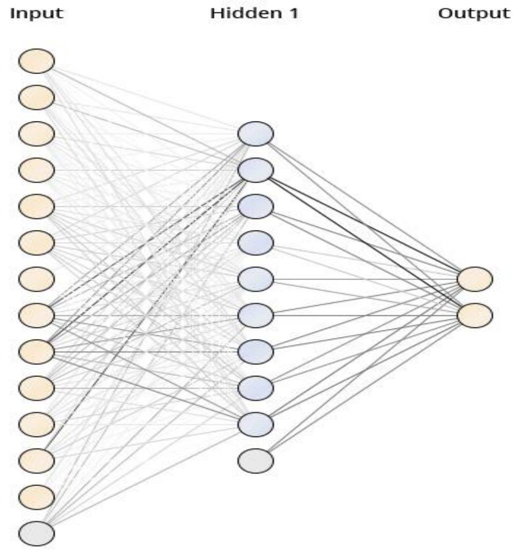
1. Training Cycles: 500
2. Learning Rate : 0.3
3. Momentum : 0.2
4. Error Epsilon : 1.0E- 5

The mathematical formulation of the artificial neural network is implemented using the neural network algorithm model in the RapidMiner framework, as illustrated in Figure 2.



Source: (Research Results, 2024)
Figure 2. Appearance Experiment *Neural Network*

The following is presented in Figure 3 the neural network architecture resulting from the experiment above produces nine hidden layer nodes with ten attributes and two output layers.



Source: (Research Results, 2024)
Figure 3. Appearance *Neural Network*

After the training process was completed, the artificial neural network produced final weight values that play a crucial role in determining the pattern recognition and classification process. These weight values indicate how much influence each input variable has on the network’s output. In this study, the network structure consists of an input layer, one hidden layer (Hidden 1), and an output layer.

In the hidden layer (Hidden 1), specifically Node 1 which uses the Sigmoid activation function, the weights obtained from the training process for each input variable are as follows: the variable Gender (male) has a weight of 0.573, while Gender (female) has a weight of -0.527. Furthermore, the variable Chest Pain (false) has a weight of -0.331, and Chest Pain (true) has a weight of 0.303. The variable Weak Condition (false) has a weight of -

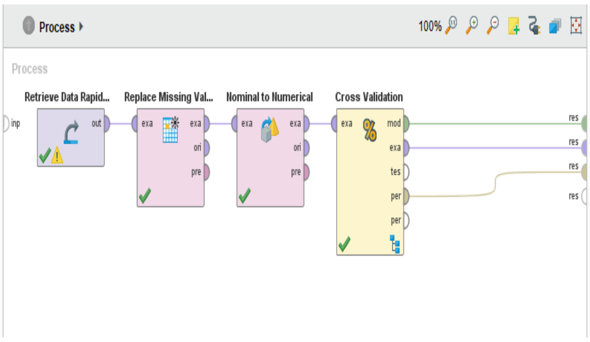
0.808, while Weak Condition (true) has a weight of 0.882. The Age variable has a weight of 0.077, Systolic pressure 1.911, Diastolic pressure 2.106, LDL 0.740, HDL 0.491, Total Cholesterol -0.653, and Triglycerides 0.104. Additionally, a bias value of 1.423 is assigned to this node.

Moving on to the output layer, the network maps the final results into two categories, namely 'healthy' and 'sick', both using the Sigmoid activation function. The weights connecting the hidden layer to the output layer for each class are as follows: For the 'healthy' class, the weights for each node are
Node 1: -2.525
Node 2: 5.213
Node 3: -2.779
Node 4: -1.184
Node 5: -2.011
Node 6: -2.749
Node 7: -2.820
Node 8: -2.513
Node 9: -3.007
With a threshold value of 2.678.

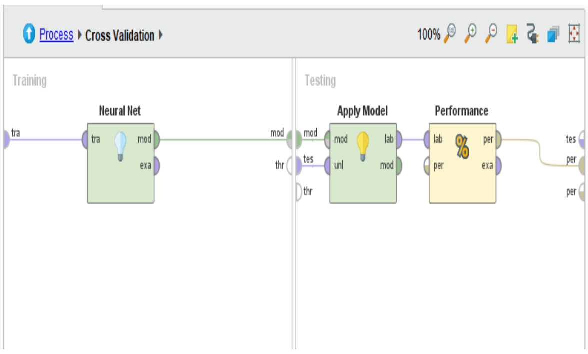
Meanwhile, for the 'sick' class, the weights for each node are:
Node 1: 2.497
Node 2: -5.234
Node 3: 2.750
Node 4: 1.224
Node 5: 2.040
Node 6: 2.729
Node 7: 2.824
Node 8: 2.501
Node 9: 3.007
With a threshold value of -2.649.

All of these weight values are the results of the learning process performed by the artificial neural network and serve as the foundation for the testing phase or the application of this heart attack detection system.

The results of the model testing are to determine the detection of heart attacks with an artificial neural network to determine the values of accuracy, precision, recall, and AUC (Area Under the Curve). In determining the level of accuracy in the neural network model using cross validation in its testing. The validation model's design presentation in Rapid Miner is illustrated in Figure 4 and Figure 5.



Source: (Research Results, 2024)
Figure 4. Appearance Design Model Validation



Source: (Research Results, 2024)
Figure 5. Neural Network Validation Testing Model Design.

The following display of the Algorithm Performance results from Rapid Miner validation can be seen in Figure 6 to Figure 11.

accuracy: 96.47% +/- 4.71% (mikro: 96.45%)

	true healthy	true sick	class precision
pred. healthy	31	3	91.18%
pred. sick	3	132	97.78%
class recall	91.18%	97.78%	

Source: (Research Results, 2024)
Figure 6. Algorithm Performance (Accuracy).

Figure 6 presents the confusion matrix for the Backpropagation Neural Network algorithm's performance in detecting heart attacks. This matrix summarizes the model's prediction outcomes, showing the counts of "true healthy" (healthy patients correctly predicted as healthy) and "true sick" (sick patients correctly predicted as sick) cases, alongside misclassifications such as "false healthy" (sick patients predicted as healthy) and "false sick" (healthy patients predicted as sick). The overall accuracy of the model is reported as 96.47%, with a micro accuracy of 96.45%, indicating a high capability in correctly classifying patient health status.

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precision: 97.85% +/- 3.29% (mikro: 97.78%) (positive class: sick)

	true healthy	true sick	class precision
pred. healthy	31	3	91.18%
pred. sick	3	132	97.78%
class recall	91.18%	97.78%	

Source: (Research Results, 2024)
Figure 7. Algorithm Performance (Precision).

Figure 7 illustrates the performance of the Backpropagation Neural Network algorithm with respect to the precision metric. Precision measures the accuracy of the model in predicting the positive class, in this case, "sick" patients, out of all instances predicted as positive. The results indicate a precision of 97.85% with a micro precision of 97.78% for the "sick" class, signifying that a large majority of the model's predictions for sick patients are indeed correct. This high precision is crucial for minimizing false positives, which would involve classifying healthy patients as sick, thus preventing unnecessary patient anxiety and unwarranted medical procedures.

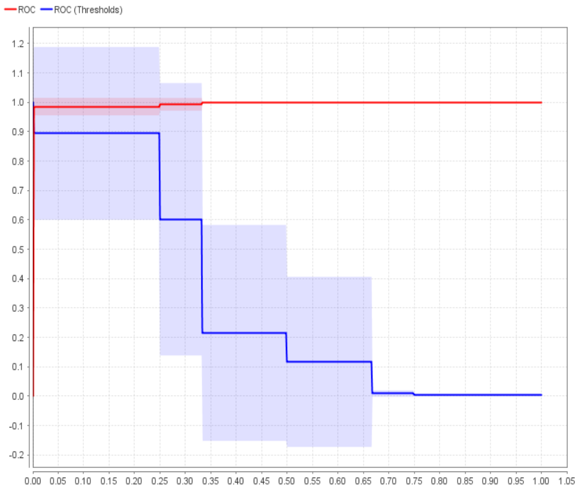
recall: 97.80% +/- 4.64% (mikro: 97.78%) (positive class: sick)

	true healthy	true sick	class precision
pred. healthy	31	3	91.18%
pred. sick	3	132	97.78%
class recall	91.18%	97.78%	

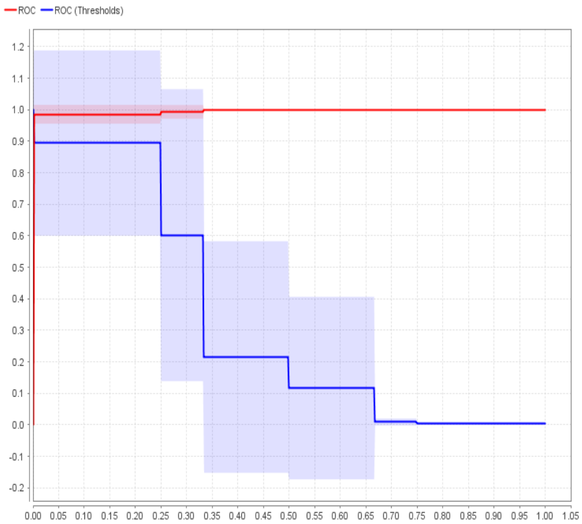
Source: (Research Results, 2024)
Figure 8. Algorithm Performance (Recall).

Figure 8 details the algorithm's performance based on the recall metric. Recall (sensitivity) assesses the model's ability to identify all actual positive cases, i.e., all sick patients who are genuinely ill. With a recall of 97.80% and a micro recall of 97.78% for the "sick" class, the model demonstrates excellent capability in detecting actual heart attack cases. A high recall for the 'sick' class is vital as it effectively minimizes false negatives, where sick patients are incorrectly classified as healthy, thereby preventing critical delays in medical intervention that could lead to severe heart damage or even fatality.

Figure 9 displays the Receiver Operating Characteristic (ROC) curve and the Area Under the Curve (AUC) value from an optimistic perspective. The ROC curve visually represents the trade-off between the true positive rate (sensitivity) and the false positive rate (1-specificity) for various classification thresholds. The closer the curve is to the top-left corner, the better the model's performance. An optimistic AUC value of 0.996 suggests an exceptionally high discriminative power, indicating that the model is highly effective in distinguishing between "healthy" and "sick" patients.



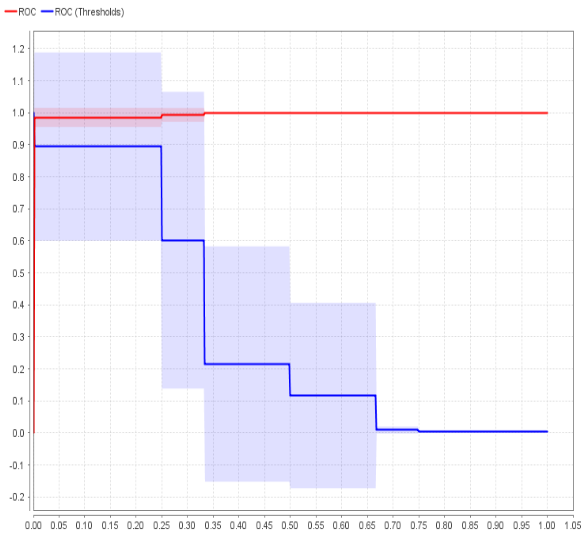
Source: (Research Results, 2024)
Figure 9. Algorithm Performance (AUC Optimistic).



Source: (Research Results, 2024)
Figure 10. Algorithm Performance (AUC).

Figure 10 presents the general ROC curve and AUC value for the algorithm. Similar to Figure 9, this curve illustrates the balance between TPR and FPR across different thresholds. The consistent AUC value of 0.996 (matching the optimistic perspective) further corroborates the model's reliability in classification. This high and consistent AUC underscores the stability and effectiveness of the Backpropagation Neural Network in detecting heart attacks.

Figure 11 concludes the performance analysis by showing the ROC curve and AUC value from a pessimistic perspective. Despite the pessimistic viewpoint, the AUC value remains robustly high at 0.996. This consistency across different perspectives demonstrates the model's resilience and its low sensitivity to minor variations in data or thresholds, solidifying its standing as a highly dependable and precise tool for early heart attack detection. While the model's overall accuracy of 96.47% is strong, a deeper analysis of the confusion matrix highlights crucial practical implications. Our model yielded 3 false negatives (sick patients classified as healthy) and 3 false positives (healthy patients classified as sick). False negatives carry significant clinical risks, potentially delaying critical intervention and leading to severe heart damage or fatality. Conversely, false positives, though less life-threatening, result in unnecessary patient anxiety, unwarranted procedures, and increased healthcare costs. Despite the low number of misclassifications, understanding their impact is vital for clinical decisions. The high recall of 97.80% for the 'sick' class indicates the model's robust ability to identify actual heart attack cases, effectively minimizing dangerous false negatives. This balance underscores the model's practical utility and reinforces its validity as a supportive tool for early heart attack detection.



Source: (Research Results, 2024)
Figure 11. Algorithm Performance (Pessimistic AUC).

Based on the test analysis using the artificial neural network method, the accuracy, precision, recall , and AUC (Area Under the Curve) values obtained can be summarized as follows (Table 2):

Table 2. Algorithm Performance

Performance	Neural Network
Accuracy	96.47 %
Precision	97.85%
Recall	97.80%
AUC	0.996

Source: (Research Results, 2024)

Artificial neural network methods to detect heart attacks at Primaya Hospital Bekasi obtained an accuracy of 96.47%, with a precision value of 97.85%, a recall of 97.80% and an AUC value of 0.996.

To contextualize the performance of our developed BPNN model for heart attack detection, it is crucial to compare our findings with existing literature that employs similar methodologies or addresses related medical conditions. While direct numerical comparisons are often limited by differences in datasets, feature sets, and evaluation methodologies, a qualitative assessment of relevant studies highlights the distinct advantages of our research. Table 3 summarizes the comparison between our study and five selected previous studies.

Table 3. Comparison of Current Study with Previous Research

Study (Reference)	Method Used	Application / Domain	Comparison with Our Study / Key Distinction
Angga Aditya Pratama et al., (2024)	BPNN (Deep Learning)	General deep learning	While confirming BPNN efficacy, our study specifically applies and validates BPNN for heart attack detection with concrete metrics in a medical context.
Stonier et al., (2024)	Machine learning algorithms	Cardiac disease risk prediction	Focuses on broader cardiac disease risk prediction; our research targets detection of suspected heart attacks based on acute symptoms.
Dieste-Velasco, (2021)	Pattern-Recognition Neural Network	Electronic circuit fault detection	Uses ANN in a different domain; our research validates ANN's adaptability and high performance in human health diagnostics.
I. Hilaiwah et al., (2021)	Learning rules-based Artificial Neural Network	Foundational ANN learning mechanisms	Contributes to foundational ANN understanding; our study provides an applied solution demonstrating practical BPNN efficacy in a real-world medical setting.

Study (Reference)	Method Used	Application / Domain	Comparison with Our Study / Key Distinction
Kashimpure, (2023)	Artificial Neural Networks (ANNs)	General ANN overview	Highlights broad ANN utility; our research exemplifies this utility by delivering a highly effective and specialized ANN application in a demanding medical domain.

Source: (Research Results, 2024)

The BPNN model demonstrates significant advantages with its exceptionally high diagnostic accuracy: 96.47% accuracy, 97.85% precision, 97.80% recall, and 0.996 AUC. These robust metrics confirm its effectiveness in classifying "healthy" and "sick" patients, offering a reliable tool for early heart attack detection. A key advantage is the high recall for the 'sick' class (97.80%), indicating the model's strong ability to identify actual heart attack cases and minimize dangerous false negatives. This study also uniquely utilized real-world medical record data from Primaya Hospital Bekasi, proving the model's practical applicability and effectiveness in a clinical setting. Consequently, its high performance suggests it can serve as a reliable auxiliary tool for medical officers, enhancing the objectivity and accuracy of diagnoses by reducing reliance on intuition or limited experience.

CONCLUSION

Based on research on Artificial Neural Network (ANN) Backpropagation for heart attack detection, the trained model, optimized with 500 training cycles, a learning rate of 0.3, momentum of 0.2, and error epsilon of 1.0E-5, demonstrates high effectiveness. Its performance metrics, including 96.47% accuracy, 97.85% precision, 97.80% recall, and an AUC of 0.996, confirm its reliability in detecting heart attack symptoms. The study concludes that attributes such as age, sex, blood pressure levels, cholesterol levels, triglycerides, chest pain, and weakness/pale condition are significant indicators.

However, limitations include the dataset's origin from a single hospital (Primaya Hospital Bekasi) with 170 records, potentially limiting generalizability, and the exclusive focus on the BPNN algorithm. Future research should validate the model with larger, more diverse datasets from multiple centers, explore other advanced ANN architectures or ensemble methods, and consider incorporating additional clinical parameters. Ultimately, this model shows significant promise as a supportive tool for medical practice, recommended for integration into clinical decision support systems to aid faster, more accurate preliminary diagnoses and improve patient outcomes.

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