# Electrocardiogram signal patterns detection of myocardial ischemia rhythm using an artificial neural network based on MATLAB/Simulink

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## ABSTRACT

This study aims to design a computer program to detect myocardial ischemic heart defects through electrocardiogram (ECG) signal patterns and their accuracy. Myocardial ischemia is a heart disorder caused by the narrowing of the blood vessels in the walls of the heart. The method used is a backpropagation-based artificial neural network (ANN) based on MATLAB/Simulink. The input data is trained to recognize the target pattern of the ECG signal based on the potential and time in the ST segment. The optimal weight of the results of the ANN backpropagation algorithm is used in the process of testing the ECG signal pattern to obtain the ANN output. The ANN output was analyzed for potential depression or elevation to identify normal heart or myocardial ischemia. The results of the training show that from several architectures that have been tested, the optimal ANN architecture is 1 hidden layer with 11 hidden units. These results are obtained from the epoch parameter and the mean square error (MSE) value as well as the accuracy of each architecture. The backpropagation ANN learning process requires 8 epochs to achieve the performance goal with MSE $4.03 \times 10^{-9}$. The system can recognize target patterns with a training accuracy of 99.82%. The test results of the ANN program identification system can detect myocardial ischemia and normal heart abnormalities with an accuracy of 86.7%. Some data were not detected because the ANN output did not meet the criteria for cardiac ischemia or normal myocardium on the ECG signal. Based on the accuracy of the ANN program identification system, the detection of myocardial ischemia rhythm ECG signal patterns using ANN can be said to work well.

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## 1. INTRODUCTION

Abnormal heart symptoms are one of the deadliest causes of death in the world. In Indonesia, the death rate due to heart problems reaches 30% [1-3]. According to research by the World Health Organization in 2002, deaths from ischemic heart disease reached 12.6% worldwide [4-6]. These heart symptoms are often not known by all human groups. However, now a tool for early diagnosis of heart disease has been developed using an electrocardiogram (ECG) signal.

ECG signals display different time intervals and potentials and will produce different signal patterns [7, 8]. Normal and abnormal heart conditions can be distinguished by classifying the ECG signal patterns [9, 10]. One of the most reliable methods for classifying patterns is an artificial neural network (ANN) [11-13]. ANN is an information processing system designed to mimic how the human brain works in solving a problem. ANN is capable of solving complex or even impossible problems if solved using conventional computing [14, 15].

This study aims to design a computer program using the backpropagation ANN system to detect myocardial ischemia rhythms from ECG signal patterns. Increasing the performance of ANN classification will get the best classifier from the human neural network model so that computers can duplicate human intelligence. It is hoped that this ANN classification will make it easier for medical analysts to diagnose normal and abnormal heart conditions by presenting more objective computational analysis data.

## 2. RESEARCH METHODS

### 2.1. Myocardial Ischemia

Cardiac disorder myocardial ischemia is defined as a condition of imbalance between myocardial oxygen supply and oxygen demand resulting in hypoxia and accumulation of metabolites [16, 17]. While previous studies suggested that myocardial ischemia in the coronary arteries is caused by atherosclerotic plaques that narrow the vessel lumen and restrict blood supply, recent studies suggest that reduced blood flow is caused by a combination of permanent vascular narrowing and abnormal vascular tone leading to atherosclerosis [18, 19]. The medical diagnosis of myocardial ischemia is retrosternal pain and pressure radiating to the neck, jaw, or left shoulder and arm. Hard work can trigger this condition and it can be relieved by simply resting [20].

Myocardial ischemia conditions can be detected in one direction through the ECG signal. The signal changes that occur are deviations in the ST segment and/or changes in the T wave [4]. Deviations that occur in the ST segment are based on two conditions, namely depression (decrease) that occurs when the starting point of the ST segment (point J) is located below the horizontal axis of the P and U waves (isoelectric line), and elevation (rise) occurs when the initial segment ST (point J) is located above the horizontal axis of the P and U waves (isoelectric line) [21]. The amplitude characteristics of ST segment depression or ECG signal elevation with several heart conditions can be seen in Table 1 as follows [4].

Table 1. ST segment characteristics from heart condition to amplitude.

| Heart conditions | Amplitude (mm) |
| --- | --- |
| Normal | 0 – 0.49 |
| Ischemia | 0.5 – 1 |
| Coroner | > 1 |

### 2.2. Electrocardiogram (ECG)

ECG is the electrical activity of the heart muscle produced by the rhythmic contractions of the human heart. This signal is very effective for detecting cardiac disorders in clinical studies [22]. Normal ECG signals have amplitude and time characteristics in certain parameter sections. These characteristics can be used as the basis for diagnosing a normal or abnormal heart. Several wave parameters and ECG signal intervals have amplitude values and time values which can be seen in Table 2 as follows [23].

Table 2. The characteristics of the ECG signal are normal with respect to amplitude and time

| Parameter | A (mm) | Parameter | T (s) |
| --- | --- | --- | --- |
| P wave | 0.25 | Interval PR | 0.12 – 0.2 |
| R wave | 1.6 | Interval QRS | 0.09 |
| Q wave | 25% Gel. R | Interval QT | 0.31 – 0.44 |
| T wave | 0.1 – 0.5 | Interval ST | 0.05 – 0.15 |

### 2.3. Artificial Neural Network (ANN)

ANN is a system formed based on the same working principle as the human brain. The human brain is the center of the human nervous system which regulates almost all operations of various organs of the human body. Similar to the human brain, ANN consists of a large number of processing elements/neurons that are tightly connected and operate in parallel [24].

The ANN input will be processed by the propagation function which will add up the values of all incoming weights. The result of this sum will then be compared with a certain threshold value through the activation function of each neuron. Neurons will be active if the input has passed a certain threshold value. Furthermore, the neuron will send output via output weights to all neurons associated with it [25]. There are several activation functions that are often used in ANNs, including the identity function, binary sigmoid function, and bipolar sigmoid function.

## 3. RESULTS AND DISCUSSIONS

### 3.1. Research Description

The framework of reference for the implementation of this research is illustrated in the pilot project as shown in Figure 1. The implementation of the research begins with a literature review of the final assignment to testing and analysis of the output results.
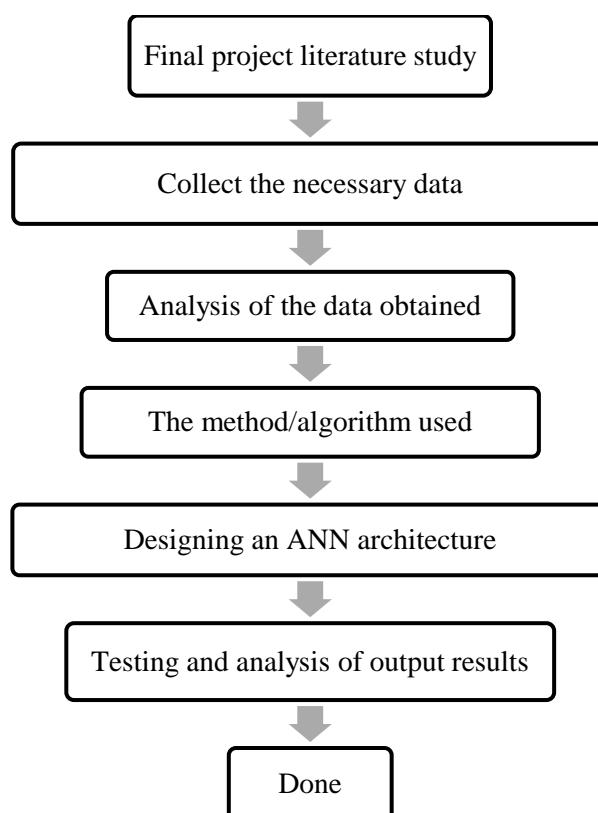


Figure 1. Structure of a research pilot project.

### 3.2. Device Use

#### 3.2.1. Hardware

The hardware used by researchers in processing data to help myocardial ischemia in this study is using a laptop with the specifications that can be seen in Table 3 as follows.

Table 3. Hardware specifications.

| Device section | Specification |
| --- | --- |
| Processor | Intel(R) Core(TM) i3–2350M CPU @ 230GHz |
| RAM | 2 GB |
| HRD | 500 GB |
| System type | 64-bit operating system |
| Monitors | 14" |

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### 3.2.2. Software

The software used by researchers in designing programs to identify myocardial ischemia in this study is to use the MATLAB R2015a application. The design of the backpropagation ANN program uses existing features in MATLAB, namely the Simulink block. The Simulink block in the Simulink library is designed based on the backpropagation ANN architecture.

### 3.3. Research Procedure

This research begins with obtaining signal pattern data from the results of ECG examinations which can be obtained from various sources such as hospitals, doctors' clinics, or research journals that have been conducted previously. The next step is to design an ANN program to detect myocardial ischemia rhythms through ECG signal patterns. The research procedure was carried out in several stages as follows.

### 3.3.1. Data Preparation

Data preparation was carried out by collecting ECG records that had been printed on millimeter paper. The ECG signal data that will be used consists of 2 types, namely ECG signals with ischemic heart rhythms and normal heart rhythms. The data that has been obtained is then calculated for the potential and time values with a scale of 1 small box on the ECG paper which represents 0.1 mV for the vertical axis, and 0.04 seconds for the horizontal axis. The calculation of potential value and time in this study uses 5 points on the ST segment. The start point for the ST segment is the end of the QRS complex and the start of the T wave.

### 3.3.2. ANN Program Design

ANN program design is generally carried out in 2 stages, namely the training process and the backpropagation ANN model testing process.

### 3.3.2.1. ANN Model Training

ANN backpropagation training is carried out to identify data patterns that have been made. The target data is experimental data from the ECG recordings that have been obtained. ANN has an architecture that can be specified according to needs. The ANN architectural map does not have a specific formula, so it needs to be tested. Training is done by adding various units to the hidden layer. Each variation is observed by calculating the mean square error (MSE) and iteration length (number of epochs). The optimal architecture is used in the ANN testing process to help ECG signal patterns.

### 3.3.2.2. ANN Model Testing

The process of testing the ANN model is the process of testing the ECG signal pattern by updating the weight of the ANN training results. The new weights generated from the training process are used in the testing process to obtain ANN output. The ANN output is identified by analyzing the amplitude/potential deviation at the start point of the ST segment to the basic ECG signal. An amplitude with a deviation of 0.5 mm to 1 mm is categorized as a myocardial ischemic rhythm, whereas a deviation of 0 mm to 0.49 mm is categorized as a normal heart rhythm. Identification results from ANN were compared with medical identification results to obtain accuracy from the ANN backpropagation programming results in this study.

### 3.4. Backpropagation ANN Algorithm

The design of the backpropagation ANN program consists of a training process and a testing process. Each process has its own algorithm. The algorithm in the training process has 3 processes, namely the feedforward process, the backward/error propagation process, and weight improvement. The ANN training algorithm can be seen in the backpropagation ANN training flowchart in Figure 2.

The algorithm in the testing process is carried out only with a feedforward process with updated weights and biased training results. The algorithm for this testing process can be seen in the backpropagation ANN test flowchart in Figure 3 as follows.
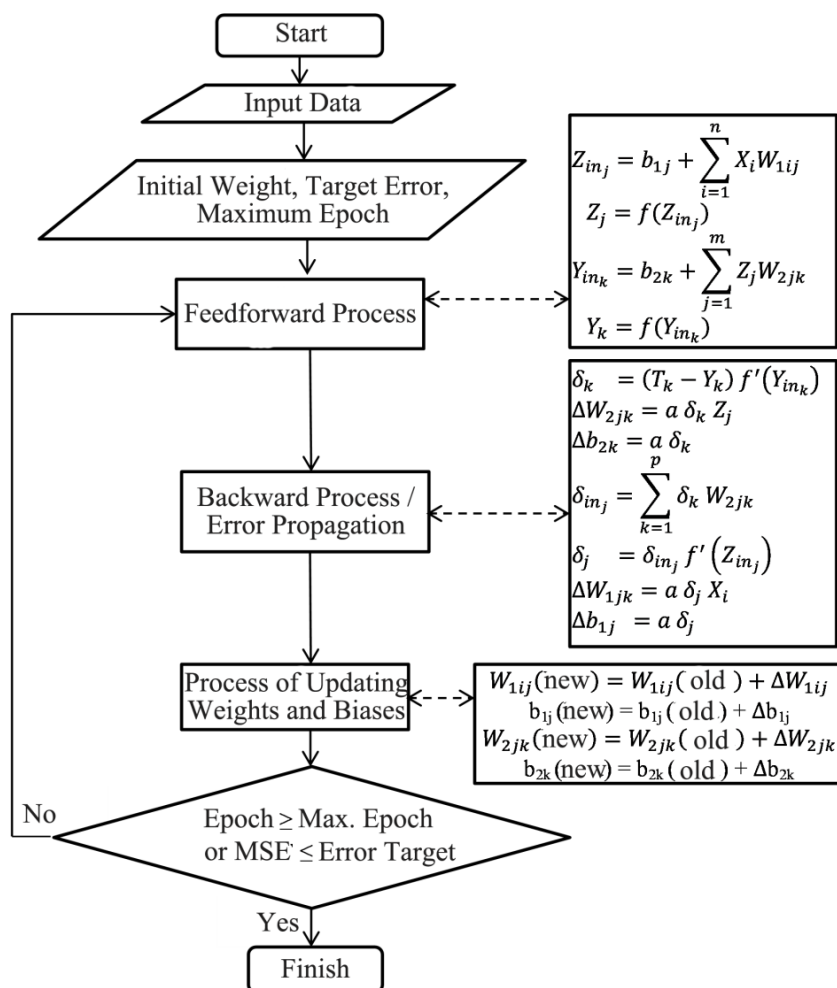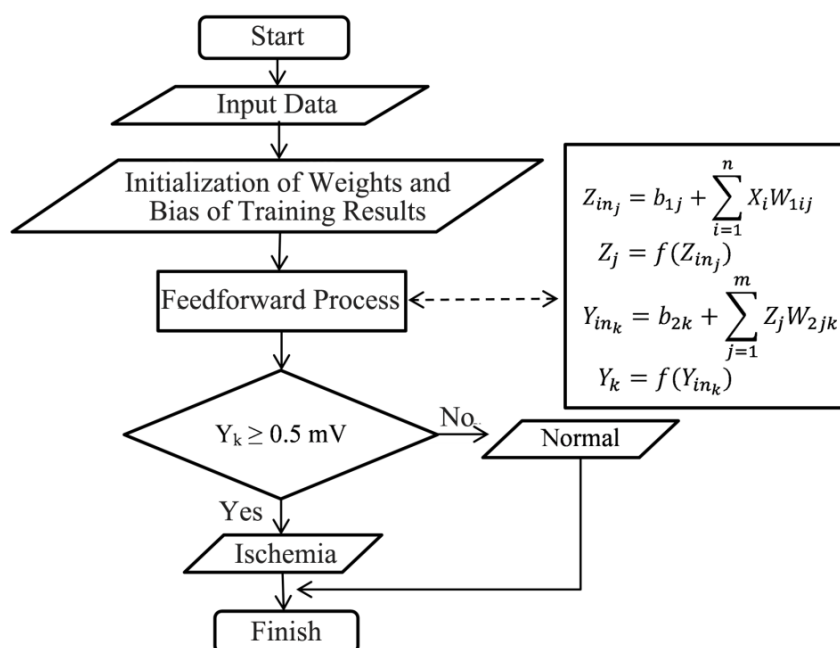
Figure 2. ANN backpropagation training flowchart.

The flowchart shows:
Start → Input Data → Initial Weight, Target Error, Maximum Epoch → Feedforward Process → Backward Process / Error Propagation → Process of Updating Weights and Biases → Epoch ≥ Max. Epoch or MSE ≤ Error Target (No → back to Feedforward Process; Yes → Finish)

Feedforward Process equations:

$$Z_{in_j} = b_{1j} + \sum_{i=1}^{n} X_i W_{1ij}$$

$$Z_j = f(Z_{in_j})$$

$$Y_{in_k} = b_{2k} + \sum_{j=1}^{m} Z_j W_{2jk}$$

$$Y_k = f(Y_{in_k})$$

Backward Process / Error Propagation equations:

$$\delta_k = (T_k - Y_k) f'(Y_{in_k})$$

$$\Delta W_{2jk} = a \, \delta_k \, Z_j$$

$$\Delta b_{2k} = a \, \delta_k$$

$$\delta_{in_j} = \sum_{k=1}^{p} \delta_k \, W_{2jk}$$

$$\delta_j = \delta_{in_j} f'\left(Z_{in_j}\right)$$

$$\Delta W_{1jk} = a \, \delta_j \, X_i$$

$$\Delta b_{1j} = a \, \delta_j$$

Process of Updating Weights and Biases equations:

$$W_{1ij}(\text{new}) = W_{1ij}(\text{old}) + \Delta W_{1ij}$$

$$b_{1j}(\text{new}) = b_{1j}(\text{old}) + \Delta b_{1j}$$

$$W_{2jk}(\text{new}) = W_{2jk}(\text{old}) + \Delta W_{2jk}$$

$$b_{2k}(\text{new}) = b_{2k}(\text{old}) + \Delta b_{2k}$$



Figure 3. ANN backpropagation test flowchart.

The flowchart shows:
Start → Input Data → Initialization of Weights and Bias of Training Results → Feedforward Process → $Y_k \geq 0.5$ mV (No → Normal; Yes → Ischemia) → Finish

Feedforward Process equations:

$$Z_{in_j} = b_{1j} + \sum_{i=1}^{n} X_i W_{1ij}$$

$$Z_j = f(Z_{in_j})$$

$$Y_{in_k} = b_{2k} + \sum_{j=1}^{m} Z_j W_{2jk}$$

$$Y_k = f(Y_{in_k})$$

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**3.5. Designing MATLAB/Simulink**

The MATLAB/Simulink design with the ANN system uses the blocks contained in the neural network toolbox. These blocks can be found by opening the MATLAB application, then opening the Simulink library on the main menu display. After the Simulink library browser appears, then select neural network toolbox, several block groups will be found including control system, net input functions, processing functions, transfer functions, and weight functions.

## 4. RESULTS AND DISCUSSIONS

**4.1. MATLAB/Simulink ANN Model Design**

The design of the process stages in the Simulink methodology uses the ANN backpropagation principle. The use of the Simulink feature is based on the working principle of analog computer circuits using the neural network toolbox. The Simulink design of the ANN model can be seen in Figure 4 which shows the design of the ANN model using the MATLAB/Simulink feature. The design of the ANN network architecture consists of several parts, including 3 main layers, namely the input layer, hidden layer, and output layer. These layers are connected with the activation function which functions to process and transmit data from one layer to the next.
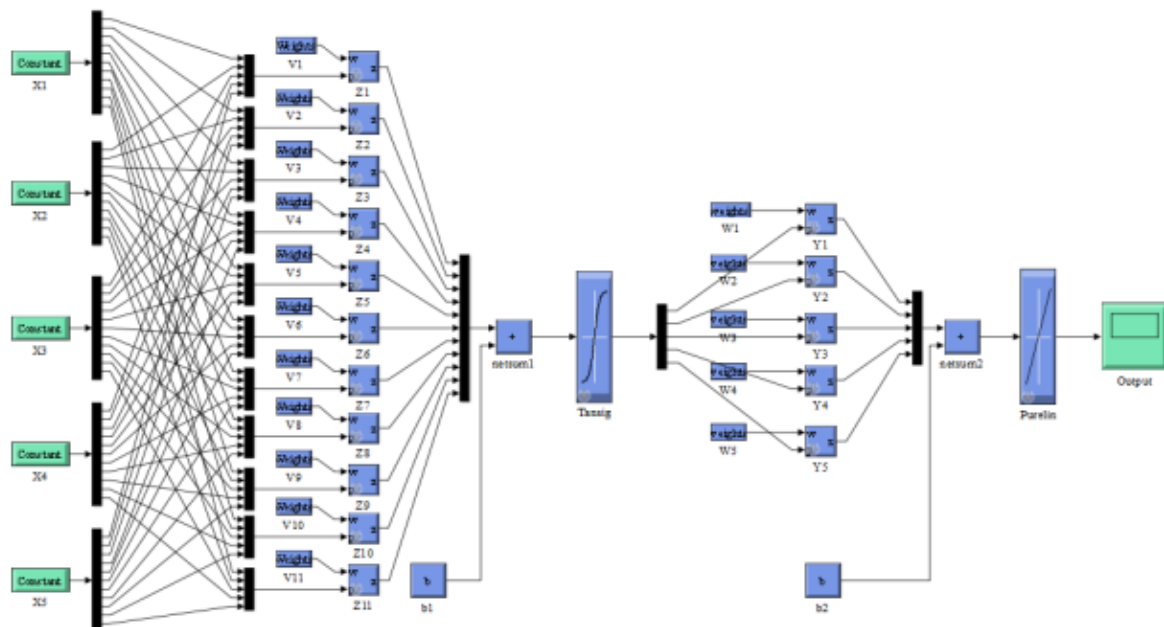
Figure 4. MATLAB/Simulink ANN model design.

**4.2. Analysis of ANN Program Results**

**4.2.1. Experiment Data**

Experimental data in this study used ECG recording data with normal heart conditions and ischemia that had been printed on millimeter paper. The ECG signal pattern used as input is 5 points on the ST segment which are calculated for potential and time based on a 1 : 0.1 mV scale for the vertical axis and a 1 : 0.04 s scale for the horizontal axis. This experimental data is used as target data in the backpropagation ANN training process.

**4.2.2. ANN Training Results**

ANN training is carried out to see the reliability of ANN in learning to recognize signal patterns on the ECG which are represented by accuracy values and MSE (Mean Square Error) values. The trained data is 30 data consisting of 3 ST segment patterns where each pattern consists of 5 potential points and 5-time points. The training is carried out by testing several ANN architectures to

obtain the optimal architecture. The results of the training process for each architecture are the epoch values and MSE values as well as the accuracy obtained by comparing the ANN output data with target data which can be seen in Table 4.

Table 4. ANN training results.

| Hidden layer | Epoch | MSE | Accuracy (%) |
|---|---|---|---|
| 3 | 17 | $1.85 \times 10^{-9}$ | 99.98 |
| 6 | 7 | $1.50 \times 10^{-8}$ | 99.80 |
| 9 | 7 | $2.04 \times 10^{-8}$ | 99.75 |
| 11 | 8 | $4.03 \times 10^{-9}$ | 99.82 |
| 22 | 7 | $3.68 \times 10^{-9}$ | 99.90 |
| 40 | 7 | $1.97 \times 10^{-9}$ | 99.93 |
| 50 | 6 | $8.14 \times 10^{-9}$ | 99.79 |
| 60 | 6 | $7.45 \times 10^{-9}$ | 99.80 |
| 80 | 7 | $1.12 \times 10^{-9}$ | 99.94 |
| 100 | 6 | $6.13 \times 10^{-9}$ | 99.85 |

Table 4 shows the results of the ANN training trials with several hidden units from 3 to 100 units. Each architecture affects the MSE value where the more the number of hidden units, the closer the MSE value is to a constant value. The results of the training trials show that the optimal architecture is 1 hidden layer with 11 hidden units because in this architecture the MSE value starts to be close to constant. The number of epochs indicates the speed of the ANN learning process to achieve the goal performance. The smaller the epoch, the faster the ANN learning process. The results of training accuracy are obtained from a comparison of the ANN output with the ANN target, then the percentage is calculated.

The training process in each epoch produces a different MSE value. The series of training processes on the 11 hidden unit architecture to achieve the target error can be seen in Figure 5 regarding the graph of the number of epochs against MSE. Figure 5 shows that at a maximum epoch equal to 8, the best MSE value is $4.03 \times 10^{-9}$. The MSE value at epoch 8 has reached the target error so the training process is stopped or finished.
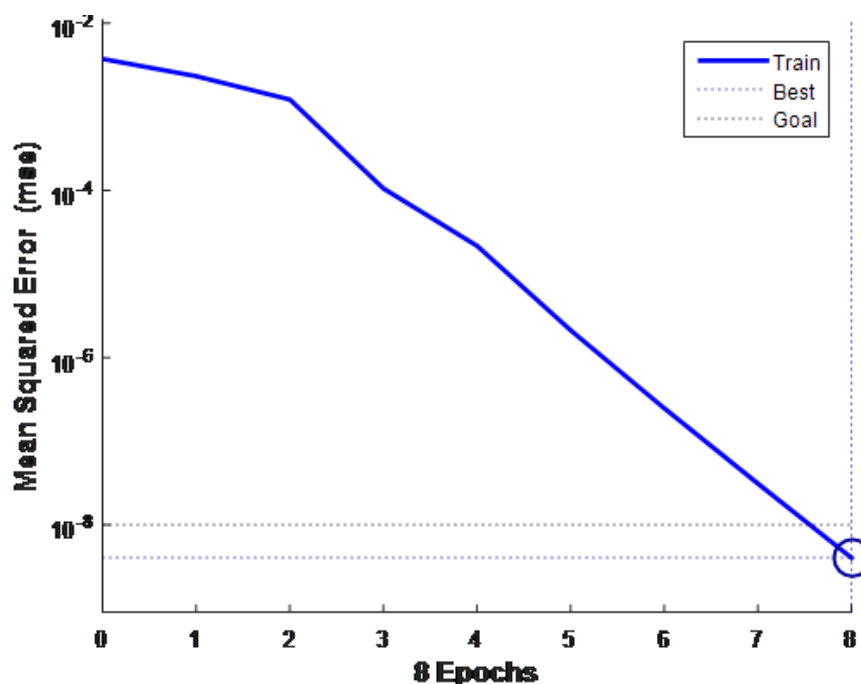


Figure 5. Graph of the number of epochs against the maximum MSE of 8 epochs.

Table 5. ANN training output results and target data on the ST segment.

| Target | | Output | |
|---|---|---|---|
| t (s) | V (mV) | t (s) | V (mV) |
| 0.03 | 0.06 | 0.030005 | 0.059988 |
| 0.06 | 0.01 | 0.059997 | 0.01007 |
| 0.11 | -0.02 | 0.10999 | -0.01998 |
| 0.13 | 0.02 | 0.12999 | 0.020037 |
| 0.16 | 0.02 | 0.15997 | 0.020185 |

The backpropagation ANN output is compared with the target data to determine the error so that the training capability of the ANN process is obtained. Target data and output data and errors can be seen in Table 5.

### 4.3. ANN Testing and Validation Results

The optimal ANN architecture from the trial training results is used for the process of testing the ECG signal pattern. The data testing process is carried out after the training process by updating the optimal weights to get the final output value. Diagnosis of cardiac abnormalities through the ECG signal pattern is if the ANN output data has a potential of 0.5 mV to 1 mV at the ST segment starting point, then the ECG signal pattern is identified as a myocardial ischemia rhythm. The output data has a potential of 0 mV to 0.49 mV at the starting point of the ST segment, then the ECG signal pattern is identified as a normal rhythm.

Table 6. Comparison of medical results with the results of the ANN system.

| Data | Medical Results | System Results | Validation |
|---|---|---|---|
| A | Ischemia | Ischemia | Detected |
| B | Ischemia | Ischemia | Detected |
| C | Ischemia | Ischemia | Detected |
| D | Ischemia | Normal | Not detected |
| E | Ischemia | Ischemia | Detected |
| F | Ischemia | Ischemia | Detected |
| G | Normal | Normal | Detected |
| H | Normal | Normal | Detected |
| I | Normal | Normal | Detected |
| J | Normal | Normal | Detected |
| K | Normal | Ischemia | Not detected |
| L | Normal | Normal | Detected |
| M | Normal | Normal | Detected |
| N | Normal | Normal | Detected |
| O | Normal | Normal | Detected |

Validation is carried out by comparing the results of medical identification with the identification results of the system that has been built. The system is said to be detected if the identification results of the ANN program are the same as the identification of medical results. Conversely, the system is said to be undetectable if the ANN program identification results are different from the medical identification results. The results of testing and validating the ANN system in this study can be seen in Table 6.

Table 6 shows the results of identifying cardiac abnormalities from ECG signal patterns based on medical diagnoses and ANN system diagnoses. The results of the identification of the ANN system are the same as the results of medical identification, it can be said that the system detects heart rhythm through ECG signal patterns. Identification results from the ANN system that are not the same as medical identification results can be said that the system does not detect heart rhythm through ECG signal patterns.

The data tested are 15 training data denoted by A-O data. The medical identification results consisted of 9 normal signals and 6 myocardial ischemia signals. After testing the ECG signal pattern data, 13 test data were detected consisting of 5 ischemia signal data and 8 normal signal data.

$$Accuracy = \frac{(n\ all\ data - n\ invalid\ data)}{n\ all\ data} \times 100\% \quad (1)$$

The accuracy of the backpropagation ANN identification system can be determined from the amount of test data minus the amount of invalid data (undetected data) divided by the amount of n data and multiplied by 100% or can be formulated as in Equation 1. So, result accuracy becomes more effective with the proportion of $86.7\% \approx 87\%$.

## 5. CONCLUSION

Optimal ANN architecture design requires trials on several architectures by analyzing the number of epochs and the MSE value of each architecture. The number of units in the hidden layer affects the MSE value, where the more units are hidden, the closer the MSE value is to a constant. The optimal ANN in this study is 1 hidden layer with 11 hidden units, because in this architecture the MSE value is close to a constant value and the number of epochs is relatively small. The backpropagation ANN system can recognize target data patterns from input data patterns that have been made with a training accuracy of 99.82%. The backpropagation ANN design is able to detect normal heart conditions and myocardial ischemia rhythms through analysis of ECG signal patterns with an accuracy of the ANN identification system reaching 87%.

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