Implementation of Back Propagation Artificial Neural Network for Heart Disease Abnormality Diagnosis

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Abstract. Heart is a very important human organ, where in normal people heart beats at 60-100 beats per second, but there are abnormalities in the heart rate that can occur due to certain causes so that it becomes slower (bradycardia) or faster (tachycardia). Electrical activity of the heart can be detected by an electrocardiogram (ECG), where the output of this device is a signal that describes the condition of a person's heart. Artificial neural network (ANN) is one of the learning methods of artificial intelligence that can be used for pattern recognition or the other. One of the ANN learning paradigms is backpropagation where the computation goes through 2 stages, namely advanced calculation and backward calculation. This study aims to simulate backpropagation neural networks to recognize patterns from the output of the electrocardiogram using the MATLAB program. The input is form of printed electrocardiogram recording, and then it is normalized, next the data is processed by backpropagation computing with two phases (training phase and testing phase). The output of this ANN is a description of a patient's condition whether normal, bradycardia or tachycardia.

1. Introduction
The electrocardiogram (ECG) is a medical tool equipment with a purpose to detect abnormalities of the heart by measuring bioelectrical activity that is generated by the heart. Machines that record ECGs are called electrocardiograph. Electrocardiograph records the electrical activity of the heart muscle and displays this data on a visual screen or on printed paper.

Artificial intelligence (AI) is a scientific concept which imitates the intelligence of human brain that is applied to a system. One branch of AI for classification, optimization, compression, forecasting, control systems and so on is the artificial neural network (ANN), which mimics the workings of the human nervous system to produce an appropriate/desired output. In this ANN system there is a training system before ANN is tested to a system that will be used. From this data training, ANN can recognize a correct pattern even when the provided data is incomplete.

In this research, ANN with backpropagation learning algorithm was applied to help diagnose abnormalities of heartbeat that is associated with bradycardia and tachycardia. ANN is a supervised method for machine learning with the output of the network compared with the expected targets, therefore error output could be obtained, and then the error is propagated back to fix the weights of the network in order to minimize the error. In the diagnostics system of heartbeat abnormalities that is based on ANN, the success depends on the data that has been used to the system at the training phase.
2. Materials and Methods

2.1 Tools and Materials
The tools used in this research were divided into hardware and software. The hardware consists of a laptop that is sufficient to run a simulation program, while the software is a Windows 10 operating system and MATLAB program. The material used is the result of ECG recording (printed paper ECG).

| No. | Data Type            | Amount of Data | Training Data | Testing Data |
|-----|----------------------|----------------|---------------|--------------|
| 1.  | Normal person        | 70 samples     | 50 samples    | 20 samples   |
| 2.  | Tachycardia patients | 40 samples     | 30 samples    | 10 samples   |
| 3.  | Bradycardia patients | 30 samples     | 20 samples    | 10 samples   |
|     | Total amount of data | 140 samples    | 100 samples   | 40 samples   |

2.2 System identification
Simply put, the system is divided into 3 sections, namely the input, process, and output. The input section contains some data such as PR interval, QRSD interval, QT interval, QTc interval, P axis, QRS axis, and T axis which are all obtained from ECG recording results (printed paper). The process part is designing the ANN by determining the network architecture, activation functions, and network variations. The last one there are 3 outputs, namely normal, tachycardia, and bradycardia.

2.3 Network Design
Network design is intended to obtain the optimal architecture, activation functions, and network variations to get output with high precision and recall. To get it all, the network needs to be trained with data sets that have been prepared. The training is divided into several levels as follows:

- Training 1 and 2 for determining the network architecture. The purpose of this step is to determine the number of hidden layers and the number of neurons for each hidden layer that produces the best performance during the training process with the smallest MSE (Mean Squared Error) and epoch.
- Training 3 for finding the best momentum and learning rate. At this step, at this stage determine the optimal learning rate and momentum with the architecture that has been obtained from the previous stage.
- Training 4, for finding training variations. This stage aims to find good training variations with architecture, learning rate, and momentum that has been obtained previously.
2.4 **Testing**

Testing is done by using a set of data that has not been drilled previously, i.e. as many as 40 data couples. Instruction given in Matlab to perform the testing is:

\[ y = \text{sim}(net, Q) \]

2.5 **Design Analysis of Testing Results**

Performance of ANN after the training has been performed can be measured by evaluating the error results of the training, and testing against a set of new data input. The results of the training and testing can be analyzed by observing the precision or accuracy of the target with the ANN output, which was formulated as:

\[
\text{Percent}_{\text{error}} = \left| \frac{\text{data}_{\text{test}} - \text{output}_{\text{error}}}{\text{data}_{\text{test}}} \right| \times 100\%
\]

3. **Result and Discussion**

The design results can be divided into 3 parts, the results of the training, the results of the test, and the analysis of the test results. The training results are also divided into 3 parts, the results of the first training to determine the network architecture, the results of the second training to determine the best activation value, and the results of the third training to determine the variation of the network. The results of the testing are also divided into 2 parts, testing for training data and testing for test data.

3.1 **First Training Results**

The first and second training intend to determine the network architecture that produces precise output. Architectural determination is done in 2 stages, the first with one hidden layer with variations in the number of neurons from 7 to 30 neurons and the second with two hidden layers with variations in the number of neurons from 5 to 20 neurons with a rapid learning constant of 0.1, a momentum constant of 0, 1, goal performance (target error) 0.001, maximum iteration of 5000 epoch and with gradient descent (trainigd) training algorithm. The results of the first training can be seen in the graph below:

![Graph with 1 hidden layer](image1)

![Graph with 2 hidden layers](image2)

From the results of the first and second training it can be concluded that the optimal network architecture based on the graph above is a network with two hidden layers with patterns 8–20–13–3. 8 shows the number of inputs, 20 indicates first layer neurons unit, 13 indicates second layer neuron unit and 3 indicates the network output unit.

3.2 **Second Training Results**

The second analysis intend to obtain the optimum value of momentum and learning rate by using the best network architecture in the first and second training. The value of learning rate and momentum is varied in the architecture that was obtained in the first training before. At this stage an experiment was carried out by varying the value of momentum and learning rate with values ranging from 0.1 to 0.9. The results of this second training can be seen in the following table.
Table 2. Second Training Result

| #  | LR  | Momentum | Epoch | MSE    | Notes                  | Input | Correct | Wrong | Percentage |
|----|-----|----------|-------|--------|------------------------|-------|---------|-------|------------|
| 50 | 0.6 | 0.5      | 5000  | 0.0013225 | target not reached      | 40    | 40      | 0     | 100        |
| 51 | 0.6 | 0.5      | 5000  | 0.0015151 | target not reached      | 40    | 40      | 0     | 100        |
| 52 | 0.7 | 0.5      | 5000  | 0.0016181 | target not reached      | 40    | 40      | 0     | 100        |
| 53 | 0.8 | 0.5      | 5000  | 0.0020197 | target not reached      | 40    | 40      | 0     | 100        |
| 54 | 0.9 | 0.5      | 5000  | 0.0012597 | target not reached      | 40    | 40      | 0     | 100        |
| 55 | 0.7 | 0.1      | 5000  | 0.0014485 | target not reached      | 40    | 39      | 1     | 97.5       |
| 56 | 0.2 | 0.5      | 5000  | 0.0011400 | target not reached      | 40    | 39      | 1     | 97.5       |
| 57 | 0.3 | 0.5      | 5000  | 0.0010636 | target not reached      | 40    | 39      | 1     | 97.5       |
| 58 | 0.4 | 4912     | 0.0009998 | 0.0009998 | target reached          | 40    | 40      | 0     | 100        |
| 59 | 0.5 | 5000     | 0.0010756 | 0.0010756 | target not reached      | 40    | 40      | 0     | 100        |

Based on the results in table 2 above, the best results occur at a learning rate of 0.7 and a momentum of 0.4 which produces an MSE of 0.0009998.

3.3 Third Training Results

The purpose of the third training is to find a variation of the network that able to produce the smallest error with fast computing time. The training was conducted with the best training results in the previous training, namely network architecture 8-20-13-3, learning rate 0.7; momentum 0.4; the target error (MSE) is 0.001 and the maximum epoch is 5000 epoch. The observations are presented in the table below.

Table 3. Third Result data for looking the best variations

| #  | Variations | MSE    | Training Result | Hasil Pengujian | Percentage (%) |
|----|------------|--------|-----------------|----------------|----------------|
| 1  | traingd    | 0.0011694 | 5000 target tidak tercapai | 40 40 0 | 100 |
| 2  | traingdm   | 0.0011091 | 5000 target tidak tercapai | 40 39 1 | 97.5 |
| 3  | traingda   | 0.0009018 | 430 target tercapai | 40 40 0 | 100 |
| 4  | traingdx   | 0.0099833 | 162 target tercapai | 40 40 0 | 100 |
| 5  | trainmp    | 0.0009717 | 35 target tercapai | 40 39 1 | 97.5 |
| 6  | traincfg    | 0.0002188 | 499 target tercapai | 40 39 1 | 97.5 |
| 7  | traincgp    | 0.0666668 | 46 target tidak tercapai | 40 30 10 | 75 |
| 8  | traincgb    | 0.1000000 | 57 target tidak tercapai | 40 30 10 | 75 |
| 9  | trainscg    | 0.0078080 | 37 target tercapai | 40 40 0 | 100 |
| 10 | trainbfj    | 0.0008823 | 53 target tercapai | 40 36 4 | 90 |
| 11 | trainos    | 0.009830 | 299 target tercapai | 40 40 0 | 100 |
| 12 | trainlmm   | 0.0007434 | 184 target tercapai | 40 21 19 | 52.5 |

From the various considerations above, the best variation is to use *traingdx*.

3.4 Test Result

From the results of the training above, it can be determined that the artificial neural network system that will be used in this research using architecture 8-20-13-3, training rate 0.7, momentum 0.4, and network variation *traingdx*.

Testing is done using data that has not been trained before. From the table below, it can be seen that the network is able to recognize the test data patterns precisely, with 100% accuracy. These results indicate that there is good accuracy between the network output and the expected target.
Based on the results of previous research and discussions, it can be concluded that the backpropagation results of ECG recording tools and test results using 8-20-13-3 architecture with a learning rate of 0.7 and momentum 0.4 as well as variations in the network training dx then the activation function using logsig shows good value.

### Table 4. The Result of testing system

| Testing No. | RATE | PR | QRSD | QT | QTc | Axis P | Axis QRS | Axis T |
|-------------|------|----|------|----|-----|--------|----------|-------|
| 1           | 80   | 136| 85   | 339| 391 | 66     | 43       | 37    |
| 2           | 97   | 169| 88   | 352| 447 | 72     | -14      | 127   |
| 3           | 92   | 173| 97   | 366| 453 | 80     | -11      | 95    |
| 4           | 85   | 149| 85   | 330| 392 | 30     | 54       | 132   |
| 5           | 80   | 149| 87   | 344| 397 | 24     | 54       | 114   |
| 6           | 94   | 147| 77   | 359| 449 | 40     | 146      | 55    |
| 7           | 76   | 203| 75   | 421| 485 | 1      | 33       | 42    |
| 8           | 84   | 146| 108  | 347| 410 | 75     | 59       | 46    |
| 9           | 76   | 208| 75   | 367| 413 | 42     | 33       | 32    |
| 10          | 80   | 145| 72   | 337| 435 | 73     | 38       | 60    |
| 11          | 61   | 173| 78   | 428| 431 | 67     | 23       | 77    |
| 12          | 90   | 149| 72   | 351| 429 | 67     | 24       | 52    |
| 13          | 88   | 194| 90   | 371| 449 | 34     | 87       | 143   |
| 14          | 77   | 157| 82   | 354| 401 | 43     | 88       | 2     |
| 15          | 94   | 166| 105  | 353| 441 | 17     | -7       | -43   |
| 16          | 64   | 149| 73   | 463| 478 | 57     | -23      | 217   |
| 17          | 64   | 180| 64   | 382| 394 | 54     | 46       | 43    |
| 18          | 88   | 163| 99   | 324| 392 | 66     | -55      | -7    |
| 19          | 91   | 167| 103  | 351| 432 | 70     | -57      | -46   |
| 20          | 95   | 165| 98   | 342| 430 | 62     | -53      | -50   |
| 21          | 105  | 120| 71   | 302| 399 | 55     | 126      | -37   |
| 22          | 130  | 135| 74   | 318| 468 | 43     | 126      | -60   |
| 23          | 178  | 120| 83   | 254| 437 | 57     | 121      | 69    |
| 24          | 168  | 131| 91   | 282| 471 | 49     | 30       | -50   |
| 25          | 110  | 149| 79   | 346| 468 | 57     | 68       | 56    |
| 26          | 101  | 143| 94   | 347| 450 | 45     | 98       | -50   |
| 27          | 104  | 143| 87   | 320| 421 | 57     | 79       | 58    |
| 28          | 163  | 139| 107  | 296| 487 | 46     | 33       | 99    |
| 29          | 105  | 129| 71   | 302| 399 | 52     | 126      | -37   |
| 30          | 130  | 137| 74   | 318| 468 | 50     | 126      | -60   |
| 31          | 58   | 128| 95   | 418| 409 | 3      | 17       | 78    |
| 32          | 58   | 166| 86   | 394| 412 | 51     | 29       | 59    |
| 33          | 59   | 136| 82   | 440| 389 | -43    | 38       | -42   |
| 34          | 57   | 174| 95   | 416| 399 | 35     | 41       | 15    |
| 35          | 57   | 181| 83   | 420| 408 | -35    | 51       | 59    |
| 36          | 56   | 168| 88   | 398| 388 | 15     | 24       | 69    |
| 37          | 56   | 121| 79   | 407| 409 | 47     | 36       | 74    |
| 38          | 53   | 121| 87   | 419| 426 | 22     | -16      | 15    |
| 39          | 54   | 197| 81   | 399| 400 | 34     | 23       | 38    |
| 40          | 58   | 177| 90   | 421| 399 | -12    | 16       | 47    |

4. Conclusion
Based on the results of previous research and discussions, it can be concluded that the backpropagation neural network can be implemented and used as a tool to diagnose heart rate abnormalities based on the results of ECG recording tools and test results using 8-20-13-3 architecture with a learning rate of 0.7 and momentum 0.4 as well as variations in the network training dx then the activation function using logsig shows good value.
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