Arrhythmia Classification System Using Deep Neural Network

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Abstract**—**Previous studies on arrhythmia were used to diagnose the abnormally fast, slow, or irregular heart rhythm through ECG (Electrocardiogram), which is one of the biological signals. ECG has the form of P-QRS-T wave, and many studies have been done to extract the features of QRS-complex and R-R interval. However, in the conventional method, the P-QRS-T wave must be accurately detected, and the feature value is extracted through the P-QRS-T wave. If an error occurs in the peak detection or feature extraction process, the accuracy becomes very low. Therefore, in this paper, we implement a system that can perform PVC (Premature Ventricular Contraction) and PAC (Premature Atrial Contraction) classification by using P-QRS-T peak value without feature extraction process using deep neural network. The parameters were updated for PVC and PAC classification in the learning process using P-QRS-T peak without feature value. As a result of the performance evaluation, we could confirm higher accuracy than the previous studies and omit the process of feature extraction, and the time required for the preprocessing process to construct the input data set is relatively reduced.

Keywords—arrhythmia; deep neural network; classification; premature ventricular contraction;

I. Introduction

Coronary artery disease (CAD), arrhythmia, and heart failure are typical types of heart disease. Frequent monitoring of electrocardiogram (ECG) signals is necessary, especially when there is a history of related events [1,2]. In the study of the detection and classification of the arrhythmia, various features were extracted by processing the ECG signal, and the types of arrhythmia were classified according to the characteristics. However, accurate P-QRS-T peak detection is necessary for ECG signal feature extraction, which requires the use of advanced equipment and a stable measurement environment. Therefore, various complicated algorithms must be used for data processing. Interindividual differences in the ECG signals represent a greater problem. The width of the normal QRS section as well as the size and position of the P wave and the T wave differ between individuals and, in severe cases, the P wave or T wave can hardly be distinguished. Therefore, monitoring of serious arrhythmia requires long-term measurements using advanced equipment in a stable environment [3]. Several methods for automatic detection and classification of cardiac arrhythmias have been reported in the literature, including algorithms based on self-organizing maps [4], filter banks [5], hidden Markov models [6], and neural networks [7-9]. In this paper, we developed a system to classify arrhythmias by updating the weights and bias values of deep neural networks using P-QRS-T peak values with the aim of developing a highly accurate arrhythmia classifier without requiring a feature extraction process.

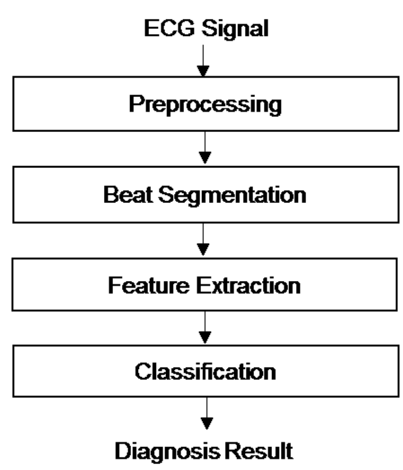

Fig. 1. Typical process flowchart of ECG based diagnosis

II. Related Work

A. Classification of Existing ECG Signal

Diagnosis of heart disease using ECG signals requires sequential preprocessing, waveform detection and segmentation, feature extraction, and classification procedures, as shown in Figure 1. Compression of the signal for each step is an essential element for effectively storing and transmitting enormous amounts of ECG data and as each step progresses, ECG signal compression proceeds.

B. QRS Peak Detection

The Pan & Tompkins QRS Peak Detection algorithm is a typical QRS peak detection algorithm, first published in 1985, which has been used in many subsequent ECG-related studies. The algorithm detection process is shown in Figure 2.

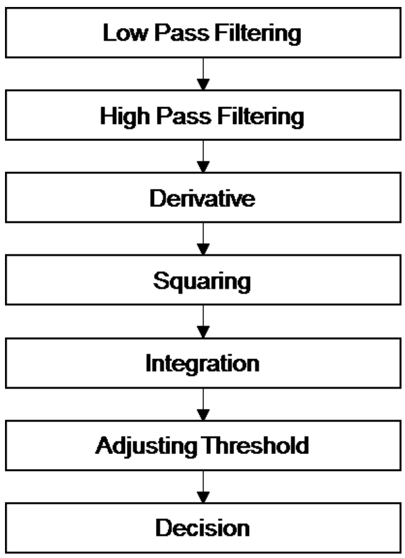

Fig. 2. QRS Detection Process

C. Deep Neural Network Model

Neural network models are among the most commonly used models in various fields, including pattern recognition. This type of model was first implemented by McCulloch and Pitts in 1943 [10]. However, because of the large number of parameters and complexity of the models, it was impossible to learn all of the parameters. Backpropagation subsequently developed by LeCun (1989) [11] enabled learning of parameters, and has been used in various fields, such as artificial intelligence, image processing, etc. However, the complexity of the 1990s models led to various problems, such as the existence of local minima. In addition, as the active function is sigmoid, it is more difficult to learn the parameters near the input layer for deeper layers. Therefore, these models fell out of use. Neural network models were reintroduced in 2000 because Hinton (2006) [12] solved the problem of local solutions through data preprocessing. In the past, the initial values of the parameters were set at random, but the initial values were determined from data preprocessing through the Restricted Boltzmann Machines (RBM) learning method and the results were improved. In addition to the RBM, which has the disadvantage that preprocessing takes a long time, there are many methods available for specifying the initial values of other parameters. A typical example is the initialization process designed by He (2015) [13], which gives a random initial value of the parameter, but it determines the variance of the parameter's initial value distribution considering the numbers of input nodes and output nodes. There are many ways to improve the performance of the neural network model, such as by using dropout and batch normalization.

III. Deep Neural Network Model for Arrhythmia Classification

The overall structure of the arrhythmia classification system based on the proposed neural network is shown in Figure 3. First, the noise is removed from the ECG signal by preprocessing, and then the R wave is detected, and Q and S waves are detected based on the detected R wave. Then, P and T waves are detected using the detected R, Q, and S waves. Learning and testing data sets consist of P, Q, R, S, and T waves, and label data in one file. The label data are configured in one-hot encoding format. The mini-batch is then obtained for the training data and the parameters are updated using the error backpropagation algorithm through the mini-batch data. After the learning process is completed, the updated parameters are evaluated using the test data set to verify the performance.

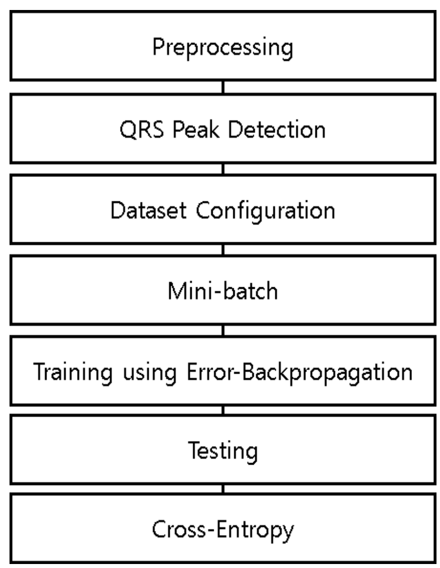

Fig. 3. Configuration of Arrhythmia Classification System

A. Training and Test Data Set Configuration

The MIT-BIH Arrhythmia Database was used as a data set for learning and testing. The data set used in this paper is shown in Table 1.

TABLE I. MIT-BIH ARRHYTHMIA DATA SETS USED FOR TRAINING AND TESTING

100 Record	*103 Record*	*106 Record*	*119 Record*
200 Record	*202 Record*	*203 Record*	*205 Record*
209 Record	*210 Record*	*213 Record*	*215 Record*
220 Record	*221 Record*	*228 Record*	*233 Record*

In MATLAB, the length of data per record using the rdsamp library is 30 minutes. The total number of data per record is 650000 and the sample rate is 360 Hz. QRS peaks were detected after preprocessing by the Pan & Tompkins QRS Peak Detection algorithm. The results of QRS peak detection are shown in Figure 4.

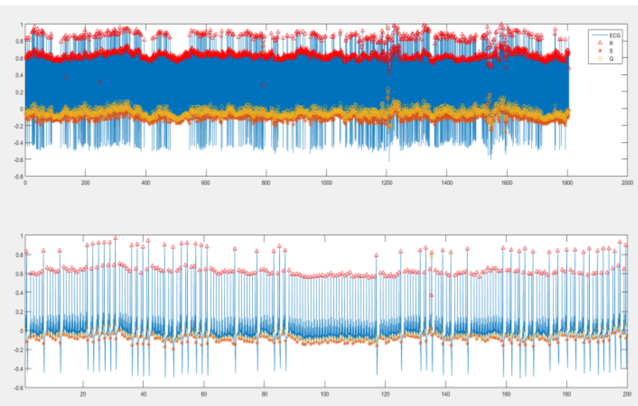

Fig. 4. Example of QRS Peak Detection Results

The label data and the Q, R, and S peak data are integrated into a single csv file. The format of the label data is constituted by the one-hot encoding format. As the label data are in the one-hot encoding format, the signal is represented as 1,0,0 for normal waveforms, 0,1,0 for premature ventricular contraction, 0,0,1 for premature atrial contraction. In the deep neural network model, learning and test data from the first column to the fifth column, and learning and test target data from the sixth column to the eighth column are loaded. In the entire data set, the ratio of training data to test data was 7:3.

B. *Implementation of Deep Neural Network Model*

In this paper, a deep neural network model for arrhythmia classification was implemented in Tensorflow-GPU version and learning was performed through GPGPU (General-Purpose Computing on Graphics Processing Units).

The input nodes of the neural network were composed of three layers, the hidden nodes were composed of five layers, and the output nodes were composed of two layers. We used the sigmoid function as the activation function in the hidden layer and the softmax function as the activation function in the output layer.

Figure 5 shows the structure of the proposed neural network. Previously, we used the features of the ECG signal for classification and detection of arrhythmia. Arrhythmias, such as premature ventricular contraction, could be easily identified by the RR Interval feature. However, extracting features is time consuming. Therefore, we designed to extract the features of the electrocardiogram signal during the learning process for arrhythmia classification.

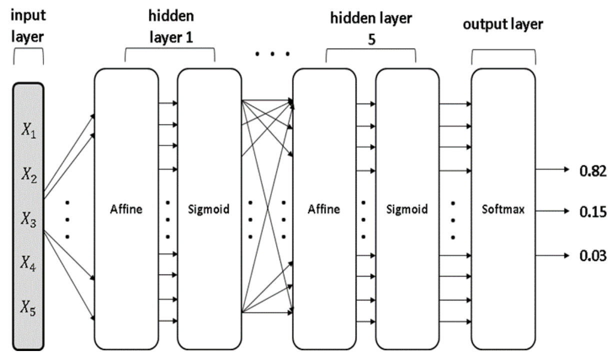

Fig. 5. Proposed Deep Neural Network Model Configuration

IV. EXPERIMENT RESULTS

To evaluate the proposed system, we extracted a data set from the MIT-BIH Arrhythmia Database; 16 records were used for premature ventricular contraction and premature atrial contraction classification. Table 2 shows the records used for learning and testing. Normal Beats, PVC Beats, and PAC Beats refer to the number of waveforms.

TABLE II. MIT-BIH DATASET USED FOR OUR EXPERIMENTS

Record	Normal Beats	PVC Beats	APC Beats	Total
100	2,239	1	33	2,273
103	2,082	0	2	2,084
106	1,507	520	0	2,027
119	1,543	444	0	1,987
200	1,743	828	30	2,601
202	2,061	20	55	2,136
203	2,529	445	2	2,976
205	2,571	71	11	2,656
209	2,621	1	383	3,005
210	2,423	204	22	2,649
213	2,641	582	28	3,251
215	3,195	165	3	3,363
220	1,954	0	94	2,048

221	2,031	396	0	2,427
228	1,688	362	3	2,053
233	2,230	842	7	3,079
Total	35,058	4,881	673	40,615

The final calculated values were used to determine the accuracy. The results of arrhythmia classification through the designed neural network are shown in Table 3. The proposed neural network showed 98.07% classification accuracy of normal waveforms, premature ventricular contraction waveforms, and premature atrial contraction waveforms.

TABLE III. ARRHYTHMIA CLASSIFICATION ACCURACY

Record	**Accuracy**
100	97.92
103	99.85
106	100
119	99.49
200	96.33
202	96.49
203	96.66
205	100
209	99.16
210	97.33
213	93.33
215	99.83
220	96.82
221	96.58
228	100
233	99.33
Average	**98.07**

V. CONCLUSIONS

In this study, we implemented a system that can classify arrhythmia without feature extraction using a deep neural network. In addition, time complexity was improved by using a mini-batch technique and GPGPU, and parameter classification was improved by error backpropagation. Previous studies detected P-QRS-T points in ECG signals and further extracted features corresponding to diseases related to arrhythmia. We attempted to classify arrhythmia using a machine-learning algorithm, with the extracted features as input values. In this paper, we used the MIT-BIH Arrhythmia Database to evaluate the performance of the designed neural network. The proposed neural network is comprised of the input layer from the 0th layer to the output layer of the 6th layer, and the 1st to 5th layers comprise the hidden layer.

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