자동검출을 위한 컨볼루션 신경망 최적구조 설계

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Optimal Architecture Design of Convolutional Neural Network for Automatic Detection of Premature Ventricular Contraction (PVC)

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Abstract - In this study, we designed and evaluated an optimal architecture of convolutional neural network (CNN) for automatic detection of premature ventricular contraction (PVC). For this purpose, we used MIT-BIH Arrhythmia Dataset without data preprocessing. The optimal CNN structure we have found is a four-layer structure with 120, 90, 60, 30 units respectively. This structure consists of several layers including Conv1D layer, Relu Activation, Maxpooling, and dropout (0.1). The accuracy is as high as 99.04%. The proposed model showed the possibility of detection of PVC in ECG.

1. INTRODUCTION

According to the World Health Organization (WHO), cardiovascular disease (CVD) is one of the leading causes of death in developed countries, killing 17.7 million people, 31% of the world's population each year [1]. There are several types of CVD, including heart valve problems, arrhythmia and coronary artery disease, and early detection can prevent sudden death due to proper treatment and management. In particular, arrhythmia can be prevented by premature ventricular contraction (PVC) detection[2].

PVC is an irregular heartbeat caused by premature contraction of the ventricles and is the most common arrhythmia in both nor mal and heart patients. Frequent occurrence of PVC can cause lif e-threatening ventricular tachycardia and fibrillation to older patie nts with impaired cardiac function or to patients with CVD.[3]. T herefore, real-time detection and initial diagnosis of PVC is essen tial for the elderly, CVD patients, or normal persons.

Previously, QRS complex waveforms or T waves were analyze d to detect PVC based on waveform or signal distortion. The QR S complex was detected by comparing extracted features with th reshold values. For example, Bert-Uwe Köhler et al. have describ ed the principle of detecting QRS complexes using a heuristic me thod based on genetic algorithms, wavelet transforms, filter bank s, and nonlinear transformations.

There are many studies on automatic detection of PVC, but th e existing methods are affected by noise or existence of P wave and the processing time is long, so the accuracy of detection is l ow and it is difficult to detect in real time. In order to solve thi s problem, Jeon Hong-gyu, Ik-sung Cho and Kwon Hyeog-soong [3] automatically detected PVC through rhythm analysis and bit matching. However, this has a disadvantage that the performance is relatively low, with a sensitivity of 93.91% and a positive pred ictivity of 96.48%.

Kim, Chan-Woo, Choi, Woo-Young and Kim, Jeong-guk [8] a nalyzed the feature points of ECG signals and detected QRS and PVC waves in real time and showed high detection rate of 98.1 2%. However, There is a limit because they only used records w ith more than 100 PVC waves.

A.Khazaee and A. Ebrahimzadeh [9] detected PVC using suppo rt vector machines (SVM), genetic algorithms and feature extract ion techniques, and showed high performance with a specificity o f 99.65%. However, sensitivity was low at 95.42%.

Recently, there have been reported methods of applying deep l earning technology. For example, Jeon Taejun [5] used a 6-layer ed deep neural network (DNN) to detect PVC and showed high performance with an accuracy of 99.41%. However, since DNN w as used, the input data had to be preprocessed and the structure of the proposed DNN model was complicated. So, we propose an optimal model that does not require a preprocessing process but has a simple structure and automatically detects PVC efficiently. Therefore, in this study, the optimal structure of convolution neur al network for automatic detection of PVC is designed and evalu ated.

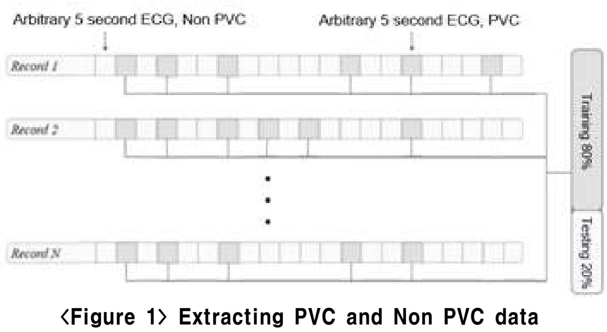
2. MATERIALS & METHOD

2.1 Data processing and Dataset

Figure 1 shows how to segment the signal and annotation of the entire record into a specific length of time according to the given annotation. When the entire signal of each record is segmented in time units of five seconds in order from the beginning, if there is time remaining in the last five seconds, the data is not used for learning. If a PVC occurs more than once during a 5-second interval corresponding to one segment of segmented data, the data annotation of the entire segment is regarded as PVC, and the result is indicated as 1. On the other hand, if there is not PVC in a given section, the data is regarded as Non PVC and the result is indicated as 0.

In this study, We used 23 out of 49 MIT-BIH Arrhythmia Dat aset records with a sampling frequency of 360 Hz and a length o f 30 minutes. The number of records in which the PVC occurs more than once in 30 minutes of the used record is 17 and whic h the number of records in which PVC occurs more than 40 tim es is 13. There are 6 Non PVC records that do not cause PVC, and 3 of them are normal records with no cardiac abnormality in the interval. In addition to PVC, the record contains other signals such as atrial premature contraction (APC).

Seventeen PVCs and six non-PVC records were segmented fo r five seconds in length of the entire data. The total number of segmented data is 6,303. Of these, 5,042 segments (80%) are use d in the training set process of the CNN algorithm model, and 1, 261 segments (20%) are used in the test set process.(Figure 1.)

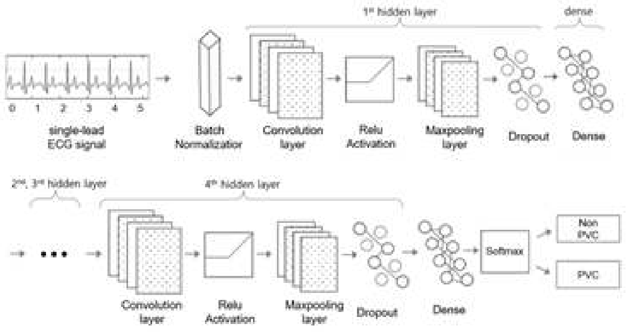


<Figure 1> Extracting PVC and Non PVC data

2.2 CNN model

The optimal structure of the CNN model designed for automati c PVC detection proposed in this study is as follows (Figure 2). After batch normalizing the input data segment, we apply convol ution layer and Relu activation function and pass through Maxpo oling layer. To prevent gradient overfitting, a Dense layer was u sed in the middle of the process of passing four layers in turn.

The values output through all four convolutions layers are divided into Non PVC values and PVC values by the final dense layer. At this time, Softmax was used as the activation function.



<Figure 2> The proposed CNN model

2.3 Selection of optimal CNN structure

In this study, we conducted the following experiments to select the optimal structure of CNN model for automatic PVC detection.

<Table 1> Comparison of accuracy with structure of filters.

Structure	2 layer	3 layer	4 layer	5 layer
Arithmetic	94%	96%	99%	93%
Geometric	93%	97%	98%	98%

<Table 2> Comparison of accuracy with absence or presence of dense.

Fitting	2 layer	3 layer	4 layer	5 layer
With Dense	94%	96%	99%	94%
Without Dense	93%	98%	99%	98%

First, when the number of convolution neural networks is changed to 2, 3, 4, and 5 layers, the performance is highest in the fourth layer

Second, we compared performance on two criteria as the layer deepens, when the number of filters decreases in arithmetic intervals and in geometric intervals. As a result, the structure decreased at the geometric intervals on the third and fifth floors, and at the arithmetic intervals, on the second and fourth floors, showed higher performance. Especially, the structure of fourth layer among the whole layers showed the highest performance with accuracy of 99%(Table 1).

Third, even when the performance according to the presence or absence of the dense is compared, the accuracy of the fourth layer is the highest regardless of the dense condition(Table 2). As a result, it was confirmed that the highest performance is obtained in a four-layer structure in which the number of filters decreased at the arithmetic intervals. A detailed fitting Dense layer was used and the dropout rate was set to 0.1.

2.4 Implementation and Training

To create the CNN algorithm for PVC detection, the software was created using the Keras library in the background of Tensorflow based on the Python language. The hardware used GeForce GTX 1080 TI, Window 10, and the input data set was processed using Matlab R2018a. The number of epochs in learning was set to 100.

3. RESULT

In this study, we confirmed that the best performance is obtained when the dense is present and the dropout ratio is 0.1 in a four-layer structure in which the number of filters decreased at the arithmetic intervals. As a result of the experiment with Epoch number 100, the accuracy was 99.04%, the sensitivity was 98%, the specificity was 99%, and the F1-score was 99%(Table 3). In the 200 Epoch, the accuracy was 98.68%, the sensitivity was 98%, the specificity was 99%, and the F1-score was 99%.

<Table 3> The result of the CNN model.

Study	Accuracy	Recall	F1−score
Training set	100%	100%	100%
Test set	99%	99%	99%

4 DISCUSSION

In this study, the optimal structure of the convolution neural network for automatic detection of PVC was designed and the model was trained and evaluated. For this, the MIT-BIH Arrhythmia Dataset was used and analyzed using a 5-second data segment that was not preprocessed. The optimal CNN structure to increase the accuracy of the PVC automatic detection algorithm was selected experimentally. The selected optimal structure showed high detection performance of 99.04%. The designed PVC algorithm showed a lower accuracy of 99.04% and a higher sensitivity of 98.00% than the paper of Jeon Taejun[5](Table 4). This result shows that the performance of the model is good as in the previous studies.

<Table 4> Comparison with previous studies.

Study	Sensitivity	Accuracy
Tae Joon Jun et al,	96.08%	99.41%
Our study	98.00%	99.04%

Jeon Taejun et al.[5] used a 6-layered deep neural network (DNN) to detect PVC. However, since DNN was used, the input data had to be preprocessed and the structure of the proposed DNN model was complicated. So in this study, we propose an optimal model that does not require a preprocessing process and has a simple structure.

The advantages of the proposed CNN model are as follows. First, PVC can be efficiently detected without extracting a specific signal from a raw signal or calculating it to predefine a feature. Second, even if other signals except PVC, for example, motion noise and various noises, are included in the input signal, the performance of detecting PVC is excellent and practical.

The limitations are as follows. First, the accuracy of detecting PVC is about 4% lower than in previous studies. Second, it can not distinguish signals other than PVC. Third, the frequency of how many PVCs occur in the same segment is unknown. Fourth, the model learning is limited by the number of epochs to 100. Fifth, the total number of data sets used is only 6,303. The limitations are as follows. First, the accuracy of detecting PVC is about 4% lower than in previous studies. Second, it can not distinguish signals other than PVC. Third, the frequency of how many PVCs occur in the same segment is unknown. Fourth, the model learning is limited by the number of epochs to 100. Fifth, the total number of data sets used is only 6,303. Finally, there is a limitation in that it is not possible to generalize the structure because the experiments were conducted only for the limited cases of arithmetic, geometric structure, and 2, 3, 4, and 5 layers.

Future studies will need to design a model that can distinguish between PVC and other signals. At this point, increasing the number of available datasets will improve the performance of the model. In addition, if the number of epochs is increased, the result obtained from the model is generalized and converged to the av erage value, so that a more reliable detection result can be obtai ned.

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