Building Normal ECG Models to Detect Any Arrhythmias Using Deep Learning

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Abstract

In the studies of arrhythmias detection using deep learning, most methods train neural networks to categorize input electrocardiograms (ECGs) to typical arrhythmias using annotated training ECG data. Such methods can neither detect unknown arrhythmias nor explain why they are considered as arrhythmias. To detect any arrhythmias automatically, this study proposes a method that learns normal ECGs and can explain the reason for its judgment clearly. Our method builds a model of normal ECGs using Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM). The model inputs normal ECGs and trains to predict the succeeding normal ECGs. If an abnormal ECG is given, our model predicts the succeeding ECG far from the actual one and can judge that the input is abnormal. This means that our method can judge any arrhythmias because it uses no prior knowledge about the annotations. The experimental results confirmed that the proposed method was able to detect arrhythmias appropriately without learning them. We also proposed a GUI that can show the location where an abnormality is suspected to the user using the proposed method.

1. Introduction

In recent years, there has been remarkable progress in research on deep learning technology in the field of machine learning. Since this technology has the potential to bring about breakthroughs in pattern recognition problems that have been difficult to solve in the past, applications of deep learning techniques to various fields are being attempted. Even in the medical field, some attempts have been made to apply deep learning technology to image diagnosis[1] and disease diagnosis from electronic medical records[2].

The application of deep learning techniques to electrocardiographic analysis has also been actively studied[3-6]. In particular, the study in [7] reported that the proposed method could obtain diagnostic results comparable to those obtained by the average cardiologists. The application of deep learning techniques to electrocardiogram (ECG) analysis is likely to be attempted in various ways in the future.

In conventional deep learning techniques for ECG analysis, normal ECG waveforms and typical arrhythmia waveforms are trained by neural networks using supervised learning. In this case, the trained network detects the abnormal waveforms in the ECG and only classifies them into typical arrhythmia types. It is difficult for such methods to detect untrained arrhythmias as suspected abnormalities and to explain why it is determined to be abnormal. In the future, as research on ECG analysis using deep learning technology progresses, we will need the techniques that can detect not only typical arrhythmias but also suspected unlearned arrhythmias. Such a technique should be able to explain the reasons for suspecting arrhythmias.

In this study, we propose a method to generate a normal waveform model by learning only a normal ECG, and to acquire waveforms that do not fit the model as abnormal. The purpose of this study is to explore the possibility of automatically detecting unknown arrhythmias by learning only normal waveforms, rather than learning the relationships between the typical arrhythmias and their types. In addition, our method can also present portions different from the normal waveform in order to explain the reason why the arrhythmia is suspected. The proposed method combines Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM), which are commonly used for image recognition and time series data analysis respectively, to construct a model that represents normal waveforms. In experiments, we will show how much performance could be obtained by using our method without learning the relationships between typical arrhythmia waveforms and their types. We also propose the GUI that presents the users with the parts judged to be abnormal.

2. Proposed method

The proposed method builds a model that can predict a future wave from the ones in a certain period in the ECG by learning the normal waveforms in advance. If the predicted and actual waves match, the ECG can be

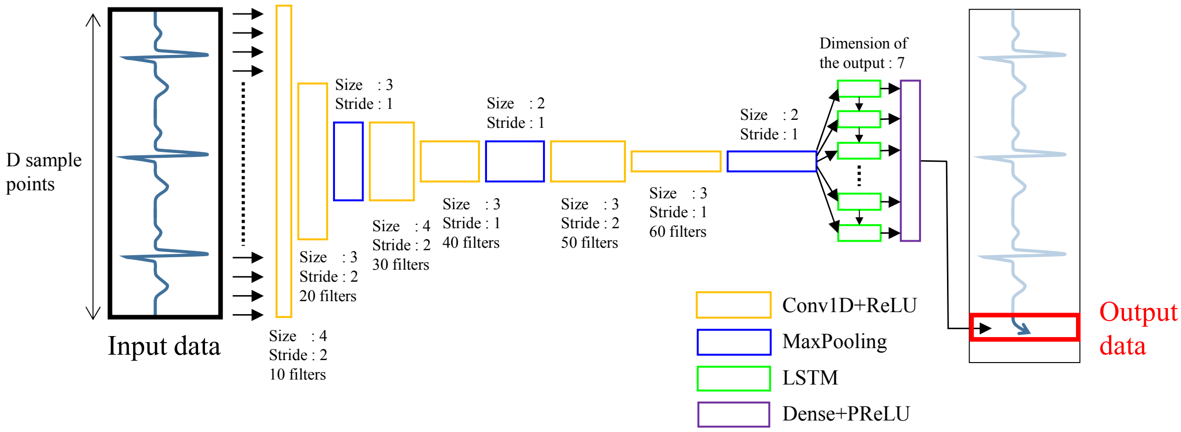

Figure 1. The proposed model for predicting normal ECG waveform.

considered normal. On the other hand, if the predicted wave differs greatly from the actual one, it can be interpreted that there is an abnormality at that part. This method can presents both the predicted and actual waveforms simultaneously on the GUI, which provides users with a visual indication of the location of anomalies.

2.1. The model for predicting ECG waveforms

The input/output data used in the proposed method and the model for predicting ECG waveforms are shown in Figure 1. The proposed model is populated with trimmed waveforms from an ECG section consisting of D sample points that contains several R waves. The output of this model is the height of the wave following the waveform in this section. By comparing the wave height predicted by the model with the actual wave height, the proposed method determines whether the ECG is normal or abnormal.

As shown in Figure 1, the proposed ECG waveform prediction model is composed of CNN and LSTM. The value of each hyperparameter was determined based on some basic experiments.

2.2. Judgement of abnormal waveform

The input and output data to the model shown in Figure 1 will be described in detail using Figure 2. Our method assumes that each waveform in the ECG corresponds to a section represented by W sample points centered on a R wave. In order to analyze the waveforms of this section, the proposed method analyzes W pairs, each of which consists of a D-dimensional input vector representing the ECG wave immediately before a sample point and the output value representing the height of the ECG wave at the sample point.

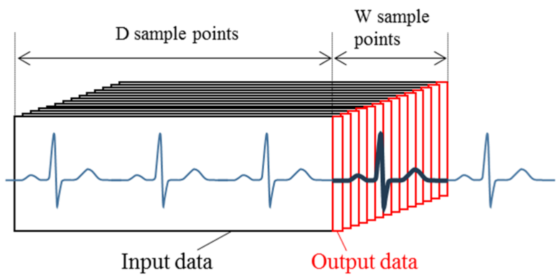

Figure 2. The input and output data for the proposed model.

The proposed method learns only the normal ECGs without learning arrhythmia and generates a normal ECG waveform model. The user selects the parts that are considered to be normal from the ECGs, cuts them out, and uses them as learning data. The learning data is the set of W pairs of the input vector and output values corresponding to the waveforms deemed normal. These learning data are divided into training data and validation data, and the proposed model is trained using the training data. In this training, if the error between the model-predicted and actual wave height is not improved for a certain number of times using the validation data, early stopping is applied to terminate this process. At that time, the mean and standard deviation of these errors are calculated as evaluation criteria for determining whether an ECG waveform to be analyzed is normal or abnormal.

When judging if a waveform is normal, our method feeds W pairs of input vector and output values related to this waveform to the trained model and predicts wave heights. If the error between this predicted wave height and the actual one is more than three times the standard deviation obtained in advance, this actual wave height is judged to be abnormal. The waveform to be analyzed is judged to be abnormal if the ratio of the number of sample points whose wave heights are determined to be abnormal to W sample points that represent this entire waveform is above a certain threshold. We call this ratio abnormal waveform ratio.

3. Experiments

In this section, we describe the experimental results of the proposed method. The proposed method is implemented on Intel Xeon E5-2620 2.10GHz CPU with 16.0GB RAM and GeForce GTX760 GPU chip. The model for predicting ECG waveforms is implemented with Keras and Tensorflow in Python. The GUI of this system is implemented with wxPython.

3.1. Evaluation of the performance

In the experiment, ECGs of 42 patients in the MIT-BIH arrhythmia database were used. In this database, the RR interval corresponds to about 300 sample points. Therefore, the number of sample points W corresponding to the length of each waveform in the ECG described in 2.2 was set to 300. As described in 2.1, D, which represents the number of sample points of the ECG to be input, was set to 900 in order to process an ECG containing several R waves in the proposed method. From the ECGs of 42 patients, 500 waveforms annotated with normal heartbeats were obtained. 300, 50, and 150 waveforms out of the 500 waveforms were used as training data, validation data and test data, respectively. As shown in Figure 2, since one waveform is composed of W pairs of input vectors and output values, the training data described above, for example, is composed of 90000 pairs of input vectors and output values. The validation data was used to apply early stopping termination when training the model. In order to confirm whether the normal ECG waveform model learned by the proposed method is capable of judging arrhythmias as abnormal, the waveforms annotated with typical arrhythmias were obtained from the ECGs of 42 patients. As the typical arrhythmia test data, 150 waveforms of left bundle branch block beats, right bundle branch block beats, atrial premature beats, premature ventricular contractions, and fusion of ventricular and normal beats, respectively, were obtained.

In order to evaluate the performance of the proposed method, we obtained ROC curves representing the changes in the true and false positive rates obtained by varying the threshold of the abnormal waveform ratio described in 2.2. Figure 3 shows the ROC curve obtained by applying the proposed method to 150 waveforms annotated with an arrhythmia and 150 normal waveforms and changing the threshold of the abnormal waveform ratio. Because the difficulty of diagnosis varies depending on the type of arrhythmia, the ROC curve for each type of arrhythmia was obtained. Good results were obtained for arrhythmias that are easy to diagnose, such as premature ventricular contraction, while the overall diagnostic performance is far inferior to the conventional methods such as [7]. However, it should be noted that the proposed method does not learn any arrhythmia waveforms. This indicates that the proposed method has the potential to diagnose ECG waveforms that are slightly different from

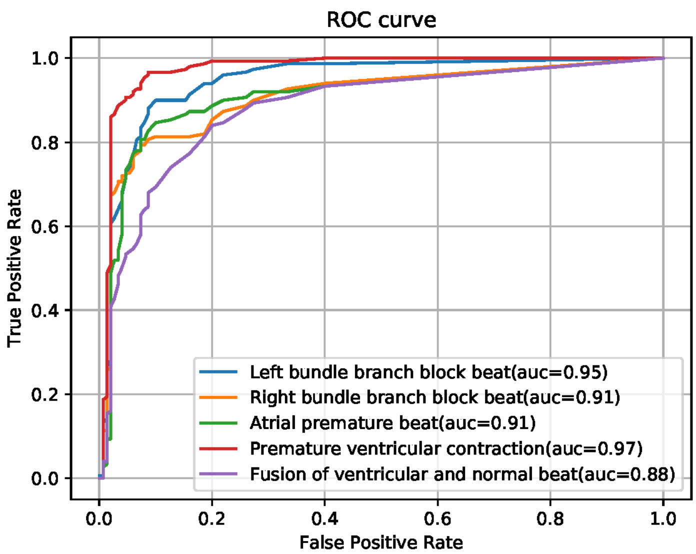

Figure 3. ROC curve obtained by applying the proposed method.

normal ECG waveforms as suspected arrhythmias. In the future, it is necessary to improve the proposed method based on the opinions of cardiologists.

3.2. GUI

The GUI currently under development is shown in Figure 4. One of the purposes of this method is to show the user where anomalies are suspected. This GUI also displays the predicted waves at the sample points where the actual wave height is judged to be abnormal by the method described in 2.2. This allows the user to know where the deviation from the normal waveform is determined to occur. We also plan to improve such information presentation on GUI based on the opinions of cardiologists in the future.

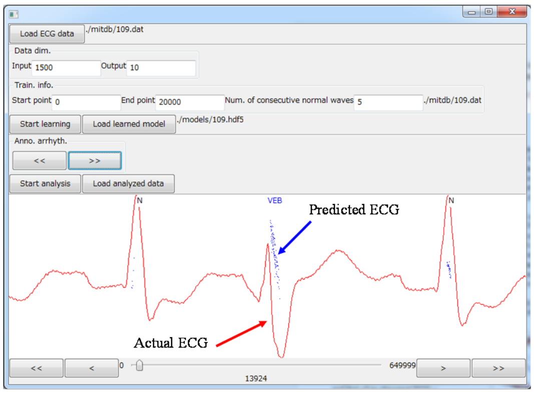

Figure 4. GUI of the proposed method.

4. Conclusions

In this study, we proposed a method to construct a normal waveform model by learning only the normal ECGs, and to judge waveforms that do not fit the model as abnormal. Experimental results showed that the performance of the proposed method was inferior to existing methods that use supervised learning of arrhythmia waveforms by training neural networks. However, we were able to demonstrate the possibility of detecting arrhythmias by simply learning normal ECGs. This may lead to advice on the diagnosis of waveforms that are not typical of arrhythmias and difficult to determine whether they are normal or not. As part of such support, we have also developed the GUI that shows the location of anomalies. We believe that this can assist in the diagnosis by presenting the doctor with areas that differ from a normal ECG.

Our current method can only judge whether given an ECG is normal or abnormal. We will improve this method to be able to classify arrhythmias by expressing the difference between a waveform diagnosed as abnormal and a normal waveform as a feature vector, and clustering these feature vectors. In addition, we would like to improve the GUI to support the diagnosis of arrhythmias with the advice of cardiologists.

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