Fuzzy Systems and Data Mining IX
A.J. Tallón-Ballesteros and R. Beltrán-Barba (Eds.)

doi:10.3233/FAIA231101

ECG Quality Assessment Framework by Using Attentional Convolution Neural Network

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Abstract. ECG is an important means of diagnosis of arrhythmia. In daily health monitoring, serious noise pollution, reverse leads connection, and so on make cannot meet the requirements of subsequent automatic diagnosis. Thus, it is of great significance to further evaluate the ECG quality and screen out the ECG that meet the requirements of subsequent diagnosis. However, complex interference factors affect the quality of the signal and has brought the huge challenge to quality assessment. Additionally, the current algorithms depend on the wave detection, which also brings additional cumulative error. Meanwhile, the current algorithms cannot intuitively present the attention degree to ECG signals during the assessment process. This paper proposes a novel method (ACNN) for evaluating the ECG quality. ACNN directly targets the whole ECG signal and does not detect the waveform of the ECG signal. Then, ACNN uses convolutional blocks to extract the deep features and designs a novel attention layer to enhance the beneficial features of the results. Finally, the fully connected layer is employed for obtaining the final quality evaluation. Compared with existing methods, ACNN obtains better performance, with 100.0% sensitivity, 83.33% specificity and 98.0% accuracy, which shows ACNN can be applied in clinical scenarios.

Keywords. Attention layer; Convolution block; ECG quality assessment framework

1. Introduction

Arrhythmias are the important type of cardiovascular disease, which leads to about 31% of global deaths [1, 2]. Electrocardiogram (ECG) is utilized as a main noninvasive tool for detecting arrhythmia [3, 4]. However, in the actual signal acquisition process, the ECG signal is prone to be affected by serious noise pollution, lead drop, and incorrect placement of lead electrodes. At this time, the user should be prompted to resample in time, rather than input the signal into the subsequent automatic diagnosis

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system for analysis, which will cause a waste of diagnostic resources. Therefore, accurate ECG quality assessment methods have attracted lots of attention in recent years.

Generally, traditional machine learning (ML) algorithms and deep learning (DL) algorithms are there are two main methods for ECG quality assessment. Traditional ML algorithms need characteristics according to expert knowledge of artificial extraction [5-11], then the evaluation characteristics of input into the subsequent classifier to complete the quality evaluation of ECG signal.

With the development of DL technology, many researchers have shown that DL algorithms can be based on many automatic feature extractions, greatly improve the ECG signal quality evaluation model of performance. Compared with traditional ML methods, DL algorithms can automatically acquire many features to represent signal quality. Nowadays, some researchers have utilized DL algorithms for assessment. Zhao et al. [12] proposed a new noise suppression method by using Convolutional neural network (CNN). Huerta et al. [13] used continuous wavelet transform for converting heart electric signal to measure and utilized the time-frequency representation into CNN to acquire efficient quality evaluation model. Zhang et al. [14] designed a new type of cascade CNN, which contained two parts: the first part is used for distinguishing the interference type and the second part is utilized for determining the interference degree, to complete ECG quality assessment.

The current DL algorithms cannot intuitively display attention during the evaluation process, that is, the current researchers at home and abroad have not tried to study which parts of ECG signal the DL model focuses on to have an impact on the final quality evaluation. Therefore, the current DL-based quality assessment algorithms belong to completely black box model. This paper builds a novel attentional convention neural network (ACNN) for quality assessment, which is devoted to improving the quality assessment performance and studying the model interpretability to a certain extent. ACNN targets the whole ECG signal and does not detect the whole ECG waveform to avoid superposition error caused by waveform detection.

2. Materials

This paper assesses ECG quality from PhysioNet/CINC challenge 2011 (Challenge2011) [15]. Each ECG recording in Challenge2011 are collected by 500 Hz sampling frequency and 16 bits resolution with 10s duration. All recordings are manually annotated by technicians, nurses, and volunteers with varying degrees of training, for more accurate labeling. Similar to literature [16, 17], data set A in Challenge2011 is used to verify the proposed quality assessment mode. In addition, ECG recordings in the dataset are uniformly segmented for obtaining the corresponding ECG, and the sampling length of each ECG signal is 4096 sampling points. The Challenge2011 dataset contains 225 electrocardiographic signals with poor quality and 773 electrocardiographic signals with good quality.

3. Methodology

3.1. Overview of ACNN

Figure 1 represents the flow chart of ACNN in this paper. The acquired ECG signal from wearable device is directly input to the network input layer and then is fed into the construction of a complete quality assessment of ECG signals based on CNN and attention mechanism model, and then complete the quality evaluation of ECG signal.

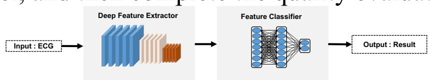


Figure 1. Overview of ACNN

3.2. Overview of ACNN

CNN was proposed in the article [18] and has been applied in medical applications [19-21], fault diagnosis [22], and other fields in recent years. CNN can learn deep representation from labelled data and acquire deep features for classifying. Therefore, this paper utilizes CNN for extracting features.

Attention mechanisms are commonly used in image analysis and natural language processing. Recently, the attention mechanism has also been widely used in medical diagnosis [23, 24]. However, we find that the use of attention mechanisms in ECG quality assessment have not been investigated by researchers. Therefore, this paper designs a novel attention mechanism combined with CNN to realize the ECG signals quality evaluation. Figure 2 illustrates the flow of the designed attention mechanism.

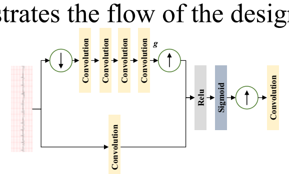


Figure 2. The flow of the designed attention mechanism

For a given input data X, as well as the input data through a series of convolution operation for gating characteristics of g. The gating feature g is to facilitate the co-production of the corresponding attention weight in combination with X in the subsequent structure. Equation (1) and (2) represent that attention weights are obtained through a series of convolution operations using input data and gating features. It is worth noting that convolution operation is introduced here instead of other operations. On this basis, the output of the weight and dimension of the input data consistent attention and input data Elementwise operation, should be to obtain the final phase characteristics.

$$q_{att} = \psi\left(\sigma_1\left(W_x * x + W_g * g\right)\right) \tag{1}$$

$$\alpha_i = \sigma_2\left(q_{att}\left(x_i, g_i\right)\right) \tag{2}$$

3.3. The Architecture of ACNN

Figure 3 depicts the proposed the structure of the network. ACNN consists of four convolutional blocks, an attention layer, and a fully connected classification layer. Convolution block includes convolution layer and pooling layer. The convolution layer is mainly to various nonlinear data processing, and then to extract the ECG signal data contained in the deep hidden features. It is worth noting that since the ECG signal is a one-dimensional discrete signal, a one-dimensional convolutional layer is used here. Additionally, to simplify the model structure and improve training and testing speed, the pooling layer directly adopts the maximum pooling operation. Four convolutional blocks are applied for automatically extracting the deep feature, and many extracted deep features are input into the attention layer. The attention weight is used to multiply the deep features to highlight the significant features and relatively suppress the features that are not related to the final quality assessment task. Then, the weighted features are flattened and input into a fully connected layer for nonlinear processing to enhance the nonlinear characteristics of the features, and finally output to the classifier for classification.

Finally, ACNN is trained by a workstation, which contains two NVIDIA GTX 1080 GPUs. Further, this paper selects Adam optimizer [25] as optimizer and 256 as batch size.

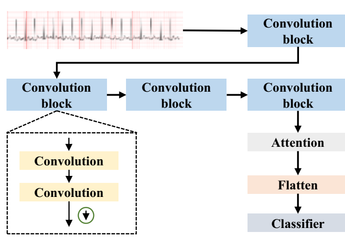


Figure 3. The architecture of the proposed ACNN

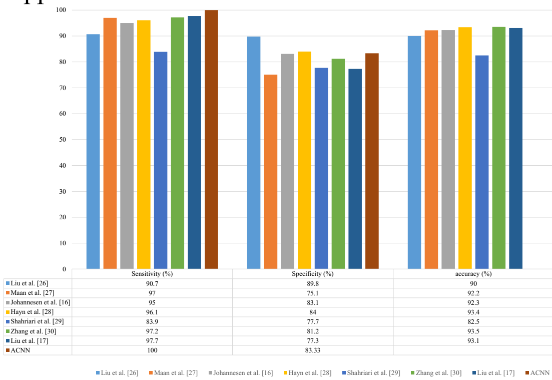
4. Results and discussion

In this paper, we randomly select 80%, 10% and 10% of the data in the Challenge2011 dataset as the training set, validation set and test set. To further compare the effectiveness of the proposed ACNN, we compare ACNN with the latest existing methods. The same Challenge2011 dataset is used for comparison to allow for reasonability. In this paper, specificity, sensitivity and accuracy are utilized for evaluating the model assessment performance.

4.1. Model Performance

In comparison experiments, ACNN is compared with existing methods to verify the superiority of ACNN. Figure 4 indicates the comparison results with existing methods based on Challenge2011 dataset. From Figure 4 you can see, compared with the existing methods [16, 17, 26-30], ACNN creatively combines CNN with the attention layer, uses multi-layer convolutional layers to automatically extract many deep features, and enhances effective features and inhibits invalid features through the attention layer. After manual correction of wrong label, ACNN obtained better performance with 100%

sensitivity, 83.33% specificity and 98% accuracy, which indicates that ACNN have potential to practical application.



	Sensitivity (%)	Specificity (%)	accuracy (%)
Liu et al. [26]	90.7	89.8	90
Maan et al. [27]	97	75.1	92.2
Johannesen et al. [16]	95	83.1	92.3
Hayn et al. [28]	96.1	84	93.4
Shahriari et al. [29]	83.9	77.7	82.5
Zhang et al. [30]	97.2	81.2	93.5
Liu et al. [17]	97.7	77.3	93.1
ACNN	100	83.33	

Figure 4. Comparison results with the existing methods

4.2. Model Interpretability

The proposed attention layer is used to improve the model quality assessment performance, and to establish the relationship between the classification results and the ECG signals. Figure 5 shows the attention weight of the ECG signal. Compared to the ECG signals in other regions, the middle segment of the input ECG signal is most severely disturbed, and its waveform could not be applied in the subsequent analysis at all. The attention weight provided by the attention layer also shows the greatest degree of attention in this region, that is, enhances the features of this region. On the contrary, although the interference of ECG signals in other regions is not as great as that in the middle region, they are also greatly interfered, and the attention layer also shows a greater degree of attention.

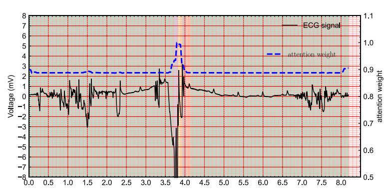


Figure 5. The effect of attention weights of ECG recording

5. Conclusion

This paper designs a relatively interpretable, automated, and accurate method for ECG quality assessment. ACNN uses CNN to extract deep representations from ECG signals. Additionally, this paper proposes attention layer to enhance the useful deep features and suppress the invalid deep features. Further, the attention layer can intuitively show the attention degree of the model to different time periods on the ECG signal. And then, by comparing with the existing methods, ACNN achieves better performance, with 100.0% sensitivity, 83.33% specificity and 98.0% accuracy. Therefore, ACNN has superior quality assessment performance and a certain interpretability ability, which represents that it has the potential to be used as signal quality assessment system in clinical centers.

Acknowledgements

This work was supported by National Postdoctoral Program for Innovative Talents (No. BX20230215), China Postdoctoral Science Foundation (No. 2023M732219) and Shanghai Municipal Science and Technology Major Project (No. 2021SHZDZX0102).

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