ECG Heartbeat Classification Detection Based on WaveNet-LSTM

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***Abstract*—Electrocardiogram (ECG) can effectively record the potential difference of the body surface generated during the physiological function of the heart, and analyze and accurately discriminate the potential difference signal generated by the electrocardiogram, which can effectively prevent sudden diseases and reduce suddenness. ECG heartbeat is a powerful tool to diagnose several abnormal arrhythmias. Although the classification methods of arrhythmia improved significantly, but when detecting different types of cardiac abnormalities, especially when dealing with unbalanced data sets, it still does not provide acceptable performance. In this paper, we propose a method of data processing combined with the deep WaveNet-LSTM convolution model to solve this limitation of the current classification method. Furthermore, to prove the effectiveness of proposed method, using the MIT-BIH arrhythmia database, which considers intra- and inter-patient paradigms, and the AAMI EC57 standard. The evaluation results show that our method has achieved very good performance, and its accuracy of ECG abnormal signal detection reaches 96.8%.**

Keywords-ECG analysis; heartbeat classification; deep learning; WaveNet model; confusion matrix

I. INTRODUCTION

With the development of economy and society, people's life rhythm is speeding up and work pressure is increased. The morbidity and mortality of cardiovascular and cerebrovascular diseases remain high. Heart disease gradually become an important disease threatening health. The electrocardiogram (ECG) can record the difference in body surface potential generated during the physiological function of the heart, effectively prevent sudden diseases and reduce the mortality of sudden diseases.

Although the traditional ECG diagnosis is done by the electrocardiogram diagnosis doctors. However, for patients who need to detect dynamics for a long time, it is time-consuming and laborious to diagnose all the information obtained in 24 hours by the physician. Due to factors such as physician fatigue, the accuracy of diagnosis will also decline. Therefore, it is particularly important to perform efficient, accurate, and low-cost automatic analysis of ECG signals.

Artificial intelligence technology can apply the ECG signals collected by the existing electrocardiograph for automatic analysis and diagnosis. Effective machine learning methods, such as Support Vector Machines (SVM), Multilayer Perceptron (MLP), reservoir computing with logistic regression (RC) and Decision Trees (DT) applied to ECG signals arrhythmia detection [1], [2], [3], [4]. The application of these methods requires preprocessing of the signal and extraction of artificial features from the signal (specifically, wavelet packet analysis [2], power spectrum estimation [5], energy entropy [6], etc.), which are used to implement the classification task. These artificially extracted signal features can reflect the shape of a certain aspect of the signal, but it is difficult to use all the feature information of the signal. For a specific classification task, the manually extracted features cannot provide all the information for machine learning algorithm to learn the classification task, and for some heart changes that are small and difficult to detect, the intelligent algorithm may lose its role.

Automatic feature extraction and representative methods have proved to be more scalable and able to improve prediction accuracy. Deep learning methods have achieved remarkable results in various domains ranging from machine vision and natural language processing [5] [6], and it has more applicable outcomes in biomedical signal processing. Many methods use all the information of the signal to build an end-to-end deep learning framework, which can automatically learn the most suitable features for

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classification tasks. Traditional deep supervised learning techniques include Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). Many deep learning frameworks have emerged to implement ECG classification in recent years, and the classic method is to build CNNs. Acharya [7] proposed a 9-layer deep convolutional neural network to automatically recognize 5 types of ECG signals. Kiranyaz [8] designed an adaptive convolutional neural network to extract the features of the patient, which can be further Improve classification performance. Jin and Dong [9] constructed a lead convolutional neural network to classify normal and abnormal ECG signals [10], etc. These methods prove that the convolutional neural network structure can classify ECG signals well. In addition, other deep learning frameworks that can also perform reliable ECG signal classification. For example, ShirinShadmand [11] proposed an ECG signal classification algorithm based on block neural network and particle swarm optimization. ÖzalYildirim [12] applied a deep bidirectional long-term memory network model for the classification of ECG signals. There are also researchers who classify ECG signals through residual network (ResNet) based on CNNs. Rai-Jpurkar et al. used 34-layer ResNet to divide 30-second single-lead ECGs into 14 different categories.

In this paper, we extract the time-frequency domain characteristics of the ECG signal, use the oversampling method to balance the training set samples, and build a WaveNet-LSTM deep learning network model to classify the signal. Based on the classification of ECG signals by Mohammad Kachuee [13], we make changes to the CNN structure, propose to apply the WaveNet structure, combine with long and short-term memory networks (LSTM), and propose a WaveNet-LSTM framework to classify and detection ECG signals. Compared with other methods, the classification accuracy of ECG signals improved to 96.8%. Furthermore, the network model we proposed take full advantage of the structural of WaveNet and LSTM, which can not only realize the effective classification of heartbeat signals, but also can be used for other heart rate signal classification activities. It provides a solution for the improvement of ECG diagnosis technology.

II. Dataset

In this paper, we utilized the PhysioNet MIT-BIH Arrhythmia database to evaluate the performance of other methods and our proposed method. The MIT-BIH dataset includes ECG records from different subjects (at a sampling rate of 360 Hz), and each sample is endorsed by at least two cardiologists.

In the following section of the study, we use the ECG leads resampled to a sampling frequency of 125 Hz as the original data set for classification tasks. The database are provided by the American association of medical instrumentation (AAMI) [14], since it includes the five beat categories as described in Table I. The heartbeat of the MIT-BIH database (44 records based on AAMI) is divided two sets of records:

DS1 = {101, 101, 106, 108, 109, 112, 114, 115, 116, 118, 119, 122, 124, 201, 203, 205, 207, 208, 209, 215, 220, 223, 230}

DS2 = {100, 103, 105, 111, 113, 117, 121, 123, 200, 202, 210, 212, 213, 214, 219, 221, 222, 228, 231, 232, 233, 234}

The DS1 used to build classification model and DS2 applied to test the model. With this division method, we no longer need to concern about the heartbeats from the same patient in both the training and test sets.

TABLE I. Categories of Heartbeats Existed in the MIT-BIH Database Based on AAMI EC57

Category	Class
N	Normal beat (N) Left and right bundle branch block beats (L, R) Atrial escape beat (e) Nodal (junctional) escape beat (j)
S	Atrial premature beat (A) Aberrated atrial premature beat (a) Nodal (junctional) premature beat (J) Supraventricular premature beat (S)
V	Premature ventricular contraction (V) Ventricular escape beat (E)
F	Fusion of ventricular and normal beat (F)
Q	Paced beat (/) Fusion of paced and normal beat (f) Unclassifiable beat (U)

III. Method

A. Processing

The ECG is aperiodic highly repetitive sequence, as shown in Fig. 1. Therefore, a simple and effective ECG signal preprocessing method used to extract the beat of ECG signal. For the training set sample, we used SMOTE oversampling [15] to properly expand the sample's capacity before modeling, unlike the previous simple replication of the existing method, the SMOTE method adopted in this paper is the boundary SMOTE algorithm [16], which finds an area in the sample, so that it can reflect the nature of the data set well, interpolates in the region, re-creates the sample, avoids the model overfitting caused by sample repetition, and solves the problem of model overfitting caused by sample repetition problem.

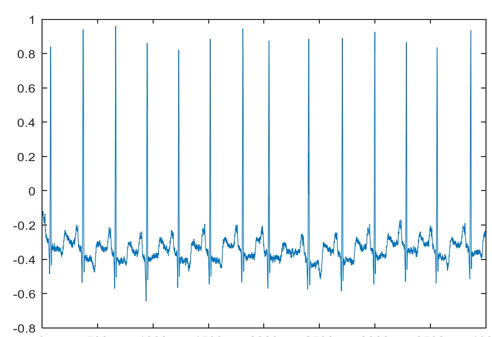

Figure 1. ECG recording graph.

B. WaveNet

WaveNet is the latest speech generation model based on deep learning launched by Google deepmind. The model can directly model the original speech data, and has good performance in text to speech and speech generation tasks. WaveNet adopts the method of expanding convolution and causal convolution, which makes the receptive field multiply with the depth of the network, and can model the original voice data.

The main component of WaveNet is causal convolution, which can ensure that the model does not violate the data order when modeling the data, by using causal convolutions. As shown in Fig. 2. For images, the equivalent of causal convolution is masking convolution, which can realized by constructing a masking tensor and convolution kernel for point multiplication before use. For one-dimensional data such as audio, it is easier to implement, and the output of normal convolution can offset in a few time steps.

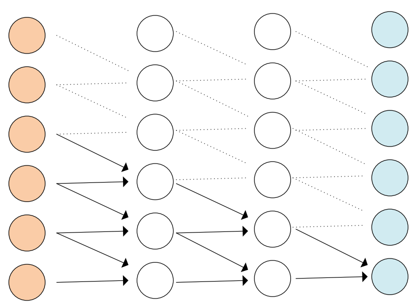

Figure 2. Structure diagram of causal convolution.

C. LSTM

Long short-term memory (LSTM) is a special structure of RNN, which used to solve the problem of long-term dependence of RNN. In other words, with the increasing time interval of input information into RNN, ordinary RNN will appear the phenomenon of "gradient disappearance" or "gradient explosion", which is the long-term dependence of RNN. The introduction of LSTM can solve this problem.

D. Ecg Heartbeat Classification Detection Based on WaveNet-LSTM

Based on the MIT-BIH beat dataset, this paper trains a deep learning framework combining WaveNet and LSTM, which is applied to the classification of ECG heartbeat and is more accurate than previous methods. For ECG signal, it is reasonable and effective to use multi-layer convolution for automatic feature extraction and memory network to check whether the time point information is useless. In addition, a series of incentive mechanism, dropout mechanism and softmax mechanism added to the network structure to improve the performance of the network.

The basic network structure of WaveNet-LSTM shown in Fig. 3. The extracted beat signal length (less than 0) are taken as the input of the network and enters the convolution layers, all the convolution layers below are one-dimensional convolution layers, that we only extract the signal features automatically on the one-dimensional signal sequence. Then each convolution layer is followed by a leaky-relu in the activation layer, the number of filters is 8, and the convolution kernel size is 5. Then it enters the convolution layer with the same configuration, and then enters the pooling layer. The pooling layer uses Max pooling with size 5, and the step size was set 2. After coming out of the pooling layer, it enters the convolution layer cycle again. The size of convolution layer filter is 16, 32, 64, the convolution sum size is unchanged, and the pooling layer setting is unchanged. The last 64 dimensional features coming from the pooling layer connected into the long short time memory network for secondary sharpening. Then dropout mechanism is set and embedded in the hidden layer. Finally, ECG signals classified with softmax.

In addition, in the process of training the network, the cross entropy on the softmax output layer is used as the loss function of the whole network, and Adam's optimization method is adopted. The learning rate is set to 0.001, beta1 to 0.9, beta2 to 0.999, iterations to 50, batch_size is 500, the convergence property of the network is good, and the training time of the network is within a reasonable range.

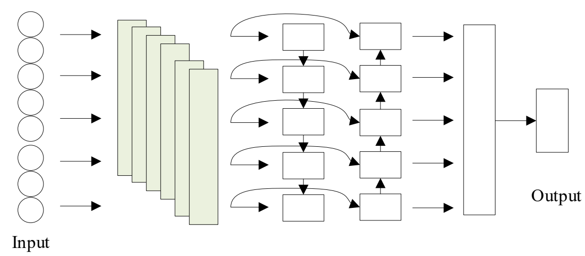

Figure 3. Architecture of the proposed network.

Using the advantages of the WaveNet-LSTM, the network parameters are continuously tuned. As shown in Fig. 4, the beginning and ending indicated through a stadium box, the process of inputting and outputting data was denoted by a parallelogram box, a rectangular box represents a processing step or a set of operation, and a diamond box shows a conditional operation determining which one of the two paths the program will take.

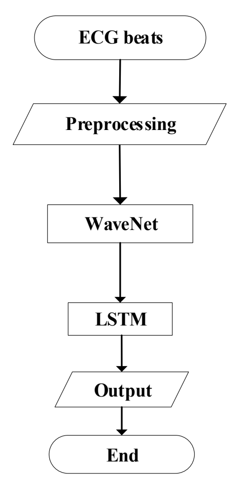

Figure 4. Procedure of the proposed method.

IV. EXPERIMENT

A. Experimental Process

In this study, the network training process curve is as shown in Fig. 5. In the figure, the red and blue curves represent the accuracies of the training set and validation set, respectively. The green and black curves represent the losses in the training set and validation set, respectively. It is clear that as the training progresses, starting from the third epoch, the validation set loss curve exhibits an upward trend, and intersects the training set loss curve.

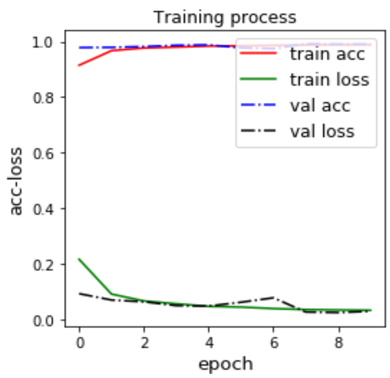

Figure 5. Learning curve of model training process.

B. The Results of the Experiment Were Compared

After the network training is good, use this network to predict the classification of 4000 tagged samples that did not enter the network training. The confusion matrix for the test results is as shown in Fig. 6. The match between the real label and the prediction label is as recorded in the confusion matrix, and if the prediction is accurate, the sample falls into the veragonal area, otherwise it will be scattered through through the matrix. It can be seen from the confusion matrix, the WaveNet-LSTM model proposed in this paper can classify the five types of PCNs well, and the accuracy of class S samples and F samples is lower than that of other classes, at 94% and 93%, respectively, but the accuracy of the other three types of PCNs is very high.

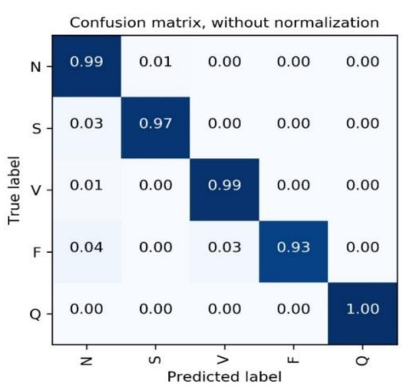

Figure 6. Confusion matrix for heartbeat classification on the test set. Total number of samples in each class is indicated inside parenthesis. Numbers inside blocks are number of samples classified in each category normalized by the total number of samples and rounded to two digits.

Table II presents the average accuracy of the proposed method and compares it with other relevant methods in the literature. As can be seen from the table, compared with other methods, the proposed method has obvious advantages. The average accuracy of MIT-BIH data set classification in Mohamad kachuee [13] is 93.4%. The average prediction accuracy of Li [19] and others is 94.6% by traditional DWT + RF method. After the construction of the network structure, the average accuracy of the prediction set samples improved to 96.8%. While suggesting a predictor for MIT-BIH is not the sole purpose of this study, according to the results, the accuracies achieved in this paper are competitive to the state of the art methods.

TABLE II. ACCURACY OF DIFFERENT METHODS

Source	Compare	
	Methods	***Average Accuracy (%)***
This Paper	Deep WaveNet-LSTM	**96.8%**
Mohammad Kachuee[13]	Deep residual CNN	93.4%
Acharya et al.[17]	Augmentation + CNN	93.5%
Martis et al.[18]	DWT + SVM	93.8%
Li et al.[19]	DWT + Random Forest	94.6%

V. CONCLUSION

The deep learning model proposed in this paper has a good performance on the dataset used in this paper. Compared with the existing technical methods in the literature, it has good competitiveness.

However, the datasets used in this paper also have some limitations such as limited data, fewer data types, etc. In order to verify the effectiveness of the proposed model, transfer learning can considered in the later stage, which can be apply to the related signal classification field.

Transfer learning that can be divide into two aspects: Firstly, we can consider the prediction and discrimination of other human generated signals (such as brain wave signal, pulse wave signal, and other signals). Secondly, we can consider migrating to other multi classification tasks of ECG signals, and extend it to more detailed classification of more than ten or even dozens of categories of ECG signals, and I believe it will also have a good performance. The deep learning model based on WaveNet-LSTM proposed in this paper may be of greater value in the field of medical signals and will be more helpful for future research.

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REFERENCES

[1] Q. Li, C. Rajagopalan, and G. D.Clifford, “A machine learning approach to multi-level ECG signal quality classification”,Computer Methods and Programs in Biomedicine, vol. 117, no. 3, Dec. 2014, pp. 435-447, doi: 10.1016/j.cmpb.2014.09.002.

[2] L. Taiyong, M. Zhou, “ECG classification using wavelet packet entropy and random forests”, Entropy. vol. 18, 2016, pp. 1-16, doi:10.3390/e18080285.

[3] X. Ping, X. Min, L. Yingjun. “The Automatic Identification of PVC Based on Wavelet Transform and BP Neural Network”, Chinese Journal of Medical Physics, vol. 27, no. 2, 2010, pp. 1762-1765.

[4] Z. Cömert, A. F. Kocamaz, “Comparison of Machine Learning Techniques for Fetal Heart Rate Classification”, Acta Phys. Pol. A. vol. 132, 2017, pp. 451-454. doi:10.12693/APhysPolA.131.451.

[5] Z. Zhao, S. Särkkä, and A. B. Rad. "Kalman-based Spectro-Temporal ECG Analysis using Deep Convolutional Networks for Atrial Fibrillation Detection." Journal of Signal Processing Systems, vol. 92, no.7, 2020, pp. 621-636, doi:10.1007/s11265-020-01531-4.

[6] H. Beyramienanlou, N. Lotfivand, “Shannon's Energy Based Algorithm in ECG Signal Processing”, Comput. Math. Methods Med. 2017, pp. 1-16, doi:10.1155/2017/8081361.

[7] U. R. Acharya, S. L. Oh, Y. Hagiwara, J. H. Tan, M. Adam, A. Gertych, and R. S. Tan, “A deep convolutional neural network model to classifyheartbeats,” Computers in Biology and Medicine, vol. 89, 2017, pp. 389–396, doi:10.1016/j.compbiomed.2017.08.022.

[8] S. Kiranyaz, T. Ince, and M. Gabbouj, “Real-Time Patient-Specifific ECG Classifification by 1-D Convolutional Neural Networks,” IEEE Transactions on Biomedical Engineering, vol. 63, no. 3, 2016, pp. 664–675, doi:10.1109/TBME.2015.2468589.

[9] L. Jin and J. Dong, “Classifification of normal and abnormal ECG recordsusing lead convolutional neural network and rule inference,” ScienceChina Information Sciences, vol. 60, no. 7, 2017, doi:10.1007/s11432-016-9047-6.

[10] M. Zubair, J. Kim and C. Yoon. “An automated ECG beat classification system using convolutional neural networks”, IT Convergence and Security (ICITCS), 2016 6th International Conference on. IEEE, 2016.

[11] S. Shadmand and B. Mashoufi. “A new personalized ECG signal classification algorithm using Block-based Neural Network and Particle Swarm Optimization”, Biomedical Signal Processing & Control, vol. 25, Mar. 2016, pp. 12-23, doi:10.1016/j.bspc.2015.10.008.

[12] O. Yildirim. “A novel wavelet sequence based on deep bidirectional LSTM network model for ECG signal classification”, Computers in Biology and Medicine, vol. 96, May 2018, pp.189-202, doi: 10.1016/j.compbiomed.2018.03.016.

[13] M. Kachuee, S. Fazeli, M. Sarrafzadeh. “ECG Heartbeat Classification: A Deep Transferable Representation”, 2018 IEEE International Conference on Healthcare Informatics (ICHI). IEEE, Jul. 2018, doi: 10.1109/ichi.2018.00092.

[14] A. for the Advancement of Medical Instrumentation et al., “Testing and reporting performance results of cardiac rhythm and st segment measurement algorithms,” ANSI/AAMI EC38, vol. 1998, doi:

[15] H. Han, W. Wang and B. Mao. “Borderline-SMOTE: a new over-sampling method in imbalanced data sets learning”, ICIC: Advances in Intelligent Computing. 2005, pp. 878-887, doi: 10.1007/11538059_91.

[16] D. Kingma and J. Ba, “Adam: A method for stochastic optimization,” arXiv preprint arXiv:1412.6980, 2014.

[17] U. R. Acharya, S. L. Oh, Y. Hagiwara, J. H. Tan, M. Adam, A. Gertych and R. San Tan, “A deep convolutional neural network model to classify heartbeats,” Computers in biology and medicine, vol. 89, 2017, pp. 389–396, doi: 10.1016/j.compbiomed.2017.08.022.

[18] R. J. Martis, U. R. Acharya, C. M. Lim, K. Mandana, A. K. Ray, and C. Chakraborty, “Application of higher order cumulant features for cardiac health diagnosis using ecg signals,” International journal of neural systems, vol. 23, no. 4, 2013, pp. 1350014, doi: 10.1142/S0129065713500147.

[19] T. Li and M. Zhou, “Ecg classifification using wavelet packet entropy and random forests,” Entropy, vol. 18, no. 8, 2016, pp. 285, doi: 10.3390/e18080285.