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Research article

A new deep learning model for assisted diagnosis on electrocardiogram

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Abstract: In order to enhance the accuracy of computer aided electrocardiogram analysis, we propose a deep learning model called CBRNN to assist diagnosis on electrocardiogram for clinical medical service. It combines two sub networks which are convolutional neural network (CNN) and bi-directional recurrent neural network (BRNN). In the model, CNN with one-dimension convolution is employed to extract features for each lead of ECG, and BRNN is used to fuse features of different leads to represent deeper features. In the training step, we use more than 40 thousand training data and more than 19 thousand validation data to obtain the optimal parameters of the model. Besides, by validating our model on more than CCDD 120,000 real data, it achieves an 87.69% accuracy rate, higher than popular deep learning models such as CNN and ResNet. Our model has better accuracy than state-of-the-art models and it is also slightly higher than the average accuracy of human judgement. It can be served for the first round screening of ECG examination clinical diagnosis.

Keywords: clinical medicine; electrocardiogram; multi-lead; convolutional neural network; bi-directional recurrent neural network

1. Introduction

Electrocardiogram (electrocardiogram, ECG) is the process of recording the electrical activity of the heart over a period of time using electrodes placed on the skin. These electrodes detect the minor electrical changes on the skin that arise from the heart muscle's electrophysiologic pattern of depolarizing and repolarizing during each heartbeat. It has been widely applied in clinical medicine to detect any cardiac problems. However, most electrocardiograms need manual examination with long-term patience which is very time-consuming and boring. Besides, because the huge amount of ECG data is produced every day, the diagnostic doctors for ECG are not willing to analyze ECG in details, instead only determine whether it is abnormal. Thus many details may be missed. The reality is that it has some possibility to misdiagnose ECG for doctors' careless of overworked state. In order to help improve doctors' efficiency and accuracy, machine learning based electrocardiogram analysis can be employed. The normal electrocardiogram can be filtered out by machines quickly according to machine learning algorithms based on historical data sets. While the doubtful examination reports can be left for doctors for carefully studying later. Therefore, machine learning tools for electrocardiogram reports examination play a very important role in the first round screening of clinical diagnosis.

An electrocardiogram record usually contains 12 leads [1], which are: I, II, III, avL, avF, avR, v1, v2, v3, v4, v5, v6. Each lead is a time series, which consists of multiple heartbeat cycles. A heartbeat produces a higher pulse, as shown in Figure 1. Our model can be served for the first round screening of ECG examination clinical diagnosis. Given a 12-lead ECG record, our model can be employed to determine whether it is normal or not. Once a doutful examination report is determined, the doctor would further analyze it to make a final clinical diagnosis report.

In this paper, a deep learning model, called CBRNN, is proposed for the data dependence of multi-lead electrocardiogram in the same lead and the independence of data between different leads. We evaluate the performance of our model on Chinese Cardiovascular Disease Database (CCDD) which is an big public dataset, the accuracy of the model is up to 87.69%, which is quite valueable for actual electrocardiogram diagnosis.

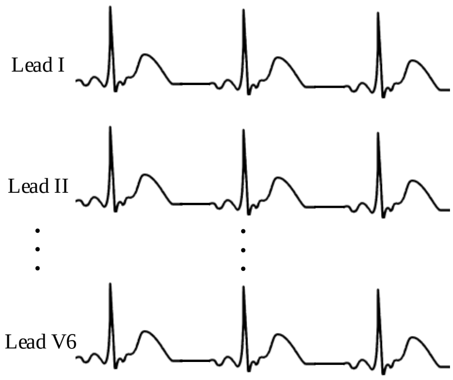

Figure 1. 12-lead electrocardiogram for clinical diagnosis.

2. Related work

The techinques of computer aided electrocardiogram have been greatly developed in recent years, and some of them have been widely used in the clinical electrocardiogram examination. Various methods of detecting normal or abnormal electrocardiogram have been proposed, most of them are based on traditional classification of heartbeat data. The heartbeat classification is that classifying these heartbeat by rule reasoning [2] or statistical learning methods [3,4]. Because all the R waves in the waveform need to be detected by the heartbeat classifier, it may occur some errors in the division process of heartbeat waves before classification, which would also reduce the accuracy of ECG classification in the next step. In order to overcome this deficiency, the way of classifying the whole ECG were developed later (without division of the heartbeat). It is popular to empoy machine learning method to classify ECG, but features such as Time domain, Waveform, Wavelet [5], Higher order [6], Power spectrum [7], Lyapunov coefficient [8], Hermit coefficient [9], Shannon entropy [10], Hermite Polynomial coefficient [11], characteristics of linear prediction error [12] etc., are extracted by manual work. The Common used machine learning algorithms are: Principal Component Analysis (PCA) [13], Linear Discriminant Analysis (LDA) [14], Independent Components Analysis (ICA) [15], Support Vector Machine (SVM) [16] etc. Some researchers tried using deep learning tool to extract the features of the electrocardiogram waves, for example,Kiranyaz et al. [17] employed Convolutional Neural Network (CNN) to exact features, and then utilized the SVM as the classifier, as a result, they achieved a good performance. Therefore, deep learning method began to be noticed.

Besides, there are some machine learning methods for solving one type of special cardiac problems. In [23], it is a survey paper about the atrial fibrillation detection based on ECG signals. It mainly reviews the machine learning methods to detect atrial fibrillation problems. For the papers [24–27], they are mianly solving one area problem such as myocardial infarction detection, ventricular arrhythmias detection, Glaucoma detection, congestive heart failure detection. But we can detect multiple cardiac problems instead of only detect one.

In machine learning, feature extraction by manual work cannot accurately reflect the exact feature of the electrocardiogram itself. Besides, the extraction of these features requires a better understanding of ECG domain knowledge, which is difficult for technique researchers without deep medical background. In the proposals of deep learning based ECG detection, most of them employs convolutional neural networks (CNN). While, multi-lead ECG is commonly treated as a two-dimensional image since two-dimensional convolutional operation is used inside the CNN network. However, Because of the particularity of the leads of ECG, it is not appropriate to treat it as two-dimensional image only. In this paper, we propose a model combining convolutional neural network and recurrent neural network. For each lead of electrocardiogram, we firstly employ one-dimensional convolutional operation to extract features, then employ recurrent neural network to fuse features of leads to get deeper feature maps. Finally, the validity of the proposed model was verified in this paper.

3. Methods

In general, there are 12 leads in a electrocardiogram, each lead is a waveform of a ECG signal. Each lead usually collects 10 seconds electrocardiogram data, including 12 to 18 times cardiac pulsation, 500Hz sampling frequency, and the ECG signal is corresponding to a 5000 dimensional vector each lead, so the 12 leads of ECG recording of each individual data have 12*5000 dimensions. Our task is to make the classification of the normal and abnormal of the 12 leads electrocardiogram, which is a binary classification problem. Multi-lead ECG is similar to two-dimensional image. But there is still some difference between the multi-lead electrocardiogram and the two-dimensional image. Because there is strong correlation between the data in the row direction and the column direction of the two-dimensional image while Multi-lead ECG has strong correlation with data in the same lead (row direction), but data from different lead directions (column direction) can be regarded as independent one. A series of one-dimensional convolutional and pooling operations are used to obtain the low dimensional vector representation of ECG signals based on the special two-dimensional structure of multi-lead electrocardiogram. At the same time, there is a certain time series between the different leads. The low dimensional vector representation of each lead is input into the LSTM layer. Finally, the Softmax layer is utilized to classify it and the class labels of normal or abnormal can be achieved.

Our model (CBRNN) combines the advantages of CNN and RNN. In our model, not only the features of the leads are considered, but also the deeper features to be learned are aslo involved, which is quite helpful for enhancing the accuracy of the deep learning model on ECG. The model architecture is shown in Figure 2.

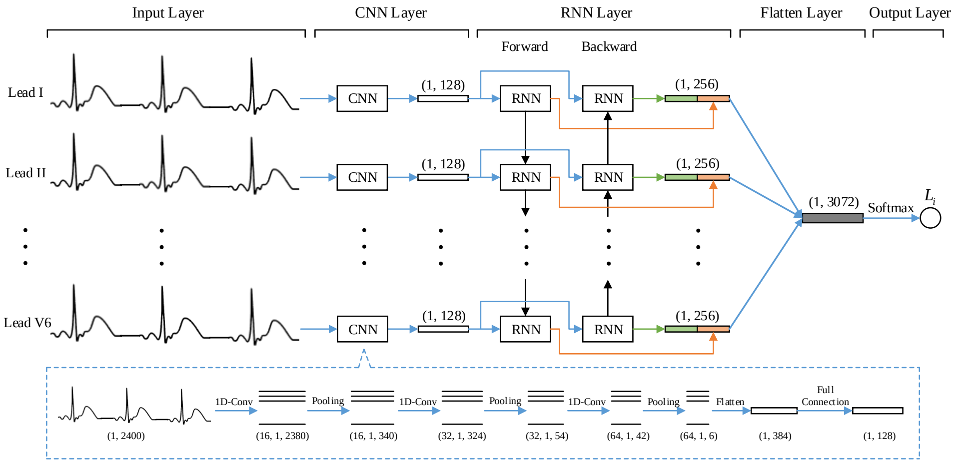

Figure 2. The architecture of our model.

The architecture is divided into the following layers:

(1) Input layer. The pre-processed 12-lead electrocardiogram was input into the input layer. A lead is a one dimensional vector, the length of which is 1*2400.

(2) CNN layer. Each lead of the ECG is passed through a convolutional neural network layer and then a 1*128 one-dimension vector can be created, but the parameters of the lead are not shared. Inside the CNN layer, the workflow is as follows: the dimension of the input layer is 1*2400, in the first CNN layer C_1, it has 16 feature maps, each feature map uses a convolutional kernel of 1*21, this layer outputs 16 feature maps with 1*2380 dimensions. Then, a pooling layer P_1 with a 1*7 pooling kernel is employed to produce 16 feature maps with 1*340 dimension; the second convolutional neural network layers C_2 has 32 feature maps, 1*17 convolutional kernels, the second pooling layer P_2 has a 1*6 pooling kernel; the third convolutional neural network C_3 has 64 feature maps, 1*13 convolutional kernels; the third pooling layer P_3 has a 1*7 convolutional kernel and produces 64 1*6 feature maps. Then, the feature maps are flattened. A 1*384 one dimensional vector can be generated. At last, the vector connects a fully connected layer and a 1*128 one dimensional vector can be finally generated. Since the ECG of each individual has 12 leads, the finally obtained vector through the CNN layer is 12*1*128 dimensions.

(3) RNN layer. we employed Bidirectional RNN (BRNN) [18]. The basic idea of BRNN is that each training sequence consists of two RNNs, which represent forward and backward, and both are connected to an output layer. The structure provides the complete privious and subsequent context information for each point in the input layer. We believe that the information is not only related to the previous information, but also the subsequent, therefore we choose BRNN as the main framework. Besides, the performance of BRNN should be better than original RNN, and we employ Long Short Term Memory Network (LSTM) as BRNN basic cell, The structure of LSTM is shown in Figure 3. Since BRNN can consider both the previous and the latter influnce in one moment, the historical information is actually more abundant. Suppose the output of forward recurrent neural network is h_{ft}, the output of reverse recurrent neural network is h_{bt}, then the output of BRNN is $h_t = [h_{ft}^T, h_{bt}^T]^T$.

The input of each neural in RNN is a one-dimension vector of 1*128, after the forward RNN and the backward RNN, the final output of bi-directional LSTM layer is a vector of 1*256 dimension.

(4) Flatten layer. Flatten all the outputs of RNN neural, a one-dimension vector of 1*3072 dimension can be generated.

(5) Output layer. Softmax is employed to classify the output of the last layer (two classifications), the label L_i can be achieved.

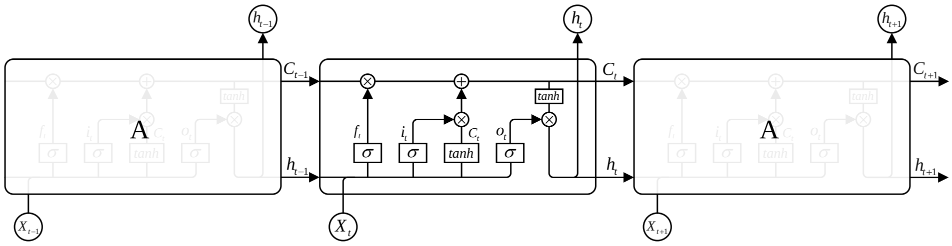

Figure 3. LSTM structure in BRNN.

4. Results

4.1. Dataset

With the continuous development of ECG acquisition equipment and the rapid expansion of the demand, existing standard database such as MIT-BIH, QT, CSE and AHA have showed a lack of scale and representativeness to varying degrees. While Chinese Cardiovascular Disease Database (CCDD) is a big dataset and it has 193690 cases. Each electrocardiogram has 10 to 20 seconds 12-lead electrocardiogram data. Each electrocardiogram record has a corresponding label of disease types, which is of great practical value.

All the data in CCDD are all real data instead of simulation data, so some data should be cleaned to be used for deep learning. We discard about 4850 pieces of data where the annotation records is 0×00 which is invalid), Each lead of each valid record is only intercepted by the first 4850 points. Then the records of the annotation for 0×0101, 0×020101 and 0×020102 are normal, and the other annotation results are abnormal. Then the electrocardiogram is sampled from 500Hz to 250Hz, to reduce the data dimension without affecting the data quality. At the same time, for the stability of the waveform of the electrocardiogram, we skipped the beginning of the 25 sampling points, and finally got the 12*2400 dimension of each individual electrocardiogram. The CCDD dataset consists of many batches of the data, After these pre-treatments are carried out above, the positive anomaly distribution of each batch of datasets can be studied out which is shown in **Error! Reference source not found.**.

Table 1. The distribution of each package of datasets.

Dataset	Package	Valid		Invalid
		Normal	Abnormal	
Training	data95830-119551	10347	12940	435
	data119552-141104	9704	11526	323
Validation	data141105-160913	9710	9828	271
Test	data1-943	197	746	0
	data944-25693	17461	7204	85
	data25694-37082	4910	6350	129
	data37083-72607	25014	10246	265
	data72608-95829	16203	6507	512
	data141105-160913	9710	9828	271
	data160914-175871	6942	7777	239
	data175872-179130	2289	936	34
	data179131-193690	4670	9562	328

In order to avoid the problem of imbalanced distribution of normal and abnormal samples in training centralization, the package “data95830-119551” and the package “data119552-141104” are selected to be our training sets, the package “data141105-160913” are selected to be the validation datasets, the rest are used as test datasets. Consequently, the number of the training data, validation data and the test data are 44517, 19538 and 127014. Most of the samples are selected as test sets because the small test set may have some overfitting problems. The final goal is to make our model help in clinical diagnosis. We need to verify the performance of the model on a large real test set so that it reflects the real environment of clinical medicine.

`According to the definition of medical diagnosis, the normal electrocardiogram was negative, and the abnormal electrocardiogram was positive. Table 2 describes the possible relationship between the gold label and the decision label.

Table 2. Possible relationship between true and prediction label.

Decision label	Gold label	
	Negative(normal ECG)	Positive(abnormal ECG)
Negative	True Negative(TN)	False Negative(FN)
Postive	False Positive(FP)	True Positive(TP)

In order to measure the performance of an electrocardiogram classification model, the diagnostic indicators we used include Specificity S_p, Sensitivity S_e and Accuracy Acc. Specificity S_p means that the proportion of the normal electrocardiogram is correctly detected, and sensitivity S_e is the correct detection of the proportion of the abnormal electrocardiogram. Accuracy S_e is the proportion of the correct classification of the electrocardiogram. In general, Accuracy is regarded as the main reference. These evaluation criteria are calculated as follows:

$$S_p = \frac{TN}{TN + FP} \tag{4-1}$$

$$S_e = \frac{TP}{TP + FN} \tag{4-2}$$

$$Acc = \frac{TP + TN}{TP + FP + FN + TP} \tag{4-3}$$

4.2. Experiment Setup and Results

The original electrocardiogram signals often contain various interference signals, for example, the frequency of respiratory movement is lower than 0.5Hz, 50–60Hz high frequency wave is induced by power frequency, about 33Hz is produced by body muscle activity etc. Therefore, the dianoising process needs to be done before the classification of the electrocardiogram. The low pass filter and band-pass filter are used to filter the noise. Then each ECG in the CCDD dataset is sampled as 250Hz, meanwhile, the first 25 sampling points are skipped, a 12*2400 vector of the ECG for each individual is obtained. Finally, the model we have built to classify the class label of the electrocardiogram and get the category it belongs to.

Our model is data driven and end-to-end training, we train all models on the whole training dataset and tune our hyper parameters on the validation set, and we use test set to evaluate our model. Parameters inside the model are shown in Figure 2. At the same time, we set the maximum number of iterations to be 1000 and learning rate to be 0.01. The early stopping mechanism is used to stop the iteration ahead of time in order to prevent the model from overfitting.

In order to highlight the performance of the model we have built, we built another two convolutional neural networks in our experiment to be compared with. With the original CNN model solving ECG data, it commonly treats them as a two-dimensional image. Therefore, we firstly construct an ordinary three layers' two-dimensional CNN model. The model through the convolutional layer and the pooling layer three times to extract the features of the electrocardiogram signal. Three convolutional kernels are 3*21, 3*17 and 3*13 separately and three pooling kernels are 1*7, 1*6 and 1*7. At last, after the same flattening operation, Softmax layer is used for classification. At the same time, the Residual network (ResNet) is constructed as a contrast. Residual connection is different from the traditional network structure, and the corresponding network Resnet proposed by Kaiming He [19] who won the championship in 2015 ImageNet competition. In view of the excellent performance of the ResNet network, we employ the ResNet network to classify the electrocardiogram. Thus, we also implement two contrast models, which are traditional CNN and ResNet model, to compare with our CBRNN. The experimental results are shown in Table 3.

From Table 3, it is clearly that ResNet network from Google is better than the traditional CNN model and the Acc is increased by 1.06%, which showed the advantages of the ResNet network. However, both the traditional CNN model and the ResNet model are the two dimensional convolutional operation for the multi-lead electrocardiogram. Multi-lead ECG is strongly correlated with data in the same lead (row direction), but the data on each lead (column direction) can be regarded as individual. Therefore, two-dimensional convolutional operation is not that accurate. In this paper, a CBRNN model is designed for multi-lead ECG. For each lead, one-dimension convolutional operation is adopted. At the same time, bidirectional RNN is used to fuse different lead features to get deeper feature representation. Consequently, our CBRNN model shows more consistent with the lead feature of ECG itself, and experiments result shows better than that of CNN model and ResNet model, Acc of which are increased by 3.41% and 2.35%, respectively. It is proved that the CBRNN model we proposed is effective in dealing with the problem of classification on electrocardiogram.

Table 3. Comparison of experimental results.

Model	Classification result	Gold result Normal	Abnormal	S_p	S_e	Acc
CNN	Normal	65601	17710	75.06	70.06	**84.28**
	Abnormal	21795	41446			
Resnet	Normal	65769	16531	75.25	72.06	**85.34**
	Abnormal	21627	42625			
CBRNN	Normal	66703	14480	76.32	75.52	**87.69**
	Abnormal	20693	44676			

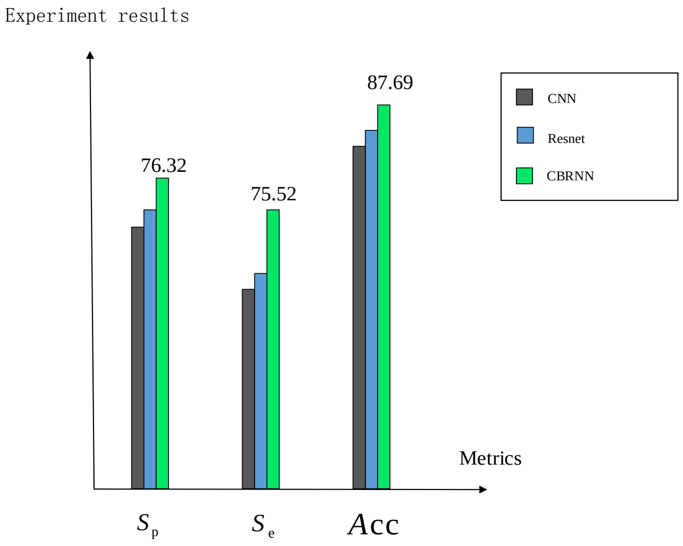

Figure 4. Comparison of experimental results.

To further evaluate the performance of our proposed approach, we compare it with the existing classification algorithms of electrocardiogram. According to the second chapter of related work, the model proposed by Ye et al. [5] is the best model currently. Hence, we train a heartbeat classifier based on the method proposed by Ye et al. First, we need to intercept the heartbeat on each ECG record from the dataset, which need to first detect the R wave in the waveform, so we utilized the method proposed by Zhu et al. [20] to detect all the R waves on an ECG record and then intercept the heart beat according to the position of the R wave. There are usually two ways to intercept the heartbeat, namely, the average heart beat method and the exception priority method [21]. Finally, the heartbeat classifier is constructed to determine the conclusion of the test centralized electrocardiogram. Since the interception method has average beat and abnormal priority, we use the data set mentioned in this paper to achieve two different heartbeat classifiers, that are HBClassifier[A] and HBClassifier[B].The experiment results are shown in Table 4.

Table 4. Comparison of different ECG classification models.

Model	Classification result	Gold result Normal	Gold result Abnormal	S_p	S_e	*Acc*
HBClassifier[A]	Normal	53396	18282	61.10	69.10	**74.22**
	Abnormal	34000	40874			
HBClassifier[B]	Normal	50421	18343	57.69	68.99	**71.83**
	Abnormal	36975	40813			
CBRNN	Normal	66703	14480	76.32	75.52	**87.69**
	Abnormal	20693	44676			

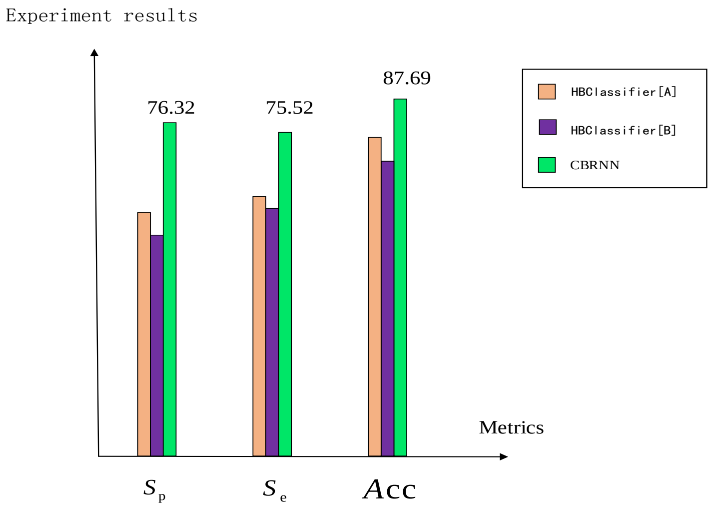

Figure 5. Comparison of different ECG classification models.

4.3. Discussion

All of these models use the same training set and validation set to build models, and test the performance of models on the same test set, so that the results are comparable. From Table 4, we can see that the CBRNN model proposed in this paper is much higher than the HBClassifier[A] model and HBClassifier[B] model in all performance indicators, and the accuracy rate is higher than 13.47% and 15.86% respectively. It can be seen that the robustness of the model proposed by Ye et al. is not strong enough. The possible reason is that there are only 48 individual ECG records in MIT-BIH-AR dataset. The size of the dataset is small, and there may be contingency and imbalance in data distribution. The CCDD database has more than 190 thousand individual clinical ECG records, and there is no imbalance in data distribution, where Ye' model shows a relative poor result. Hakacova et al. [22] survey and compare the performance of automatic diagnosis and human diagnosis of electrocardiogram equipment on the market, and they concluded that human diagnosis has a higher average accuracy than the automatic diagnosis , which is about 85% of 3 professional doctors to diagnose the clinical ECG data. While the accuracy of our proposed model in the large scale clinical ECG data set is up to 87.69%. Therefore, our model proposed in this paper has an advantage to apply to the clinical medicine.

5. Conclusion

In this paper, we propose a deep learning model to classfiy ECG data for assisited ECG diagnosis by machine. The model has a comination design of CNN and bidirectional RNN, which make full use of the features of ECG data. We test the performance of the model on some open dataset including a big dataset Chinese Cardiovascular Disease Database (CCDD), the accuracy of the model is up to 87.69%, exceeds the existing models of ECG classfication. It has value for clinical application in the future.

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Conflict of interest

We declare that there is no conflict of interests regarding the publication of this article.

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