A LSTM AND CNN BASED ASSEMBLE NEURAL NETWORK FRAMEWORK FOR ARRHYTHMIAS CLASSIFICATION

Fan Liu[1,3], *Xingshe Zhou*[1], *Jinli Cao*[2], *Zhu Wang*[1], *Hua Wang*[3], *Yanchun Zhang*[3]

[1] School of Computer Science, Northwestern Polytechnical University, Xi'an, China
[2] Department: Computer Science and Computer Engineering, La Trobe University, Melbourne, Australia
[3] College of Engineering and Science, Victoria University, Melbourne, Australia

ABSTRACT

This paper puts forward a LSTM and CNN based assemble neural network framework to distinguish different types of arrhythmias by integrating stacked bidirectional long shot-term memory (SB-LSTM) network and two-dimensional convolutional neural network (TD-CNN). Particularly, SB-LSTM is used to mine the long-term dependencies contained in electrocardiogram (ECG) from two directions to model the overall variation trends of ECG, while TD-CNN aims at extracting local information of ECG to characterize the local features of ECG. Moreover, we design an ensemble empirical mode decomposition (EEMD) based signal decomposition layer and a support vector machine based intermediate result fusion layer, by which ECG can be analyzed more effectively, and the final classification results can be more accurate and robust. Experimental results on public INCART arrhythmia database show that our model surpasses three state-of-the-art methods, and obtains 99.1% of accuracy, 99.3% of sensitivity and 98.5% of specificity.

Index Terms**—** Arrhythmia Classification, LSTM, CNN, ECG, Ensemble Empirical Mode Decomposition (EEMD)

1. INTRODUCTION

Arrhythmias are irregular heart rhythms caused by abnormal electrical activities of the heart, which can induce serious complications, such as stroke, heart failure, sudden cardiac death [1], and result in over 4.7 million death in the US and EU per year [2]. Clinically, heartbeats are usually categorized into many different types, such as normal beat (N), premature ventricular contraction (PVC), right bundle branch block beat (RBBB), atrial premature contraction (APC), etc [3]. Each of them shows different symptoms and requires different kind of treatments. Hence, it is crucial to classify different types of arrhythmias accurately, so as to provide effective and timely treatments [4].

Electrocardiogram (ECG) is a non-invasive and easily accessible physiological signal, has been diffusely utilized in existing computer-aided arrhythmias classification methods [5-11]. These methods were designed to follow the classical pattern recognition paradigm. To be specific, they first extract several features to model the fluctuation patterns of ECG by using techniques like time-frequency analysis [5, 6], spectral analysis [7], and so on. These features are then processed by feature selection algorithms to get the most informative ones. Finally, classifiers such as random forest [8], neural networks [9] was built based on the selected features. These methods have obtained good classification performance, however, the performance is hard to be further boosted. It's mainly because the noise in ECG can distort the waveform of ECG, hence the values of the extracted features may be not valid [8]; 2) ECG usually shows obvious inter- and intra-subjects variability, so the predesigned features may not be capable of characterizing every heartbeat accurately [8]. By comparison, deep learning-based approaches do not require explicit feature extraction procedure, and usually can obtain better performance [10, 11].

A normal heartbeat usually consists of P, Q, R, S, and T waves [11]. Different arrhythmias present some differences on these five waves. For example, the Fig. 1 of [10] indicates that the T wave of ventricular ectopic beat are significantly higher than that of non-ectopic beat. In other words, different arrhythmias types exhibit quite different overall variation trends in ECG wave. In addition, there are also obvious local differences between different arrhythmias types. For instance, the Fig. 1 of [10] shows that the R wave of non-ectopic beat is sharp, while that of supra-ventricular beat and unknown beat usually show some volatility. To sum up, both the overall variation trends and local features of ECG are useful for distinguishing different arrhythmias types. However, most existing studies only focus on one of them [10, 11], which we argue is hard to characterize the fluctuation patterns of ECG accurately.

To this end, this paper proposes a hybrid neural network-based arrhythmias classification model. The promising long short-term memory (LSTM) network [11] and convolutional neural network (CNN) [12] are used in the model. Concretely, we design a stacked bidirectional LSTM (SB-LSTM) layer and a two-dimensional CNN (TD-CNN) layer. These two layers are employed to extract the overall variation trends and local features respectively, aiming to model the fluctuation pattern of ECG more accurately. In addition, we design an

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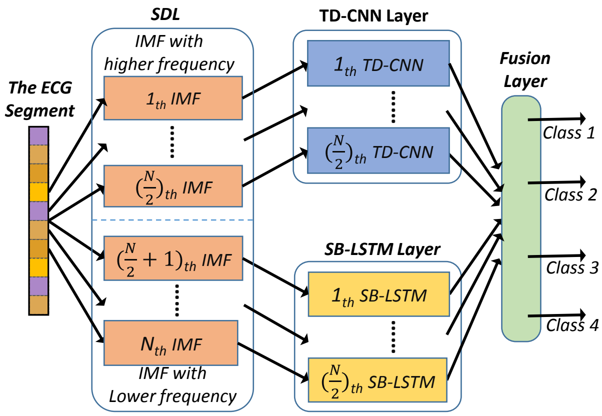

Fig. 1: The proposed arrhythmias classification model framework.

ensemble empirical mode decomposition (EEMD) [13] based ECG signal decomposition layer (SDL), and a SVM [14] based intermediate classification result fusion layer (FL). SDL is utilized to analyze ECG from multiple time-frequency resolutions, and obtains a set of intermediate classification results which are then fused into a final result by using FL. The proposed model achieves higher classification accuracy based on INCART arrhythmia dataset [3].

2. METHOD

2.1. The Arrhythmias Classification Model Framework

The framework of our model consists of four layers, i.e., SDL, SB-LSTM layer, TD-CNN layer, and FL, which is displayed in Fig. 1. Concretely, the ECG signal is first decomposed into multiple intrinsic mode functions (IMFs). Then, the IMFs with lower frequency and higher frequency are respectively fed into SB-LSTM layer and TD-CNN layer, with each IMF obtains an intermediate classification result. Finally, they are fused into a final classification result via FL. At a holistic level, the proposed model resembles a bagging classifier [15-16]. Specifically, SDL is used to create new instances, SB-LSTM and TD-CNN play the role of weak classifiers, and FL is used to fuse the intermediate classification results.

2.2. The ECG Signal Decomposition Layer (SDL)

EEMD is a noise assisted signal processing technique which is suitable for analyzing non-linear signals [13]. EEMD has been successfully applied in many fields, including biological signal analysis [17-20]. In SDL, we use EEMD to decompose ECG into multiple time-frequency resolutions, in order to extract more hidden information from ECG for classification.

The EEMD analysis includes 3 main steps. First, we add white noise whose average value is zero to the ECG signal.

$$x_t(t) = x(t) + n_i(t) \tag{1}$$

where $x_i(t)$ is the i_{th} ECG sample added with the i_{th} white noise. Second, we utilize the Empirical mode decomposition (EMD) algorithm [3] to decompose the $x_i(t)$ into several IMFs and a residue. Let $c_{ij}(t)$ and $r_i(t)$ are the j_{th} IMF after decomposition and the residue, respectively. Third, calculate the above corresponding IMFs and fuse them by utilizing an ensemble manner as follows:

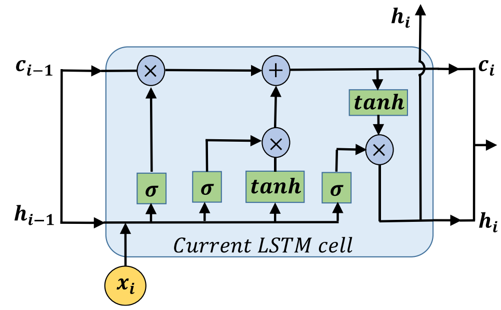

Fig. 2: An illustration of the internal structure of LSTM cell.

$$c_j(t) = \frac{1}{N}\sum_{i=1}^{N} c_{ij}(t) \tag{2}$$

where $c_j(t)$ denotes the j_{th} IMF of EEMD.

In this study, a total of 6 IMFs are obtained. Particularly, the first three IMFs are with higher frequency which contain more information about the detailed information of the ECG signal, while the last three IMFs are with lower frequency which contain more information about the trends of the ECG signal. Finally, the obtained IMFs are fed into the following network for further processing.

2.3. The Stacked Bidirectional LSTM (SB-LSTM) Layer

Medically, each heartbeat sequentially produces P, Q, R, S, T wave components in ECG [6]. The Fig.1 of [10] shows that although the same wave components derived from different arrhythmias types are not that different from each other, the waveform of the whole heartbeat is quite different from each other from an overall perspective. To model this kind of long-term fluctuation pattern of ECG, the LSTM was employed.

LSTM is a kind of recurrent neural network (RNN). It mitigates the problem of vanishing gradient of RNN, and is particularly suitable for processing time series signals [21-23]. The internal structure of LSTM cell is illustrated in Fig. 2, for a given input sequence $\mathrm{x_t}$ at time *t*, the corresponding output h_t and internal state c_t can be calculated as follows:

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{3}$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{4}$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{5}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \tag{6}$$

$$h_t = o_t \odot tanh(c_t) \tag{7}$$

where f_t, i_t and o_t are the forget gate, input gate and output gate of LSTM respectively, which jointly control the update of the h_t. Specifically, f_t is utilized to discard useless information contained in LSTM's past state, i_t determines what information should be added to LSTM's current state, and o_t decides what information should be output. Benefiting from these three gates, the long-term dependencies in time series can be effectively extracted.

In this study, we design a SB-LSTM to characterize the overall variation trends of ECG. Concretely, the proposed SB-LSTM is comprised of three LSTM layers, and the output of non-last layers is used as the input of the next layer. Each layer contains two LSTM cells that have opposite directions, aiming at capturing the forward and backward dependency respectively. Specifically, each LSTM has 32 neurons, which is the trade-off between the fitting ability and the complexity of the network. In order to reserve more useful information, we fuse the output of SB-LSTM corresponding to each time step to a one-dimensional vector as follows:

$$Y = [Y_{1,f}, Y_{1,b}, \dots Y_{i.f}, Y_{i,b}, \dots, Y_{N,f}, Y_{N,b}], \quad (8)$$

where $Y_{i,f}$ and $Y_{i,b}$ are the forward and backward dependency corresponding to the i_{th} ECG sample. Furthermore, to avoid the impact of detailed information of ECG on the accuracy of the extracted long-term dependencies, we feed the three IMFs with lower frequency to mutually independent SB-LSTMs. Finally, each IMF got an intermediate classification result by using a fully-connected layer (FCL) containing five neurons and a softmax function [11, 23].

2.4. The Two-dimensional CNN (TD-CNN) layer

Recently, CNN has shown powerful ability to extract local spatial-time features in image recognition field [24]. Hence, we design a TD-CNN to mine short-term fluctuation patterns of ECG, in order to depict ECG more accurately [25].

CNN is the first neural network that is characterized by employing hierarchical neuron layers to effectively extract local features from data. It has been successfully applied to many research areas, including image recognition [24]. In CNN, the spatial features are extracted by convolutional layers (CLs). Let $F_{i,j,k}$ and $K_{i,j,k}$ denote the element of the i_{th} row, j_{th} column and k_{th} channel of the feature map F, and the corresponding convolution kernel K respectively, the $A_{i,j}$, i.e., the element of the i_{th} row and j_{th} column of the convolved result A can be computed as follows:

$$A_{i,j} = \sigma\left(\sum_{d=0}^{C-1}\sum_{m=0}^{H-1}\sum_{n=0}^{W-1} K_{d,m,n} \cdot F_{d,i+m,j+n} + w_b\right), \quad (9)$$

The proposed TD-CNN consists of two convolutional layers, one max-pooling layer, one average-pooling layer and two FCLs. In particular, the convolutional layers are used to extract local features from input data, while the two pooling layers aim to learn higher level features without enlarging the size of the filters. Concretely, the two convolutional layer are the same, and contains 32 filters whose size are 4×4 with a stride of 2. The size of the two pooling layers are set to 2×2. The two FCLs contains 32 and 5 neurons respectively. It's notable that all these hyper parameters are set empirically. In this study, the three IMFs with higher frequency obtained in SDL are fed into three mutually independent TD-CNN, so as to eliminate the trend-related information from ECG. In particularly, to adapt to the input format of the TD-CNN, we reshape each IMF into a square matrix-like two-dimensional vector by stacking itself in column. Finally, each IMF gets an intermediate classification result by using a softmax function.

2.5. The Fusion Layer (FL)

In our arrhythmias classification framework, the ECG signal segment corresponding to each heartbeat is decomposed into several IMFs. The IMFs with lower higher frequency are fed into SB-LSTM and TD-CNN respectively, and finally obtain a mutually intermediate classification result. However, these results may be not the same. In order to obtain more accurate classification results, we design a support vector machine (SVM) based fusion layer to fuse these results into a final one. SVM is an effective machine learning based classifier, which has been widely used to tackle classification and regression problems [26]. Usually, SVM projects instances into a high-dimensional feature space, and then utilizes a hyperplane to divide them into two classes. In this study, the intermediate classification results obtained by each SB-LSTM and TD-CNN are first integrated into a feature vector, which is then fed into a SVM classifier to get the final classification result. In this way, we can take advantages of the fitting ability of multiple SB-LSTMs and TD-CNNs, and hence obtain higher classification accuracy.

3. EXPERIMENTAL EVALUATION

3.1. Dataset and Data Preprocessing

The public INCART database [3] is utilized to evaluate the performance of our model. It consists of 75 annotated ECG segments extracted from 32 Holter records (sampled at 257 Hz) collected from 17 men and 15 women (aged 18-80). Each of them lasts 30 minutes and contains 12 leads, with only the first lead used in this study. Four types of beats including N, PVC, RBBB and APC are extracted from the dataset. First, we use the 256 samples around the P-peaks to represent each heartbeat [10]. Particularly, the first and the last beats which may lose necessary ECG wave components and the beats that do not contains enough samples are discarded. Afterwards, the SOMTE algorithm is utilized [27] to synthesize heartbeats for the class with fewer instance (i.e., PVC, RBBB and APC). Finally, a total of 598828 heartbeats are obtained, with each arrhythmia type has the same number of heartbeats (149707).

3.2. Experimental Setup

We represent the class label by utilizing the one-hot encoding, and employ the categorical cross-entropy function to denote the loss of the network as follows:

$$\mathcal{L} = \frac{1}{\widetilde{N}}\sum_{i=1}^{\widetilde{N}}(y_i\, log(\widehat{y_i}) + (1 - y_i)log(1 - \widehat{y_i})), \quad (10)$$

where $\widetilde{N}$ denotes the number of heartbeats in a mini-batch, while y_i and $\widehat{y_i}$ represent the true label and predicted label of the i_{th} heartbeat, respectively. The LeakyRelu [10] is used as activation function so as to avoid shielding negative outputs, which is conducive to retaining more useful information. We employ the Adam optimizer [11] to update the parameters. In particular, a dropout layer is applied to avoid over-fitting. In addition, decayed learning rate is utilized exponentially every 1000 iterations to accelerate the training process, where the learning rate is initialized as 0.002 with a decay factor of 0.9. We randomly divide the dataset into training set, validation set and test set at a ratio of 0.7:0.1:0.2. Specifically, we record the performance every 100 iterations and the network with the highest accuracy is chosen as the final model. The dataset five times

Accuracy (ACC), sensitivity (SEN) and specificity (SPE) are used as the evaluation metrics. Obviously, a good model should obtain high ACC, SEN and SPE simultaneously.

3.3. Evaluation Results

3.3.1. Comparison with state-of-the-art models

We compare the proposed model with 3 baselines proposed in [7], [10] and [11]. In particular, Ref. [7] is a traditional feature engineering based approach, while Ref. [10] and Ref. [11] are deep neural network based models where LSTM and CNN are separately employed. We recurred these baselines based on our balanced dataset so as to guarantee the fairness of the comparison. As shown in Table 1, our model achieves the highest performance, and surpasses the method in [7] by 5.6% of ACC, 5.2% of SEN and 6.8% of SPE. Although the LSTM-based model [11] and the CNN-based model [10] can obtain better results comparing with the method in [7], their performance is still lower than our model, which indicates that extracting only overall variation trends or local features is difficult to characterize the fluctuation pattern of ECG comprehensively. In addition, the performance of our model and the methods proposed in [10] and [11] are better than that of [7], which shows the stronger information extraction and fitting ability of deep neural network.

3.3.2. Effect of Different Network Layer

To evaluate the contribution of designed network layers, we display the performance of different combinations of network layers in Table 2, from which we find that: 1) the SB-LSTM layer obtains similar performance when compared with TD-CNN, which indicates that the overall variation trends and the local features of ECG are equally important for distinguishing different arrhythmias types; 2) the combination of SB-LSTM and TD-CNN bring more than 2% performance improvement, which means that more useful information can be extracted in this case; 3) benefiting from the utilization of SDL and FL, the performance reaches 99.1% of ACC, 99.3% of SEN and 98.5% of SPE, which shows the effectiveness of our bagging classifier-like assemble neural network architecture.

3.3.1. Comparison with Similar Network Structures

To demonstrate the superiority of our network architecture, we compare it with some similar network structures by replacing the designed network layers with similar variants. Concretely, for SB-LSTM, three variants, i.e., stacked directional LSTM (SD-LSTM), unstacked bidirectional LSTM (UB-LSTM) and unstacked directional LSTM (UD-LSTM) are created. As for TD-CNN, we use a one-dimensional CNN layer (OD-CNN) as the variant. In addition, the inclusion or exclusion of SDL and FL are also considered, which are denoted as with-SF and without-SF, respectively. Eventually, 15 similar structures are obtained, whose performance is summarized in Table 3.

Table 3 shows that our network structure achieves the best classification performance. In particular, three observations are obtained: 1) the use of SDL and FL significantly improves the classification performance no matter which kind of LSTM layer and CNN layer are utilized, which maybe because that decomposing ECG into IMFs is conducive to exposing more hidden information for classification, and that the utilization of FL can effectively eliminate the bias of each intermediate classification result and hence yields more accurate results. 2) SB-LSTM and UD-LSTM respectively obtain the highest and lowest performance among all LSTM-based variants. It may be due to that SB-LSTM can extract long-term dependencies from two directions, which is helpful for characterizing the overall variation trends of ECG signal more accurately. 3) The performance of TD-CNN is higher than that of OD-CNN in most cases, which is because that the input of TD-CNN is comprised of the outputs of LSTM-based layer corresponding to each time step while the input of OD-CNN only contains the output corresponding to the last time step, therefore, more useful information can be mined by TD-CNN.

Table 1: Comparison with state-of-the-art models.

Combinations of Layers	*ACC (%)*	*SEN (%)*	*SPE (%)*
Our Method	99.1	99.3	98.5
Elhaj et al. [7]	93.5	94.1	91.7
Acharya et al. [10]	95.0	95.3	94.0
Yildirim et al. [11]	96.3	97.0	94.3

Table 2: The effect of different network layers.

Combinations of Layers	*ACC (%)*	*SEN (%)*	*SPE (%)*
SB-LSTM	95.2	95.9	9.31
TD-CNN	95.0	95.4	93.7
SB-LSTM + TD-CNN	97.2	97.4	96.4
SDL+SB-LSTM+TD-CNN+FL	99.1	99.3	98.5

Table 3: Comparison with Similar Network Structures.

Network Structures			*ACC (%)*	*SEN (%)*	*SPE (%)*
With_SF	UD-LSTM	OD-CNN	91.3	91.4	90.9
		TD-CNN	95.2	95.7	93.7
	UB-LSTM	OD-CNN	93.9	94.6	91.7
		TD-CNN	96.5	96.8	95.8
	SU-LSTM	OD-CNN	96.0	96.6	94.2
		TD-CNN	97.6	97.8	97.1
	SB-LSTM	OD-CNN	96.4	96.6	95.8
		TD-CNN	99.1	99.3	98.5
Without-SF	UD-LSTM	OD-CNN	91.5	91.7	91.0
		TD-CNN	92.1	92.1	91.9
	UB-LSTM	OD-CNN	91.0	91.4	90.0
		TD-CNN	93.0	93.2	92.5
	SU-LSTM	OD-CNN	92.7	93.8	89.4
		TD-CNN	93.1	93.5	91.9
	SB-LSTM	OD-CNN	94.4	94.7	93.5
		TD-CNN	95.6	95.8	94.9

4. CONCLUSION AND FUTURE WORK

In this paper, a novel arrhythmias classification model is proposed based on SB-LSTM and TD-CNN. It's an end-to-end method that doesn't require complex feature extraction and feature selection procedures. Experimental results shows that the integration of SB-LSTM and TD-CNN brings about 2% performance improvement. Moreover, the decomposition of ECG and the fusion of intermediate classification results are also proved to be useful. In addition, our model has the optimal network structure, and yield unbiased classification results. Finally, it outperforms 3 state-of-the-art methods, and obtains 99.1% of accuracy, 99.3% of sensitivity and 98.5% of specificity. Future work focuses on designing a simpler but more effective network structure.

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