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ECG ARRHYTHMIAS CLASSIFICATION BASED ON DEEP LEARNING APPROACH

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Abstract. *In this paper, a novel approach based on deep learning for ECG arrhythmias classification is proposed. It consists of four steps: ECG signals preprocessing, segmentation & resampling, features learning, and classification. Different from other segmentation methods, we add resampling to change all segmented ECG beats into the same periodic length for the deep learning model. For learning features from resampled ECG signals, a deep belief network is constructed with two types of restricted Boltzmann machine including Gaussian-Bernoulli and Bernoulli-Bernoulli. In order to enhance performance of deep belief network, a fine-tuning process is carried out, which uses back-propagation by adding a softmax regression layer on the top of the feature vector layer to perform multiclass classification. The feature vector of each heartbeat includes the abstract features learning from deep belief network and temporal features. The method is then validated by experiments on the well-known MIT-BIH arrhythmia database. The experiment results show our approach achieves better performance than traditional hand-designed methods on the classification of ECG arrhythmias.*
Keywords: ECG arrhythmias classification, Deep learning, Deep belief network, Feature extraction

1. **Introduction.** Electrocardiography (ECG) is the process of recording the electrical activity of the heart over a period of time using electrodes placed on the skin. It is the most widely used non-invasive technique in arrhythmias diagnoses. However, some arrhythmias appear infrequently, and then a mobile cardiac device such as the Holter or Loop Recorder is often used to record the ECG data. The mobile devices of cardiac event monitoring usually work 24hr, 48hr and even 14 months and store a large number of ECG data [1]. Thus, automatic classification of these arrhythmias is of great assistance to the clinician.

There are two key steps in the classification systems of ECG arrhythmias: feature learning and classification algorithms. In the past decade, many feature extraction methods of ECG signal have been proposed in the literatures such as morphological features [2], temporal intervals [3], wavelet transform [4,5], and statistical features [6]. In order to get most suitable set of features, multiple feature extraction methods are often combined in applications. Moreover, feature reduction techniques such as principal component analysis (PCA) and independent component analysis (ICA) [5,7] have also been applied to projecting hundreds of ECG features into a lower dimensional feature space. Once the lower dimensional feature space is defined, the classification models for arrhythmia can be constructed by using intelligence algorithms such as neural network [8], optimum-path forest (OPF) [9], and swarm intelligence algorithms (SI) [10].

Although the above-mentioned techniques have been experimented on standard arrhythmias dataset and have a high accuracy in ECG classification, there are several issues.

- The process of feature extraction requires participation of the ECG data expertise that consumes more time and cost.
- Some feature information in the ECG source data could be lost since the ECG feature extraction method is hand-crafted.
- The constructed model of ECG classification has low adaptability in the inter-patient.

In order to solve the abovementioned problems, deep learning (DL) attracted much attention in recent years. The idea of DL is to learn a layer of good feature representations automatically from the input data. Compared with traditional methods, DL has shown outstanding results in many applications such as image classification [11], speech recognition [12] and physiological data [13]. Typical DL architectures consist of deep belief network (DBN) [14], stacked auto-encoder (SAE) [15], and convolutional neural network (CNN) [16]. Some researchers have achieved positive results on the ECG classification using DL technology. Kiranyaz et al. [17] used 1-D CNN for patient-specific ECG real-time classification, and experimented with inner-patient ECG data represented by 64 and 128 samples. Rahhal et al. [13] used SAE to learn features from the raw ECG data for ECG classification and verified by the raw inter-patient ECG data including morphology and temporal features equaling 54 for each beat. Yan et al. [18] and Meng and Zhang [19] all used DBN to automatically extract features for ECG classification and experiment with inner-patient ECG data represented by 340 samples and 250 samples respectively. These papers used different raw ECG data representations for the input sample of DL model. However, every sample should include all hidden features which are used to distinguish the arrhythmias.

In this paper, we propose a new method based on deep learning for ECG arrhythmias classification. All segmented ECG beats are resampled into a same periodic length. A DBN stacked with two types of restricted boltzmann machine (RBM) such as Gaussian-Bernoulli (GBRBM) and Bernoulli-Bernoulli (BBRBM) is used to automatically learn features from them. In order to fine-tune DBN, a softmax regression layer is added on the top of feature vector layer to perform multiclass classification. The feature vector consists of the abstract features learning from deep belief networks and RR temporal features. At last the proposed approach is validated on real ECG signals from the well-known MIT-BIH arrhythmia database and following the recommendations of the association for the advancement of medical instrumentation (AAMI). The experimental results show that the proposed method achieves higher accuracy than traditional hand-designed methods on the classification of ECG arrhythmias.

The rest of the paper is organized as follows. Section 2 presents the proposed method including ECG signals preprocessing, segmentation, resampling, feature learning and classification. The results obtained from the experiments on MIT-BIH dataset are discussed in Section 3. Finally, conclusions are drawn in Section 4.

2. **Proposed Method.** Figure 1 depicts the stages of ECG arrhythmias classification. It consists of four steps: ECG signals preprocessing, segmentation & resampling, features learning, and classification. As the figure shows, all steps are interrelated and determine the quality of classification result.

ECG signals preprocessing. Prior to using the ECG signal in the subsequent processing of heartbeat segmentation and features learning all signals are removed of the baseline wander and the noise of power-line and high-frequency. Following the literature [2], two-stage median filters of 200 ms and 600 ms are used to remove the baseline wander respectively. The first median filter suppresses the QRS (Q wave, R wave and S wave)

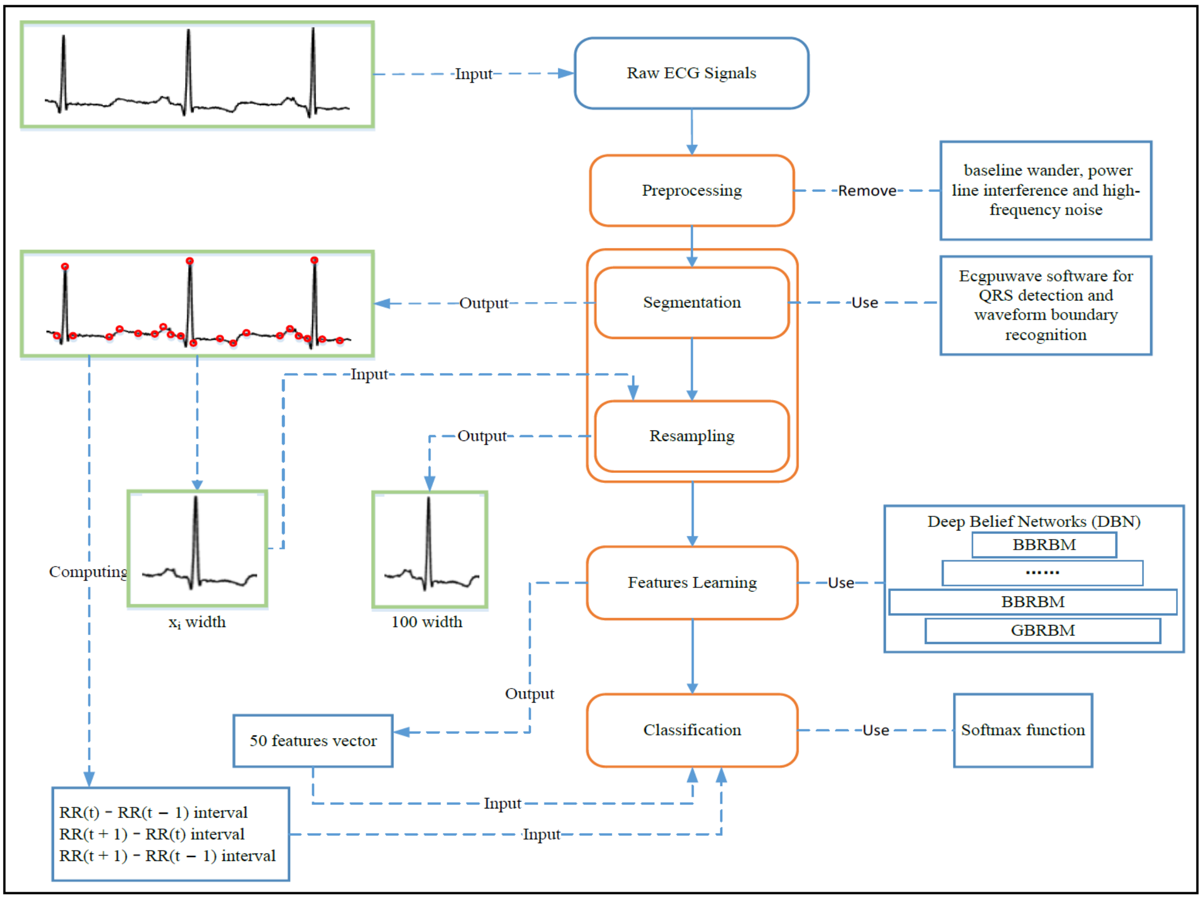

FIGURE 1. Stages of ECG arrhythmias classification

complexes and P waves while the second median filter suppresses the T waves. Then a 12-tap low-pass filter with 3-dB point at 35 Hz is used to remove the power-line and high-frequency noise from the baseline corrected ECG signal. The filtered ECG signals are used in all subsequent processing.

Segmentation and resampling. The ecgpuwave software available on "http://www.physionet.org/physiotools/ecgpuwave/" is firstly utilized to perform the QRS-complexes detection and ECG wave boundary recognition. Then the ECG heartbeat waveform can be segmented according to the P-wave onset and T-wave offset times. In addition, considering the importance of the temporal information, three RR intervals such as RR(t) – RR(t−1) interval, RR(t+1) – RR(t) interval, and RR(t+1) – RR(t−1) interval are computed according to the R-peak time. Since everyone has different heartbeat intervals, for retaining characteristics of waveform we resample all segmented ECG beats into the same periodic length with 100 samples for the DL model.

Feature learning and classification. Different from the traditional hand-designed methods, an unsupervised method based on DBN is used to learn ECG features from uniformly distributed samples. In this paper, a six-layer DBN with one visible layer and five hidden layers is structured as shown in Figure 2. For learning the continuous ECG data, a GBRBM is used to accept the continuous heartbeat data at the bottom of the DBN. In general, the building process of a DBN includes two phases: unsupervised training and supervised fine-tuning. The unsupervised training aims to learn the parameters of each RBM in the DBN. Then the supervised fine-tuning aims to optimize the parameters of the DBN with labeled ECG data.

2.1. **Unsupervised training.** Given a set of ECG training data DS1 $= \{(x_i, y_i)\}_{i=1}^{R}$, where x_i is the resampled ECG beat vector of the DS1 and $y_i \in \{1, 2, \ldots, k\}$ is the

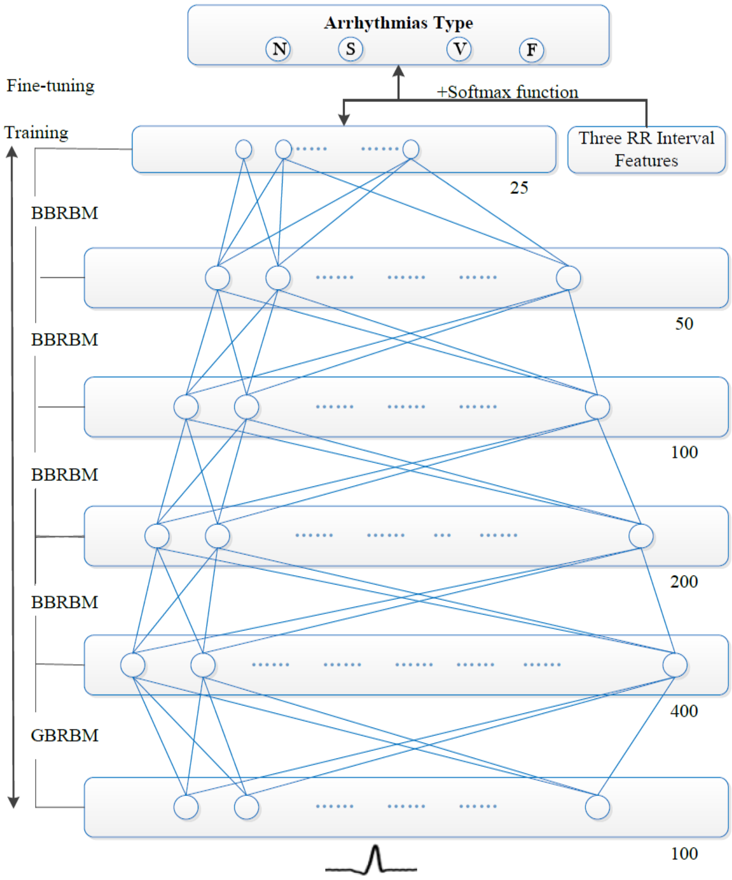

FIGURE 2. A six-layer DBN with one visible layer and five hidden layers

corresponding class label. The goal is to maximize the average log probability of DS1 as:

$$\theta^* = \arg\max \log(\theta) = \arg\max \sum_{i=1}^{R} \log p\left(x_i|\theta\right) \tag{1}$$

where θ is denoted as the parameter vector such as $\theta = \{w, a, b\}$ (for BBRBM) or $\theta = \{w, a, b, o'\}$ (for GBRBM). Here w is the undirected weight matrix between the visible layer and the hidden layer of an RBM, a and b are the bias vector, and o' is the standard deviation vector of the Gaussian noise for visible unit.

Since a probability distribution over the joint (v, h) of the visible and the hidden units has an energy function, we can compute the conditional probabilities of m visible and n hidden units as below (2) (for BBRBM) and (3) (for GBRBM).

$$\begin{aligned} p\left(v_m = 1|h, \theta\right) &= \delta\left(a_m + \sum_{n=1}^{s} h_n w_{mn}\right) \\ p\left(h_n = 1|v, \theta\right) &= \delta\left(b_n + \sum_{m=1}^{t} v_m w_{mn}\right) \end{aligned} \tag{2}$$

$$\begin{aligned} p\left(v_m = v|h, \theta\right) &= \eta\left(v|a_m + \sum_{n=1}^{s} h_n w_{mn}, \sigma_m^2\right) \\ p\left(h_n = 1|v, \theta\right) &= \delta\left(b_n + \sum_{m=1}^{t} \frac{v_m}{\sigma_m^2} w_{mn}\right) \end{aligned} \tag{3}$$

where $\delta = 1/(1+e^{-x})$ is the logistic function, $(.|u, o'^2)$ denotes the Gaussian probability density function with mean μ and variance o'^2, s is number of hidden units, and t is number of visible units. Then we use the rules as shown in (4) and (5) to update the parameters of BBRBM and GBRBM.

$$\begin{aligned}
\Delta w_{mn} &\approx \varepsilon(< v_m h_n >_{data} - < v_m h_n >_{model}) \\
\Delta a_m &\approx \varepsilon(< v_m >_{data} - < v_m >_{model}) \\
\Delta b_n &\approx \varepsilon(< h_n >_{data} - < h_n >_{model})
\end{aligned} \tag{4}$$

$$\begin{aligned}
\Delta w_{mn} &\approx \varepsilon \left(< \frac{v_m}{\sigma_m^2} h_n >_{data} - < \frac{v_m}{\sigma_m^2} h_n >_{model} \right) \\
\Delta a_m &\approx \varepsilon \left(< \frac{v_m}{\sigma_m^2} >_{data} - < \frac{v_m}{\sigma_m^2} >_{model} \right) \\
\Delta b_n &\approx \varepsilon(< h_n >_{data} - < h_n >_{model})
\end{aligned} \tag{5}$$

where ε is learning rate, *model* denotes the distribution after one steps of Gibbs sampling, and *data* is the probability distribution $P(h|v,\theta)$.

2.2. **Supervised fine-tuning.** After layer-by-layer pre-training of DBN, a softmax regression layer can be added on the top of the resulting hidden representation layers to perform arrhythmias classification. The parameters for the entire DBN can be tuned using backpropagation by minimizing the cost function $J(\theta)$ as shown in (6). The following algorithm provides the main steps of the proposed approach called ECG-DBN.

$$J(\theta) = -\frac{1}{R}\left[\sum_{i=1}^{R}\sum_{j=1}^{k} 1\{y_i = k\} \log \frac{e^{\theta_j^T x_i}}{\sum_{l=1}^{k} e^{\theta_l^T x_i}}\right] + \frac{\lambda}{2}\sum_{i=1}^{k}\sum_{j=1}^{n}\theta_{ij}^2 \tag{6}$$

Algorithm: ECG-DBN
Input: training data DS1 $= \{(x_i, y_i)\}_{i=1}^{R}$; testing data DS2 $= \{(x_j, y_j)\}_{j=1}^{T}$
DBN parameters:
- value type of every layer {Binary, Gaussian};
- number of layers N; number of units in every hidden layer $H_1, \ldots, H_N$;
- number of epochs E; weight space $W = \{w_1, \ldots, w_N\}$; biases b, c;
- momentum ϑ; learning rate η; penalty P; batch size S;

Output: classification result
Step 1: Greedy layer-wise unsupervised learning.
for $k = 1$; $k < N$ do
if $k = 1$ do set value type of Gaussian
else do set value type of Binary
end
for $e = 1$; $e <= E$ do
for $r = 1$; $r <= R$ do
Calculate the non-linear positive and negative phase using Equations (2) and (3)
Update the weights and biases based on Equations (4) and (5).
end
end
end
Step 2: Supervised learning with DBN architecture using softmax function.
Step 3: Fine tune parameters based on BP by minimizing Equation (6).
Step 4: Classify the arrhythmias based on the trained DBN architecture using DS2.
Step 5: Output the classification result.

3. **Experimental Results.** In this study, ECG signals are taken from the MIT-BIH arrhythmia database, which contains 48 half-hour recordings, sampled at 360 HZ. For comparative analysis, the classification system follows the AAMI standardization. This standardization is specified in ANSI/AAMI EC57:1998/(R) 2008 and defines the protocol to perform the evaluations to make sure the experiments are reproducible and comparable. According to the AAMI recommendations, the heartbeat types can be grouped into five heartbeats classes: (1) normal beat (N), (2) supraventricular ectopic beat (SVEB, here just S), (3) ventricular ectopic beat (VEB, here just V), (4) fusion (F) of a V and an N, and (5) unknown beat type (Q). Considering the real clinical application, the heartbeat dataset is defined by inter-patient as shown in Table 1.

In the experiment, a DBN with six layer {100-400-200-100-50-25} is designed to extract high-level features, common training parameters are defined as learning moment ([0.5 0.4 0.3 0.2 0.1 0]), batch size (100), first epoch (50), fine-tuning epoch (200), penalty (0.0002). It should be noted that the experiments are carried out on a desktop with the following characteristics (Intel Core i7-4790, CPU 3.6 GHz, RAM 16 GB, and GPU Intel HD graphics 4600).

Table 1. Inter-patient heartbeat dataset of DS1 (training) and DS2 (testing)

DS1	N	S	V	F	Total	DS2	N	S	V	F	Total
101	1859	3	0	0		100	2237	33	0		
106	1507	0	520	0		103	2080	2	0		
108	1731	4	17	2		105	2526	0	41		
109	2489	0	38	2		111	2115	0	1		
112	2535	2	0	0		113	1788	6	0		
114	1793	12	43	4		117	1533	1	0		
115	1952	0	0	0		121	1859	1	1		
116	2287	1	108	0		123	1514	0	3	0	
118	2165	96	16	0		200	1742	30	826	2	
119	1543	0	444	0		202	2060	54	18	1	
122	2474	0	0	0		210	2421	22	193	8	
124	1535	31	46	5		212	2747	0	0	0	
201	1633	121	198	2		213	2640	28	220	362	
203	2527	2	444	1		214	1999	0	256	1	
205	2568	3	71	11		219	2082	7	64	1	
207	1541	107	193	0		221	2030	0	396	0	
208	1579	2	990	370		222	2268	209	0	0	
209	2620	383	1	0		228	1687	3	362	0	
215	3194	3	164	1		231	1567	1	2	0	
220	1952	94	0	0		232	398	1382	0	0	
223	2044	73	473	14		233	2229	7	830	11	
230	2253	0	1	0		234	2700	50	3	0	
Total	45781	937	3767	412	50897		44222	1836	3216	386	49660

Table 2. Confusion matrix for ECG arrhythmias classification on DS2

Heartbeat class	Recognized				
	N	**S**	**V**	**F**	**Total**
N	43571	138	477	36	44222
S	75	1756	5	0	1836
V	32	2	3176	6	3216
F	11	6	40	329	386

Table 3. Performance comparison in terms of V and S

Method	S (%)			V (%)		
	Se	Sp	Acc	Se	Sp	Acc
Chazal et al. [2]	75.9	N/A	94.6	77.5	N/A	96.4
Chazal and Reilly [3]	87.7	N/A	95.9	94.3	N/A	99.4
Ince et al. [4]	81.8	98.5	96.1	90.3	98.8	97.9
Jiang and Kong [8]	74.9	98.8	97.5	94.3	99.4	98.8
Proposed	95.6	99.7	99.5	98.7	98.9	98.9

The classification performance is measured using the three standard metrics: sensitivity (Se), specificity (Sp) and classification accuracy (Acc). Table 2 shows the confusion matrix for ECG arrhythmias classification on DS2 using the ECG-DBN. Classification performance comparison is presented in terms of S and V as shown in Table 3. From Table 3, the proposed method has higher classification accuracy, especially the S class (Se 95.6%, Sp 99.7%, and Acc 99.5%).

4. **Conclusions.** In this article, a method for ECG arrhythmias classification using DBN is tested on MIT-BIH arrhythmia data. The classification performance comparison in terms of V and S is shown in Table 3. The results show that the method achieves higher accuracy on the classification of ECG arrhythmias. Compared to hand-crafted features based traditional methods, the approach has several desirable proprieties: 1) it can automatically learn abstract feature representations from the continuous ECG; 2) the constructed classification model has high adaptability in the inter-patient. The future plans of our project involve increasing the classification accuracy by embedding prior knowledge into the learning structure and then testing in other arrhythmia data.

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