ECG Arrhythmia Classification By Using Convolutional Neural Network And Spectrogram

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Abstract— **In this study, the electrocardiography (ECG) arrhythmias have been classified by the proposed framework depend on deep neural networks in order to features information. The proposed approaches operates with a large volume of raw ECG time-series data and ECG signal spectrograms as inputs to a deep convolutional neural networks (CNN). Heartbeats are classified as normal (N), premature ventricular contractions (PVC), right bundle branch block (RBBB) rhythm by using ECG signals obtained from MIT-BIH arrhythmia database. The first approach is to directly use ECG time-series signals as input to CNN, and in the second approach ECG signals are converted into time-frequency domain matrices and sent to CNN. The most appropriate parameters such as number of the layers, size and number of the filters are optimized heuristically for fast and efficient operation of the CNN algorithm. The proposed system demonstrated high classification rate for the time-series data and spectrograms by using deep learning algorithms without standard feature extraction methods. Performance evaluation is based on the average sensitivity, specificity and accuracy values. It is also worth to note that spectrogram increases the performance of classification since it extracts the useful time-frequency information of the signal.**

Keywords— Deep learning, electrocardiogram, arrhythmia detection, convolutional neural network.

I. INTRODUCTION

Electrocardiography (ECG) is used for monitoring and recording of the electrical activities in the heart. ECG signals' analyzing has crucial importance for detecting arrhythmias. In most cases, visual recognition is used for diagnosing and detecting of different arrhythmias by cardiologists accordingly short-time ECG signals. If there are some abnormalities in the electrical signal, it can be seen in the QRS complexes. The QRS complexes have great information about the signal characteristics. Feature extraction has significant difficulty in classification of ECG signals.

In the last ten years, several feature extraction approaches have been recommended of ECG signals in the publications likewise ECG morphology [1], heartbeat interval features [2], Wavelet Transform [3], statistical properties [4] and fast Fourier Transform [5] for categorization. Moreover, principal component analysis (PCA) [6-7] and independent component analysis (ICA) [8-9] are known as classical/traditional feature extraction and selection methods. As mentioned before, all these methods have been adapted to many ECG features towards a reduced dimensional feature plane.

In recent years, deep learning algorithms that include neural network structures have a growing importance in biomedical signal processing and digital image processing. The idea of the deep learning is to determine a layer of favorable features from the input data without any feature extraction method. Deep learning techniques have shown superior results comparing with traditional methods such as image categorization [10], speech identification [11] and analysis of physiological information [12-14].

Many investigators have obtained successful outcomes on the ECG classification by using deep learning approaches with MIT-BIH arrhythmia database [15]. The performance of the classifier is difficult to compare with other classification studies in the literature, because of the difference of usage between dataset and method. Nevertheless, the results of similar studies may give an idea for comparison. For instance, Kiranyaz et al. [16] stated that their research based on representation of one-dimensional convolutional neural network (CNN) for real-time ECG data categorization, and analyzed real patient ECG data with 64 and 128 samples. Rahhal et al. [17] said that their proposed system is about morphology ECG data classification with the raw ECG data, and features of each beat equal to 54. In these papers, it has been used different ECG data as a raw form for input instances of deep learning algorithm.

In this research, it has been purposed to classify the raw ECG data from MIT-BIH database and segmented ECG beats have 260 samples long. At the end, raw ECG time-series data and ECG signal spectrograms classified by using convolutional neural network with higher accuracy rates. The study aim is to improve the classification performance. The section II explains the material and method used in the proposed system. Then the results are given with the discussions in the following sections. Finally, conclusions are drawn and future studies are mentioned in the last section.

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II. MATERIAL AND METHOD

A. Data Description

The ECG signals has been taken from public MIT-BIH arrhythmia database. The dataset consists of different types of cardiac arrhythmia and total of 48 records. Each record is sampled at 360 Hz with a precision of 11 bits at 10 mV. All records has clinical wave shapes and complexity. In this study, the records have been arranged 30-minutes samples and used as two-channel 24-hour records [18].

QRS complexes have been obtained by using Pan Tompkins algorithm. The algorithm contains pre-filtering, calculation slope of signal waves, and removal of negative parts and detection of R peaks [19]. Each type of QRS complexes analyzed as beat-by-beat format.

B. Methodology

In the beginning of 1980s, CNNs were improved by Fukushima [20]. The first deep learning approach based on consecutive layers are trained by the gradient descent algorithm. It is also well-known approach for feature extraction and time-series data classification. It barely requires data pre-processing and pre-training approaches [21]. This research includes two different approach. The first approach is to examine MIT-BIH heartbeats without any feature extraction stage for classification.

In the second approach, the spectrogram of heartbeats are obtained by using Short Time Fourier Transform (STFT). STFT of discrete time signal $x[n]$ is calculated as discrete time Fourier transform (DTFT) of windowed sequence as

$$X_n\left(e^{j\Omega}\right) = \sum_{m=-\infty}^{\infty} x[m]w[n-m]\ e^{-j\Omega \mathrm{m}}$$

where Ω is frequency variable, n and m are time indices and $w[n]$ is the window function.

The spectrogram is obtained by the squared magnitude of STFT coefficient and represents how the energy of signal is distributed over time-frequency plane [22].

These spectrograms have been converted into image form by using image processing techniques. Images have been resized as 224x224x3 form. By using this approach, the extracted features have been classified from images into 3 essential class such as Normal beat, PVC beat and RBBB beat.

All raw ECG time-series signals and ECG spectrogram images are used as inputs in CNN for the both approaches. In this framework, the number of beats have been used as equal in both two methods. The total number of beats have been adjusted as 8475 N, 223 PVC and 5605 RBBB into three essential classes. One sample from each class and their spectrogram are given in Figure 1.

The used CNN model has three main layers such as convolutional layer, pooling layer and fully-connected layer. In the convolutional layer, it can be obtained to ensure the feature map, after that, batch normalization layer, activation with rectified linear unit (ReLU) and down-sampled with the max pooling layer consecutively. Fully- connected layer has 3 outputs. Softmax function and classification layer provides to divide outputs into the classes such as 'Normal beat', 'PVC beat' and 'RBBB beat'. The output layers of the both two methods are shown in the Table 1.

C. Evaluation Criteria

MATLAB program was used for data processing and classification. The performance of classifier has been determined according to following criteria:

$$Sensitivity = \frac{TP}{TP+FN} * 100(\%) \quad (1)$$

$$Specificity = \frac{TN}{TN+FP} * 100(\%) \quad (2)$$

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} * 100(\%) \quad (3)$$

where True Positive (TP) is the number of beats classified correctly for the given class, True Negative (TN) is the number of entries which does not belong to given class and classified correctly. Similarly, False Positive (FP) is the number of beats which are classified belonging to the given class incorrectly and False Negative (FN) is the number of beats classified incorrectly as not a member of the given class.

III. EXPERIMENTAL STUDY

In this research, two different approaches applied to classify ECG heartbeat types in time-series signal and spectrogram images. Each heartbeat instances separated into train, test, and validation instances as 70%, 15% and 15% for training, testing and validation process, consecutively.

A. ECG Time-Series Signal Classifed by CNN

The signals have been given as raw data in time-series ECG signal for classification. The form of each signal was 1-D vector in time-domain. 1-D vectors converted belonging to all classes are formed into 4-D array to have an efficient processing for the CNN. After the construction of 4-D array, the data have been given directly into convolutional neural network for classification. The block diagram of the system is shown in the Figure 2 (a).

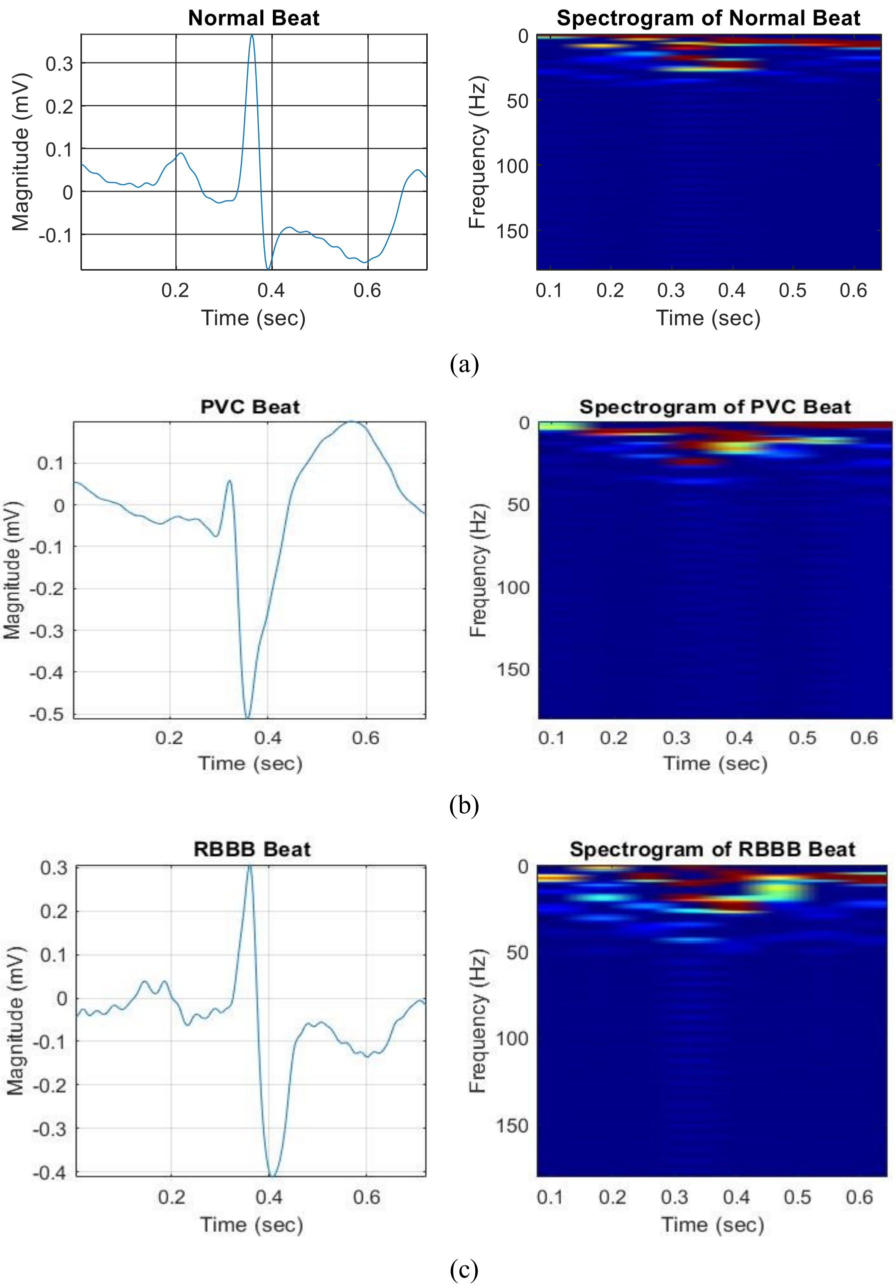

Figure 1. ECG time-series signal and their corresponding spectrogram for one sample for each beat class

Layers	Type	Output Layer		Filter Size	Stride
		Time-Series	Spectrogram		
1	Image Input	1x260x1	224x224x3	-	-
2	Convolution	1x260x8	224x224x8	[3,3]	[1,1]
3	Batch Normalization	1x260x8	224x224x8	-	-
4	ReLU	1x260x8	224x224x8	-	-
5	Max Pooling	1x87x8	75x75x8	[1,1]	[3,3]
6	Convolution	1x87x16	75x75x16	[3,3]	[1,1]
7	Batch Normalization	1x87x16	75x75x16	-	-
8	ReLU	1x87x16	75x75x16	-	-
10	Convolution	1x29x32	25x25x32	[1,1]	[3,3]
11	Batch Normalization	1x29x32	25x25x32	-	-
12	ReLU	1x29x32	25x25x32	-	-
13	Fully Connected	1x1x3	1x1x3	-	-
14	Softmax	1x1x3	1x1x3	-	-
15	Classification Output	3	3	-	-

Table 1. The proposed CNN model

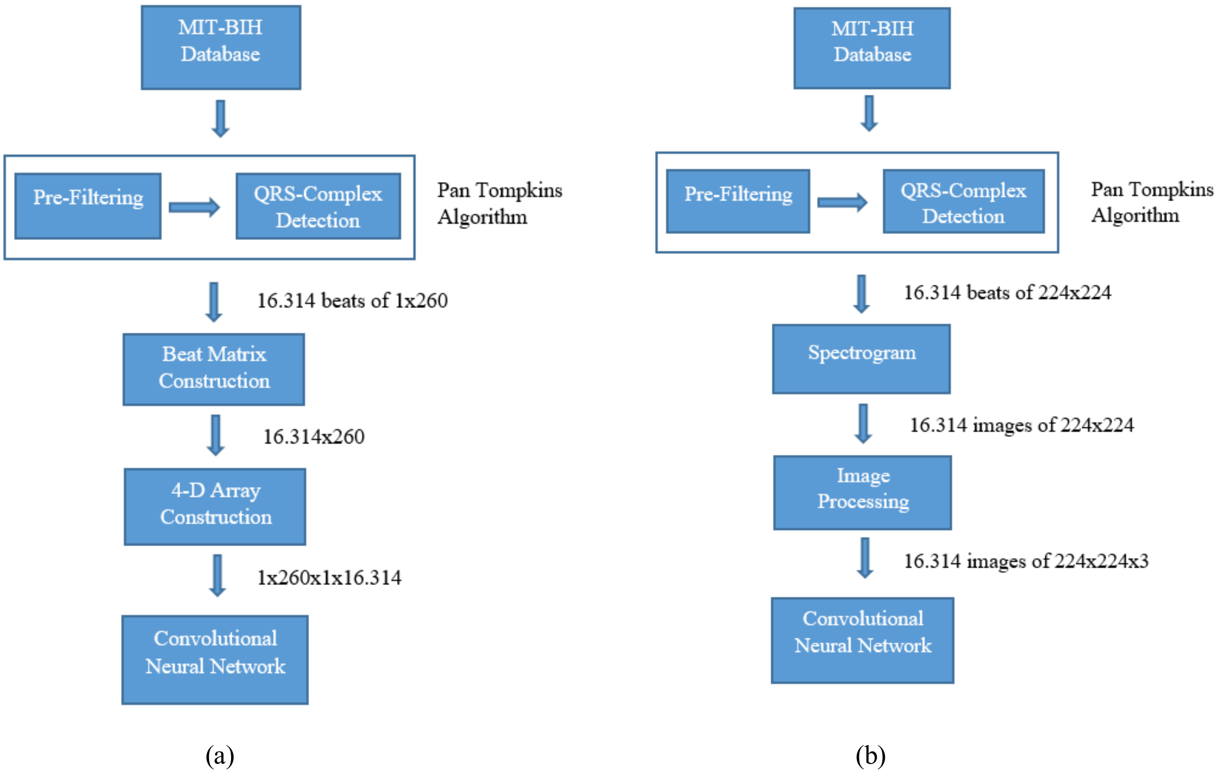

Figure 2. Block diagram for (a) ECG time-series signal (b) ECG spectrogram images classification by CNN

B. ECG Spectrogram Images Classified by CNN

The QRS complexes were transformed into image form by using spectrogram method in time-frequency domain. These images were standardized with a value of 224 x224x3 pixels as an RGB image for the CNN algorithm application. The diagram of the system is shown in the Figure 2 (b). The details of the used CNN for both approaches are summarized in Table 1.

IV. RESULTS AND DISCUSSION

ECG time-series signals and spectrogram images were separated into train, validation and test sets as described in the previous section and two CNN were trained. All results represented as the rate of accuracy, sensitivity and specificity for both two approaches. Table 2 indicates that test results of time-series signal classification and also Table 3 indicates that the test results of spectrogram images classification according to evaluation criteria. It is observed that spectrogram images classification approach has been more successful than time-series signal classification approach. This difference is notable especially for the sensitivity comparison. The sensitivity for PVC class is increased by 20% by the spectrogram method.

	ACTUAL					
PREDICTED	Normal	PVC	RBBB	Accuracy	Specificity	Sensitivity
Normal	**1266**	16	23	98,15%	96,48%	99,60%
PVC	0	**250**	0	96,44%	100%	74,40%
RBBB	5	70	**819**	96,73%	96,52%	97,26%
	All Accuracy Rates			**97,10%**	**97,66%**	**90,42%**

Table 2. Results of time-series classification by CNN

	ACTUAL					
PREDICTED	Normal	PVC	RBBB	Accuracy	Specificity	Sensitivity
Normal	**1271**	3	3	99,75%	99,48%	100%
PVC	0	**327**	1	99,63%	99,95%	97,61%
RBBB	0	5	**837**	99,63%	99,68%	99,63%
	All Accuracy Rates			**99,67%**	**99,70%**	**99,08%**

Table 3. Results of spectrogram images classification by CNN

The performance of the classifier is difficult to compare with other classification studies in the literature, because of the difference of usage between dataset and method. Nevertheless, the results of similar studies may give an idea for comparison. For instance, Hosseini et al. stated that their research accomplished 88.3% accuracy rate to classified for 6 arrhythmia types [23]. Osowski et al. pointed out that approach was classified 7 arrhythmia type and reached approximately 96% accuracy rate [24]. Acır et al. said that their proposed study achieved 95.2% accuracy rate to classified for 5 arrhythmia types [25]. In last comparison, Song et al. stated that the highest accuracy rate accomplished as 99.35% for 6 arrhythmia types [26].

V. CONCLUSIONS

In this paper, a CNN heart beat arrhythmia classification was accomplished by two approaches, namely ECG time-series signal classification and ECG spectrogram images classification. It is observed from the experiments that CNN is a successful feature extractor and a classifier for both approaches. It is also important to note that time-frequency domain representation reveals the hidden features of ECG waveform and performance of the classifier is improved especially in terms of sensitivity. The different arrhythmia types will be investigated and CNN parameters will be optimized in the future studies.

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