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ECG Based Cardiac Arrhythmia Detection using a Deep Neural Network

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Abstract— *In this paper a system to detect Arrhythmia based on the ECG signals is presented.*

*Traditionally, it is divided into two steps, including the step of feature extraction and the step of pattern classification. The process of classification of ECG signals is done using deep neural network. Deep neural network is a type of Artificial Neural Network (ANN). In this paper Deep convolutional neural network (CNN) algorithm is used. The time domain signals of ECG, belonging to five heart beat types including normal beat (NOR), normal sinus rhythm (*NSR*), Atrial fibrillation (AFIB or AF),* Supraventricular tachycardia *(SVTA), and an atrial premature beat (APB), were firstly transformed into time-frequency spectrograms by short-time Fourier transform. Subsequently, the spectrograms of the five arrhythmia types were utilized as input to the 2D-CNN such that the ECG arrhythmia types were identified and classified finally. We evaluate the performance of our technique on the MIT-BIH database, to obtain 97% beat classification accuracy and perfect rhythm identification result.*

Keywords- Electrocardiogram (ECG), convolutional neural network, arrhythmia detection.

I. INTRODUCTION

The world health organization estimation that 17.5 million represent 30% people died around global due to cardiovascular diseases. Among these 7.6 million dues to coronary artery diseases (CAD). One of the most common causes of death in the world is arrhythmia. Cardiac arrhythmias are disturbances in the rhythm of the heart, manifested by irregularity or by abnormal fast rates or slow rates. Different reason to occur arrhythmia is not enough generation of rhythm in sinus node. Other is interruption in electrical signals of the heart causing ventricle to beat separately from the atria. In worst case, the ventricles are not able to beat effectively creating a condition called ventricular fibrillation.[1] When this happen heart cannot pump blood and patient died quickly. The most common reason for sudden death is ventricular fibrillation. Patient with cardiac arrest over30 years of age most frequently have coronary heart disease often involving three vessels, previous myocardial infarction and reduce ventricular function.

An electrocardiogram — abbreviated as EKG or ECG — is a test that measures the electrical activity of the heartbeat. With each beat, an electrical impulse (or "wave") travels through the heart. This wave causes the muscle to squeeze and pump blood from the heart. A normal heartbeat on ECG will show the timing of the top and lower chambers. ECG records the bio-electric response of heart's beating and characterizes a normal heart beat using a P wave, a QRS-complex and a T wave. Based on the shape of QRS-complex the diseases are categorized.

According to the Association for the Advancement of Medical Instrumentation (AAMI), the ECG signals define five kinds of cardiac diseases: unknown beats (Q), normal (N), ventricular (V), supraventricular (S) and fusion of normal and ventricular (F). The important point here is that the ECG signal is analyzed and one of the five diseases is detected correctly. At this point, machine learning-based methods are used to find out all the distinctive features in the signal.[2]

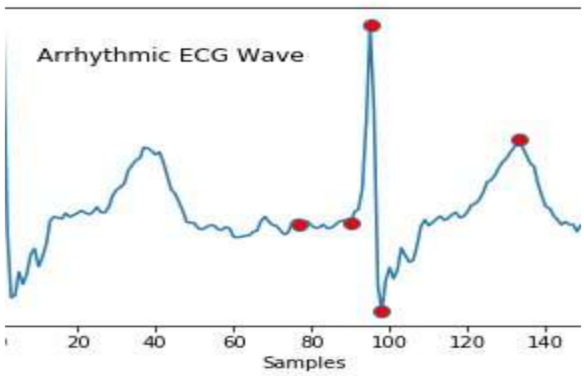


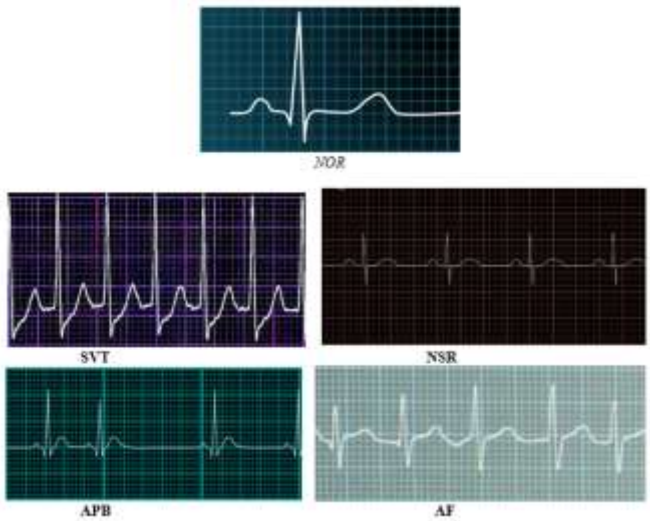
Fig. 1 *Arrhythmic ECG wave representing five classes of ECG beat.*

II. METHODOLOGY

A. Method Overview

The overall procedures of the proposed ECG arrhythmia classification model are shown in Figure 2. The ECG spectrogram images are fed into the proposed deep two-dimensional convolutional neural network (CNN) model. With these obtained ECG spectrogram images, classification of the five ECG types is performed in the 2D-CNN classifier automatically and intelligently.[3] The five

ECG types are normal beat (NOR), normal sinus rhythm (*NSR*), Atrial fibrillation (AFIB or AF), *Supraventricular tachycardia* (SVTA), and an atrial premature beat (APB) are represented in Figure 2.



The ECG classification system in this work can be split into four main stages

Indicated in Figure 3. Those stages are:

- ECG pre-processing and detrending
- QRS detection and signal segmentation
- Parameter extraction
- Clustering and classification of extracted parameters classification system [7]

Fig 3. *Main blocks of the proposed ECG*

B. Data acquisition and selection

In this subsection, we conducted experimental analysis in order to evaluate the performance of the proposed method. Five types of ECG signals, of which the sampling rate was uniformly set as 360 Hz, were obtained from the PHYSIONET 2016arrhythmia database [4].

Dataset for this problem has been provided by PHYSIONET 2016. The dataset has been collected by thoroughly going through research databases from numerous research groups.

The dataset consists of 2435 recordings from 1297 patients and it is a mix of a variety of conditions whether it be a heart valve disease or coronary disease.

C. ECG arrhythmia classifier

In this paper, CNN is adopted as the ECG arrhythmia classifier. CNN was first introduced by LeCun and was developed through a project to recognize handwritten zip codes. With the advent of the CNN model, correlation of spatially adjacent pixels can be extracted by applying a nonlinear filter and by applying multiple filters, and it is capable of extracting various local features of the image.

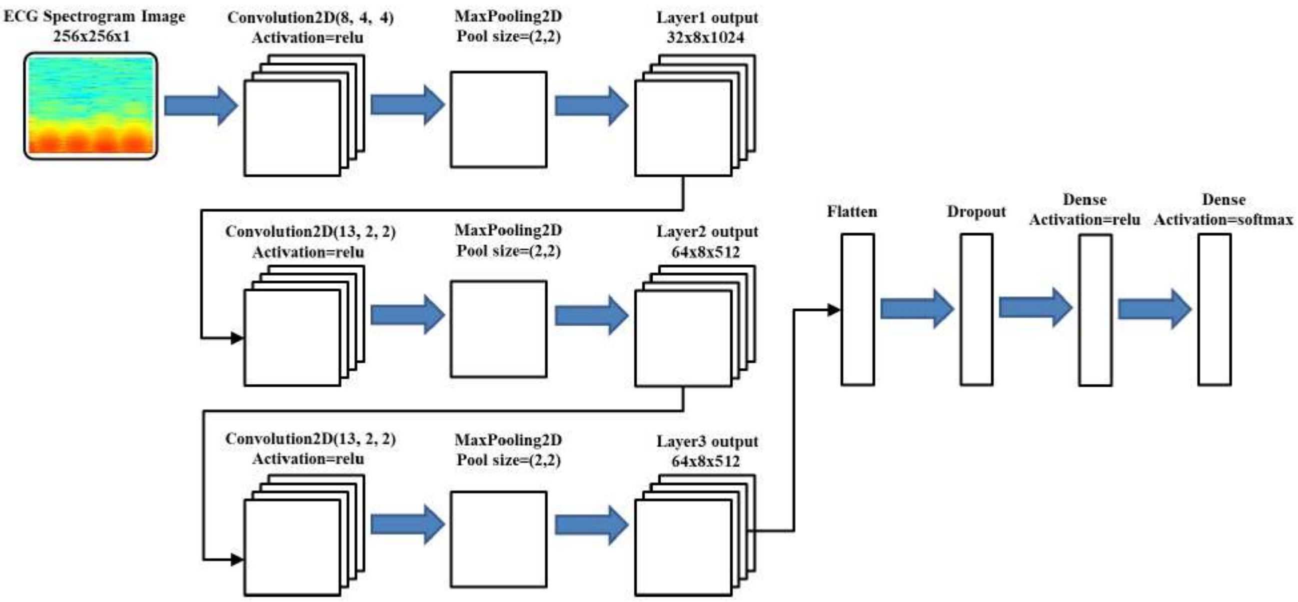
2D convolutional and pooling layers are more suitable for filtering the spatial locality of ECG images. Therefore, to facilitate 2D-CNN in ECG signal classification, we convert ECG signals in the time domain into 2D spectrograms in time-frequency representations. The structure of the 2D-CNN is illustrated in Figure 4.

The explanations for the applied functions in the 2D-CNN model are shown in Table 1.

TABLE 2

The explanations for the applied functions in the 2d-cnn model

Function	*Explanations*
Convolution2D	Convolutional layer, sliding window convolution to 2-dimensional input information;
MaxPooling2D	Maximum pooling layer, imposing a maximum pooling on the spatial domain signal;
RELU	Rectified Linear Unit, which performs linear rectification activation on the input vector of the upper layer neural network and outputs nonlinear results.
Flatten	The Flatten layer is used to translate the multidimensional input information into one-dimensional information.
Dropout	It is an regularization layer to prevent overfitting;
Softmax	It is an activation function for multi-class neural network output.



III. RELATED WORKS

Arrhythmia detection methods can be roughly categorized as those based on time domain or frequency domain features. The time domain features are typically derived out of intervals between the PQRST waves in the ECG signal, but such segmentation of the ECG signal is often not reliable as the detection of waves other than the R-peaks can be difficult. The use of RR intervals with knowledge-base for arrhythmia detection is presented in [5]. However, frequency domain features can be extracted more reliably after detecting Rpeaks. Use of Wavelets features has also been proposed. Beat-level classification using support vector machine (SVM) classifier and extreme learning machine have been reported for arrhythmia detection. Although the beat classifier can identify the type of abnormal beat based on the features extracted at the beat-level, it also required to identify the rhythm-level arrhythmias. A method for detecting bigeminy and trigeminy rhythms using distribution pattern.[6]

IV. RESULT

A. Evaluation metrics

In this section, we attempt to evaluate the classification performance using metrics, e.g., the accuracy and the loss.
The indicator of the accuracy is the ratio between the number of correctly classified samples and that of the whole test samples. Its mathematical expression is defined as

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

where TP stands for true positive, meaning the correct classification as arrhythmia; TN stands for true negative, meaning correct classification as normal; FP stands for false positive, meaning incorrect classification as arrhythmia; FN represents false negative, meaning incorrect classification as normal
Similarly Sensitivity and specificity metrics are calculated using the below mentioned formulas,

Sensitivity = (TP/(TP+FN))
Specificity = (TN / (TN+ FP))

B. Comparison with other existing approaches

We compared the performance of the CNN algorithm with previous ECG arrhythmia classification works, including SVM (Support Vector Machine), RNN (Recurrent Neural Network), RF (Random Forest), K-NN (K Nearest Neighbor). Since these works have a different number of the test set and types of arrhythmia, it is unfair to directly compared with accuracy itself.[8],[9]

However, the CNN model achieved successful performance compared to other previous works while introducing the different approach of classifying ECG arrhythmia using convolutional neural network.

V. CONCLUSION

In this paper by using CNN algorithm method it can reliably discriminate between 10 categories of heartbeats based on ECG features; it has been validated over the entire MIT-BIH Arrhythmias Database and yields an accuracy of 95%.

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