Atrial Fibrillation Classification from a Short Single Lead ECG Recording Using a Deep Convolutional Neural Network

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Abstract—**In this work, a deep convolutional neural network (CNN) is proposed to detect atrial fibrillation (AF) among the normal, noisy and other categories of cardiac arrhythmias electrocardiogram (ECG) recordings. The proposed CNN is trained by stochastic gradient descent with the categorical cross-entropy loss function. The network performance is evaluated on training (75%) and validation (25%) data sets that are obtained from 2017 Physionet/CinC challenge database. The proposed CNN model respectively achieves the average accuracy and F1 score of 87% and 0.84 on validation data set.**

One of the main advantages of this work besides high accuracy and reliability, is to simplify the feature extraction process and to remove the need for detecting ECG signal fiducial points and extracting hand-crafted features unlike conventional methods available in the literature. Moreover, it provides an opportunity for ECG screening in a large population, especially for atrial fibrillation screening, using wearable devices such as OM apparel that records high-quality single channel ECG signal.

I. Introduction

Atrial fibrillation (AF) is one of the life threatening cardiac arrhythmias which are associated with increased mortality and morbidity. AF is an irregular and rapid heart rate which can lead to an increased risk of strokes, heart failures and other heart-related complications if it is not detected on time [1]. During AF, the atria experience a number of chaotic and irregular electrical impulses that cause the atria to quiver rapidly. Hence, the atria-ventricular (AV) node is bombarded with impulses trying to get through to the ventricles. The result is a fast and irregular heart rhythm. The heart rate during an atrial fibrillation episode may range from 100 to 175 bpm.

Although the definitive diagnosis of AF is the 12-lead ECG, it is more cost effective to screen patients through the use of one lead of the ECG signal. In order to avoid any delay in the AF diagnosis and to diminish the subsequent risks, physicians generally recommend that patients use an ECG wearable device for daily monitoring. During long-term, remote ECG monitoring, a massive amount of data is collected which is infeasible for visual inspection by a physician. Therefore, automated computer-based ECG classification approaches have been developed in the literature to detect AF and to also reduce false alarms that were common in traditional ECG monitoring systems.

To date, most of the available ECG classification approaches solely rely on extracting features from the ECG signal which normally requires deep domain knowledge and human expertise. The quality of extracted features has significant impact on the reliability and performance of a given ECG classification algorithm. Different statistical and morphological features in the time and frequency domains can be extracted from the ECG signal to diagnose AF episodes [2]–[8]. The extracted features are then fed either to generative or discriminative models to predict or classify the ECG signals.

In general, ECG signal feature extraction particularly extracting morphological features that requires detecting the ECG signal fiducial points is an error-prone strategy. Usually, the extracted features are not sufficiently robust with respect to many variations, such as translations, noise, scaling, displacement, etc. Moreover, the ECG signal characteristics are highly subject-dependent and extracting effective features usually require a deep domain knowledge and expertise. Moreover, any automatic cardiac arrhythmia detection algorithms must implicitly recognize the distinct wave types and discern the complex relationships between them over time which is a difficult task due to the variability in wave morphology among patients.

Recently, deep neural networks have received a great deal of attention in various applications such as object detection, computer vision, activity recognition and biomedical signal processing. The strong feature learning capability of a deep convolutional neural network (CNN) makes it a very promising approach for solving ECG signal classification problems. Deep CNN can be directly applied on raw ECG signals with no need of any pre-processing or filtering or fiducial point detection. It enables us to extract temporal features from ECG signals in order to address the desired classification problem. In this work, a deep CNN structure is proposed to address the 2017 Physionet/CinC challenge. The goal of this challenge is to develop an algorithm to classify normal sinus rhythm (NSR), AF, other rhythms (O) and noisy recordings from a short single-channel ECG recording (9 - 60 seconds). Our work is inspired by different deep CNN structures that were utilized in the literature to solve various ECG signal classification and arrhythmia detection problems [9]–[19].

The major benefit of our proposed approach is to simplify the feature extraction process corresponding to AF detection

TABLE I. THE STRUCTURAL AND LEARNING PARAMETERS FOR THE OPTIMIZED CNN DURING THE TRAINING MECHANISM.

Parameters	Value
Initial Learning Rate	0.01
Momentum	0.9
Kernel Size	3
Pooling Size	5
Convolutional Filters	64
Number of Neurons in Fully Connected Layer	100
Batch Size	64
Iteration per Epoch	100
Stopping Epoch	86

and to remove the need for using a human expert to define appropriate and critical features working with a large data set. Our proposed CNN reaches the highest accuracy on both training and validation data set as compared to the other similar approaches that are applied on the 2017 Physionet/CinC challenge [20]–[22]. The details on the general structure of our proposed CNN-based AF detection method are provided below.

II. CONVOLUTIONAL NEURAL NETWORK DESIGN

Convolutional neural networks (CNN) were initially developed in the 1980s by K. Fukushima [23]. It is the first deep learning approach whose hierarchical layers are trained robustly by means of the stochastic gradient decent algorithm. It is also a popular method for feature extraction and time-series classification.

In this work, the CNN is used to solve the task that was presented in the 2017 Physionet/CinC challenge. The CNN is composed of a batch normalization applied on an input of raw ECG recordings, multiple convolutional layers followed by max-pooling layers, a certain number of fully connected layers as well as a softmax output layer. Batch normalization and dropout layers are also applied after each set of convolutional and max-pooling layers to avoid over-training [24].

The network parameters are trained via the stochastic gradient descent algorithm with the categorical cross-entropy loss function. The time-based learning rate schedule is also used which decreases the learning rate in each epoch with the rate of $\frac{1}{\text{Epoch Number}}$. The exponential linear unit (*elu*) and *tanh* are respectively used as the activation functions of convolutional and fully connected layers. The overall structure of our proposed CNN is depicted in Fig. 1. Also, our proposed CNN structural and learning parameters are indicated in TABLE I.

III. 2017 PHYSIONET/CINC CHALLENGE DATABASE

The 2017 PhysioNet/CinC Challenge aims to encourage the development of algorithms to classify, from a single short ECG lead recording (between 9 to 60 seconds in length), whether the recording shows normal sinus rhythm (NSR), atrial fibrillation (AF), an alternative rhythm (O), or is too noisy to be classified. The ECG data is collected by the AliveCor device. The training set contains 8528 single lead ECG recordings sampled at 300

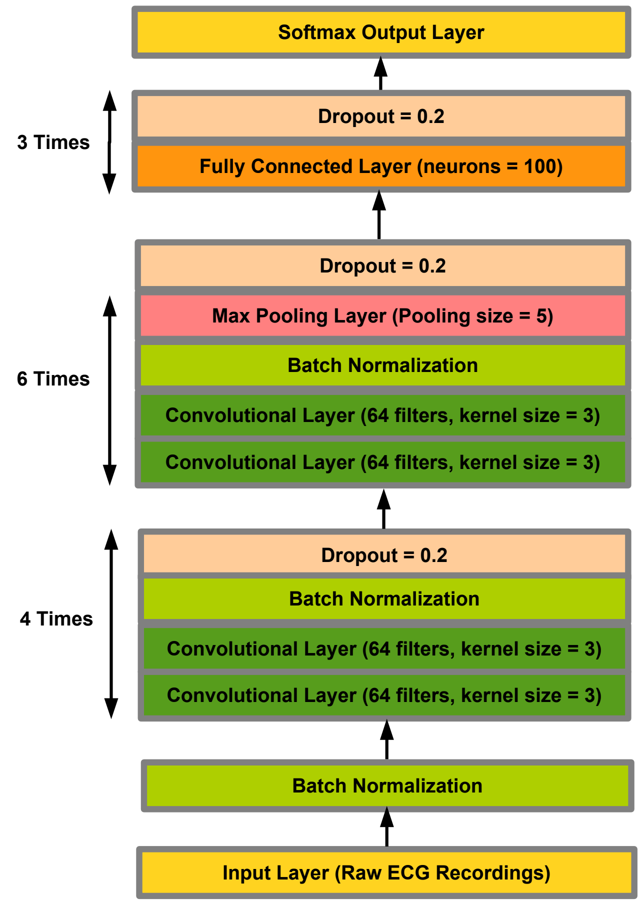

Fig. 1. The overall structure of our proposed CNN to solve AF detection problem presented in 2017 Physionet/CinC challenge.

Hz, where 5145 are NSR, 771 are AF, 2557 are other rhythms and 46 are noisy recordings. Fig. 2 shows the examples of the ECG waveforms (lasting for 20 seconds) for the four classes in this Challenge.

A number of the original ECG recordings are inverted probably due to the electrode misplacement. Inverted records are more likely to be classified as abnormal due to the presence of infrequent QRS and T wave morphologies, as well as to the greater difficulty to identify P waves. Therefore, the inverted version of all the given original ECG recordings are also generated and then used as the CNN input data.

IV. CNN PERFORMANCE EVALUATION

In this section, the performance of our trained CNN with the topology displayed in Fig. 1 is investigated. For this purpose, the 2017 Physionet/CinC challenge data is divided into training and validation data sets. 75% of data is used for training the CNN and 25% of data is used for validating the performance of our proposed CNN. In each epoch, a batch of 64 samples is selected from the training data set for which the CNN model is trained and this procedure is repeated 100 times. By the

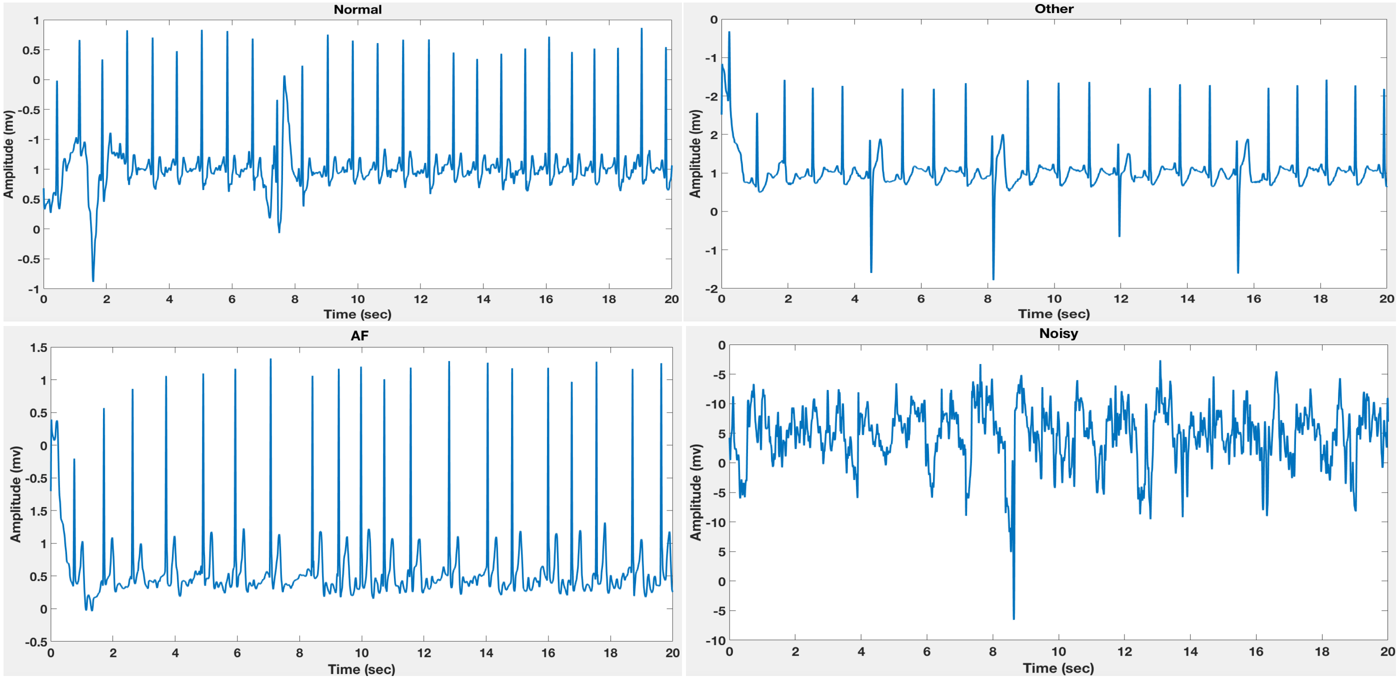

Fig. 2. Four 20-second ECG signals corresponding to NSR, AF, O and noisy classes in 2017 Physionet/CinC Challenge database.

TABLE II. THE STRUCTURAL AND LEARNING PARAMETERS FOR THE OPTIMIZED CNN DURING THE TRAINING MECHANISM.

	Precision	Recall	F1 Score
Normal	0.9367	0.9090	0.9227
Other	0.7527	0.8023	0.7767
Noisy	0.6615	0.8113	0.7288
AF	0.8507	0.8210	0.8356

end of each epoch, the categorical accuracy is calculated for training and validation data sets. The model is saved when it reaches either the highest accuracy or the lowest loss values on validation data.

In average after performing 5-fold cross-validation, the proposed CNN reaches almost 91% and 87% accuracy respectively associated with training and validation data sets. The average values of precision, recall and F1 score are indicated in TABLE II.

It must be noted that precision (positive predictive value), recall (true positive rate) and F1 score are calculated as follows:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$
$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$
$$\text{F1 Score} = \frac{2}{\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}} \tag{1}$$

where TP, FP and FN are true positive, false positive and false negative, respectively.

V. CONCLUSION

In this work, a deep CNN architecture is proposed as a feature learning and classification methodology to detect AF with no need to find fiducial points and to extract hand crafted features. The proposed CNN network is capable of operating with raw ECG time-series signals to extract and down-sample features through computing convolutions among the input vectors with their associated weights as well as determining the maximum outputs among the adjacent neurons. The proposed methodology enables one to detect cardiac arrhythmias particularly AF, as it is one of the most life-threatening heart disorders that can be prevented and treated if it is detected on time.

The performance of our proposed CNN is measured on the 2017 Physionet/CinC challenge dataset and the overall accuracy and F1 score are higher than other techniques presented in CinC 2017. It must be noted that the testing dataset containing 3658 ECG recordings of similar lengths is unavailable to the public and was only used for scoring for the duration of the Challenge. Hence, it is not possible to evaluate the performance of our CNN model on testing dataset. However, based on our cross-validation process, it is expected that our proposed model is still capable of performing comparably on the testing data.

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