ECG heartbeat classification

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Abstract

The electrocardiogram (ECG) can be reliably used as a measure to monitor the functionality of the cardiovascular system. Recently, there has been a great attention towards accurate categorization of heartbeats. While there are many commonalities between different ECG conditions, the focus of most studies has been classifying a set of conditions on a dataset annotated for that task rather than learning and employing a transferable knowledge between different tasks. In this paper, we propose a method based on deep convolutional neural networks for the classification of heartbeats which is able to accurately classify five different arrhythmias in accordance with the AAMI EC57 standard. We evaluated the proposed method on PhysionNet's MIT-BIH datasets. According to the results, the suggested method is able to make predictions with the average accuracies of 82.03% on arrhythmia classification.

1 Introduction

Automatic analysis of ECG signals is a crucial aspect of cardiovascular health monitoring. However, manually analyzing ECG signals is time-consuming and prone to errors, making it challenging to detect and categorize different waveforms accurately. Since cardiovascular diseases are a leading cause of death worldwide, it is vital to diagnose them accurately. Arrhythmic heartbeats, for example, can be life-threatening. Therefore, there is a high demand for accurate and cost-effective diagnosis of such conditions.

To address the limitations of manual analysis, researchers have explored the use of machine learning techniques to detect anomalies in ECG signals. These approaches typically involve preprocessing the signal and extracting handcrafted features that summarize the signal's statistical characteristics. Conventional machine learning algorithms like Support Vector Machines, decision trees, and multi-layer perceptrons are then employed for further analysis and classification.

While handcrafted features provide acceptable signal representations, recent studies have demonstrated that automated feature extraction methods integrated with deep learning frameworks can yield more scalable and accurate predictions. End-to-end deep learning allows machines to learn task-specific features, enabling them to compete with human cardiologists in analyzing ECG signals. However, deep learning approaches require vast amounts of training data due to their large number of parameters.

One way to address the data requirements is through knowledge transfer, where insights gained from one task are applied to another related task. This concept has been successfully applied in computer vision and natural language processing. However, its application in health informatics has been limited. For example, knowledge transfer has been used to transfer expertise from patients with stable conditions to those with deteriorating conditions.

In this paper, we propose a novel framework for ECG analysis that facilitates transfer learning between different tasks. We introduce a deep neural network architecture capable of learning transferable signal representations. The network is initially trained on arrhythmia detection, as this task

Category	Annotations
N	Normal Left/Right bundle branch block Atrial escape Nodal escape
S	Atrial premature Aberrant atrial premature Nodal premature Supra-ventricular premature
V	Premature ventricular contraction Ventricular escape
F	Fusion of ventricular and normal
Q	Paced Fusion of paced and normal Unclassifiable

Table 1: Summary of mappings between beat annotations and AAMI EC57 [18] categories.

requires learning shape-related features of ECG signals and benefits from a large labeled dataset. We demonstrate that the learned signal representations can be successfully transferred to the task of myocardial infarction prediction using ECG signals. This approach allows for knowledge sharing between ECG recognition tasks, even when limited data is available for training deep architectures.

2 Dataset

In this study, we utilized the PhysioNet MIT-BIH Arrhythmia [15], [16], [17] as our data source for labeled ECG records. For all experiments, we used ECG lead II resampled to a sampling frequency of 125Hz as the input. The MIT-BIH dataset consists of ECG recordings from 47 different subjects, recorded at a sampling rate of 360Hz. Each beat is annotated by at least two cardiologists. In accordance with the Association for the Advancement of Medical Instrumentation (AAMI) EC57 standard [18], we created five beat categories based on the annotations in this dataset. All the samples are cropped, downsampled and padded with zeroes if necessary to the fixed dimension of 188. Refer to Table 1 for a summary of the mappings between beat annotations and each category. In this study, we focused on using ECG lead II and healthy control categories.

3 Methodology

3.1 Preprocessing

The dataset consists of 109,446 samples categorized into 5 classes. However, it is important to note that the dataset exhibits a significant class imbalance issue. The distribution is shown in the figure 1 below.

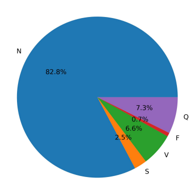

Figure 1: Raw data distribution

So we cut out some of the N instances to balance the dataset

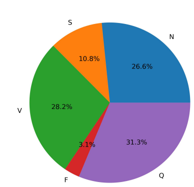

Figure 2: After cut out

3.2 Training the Arrhythmia Classifier

In this paper we suggest training a convolutional neural network for classification of ECG beat types on the MIT-BIH dataset. The trained network not only can be used for the purpose of beat classification, but also in the next section we show that it can be used as an informative representation of heartbeats.

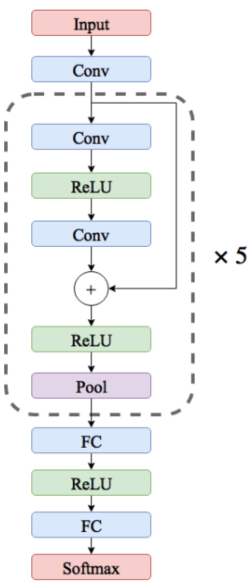

Figure 3: Architecture of the proposed network.

Fig. 3 illustrates the network architecture proposed for the beat classification task. Extracted beats, as explained in Section III-A, are used as inputs. Here, all convolution layers are applying 1-D convolution through time and each have 32 kernels of size 5. We also use max pooling of size 5 and stride 2 in all pooling layers. The predictor network consists of five residual blocks followed by two fully-connected layers with 32 neurons each and a softmax layer to predict output class.

3.3 Experimental setting

We use torch library to implement the model architecture. Cross entropy loss on the softmax outputs is used as the loss function. For training the networks, we trained the model for 50 epochs and used Adam optimization method [22] with the learning rate of 1e-3 and a ReduceOnPlateau scheduler to reduce the learning rate 10 times when the validation loss doesn't decrease after 2 epochs. Training all the networks took around 3 minutes on a GPU P100 processor.

Approach	Average accuracy (%)
Augmentation + CNN[23]	93.5
DWT + SVM[24]	93.8
DWT + random forest[25]	94.6
Deep residual CNN	89.6

Table 2: Comparison of heartbeat classification results.

4 Results

The arrhythmia classifier was assessed using a test set consisting of 4079 heartbeats, with approximately 819 heartbeats from each class. These heartbeats were not used during the training phase of the network. To ensure balance in the number of beats in each category, the dataset was augmented.

Figure 4 displays the confusion matrix obtained from applying the classifier to the test set. The confusion matrix illustrates the model's ability to make precise predictions and effectively differentiate between the various classes.

5 Conclusion

In this study we have presented a method for ECG heartbeat classification based on a transferable representation. Specifically, we have trained a deep convolutional neural network with residual connections for the arrhythmia classification task. According to

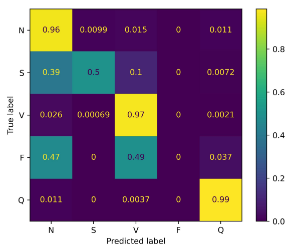

Figure 4: Confusion matrix

the results, the suggested method is able to make predictions with accuracy less than the state of the art methods in the literature.

6 Future work