Arrhythmia Detection Using Convolutional Neural Models

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Abstract

Our main goal was studying the effectiveness of transfer learning using 2D CNNs. For this task, we generated spectrograms from ECG segments that were fed to a CNN to automatically extract features. These features are classified by a MLP into arrhythmic or normal rhythm segments, achieving 90% accuracy.

Introduction

Electrocardiograms (ECG) are electrical signals that show information about heart activity. As they present complex waveforms, algorithms have difficulties to achieve great results, so machine learning entered in this field trying to overcome these problems. Most researchers that study ECGs usually apply some pre-processing to the signal before feeding the data to the neural network. Instead, we tried a different approach using a well-kwon Convolutional Neural Network (CNN), called AlexNet [1], to automatically extract the relevant features from an ECG segment. This idea was inspired by the research of Nguyen and Bui [2] where they classified vocal audio signals using the spectrogram generated from the signal. With the features extracted by the CNN, we trained a Multi-Layer Perceptron (MLP) to classify them between an arrhythmic segment or a normal rhythm segment.

The ECG signals were extracted from the MIT-BIH Arrhythmia Database [3]. This database was selected due to its great popularity in the arrhythmia detection field. It contains 48 half-hour records, where each one presents two ECGs taken from different derivations. Also, its signals have been revised by independent cardiologists, adding and improving annotations over time. That makes this database well suited for machine learning, so we used these signals to generate training and validation samples.

Methodology

We split ECG segments into smaller segments of 5-6 seconds. As Fig. 1 shows, each sample from the database contains two derivations, so we took segments from both derivations using the same starting point and the same number of samples. Then, we calculated their spectrograms and joined both into one final spectrogram. Fig 2. shows an example of spectrograms generated from ECG segments.

Both spectrograms were joined along the temporal axis, resizing them to output a spectrogram of size 256x256. Each spectrogram was scaled to balance the power between them, they were concatenated and then saved as an image of 256x256 pixels. This value was selected to accommodate the images to the characteristics expected by AlexNet inputs. We fed AlexNet with these images and the outputs were extracted from its second convolutional layer. These features were used as relevant features to train a MLP which has a binary neuron in its last layer to classify whether the segment is an arrhythmic or a normal one.

First Experiment

We tried different MLP architectures, searching for the most accurate model. First, we used a simple MLP with one hidden layer and we test different number of hidden neurons, trying with 60, 80, 100, 110, 120, 130, 150 and 200 neurons. This model reached an 82-85% accuracy, so, for the next step, we studied if a two hidden layer MLP could improve these results.

We tried a pyramidal architecture, using a big number of neurons in the first hidden layer and a small number in its second hidden layer, testing

100-25-1, 120-30-1, 120-50-1 and 300-100-1 models, which increased the overall accuracy in 2%.

Second Experiment

Simonyan and Zisserman claimed in their research [5] that increasing the number of convolutional layers helps in the image processing. So, as a final experiment, we tested if extracting the features in the last convolutional layer from AlexNet could improve the results. With the features from the last convolutional layer, we trained MLPs using the same architectures from the first experiment. These models outperformed the results from the previous ones and reached an accuracy of 90%.

Conclusion

We tried a new approach in electrocardiogram analysis, avoiding the hand-made signal preprocessing and extracting the relevant characteristics automatically, while studying the effectiveness of transfer learning. The results show that our first try can classify ECG segments with a 90% accuracy, which is in the state-of-the-art level. This result confirms that transfer learning strategy can be applied as first development stage in medical image classification tasks. Our future research is focused on generate CNNs, trained using spectrograms of bioelectric signals, which can be used as transferable modules for automatic feature generation in other biomedical fields.

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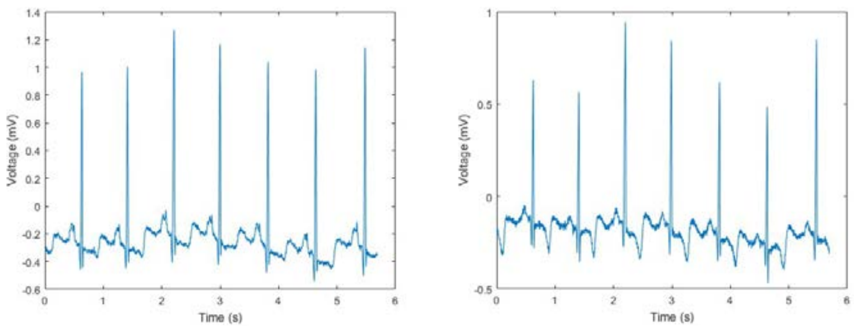

Fig. 1. The left image shows an ECG segment obtained from the first derivation of a MIT-BIH database sample, and the right image plots a segment from its second derivation. Both segments start at the same point and have the same length, 2048 samples.

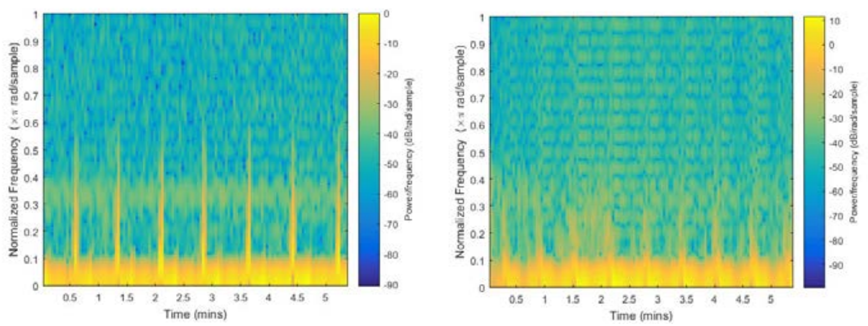

Fig. 2. Example of two spectrograms generated from two ECG segments, each one from a different patient, where the left belongs to a normal rhythm and the right to an arrhythmic segment. It can be noticed the different power spectrum the heart pathology outputs, having more power across higher frequencies