Detecting Arrythmia with Wavelet Transformation and Convolutional Neural Networks

Dajka Bence

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1 Motivation

With the rapid development of artificial intelligence and new and exciting machine learning methods, we can train computers to process large amount of data really quickly. Today we can automate important procedures, such as, fault diagnosis in equipment, or in fact humans. We can use these tools to monitor our health and in this project I studied Electrodiagrams (ECG), to monitor the proper functioning of the cardiovascular system. With these methods professionals can save some time from scattering endless ECG results and focus on things only humans can do.

2 Introduction and background

2.1 Introduction

Scientists achieved excellent results working with machine learning in the classification of ECG signals [[KFS18], [UABM20]]. They can classify the different ECG heartbeat classes: the normal beat [N], left bundle branch block beat[L], right bundle branch block beat[R], atrial premature beat (A) and ventricular beat [V], to more than 90 percent accuracy. In this project I will try to recreate these results with Neural Networks and signal processing methods.

2.2 Neural Networks

Artificial neural networks are machine learning methods, it is a circuit of artificial neurons, which communicate information between each other, inspired by biological neural networks, mimicing the connections between them with weights corresponding to each node (neuron). They can be trained to form probability-weighted associations between input and result. This can be achieved by feeding it enough examples of the certain problem, and than the model adjusts to the criteria. This is called supervised leaning.

The neural network I choose to work with is the Convolutional Neural Network (CNN). These are fully connected networks, that uses the method of convolution to scan through the data, typically an image and give them weights and pass them to the next layer. The full connectivity means each node in one layer is connected to every node in the next. This means the CNN is prone to overfitting, which means it knows the training data to well and cant generalize. To help regularize this, we use penalties, such as dropping a chunk of the data before the next layer to prevent overfitting.

2.3 Wavelet Transform

The signal processing part of my project is the implementation of the wavelet transform. Similarly to the Fouirer transform, but it uses wavelets instead of sine waves to analyze dynamical frequency spectrums. It has high resolution in both the frequency and time domain which means, it can tell which frequencies are present in the signal and which time they occurred. Wavelet transforms use a process called convolution, which means we move our original (mother) wavelet through the signal step-by-step. Then we can scale the wavelet and repeat. The Wavelet transform of a 1-D signal have two dimensions. The formula of the CWT is:

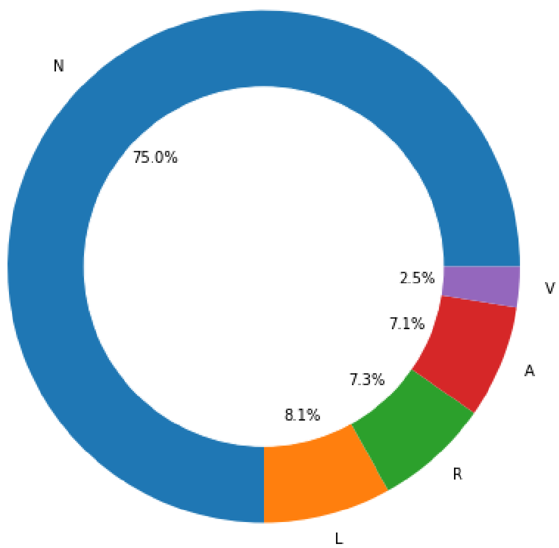

Figure 1: Piechart of heartbeats.

$$X_w(a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} x(t)\psi^* \left(\frac{t-b}{a}\right) dt$$

where psi is the continuous mother wavelet that gets scaled by the a factor and translated by the b factor. These values are continuous, so there can be infinite amounts of wavelets. In the project I use the continuous wavelet transform of the ECG signals to make a scaleogram which I can use to train a 2D convolutional neural network.

2.4 Discussion

The dataset I used is the MIT-BIH Arrhythmia Database MIT-BIH Arrhythmia Dataset[[MM01]], and I got the dataset in a more friendly formatum from Kaggle. I used Python language and Jupyter Notebook environment. For the wavelet transformation I used the Pywavelets package [[LGW+19]]. The neural networks were made with Keras and Tensorflow.

2.5 Data

The data has 48 subjects ECG signals and the corresponding annotations, which tell, me that their heartbeats belong to what category. I linked the correct labels to the corresponding heartbeats and placed them in a big dataframe. It was clear that the majority of the heartbeats were normal 1, so I downsampled the normal class and resampled the other ones.

2.6 Model

The next step was to prepare the dataset to the training of the CNN model, so I used the $train_test_split$ method to make a training and testing set from the data. I switched the labels to numerical classes, in order to use them as the training and testing label set with the CNN model.

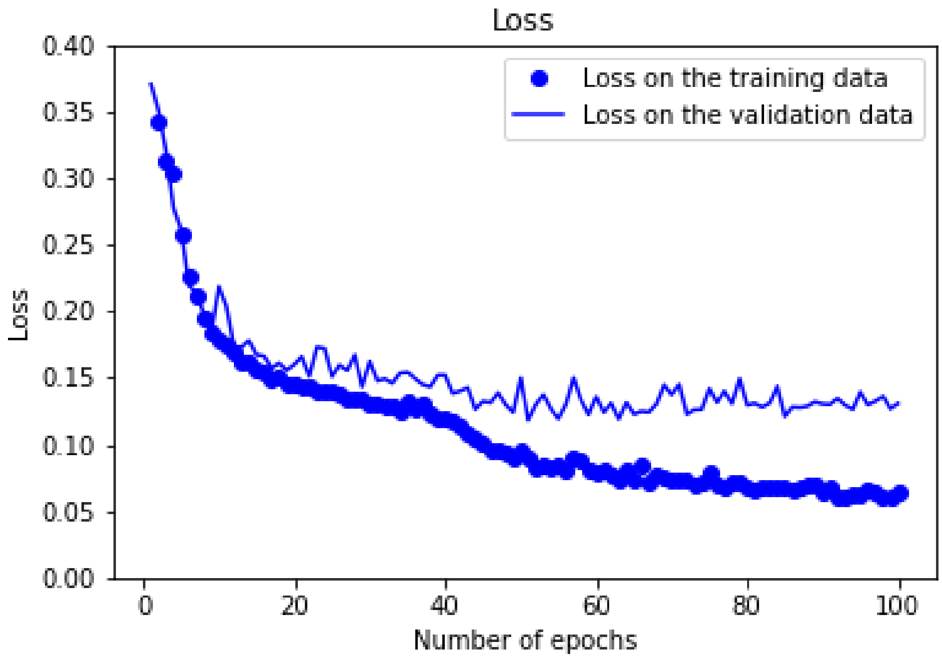

Figure 2: Loss of the model.

I choose the combinatiton of Conv1d and MaxPooling layers in my model, because the can excecute convolution on 1D data, then I used a Dense layer to make the final output prediction.

The model achieved 94 percent accuracy on the testing data, which means it can accurately predict the class of a signal the model never seen before. The loss and accuracy of the model in each epoch can be seen on 2 and 3. The epochs mean that the model constantly recalculates the predictions and changes the weights accordingly, and it is clear that with each epoch the model looses less information and becomes more accurate.

2.7 Using CWT to make the model better

In the articles cited above, the writes could make a model that performs better than the model with the Conv1D layers. They took the Continuous wavelet transform of the signals and made a scaleogram of them and trained a 2D convolutional neural network model with them. The results were better than the 1D convolutional model, however for some reason, which I did not have the proper time to find out, my attempt of this method ended up with a worse model.

3 Conclusion

We saw that with a very simple neural network we can accurately classify real world datasets, and despite my failure to make it better with wavelet transform, the literature proves it can achieve really high accuracy with it.

References

[KFS18] Mohammad Kachuee, Shayan Fazeli, and Majid Sarrafzadeh. Ecg heartbeat classification: A deep transferable representation. *2018 IEEE International Conference on Healthcare Informatics (ICHI)*, Jun 2018.

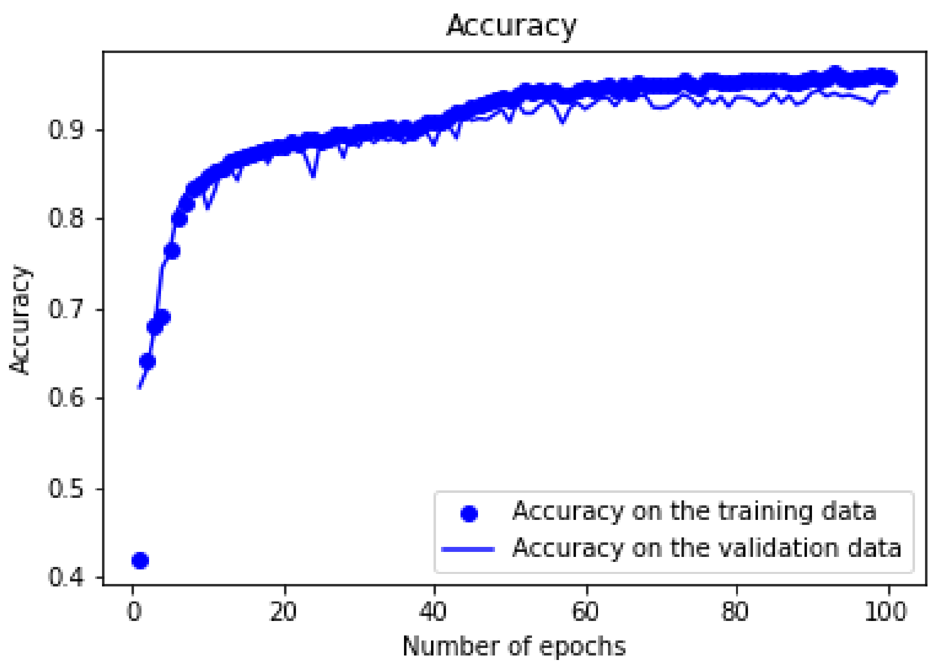

Figure 3: Accuracy of the model.

[LGW+19] Gregory R. Lee, Ralf Gommers, Filip Waselewski, Kai Wohlfahrt, and Aaron Oamp;8217;Leary. Pywavelets: A python package for wavelet analysis. *Journal of Open Source Software*, 4(36):1237, 2019.

[MM01] G.B. Moody and R.G. Mark. The impact of the mit-bih arrhythmia database. *IEEE Engineering in Medicine and Biology Magazine*, 20(3):45–50, 2001.

[UABM20] Amin Ullah, Syed Muhammad Anwar, Muhammad Bilal, and Raja Majid Mehmood. Classification of arrhythmia by using deep learning with 2-d ecg spectral image representation. *Remote Sensing*, 12(10):1685, May 2020.