

Detection of myocardial infraction from ECG signals using convolutional neural networks

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1. Introduction

The objective of this thesis is a development of a method of myocardial infraction detection from ECG signals using deep learning algorithms. Basing on information from scientific publications on the subject, the following approach was adopted: 1D signals are converted to 2D images, subsequently image classification using convolutional neural networks is performed. The project involves learning basics of electrocardiology, processing data, selecting architecture of neural network, building, improving and evaluating training model and analyzing the results. The study was conducted on data from PTB Diagnostic ECG Database which is available on *Physionet.org* website. The method was implemented in Python programming language, using Tensorflow and Keras libraries.

2. Data preparation

Original database of 549 ECG signals was limited to records classified as myocardial infraction in inferior part of the heart and healthy patient (80 records each). These two sets were split in 1:4 ratio into validation and training datasets. First step of signal processing operation was noise reduction using band-pass filter, as it proved to increase obtained classification accuracy in similar analysis. Then, Hamilton method was applied to detect R-peaks in ECG signal. Basing on their position, 600ms long parts of the records, representing one heartbeat were extracted. Finally, obtained fragments were converted to 2D grayscale images, compressed to 128x128px resolution.

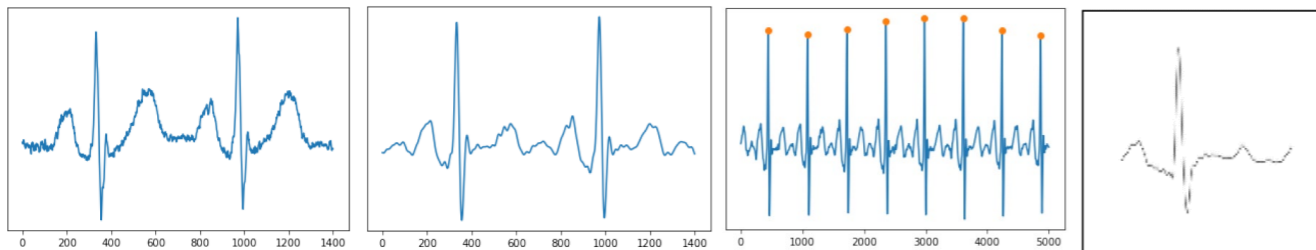


Figure 1: Successive stages of signal processing. From the left hand side: Raw Signal, Filtered Signal, R-peaks Detection, 2D One Heartbeat Image Extraction

3. Image classification

The realization of binary classification task was started with creation of base model, consisting of 6 convolutional layers, 3 max-pooling layers, 2 fully-connected layers of 128 neurons and 1 neuron fully-connected layer in the end. The influence of dropout regularization and data augmentation using rescaling, rotation, shifting and flipping was investigated. Finally, the technique of transfer learning, taking initial weights and structure from VGG-Net16 was implemented.

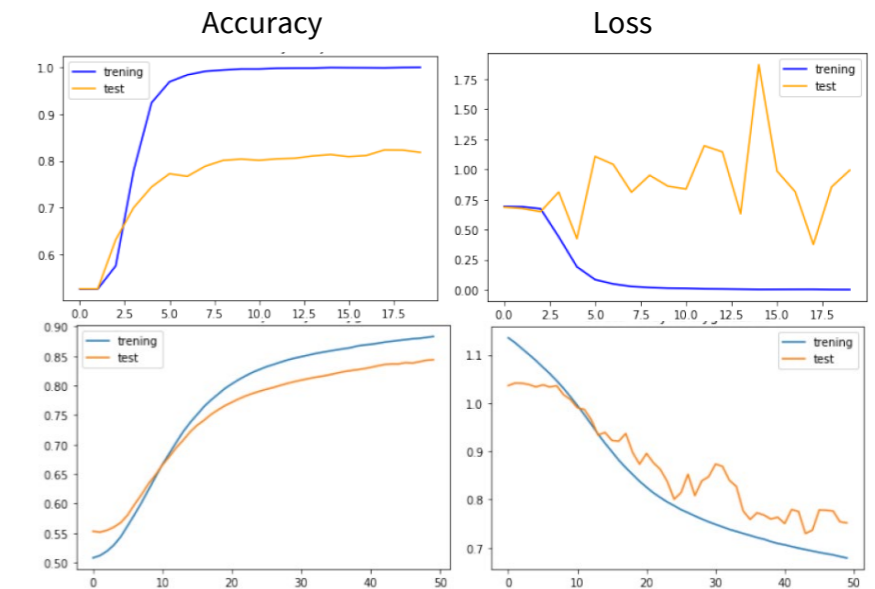


Figure 2: Accuracy and Loss for Base model (top) and best performing model with transfer learning and fine tuning (bottom)

4. Results

Table: Performance of prepared models

Model	Accuracy [%]	Sensitivity [%]	Specificity [%]
Base model	81,81	86,04	77,79
Dropout regularization	84,78	84,08	85,72
Data agumentation (ELU activation)	77,66	88,86	65,43
Transfer Learning (Features extraction)	79,63	82,51	76,67
Transfer Learning & Fine Tuning	85,27	77,46	94,08

Results for the base model, were satisfactory, but in this case overtraining was diagnosed. As expected, regularization improved model performance. Surprisingly however, data augmentation led to decrease in accuracy and resulted in very poor specificity. The method of transfer learning, combined with fine tuning proved to be the best. Not only was it the most accurate, but also achieved specificity of over 90%, meaning that algorithm learnt well recognizing healthy patients.

4. Conclusions

- The results form a good basis for further analyses. For the moment obtained performance is not sufficient to serve as diagnostic tool.
- It is suggested that analysis is conducted with more data. Moreover, the results can be more precise if k-fold validation is applied.
- Data augmentation shall be performed using artificially created full ECG signals, rather than operations on images.