



Deep Learning for Cardiologist-level Myocardial Infarction Detection in Electrocardiograms

Arjun Gupta, Eliu Huerta and Issam Moussa

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Arjun Gupta,^{1,2,6} E. A. Huerta,^{1,3} Issam Moussa^{4,5}

¹NCSA, University of Illinois at Urbana-Champaign, Urbana, Illinois 61801, USA

²Department of Electrical and Computer Engineering, University of Illinois at Urbana-Champaign, Urbana, Illinois 61801, USA

³Department of Astronomy, University of Illinois at Urbana-Champaign, Urbana, Illinois 61801, USA

⁴Beckman Institute for Advanced Science and Technology, University of Illinois at Urbana-Champaign, Urbana, Illinois 61801, USA

⁵Department of Clinical Sciences, Carle Illinois College of Medicine, University of Illinois at Urbana-Champaign, Urbana, Illinois 61820, USA

⁶arjung2@illinois.edu, 312-358-1639

Abstract

Heart disease is the leading cause of death worldwide. Amongst patients with cardiovascular diseases, myocardial infarction is the main cause of death. Thus, detection of myocardial infarction in a timely manner is a serious challenge with a significant potential for impact. Here, we study the impact of multiple channels of observation to correctly classify heart conditions, finding that lead I and lead II are critical to obtain correct classifications using data from the Physikalisch-Technische Bundesanstalt (PTB) database. Based on these findings, we develop a convolutional neural network to detect myocardial infarction using lead I and lead II electrocardiogram (ECG) signals. Our approach differs from others in the community in that it does not require any kind of manual feature extraction or pre-processing of any kind. Rather, the raw ECG signal is fed into the neural network. When evaluated, the model achieves a 99.15% accuracy, reaching cardiologist-level performance level for myocardial infarction detection. Preliminary experiments indicate that coupling this neural network model with a denoising deep learning model increases classification accuracy even further.

In recent years, deep learning has brought forth a paradigm shift in many industries, with healthcare being one of the most significantly impacted domains. Advancements in statistical learning techniques that are able to recognize patterns in large datasets in conjunction with the presence of a vast amount of medical data presents an opportunity to revisit automated medical diagnosis efforts.

The Physikalisch-Technische Bundesanstalt (PTB) database consists of 549 ECG records from 290 unique patients, with a mean length of over 100 seconds for each record (Goldberger et al. 2000). The dataset provides data from the 12 conventional ECG leads, along with 3 Frank leads, all sampled at 1000 Hz. This dataset was used for both training and testing the model. No pre-processing was done to these raw ECG signals before they were fed into the neural network.

In this study, we developed an eight-layer convolutional neural network to detect myocardial infarction given a 10-second long ECG signal. Recently, Perol et al. developed

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ConvNetQuake, a convolutional neural network capable of extracting meaningful patterns from seismic records (Perol, Gharbi, and Denolle 2018). Inspired by the model’s success, our model is based on ConvNetQuake with modifications made to better suit our domain and dataset. The ReLU activation function is used immediately after each convolutional layer, and this output is then passed through a batch normalization layer.

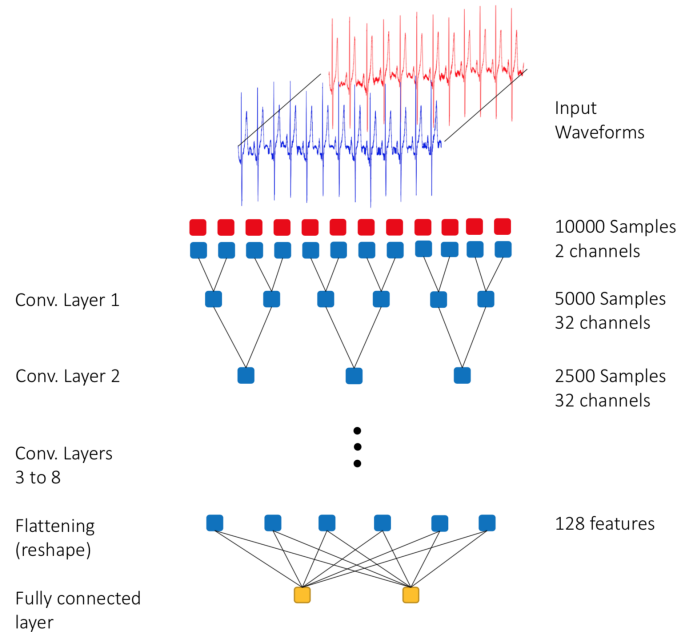


Figure 1: Model architecture

While other works in this domain have employed simply one or two of the 15 leads that the PTB database provides for each record, strong justification for their choice of lead(s) hasn’t been provided. Here, we trained our model on each of the 15 leads—first individually, and then in pairs—to see which lead contained the most meaningful information for the detection of myocardial infarction. The table below shows our results:

Lead	i	ii	iii	avl	avr
Accuracy (%)	91.81	92.73	82.67	73.52	88.35

Table 1: Quantification of accuracies for single channels [i - avr]

Lead	avf	v1	v2	v3	v4
Accuracy (%)	82.85	73.87	85.39	87.45	80.49

Table 2: As Table 1, for channels [avf - v4]

Lead	v5	v6	vx	vy	vz
Accuracy (%)	92.8	95.52	84.2	71.23	66.01

Table 3: As Table 1, for channels [v5 - vz]

Based on these results, we selected the top five best performing leads and paired them up to see which pair would perform the best. Our results are presented below:

Leads	i, ii	i, avr	i, v5	i, v6	ii, avr
Accuracy (%)	99.15	95.55	95.83	93.29	97.35

Table 4: Quantification of accuracies for pairs of channels

Leads	ii, v5	ii, v6	avr, v5	avr, v6	v5, v6
Accuracy (%)	79.47	97.63	86.93	98.96	90.03

Table 5: As Table 4, continued

The above table indicates that when lead I and lead II are paired and fed into the neural network as a 2-channel input, the model is most successful at the task at hand.

A number of specific techniques were employed to improve the performance of the model. One such technique was label smoothing; label smoothing refers to the act of relaxing our confidence on the labels and is known to help discourage the model from making over-confident predictions. We also decayed the learning rate during training. Our experiments showed that both of these techniques helped increase the accuracy of our models.

The WaveNet architecture (Oord et al. 2016) has been shown to be a robust model for denoising. Inspired by the results that Wei et al. (Wei and Huerta 2019) obtained in denoising gravitational waves, we modified the WaveNet architecture in a similar fashion to de-noise ECG signals. That is, we removed the causal structure of the network, dilated the convolutional layers for an increase in the size of the receptive field, and decreased the depth of the architecture. ECGSYN (Goldberger et al. 2003), a realistic ECG waveform generator was used to train our de-noising model. Models have previously been developed specifically for the purpose of ECG denoising, and our model was able to achieve an order of magnitude decrease in the mean-squared error relative to work by Antczak et al. (Antczak 2019)

Preliminary experiments indicate that feeding the raw ECG signals through our WaveNet-based denoising model

may help increase the accuracy of our classification model. The figure below shows the validation set accuracy of our classification model during training with and without denoising:

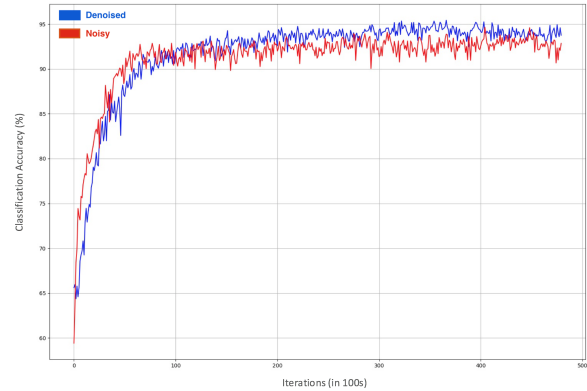


Figure 2: Raw signal vs denoising before classification

Our current and future work includes experimenting with multiple instance learning, inspired by the success of the work of Shanmugam et al. on applying this to ECG data (Shanmugam, Blalock, and Gutttag 2003). We are also in the search for a larger dataset – if we are able to further increase the accuracy of our model with the help of a larger dataset, the model could potentially be deployed to aid cardiologists in their work.

References

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