

# Electrocardiogram Delineation Using Deep Neural Networks

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**Abstract.** Background: In recent years, there has been a rising interest in the application of deep neural networks (DNN) for the delineation of the electrocardiogram (ECG). Objectives: A variety of DNN architectures has been investigated in a 5-fold cross-validation approach. Results: The best performing network achieved 100% sensitivity and >97% positive predictive value for all ECG waves. Conclusion: Our DNN could achieve similar classification performance as other DNN approaches described in the literature at a reduced computational cost.

**Keywords.** Electrocardiogram Delineation, Deep Neural Network

## 1. Introduction

The electrocardiogram (ECG) exhibits distinct features called waves, which represent the excitation and relaxation of the cardiac muscle. Temporal relationships between these components provide insights into cardiac physiology and pathophysiology. Although there are many algorithms for QRS-complex detection [1,2], the automatic identification of P-waves and T-waves remains challenging. In recent years, there is rising interest in deep neural networks (DNNs) for ECG delineation. For example, Peimankar et al. [3] used a combination of convolutional neural networks (CNN) and bidirectional long-short-term memory (BiLSTM) layers to delineate ECG signals. In this work, we explored a broader variety of DNN architectures to find a network with improved computational efficiency and comparable classification performance.

## 2. Methods

A variety of DNN architectures for ECG feature detection (P- and T-wave, and QRS-complex) was explored. The networks were trained on 532 min of ECG recordings

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acquired from 6 animal experiments conducted on rabbits. The experiments were approved by the local ethics committee (BMBWF 2020-0.016.858 – GZ 2020-0.016.858). All ECG signals were annotated, marking the start, peak, and end of P-waves ( $P_{ON}$ ,  $P_{PEAK}$ ,  $P_{POFF}$ ) and T-waves ( $T_{ON}$ ,  $T_{PEAK}$ ,  $T_{OFF}$ ) as well as, Q-, R- and S-peaks, and regions containing no waves (N). The data was augmented by rescaling P- and T-waves of all segments by randomly sampled factors in a range of 0.5 to 1.5. The investigated networks included multiple combinations of LSTM-, BiLSTM-, gated recurrent unit (GRU)- and CNN layers. The effect of layer number and neurons per layer on the classification performance was studied. All architectures were tested in a 5-fold cross-validation approach. The signals were split into 2-second segments which contain about two to three heartbeats. All segments were then randomly divided into training and validation sets in a ratio of 2:3. The classification performance was quantified by sensitivity and positive predictive value.

### 3. Results

The network with the best performance consisted of 3 1-D CNN layers with 32, 64, and 128 filters, followed by a sequence of 1 GRU-, 1 BiLSTM-, and 1 GRU layer with 256, 128, and 64 neurons, and an output dense layer with 10 neurons. The best performing network was evaluated on a test set comprising 27 min of yet unseen ECG traces obtained in another animal experiment. On this set, the network could detect P-, Q-, R-, S- and T-peaks as well as regions with no waves with 100% sensitivity and a positive predictive value of  $P_{PON}=99.4\%$ ,  $P_{POFF}=99.91\%$ ,  $P_{TON}=98.99\%$ ,  $P_{TOFF}=97.73\%$ ,  $P_P=99.91\%$ ,  $P_Q=100\%$ ,  $P_R=99.92\%$ ,  $P_S=99.07\%$ ,  $P_T=99.92\%$ , and  $P_N=100\%$ , respectively.

### 4. Discussion

The results indicate that our network performs well in ECG feature detection. It shows a comparable classification performance compared to the one proposed by Peimankar et al. [3] who used a similar architecture consisting of a sequence of 3 1-D CNN layers with 32, 64, and 128 filters, followed by 2 BiLSTM layers with 250 and 125 neurons and an output dense layer with 10 neurons, respectively. However, one should note, that our network was trained and validated on animal data only. Current work is directed towards the evaluation of the network on standard human ECG databases. Overall, our findings suggest that our network may achieve a similar classification performance as previous approaches [3] in ECG delineation at a reduced computational cost.

### References

- [1] Pan, J. and Tompkins, W.J., "A real-time QRS detection algorithm." *IEEE transactions on biomedical engineering* 3 (1985): 230-236.
- [2] Zidelmal, Z., et al., "QRS detection based on wavelet coefficients." *Computer methods and programs in biomedicine* 107.3 (2012): 490-496.
- [3] Peimankar, A., and Puthusserypady, S., "DENS-ECG: A deep learning approach for ECG signal delineation." *Expert Systems with Applications* 165 (2021): 113911.