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# A Convolutional Neural Network for ECG Annotation as the Basis for Classification of Cardiac Rhythms

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51th Statistical Computing

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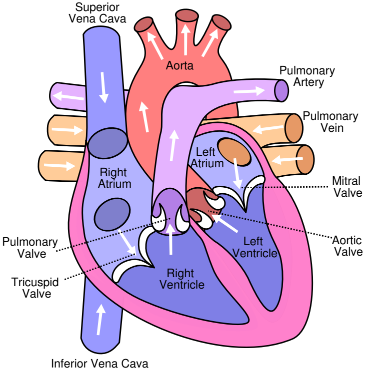
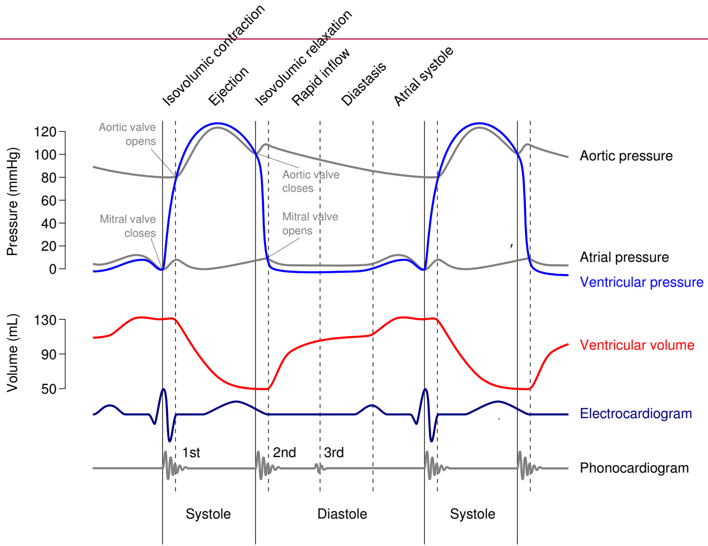
# Content

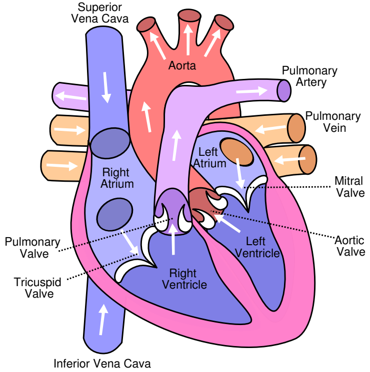
# 1. Motivation

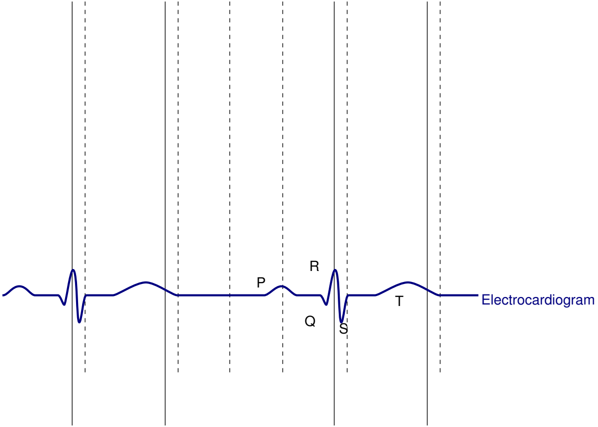
# Cardiac Cycle



# Cardiac Cycle

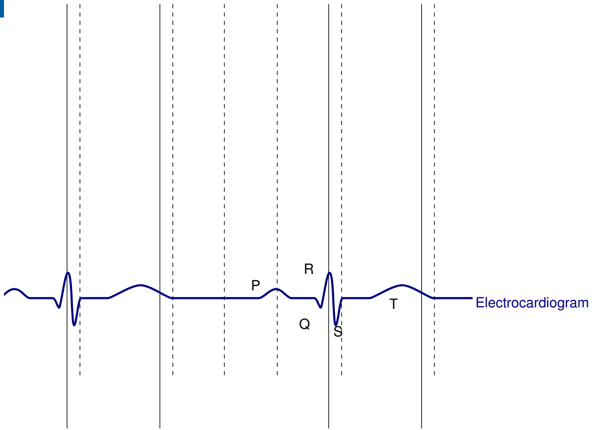


# Cardiac Cycle

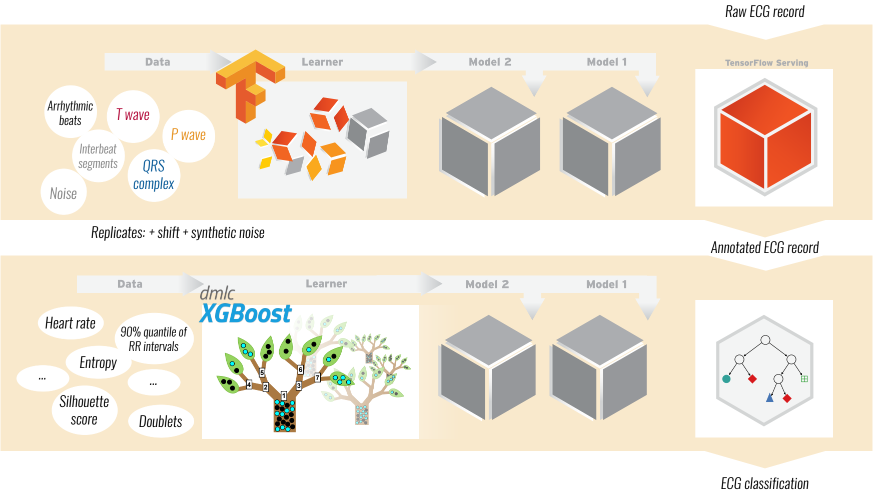
## ECG segmentation

- Interval data used for
  - Heart rate determination
  - Heart rate variability analysis
  - Arrhythmia detection (long-QT syndrome, atrial fibrillation, ventricular arrhythmia)
- Manual inspection is time-consuming
- Only a few automated methods publicly available



# 2. Methods

# A schematic representation of our workflow [1, 2]



# Information gathering

## Labeled input data to train the CNN:

- QT database [3]
  - 222,202 $R$ peaks
  - 192,200 $P$ waves
  - 256,966 $T$ waves
  - 3,311,487 interbeat segments
- Realistic noisy segments
  - Noise stress test function of the WaveForm DataBase (WFDB) applied to clean recordings at different and very low signal-to-noise ratios [4, 5]
- MIT-BIH Arrhythmia Database [6]
  - 106,112 $R$ peaks
  - 74,985 $P$ waves labeled by Elgendi [7]
  - 109,267 $T$ waves labeled by Elgendi [7]
  - Extrasystoles labeled as $O$:
    2,545 atrial premature beats,
    7,127 premature ventricular contractions,
    7,020 paced beats,
    982 fusions of paced and normal beats,
    8,070 left and 7,251 segments of right bundle branch block beats

# Input layer

## Labeled input data to train the CNN

- ECG segment consists of 450 samples (1500 ms)
- Normalized to a range between -1 to 1
- Data augmentation was performed shifting labels up to $\pm 3$ ms
- Adding gaussian noise ($\sigma = 0.02$) for a better generalization and to reduce overfitting

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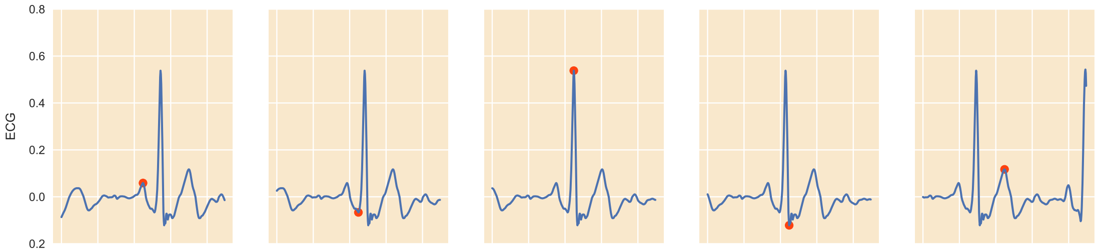
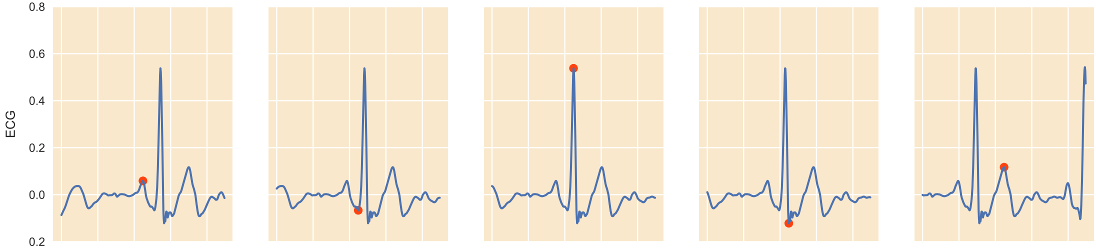


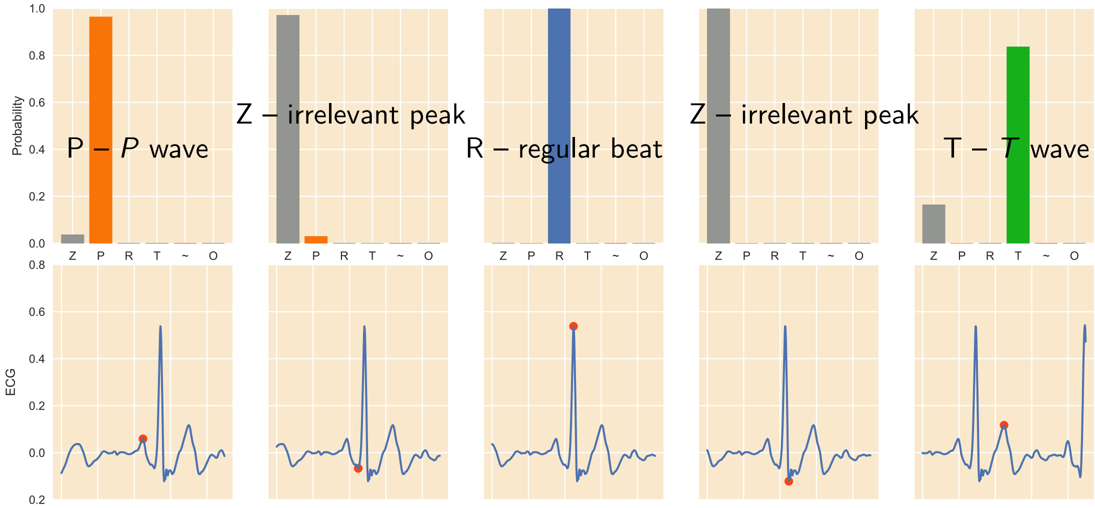
# Input layer

Approximately **12,000,000 characteristic waveforms** served as **input volume**. The assigned **annotation codes of the midpoint peaks** in each ECG segment were used as **output volume**.

▸ CNN architecture



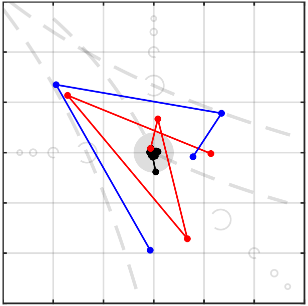
# Activation functions of a regular ECG



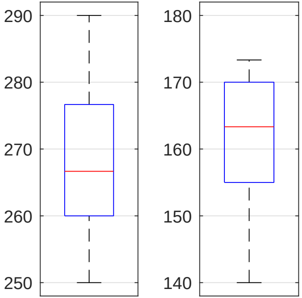
# Feature extraction

- **Interval data**: absolute values, percentiles, and interquartile ranges for *RR*, *RT*, and *PR* intervals
- **Entropy** of relative *RR* intervals (using standard deviation)
  Entropy on higher grades: considering a lag when computing relative *RR* intervals
- **Atypical beats**: absolute counts and percentage of extrasystoles with and without compensatory pause, doublets, triplets
- **Normalization**: adjusting interval data by heart rate (estimated by the $25\%$ trimmed mean of *RR* intervals) or using relative intervals, defined as successive differences divided by their mean [8]
- **ECG morphology**: basic cluster characteristics like the silhouette score and distance information derived from k-Means and hierarchical clustering (average linkage, euclidean metric) on the basis of the cross-correlation for each pair of ECG segments

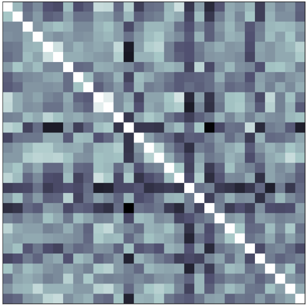
# Feature extraction



**Atypical beat classification**
*rr* intervals and classification rules based on relations of successive intervals [9].




**Interval data**
Distribution of *RT* (left) and *PR* intervals (right) [ms].



**ECG morphology**
Cross-correlation matrix of ECG segments for beat classification.

# Boosting trees for heart rhythm classification

Once the features were extracted, **gradient boosting decision trees were trained with these features on expert labeled data** to classify the heart rhythm of ECG recordings:

- Normal sinus rhythm ($N$)
- Atrial fibrillation ($A$)
- Alternative rhythm ($O$),
- Too noisy to classify ($\sim$).

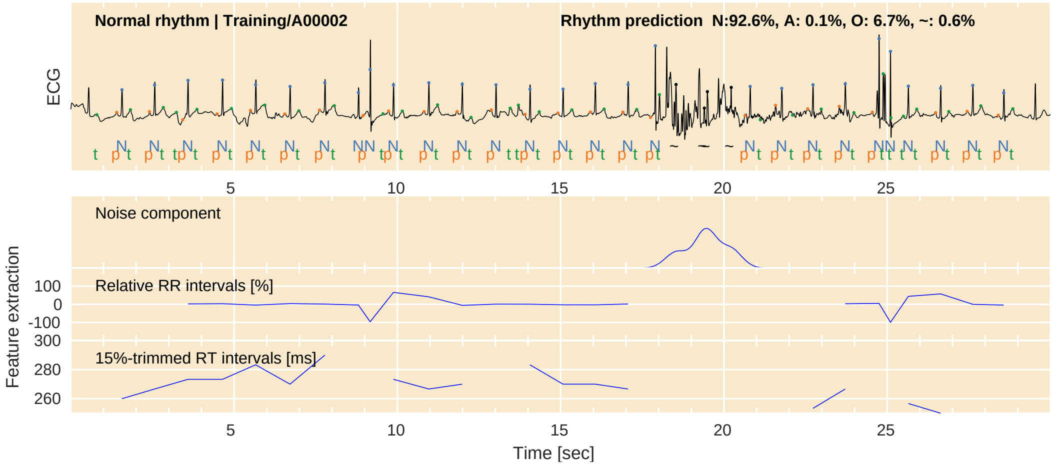
Since the training data is highly imbalanced, we selected the $F_1$ score as the arbitrary differentiable loss function to optimize the prediction.

# 3. Results

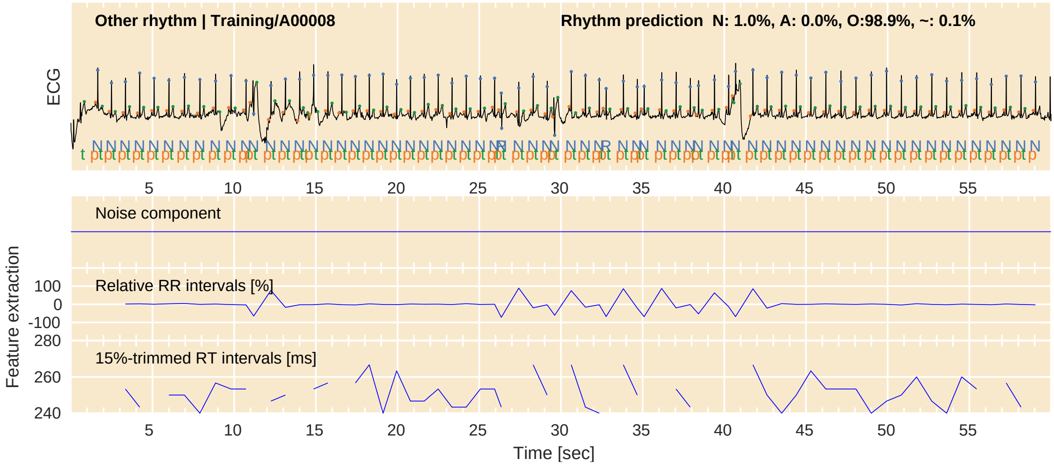
# Annotation performance

| Dataset | | | Counts | | TPR | | PPV | |
|---|---|---|---|---|---|---|---|---|
| | | | Reference | Test | 10 ms | 50 ms | 10 ms | 50 ms |
| QT | R | CNN | 87003 | 86243 | 0.922 | 0.977 | 0.930 | 0.985 |
| | | gqrs | | 87174 | 0.966 | 0.993 | 0.964 | 0.991 |
| | P | CNN | 78665 | 85616 | 0.868 | 0.922 | 0.796 | 0.846 |
| | T | CNN | 86722 | 86530 | 0.807 | 0.879 | 0.802 | 0.874 |
| MIT-BIH P-wave | R | CNN | 25028 | 25034 | 0.963 | 0.996 | 0.963 | 0.996 |
| | | gqrs | | 25372 | 0.959 | 0.981 | 0.946 | 0.968 |
| | | ecgpuwave | | 16584 | 0.557 | 0.598 | 0.841 | 0.902 |
| | P | CNN | 22108 | 24883 | 0.695 | 0.945 | 0.618 | 0.837 |
| | | ecgpuwave | | 9266 | 0.271 | 0.345 | 0.645 | 0.824 |
| | | gqrs+ecgpuwave | | 13092 | 0.351 | 0.477 | 0.671 | 0.912 |

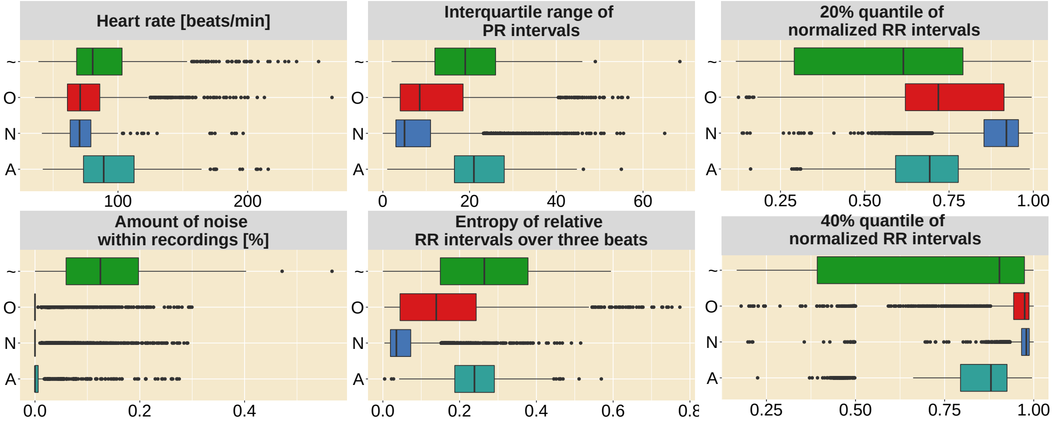
# Example ECG recording with normal heart rhythm



# Example ECG recording with other heart rhythm



# Feature distributions of heart rhythm classes




Gain Index

# Classification performance

Rhythm classes trained on avg. 30 s single lead ECG recordings (LA-RA) provided by AliveCor through the PhysioNet/CinC Challenge 2017 [10]. ▸ PhysioNet.org

Post-challenge entry:

| | Recordings | Overall | Normal | Atrial Fibrillation | Other rhythm | Noisy |
|---|---|---|---|---|---|---|
| Training set | 8528 | 0.99 | 0.99 | 0.99 | 0.98 | 0.99 |
| Test set | 3658 | 0.82 | 0.91 | 0.82 | 0.74 | - |

▸ Certainty of rhythm classification

# 4. Summary & Outlook

# CNN usage for ECG segmentation

## Strength

- Fully automated
- Real-time applicable
- Database expandable
- Extendable to other ECG characteristics
- Annotation accuracy expressed as stochastic vectors

## Limitations

- Accuracy depends strongly on labeled input data
- Abnormal waveforms, which are not trained, cannot be correctly annotated

## Future ideas

- Noise robust search for local extrema
- Use of different CNNs for P,T and R peak location (multi-step approach)
- Use of heart rate normalized ECG segments
- Prior knowledge as input layer (e.g. known R peaks, PQRT locations of previous heart beat)

# Thank You for Your Attention

# 5. Appendix

# Literature I


- M. Vollmer, P. Sodmann, L. Caanitz, N. Nath, and L. Kaderali, "Can Supervised Learning Be Used to Classify Cardiac Rhythms?," in *2017 Computing in Cardiology (CinC)*, vol. 44, pp. 1–4, IEEE, 2017.
- P. Sodmann, M. Vollmer, N. Nath, and L. Kaderali, "A convolutional neural network for ecg annotation as the basis for classification of cardiac rhythms," *Physiological measurement*, vol. 39, no. 10, p. 104005, 2018.
- P. Laguna, R. G. Mark, A. Goldberg, and G. B. Moody, "A database for evaluation of algorithms for measurement of QT and other waveform intervals in the ECG," in *Computers in Cardiology*, pp. 673–676, 1997.
- G. B. Moody, *WFDB applications guide*.
  Harvard-MIT Division of Health Sciences and Technology, 10 ed., 2003.

# Literature II


- M. Vollmer, “Noise Resistance of Several Top-Scored Heart Beat Detectors,” in *Computing in Cardiology*, vol. 44, p. in press, 2017.
- G. B. Moody and R. G. Mark, “The impact of the MIT-BIH arrhythmia database,” *IEEE Engineering in Medicine and Biology Magazine*, vol. 20, no. 3, pp. 45–50, 2001.
- M. Elgendi, B. Eskofier, and D. Abbott, “Fast T Wave Detection Calibrated by Clinical Knowledge with Annotation of P and T Waves,” *Sensors*, vol. 15, no. 7, pp. 17693–17714, 2015.
- M. Vollmer, “A Robust, Simple and Reliable Measure of Heart Rate Variability using Relative RR Intervals,” in *Computing in Cardiology*, vol. 42, pp. 609–612, 2015.
- M. Vollmer, “Arrhythmia Classification in Long-Term Data Using Relative RR Intervals,” in *Computing in Cardiology*, vol. 44, p. in press, 2017.

# Literature III


- G. Clifford, C. Liu, B. Moody, I. Silva, Q. Li, A. Johnson, and R. Mark, "AF Classification from a Short Single Lead ECG Recording: the PhysioNet Computing in Cardiology Challenge 2017," in *Computing in Cardiology*, vol. 44, 2017.
- P. T. Baker, S. Caudill, K. A. Hodge, D. Talukder, C. Capano, and N. J. Cornish, "Multivariate classification with random forests for gravitational wave searches of black hole binary coalescence," *Physical Review D*, vol. 91, no. 6, p. 062004, 2015.

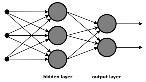
# Image Sources

Heart illustration: Wikimedia Commons | Wapcaplet
Cardiac cycle: Wikimedia Commons | DestinyQx/DanielChangMD
TensorFlow logo by Wikimedia/FlorianCassayre (CC-BY-SA 4.0)
TensorFlow serving chart adapted from www.tensorflow.org/serving/ (CC-BY-SA 3.0)
Random Forest illustration adapted from [11].

# Architecture of the CNN

Preprocessing | Block #0 | Block #1 | Pooling #1 (1×) | Block #2 | Block #2 | Pooling #2 (2×) | Block #2 | Pooling #2 (1×) | Flatten | Softmax

*Fully connected layers*




## Preprocessing

- *Data augmentation*
- *Adding resampling noise*
- *Discrete wavelet transform*

## Block

| | | #0 | #1 | #2 |
|---|---|---|---|---|
| *Convolution* | filter<br>kernel size | 16<br>3 | 16<br>3 | 32<br>3 |
| *Batch normalization* | | | | |
| *Activation* | | Tanh | PReLu | PReLu |
| *Dropout* | | 30% | 10% | 10% |

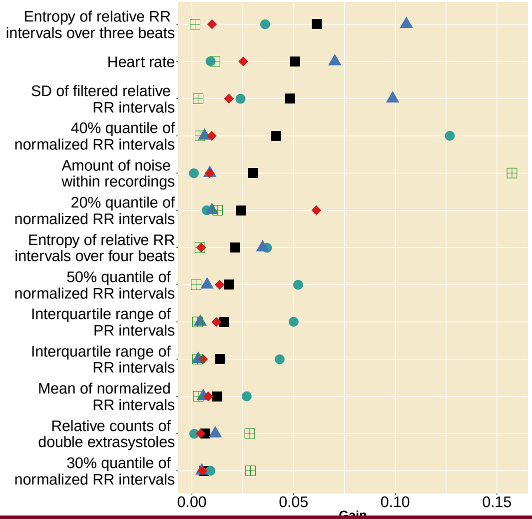
## Pooling

| | | #1 | #2 |
|---|---|---|---|
| *Max pooling* | filter<br>stride | 3<br>3 | 2<br>2 |
| *Batch normalization* | | | |
| *Activation* | | PReLu | PReLu |
| *Dropout* | | 10% | 10% |

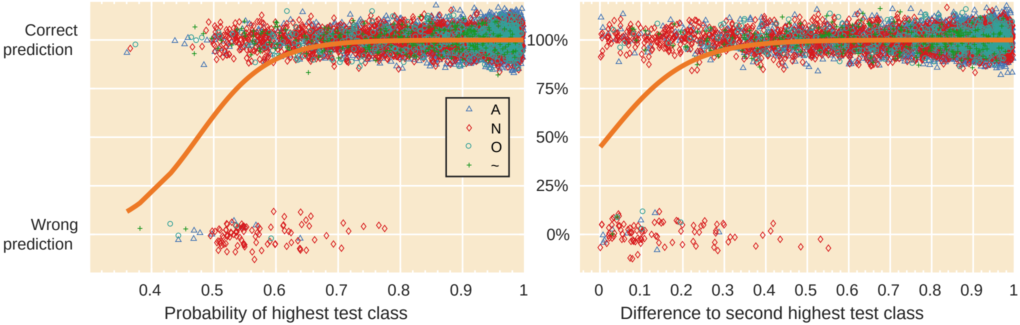
## Flatten

| | |
|---|---|
| *Flatten* | |
| *Dense* | 420 neurons |
| *Activation* | PReLu |
| *Dropout* | 10% |
| *Dense* | 11 neurons |

# Overall importance based on Gain index



# Certainty of rhythm classification




The left plot shows the probabilities of our estimates and a logistic regression fit.
The right plot shows the certainty of the estimate based on the difference between the two highest probabilities of the stochastic vector.