Can Supervised Learning be used to Classify Cardiac Rhythms?

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

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Outline

1. Motivation
2. Methods
3. Results
4. Summary & Outlook

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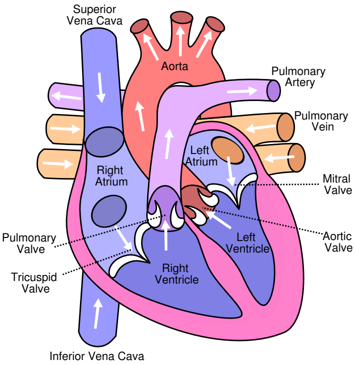
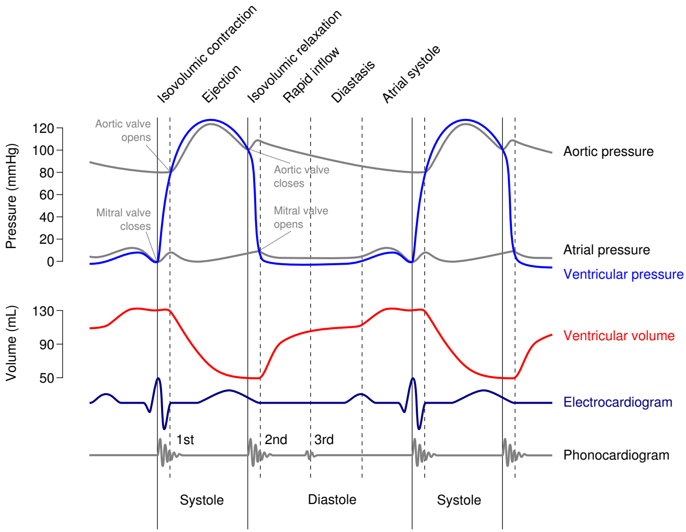
Motivation

Cardiac Cycle





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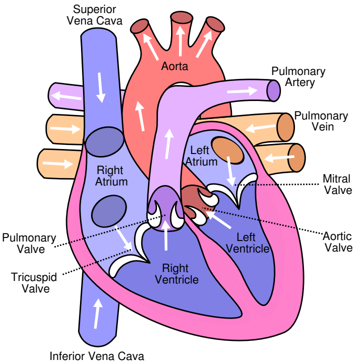
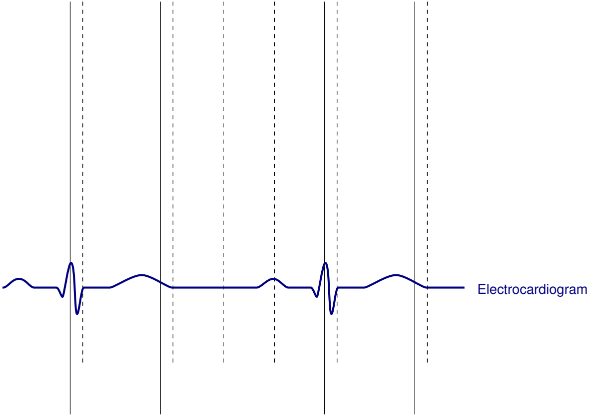
Cardiac Cycle





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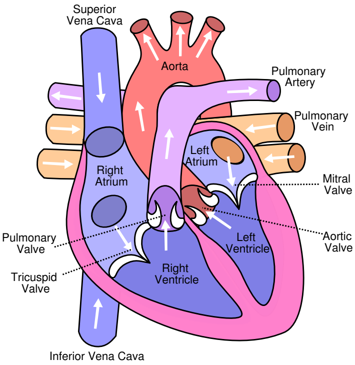
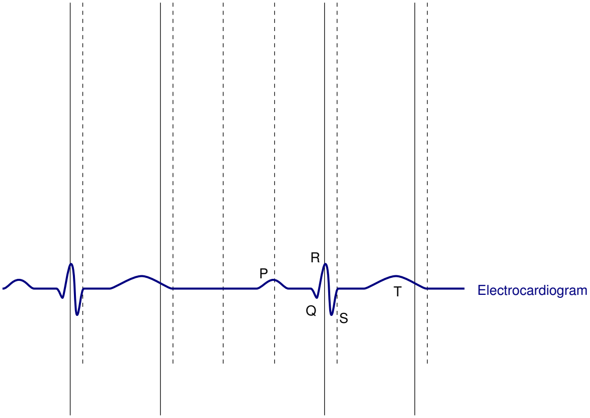
Cardiac Cycle

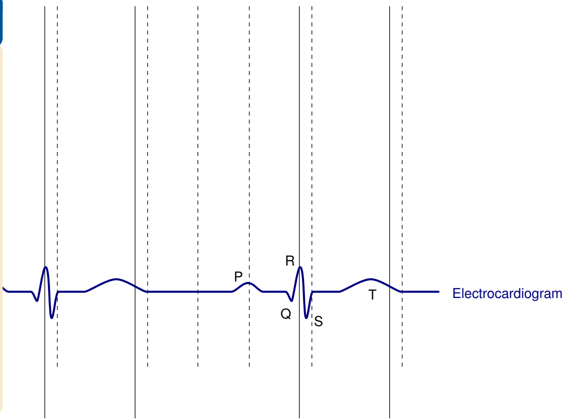




Cardiac Cycle

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 freely available



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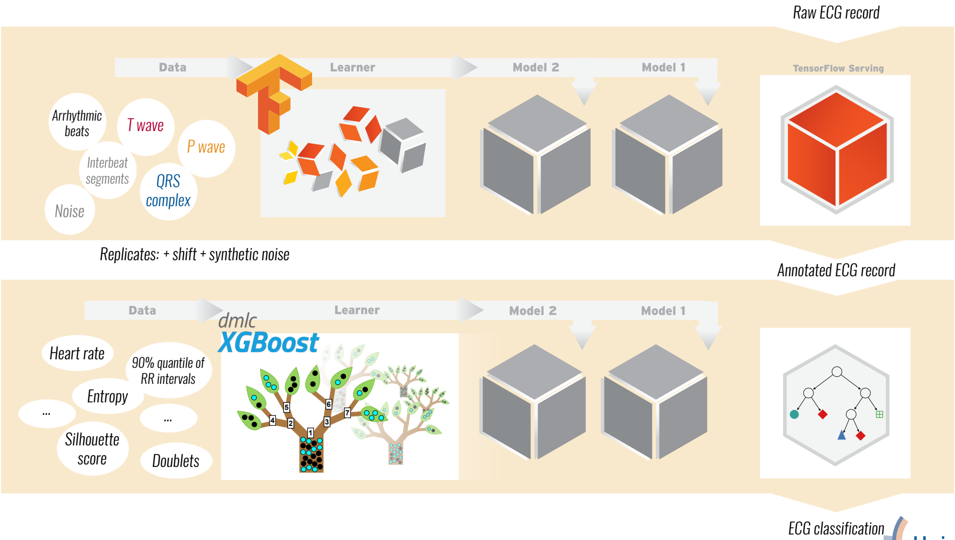
Methods

A schematic representation of our workflow [1]



Information gathering

Labeled input data to train the CNN:

- QT database[2]
  - 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 [3, 4]
- MIT-BIH Arrhythmia Database [5]
  - Extrasystoles labeled as *O*
    2,545 atrial premature beats, 7,127 premature ventricular contractions, 7,020 paced beats, 982 of fusions of paced and normal beats, 8,070 left and 7,251 segments of right bundle branch block beats
  - 106,112 *R* peaks
  - 74,985 *P* waves by Elgendi [6]
  - 109,267 *T* waves by Elgendi [6]

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 ± 3 ms
- Adding gaussian noise ($\sigma = 0.02$) for a better generalization and to reduce overfitting

In total approximately **12,000,000 characteristic waveforms** were used as **input volume**.
The assigned **annotation codes of the midpoint peak** of each segment were used as **output volume**.

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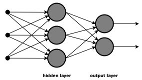
Architecture of the CNN

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*	16	16	32
	kernel size	3	3	3
Batch normalization				
Activation		Tanh	PReLu	PReLu
Dropout		30%	10%	10%

Pooling

		#1	#2
Max pooling	*filter*	3	2
	stride	3	2
Batch normalization			
Activation		PReLu	PReLu
Dropout		10%	10%

Flatten

Flatten	
Dense	420 neurons
Activation	PReLu
Dropout	10%
Dense	11 neurons

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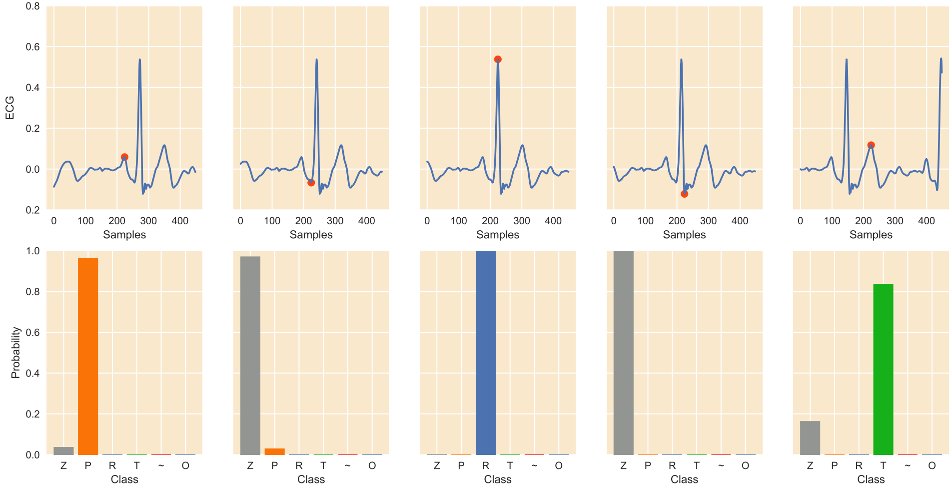
Activation functions at different extrema of a normal ECG



Z – irrelevant peak, P – *P* wave, R – regular beat, T – *T* wave, ∼ – noise, O – irregular beat

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
- **Extra 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[7]
- **Shape information**: 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 heart beat waveforms

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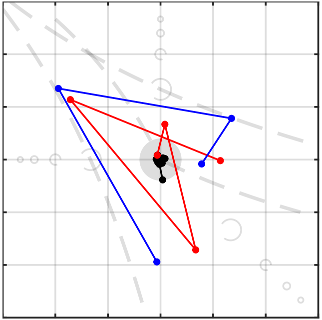
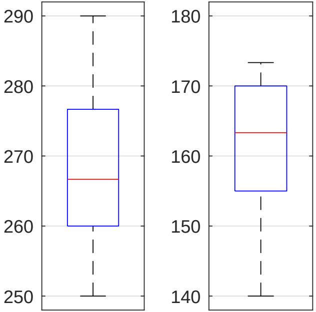
Feature extraction



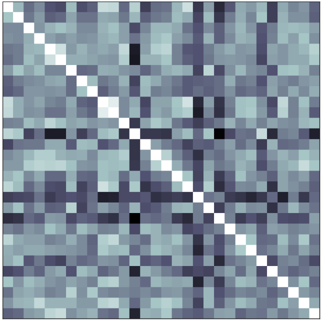
Identification of extra beats.

Relative *RR* intervals and classification rules based on relations of successive intervals[8].



Interval data

Range of *RT* (left) and *PR* intervals (right) in milliseconds.



Shape information

Cross-correlation matrix of heart beats to identify classes of beats, e.g. multifocal PVCs.

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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 ($\sim$).

Gradient boosting is a machine learning technique for regression and classification problems. It optimizes an arbitrary differentiable loss function. We selected the F_1 score.

Results

Annotation performance

Dataset			Counts		TPR		PPV		MAD
			Reference	Test	10 ms	50 ms	10 ms	50 ms	[ms]
QT	R	CNN	87003	86243	0.922	0.977	0.930	0.985	4.2
		gqrs		87174	0.966	0.993	0.964	0.991	3.1
	P	CNN	78665	85616	0.868	0.922	0.796	0.846	4.9
	T	CNN	86722	86530	0.807	0.879	0.802	0.874	15.8
MIT-BIH P-wave	R	CNN	25028	25034	0.963	0.996	0.963	0.996	2.7
		gqrs		25372	0.959	0.981	0.946	0.968	3.1
		ecgpuwave		16584	0.557	0.598	0.841	0.902	3.8
	P	CNN	22108	24883	0.695	0.945	0.618	0.837	12.3
		ecgpuwave		9266	0.271	0.345	0.645	0.824	9.4
		gqrs+ecgpuwave		13092	0.351	0.477	0.671	0.912	7.8

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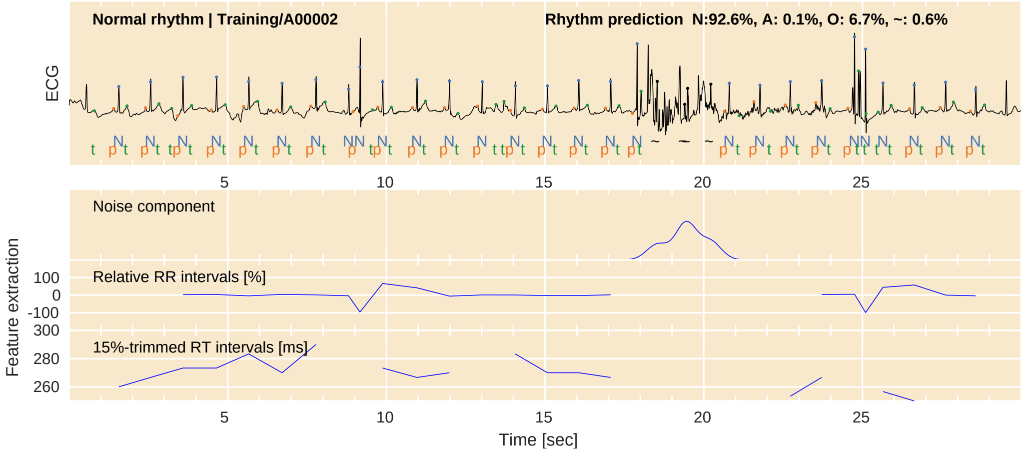
Example ECG recording with normal heart rhythm



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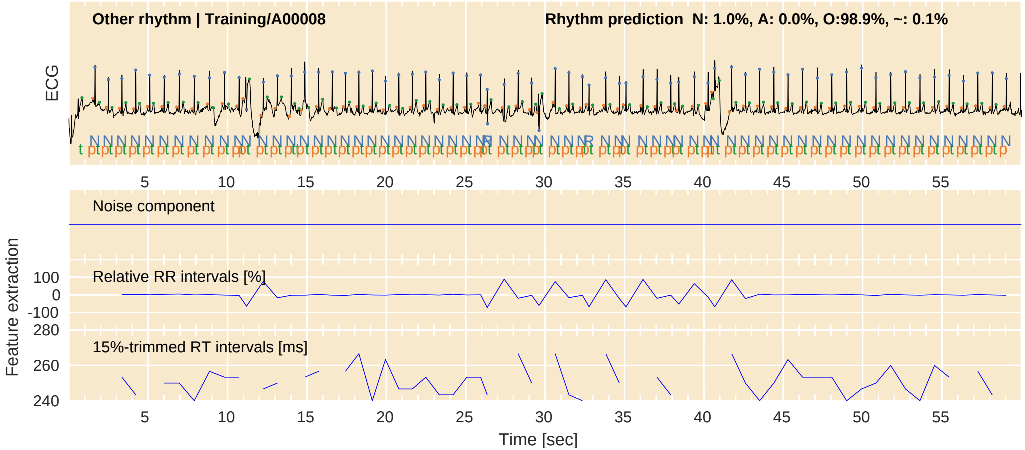
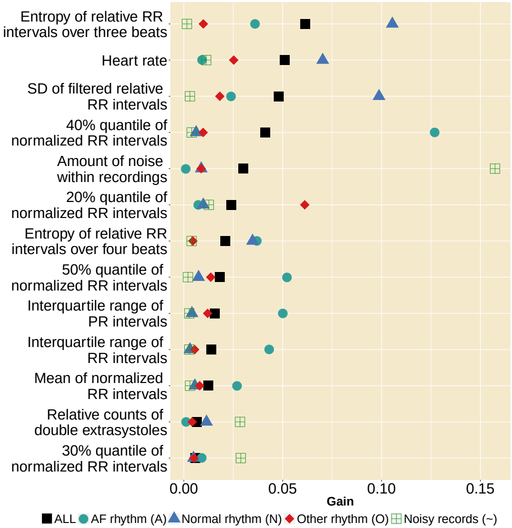
Example ECG recording with other heart rhythm



Overall importance based on Gain index



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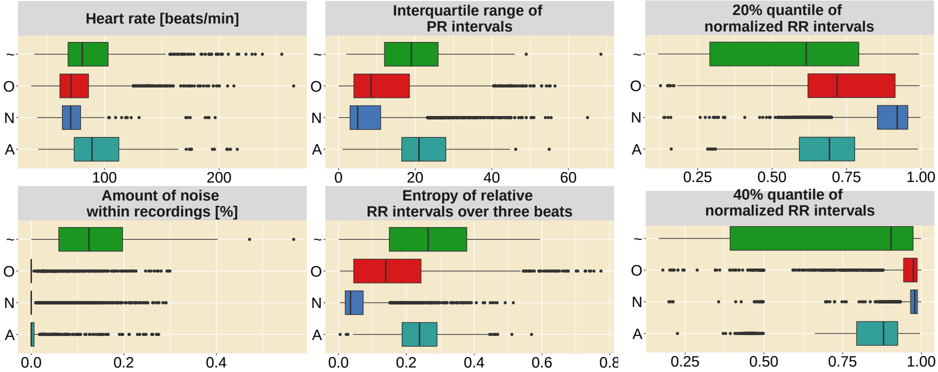
Feature distributions in different heart rhythm classes



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Classification performance

Rhythm classes trained on avg. 30 s ECG recordings provided by the PhysioNet/CinC Challenge 2017 [9].

PhysioNet.org

Recordings origin: AliveCor single lead ECG (LA-RA), labeled by a single expert.

	Recordings		Overall	Normal	Atrial Fibrillation	Other rhythm	Noisy
Enhanced post-challenge entry	Training set	8528	0.99	0.99	0.99	0.98	0.99
	Test set	3658	0.82	0.91	0.82	0.74	-

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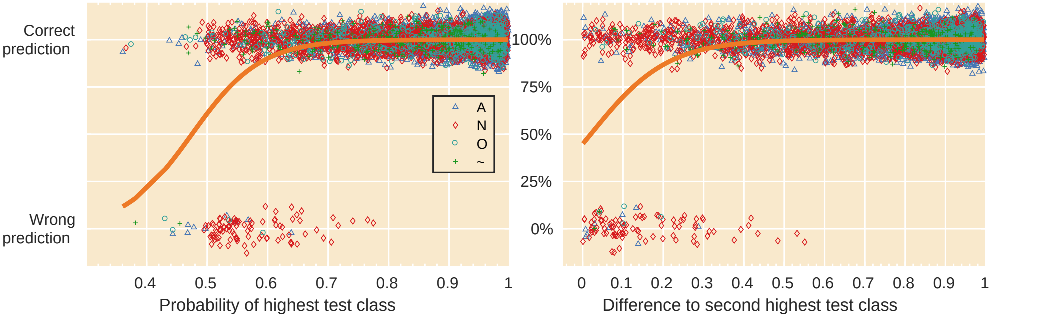
Certainty of heart rhythm classification



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

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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

- Use of 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
- Pass prior knowledge as input layer to the CNN (e.g. known R peaks, PQRT locations of previous heart beat)

Thank You for Your Attention!

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Appendix

Literature I

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Image Sources

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TensorFlow serving chart adapted from www.tensorflow.org/serving/ (CC-BY-SA 3.0)
Random Forest illustration adapted from [10].