ResNet-based ECG Diagnosis of Myocardial Infarction in the Emergency Department

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Machine learning from ground truth: New medical imaging datasets for unsolved medical problems.

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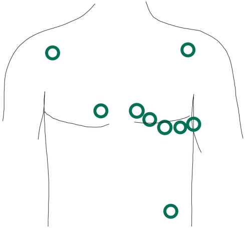
Background

- Emergency Department (ED)
- Myocardial Infarctions (MIs):
  - 9M deaths/year, 200M disability-adjusted life years/year, and rising.
  - False negatives: 10-50,000 missed cases/year at EDs in the United States.
  - False positives: Less than half of those hospitalized for a suspected MI are diagnosed.

  $\rightarrow$ High burden on public health.
- Electrocardiogram (ECG):
  - ST-elevation MI (STEMI) $\rightarrow$ detect in ECG
  - non-ST-elevation-MI (NSTEMI) $\rightarrow$ require blood testing



Background

Baselines:

- Human baseline (cardiologists): 75% acc. for STEMI[1]; much lower for NSTEMI.
- Deep learning models reach super-human performance but:
  - only classify STEMIs[2]
  - use managed data sets[2,3]

Goal: Provide well-calibrated prob. for STEMI/NSTEMI from ECGs at the ED.

Our contribution:

1. Extract a novel data set resembling the real-world setup.
2. Deep learning based model for diagnosing MIs in the ED.

[1] McCabe et al., "Physician accuracy in interpreting potential ST-segment elevation myocardial infarction electrocardiograms".

[2] Cho et al., "Artificial intelligence algorithm for detecting myocardial infarction using six-lead electrocardiography".

[3] Liu et al., "A Deep-Learning Algorithm for Detecting Acute Myocardial Infarction".

Data Set

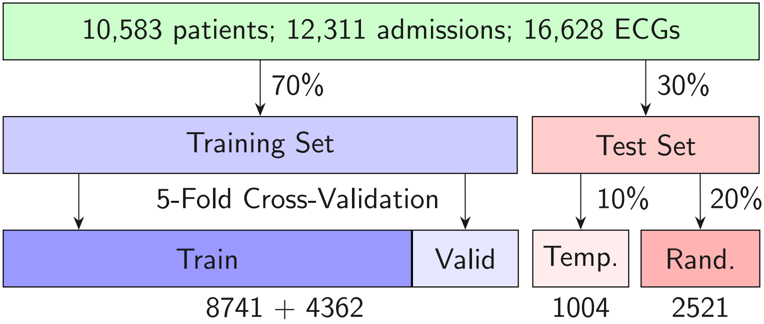
- Standard 10 seconds 12-lead ECGs.
- Adult patients at local ED visits in Stockholm region between 2007 and 2016.
- High risk patients $\rightarrow$ admitted to coronary care unit (CCU).
- Labels:
  - From SWEDEHEART registry[4]
  - By discharging physician that followed entire patient journey during hospitalisation.
- Filter to ensure:
  - inclusion of at event before-treatment ECGs
  - availability of outcome label

$\Rightarrow$ real-world scenario for unsolved problem

[4] `https://www.ucr.uu.se/swedeheart/dokument-sh/variabellista`

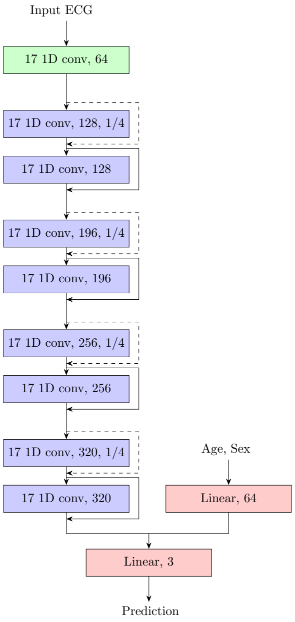
Data Set

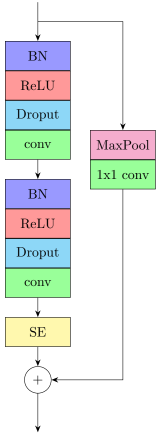
Splitting of the data set:



- Use repeated recordings during training as a form of data augmentation.
- Records from the same patient in the same split.
- Preprocess: Remove low frequency baseline, re-sample, zero-pad.

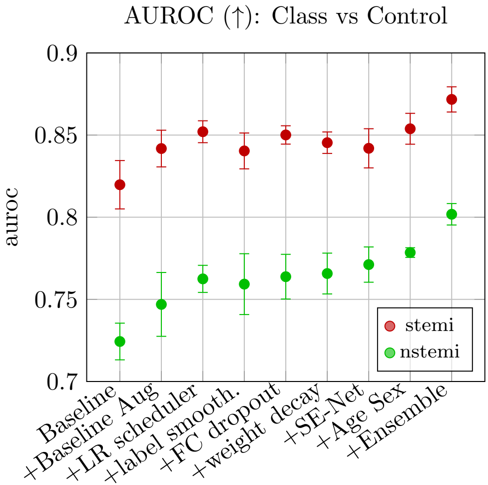
Model Architecture





Model Training

- Baseline from Ribeiro et al.[5]
- Results for 5-fold cross-validation:



[5]Ribeiro et al., "Automatic Diagnosis of the 12-Lead ECG Using a Deep Neural Network".

Results - Main

- Novel data set for unsolved problem $\rightarrow$ no direct baseline available.
- Results over 10 model seeds:

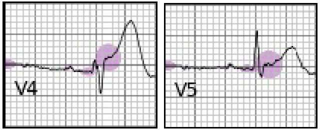
		Random	Temporal
AUROC (↑)	NSTEMI	0.76 (0.003)	0.74 (0.003)
	STEMI	0.85 (0.002)	0.82 (0.003)
AUPR (↑)	NSTEMI	0.69 (0.003)	0.64 (0.005)
	STEMI	0.76 (0.005)	0.64 (0.006)
Brier (↓)	NSTEMI	0.19 (0.001)	0.27 (0.002)
	STEMI	0.10 (0.001)	0.13 (0.001)
ECE (↓)	Multiclass	0.25 (0.004)	0.11 (0.012)

$\Rightarrow$ Super-human-level performance

Results - Model Analysis

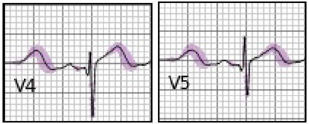
Grad-CAM plots → identify patterns of the model

STEMI



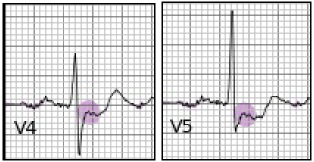
- ST-segment elevation
- typical for humans

STEMI



- Down-sloping T-wave
- untypical for humans

NSTEMI



- ST-segment depression
- humans would not suspect a MI

Extension - Larger Patient Population

- More general patient population: All patients at ED
- Data set statistics:

		Current CCU patients	*Extension* all ED patients
ECGS	Train	8,741+4,362	307,549+67,173
	Test Temp.	1,004	27,937
	Test Rand.	2,521	89,782
	Total	16,628	492,441
Patients		10,583	214,431
	Control	55.9%	98.5%
	STEMI	11.4%	0.4%
	NSTEMI	33.1%	1.1%

- Initial results: similar performance as in current study

Contact

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APPENDIX

Appendix: Data Set

Similar data set: CODE[6,7]

- 811 counties in the state of Minas Gerais, Brazil.
- Collected between 2010 and 2016.
- 2.3M ECGs with 6 heart related labels; more available upon request.
- Separate high quality test data set[8].
- Example usage for anomaly classification[9], ecg-age[10], explaining ECG diagnosis[11] and many more.
- Available for research upon request.

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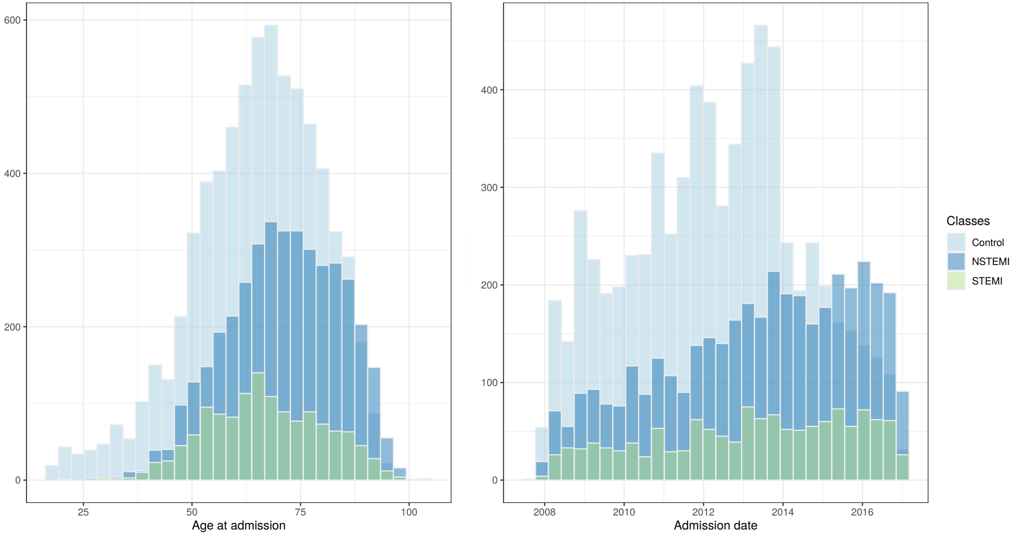
[6] Alkmim et al., "Improving patient access to specialized health care: the Telehealth Network of Minas Gerais, Brazil".
[7] Ribeiro et al., "Tele-electrocardiography and bigdata: The CODE (Clinical Outcomes in Digital Electrocardiography) study".
[8] doi.org/10.5281/zenodo.3765780
[9] Ribeiro et al., "Automatic Diagnosis of the 12-Lead ECG Using a Deep Neural Network".
[10] Lima et al., "Deep neural network-estimated electrocardiographic age as a mortality predictor".
[11] Oliveira et al., "Explaining End-to-End ECG Automated Diagnosis Using Contextual Features".

Appendix: CCU Admission Statistics



Appendix: Hyperparameter Selection

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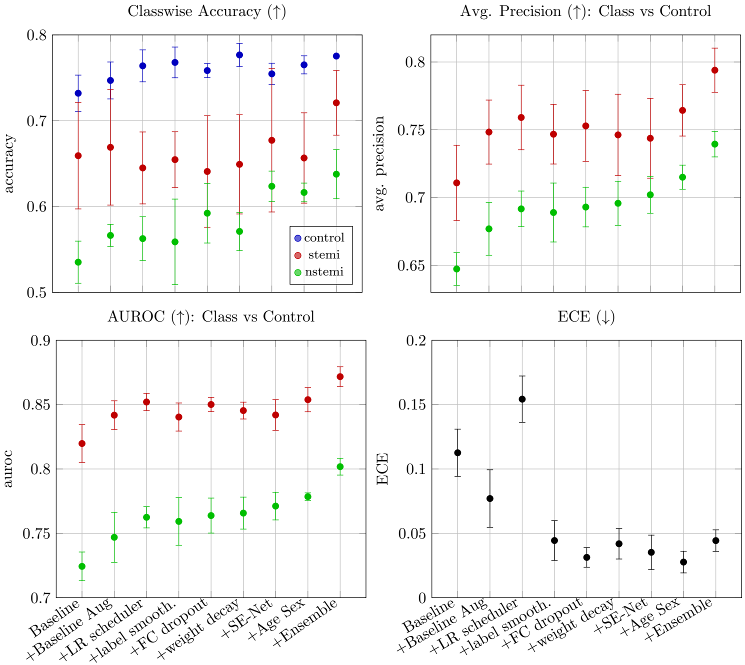
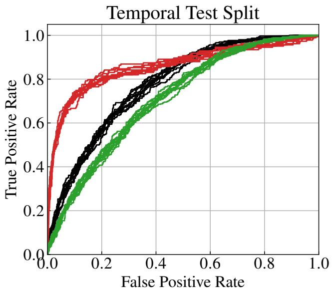
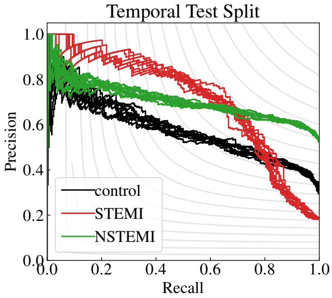
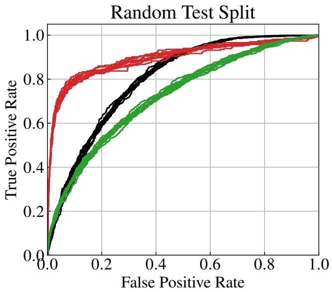
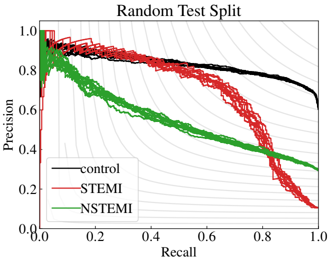


Appendix: Results ROC and PR curves

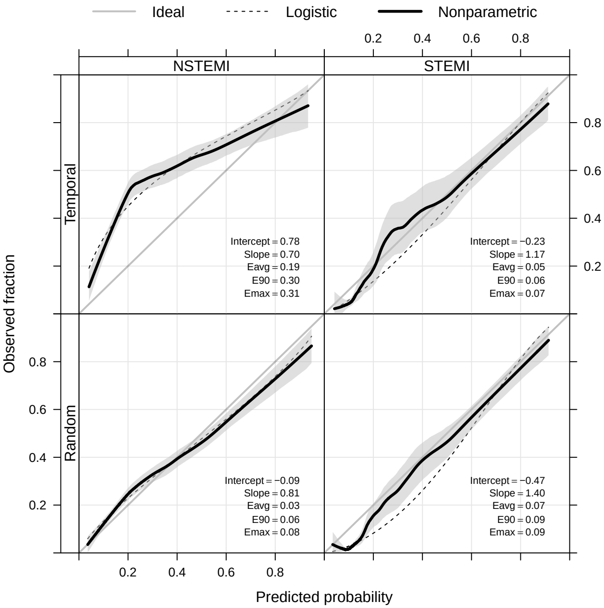








Results - Calibration Plot



Appendix: Discussion

Misclassifications:

- Follows known clinical / machine learning patterns.
- Myocarditis as imposter.

Limitations:

- Lack of external validation.
  $\rightarrow$ Temporal test set simulates new data distributions.
- Selected ECG trace:
  - Label was decided upon discharge from CCU.
  - We cannot ensure that the ECG we use is the one which guided the final diagnosis.

  $\rightarrow$ We mitigate partially by using repeated recordings during training if available.

Appendix: Extensions - (2) Blocked Artery

- Current medical classification: no MI, STEMI, NSTEMI
- Proposal of new classification: identify exact artery which is blocked

  → more fine grain classification

  → direct use for practicing physicians

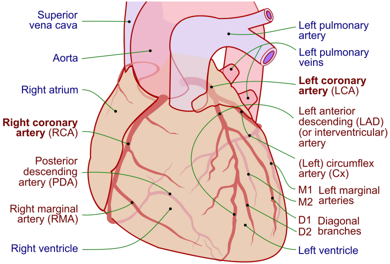


Figure: Coronary Arteries[12]

[12] en.wikipedia.org/wiki/Coronary_circulation

Appendix: Comparison with other Models

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Main comparison with Liu et al., “A Deep-Learning Algorithm for Detecting Acute Myocardial Infarction”.

Similarities:

- Residual blocks but not standardized ResNet structure.

Differences:

- Lead-wise residual network instead of combining all leads.
- No SE-net block but attention mechanism for each lead.

$\rightarrow$ Ability to use Grad-CAM plots with different highlight for different leads.
$\rightarrow$ Assume that leads are independent but they are highly correlated.