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Deep Learning-based ECG Reading in the Emergency Department—Diagnosis of Myocardial Infarctions

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Joint DSBS/FMS Meeting

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Part I

ERC Project: *Decision support in the emergency department*
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Focus on Emergency Department (ED):

1. Financial perspective:
   - $>$ 10% of healthcare costs
   - ED costs are rising
2. Medical perspective:
   - Limited data
   - Chaotic environment
   - Short decision time
   - Evaluate probabilities for large number of diagnoses and risks

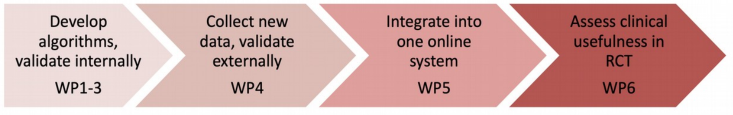
→ Diagnostic error is not uncommon

→ Need for decision support

Aim of the project

Develop decision support models for the ED

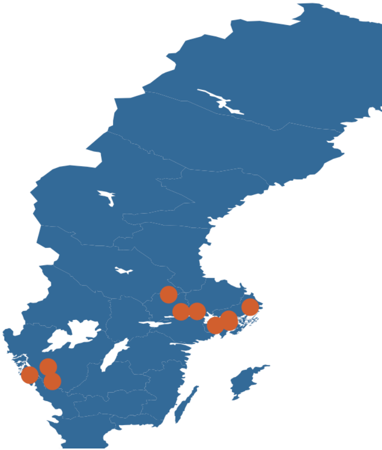
1. **ECG based prediction of diagnoses**
2. Risk prediction of common/dangerous outcomes based on age, sex, previous diagnoses, presenting complaint and vital parameters
3. Risk prediction based on 3D symptom drawings
4. Recommender system for next test based on previous test results



- Ethical aspects of a decision support system
- Train medical staff

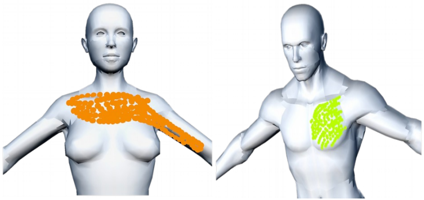
- When: 2005-2017
- Where: Region Stockholm, ...
- Who: all-comer ED visits $\geq$ 18y old.
- What: ED visit linked to national/regional databases
  - patient, prescribed drug, death, cancer registry
  - SWEDEHEART registry
  - regional electronic health records

$\rightarrow$ In total: 6,000,000 ED visits



Symptoms database

- When: to be collected
- Where: Region Uppsala
- Who: ED visits $\geq$ 18y old who
  - can provide informed consent
  - draw their symptoms in a digital interface



Part II

Example for aim "ECG based prediction of diagnoses"

scientific reports

Article | Open Access | Published: 15 November 2022

Development and validation of deep learning ECG-based prediction of myocardial infarction in emergency department patients

Stefan Gustafsson, Daniel Gedon, Erik Lampa, Antônio H. Ribeiro, Martin J. Holzmann, Thomas B. Schön & Johan Sundström

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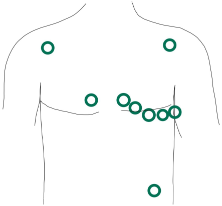
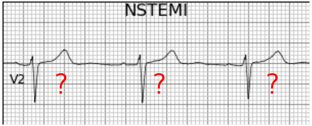
- Myocardial Infarctions (MIs):
  - 9M deaths/year, 200M disability-adjusted life years/year, and rising
  - False negatives: 10-50,000 missed cases/year at EDs in the United States
  - False positives: Less than half of those hospitalized for a suspected MI are diagnosed

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





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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 diagnosis support of 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
- All-comers to ED
- 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

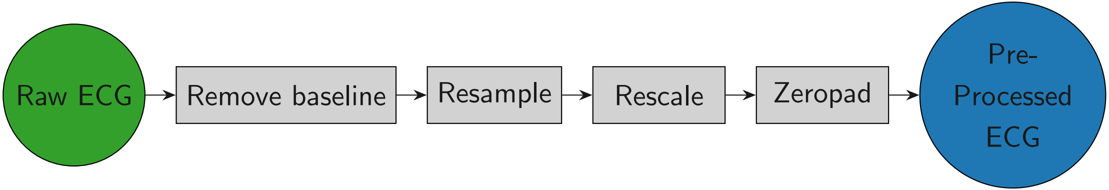
[4] https://www.ucr.uu.se/swedeheart/dokument-sh/variabellista

Data Set

Data set characteristics:

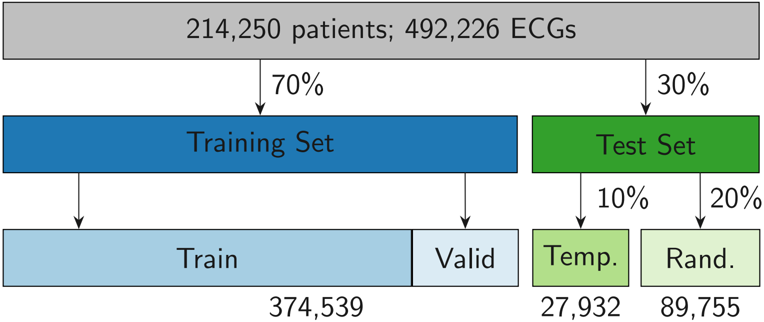
	Control	NSTEMI	STEMI
ECGs	484,992 (98.5%)	5,416 (1.1%)	1,818 (0.4%)
Age	65.0 (47.0,78.0)	71.0 (62.0,81.0)	66.0 (57.0,77.0)
Male	47.3%	65.4%	73.7%

Pre-processing:



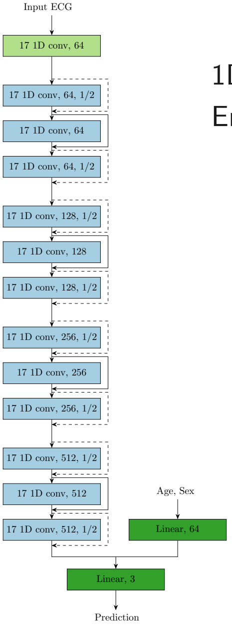
Data Set

Splitting of the data set:



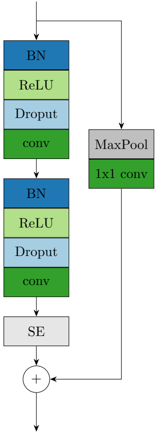
- Use repeated recordings during training as a form of data augmentation
- Records from the same patient in the same split

Model Architecture



1D-ResNet structure

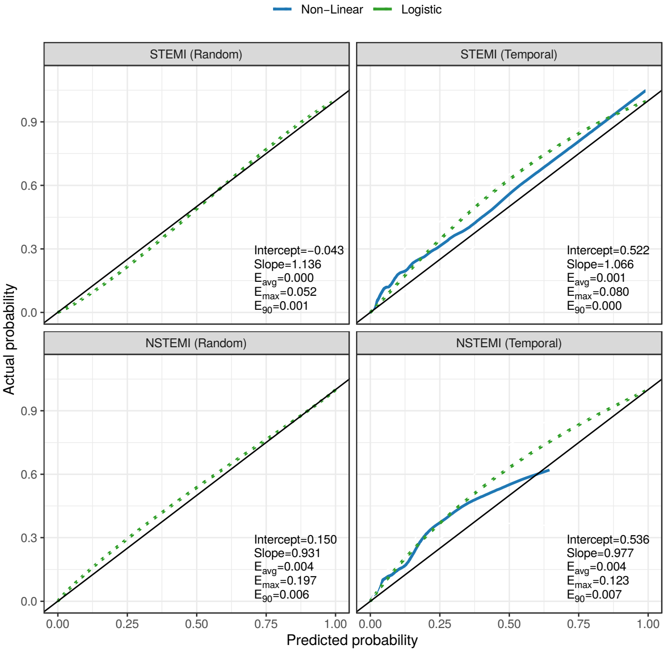
Ensemble of 5 members



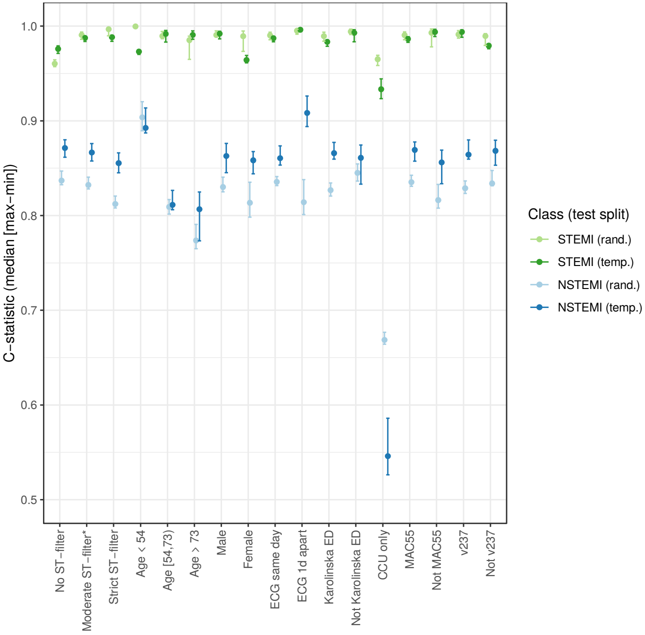
- Novel data set for unsolved problem $\rightarrow$ no direct baseline available.
- Results over 10 model seeds:

		Random	Temporal	PTB-XL
AUROC (↑)	Control	0.863	0.903	0.962
	STEMI	0.991	0.985	0.932
	NSTEMI	0.832	0.867	N/A
AP (↑)	Control	0.998	0.998	0.955
	STEMI	0.692	0.744	0.954
	NSTEMI	0.160	0.184	N/A

Results - Calibration Plot



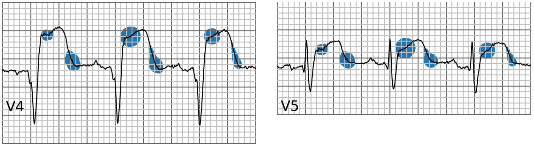
Results - Stratification



Results - Model Analysis

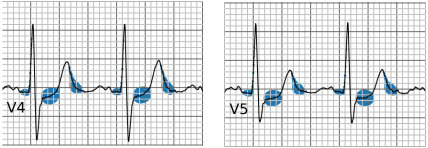
Grad-CAM plots → identify patterns of the model

STEMI



- ST-segment elevation
- Down-sloping T-wave
- Partly typical for humans

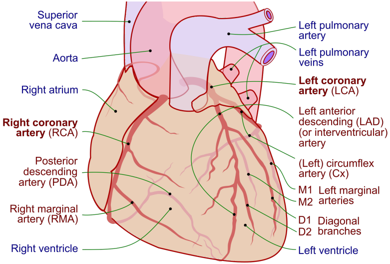
NSTEMI



- ST-segment
- Last part of T-wave
- PQ-segment
- Untypical for humans

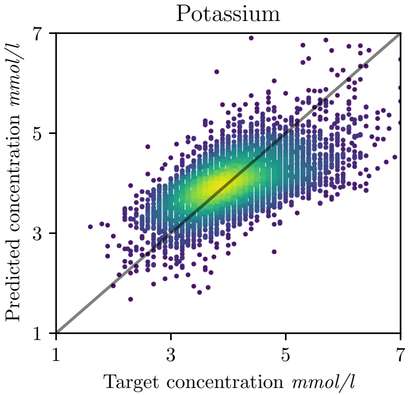
Extensions - Blocked Artery

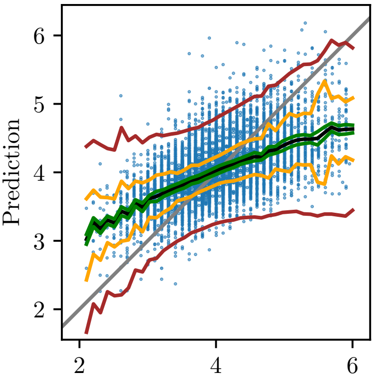
- Current medical classification: no MI, STEMI, NSTEMI
- Proposal of new classification: identify exact artery which is blocked
  $\rightarrow$ more fine grain classification
  $\rightarrow$ direct use for practicing physicians



Regression of electrolyte concentration from ECG

- Goal: predict potassium, calcium, sodium, creatinine
- Sample size: 165,508 patients, 290,889 ECGs





Thank you!

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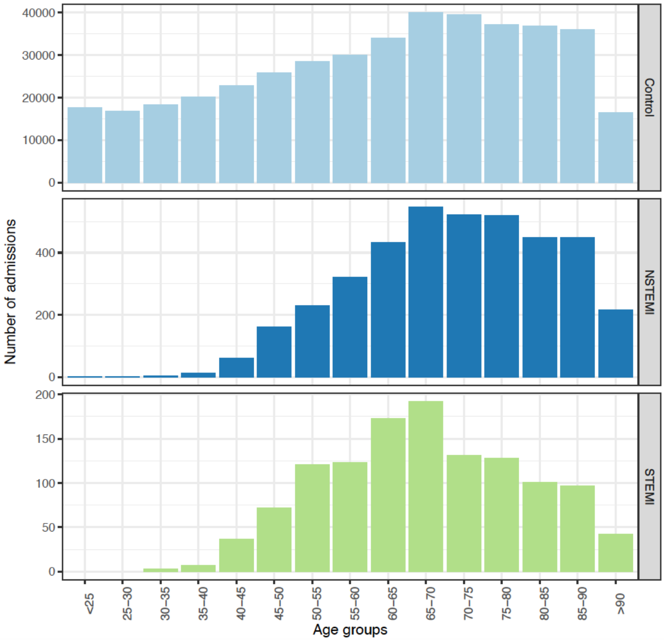
APPENDIX

Appendix: Data Set



Appendix: Results ROC and PR curves

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Temporal Test Split (top) and Random Test Split (bottom)