

# Track patient recovery in real-time by processing streaming data

#### BIOMEDICAL DATA DESIGN

TA: Haoyin Xu

Group:Zhenyu Xiao Haobin Zhou Yimeng Xu Emma Cardenas

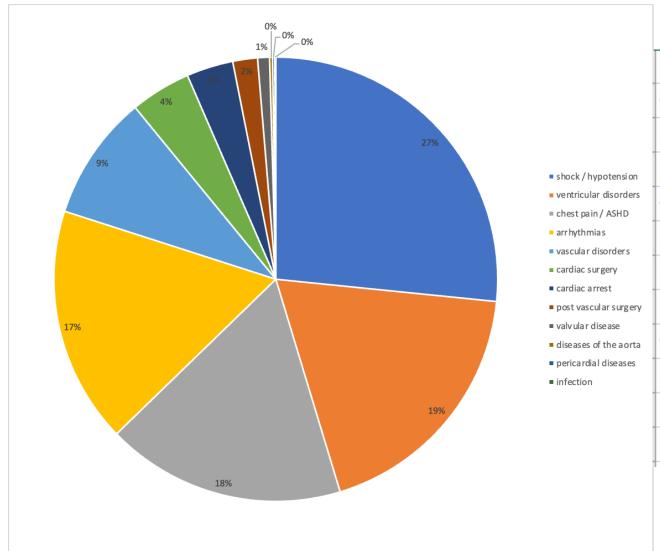
# Content

EICU Prediction

Dataset Analysis

Next Step

#### Main symptoms of the disease:

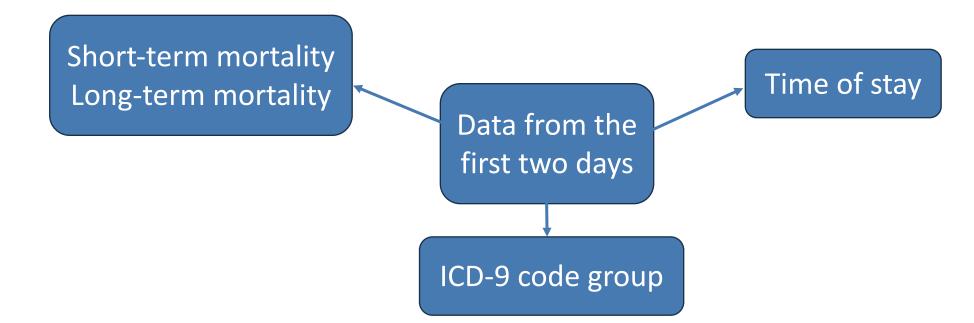


shock / hypotension	1815
ventricular disorders	1277
chest pain / ASHD	1189
arrhythmias	1174
vascular disorders	622
cardiac surgery	301
cardiac arrest	232
post vascular surgery	123
valvular disease	59
diseases of the aorta	15
pericardial diseases	11
infection	5
	and the second s

- 1.heart rate
- 2.blood pressure
- 3. Cardic Output
- 4. Coronary Artery Blood Flow
- 5.Body Temperature (BT)
- 6.Oxygen Saturation
- 7. Peripheral Capillary Oxygen Saturation (SpO2)
- 8. Oxygen Saturation (O2sat)
- 9. C-reactive Protein (CRP)
- 10. Lipid Profile
- 11.age, sex, smoke history, etc...

# Benchmarking deep learning models on large healthcare datasets

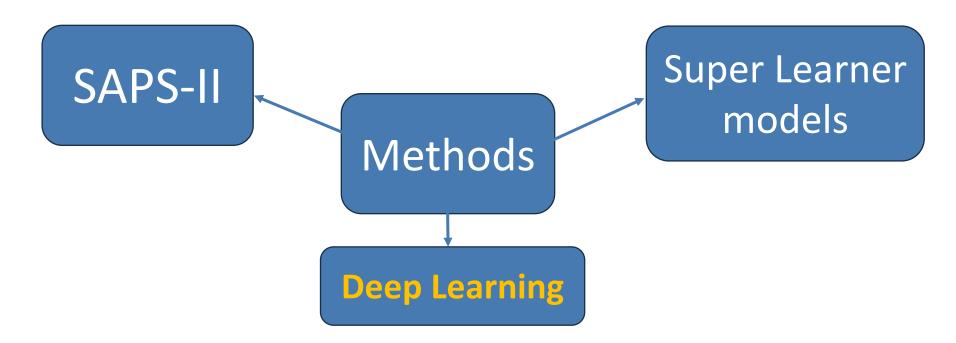
```
Sanjay Purushotham ^{a \, 1} \boxtimes , Chuizheng Meng ^{b \, 1} \boxtimes , Zhengping Che ^{a} \boxtimes , Yan Liu ^{a} \supseteq \boxtimes  Show more \checkmark
```



# Benchmarking deep learning models on large healthcare datasets

<u>Sanjay Purushotham</u> <sup>a 1</sup> ⋈, <u>Chuizheng Meng</u> <sup>b 1</sup> ⋈, <u>Zhengping Che</u> <sup>a</sup> ⋈, <u>Yan Liu</u> <sup>a</sup> 😃

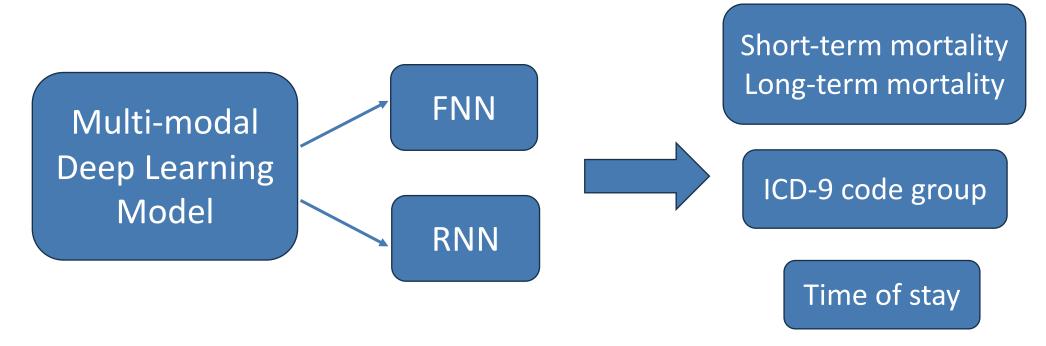
Show more V



# Benchmarking deep learning models on large healthcare datasets

<u>Sanjay Purushotham</u> <sup>a 1</sup> ⋈, <u>Chuizheng Meng</u> <sup>b 1</sup> ⋈, <u>Zhengping Che</u> <sup>a</sup> ⋈, <u>Yan Liu</u> <sup>a</sup> 🚨

Show more V



#### **Mortality**

Method	Algorithm	Feature Set A, 24-h data		Feature Set A, 48-h data	
		AUROC score	AUPRC score	AUROC score	AUPRC score
	SuperLearner-II	0.8673±0.0045	0.4968±0.0097	0.8595±0.0035	0.4422±0.0200
Deep learning	FFN	0.8496±0.0047	0.4632±0.0074	0.8375±0.0041	$0.4090 \pm 0.0169$
	RNN	0.8544+0.0053	0.4519±0.0145	0.8618+0.0059	0.4458±0.0144
	MMDL	0.8664±0.0056	0.4776±0.0162	0.8737±0.0045	0.4714 ± 0.0176

#### ICD-9 code & Time of stay



Analysis | Open Access | Published: 17 June 2019

# Multitask learning and benchmarking with clinical time series data

<u>Hrayr Harutyunyan</u>, <u>Hrant Khachatrian</u> □, <u>David C. Kale</u>, <u>Greg Ver Steeg</u> & <u>Aram Galstyan</u>

Scientific Data 6, Article number: 96 (2019) Cite this article

41k Accesses 231 Citations 18 Altmetric Metrics

elCU Real time Data

Time of stay



# 03 Dataset Analysis

### **Dataset Analysis**

vitalPeriodic & vitalAperiodic & nurseCharting

Vital signs — Time series

diagnosis & patient

Patients' information —— Labels

# **Dataset Analysis**

diagnosisid	patientunitstayid	activeupondischarge	diagnosisoffset diagnosisstring
4035907	143870	TRUE	10 cardiovascular chest pain / ASHD coronary artery disease
3843251	143870	TRUE	10 cardiovascular post vascular surgery s/p cartoid endarterectomy
3460672	143870	TRUE	10 cardiovascular arrhythmias bradycardia
3717065	151179	FALSE	29 cardiovascular shock / hypotension septic shock
4102418	151179	FALSE	120 cardiovascular shock / hypotension septic shock
3885168	151179	TRUE	3929 cardiovascular shock / hypotension septic shock
4053934	151179	TRUE	3929 cardiovascular shock / hypotension hypotension
3850876	151900	FALSE	148 cardiovascular shock / hypotension septic shock
3707280	151900	FALSE	939 cardiovascular shock / hypotension septic shock
4192192	151900	FALSE	939 cardiovascular chest pain / ASHD acute coronary syndrome
3379776	151900	TRUE	2895 cardiovascular chest pain / ASHD acute coronary syndrome
3892141	151900	TRUE	2895 cardiovascular shock / hypotension septic shock
3678632	152954	FALSE	39 cardiovascular shock / hypotension signs and symptoms of sepsis (SIRS)
3977729	152954	FALSE	39 cardiovascular ventricular disorders congestive heart failure
4144394	152954	FALSE	219 cardiovascular shock / hypotension signs and symptoms of sepsis (SIRS)
3757248	152954	FALSE	219 cardiovascular ventricular disorders congestive heart failure

# O4 Next Step

## **Next Step**

- 1.Extract more meaningful data
- 1.1 Extraction
- 1.2 Interpolation, Correction

2. Replicate the deep learning model as baseline and try new models.

# References

Purushotham, S., Meng, C., Che, Z., & Liu, Y. (2018). Benchmarking deep learning models on large healthcare datasets. Journal of Biomedical Informatics, 83, 112-134. <a href="https://doi.org/https://doi.org/10.1016/j.jbi.2018.04.007">https://doi.org/https://doi.org/https://doi.org/10.1016/j.jbi.2018.04.007</a>

Harutyunyan, H., Khachatrian, H., Kale, D. C., Ver Steeg, G., & Galstyan, A. (2019). Multitask learning and benchmarking with clinical time series data. Scientific Data, 6(1), 96. <a href="https://doi.org/10.1038/s41597-019-0103-9">https://doi.org/10.1038/s41597-019-0103-9</a>

Kannel W B, DAWBER T R, FRIEDMAN G D, et al. Risk factors in coronary heart disease: the Framingham Study[J]. Annals of internal medicine, 1964, 61(5\_Part\_1): 888-899.

Churpek MM, Yuen TC, Park SY, Meltzer DO, Hall JB, Edelson DP. Derivation of a cardiac arrest prediction model using ward vital signs\*. Crit Care Med. 2012 Jul;40(7):2102-8. doi: 10.1097/CCM.0b013e318250aa5a. PMID: 22584764; PMCID: PMC3378796. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3378796/

Kwon, J., Lee, Y., Lee, Y., Lee, S., & Park, J. (2018). An algorithm based on Deep Learning for predicting in-hospital cardiac arrest. Journal of the American Heart Association, 7(13). https://doi.org/10.1161/jaha.118.008678

Wilhelmsen L, Wedel H, Tibblin G. Multivariate analysis of risk factors for coronary heart disease[J]. Circulation, 1973, 48(5): 950-958.

