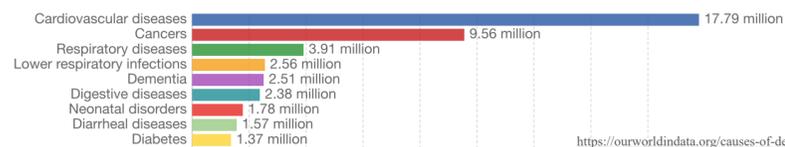


Motivation

- About **6.5 million (1 in 8 deaths)** American adults have heart failure [1,2].
- Electronic Health Records (EHRs)** consist of patient information such as diagnosis codes, medications, vital signs, demographics, and procedures.
- The large electronic data on health records in the past 15 years opens new opportunities to implement early detection surveillance.

Number of deaths by cause, World, 2017

Our World in Data



Objectives

We categorize factors causing heart failure (HF) into two:

- Time Variant Factors:** these factors change with time.



Vital Signs



Medication



Diagnosis

- Time-invariant Factors:** these are factors that are not evolving with time or changing very slowly.



Gender



Race & Ethnicity



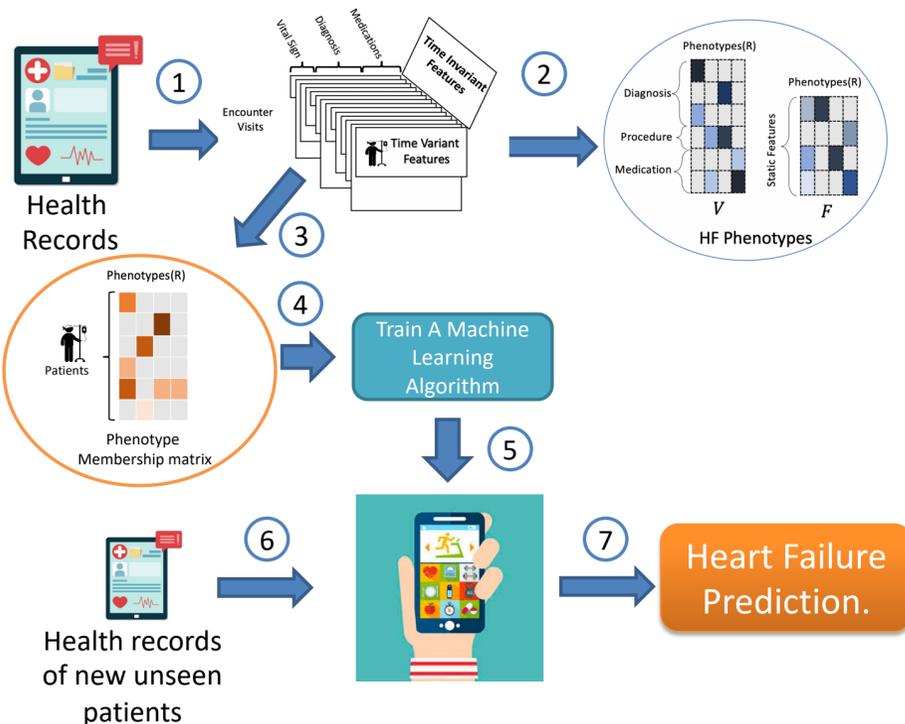
Body Mass Index (BMI)



Smoking Status

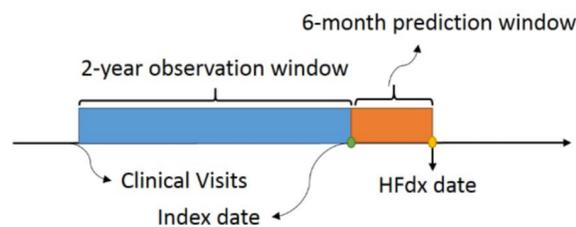
How to combine Time Variant and Time-invariant factors to improve early prediction of heart failure?

Methodology [3]



Data Collection

- A nested case-control design was applied to the primary care population from Sutter Clinics.



STATISTICS SUMMARY	COUNT
# CASE PATIENTS	3244
# CONTROL PATIENTS	31869
# PATIENTS (K)	35113
# DIAGNOSIS FEATURES	178
# MEDICATION FEATURES	142
# VITAL SIGNS FEATURES	5
# TIME VARIANT FEATURES (J)	323
# TIME-INVARIANT FEATURES (P)	22

Computational Phenotyping Results

- Phenotyping:** Identifying patient sub-groups sharing common clinically meaningful Characteristics.
- Why Phenotyping is important?** phenotype characterizations can be used to predict an individual's risk of disease or response to drug therapy.

Elderly Heart Failure with Preserved Ejection Fraction

Diagnosis

- Essential hypertension
- Chronic kidney disease
- Diabetes with renal manifestations

Medication

- Calcium Channel Blockers
- ACE Inhibitors
- Beta Blockers Cardio-Selective
- Angiotensin II Receptor Antagonists

Demographics and Life-Style Behavior

- Gender: Female
- Age: Between 70 to 79.
- Race: White
- No Smoking No Alcohol

Vital Signs

- Pulse: High

Cardiometabolic Driving Heart Failure

Diagnosis

- Diabetes mellitus without complication.
- Cardiac dysrhythmias
- Heart valve disorders

Medication

- Biguanides
- Sulfonylureas
- Insulin
- Angiotensin II Receptor Antagonists

Demographics and Life-Style Behavior

- Gender: Male
- Age: Between 60 to 69.
- BMI: Severely Obese

Vital Signs

- Blood Pressure: High
- Pulse: Normal

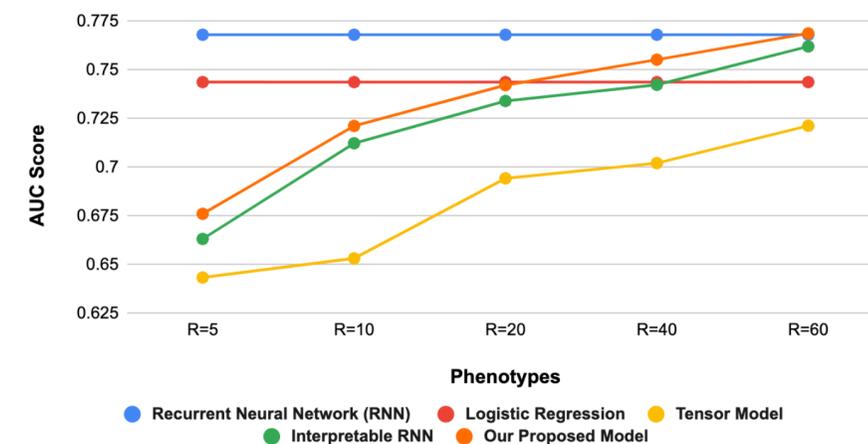
Predictive Performance Results

Why Predictive modeling is important? It helps us to identify people at high risk and prioritize them for early intervention strategies.

AUC Score is a performance measurement for classification problem when data in imbalance.

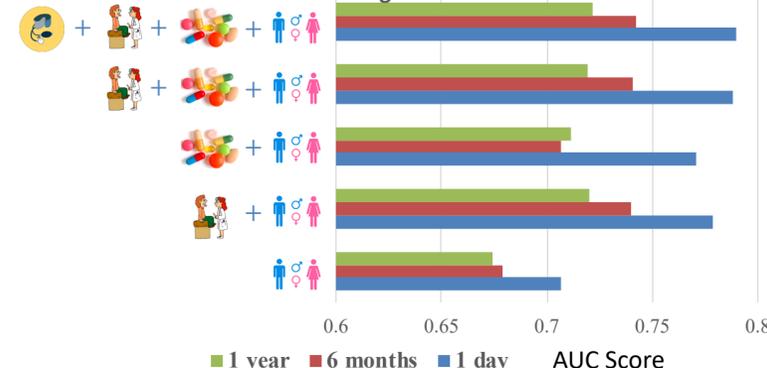
How is the predictive power our proposed model in compare to other baselines?

The average AUC score of our proposed model in compare to other baselines.



What is the effect of different feature domains and various prediction window lengths on early detection of HF ?

The average of AUC score of our proposed model with 20 phenotypes (R=20) for different data domains and prediction window lengths.



Conclusion

- We proposed an interpretable model to tackle two important challenges in healthcare.
- The predictive performance of our model is comparable with state-of-the-art deep learning models with the advantage of interpretability.

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- Centers for Disease Control and Prevention, National Center for Health Statistics. *Underlying Cause of Death, 1999–2017*. Accessed January 7, 2019.
- Afshar, Ardavan, Ioakeim Perros, Haesun Park, Christopher deFilippi, Xiaowei Yan, Walter Stewart, Joyce Ho, and Jimeng Sun. "TASTE: Temporal and Static Tensor Factorization for Phenotyping Electronic Health Records." *arXiv preprint arXiv:1911.05843* (2019). Richesson, Rachel L, et al. "Clinical phenotyping in selected national networks: demonstrating the need for high-throughput, portable, and computational methods." *Artificial intelligence in medicine* 71 (2016): 57-61.