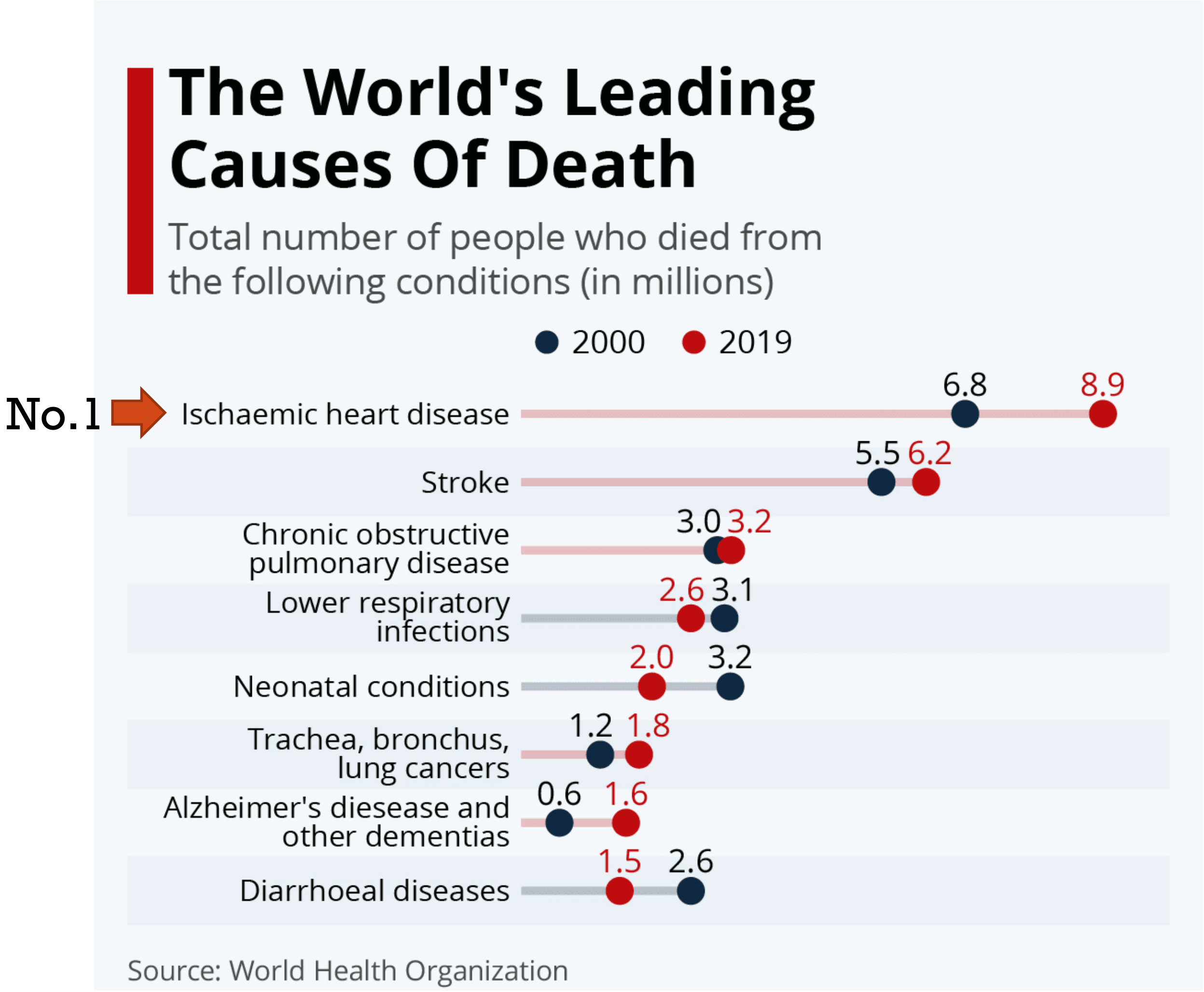
DEVELOPING A DEEP SURVIVAL MODEL FOR PREDICTING TIME TO DEATH FOR IN-HOSPITAL PATIENTS DIAGNOSED WITH ISCHEMIC HEART DISEASE

Code Link: **https://github.gatech.edu/ressomba3/bigdata_healthcare**

Hanjun, Li (hli735@gatech.edu); Lingxiao, He (lhe90@gatech.edu); Rene F, Essomba (ressomba3@gatech.edu); Wei Xuan, Ng (wng33@gatech.edu)

PURPOSE OF PROJECT



? Problem to be Solved ?

- IHD is the No.1 cause of death in the world
- 40% fatal IHD events led to in-hospital death

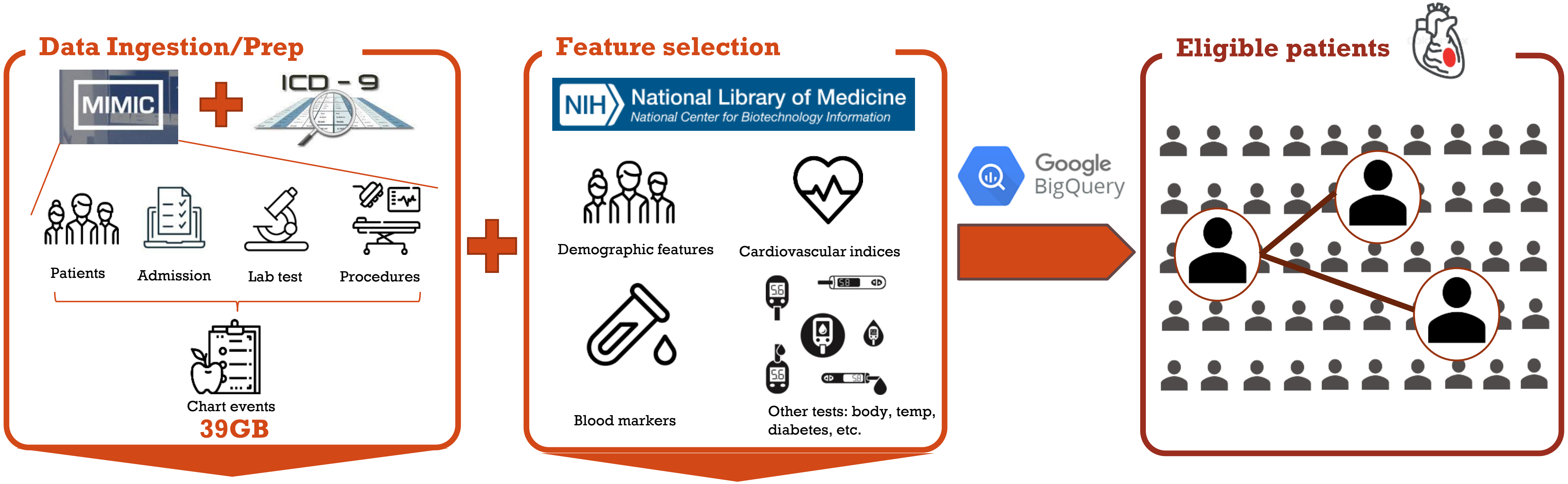
Purpose of Project

- Using machine learning/deep learning methods to predict patients' risk of death

Novelty

- This is the first study utilizing **sequence-based survival models** for the prediction of in-hospital mortality risk in IHD patients

DATA PREPARATION

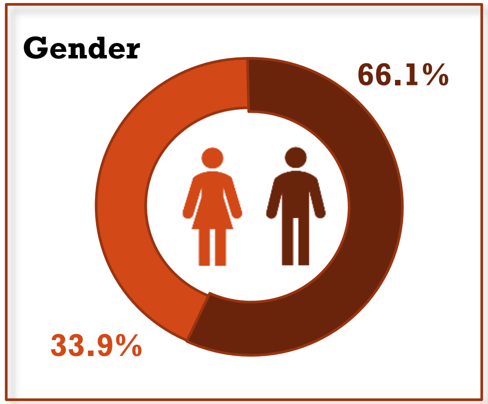


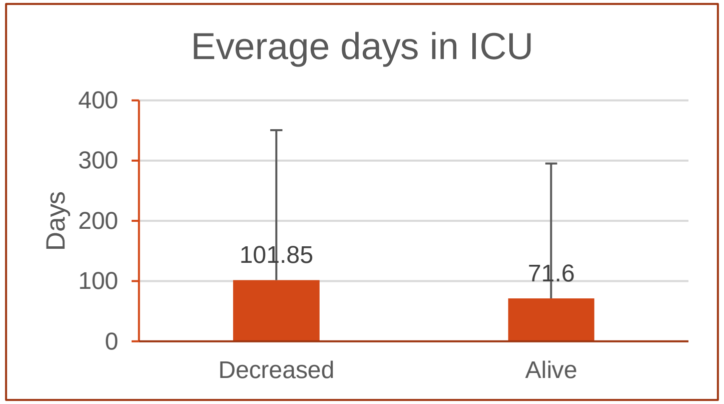
MIMIC III v1.4 database contains de-identified data of 58,976 patients admitted in ICU between June 2001 and October 2012

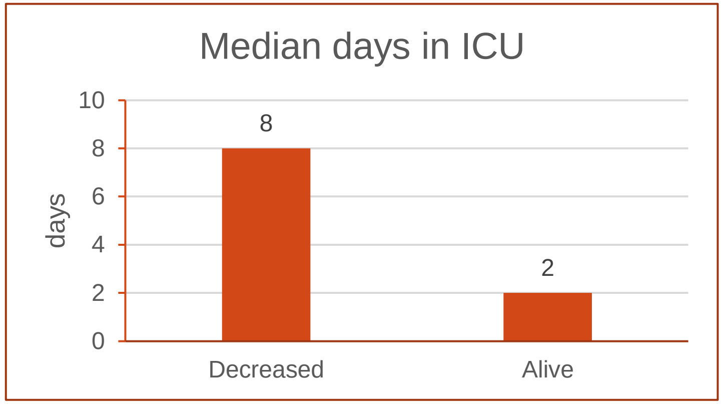
Feature selection is based on the literature review: 35 features that are relevant to IHD were selected

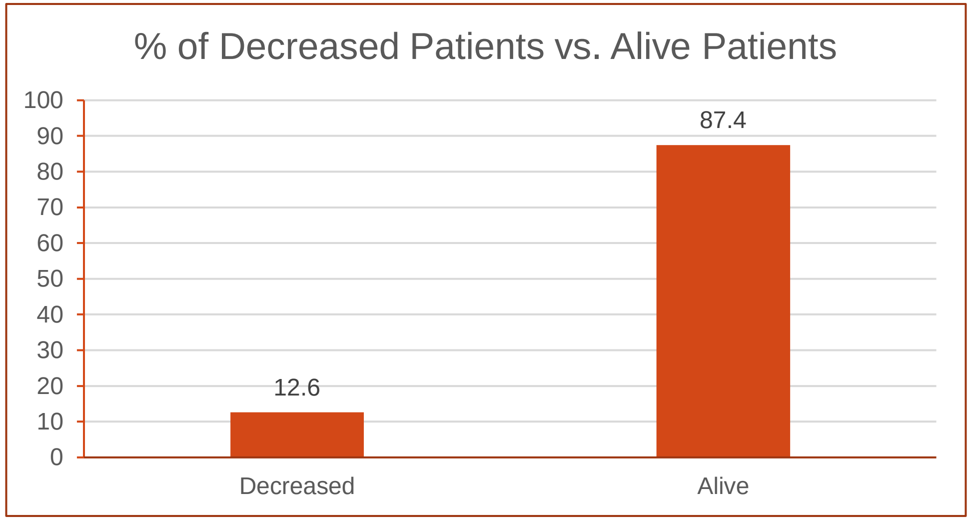
6244 IHD patients are eligible for analysis

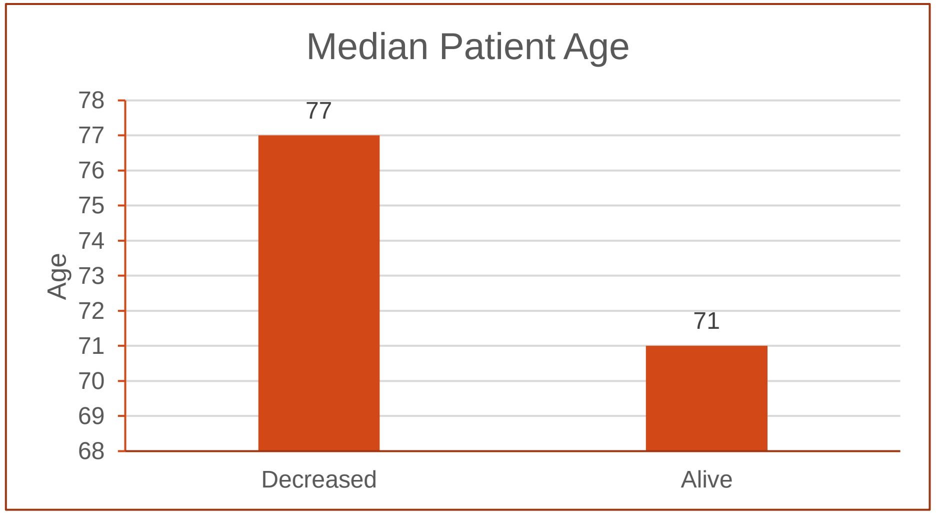
DATA DISCRIPTION









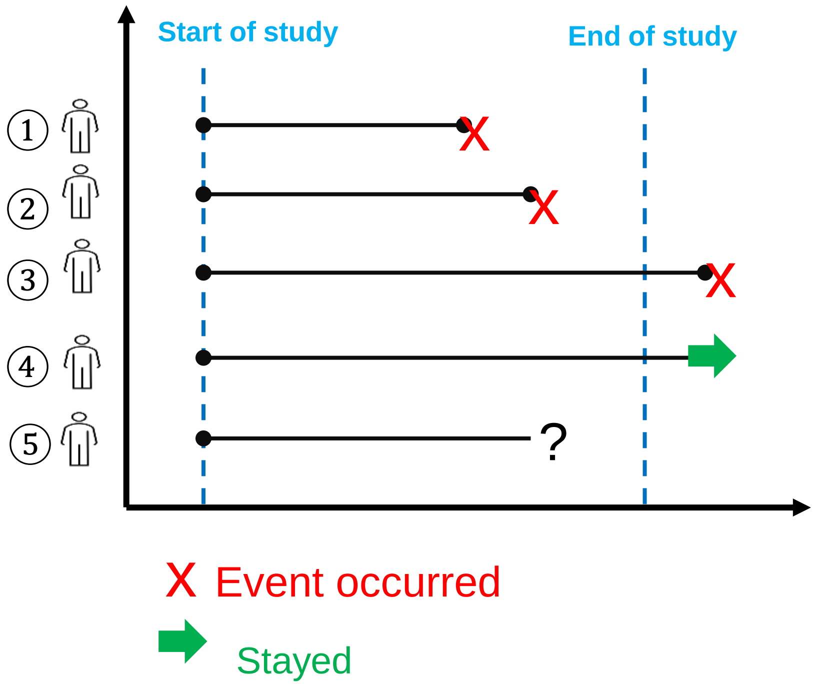


APPROACH (1/2) – COMPARISON OF TRADITIONAL APPROACH AND OUR APPROACH

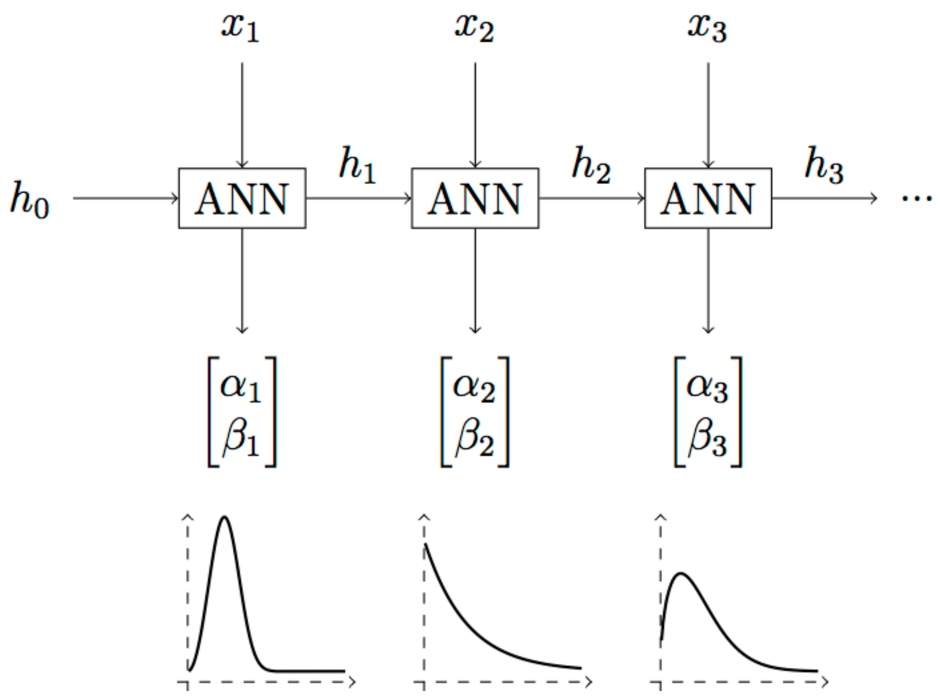
CLASSIFICATION

- Mortality probability can only be inferred at the end of the observation window
- The length of observation window impacts the accuracy of the classification model
- Complete/aggregated information must be collected to fit the entire timeframe
- Temporal characteristics of features cannot be accommodated

SURVIVAL ANALYSIS



APPROACH (2/2) - SURVIVAL ANALYSIS +SEQUENCE BASED NEURAL NETWORK WITH WEIBULL DISTRIBUTION



- The loss function* is the following:

$$-\frac{1}{N}\sum_{t=1}^{N} u \,*\, log(exp(\frac{y_i{}^{\beta}}{\alpha} - \frac{y_i+1^{\beta}}{\alpha}) - 1 - \frac{y_i+1^{\beta}}{\alpha})$$

- We used Adam optimizer
- NVIDIA Tesla K80 GPU
- Metric: Concordance Index
- Alpha initialized by the mean of the target

EXPERIMENTS - HYPERPARAMETER TUNING STRATEGY

Evaluation sets: 70% training 20% validation 10% test set

Challenge: Large hyperparameter search space

Approach: Tune each hyperparameters incrementally. Repeat for RNN, LSTM, GRU, and transformer architecture. Evaluation on validation set.

Interpretation:

- Batch normalization only creates better performance for GRU

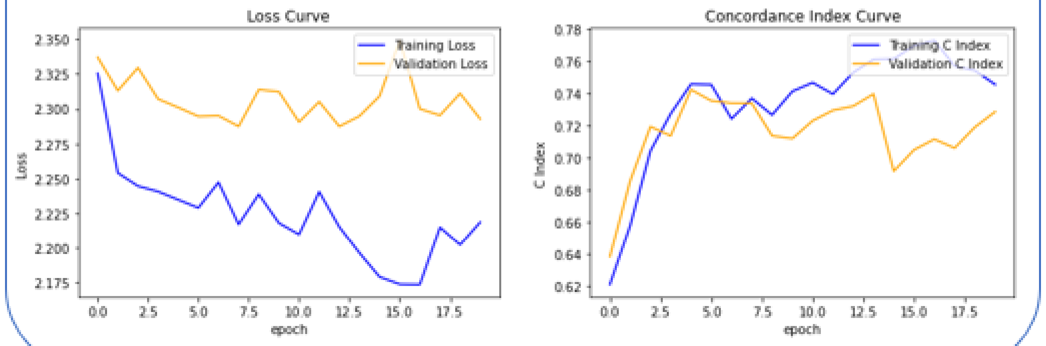
- Increasing the number of linear layers helps improve the models in general

- There is no significant improvement in tuning batch sizes

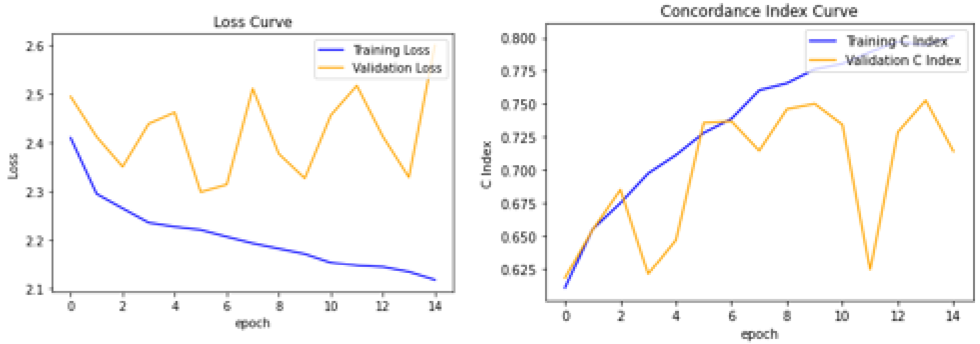
- Dropout tends to improve the RNN and GRU model

TRAINING AND VALIDATION CURVES - FINAL MODELS SELECTED

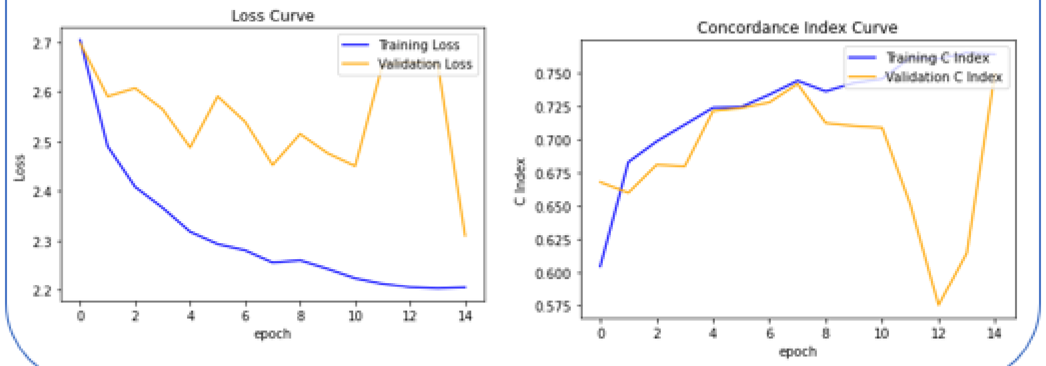
RNN



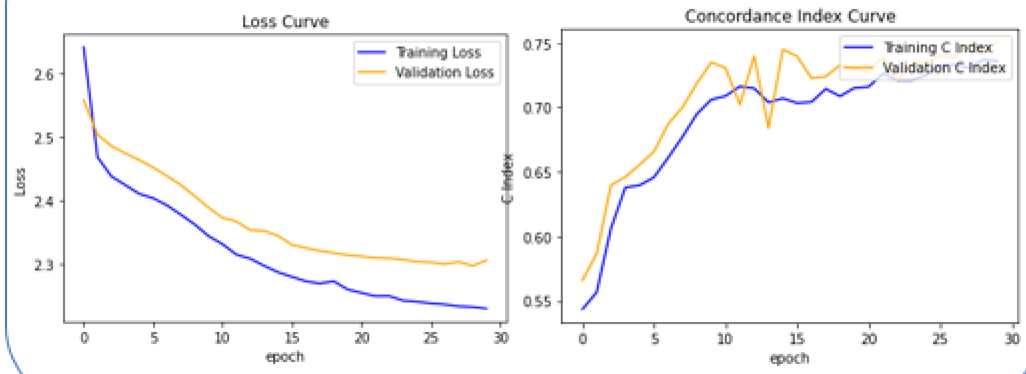
GRU



LSTM



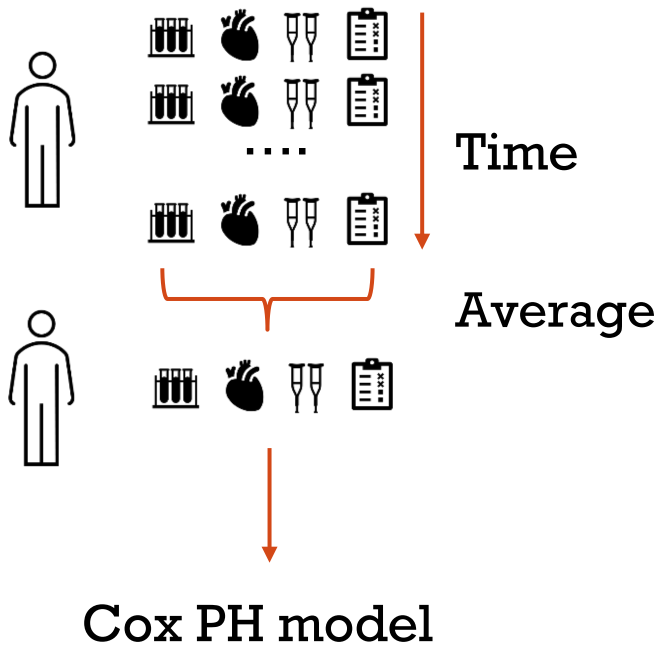
Transformers



EXPERIMENT RESULTS

Best Model for each architecture	Batch size	Batch Norm applied?	**Test set Concordance Index**
RNN: 32 hidden units, bidirectional, dropout 0.3, 1 layer LInear Layer: hidden layer of 16 and 2 output units	64	No	0.709
GRU: 32 hidden units bidirectional,, 1 layer of GRU Linear Layer: Output layer 2 output units	64	No	**0.712**
LSTM: 16 hidden units, bidirectional, 3 layers of LSTM Linear Layer: Output layer of 2 output units	64	Yes	**0.712**
Transformers: 3 hidden layers with ReLU activation function, 8 heads Linear layer: Hidden layer of 32 and 2 output units	32	No	0.691

COX PROPORTIONAL HAZARDS MODEL AND EVALUATION



Results:

- Training set:
  - concordance index of 0.77
  - 17 features are significantly related to survival time ($p < 0.05$)
- Test set:
  - concordance index of 0.718

CONCLUSION

- The present study applied a novel deep learning survival model for survival length prediction leveraging data in the MIMIC III v1.4 database
- With no budget and limited computational power, the performance of deep learning survival model is comparable to the traditional Cox survival model (Concordance Index is around 0.71)
- We are confident that our new approach could be superior to traditional model if we could further tune hyperparameters and test more complex models