Understanding Risk Factors for Mortality Among Older Individuals

(A Comprehensive Analysis using Classical, Ensemble and Deep Learning Models)

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Outline

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The Problem

- As populations around the world continue to age, understanding the determinants of healthy aging and longevity becomes increasingly vital.
- While physical activity has been shown to reduce mortality risk, the complex interplay between lifestyle behaviors, demographic characteristics, and health conditions remains poorly understood.
- Leveraging advancements in statistical modeling and machine learning, this project aims to create a comprehensive framework for predicting mortality risk—enabling more precise identification of high-risk individuals and informing public health strategies for aging populations.

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Research Questions

- How are physical activity, demographic factors, and health indicators related to mortality in older adults?
- What are the key risk factors that contribute to mortality in older adults?
- How do classical statistical models, ensemble methods, and deep learning approaches compare in their effectiveness at predicting mortality risk?

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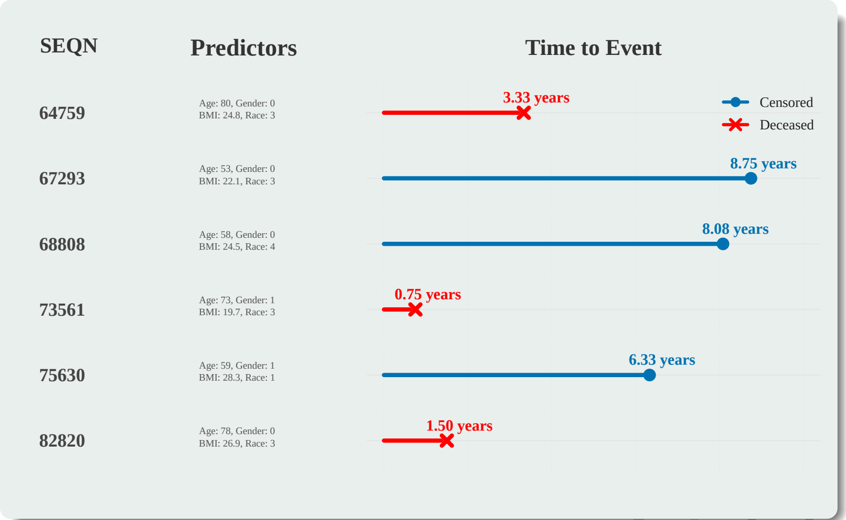
Data Source

The study will use data from the National Health and Nutrition Examination Survey (NHANES) 2011-2014, "***https://wwwn.cdc.gov/nchs/nhanes/Default.aspx***", which includes demographic, lifestyle, and health-related variables. The mortality information is linked to the National Death Index (NDI).

Outline

The Survival Data

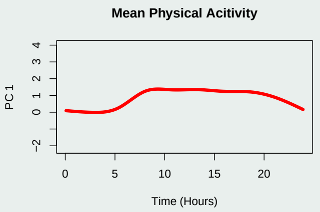


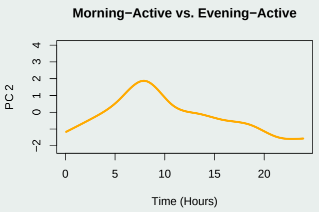
Outline

Preprocessing

FPCA

$$X_i(t) = \mu(t) + \sum_{k=1}^{K} \xi_{ik}\phi_k(t) + \epsilon_i(t)$$





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1. Introduction
   - The Problem
   - Research Questions
2. The Data
   - Data Source
   - The Survival Data
   - Preprocessing (Physical Activity Data)
3. The Models
   - Structures
   - Output
4. Conclusion and Future Work

Models

Model	Type	Loss Function
Cox	Classical	$\mathcal{L}(\beta) = -\sum_{i:\delta_i=1}\left(x_i^\top\beta - \log\sum_{j\in R(T_i)}\exp(x_j^\top\beta)\right)$
Penalized Cox	Classical	$\mathcal{L}(\beta) = -\sum_{i:\delta_i=1}\left(x_i^\top\beta - \log\sum_{j\in R(T_i)}\exp(x_j^\top\beta)\right) + \lambda\|\beta\|_1$
GAM Cox	Classical	$\mathcal{L}(f,\beta) = -\sum_{i:\delta_i=1}\left(\eta_i - \log\sum_{j\in R(T_i)}\exp(\eta_j)\right) + \lambda\sum_{j=1}^{p}\int\left(f_j''(x)\right)^2 dx$ where $\eta_i = \sum_{j=1}^{p} f_j(X_{ij}) + \sum_{k=1}^{q}\beta_k Z_{ik}$
DeepSurv	Deep Learning	$\mathcal{L}(\theta) = -\frac{1}{N_E}\sum_{i:\delta_i=1}\left[h_\theta(x_i) - \log\sum_{j\in R(T_i)}\exp(h_\theta(x_j))\right] + \lambda\|\theta\|_2^2$

Model	Type	Split Rule
RSF	Ensemble	Log-rank test statistic: $L(x,c) = \sum_{i=1}^{N}\frac{\left(d_{i,1} - \frac{Y_{i,1}d_i}{Y_i}\right)}{\sqrt{\sum_{i=1}^{N}\frac{Y_{i,1}}{Y_i}\left(1-\frac{Y_{i,1}}{Y_i}\right)\frac{(Y_i-d_i)}{(Y_i-1)}d_i}}$

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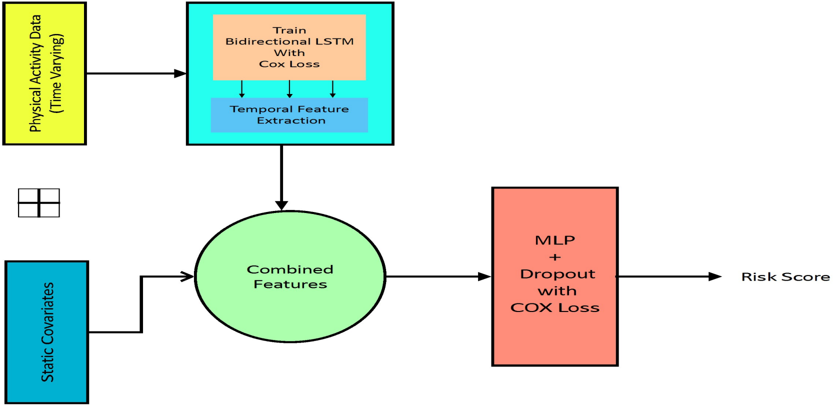
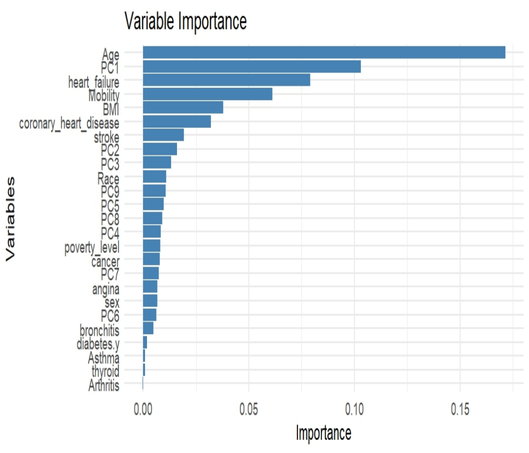
BiLSTM-Deepsurv Architecture



Outline

Output

Variable	exp(coef.)	Pr(>|z|)
Age	1.06	< 2e-16
BMI	0.96	4.67e-07
Mobility2	0.58	2.03e-08
povertylevel	0.92	0.00517
heartfailure1	1.87	7.23e-08
PC1	0.86	3.04e-14

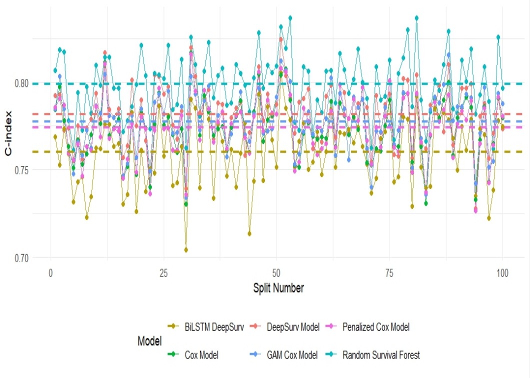


C-Index Comparison

$$C = \frac{\sum 1(h(X_i) > h(X_j)) \cdot 1(T_i < T_j)}{\sum 1(T_i < T_j)}$$

where $h(X)$ is the model's predicted risk score, and T is the observed survival time.

Model	Average C-Index
Cox	0.77421
GAM Cox	0.0.77763
Penalized Cox	0.77424
RSF	0.79895
Deepsurv	0.78173
BiLSTM Deepsurv	0.76041



Conclusion and Future Work

- If your primary goal is achieving high accuracy, Random Survival Forest (RSF) is the best-performing model.
- If your primary goal is interpretability, the Generalized Additive Cox model is one of the best reliable choices.
- DeepSurv is a strong deep learning-based alternative that shows good result in prediction.
- The BiLSTM-DeepSurv model appears promising, but it still requires improvement. With more computational resources and further tuning, it may perform better in future experiments.

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