# Cancer survival prediction and integration of multi-omics integration with Supervised Autoencoders, Stacked Autoencoders and Concrete Supervised Autoencoders for multiple correlated driver genes

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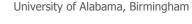


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# Project Overview

Breast cancer is the second most diagnosed cancer among women in the United States.

- Heterogeneous
- Several different molecular subtypes
- Clinical, pathological, and molecular characteristic differences contribute to breast cancer progression
  Patient prognosis, survival and therapeutic significance

### Purpose:

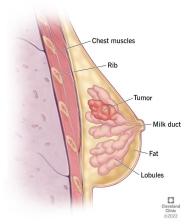
- Deep learning methods are utilized in cancer prognosis prediction using genomic information
  Single layer omics data (mRNA)
- Autoencoders are tools that allow for the integration of multi-omics data for cancer prognosis prediction

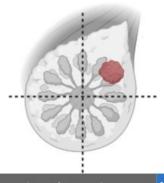
#### Goal:

To compare these existing algorithms to advance and optimize the methods for better utilities

- Categorizing molecular subtypes
- Risk-level for cancer staging

#### Breast cancer





## Remarks on selected frameworks

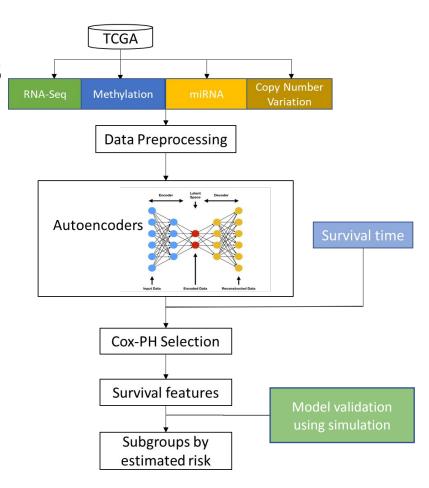
Denoising Autoencoder for accurate cancer prognosis prediction (DCAP) is a framework that allows for the integration of multi-omics data by denoising that is utilized to accurately estimate cancer risks through the Cox model.

The DCAP in this study improved the C-index values by 6.5% compared to that of previous methods.

eXtreme Gradient Boosting (XGboost) was used for selection of a small number of genomic features that are considered to be correlated to tumorigenesis and risk factor level of breast cancer

The XGboost models were shown to achieve an average C-index values of 0.627.

Moanna (Multi-Omics Autoencoder-based Neural Networks Algorithm) DL based model facilitating classification with semi-supervised autoencoders



# Future work and next steps

#### Experiments

- Integration of GAN based autoencoders (Ahmed et al, Bioinformatics 2022 & Yang et al, Bioinformatics 2021)
- 2. Cancer survival analysis utilizing subtype detection techniques
- 3. Prioritize omics profiles/modifications

### Room for improvements

- Assessment through k-fold Cross-validation
- Scale-up training pipeline with Apache Spark
- 3. Integrating other types of omics data, e.g., metabolomics, proteomics (Alakwaa et al, J Proteome Res 2018 & Lewis et al, Nat Commun 2021)

# Thank you for your kind attention!

Questions and Feedback?



Thanks again to all the team members and organizers for hosting this amazing hackathon!