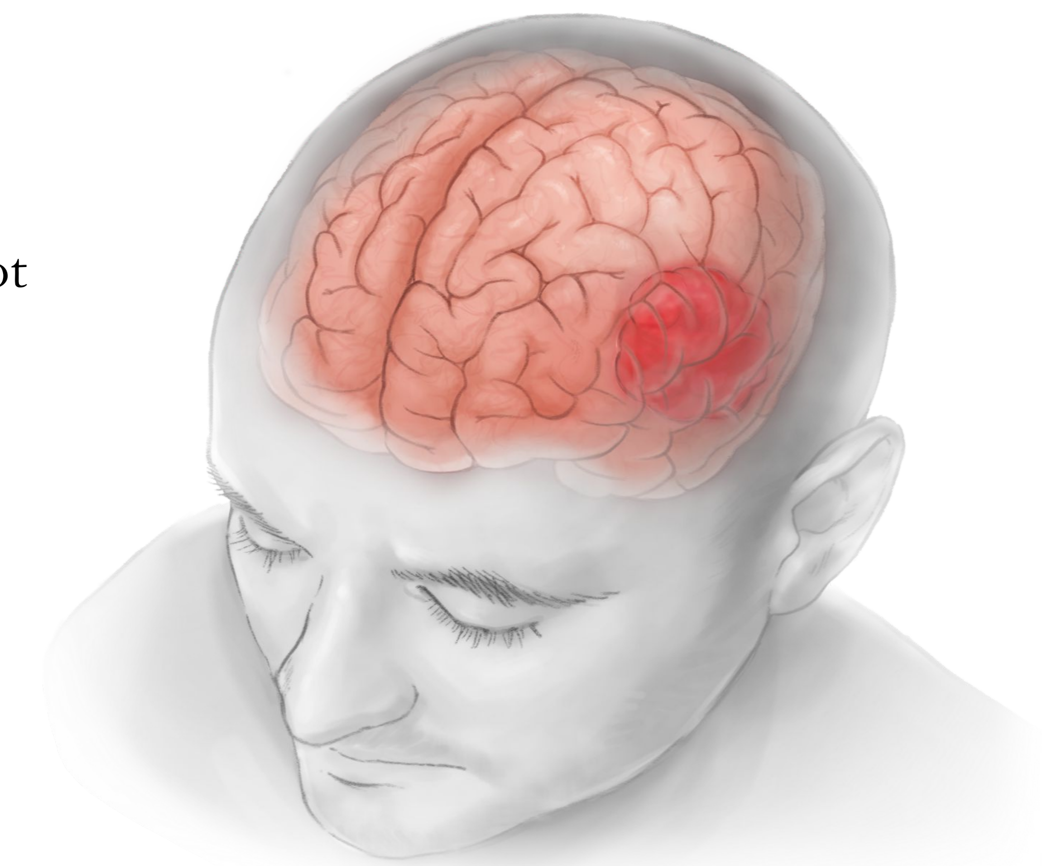
Deep Learning-based Integration of Histology and Radiology for Improved Survival Prediction in Glioma Patients

HARVARD MEDICAL SCHOOL
BRIGHAM HEALTH
BWH BRIGHAM AND WOMEN'S HOSPITAL
Mahmood Lab
AI for Pathology
Luoting Zhuang, Jana Lipkova, Richard J. Chen, Faisal Mahmood
lzhuang1@bwh.harvard.edu - faisalmahmood@bwh.harvard.edu
www.mahmoodlab.org
SCAN ME
BROAD INSTITUTE
Dana-Farber Cancer Institute

Introduction

- More than **80%** of primary malignant brain tumors are gliomas. Accurate and robust survival predictions for glioma patients are crucial for clinicians' medical decision-making.
- Complex processes driving **glioma recurrence** and **treatment resistance** cannot be fully understood **without the integration of multiscale factors** such as cellular morphology, tissue microenvironment, and macroscopic features of the tumor and the host tissue.
- **AI** provides a wonderful tool to examine and **integrate complex features from diverse data** and enhance patient outcome prediction.
- We present a **weakly-supervised**, **multimodal deep learning-based** model fusing **histopathological** and **radiology** data for **glioma survival predictions**.
- The proposed approach allows training models using **patients' survival** as the **only label, without** the burden of **manual annotation** of predictive regions or **tumor segmentation** as done in previous studies.



Methods

Dataset

- The Cancer Genome Atlas and The Cancer Imaging Archive
- 205 patients with **paired whole-slide H&E-stained images**, **multimodal MRI scans** (including preoperative T1Gd, FLAIR, T2-w, and T1-w MRI brain scans), and **ground truth survival labels**

Feature Extraction

- Both histopathology patches and MRI slices were passed into the **ResNet50**, pre-trained on ImageNet, and then converted to a **low-dimensional feature vector.**

Attention-based Multiple Instance Learning

- The model assigns **attention scores** to each biopsy region and MRI region, reflecting its relevance to survival and **aggregates** patches and slices into a single low-dimensional embedding.

Kronecker product

- **Such fusion** captures predictive features **within** and **across** radiology and histopathology data.

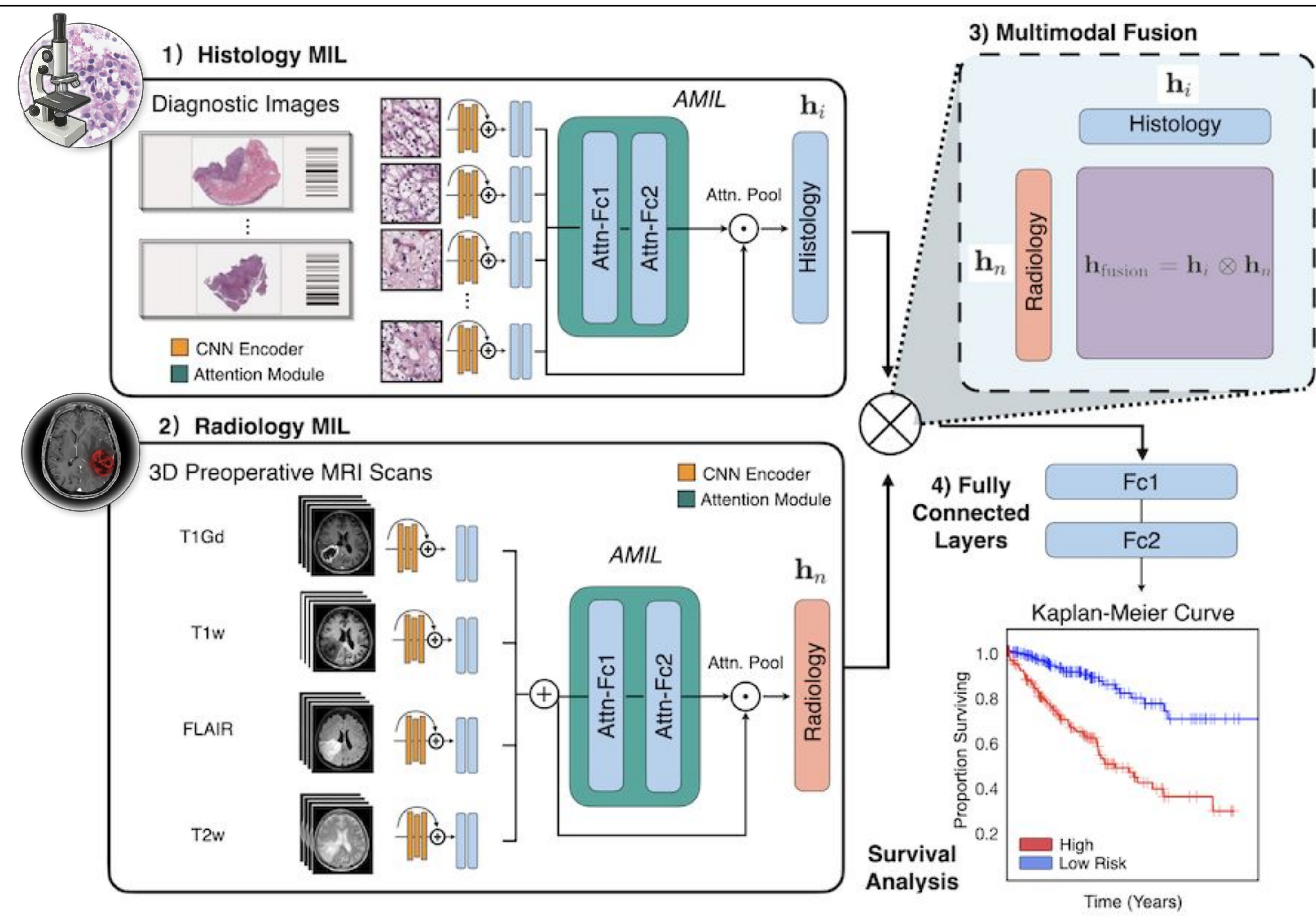


Figure 1: Deep Learning-based Multimodal Fusion of Histology and Radiology Data for Prognosis. Our multimodal algorithm consists of 1) an attention-based multiple instance learning network for WSIs, 2) an attention-based multiple instance learning network for three-dimensional MRI scans, 3) multimodal fusion using Kronecker Product, and 4) fully connected layers supervised by cox proportional likelihood loss.

Results

- Performing 10-fold cross-validation, the **unimodal algorithms** trained on radiology or pathology data obtained an **average validation concordance index (c-index)** of **0.704** and **0.712,** respectively. By incorporating information from different modalities, the **multimodal algorithm** resulted in **higher** performance, with an average c-index of **0.733**.
- The **standard deviation** of the validation c-index also decreased from **0.124 (radiology)** and **0.096 (pathology)** to **0.077** after the fusion of radiology and pathology features.

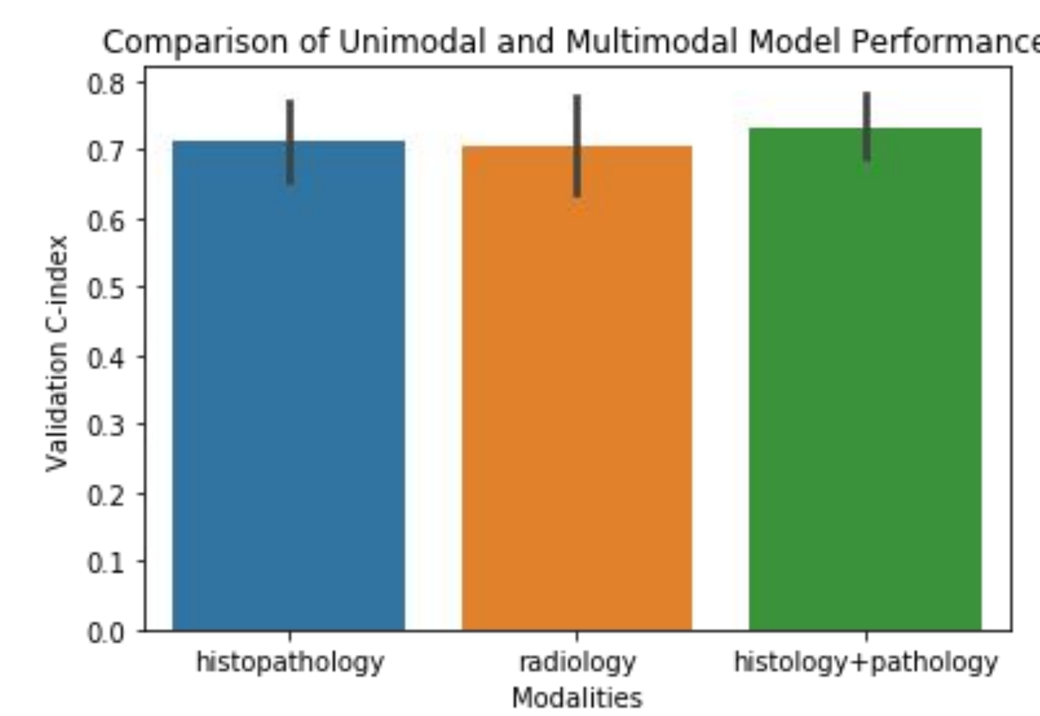


Figure 2: Performances of Unimodal and Multimodal Model. The multimodal model outperformed the unimodal model and gave results with smaller variance.

Conclusion and Future Work

- The presented framework demonstrates **feasibility** of **multimodal integration** of radiology and histology data for **improved survival prediction** in glioma patients.
- The **weakly-supervised** model does **not** require any handcrafted feature extraction or tumor segmentation on radiology images **nor** pixel-level annotation for histopathology images.
- The proposed framework can be easily extended to **accommodate other modalities**, such as genomics or proteomics data.
- We hope to evaluate the multimodal model on **other cohorts** to test the generalizability of the model.