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

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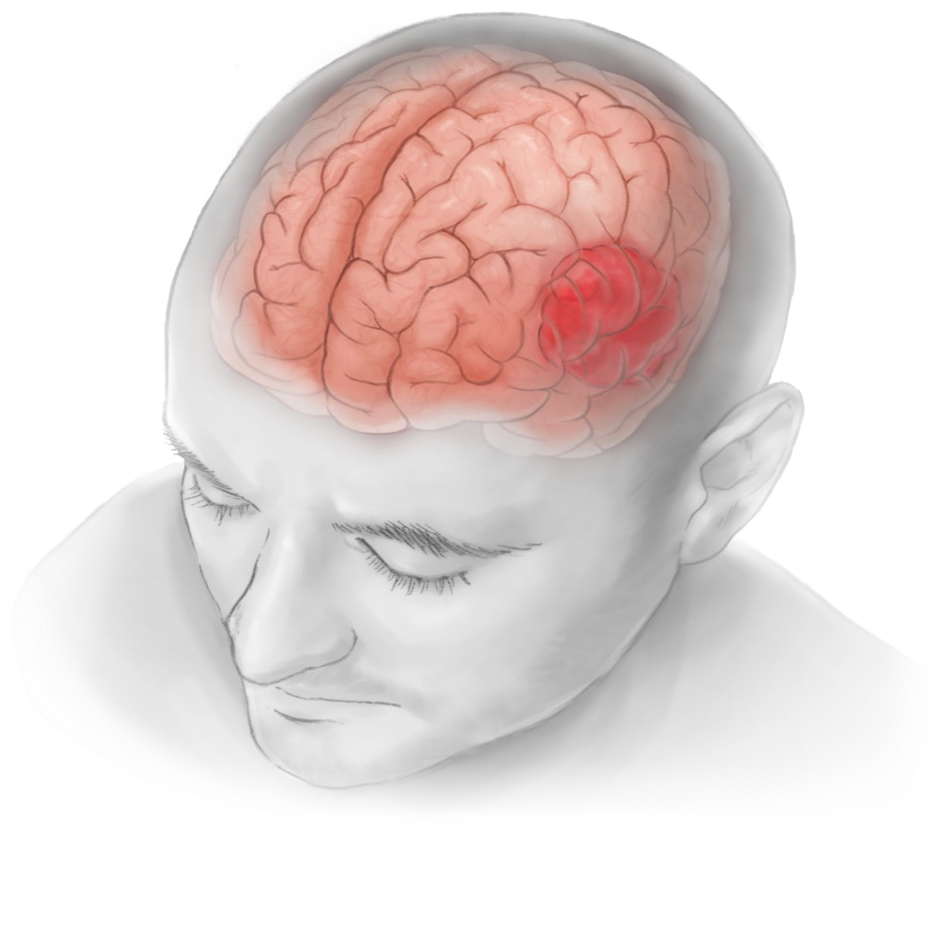
Introduction



- 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.

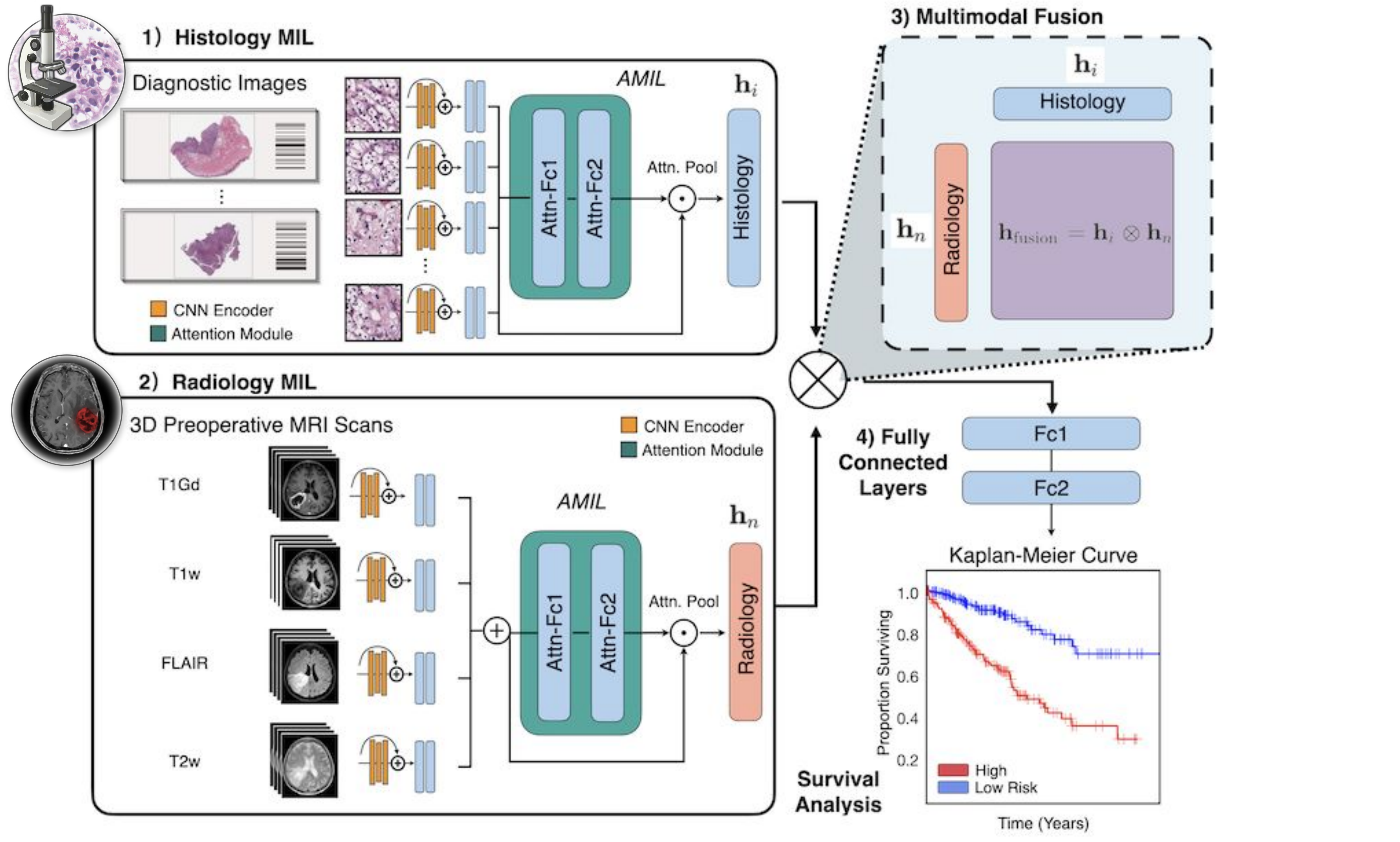


Figure 1: Deep Learning-based Multimodal Fusion of Histology and Radiology Data for Prognosis. Our multimodal algorithm consists of 1) an attention-based multiple instance learning network for WSIs, 2) an attention-based multiple instance learning network for three-dimensional MRI scans, 3) multimodal 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.

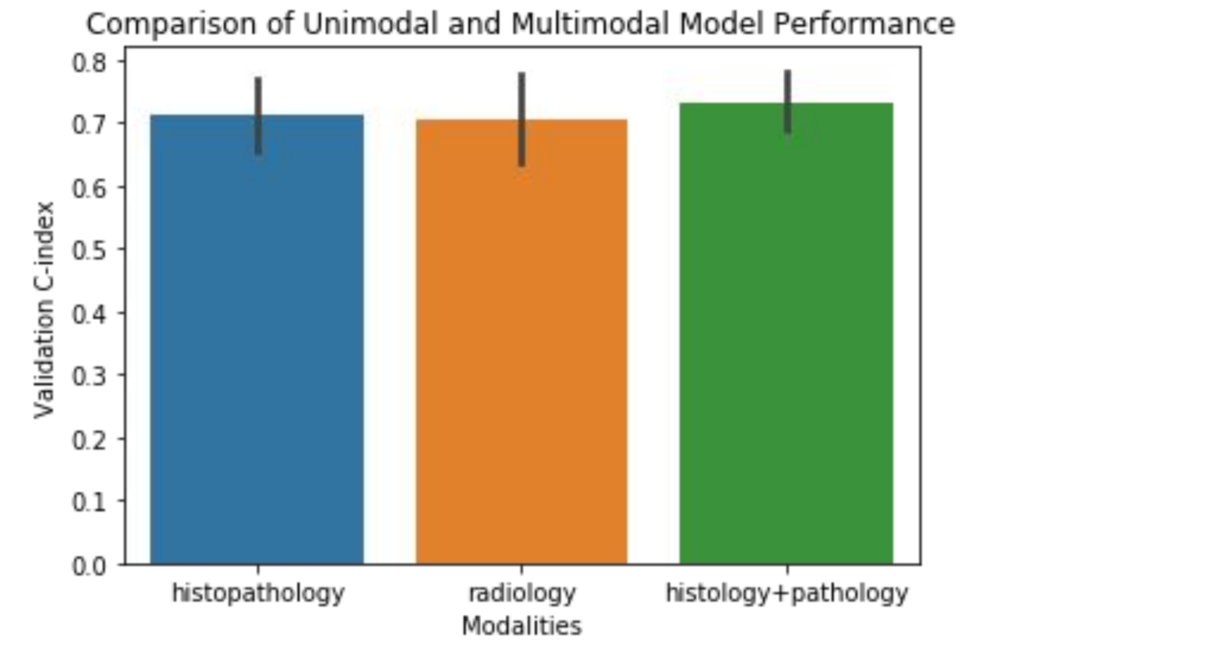


Figure 2: Performances of Unimodal and Multimodal Model. The multimodal model outperformed the unimodal model and gave results with smaller variance.

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.