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.

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.

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.