Background Reading Presentation: Project 19 Glioma classification and biopsy guidance with multimodal MRI and Deep Learning

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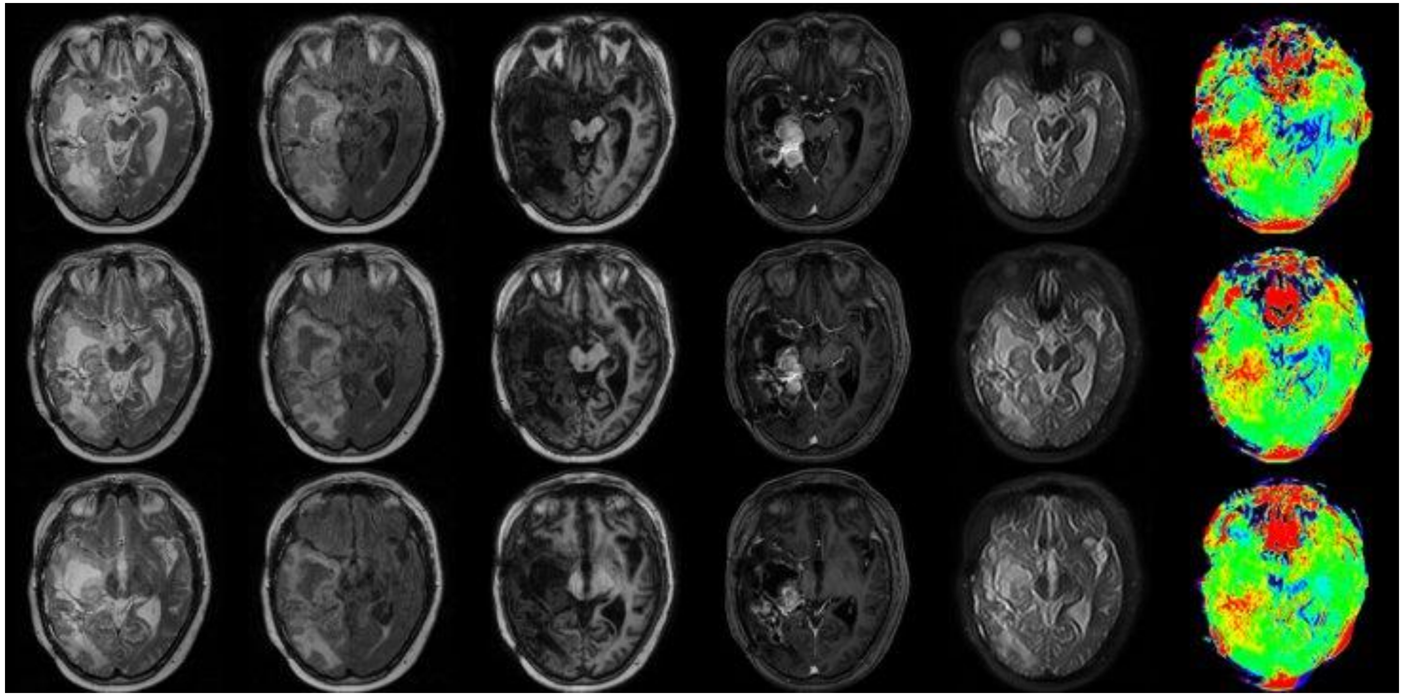
Project Background

- Gliomas
  - Common type of brain tumor
  - Average survival time 12-18 months
  - Conventional MRIs and biopsy
- Amide proton transfer-weighted (APTw)
  - New MRI sequence with clinical values for glioma diagnosis
    - More tissue-specific
    - Hyperintensity region with a ring indicates high-grade gliomas
- Goal: automated pipeline with deep learning for glioma classification and grading



Paper overview

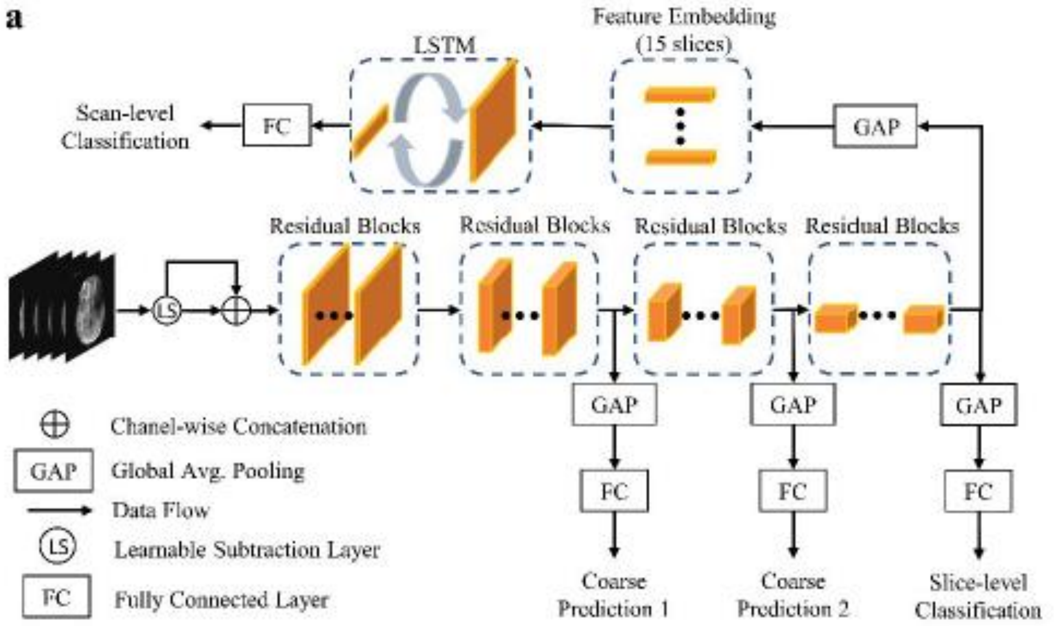
- Paper to be discussed:

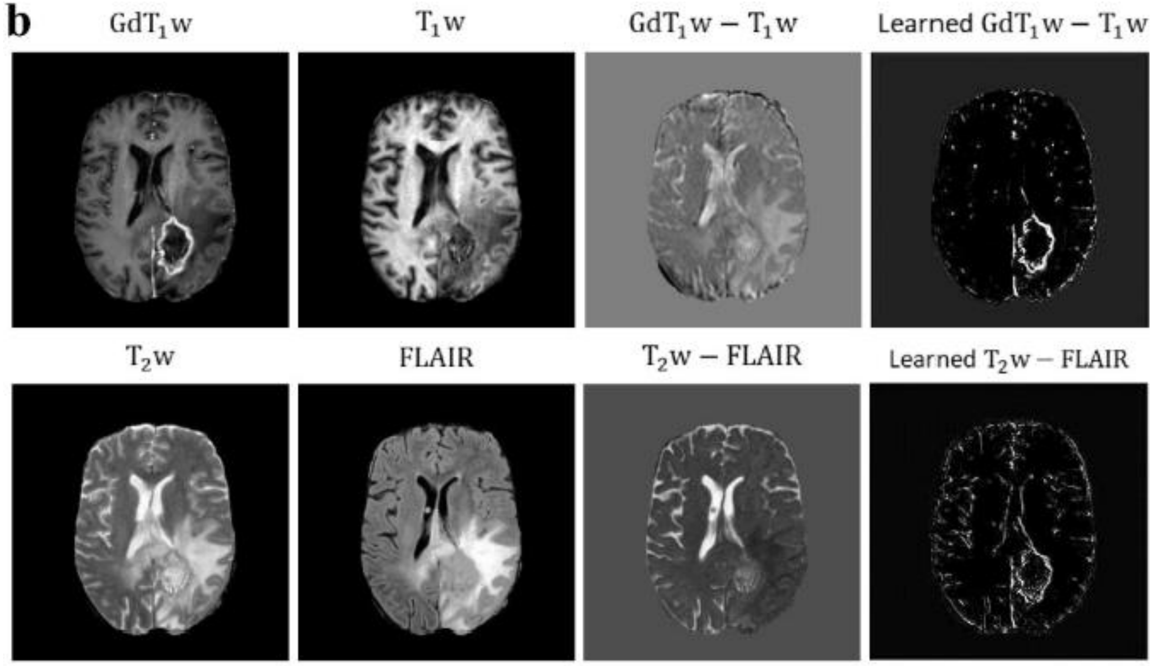
Learning-Based Analysis of Amide Proton Transfer-Weighted MRI to Identify Tumor Progression in Patients with Post-Treatment Malignant Gliomas. By Guo et al.

- Previous work of Dr. Jiang's APT group (JHU Radiology Dept) on similar problems with glioma using a subset of current dataset
- Recently submitted and under review
- Pertinent information for this project
  - Preprocessing pipeline – how the dataset is originally developed
  - Consideration and usage of deep learning algorithms

Methods

- CNN (Modified ResNet-18) for slice-level classification
  - Hierarchical classification
    - Normal vs. abnormal, tumor vs. no tumor, recurrent vs. non-recurrent
  - Learnable subtract module
- LSTM (long-short term memory) to aggregate information across 15 slices for scan-level classification





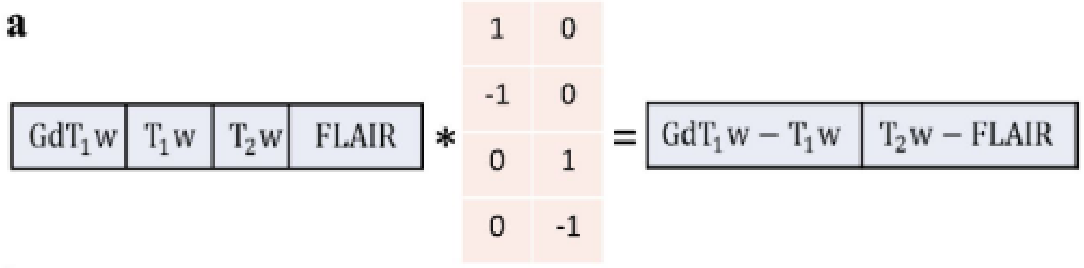
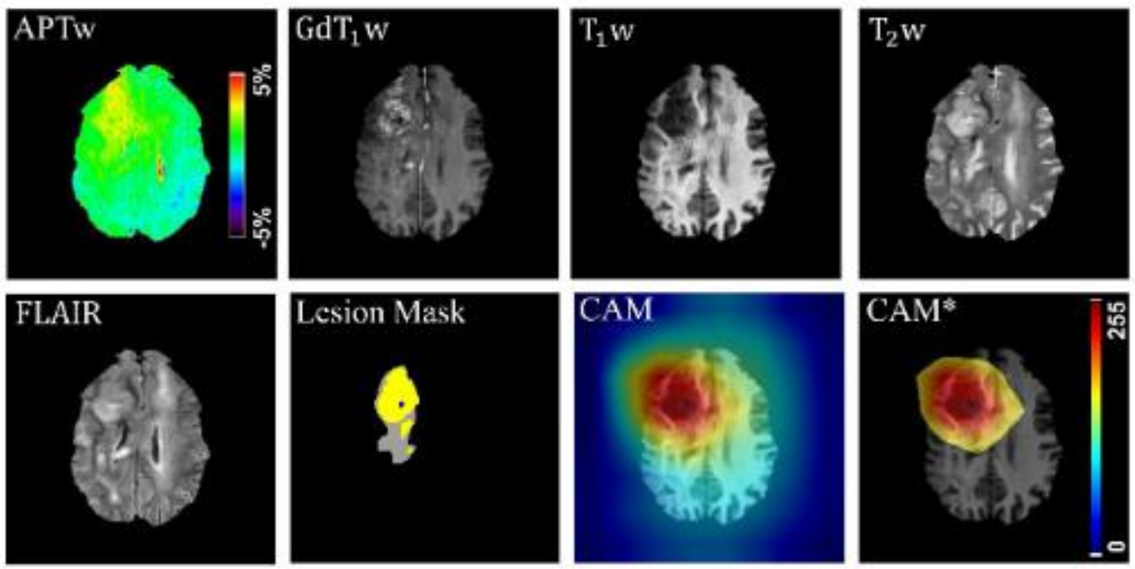


Image Courtesy: Pengfei Guo

Result summary

- A CNN could learn from the data to predict tumor recurrence at slice-level
- Using APTw images improves classification performance:
  - Slice-level AUC: increased from 0.88 to 0.90
  - Scan-level AUC: increased from 0.85 to 0.90
- Additional modules (learnable subtraction layer, hierarchical classification, LSTM) also improve the performance and extend the task to scan-level classification with ablation study
- Using class activation map could broadly highlight tumor regions



Assessment

- Pros
  - Functional preprocessing pipeline and deep learning architecture with key contributions
    - Can be used as baseline model for our project
  - Ablation study to show effectiveness of each key design
  - Reasoning and insights on the choice of algorithm
- Cons
  - Validation method
    - Dataset split by chronological order of patient enrollment instead of k-fold cross validation
  - Lack of documentation in the paper for training and data augmentation schemes
    - No public code repository available
    - Certain important information only found in source code

References

- Discussed paper:

Guo, Pengfei and Unberath, Mathias and Heo, Hye-Young and Eberhardt, Charles and Lim, Michael and Blakeley, Jaishri and Jiang, Shanshan, Learning-Based Analysis of Amide Proton Transfer-Weighted MRI to Identify Tumor Progression in Patients with Post-Treatment Malignant Gliomas. Available at SSRN: https://ssrn.com/abstract=4049653 or http://dx.doi.org/10.2139/ssrn.4049653

- Project bibliography:

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[2] Zhou, J., Heo, H. Y., Knutsson, L., van Zijl, P. C., & Jiang, S. (2019). APT-weighted MRI: Techniques, current neuro applications, and challenging issues. Journal of Magnetic Resonance Imaging, 50(2), 347-364.

[3] Arnab, A., Dehghani, M., Heigold, G., Sun, C., Lučić, M., & Schmid, C. (2021). Vivit: A video vision transformer. In Proceedings of the IEEE/CVF International Conference on Computer Vision (pp. 6836-6846).

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[5] Liu, L., Hamilton, W., Long, G., Jiang, J., & Larochelle, H. (2020). A universal representation transformer layer for few-shot image classification. arXiv preprint arXiv:2006.11702.

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[7] Chen, H., Li, H., Li, Y., & Chen, C. (2021). Sparse spatial transformers for few-shot learning. arXiv preprint arXiv:2109.12932.