Glioma Classification and Biopsy Guidance with Multimodal MRI and Deep Learning

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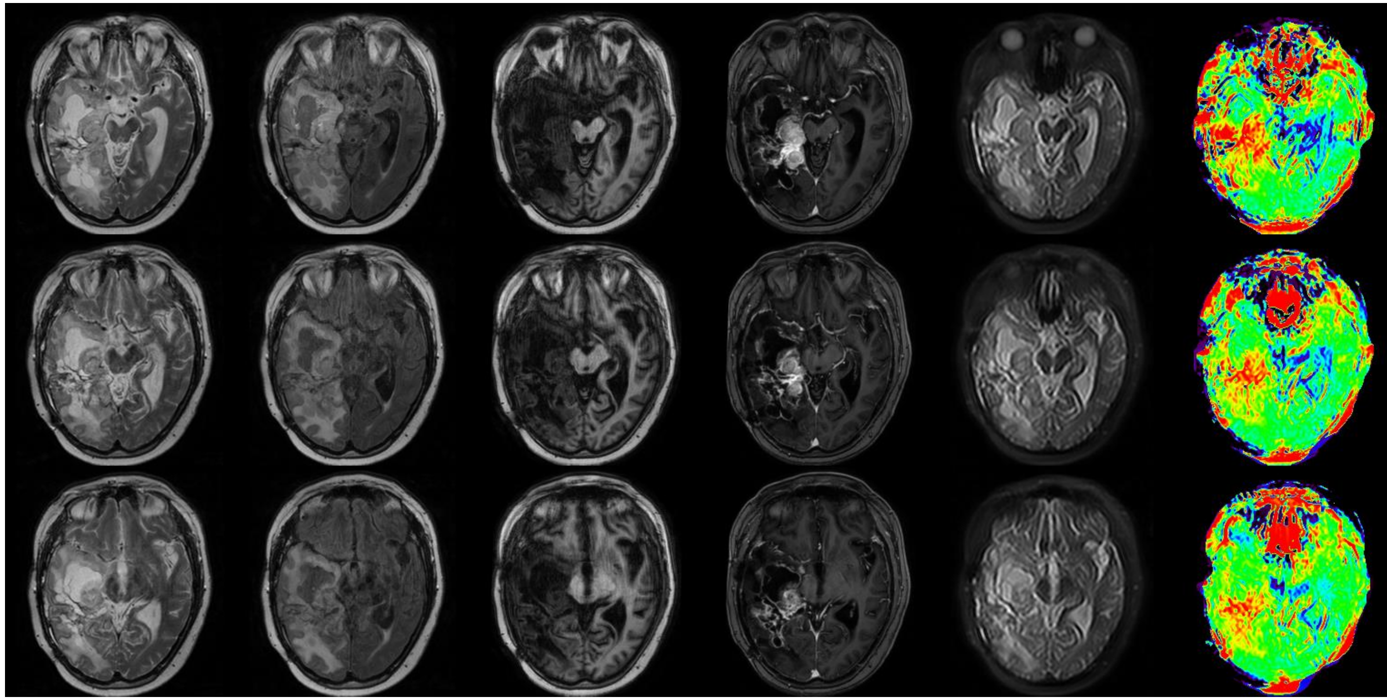
Background

- Gliomas
  - Common type of brain tumor
  - Average survival time 12-18 months
  - Conventional MRIs and biopsy for diagnosis
    - Not sufficiently tissue-specific to guide treatment decisions
- Amide proton transfer-weighted (APTw) MRI
  - Clinical values in brain tumor detection, grading, and assessment of tumor recurrence
  - Required expert knowledge
- Deep learning is the SOTA solution for automated image-based diagnostic tools
  - Transformers emerge as the prominent architecture for vision tasks



Project Goals

- Develop a deep learning pipeline that performs following tasks
  - Newly-diagnosed patients grading
    - Low-grade tumors(1, 2)
    - High-grade tumors (3, 4)
  - Post-treatment assessment
    - Recurrent tumors
    - Treatment effects
  - Localize/highlight salient regions
- Show that APTw images add valuable information to the automated pipeline
- Analyze the performance using single, 2-averaged, 4-averaged APT images

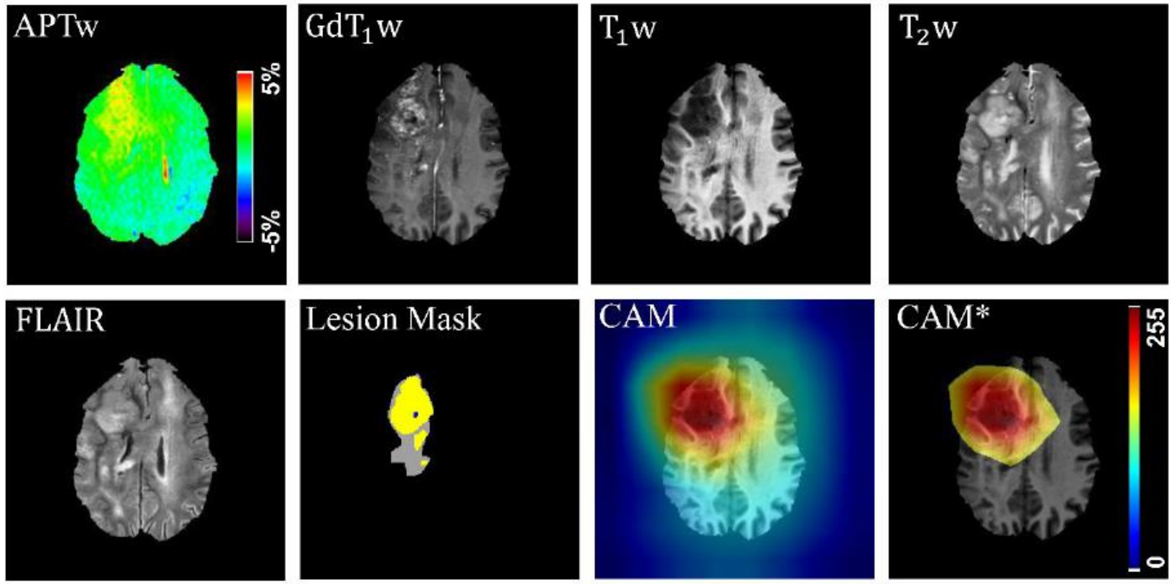
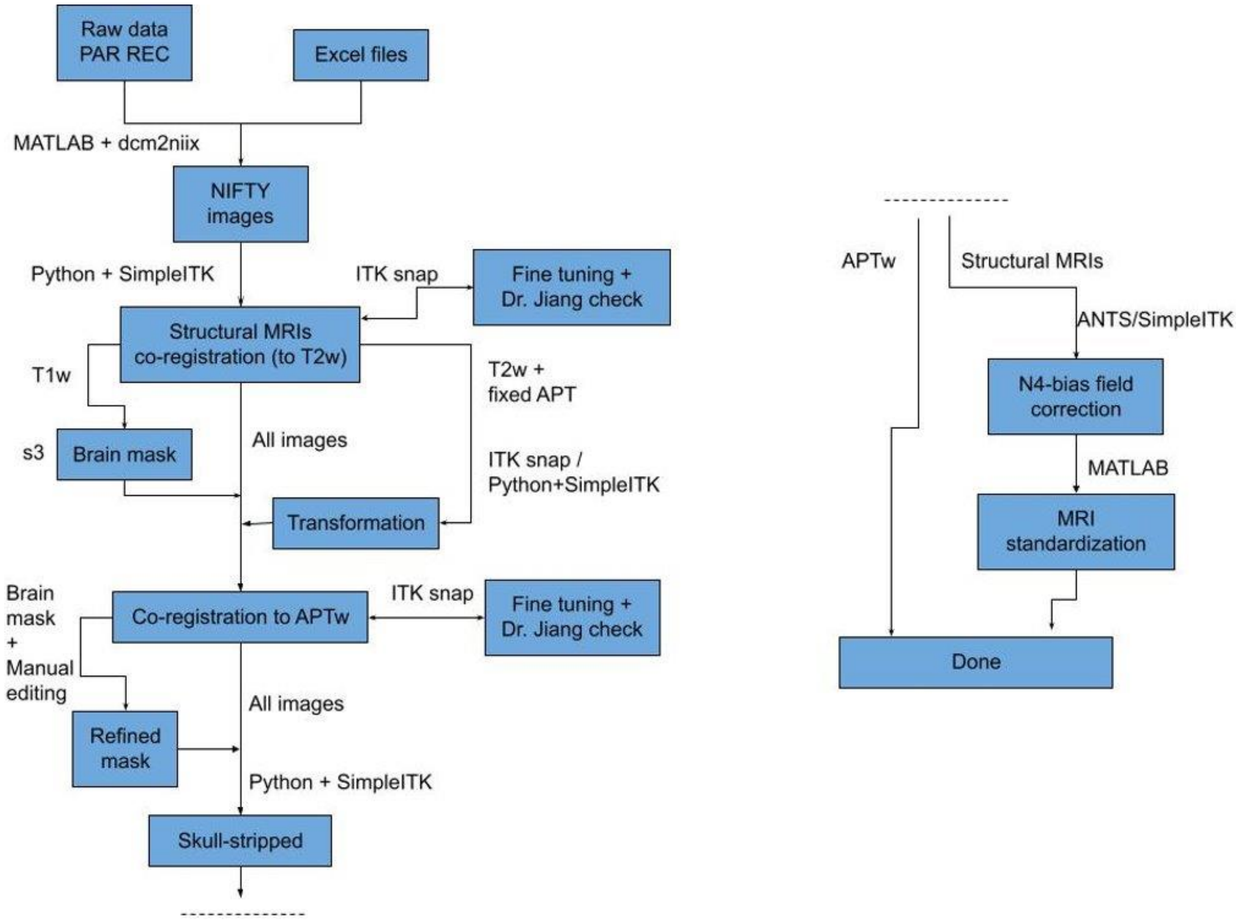


Image Credit: Pengfei Guo

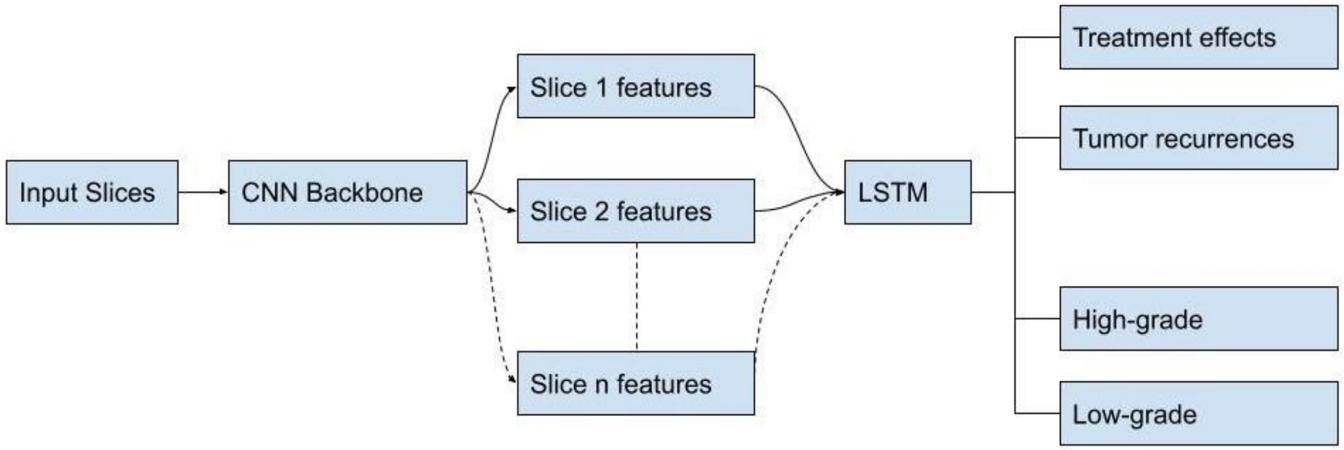
Dataset

- Around 215 patient brain scans
  - Each with 15 slices and 5 modalities
    - Structural MRIs and APT
    - APT – single & averaged
  - DICOM/NIFTY format
  - Preprocessed
- Labels
  - Scan-level annotations
  - Slice-level annotations
  - Pixel-level annotations

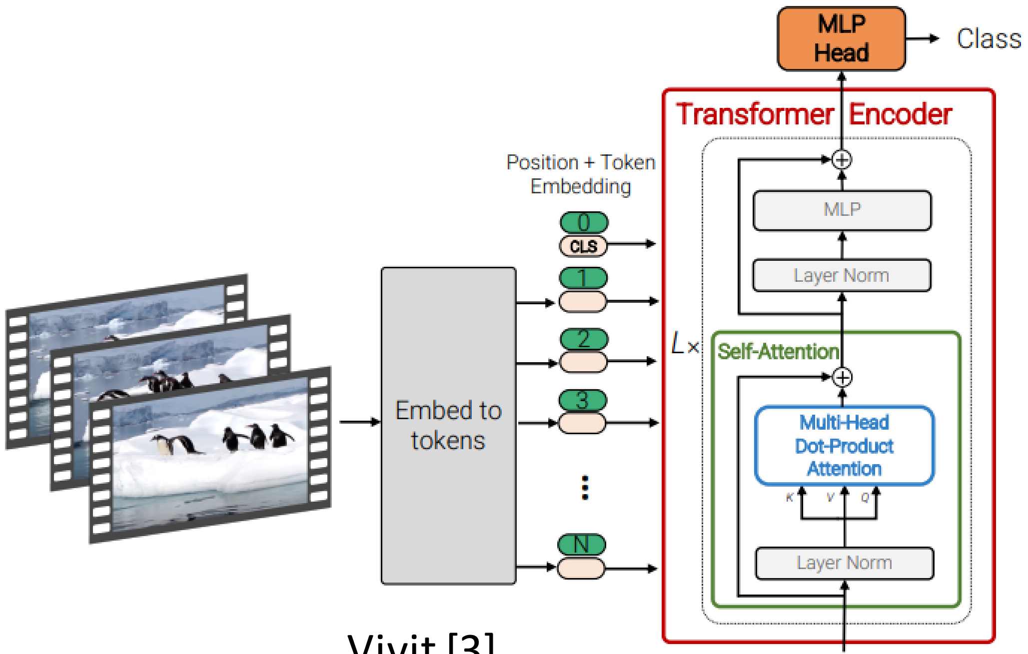


Technical Approach

- Similar to a video classification problem
  - Scan as a sequence of 2D slices
- Baseline models:
  - Baseline 1: CNN – LSTM
    - CNN (ResNet) as feature extractor
    - LSTM as aggregator
  - Baseline 2: Vivit (Video Vision Transformer)
    - Pure transformer approach
- Improved methods:
  - Extensions of baseline model 2
    - Few-shot classification (URT, SST, etc.)
    - Learning global representation
  - Attention scores for salient regions

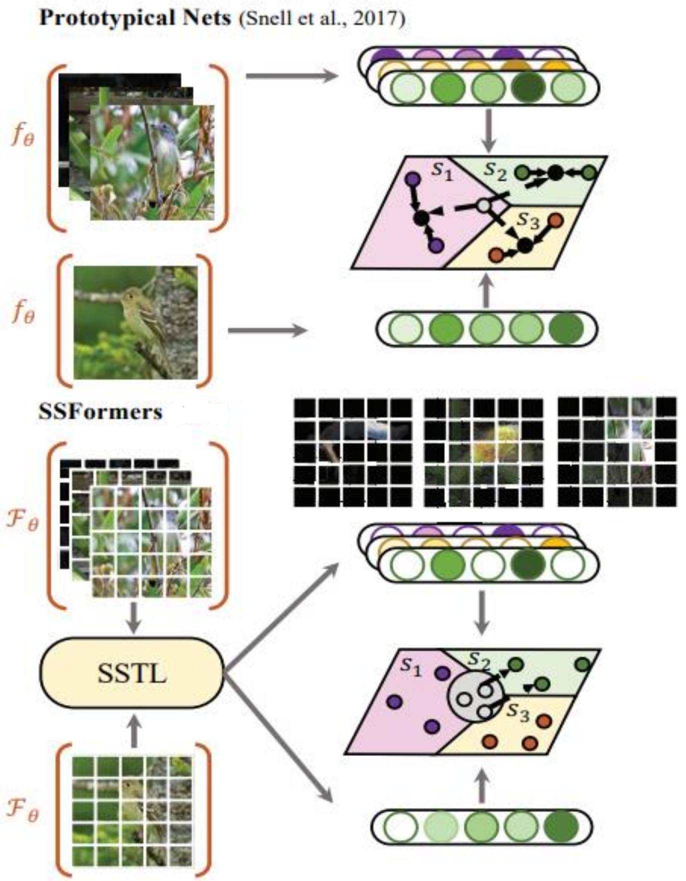


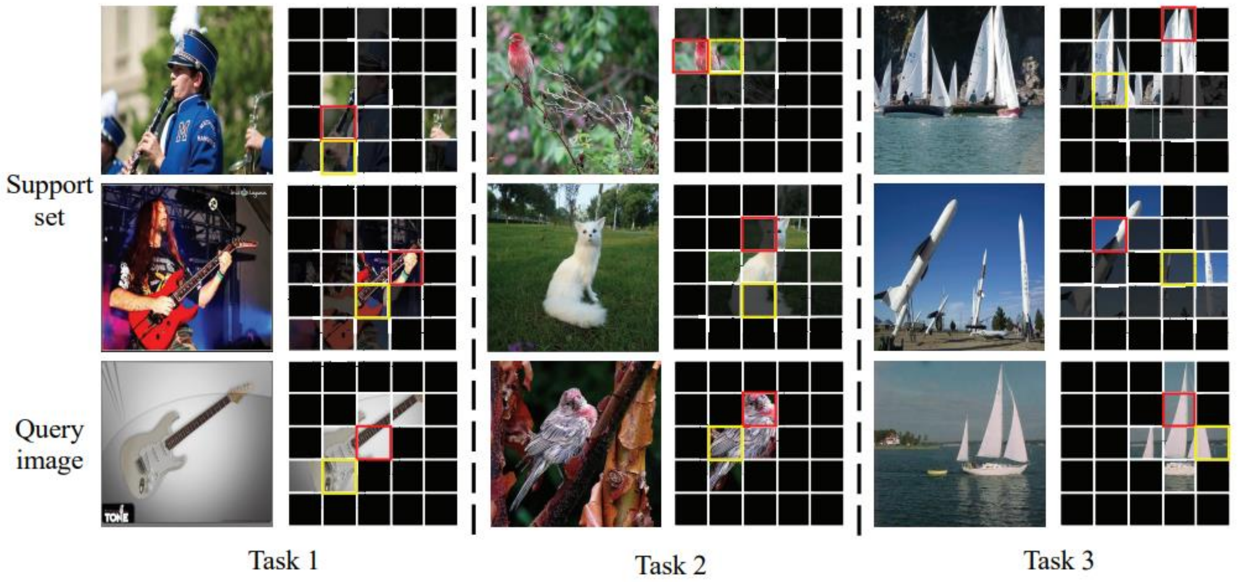
CNN-LSTM



Vivit [3]

Technical Approach



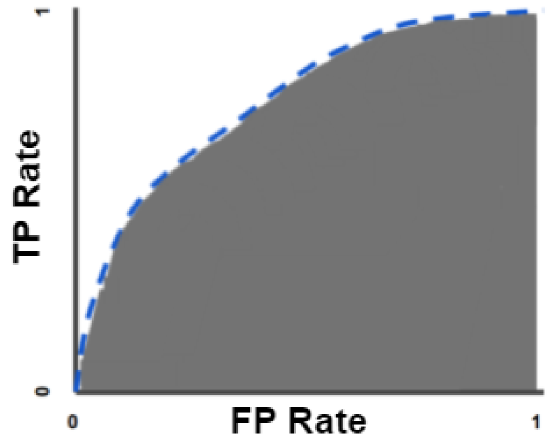


- Using cross-attention mechanism to highlight similarities between support set and query image

Images from [7]

Technical Approach

- Training
  - Pretraining
  - Data augmentation
  - Stratified sampling
  - Hyperparameters tuning
- Evaluation
  - Performance
    - AUC/ Precision-Recall AUC
    - Overall accuracy
    - Salient regions (qualitative)
  - Design features
    - Ablation study
      - Image modalities
      - Network components



ROC Curve

$$\text{Precision} = \frac{tp}{tp + fp}$$

$$\text{Recall} = \frac{tp}{tp + fn}$$

Deliverables

- Minimum:
  - Validated pipeline for classification tasks with existing deep learning algorithms
  - Analysis on effectiveness of using APT-weighted images
  - Documentation of the dataset
- Expected:
  - Improved methods to increase classification and localization performance
- Maximum:
  - A precise method validated in clinical context

Project Timeline

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Task	Start	End	Week	Milestone
Literature Review	1/31/2022	3/4/2022	Week 2-6	
Data Preparation	2/7/2022	2/25/2022	Week 3-5	
Plan Proposal	2/7/2022	3/1/2022	Week 3-5	Proposal sent to mentors by 2/25
Baseline 1 evaluation	2/27/2022	3/5/2022	Week 6	
Baseline 2 evaluation	3/6/2022	3/12/2022	Week 7	
Checkpoint presentation + minimum deliverables	3/13/2022	3/19/2022	Week 8	Minimum deliverables by 3/19
Designs for improved method	3/13/2022	3/26/2022	Week 8-9	Initial designs approved by 3/26
Implementation of improved method	3/26/2022	4/2/2022	Week 10	
Evaluation of improved method + expected deliverables	4/3/2022	4/16/2022	Week 11-12	Expected deliverables by 4/16
Additional designs and experiments	4/10/2022	4/23/2022	Week 12-13	Maximum deliverables (if possible) by 4/23
Final report + poster	4/24/2022	4/30/2022	Week 14	
Final presentation	5/1/2022	5/7/2022	Week 15	

Dependencies

Dependency	Type	Status	Needed by	Alternative	Notes
GPU Server (Dr. Jiang)	Hardware	Available from Dr. Jiang's lab (access acquired)	2/27	Backup GPUs available (access acquired)	Required for deep learning
Data annotations (Dr. Jiang)	Annotation	In progress (Expected 2/26 for scan-level)	2/27	Training on subset of data	Limitations on pretraining and design choices Required scan-level labels as minimum
IRB & HIPAA (Dr. Zhou)	Training	Completed	2/12	N/A	Training and study approval required for new members
DL tools (CUDA, PyTorch, etc.)	Software	Acquired Open-source	2/27	Other DL frameworks	

Management Plan

- Progress report in weekly lab meetings
- One-on-one meeting upon request
- Code management: GitHub
- Results and notes: OneDrive, project page

Reading list

[1] Khan, S., Naseer, M., Hayat, M., Zamir, S. W., Khan, F. S., & Shah, M. (2021). Transformers in vision: A survey. *ACM Computing Surveys (CSUR)*.

[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).

[4] Lee, J., Wang, N., Turk, S., Mohammed, S., Lobo, R., Kim, J., ... & Rao, A. (2020). Discriminating pseudoprogression and true progression in diffuse infiltrating glioma using multi-parametric MRI data through deep learning. *Scientific reports*, *10*(1), 1-10.

[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*.

[6] Hou, R., Chang, H., Ma, B., Shan, S., & Chen, X. (2019). Cross attention network for few-shot classification. *Advances in Neural Information Processing Systems*, *32*.

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