Glioma Classification and Biopsy Guidance with Multimodal MRI and Deep Learning

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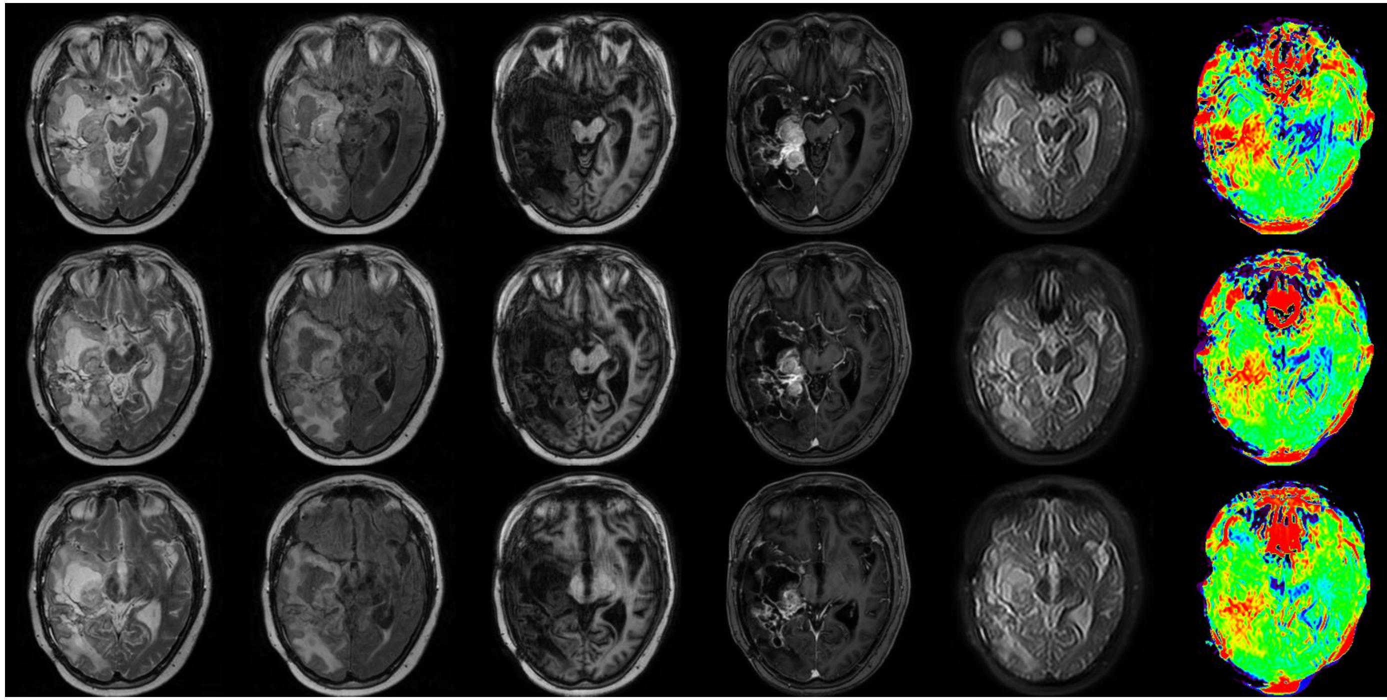
Background

- 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

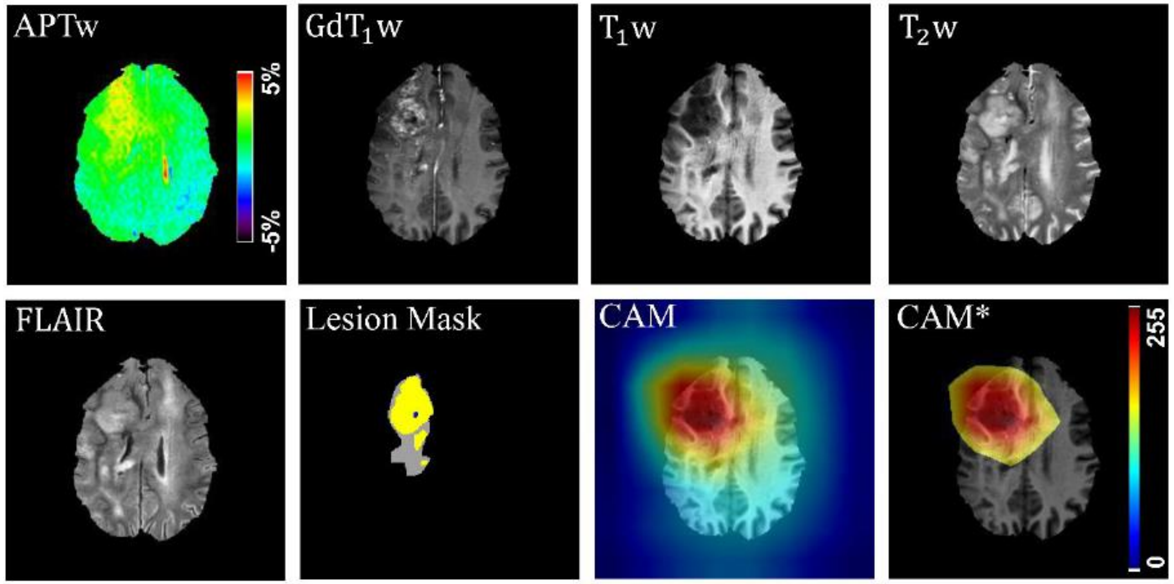
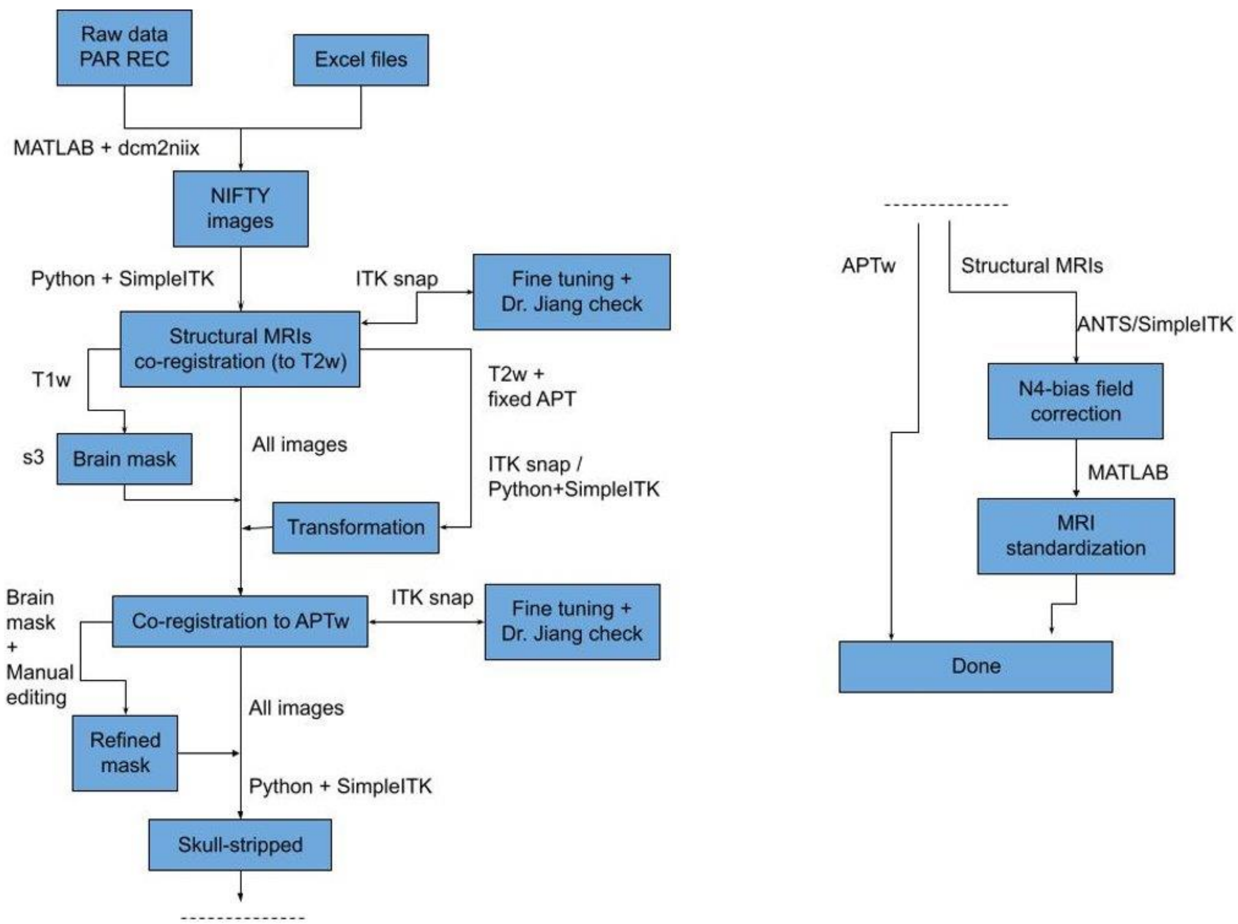


Image Credit: Pengfei Guo

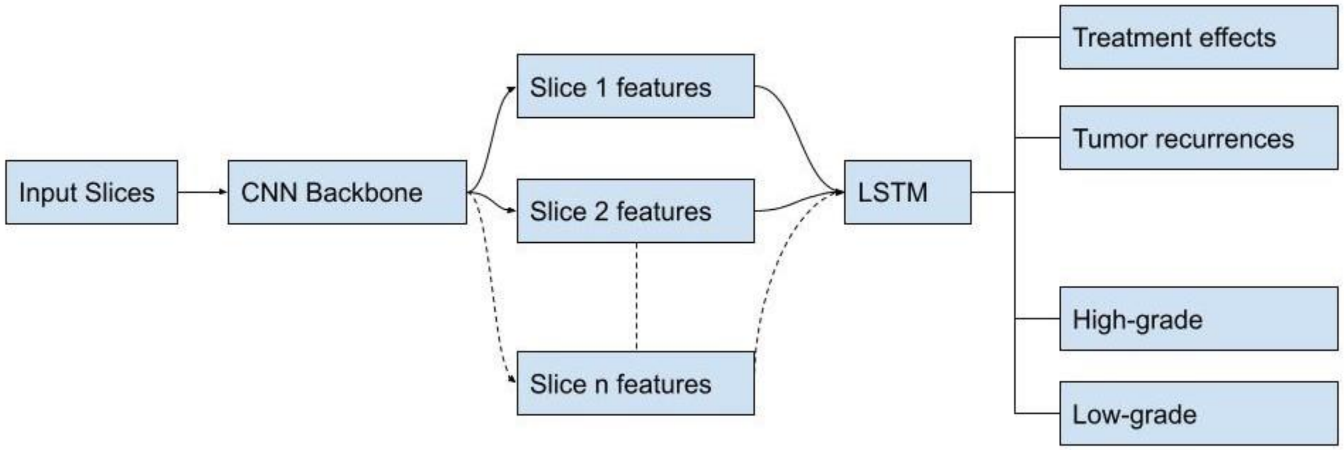
Dataset

- 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

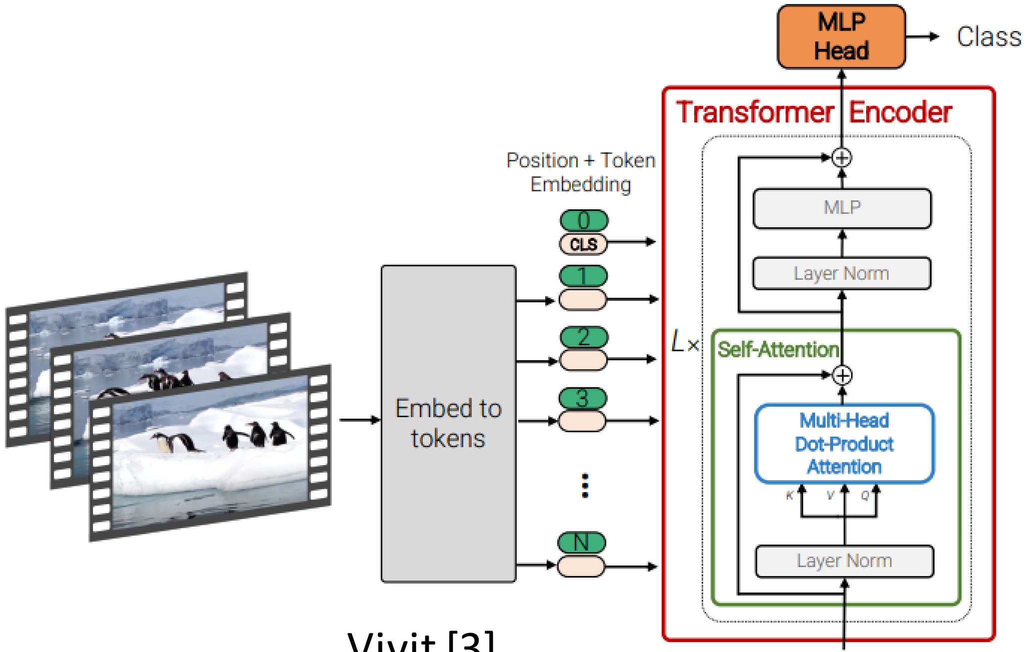


Technical Approach

- 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

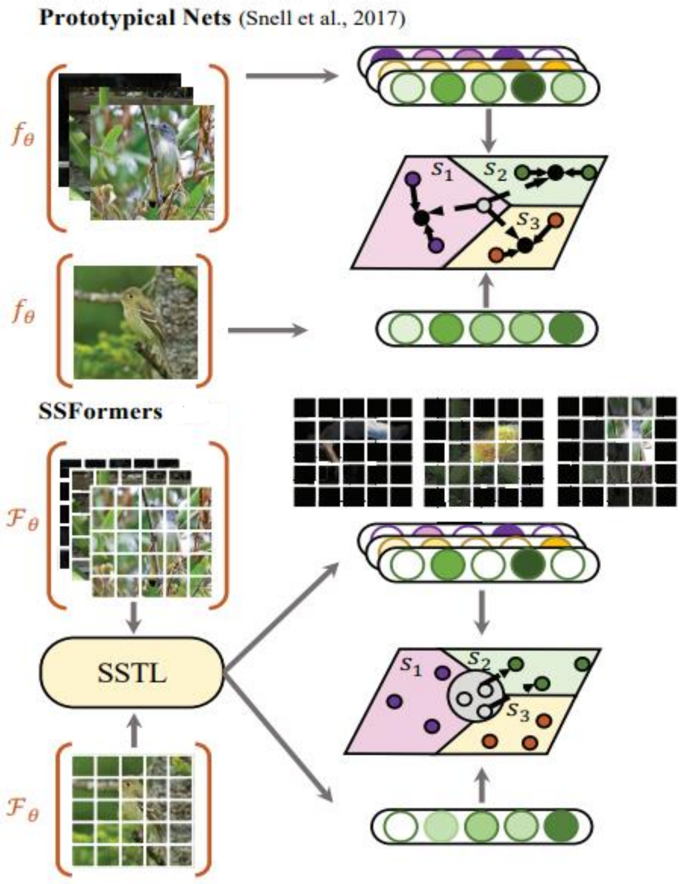


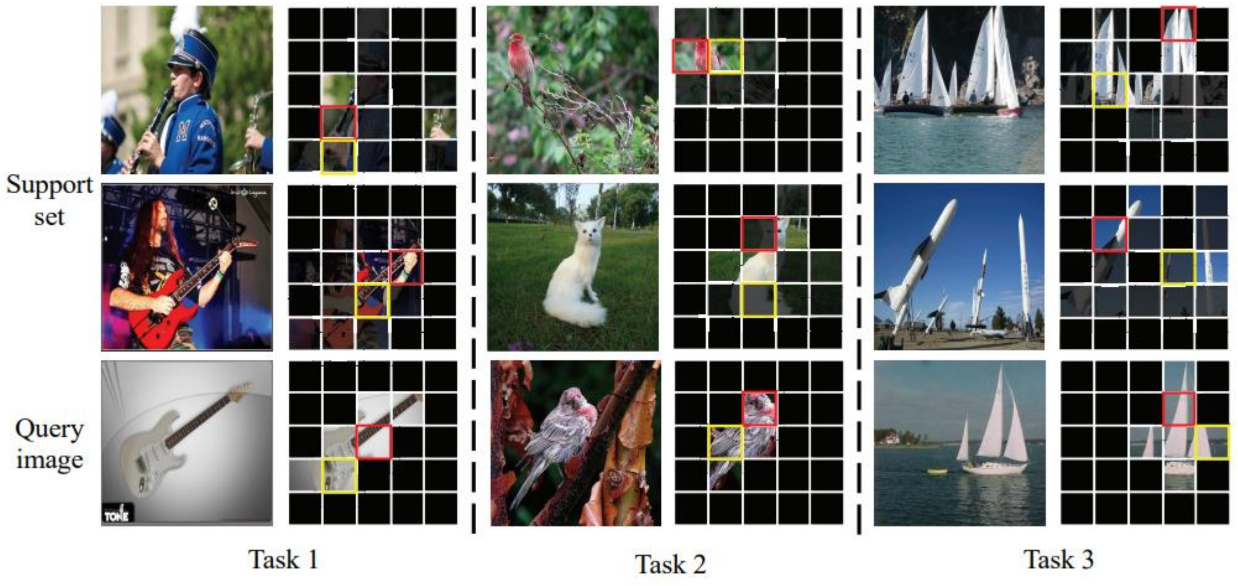
CNN-LSTM



Vivit [3]

Technical Approach



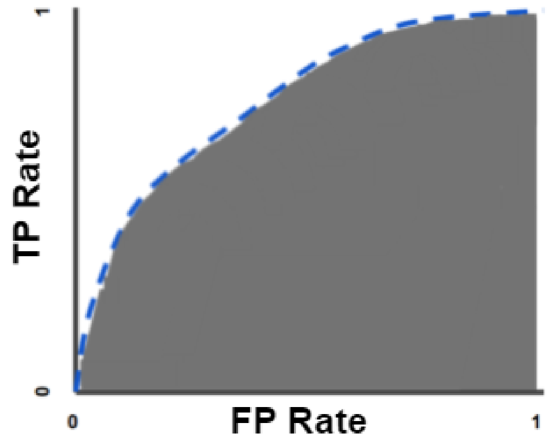


- Using cross-attention mechanism to highlight similarities between support set and query image

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

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*.