A Comparison of Histopathology Imaging Comprehension Algorithms based on Multiple Instance Learning

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Introduction

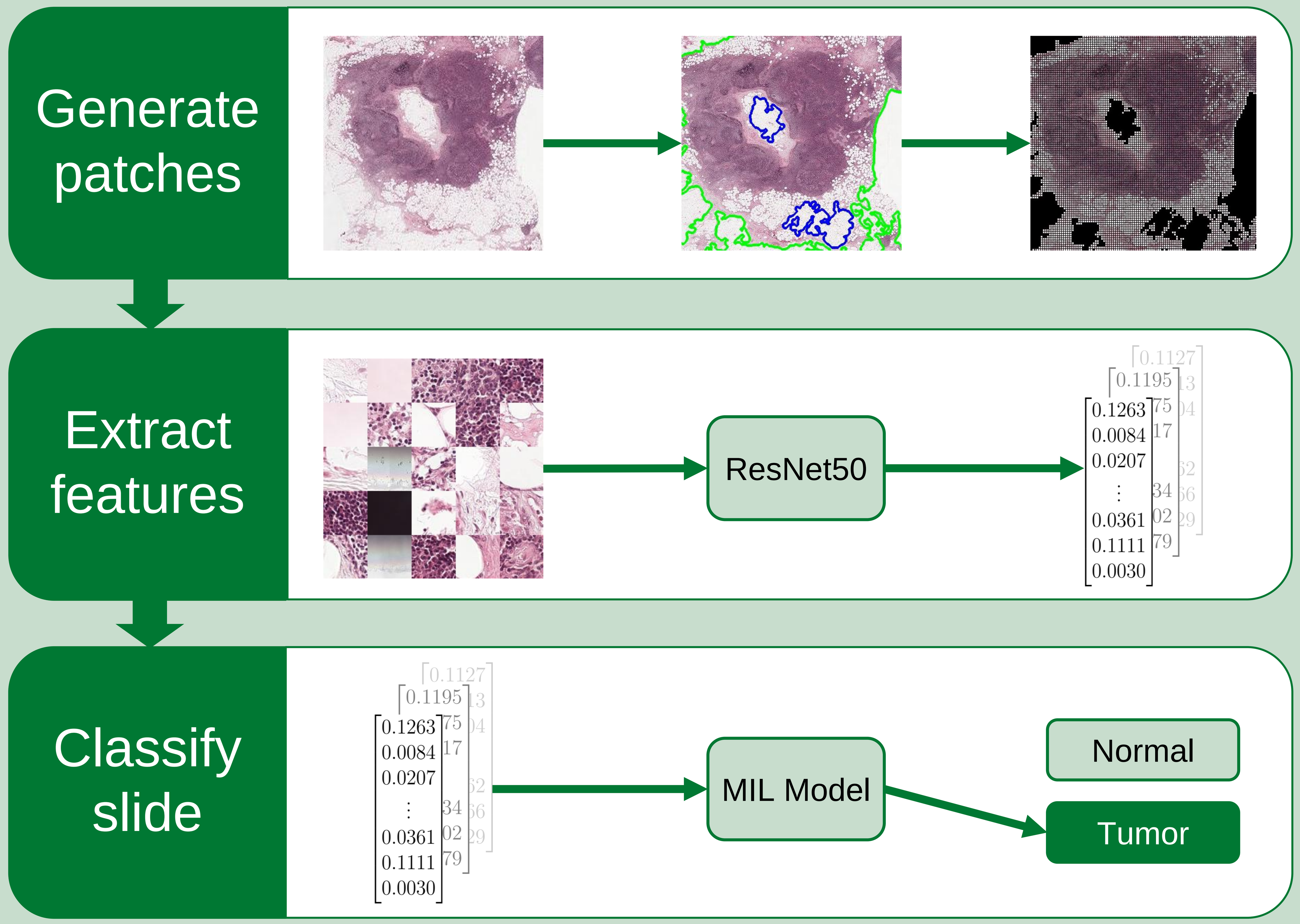
- Cancer pathology involves evaluating tissue samples on glass slides, which is tedious and error-prone
- Whole-slide imaging allows for digital analysis of tissue samples using machine learning
- One state-of-the-art method is multiple instance learning (MIL), which involves splitting the slide into many patches
- Attention-based MIL models have performed better than other MIL models [1]
- Transformer-based models, which use self-attention, have reported a high AUC [2]

We are interested in comparing MIL algorithms to find an optimal model for classifying whole-slide images. Also, we want to verify that Transformer-based algorithms achieve a higher performance than other attention-based algorithms.

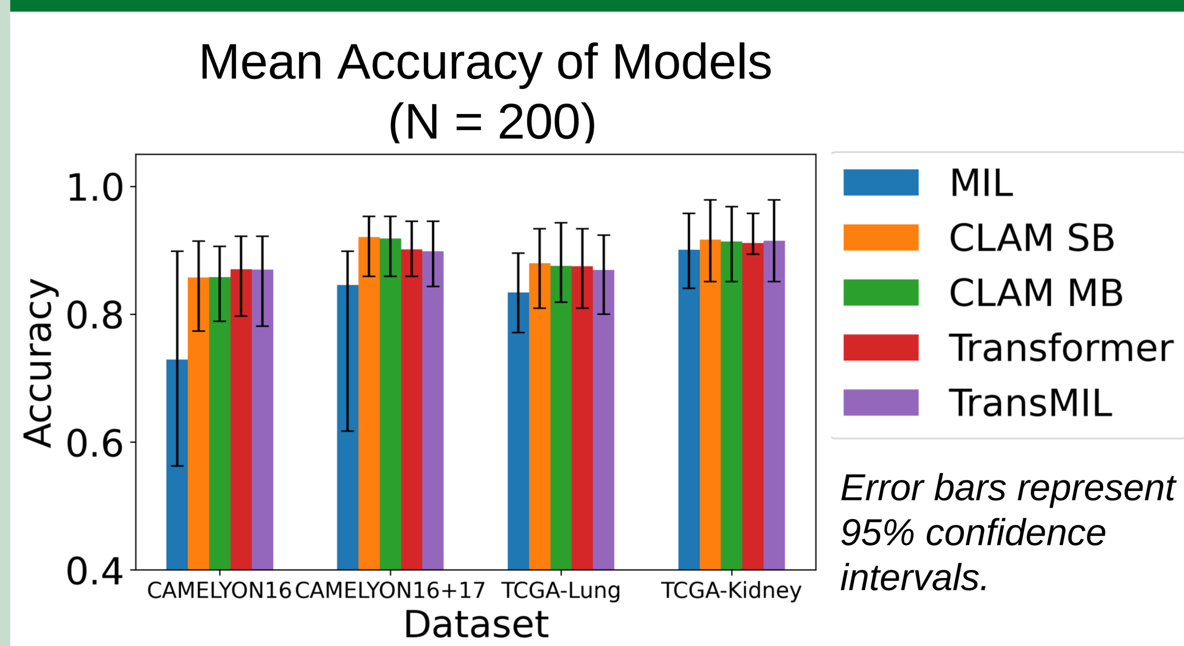
Methods

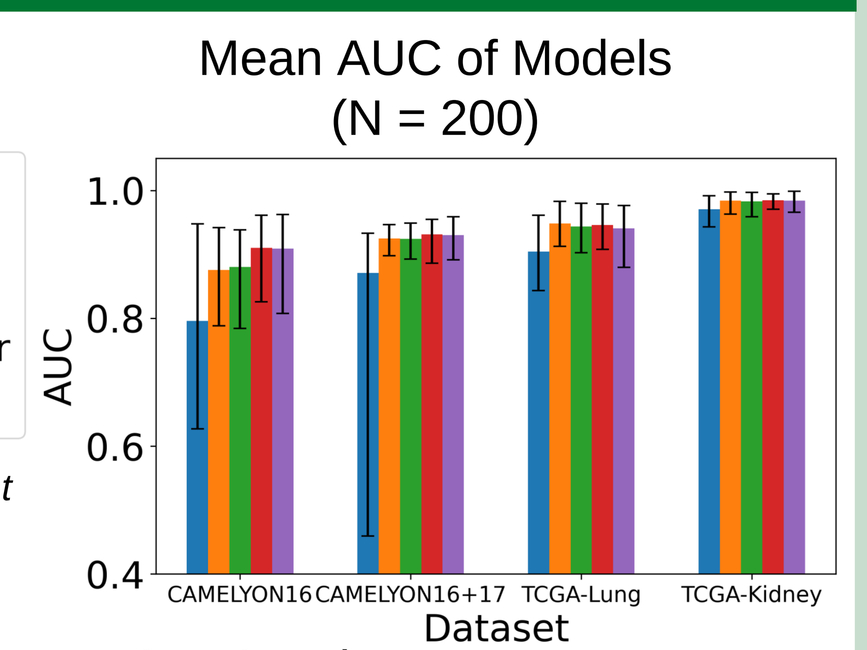
- We trained and tested five MIL models using three datasets: CAMELYON16+17 (breast cancer), TCGA-Lung (lung cancer), and TCGA-Kidney (kidney cancer)
- We estimated the mean accuracy and AUC using bootstrapping over 200 folds

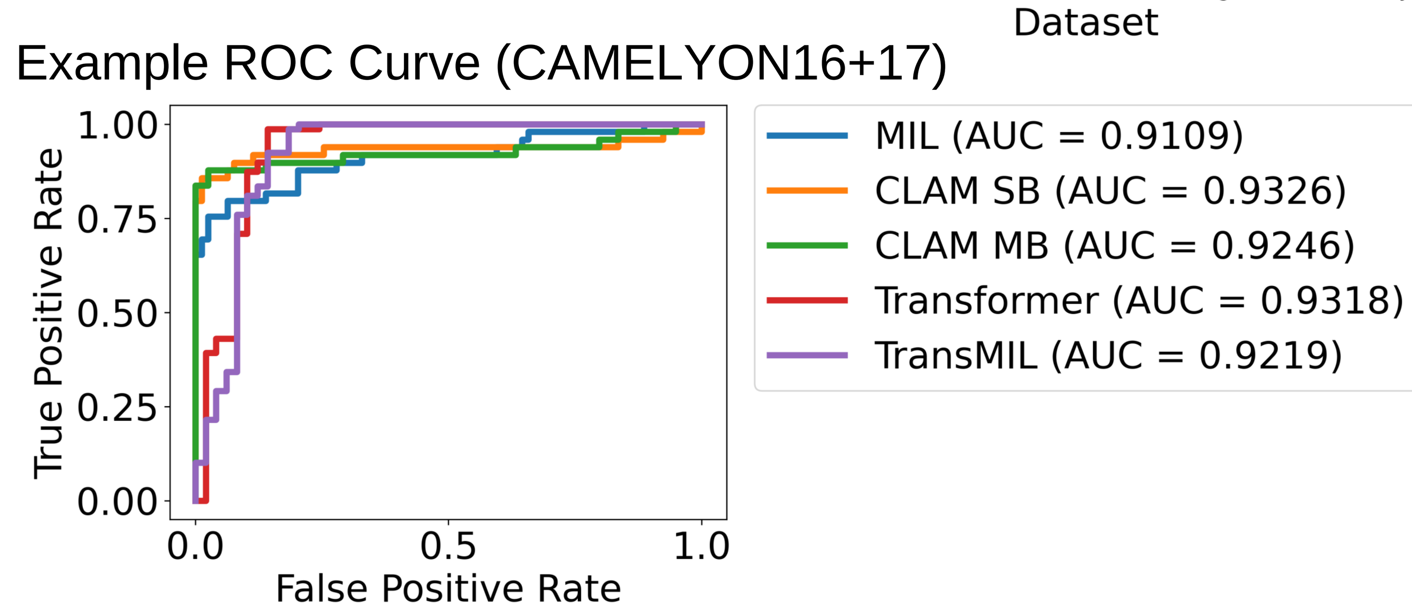
Model	Aggregation Operation	Trainable Parameters
MIL	max pooling	525,826
CLAM SB [1]	single-branch attention	790,791
CLAM MB [1]	multiple-branch attention	791,084
Transformer	Transformer	2,628,114
TransMIL [2]	Transformer with positional encoding	2,672,146



Results







Conclusions

- Attention-based MIL models performed better than the standard MIL model
  - On average, the attention-based MIL models achieved a higher accuracy and AUC than standard MIL models
- No attention-based MIL model clearly outperformed the others
- Transformer-based models did not achieve a higher accuracy and AUC than other attention-based models
  - Also, the Transformer used a lot of memory, which made training difficult
  - Positional encoding did not have a large effect on accuracy or AUC
- Therefore, for whole-slide imaging tasks, we recommend an attention-based MIL model
  - However, for large datasets, we do not recommend Transformer-based models due to the memory required for training
- Further research could focus on improving the Transformer by reducing memory usage

References

[1] M.Y. Lu et al. (2021). Data-efficient and weakly supervised computational pathology on whole-slide images. *Nat. Biom. Eng.*, **5**, 555-570.
[2] Z. Shao et al., TransMIL: Transformer based Correlated Multiple Instance Learning for Whole Slide Image Classification. *35th Conference on Neural Information Processing Systems.*

Further Information

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