



A Convolutional Neural Network Classifier for Macroscopic Whole Slide Images

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BACKGROUND

- Post-mortem brain tissue analysis is important for Alzheimer's disease research.
- Digital pathology is an increasingly popular and powerful tool for this analysis.
- Accurate brain region identification is critical as disease patterns vary across regions.
- AIM:** Develop a CNN-based classifier to determine tissue origin directly from the slide.

METHODS

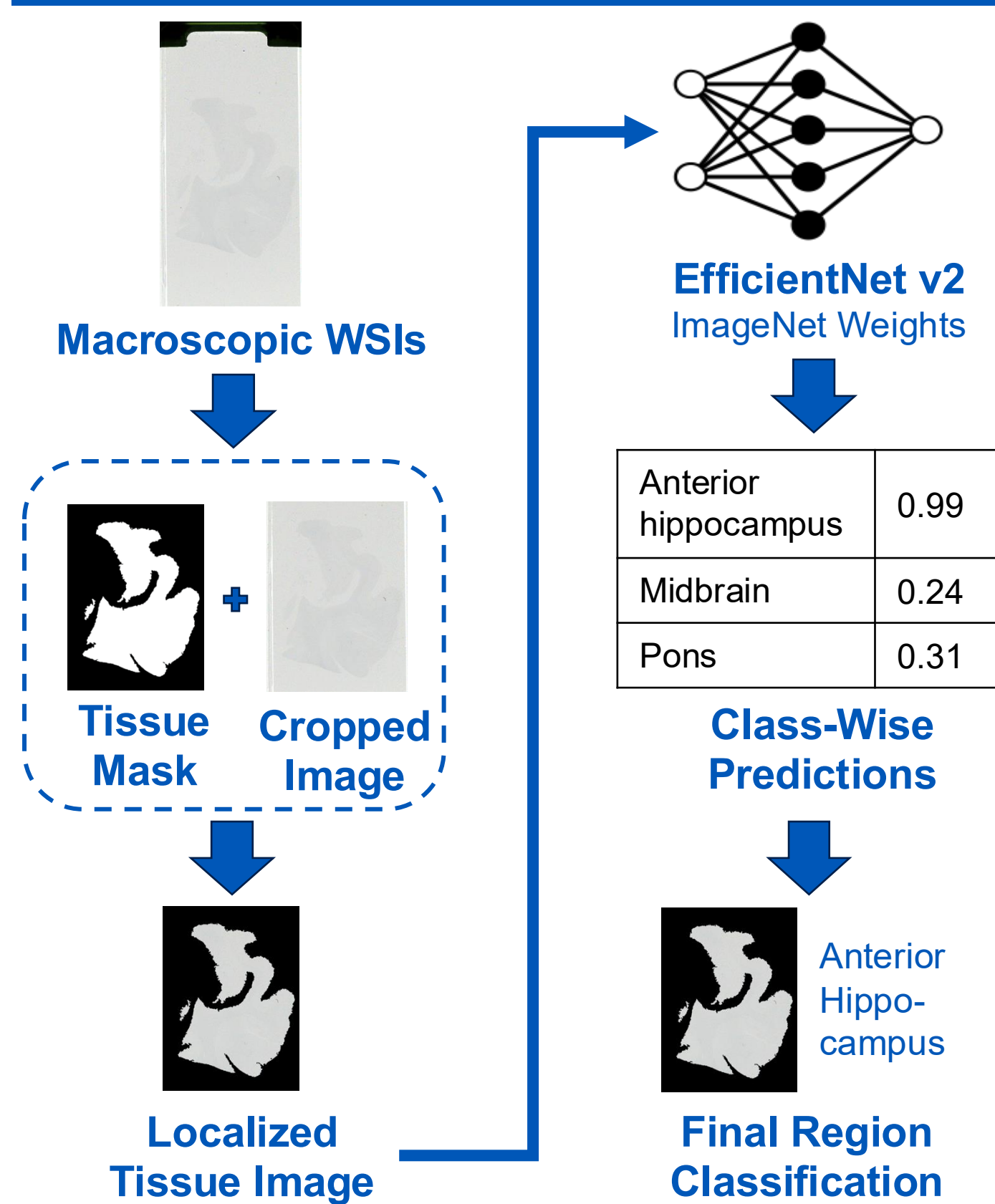


FIGURE 1: TISSUE CLASSIFICATION PIPELINE
Computational pipeline for classifying slide images using an EfficientNet [1] backbone with ImageNet [2] weights.

TABLE 1: IMAGE SELECTION

Equal numbers of slides were selected from the 17 regions in the Mayo Clinic Department of Neuroscience Brain Bank.

Region from the Brain Bank	Images For Training	Images for Testing	Correct Labels in Original Dataset
Medial frontal	75	60	80.00%
Superior temporal	75	60	83.33%
Inferior parietal	75	60	33.33%
Motor cortex	75	60	65.00%
Visual cortex	75	60	98.33%
Posterior hippocampus	75	60	81.67%
Basal forebrain (amygdala and nucleus basalis of Meynert)	75	60	66.67%
Cerebellar vermis	75	60	90.00%
Caudate/Putamen/Nucleus Accumbens	75	60	83.33%
Cingulate cortex & Superior frontal	75	60	51.67%
Subthalamic nucleus (level of mammillothalamic track)	75	60	73.33%
Anterior hippocampus	75	60	55.00%
Midbrain (level of red nucleus)	75	60	81.67%
Pons (obex)	75	60	71.67%
Medulla	75	60	63.33%
Cerebellum (dentate nucleus)	75	60	86.67%
Blood vessels or spinal cord	75	60	66.67%

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RESULTS AND DISCUSSION

- The model achieved a macro-average **accuracy 95.7%, precision 95.8%, recall 95.7%, ROC-AUC 99.8%, and PR-AUC 97.5%.**
- Poor performance was seen in morphologically similar regions like the Midbrain/Pons and Medial Frontal/Inferior Parietal

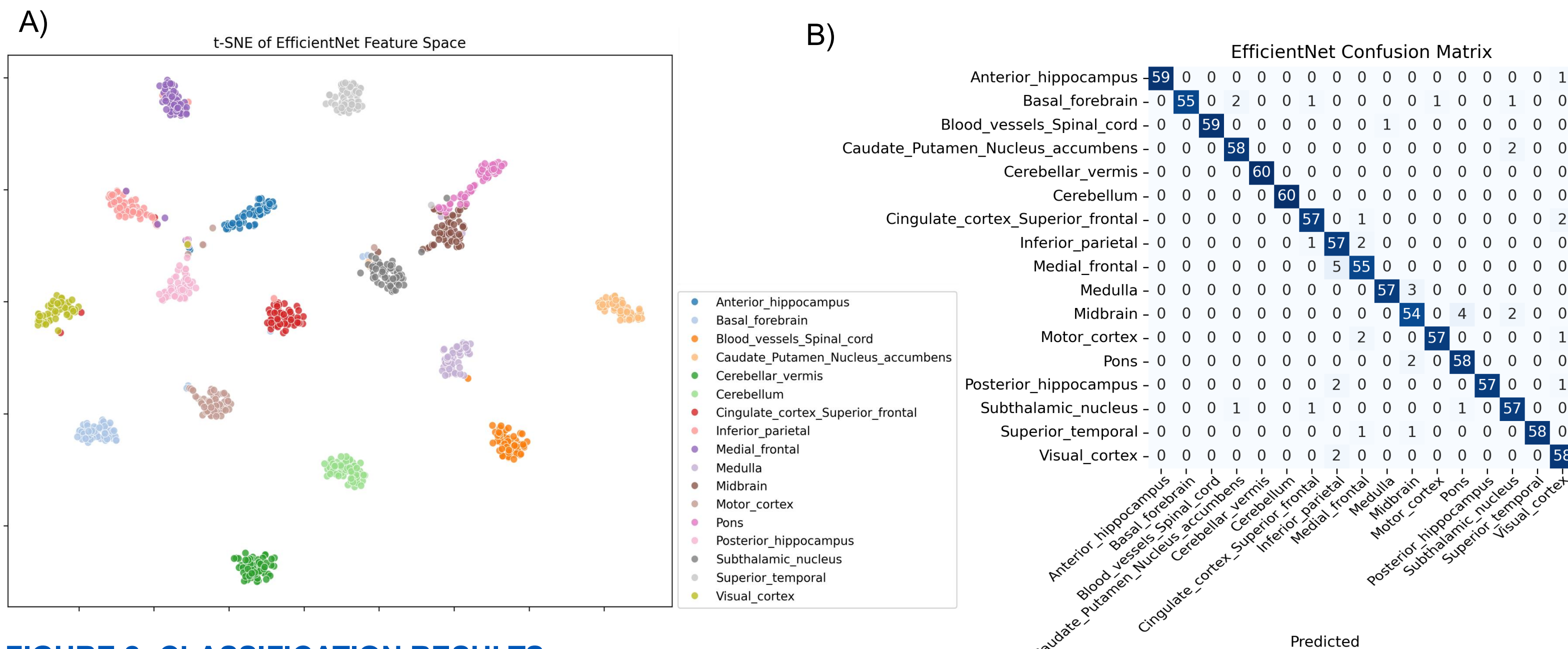


FIGURE 2: CLASSIFICATION RESULTS

A) t-SNE plot displaying the clustering of images and their regions. Each point represents an image, and each color represents the true region the slide was from. B) Confusion matrix of the EfficientNet classification performance. The limited off-diagonal errors show the high accuracy of the model.

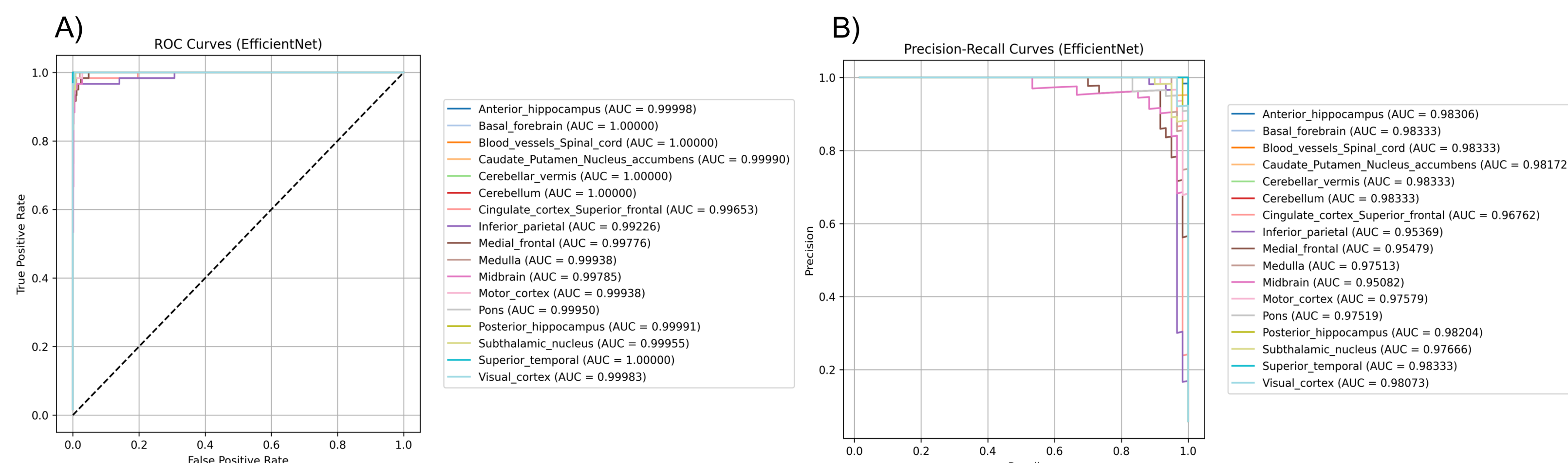


FIGURE 3: DISCRIMINATIVE PERFORMANCE METRICS

A) Receiver Operating Characteristic (ROC) and B) Precision-Recall (PR) curves for each brain region. The high class-wise ROC-AUC indicates the model can strongly discriminate between images. There is still high class-wise PR-AUC, but noticeably lower. The regions with the lowest AUC correspond to the problematic regions listed above: Medulla/Pons and Medial frontal/Inferior parietal.

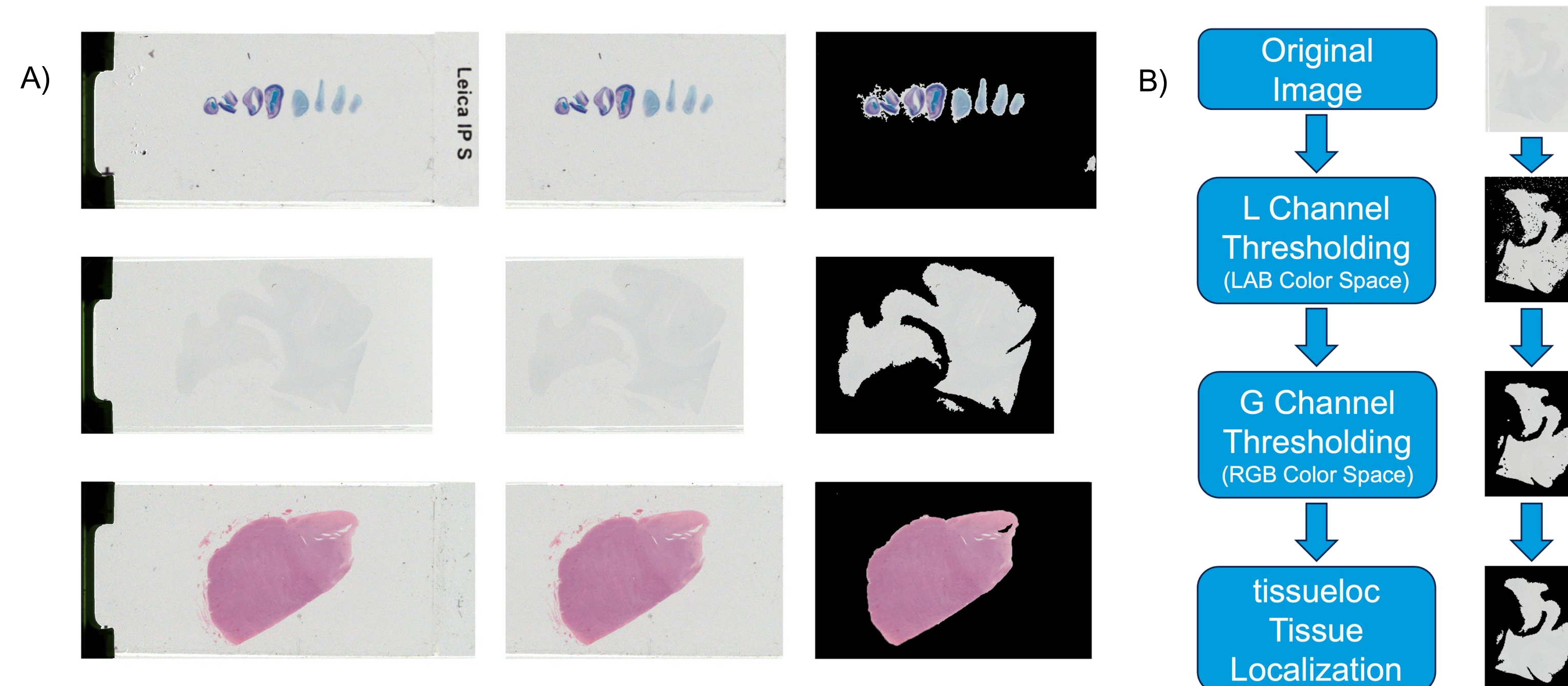


FIGURE 4: IMAGE PRE-PROCESSING PIPELINE

A) Representative WSIs depicting the image pre-processing pipeline with tissues of various sizes, stains, and regions. Column 1: Macroscopic WSIs, 2: Border crop, 3: Background Removal. B) Background removal pipeline for isolating the tissue from the original WSI. This was adapted from the tissueloc [3] package.

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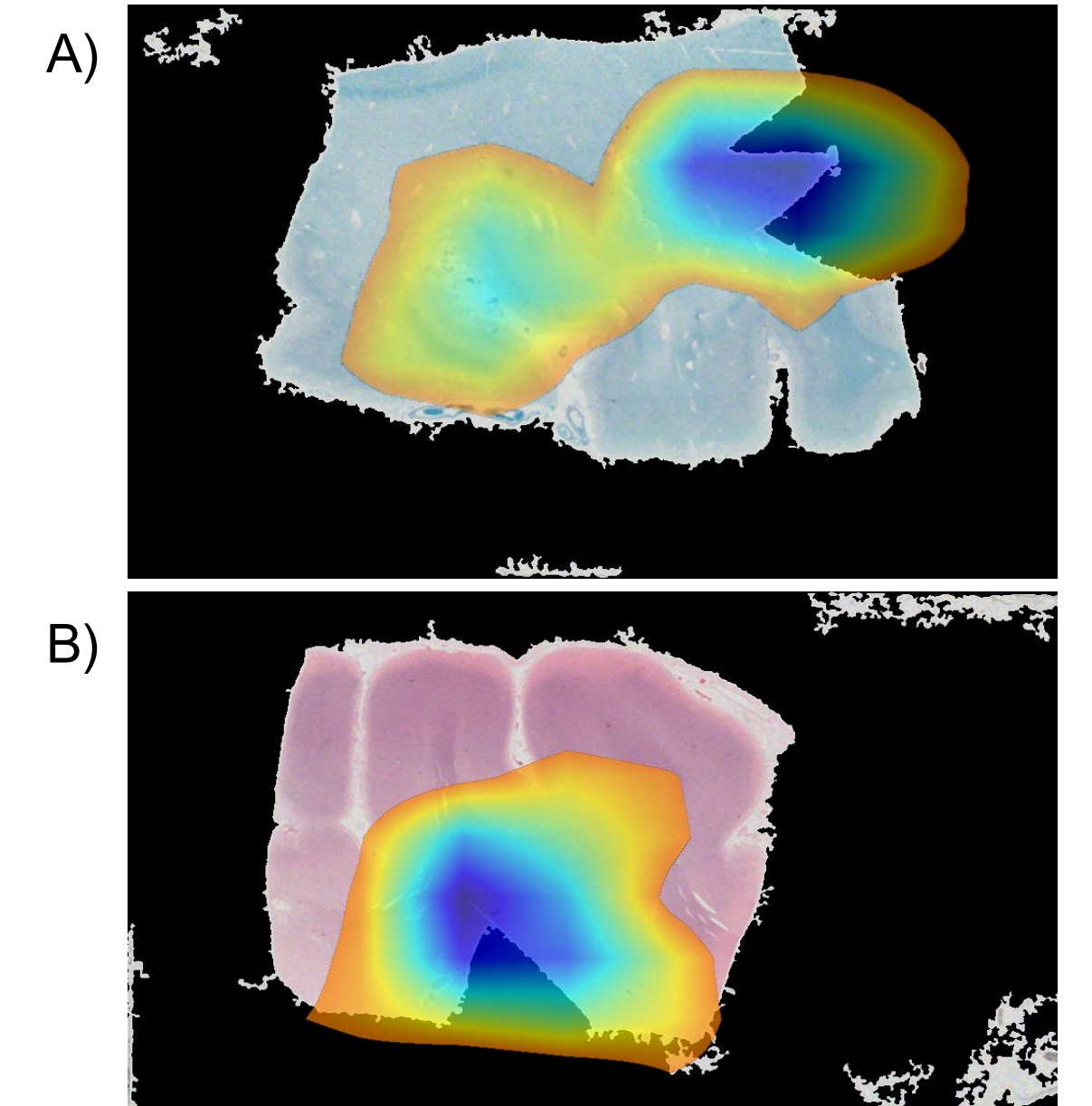


FIGURE 5: IMAGE CLASSIFIER GRADIENT ACTIVATION MAP
Gradient class activation heatmap for (A) Inferior Parietal and (B) Medial Frontal slides. The model correctly learns from the notches—a distinguishing characteristic of this region.

CONCLUSION

- The classifier achieved high accuracy and demonstrated strong discrimination across tissue regions.
- The model's small size and inference speed support scalable deployment across all slide images within the Mayo Clinic Brain Bank.
- These findings support the utility of the model as an automated complement to existing slide labeling workflows.

NEXT STEPS

- The classification errors point to the model's overdependence on tissue morphology.
- Future improvements will focus on enhanced image segmentation and learning additional features such as tissue texture, contrast, and gray-white matter proportion.
- The model will be integrated into the Brain Bank Data Platform for improved slide organization.

REFERENCES

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