



# INTERPRETABLE CLASSIFICATION OF RENAL AND COLONIC NEOPLASIA ON HISTOPATHOLOGICAL SLIDE IMAGES USING PROTOTYPICAL EXPLAINABILITY

Achilles Gatsonis, Geisel School of Medicine

Advisor: Professor Saeed Hassanpour (Biomedical Data Science, Epidemiology)

## INTRODUCTION

### Clinical Significance:

Histopathology is the gold standard for identification of malignancies, and digital slide images can be applied to computer vision tasks for image analysis

### Epidemiology:

Renal cell carcinoma: 400,000 cases and 200,000 deaths annually [1]

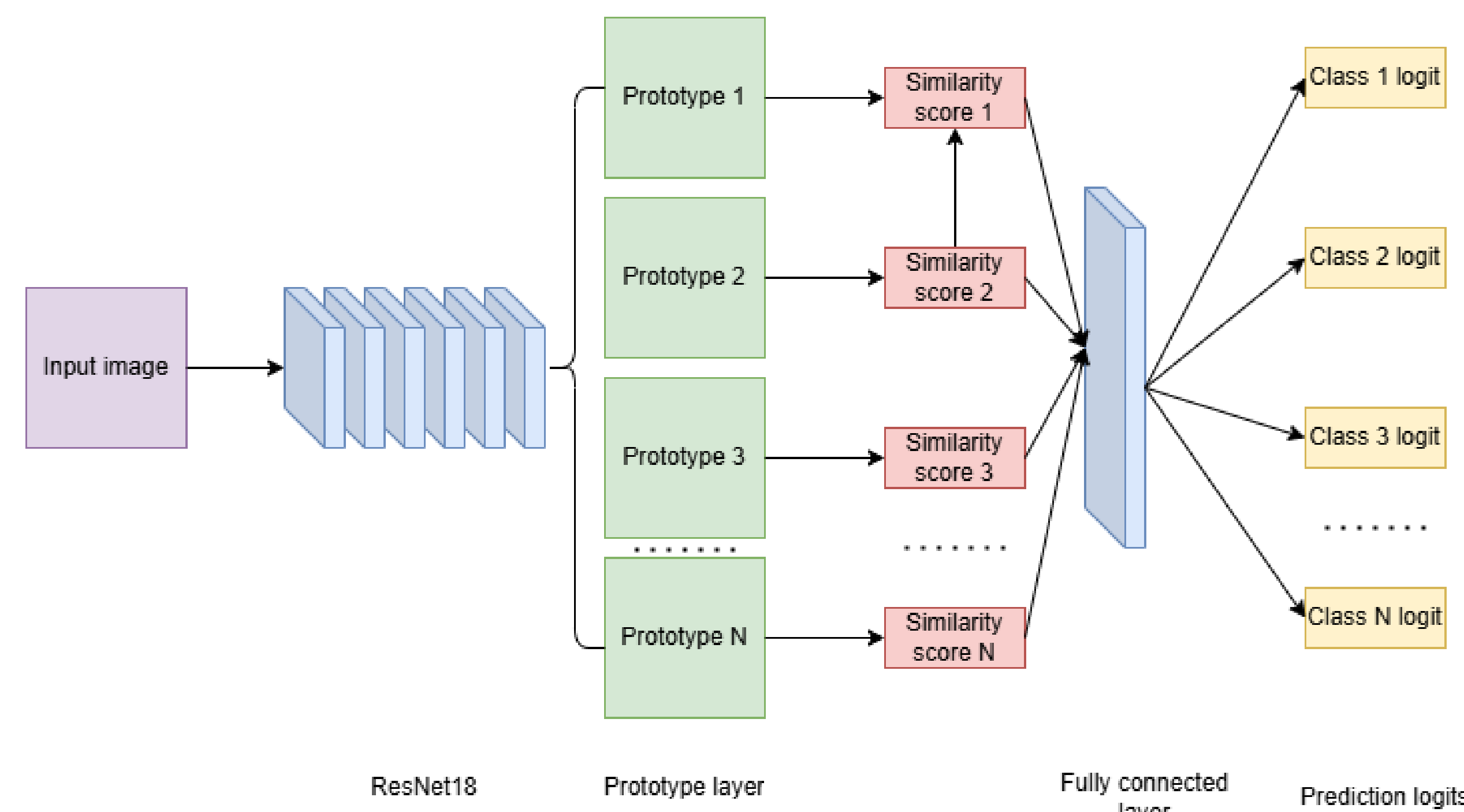
Colorectal carcinoma: 14 million cases and 8 million deaths annually [2]

### Clinical Need:

Accurate and interpretable AI methods can be implemented to classify histopathology images and support decision making of pathologists

### Prototypical Part Network:

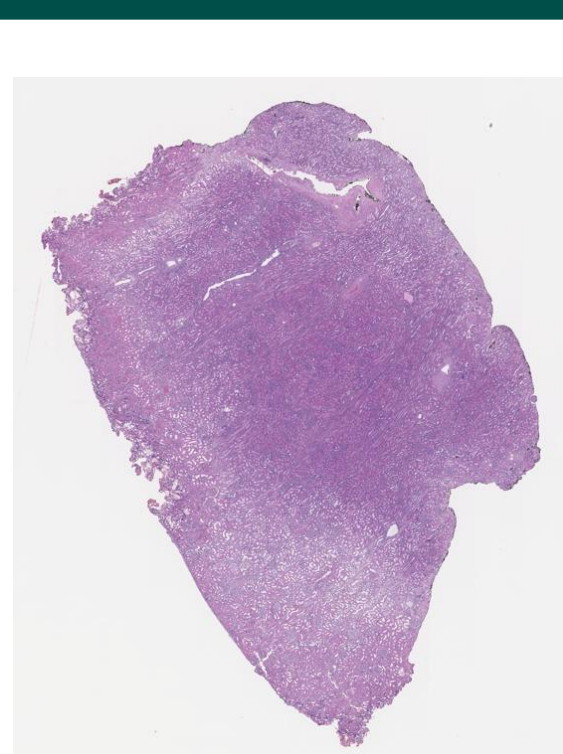
Deep neural network that classifies images by comparing regions of input to **class-specific prototypes**, providing **built-in, human-interpretable** “this-looks-like-that” reasoning and transparency [3]



### Datasets:

#### RCC Dataset

484 whole-slide images of renal resections from DHMC [4]



5 classes:  
Benign  
Chromophobe  
Clear cell  
Oncocytoma  
Papillary

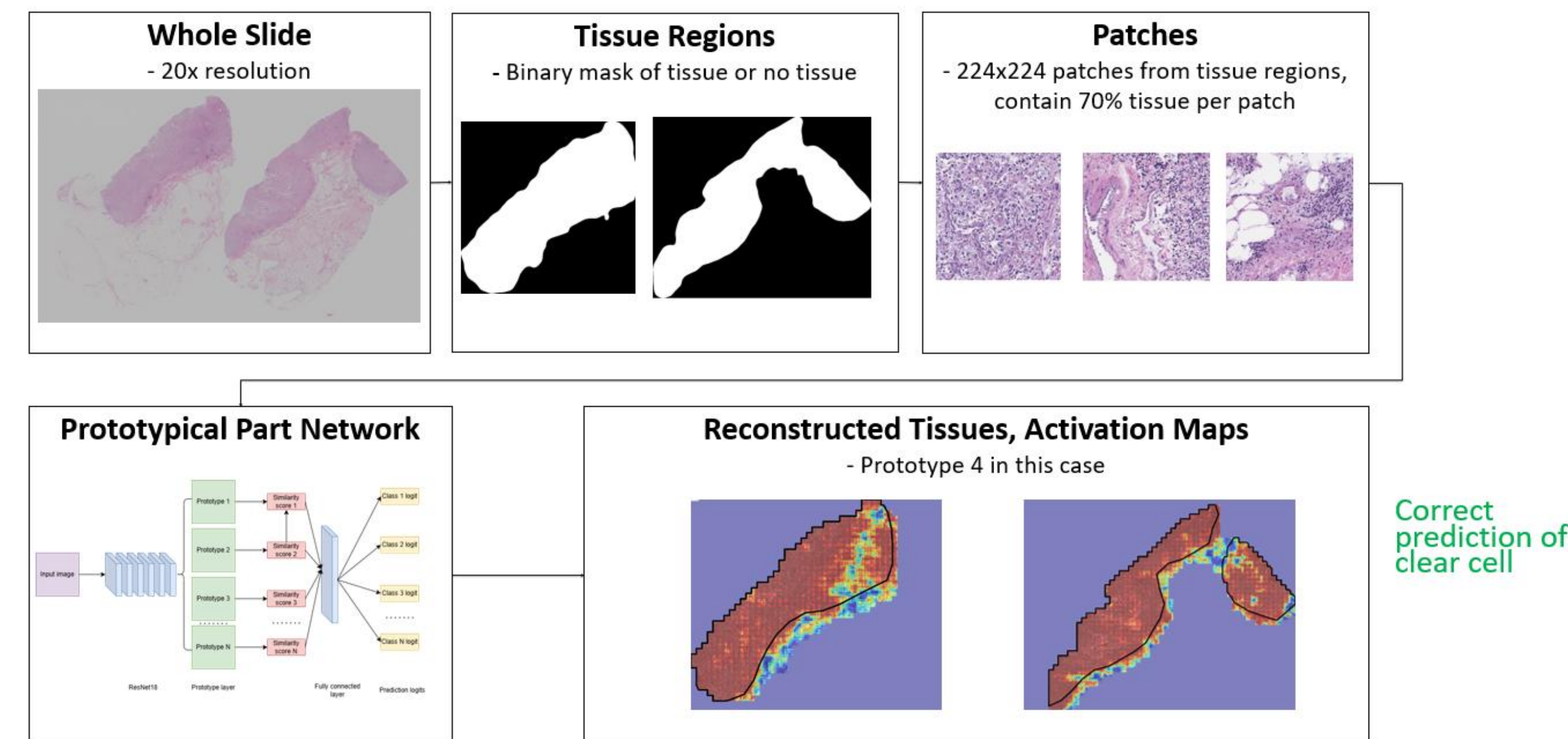
#### MHIST Dataset

3,152 patches from whole-slide images of colonic biopsies from DHMC [5]



Sessile serrated adenoma (SSA)

## METHODS

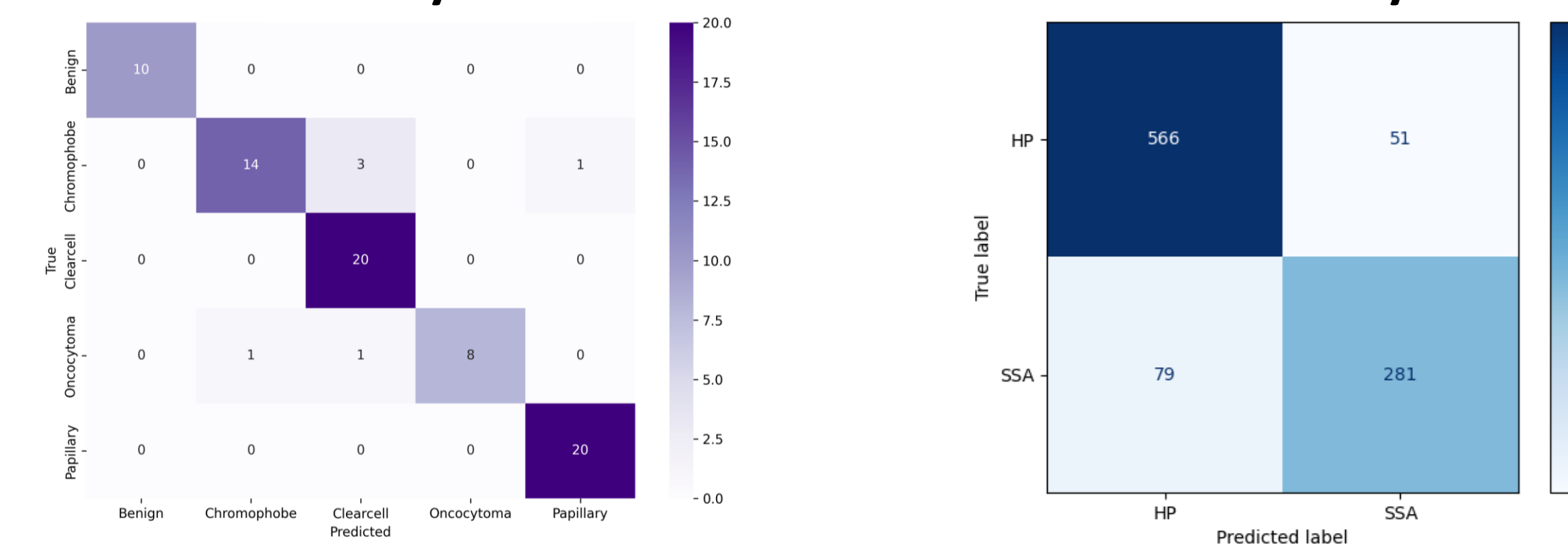


Whole slides are disassembled into patches, which are passed through the model. Individual patches are classified, and whole slides are reconstructed. Regions of malignancy are marked as “hot spots.”

## RESULTS

### 1 MODEL ACCURACY

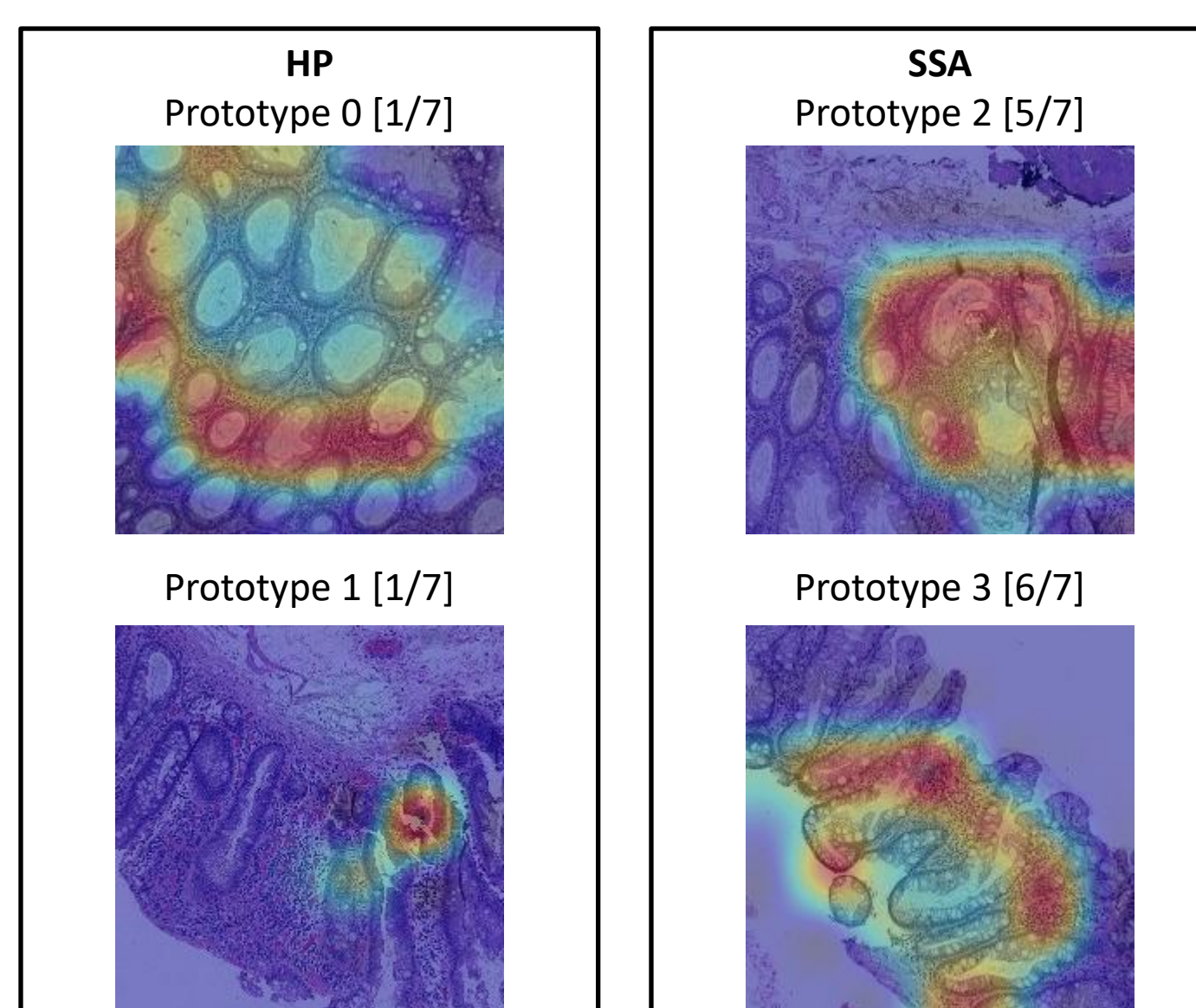
RCC Dataset: accuracy reaches 92.3% MHIST Dataset: accuracy reaches 85.5%



### 2 MODEL PATCH-LEVEL PERFORMANCE

Model learns “prototype” images to compare to test images, providing a human-interpretable reasoning behind predictions

MHIST Dataset Prototypes



Blue = weak activation Red = strong activation

“Tough” Example (5/7 pathologists labeled as SSA)

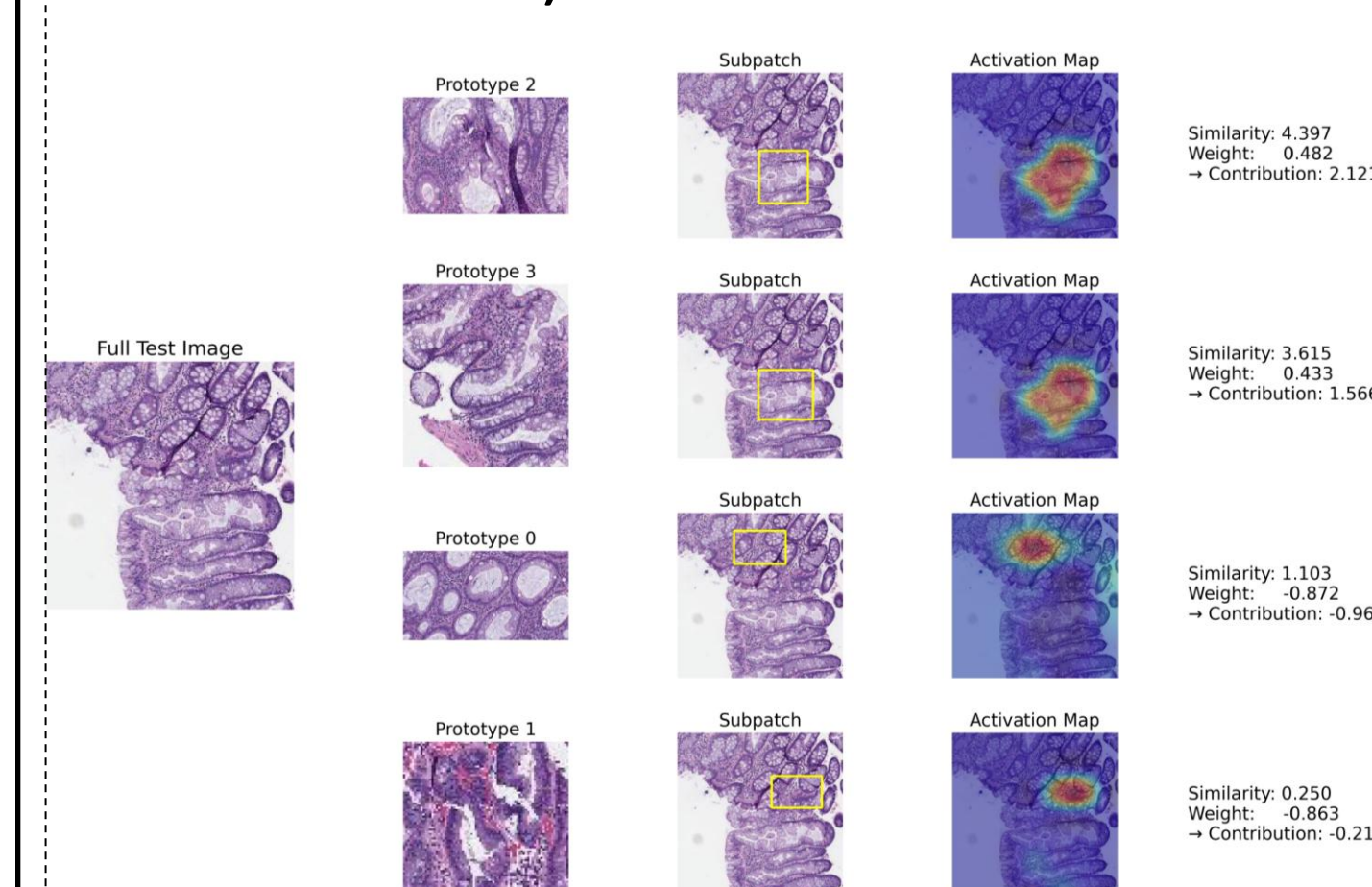
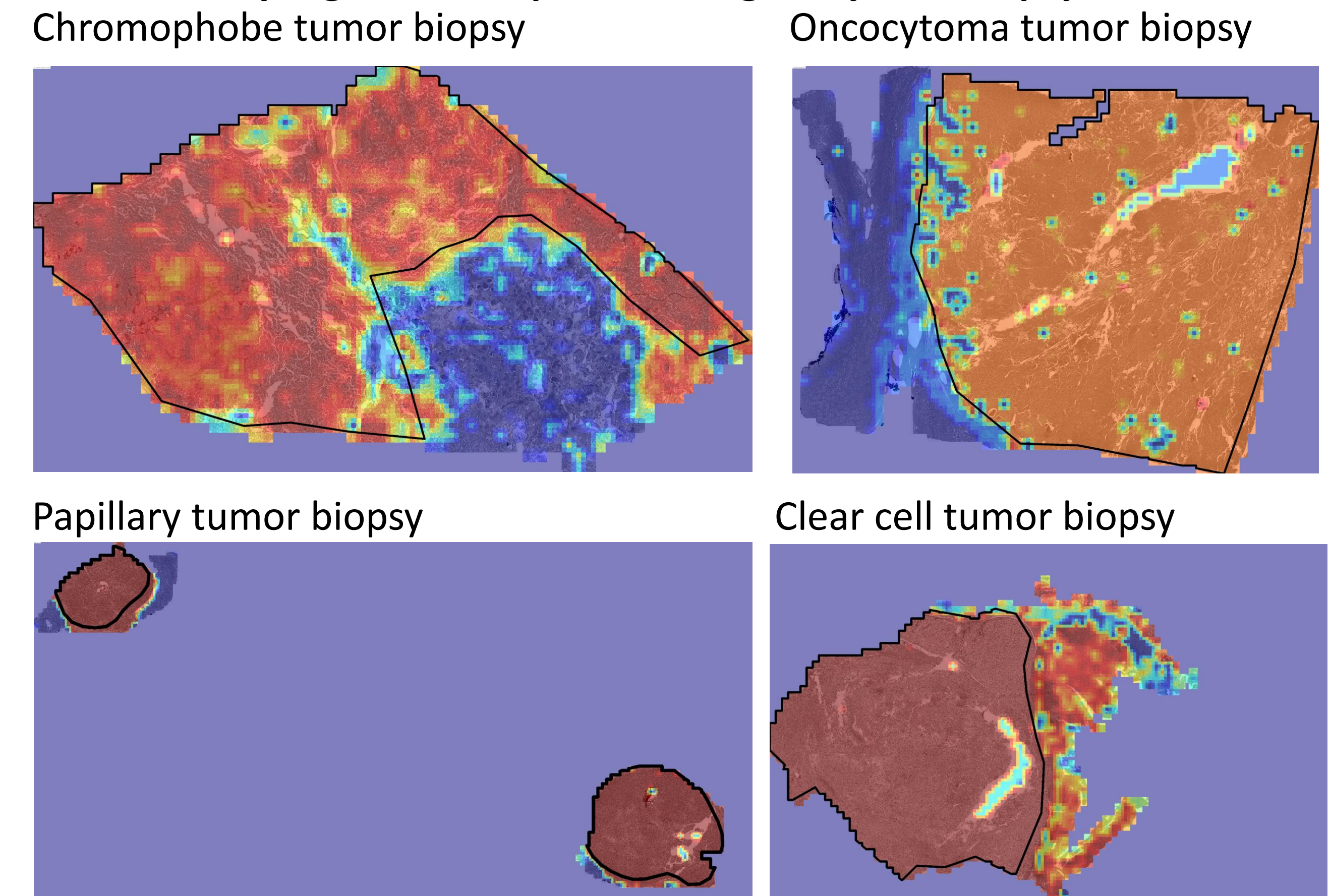


Image has higher similarity scores for SSA prototypes (2 and 3)

### 3 MODEL SLIDE-LEVEL PERFORMANCE

Model capable of analyzing whole-slide at the subpatch-level to identify regions of suspected malignancy on a biopsy slide



Blue = weak activation Red = strong activation Black border = pathologist border of malignancy

## DISCUSSION & CONCLUSIONS

### Performance:

Model obtains high accuracy on MHIST and RCC Datasets

### Interpretability:

1. Prototype activations reveal model logic for both correct and incorrect predictions, aiding in error analysis
2. Subpatch-level activations provide fine-grained context for whole slide images, which can align with histologic structures

### Clinical impact:

1. The prototypical part network can enable pathologists to audit AI decisions and builds trust
2. The model’s interpretability reduces black-box opacity, which is a large barrier to clinical adoption

## ACKNOWLEDGEMENTS

Professor Saeed Hassanpour and the Hassanpour Lab  
The Department of Pathology and Laboratory Medicine at DHMC

## REFERENCES

[1] Makino, T., Kadamoto, S., Izumi, K., & Mizokami, A. (2022). Epidemiology and prevention of renal cell carcinoma. *Cancers*, 14(16), 4059. <https://doi.org/10.3390/cancers14164059>  
[2] Ferlay, J., Soerjomataram, I., Dikshit, R., Eser, S., Mathers, C., Rebelo, M., Parkin, D. M., Forman, D., & Bray, F. (2014). Cancer incidence and mortality worldwide: Sources, methods and major patterns in Globocan 2012. *International Journal of Cancer*, 136(5). <https://doi.org/10.1002/ijc.29210>  
[3] Chen, C., Li, O., Tao, C., Barnett, A. J., Su, J., & Rudin, C. (2019). This Looks Like That: Deep Learning for Interpretable Image Recognition. *arXiv*. <https://arxiv.org/abs/1806.10574>  
[4] Zhu, M., Ren, B., Richards, R., Suriawinata, M., Tomita, N., & Hassanpour, S. (2021). Development and evaluation of a deep neural network for histologic classification of renal cell carcinoma on biopsy and surgical resection slides. *Scientific Reports*, 11(1). <https://doi.org/10.1038/s41598-021-86540-4>  
[5] Wei, J., Suriawinata, A., Ren, B., Liu, X., Lisovsky, M., Vaickus, L., Brown, C., Baker, M., Tomita, N., Torresani, L., Wei, J., & Hassanpour, S. (2021). A Petri dish for histopathology image analysis. *Lecture Notes in Computer Science*, 11–24. [https://doi.org/10.1007/978-3-030-77211-6\\_2](https://doi.org/10.1007/978-3-030-77211-6_2)