Real Time, Point-of-Care Pathology Diagnosis via Embedded Deep Learning

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Abstract

- With the growth of telepathology, remote diagnosis has become a viable solution to address the lack of skilled pathologists in developing areas
- Current telepathology systems for cancer diagnosis relies on pathologists performing remotely, which is low-throughput and requires more time and resources
- In this work, we propose a cost-efficient device that incorporates embedded deep learning to achieve real-time, point-of-care diagnosis of whole pathology slides

Motivation

- There is an urgent need for widespread cancer diagnosis in low resource settings, especially in contrast to areas with developed healthcare systems.
- Our group has previously developed a deep-learning based, weakly-supervised method that uses attention-based learning to automatically identify subregions of high diagnostic value in order to accurately classify the whole slide (Lu et al.)
- A cost-effective, easy-to-use device running a portable version of this model would be able to image and classify whole pathology slides in a streamlined and efficient process

Imaging and Classification Pipeline

We use 3D printed resin components, based on the design of the Openflexure Microscope (Collins et al.), for the microscope body and stage and to house the optics module. We also port the trained deep learning model on an Nvidia Jetson Nano to achieve real-time analysis of acquired images. Below is a schematic of our overall process.

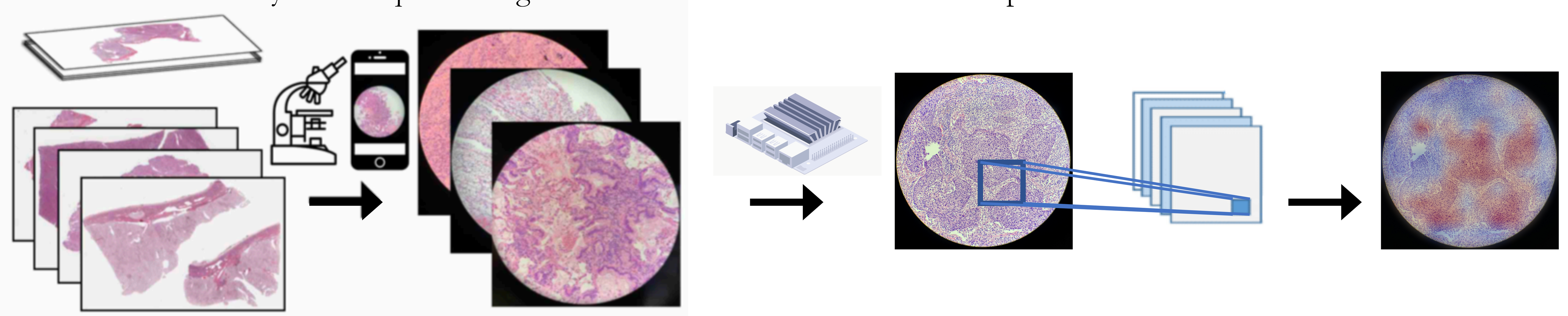


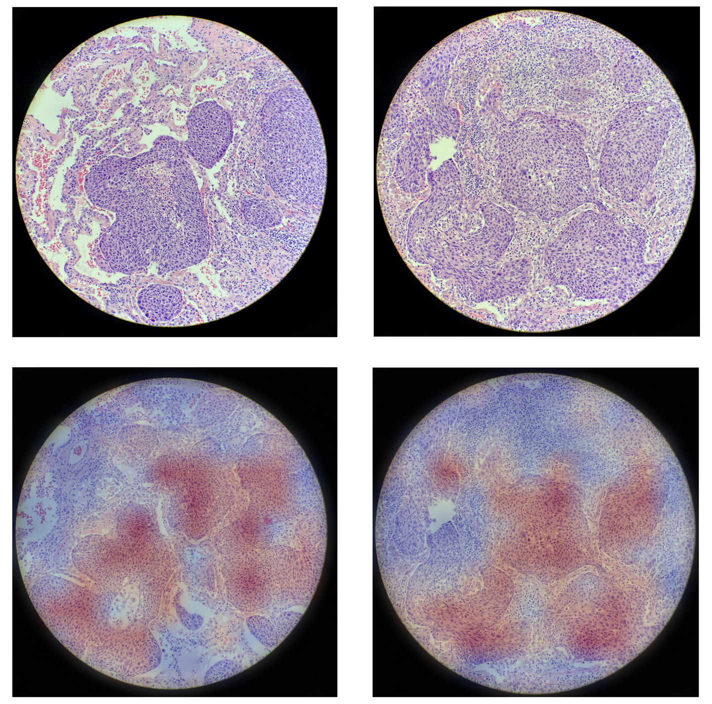
Image acquisition

Capture images of whole pathology slides using smartphone camera externally or Raspberry Pi Camera Module V2

Classification on Jetson Nano

Feed images as input to our model, which performs segmentation of the slide, inference, and generates a heatmap of the attention scores used to determine the final classification of the image section

Results



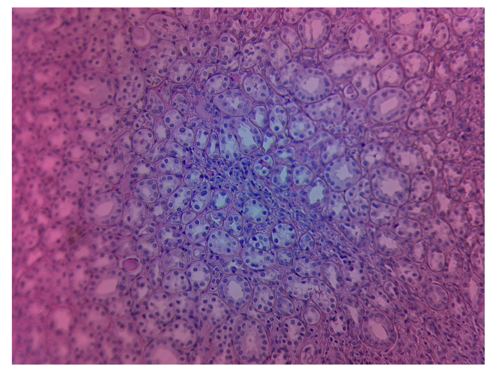
Cellphone Acquired Images (left)

We first tested our portable deep learning model on separately acquired cellphone images of whole pathology slides. The left figure shows sections of a lung squamous cell carcinoma sample and corresponding generated heatmaps.

Turning off Gaussian blurring for the heatmap generation process significantly improves the overall time. We measured the average time over 5 runs for cellphone images and obtained the following, in seconds per region of interest:

Initialize	Patching and feature extraction	Heatmap generation	Inference
1.63s	11.36s	4.16s	2.49s

Aberrations



Since we replace the built-in lens for the Raspberry Pi Camera with our own optics setup, we observe chromatic and spherical aberrations (as shown in the left figure). We correct for this in post-processing using a pipeline created by Bowman et al.

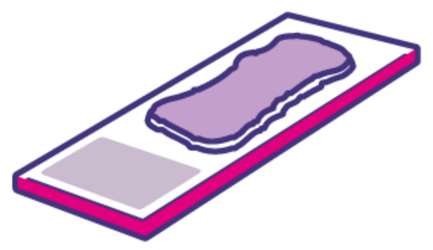
Discussion

- Our setup was able to classify whole pathology slide images acquired separately from a conventional smartphone camera, along with generating interpretable heatmaps for each image section
- The current run time for each region of interest is adequate for a resource-constrained setting
- **Future work** will include training a multiclass classification model specifically for whole slide images at 20x magnification. We think that this may increase overall efficiency and ease-of-use by requiring fewer images to be captured for each slide
- We also plan on modifying the device to be directly compatible with a smartphone camera and automating the image section collection process by introducing a moveable stage.

References

1. Ming Y. Lu, Drew F. K. Williamson, Tiffany Y. Chen, Richard J. Chen, Matteo Barbieri and Faisal Mahmood, "Data Efficient and Weakly Supervised Computational Pathology on Whole Slide Images" arXiv:2004.09666 (2020).
2. Collins, Joel T et al. "Robotic microscopy for everyone: the OpenFlexure microscope." Biomedical Optics Express 11 (2020): 2447 - 2460.
3. Bowman R., Vodenicharski B., Collins J., Stirling J., "Flat-field and colour correction for the raspberry pi camera module," https://arxiv.org/abs/1911.13295 (2019).

Supplement



Poster

Lab Website