A 3D Printed Embedded AI-based Microscope for Pathology Diagnosis

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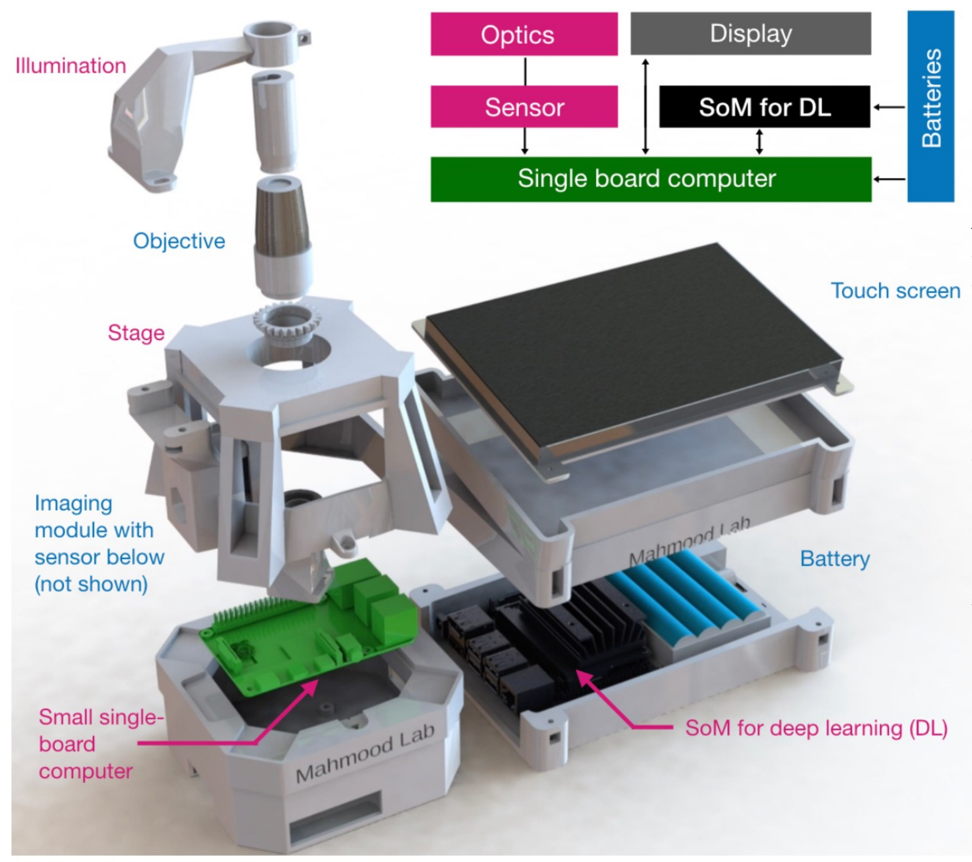
Abstract

- 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 rely 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

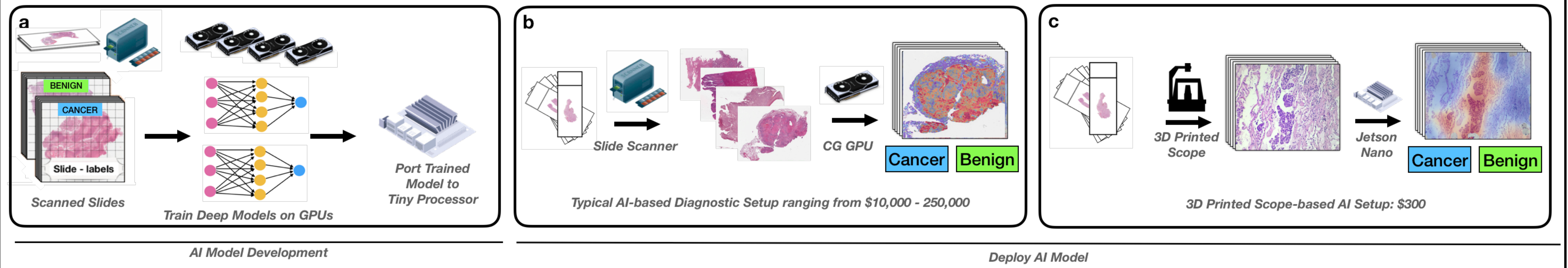
3D Printed Setup



Exploded rendering and schematic of our setup. The design features a microscope imaging component in the left half and a deep learning component with a touch screen mounted on top in the right half. We use a Raspberry Pi Camera Module V2 for imaging (using a pipeline developed by Bowman *et al.* to correct for aberrations) and a Jetson Nano for deep learning inference.

Embedded AI-based Diagnostic Pipeline

We use 3D printed resin components 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.



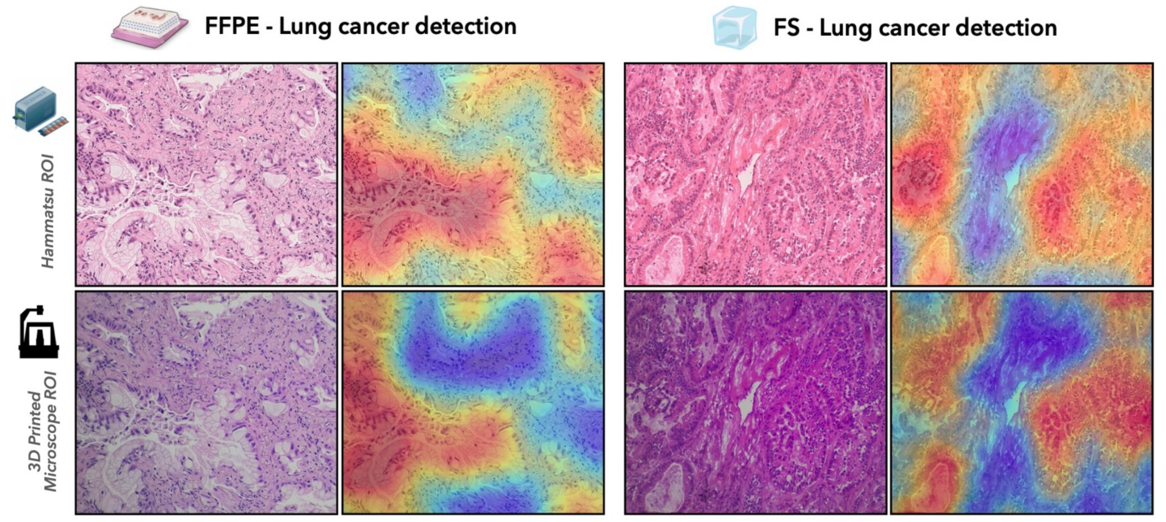
Model development

Deep learning models were trained from digitized H&E histology whole slide images (WSI) from the public TCGA and CPTAC pathology image portal, with corresponding slide-level diagnosis (**a**). All slides were processed at 20x magnification. The trained model was ported onto a Jetson Nano as part of our setup.

Model deployment

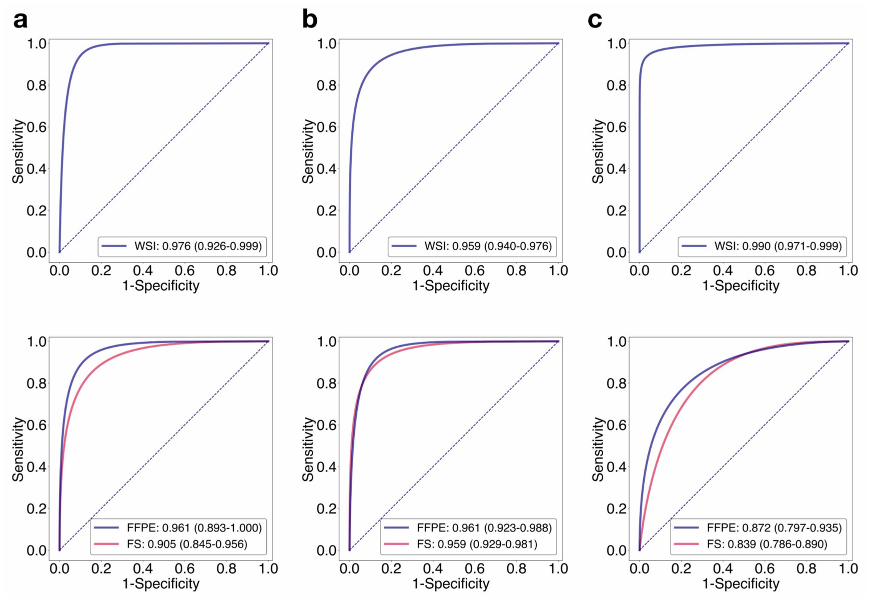
A typical AI-based diagnostic setup (**b**) involves scanning pathology slides with a slide scanner to obtain digitized WSIs. The expensive equipment such as a slide scanner and a high-performance GPU can add up to a total price of more than $10,000. Our setup (**c**) involves imaging regions from a pathology slide using an easy-to-assemble 3D printed microscope. The images are then processed by the model on the Jetson Nano as one pipeline. The total cost of our setup can be around $300 with optics and electronic components purchased in bulk.

Evaluation of Model Performance



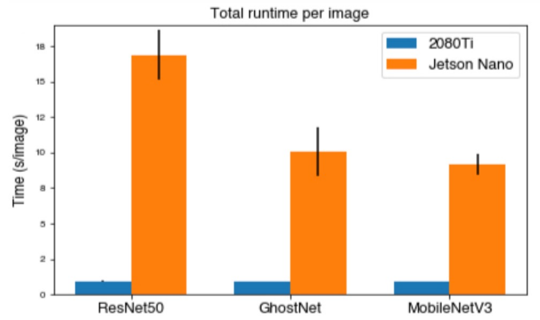
Attention heatmaps

Regions of interests from lung cancer samples (left FFPE and right frozen sections) captured using a Hamamatsu slide scanner and using our 3D printed microscope setup. From the heatmaps, the algorithm highlights nests of atypical epithelial cells.



Model ROC curves

WSI test sets (top) vs. in-house microscopy images. We compared lung tumor vs. non-tumor (**a**), LUAD vs. LUSC (**b**), and head and neck tumor vs. non-tumor (**c**).

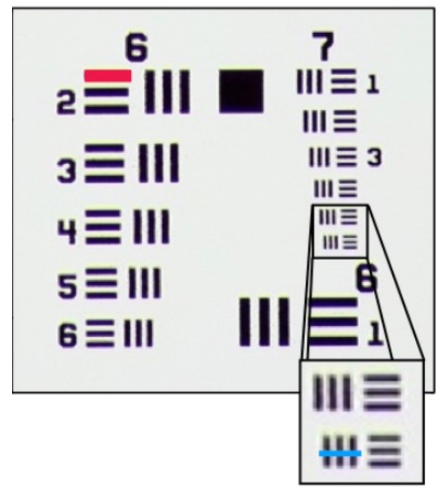


Model runtime comparison

Total runtimes per image on RTX 2080 Ti vs. Jetson Nano for ResNet50, GhostNet, and MobileNetV3 (16.9, 10.1, and 9.1 seconds per image, respectively).

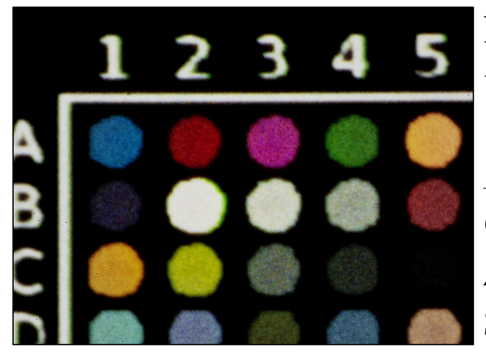
Assessing Microscope Imaging Quality

Resolution target



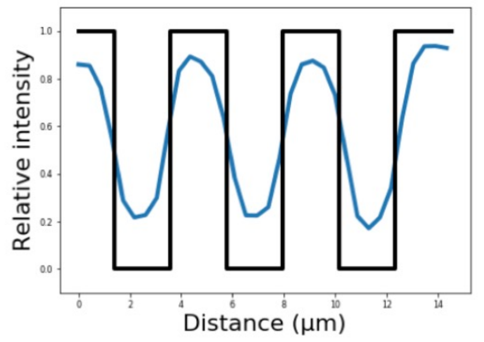
Top: USAF resolution test chart using 10x objective, 0.435 µm/px; 20x objective = 0.2245 µm/px;

Transmission color target



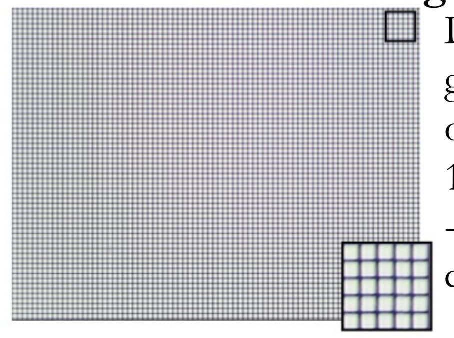
NIST color transmission, 10x objective, Average CIEDE ΔE^* = 10.47 SD = 3.23

Average ΔE^* for Olympus scope: 12.54 and for slide scanner: 16.53



Bottom: relative intensity along smallest line pair shows clear separability

Distortion target



Distortion grid, 10x objective, 10 µm grids, -0.19% distortion

Discussion

- Our setup was able to classify whole pathology slide images (both from FFPE and frozen sections) acquired through our low-cost custom-built microscope, along with generating interpretable heatmaps for each image section
- **Future work** will include testing the accuracy and robustness of our device on more disease models and subtypes, as well as field testing in resource-constrained clinical settings.
- We plan on exploring automated focusing and automated stage movement to simplify and aid in the image collection process. Other possible areas of improvement include modifying the device to make it compatible with a smartphone camera.

References

1. Ming Y. Lu, Drew F. K. Williamson, Tiffany Y. Chen, Richard J. Chen, Matteo Barrberi 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).