Classifying and Localizing Metastatic Tumor Cells Using Deep Neural Networks

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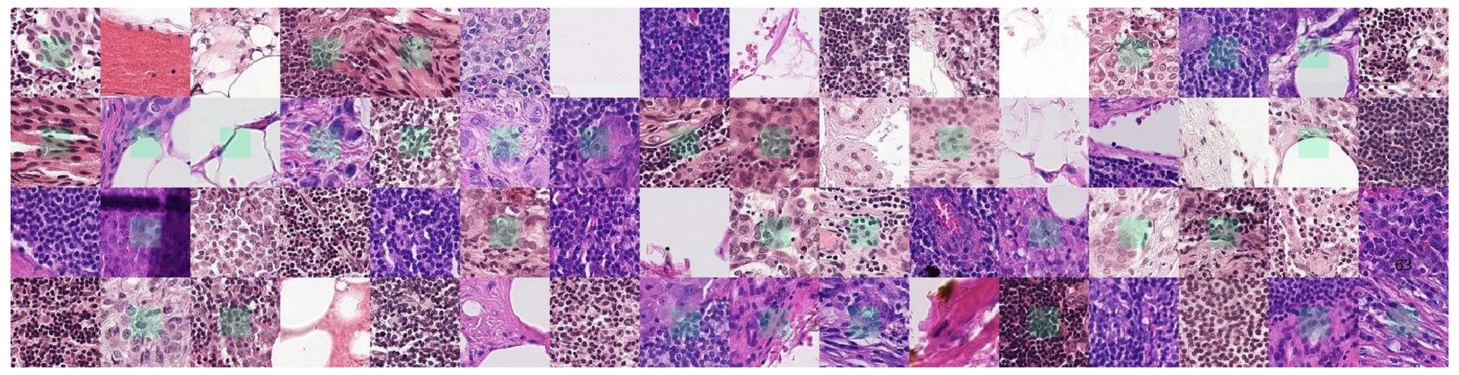
Motivation



Cancer detection is a large challenge in the medical field. Some types of cancer can be detected through blood tests, but many other types require some form of imaging technology combined with expert knowledge to identify if cancer is present. In the past couple decades machine learning algorithms have advanced greatly in the field of image analysis. That fact in addition to the large amount of medical imaging data the we've created makes tumor identification a perfect task to attempt wi AI.

Problem Define:

Given microscope images of lymph nodes cells, we aim to identify if the image contains tumor cells or not.

Introduction

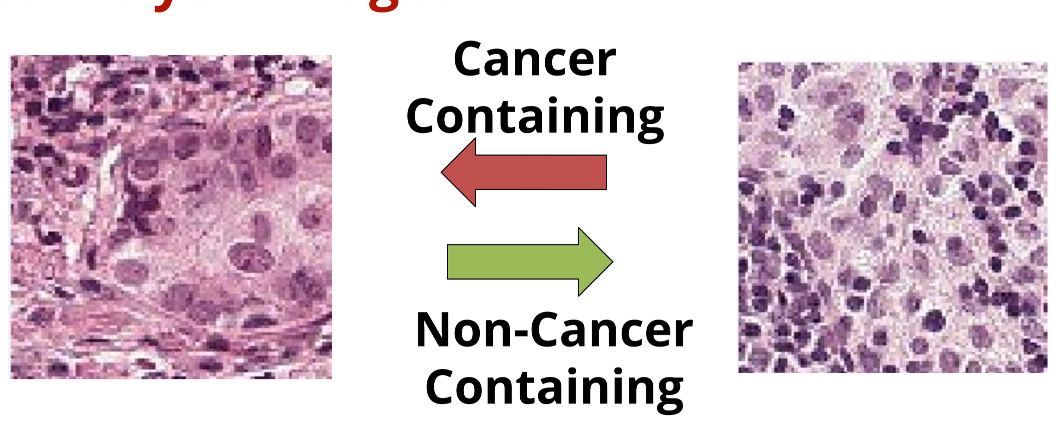
Dataset

Kaggle Abridged PatchCamelyon (PCam)

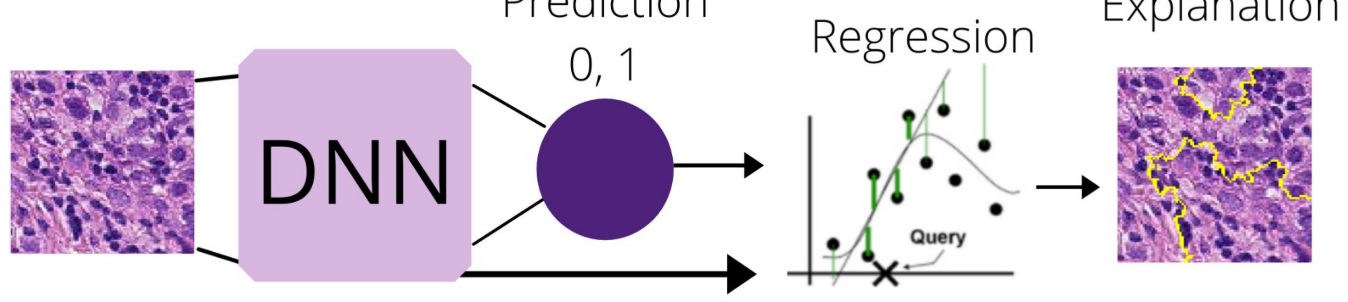
- ~ 220,000 images

- Intended to be like benchmark dataset, like MNIST, for medical image classification
- 96 x 96 pixel color images

PatchCamelyon Images

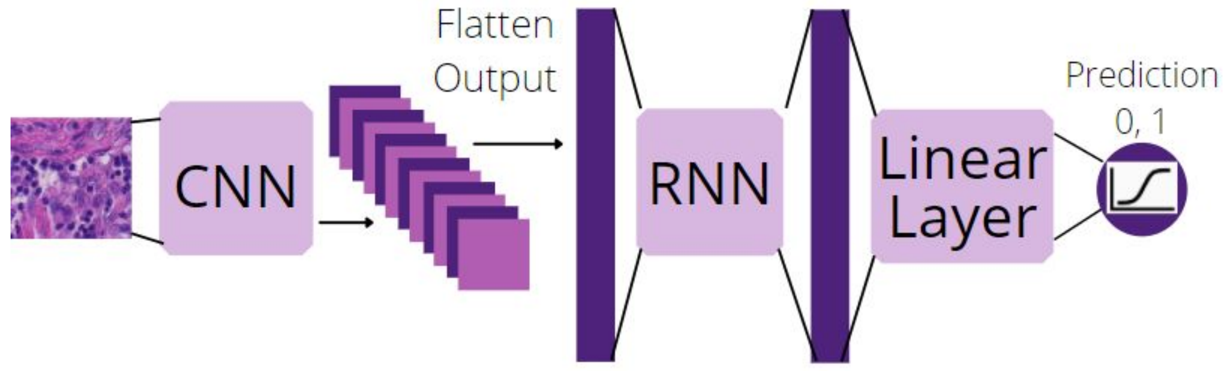


Object Classification and Localization

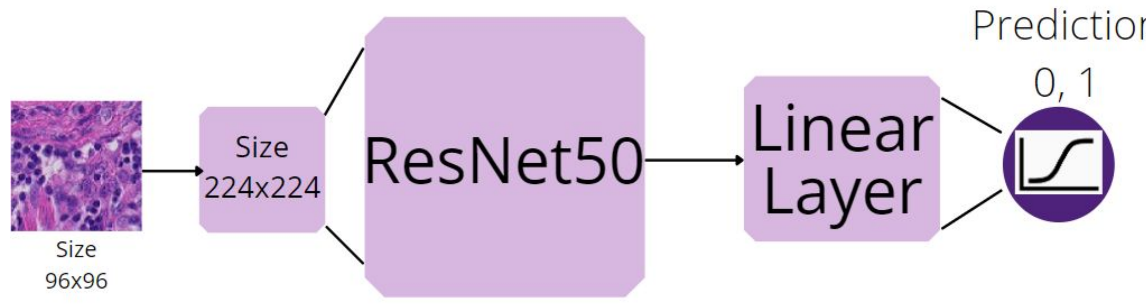


Methodology

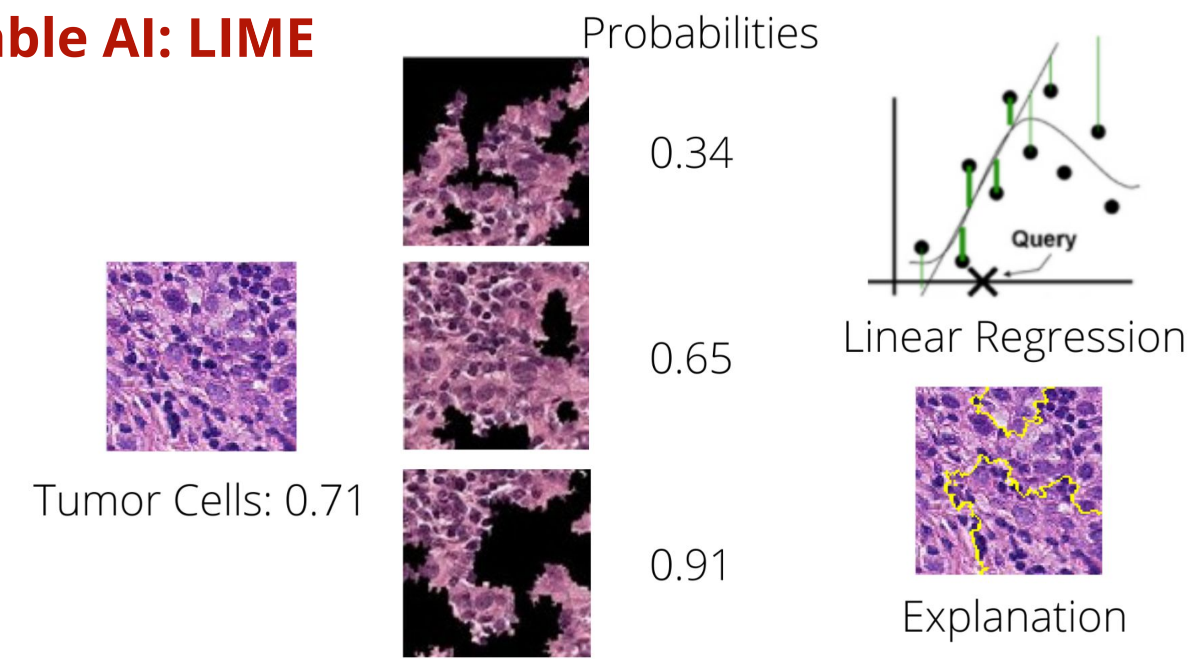
Model Structure #1: CNN-RNN



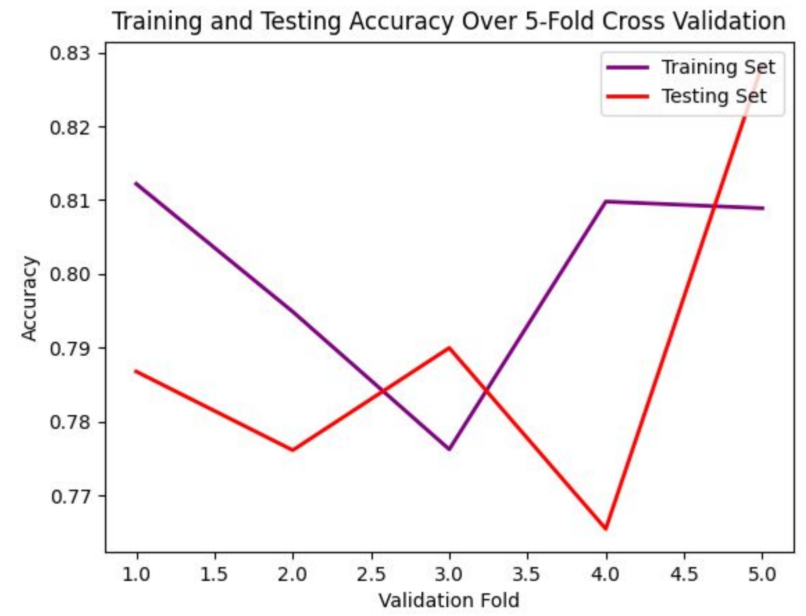
Model Structure #2: Transfer Learning

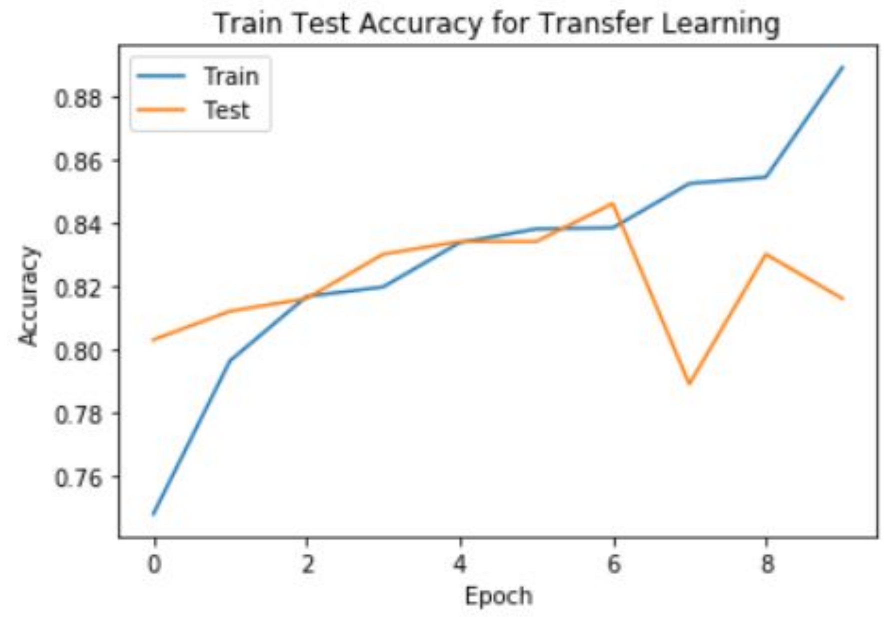


Explainable AI: LIME



Results





Result for CNN-RNN

- 82% after 30 Epochs
- Using 14 minutes to train on 4000 images

Result for ResNet50

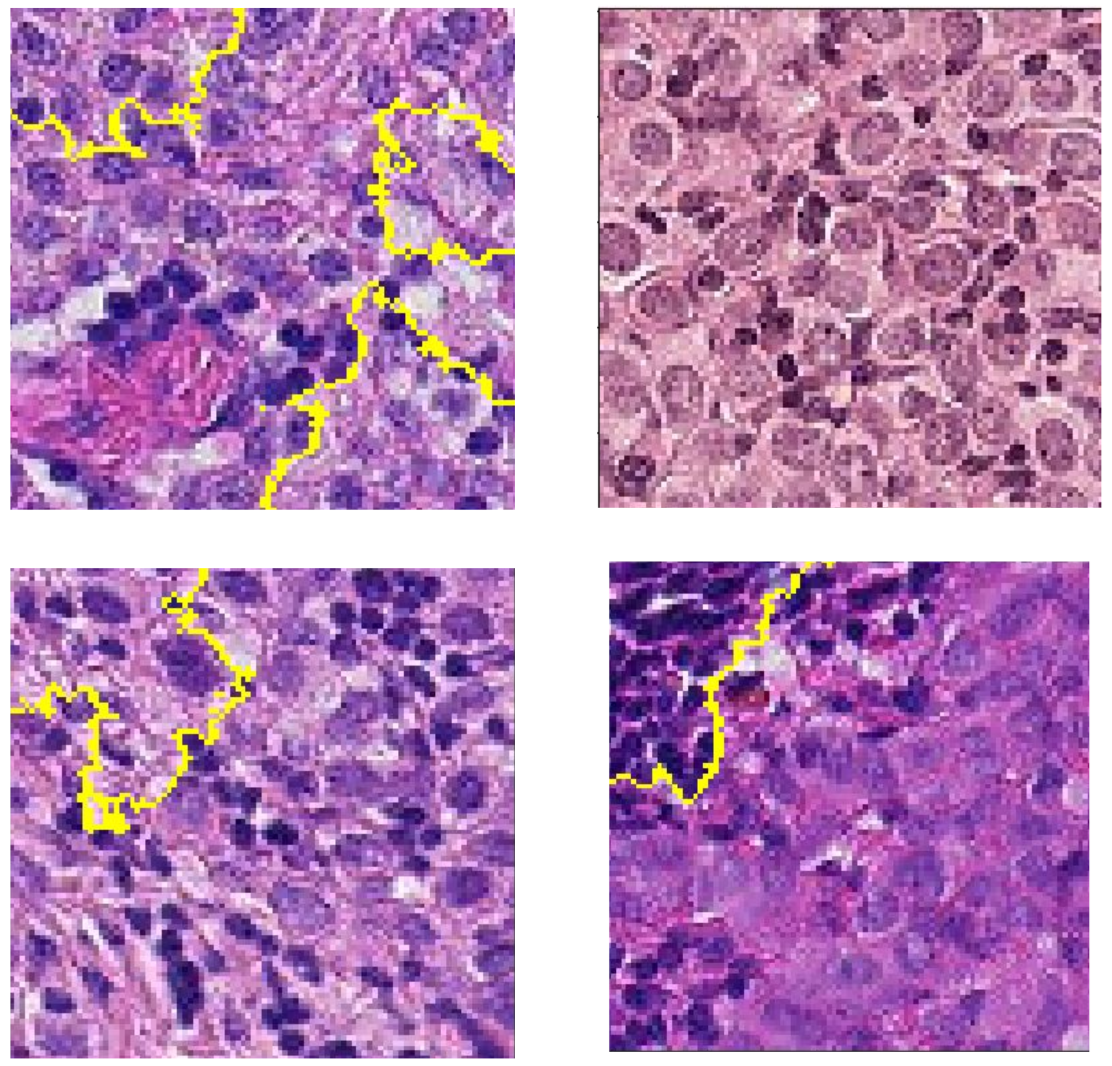
- 80% after 10 Epochs
- Using 2 hours to train on 4000 images

Discussion

- Transfer learning is more thorough than CNN-RNN
- CNN-RNN are trained faster than ResNet50

Explainable AI

Tumor Localization Results



Discussion

- The LIME Framework can be used to help medical professionals understand how our model identifies tumors.
- This can be useful to understand why the model may return a false positive classification

Conclusion

- 82% from CNN-RNN model is the maximum we could reach.
- Reached 80% accuracy with ResNet50 transfer learning model.
- Localization of tumor cells is possible LIME XAI framework using the prediction result from CNN-RNN model.

References

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