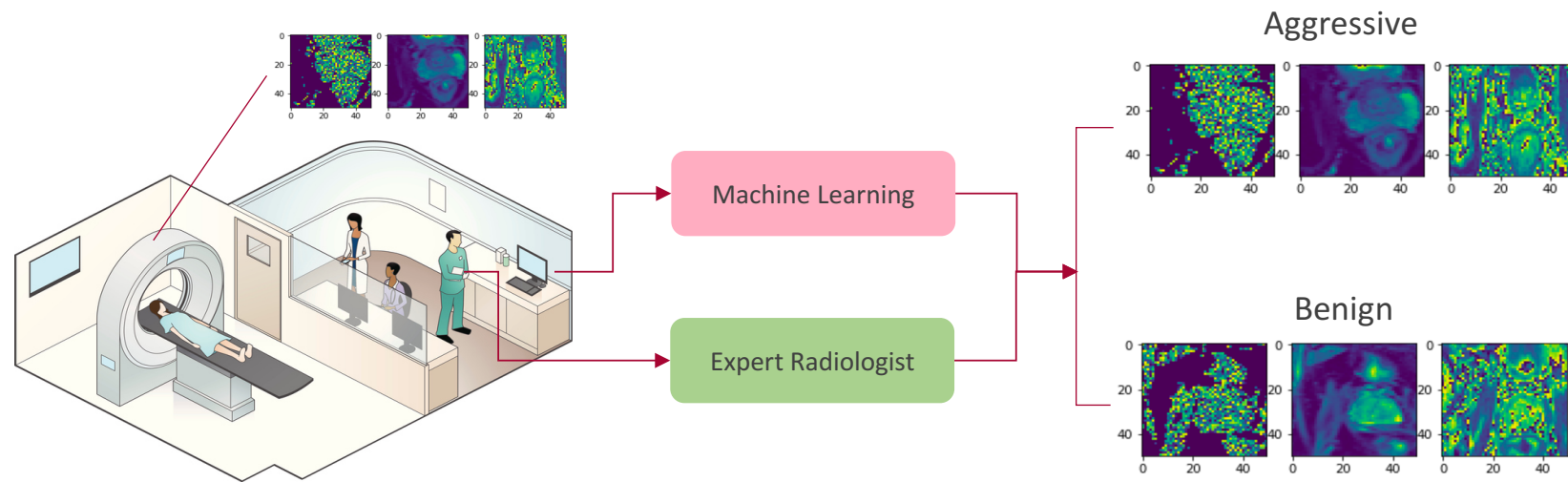


Background

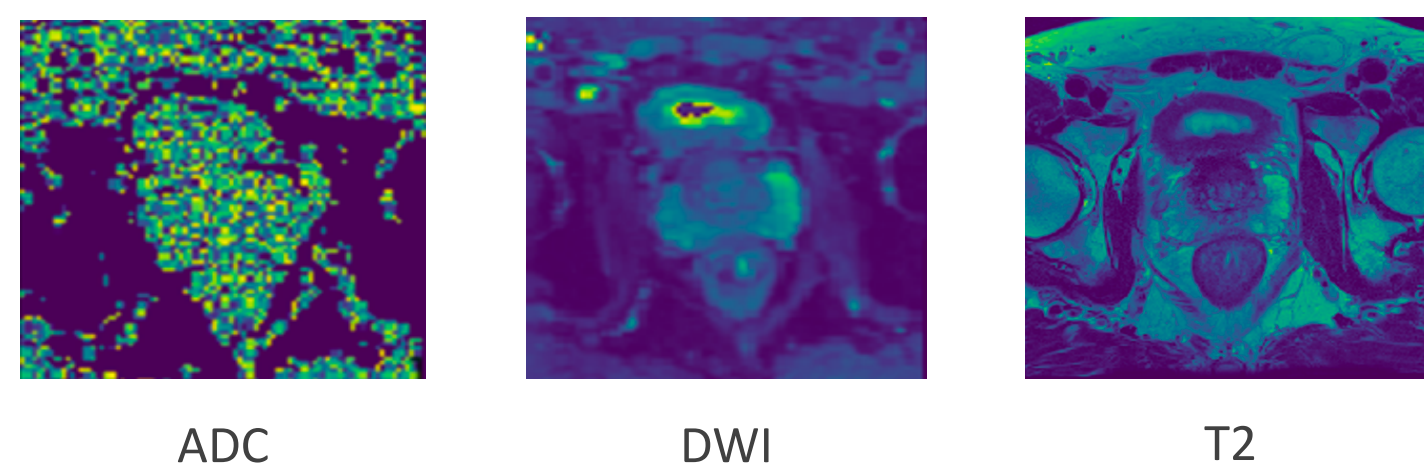
- **Prostate cancer** is the second leading cause of cancer death among American men. Early detection of prostate cancer usually comes with a **17 - 50% overdiagnosis** of the cancer leading to discouragement in using treatment.
- **Multi-parametric MR** is a powerful imaging technique used in detecting the prostate cancer. However, analysis is plagued by inter-radiologist variability. To improve the analysis of MR imaging, conventional machine learning techniques are used to reduce the overdiagnosis.
- We propose a convolutional neural networks (CNNs) model to improve the performance of automated multi-parametric MR image analysis of prostate cancer to classify an **aggressive type** and **benign type**.



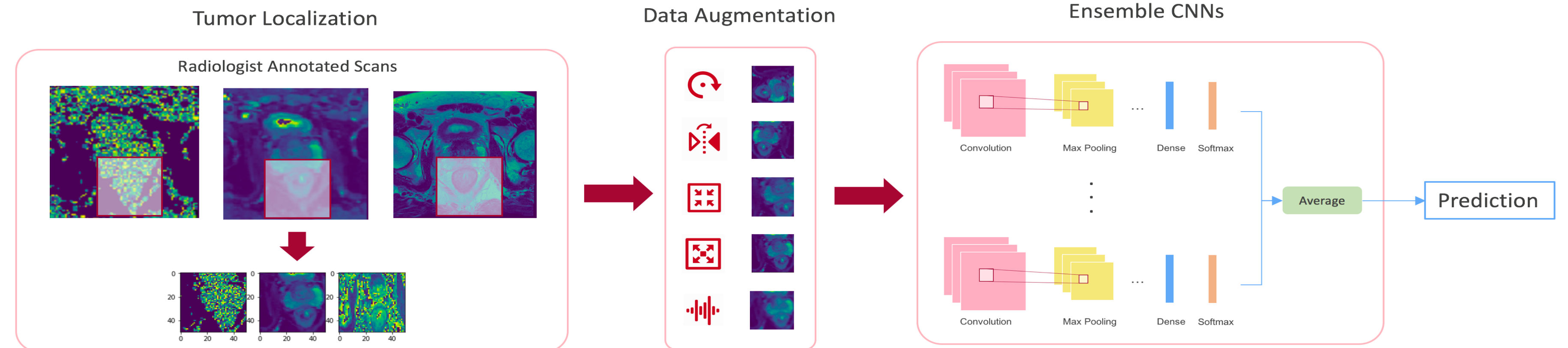
Dataset

- The data set consists of **197 patients multi-parametric MR images** obtained from the Radiology Department, Stanford Medical School.
- 138 patients are diagnosed with aggressive prostate cancer and 59 patients are diagnosed with benign prostate cancer.
- All the images were acquired in the axial plane, and an expert radiologist identified and circumscribed the suspicious lesion.
- Each MRI includes 3 image modularities:
 1. Apparent Diffusion Coefficient (ADC)
 2. Diffusion Weight Imaging (DWI)
 3. T2 Weighted Image (T2)

Sample MR images



Approach



- The full scans are cropped to 50 x 50 pixels at the radiologist annotated point.
- Due to the small sample size, the images are augmented using rotation, reflection, scaling, Gaussian noise, and Salt and Pepper noise.

Ensemble CNNs

- The main idea is to have many CNNs jointly make the decision by averaging the result from individual models.
- 20 different CNNs are sampled with dropout probability in (0.5, 0.9) and the output size of the last affine-ReLU in [128, 256, 512].

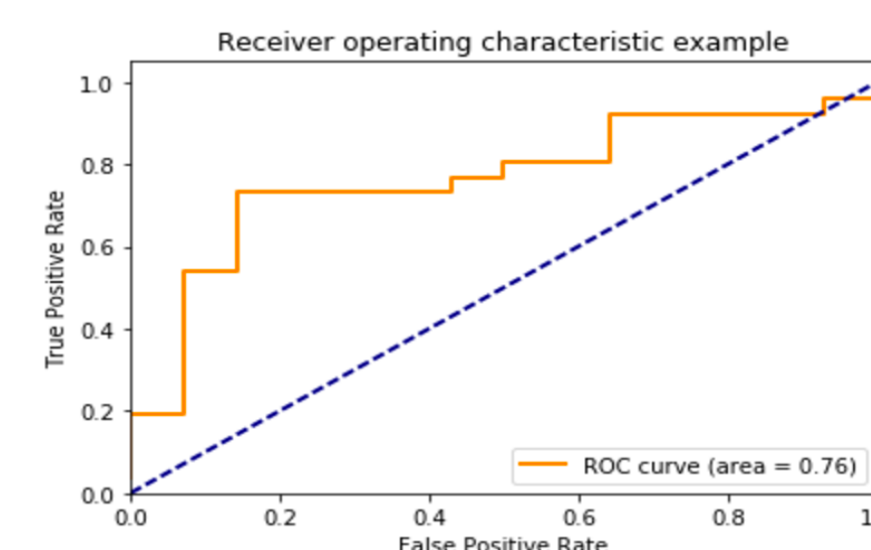
Ensemble Q-Learning CNNs

- We search for the best CNN architecture for the problem with Q-Learning agent that learns to select the layers to achieve high validation accuracy.
- The models in the ensemble are replaced with the top CNN architecture from the Q-learning agent.

Experiment Result

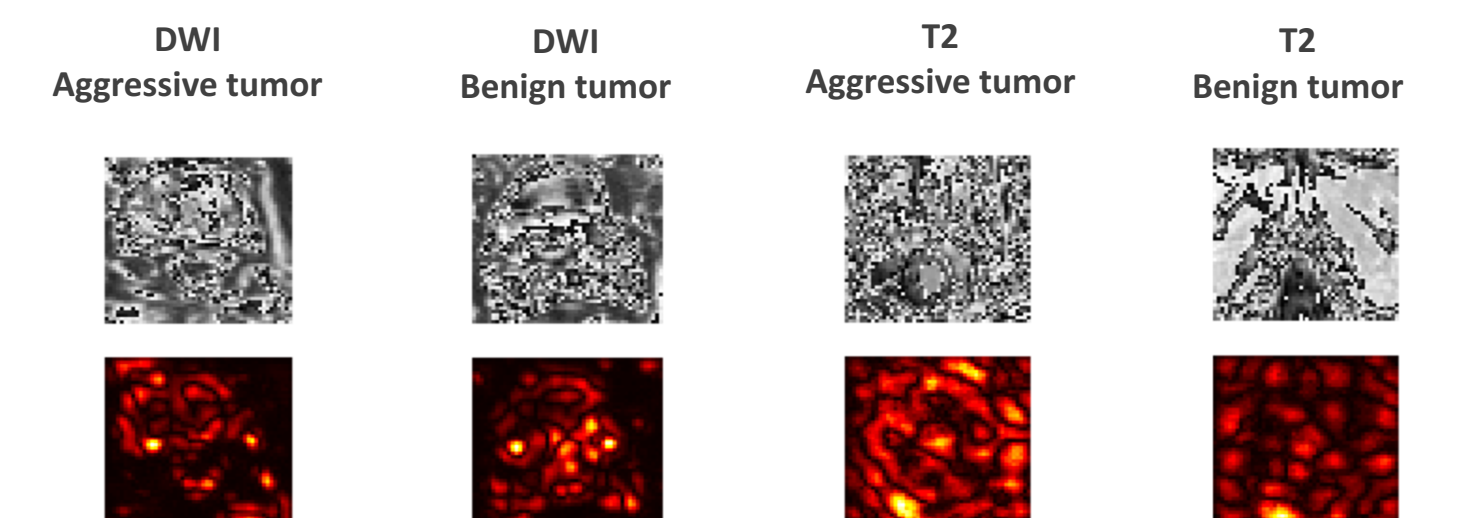
Type	Model	Accuracy	AUC
Individual Model	Linear SVM	48 %	0.54
	LASSO	52 %	0.53
	Elastic Net	55 %	0.56
	Simple CNN	58 %	0.61
	CIFAR-10 CNN	65 %	0.54
Ensemble Model	Q-Learning CNN	67 %	0.52
	Simple CNNs	72 %	0.76
State of the art	Q-Learning CNNs	73 %	0.73
	Elastic Net with Custom Feature	73 %	0.73

ROC curve for Ensemble CNNs

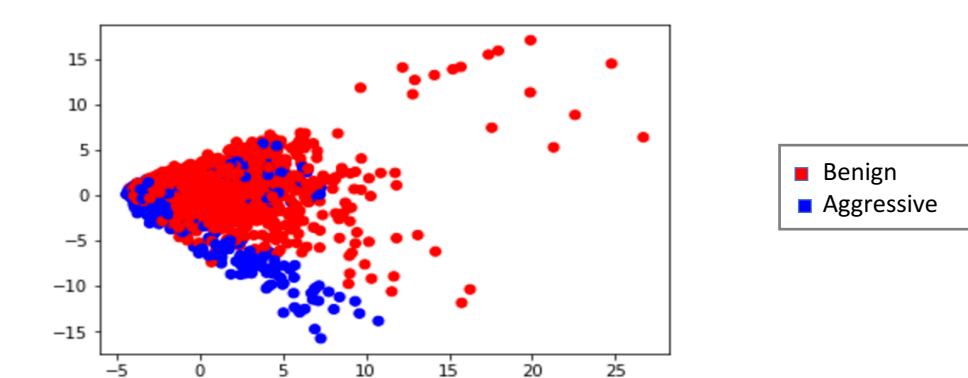


Network Visualization

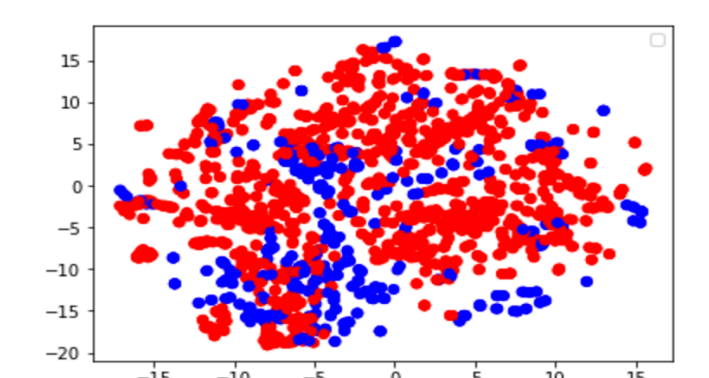
Saliency Map



PCA



t-SNE



Conclusion & Future Works

- End-to-end ensemble CNNs achieves similar performance with the state-of-the-art without feature extraction.
- Extract visual features via CNN, then use features to run on other algorithms such as boosting trees.

Acknowledgement

We thank Imon Banerjee (from Stanford Laboratory of Quantitative Imaging) for providing the dataset as well as project guidelines.