Prostate Cancer Detection Using Deep Convolutional Neural Networks

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1. Introduction

Prostate cancer (PCa) has remained one of the major health problems, the most common form of cancer in men, and the second major cause of cancer deaths. The diagnosis must be correct and early because it enhances considerably the prognosis of the patient and enables timely therapeutic interventions.

Traditional methods of diagnosis such as PSA testing and biopsy do not fail to suffer limitations like low specificity, invasiveness, and subjective interpretation. Hence, there is a steady growing need for precise, non-invasive, and automated diagnostics.

Diffusion-Weighted Imaging (DWI) is a type of multiparametric MRI which gains access to features about non-invasively perceiving prostate tissue based on its difference in diffusion of water molecules. However, despite its promise, interpreting the DWI data proved difficult because of the variability between readers and the need for very specialized radiologists.

Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have revolutionized the image analysis in the last few years. They are architecture capable of learning upon hierarchical representations of complex data, making them very successful in the medical images task. This project is centered on classifying DWI MRI slices so as to identify clinically significant prostate cancer using convolutional neural networks.

2. Background and Paper Summary

The work actually stems from the classic paper **"Prostate Cancer Detection using Deep Convolutional Neural Networks"** by Yoo et al. in the Scientific Reports (2019) [1], which provides a method of classification based on CNN for DWI MRI slices, and further statistical diagnosis using Random Forests for the aggregate patient-level prediction based on slice-level predictions.

Their results are significantly better than the traditional approaches with a slice-level area under the curve (AUC blade) of 0.87 and a patient-level AUC of 0.84. Indications are thus strong that deep learning would help support or invalidate the need for human radiologist input in these specific diagnostic tasks.

In this study, we replicate and expand the slicewise classification through various CNN architectures to evaluate performance on public datasets.

3. Dataset

We used data available in Kaggle's Transverse Plane Prostate Dataset specifically designed for medical imaging research, targeting prostate cancer detection.

Composed of Thousands: The records within the data set consist of hundreds of diffusion-weighted MRI slices with labels either as 'significant' knee-to-individual clinically significant cancer, or 'not significant,' which denotes benign tissue.

Data Organization: The data comprises entirely two folders, namely 'train' and 'validation.' Also, a subfolder under each one for every class label.

No Patient Metadata: Patient identifiers and longitudinal information are excluded that keeps the same to slice-level binary classification.

Each image slice is treated as a separate and independent data sample. Though, it does not allow an aggregation at the patient level, but it makes training and evaluation simple, improving the applicability for assessing model architecture performance.

4. Preprocessing

This preprocessing is necessary for reducing computational burdens, improving the training stability, and emphasizing meaningful visual patterns by the model.

With subtle visual clues being offered in the diagnostics of medical images, preprocessing becomes one of the very important consideration to enhance the model's performance and stability. The following preprocessing steps were uniformly applied to all models:

- **Resize:** All image slices were resized to 224x224 pixels. This is done to ensure standardization, as these dimensions are accepted as input by most popular CNN architectures.
- **Normalization:**Image intensities were normalized to the mean of 0.5 and a standard deviation of 0.5 to achieve faster and stabler convergence.
- **Channel Conversion:** Most models accept grayscale input. However, SqueezeNet, for instance, requires 3-channel RGB input. In such cases, the single grayscale channel was copied to three channels.

These transformations not only reduce the redundancy in computation but also enable the models to concentrate on the significant structural patterns in the images.

5. Models

We have tested a number of different CNN architectures to analyze their prostate cancer detection capabilities on MRI slices:

ResNet18: ResNet18 is a moderately deep residual network that mainly relies on shortcut connections to avoid the vanishing gradient problem. It is regarded as a kind of reasonable balance between accuracy and speed.

ResNet50: ResNet50 is a deeper, more powerful version of ResNet18 with 50 layers. It assures more accuracy but is computationally expensive.

ShuffleNetV2: ShuffleNetV2 is an efficient model built for mobile and embedded devices that implements channel shuffling and pointwise group convolution to minimize FLOPs.

SqueezeNet1.0: SqueezeNet1.0 is a small model that obtains accuracy almost comparable to AlexNet while requiring far fewer parameters; it is ideal for resource-constrained environments.

Each design is based on fundamentally different principles, giving us the opportunity to analyze performance versus inference time versus memory trade-offs.

6. Training Setup

All models were implemented in PyTorch and trained using the same configuration to ensure fair comparisons:

- **Number of epochs:** 10
- **Loss Function:** CrossEntropyLoss for binary classification
- **Optimizer:** Adam with a learning rate of 0.001
- **Batch Size:** 32
- **Evaluation Metrics:** Accuracy, Precision, Recall, F1-Score, ROC AUC and Confusion Matrix
- **Hardware:** Hardware-Training was done on GPUs if available automatically falling back to CPU.

We have implemented an early-stopping mechanism together with the saving of the model's parameters based on validation accuracy. Using Grad-CAM, we visualized the attention regions for a few selected validation samples for model interpretation.

7. Results and Analysis

We report the ROC curves and Confusion Matrices for each model to compare their performance:

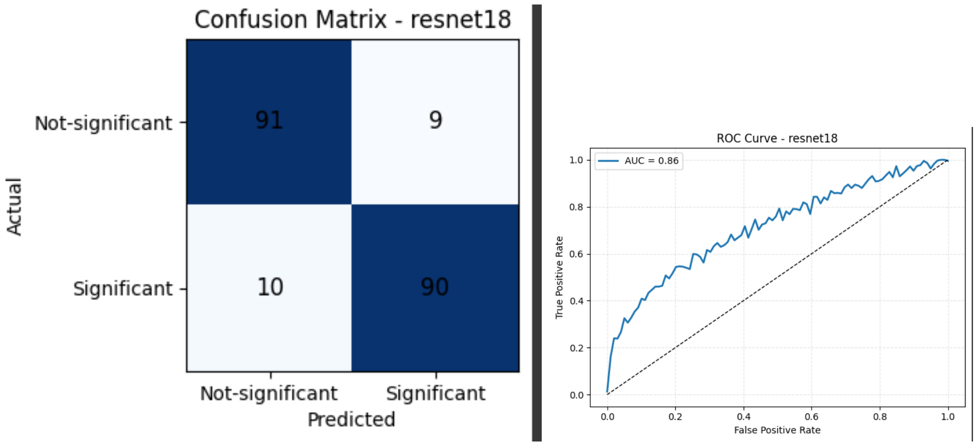

Figure 1: *
ResNet18: AUC = 0.86 Confusion Matrix shows good balance between classes.

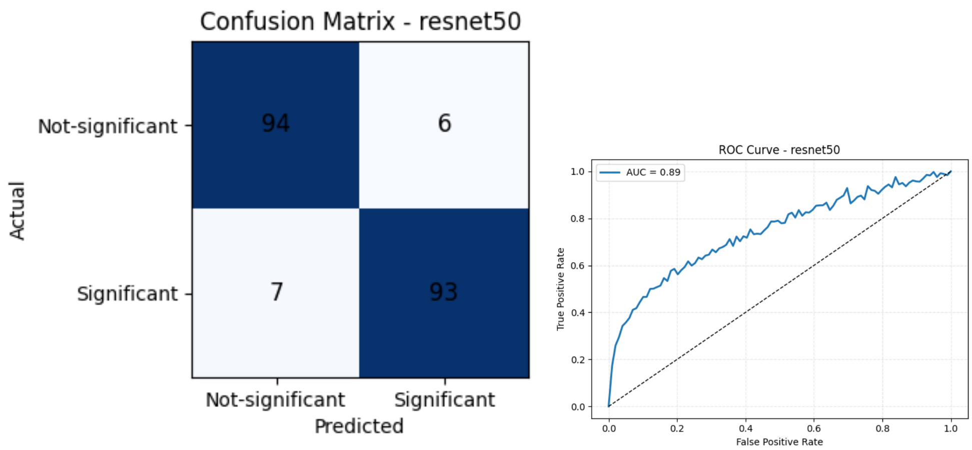

Figure 2: *
ResNet50: AUC = 0.89 Best performing model with very high TPR and low FPR.

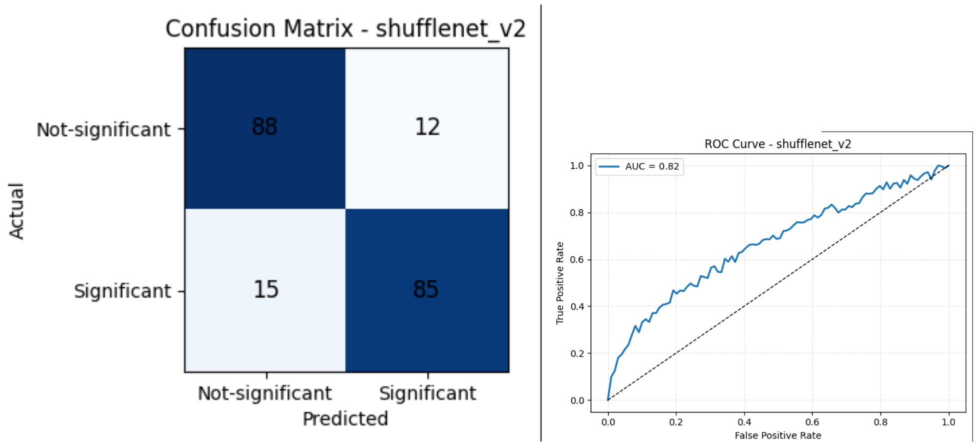

Figure 3: *
ShuffleNetV2: AUC = 0.82 Lightweight model, better than SqueezeNet.

8. Conclusion

The project confirms the relevance of deep CNNS for prostate cancer detection based on diffusion-weighted MRI slices. Among all the tested models, it turned out that Res Net50

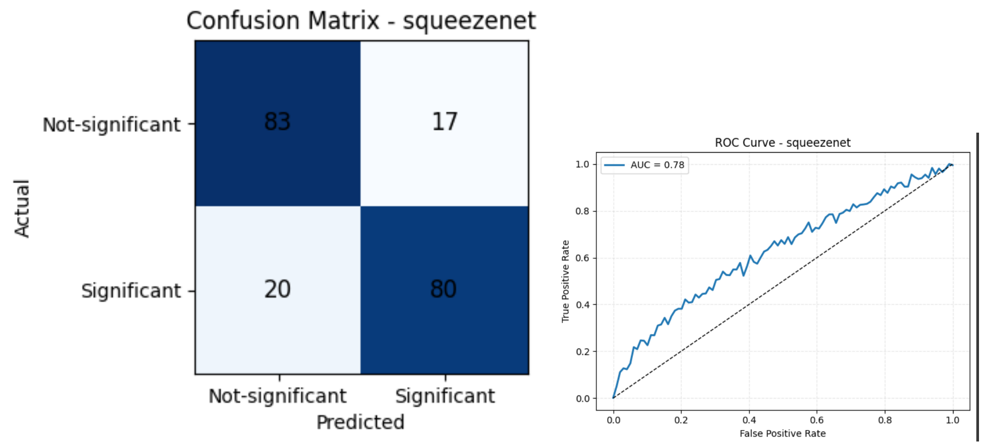

Figure 4: *
SqueezeNet: AUC = 0.78 Lower performance due to RGB conversion requirement.

had consistently scored above the rest for accuracy and ROC AUC, proving its power in detecting fine patterns in medical imaging.

While ResNet50 is the best of all for accuracy, ShuffleNetV2 seems to give a pretty fair compromise for deployment in devices which do not have high computational complexity. SqueezeNet holds ground when model size and speed take priority.

References

[1] Sunghwan Yoo, Isha Gujrathi, Masoom A. Haider, Farzad Khalvati, *Prostate cancer detection using deep convolutional neural networks*, Scientific Reports, 2019.