Diagnosing Retinal Pathology from Optical Coherence Tomography with Deep Learning

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Introduction

Background

- About 10 million people suffer from age related macular degeneration (AMD), 750,000 from diabetic macular edema (DME), and 200,000 develop choroidal neovascularization (CNV) [1] [2].
- Optical coherence tomography (OCT) is critical to image retina for diagnosis

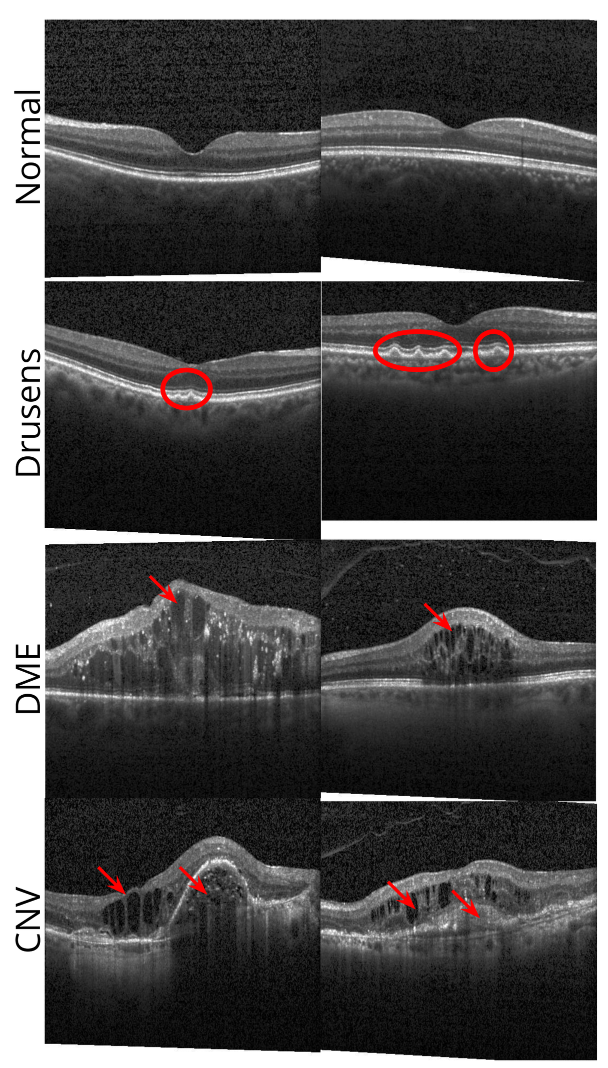
Problem

- Increasing demand of imaging studies outpace the capacity of practicing radiologists
- Current manual procedure requires many skilled people, a lot of time, and is computationally expensive [3]

Solution

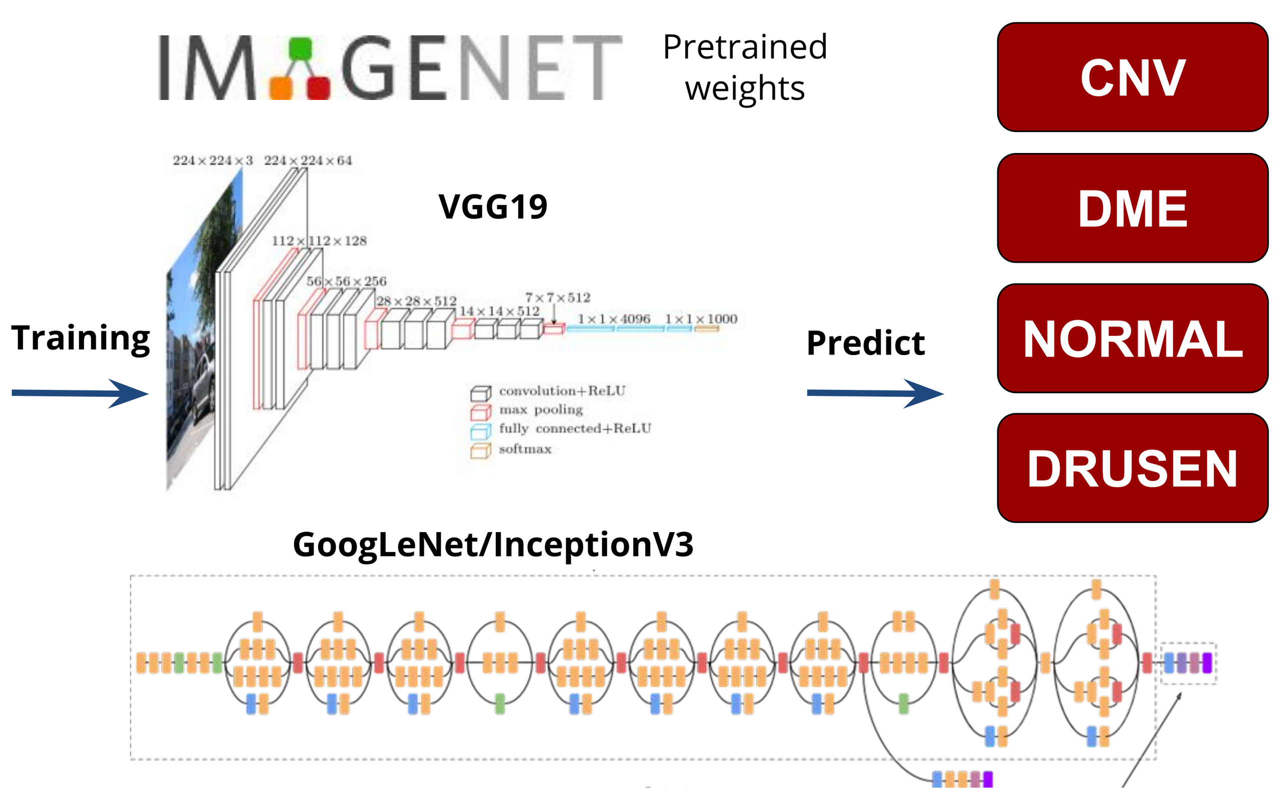
- Deep learning approaches can be used to classify pathology, expediting the process and leading to more favorable clinical outcomes

Methods



88,484 OCT images from 4,686 patients [4]

VGG19	InceptionV3
Batches of 128 images	Batches of 1000 images
SGD w/ momentum	Adam
FC layers re-trained	Only classifier re-trained



Model Training

- Transfer learning with stochastic gradient descent on VGG19 and InceptionV3 architectures pretrained on ImageNet
- Data augmentation used to randomly transform position and orientation to expand dataset

Visualization

- Saliency maps and class activation maps used to visualize networks

Results and Discussion

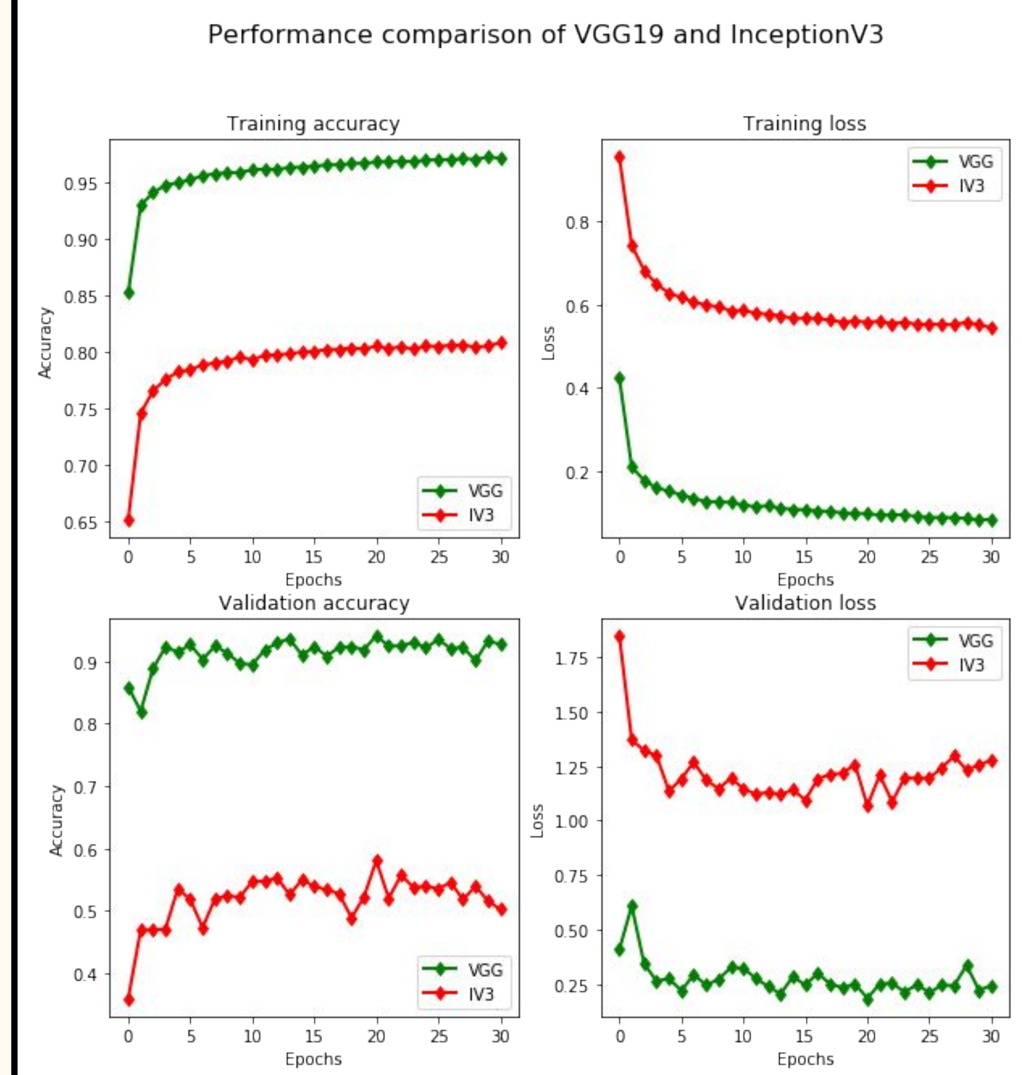


Figure 1: Comparison of the VGG19 and InceptionV3 training and validation accuracies and losses.

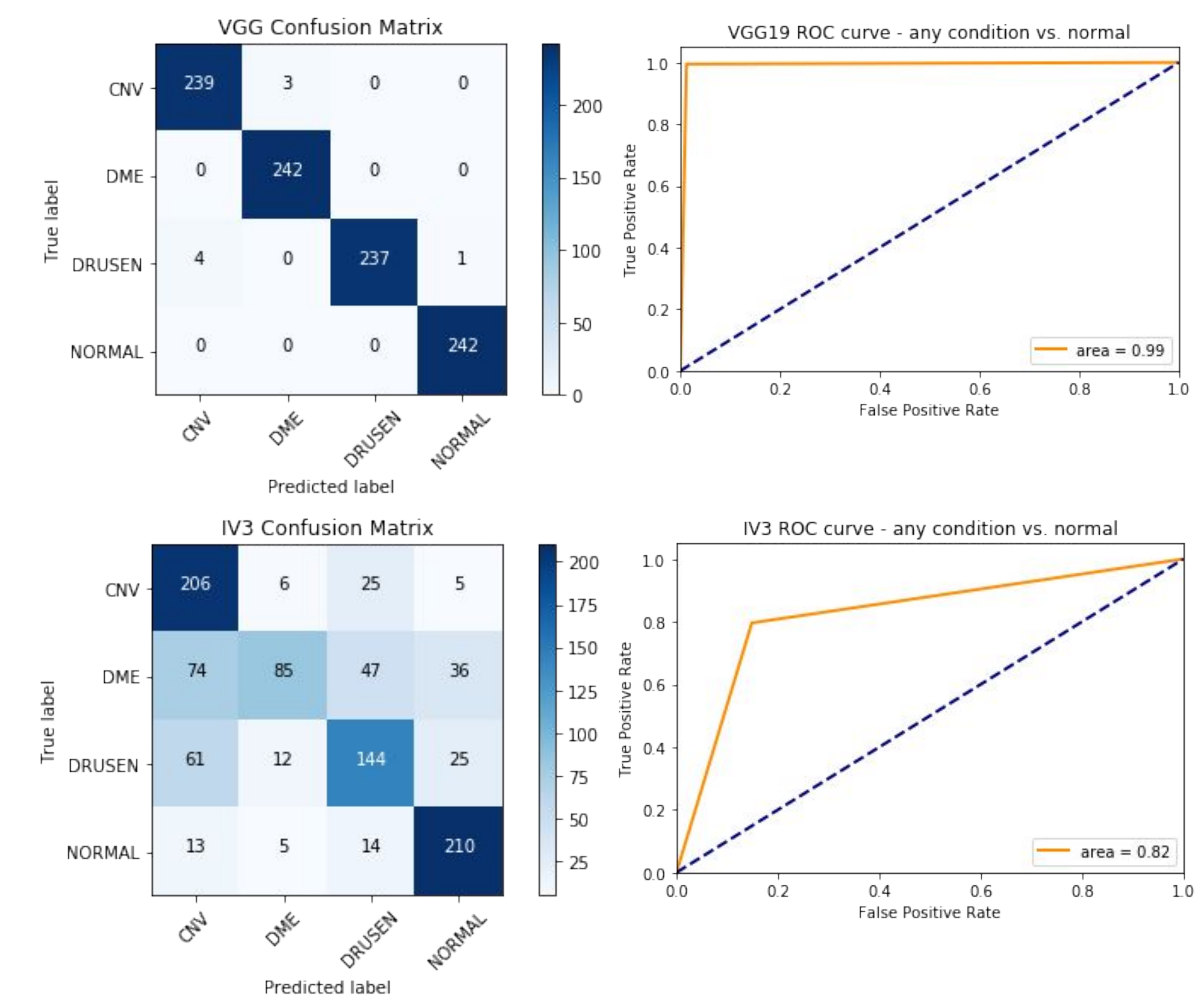


Figure 2: Confusion matrices and ROC curves for both models. Precision and recall for VGG was 100% and 99.8%, respectively. Precision and recall for IV3 was 95.4% and 90.9%, respectively.

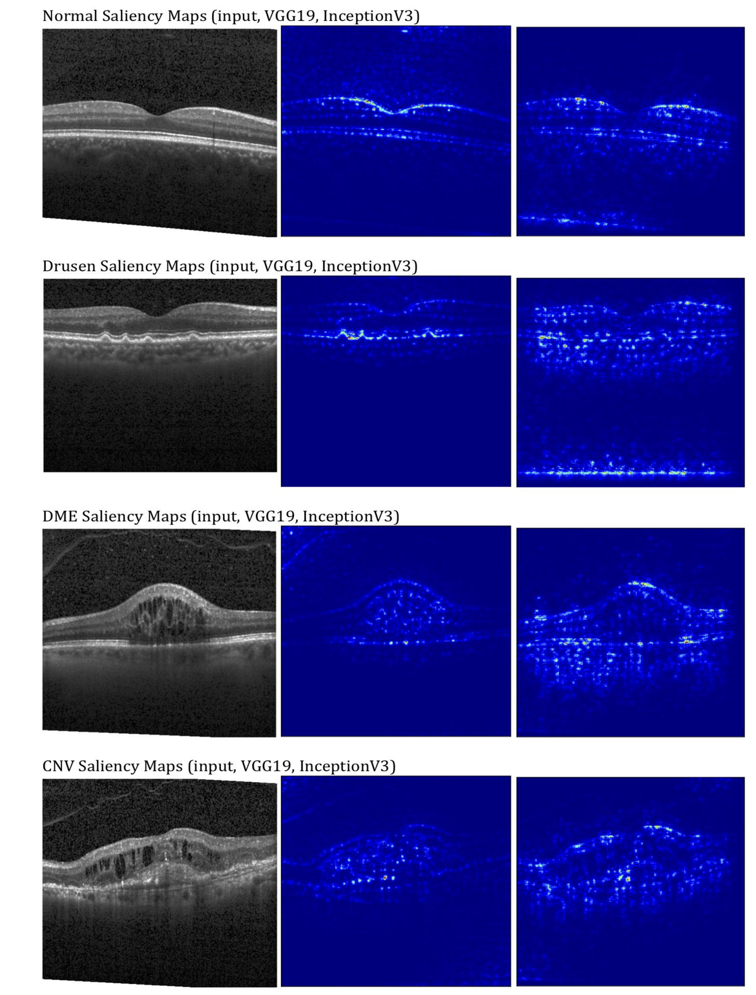


Figure 4: Saliency maps of both models indicating which pixels in each sample image contribute most to class score.

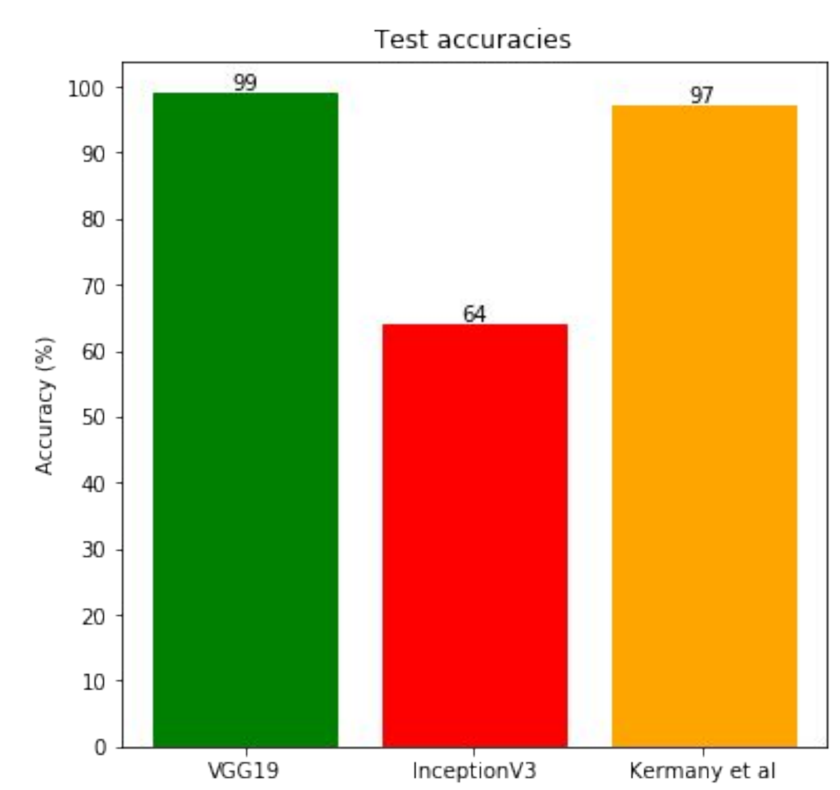


Figure 3: Comparison of performances of each model on the test dataset, rounded to the nearest percent.

- InceptionV3 consistently performed worse than VGG by 20% in training accuracy, 40% in validation accuracy, despite its touted ability to capture finer features within the images
- IV3 model misclassifications and class activation maps indicate that the model is not picking up important features in the images and could have been trained incorrectly
- VGG19 performed better than previous study [4] and IV3 on test dataset, and can identify pathophysiologically relevant features

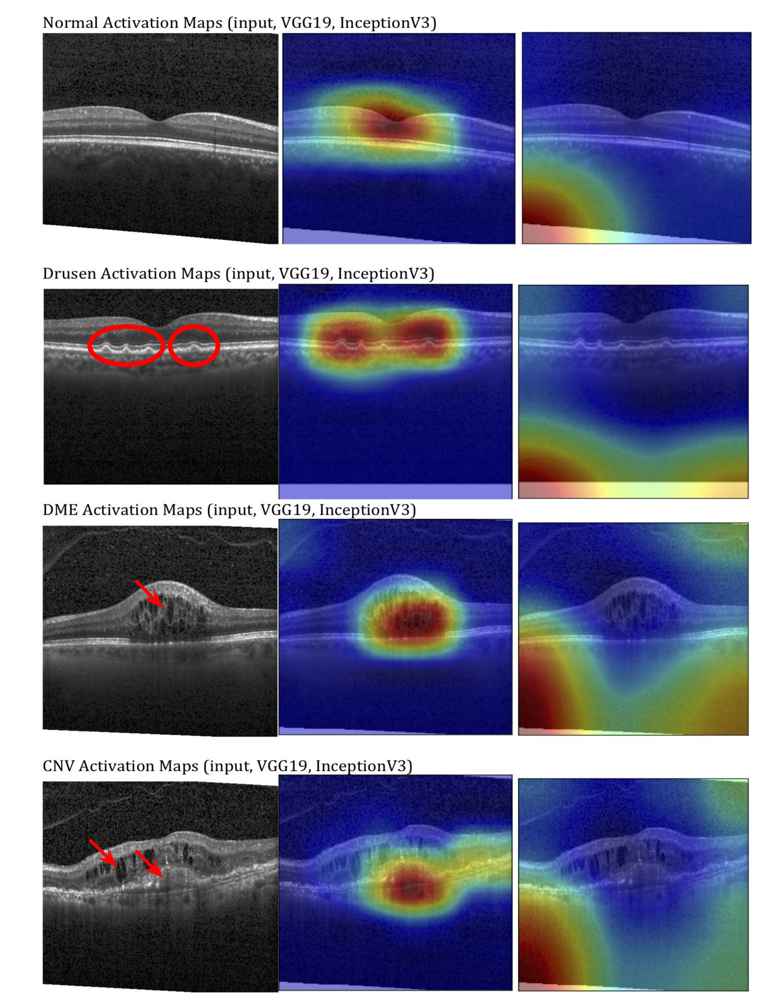


Figure 5: Class activation maps of both models indicating image regions CNN classifiers utilized to determine category.

Conclusions

- Transfer learning can be effectively applied to train deep learning classifiers on medical images
- VGG model can successfully determine OCT images containing pathological features
- VGG model can be used to highlight physiologically relevant regions of interest to assist practitioner

References

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