Convolutional Neural Networks For Interpretation Of Coronary Angiography

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None.

Background

Management of complex coronary artery disease requires accurate assessment of coronary angiogram by catheterization. However, SYNTAX score interobserver variability is high. Convolutional neural networks have revolutionized computer vision.

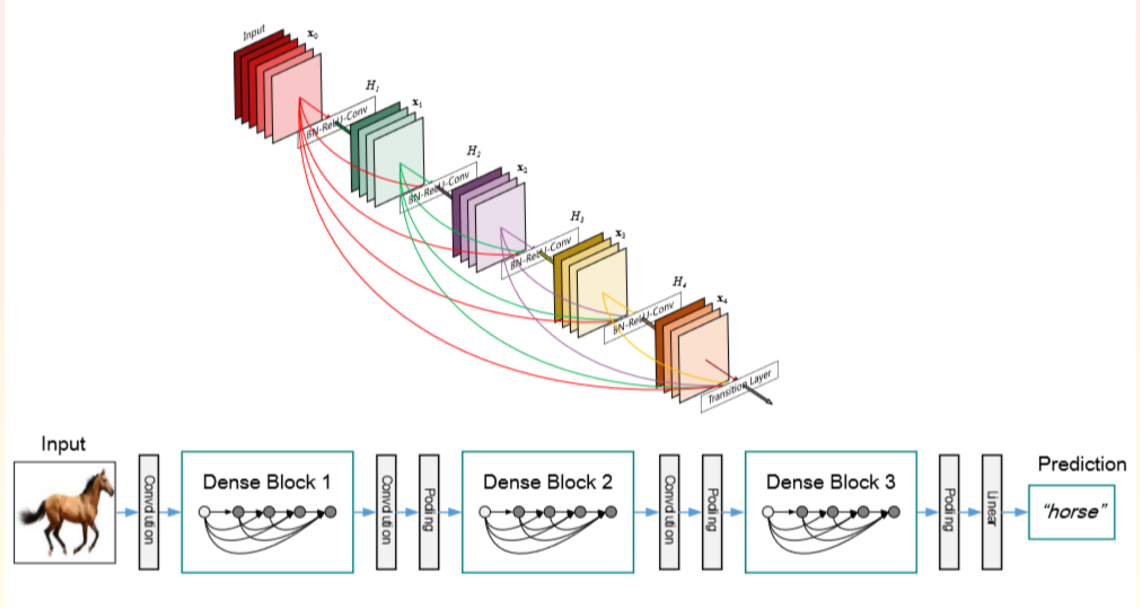
Objective

Can Convolutional Neural Networks (CNN) can be used to interpret coronary angiograms?

Methods and Material

Coronary angiogram images were obtained via web crawling of PCI cases, journals, and textbooks to protect patient privacy and to rapidly maximize training data. Each example was labelled for binary classification of stenosis (defined by the presence of clinically significant coronary stenosis), and for multiclass classification of anatomy (RCA, LAD, LCx, or left main, based on prominent artery).
The final dataset: 4980 figures, with 3390, 1450, and 140 as train/validation/test split.

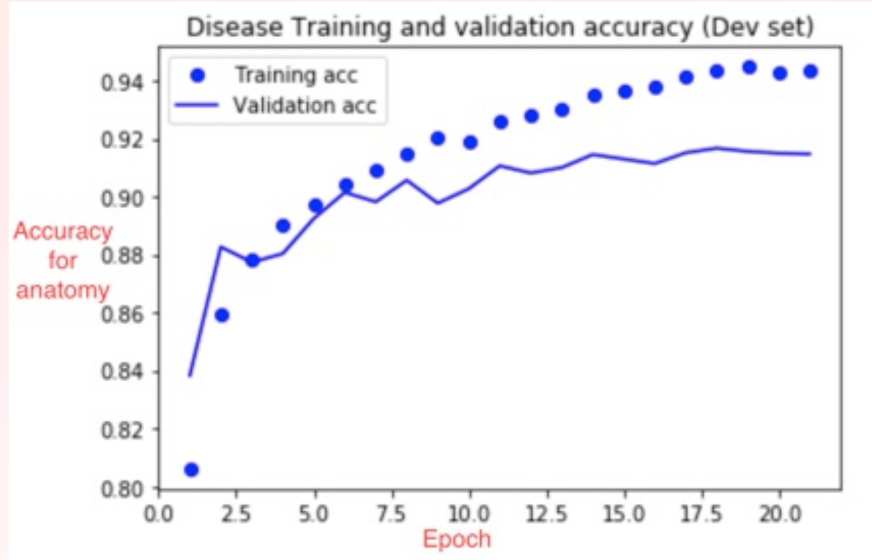
We performed transfer learning using VGG16, VGG19, ResNet, Densenet, and Inception-ResNet V2 pretrained on ImageNet.
Neural nets were trained on NVIDIA RTX 2080 Ti x 4 GPUs with NVLink standard hyperparameter optimization technique.



DenseNet Convolutional Neural Network Architecture

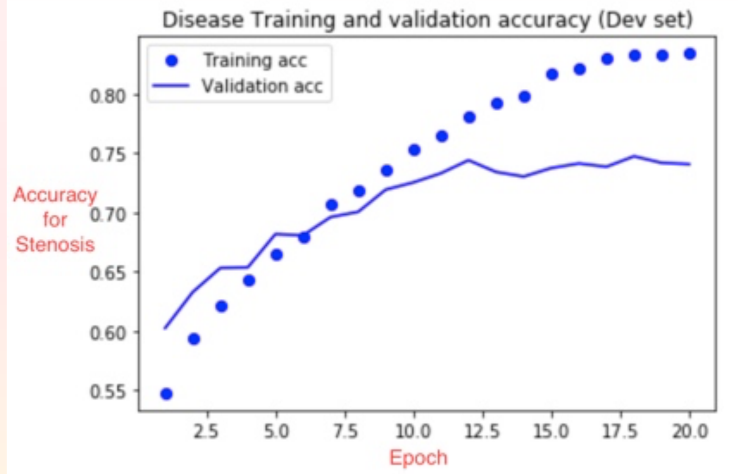
Summary

Anatomy: Both DenseNet121 and VGG16 with ImageNet pre-trained weights provided high level of accuracy for anatomy, using conventional technique (accuracy for test set= 86% for both.)

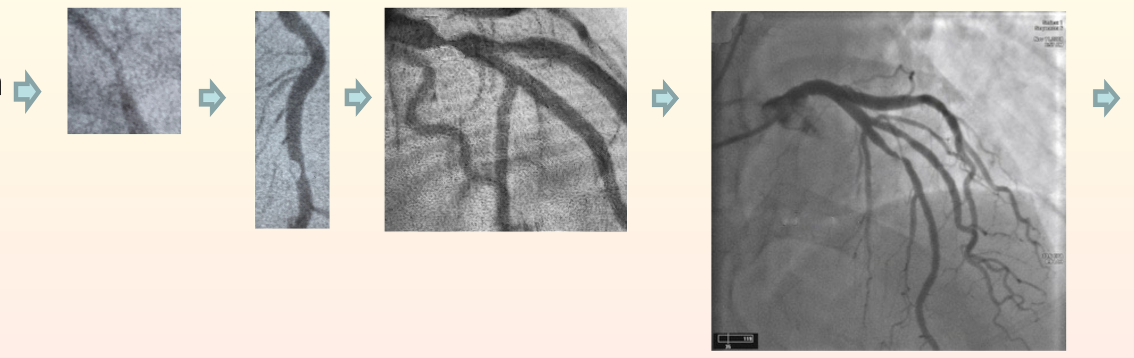


Stenosis:

Conventional ConvNet: at best we could only achieve 65% test set accuracy with DenseNet121:



Curriculum training: instead of learning a big set of data in one shot, we created a curriculum of 4 sets of data, starting with dataset with simple lesions ("what is stenosis?"), and then gradually increase complexity ("stenosis in context".) Test accuracy increased to 81%.



Network	Curriculum	accuracy	AUC	F1
VGG 16	None	0.67	0.79	0.65
Resnet	2 steps Curriculum	0.74	0.8	0.67
DenseNet121	2 steps Curriculum	0.77	0.78	0.69
DenseNet121	4 steps Curriculum	0.81	0.88	0.78

Application

We incorporated the best performing DenseNet121 neural networks into an iPhone app (see video):

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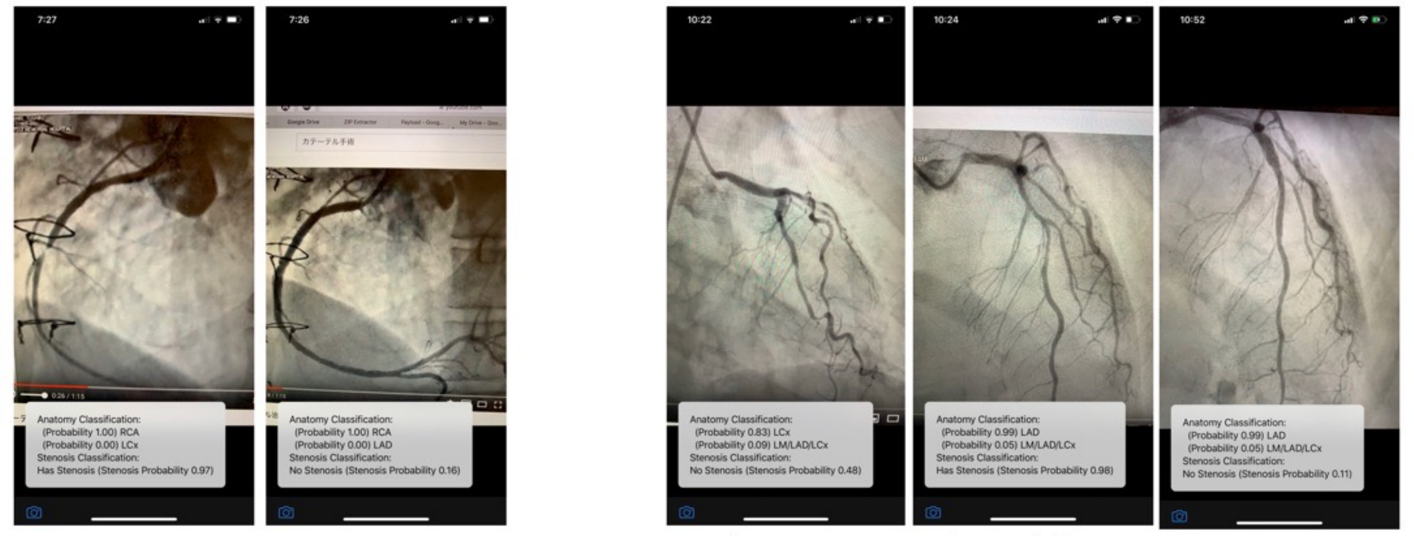
Result: Example of Screen-shots of the CathNet iPhone app



Simple RCA lesion before and after PCI: CathNet AI app clearly visualizes the lesion and identified the artery as RCA

Complex LAD stenosis: Before and after PCI
CathNet could not visualize the foreshortened LAD lesion initially due to overlapping and foreshortening (left figure). With proper the pre- and post mid LAD lesions were clearly identified (middle and right figures).

References

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