Classifying Interesting/ Not-Interesting in an Image

Final Project Machine Learning II

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Introduction

 NOAA spends billions of dollars on expeditions, collecting so much data that much goes unanalyzed due to the enormity and difficulty in finding specific information in hundreds of hours of videos, plus the time needed to spend to watch the videos

Purpose

- This project identifies interesting/not-interesting in images, and is the first step in ultimately classifying video live from an ROV filming from the ocean floor
- Just this basic identification will cut a 20 hour video down to an hour of viable images
- Ultimately, Species classification is the goal, emailing the scientist about where in the video, is the species they are interested in studying

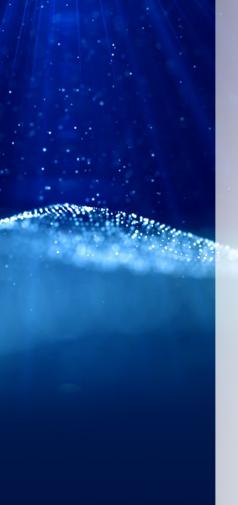
Dataset

- Obtained with authorization from NOAA Federal to download images from a deep ocean expedition
 - Images in 1 second intervals
 - Manually classified 1500 images



Experimental Setup

- Images will be put through a Convolution Neural Network using a pretrained model, VGG16.
- Adam is the optimizer used
- BCE with logits Loss will be used

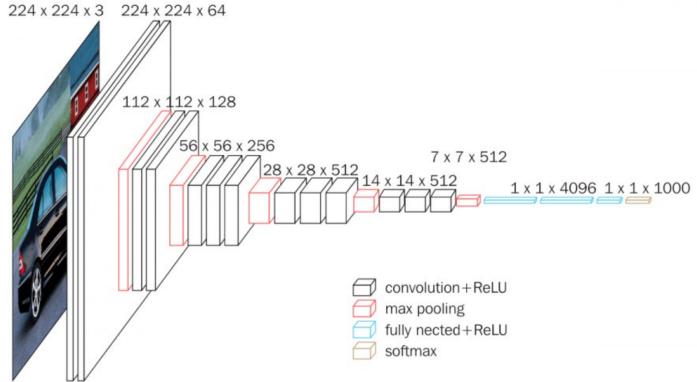


Setup (cont)

- Training/Testing split is 80/20
- Batch sizes are 16
- 1500 images
 - Original size 1920 (w) x 1080 (h)
- 24 bit depth



VGG16 – Convolutional Network for Classification and Detection

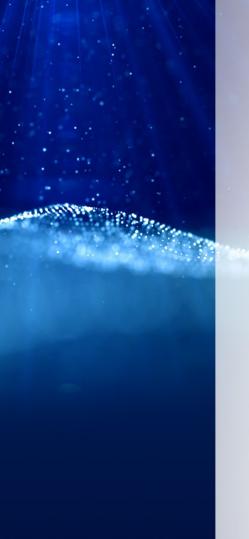


https://neurohive.io/en/popular-networks/vgg16/



VGG16 – Convolutional Network for Classification and Detection

 The model achieves 92.7% top-5 test accuracy in ImageNet, which is a dataset of over 14 million images belonging to 1000 classes.



VGG16 – Convolutional Network for Classification and Detection

	ConvNet C	onfiguration		
A-LRN	В	C	D	Е
11 weight	13 weight	16 weight	16 weight	19 weight
layers	layers	layers	layers	layers
i	nput (224×2)	24 RGB image	e)	
conv3-64	conv3-64	conv3-64	conv3-64	conv3-64
LRN	conv3-64	conv3-64	conv3-64	conv3-64
	max	pool		
conv3-128	conv3-128	conv3-128	conv3-128	conv3-128
Paration Michigan	conv3-128	conv3-128	conv3-128	conv3-128
	max	pool		
conv3-256	conv3-256	conv3-256	conv3-256	conv3-256
conv3-256 conv3-256	conv3-256	conv3-256	conv3-256	conv3-256
		conv1-256	conv3-256	conv3-256
				conv3-256
	max	pool		
conv3-512	conv3-512	conv3-512	conv3-512	conv3-512
conv3-512 conv3-512	conv3-512	conv3-512	conv3-512	conv3-512
		conv1-512	conv3-512	conv3-512
				conv3-512
				, (
conv3-512	conv3-512	conv3-512	conv3-512	conv3-512
conv3-512 conv3-512	conv3-512	conv3-512	conv3-512	conv3-512
		conv1-512	conv3-512	conv3-512
				conv3-512
	(2022)			
	soft-	-max		
	11 weight layers it conv3-64 LRN conv3-128 conv3-256 conv3-256 conv3-512 conv3-512	A-LRN B 13 weight layers	11 weight 13 weight 16 weight layers layers	A-LRN

https://neur ohive.io/en/ popularnetworks/vg g16/



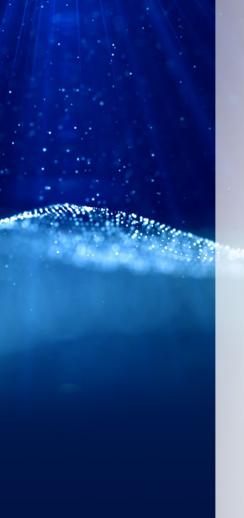
30 epochs/400 images

30 epochs/1500 images

Validation Loss 0.56569 Validation Loss 0.56560 Validation Accuracy: 78.0

68% accuracy

Overfitting was probably occurring, thus the better accuracy



Conclusion

- VGG16 had a marked improvement over my first model, and reached 78% accuracy initially
- Improvements could be made by adding another model to this, like AlexNet
- More data would help as well