UC San Diego

JACOBS SCHOOL OF ENGINEERING



Background

- Researchers at the Woods Hole Oceanographic Institute (WHOI) developed an instrument to collect deep ocean microscopic marine plankton images
- Millions of images are generated each day for classification
- Before machine learning methods, researchers had to classify these images manually by eye
- With neural networks, the classification process is significantly faster

Objectives

- Classify the flagellates species from the WHOI plankton dataset
- Compare performances among different neural network architectures
- Utilize various data augmentation techniques to increase dataset
- Fine tune model using different optimizers and hyperparameters
- Use different deep learning techniques to classify, specifically with transfer learning



Methods

- Split WHOI dataset into 70% training, 15% validation, and 15% testing sets
- Apply data augmentation (horizontal and vertical flipping) on training set
- Perform transfer learning with VGG16 and VGG19 using ImageNet weights
- Fine tune Xception model by retraining from ImageNet weights
- Vary learning rates (0.1, 0.01, 0.001, 0.0001)
- Vary optimizers (Adam, SGD, RMSprop)
- Experiment with different classification layers
- Analyze inter-class accuracies and compare for each model

Flagellates Classification via Transfer Learning University of California, San Diego Eric Ho, Brian Henriquez, Jeffrey Yeung

Results

The following are the testing accuracies from varying the optimizer, the learning rate, and the classification layer:

Optimizer	Adam	SGD	RMSprop		
VGG16	0.97425	0.97426	0.97204		
VGG19	0.97572	0.97278	0.97241		
Xception	0.93159	0.98675	0.95476		

Learning rate	0.1	0.01	0.001	0.0001
VGG16	0.96800	0.97426	0.96947	0.95733
VGG19	0.79771	0.96175	0.96837	0.96800
Xception	0.97535	0.98675	0.98197	0.97315

Classification			
Layer	Type 1	Type 2	Type 3
VGG16	0.96469	0.82898	0.97278
VGG19	0.95549	0.44795	0.97241
Xception	0.98675	0.98161	0.98675

Type 1: GlobalAveragePooling2D -> Dense -> ReLu -> Dense -> Softmax Type 2: Flatten -> Dense -> ReLu -> Dropout -> Dense -> Softmax Type 3: Flatten -> Dense -> ReLu -> Dropout -> BatchNorm -> Dense -> Softmax



Epoch

		(AS)									UNIVE		
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	-					Confusi	on Matr	rix for X	ception				
	Amoeba -	0.97	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03
	Chrysochromulina -	0.00	0.96	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.01
	Clusterflagellate -	0.00	0.00	0.85	0.02	0.02	0.00	0.00	0.00	0.00	0.07	0.00	0.02
	Dictyocha -	0.00	0.00	0.00	0.99	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
abel	Dinobryon -	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
rue L	Euglena -	0.00	0.02	0.00	0.01	0.01	0.90	0.00	0.01	0.00	0.00	0.04	0.01
F	Flagellate_sp3 -	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00
	Kiteflagellates -	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.97	0.00	0.00	0.00	0.00
	Parvicorbicula_socialis -	0.00	0.00	0.00	0.00	0.08	0.00	0.00	0.00	0.92	0.00	0.00	0.00
	Phaeocystis -	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.99	0.00	0.00
Pseud	lochattonella_farcimen -	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.98	0.00
Pyr	amimonas_longicauda -	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.99
	l	noeba	mili	ina tella	ie wocha	abryon	ulena	Je S	3 allate	2	cialis cystis	T	cimen caude
		b.	ysochron di	usterflass	Dices	Dinu	4 ³⁷	agellat 4	reflage	orbicula	phaeo	attonella	al onas longit
		÷				Pred	licted	Label	Para	с. 	pseudoc	no pyrami	ų.

- Fine tuning after transfer learning has the best performance in classifying flagellates
- Xception is able to learn the internal representation of the data marginally better than VGG16 and VGG19 due to a higher number of trainable parameters.
- In general, SGD is the best optimizer to use for plankton classification with a learning rate of 0.001.
- Using two fully connected layers and batch normalization in the classification layers allows the network to extract important features.
- VGG architectures provide a relatively light-weight alternative than deeper models with exceptional accuracy

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Conclusion

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