Flagellates Classification via Transfer Learning

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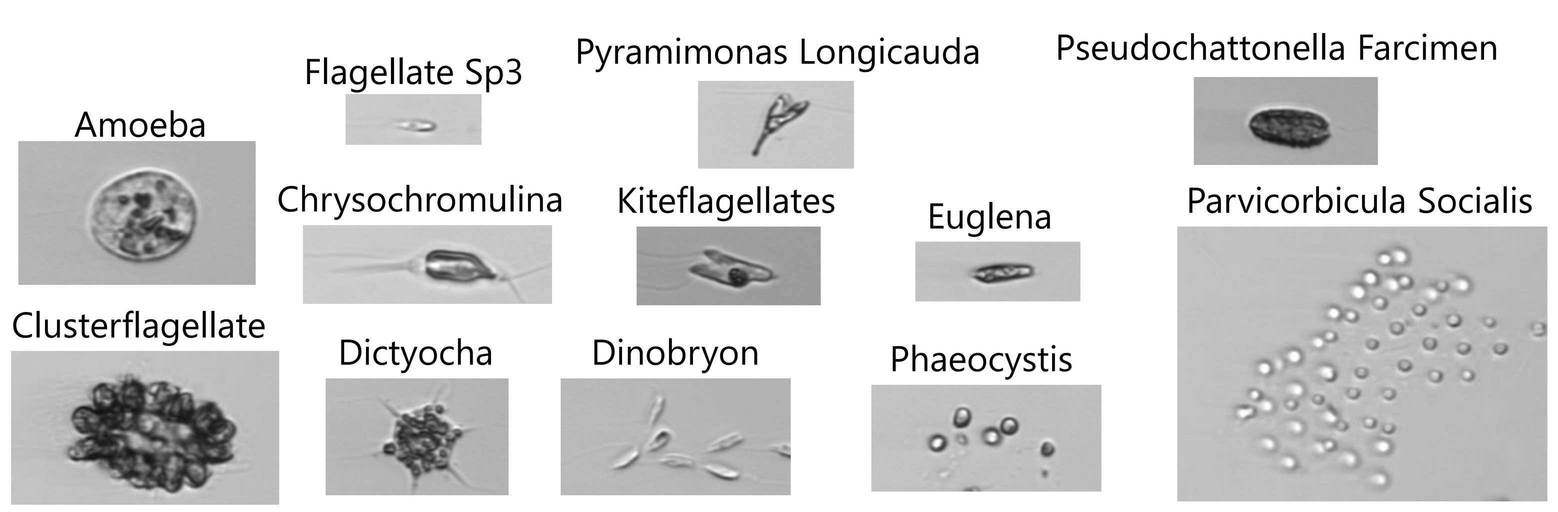
Background

- 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

Results

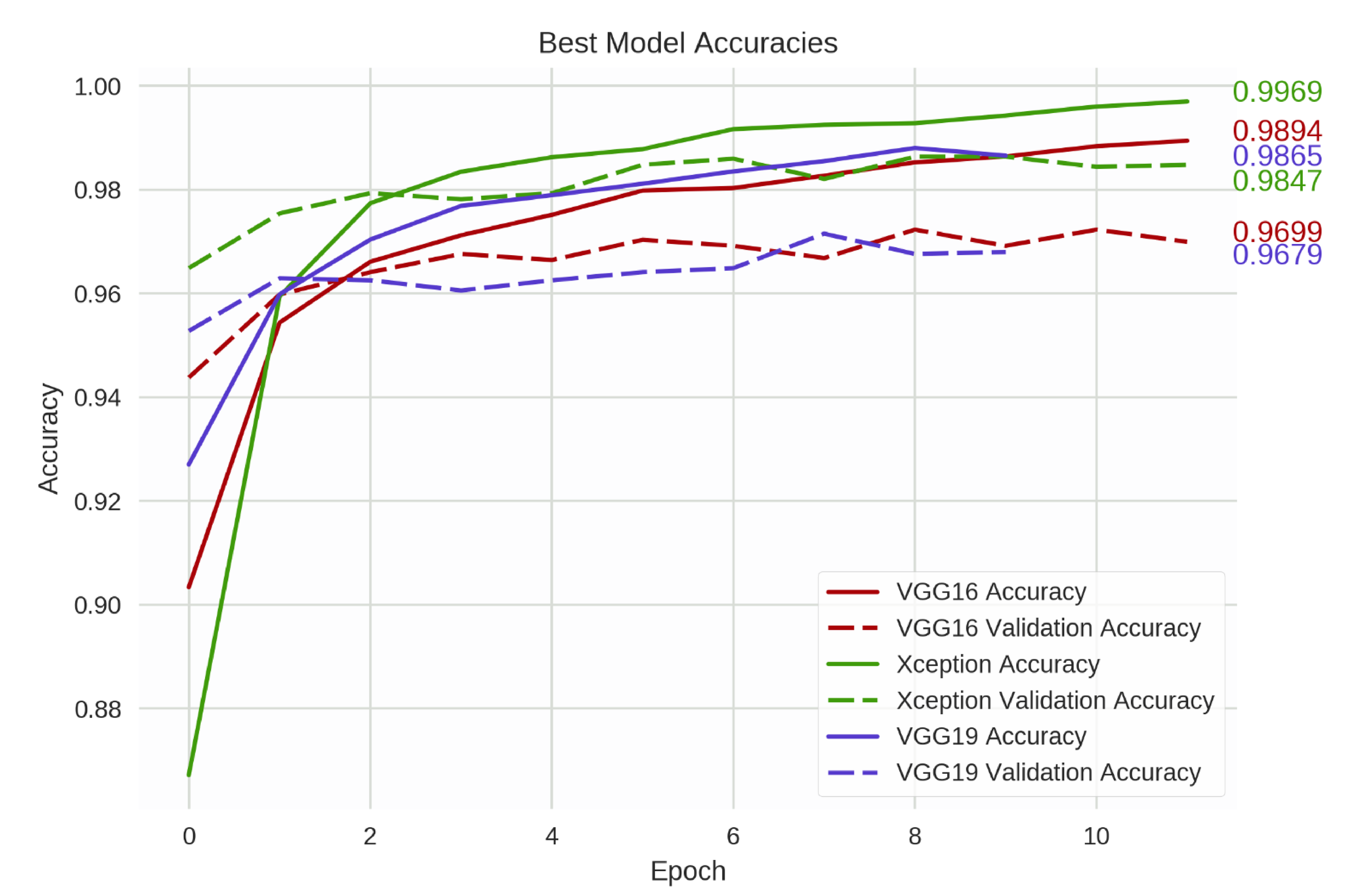
The following are the testing accuracies from varying the optimizer, the learning rate, and the classification layer:

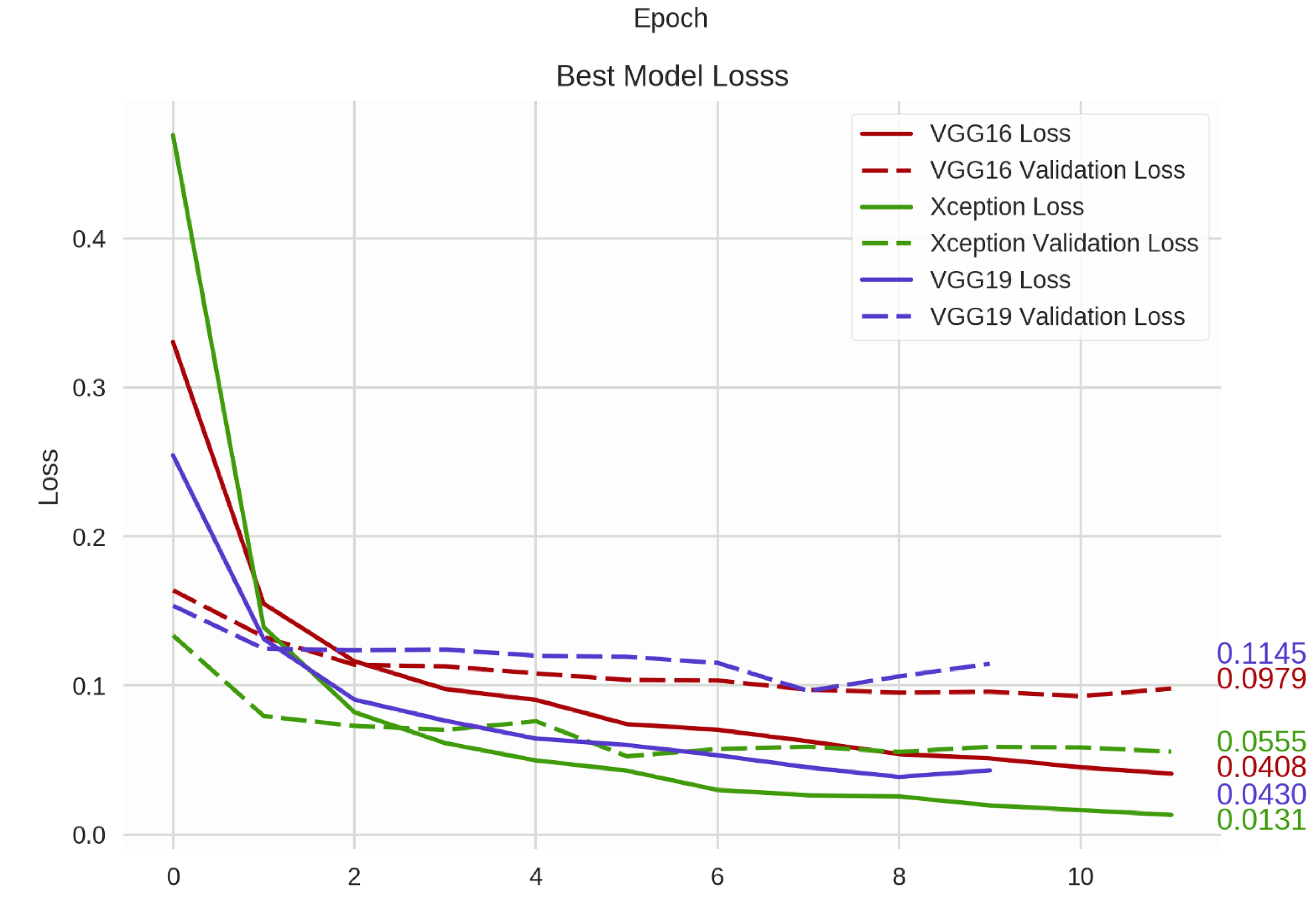
Optimizer	***Adam***	***SGD***	***RMSprop***
VGG16	0.97425	**0.97426**	0.97204
VGG19	**0.97572**	0.97278	0.97241
Xception	0.93159	**0.98675**	0.95476

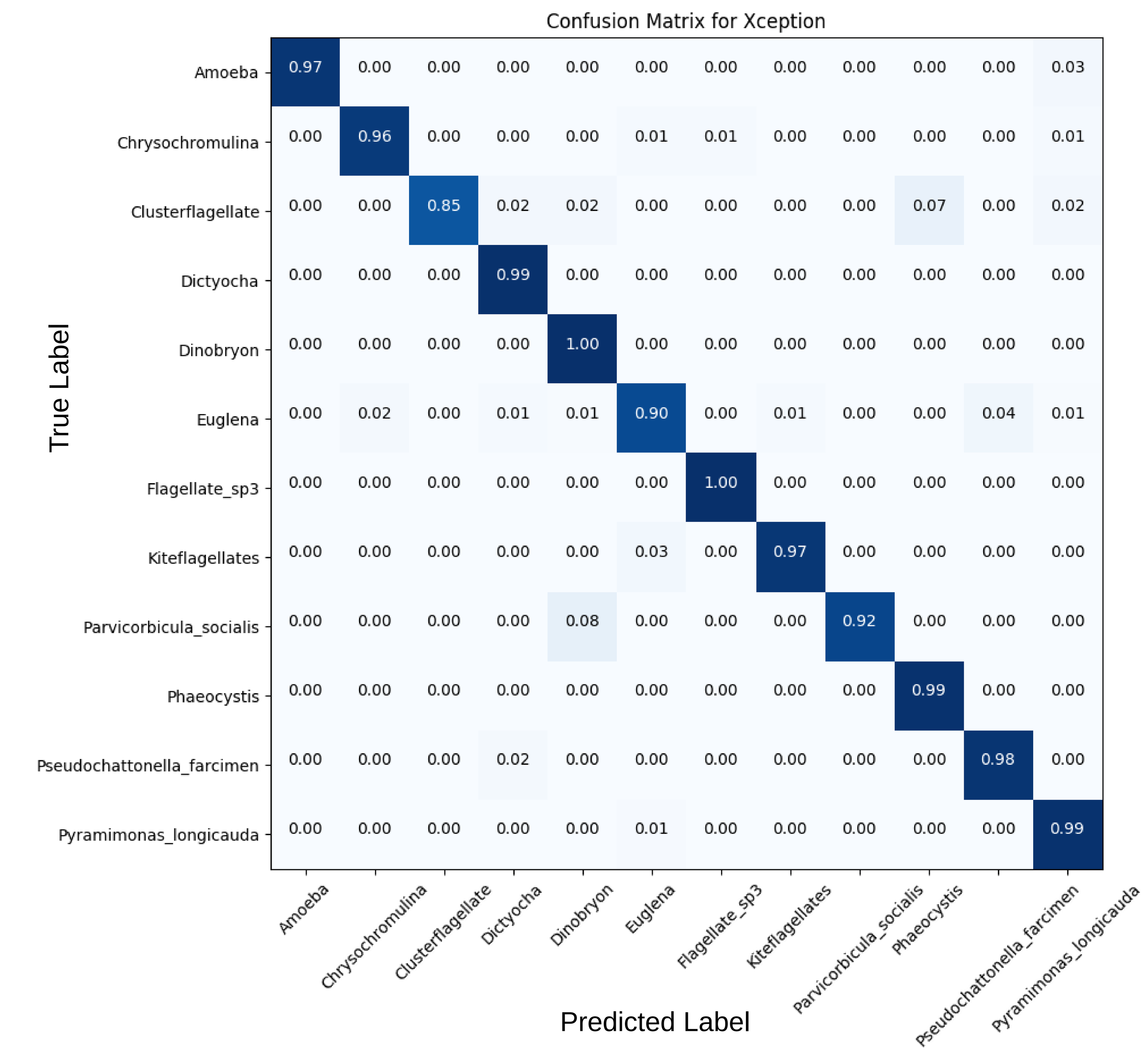
Learning rate	***0.1***	***0.01***	***0.001***	***0.0001***
VGG16	0.96800	**0.97426**	0.96947	0.95733
VGG19	0.79771	0.96175	**0.96837**	0.96800
Xception	0.97535	**0.98675**	0.98197	0.97315

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







Conclusion

- 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

References

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