Humpback Whales Identification

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Outline

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Introduction

- The humpback whales is a species of baleen whales, it has a distinctive body shape with long fines and knobbly head.
- At the beginning of the 20th century whales population dropped but increased briefly in the mid -20th century due to the creation of international whaling committee and their preservation efforts.
- Features such as the whales tail, marking, shape help researchers to identify the type of whale they are analyzing.
- Deep Learning neural networks are presently the main tool used for image analysis and classification purposes.

Review of Related works

Author(s)	Title	Model	Accuracy
He et al., 2016	Deep residual learning for image recognition	ResNet	80%
Zhang et al., 2006	SVM-KN: Discriminative nearest neighbor classification for visual category recognition	SVM KNN	85%
Brust et al., 2017	Towards automated visual monitoring of individual gorillas in the wild	SVM	62.40%
Yuan et al., 2020	Aquatic animal image classification technology based on transfer learning	Transfer Learning	89.10%
Bergamini et al., 2018	Multi-views embedding for re-identification	KNN	81.70%
Freytag et al.,2016	Chimpanzee faces in the wild	Log Euclidean CNN	90%

Architecture

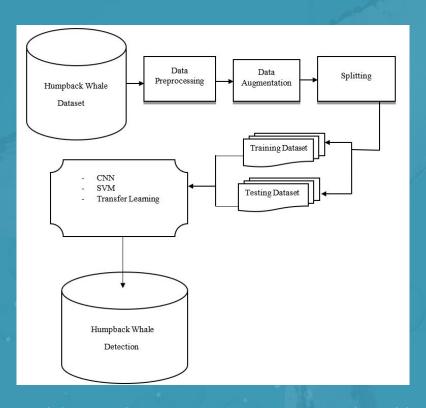


Figure 1: Architecture Diagram of Humpback whales identification

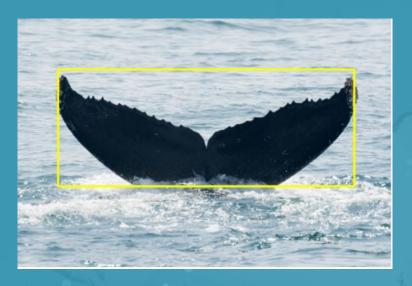
Methodology

Dataset description: The Humpback whale Identification datasets contains thousand images in which 25,361 images (76.11%) was used for training and 7,960 (23.89%) for testing.

Data Preprocessing: Preprocessing was conducted to remove noise and crop to show only the fluke.

Dataset Augmentation: Augmentation such as filipping, rotating and scaling of images was done to increase dataset size and reduce overfitting.

Model(s): CNN, transfer learning and SVM









Model 1 - CNN

Model training and testing: CNN using python library keras model was utilized as the first model. Data was formatted for use in model.

- Padding was set to "same".
- Max pooling was utilized on the model.
- Batch Normalization and Dropout was utilized in other to prevent overfitting.
- Adam Optimizer was used to optimize the gradient descent of the model.

Model 1 - CNN Proof of Concept

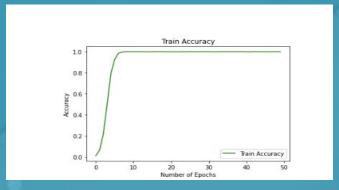


Figure 2a: Training accuracy on 10% of Training Data

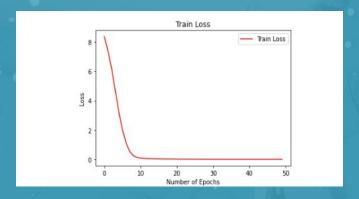
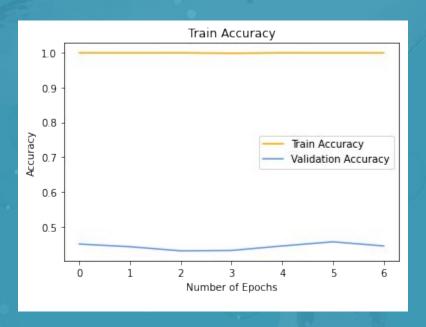


Figure 2b: Training loss on 10% of Training Data

Model 1 - CNN Tuning

With Proof of Concept, we expanded to the rest of the dataset but it was overfitting onto the training set.

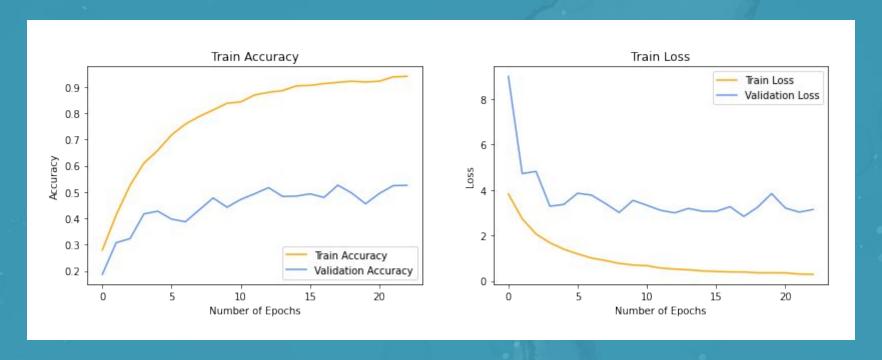


Model 1 - CNN Tuning

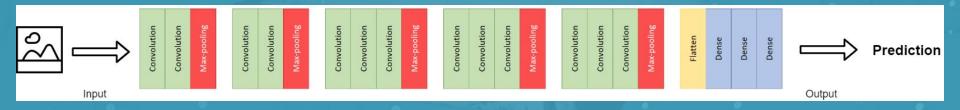
We tested the following hyperparameters:

- Activation Functions (relu vs. tanh)
- Dense Layer Units
- Number of Dropout Layers and Rates
- L2 regularization and rates
- Data Augmentation

Model 1 - CNN Results



Model 2 - Transfer Learning



Model 2 - Transfer Learning



Figure 3a: Transfer Learning with VGG16_20+ - Accuracy

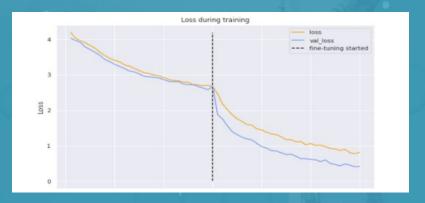


Figure 3b: Transfer Learning with VGG16_20+ - Loss

Model 2 - Transfer Learning

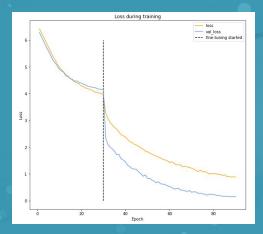
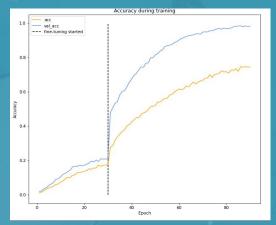


Figure 3d: Transfer Learning with VGG16_20+ - Loss

Figure 3c: Transfer Learning with VGG16_20+ - Accuracy



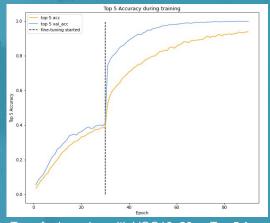


Figure 3e: Transfer Learning with VGG16_20+ - Top 5 Accuracy

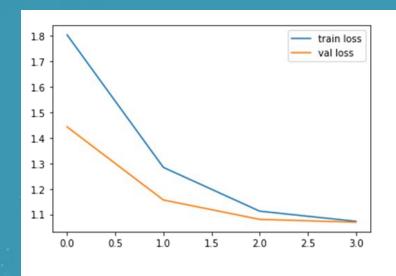
Model 3 - SVM

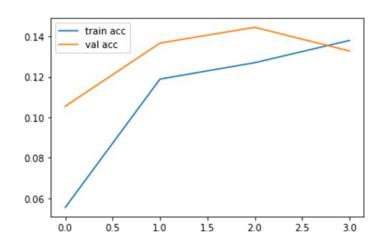
We also wanted to test a more basic model against the two more complex models as a baseline. The model used:

- Multi-class Classification
 - Softmax activation and Squared Hinge Loss
- L2 Regularization

As expected, it did not perform well having a very low validation accuracy.

Model 3 - SVM contd.

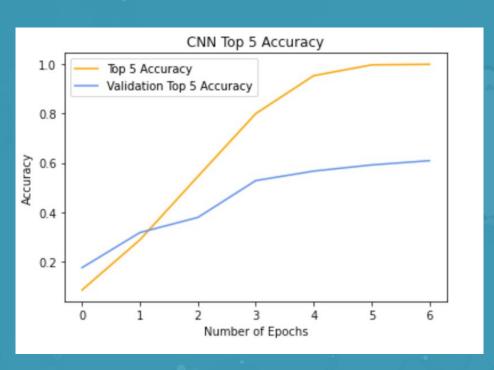


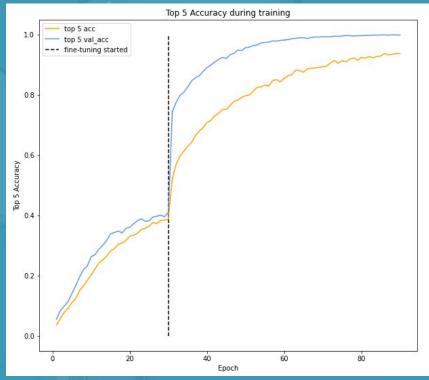


Results

- We attempt to use traditional methods such as SVM. It gave a very low validation accuracy
- CNN and Transfer Learning perform well in the whale identification task while SVM is not suitable for the problem.
- Transfer learning gave an accuracy of 98.18% (top-5 acc 99.8%) while Convolutional Neural Network gave 99% training and top-5 accuracy but only 41% validation accuracy (61% val top-5).
- However, CNN is overfit on the training set so in the end Transfer Learning is the better model despite the close training accuracies.

CNN and Transfer Learning Comparison





Conclusion

Architecture such as the Transfer Learning or CNN done in this project clearly works well for tasks such as this.

In the future it would be interesting to see You Only Look Once (YOLO) architecture be utilized which uses high dimensional features as input to a deep neural network.

Selected References

- A. Brust, T. Burghardt, M. Groenenberg, C. Kading, H. S. Kuhl, M. L. Manguette, and J. Denzler, "Towards automated visual monitoring of individual gorillas in the wild," in Proceedings of the IEEE International Conference on Computer Vision Workshops, pp. 2820–2830, 2017.
- A. Shukla, G. Sigh Cheema, P. Gao, S. Onda, D. Anshumaan, S. Anand, R. Farrell, et al., "A hybrid approach to tiger re-identification," in Proceedings of the IEEE/CVF International Conference on Computer Vision Workshops, pp. 0–0, 2019.
- L. Bergamini, A. Porrello, A. C. Dondona, E. Del Negro, M. Mattioli, N. D'alterio, and S. Calderara, "Multi-views embedding for cattle re-identification," in 2018 14th international conference on signal-image technology & internet-based systems (SITIS), pp. 184–191, IEEE, 2018
- H. Yuan, S. Zhang, E. Qin, and H. Zhou, "Aquatic animal image classification technology based on transfer learning and data augmentation," Journal of coastal research, vol. 105, no. spl, pp. 129–133, 2020

Thanks for Listening !!!