Application of deep-learning methods to estimate fish ages using otolith images

DFOBot

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Draft document to put down ideas and preliminary results

Abstract

1 Introduction

Obtaining age estimates from hard structures such as fish otoliths is a key component of stock assessments methods that examine population dynamics using age-structured models. Traditionally, age estimates are obtained from a representative set of individuals in order to derive an age-length key that can then be used to estimate the age composition of a population based on the distribution of lengths.

Age estimates are obtained from otoliths through the examination of regular concentric patterns associated with the alternation of opaque and hyaline zones. In temperate systems, these patterns often correspond to yearly changes in environmental conditions and can be used to estimate age.

The number of age estimates required to obtain an unbiased age-length key is often large and it is not uncommon for thousands of fish age estimates to be determined by fisheries technicians in support of age-based assessments.

We apply a neural network approach to build a deep learning system that uses otolith images to estimate ages. The model is developed using otoliths from six marine fish species from the southern Gulf of St. Lawrence.

[1], [2], [3], [4]

[5]

2 Methods

2.1 Otolith images

Otolith images were captured during age estimation programs conducted by the Gulf Region of Fisheries and Oceans Canada. The seven species examined in the current document are American Plaice (*Hippoglossoides platessoides*), Yellowtail Flounder (*Myzopsetta ferruginea*), Winter Flounder (*Pseudopleuronectes americanus*), Atlantic Cod (*Gadus morhua*), White Hake (*Urophycis tenuis*), Atlantic Herring (*Clupea harengus*).

Otolith images are captured from a Leica S9i microscope equipped with a digital camera. To minimise glare and improve contrast, image capture is done using diffuse indirect light on a dark background. The preparation methods differ by species, some otoliths are photographed whole while other

Table 1: Fish species used.

Common name	Scientific name	Preparation method	Number of availa
American Plaice	*Hippoglossoides platessoides*	Whole untreated	
Yellowtail Flounder	*Myzopsetta ferruginea*	Whole untreated	
Winter Flounder	*Pseudopleuronectes americanus*	Whole untreated	
Atlantic Cod	*Gadus morhua*	Sectioned from epoxy	
White Hake	*Urophycis tenuis*	Thin section	
Atlantic Herring	*Clupea harengus*	Whole in clear resin	

are sectioned after being embeded in a two-part epoxy resin. Example of photos from the different species appear in Figure 2.4.

2.2 Age estimates

Age estimates were obtained by visual examination of whole otoliths, or otolith cross-sections (Table 2.1).

2.3 Neural Network

A convolutional neural network (ResNet50) is used as the main engine for the machine learning. The implementation of the neural network is done in the Python programming language using the ResNet50 capabilities of the TensorFlow package.

Otolith images are first processed to make them suitable as inputs to the neural network.

The first step is to train the neural network using a subset of the available images.

The second step is to use the neural network with another set of images to predict age estimates for each sample.

2.4 Validation of age estimates

Comparison of age estimates determined by trained fisheries technicians to those obtained from the neural network are done by computing the percent agreement of age estimates, the coefficient of variation of the predicted and observed estimates and by generating bias plots.

[6]

Figure 2.4 shows the steps to go from otolith images to predicted ages.

3 Results

3.1 Neural network training

3.2 Neural network validation

4 Discussion

4.1 Pre-processing of images

4.2 Frequency of neural network retraining

5 Conclusion


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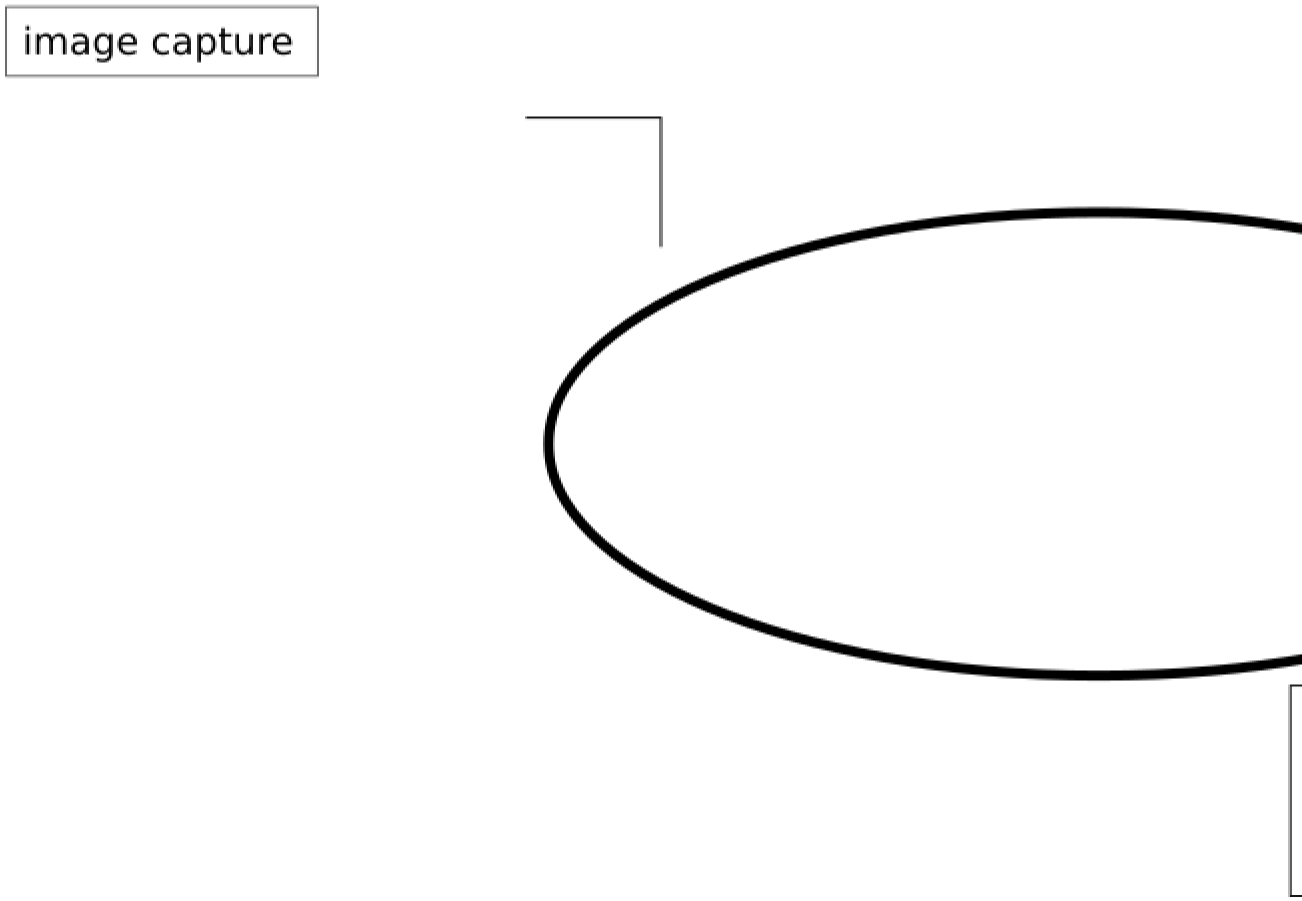

Figure 2: Diagram of the analytical pipeline used.

References

[1] E. Moen, N. O. Handegard, V. Allken, O. T. Albert, A. Harbitz, and K. Malde. Automatic interpretation of otoliths using deep learning. *PLoS One*, 13(12):e0204713, 2018. Early ML Otolith work, used InceptionV3, fine tuned it.

[2] Miroslav Poláček, Alexis Arizpe, Patrick Hüther, Lisa Weidlich, Sonja Steindl, and Kelly Swarts. Automation of tree-ring detection and measurements using deep learning. *Methods in Ecology and Evolution*, 14(9):2233–2242, 2023. Did trees yo!

[3] Dimitris V. Politikos, Georgios Petasis, Archontia Chatzispyrou, Chryssi Mytilineou, and Aikaterini Anastasopoulou. Automating fish age estimation combining otolith images and deep learning: The role of multitask learning. *Fisheries Research*, 242, 2021. 5000 image training set, 6 classes, 64

[4] Andrea Rakel Sigurðardóttir, Þór Sverrisson, Aðalbjörg Jónsdóttir, María Gudjónsdóttir, Bjarki Þór Elvarsson, and Hafsteinn Einarsson. Otolith age determination with a simple computer vision based few-shot learning method. *Ecological Informatics*, 76, 2023. Did few-shot (1000 images) approach using CLIP, compared to ResNet, InceptionV3, etc. GOt 55

[5] Troels Arnfred Bojesen, Côme Denechaud, and Ketil Malde. Annotating otoliths with a deep generative model. *ICES Journal of Marine Science*, 81(1):55–65, 11 2023.

[6] S.E. Campana, M.C. Annand, and J.I. McMillan. Graphical and statistical methods for determining the consistency of age determinations. *Transactions of the American Fisheries Society*, 124:131–138, 1995.