**DeepOtolith: A web-tool for automating fish otolith reading using deep learning**

**Summary**

Fish otoliths are well-established recorders of fish age, used to estimate demographic and population dynamics parameters of fish populations and stock assessment models. However, age information is often costly to obtain, requiring a considerable effort by experienced readers. This suggests a need for cost-effective approaches. We present an automatic system, called DeepOtolith, for estimating fish age combining otolith images and deep learning. The proposed approach is based on Convolutional Neural Networks (CNNs), a class of deep neural networks efficient for resolving image tasks. CNNs are trained on a set of otolith images for a specific fish species and then used to make the predictions. DeepOtolith contains at present three species. DeepOtolith is easy to use, receiving as input an otolith image and returning the age of fish. DeepOtolith welcomes collaborations with researchers who want to contribute towards the automation of fish age determination. It is accessible via the following web-based environment: <http://otoliths.ath.hcmr.gr/>.

**1. Introduction**

Each year, thousands of fish are aged from otoliths in the frame of the national Data Collection Fisheries Programs, providing useful information for fitting fish stock assessment models and estimating demographic and population dynamics parameters of fish populations (Carbonara and Follessa, 2019; Wang et al., 2019). Traditional ageing techniques include the counting of annuli number from otolith images, which exhibit a range of incremental structures, related to the fish growth. This makes otoliths a reliable recorder of fish age (Williams and Bedford 1974; Wang et al. 2019). However, age information is often costly to obtain, requiring a considerable effort by experienced readers (Cardinale et al., 2000). This urges the need for automated methods of fish ageing. FAbOSA project[[1]](#footnote-1) attempted to automate fish age estimation using otolith shape analysis but appears inactive for practical use nowadays. In addition, AFORO[[2]](#footnote-2) processes otolith images for fish species identification (Lombarte et al., 2006). These tools illustrate the importance of developing tools for otolith scientists.

Diverse methods for fish ageing have been tested based on image-based approaches (Fisher and Hunter, 2018), neural networks (Robertson and Morison, 2001) and statistical learning (Fablet and Le Josse, 2005) attaining varying performance. Over the last years, deep learning has received increased attention for automating fish ageing from otolith images. Recent examples are the case studies for Greenland halibut (Moen et al., 2018), snapper and hoki (Moore et al., 2019) and red mullet (Politikos et al., 2021) and salmon (Vabo et al. 2021). These studies have used Convolutional Neural Networks (CNNs), a class of deep neural networks suitable for resolving image tasks (Goodfellow et al., 2015). CNNs are built in series of subsequent layers that apply filters to recognize meaning features within the images. Once they are trained on a set of images, then they can be used to make predictions.

In this work, we release a web-based automatic tool, called DeepOtolith, for estimating fish age combining otolith images and CNNs. DeepOtolith is easy to use, receiving as input an otolith image and returning fish age estimation. DeepOtolith is accessible through a web-based environment, in which a server links the code with a search page (Fig. 1). At present, three case studies are available for experimentation with DeepOtolith (Table 1). CNNs were built using Python and the web interface was developed with Flask, Bootstrap and React.

Graphical user interface, website

Description automatically generated

**Fig. 1.** Search page of DeepOtolith.

|  |  |  |  |
| --- | --- | --- | --- |
| **Species** | **Age groups** | **Regions** | **References** |
| Mullus barbatus | 6 | Greece | Politikos et al. (2021) |
| Pagellus Erithrinus | 9 | Greece | HCMR |

**Table 1.** Case studies currently available at DeepOtolith.

**2. Case studies**

*2.1 Greek red mullet*

This automatic fish age estimation of otoliths for red mullet (*Mullus barbatus*) species is based on Politikos et al. (2021). The dataset included 5027 otolith images of red mullet, provided by the Hellenic Centre for Marine Research (HCMR) database along with the age readings and fish length (body size in mm) of each individual fish. Red mullet age ranged between 0 and 11 years. Due to the low number of specimens with age >5 years old (~6%), these were merged into the 5+ age group. In total, we considered six age groups (Age-0, Age-1, Age-2, Age-3, Age-4, Age-5+). The Inception v3 CNN model (Szegedy et al., 2015) trained considering fish age estimation as a multi-class classification task. Additionally, the potential benefit of multitask learning for improving network’s predictability, with the auxiliary task being the prediction of fish size. A schematic view of the CNN model is shown in Fig. 2. Results showed that, without multitask learning, the ages of the red mullet were predicted correctly by 64.4%, performing better on the younger Age-0 and Age-1 classes (F1 score > 0.8) and moderately on older age classes (F1 score between 0.50-0.54). Multitask learning increased the correct age prediction to 69.2% and was proved a better approach to estimate older age groups, with F1 score being between 0.57-0.64. For fish age-length multitask network, age was correctly estimated for 522 otoliths (69.2%) with additional 231 images (28.2%) being within year error.

**3. Web-tool in practice**

The web-tool is easy to apply and involves the following basic steps:

1. Select Fish species

2. Upload Images (in .png. or .jpg)

3. Make the Prediction

The web-based interface will automatically produce the selected images and predict fish age across the different age groups (%) (Fig. 2). The highest percentage defines the resulting fish age prediction. Nearby predictions imply the uncertainty in fish age estimation. Snapshots of a sample image along with predictions is shown in Fig. 2. The user can upload 50 images at maximum each time and extract the outputs in a JSON file (default name: “MyFile.txt”) through the Download JSON button (Fig. 2). An auxiliary R function can be downloaded (Fig. 2) to convert the JSON file in excel file.

Graphical user interface

Description automatically generated

**Fig. 2.** Sample otolith image along with fish age predictions. The user can upload 50 images at once to make predictions.

**5. Concluding remarks**

To our knowledge, this is the first friendly-user web-tool for estimating fish age from otolith images using deep learning. We acknowledge that DeepOtolith is currently implemented for selective species but other species can be included as relative works get published in the future. For research needs, DeepOtolith welcomes collaborations with researchers working with other fish species who want to contribute towards the automation of fish age determination. Furthermore, the collection of more images for the existing case studies can provide a valuable way for retraining the CNNs and potentially improve their predictability. We declare that images are not stored neither are sent to third parties.

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1. https://www.imagescience.de/old\_pages/fabosa/start.htm [↑](#footnote-ref-1)
2. http://aforo.cmima.csic.es/ [↑](#footnote-ref-2)