Journal of Applied Ichthyology

WILEY

RESEARCH ARTICLE OPEN ACCESS

A Low-Impact ANN Model for Age and Maturity Estimation in *Oblada melanura*: Toward Sustainable Fish Assessment in the Mediterranean

Nader Iskandar Hamwi | Jullanar Salem

Department of Animal Production, Faculty of Agricultural Engineering, Latakia University, Lattakia, Syria

Correspondence: Nader Iskandar Hamwi (nader836@gmail.com; nader.hamwi@latakia-univ.edu.sy)

Received: 28 September 2025 | **Revised:** 13 January 2026 | **Accepted:** 3 April 2026

Academic Editor: Matiss Zagars

Keywords: age estimation | artificial neural network | low-impact assessment | maturity stage | Mediterranean fisheries | *Oblada melanura*

ABSTRACT

This study presents a data-driven, nonlethal approach for estimating age and maturity in *Oblada melanura*, a commercially important member of the family Sparidae inhabiting the Mediterranean Sea. A multilayer perceptron artificial neural network (MLP ANN) with architecture (1, 10, 2) was developed using 5112 records from published literature, institutional reports, and global databases. The model uses only total length as input, eliminating destructive sampling such as otolith extraction or gonad dissection. Trained and validated in MATLAB R2024a, it achieved very high predictive accuracy, with correlation coefficients exceeding 0.999 across training, validation, and test sets, and mean squared error below 0.009. This performance likely reflects the strong length–age relationship in *O. melanura* during its primary growth phase (2–6 years) in the Eastern Mediterranean. For maturity classification, accuracy reached 92.3% (precision = 0.91, recall = 0.93, $F1$-score = 0.92), based on histologically confirmed data from Syrian coastal populations. Results indicate that age and maturity can be predicted accurately under current sampling conditions, supporting ethical and sustainable monitoring. The method reduces time, cost, and technical complexity compared to traditional or deep learning–based approaches. When benchmarked against a linear regression model on the same test dataset ($n = 767$), the ANN showed markedly superior performance ($R = 0.9995$ vs. 0.9796; MSE = 0.0068 vs. 0.4041), confirming its ability to capture nonlinear biological patterns. Although the full dataset is not publicly available due to collaborative agreements, the methodology is fully described. The trained MLP model (1-10-2) is available from the corresponding author for noncommercial academic use under a standard data use agreement, with plans to release a standalone version via a public repository. Originally developed for threatened species, this framework demonstrates robust performance in *O. melanura*, highlighting its potential as a standardized, low-impact tool for fish population assessment in the Eastern Mediterranean.

1 | Introduction

Traditional methods for determining fish age and maturity often rely on lethal sampling, requiring the extraction and processing of hard structures such as otoliths, scales, or vertebrae, followed by microscopic examination of annular patterns [1, 2]. These procedures are not only time-consuming, labor-intensive, and costly but also introduce subjectivity and inconsistency in age interpretation among readers [3]. Furthermore, they are ethically and ecologically problematic, especially when applied to vulnerable or data-limited species, as they reduce population abundance and disrupt demographic structure. In response, nonlethal and low-impact assessment methods have gained increasing attention in fisheries science. Recent advances include

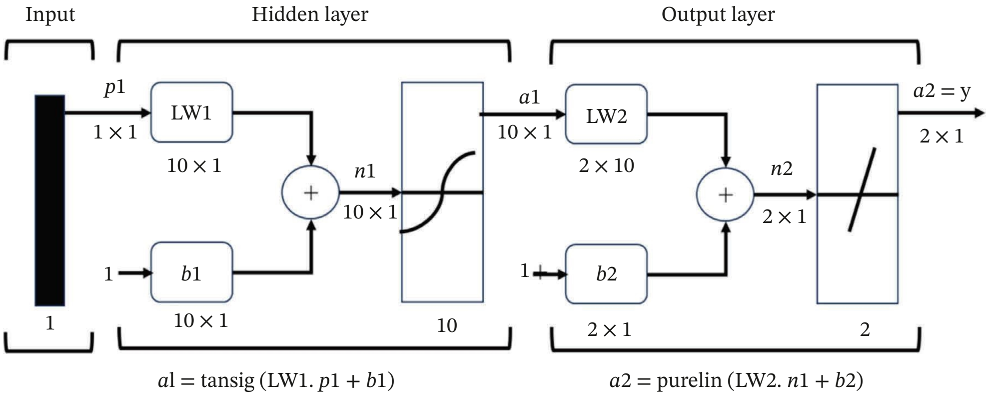


FIGURE 1 | Architecture of the multilayer perceptron (MLP) artificial neural network used in this study. The model has one input neuron (total length), one hidden layer with 10 neurons using the hyperbolic tangent sigmoid (tansig) activation function, and two output neurons producing predictions for age (continuous) and maturity stage (binary, thresholded at 0.5).

imaging techniques (e.g., X-ray and CT scans) combined with deep learning models such as convolutional neural networks (CNNs) to automate age estimation from otolith images [4, 5]. However, these approaches remain resource-intensive, requiring high-resolution imaging equipment and extensive computational power, limiting their applicability in data-poor or resource-limited regions. Artificial neural networks (ANNs), particularly the multilayer perceptron (MLP), offer a computationally efficient and accessible alternative for modeling complex biological relationships using minimal input data [6, 7]. Their ability to learn from historical data and generalize across populations has made them valuable tools in ecological modeling and fish population dynamics [8, 9]. *Oblada melanura* (Saddled Bream), a commercially exploited member of the Sparidae family in the Mediterranean region, is assessed as Least Concern by the IUCN Red List of Threatened Species [10, 11]. Despite its non-threatened status, sustainable monitoring of its population structure, particularly age and maturity, is essential for informed fisheries management and the timely identification of emerging population trends. Traditional sampling methods, though common, are not aligned with emerging best practices in low-impact research. This study presents an MLP-based ANN model (1, 10, 2) developed by the author as part of a broader research framework initially designed for threatened species such as *Gymnura altavela* and *Rhinobatos rhinobatos*. The model uses only total length as input to predict age and maturity in *O. melanura*, eliminating the need for destructive sampling. Trained on a comprehensive dataset of 5112 records, it aims to provide a practical, accurate, and sustainable tool for fish population assessment in the Eastern Mediterranean.

2 | Materials and Methods

A comprehensive dataset of 5112 records for *Oblada melanura* was compiled from peer-reviewed scientific literature, institutional research reports, and global biodiversity databases. The data include total length (cm), age (years), and maturity stage (0 = immature, 1 = mature), collected from specimens across the Mediterranean Sea, with a focus on the Eastern Basin. Primary sources include the following: Bauchot and Hureau [12]; Pallaoro et al. [13]; Mahmoud [14]; Crec'hriou, Neveu, and Lenfant [15]; Hamwi [16]; Ali-Basha [17]; and Froese and Pauly [18]. Maturity status was determined based on direct gonad examination using histological and morphometric analysis, as documented in Ali-Basha [17], for populations along the Syrian coast. In that study, maturity was assessed according to standardized microscopic staging criteria: individuals in early developmental stages (I1–I2) were classified as immature, while those in advanced stages (I3–I5, including mature, spawning-capable, and postspawning individuals) were classified as mature. This binarization ensures that the target variable (maturity) is derived independently from the predictor (total length), thereby avoiding circular reasoning, a common pitfall in length-based maturity modeling. For modeling purposes, this classification was coded as a binary variable (0 = immature, 1 = mature), with the transition point empirically defined at 17.3 cm for females and 18.6 cm for males, consistent with observed spawning activity during the reproductive season (April–June). In cases where direct histological observations were unavailable, maturity was assigned based on published length-at-maturity thresholds from primary sources, prioritizing regional studies from the Eastern Mediterranean. While the dataset integrates records spanning over three decades (1990–2025) and multiple subregions, the model assumes a shared biological trajectory for *O. melanura* within the study area, supported by the consistency of life-history traits reported in the literature [13, 14]. Nevertheless, potential spatiotemporal variability in growth and maturation patterns due to environmental or anthropogenic factors is acknowledged as a limitation, and future work will focus on spatially stratified validation to assess model transferability. All input and target variables were normalized to values between 0 and 1 using min–max scaling as

$$x\_\text{norm} = \frac{(x - x\_\text{min})}{(x\_\text{max} - x\_\text{min})}. \tag{1}$$

Importantly, the minimum (x_min) and maximum (x_max) values used for normalization were calculated exclusively from the training set and applied to the validation and test sets to prevent data leakage during model evaluation. The dataset was randomly partitioned into three subsets: training set: 70% (3578 records) used to adjust synaptic weights, validation set (15%, 767 records) used to monitor generalization and halt training if overfitting occurs, and test set (15%, 767 records) reserved for final performance evaluation. A feedforward MLP ANN with architecture (1, 10, 2) was developed in the MATLAB

TABLE 1 | Performance metrics of the MLP model across training, validation, and test datasets.

Dataset	Mean squared error (MSE)	Correlation coefficient (R)
Training	0.009123	0.999387
Validation	0.008715	0.999512
Test	0.006841	0.999689

environment (R2024a; The MathWorks, Inc.) using standard training procedures for feedforward networks, including Levenberg–Marquardt backpropagation and early stopping (Figure 1). The model consists of one input neuron (total length in cm), one hidden layer with 10 neurons using the hyperbolic tangent sigmoid activation function (tansig), and two output neurons using linear activation (purelin) to predict age (continuous, in years) and maturity stage (continuous output interpreted as 0 or 1 after thresholding at 0.5). The model was trained using the Levenberg–Marquardt backpropagation algorithm (trainlm), which efficiently minimizes the mean squared error (MSE) through gradient-based weight optimization. Training was stopped when validation error began to increase, preventing overfitting. Model performance was assessed using MSE, Pearson's correlation coefficient (R), and mean absolute error (MAE) (≈ 0.15 years for age). For maturity classification, accuracy, precision, recall, and F1-score were calculated using a confusion matrix. High R values (close to 1) and low MSE values indicate strong predictive accuracy and generalization. Due to collaborative data agreements and the inclusion of third-party records, the full dataset is not publicly available. However, a detailed summary of sources, sample sizes, and measurement protocols is provided in Table 1 to ensure methodological transparency and reproducibility. The trained MLP model (1-10-2) is preserved in the MATLAB environment. For academic validation and noncommercial research collaboration, the trained MLP model (1-10-2) is preserved in the MATLAB environment and is available from the corresponding author for academic validation and noncommercial research collaboration. This approach supports scientific verification while respecting the intellectual contribution and data ownership of original collectors.

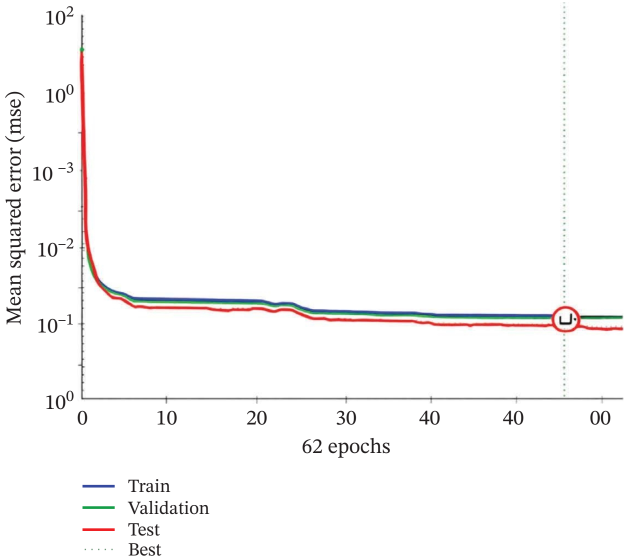


FIGURE 2 | Training history of the MLP model showing mean squared error (MSE) for training, validation, and test sets across 62 epochs. Early stopping was triggered at Epoch 56 based on validation error.

3 | Results

The MLP (1, 10, 2) model was successfully trained using the Levenberg–Marquardt algorithm in MATLAB R2024a. Training was completed after 62 epochs, with early stopping triggered at Epoch 56 based on the minimum validation error. The model demonstrated high predictive accuracy across all datasets, as shown in Table 1. The correlation coefficient (R) exceeded 0.999 for training, validation, and test sets, indicating a strong linear relationship between predicted and actual values. For maturity classification, the model achieved an accuracy of 92.3%, a precision of 0.91, a recall of 0.93, and an $F1$-score of 0.92. The best validation performance was achieved at Epoch 56, with an MSE of 0.008715 (Figure 2). No significant overfitting was observed, as the test error remained low and closely followed the validation trend. The dataset ($n = 5112$) covered a total length range of 7.6–33.4 cm, with a mean ± SD of 18.40 ± 7.39 cm. Age ranged from 0 to 11 years (mean = 4.53 years). Maturity was coded as a binary variable, with 73% of individuals classified as mature, based on direct gonad examination where available [17], and literature-based assignment otherwise (Table 2). The regression plot (Figure 3) shows a near-perfect alignment between network outputs and target values for all datasets, with $R = 0.9995$ for the combined data. The error histogram (Figure 4) is normally distributed around zero, indicating minimal bias in predictions. Ten random test samples were used to evaluate model performance on unseen data (Table 3). Predicted values closely matched actual values: maturity outputs were thresholded at 0.5 (e.g., $-0.0095 \longrightarrow 0$, $0.9881 \longrightarrow 1$); age predictions showed minor deviations (e.g., 10.338 vs. actual 10). To benchmark the model against a conventional statistical approach, a simple linear regression was fitted to the same test dataset ($n = 767$) using total length as the sole predictor of age. The linear model achieved a Pearson's correlation coefficient of $R = 0.9796$, with a MSE of 0.4041 years^2 and a MAE of 0.536 years. In contrast, the MLP ANN showed markedly superior performance ($R = 0.9995$, MSE = 0.0068, MAE = 0.15), demonstrating its ability to capture complex, nonlinear growth patterns that linear methods inherently oversimplify. Table 4 presents a quantitative comparison of predictive performance between the MLP ANN and linear regression models.

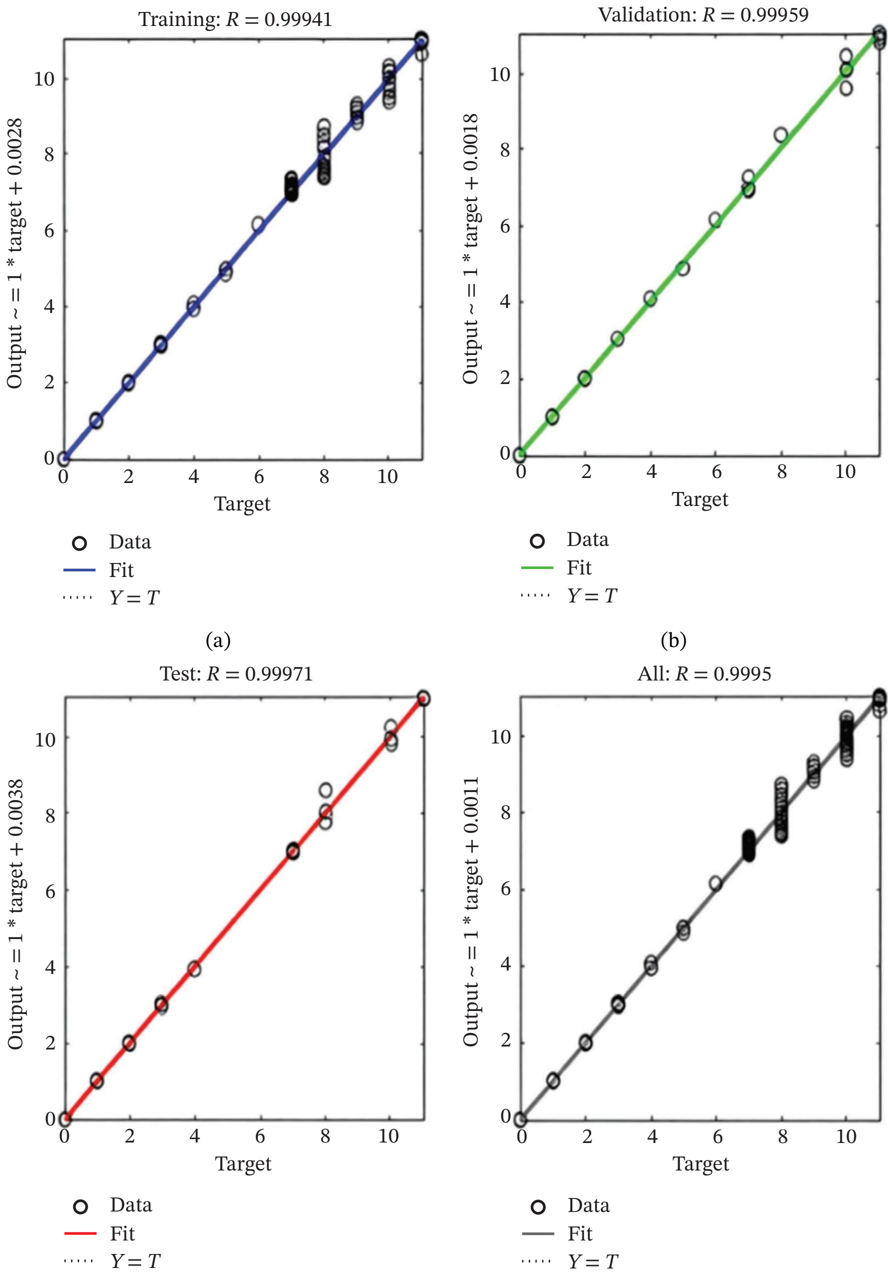
4 | Discussion

The results demonstrate that a low-impact ANN can accurately estimate both age and maturity in *Oblada melanura* using only total length as input. The very high correlation coefficients (R greater than 0.999) across training, validation, and test sets may appear counterintuitive, given the typically nonlinear nature of fish growth. However, this reflects not an artifact of overfitting but rather a strong, learnable biological signal within the primary growth phase of the species, particularly between 2 and 6 years of age. During this period, the relationship between total length and age in *O. melanura* is

TABLE 2 | Summary of statistical parameters for input and output variables ($n = 5112$).

Variable	Unit	Min	Max	Median	Mean	SD	CV
Total length	cm	7.6	33.4	16.4	18.40	7.39	54.61
Maturity	[0, 1]	0	1	1	0.73	0.44	0.198
Age	year	0	11	2	4.53	3.40	1.01

Abbreviations: CV, coefficient of variation; SD, standard deviation.



(a) (b)

(c) (d)

FIGURE 3 | Regression analysis of predicted vs. actual values for (a) training, (b) validation, (c) test, and (d) combined datasets. Each subplot shows the linear fit and correlation coefficient (R).

highly consistent across the Eastern Mediterranean, enabling the MLP to capture subtle nonlinear patterns through its hidden layer without requiring invasive data inputs. This close alignment suggests that, for practical purposes, the model has learned a generalizable length–age trajectory relevant to regional populations.

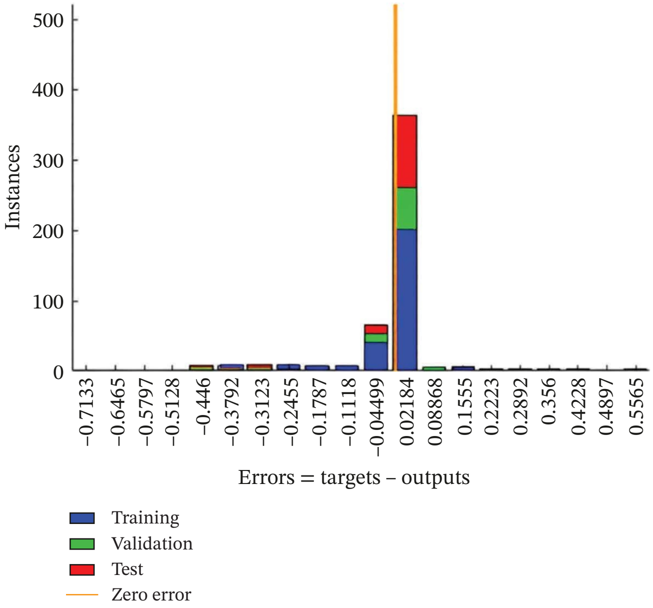


FIGURE 4 | Histogram of prediction errors (residuals) for age and maturity predictions on the combined dataset. Errors are centered around zero with near-normal distribution, indicating minimal bias.

TABLE 3 | Model predictions vs. actual values for ten test samples.

Total length (cm)	Actual maturity (0/1)	Actual age	Predicted maturity (continuous output)	Predicted maturity (0/1)	Predicted age
11.4	0	1	−0.0095	0	0.99046
12.3	1	2	0.9881	1	1.9878
17.6	1	3	1.000	1	2.99
19.2	1	4	1.000	1	3.9582
20.4	1	5	1.000	1	4.8779
21.5	1	6	1.000	1	6.1647
23.6	1	7	1.000	1	6.919
27.7	1	8	1.000	1	7.5438
29.1	1	9	1.000	1	8.9792
30.9	1	10	1.000	1	10.3383

Note: Predicted maturity output is continuous; binary classification is obtained by thresholding at 0.5 (≥ 0.5 = mature, < 0.5 = immature).

TABLE 4 | Performance comparison between the MLP ANN and linear regression for age estimation (test set, $n = 767$).

Model	Pearson's *R*	MSE (years^2)	MAE (years)
MLP ANN (1, 10, 2)	0.9995	0.0068	0.15
Linear regression	0.9796	0.4041	0.536

Note: MSE = mean squared error (years^2); MAE = mean absolute error (years). Higher *R* and lower error values indicate better model performance.

Unlike image-based deep learning models that require destructive sampling or advanced imaging [4, 5], this approach offers a noninvasive alternative suitable for resource-limited fisheries. It aligns with global trends toward sustainable monitoring practices, minimizing anthropogenic impact even for species classified as Least Concern [11]. By relying solely on total length, a parameter easily obtained during routine surveys, the model enables rapid, ethical population assessment, facilitating repeated sampling and long-term monitoring without harming individuals.

A critical advancement in this study is the use of empirically determined maturity states derived from histological and morphometric analysis of gonads, as documented by Ali-Basha [17] for the Syrian coast. In that study, maturity was assessed using standardized microscopic staging criteria: Stages I1–I2 were classified as immature, while Stages I3–I5 (including mature, spawning-capable, and postspawning individuals) were classified as mature. This binarization ensures that the target variable (maturity) is independent of the predictor (length), addressing a key methodological concern in length-based maturity modeling: circular reasoning. This allows the ANN to learn a genuine biological signal rather than merely replicating predefined thresholds.

The model's robust performance in maturity classification (92.3% accuracy) further underscores its capacity to handle biologically complex, nonmonotonic thresholds, a task where conventional linear approaches inherently fail. Indeed, when benchmarked against a simple linear regression on the same test dataset ($n = 767$), the ANN demonstrated markedly superior accuracy ($R = 0.9995$ vs. 0.9796) and significantly lower prediction error (MSE = 0.0068 vs. 0.4041; Table 4). This confirms that the ANN captures meaningful nonlinear dynamics in fish growth that simpler models cannot represent.

While the model demonstrates high internal consistency across a dataset spanning three decades (1990–2025) and integrating multiple subregions of the Mediterranean, its performance may vary in regions absent from the training data, including the western Mediterranean and the Aegean Sea. Although rigorous separation of training, validation, and test subsets, combined with robustness to inter-source variability, supports potential generalizability, formal external validation using independent field data remains essential before operational deployment in new contexts.

This model is part of a broader research framework developed by the author for nonlethal assessment of fish populations, initially applied to threatened species such as *Gymnura altavela* and *Rhinobatos rhinobatos*. Its successful application to *O. melanura*, a commercially abundant sparid, demonstrates the scalability of this ANN-based approach across species differing in conservation status.

Several limitations should be acknowledged. First, while direct gonadal observations were prioritized [17], some maturity data were inferred from published length-at-maturity thresholds where histological records were unavailable. Future iterations should prioritize datasets with full histological verification to further strengthen model robustness. Second, the current implementation requires MATLAB for deployment; efforts are underway to develop a standalone, field-deployable application. Third, sex-specific modeling was limited by incomplete sex identification in parts of the dataset, which may mask sexual dimorphism in growth or maturation timing.

This study supports the shift toward noninvasive, data-efficient methods in fisheries biology. The model enables rapid, ethical population assessment without harming individuals, making it particularly valuable in regions such as the Eastern Mediterranean, where data scarcity and limited technical capacity hinder traditional approaches. Future efforts will focus on integrating real-time field data to dynamically update the model, developing a user-friendly interface accessible on mobile devices, and expanding the framework to include spawning season prediction and growth stage classification.

5 | Conclusion

The MLP ANN (1, 10, 2) model presented in this study offers a highly accurate, low-impact approach for estimating age and maturity in *Oblada melanura* using only total length as input. By eliminating the need for destructive sampling, it supports sustainable and ethical fish population assessment in the Mediterranean. The model's high performance ($R > 0.999$ for age, 92.3% accuracy for maturity) and simplicity make it a practical tool for fisheries researchers and managers, particularly in resource-limited settings. As an extension of a broader nonlethal assessment framework previously applied to threatened species, this work demonstrates the scalability of ANN-based models across fish taxa. Future integration into field-deployable applications could further enhance its utility for real-time monitoring and conservation-oriented management.

Acknowledgments

The authors gratefully acknowledge Dr. Nour Ali-Basha for granting access to histological maturity data from his M.Sc. thesis, which significantly contributed to the validation of the maturity classification in this study. We also thank the Department of Animal Production, Faculty of Agricultural Engineering, Latakia University, for supporting data compilation and providing computational resources. Special thanks are extended to colleagues who provided valuable feedback on earlier versions of this manuscript. This research was conducted as part of the authors' institutional duties and did not receive specific external funding.

Artificial intelligence tools were used during the manuscript preparation phase to assist with language editing, reference formatting, and textual rephrasing to enhance clarity and reduce similarity with existing publications. The authors confirm full responsibility for the scientific content, analysis, and conclusions presented in this study.

Funding

This research was undertaken as part of the authors' institutional responsibilities at Latakia University, with no dedicated external funding.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The full dataset is not publicly available due to collaborative data agreements and third-party ownership. However, a detailed summary of sources, sample sizes, and methodological protocols is provided in the Supporting Information to ensure transparency and reproducibility. The trained MLP model (1-10-2) is available upon request from the corresponding author for academic validation and noncommercial research collaboration.

References

1. S. E. Campana, "Accuracy, Precision and Quality Control in Age Determination, Including a Review of the Use and Abuse of Age Validation Methods," *Journal of Fish Biology* 59, no. 2 (2001): 197–242, https://doi.org/10.1111/j.1095-8649.2001.tb00127.x.

2. M. King, *Fisheries Biology, Assessment and Management*, 2nd ed. (Oxford: Blackwell Publishing Ltd, 2007), https://doi.org/10.1002/9781118688038.

3. B. R. Moore, J. Maclaren, C. Peat, M. Anjomrouz, P. L. Horn, and S. D. Hoyle, "Feasibility of Automating Otolith Ageing Using CT Scanning and Machine Learning," *New Zealand Fisheries Assessment Report* no. 58 (2019).

4. D. V. Politikos, N. Sykiniotis, G. Petasis, et al., "Deep Otolith v1.0: an open-source AI Platform for Automating Fish Age Reading from Otolith or Scale Images," *Fishes* 7, no. 3 (2022): 121, https://doi.org/10.3390/fishes7030121.

5. E. Moen, R. Vabø, S. Smoliński, C. Denechaud, N. O. Handegard, and K. Malde, "Age Interpretation of Cod Otoliths Using Deep Learning," *Ecological Informatics* 78, no. 2 (2023): 102325, https://doi.org/10.1016/j.ecoinf.2023.102325.

6. S. Lek and J. F. Guégan, "Artificial Neural Networks as a Tool in Ecological Modelling, an Introduction," *Ecological Modelling* 120, no. 2–3 (1999): 65–73, https://doi.org/10.1016/S0304-3800(99)00092-7.

7. A. M. Melesse and R. S. Hanley, "Artificial Neural Network Application for multi-ecosystem Carbon Flux Simulation," *Ecological Modelling* 189, no. 3–4 (2005): 305–314, https://doi.org/10.1016/j.ecolmodel.2005.03.014.

8. N. I. Hamwi and N. Ali-Basha, "Estimation of the Vulnerability of Some Sparidae Species to Fishing in the Eastern Mediterranean Sea (Syrian Coast) by Fuzzy Logic Method," *Journal of Al-Baath University* 41, no. 10 (2019): 129–160.

9. N. I. Hamwi, N. Ali-Basha, H. Al-Tajer, and T. Farah, "A Proposed Model to Estimate the Growth of the Fishery Populations by Expert System," *Journal of Hama University* 5, no. 9 (2022): 92–106.

10. B. Russell, K. E. Carpenter, and D. Pollard, "*Oblada melanura*. the IUCN Red List of Threatened Species" (2014), https://doi.org/10.2305/IUCN.UK.2014-3.RLTS.T170197A1291218.en.

11. Iucn, "The IUCN Red List of Threatened Species," (2025), https://www.iucnredlist.org.

12. M.-L. Bauchot and J.-C. Hureau, "Sparidae," in *Check-List of the Fishes of the Eastern Tropical Atlantic (CLOFETA)*, ed. J. C. Quero, J. C. Hureau, C. Karrer, A. Post, and L. Saldanha (Lisbon: JNICT; Paris: SEI, 1990), 790–812.

13. A. Pallaoro, P. Cetinić, J. Dulčić, I. Jardas, and M. Kraljević, "Biological Parameters of the Saddled Bream *Oblada melanura* in the Eastern Adriatic," *Fisheries Research* 38, no. 2 (1998): 199–205, https://doi.org/10.1016/s0165-7836(98)00120-9.

14. H. H. Mahmoud, "Growth and Mortality of Saddled Bream, *Oblada melanura* (Linnaeus, 1758) in Abu Qir Bay, Egypt," *Egyptian Journal of Aquatic Research* 36 (2010): 193–200.

15. R. Crec'hriou, R. Neveu, and P. Lenfant, "Length-Weight Relationship of Main Commercial Fishes from the French Catalan Coast," *Journal of Applied Ichthyology* 29, no. 5 (2013): 1191–1192, https://doi.org/10.1111/jai.12320.

16. N. I. Hamwi, "Growth Biology and Mortality, Survival and Exploitation Rates of *Oblada melanura* (Sparidae) at Syrian Coast," *Journal of Al-Baath University* 39, no. 18 (2017): 11–34.

17. N. Ali-Basha, "Biological Study of Reproductive and Feeding Habitat for *Oblada melanura* in the Coastal Waters of Tartous," (Tishreen University, Faculty of Agriculture, Department of Animal Production (Ichthyology), 2018), 65, M.Sc. Thesis.

18. R. Froese and D. Pauly, eds., *Fishbase* (World Wide Web electronic publication, 2025), https://www.fishbase.org.

Supporting Information

Additional supporting information can be found online in the Supporting Information section. *(Supporting Information)*

Supporting Table S1. Data sources and methodological details for the *Oblada melanura* dataset, including citation, country/region, data type, length measurement, age determination method, and maturity criteria.

Supporting Table S2. Geographical and temporal composition of the dataset used for ANN training ($n = 5112$).

Supporting Note S1. Data provenance and compilation: details on data collection, digitization, harmonization, and integration of published and unpublished sources, including histologically validated specimens from 2023 to 2025.

Supporting Note S2. Ethical and collaborative data use: explanation of data sharing restrictions due to collaborative agreements and third-party ownership.

Supporting Note S3. Availability of the trained model: information on how to request the trained MLP model for noncommercial academic use, subject to a standard data use agreement.