Oceanological and Hydrobiological Studies

International Journal of Oceanography and Hydrobiology

Volume 53, No. 4 December 2024
pages (346-354)

sciendo

ISSN 1730-413X
eISSN 1897-3191

Are conventional methods sufficient to calculate growth parameters of *Pontastacus leptodactylus* (Eschscholtz, 1823)? A case study of artificial intelligence from Keban Dam Lake

by

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DOI: **https://doi.org/10.26881/oahs-2024.4.02**
Category: **Original research paper**
Received: **July 30, 2023**
Accepted: **April 30, 2024**

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Abstract

In this study, the length–weight relationships of *Pontastacus leptodactylus*, a freshwater crayfish species found in the Keban Dam Lake, were assessed using both conventional methods and artificial intelligence techniques. Throughout the research process, all biometric measurements of the crayfish were meticulously recorded, including *TL*, *TW*, and other biometric data. These measurements were analyzed using both the conventional length–weight relationship method and artificial neural networks. The results obtained using artificial neural networks and conventional methods were compared, and the analysis was based on MAPE and R^2 performance criteria. The study showed that the ANNs method outperformed the conventional LWR method, showing more accurate results. The models employed to predict the length–weight relationships of the crayfish demonstrated high accuracy, and the Artificial Neural Networks method was identified as the most effective model. These results provide strong evidence that the ANNs method performs significantly better in predicting the LWRs of freshwater crayfish.

Key words: *Pontastacus leptodactylus*, freshwater lobster, growth, Keban Dam Lake

online at www.oandhs.ug.edu.pl

1. Introduction

Growth parameters of aquatic organisms are crucial for assessing their development and health in aquatic ecosystems. These parameters are used to understand the vital functions of aquatic organisms and their interactions with the environment (Naz et al. 2023). For example, monitoring the growth rate of aquatic animals helps to determine population dynamics, food web relationships, and their impact on water quality. By determining these parameters, necessary data are provided for assessing the well-being of aquatic ecosystems (Rahman et al. 2023), tracking the effects of environmental changes (Saemi-Komsari et al. 2023), and formulating sustainable management strategies (Lu et al. 2023). Therefore, growth parameters serve as an essential tool for understanding the ecological role of aquatic organisms and the state of ecosystem equilibrium.

Pontastacus leptodactylus is a common species of freshwater crayfish in Europe (Alvanou et al. 2022). It is a member of the Astacidae family and is of considerable ecological importance in both terrestrial and aquatic ecosystems. Individuals of this species are usually characterized by a greenish or brownish body color and are distinguished by elongated and slender legs, which differentiate them from other species of freshwater crayfish. They are usually found in benthic environments in rivers, ponds, and marshes (Alekhnovich 2021). In the comprehensive systematics of freshwater crayfish worldwide by Crandall & De Grave (2017), *Pontastacus leptodactylus* Eschscholtz, 1823 is synonymous with *Astacus leptodactylus* Eschscholtz, 1823.

In the case of aquatic organisms such as *Pontastacus leptodactylus*, growth parameters provide essential data for understanding population dynamics, assessing food web interactions, understanding their ecological role and examining their responsiveness to environmental changes (Galib et al. 2022). Conventional methods typically involve measuring body size, weight and age of individuals to calculate growth rates, age-related growth patterns, inter-individual growth variations, and other growth parameters. These well-established methods have been successfully used in scientific studies for many years (Flinn & Midway 2021; Pauly & Morgan 1987). In recent years, however, the development of technologies such as artificial intelligence and machine learning has underscored the importance of incorporating artificial intelligence (AI) supported approaches to determining and analyzing growth parameters (Suryanarayana et al. 2008; Sholahuddin et al. 2015; Benzer & Benzer 2022). AI algorithms can effectively assist in more precise and efficient calculations of growth parameters due to their ability to detect complex patterns and make predictions from large datasets (Misra et al. 2022). For example, image processing and deep learning techniques can be employed for automated measurement of body size and weight of aquatic organisms. Furthermore, AI can facilitate comprehensive analysis of growth rates and patterns, establishing associations with environmental factors.

AI-supported growth parameter analyses can offer a faster, more precise, and efficient approach to scientific research and management of aquatic ecosystems. However, the use of these technologies should be based on reliable data and employ accurate algorithms and data quality to produce verifiable results. Therefore, it is necessary to integrate AI-supported studies with conventional methods to gain a better understanding of growth parameters and develop more effective conservation strategies for the ecological health of aquatic organisms.

In this article, in addition to conventional approaches, the objective is to determine the ecology, age, and growth parameters of the species *Pontastacus leptodactylus*, which belongs to the family Astacidae, using AI methods. These features are intended to provide a valuable contribution to the definition of Astacidae and the widely employed traditional taxonomy.

2. Materials and methods

The Keban Dam Lake is the first artificial lake constructed near the Keban district, located approximately 45 km northwest of Elazığ province and 65 km northeast of Malatya province in Turkey. Constructed on the Euphrates River in 1974, the lake covers an area of 676 km^2. The dam site is situated around 10 km away from the confluence of the Karasu and Murat Rivers. The lake area spans across the provinces of Elazığ, Tunceli, Erzincan, Sivas, and Malatya. Moreover, the Keban Dam Lake serves as a significant source for hydroelectric energy production and contributes to the economy through various sectors, including environmental management and fisheries (DSI, 1982).

In this study, freshwater crayfish were caught for commercial purposes by local fishermen during the 2022 fishing season (July 1 to October 31) using fyke nets (34 mm mesh size). A total of 174 crayfish specimens were examined, of which 82 were females and 92 were males. The captured crayfish were transported to the Fisheries Artificial Intelligence

Laboratory, where the necessary measurements were taken and their sex was determined. The measurements of freshwater crayfish, including carapace length (*CL*), abdomen width (*Aw*), abdomen length (*AL*), carapace width (*Cw*), chela length (*ChL*), chela width (*Chw*), total length (*TL*), and total weight (*TW*), were taken using a measurement instrument with an accuracy of 0.5 mm, and their weight was recorded using a balance with an accuracy of 0.01 g. The collected specimens were placed in nylon containers containing a 4% formaldehyde solution.

The relationship between the length (*TL*) and weight (*TW*) of freshwater crayfish is expressed by a mathematical equation known as the 'length–weight relationship'. This equation is usually expressed as follows:

$$TW = a \times TL^{b}$$

where *TW* is the weight of freshwater crayfish in grams, and *TL* is the length of freshwater crayfish in centimeters (cm). The constants *a* and *b* determine the specific form of the equation. The constant *a* reflects the average weight of crayfish per unit length, while the constant *b* represents the effect of length on crayfish weight.

Artificial Neural Networks (ANNs), inspired by the complex data analysis and learning capabilities of the human brain, have been proposed to automate the process of analyzing complex data and ultimately make intelligent decisions by mimicking the learning function of the brain's neural system. In this study, a network structure with a supervised learning method known as Backpropagation Neural Networks will be used to solve problems. After data normalization, ANNs results were obtained using the Weka application. In general, artificial neural networks start with an input layer and are connected to one or more hidden layers where data are processed. The results are obtained in the output layer (Figure 1). Activation

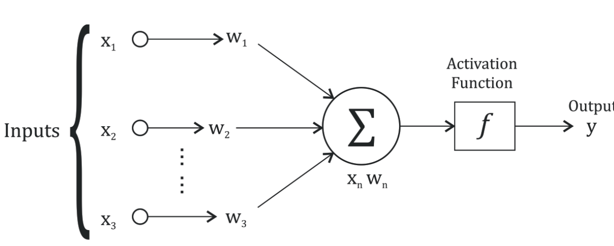

Figure 1

Schematic model of an Artificial Neural Networks (ANNs).

functions or transfer functions in ANNs are typically sigmoid, but they can be replaced by other functions such as a Hopfield network (1988).

Weka, machine learning software written in the Java programming language, stands for "Waikato Environment for Knowledge Analysis". It was developed by researchers at the University of Waikato in New Zealand. Weka is versatile and can be used for various machine learning tasks, including data mining, pattern recognition, exploratory data analysis, prediction, and visualization. It offers a user-friendly graphical interface and also supports a command-line interface. In addition, Weka supports several data formats (CSV, ARFF, C4.5, etc.) and implements various machine learning algorithms (k-NN, Bayes, decision trees, SVM, etc.). Weka is a popular choice for both academic research and industrial applications (Bouckaert et al. 2016).

MAPE, which stands for Mean Absolute Percentage Error, is a common performance measure used to assess the accuracy of predictions made by a model. It is a percentage error measure that represents the average of the absolute differences between the actual values and the predicted values, relative to the actual values. The formula to calculate MAPE is as follows (Montaño Moreno et al. 2013):

$$MAPE = \frac{100}{n}\sum_{j}^{n}\frac{|e_j|}{|A_j|}$$

where:

n = number of samples in the dataset
e_j = actual value of the target variable
A_j = predicted value of the target variable

MAPE provides a useful indication of the model's accuracy by quantifying the average percentage difference between the actual and predicted values for the target variable in the dataset. A low MAPE score indicates that the model is accurate and has a high level of performance, whereas a high MAPE score suggests that the model is less accurate and has a lower level of performance. It should be noted that MAPE is not suitable for datasets containing zero or negative values, as it may result in division by zero error. In summary, MAPE is a commonly used and simple yet effective way to evaluate the performance of machine learning models and measure the accuracy of predictions.

In addition to MAPE, other statistics commonly used to measure the forecasting accuracy (prediction performance) of models (Wang & Lu 2018) include Mean Absolute Error (MAE):

$$MAE = \frac{1}{n}\sum_{j}^{n}\left|e_j\right|$$

and Root Mean Squared Error (RMSE):

$$RMSE = \sqrt{\frac{1}{n}\sum_{j}^{n}\left(e_j\right)^2}$$

The flow chart shown in Figure 2 was used to determine the correlation between total length and total weight using both conventional and AI-based methods.

1.60 cm and 7.50 cm, *AL* (abdomen length) between 2.00 cm and 7.00 cm, *Aw* (abdomen width) between 1.0 cm and 10.50 cm, *ChL* (chela length) between 1.50 cm and 14.00 cm, and *Chw* (chela width) between 0.40 cm and 9.50 cm. Weight values of freshwater crayfish ranged from 11.18 g to 85.94 g, with an average weight of 38.60 g (Table 1). The length (*TL*) ranges of freshwater crayfish in the Keban Dam Lake are shown in Figure 3.

The *TL–TW* relationships were examined for freshwater crayfish in the Keban Dam Lake. The relationship for female crayfish was $W = 0.02172744\ L^{3.0598}$ ($R^2 = 0.949$), while for male crayfish $W = 0.02742281\ L^{3.0569}$ ($R^2 = 0.949$), and for both sexes

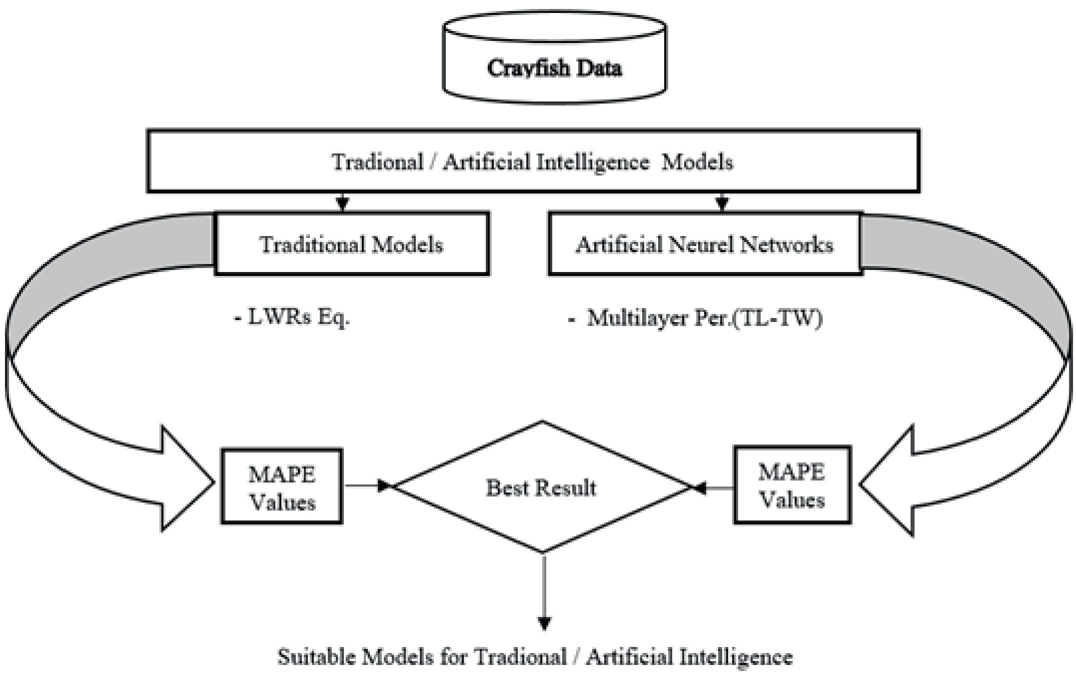

Figure 2

Schematic workflow.

3. Results and discussion

In the conducted study, a total of 174 freshwater crayfish were examined, of which 82 (47.13%) were females and 92 (52.87%) were males, resulting in a female/male ratio of 0.89/1.00. In addition, it was found that the measurements of freshwater crayfish varied within the following ranges: *TL* (total length) between 7.80 cm and 13.70 cm, *CL* (carapace length) between 4.00 cm and 8.00 cm, *Cw* (carapace width) between

combined the relationship was $W = 0.02883869\ L^{2.9909}$ ($R^2 = 0.944$).

The *CL–Cw* relationship was $W = 0.16220909\ L^{1.9137}$ ($R^2 = 0.946$) for female crayfish, $W = 0.26391077\ L^{1.5939}$ ($R^2 = 0.948$) for male crayfish and $W = 0.22762450\ L^{1.6944}$ ($R^2 = 0.947$) for box sexes combined. The *AL–Aw* relationship was $W = 1.06538282\ L^{0.4648}$ ($R^2 = 0.899$) for female crayfish, $W = 1.17325329\ L^{0.3545}$ ($R^2 = 0.857$) for male crayfish and $W = 1.08226637\ L^{0.4302}$ ($R^2 = 0.978$) for both sexes combined. The *ChL–Chw* relationship was $W = 0.38485400\ L^{0.688}$ ($R^2 = 0.920$) for female crayfish, $W = 1.00480182\ L^{0.2419}$ ($R^2 = 0.791$) for male crayfish

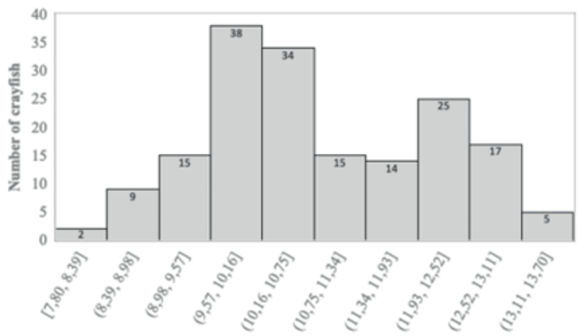

Figure 3

Total length (TL) range.

and $W = 0.64438366\ L^{0.4371}$ ($R^2 = 0.830$) for both sexes combined (Table 2). The graphs of the freshwater crayfish length–weight (*TL–TW*) relationships are shown in Figure 4.

In the artificial neural network approach, the values of carapace length (*CL*), abdomen width (*Aw*), abdomen length (*AL*), carapace width (*Cw*), chela length (*ChL*), chela width (*Chw*), and total weight (*TW*) were input into the system, and the total length (*TL*) value was set as the output to construct the model.

Table 1

Metric characteristics.

Metric characteristic	Sex	Mean ± Sx	Min–Max	t test
TL	♀ ♂ ♀♂	10.88 ± 1.26 10.80 ± 1.37 10.82 ± 1.32	8.80–13.70 7.80–13.50 7.80–13.70	$p < 0.05$
TW	♀ ♂ ♀♂	39.17 ± 15.01 38.48 ± 18.59 38.60 ± 17.35	15.15–73.00 11.18–85.94 11.18–85.94	$p < 0.05$
CL	♀ ♂ ♀♂	5.28 ± 0.65 5.47 ± 0.79 5.38 ± 0.73	4.00–7.00 4.00–8.00 4.00–8.00	$p < 0.05$
Cw	♀ ♂ ♀♂	4.24 ± 1.72 4.28 ± 1.68 4.26 ± 1.70	1.70–7.50 1.60–7.50 1.60–7.50	$p < 0.05$
AL	♀ ♂ ♀♂	5.29 ± 1.09 4.85 ± 1.11 5.06 ± 1.12	2.20–7.50 2.00–7.00 2.00–7.00	$p > 0.05$
Aw	♀ ♂ ♀♂	2.51 ± 1.30 2.23 ± 1.30 2.36 ± 1.30	1.30–8.00 1.00–10.50 1.00–10.50	$p < 0.05$
ChL	♀ ♂ ♀♂	6.30 ± 1.37 7.77 ± 2.19 7.08 ± 1.99	2.00–11.50 1.50–14.00 1.50–14.00	$p < 0.05$
Chw	♀ ♂ ♀♂	1.48 ± 0.75 1.94 ± 1.50 1.74 ± 1.22	0.40–4.50 0.50–9.50 0.40–9.50	$p < 0.05$

Sx – standard error; *TW* – total weight; *Cw* – carapace width; *CL* – carapace length; *Chw* – chela width; *ChL* – chela length; *TL* – total length; *AL* – abdomen length; *Aw* – abdomen width; ♀ – female; ♂ – male; ♀♂ – females + males

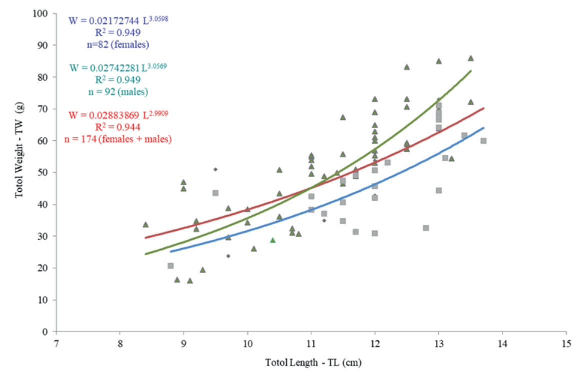

Figure 4

Length–weight relationships for freshwater crayfish from Keban Dam Lake.

Table 2

Relationship parameters, equations, and correlation coefficients.

Metric characteristic	Sex	LWRs	R^2
TL – TW	♀ ♂ ♀♂	$W = 0.02172744\ L^{3.0598}$ $W = 0.02742281\ L^{3.0569}$ $W = 0.02883869\ L^{2.9909}$	0.949 0.949 0.944
CL – Cw	♀ ♂ ♀♂	$W = 0.16220909\ L^{1.9137}$ $W = 0.26391077\ L^{1.5939}$ $W = 0.22762450\ L^{1.6944}$	0.946 0.948 0.947
AL – Aw	♀ ♂ ♀♂	$W = 1.06538282\ L^{0.4648}$ $W = 1.17325329\ L^{0.3545}$ $W = 1.08226637\ L^{0.4302}$	0.899 0.857 0.878
ChL – Chw	♀ ♂ ♀♂	$W = 0.38485400\ L^{0.688}$ $W = 1.00480182\ L^{0.2419}$ $W = 0.64438366\ L^{0.4371}$	0.920 0.791 0.830

LWRs – length–weight relationship; R^2 – correlation coefficients

The data obtained from the Keban Dam Lake were split into 70% for training and 30% for prediction. Following the examination of 174 individual freshwater crayfish, the predicted *TL* results are shown in Figure 5. Statistical results for the obtained ANN results are presented in Table 3, and the correlation is shown in Figure 6. The results show that the data for *TL* and *TW* are well modeled with a correlation coefficient of approximately 99% and 96%, respectively (Table 3).

Table 3

Results of statistical analyses with ANNs.

Statistical approach and sample size	Results (Length)	Results (Weight)
Correlation Coefficient	0.9927	0.9625
Kendall's tau	0.9453	0.8314
Spearman's rho	0.9921	0.9603
Mean Absolute Error (MAE)	0.1320	7.5331
Root Mean Squared Error (RMSE)	0.1787	8.5914
Number of samples in prediction	174	174

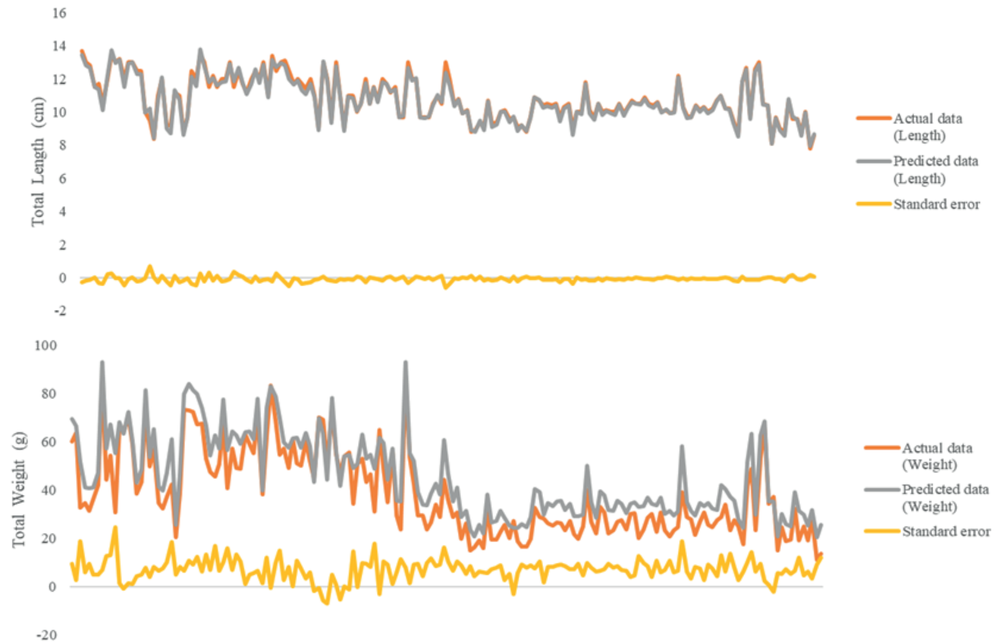

Figure 5

ANNs *TL* and *TW* prediction results and standard error graph.

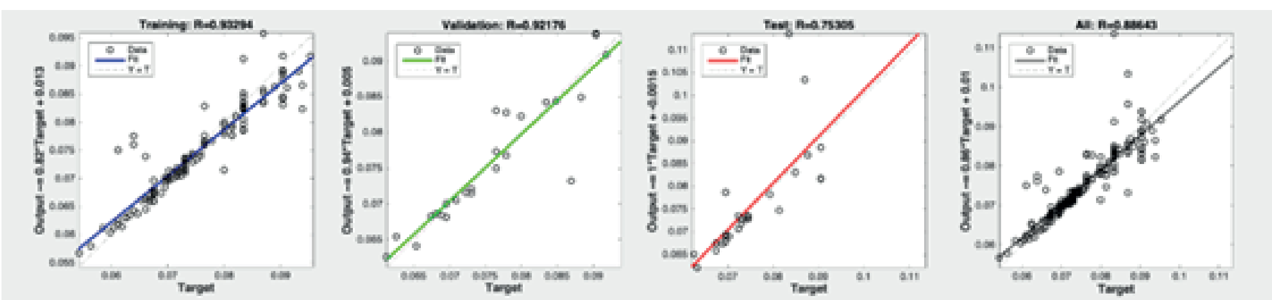

Figure 6

Correlation graph of *TL* predictions by ANNs.

Table 4 shows the results of ANNs and *LWR* for the values of freshwater crayfish from the Keban Dam Lake. It was observed that the measurements of certain characteristics of freshwater crayfish from the Keban Dam Lake are similar to those in the available literature (Table 5).

In this study conducted in the Keban Dam Lake, it was observed that the number of male individuals was higher than the number of female individuals, and the female-to-male sex ratio was 0.89:1. Several studies (Balık et al. 2005; Aydın et al. 2015; Benzer et al. 2015; Benzer & Benzer 2015; Benzer et al. 2017; Roljić et al. 2019) have reported that the number of males is higher than the number of females. However, Benzer & Benzer (2020) found in their study conducted in Lake Yeniçağa that the number of female individuals was higher

Table 4

Results of ANNs and *LWRs* for freshwater crayfish from the Keban Dam Lake.

Sex	Keban DamLake		ANNs		MAPE (%)		LWRs		MAPE (%)	
	TL	*TW*	*TL*	*TW*	*TL*	*TW*	*TL*	*TW*	*TL*	*TW*
♀	10.88	39.17	10.795	46.360	0.79	15.51	11.14	32.58	2.33	20.23
♂	10.81	38.48	10.725	45.656	0.79	15.72	11.02	38.88	1.91	1.03
♀♂	10.82	38.60	10.740	45.793	0.74	15.71	11.20	35.76	3.39	7.94

Table 5

Comparison of parameters for freshwater crayfish available in the literature.

Study Area	Sex	*TL*	*TW*	LWRs parameters			Sex ratio (females/males)
				a	*b*	R^2	
Balık et al. (2005) Demirköprü Dam Lake	♀ ♂	92.88 90.18	24.19 25.43	0.00002 0.00001	3.06 3.27	0.97 0.98	0.49:1
Wang et al. (2011) Ponds	♀ ♂	68.50 69.90	18.85 17.50	0.033 0.074	3.023 2.638	-	-
Aydın et al. (2015) Lake İznik	♀ ♂	104.17 95.71	32.50 28.82	0.00003 0.000008	3.01 3.30	0.97 0.97	0.89:1
Benzer et al. (2015) Lake Mogan	♀	108.71	28.64	0.00220024	2.021	0.99	0.14:1
	♂	102.93	32.49	0.00095247	2.229	0.99	
Benzer & Benzer (2015) Dikilitaş Pond	♀ ♂	110.6 113.5	38.52 50.02	0.03105469 0.05958618	2.98 2.76	0.98 0.99	0.68:1
Benzer et al. (2017a) Lake Eğirdir	♀ ♂ ♀♂	128.40 135.50 133.10	59.79 82.95 75.12	0.05425196 0.05272102 0.03589889	2.7357 2.8094 2.9374	0.986 0.976 0.971	0.51:1
Hossain et al. (2017) Culture	♀♂	50.2	32.30	0.4304	2.8216	0.94	-
Benzer et al. (2017b) Hirfanlı Dam Lake	♀ ♂ ♀♂	126.00 128.50 127.50	52.80 75.52 66.43	0.032933 0.041409 0.022299	2.91 2.89 3.02	0.96 0.97 0.96	0.66:1
Benzer & Benzer (2018) Lake Uluabat	♀ ♂ ♀♂	118.72 117.80 118.26	40.86 45.43 43.16	0.04059605 0.02999258 0.03634341	2.775 2.947 2.845	0.968 0.959 0.961	1:1
Roljic et al. (2019) Vrbas River	♀♂	98.86	27.28	-	-	-	0.56:1
Mazlum et al. (2019) Keban Dam Lake	♀♂	97.40	27.14	0.024	3.08	0.96	-
Benzer & Benzer (2020) Lake Yeniçağa	♀ ♂ ♀♂	118.17 122.15 119.88	42.04 49.09 45.06	0.12949911 0.18113315 0.14162875	2.326 2.218 2.301	0.975 0.964 0.968	1:0.75
Shaaban et al. (2021) Nile River (Helwan)		-	26.81	–1.867	3.169	0.821	-
This study Keban Dam Lake	♀	10.88*	39.17	0.02172744	3.060	0.949	0.89:1
	♂	10.81*	38.48	0.02742281	3.057	0.949	
	♀♂	10.82*	38.60	0.02883869	2.991	0.944	

than the number of male individuals. These divergent results are believed to be due to biological factors and fishing methods used in wetlands with different ecological characteristics.

Although the mean total lengths and total weights of both sexes were almost the same, it was observed that males had higher mean lengths and weights compared to females. It was found that the total length (*TL*) values of freshwater crayfish in the Keban Dam Lake were higher than those in the Demirköprü Dam Lake (Balık et al. 2005), culture ponds located at the Zhougang Field Stations (Wang et al. 2011), Lake İznik (Aydın et al. 2015), culture ponds located at the Research Institute of Fish Culture in Vodnany (Hossain et al. 2017), the Vrbas River (Roljić et al. 2019), and the Keban Dam Lake (Mazlum et al. 2019). Some researchers have reported that *TL* values of males and females were higher than those in the Keban Dam Lake (Benzer et al. 2017a; Benzer et al. 2017b; Benzer & Benzer 2018; Benzer & Benzer, 2020). Similar results were obtained for total weight (*TW*) values (Table 5).

In this study, the slope (*b*) values of the length–weight relationship were determined as 3.060, 3.057, and 2.991 for females, males, and all individuals, respectively. The intercept of the relationship (*a*) for all individuals was 0.02883869. The obtained b values were similar to those reported in other studies (Table 5). Growth in this study exhibited a positive allometric pattern. Similar results were also reported in previous studies conducted in the Demirköprü Dam Lake (Balık et al. 2005), culture ponds located at the Zhougang Field Stations (Wang et al. 2011), Lake İznik (Aydın et al. 2015), and the Keban Dam Lake (Mazlum et al. 2019). However, negative allometric growth patterns were observed in studies conducted in Lake Mogan (Benzer et al. 2015), Dikilitaş Pond (Benzer & Benzer 2015), Lake Eğirdir (Benzer et al. 2017a), culture ponds located at the Research Institute of Fish Culture in Vodnany

(Hossain et al. 2017), and Lake Yeniçağa (Benzer & Benzer 2020) (Table 5). These differences can be attributed to factors such as environmental conditions, food availability, population density, and the selectivity of traps or fyke nets used in the studies.

Estimation of length–weight relationships in fisheries studies is model-dependent. This can be a challenge when evaluating a dataset, especially when the amount of data is insufficient and confidence intervals of parameters fall below the nominal level (May et al. 2011; Sun et al. 2022). Therefore, when comparing the results obtained from artificial neural networks (ANNs) with those obtained from the traditional length–weight relationship (*LWR*) approach, it is crucial to assess their accuracy. When analyzing the Mean Absolute Percentage Error (MAPE) results of LWR and ANNs, it appears that ANNs are likely to yield better results than *LWR* (Table 4). Specifically, in predicting Total Length (*TL*) data, ANNs achieved approximately 99% accuracy with MAPE values of 0.79, 0.79, and 0.74 for females, males, and all individuals, respectively. In contrast, *LWR* showed MAPE values of 2.33, 1.91, and 3.39, resulting in around 97% accuracy. Similarly, when estimating total weight, ANNs achieved a MAPE value of 15.51 for females, while *LWR* obtained a MAPE value of 20.23, indicating that ANNs are more suitable in this context. As shown in Table 4, however, *LWR* outperforms ANNs when considering males and all individuals. In this context, it is anticipated that conventional methods can be considered alongside artificial neural network (ANN) methods, and ANNs can serve as an alternative prediction tool for various parameters.

4. Conclusions

In this study, the ANNs method showed better results compared to the *LWRs* method. A comparative study using all the models determined that they all provide high accurate predictions. Of these models, the ANNs model was identified as the best-performing model. Similar results were found in other studies. Therefore, researchers have concluded that ANNs models should be considered a valuable technique in fisheries prediction. High R^2 and low MSE and MAPE values are considered by researchers as indicators of a good model. Hence, it is known that compared to regression analysis, ANNs yield fewer erroneous results and achieve a higher rate of accurate predictions. In this study, the ANNs method was found to have significantly high performance in predicting the length–weight relationships for freshwater crayfish. Overall, the results indicate that the ANNs method exhibits a robust performance in predicting the length–weight relationships of freshwater crayfish, making it a valuable approach for fisheries forecasting.

References

Alekhnovich, A. (2021). Characteristics of populations of narrow-clawed crayfish *Pontastacus leptodactylus* in three Belarusian lakes of the Baltic sea catchment area. *Baltic Coastal Zone, 25*, 19–30.

Alvanou, M. V., Papadopoulos, D. K., Lattos, A., Georgoulis, I., Feidantsis, K., Apostolidis, A. P., Michaelidis, B., & Giantsis, I. A. (2022). Biology, distribution, conservation status and stocking perspective of freshwater crayfish in Greece: An updated review. *Aquaculture Research, 53*(15), 5115–5128. https://doi.org/10.1111/are.16009

Aydın, H., Harlioglu, M. M., & Deniz, T. (2015). An investigation on the population parameters of freshwater crayfish (*Astacus leptodactylus* Esch., 1823) in Lake Iznik (Bursa). *Turkish Journal of Zoology, 39(4)*, 660–668. https://doi.org/10.3906/zoo-1406-6

Balık, S., Ustaoğlu, M. R., Sarı, H. M., & Berber, S. (2005). Determination of traits some growth and morphometric of crayfish (*Astacus leptodactylus* Eschscholtz, 1823) at Demirköprü Dam Lake (Manisa). [in Turkish]. *Ege Journal of Fisheries and Aquatic Sciences, 22*(1-2), 83–89.

Benzer, R., & Benzer, S. (2020). Alternative approaches to traditional methods for growth parameters of fisheries industry: Artificial Neural Networks. Enterprise & Business Management: A Handbook for Educators. Consultants, and Practitioners.

Benzer, S., Benli, Ç. K., & Benzer, R. (2015). The comparison of growth with length-weight relation and artificial neural networks of crayfish, *Astacus leptodactylus*, in Mogan Lake. *Journal of the Black Sea/Mediterranean Environment, 21*(2), 208–223.

Benzer, S., & Benzer, R. (2015). Determine some morphological characteristics of crayfish (*Astacus leptodactylus* Eschscholtz, 1823) with traditional methods and artificial neural networks in Dikilitas Pond, Ankara, Turkey. *Fresenius Environmental Bulletin, 24(11A)*, 3727–3735.

Benzer, S., Benzer, R., & Günal, A. (2017a). Artificial neural networks approach in length-weight relation of crayfish (*Astacus leptodactylus* Eschscholtz, 1823) in Eğirdir Lake, Isparta, Turkey. *Journal of Coastal Life Medicine, 5(8)*, 330–335. https://doi.org/10.12980/jclm.5.2017J7-19

Benzer, S., Benzer, R., & Günal, A. (2017b). Artificial neural networks approach in morphometric analysis of crayfish (*Astacus leptodactylus*) in Hirfanlı Dam Lake. *Biologia, 72*(5), 527–535. https://doi.org/10.1515/biolog-2017-0052

Benzer, S., & Benzer, R. (2018). New perspectives for predicting growth properties of crayfish (*Astacus leptodactylus* Eschscholtz, 1823) in Uluabat Lake. *Pakistan Journal of*

Zoology, 50(1), 35–45.

Benzer, S., & Benzer, R. (2022). Morphometric analysis of Crayfish–traditional and artificial intelligent approach. *Thalassas, 38*(2), 989–996. https://doi.org/10.1007/s41208-022-00447-z

Bouckaert, R. R., Frank, E., Hall, M., Kirkby, R., Reutemann, P., Seewald, A., & Scuse, D. (2016). WEKA manual for version 3-9-1. University of Waikato.

Crandall, K. A., & De Grave, S. (2017). An updated classification of the freshwater crayfishes (Decapoda: Astacidea) of the world, with a complete species list. *Journal of Crustacean Biology, 37*(5), 615–653. https://doi.org/10.1093/jcbiol/rux070

DSI. (1982). Keban Fishery Project Aquaculture Turkey. IDRC 3- P-75-0034. General Directorate of State Hydraulic Works Reports. Turkish.

Flinn, S. A., & Midway, S. R. (2021). Trends in growth modeling in fisheries science. *Fishes, 6*(1), 1-18. https://doi.org/10.3390/fishes6010001

Galib, S. M., Sun, J., Gröcke, D. R., & Lucas, M. C. (2022). Ecosystem effects of invasive crayfish increase with crayfish density. *Freshwater Biology, 67*(6), 1005–1019. https://doi.org/10.1111/fwb.13897

Hossain, M. S., Kouba, A., & Buřič, M. (2019). Morphometry, size at maturity, and fecundity of marbled crayfish (*Procambarus virginalis*). *Zoologischer Anzeiger, 281*, 68–75. https://doi.org/10.1016/j.jcz.2019.06.005

Lu, W., Li, P., Ma, B., Huo, T., Yin, Z., Tang, F., & Wang, J. (2023). Assessment of fishery management parameters for major prey fish species in the lower reaches of the Songhua River. *Frontiers in Marine Science, 10*, 1166634. https://doi.org/10.3389/fmars.2023.1166634

May, R., Dandy, G., & Maier, H. (2011). Review of input variable selection methods for artificial neural networks. *Artificial neural networks-methodological advances and biomedical applications*, 10(1), 19-45. https://doi.org/10.5772/16004

Mazlum, Y., Can, M. F., & Öksüz, A. (2019). Diversification of narrow-clawed crayfish (*Pontastacus leptodactylus* Eschscholtz, 1823) populations from different parts of Turkey. *Marine and Life Sciences, 1*(1), 1–9.

Misra, N. N., Dixit, Y., Al-Mallahi, A., Bhullar, M. S., Upadhyay, R., & Martynenko, A. (2020). IoT, big data, and artificial intelligence in agriculture and food industry. *IEEE Internet of Things Journal, 9*(9), 6305–6324. Advance online publication. https://doi.org/10.1109/JIOT.2020.2998584

Montaño Moreno, J. J., Palmer Pol, A., Sesé Abad, A., & Cajal Blasco, B. (2013). Using the R-MAPE index as a resistant measure of forecast accuracy. *Psicothema, 25*(4), 500–506. https://doi.org/10.7334/psicothema2013.23 PMID:24124784

Naz, S., & Chatha, A. M. M. (2023). Efficacy of Insect Feed as Protein Source in Aqua Feed and its Impact on Growth Performance of Fish. *BioScientific Review, 5*(2), 39–49. https://doi.org/10.32350/BSR.52.05

Pauly, D., & Morgan, G. R. (Eds.). (1987). Length-based methods in fisheries research (Vol. 13). WorldFish.

Rahman, M. A., Manon, M. R. K., Ullah, M. R., Alam, A., Islam, M. J., Siddik, M. A. B., & Iqbal, M. M. (2023). Biometric indices, growth pattern, and physiological status of captive-reared indigenous Yellowtail brood catfish, *Pangasius pangasius* (Hamilton, 1822). *Environmental Science and Pollution Research International, 30*, 83388–83400. https://doi.org/10.1007/s11356-023-28328-9 PMID:37340162

Roljić, R., Nikolić, V., & Savić, N. (2019). Morphological Variability and Sexual Dimorphism of Danube Crayfish *Pontastacus leptodactylus* Eschscholtz, 1823 from the Vrbas River. *Water Resources Management, 9*(2), 27–32.

Saemi-Komsari, M., Esmaeili, H. R., Keshavarzi, B., Abbasi, K., Birami, F. A., Nematollahi, M. J., Tayefeh, F. H., & Busquets, R. (2023). Characterization of ingested MPs and their relation with growth parameters of endemic and invasive fish from a coastal wetland. *The Science of the Total Environment, 860*, 160495. https://doi.org/10.1016/j.scitotenv.2022.160495 PMID:36455731

Shaaban, E., El-Sayed, A., El Feky, F., Gawad, A., Soad, M., & Mohammed, N. H. (2021). Spatial Variations in The Length-Weight Relationship and Relative Condition Factor of The Introduced Freshwater Crayfish, *Procambarus clarkii*,(Girard, 1852) from the River Nile and Its Tributaries, Egypt. *Egyptian Academic Journal of Biological Sciences. B, Zoology, 13*(2), 135–146. https://doi.org/10.21608/eajbsz.2021.201694

Sholahuddin, A., Ramadhan, A. P., & Supriatna, A. K. (2015). The application of ANN-Linear Perceptron in the development of DSS for a fishery industry. *Procedia Computer Science, 72(2015)*, 67–77. https://doi.org/10.1016/j.procs.2015.12.106

Sun, Q., Zhang, M., Zhou, L., Garme, K., & Burman, M. (2022). A machine learning-based method for prediction of ship performance in ice: Part I. ice resistance. *Marine Structures, 83*, 103181. https://doi.org/10.1016/j.marstruc.2022.103181

Suryanarayana, I., Braibanti, A., Rao, R. S., Ramam, V. A., Sudarsan, D., & Rao, G. N. (2008). Neural networks in fisheries research. *Fisheries Research, 92*(2-3), 115–139. https://doi.org/10.1016/j.fishres.2008.01.012

Wang, Q., Yang, J. X., Zhou, G. Q., Zhu, Y. A., & Shan, H. (2011). Length–weight and chelae length–width relationships of the crayfish *Procambarus clarkii* under culture conditions. *Journal of Freshwater Ecology, 26*(2), 287–294. https://doi.org/10.1080/02705060.2011.564380

Wang, W., & Lu, Y. (2018). Analysis of the mean absolute error (MAE) and the root mean square error (RMSE) in assessing rounding model. In IOP conference series: Materials Science and Engineering *324, 012049*. IOP Publishing., https://doi.org/10.1088/1757-899X/324/1/012049