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RESEARCH PAPER

A Novel Artificial Neural Network Based Approach for Validating Length–Weight Relationships and Assessing Condition Factor in Whiting (*Merlangius merlangus euxinus* L., 1758)

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Abstract

The popularity of artificial neural networks (ANNs) in the field of fish population management studies is increasing daily, with the potential to provide more rapid and efficient results. Length-weight relationship (LWR) and condition factor (CF) are very important in fisheries management. In addition, it enables the estimation of the amount of fish at the beginning of the fishing period by using LWR in terms of sustainable fishing. In this study, data was estimated with alternative models of ANN to calculate the classical CF used to evaluate the LWR. For the case application, whiting (*Merlangius merlangus euxinus L., 1758*) samples (n=1408) caught from the Black Sea coast of Giresun were used. The root mean square error (RMSE), mean absolute percent error (MAPE) and R^2 of the model were 0.1674, 0.0930, and 0.99869, respectively. The results showed that the Single Multiplicative Neuron (SMN)-ANN model yielded the highest accuracy according to performance criteria. Consequently, the findings indicate that the model effectively predicts the CF, thus validating its estimation capability. This study represents the initial research in predicting the CF for whiting by the SMN-ANN model.

Introduction

In fisheries management, the success of breeding programs and production systems depends on accurately measuring and evaluating specific phenotypic features in individual organisms (Fernandes et al., 2020). The biology of the fishes and its living surroundings determine the necessary control instruments to manage the populations of fish sustainably (Costa et al., 2022). Biological indices used in aquaculture are also regarded as biological indicators of the variability within species, populations, and ecosystems, for example, density and biomass, and also condition indices such as hepatosomatic index (HSI) and condition factor (CF) (Costa et al., 2022; Matthias et al., 2018; Rau et al., 2019).

Length-Weight Relationship (LWR) is primarily used in estimating the biomass of the length distributions and or obtaining status indices (Gerritsen & McGrath, 2007). It provides critical data for estimating the population metrics and bio-energetics of the fish (Dinh et al., 2022; Jisr et al., 2018). Most analyses involving fisheries data typically require the estimation of LWR model parameters which is considered fundamental (Andrade & Campos, 2002). A correct prediction of LWR is of great importance not only for stock management and biomass estimation, but also for the increasingly important issue of protecting biodiversity (Dash et al., 2023). Biodiversity conservation is an increasingly important issue, and special attention needs to be focused on non-destructive monitoring of fish, especially endemic or vulnerable species (Yang et al., 2022). While LWRs offer an efficient but invasive method for monitoring fish populations, recent developments in artificial intelligence (AI) and machine learning (ML) present novel opportunities to automate and improve the prediction of critical fisheries indicators like CF (Álvarez-Ellacuría et al., 2020). AI-focused methods allow for large-scale, real-time monitoring, improving prediction accuracy and supporting sustainable fishing and protective efforts (Gesami & Nunoo, 2024).

The Artificial Neural Networks (ANNs) are models inspired from the structure and the working of the processes of biological thinking and learning, they can effectively create robust models from a few inputs and high degree of data dispersion and depend on the data being modeled from which non-linear data can be derived (Brosse et al., 2001). ANNs are capable of generating robust models from a small number of inputs that can effectively cover highly dispersed and non-normal data and produce credible forecasts, depending on the strongly non-linear data being modeled (Czerwinski et al., 2007). ANNs are increasingly accepted as a technique that offers an innovative approach to overcoming complex and well-defined problems. Once trained, they can learn from examples, are robust to error in the sense that they can process missing data and noisy data, can deal with non-linear problems, and are capable of high-speed forecasting and generalizations (Kalogirou, 2001). The ANN is noted as a dependable, and alternative way of studying the growth patterns of some species of fish (Ozcan, 2019). There is an increasing number of studies that have sought to understand the dynamics of fish populations leveraging ANNs. The Mediterranean bottom fish species distribution estimation was done with Maravelias et al. (2003). Zheng and Zhang, (2010) attempted to calculate the number of a fish population through a fuzzy neural network method; Ordonez et al. (2020) studied the fish age estimation by a trained neural network model through fish otolith image analysis; Andayani et al. (2019) classification of fish species with the probabilistic neural network; Fish weight estimation through image analysis was done by Konovalov et al. (2019). The ANN captures the attention of many scholars due to its potential applications. For instance, advances in condition factor (CF) estimation have shown that ANN approaches are more convenient and useful than existing calculation methods owing to their reliable and accurate results.

In recent years, Single Multiplicative Neuron (SMN), which has been offered as an alternative to general ANNs, has been proposed because of its simple network structure and fast learning ability (Bas et al., 2016, 2016; Herz et al., 2006). In addition, it has been successfully applied to time series estimation in the study (Bas et al., 2016; Cagcag Yolcu et al., 2018; Egrioglu et al., 2023; Egrioglu & Bas, 2022; Gul et al., 2024; Işık et al., 2024). The SMN model is characterized by several benefits, such as greater approximation abilities, easier network architectures, and quicker training algorithms (Bas et al., 2023; Gul et al., 2024). Nonlinear filters are able to manage additional disturbances, and owing to the iterative design of the algorithm, they can also adjust the modeling settings as new data are received (Wu et al., 2013). The SMN-ANN is a very simple structure and requires less number weighting and bias compared to well-known ANN models (Egrioglu et al., 2023). The SMN methodology is far easier to implement than the traditional MLP method, and it can provide much higher efficiencies if trained appropriately. Moreover, their achievement, like MLP, is based on the estimation of the model variables during the offline training and online training steps (Samanta, 2015).

This is the first study to predict the CF of whiting (*Merlangius merlangus euxinus* L., 1758) using SMN-ANN and machine learning techniques. Our study primarily innovates by predicting the traditionally calculated CF using the SMN-ANN approach and machine learning ANN. It is important to note that this methodology provides a framework for subsequent comparison of the data. In this application, CF prediction can be made with big data sets without the requirement for manual calculations. Thus, the proposed methodology offers a viable solution that offers the potential to engender significant reductions in the time and labour required. It is also intended to identify areas for improvement in the work, with the main outputs to be obtained.

Material and Method

The fish were studied on whiting (*Merlangius merlangus euxinus* L., 1758) (n=1409) bought from the local fish market in Giresun province in the eastern Black Sea region of Türkiye. The total length (TL) of each specimen was measured to the nearest 0.1 cm and their weight was determined using digital balance with precision of 0.01 g.

Statistical Calculations

The homogeneity as well as the normality of the data were checked and verified by the Kolmogorov-Smirnov test and the Shapiro-Wilk normality test by SPSS 26 software.

Length-Weight Relationships

The LWR studies have been widely performed for fisheries. They are important as they provide information about the growth, general welfare and suitability in the marine habitat (Dağtekin et al., 2022) and the b-value from the LWR is important for assessing fisheries status (Dinh et al., 2022; Froese & Pauly, 2002). The 'b' value in fish indicates the growth type according to the conditions in the environment where the fish live (Çayır and Bostancı, 2022). In determining the LWR, irrespective of the sex of the fish samples, the relationship is expressed as:

$$W = a \times L^{b} \quad (1)$$

The LWR was linearized as $log(W) = log(a) + b \times log(L)$, where W is body weight (g), L is total length (cm), a is the intersection point and b is the slope of the linear regression (Froese, 2006).

Condition Factor

The CF value assesses nutritional status based on height and weight measurements (Jin et al., 2015). Kumolu-Johnson and Ndimele, (2010) as well as Oni et al. (1983) believe this value is important in monitoring the density of feeding, growth, and the age of fish. The current and future populations will be measured based on CF, which quantifies fish welfare and thus influences their growth, reproduction, and survival (Jana et al., 1974). The following formula expresses the strain's Fulton calculation with the CF.

$$K = 100 \times (W/L^3) \text{ (2)}$$

where, W is weight in grams and L is total lenght in cm (Fulton, 1904).

Artificial Neural Networks

Artificial intelligence (AI) is often defined as a computer with human-level intelligence and can be applied in business, healthcare, travel industry, autonomous vehicle, social media and education. ANN is a kind of artificial intelligence model that imitates the operation of the human brain (Aniza et al., 2022; Raj et al., 2021). ANNs represent a new approach to time series estimation. In the last decade there has been a growing interest in using ANNs to model and predict time series (Wu et al., 2015). ANN generally consists of input, hidden and output layers. Each layer consists of several nodes and neurons with weights assigned to perform simple operations to calculate the output (Relvas & Miranda, 2018). ANNs can derive optimum values from complex and nonlinear data with acceptable efficiency. ANN works on the principle of transmitting information through the interconnection of several neurons. They simulate the human nervous system and work like the brain (Paturi et al., 2022). A general network is presented in Figure 1.

Traditionally, neural networks have a very simple structure consisting of only input and output layers, and these are called single-layer neural networks or shallow neural networks. Neural networks with more than one hidden layer are called multilayer neural networks or deep neural networks. Most of the contemporary neural networks used in practical applications are deep neural networks (Kim, 2017; Matel et al., 2022). A few examples of machine learning techniques are support vector machines (SVM), decision trees (DT), random forests (RF), extreme gradient boosting (XGBoost), artificial neural network (ANN) models, and more new models. ANN models are based on the neural networks seen in living things. The perceptron method, radial basis function network (RBF), extreme learning machine (ELM), and back propagation (BP) are examples of ANN learning algorithms (Li et al., 2022).

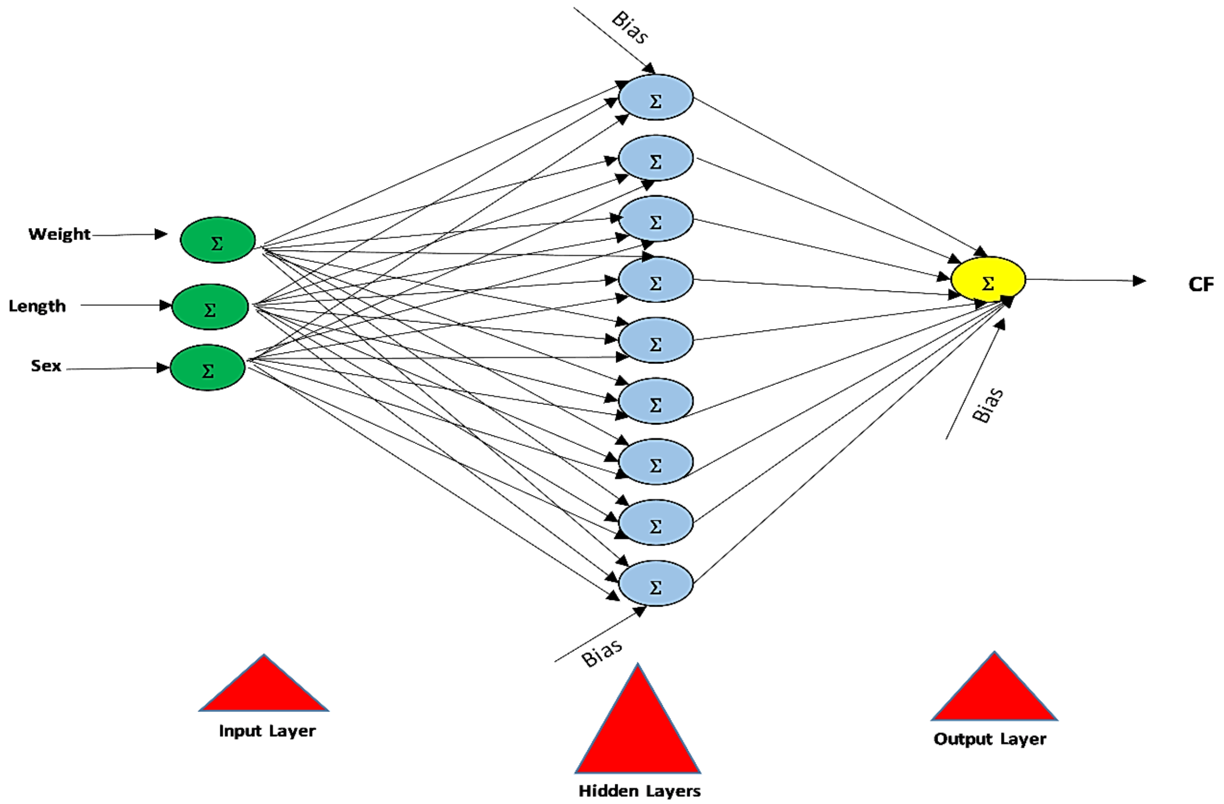

Figure 1. ANN architecture utilized in this study.

Single Multiplicative Neuron-ANN

The Single Multiplicative Neuron (SMN) model was used to generate the nonlinear observed mapping of dynamic filters. Dynamic filters are used to train the SMN model sequentially online by adjusting the model parameters within the framework of minimum variance (Wu et al., 2015). The new SMN model has been put forth as a new approach to the general MLP type of ANN. The SMN model is derived from neuroscience's single neuron computation (Koch, 1997; Koch & Segev, 2000; Samanta, 2011). As stated in Kolay and Tunç, (2021) SMN has a lower computation cost than MLP and PSNN because it has a simpler structure with fewer parameters. The SMN neuron model is based on the average of the multiplicative inputs. In other words, the SMN neuron model has input of the weighted sum of its inputs (Attia et al., 2012). In this work, the multiplicative single neuron model function approach proposed in Yadav et al., (2007) implemented as a machine learning. Because the number of neurons required is much lower, the model's generalization ability exceeds that of a multilayer perceptron configured neural network. The architecture of the single multiplicative artificial neural network is illustrated in Figure 2.

In the SM-ANN, the output is computed as a non-linear transformation of the product of the linear transformations of the inputs. The computations of the outputs of the single multiplicative artificial neural network with p inputs are computed using the following formulas:

$$net = \prod_{i=1}^{p}(w_i \times input_i + b_i) \quad (3)$$

$$output = \frac{1}{1+\exp(-net)} \quad (4)$$

The ANN contains a total of 2p weights and biases values. Training this neural network is a problem of estimating 2p parameters. The objective function in the optimization problem can be used as the sum of squares of error. The optimization problem is expressed as follows:

$$\min_{\{w_1,\dots,w_p,b_1,\dots,b_p\}} \sum_{j=1}^{n}\left(output_j - target_j\right)^2 \quad (5)$$

In formula (5), n stands for the amount of learning examples. The solution to the problem of optimization gives a set of the parameters that will make the network outputs as close as possible to the targets (or also called set point).

The optimization problem presented in formula (5) can be addressed using methods of nonlinear least squares as well as a whole range of artificial intelligence optimization approaches such as genetic and particle swarm optimization. It is well recognized that particle swarm optimization yields very effective outcomes during the training of artificial neural networks. In this investigation, a PSO training algorithm that simulates flock intelligence devised for numerical optimization problems is adopted. The training algorithm based on PSO is outlined stepwise below.

Algorithm 1. The PSO-based training algorithm for a single multiplicative artificial neural network manual.

Step 1. The parameters relating to the processes of the training are set.

pn: The size of the swarm or the number of particles, c_1: Social coefficient, c_2: Cognitive coefficient, w: Inertia weight, ε: error tolerance for relative error difference, $maxitr$: maximum number of iterations.

The counters are established. The re-start strategy counter (rsc) and early stopping counter (esc) are assumed to be zero.

Step 2. The following outlines how the starting coordinates and velocities are chosen in a random manner:

$$X_{i,j}^{(0)} \sim Uniform(0,1) \quad (6)$$

$$V_{i,j}^{(0)} \sim Uniform(-1,1) \quad (7)$$

$X_{i,j}^{(k)}$ is j^{th} position value of ith particle of the population at k^{th} iteration. The positions of an element in a population correspond to the weights and biases values of the neural network, and there are $2p$.

Step 3. The CF function values are calculated for each swarm member. The CF function is selected as the sum of square errors.

$$SSE = \sum_{j=1}^{n}(output_j - target_j)^2 \quad (8)$$

Step 4. Based on the computed values of the CF function, the optimal value from the population, (X_{best}^{k}) is selected as gbest and its CF value (SSE_{best}^{k}) stored. In addition, the Pbest matrix is formed as a storage for every particle in the swarm.

Step 5. A new swarm is created by replacing the positions of all elements in the swarm with the following equation.

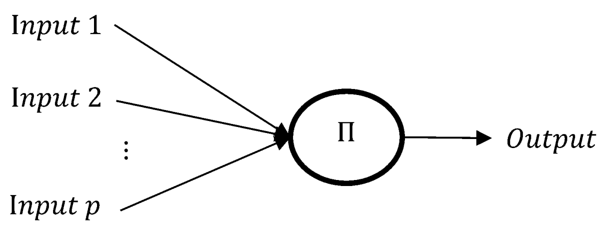

Figure 2. The architecture of the single multiplicative artificial neural network.

$$V_{i,j}^{(k+1)} = wV_{i,j}^{(k+1)} + c_1 r_1 (Pbest_{i,j}^{(k)} - X_{i,j}^{(k)}) + c_2 r_2 (Xbest_j^{(k)} - X_{i,j}^{(k)}) \quad (9)$$

$$X_{i,j}^{(k+1)} = X_{i,j}^{(k)} + V_{i,j}^{(k+1)} \quad (10)$$

Step 6. The CF function values are calculated for each swarm member by using equation (9). According to the calculated CF function values, the best element (X_{best}^{k}) in the population and its CF value (SSE_{best}^{k}) are obtained and compared with SSE_{best}^{k-1}. If $SSE_{best}^{k} > SSE_{best}^{k-1}$ then $SSE_{best}^{k} = SSE_{best}^{k-1}$.

Step 7. The re-starting strategy counter ($rsc = rsc + 1$) is increased and its value is checked. If the $rsc > limit1$ then all positions are re-generated by using (6) and (7), the rsc is taken as zero.

Step 8. The early stopping rule is checked. The esc counter is increased depending on the following condition.

$$esc = \begin{cases} esc + 1, if \ \frac{SSEbest^{(k)} - SSEbest^{(k-1)}}{SSEbest^{(k)}} < \varepsilon \\ 0, \ otherwise \end{cases} \quad (11)$$

If $esc > limit2$ is satisfied, the algorithm is stopped otherwise go to Step 5.

Machine Learning Algorithms

In order to evaluate ANN models for CF prediction, the machine learning Toolbox 12.4 in the MATLAB environment was used. Using the cross-validation procedure reduced the possibility of overestimation. For testing purposes, the data set was split up into five levels, and each layer's prediction and validation were assessed independently. The objective of this approach is to enhance the overall performance of the model and prevent overfitting.

In this study, the weight and bias parameters for the customized ANN model were optimized, with the following hyperparameters set: Activation=ReLU, Iteration limit=1000, Optimiser=Bayesian optimisation, Number of fully connected layers=3, First layer size=10, Second layer size=10, Third layer size=10, and Activation=ReLU. The machine learning ANN algorithms used in the study are listed in Table 1 along with their corresponding kernel functions.

Neural Network Models and Hyperparameter Configurations

This study examines different ANN models used in MATLAB. The data in Table 2 contains the hyperparameters of six different ANN models. The Optimisable Neural Network stands out as a flexible model that can vary between 1 to 3 layers and utilize different activation functions. Other models have predefined layer and neuron structures. The Wide Neural Network consists of a single wide layer with 100 neurons, while the Bilayered and Trilayered Neural Networks contain two and three layers, respectively. The Medium and Narrow Neural Networks are single-layer architectures with 25 and 10 neurons, respectively.

The ReLU activation function is predominantly used across all models, except for the Optimisable Neural Network, which also explores Sigmoid, Tanh, ReLU, and None as activation options. The regularization strength (Lambda) is set to zero in most models, with the exception of the Optimisable Neural Network, which optimizes it within a defined hyperparameter range. This raises concerns about the risk of overfitting, suggesting the necessity of regularization. Additionally, all models apply data standardization.

In conclusion, the Optimisable Neural Network offers the highest flexibility due to its broad hyperparameter search space, whereas other models are optimized for specific configurations. Future studies could analyze the impact of different activation functions and regularization parameters on performance to determine the most suitable model configurations.

Determining the Correctness of the Model

To assess the models, they were evaluated using the criteria of mean square error (RMSE), coefficient of determination (R^2) and mean absolute percent error (MAPE) respectively Equations given in, respectively were used to determine RMSE (12), MAPE (13) and R^2 (14) Training the model, performing statistical analysis of parameters, and calculating correlations coefficients, error analysis, etc. mainly performed on the MATLAB 2018b by using notebook with Intel(R) Core (TM) i5-1235U CPU 4.40 GHz processor.

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(output_t - target_t)^2} \quad (12)$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{output_t - target_t}{target_t}\right| \quad (13)$$

$$\mathrm{R}^2 = 1 - (\sum_{t=1}^{n}(\mathrm{output_t} - \mathrm{target_t})^2 / (\mathrm{output_t} - \mathrm{target_t}^{-})^2 \quad (14)$$

It presents the predicted data in relation to the observed data. n is the total number of time series data

Table 1. Machine learning ANN algorithms used in the study

Neural Network & Algorithm / Kernel Function					
Narrow Neural Network	Medium Neural Network	Wide Neural Network	Two-Layer Neural Network	Three-Layer Neural Network	Custom Neural Network

sets. RMSE refers to the mean of the forecasts' errors on the same forecast line, while for the data set, n MAPE refers to the mean of absolute errors on the given forecast line. The larger the accuracy of the model is the smaller the value of RMSE and MAPE (Chicco et al., 2021). Furthermore, the RMSE specifies whether the observed value corresponds with the predetermined value of the model. The investigation of the relation between dependent and independent variables is realized using correlation, whereas the variance of dependent and independent variables is explained using R^2 (Jasmin et al., 2022).

Results and Discussion

In this part, we provide the computed outcomes for the condition factor alongside the estimation results derived from performing the SMN-ANN algorithm. The MATLAB environment was used for the programming of this algorithm. In the end, some performance evaluation tests were conducted to check the accuracy obtained in forecasting the CF results.

Length-Weight Relationship and CF

The total lengths of 1409 specimens varied between 10.1 and 27.6 cm, with the average of 14.90±0.041 cm and their weights varied between 8.0 and 94.0 g, with the average of 24.45±0.22 g. The length-weight relationship for all individuals was calculated as $W=0.0184*L^{2.648}$ (Figure 3). The lengths and weights of the fish vary between 27.6 and 10.1 cm and 94.0 and 8.0 g, respectively. The b value, which was calculated according to the least squares method and showing the body shape of the fish, was calculated as 2.648. This shows that the fish grew negatively allometrically. In this study, while calculating the condition factor, the value of 3 was taken assuming that the fish grows isometrically. The mean condition factor was 0.72±0.003.

Application of Single Multiplicative Neuron-ANN for CF

Accuracy criteria were used to evaluate the effectiveness of the CF calculated from whiting (*Merlangius merlangus euxinus L., 1758*) fish in estimating based on the SMN-ANN algorithm. In this way, estimations were made on all data of each condition factor with calculations. RMSE and MAPE criteria were chosen for the accuracy of the actual estimation. The all-ANN applications were conducted in Matlab by using notebook with Intel(R) Core (TM) i5-1235U CPU 4.40 GHz processor. The weight and bias estimates obtained for the optimal neural network architectures and CF values are given in Figure 4 and Table 3.

Lewis scale was used in this study to interpret the MAPE result. According to the Lewis scale, MAPE less than 10% signifies highly accurate forecast, whereas MAPE within 10% to 20% range shows good forecast, MAPE within 20% to 50% range implies a reasonable forecast, and MAPE greater than 50% reflects inaccurate forecast (Dey et al., 2023). As shown in Table 3, the SMN-ANN achieved a MAPE of 0.0930 in predicting CF, denoting high predictive accuracy. Unlike many studies, the MAPE value of SMN-ANN was found to be quite low (Benzer et al., 2017; Benzer and Benzer, 2018; 2016; Ozcan, 2019). The model with lower RMSE value is considered as the best prediction performance model (Ibrahim et al., 2023). When the literature was examined, no study on fish condition factor related to RMSE verification method was found. However, it was determined that RMSE was widely used in different studies. This study determined that the RMSE applied to the condition factor was relatively low compared to other studies (Chou et al., 2018; Zhou et al., 2018 ; Latif et al.,2022). Figure 5. shows the comparative analysis of the model's prediction results. It can be seen from the figure that the SMN-ANN algorithm can predict the approximate trend when compared with the observed values.

Table 2. Neural networks models types and hyperparameters

Model Type	Preset	Hyperparameters
Neural Network	Optimisable Neural Network	Iteration limit: 1000; Optimized Hyperparameters; Number of fully connected layers: 1; Activation: Sigmoid; Regularization strength (Lambda): 2.2828e-08; Standardize data: Yes; First layer size: 16; ; Hyperparameter Search Range; Number of fully connected layers: 1-3; Activation: ReLU, Tanh, Sigmoid, None; Standardize data: Yes, No; Regularization strength (Lambda): 7.1023e-09-71.0227; First layer size: 1-300; Second layer size: 1-300; Third layer size: 1-300
	Wide Neural Network	Number of fully connected layers: 1; First layer size: 100; Activation: ReLU; Iteration limit: 1000; Regularization strength (Lambda): 0; Standardize data: Yes
	Bilayered Neural Network	Number of fully connected layers: 2; First layer size: 10; Second layer size: 10; Activation: ReLU; Iteration limit: 1000; Regularization strength (Lambda): 0; Standardize data: Yes
	Trilayered Neural Network	Number of fully connected layers: 3; First layer size: 10; Second layer size: 10; Third layer size: 10; Activation: ReLU; Iteration limit: 1000; Regularization strength (Lambda): 0; Standardize data: Yes
	Medium Neural Network	Number of fully connected layers: 1; First layer size: 25; Activation: ReLU; Iteration limit: 1000; Regularization strength (Lambda): 0; Standardize data: Yes
	Narrow Neural Network	Number of fully connected layers: 1; First layer size: 10; Activation: ReLU; Iteration limit: 1000; Regularization strength (Lambda): 0; Standardize data: Yes

Performance Evaluation of Artificial Neural Network Models

The assessment of different ANN models using basic evaluation criteria namely RMSE, MSE, R^2 and MAE is presented in Table 4. These criteria give an idea regarding the accuracy and generalisability of the models. The model with the lowest error rates and the highest R^2 score was taken as the best model.

According to the results of the RMSE value, the best one is the Optimisable Neural Network with a RMSE value of 0.00425, the MSE value of 0.00002 and MAE value of 0.00075 along with a highest R^2 value of 0.99869. This shows the model can predict better than other ANN structures. The better performance of the Optimisable Neural Network is due to its optimised hyperparameter setting, the use of different activation functions and the ability to dynamically adjust layers. Unlike that, models error are more while the R^2 value was less. Comparatively, predictive faculties are poor comparing with this model. In view of these results, the Optimisable Neural Network is the best-performing model in this study. Research in future should test it on other dataset, analyse overfitting robustness and check performance with more layers. These investigations will provide additional insight into the generalization ability and applicability of ANN models in practice. As compared to earlier literature on machine learning-based predicting studies, this study has improved performance significantly. The results achieved at several measuring stations, with high R^2 values (up to 0.99), demonstrate the accuracy of the proposed model.

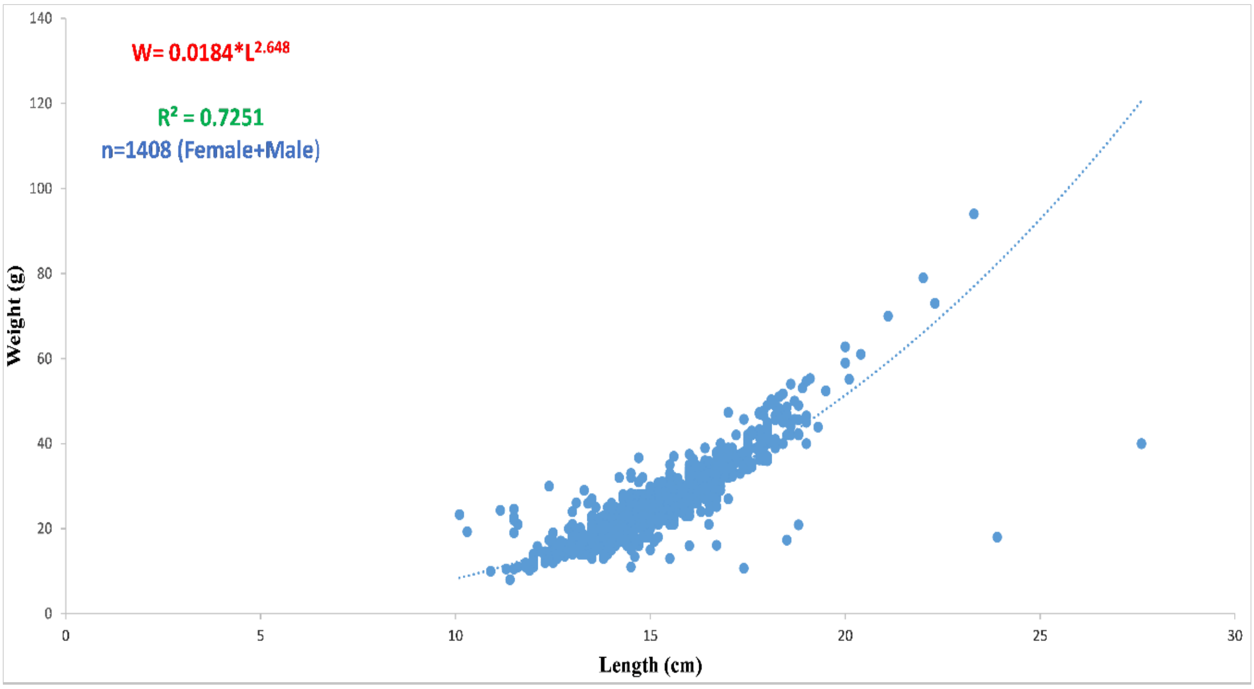

Figure 3. Lenght-weight relationship for all individuals.

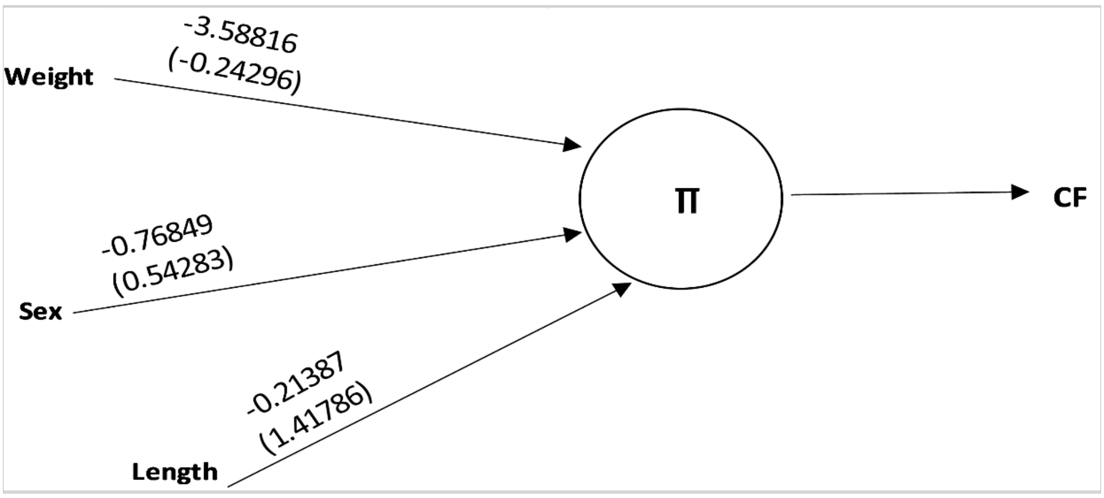

Figure 4. The optimum single multiplicative neuron model artificial neural network for CF.

These results show a greater success rate than other similar strategies that have been reported in literature. Ozcan, (2024) revealed 0.96297 to be the highest R^2 value obtained for validation. Moreover, the low RMSE values (0.00425) further reinforce the efficiency and accuracy capacity of the model. The results obtained in the same way indicate a higher level of success compared to similar studies in the literature. Khan & See, (2016) reported the highest RMSE value reached in the validation process as 0,0181. Mutlu & Akkan, (2025) reported that the GPR model predicted the condition factor for horse mackerel (*Trachurus mediterraneus* Steindachner, 1868) in the Black Sea with the highest accuracy, giving an RMSE value of 0.0017240. Furthermore, Akkan et al., (2024) showed that the GPR model most accurately predicted the CF of *Nemipterus randalli* Russel, 1986 in the Mediterranean Sea, yielding an RMSE value of 0.00100807.

The Optimisable Neural Network model employed in this study effectively depicts the relationships between predicted and observed values. As can be seen from the Figure 6, the model has generated accurate predictions by capturing the general structure of the data to a large extent. The model's predictions are particularly close to the observed values in the dominant dataset range, indicating that it is well adapted to the data. As for the model's performance, low error rates (RMSE and MSE) and a high coefficient of determination (R^2=0.99869) indicate that the model has a very successful generalization capacity, demonstrating that it operates largely without producing systematic errors and that the predicted values are highly reliable.

Table 3. Data and validation values used for SMN-ANN simulation

CF						Weights and Biases		
Test Values	Predicted Values	Test Values	Predicted Values	Test Values	Predicted Values	$CF1$	$CF2$	$CF3$
0.7726	0.7424	0.7500	0.7887	0.6068	0.6708	-3.588169	-0.7684929	-0.2138756
0.7438	0.7577	0.6499	0.7753	0.8163	0.7474	**b1**	**b2**	**b3**
0.7445	0.7340	0.6600	0.7291	0.6552	0.6996	-0.24297	0.542833	1.417865
0.7210	0.7114	0.6024	0.6489	0.7052	0.7236			
0.7970	0.7329	0.7268	0.7563	0.7040	0.7068	**RMSE**	**0.1674**	
0.7572	0.7282	0.6506	0.7013	0.7544	0.6802	**MAPE**	**0.0930**	
0.7187	0.7106	0.7629	0.7752	0.6954	0.7223			
0.6593	0.7059	0.7429	0.7236	0.7294	0.7252			
0.7718	0.7224	0.6757	0.7196	0.7089	0.7102			
0.6460	0.6930	0.7335	0.7241	0.8127	0.7130			
0.6590	0.6955	0.7249	0.6835	0.6528	0.7164			
0.6798	0.7003	0.6166	0.6836	0.6077	0.6808			
0.8185	0.7353	0.7052	0.7236	0.6692	0.6805			
0.6516	0.7315	0.6439	0.6671	0.6773	0.7087			
0.6703	0.6858	0.7157	0.7198	0.6162	0.7139			
0.7848	0.7418	0.6462	0.7155	0.7722	0.7546			
0.6669	0.7304	0.8634	0.7263	0.8348	0.7832			
0.7174	0.7686	0.7230	0.7181	0.7566	0.7266			
0.7407	0.7398	0.6976	0.7268	0.8436	0.7519			
0.6570	0.7108	0.6838	0.7089	0.6773	0.7370			
0.7004	0.7238	0.7064	0.7184	1.6175	0.8540			
0.6757	0.7060	0.6865	0.6857	0.6606	0.7046			
0.6924	0.7333	0.7378	0.6827	0.8179	0.7334			
0.6736	0.7303	0.7502	0.6809	0.7752	0.7522			
0.6869	0.7126	0.6008	0.6941	1.1610	0.7964			
0.6899	0.7055	0.7118	0.7197	0.7729	0.7364			
0.6961	0.7417	0.6950	0.7288	2.2615	0.9088			
0.6698	0.6832	0.7551	0.6922	0.6305	0.6893			
0.7232	0.7198	0.7198	0.7238	0.5411	0.6613			
0.6530	0.7083	0.7678	0.7518	0.7838	0.7143			
0.7500	0.7406	0.6651	0.7160	0.6321	0.7211			
0.6928	0.7204	0.6385	0.6683	0.6961	0.7084			
0.6445	0.6927	0.6380	0.6566	0.7352	0.7141			
0.9074	0.7712	0.6779	0.7527	0.6338	0.6573			
0.6758	0.7519	0.7407	0.7211	0.6396	0.7146			
0.8919	0.7825	0.7704	0.7260	0.6422	0.6591			
0.7098	0.7220	0.4306	0.6830	0.7523	0.7797			
0.7192	0.7065	0.7647	0.7687	0.4947	0.6798			
0.6422	0.7426	0.5894	0.7104	0.7530	0.7180			
0.6739	0.7224	0.6122	0.7365	0.6971	0.7170			
0.7039	0.7398	0.5846	0.7242	0.6322	0.6588			
0.6503	0.7088	0.6519	0.7063	1.7530	0.8674			
0.7396	0.7574	0.7881	0.7805	1.0924	0.7930			
0.6963	0.7533	0.7378	0.7206	0.7010	0.7326			
0.6178	0.7403	0.7072	0.7486	0.6265	0.7128			
0.6883	0.7440	0.6284	0.6529	0.7184	0.7254			
0.7556	0.7372	0.7531	0.7269					

Analysis of the graph reveals that the model's predictions are comparatively less sensitive at specific extremes and that the anticipated values are concentrated in a particular region. This implies, however, that the model is not too sensitive to extremes and has a more balanced structure in detecting extreme values. Furthermore, the model has effectively learned the data distribution and struck the ideal balance between accuracy and precision, as seen by the fact that most of the projected values are near to the observed values.

The observed and anticipated values were compared in order to assess the prediction accuracy of the Optimisable Neural Network model that was employed in this investigation. Analysis of Figure 7 reveals that the majority of the projected values have a distribution that is quite near to the ideal prediction line (y=x line). This demonstrates that the model successfully learns the patterns on the dataset and can predict the real values with a high accuracy rate.

The model's error analysis reveals that there are very few differences between the expected and observed values. It was discovered that only a small number of extremes deviated from the ideal prediction line, indicating that while the model can generate predictions that are generally applicable, there may be tiny error margins at some extreme values. Nonetheless, the model's general stability and dependability are supported by the small number of deviations. Figure 8 illustrates the evolution of the Optimizable Neural Network model's minimal MSE throughout training as well as the effectiveness of the hyperparameter optimization procedure. The iterations are shown on the X-axis, while the minimal MSE value is shown on the Y-axis. Examining the model's optimization process reveals that the error value fluctuates significantly in the initial iterations, but that the model's error rate slowly drops and stabilizes at a specific level in subsequent iterations.

In the early phases, the model's sensitivity to the optimization process and its quick learning ability are demonstrated by the abrupt drops in the MSE value. The error value, however, is seen to follow a horizontal trajectory after a specific number of iterations,

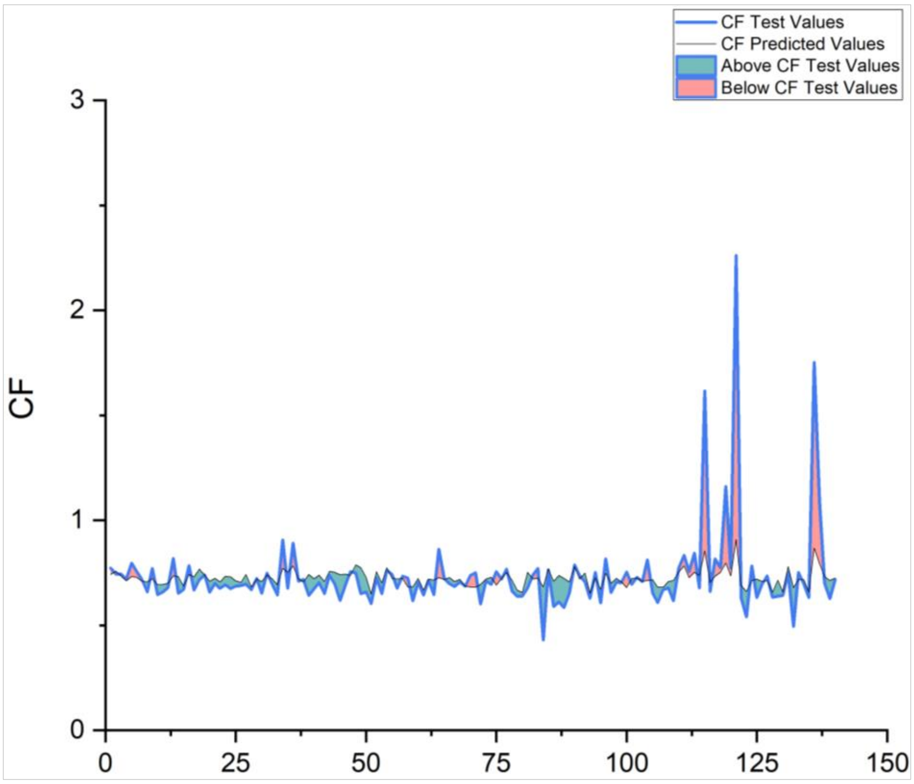

Figure 5. Comparison results between test data and prediction results.

Table 4. Performance evaluation of various neural network architectures in prediction

Model	RMSE	MSE	R^2	MAE
Optimisable Neural Network	0.00425	0.00002	0.99869	0.00075
Wide Neural Network	0.00851	0.00007	0.99475	0.00168
Bilayered Neural Network	0.01128	0.00013	0.99076	0.00329
Trilayered Neural Network	0.01179	0.00014	0.98990	0.00291
Medium Neural Network	0.01900	0.00036	0.97379	0.00343
Narrow Neural Network	0.02804	0.00079	0.94290	0.00717

suggesting that the model offers a steady convergence and that the optimal hyperparameters are achieved. The stages in which the optimal parameters were identified are denoted by the square (best point hyperparameters) and circle (least error hyperparameters) symbols on the graph. These results show that the model's hyperparameter optimization procedure was successfully finished and that the model achieved the lowest possible error level. Consequently, the learning process continually obtained the lowest error rate, and the model hyperparameter optimization procedure was effectively finished. This demonstrates the model's strong potential for generalization as well as its consistent and dependable predicting performance.

Conclusion and Suggestions

In this study, the performance of the SMN-ANN based prediction model was evaluated for the prediction of CF obtained from whiting. The estimation of this standard value, which provides crucial information about the condition factor, the morphological structure of fish, and their nutritional and developmental status, will be of great convenience. The fact that the estimation results of the SMN algorithm are close to the test data indicates that this application has yielded a successful outcome. The low MAPE value (0.0930) also enhances the reliability of the algorithm. However, further analysis revealed that the Optimisable Neural Network model significantly outperformed the SMN-ANN model in terms of prediction accuracy. The model achieved an exceptionally low RMSE (0.00425) and MAE (0.00075), indicating minimal error margins. In addition, the high R^2 value of 0.99869 indicates that the model explains nearly all the variance in the dataset, proving its reliability. These findings underscore the neural networks better performance optimization and CF value forecasting accuracy driven by the Optimisable Neural Network approach.

The SMN model, while exhibiting a solid learning ability, highly reliable results, and further contributing to the literature, was outperformed by the Optimisable Neural Network model that showcased superior accuracy and efficiency. More precise forecasting models enable better monitoring of the fish growth and development processes, resulting in the sustainable and efficient production of aquaculture. Future studies should test these models' generalizability by using different datasets and applying cross-validation to check their reliability under different conditions. Furthermore, the models are compatible with a wide variety of data types, including survey data (measurements), satellite

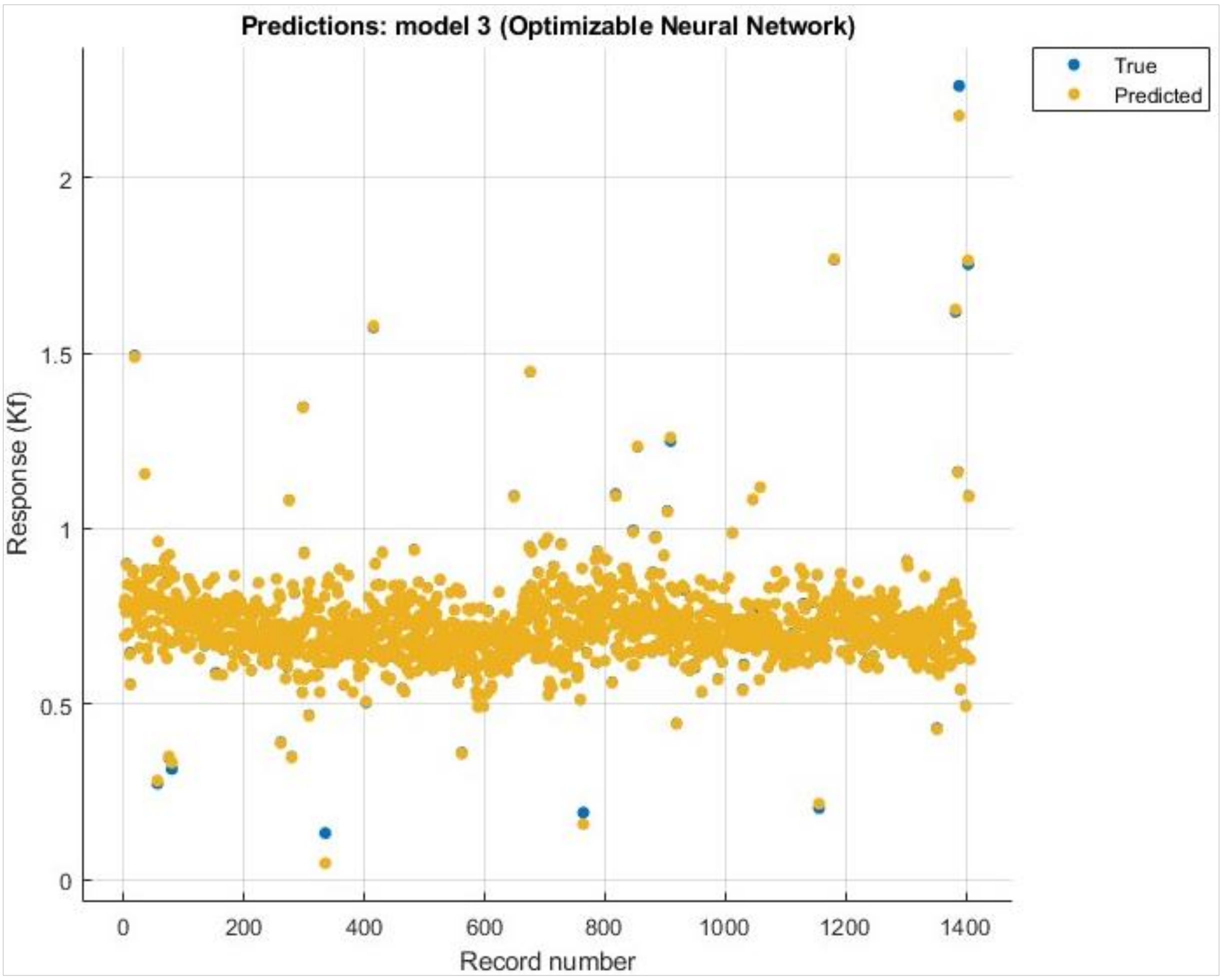

Figure 6. Scatter point analysis for predicted and observed values.

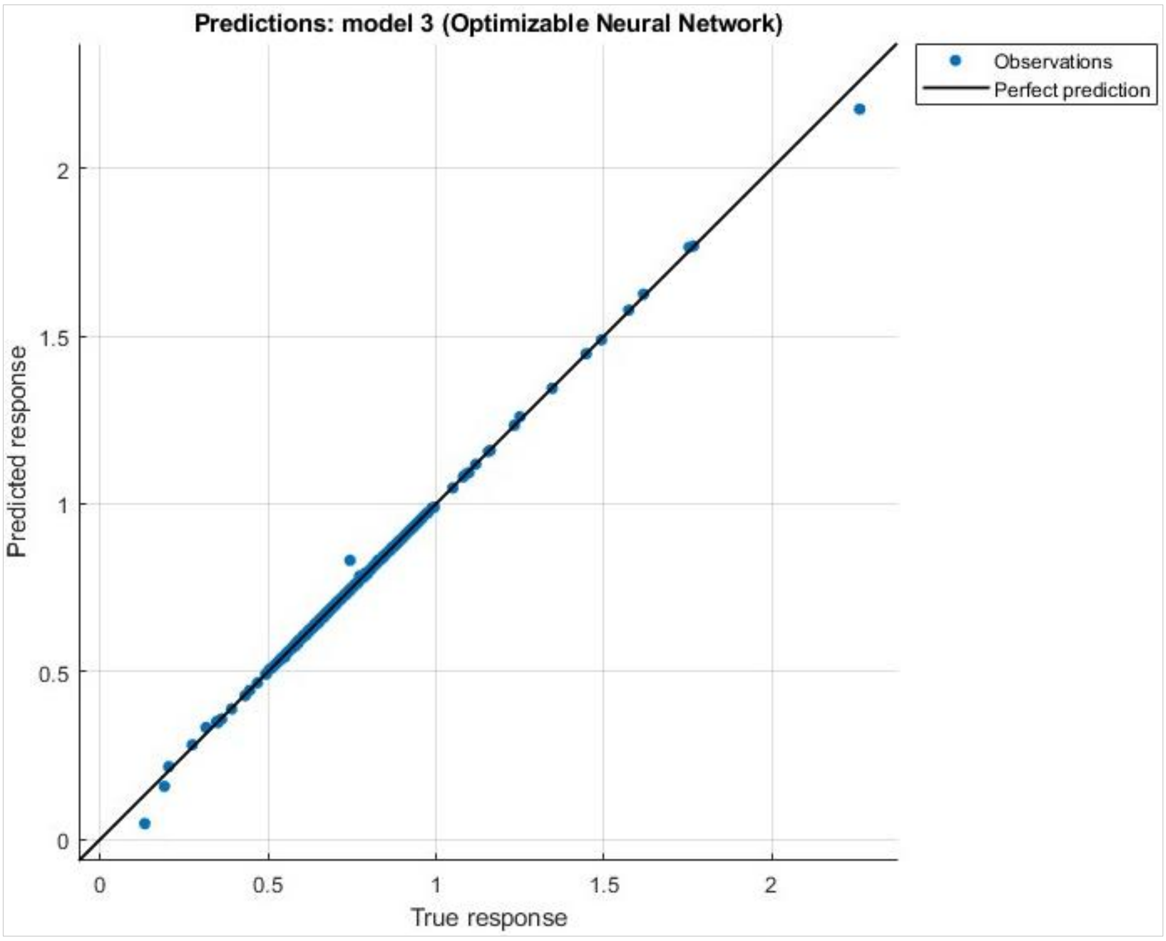

Figure 7. Correspondence between predicted and observed values.

data (water temperature, chlorophyll), and laboratory data (nutrient content), and thus represent a valuable contribution to bioecological studies.

Ethical Statement

Ethics approval and consent to participate not applicable for this study.

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Author Contribution

The author confirms sole responsibility for the following: study conception and design, data collection, analysis and interpretation of results, and manuscript preparation.

Conflict of Interest

The author declare that they have no known competing financial or non-financial, professional, or personal conflicts that could have appeared to influence the work reported in this paper.

References

Akkan, T., Mutlu, C., Işik, H., Yazicioğlu, O., Yazici, R., Yilmaz, M., & Polat, N. (2024). Determination of fish condition factor using artificial neural networks and machine learning algorithms. *Acta Biologica Turcica*, *37*(1), J8-11.

Álvarez-Ellacuría, A., Palmer, M., Catalán, I. A., & Lisani, J.-L. (2020). Image-based, unsupervised estimation of fish size from commercial landings using deep learning. *ICES Journal of Marine Science*, *77*(4), 1330–1339. https://doi.org/10.1093/icesjms/fsz216

Andayani, U., Wijaya, A., Rahmat, R., Siregar, B., & Syahputra, M. (2019). Fish species classification using probabilistic neural network. *Journal of Physics: Conference Series*, *1235*(1), 012094. https://doi.org/ 10.1088/1742-6596/1235/1/012094

Andrade, H. A., & Campos, R. O. (2002). Allometry coefficient variations of the length–weight relationship of skipjack tuna (*Katsuwonus pelamis*) caught in the southwest South Atlantic. *Fisheries Research*, *55*(1–3), 307–312. https://doi.org/10.1016/S0165-7836(01)00305-8

Aniza, R., Chen, W.-H., Yang, F.-C., Pugazhendh, A., & Singh, Y. (2022). Integrating Taguchi method and artificial neural network for predicting and maximizing biofuel production via torrefaction and pyrolysis. *Bioresource Technology*, *343*, 126140. https://doi.org/10.1016/j.biortech.2021.126140

Attia, M. A., Sallam, E. A., & Fahmy, M. M. (2012). A proposed generalized mean single multiplicative neuron model.

2012 IEEE 8th International Conference on Intelligent Computer Communication and Processing, 73–78. https://doi.org/10.1109/ICCP.2012.6356163

Bas, E., Egrioglu, E., Yolcu, U., & Chen, M.Y. (2023). A robust learning algorithm based on particle swarm optimization for Pi-Sigma artificial neural networks. *Big Data*, *11*(2), 105–116. https://doi.org/10.1089/big.2021.0064

Bas, E., Yolcu, U., Egrioglu, E., Yolcu, O. C., & Dalar, A. (2016). Single multiplicative neuron model artificial neuron network trained by bat algorithm for time series forecasting. *Am J Intell Syst*, *6*(3), 74–77. https://doi.org/10.5923/j.ajis.20160603.03

Benzer, S., & Benzer, R. (2016). Evaluation of growth in pike (*Esox lucius* L., 1758) using traditional methods and artificial neural networks. *Applied Ecology and Environmental Research*, *14*(2), https://doi.org/543–554. 10.15666/aeer/1402_543554

Benzer, S., & Benzer, R. (2018). New perspectives for predicting growth properties of crayfish (A*stacus leptodactylus* Eschscholtz, 1823) in Uluabat Lake. *Pakistan Journal of Zoology*, *50*(1).

Benzer, S., Benzer, R., & Günal, A. Ç. (2017). 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

Brosse, S., Lek, S., & Townsend, C. R. (2001). Abundance, diversity, and structure of freshwater invertebrates and fish communities: An artificial neural network approach. *New Zealand Journal of Marine and Freshwater Research*, *35*(1), 135–145. https://doi.org/10.1080/00288330.2001.9516983

Cagcag Yolcu, O., Bas, E., Egrioglu, E., & Yolcu, U. (2018). Single multiplicative neuron model artificial neural network with autoregressive coefficient for time series modelling. *Neural Processing Letters*, *47*, 1133–1147. https://doi.org/10.1007/s11063-017-9686-3

Çayır, Z., & Bostancı, D. (2022). Determination of Length-Weight and Length-Length Relationships for Garfish *Belone belone* inhabiting in Different Coasts of Kocaeli (Turkey). *The Black Sea Journal of Sciences*, *12*(1), 33–42. https://doi.org/10.31466/kfbd.906270

Chicco, D., Warrens, M. J., & Jurman, G. (2021). The coefficient of determination R-squared is more informative than SMAPE, MAE, MAPE, MSE and RMSE in regression analysis evaluation. *Peerj Computer Science*, *7*, e623. https://doi.org/10.7717/peerj-cs.623

Costa, E. F., Teixeira, G. M., Freire, F. A., Dias, J. F., & Fransozo, A. (2022). Effects of biological and environmental factors on the variability of *Paralonchurus brasiliensis* (Sciaenidae) density: An GAMLSS application. *Journal of Sea Research*, *183*, 102203. https://doi.org/10.1016/j.seares.2022.102203

Czerwinski, I. A., Gutierrez-Estrada, J. C., & Hernando-Casal, J. A. (2007). Short-term forecasting of halibut CPUE: Linear and non-linear univariate approaches. *Fisheries Research*, *86*(2–3), 120–128. https://doi.org/10.1016/j.fishres.2007.05.006

Dağtekin, M., Genç, Y., Kasapoğlu, N., Erik, G., Misir, D. S., Ilhan, S., Ok, M., Altuntaş, C., Özsandıkçı, U., & Büyükdeveci, F. (2022). Length-weight relationships of 28 fish species caught from demersal trawl survey in theMiddle Black Sea, Turkey. *Turkish Journal of Zoology*, *46*(1), 67–73. https://doi.org/10.1016/10.3906/zoo-2109-21

Dash, G., Sen, S., Pradhan, R. K., Ghosh, S., Josileen, J., & Jayasankar, J. (2023). Modeling framework for establishing the power law between length and weight of fishes and a meta-analysis for validation of LWRs for six commercially important marine fishes from the northwestern Bay of Bengal. *Fisheries Research*, *257*, 106496. https://doi.org/10.1016/j.fishres.2022.106496

Dey, B., Roy, B., Datta, S., & Ustun, T. S. (2023). Forecasting ethanol demand in India to meet future blending targets: A comparison of ARIMA and various regression models. *Energy Reports*, *9*, 411–418. https://doi.org/10.1016/j.egyr.2022.11.038

Dinh, Q. M., Nguyen, T. H. D., Nguyen-Ngoc, L., & Nguyen, T. T. K. (2022). Temporal variation in length-weight relationship, growth and condition factor of *Acentrogobius viridipunctatus* in the Mekong Delta, Viet Nam. *Regional Studies in Marine Science*, *55*, 102545. https://doi.org/10.1016/j.rsma.2022.102545

Egrioglu, E., & Bas, E. (2022). A new automatic forecasting method based on a new input significancy test of a single multiplicative neuron model artificial neural network. *Network: Computation in Neural Systems*, *33*(1–2), 1–16. https://doi.org/10.1080/0954898X.2022.2042609

Egrioglu, E., Bas, E., Cansu, T., & Kara, M. A. (2023). A new nonlinear causality test based on single multiplicative neuron model artificial neural network: A case study for Turkey's macroeconomic indicators. *Granular Computing*, *8*(2), 391–396. https://doi.org/10.1007/s41066-022-00336-z

Fernandes, A. F., Turra, E. M., de Alvarenga, É. R., Passafaro, T. L., Lopes, F. B., Alves, G. F., Singh, V., & Rosa, G. J. (2020). Deep Learning image segmentation for extraction of fish body measurements and prediction of body weight and carcass traits in *Nile tilapia*. *Computers and Electronics in Agriculture*, *170*, 105274. https://doi.org/10.1016/j.compag.2020.105274

Froese, R. (2006). Cube law, condition factor and weight–length relationships: History, meta-analysis and recommendations. *Journal of Applied Ichthyology*, *22*(4), 241–253. https://doi.org/10.1111/j.1439-0426.2006.00805.x

Froese, R., & Pauly, D. (2002). FishBase: A global information system on fishes. *World Wide Web Electronic Publication: www. fishbase. org.*

Fulton, T. W. (1904). The rate of growth of fishes. *Twenty-Second Annual Report*, 141–241.

Gerritsen, H. D., & McGrath, D. (2007). Significant differences in the length–weight relationships of neighbouring stocks can result in biased biomass estimates: Examples of haddock (*Melanogrammus aeglefinus*, L.) and whiting (*Merlangius merlangus*, L.). *Fisheries Research*, *85*(1–2), 106–111. https://doi.org/10.1016/j.fishres.2007.01.004

Gesami, B. K., & Nunoo, J. (2024). Artificial intelligence in marine ecosystem management: Addressing climate threats to Kenya's blue economy. *Frontiers in Marine Science*, *11*, 1404104. https://doi.org/10.3389/fmars.2024.1404104

Gul, H. H., Egrioglu, E., & Bas, E. (2024). A new statistical training algorithm for a single multiplicative neuron model artificial neural network. *Granular Computing*, *9*(2), 28. https://doi.org/10.1007/s41066-024-00456-8

Herz, A. V., Gollisch, T., Machens, C. K., & Jaeger, D. (2006). Modeling single-neuron dynamics and computations: A balance of detail and abstraction. *Science*, *314*(5796), 80–85. https://doi.org/10.1126/science.112724

Ibrahim, A., Ismail, A., Juahir, H., Iliyasu, A. B., Wailare, B. T., Mukhtar, M., & Aminu, H. (2023). Water quality modelling using principal component analysis and artificial neural network. *Marine Pollution Bulletin*, *187*, 114493.

Işık, H., Bas, E., Egrioglu, E., & Akkan, T. (2024). A new single multiplicative neuron model artificial neural network based on black hole optimization algorithm: Forecasting the amounts of clean water given to metropolis. *Stochastic Environmental Research and Risk Assessment*, *38*(11), 4259–4274. https://doi.org/10.1007/s00477-024-02802-3

Jana, A., Sit, G., Chanda, A., Nayak, S., & Sahu, S. K. (1974). *Seasonal length-weight relationships and condition factors of Pachypterus atherinoides (Bloch, 1794) in two habitats*. Ecology, Environment and Conservation, 28, S515-S521. http://doi.org/10.53550/EEC.2022.v28i06s.0083

Jasmin, S. A., Ramesh, P., & Tanveer, M. (2022). An intelligent framework for prediction and forecasting of dissolved oxygen level and biofloc amount in a shrimp culture system using machine learning techniques. *Expert Systems with Applications*, *199*, 117160. https://doi.org/10.1016/j.eswa.2022.117160

Jin, S., Yan, X., Zhang, H., & Fan, W. (2015). Weight–length relationships and Fulton's condition factors of skipjack tuna (*Katsuwonus pelamis*) in the western and central Pacific Ocean. *PeerJ*, *3*, e758. https://doi.org/10.7717/peerj.758

Jisr, N., Younes, G., Sukhn, C., & El-Dakdouki, M. H. (2018). Length-weight relationships and relative condition factor of fish inhabiting the marine area of the Eastern Mediterranean city, Tripoli-Lebanon. *The Egyptian Journal of Aquatic Research*, *44*(4), 299–305. https://doi.org/10.1016/j.ejar.2018.11.004

Kalogirou, S. A. (2001). Artificial neural networks in renewable energy systems applications: A review. *Renewable and Sustainable Energy Reviews*, *5*(4), 373–401. https://doi.org/10.1016/S1364-0321(01)00006-5

Khan, Y., & See, C. S. (2016). Predicting and analyzing water quality using machine learning: A comprehensive model. *2016 IEEE Long Island Systems, Applications and Technology Conference (LISAT)*, 1–6. https://doi.org/10.1109/LISAT.2016.7494106

Kim, P. (2017). *Matlab deep learning with machine learning, neural networks and artificial intelligence*. Springer. https://doi.org/10.1007/978-1-4842-2845-6

Koch, C. (1997). Computation and the single neuron. *Nature*, *385*(6613), 207–210. https://doi.org/10.1038/385207a0

Koch, C., & Segev, I. (2000). The role of single neurons in information processing. *Nature Neuroscience*, *3*(11), 1171–1177. https://doi.org/10.1038/81444

Kolay, E., & Tunç, T. (2021). A new hybrid neural network classifier based on adaptive neuron and multiplicative neuron. *Soft Computing*, 1–12. https://doi.org/10.1007/s00500-021-06093-6

Konovalov, D. A., Saleh, A., Efremova, D. B., Domingos, J. A., & Jerry, D. R. (2019). Automatic weight estimation of harvested fish from images. *2019 Digital Image Computing: Techniques and Applications (DICTA)*, 1–7. https://doi.org/10.1109/DICTA47822.2019.8945971

Kumolu-Johnson, C. A., & Ndimele, P. E. (2010). Length-weight relationships and condition factors of twenty-one fish species in Ologe Lagoon, Lagos, Nigeria. *Asian Journal of Agricultural Sciences*, *2*(4), 174–179.

Latif, S. D., Birima, A. H., Ahmed, A. N., Hatem, D. M., Al-Ansari, N., Fai, C. M., & El-Shafie, A. (2022). Development of prediction model for phosphate in reservoir water system based machine learning algorithms. *Ain Shams Engineering Journal*, *13*(1), 101523. https://doi.org/10.1016/j.asej.2021.06.009

Li, R., Wang, C., Zhang, H., Guo, C., & Wu, Z. (2022). Using Wavelet Packet Denoising and a Regularized ELM Algorithm Based on the LOO Approach for Transient Electromagnetic Inversion. *IEEE Transactions on Geoscience and Remote Sensing*, *60*, 1–17. https://doi.org/10.1109/TGRS.2022.3151339

Maravelias, C. D., Haralabous, J., & Papaconstantinou, C. (2003). Predicting demersal fish species distributions in the Mediterranean Sea using artificial neural networks. *Marine Ecology Progress Series*, *255*, 249–258. https://doi.org/10.3354/meps255249

Matel, E., Vahdatikhaki, F., Hosseinyalamdary, S., Evers, T., & Voordijk, H. (2022). An artificial neural network approach for cost estimation of engineering services. *International Journal of Construction Management*, *22*(7), 1274–1287. https://doi.org/10.1080/15623599.2019.1692400

Matthias, B. G., Ahrens, R. N., Allen, M. S., Tuten, T., Siders, Z. A., & Wilson, K. L. (2018). Understanding the effects of density and environmental variability on the process of fish growth. *Fisheries Research*, *198*, 209–219. https://doi.org/10.1016/j.fishres.2017.08.018

Mutlu, C., & Akkan, B. E. (2025). An Up-to-date Approach Using Machine Learning Methods in Fish Condition Factor Estimation. *Turkish Journal of Fisheries and Aquatic Sciences*, *25*(7). https://doi.org/10.1016/10.4194/TRJFAS25498

Oni, S. K., Olayemi, J. Y., & Adegboye, J. D. (1983). Comparative physiology of three ecologically distinct freshwater fishes, *Alestes nurse* Ruppell, *Synodontis schall* Broch & Schneider and *Tilapia zillii gervais*. *Journal of Fish Biology*, *22*(1), 105–109. https://doi.org/10.1111/j.1095-8649.1983.tb04730.x

Ordonez, A., Eikvil, L., Salberg, A.-B., Harbitz, A., Murray, S. M., & Kampffmeyer, M. C. (2020). Explaining decisions of deep neural networks used for fish age prediction. *PloS One*, *15*(6), e0235013. https://doi.org/10.1371/journal.pone.0235013

Ozcan, E. I. (2019). Artificial Neural Networks (A new statistical approach) Method in Length-Weight Relationships of *Alburnus mossulensis* in Murat River (Palu-Elazığ) Turkey. *Applied Ecology and Environmental Research*, *17*(5), 10253–10266. http://dx.doi.org/10.15666/aeer/1705_1025310266

Ozcan, E. I. (2024). Performance of artificial neural networks and traditional methods in determining selected growth parameters of *Alburnus sellal* Heckel, 1843. *Oceanological and Hydrobiological Studies*, *53*(2), 153–163. https://doi.org/10.26881/oahs-2024.2.06

Paturi, U. M. R., Cheruku, S., Salike, S., Pasunuri, V. P. K., & Reddy, N. (2022). Estimation of machinability performance in wire-EDM on titanium alloy using neural networks. *Materials and Manufacturing Processes*, *37*(9), 1073–1084. https://doi.org/10.1080/10426914.2022.2030875

Raj, J. V. A., Kumar, R. P., Vijayakumar, B., Gnansounou, E., & Bharathiraja, B. (2021). Modelling and process optimization for biodiesel production from

Nannochloropsis salina using artificial neural network. *Bioresource Technology*, *329*, 124872. https://doi.org/10.1016/j.biortech.2021.124872

Rau, A., Lewin, W.-C., Zettler, M. L., Gogina, M., & von Dorrien, C. (2019). Abiotic and biotic drivers of flatfish abundance within distinct demersal fish assemblages in a brackish ecosystem (western Baltic Sea). *Estuarine, Coastal and Shelf Science*, *220*, 38–47. https://doi.org/10.1016/j.ecss.2019.02.035

Relvas, H., & Miranda, A. (2018). An urban air quality modeling system to support decision-making: Design and implementation. *Air Quality, Atmosphere & Health*, *11*, 815–824. https://doi.org/10.1007/s11869-018-0587-z

Samanta, B. (2011). Prediction of chaotic time series using computational intelligence. *Expert Systems with Applications*, *38*(9), 11406–11411. https://doi.org/10.1016/j.eswa.2011.03.013

Samanta, B. (2015). Single multiplicative neuron model as an alternative to multi-layer perceptron neural network. *Neural Parallel Sci Comput*, *23*(2–4), 367–375.

Wu, X., Mao, J., Du, Z., & Chang, Y. (2013). Online training algorithms based single multiplicative neuron model for energy consumption forecasting. *Energy*, *59*, 126–132. https://doi.org/10.1016/j.energy.2013.06.068

Wu, X., Zhu, Z., & Fan, S. (2015). A novel online adaptive time series prediction model with input and output uncertainties. *Optik*, *126*(11–12), 1213–1220. https://doi.org/10.1016/j.ijleo.2015.02.089

Yadav, R. N., Kalra, P. K., & John, J. (2007). Time series prediction with single multiplicative neuron model. *Applied Soft Computing*, *7*(4), 1157–1163. https://doi.org/10.1016/j.asoc.2006.01.003

Yang, Z., Feng, X., Li, J., & Zhang, F. (2022). Length–weight relationship of six endemic fish species in the Qinghai-Tibet Plateau, China. *Journal of Applied Ichthyology*, *38*(2), 255–258. https://doi.org/10.1111/jai.14262

Zheng, X., & Zhang, Y. (2010). A fish population counting method using fuzzy artificial neural network. *2010 IEEE International Conference on Progress in Informatics and Computing*, *1*, 225–228. https://doi.org/10.1109/PIC.2010.5687462

Zhou, C., Zhang, C., Tian, D., Wang, K., Huang, M., & Liu, Y. (2018). A software sensor model based on hybrid fuzzy neural network for rapid estimation water quality in Guangzhou section of Pearl River, China. *Journal of Environmental Science and Health, Part A*, *53*(1), 91–98. https://doi.org/10.1080/10934529.2017.1369815