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ORIGINAL ARTICLE

Prediction of storage time in different seafood based on color values with artificial neural network modeling

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Abstract The determination of storage time in seafood could be performed by microbiological, chemical and sensory analysis. Among these mentioned methods color changes are one part of sensory analysis and are prior acceptance criteria from the point of consumers' view. In this study, a feedforward artificial neural network (ANN) model was developed to predict the storage time of seafood based on L*, a* and b* values. A total of 205 data set were compiled from the literature that represents the color changes of different seafood products to train and test the ANN model. Another set of data (n = 45) were used for the validation of developed ANN model. A multi-layer perceptron (MLP) was applied for the determination of agreements between input and output data. The most accurate topology were determined in accordance with the changes in the values of correlation coefficients (R^2) and mean square errors (MSE) and found to be 30 neurons in the layer (R^2 = 0.81 and MSE = 0.2). The performance of ANN model was evaluated based on 6 criteria such as Mean Absolute Deviation (MAD), Mean Square Errors (MSE), Residual Mean Square Errors (RMSE), Correlation Coefficient (R^2), Mean Absolute Error (MAE) and *F-test* statistics and found to be 0.2, 0.05, 0.002, 0.8, 0.71 and 1.06, respectively. Moreover, predicted and observed storage time values were fitted and regression coefficient was found to be 0.85. In accordance with the results of this study, the proposed ANN model is accurate, reliable, and proper for the estimation of storage time in seafood products.

Keywords Predictive modeling · Seafood quality · Storage time · Artificial neural network · Meta-analysis

Abbreviations

ANN	Artificial Neural Network
MLP	Multi-Layer Perceptron
MSE	Mean Square Errors
MAD	Mean Absolute Deviation
RMSE	Residual Mean Square Errors
MAE	Mean Absolute Error
GDMALR	Gradient Decent with Momentum and Adaptive Learning Rate Backpropagation
LS-SVM	Least-Squares Support Vector Machine
PLSR	Partial Least Square Regression
MLR	Multiple Linear Regression
PPC	Psychrotrophic Plate Count
TVB-N	Total Volatile Basic Nitrogen
TMA-N	Trimethylamine Nitrogen

Introduction

Fresh seafood is a highly perishable product in terms of nutritional composition (i.e. high water activity, neutral pH, high protein content) (Masniyom 2011; Socaciu et al. 2018). Spoilage in seafood products could be occurred due to microbial and enzymatic activity, chemical deterioration (Boziaris 2015) and sensory loss (Mchazime and Kapute, 2018). Among the spoilage patterns in seafood, microbiological and chemical analysis are destructive, time consuming and labor intense methods to determine the quality of a particular seafood product. In contrast, sensory

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analysis is non-destructive, rapid and reliable in terms of the determination of the storage time and/or shelf life of seafood. Objective sensory tests could be divided into two groups such as discriminative (i.e. triangle test, ranking test) and descriptive tests (i.e. profiling and quality tests) (Martinsdóttir et al. 2009). To determine the storage time, the descriptive test is playing an important role in sensory analysis. There are three principal quality attributes in the sensory analysis that are color, texture and flavor profiling. Among these mentioned changes, the effect of color profiling has a significant contribution to determine the storage time during the sensory evaluation (Wrolstad and Smith 2010). Color analysis in a food matrix could be carried out by inspectors (i.e. panelists) or by using instrumental methods such as colorimeters. Determination of the color by inspectors may be subjective and variable from observer to observer (León et al. 2006). However, a uniform color space namely CIELAB proposed by International Commission on Illumination (CIE) in 1976. The definition of the colors in the uniform space is based on three values in the color coordinates, such as L* representing the luminosity from 0 to 100, a* and b* donates red–green and yellow–blue components from positive to negative values, respectively (Delgado-González et al. 2018; Luo 2006).

Prediction of the storage time in seafood could be performed by using mathematical models (Logistic, Baranyi, modified Gompertz, square-root, Arrhenius model, interaction models, generic models) regarding to the changes in bacterial growth with temperature fluctuations (Genç and Esteves 2016; Hansen et al. 2021). Mathematical models are precise for forecasting the storage time in seafood products. In recent years ANNs are gaining importance to have a modern approach for the prediction of quality changes, storage time and product quality evaluation (Goyal 2013). An ANN is a system that processes the information/data (i.e. input) similar to the human brain. Data are transferring by synapses to the nerve cells (i.e. neurons) to be processed. Consequently, processed data transmission occurs by axons between the nerve cells. In the computer applications (i.e. ANN), the neural simulations are processed by the system which has the ability to learn from the provided data (Bhotmange and Shastri 2011). In this context, ANNs are providing an effective forecasting method to determine the quality and safety changes in seafood. Ji et al. (2012) used a neural network to optimize the dense phase carbon dioxide parameters of microbial inactivation in shrimp. In another study presence and absence of Norwalk-like viruses were predicted by using ANN (Brion et al. 2005). Zhang et al. (2016) were used ANN and response surface methodology to model and optimize of Newfoundland shrimp waste hydrolysis for microbial growth. The protein hydrolysis of squid was modeled by in accordance with ANN modeling method (Abakarov et al. 2011). The quality changes of frozen shrimp (*Solenocera melantho*) were predicted by the neural network (Xu et al. 2017). Lalabadi et al. (2020) categorized the freshness of rainbow trout by developing multi class artificial neural network and support vector machines. Navotas et al. (2018) were determined the freshness classification and identify the fish species such as round scad, milkfish and tilapia by using ANN models. Several ANN model were applied to assess the quality, optimization and predicting sensory freshness in different food products (Concepcion et al. 2019; Kalathingal et al. 2020; Koyama et al. 2021). However, there is still insufficient data to determine the quality changes in seafood with non-destructive methods.

Meta-analysis compiles various independent research for quantitative evaluation of a certain aim (i.e. quality and safety evaluation of food) (Yu et al. 2018). As meta-analysis is an emerging method in terms of food science several research has been conducted in different food matrixes. Afari and Hung (2018) was evaluated the effectiveness of electrolyzed water treatments in reducing foodborne pathogens on poultry, egg, meat, fish and produce. Meta-analysis approach has been performed for the incidence evaluation of foodborne pathogens in raw milk and cheese of sheep and goat origin (Gonzales-Barron et al. 2017), *Listeria monocytogenes* in European cheeses (Martinez-Rios and Dalgaard 2018), presence of arsenic and lead in rice (Fakhri et al. 2018), shelf life prediction of frozen fruits and vegetables (Giannakourou and Taoukis 2019), bio-baseline establishment of trace metals in marine bivalves (Lu et al. 2019), inactivation of foodborne pathogens in fresh produce (Prado-Silva et al. 2015), prevalence of *Staphylococcus aureus* in poultry products (Ribeiro et al. 2018) and occurrence of foodborne pathogens in vegetables and fruits from retail establishments (Silva et al. 2017). Meta-analysis is an effective method for the quality and safety evaluation of food products. In this context, the purpose of this research is (i) to develop a storage time prediction model in seafood based on color (L*, a*, and b*) values by using ANNs, (ii) to optimize the topology of developed network and (iii) to validate the optimized network for further adaptation and possible usage in different seafood products.

Material and methods

Data collection

The collection of data was performed in accordance with the method described by Gonzales- Barron et al. (2018). The data set corresponds to the color values (L*, a* and b*) of different fresh or processed seafood products that were compiled from 205 experiments from the accessible literature data for the development of ANN (Table 1). The fresh seafood products were (n = 79) modified atmosphere, vacuum, and air packaged or stored in ice whereas the processed products (n = 126) have consisted of edible film-coated, a preservative added (i.e. nisin or phosphate) or non-thermal/thermal processed.

The 205 experiments were randomly divided into 145 (∼ 70%), 30 (∼ 15%) and 30 (∼ 15%) data sets for training, testing and validation of ANN, respectively. Prior to analyzing the data set, obtained data were transformed into normalized values for the evaluation of developed ANN topology. All the raw data in the dataset were normalized between 0 and 1 (Eq. 1).

$$Y_{normalized} = \frac{Y_i - Y_{\min}}{Y_{\max} - Y_{\min}} \quad (1)$$

In Eq. 1. Y_i donates raw input/output data, $Y_{\min}$ is the minimum value in the data set where $Y_{\max}$ is the maximum.

Development of ANN

The construction of ANN was performed in two steps. In the first step the collected data were used to train the network and in the second step trained network was validated based on unused collected data. A multilayer perceptron

Table 1 Obtained data and product characteristics of different seafood to development of ANN

Product	Processing type	Storage temperature (°C)	Number of data	Methods	Reference
Shrimp	Edible coating with sweet potato starch and added thyme essential oil	+ 4	15	Colorimeter L*, a* and b* values	Alotaibi and Tahergorabi (2018)
Catfish fillets (*Ictalurus puctactus*)	Chitosan coating	+ 4	20	Chroma meter L*, a* and b* values	Bonilla et al. (2018)
Whole seabream (*Sparus aurata*) and seabass (*Dicentrarchus labrax*)	Fresh whole, stored in ice	+ 4.42 (storage room temperature)	14	Colorimeter L*, a* and b* values	Cakli et al., (2007)
Rainbow trout (*Oncorhynchus mykiss*) fillets	Nisin added	+ 4	10	Colorimeter L*, a* and b* values	López et al. (2017)
Carp (*Cyprinus carpio*)	Fresh	+ 2	7	Colorimeter L*, a* and b* values	Agüeria et al. (2016)
Shrimp	Surumi-based coating with and without montmorillonite nanoclay	+ 4	9	Colorimeter L*, a* and b* values	Sharaf Eddin and Tahergorabi (2017)
Shrimp (*Litopenaeus vannamei*)	Chitosan–gelatin coating	+ 4	14	Colorimeter X, Y and Z values corresponding L*, a* and b* values provided by manufacturer	Farajzadeh et al. (2016)
Aurigeguula fasciata fillets	Vacuum packaged, with or without phosphate treated	+ 4	25	Chroma meter L*, a* and b* values	Ghalati et al. (2017)
Tilapia (*Oreochromis niloticus*)	Fresh, wrapped in plastic film	+ 4	4	Chroma meter L*, a* and b* values	Gutérrez Guzmán et al. (2015)
Meagre (*Argyrosomus regius*) fillets	Fresh	+ 4	6	Chroma meter L*, a* and b* values	Hernández et al. (2009)
Atlantic cod (*Godus morhua*)	Modified atmosphere (MAP) or air packaged (AP)	+ 4 or + 8	32	Spectrophotometer, L*, a* and b* values	Kuuliala et al. (2018)
Meagre (*Argyrosomus regius*)	Fresh, different rearing systems (i.e. tank and cage)	+ 1	15	Colorimeter L*, a* and b* values	Martelli et al. (2013)
Seabass (*Dicentrarchus labrax*) fillets	Fresh, MAP, Air and storage in crushed ice	+ 2	18	Chroma meter L*, a* and b* values	Poli et al. (2006)
Tench (*Tinca tinca*)	Fresh, stunned methods (i.e. carbon monoxide, electrical stunning, percussion)	+ 2.5	15	Chroma meter L*, a* and b* values	Secci et al. (2018)

(MLP) with one hidden layer was trained and tested in this study. The architecture of the network was consisted of input, hidden and output layer and schematically shown in Fig. 1. The input layer contains 3 variables from the color value of different seafood while the hidden layer contains one or more neurons (1 to 40 neurons).

The Marquardt algorithm which is incorporated into the backpropagation algorithm was applied for training the feed-forward backpropagation network which is used as the network type in this study (Hagan and Menhaj 1996). Gradient Decent with Momentum and Adaptive Learning Rate Backpropagation (GDMALR) function was selected as training function which updates weight and bias values according to gradient descent momentum and an adaptive learning rate. Additionally, GDMALR function runs by adaptively changing the momentum in the neural network and works faster and more accurate compared to other learning functions (i.e. Gradient Descent Method with Adaptive Gain and Gradient Descent with Simple Momentum) (Rehman and Nawi 2011). The algorithm of the training function is shown in Eq. 2.

$$dX = \frac{(mc * dXprev) + (lr * mc * dperf)}{dX} \tag{2}$$

where dX is the derivative of the variables, mc donates the momentum coefficient, $dXprev$ is the previous change to the weight or bias, lr is representing the learning rate and $dperf$ derivatives of performance with respect to the weight and bias variables X (Demuth and Beale 2002). Values from the GDMALR functionis then transformed by hyperbolic tangent sigmoid transfer function to calculate a single output (Eq. 3).

$$y_j = (f_n) = \frac{2}{1 + e^{-2n}} - 1 \tag{3}$$

The architecture of ANN was designed in accordance with the training function. The maximum number of epochs was adjusted 10.000, the learning rate was 0.01, and the momentum constant was 0.9. A variable number of neurons were used (i.e.1 to 40) in the hidden layer to decide the optimum number of neurons. The network was trained until the maximum number of epochs was reached. To design and test the network, a neural network toolbox from MATLAB® (R2014a, USA) was used.

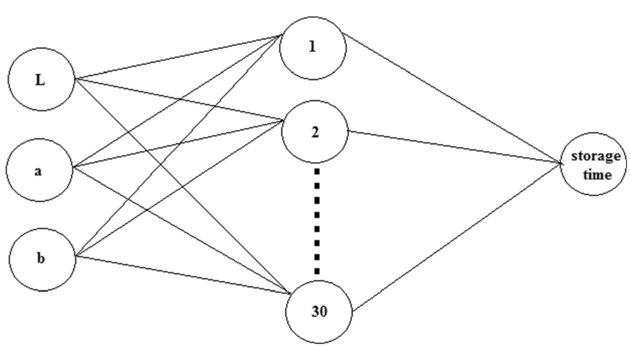

Fig. 1 Schematic view of ANN. Input layer consisted of color values (L*, a* and b*), hidden layer contains up to 30 neurons and output layer representing the storage time

Performance evaluation of ANN

The evaluation of the performance of developed ANN was carried out based on Mean Absolute Deviation (MAD), Mean Square Errors (MSE), Root Mean Square Errors (RMSE), Correlation Coefficient (R^2), Mean Absolute Error (MAE) and *F-test* statistics. The MAD is a measure of scale of individual differences that explains how two independent data were agreed each other (Bohlscheid-Thomas et al. 1997) (Eq. 4). MAE and RMSE are donating the average model prediction error (Willmoth and Matsuura 2005). The correlation coefficient (R^2) is widely used to compare the relationship between repeated outcomes (Edwards et al. 2008).

$$MAD = \sum_{i=1}^{n} |x_i - \bar{x}| \tag{4}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y^i_{calc} - y^i_{\exp}\right)^2 \tag{5}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y^i_{calc} - y^i_{\exp}\right)^2} \tag{6}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y^i_{calc} - y^i_{\exp}\right)^2}{\sum_{i=1}^{n}\left(y^i_{calc} - \bar{y}\right)^2} \tag{7}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y^i_{calc} - y^i_{\exp}\right| \tag{8}$$

where in Eq. 4. $\bar{x}$ represents the mean, x_i is the absolute differences between output values in Eqs. 5, 6, 7 and 8 y^i_{calc} is the calculated and y^i_{exp} is the observed values. Finally, n is the number of subjects.

Results and discussion

Optimization of topology

Significant attention should be paid to the determination of topology during the development of ANN model. In this study, the best topology was selected based on the R^2 and MSE values. At the total 40 neurons were structured in ANN and evaluated. The results of the ANN topology are shown in Table 2. The selection of an optimum number of the neurons was performed with the purpose of maximizing

Table 2 Correlation coefficients (R^2) and Mean square errors (MSE) of neurons in the optimization of the topology

Number of the neurons	R^2	MSE
1	0.23	0.05
2	0.43	0.05
3	0.44	0.04
4	0.55	0.11
5	0.35	0.37
6	0.60	0.12
7	0.61	0.31
8	0.54	0.07
9	0.46	0.50
10	0.71	0.10
11	0.76	0.33
12	0.70	0.05
13	0.74	0.18
14	0.68	0.08
15	0.51	0.21
16	0.61	0.13
17	0.62	0.05
18	0.58	0.33
19	0.62	0.10
20	0.59	0.08
25	0.62	0.48
30	0.81	0.20
40	0.81	0.14

R^2 and minimizing MSE values. The changes in R^2 and MSE values were varied regardless of the number of neurons until the neuron number reached to 25. However, 30 and 40 neurons in the hidden layer donated the same R^2 values which found to be 0.81. Similar to the changes in R^2 values, MSE values were also varied independently from the number of the neurons. The term of correlation coefficient is the measure of the degree of association between two variables that are both measured on a series. Additionally, the strength of correlation is donated by correlation of coefficient. Regardless to the method conducted the coefficient could have a magnitude between 0 and 1. The highest correlations are defined when the magnitude has a values of − 1 and + 1 (Brower, 2000a). The association degree in magnitude of correlation coefficient could be categorized in four groups namely strog 0.8–1.0, moderate 0.5–0.8, weak 0.2–0.5 and finally negligible 0.1–0.2 (Brower, 2000b). The correlation coefficient which was calculated to be 0.81 in this study there is a strong correlation in the variable which used for development and optimization process.

The lowest MSE was reported for 1, 2 and 17 neurons while the highest was found to be 0.5 for 9 neurons. The MSE values of 40 neurons were slightly lower than those of 30 neurons. While the aim of the topology optimization is to maximize the R^2 and minimize the MSE, the highest R^2 and the lowest MSE was found in 40 neurons. However, as the R^2 and MSE values remained, the use of the best topology was decided with 30 neurons in the hidden layer and the network was trained with 30 neurons. Similar results were reported with lower neurons by Zhang et al. (2016) who reported that the MSE values were reached the minimum value after 11 nodes contained in the hidden layer and become stable during the development of ANN model for Newfoundland shrimp waste hydrolysis. In another study, the quality changes in rainbow trout (*Oncorhynchus mykiss)* fillets were predicted by using ANN model. Researchers constructed the ANN model with one hidden layer and reported the lowest MSE and highest r^2 values as 0.00418 and 0.9697 with 6 neurons, respectively (Liu et al. 2015). Bai et al. 2018 were studied drying kinetics and color changes of ginkgo biloba seeds during microwave drying process and modeled the changes by using ANN. The model was applied to estimate the moisture ratio color parameters (i.e. L*, a* and b*). The researchers were concluded their study that ANN model was able to precisely predict the experimental data with correlation coefficients and MSE of between 0.90–0.98 and 0.0014–2.2044, respectively. The results that reported by the authors were similar to current study, as in Table 2, developed ANN model was used 40 neurons with high correlation coefficient (R^2 = 0.81) and low MSE which is 0.14.

Validation of ANN model

A total of 45 data sets were used for the validation of ANN model and compiled from the accessible literature that is shown in Table 3. The selected data set represents the color changes (L*, a* and b*) of different seafood stored under chilled conditions (+ 2 to + 4̊C).

The storage time of different seafood was predicted by the network with 30 neurons in the hidden layer and the performance evaluation of the model is shown in Table 4. For the performance evaluation of developed ANN model MAD, MSE, RMSE, R^2, MAE and *F-test* values were found to be 0.20, 0.05, 0.002, 0.80, 0.71 and 1.06, respectively. The model performance showing that the developed ANN model successfully validated in accordance with the performance criteria indicating that good agreement was reached between the predicted values and observed data. Additionally, properly-trained network must highly be predictable for the new data set (Razavi et al. 2004; Nourbakhsh et al. 2014; Tan et al. 2020).

Khoshnoudi-Nia and Moosavi-Nasab (2019) were evaluated the multispectral imaging system for the

Table 3 Data used for the validation of developed ANN in different seafood

Product	Processing type	Storage temperature (°C)	Number of data	Reference
Tench (*Tinca tinca*)	Fresh, stunned methods (i.e. carbon monoxide, electrical stunning, percussion) were evaluated	+ 2.5	15	Secci et al. (2018)
Seabream (*Sparus aurata*)	Fresh, different starvation times were evaluated (i.e. 24, 48 and 72 h)	+ 4	13	Álvarez et al. (2008)
Smoked salmon (*Salmo salar*)	MAP and VP	+ 2	4	Bugueño et al. (2003)
Salted bonito (*Sarda sarda*)	Plastic film, MAP and VP	+ 2	16	Caglak et al. (2012)
Hilsa (*Tenualosa ilisha*) fillets	High pressure processing (HPP) and thermal treatment	+ 4	7	Chouhan et al. (2015)

Table 4 Performance evaluation of the ANN

MAD	MSE	RMSE	R^2	MAE	*F-test*
0.20	0.05	0.002	0.80	0.71	1.06

MAD Mean Absolute Deviation, *MSE* Mean Squared Errors, *RMSE* Residual Mean Squared Errors, R^2: Correlation Coefficient, *MAE* Mean absolute Error

prediction of various freshness indicator in rainbow trout fillets. Researchers were applied linear (Partial Least Square Regression (PLSR), Multiple Linear Regression (MLR)) and nonlinear (least-squares support vector machine (LS-SVM), back-propagation artificial neural network (BP-ANN)) models to predict the changes in Psychrotrophic Plate Count (PPC), Total Volatile Basic Nitrogen (TVB-N) and sensory scores. For BP-ANN models the prediction correlation coefficient and RSMEP were calculated to be 0.92 and 0.594, 0.85 and 3.65, 0.91 and 1.848 for PPC, TVB-N and sensory scores, respectively. Compared to our results researchers were reported higher correlation coefficient for the data predicted by BP-ANN model. However, RMSE was found lower compared to those results reported by Khoshnoudi-Nia and Moosavi-Nasab (2019). This differences between the research findings could be due to the methods (traditional and instrumental) used to predict the changes in quality parameters (i.e. PPC, TVB-N). Microbiological and chemical changes have great potential to determine the quality loss in seafood. However, On the other hand color changes in seafood also have direct influence on the quality changes in fishery products (Hassoun and Karoui 2017; Prabhakar et al. 2020). In this context, it is presumable to have different performance values (i.e. RMSE or R^2) in the validation process.

Comparison of observed and predicted storage time

The agreements between predicted storage time which are obtained by developed ANN and observed storage time that belongs to different seafood and compiled from the accessible literate are shown in Fig. 2. The R^2 value of the regression line is found to be 0.85. Higher correlations reported by Niamnuy et al. (2012) who were studied the physicochemical changes of shrimp during boiling and an ANN model has been developed to predict the protein changes of shrimp. The ANN model was developed and consisted of two hidden layers and twelve neurons per layer. Researchers were agreed that the ANN model was precisely predicted the protein and physical changes in boiling shrimp with the coefficient of $R^2 = 0.994$ and 0.972, respectively. Similar correlations between predicted and observed values has been reported in another study which includes the development of ANN to predict the storage time of yogurt stored under refrigeration temperatures (+ 4 to + 7). In accordance with the conclusions of

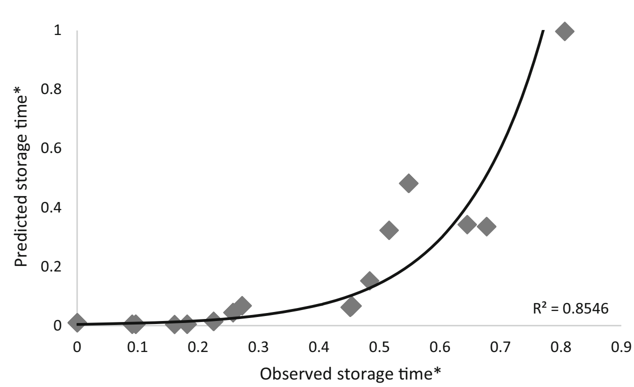

Fig. 2 Predicted vs observed storage time plot obtained by developed ANN. *storage time values are shown in normalized scale. The optimum network with 1 hidden layer and 30 neurons per hidden layer was used. The validation data set was consisted of 45 data which belong different seafood

the authors, ANN model was able to predict the storage time in yogurt with high correlation that were reported to be 0.9996 (Sofu and Ekinci, 2007).

Khanzadi et al. (2010) applied the ANN to predict the growth of *Clostridium botulinum* as a function of environmental factors such as essential oils, pH, NaCI and temperature. The probability percentage of the growth of *C.botulinum* was predicted by ANN with the R^2 value of 0.988. The determination coefficient cannot be a good criterion alone to evaluate prediction accuracy (Gorgulu 2012). The differences between the literature findings and this study could be the result of using pooled data. The quality indices data for seafood (microbiological, chemical, biochemical, sensory) with different processing techniques (i.e. packaged (vacuum or modified atmosphere), marinated, preservative added etc.) creates a data pool with variances. However, using variated data in prediction studies reinforce the prediction intervals and eventually requires fewer calibrations for further experiments. Additionally, pooling dependent and independent data could support to meet more robust parameter estimates including more biological variations (Hensen et al. 2021). Moreover, due to using of pooled data which represents the color values of different seafood relatively lower R^2 value (0.85) has been achieved compared to literature findings in this study. However, it is obvious that a good agreement has been achieved in this study between observed and predicted storage time values (Fig. 2).

Conclusions

Storage time prediction of seafood by artificial neural network based on color (L*, a* and b*) values has been proven to be an accurate method. The architecture of the model was optimized with one hidden layer and thirty neurons in the hidden layer. Model evaluation indicating a good agreement between observed and predicted values. Low RSME and MAE values indicating that the model has been successfully validated. Developed ANN model could predict the storage time of fresh or processed seafood with a high R^2 value of 0.80. Among other quality indicators (i.e.TVB-N, Trimethylamine Nitrogen (TMA-N), K-value, Microbiological changes etc.) color measurements are non-destructive and not time-consuming and does not require preliminary training for the evaluation like sensory analysis. In this context, color measurements were used in this study to estimate the storage time in seafood products and should be emphasized that the combination of ANN models and color parameters as an input in the models has great potential and advantage to predict the storage time in seafood while it is fast, accurate and reliable. Additionally, another advantage of the developed ANN model is that the model can be adapted in different seafood products to predict the storage time.

Appendix

Weights to layer 1 from input 1.
[0.215 1.0299 0.44519; 0.81905 − 0.25125 0.60449; 0.71524 − 0.40438 0.18169; 0.15737 0.53082 − 0.8139; − 1.0941 − 0.49792 0.13041; − 0.76441 0.89052 − 0.9176; 0.1436 0.79021 0.50513; 0.77111 − 0.18732 0.33336; 0.65459 − 0.29249 0.20499; 0.70678 0.48637 − 0.5326].
Biases to layer 1.
[0.26711; 0.41961; − 0.23041; − 0.84587; 0.53745; 0.59623; 0.15577; 0.24032; 0.52489; − 0.52791]

Author contributions İsmail Yüksel GENÇ has compiled, analyzed the data, developed the model and module and constructed the article.

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Data availability The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Code availability The module developed during the current study is available from the corresponding author on reasonable request.

Declarations

Conflict of interest All the authors that they have no conflict of interest.

Ethical approval I declared that I followed the ethical rules and good scientific practices as mentioned in Journal of Food Science and Technology Author Guidelines.

References

Abakarov A, Teixeira A, Simpson R, Pinto M, Almonacid S (2011) Modeling of squid protein hydrolysis: artificial neural network approach. J Food Process Eng 34(6):2026–2046. https://doi.org/10.1111/j.1745-4530.2009.00567.x

Afari GK, Hung YC (2018) A meta-analysis on the effectiveness of electrolyzed water treatments in reducing foodborne pathogens on different foods. Food Control 93:150–164. https://doi.org/10.1016/j.foodcont.2018.06.009

Agüeria D, Sanzano P, Vaz-Pires P, Rodríguez E, Yeannes MI (2016) Development of quality index method scheme for common carp (cyprinus carpio) stored in ice: shelf-life assessment by physicochemical, microbiological, and sensory quality indices. J Aquat Food Prod Technol 25(5):708–723

Alotaibi S, Tahergorabi R (2018) Development of a sweet potato starch-based coating and its effect on quality attributes of shrimp during refrigerated storage. LWT, 88:203–209

Álvarez A, García BG, Garrido MD, Hernández MD (2008) The influence of starvation time prior to slaughter on the quality of commercial-sized gilthead seabream (Sparus aurata) during ice storage. Aquaculture 284(1–4):106–114

Bai JW, Xiao HW, Ma HL, Zhou CS (2018) Artificial neural network modeling of drying kinetics and color changes of ginkgo biloba seeds during microwave drying process. J Food Qual 2018:1–8

Bhotmange M, Shastri P (2011) Application of artificial neural networks to food and fermentation technology. Artificial neural networks—industrial and control engineering applications. InTech, Rijeka, pp 201–222

Bohlscheid-Thomas S, Hoting I, Wahrendorf J, Boeing H (1997) Reproducibility and relative validity of food group intake in a food frequency questionnaire developed for the German part of the EPIC project. Int J Epidem 26(SUPPL. 1):59–70. https://doi.org/10.1093/ije/26.suppl_1.s59

Bonilla F, Chouljenko A, Reyes V, Bechtel PJ, King JM, Sathivel S (2018) Impact of chitosan application technique on refrigerated catfish fillet quality. LWT 90:277–282

Boziaris IS (2015) Current trends on the study of microbiological spoilage of fresh fish. Fish Aquac J 06(01):10–12. https://doi.org/10.4172/2150-3508.10000e115

Brion G, Viswanathan C, Neelakantan TR, Lingireddy S, Girones R, Lees D, Vantarakis A (2005) Artificial neural network prediction of viruses in shellfish. Appl Environ Microbiol 71(9):5244–5253. https://doi.org/10.1128/AEM.71.9.5244-5253.2005

Brower AJ (2000a) Statistics for food science - VI: correlation and regression (Part A). Nutr Food Sci 30(6):295–299

Brower AJ (2000b) Statistics for food science - VI: correlation and regression (Part A). Nutr Food Sci 30(2):80–85

Bugueño G, Escriche I, Martınez-Navarrete N, del Mar Camacho M, Chiralt A (2003) Influence of storage conditions on some physical and chemical properties of smoked salmon (Salmo salar) processed by vacuum impregnation techniques. Food Chem 81(1):85–90

Caglak E, Cakli S, Kilinc B (2012) Effect of modified atmosphere packaging on quality and shelf life of salted bonito (Sarda sarda). J Aquat Food Prod Tech 21(3):206–221

Cakli S, Kilinc B, Cadun A, Dincer T, Tolasa S (2007) Quality differences of whole ungutted sea bream (Sparus aurata) and sea bass (Dicentrarchus labrax) while stored in ice. Food Control 18(5):391–397

Concepcion RS, Sybingco E, Lauguico SC, & Dadios EP (2019) Implementation of multilayer perceptron neural network on quality assessment of tomato puree in aerobic storage using electronic nose. In: IEEE International Conference on Cybernetics and Intelligent Systems (CIS) and IEEE Conference on Robotics, Automation and Mechatronics (RAM) 65–70 2019

Chouhan A, Kaur BP, Rao PS (2015) Effect of high pressure processing and thermal treatment on quality of hilsa (Tenualosa ilisha) fillets during refrigerated storage. Innovat Food Sci Emerg Tech 29:151–160

Delgado-González MJ, Carmona-Jiménez Y, Rodríguez-Dodero MC, García-Moreno MV (2018) Color space mathematical modeling using microsoft excel. J Chem Educ 95(10):1885–1889. https://doi.org/10.1021/acs.jchemed.7b00681

Demuth H, Beale M (2002) Neural network toolbox for use with Matlab—User'S Guide Verion 3.0

Edwards LJ, Muller KE, Wolfinger RD, Qaqish BF, Schabenberger O (2008) An R2 statistic for fixed effects in the linear mixed model. Stat Med 27(29):6137–6157

Fakhri Y, Bjørklund G, Bandpei AM, Chirumbolo S, Keramati H, Hosseini Pouya R, Ghasemi SM (2018) Concentrations of arsenic and lead in rice (*Oryza sativa* L.) in Iran: a systematic review and carcinogenic risk assessment. Food Chem Toxic 113:267–277. https://doi.org/10.1016/j.fct.2018.01.018

Farajzadeh F, Motamedzadegan A, Shahidi SA, Hamzeh S (2016) The effect of chitosan-gelatin coating on the quality of shrimp (Litopenaeus vannamei) under refrigerated condition. Food Control 67:163–170

Genç IY, Esteves E (2016) Computer based applications for monitoring the quality and safety of seafood. In: Genç IY, Esteves E, Diler A (eds) Handbook of Seafood Quality and SAfety Maintenance and Applications, Nova Sci. Publishers, NY

Ghalati LN, Khodanazary A, Hosseini SM, Matroodi S (2017) combination effect of phosphate and vacuum packaging on quality parameters of refrigerated Aurigequula fasciata fillets. J Pack Tech Res 1(2):101–112

Giannakourou MC, Taoukis PS (2019) Meta-analysis of kinetic parameter uncertainty on shelf life prediction in the frozen fruits and vegetable Chain. Food Eng Revs 11(1):14–28. https://doi.org/10.1007/s12393-018-9183-0

Gonzales- Barron U, Cadavez V, Alvarenga V, Silva LP, Sant'Ana A (2018) An extended bigelow-type meta-regression model describing the heat resistance of neosartorya spores. AgroStat Conference.

Gonzales-Barron U, Gonçalves-Tenório A, Rodrigues V, Cadavez V (2017) Foodborne pathogens in raw milk and cheese of sheep and goat origin: a meta-analysis approach. Curr Opin Food Sci 18:7–13. https://doi.org/10.1016/j.cofs.2017.10.002

Gorgulu O (2012) Prediction of 305-day milk yield in Brown Swiss cattle using artificial neural networks. S Afr J Anim Sci. https://doi.org/10.4314/sajas.v42i3.10

Goyal S (2013) Artificial neural networks (ANNs) in food science–a review. Int J Sci World 1(2):19–28. https://doi.org/10.14419/ijsw.v1i2.1151

Gutérrez Guzmán N, Fernández Segovia I, Fuentes López A, Ruiz Rico M, Barat Baviera JM (2015) Physico-chemical and microbiological changes in commercial tilapia (Oreochromis niloticus) during cold storage. Vitae 22(2):140–147

Hagan MT, Menhaj MB (1996) Training feedforward networks with the marquardt algorithm. Brief Papers 32(2):273–344. https://doi.org/10.1006/brcg.1996.0066

Hansen TB, Abdalas S, Al-Hilali I, Hansen LT (2021) Predicting the effect of salt on heat tolerance of *Listeria monocytogenes* in meat and fish products. Int J Food Microb 1:109265

Hassoun A, Karoui R (2017) Quality evaluation of fish and other seafood by traditional and nondestructive instrumental methods: advantages and limitations. Crit Rev Food Sci Nutrition 57(9):1976–1998

Hernández MD, López MB, Álvarez A, Ferrandini E, García BG, Garrido MD (2009) Sensory, physical, chemical and microbiological changes in aquacultured meagre (Argyrosomus regius) fillets during ice storage. Food Chem 114(1):237–245

Ji H, Zhang L, Liu S, Qu X, Zhang C, Gao J (2012) Optimization of microbial inactivation of shrimp by dense phase carbon dioxide. Int J Food Microb 156(1):44–49. https://doi.org/10.1016/j.ijfoodmicro.2012.02.020

Kalathingal MSH, Basak S, Mitra J (2020) Artificial neural network modeling and genetic algorithm optimization of process parameters in fluidized bed drying of green tea leaves. J Food Process Eng 43(1):e13128

Khanzadi S, Gharibzadeh S, Raoufy MR, Razavilar V, Khaksar R, Radmehr B (2010) Application of artificial neural networks to predict Clostridium botulinum growth as a function of Zataria multiflora essential oil, pH. NaCl and Temperature J Food Saf 30(2):490–505. https://doi.org/10.1111/j.1745-4565.2010.00222.x

Khoshnoudi-Nia S, Moosavi-Nasab M (2019) Prediction of various freshness indicators in fish fillets by one multispectral imaging system. Sci Rep 9(1):1–11

Koyama K, Tanaka M, Cho BH, Yoshikawa Y, Koseki S (2021) Predicting sensory evaluation of spinach freshness using machine learning model and digital images. Plos one 16(3):e0248769

Kuuliala L, Al Hage Y, Ioannidis AG, Sader M, Kerckhof FM, Vanderroost M, Boon N, De Baets B, De Meulenaer B, Ragaert P, Devlieghere F (2018) Microbiological, chemical and sensory spoilage analysis of raw Atlantic cod (Gadus morhua) stored under modified atmospheres. Food Microb 70:232–244

Lalabadi HM, Sadeghi M, Mireei SA (2020) Fish freshness categorization from eyes and gills color features using multi-class artificial neural network and support vector machines. Aquac Eng 90:102076

León K, Mery D, Pedreschi F, León J (2006) Color measurement in L*a*b* units from RGB digital images. Food Res Int 39(10):1084–1091. https://doi.org/10.1016/j.foodres.2006.03.006

Liu X, Jiang Y, Shen S, Luo Y, Gao L (2015) Comparison of Arrhenius model and artificial neuronal network for the quality prediction of rainbow trout (*Oncorhynchus mykiss*) fillets during storage at different temperatures. LWT - Food Sci Tech 60(1):142–147. https://doi.org/10.1016/j.lwt.2014.09.030

López CC, Serio A, Montalvo C, Ramirez C, Álvarez JAP, Paparella A, Mastrocola D, Martuscelli M (2017) Effect of nisin on biogenic amines and shelf life of vacuum packaged rainbow trout (Oncorhynchus mykiss) fillets. J Food Sci Tech 54(10):3268–3277

Lu G, Zhu A, Fang H, Dong Y, Wang WX (2019) Establishing baseline trace metals in marine bivalves in China and worldwide: meta-analysis and modeling approach. Sci Total Environ 669:746–753. https://doi.org/10.1016/j.scitotenv.2019.03.164

Luo MR (2006) Applying colour science in colour design. Optics Laser Technol 38(4–6):392–398. https://doi.org/10.1016/j.optlastec.2005.06.025

Masniyom P (2011) Deterioration and shelf-life extension of fish and fishery products by modified atmosphere packaging. Songklanakarin J Sci Tech 33(2):181

Martelli R, Parisi G, Lupi P, Bonelli A, Zotte AD, Franci O (2013) Effect of rearing system on body traits and fillet quality of meagre (Argyrosomus regius, Asso 1801) chilled for a short time. Italian J Anim Sci 12(2):e30

Martinez-Rios V, Dalgaard P (2018) Prevalence of listeria monocytogenes in European cheeses: A systematic review and meta-analysis. Food Control 84:205–214. https://doi.org/10.1016/j.foodcont.2017.07.020

Martinsdóttir E, Schelvis R, Hyldig G, Sveinsdóttir K (2009) Sensory evaluation of seafood: methods. Quality, Safety and Authenticity, In Fishery Products. https://doi.org/10.1002/9781444322668.ch4

Mchazime I, Kapute F (2018) Sensory and nutrient quality of wild captured *Oreochromis shiranus* (Boulenger, 1897) stored at ambient temperature. Int Food Res J 25(1):127–132

Navotas IC, Santos CNV, Balderrama EJM, Candido FEB, Villacanas AJE, Velasco JS (2018) Fish identification and freshness classification through image processing using artificial neural network. ARPN J Eng Appl Sci 13(18):4912–4922

Niamnuy C, Kerdpiboon S, Devahastin S (2012) Artificial neural network modeling of physicochemical changes of shrimp during boiling. LWT - Food Sci Technol 45(1):110–116. https://doi.org/10.1016/j.lwt.2011.07.013

Nourbakhsh H, Emam-Djomeh Z, Omid M, Mirsaeedghazi H, Moini S (2014) Prediction of red plum juice permeate flux during membrane processing with ANN optimized using RSM. Comput Electron Agric 102:1–9

Poli BM, Messini A, Parisi G, Scappini F, Vigiani V, Giorgi G, Vincenzini M (2006) Sensory, physical, chemical and microbiological changes in European sea bass (Dicentrarchus labrax) fillets packed under modified atmosphere/air or prepared from whole fish stored in ice. Int J Food Sci Tech 41(4):444–454

Prabhakar PK, Vatsa S, Srivastav PP, Pathak SS (2020) A comprehensive review on freshness of fish and assessment: analytical methods and recent innovations. Food Res Int 133:109157

Prado-Silva L, Cadavez V, Gonzales-Barron U, Rezende ACB, Sant'Ana AS (2015) Meta-analysis of the effects of sanitizing treatments on Salmonella, *Escherichia coli* O157:H7, and *Listeria monocytogenes* inactivation in fresh produce. App Environ Microbiol 81(23):8008–8021. https://doi.org/10.1128/AEM.02216-15

Razavi MA, Mortazavi A, Mousavi M (2004) Application of neural networks for crossflow milk ultrafiltration simulation. Int Dairy J 14(1):69–80

Rehman MZ, Nawi NM (2011) The effect of adaptive momentum in improving the accuracy of gradient descent back propagation algorithm on classification problems. In: International conference on software engineering and computer systems. Springer, Berlin, Heidelberg, pp 380–390

Ribeiro CM, Stefani LM, Lucheis SB, Okano W, Cruz JCM, Souza GV, Afreixo V (2018) Methicillin-resistant Staphylococcus aureus in poultry and poultry meat: a meta-analysis. J Food Protect 81(7):1055–1062. https://doi.org/10.4315/0362-028X.JFP-17-445

Secci G, Parisi G, Meneguz M, Iaconisi V, Cornale P, Macchi E, Gasco L, Gai F (2018) Effects of a carbon monoxide stunning method on rigor mortis development, fillet quality and oxidative stability of tench (Tinca tinca). Aquaculture 493:233–239

Sharaf Eddin A, Tahergorabi R (2017) Application of a surimi-based coating to improve the quality attributes of shrimp during refrigerated storage. Foods 6(9):76

Silva BN, Cadavez V, Teixeira JA, Gonzales-Barron U (2017) Meta-analysis of the incidence of foodborne pathogens in vegetables and fruits from retail establishments in Europe. Curr Opin Food Sci 18:21–28. https://doi.org/10.1016/j.cofs.2017.10.001

Socaciu MI, Semeniuc C, Vodnar D (2018) Edible films and coatings for fresh fish packaging: focus on quality changes and shelf-life extension. Coatings 8(10):366. https://doi.org/10.3390/coatings8100366

Sofu A, Ekinci FY (2007) Estimation of storage time of yogurt with artificial neural network modeling. J Dairy Sci 90(7):3118–3125. https://doi.org/10.3168/jds.2006-591

Tan M, Wang J, Li P, Xie J (2020) Storage time prediction of glazed frozen squids during frozen storage at different temperatures based on neural network. Int J Food Prop 23(1):1663–1677

Willmoth CJ, Matsuura K (2005) Advantages of the mean absolute error (MAE) over the root mean square error (RMSE) in assessing average model performance. Clim Res 30:79–82

Wrolstad RE, Smith DE (2010) Color analysis. In: Nielsen SS (ed) Food analysis. Springer, United States, pp 573–586.

Xu Z, Liu X, Wang H, Hong H, Luo Y (2017) Comparison between the Arrhenius model and the radial basis function neural network (RBFNN) model for predicting quality changes of frozen shrimp (*Solenocera melantho*). Int J Food Prop 20(11):2711–2723. https://doi.org/10.1080/10942912.2016.1248292

Yu H, Li J, Luan Y (2018) Meta-analysis of soil mercury accumulation by vegetables. Sci Rep 8(1):1–10. https://doi.org/10.1038/s41598-018-19519-3

Zhang K, Zhang B, Chen B, Jing L, Zhu Z, Kazemi K (2016) Modeling and optimization of Newfoundland shrimp waste hydrolysis for microbial growth using response surface methodology and artificial neural networks. Mar Pollut Bull 109(1):245–252. https://doi.org/10.1016/j.marpolbul.2016.05.075