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Artificial neural networks models used for fishery products

Modelle künstlicher neuronaler Netze für die Fischereitechnik

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Summary

The statistical methods have many benefits in acquiring results in a variety of areas such as the optimization the conditions of processing, estimating the shelf life of food products, predicting the bacteria growth on foods, and also predicting the risk formation of chemicals and pathogenic bacteria on food products. The Artificial Neural Network (ANN) model is just one of many mathematical models used today, and its applications in many areas of food and aquatic products will be enhanced in the future. In addition, in the near future, the most appropriate ANN model will be determined by combining the data produced with advanced processing technologies or obtained from food products and different models for each type of food product, and relible predictions can be made for the future. In the lights of the importance of the subject in this review; the meaning, importance, types, formulations of the ANN models were explained. Additionally, the usages of the ANN models not only in aquaculture and fisheries studies, but also the usages of the ANN models for evaluation of safety assessments of the processing technologies of fishery products were highlighted. Moreover, the usages of the ANN models for determining the freshness and shelf life of fishery products were reviewed. It is expected that future development of various mathematical models, as well as studies to adapt the use of these models together, will benefit the aquaculture, fisheries, food and seafood processing industries.

Keywords: fishery products, the artificial neural network, models

Introduction

Fish is highly nutritious accounting for a huge proportion of the world's food production, but it is very perishable and vulnerable to pre-harvest and post-mortem factors. Previous techniques are time-consuming and cheap labour, and they also do not support local or in-field applications in fishery products monitoring and quality control (Saeed et al., 2022). For this reason, advanced, faster and smarter methods have been preferred in determining the freshness and quality of aquaculture products depending on the development of technology recently (Kılınç and Kılınç, 2022). Sensors are promising alternatives; thus, recent studies highlight the novel electrochemical, colorimetric, enzyme, and gas sensors in fish quality assessment based on sensing principles. Machine learning (ML) has become an effective method for the quality assurance and estimation by utilizing enormous amounts of data obtained by onsite sensing devices (Saeed et al., 2022). In recent years, Artificial Intelligence (AI) has gained significant traction, which, if properly harnessed, has the potential to deliver on many application sectors. In order for this to happen soon in ML, the entire community must overcome the barrier of understandability, which is an obvious issue of the recent innovations brought about by sub-symbolism (Arrieta et al., 2019).

Various methods have been implemented to improve food security, and AI is one of the current technologies utilized in numerous different stages throughout the food system. AI is evaluated in the entire food production ecosystem, including food waste management, food consumption, food processing, food distribution, livestock production, crop production, harvesting/slaughtering, and postharvest management (Kutyauripo et al., 2023). To address the global challenge of food shortages, hunger, and malnutrition, food waste must be eliminated at all stages of the food chain. Modern techniques such as omics (proteomics, metagenomics, transcriptomics, diseaseomics, wasteomics etc), enzymatic treatments, and AI in food waste elimination and control can provide a long-term solution to food loss planning, food shortages, and environmental risks (Sharma et al., 2022). Many studies on the usage and advantages of AI or ANN have been conducted (Trafialek et al., 2015; Zhang, 2019; Rezende-de-Souza et al., 2022; Ranjan et al., 2023; Hassoun et al., 2023). Additionally, various studies have been done about mathematical models (Kılınç et al., 2022a; Kılınç et al., 2022b). Moreover, numerous models have been discovered that have the potential of various ML models, including the Long Short-Term Memory networks, Feedforward neural networks, Holt-Winters statistical model, and Support Vector Regression, as well as a Random Forests (Migueis et al., 2022). In the lights of the above sentences, and also on the importance of the subject that the developments and adaptability of this advanced ML models have been reviewed. In addition, to estimate the shelf life of fishery products, and also to determine the optimization conditions of the used techniques for the fishery products, compared with the other used models have been given in this review.

Artificial neural networks (ANN) and the types of artificial neural networks (ANN) models

ANN is a computational model made up of interconnected simple processing units that can learn from experiences by altering their connections, largely inspired by the human brain. Every neuron in the human brain is interconnected and information flow is provided from the neurons. The neuron illustration with its mathematical model is given in Figure 1.

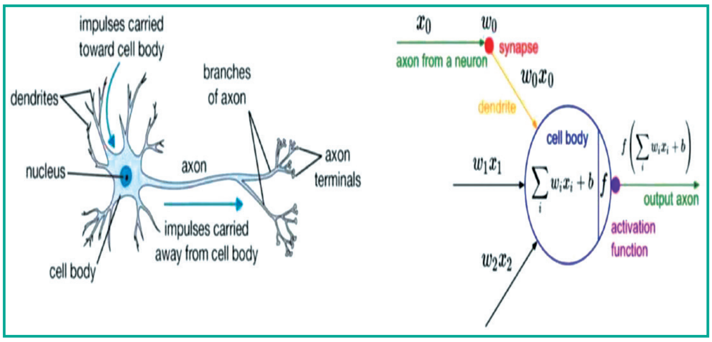

FIGURE 1: *The neuron illustration with its mathematical model (Konaté, 2019).*

Basically, neurons receive electrical signals from other neurons with which they come in contact. These received signals accumulate in the neuron's body and determine what to do next. In case the total electrical signal received by the neuron is large enough, the neuron becomes active or, conversely, inactive. When a neuron becomes active, it transmits an electrical impulse to the neurons with which it is in contact, for example, it acts as an input to other neurons or a stimulus in some muscles (Francisco-Caicedo and López-Sotelo, 2009).

ANNs are machines designed to create a neural network consisting of thousands of artificial neuron units. Practical application of neural networks is unlikely because they are highly parallel computing systems consisting of many basic processing units (neurons) that are interconnected and learn from their environment, with synaptic weights capture and storing power (Haykin, 2009).

An artificial neuron basically consists of the following parts.

1. Inputs, which are data coming into neurons,
2. Link weights that adjust the impact of inputs on output,
3. An aggregation function that calculates the net input to a neural cell by summing the inputs multiplied by weights,
4. Activation function that takes the weighted totals of all inputs from the previous layer and then produces an output value and passes it to the next layer.
5. Outputs produced from the activation function.

There are different ANN models developed for various problem structures, according to these basic sections. The most well-known of these are known as single and multi-layer perceptrons, vector quantization models (LVQ), self-organizing map (SOM), adaptive resonance theory (ART), Hopfield networks, Elman network, and radial based network models.

Single-Layer Perceptron (SLP)

This model, which does not use hidden layers, just provides a set of training data, and looks for the appropriate weight vector to get the results (Figure 2). It is not preferred for

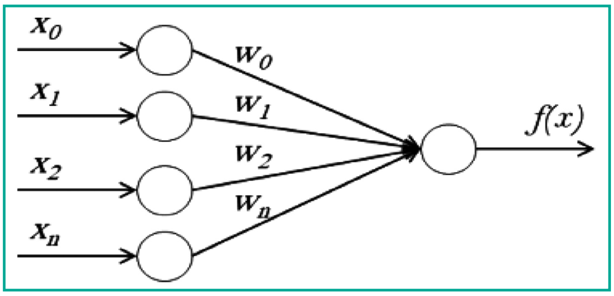

FIGURE 2: *Single-layer perceptron illustration (Wibowo and Wihayati, 2021.*

nonlinear problems. SLP can have multiple input values. For example, the output value is calculated by multiplying the input value x's with the weight value w.

Multilayer Perceptron (MLP)

MLP consists of three or more layers. It is used to classify data that cannot be linearly separated. It is a form of a fully connected neural network in which every node in one layer is connected to every node in the next layer (Sankar and Mitra, 1992). A nonlinear activation function (hyperbolic tangent or logistic function) is used by a multilayer perceptron (Thakur and Konde, 2021). The example of multilayer perceptron illsutration is given in Figure 3.

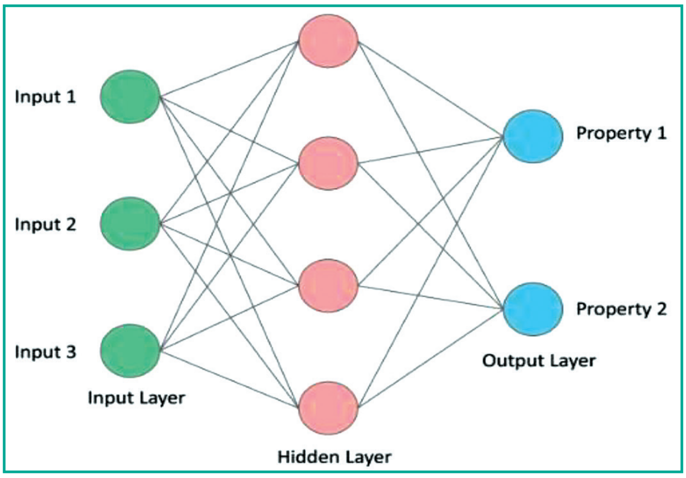

FIGURE 3: *Multilayer perceptron illustration (Zhang et al., 2023).*

Self-Organizing Map (SOM)

SOM is an ANN related to feed forward networks. However, such an architecture is fundamentally different in terms of the arrangement of neurons and motivation. A self-organizing map differs from other neural networks used neighborhood functions to preserve the properties of the input space. SOM uses the unsupervised learning paradigm to produce a discrete and low dimensional representation of the input field of education (Krenker et al., 2011). The common arrangement of neurons is in a rectangular or hexagonal grid structure (Figure 4).

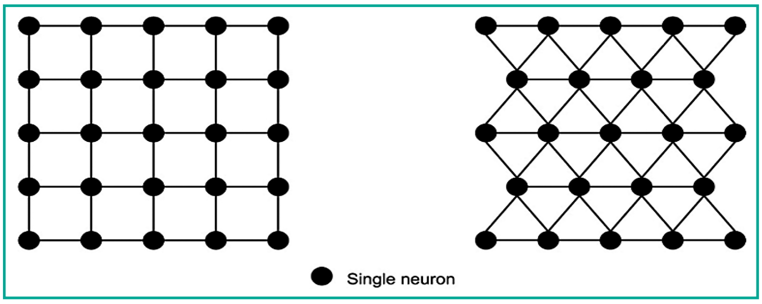

FIGURE 4: *Self-organizing Map (SOM) in rectangular (left), hexagonal (right) structure (Krenker et al., 2011).*

Vector Quantization Models (LVQ)

Introduced by Kohonen, LVQ is a reinforcement learning-based model. Only the inputs desired to be learned are given to the network during training and the network is asked to produce the output itself. It is determined whether the output is true or false. The basic philosophy of the LVQ network is to map the input vector presented to the network to one of the reference vectors representing the problem space (Kohonen et al., 1992).

Adaptive Resonance Theory (ART)

ART was introduced by Geossberg as neural models (Grossberg, 1976a; Grossberg, 1976b). It is possible to create as many classes as the number of samples in the ART network. Various ART networks have been developed. The first ART network developed was the ART1 network (Carpenter and Grossberg, 1987a), which only accepts input vectors consisting of binary values. The ART2 (Carpenter and Grossberg, 1987b) network also accepts continuous values. Apart from these, other models such as Fuzzy ART (Carpenter et al., 1991), fuzzy min–max neural network (Simpson, 1993,) distributed ART (Carpenter, 1996a; Carpenter, 1996b; Carpenter, 1997), Gaussian ART (Williamson, 1996), Hypersphere ART (Anagnostopoulos and Georgiopulos, 2000), Ellipsoid ART (Anagnostopoulos and Georgiopoulos, 2001a; Anagnostopoulos and Georgiopoulos, 2001b), quadratic neuron ART model (Su and Liu, 2002; Su and Liu, 2005), Bayesian ART (Vigdor and Lerner, 2007), The Grammatical ART (Meuth, 2009), validity index-based vigilance fuzzy ART (CVIFA) (Brito da Silva and Wunsch II, 2017), dual vigilance fuzzy ART (Silva et al., 2019) have been developed. The most important advantages of these networks are their ability to work in real time and to learn online.

Hopfield Network

Hopfield artificial neural network, which has a feedback structure, was developed by Hopfield (Hopfield, 1982). The network, which constitutes a theoretical prototype for a wide class of associative memory models, is defined assuming certain mathematical and physical properties (Marullo and Agliari, 2020). Hopfield network can be implemented in two ways, binary and continuous (Jain et al., 1996).

Elman Network

The Elman network is a type of recurrent neural network. The standard back propagation algorithm used is called the Elman back propagation algorithm. The Elman network allows the network to detect and produce patterns that change over time, as it contains repetitive connections between layers (Massinaei et al., 2013). EN with a hidden layer were given in Figure 5.

Radial Based Network

Radial based network introduced by Powell (1987) is an artificial neural network model introduced to solve the problem of interpolation in a multidimensional space that requires as many centers as data points. Then Broom head and Lowe (1988) removed this strict restriction, allowing the implementation of RBNs with many samples, using fewer centers in samples (Montazer et al., 2018).

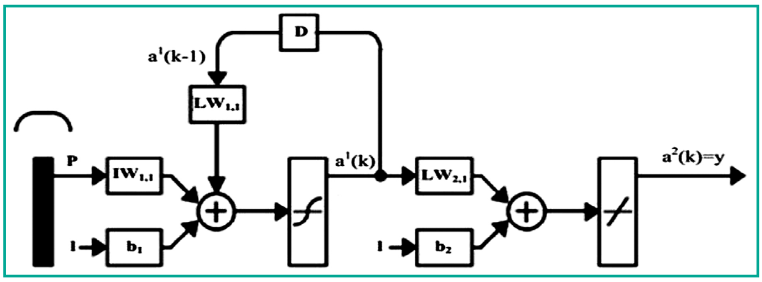

FIGURE 5: *Elman network with a hidden layer (Hagan et al., 1996).*

The formulations of the ANN models

In ANNs, interconnected neurons can learn complex linear and nonlinear input-output relationships by varying the synaptic weights of the network using sequential training procedures. It has been determined that ANNs are generalized nonlinear statistical models. (Montesinos-López et al., 2022).

Artificial neurons calculate their output in its simplest form as follows:

$$y = f\,(wx + b)$$

Where; x inputs, w the vector of synaptic weights and b represents the bias of the neuron. Mathematically, after multiplying the input values and weights (w) in the neuron (wx), they are transmitted to the neuron and the weights and input products from all dendrites are summed. They are then summed with a bias(b) and then transferred to the output after the activation function. This output can be the final output or the input of another cell. Thus, a simple mathematical model is obtained. The basic process in ANN is to calculate the weight parameter and bias value that will give the model the best score. In ANN, various activation functions are used that take the weighted sum of all inputs in the previous layer and then pass it to the next layer by producing a nonlinear output value.

Apart from activation functions, ANNs also use Mean Squared Error (MSE), a widely used loss function to measure the difference between the predicted output of the network and the actual output.

MSE is calculated by taking the squared difference between the estimated and actual output values, and then taking the mean of these squared differences. Mathematically, it can be represented as (Wackerly and Scheaffer, 2008):

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(\hat{y_i} - y_i)^2$$

where y_i is the actual output, $\hat{y}_i$ is the estimated output, and n is the number of samples. The MSE is used as a cost function in the training process of the neural network, where the goal is to minimize the MSE value by adjusting the weights and biases of the network. This is typically achieved using optimization algorithms such as Gradient Descent or Adam optimization, which iteratively adjust the biases, and weights to minimize the MSE. By minimizing the MSE, the neural network learns to make more accurate predictions and generalize better to data.

The meaning and importance of the ANN model

The ANN algorithm, utilized in order to control electronic equipment, seems to be an essential topic in the area of regulation and control, as well as its usage is becoming more widely spread. This algorithm is an extremely effective teaching methodology that is redundant used to manage electronic devices. This model has good and high availability, generalizability of the findings, and also non-linear mapping properties. Nevertheless, it has numerous limitations in practice. To address these issues, an ANN-based algorithm that enables the neural network to be optimized can be introduced (Liu and Wang, 2022). The longshort-term memory neural network (LSTM-NN) model outperformes the backpropagation neural network (BP-NN) model in several ways including higher accuracy estimation as well as a memory mechanism that is selective. However, when it comes to training time, the LSTM-NN model falls short of the BP-NN model. Therefore, the next researches should be focused on how to implementing the optimization mechanism to estimate more quickly and accurately (Tan et al., 2020). It has also been shown over the last years the emphasis has been placed of optimisation food engineering techniques with artificial intelligence (AI) in the development of affordable products with improved health and nutrition conditions. Consequently, it is reported to be necessary to comprehend how food processing variables affect nutrient digestion and capable of enhancing, mathematical model improve them, and, as a result, define the health and nutritional value of the foods (Sandavol et al., 2023). Additionally, AI can help growers make essential management decisions in aquacultural systems by answering fish production-related questions (RAS) (Ranjan et al., 2023).

The ANN Models have been used in various sectors, which including prediction, optimisation, risk assessment of the processing technologies of foods. This model can be used to estimate food spoilage during storage, which is useful during the risk evaluation procedure or when evaluating the quality and safety of foods (Stangierski et al.,2019). Design of experiments (DOE) is a group of statistical techniques used in food technology to optimize recipes and facilitate the creation of novel foods. In a novel cross-disciplinary twist, the authors recommend adapting the DOE technique to restaurant atmosphere optimization. In this study, the ANN with the algorithm for particle swarm optimization (PSO; hereafter ANN-PSO) was chosen and particularly in comparison to the classical Response Surface Method (RSM), as ANN-PSO has been shown to have high level of reliability and predictability than RSM (Kantona et al., 2022).

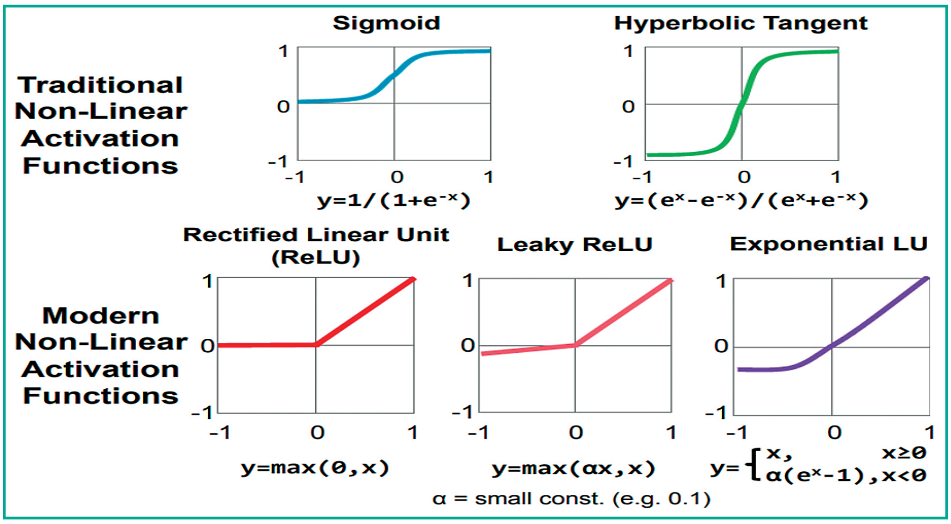

FIGURE 6: *The most used nonlinear activation functions and graphics (Sze et al., 2017).*

ML approaches aided by the convolutional neural networks (CNN) on the other hand, are data-intensive, with prediction accuracy of the model dependent on the quality of the input image. The acquisition of high-quality imagery data is hampered by acquisition of information from underwater imagery, reasonably high fish density, and turbidity of the water (Ranjan et al., 2023). Additionally, the ANN model is capable of confirming positive performance for the application of the produced alternative in estimations for the future of freshness in fishery products, showing its viability for a more reliable quality assurance, through the assessment of the merit figures. In light of the foregoing, colorimetric data modeling by the ANN models is in line with the expectations of the 4.0 food industry, as it is a quick method and a maintainable option not only environmentally friendly, but also financially, as it stimulates the usage of low-cost and green machines (Rezende-de-Souza et al., 2022). By combining e-commerce sales data, this model has a significant advantage in accumulating a huge amount of historical data, and it can shorten the modeling time while producing good prediction results. It introduces a new efficient technique for forecasting aquatic product exports (Zhang, 2019). The importance of robotic systems, sensor technologies, AI, the the Internet of Things, and big data as key enablers of Food Processing 4.0. benefits in regard to control of quality, safeness, and productivity improvement. Nevertheless, extensive investigations still are required to address important difficulties as well as provide great insights into each Food Processing 4.0 enabling technology, such as the creation of particular effectors for robotics, miniaturization and ease of handling for sensors, standardization of processes and better information ability to share big amounts of data and reduced of beginning and ongoing costs for these technologies (Hassoun et al., 2023). The ANNs not only can be proved to be very important and useful statistical tool for analyzing the results, but also can be enabled the identification of similar opinions and their clustering. The majority of businesses surveyed stated that they used or more one HACCP principal verification, which was acceptable. However, misinterpretation of a component of the HACCP system was frequently demonstrated as inadequate. It was difficult to separate the popular view and create a cluster implemented to the problems and benefits associated with applying HACCP principles, confirming that each of the businesses that conducted a survey defined the unique point of view on their own system‘s procedure (Trafialek et al., 2015).

For many years, modeling has been used in food design process. Modeling has become extremely popular for optimisation in the food industry due to its ease of use and high predictive ability. Improving model reliability and precision is a challenging issue in modeling. As a result, new modeling techniques are continually being created (Therdthai, 2021).

The usage of the ANN model in aquaculture and fisheries studies

ML techniques for monitoring in the fish production environment and designed to detect situations that result in significant losses have enormous potential to boost productivity and sustainability. Potential factors such as water physicochemical characteristics and heavy metal load on pathogens (*Vagococcus* spp. and *Lactococcus garvieae*) in a disease-causing state were investigated in a trout farm using ML algorithms. To model the dataset, the three best known machine learning techniques (Logistic Regression, Nave Bayes, and Support Vector Machine) were chosen. All three models were reported to produced comparable results, with the Support Vector Machine (93.3% accuracy) having the greatest precision (Yılmaz et al., 2023). One current study investigated a real-time, high-precision, portable 3D ResNet-Glore fish feed intake intensity quantitative network capable of precisely locating the four levels of fish feeding levels of intensity in a video stream. The proposed network increased recognition and training speed while decreasing hardware equipment necessities, which could serve as a theoretical foundation for future feeding choices (Feng et al. 2022). The authors recommended a method that combined the VGG16 network with active learning to decrease the amount of labeled data needed for determining fish feed intake status. The findings revealed that the proposed algorithm developed sufficient outcomes in terms of precision (98% accuracy) and the percentage of labeled data (roughly one-tenth of the original dataset). As a result of this study, the method suggested in this research had the potential to serve as a reference for feeding operations in aquaculture production (Kong et al., 2022). Additionally, the impacts of image quality, sensor selection, imaging conditions, data size, and pre-processing operations on the ML model accuracy for fish detection under recirculating aquaculture systems (RAS) production conditions were examined in one study. Four off-the-shelf sensors were specially designed for imaging underwater acquisition to create an imaging platform (RASense1.0). Data collected from imaging sensors in two light conditions were organized into 100-image sets and annotated. A one-stage YOLOv5 model was used to augment and train the annotated images. In terms of the MAP scores, the one-stage YOLOv5 performed similarly to the two-stage Faster R-CNN; however, training time for the former was 6–14 times less than that of the latter (Ranjan et al., 2023). Another discovery offered an important reference for practical as well as fast microalgae harvesting that used low-cost bioflocculant, and the ANN algorithm could be used in microalgae process industries to make critical evaluations regarding the system operational conditions (Suparmaniam et al., 2022). The authors proposed an ensemble the artificial neural network (EANN) that took into account different hydrogeological and environment factors as well as their correlation in this study to enhance fish assessment index (FAI) prediction for stream environmental health screening and management of water resources. The findings demonstrated that the EANN was appropriate for solving large and complicated issues while offering better FAI forecasts than the support vector machine (SVM), making it possible to control conditions of the environment (Kang et al., 2022).

Variance in model predictions may be due to climatic changes, the constant indicator of species diversity used, and the possibility of seals *(Arctocephalus forsteri)* switching major host species between years. To better predict the colonization process and understand the ecological processes that occur, future models should incorporate indices of temporal changes in available resources as well as the density of population (Bradshaw et al., 2002). One paper described the machine learning methodology for classifying pelagic fish species schools using environmental and acoustic data. A classifier based on an optimized two-layer feed-forward neural network was used in the suggested algorithm. Bathymetric, morphological, energetic, and positional functionalities extracted from acoustic data, as well as other environmental collected data, were applied as input. This model gave rise to identifying sardine, horse mackerel and anchovy recognition with a 95% accuracy (Aronica et al., 2019).

The usage of ANN model for the safety and processing technologies of fishery products

Food safety is a collection of guidelines and decisions that must be followed at all stages of the food harvesting, manufacturing, and retailing procedure to guarantee consumer health and safety. This is also true for fish processing. Some parasite species found in fish are particularly hazardous to human beings. As a necessary consequence, the article‘s objective was to create a model that would incorporate both biological features of fish and also environmental parameters in order to be used it to forecast the presence

TABLE 1: *The usage of the ANN model in aquaculture and fisheries.*

Model	Application Areas	Usage of the Model	References
Logistic Regression, Naive Bayes, and Support Vector Machine	Aquaculture Environment	Created a dataset for determining the physico-chemical properties of water quality and the presence of the bacteria in trouts	(Yılmaz et. al., 2023)
VGG16 network model	Fisheries/Aquaculture	Served as a primarily method for feeding operations in aquaculture production	(Kong et al., 2022)
YOLOv5 model	Aquaculture	Used for observing and detecting underwater fish	(Ranjan et al., 2023)
ANN model	Aquaculture	Offered practical as well as fast microalgae harvesting that used low-cost bioflocculant	(Suparmaniam et al., 2022)
EANN model	Environment science	Used for predicting stream environmental health screening and management of water resources	(Kang et al., 2022)
3D ResNet-Glore fish feed intake intensity quantitative network model	Aquaculture	Used network not only increased recognition fish cultivation speed but also decreased hardware equipment necessities	(Feng et al. 2022)
ANN model	Fisheries	Used this model for determining was specifically tuned for sardine, horse mackerel and anchovy recognition	(Aronica ve ark., 2019)

of parasites in raw aquatic products. Intelligent systems based on AI are perfect for this kind of assignment. Rough sets and AI methods were employed in order to create a model with this goal in mind (Wasikowska and Linowska, 2021). Fish lice (Argulus japonicus), Monogenea (Gyrodactylus kobayashii), and Ichthyophthirius (Ichthyophthirius multifiliis), are the most common infectious parasites that cause significant economic losses in the aquatic industry. Therefore, a visual system capable of rapidly detecting and counting these three types of parasites was developed using Python and a one-stage object detection deep learning algorithm called YOLOv4 in this study. The authors improved the detection performance of smaller targets like Monogenea by adding additional detection layers to the YOLOv4 PANet. This artificial intelligence-based method, when combined, could allow for the rapid diagnosis and detection of fish parasites in video and images (Li et al., 2023).

Fish health/quality concerns are becoming more prominent all through transportation that is both waterless and low-temperature. Non-destructive monitoring is an essential requirement for an efficient way to enhance fish safety. The arising Internet of Things, novel wearable electronics, and image fusion technology are currently attracting a lot of attention for non-destructive detection of fresh fish safety (Feng et al., 2023). Since its inception, the ANN has grown in popularity and has played an important role in the advancement of recent technology. With the advancement of industrial automation and the Internet of Things, it has become simpler to than ever before collect information and follow food drying, extrusion, and sterilization, among other processes. In this industrial revolution, the application of the ANN has been demonstrated to be effective in food processing types of work such as food grading, safety, and quality control, among others (Nayak et al., 2020). In one research, Response surface methodology (RSM), the ANN, and the Adaptive neuro fuzzy inference system (ANFIS) were used to determine the optimal manufacturing process and ultrasonic conditions for the preparation of clove essential oil (CEO) nanoemulsion. When stored at 45°C, 25°C, and 5°C for 100 days, the best nanoemulsion maintained good droplet size and polydispersity index (PDI) stability (Chouaibi, 2022). In another research, the technologies gas chromatography-ion mobility spectrometry (GC-IMS), and the electronic nose (E-nose) were used to investigate the changes in volatile components responsible for the advancement of the golden pomfret *(Trachinotus ovatus)* odour characteristic throughout the fermentation period. The Back propagation artificial neural network (BP-ANN) estimated the fermentation period, allowing better techniques to try to control golden pomfret fermentation to be developed. This research laid the groundwork for real-time measuring as well as the control of Chinese fermented *Trachinotus ovatus* (Chen et al., 2021). The ANN model was also used for the enzymatical hydrolysing of fish horse mackerel. The modeling of the degree of hydrolysis (DH) in enzymatic reactions was desirable because of its impact on the many functional as well as bioactivities. Besides that, the former optimal efficiency was achieved at a lower reaction temperature, lowering both nutritional and operational costs (Morales-Medina et al., 2016). An additional study of the impact of specific aspects of the grilling process and also their affects on the production of polycyclic aromatic hydrocarbons (PAHs) was conducted in this research. Furthermore, the ANN optimized with Differential Evolution (DE) was created to model the formation of PAHs in processed meat products. Several models (ANN with DE) were developed, with the best results suggesting that the proposed method could reliably predict the PAHs content in processed meats (Pirsaheb et al., 2022). To predict the characteristics of extruded products produced by cooking of a fish samples, the backpropagation artificial neural network (BP-ANN) model was created. In MATLAB, BP-ANN was developed for operational parameters (inputs) and for each Harndess (H), bulk density (BD), and individual extrudate measurement property expansion ratio (ER) (outputs). The BP-ANN estimation for the optimization of the process conditions outperformed the RSM values reported by the authors (Shankar and Bandyopadhyay, 2007). Based on the data from 17 food samples, a highly desired and reliable two hidden layers the BP-ANN was trained for simulating and estimating the gumminess, and hardness average score from colour and intensity. The correlation coefficients were determined higher in the BP-ANN simulation processing than in the linear fitting model (Fan et al., 2013).

The usage of ANN model for the freshness and shelf life of fishery products

Fish freshness can be characterized by the combination of various organoleptic and nutritional characteristics that quickly degrade after fish catch, i.e., during handling (cutting, eviscerating, wrapping), storage, transportation, distribution, and retail. Numerous stress factors, such as temperature, water activity, or pH, influence the rate at which this degradation occurs. The food industry understands that the freshness of fish influences consumers‘ willingness to pay for the product. As a result, tools that allow for the rapid and ac-

TABLE 2: *The usage of ANN model for the food safety and food processing technology.*

Model	Application Areas	Usage of the Model	References
YOLOv4 model with Python	Food safety	Detected various types of parasites	(Li et al., 2023)
Back propagation artificial neural network (BP-ANN) model	Food processing	Predicted the fermentation stage, allowing better techniques to try to control fermentation to be developed	(Chen et al., 2021)
ANN model	Food processing	Used for the enzymatically hydrolyzing of fish horse mackerel	(Morales-Medina et al., 2016)
ANN model optimized with Differential Evolution (DE)	Food safety/Food processing	The total PAH (ng/g) was determined in terms of the meat's source (animal), cut, presence of skin, grilling temperature, and time	(Pirsaheb et al., 2022)
(BP-ANN) model with MATLAB	Food processing	Created to predict the food properties of extrusion process of a fish muscle-rice flour mixture	(Shankar and Bandyopadhyay, 2007)
BP-ANN model	Food processing	Based on the data from various food samples, the model used to simulate and estimate the gumminess and hardness	(Fan et al., 2013)

curate evaluation and forecasting of the freshness attributes are becoming increasingly important (Garcia et al., 2022). In one study, the MobileNetV1 (MNV1) and a Depthwise Separable Convolution Bottleneck (MB-BE) with Expansion to classify the freshness of fish eyes were used. With a specific strategy, CNN managed to achieve maximum efficiency. The MNV1 reduced the number of parameters for advanced deep learning by transferring from the clearly consistent approach to the complexity separate and distinct convolution concept. The Fish eyes freshness data-sets results showed that the MB-BE was determined to be outperformed other models such as original MNV1, VGG16, Densenet, and Nasnet Mobile (Prasetyo et al., 2022). In another study, the fish freshness was determined using voltametric detection of both xanthine (XT) and hypoxanthine (HX) in fish samples with varying storage times, and the ML model with the ANN algorithm was developed to achieve smart analysis and digital signals for determining freshness of fish species. This work provided an experimental evidence for a biomaterial adaptable nano-sensing system based on 3D porous graphane nanozyme flexible electrodes through simple and rapid one-step mass production. In addition to this, an intelligent nano-sensing platform based on ML model for intelligent operating condition for smart analysis and intelligent transition for digital signal were assessed (Zhu et al., 2021).

Fish is a significant source of high-quality protein for humans. The survival situation (premortem) and freshness (postmortem) of the fish are critical indicators in determining the quality of fishery products. A variety of traditional analysis methods have been used to assess the quality of fishery products, but they are either prohibitively expensive or have practical issues. Biosensors appear as good candidates for the evaluation of fish product quality due to their ease of procedure and early diagnosis (Xiong et al., 2022). Developing new techniques for determining the quality and freshness of fishery products are very important. Digital image analysis was used in this study to evaluate the freshness of rainbow trout fish by identifying the color characteristics of its eyes and gills. The accuracy obtained of the developed models showed that the ANN outperformed the support vector model (SVM) for both the features extracted from the eyes and gills. Furthermore, the extracted features from the gills could better describe the variation in storage periods than any of those obtained from the eyes. Eventually, it was determined that the applied colorimetric system, in conjunction with the developing models (ANN+SVM), could be used as an effective non-destructive technique for determining the fish freshness (Lalabadi et al., 2020). The recent study looked into the possibility of a novel methodology based on an ANN to detect the freshness of *Cyprinus carpio* (common carp) throughout ice storage. The results obtained show the ANN classifier's superior efficiency as a real-time, fast, reliable, and non-destructive computer-controlled method for evaluating common carp freshness all through ice storage. It demonstrated the potential of a computer vision method combined with the ANN as very intelligent technique for determining the freshness of fish species (Taheri-Garavand et al., 2019).

Fresh fish has a relatively short shelf life. Because of advancements in packaging materials and technologies, the shelf life of fish and fish products has increased. Therefore, the fishing industry has always been eager to explore new technologies for increasing shelf life. (Milijasevic et al.,2019). The main objective of one study was to develop the shelf life statistical model for channel catfish fillets using the BPNN technology and near infrared transmittance (NIT). As a result, this study provided a practical foundation and scientific support for the development of a shelf life estimation method for freshwater fillets using the BPNN based on NIT spectroscopy (Mao et al., 2023). Arrhenius models depend on EC; electrical conductivity and TAC; total aerobic counts performed well reported by Liu et al., (2015), whereas those based on SA; sensory assessments and K-value performed poorly on some days. The ANN, on the other hand, was more successful at forecasting changes in SA, TAC, EC, and K-value, throughout storage of rainbow trout *(Oncorhyncus mykiss)*. As a result of this study, the ANN model could be preferred as an useful tool in modeling quality changes in rainbow trout fillets (Liu et al., 2015). The purpose of another investigation was to look at the quality changes (K value [freshness determination], Ca2+-ATPase activity, ice crystal morphology, total sulfhydryl [SH] content, and intrinsic fluorescence intensity [IFI]) in tilapia fish *(Oreochromis niloticus)* after 112 days in storage at different temperatures. In addition to this, the ANN, and kinetic models were improved to forecast these modifications. The ANN model was reported to be outperformed the Arrhenius models for all quality and freshness indicators (Wang et al., 2022). One study used the BPNN model to develop a shelf life statistical method for *Trachinotus ovatus* in different freezing temperatures. The BP neural network model had high regression coefficients, and it could accurately predict *Trachinotus ovatus* quality change at freezing temperatures. Additionally, the (BP) neural network model had reported to be a high possibility for estimating *Trachinotus ovatus* shelf life in frozen storage conditions (Lan et al., 2022). To quantify and estimate the freshness of horse mackerel *(Trachurus japonicus)* during 90-day frozen storage, an E-tongue, colorimeter, and E-nose were created in conjunction with a data fusion strategy as well as various machine learning algorithms (extreme gradient boosting, ANN, RFR; support vector regression, SVR, and XGBoost; random forest regression). The ANN model had the best fit in predicting protein oxidation degree. Additionally, the ANN model had the best fit in estimating protein oxidation degree as well as the results showed that the combination of electronic sensor fusion signals could existing data collection and estimate the freshness of frozen fish (Li et al., 2023). For the first time, a Vis-NIR hyperspectral imaging (HSI) system coupled with the ANN was used to observe change in colour in large yellow croaker fish *(Larimichthys crocea)* fillets throughout storage period of low-temperature. The outcomes showed that HSI coupled with the ANN could replace a conventional colorimeter in determining the spatial pattern of color in fish fillets with a non-invasive and quick technique (Wang et al., 2022). An alternative freshness index technique for abalone *(Haliotis asinina)* muscle was advanced and kept at 2±1 °C under modified atmosphere (MA) packaging conditions of 40% CO2: 30% O2: 30% N2, and atmospheric air (Air). Using the ANN, instrumental, and biochemical analyses were calibrated with the freshness index. It was demonstrated that the ANN could correlate with the biochemical, and instrumental analyses as well as the freshness index (Siripatrawan et al., 2009). Fish patties were chosen as test meat products to investigate the potential application of the advanced film system. The color of the films was used as the input and the total volatile nitrogen (TVB-N) content as the output in the BP-ANN. After three days of storage at 4 °C, the TVB-N content of fish samples accelerated to spoilage levels; the color of the films transformed from pink to brown, then to dark green. The BP-ANN model successfully estimated the freshness of packaged products based on the color change of the films (Sun et al., 2022). To estimate the shelf life of the glazed large yellow croaker, the Arrhenius prediction model and long-short-term memory neural networks (LSTM-NN) estimation models were developed. The Arrhenius model and the LSTM-NN prediction model both performed well in predicting the shelf life of this fish. However, in terms of relative error, the LSTM-NN model outperformed the Arrhenius model. Furthermore, the new LSTM-NN model had a more intelligent, comfortable, and fast data computing capabilities, resulting in a superior option for estimating the shelf life of glazed large yellow croaker (Chu et al., 2021). The BP-ANN and LSTM-NN prediction models were created to estimate the storage period of glazing squid throughout frozen storage. According to the modeling results, the BP-ANN and LSTM-NN models were a reliable model for predicting the storage period of glazed frozen squid. In any case, the study offered a novel approach to adapting neural network algorithms to the estimation of glazing squid storage time (Tan et al., 2020). The results of another study showed that the models based on ML outperformed the model assessment and the statistical technique in regard to precision, with the LSTM-NN model producing the greatest overall outcomes. As a consequence, the application of these models could have a beneficial effect on the future sustainability of fresh fish species as well as customer satisfaction (Migueis et al., 2022).

Conditions where human potential is inadequate can always be fitting models, particularly with methods of deep learning and combinations. Nevertheless, choosing the correct AI technique for the design issue in question is critical for such excellent results. As a result, authors have provided an overview point of view on selecting the best AI technique for design issues according to published outcomes (Yüksel et al., 2023).

Conclusion

The devices and methods used to determine the quality and risks of fishery products develop in parallel with the continuous development of technology. In addition to the numerous benefits provided by the implementation of these methods, some disadvantages such as high costs and inadequate standards may arise over time. However, it is critical to conduct research to eliminate the disadvantages of these technologies as well as to ensure that benefits of technology are fully utilized. For this purpose, data analysis and ML methods can help to obtain more accurate results by analyzing large data sets. In addition to advanced technologies used in the processing of food and fishery products, such models provide significant benefits in obtaining results in a various areas such as optimization conditions, shelf life, pathogenic bacterial growth, risk estimation of the products in question.

The ANN model is only one of the mathematical models used today, and in the future, it will be preferred to be used in many areas of food and aquatic products such as determining product optimization conditions, estimating shelf life, estimating pathogenic bacteria development during storage. In addition, the most suitable model will be determined by combining different models in order to determine the most suitable mathematical method for the food and fish product type in which advanced processing technologies are used. There are no studies revealing the advantages/disadvantages of the models introduced in this study in their applications in the field of aquatic science and which model is economically important. In parallel with the developments in data mining, the development of these models continues and therefore more studies are needed. It is predicted that future studies on the development of various mathematical models and the use of these models together will provide benefits in the field of food and fishery products.

TABLE 3: *The usage of ANN model for the freshness and shelf-life of fishery products.*

Model	Application Areas	Usage of the Model	References
(ANN+SVM) model	Freshness/Shelf-life	Used for the model as an effective non-destructive technique for determining fish freshness	(Lalabadi et al., 2020)
BP neural network model	Freshness/Shelf-life	Provided scientific support for the development of a shelf-life estimation method for freshwater fillets	(Mao et al., 2023)
ANN model	Freshness	Used the model instrumental, and biochemical analyses with the freshness index.	(Siripatrawan et al., 2009)
BP-ANN and LSTM-NN models	Freshness/Shelf-life	Predicted the storage period of glazed frozen squid	(Tan et al., 2020)
ANN model	Freshness/Shelf-life	Used for predicting oxidation degree and estimating the freshness of frozen fish	(Li et al., 2023)
LSTM-NN model	Freshness/Shelf-life	Used for estimating the shelf life of glazed large yellow croaker	(Chu et al., 2021)
Vis-NIR hyperspectral imaging (HSI) with ANN model	Freshness/Shelf-life	Used as colorimeter in determining the spatial pattern of color in fish fillets with a quick technique	(Wang et al., 2022)

Conflict of interest

There is no conflict of interest.

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