Neutrosophic Sets and Systems, Vol. 80, 2025
University of New Mexico

Non-Destructive Detection of Fillet Fish Quality Using MQ135 Gas Sensor and Neutrosophic Logic-Enhanced System

M. Y. Shams[1], M. R. Darwesh[2,3], Roheet Bhatnagar[4], N. S. A. Al-Sattary[2], A. A. Salama[5], M. S. Ghoname[2]

[1] Deptartment of Machine Learning, Faculty of Artificial Intelligence, Kafrelsheikh University, Kafrelsheihk 33516, Egypt; mahmoud.yasin@ai.kfs.edu.eg,

[2] Department of Agriculture Engineering, Faculty of Agriculture, Tanta University, Tanta 31527, Egypt; mohamed.darwish@agr.tanta.edu.eg, salahnora94@gmail.com, mohamed.ghonaim@agr.tanta.edu.eg

[3] Department of Food Processing, Faculty of Industry and Energy, Samannoud Technological University, Egypt.

[4] Department of Computer Science and Engineering Manipal University Jaipur, Rajasthan, India, roheet.bhatnagar@jaipur.manipal.edu

[5] Department of Mathematics and Computer Science, Faculty of Science, Port Said University, Egypt, ahmed_salama_2000@sci.psu.edu.eg

* Correspondence: Roheet Bhatnagar; Email: roheet.bhatnagar@jaipur.manipal.edu

Abstract: This paper demonstrates the feasibility of using an electronic nose to assess fish quality by analyzing air quality and examining volatile organic compounds (VOCs) alongside physical variables, with pH, protein content, and VOCs serving as chemical reference points. Artificial intelligence algorithms were employed to predict quality and calculate regression coefficients. Using the reference neural network algorithm based on chemical and physical compounds, regression coefficients (R values) achieved were 0.99, 0.98, and 0.97, respectively. Additionally, ANFIS (Adaptive Neuro-Fuzzy Inference System) produced R values of 0.99, 0.85, and 0.98. Both fuzzy logic and ANFIS proved effective for predicting fish quality. Image processing techniques, including histogram analysis, color mapping, and edge detection, were also applied to assess fish quality. To enhance the inference process, Neutrosophic Logic-Enhanced Fuzzy Logic Systems were utilized, addressing uncertainty and imprecision in fish quality assessment. Neutrosophic logic combines fuzzy logic's partial truth with indeterminacy, represented by three membership functions: truth, indeterminacy, and falsity. Neutrosophic fuzzy inference integrates steps like neutrosophication, rule evaluation, aggregation, and defuzzification, ensuring improved expressiveness and fidelity. For instance, neutrosophic fuzzy rules evaluated fish freshness and appearance to determine quality ratings such as poor, good, or excellent. This integration enhances decision-making by accurately modeling complex real-world uncertainties. These methods, combining electronic nose technology, artificial intelligence, and neutrosophic inference, provide a robust, non-destructive, and cost-effective approach to detecting spoilage in fillet fish.

Keywords: Adaptive Neuro-Fuzzy Inference System, Neural Networks, Fuzzy Logic, Neutrosophic Logic.

1. Introduction

Fish is one of the most traded foods in the world because it contains nutrients beneficial to human health. The chemical composition of fish consists of the following: Fish contains 18% to 24% lipoprotein, 2% calcium and contains 22 kg / 100 grams of phosphorous, it also contains soluble vitamins **[1]**. There are many factors that affect the proportions of the chemical composition of fish, including type of food, sex, seasonal differences, differences in the composition of parts of the same fish, such as the difference between white muscle and red muscle, and the difference on the right side from the left side **[2–4]**. There are several methods for assessing the freshness of fish, firstly, sensory methods, which include change in smell, gill color, texture, buoyancy test, flesh and skin consistency, eye color, and texture **[5]**. Most of the current organic gas sensors are considered as individual machine learning methodologies and are considered as the best modern non-destructive methods for assessing freshness during fish storage period. A gas sensor was used to assess TVB-N of salmon. The correlation coefficient between freshness values and TVB-N gas sensor readings was determined to determine the sensitive gas sensor indicators. Linear models, ensemble machine learning, which includes the following models SVR, MLP, KNN, Gaussian model and decision tree were used to determine the freshness indicators by improving the analysis models in detecting the quality and freshness of salmon, which proves the effectiveness of sensors in detecting fish freshness **[6]**. There are also analytical methods for detecting the freshness of fish, such as estimation of VOCs, estimation of ammonia, estimation of sedimentation, selection of thiobarbutic acid, study of the pH concentration of the refractive index of eye fluids, total number of bacteria, and the test for total volatile nitrogen **[7,8]**. There are several factors that cause fish spoilage, including: Bacterial spoilage that occurs due to the presence of spoilage bacteria in the intestines of fish, and the degree of bacterial spoilage varies according to the temperature and the type of bacteria **[9]**. Bacteriological spoilage begins with the appearance of unpleasant odors, as a result of which a trimethylamine complex is formed, and then the formation of indole compounds, amines and hydrogen sulfide increases. The type of bacterial spoilage varies depending on several factors, the most important of which is the type of fish **[10,11]**. Red muscle fish are more prone to spoilage than white muscle fish because they contain a high percentage of hemoglobin and the condition of the fish when fishing in terms of the fullness of the stomach and the pressure on the fish, the temperature of transporting the fish after fishing, the type of pollution to which the fish are exposed. In terms of the percentage of pollution and mud in the water in it, as well as pollution, manual work in fishing, transporting and trading fish during and after fishing. There are several methods for preserving and processing fish, including fish cryopreservation, by reducing the temperature of fish to a point close to freezing, which leads to reducing biological and chemical reactions, which delays bacterial reactions **[12,13]**. Spoilage of fillet fish causes a change in color as a result of the change of myoglobin and hemoglobin responsible for the red-pink color to yellow and brown and a change in odor as a result of the release of volatile organic compounds, therefore, researchers tried to find new non-destructive detection methods for detection **[14]**. On the freshness of fish using artificial intelligence **[15]**, spectroscopic computer vision, electronic nose and NIR. Through the applications of artificial intelligence and machine learning algorithms, it is possible to classify foods and predict food quality **[16–18]**. Machine learning algorithms were also used to predict the quality of fish built on real time platform [19]. Artificial intelligence contain predictable algorithms such as The adaptive neuro-fuzzy inference system (ANFIS) and fuzzy inference system that used to predict the quality of fish [20]. As for analytical detection methods, they are not suitable in fish factories because they are considered destructive detection methods that take time, effort and costs. Recently, the fish fillet industry has spread and the consumer's demand for eating fillet fish has increased, as it contains advantages represented in providing the process of washing and cleaning to the consumer, fish fillets can be cut as desired, longitudinal or transverse slices, which facilitates the processing process for the consumer. Certain weights can also be obtained, which facilitates the marketing work [21]. Spoilage of fish causes food poisoning to humans when eaten. In this study, three models were used, Back Propagation Neural Network (BP-ANN) [22], Adaptive Neuro Fuzzy Inference System (ANFIS) to determine the extent of correlation between the chemical variables represented in pH, protein values and reference TVB-N and the physical variables represented in image features and TVB-N reading from MQ135 gas sensors. Fuzzy Inference System (FIS) was used to predict the quality of fish fillets. Despite these advancements, the inherent uncertainty and imprecision in fish spoilage assessment present significant challenges. This study aims to address these limitations by integrating neutrosophic logic—a framework that models uncertainty using three membership functions: truth (T), indeterminacy (I), and falsity (F)—with predictive algorithms to enhance the reliability and robustness of fish quality evaluation systems.

The main contribution of this study is to use the gas sensor as a non-destructive way to detect the extent of freshness by measuring volatile organic compounds through:

1. Creating a suitable system for obtaining computer data and computer vision,
2. The use of predictive algorithms such as neural networks and ANFIS for the chemical variables represented in the acidity number, protein values, measurement of volatile organic compounds in the laboratory, and the physical variables represented in the variables in the characteristics of the images and the reading of the output from the gas sensor of the volatile organic compounds
3. Building a fuzzy logic model to predict fish quality, depending on the gas sensor reading of VOCs, reference VOCs, protein values, and pH number.
4. Neutrosophic logic enhances fish quality assessment by effectively modeling uncertainty and imprecision through its truth, indeterminacy, and falsity dimensions, improving decision-making accuracy.

The study involved several key steps, including sample preparation, chemical analysis of fish fillets, image acquisition using an image conception system, and VOC measurement via a gas sensor. Machine learning models, such as a Back Propagation Neural Network and an Adaptive Neural Fuzzy Inference System (ANFIS), were developed, evaluated, and refined using the ANFIS algorithm and alongside a fuzzy logic, and neutrosophic-logic approaches with an inference system to enhance accuracy. The related work are illustrated in Section 3, the methodologies are detailed in Section 3. Section 34 presents the results and discussion, while Section 5 concludes the study and highlights directions for future research.

2. Related work

The assessment of fish quality has witnessed significant advancements over the years, transitioning from traditional destructive techniques to modern non-invasive approaches **[23]**. Traditional methods rely on measuring chemical and physical attributes such as appearance, color, texture, odor, and taste **[19,24]**. While effective, these methods have notable drawbacks, including their destructive nature, high costs, time consumption, and the need for highly skilled operators. Consequently, researchers have focused on developing innovative non-destructive techniques such as biosensors, electronic sensors, and spectroscopic methods. These approaches minimize sample preparation, avoid destruction, and provide comprehensive data from a single test, making them ideal for online and at-line process controls in food quality assessment **[25]**. Machine learning algorithms have also played a pivotal role in advancing fish quality evaluation. Models like Back Propagation Artificial Neural Networks (BP-ANN) and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) have been widely used to predict correlations between chemical variables (e.g., pH and protein content) and physical variables (e.g., VOC sensor readings and image features). These predictive models improve the reliability of quality assessments by analyzing large datasets and identifying intricate patterns in the data **[26]**.

However, the integration of neutrosophic logic into these frameworks has introduced a transformative approach to handling uncertainty, imprecision, and indeterminacy inherent in real-world conditions. Neutrosophic logic enhances traditional fuzzy systems by incorporating three membership functions: truth, indeterminacy, and falsity. This allows for a more comprehensive modeling of ambiguous scenarios, such as variations in fish spoilage conditions. For example, neutrosophic fuzzy rules can classify fish quality into categories like "poor," "good," or "excellent" with greater expressiveness and accuracy. By addressing data uncertainty, neutrosophic logic improves decision-making capabilities and ensures higher fidelity in fish freshness evaluation systems.

In one study **[27]**, a hydrogel-pH-electrode-based near-field passive volatile sensor was developed for real-time monitoring of fish spoilage. The sensor utilized a varactor-based LC resonator, which was interrogated via inductive coupling to detect changes in resonant frequency caused by total volatile basic nitrogen (TVB-N) in the fish headspace. This sensor exhibited a linear response to ammonia gas concentrations, with a detection limit of 0.001 mg/L (1.5 ppm). Trials on tilapia stored at 24 °C and 4 °C demonstrated that the sensor's readings correlated with bacterial growth patterns and accurately identified the spoilage threshold (107 cfu/g) for both storage conditions. This wireless sensor, designed for embedding in packaging materials, offers a cost-effective and scalable solution for real-time spoilage detection, leveraging advancements in printed electronics for mass production. Another notable study **[28]** employed Arduino-compatible MQ-series sensors (MQ3, MQ4, MQ5, MQ8, MQ9, and MQ135) to measure odor changes in trout, sea bream, and sea bass during storage. The odor intensity readings from the sensors were compared with microbiological and sensory data to establish spoilage thresholds. An electronic nose box, controlled by an Arduino microprocessor, was developed to rapidly assess the quality of 10 g fish samples. The system accurately identified "Fresh Fish" samples with total viable counts below 3 log CFU/g, highlighting the potential of Arduino-controlled odor sensors as a fast, simple, and low-cost solution for evaluating food quality.

3. Material and methods

3.1. Sample preparation

A 94 slices of fish fillet were purchased from the local market and divided into four sets: 24 slices for protein analysis, 24 slices for pH analysis, 24 slices for TVBN reference value analysis, and 24 slices for air quality analysis using the MQ135 gas sensor. The mass of each slice was 2.4 ± 0.48 g. The fish fillet sets were placed in sterile plastic bags and stored in a refrigerator at 4°C for 10 days. Six samples were analyzed on four different days (days 1, 4, 7, and 10) for each set.

3.2. Chemical analysis

The volatile organic compounds, protein, and pH number in fish fillets were estimated in the laboratories of the Food Technology Department at the Faculty of Agriculture, Kafr El Sheikh University, Egypt in march 2024. The pH was measured by a PH meter of fish samples during the storage period. The protein of fillet fish was estimated by the Kildahl method through the following steps: 2.2 grams of fish fillet was weighed after it is ground and placed in a beaker Kildahl capacity from 500 to 800 ml, then 15gm of anhydrous potassium sulfate powder are added, 25ml of concentrated sulfuric acid 93-98% free of nitrogen and 0.7g of mercury oxide free of nitrogen. The Kildahl beaker is heated in the Kildahl apparatus for 30 minutes until it boils, then it is left to cool down, then 200ml of water is added, then a quantity of mercury granules is added and then the beaker is placed on the distillation device, then 80ml of sodium hydroxide solution are added and then 5 to 7 drops of sodium are added. The methyl red guide and green bromocresol are dissolved in 0.16g of methyl red, then the distillation flask is shaken and heated well until the ammonia is volatilized and condensed in the receiving flasks, where at least 150ml of nitrogen is extracted and is equivalent to adding hydrochloric acid (LU et al., 2010). The Planck test is done, i.e. repeat the same previous steps without samples, then calculate the protein percentage through the following equations (1) and (2):

$$\%\text{ of nitrogen } = \frac{(\text{volume of hydrochloric} \times \text{standard hydrochloric standard} \times 14.007 \times 100)}{(1000 \times \text{weight samples})} \tag{1}$$

$$\%\text{ of protein in fillet fish} = \%\text{ of nitrogen } \times (16/100) \tag{2}$$

The content of the volatile organic compounds in the fillet was measured during the storage period using the steam distillation method through the following steps: The samples were ground with a grinder 10 ± 0.1g of the ground fish samples were taken and placed in a beaker and 100 ml of distilled water were added for 30 minutes with shaking The beaker every 10 minutes, then the solution was filtered using filter paper, then 10ml of magnesium oxide was added to produce 5ml of the alkaline filter, then the resulting solution was distilled by steam distillation for 5 minutes, then 10ml of boric acid was added to absorb the resulting solution from the distillation flask with steam **[29]**. Titration was performed by adding 0.01 hydrochloric acid. TVB-N for fish was calculated by the following equation (3):

$$\text{TVB-N} = \frac{(v_1 - v_2) \times c \times 14}{m \times 5/100} \times 100 \quad (3)$$

where v_1 is size of the sample that was calibrated, v_2 is size without samples (Blank), c is actual concentration of hydrochloric acid, Sample weight of ground fish (g).

3.3. Image conception system

Images of fillet fish were taken during the four analysis days with a charge coupled device (CCD) camera. The images were calibrated by taking ten white reference images with a reflection rate of 99% and ten black reference images with a reflection rate of 0% using the following equation (4) **[30]**.

$$M = \frac{I_S - I_D}{I_W - I_D} \times 100\% \quad (4)$$

where M is the calibrated image, I_S is the raw image, I_D is the mean dark reference image, and I_W is the mean white reference image. The size of the captured images was (2534 ×2786). The median filter was used to remove noise before determine the Region of Interest (ROI). Region of Interest in images is defined as the portion of the image being processed where the pixel value is 1 and the remaining pixels are 0 (Cheng et al., 2015 and Taheri-Garavand et al., 2019). The size of ROI in the images was (364 ×246) using a binary mask. Edge deduction of image processing was used to determine the dashed curves as pixels of image to extract the features from the images through using five types of filters they are: Sobel, log, canny, Roberts, and Prewitt filter.

3.4. Measuring VOC from fillet fishes via gas sensor

Volatile organic compounds are among the most important indicators of the quality of fish meat, which result from the decomposition of basic chemical compounds due to the activity of bacteria and the conditions of keeping fish, which is the decomposition of protein into ammonia. Hydrogen sulfide, ethyl mercaptan, etc. Carbohydrates in hydrocarbons, alcohols, ketones, aldehydes and carboxylic acid gases hydrolyze lipids into aldehydes and aldehydes **[27,31–36]**. In this research, MQ135 gas sensor was used as a non-destructive method to detect the freshness of fish by determining the percentages of volatile organic compounds produced by the fish during the storage period Figure 1. The gas sensor is a metal (MOS) because the resistance changes according to the amount of gas produced of the article. The gas sensor specification is based on a DC voltage of 5V, and can identify the gas concentration for the MQ135 gas sensor VOCs in the range between 10 to 10,000 ppm. The MQ135 gas sensor measures air quality gases, which are represented in (ammonia, nitrogen alcohols, sulifide, and oxygen), which are considered among the most important volatile organic compounds that express the quality of fish.

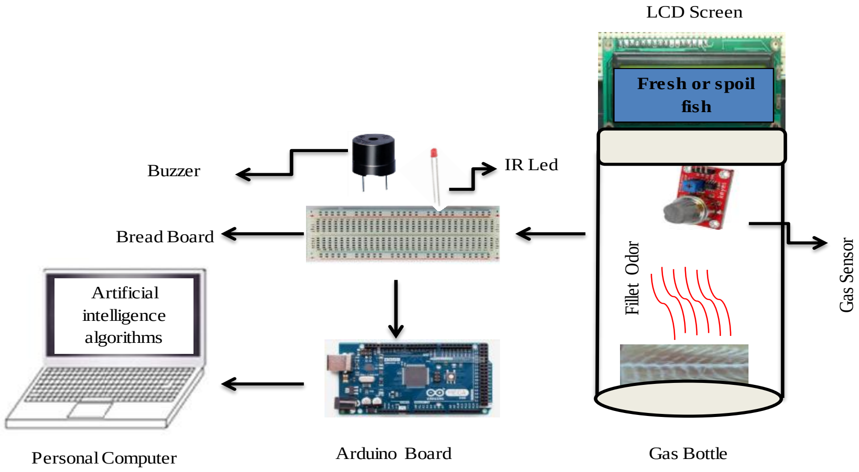

Figure 1. Scheme of gas sensor system for measuring VOCs of fish

The MQ135 gas sensor was placed in the gas bottle and readings were taken through three stages: The first stage is to calibrate the gases inside the bottle to ensure that there are no volatile organic components inside the bottle, and the second stage is to place 40 ± 0.5 grams of fish samples for 15 minutes until we obtain the gas values. VOC (Headspace Phase), by connecting the gas sensors to the massive Arduino 2560 board through four pins, A0 represents the voltage proportional to the gas concentration, VCC represents the voltage supplied to the sensor, GND is the ground pin of the sensor, and D0 represents the values of the gases produced. The gas sensor is set by the gas output voltage as an increase in gas concentration results in an increase in the output voltage which indicates an increase in VOCs and fish damage. The third stage: After taking a reading of each sample, the gas bottle is disinfected with water and air for ten minutes, and the previous two stages are repeated for each sample of fish at a temperature of 25 degrees Celsius. Humidity was kept at a level of 30±1% during the experiment. The gas sensor was set to determine the quality of fish by turning on a red infrared LED light, emitting a siren and reading the quality of the fish (fresh or spoiled) on the LCD screen when a concentration of volatile gases greater than 9000 ppm is reached, which are the air quality values after the second day of analysis. Designated as an indicator of fish spoilage.

3.5. Back Propagation Neural Network

The artificial neural network is one of the most important artificial intelligence algorithms that are used in prediction and classification, which simulate the way of human thinking. An artificial neural network consists of nodes, input layers and output layers. There are several types of neural networks, including Back Propagation - Artificial Neural Network (BP-ANN), Radial Basis Function - Neural Network (RBF-NN), and Self-Organizing - Neural Network (SO-NN) **[37]**.

Back Propagation Neural Network (BP-ANN) is a type of neural network that transmits information in the opposite direction to the original direction, and it is a type of machine learning under supervision where the network needs inputs **[38,39]**. The network is trained using forward propagation to obtain the predicted output value **[40]**. then the error value between the predicted output and the desired output is calculated, then the back propagation stage begins, in which the error value is calculated for each neuron in the network and at the end of the weights are updated and compensated with the new calculated values **[41]** as shown in Figure 2. One of the most important uses of BP-ANN in artificial intelligence are prediction and classification processes of the data **[42]**. Furthermore, it used in simulating human thinking, as it trains the network by adjusting and updating the weights that express the interconnections between the layer and the layers that follow it, the network contains only one input layer, one hidden layer, and one of output layer, Figure 3.

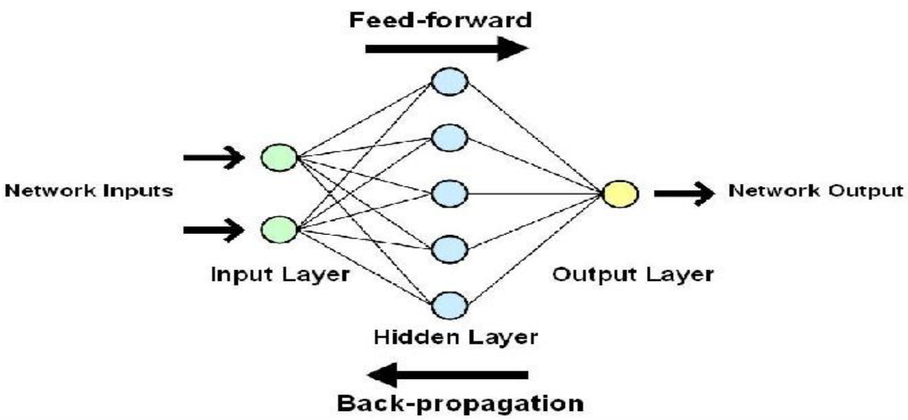

Figure 2. Architecture of BP-ANN

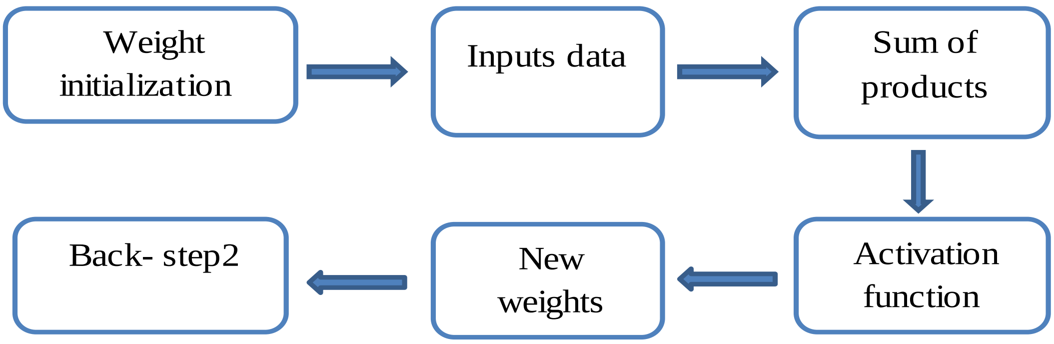

Figure 3. Flowchart of training steps of neural network

A back propagation neural network consists of a set of nodes, input layer, hidden layers, activation functions, and a set of weights that indicate the extent of the connection between communications and some of them **[43,44]**. The learning rate from 0 to 1. In this study, 2 hidden layers were used, and the number of neurons in each layer was 10 and 6 Figure 4, respectively. Number of epochs were of 1000. The learning rate of the network was set to 0.1, and the type of activation function were purline and tansiq in the two hidden layers.

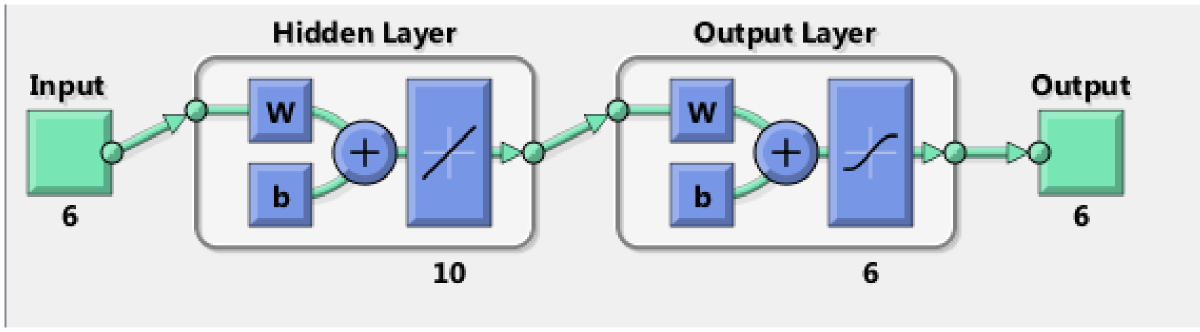

Figure 4. Type of activation functions of purline and tansiq that used in the hidden layer and output layer, respectively

3.6. The Adaptive Neural Inference System

The Adaptive Neural Inference System (ANFIS) is a system that combines the characteristics of artificial neural networks and fuzzy logic, where through this system it is possible to modify network parameters such as adjusting the number of neurons for the learning parameter and improving methods of fuzzy modeling through neural networks **[45,46]**. Figure 5 shows the components of the nervous system, which contains five layers, as illustrated by the following equations from (5) to (11). The first layer is called the "fuzzification layer", which includes the inputs and determines the type of membership function **[47,48]**. However the type of membership function were trimf (triangular function). ANFIS also determines the participation rates for the inputs.

$$\boldsymbol{\mu_{A_j}(x) = \max\left(\min\left(\frac{x-a_j}{b_j-a_j}, 1, \frac{c_j-x}{c_j-b_j}\right), 0\right)} \tag{5}$$

$$\mathbf{O_j^1} = \boldsymbol{\mu_{Aj}(x)}, \quad \text{for j = 1, 2\&3 for linguistic labels number of x} \tag{6}$$

where, $\{\boldsymbol{a_j, b_j, c_j}\}$, and $\{\boldsymbol{c_{mn}, \sigma_n^2}\}$ are the parameter sets of $\boldsymbol{\mu_{Ai}(x)}$, and $\boldsymbol{\mu_{f_{mn}}(z_n)}$, respectively. These parameters are called premise parameters. x and z are the inputs to the nodes, and $\boldsymbol{A_j}$, ***and*** $\boldsymbol{f_{mn}}$ are the linguistic labels. The second layer is called "rule layer" determines the extent of the relationship between the rule and other rules, equation 12.

$$\boldsymbol{O_i^2} = \boldsymbol{w_i} = \boldsymbol{\mu_{A_j}(x).\mu_{\beta_k}(y)}, \quad \text{for} \quad \text{j = 1, 2, 3 and k = 1, 2, 3} \tag{7}$$

where

$\boldsymbol{i = j \times k = 9}$ rules = 1, 2, 3, ……., 9.

$\boldsymbol{i}$ = number of rules which is the product of number of states of inputs x and y.
$\boldsymbol{w_i}$ is the node output which represents the firing strength of a rule.
Sugeno fuzzy system was used to express rules in ANFIS model, equation 19.

$$\text{Rule } \boldsymbol{i}\text{: If x is } \boldsymbol{A_j} \text{ and y is } \boldsymbol{\beta_k}\text{, then } \boldsymbol{f_i} = \boldsymbol{p_i}x + \boldsymbol{q_i}y + \boldsymbol{r_i}, \tag{8}$$

where $\boldsymbol{A_j}$ and $\boldsymbol{\beta_k}$ are the fuzzy sets, $\boldsymbol{f_i}$ is the output, and $\boldsymbol{p_i}$, $\boldsymbol{q_i}$, and $\boldsymbol{r_i}$ are parameters sets that are used in the training process.

Third layer is called "defuzzification layer" This layer determines the ratio of the rule and other rules.

$$\boldsymbol{O_i^3 = \overline{w_i} = \frac{w_i}{w_1+w_2+\cdots+w_9}} \quad \text{for} \quad \boldsymbol{i} = 1, 2, \ldots, 9 \tag{9}$$

Four layer is called "normalization layer" this layer can add some additional data.

$$\boldsymbol{O_i^4} = \boldsymbol{\overline{w_i} * f_i} = \boldsymbol{\overline{w_i}}\ (\boldsymbol{p_i}x + \boldsymbol{q_i}\ y + \boldsymbol{r_i}) \tag{10}$$

Five layer is called "output layer" this layer can produce the desired final product.

$$\boldsymbol{O_i^5} = \boldsymbol{\sum_i \overline{w_i} * f_i} = \boldsymbol{\frac{\sum_i \overline{w_i} * f_i}{\sum_i w_i}} \tag{11}$$

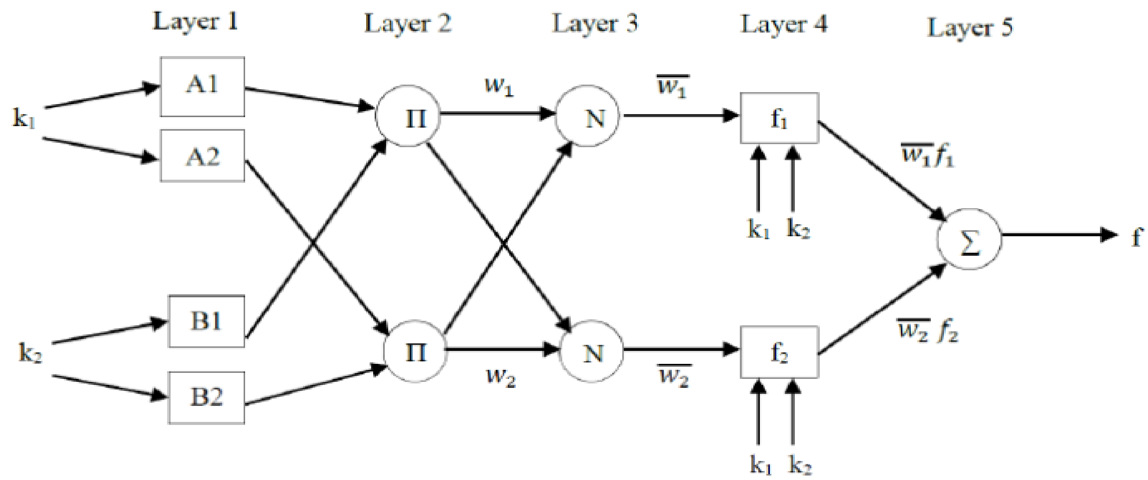

Figure 5. The architecture of ANFIS

3.7. Performance of ANFIS model

In this study, the hybrid nervous system was used with Takagi-Sugeno inference model, then the system parameters were adjusted. Members acceptance and rejection rate that determine the number of shares rejected **[49]**. Therefore, in order to calculate the regression coefficient in the ANFIS system, the previous transactions were determined and were as follows: influence radius was 0.3, maximum number of epochs was 200, error goal was 0, initial step size was 0.01, step size decrease rate was 0.9, and step size increase rate was 1.1.To reduce the Mean Square Error (MSE), neural fuzzy system parameters were set as follows, error tolerance was 0.005. Epochs was 100, range of influence was 0.5, squash factor was 1.25, accept ratio 0.5, and reject ratio was 0.15, the equation (12) of MSE as follows:

$$MSE = \frac{1}{n}\sum_{s=1}^{n}(y_j - \hat{y}_j)^2 \tag{12}$$

where n is number of value, s the absolute value of the residual, $\boldsymbol{y_j}$ is the original value, $\hat{y}_j$ is predicted value of y.

3.8. Building of machine learning model by ANFIS algorithm

The ANFIS system relies on three main steps: logical operations, membership functions, and IF-THEN rules **[32,50,51]**. Figure 6 illustrates the structure of the ANFIS model for the three different models as follows: contains one input representing in chemical analysis (protein values, pH number and TVB-N reference values) and one output that representing in physical analysis (air quality values produced from the MQ135 Gas sensor), number of structure was 3 mf . ANFIS algorithm was also used to predict quality of fish the inputs were (protein values, pH number, TVB-N reference values and air quality values produced from the MQ135 Gas sensor) and the output was quality of fish. The number of IF then-rules as the number of nodes equals 3, and 81 node, respectively, which is the product of number of states of inputs x, y and z etc., as shown in Figure 6.

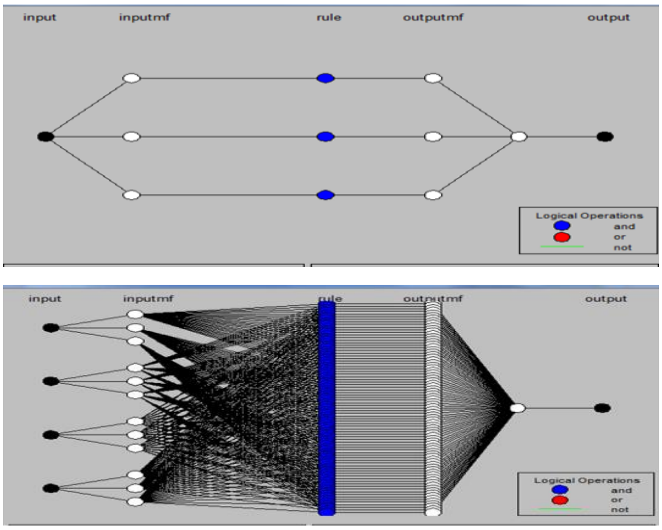

Figure 6. Structures of ANFIS to predict chemical values from physical values and quality of fillet fishes

3.9. Neutrosophic Fuzzy logic inference system

The traditional logic or Aristotle logic assumes it is impossible for the element to belong to the class and to contradict it at the same time, but fuzzy logic assumes the element belongs to a certain class, but to a certain degree **[52–54]**. Membership function, that determines degree the element that belongs to a certain category, such as (high, medium, and low), and the inference step, through which the ambiguous outputs resulting from the application of certain rules are known, Figure 7. In this study, fuzzy logic was applied as an application of artificial intelligence algorithms in determining the quality of fillet fish. The type of membership function was used, trimf as shown by the following equation:

$$f\,(x, a, b, c) \;= \max\,(\min(\frac{x-a}{b_j-a}, 1, \frac{c-x}{c-b}),0) \tag{13}$$

where a, b, c, and d are the parameter set of the trapezoidal and triangle of membership function.

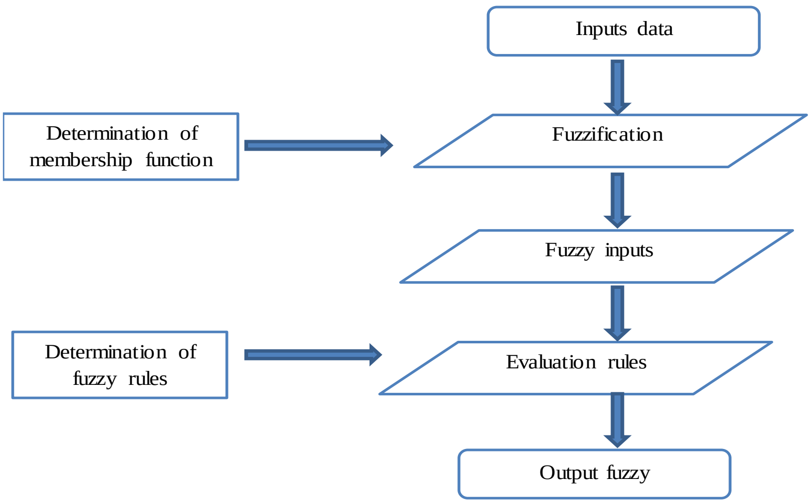

Figure 7. Steps of Fuzzy-logic inference system

Figure 8 illustrates a structured process for handling fish data using neutrosophic logic, which is designed to deal with uncertainty, imprecision, and incomplete information. The steps are as follows:

1. Input Dataset (x): The process begins with an input dataset, denoted as x which contains raw data to be analyzed.

2. Neutrosophication: This step involves transforming the input dataset into a neutrosophic representation. This process converts the data into a format compatible with neutrosophic logic by considering three aspects: truth (T), indeterminacy (I), and falsity (F).

3. Neutrosophic Inputs: The transformed dataset is represented as neutrosophic inputs, which consist of three components: T (truth degree), F (falsity degree), and I (indeterminacy degree).

4. Truth (T), Falsity (F), and Indeterminacy (I): The neutrosophic inputs are split into their respective components. These components represent the degrees of truth, falsity, and indeterminacy for each element in the dataset.

5. Inference Engine: Using the T, F, and I components, the inference engine applies rules to derive meaningful conclusions. These rules are defined as T(x), F(x), and I(x).

6. Deneutrosophication: After the inference process, the neutrosophic representation is converted back into a standard format. This step, known as deneutrosophication, produces actionable results by consolidating the T, F, and I components.

7. Output (Y(T,F,I)): Finally, the process yields an output, Y(T,F,I), Y(T,F,I), which represents the result of the analysis based on the neutrosophic framework.

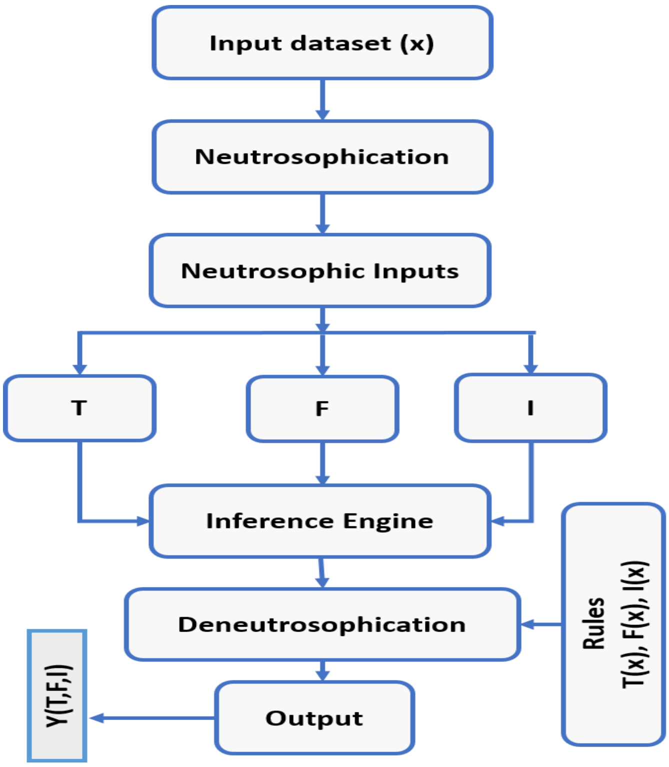

Figure 8. Steps of Neutrosophic-logic inference system

4. Results and dissuasions

3.1. Chemical and physical analysis variance

The values of the chemical parameters of the fish were measured experimentally, that represent in the protein values, pH number, TVB-N, using the Kildahl method, PH meter, and steam distillation method as a reference measure to predict the quality and viability of the fish, respectively. 72 fish slices were used to perform three different chemical analyzes and 24 fish slices were also used to do physical analysis during 10 days of storage. Table 1 shows the change in fish protein content, pH number TVB-N and air quality appeared from the second analysis day. When calculating the lowest significant difference (LSD) for differences between the averages at the level of significance is 0.05, it was found the value of ($p < 0.05$), that indicates there are significant differences between the mean values of the different variables. As a result of the proliferation of bacteria that cause spoilage of cooled fish, such as Pseudomonas, Achromobacter, Flavobacterium, they feed on the protein found in fish, which grows in neutral pH level, which results in volatilization of volatile organic compounds, which is also consider the important indicator of fish spoilage. The mean ± standard deviation of the calculated values of protein and pH count TVB-N for fillet fish fillets, at 0.05 significance.

Table 1. Change variance between chemical and physical sample during analysis days

fish samples	Analysis days			
	1-day	4-day	7-day	10 -day
Protein	0.615377 ±0.784	25.30667 $\pm.626^{a}$	23.95333 $\pm 0.3126^{b}$	23.3687 $\pm 0.2^{c}$
pH	6.45±0.297	6.456 ± 0.053^{a}	6.238 ± 0.089^{b}	5.5998 $\pm 0.324^{c}$
TVB-N	3.89±.4	6.44 ± 1.04^{a}	23.92 ± 1.18^{b}	30.2754 $\pm 1.60^{c}$
Air quality	1736.333± 275.5196	5405.833 $\pm 886.03^{a}$	12929 $\pm 2689.12^{b}$	26755.83 $\pm 4270.39^{c}$

3.2. Extracting image features of fillet fish by image processing

Figure 9 shows the jet color map of fish fillets, which shows how much fish change by color, as fish spoilage increases, from Reddish-pink color to pale pink yellow-gray and finally to brown.

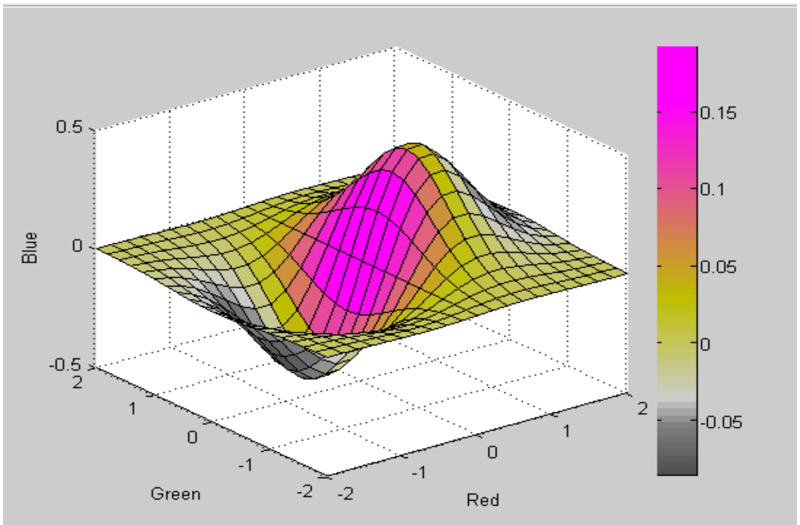

Figure 9. RGB of color bar of fillet fish during analysis

Figure 10 also shows a grayscale histogram, which shows the color gradients of images of fish fillets during the spoilage stages. The histogram consists of two axes, the first is the horizontal axis of three regions as follows: the first region represents the light color, the second region represents the medium color in the color, and the third region represents the dark color. As a result, by increasing spoil in fillet fish the yellow color increase in color map, and the number of frequencies in the right part that represents the light area decreases after the second day of analysis, the second axis is the vertical axis, which represents the size that expresses the number of pixels in each of the previous three parts. Figure 11 shows the relation between chemical and physical analysis during the four analysis days for fillet fish.

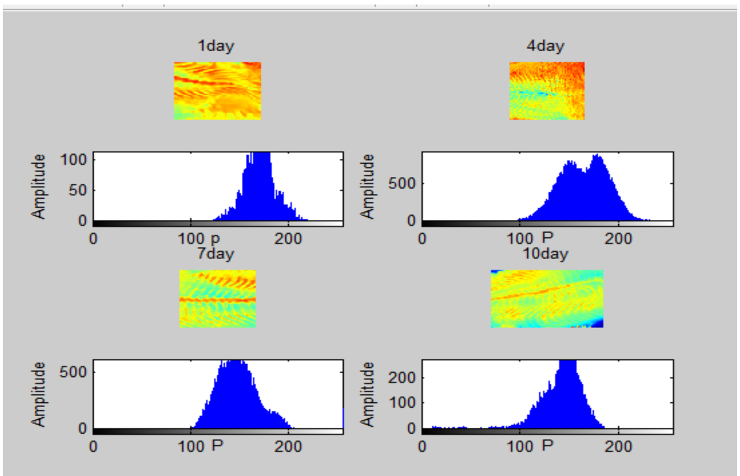

Figure 10. Color map and gray histogram of collective fillet image during analysis days

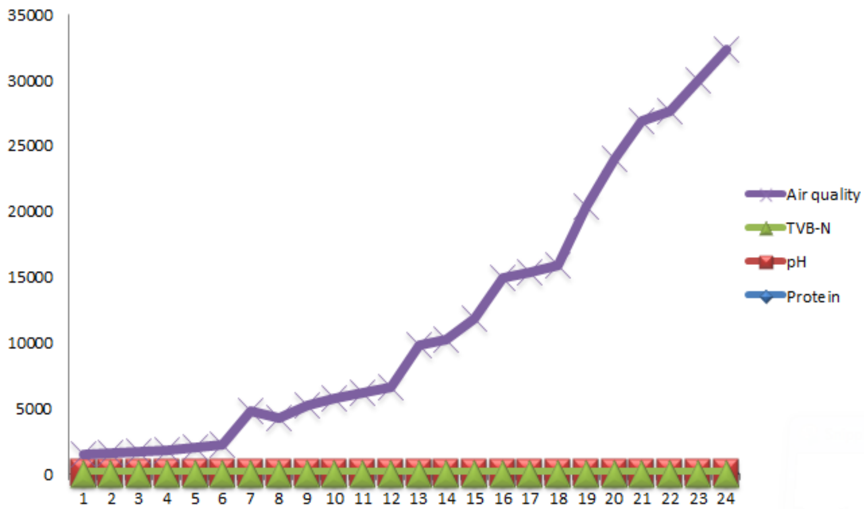

Figure 11. Charts between chemical and physical analysis during storage days

Figure 12 shows the four fillet images were used during the four analysis days to determine features from edge deduction, when the spoil of fillet increases the noise or pixels decreased in all filters in edge deduction that used.

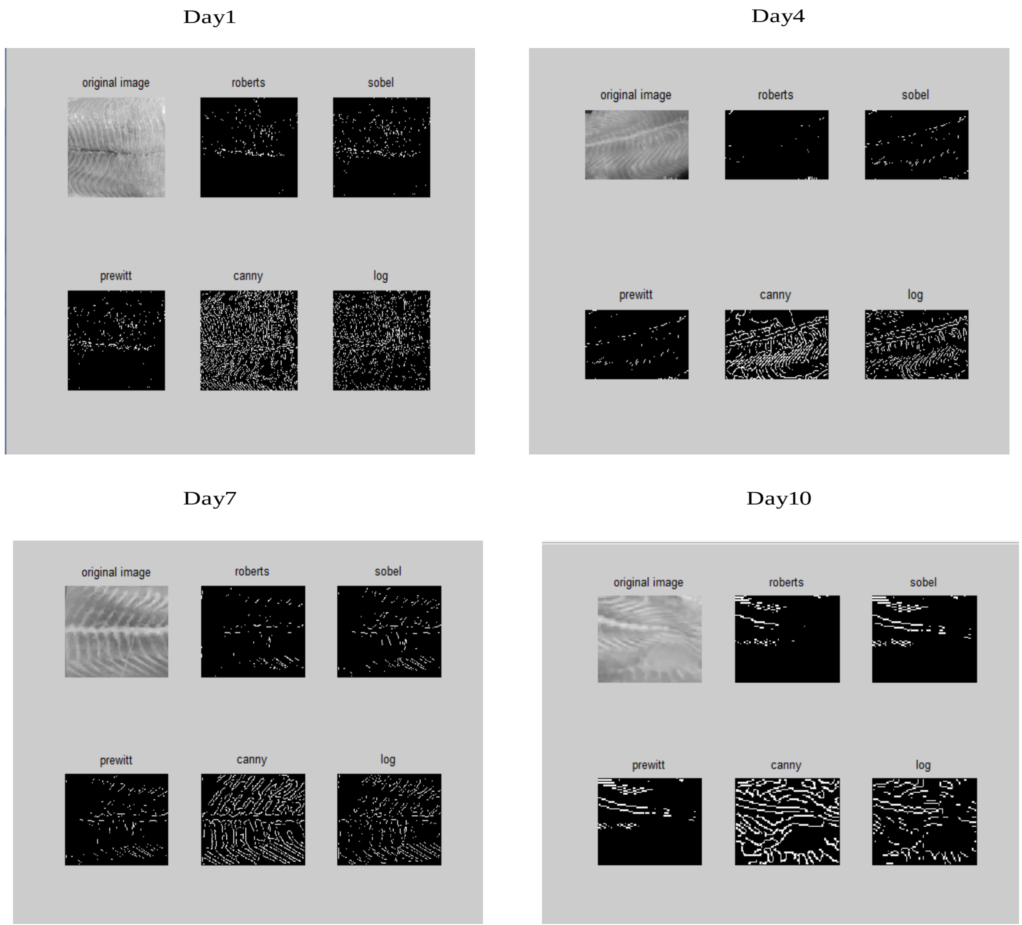

Figure 12. Digital image histograms for fillet fishes slice during different analysis days

3.3. Machine learning model BP-ANN-based for fillet fish inspection

The BP-ANN network was used for the three different prediction models to predict protein values, pH number, and the reference TVB-N from the inputs values that represent in air quality from MQ135 gas sensor for the fillet images. It was found that high regression coefficient between chemical analysis (protein, pH, and the reference TVB-N) and physical components (air quality value) in fillet through spoilage stages as shown in Table 2.

Table 2. Performance coefficients of prediction models (BP-NN)

Model No.	Variables		Number of samples	Samples set	
	Inputs	Outputs		MSE	R
1	Air quality from gas sensor	pH	48	4.15	0.999
2	Air quality from gas sensor	Protein	48	1.96	0.973
3	Air quality from gas sensor	TVB-N	48	2.02	0.987

3.4. Machine learning model ANFIS-based for fillet fish inspection

The ANFIS model was built in order to calculate values of regression coefficient and the Root Mean Square Error (MSE) to predict the protein values, the acidity number, and the reference TVB-N values for the three models that represent and the TVB-N values produced from the Gas sensor, as shown in Table 3.

Table 3. Performance coefficients of prediction models (ANFIS)

Model No.	Variables		Number of samples	Samples set	
	Inputs	Outputs		MSE	R
1	Air quality from gas sensor	pH	48	1.94	0.998
2	Air quality from gas sensor	Protein	48	3.06	0.859
3	Air quality from gas sensor	TVB-N	48	.59	0.999

Each of the inputs in the chemical analysis (protein values, pH and TVB-N reference values) has 3 different grades (high, medium and low), and the TVB-N generated by the gas sensor (air quality) also has 3 grades of linguistic nomenclature (high, medium and low). It was organic type trim. Figure 13 shows the fish quality value represented by the ANFIS model and which depends on the inputs (protein values, pH, TVB-N reference values and air quality values produced from the MQ135 gas sensor). IF rules were also generated in ANFIS as shown in Table 4 and Figure 14. Each value of the quality predictor was multiplied by % in order to obtain the output as a percentage.

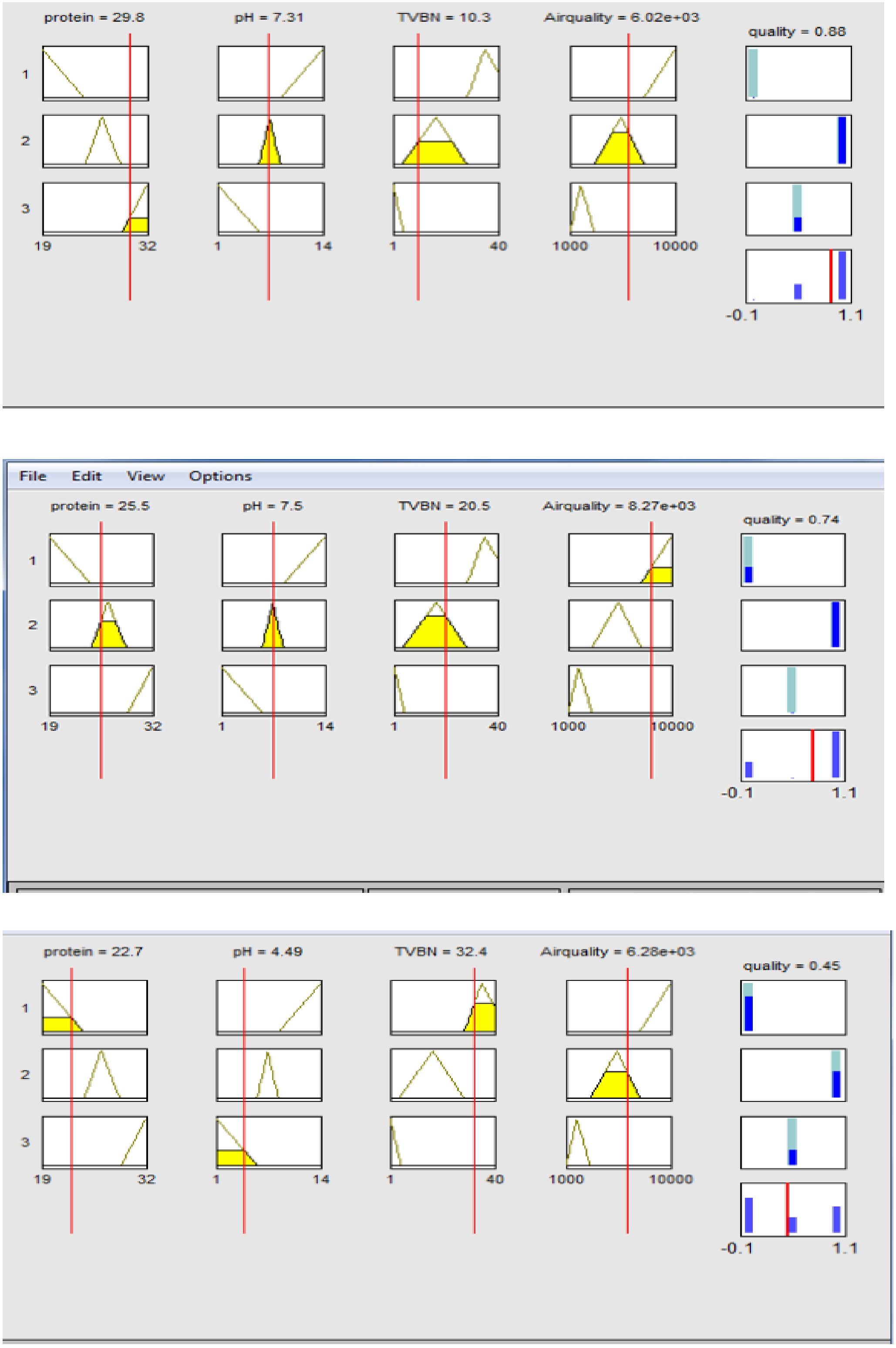

Figure 13. Quality of fillet fish in three different cases (fresh, acceptable and spoil)

3.5. Estimating quality of fillet fish via fuzzy logic system

Previous two models: BP-ANN, and ANFIS were used to predict protein values, PH, and reference TVB-N, but there is still a need to use a model to predict fish quality. The fuzzy logic model was built based on Mamdani system to predict fish quality. The inputs were chemicals analysis (pH, protein and TVBN) and physical analysis (air quality from MQ135 gas sensor). Type of membership function for input and outputs were trimf,. Three categories of inputs were (high, acceptable low, acid, neutral and alkaline) and the categories of outputs were (fresh, acceptable and spoiled). Figure 15 and Table 4 illustrate if then- rules were used to determine the quality of fillet fish.

Table 4. If-Then rules for the proposed scenario.

No.	Rules
1	IF 'protein' IS 'high' AND 'pH' IS ' acid' AND 'TVBN' IS 'low' AND 'air quality' IS ' low' AND THEN 'quality' IS 'fresh'.
2	IF 'protein' IS 'acceptable' AND 'pH' IS ' neutral' AND 'TVBN' IS 'acceptable' AND 'air quality' IS 'acceptable' AND THEN 'quality' IS 'acceptable'.
3	IF 'protein' IS 'high' AND 'pH' IS 'acid' AND 'TVBN' IS 'low' AND 'air quality' IS 'low' AND THEN 'quality' IS 'spoil'.

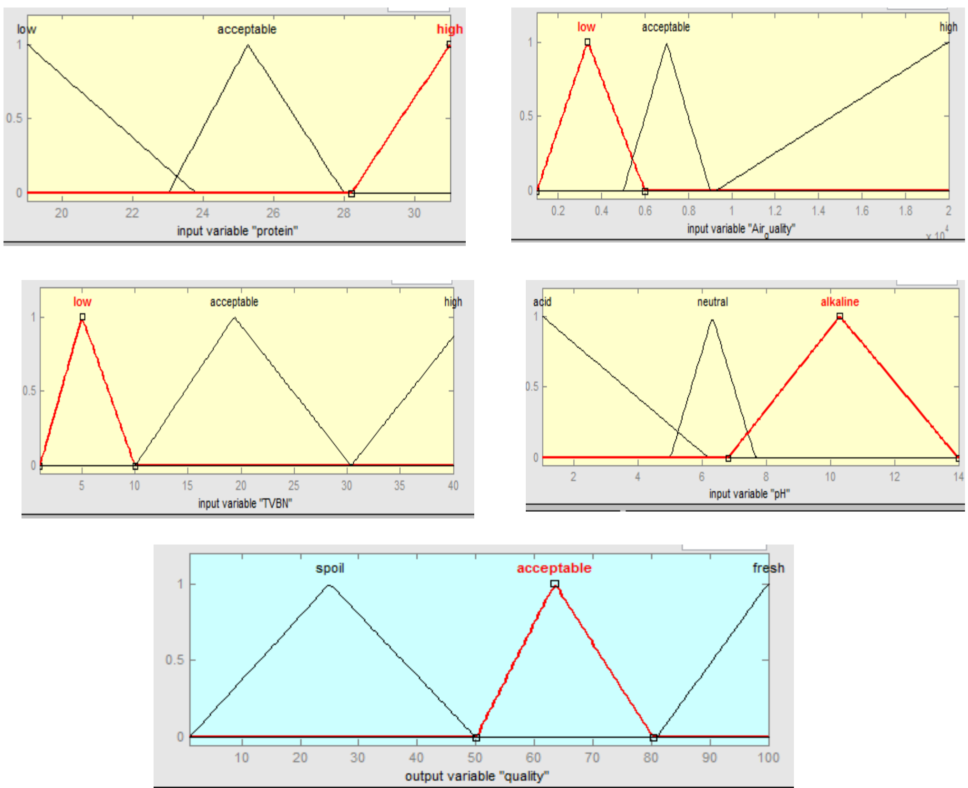

Figure 14. Membership function of the inputs values and output: pH, TVB-N, protein and air quality from gas sensor, and quality

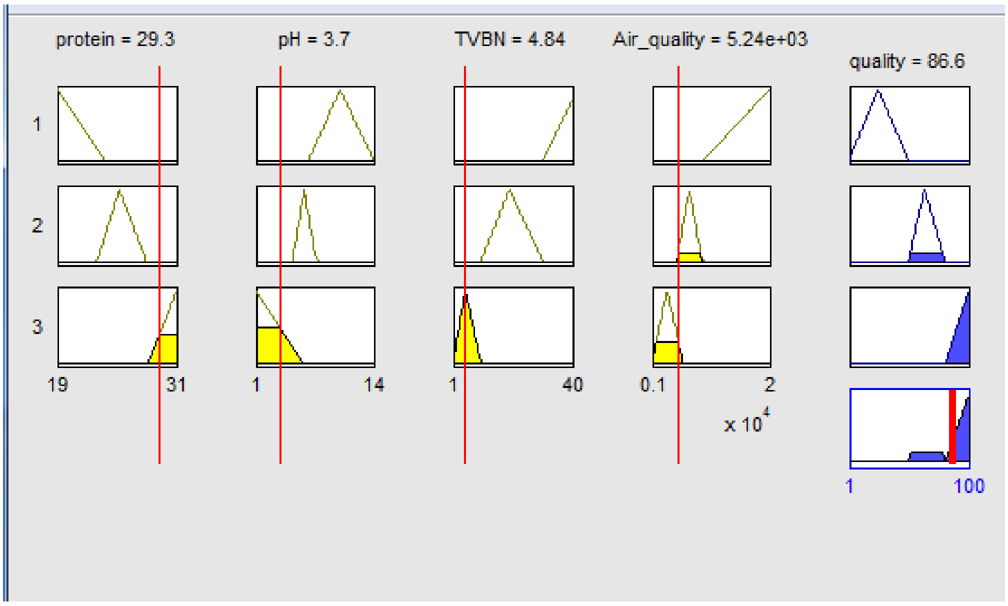

Figure 15. Predicted fish quality from if then- rules viewer

4.6. Neutrosophic Logic-Enhanced Fuzzy Logic Inference Systems

Neutrosophic Logic-Enhanced Fuzzy Logic Inference Systems combine the strengths of fuzzy sets and neutrosophic sets to address uncertainty and imprecision from different perspectives [47]. Fuzzy logic focuses on partial truth by assigning membership values between 0 and 1, while neutrosophic logic incorporates truth, indeterminacy, and falsity through three distinct membership functions [55]. This integration allows for a more comprehensive representation of complex real-world issues. Neutrosophic fuzzy sets extend traditional fuzzy sets by including indeterminacy, enabling richer behavior in uncertain environments [56]. The inference process involves neutrosophication (converting crisp inputs into neutrosophic fuzzy sets), rule evaluation using neutrosophic fuzzy rules, aggregation of rule outcomes, and defuzzification to produce crisp outputs [57]. For instance, assessing fish quality based on freshness and appearance utilizes neutrosophic fuzzy rules to determine quality ratings (e.g., poor, good, excellent). Neutrosophic values, expressed as triplets (truth, indeterminacy, falsity), capture uncertainty effectively, such as representing medium freshness as (0.7, 0.2, 0.1), indicating high truth, some indeterminacy, and low falsity as shown in Table 5. This approach improves expressiveness, fidelity, and decision-making in uncertain scenarios, despite challenges like computational complexity, data collection, and standardization.

These illustrative values would need to be adjusted based on specific data and technical expertise, as some definitions of neutrosophic sets do not require that T + I + F equals 1. This structure serves as the foundation for encoding neutrosophic concepts within the fish quality assessment as shown in Figure 16. The chart suggests that the fish is likely to have medium freshness and a good appearance, with some level of uncertainty regarding the appearance.

In practical implementation, these values would be integrated into the neutrosophic fuzzy rule-based system. Neutrosophic logic, as a generalization of fuzzy logic, addresses typical limitations such as representing incomplete or contradictory information, while fuzzy logic inference systems provide a robust framework for reasoning under uncertainty. By combining these approaches, this strategy can deliver stronger and more reliable solutions.

Table 5. Neutrosophic Values for Input Variables in Fish Quality Assessment

Input Variable	Linguistic Term	Truth (T)	Indeterminacy (I)	Falsity (F)
Freshness	Low	0.1	0.2	0.7
Freshness	Medium	0.7	0.2	0.1
Freshness	High	0.9	0.05	0.05
Appearance	Good	0.8	0.1	0.1
Appearance	Fair	0.5	0.3	0.2
Appearance	Poor	0.1	0.1	0.8
Quality	Very Poor	0.1	0.1	0.8
Quality	Poor	0.2	0.2	0.6
Quality	Okay	0.5	0.3	0.2
Quality	Good	0.7	0.2	0.1
Quality	Excellent	0.9	0.05	0.05

Further research should focus on exploring alternative neutrosophic aggregation operators and defuzzification methods, designing efficient algorithms for inference with neutrosophic fuzzy information, and applying neutrosophic fuzzy systems to real-world problems across various domains. Neutrosophic fuzzy logic offers powerful tools for developing new rule classes and gaining insights into the uncertain, gray, and aleatory aspects of complex systems, helping to characterize their behaviors, events, and outcomes when integrated into decision-making frameworks.

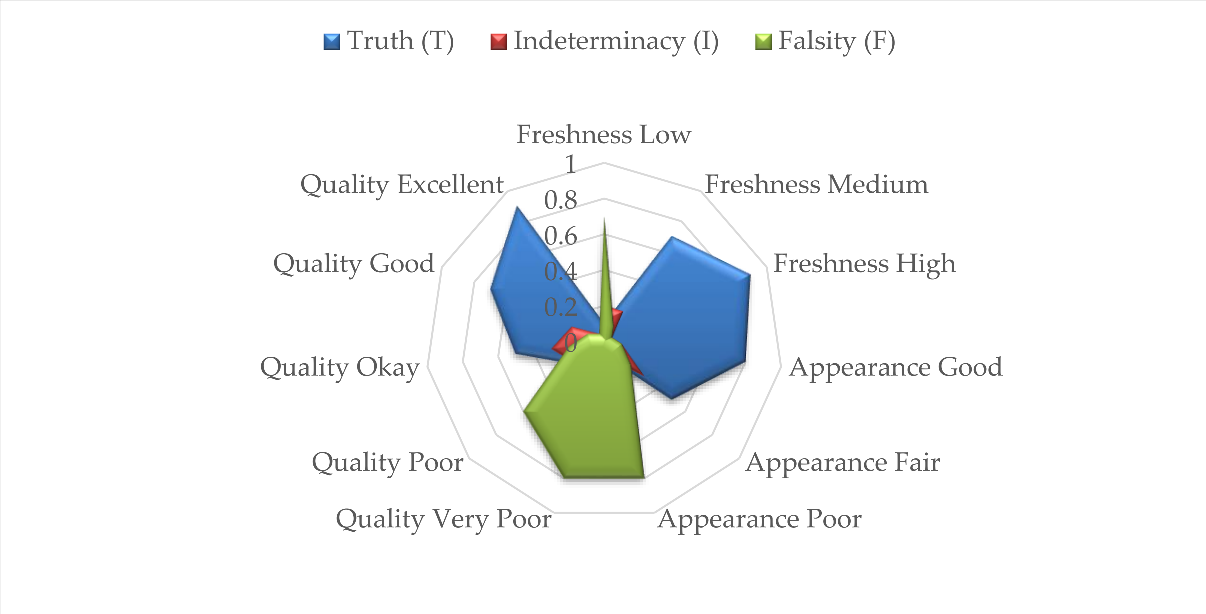

Figure 16. Neutrosophic Logic-Enhanced Fuzzy Evaluation of Fish Quality

5. Conclusions

This study demonstrates the effectiveness of combining electronic nose technology, artificial intelligence algorithms, and neutrosophic logic to assess fish quality. Two predictive models were used: a neural network model and the Adaptive Neuro-Fuzzy Inference System (ANFIS), based on chemical and physical analyses, including protein levels, pH, and TVB-N values, as well as data from an MQ135 gas sensor. The neural network model achieved the highest regression coefficients, indicating its superiority for predicting fish quality. Both fuzzy logic and ANFIS models proved to be reliable, non-destructive methods for assessing fish quality. Image processing techniques, including color mapping and edge detection, were also applied to visualize spoilage stages. The introduction of neutrosophic values for input variables such as freshness and appearance added further depth to the analysis by incorporating dimensions of truth, indeterminacy, and falsity, improving the accuracy of the quality assessment. Neutrosophic fuzzy inference processes, including neutrosophication, rule evaluation, and defuzzification, enhanced expressiveness and fidelity, allowing for a more precise representation of real-world uncertainties in the evaluation of fish quality. Ultimately, the integration of these technologies provided a robust, cost-effective, and non-destructive solution for detecting spoilage in fillet fish, demonstrating the potential for advanced decision-making in food quality assessment.

References

1. Monteiro, M.L.G.; Rosário, D.K.A.; Torres Neto, L.; Conte-Junior, C.A. Exploring High Hydrostatic Pressure for Enhancing the Preservation of White and Dark Muscle Fish Fillets Stored at Different Packaging Systems under Refrigeration. *Food Control* **2024**, *155*, 110038, doi:10.1016/j.foodcont.2023.110038.

2. Overholtz, W. Consumption of Important Pelagic Fish and Squid by Predatory Fish in the Northeastern USA Shelf Ecosystem with Some Fishery Comparisons. *ICES Journal of Marine Science* **2000**, *57*, 1147–1159, doi:10.1006/jmsc.2000.0802.
3. Poulsen, A.F.; Hortle, K.G.; Valbo-Jorgensen, J.; Chan, S.; Chhuon, C.K.; Viravong, S.; Bouakhamvongsa, K.; Suntornratana, U.; Yoorong, N.; Nguyen, T.T. Distribution and Ecology of Some Important Riverine Fish Species of the Mekong River Basin. *MRC technical paper* **2004**, *10*, 116.
4. Rigos, G.; Troisi, G.M. Antibacterial Agents in Mediterranean Finfish Farming: A Synopsis of Drug Pharmacokinetics in Important Euryhaline Fish Species and Possible Environmental Implications. *Rev Fish Biol Fisheries* **2005**, *15*, 53–73, doi:10.1007/s11160-005-7850-8.
5. Cortés-Sánchez, A.D.J.; Diaz-Ramírez, M.; Torres-Ochoa, E.; Espinosa-Chaurand, L.D.; Rayas-Amor, A.A.; Cruz-Monterrosa, R.G.; Aguilar-Toalá, J.E.; Salgado-Cruz, Ma.D.L.P. Processing, Quality and Elemental Safety of Fish. *Applied Sciences* **2024**, *14*, 2903, doi:10.3390/app14072903.
6. Liang, B.; Li, X.; Yang, M.; Zhang, Z.; Ren, J. Stacking Ensemble Learning for Gas Sensor-based Detection of Salmon Freshness and Shelf Life. *J Food Process Engineering* **2024**, *47*, e14593, doi:10.1111/jfpe.14593.
7. Castro, P.; Millán, R.; Penedo, J.C.; Sanjuán, E.; Santana, A.; Caballero, M.J. Effect of Storage Conditions on Total Volatile Base Nitrogen Determinations in Fish Muscle Extracts. *Journal of Aquatic Food Product Technology* **2012**, *21*, 519–523, doi:10.1080/10498850.2011.610917.
8. Parlapani, F.F.; Mallouchos, A.; Haroutounian, S.A.; Boziaris, I.S. Volatile Organic Compounds of Microbial and Non-Microbial Origin Produced on Model Fish Substrate Un-Inoculated and Inoculated with Gilt-Head Sea Bream Spoilage Bacteria. *LWT* **2017**, *78*, 54–62, doi:10.1016/j.lwt.2016.12.020.
9. Gram, L.; Dalgaard, P. Fish Spoilage Bacteria – Problems and Solutions. *Current Opinion in Biotechnology* **2002**, *13*, 262–266, doi:10.1016/S0958-1669(02)00309-9.
10. Ghaly, A.E.; Dave, D.; Budge, S.; Brooks, M.S. Fish Spoilage Mechanisms and Preservation Techniques. *American journal of applied sciences* **2010**, *7*, 859.
11. Huang, Z.; Jia, S.; Zhang, L.; Liu, X.; Luo, Y. Inhibitory Effects and Membrane Damage Caused to Fish Spoilage Bacteria by Cinnamon Bark (Cinnamomum Tamala) Oil. *LWT* **2019**, *112*, 108195, doi:10.1016/j.lwt.2019.05.093.
12. Reynisson, E.; Lauzon, H.L.; Magnusson, H.; Óli Hreggvidsson, G.; Marteinsson, V.T. Rapid Quantitative Monitoring Method for the Fish Spoilage Bacteria Pseudomonas. *J. Environ. Monit.* **2008**, *10*, 1357, doi:10.1039/b806603e.
13. Abbas, K.A.; Saleh, A.M.; Mohamed, A.; Lasekan, O. The Relationship between Water Activity and Fish Spoilage during Cold Storage: A Review. *J. Food Agric. Environ* **2009**, *7*, 86–90.
14. Feng, X.; Ng, V.K.; Mikš-Krajnik, M.; Yang, H. Effects of Fish Gelatin and Tea Polyphenol Coating on the Spoilage and Degradation of Myofibril in Fish Fillet During Cold Storage. *Food Bioprocess Technol* **2017**, *10*, 89–102, doi:10.1007/s11947-016-1798-7.
15. Mandal, A.; Ghosh, A.R. Role of Artificial Intelligence (AI) in Fish Growth and Health Status Monitoring: A Review on Sustainable Aquaculture. *Aquacult Int* **2024**, *32*, 2791–2820, doi:10.1007/s10499-023-01297-z.
16. Heising, J.K.; Dekker, M.; Bartels, P.V.; Van Boekel, M.A.J.S. A Non-Destructive Ammonium Detection Method as Indicator for Freshness for Packed Fish: Application on Cod. *Journal of Food Engineering* **2012**, *110*, 254–261, doi:10.1016/j.jfoodeng.2011.05.008.

17. Cheng, J.-H.; Dai, Q.; Sun, D.-W.; Zeng, X.-A.; Liu, D.; Pu, H.-B. Applications of Non-Destructive Spectroscopic Techniques for Fish Quality and Safety Evaluation and Inspection. *Trends in Food Science & Technology* **2013**, *34*, 18–31, doi:10.1016/j.tifs.2013.08.005.
18. He, H.-J.; Wu, D.; Sun, D.-W. Nondestructive Spectroscopic and Imaging Techniques for Quality Evaluation and Assessment of Fish and Fish Products. *Critical Reviews in Food Science and Nutrition* **2015**, *55*, 864–886, doi:10.1080/10408398.2012.746638.
19. Saeed, R.; Glamuzina, B.; Tuyet Nga, M.T.; Zhao, F.; Zhang, X. Supervised Learning-Based Artificial Senses for Non-Destructive Fish Quality Classification. *Biosensors and Bioelectronics* **2025**, *267*, 116770, doi:10.1016/j.bios.2024.116770.
20. Khabusi, S.P.; Huang, Y.-P.; Lee, M.-F.; Tsai, M.-C. Enhanced U-Net and PSO-Optimized ANFIS for Classifying Fish Diseases in Underwater Images. *Int. J. Fuzzy Syst.* **2024**, *26*, 2518–2535, doi:10.1007/s40815-024-01743-x.
21. Cheng, J.-H.; Sun, D.-W. Rapid and Non-Invasive Detection of Fish Microbial Spoilage by Visible and near Infrared Hyperspectral Imaging and Multivariate Analysis. *LWT - Food Science and Technology* **2015**, *62*, 1060–1068, doi:10.1016/j.lwt.2015.01.021.
22. Shams, M.Y.; Elzeki, O.M.; Abd Elfattah, M.; Medhat, T.; Hassanien, A.E. Why Are Generative Adversarial Networks Vital for Deep Neural Networks? A Case Study on COVID-19 Chest X-Ray Images. In *Big Data Analytics and Artificial Intelligence Against COVID-19: Innovation Vision and Approach*; Springer, 2020; pp. 147–162.
23. Dowlati, M.; De La Guardia, M.; Dowlati, M.; Mohtasebi, S.S. Application of Machine-Vision Techniques to Fish-Quality Assessment. *TrAC Trends in Analytical Chemistry* **2012**, *40*, 168–179, doi:10.1016/j.trac.2012.07.011.
24. Franceschelli, L.; Berardinelli, A.; Dabbou, S.; Ragni, L.; Tartagni, M. Sensing Technology for Fish Freshness and Safety: A Review. *Sensors* **2021**, *21*, 1373, doi:10.3390/s21041373.
25. Vijayakumar, R.; Sharadbhai, B.R.; Elavarasan, K.; Sivaraman, B.; Sathish Kumar, K.; Anandan, R.; C.N., R. Physical and Sensory Quality of Processed and Packaged Fish Products. In *Quality Analysis and Packaging of Seafood Products*; Elsevier, 2025; pp. 335–355 ISBN 978-0-443-22082-1.
26. Zhao, Y.; Qin, H.; Xu, L.; Yu, H.; Chen, Y. A Review of Deep Learning-Based Stereo Vision Techniques for Phenotype Feature and Behavioral Analysis of Fish in Aquaculture. *Artif Intell Rev* **2024**, *58*, 7, doi:10.1007/s10462-024-10960-7.
27. Bhadra, S.; Narvaez, C.; Thomson, D.J.; Bridges, G.E. Non-Destructive Detection of Fish Spoilage Using a Wireless Basic Volatile Sensor. *Talanta* **2015**, *134*, 718–723, doi:10.1016/j.talanta.2014.12.017.
28. Yavuzer, E. Determination of Fish Quality Parameters with Low Cost Electronic Nose. *Food Bioscience* **2021**, *41*, 100948, doi:10.1016/j.fbio.2021.100948.
29. Jinadasa, B. Determination of Quality of Marine Fishes Based on Total Volatile Base Nitrogen Test (TVB-N). *Nature and Science* **2014**, *5*, 106–111.
30. Ma, J.; Sun, D.-W.; Pu, H.; Wei, Q.; Wang, X. Protein Content Evaluation of Processed Pork Meats Based on a Novel Single Shot (Snapshot) Hyperspectral Imaging Sensor. *Journal of Food Engineering* **2019**, *240*, 207–213, doi:10.1016/j.jfoodeng.2018.07.032.
31. Alimelli, A.; Pennazza, G.; Santonico, M.; Paolesse, R.; Filippini, D.; D'Amico, A.; Lundström, I.; Di Natale, C. Fish Freshness Detection by a Computer Screen Photoassisted Based Gas Sensor Array. *Analytica Chimica Acta* **2007**, *582*, 320–328, doi:10.1016/j.aca.2006.09.046.

32. Chang, J.-R.; Wei, L.-Y.; Cheng, C.-H. A Hybrid ANFIS Model Based on AR and Volatility for TAIEX Forecasting. *Applied Soft Computing* **2011**, *11*, 1388–1395, doi:10.1016/j.asoc.2010.04.010.
33. Natale, C.D.; Olafsdottir, G.; Einarsson, S.; Martinelli, E.; Paolesse, R.; D'Amico, A. Comparison and Integration of Different Electronic Noses for Freshness Evaluation of Cod-Fish Fillets. *Sensors and Actuators B: Chemical* **2001**, *77*, 572–578, doi:10.1016/S0925-4005(01)00692-X.
34. Perera, A.; Pardo, A.; Barrettino, D.; Hierlermann, A.; Marco, S. Evaluation of Fish Spoilage by Means of a Single Metal Oxide Sensor under Temperature Modulation. *Sensors and Actuators B: Chemical* **2010**, *146*, 477–482, doi:10.1016/j.snb.2009.11.037.
35. Semeano, A.T.S.; Maffei, D.F.; Palma, S.; Li, R.W.C.; Franco, B.D.G.M.; Roque, A.C.A.; Gruber, J. Tilapia Fish Microbial Spoilage Monitored by a Single Optical Gas Sensor. *Food Control* **2018**, *89*, 72–76, doi:10.1016/j.foodcont.2018.01.025.
36. Zhang, Y.; Luo, Q.; Ding, K.; Liu, S.G.; Shi, X. A Smartphone-Integrated Colorimetric Sensor of Total Volatile Basic Nitrogen (TVB-N) Based on Au@MnO2 Core-Shell Nanocomposites Incorporated into Hydrogel and Its Application in Fish Spoilage Monitoring. *Sensors and Actuators B: Chemical* **2021**, *335*, 129708, doi:10.1016/j.snb.2021.129708.
37. Wu, D.; Zhang, D.; Liu, S.; Jin, Z.; Chowwanonthapunya, T.; Gao, J.; Li, X. Prediction of Polycarbonate Degradation in Natural Atmospheric Environment of China Based on BP-ANN Model with Screened Environmental Factors. *Chemical Engineering Journal* **2020**, *399*, 125878, doi:10.1016/j.cej.2020.125878.
38. Amin, S. Backpropagation – Artificial Neural Network (BP-ANN): Understanding Gender Characteristics of Older Driver Accidents in West Midlands of United Kingdom. *Safety Science* **2020**, *122*, 104539, doi:10.1016/j.ssci.2019.104539.
39. Souza, P.R.; Dotto, G.L.; Salau, N.P.G. Artificial Neural Network (ANN) and Adaptive Neuro-Fuzzy Interference System (ANFIS) Modelling for Nickel Adsorption onto Agro-Wastes and Commercial Activated Carbon. *Journal of Environmental Chemical Engineering* **2018**, *6*, 7152–7160, doi:10.1016/j.jece.2018.11.013.
40. Shams, M.Y.; Tolba, A.S.; Sarhan, S.H. Face, Iris, and Fingerprint Multimodal Identification System Based on Local Binary Pattern with Variance Histogram and Combined Learning Vector Quantization. *Journal of Theoretical and Applied Information Technology* **2016**, *89*, 53.
41. Sarhan, S.; Nasr, A.A.; Shams, M.Y. Multipose Face Recognition-Based Combined Adaptive Deep Learning Vector Quantization. *Computational Intelligence and Neuroscience* **2020**, *2020*.
42. Shams, M.Y.; Tarek, Z.; Elshewey, A.M. A Novel RFE-GRU Model for Diabetes Classification Using PIMA Indian Dataset. *Sci Rep* **2025**, *15*, 982, doi:10.1038/s41598-024-82420-9.
43. Leng, X.; Wang, J.; Ji, H.; Wang, Q.; Li, H.; Qian, X.; Li, F.; Yang, M. Prediction of Size-Fractionated Airborne Particle-Bound Metals Using MLR, BP-ANN and SVM Analyses. *Chemosphere* **2017**, *180*, 513–522, doi:10.1016/j.chemosphere.2017.04.015.
44. Xiang, X.; Fan, Y.; Fan, A.; Liu, W. Cooling Performance Optimization of Liquid Alloys GaIny in Microchannel Heat Sinks Based on Back-Propagation Artificial Neural Network. *Applied Thermal Engineering* **2017**, *127*, 1143–1151, doi:10.1016/j.applthermaleng.2017.08.127.
45. Çaydaş, U.; Hasçalık, A.; Ekici, S. An Adaptive Neuro-Fuzzy Inference System (ANFIS) Model for Wire-EDM. *Expert Systems with Applications* **2009**, *36*, 6135–6139, doi:10.1016/j.eswa.2008.07.019.
46. Wei, L.-Y. A Hybrid ANFIS Model Based on Empirical Mode Decomposition for Stock Time Series Forecasting. *Applied Soft Computing* **2016**, *42*, 368–376, doi:10.1016/j.asoc.2016.01.027.

47. Ahmed Mohamed Shitaya; Mohamed El Syed Wahed; Saied Helemy Abd El khalek; Amr Ismail; Mahmoud Y. Shams; A. A. Salama Predicting Student Behavior Using a Neutrosophic Deep Learning Model. *Neutrosophic Sets and Systems* **2024**, *76*, 288–310, doi:10.5281/ZENODO.13997076.
48. Salama, A.A.; Mossa, D.E.; Shams, M.Y.; Khalid, H.E.; Essa, A.K. Neutrosophic Topological Spaces for Lung Cancer Detection in Chest X-Rays: A Novel Approach to Uncertainty Management. *Neutrosophic Sets and Systems* **2025**, *77*, 432–449.
49. Şahin, M.; Erol, R. A Comparative Study of Neural Networks and ANFIS for Forecasting Attendance Rate of Soccer Games. *MCA* **2017**, *22*, 43, doi:10.3390/mca22040043.
50. Zamani, A.; Sorbi, M.R.; Safavi, A.A. Application of Neural Network and ANFIS Model for Earthquake Occurrence in Iran. *Earth Sci Inform* **2013**, *6*, 71–85, doi:10.1007/s12145-013-0112-8.
51. Sremac, S.; Tanackov, I.; Faculty of Technical Sciences, University of Novi Sad, Novi Sad, Serbia; Kopić, M.; Faculty of Technical Sciences, University of Novi Sad, Novi Sad, Serbia; Radović, D.; Faculty of Transport and Traffic Engineering, University of East Sarajevo, Doboj, Bosnia and Hercegovina ANFIS Model for Determining the Economic Order Quantity. *Decis. Mak. Appl. Manag. Eng.* **2018**, *1*, doi:10.31181/dmame1802079s.
52. Zhai, P.; Williams, E.D. Analyzing Consumer Acceptance of Photovoltaics (PV) Using Fuzzy Logic Model. *Renewable Energy* **2012**, *41*, 350–357, doi:10.1016/j.renene.2011.11.041.
53. Baskar, C.; Nesakumar, N.; Balaguru Rayappan, J.B.; Doraipandian, M. A Framework for Analysing E-Nose Data Based on Fuzzy Set Multiple Linear Regression: Paddy Quality Assessment. *Sensors and Actuators A: Physical* **2017**, *267*, 200–209, doi:10.1016/j.sna.2017.10.020.
54. Nadiri, A.A.; Shokri, S.; Tsai, F.T.-C.; Asghari Moghaddam, A. Prediction of Effluent Quality Parameters of a Wastewater Treatment Plant Using a Supervised Committee Fuzzy Logic Model. *Journal of Cleaner Production* **2018**, *180*, 539–549, doi:10.1016/j.jclepro.2018.01.139.
55. Salama, A.A.; Shams, M.Y.; Khalid, H.E.; Mousa, D.E. Enhancing Medical Image Quality Using Neutrosophic Fuzzy Domain and Multi-Level Enhancement Transforms: A Comparative Study for Leukemia Detection and Classification. *Neutrosophic Sets and Systems* **2024**, *65*, 3.
56. Salama, A.A.; Shams, M.Y.; Elseuofi, S.; Khalid, H.E. Exploring Neutrosophic Numeral System Algorithms for Handling Uncertainty and Ambiguity in Numerical Data: An Overview and Future Directions. *Neutrosophic Sets and Systems* **2024**, *65*, 15.
57. Alhabib, A.; Alhabib, R.; Khalid, H.E.; Salama, A.A. A Neutrosophic Study for the Transmission of Infection with Pathogenic Fungi from Males of Olive Fly Insects to Their Females. *Neutrosophic Sets and Systems* **2024**, *64*, 38–45.

Received: Oct 10, 2024. Accepted: Jan 27, 2025