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Effects of chilled storage on fish freshness using computer vision and artificial neural network modeling

Efectos del almacenamiento refrigerado en la frescura del pescado utilizando visión por computadora y modelado bajo red neuronal artificial

***Saliha Lakehal*[1]*, *Brahim Lakehal*[2]**

[1]*ESPA laboratory, University of Batna 1, Institute of Veterinary Science and Agricultural Sciences, Department of Veterinary Sciences. Batna, Algeria.*
[2]*University of Batna 2, Institute of Hygiene and Industrial Security. Batna, Algeria.*
**Corresponding author: saliha.lakehal@univ–batna.dz*

ABSTRACT

The present study investigates the impact of refrigeration storage on the freshness and shelf life of European sea bass (*Dicentrarchus labrax*). This investigation utilises computer vision systems and artificial neural networks (ANNs) to analyse the dynamics of the process. A non-destructive assessment approach was established by analysing the eye colour characteristics (RGB, Lab*, and HSI values) of fish stored at +4 °C for 15 days, with sampling occurring every three days. There were considerable changes in the colour range throughout the time, particularly a reduction of brightness (L*), which can be one indicator of the progressive deterioration of the fish›s freshness. The neural network multilayer perceptron was optimised with 20 neurons in the hidden layer and demonstrated a high correlation coefficient (R^2 = 0.98) between predicted and experimental shelf life values. The data indicates that the values of rack life, which were initially determined to be cautious, exhibited a high degree of correlation with the estimated values. The R^2 value was determined to be 0.98. The technique offers a rapid and reliable non-destructive method for determining the freshness of fish, with potential applications in relevant areas such as quality control and natural security examination for aquaculture products.

Key words: color analysis; fish meat; eye color; quality control; storage time.

RESUMEN

Este estudio examina el efecto del almacenamiento refrigerado en la frescura y vida útil de la lubina europea (*Dicentrarchus ladrax*) mediante sistemas de visión artificial y redes neuronales artificiales (RNA). Se estableció un enfoque de evaluación no destructiva mediante el análisis de las características del color de los ojos (valores RGB, Lab* y HSI) del pescado almacenado a +4 °C durante 15 días, con muestreos cada tres días. Se observaron cambios considerables en la gama de colores a lo largo del tiempo, en particular una reducción del brillo (L*), que puede ser un indicador del deterioro progresivo de la frescura del pescado. Se entrenó un perceptrón multicapa de red neuronal optimizado con 20 neuronas en la capa oculta, con un alto coeficiente de correlación (R^2 = 0,98) entre los valores predichos y experimentales de vida útil. Los valores de vida útil temporalmente prudentes presentaron una alta correlación con los valores estimados (R^2 = 0,98). Esta técnica ofrece una técnica no destructiva rápida y fiable para la determinación de la frescura del pescado, con potencial aplicación en áreas relevantes como el control de calidad y la evaluación de la seguridad natural de productos acuícolas.

Palabras clave: Análisis de color; carne de pescado; color del ojo; control de calidad; tiempo de almacenamiento.

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INTRODUCTION

The European sea bass (*Dicentrarchus labrax*) is among the most economically valuable marine fish species for aquaculture in the Mediterranean region [1]. In Algeria, although aquaculture has yet to reach the production stage, but it is emerging in the coastal region through some private schemes being developed, particularly those involving the farming of European sea bass (*Dicentrarchus labrax*) [2]. As stated in [3], the freshness of fish is a significant parameter. This is due to the fact that it is related not only to the health of the fish, but also to the assurance of consumer acceptance. However, the quality and freshness of European sea bass can deteriorate at various levels, including processing, transportation, retail, and domestic storage [3 ,4]. Denaturation of proteins, oxidation of lipids, bacterial growth, and autolytic processes are also among the reasons for such loss [5 ,6].

Quantitative analysis of stored fish quality is typically accomplished through the utilisation of microbiological and chemical methodologies. These methodologies encompass the measurement of volatile basic nitrogen, thiobarbituric acid content, and the total number of bacteria [7 ,8 ,9]. The researchers have expressed confidence in their findings, but it should be noted that the study is not without its inherent limitations. The process is costly, time-consuming, destructive, and in certain cases, hazardous when the reagents are considered [10 ,11]. These disadvantages are indicative of the urgent need to develop a cost-effective, rapid, accurate, and environmentally sound method for the effective evaluation of fish quality.

Advances in image technologies and computer vision systems are creating new opportunities for the non-destructive assessment of fish freshness [1]. A computer vision system provides valuable information about color properties and can be utilized in overall fish quality prediction [12 ,13]. Previous studies have already demonstrated the effectiveness of computer vision in measuring the freshness of fish [14 ,15 ,16 ,17 ,18].

Artificial neural networks (ANN) have also become highly potent prediction and modeling tools [19]. Such systems are coded to replicate the functioning of biological neurons, particularly those within the nervous system and brain [20] In the context of computer applications, an artificial neural network is distinguished by its remarkable capacity to learn and to identify and represent intricate, non-linear relational patterns between the input and output of a system [21]. This study demonstrated that this method, employing computer vision and artificial intelligence, enables non-destructive and accurate meat quality assessment. Similarly, Lalabadi *et al*. [22] suggested a non-destructive method for evaluating fish freshness by observing the eyes and gills color using artificial neural networks (ANNs). Similar studies on fish freshness classification (large yellow croaker) have also been conducted with computer vision techniques using artificial neural networks [23].

Among external indicators, the eye is a particularly practical choice for imaging analysis, which makes the process quicker and more hygienic. On the other hand, examination of gills although informative, requires opening and manipulation of internal tissues, which is more invasive and not suitable for non-destructive method.

Computer vision technology and predictive modeling studies have not been thoroughly studied to enhance the accuracy of fish freshness detection in cold storage. In the present study, the cornea of the eye of *Dicentrarchus labrax* was selected as the research subject, with measurement undertaken using colour parameters L*, a*, b*, R, G, B, and H, S, I. The objective is to develop a reliable prediction model of fish spoilage by employing an artificial neural network (ANN) to analyse eye colour.

MATERIALS AND METHODS

Sea bass samples

Ten whole, non-eviscerated European sea bass (*Dicentrarchus labrax*) were purchased from a local fish market in Batna, Algeria. The fish were placed in a polystyrene bag filled with ice blocks and transported to the laboratory within 24 hours (h). All fish were stored in a refrigerator (CRF–NT64GF40, Condor, Algeria) at a stable temperature of +4 ± 0.2 °C. Samples were taken for imaging every three days (d).

Computer vision system

The image acquisition setup comprised a custom-designed enclosure equipped with two adjustable lamps positioned 50 cm above the samples at a 45° angle to achieve consistent illumination. A digital camera (Canon DS126621, China) was fixed vertically at a distance of 30 cm from the sample surface. To reduce external light interference, the interior of the enclosure was covered with light-absorbing black fabric [24]. Digital analysis of colorimetric parameters, including Lab, HSI, and RGB, was performed using Adobe Photoshop CS3 software (FIG. 1).

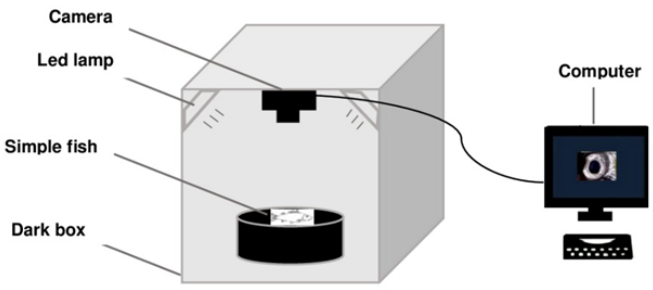

FIGURE 1. Computer Vision System

Modelling with ANN

The development and integration of artificial neural networks (ANNs) are a strict selection of some architectural features. Among the numerous ANN architectures available, a multilayer perceptron (MLP) was employed in this research. The MLP architecture has three major layers: an input layer, one or multiple hidden layers, and an output layer [25]. The neurons of the input layer portray three color attributes like Lab, HSI, and RGB of frozen/thawed fish, while the output layer depicts the shelf life. The hidden layer(s) contain adjustable neurons, and the correct number of nodes is determined empirically because there is no rigid rule to determine the size of the hidden layer. The design and optimization were conducted via the MATLAB interface.

For performance evaluation of the network, standard statistical measures were employed, i.e., correlation coefficient (R^2), mean squared error (MSE), and mean absolute error (MAE). R^2 value reflected goodness-of-fit of the model through estimation of how closely predicted points coincided with actual points. MSE provided a well-established predictive accuracy measure, particularly for external validation sets. In addition, MAE was used as a measure of performance in predictive models, with smaller values representing greater accuracy [21].

Statistical analysis

Data analysis was carried out using analysis of variance (ANOVA) through SPSS software version 22 (IBM SPSS Statistics v22). Tukey's post hoc test was applied to compare the means. Statistical significance was defined at a threshold of $P < 0.05$, while P values equal to or greater than 0.05 were considered not significant.

RESULTS AND DISCUSSION

Analysis of fish freshness through eye observation

Over time, the fish eye undergoes a sequence of changes, which mirror the increasing loss of freshness. Initially, in FIG. 2, the fresh eye (0 d) of the sea bream was clear, shiny, and slightly protruding, which indicated maximum freshness. With longer storage periods, the eye became duller and brownish in color (FIG. 2), indicating advanced decomposition [26].

Fish eyes, which contain high levels of lipids, are susceptible to oxidation when stored due to the action of endogenous enzymes and microbial metabolism [22]. Oxidation of lipids results in the formation of peroxides, which subsequently deteriorate into low-molecular-weight alcohols and carbonyl compounds. These compounds have been shown to affect the color, odor, texture, and flavor of the fish [27]. Furthermore, the high water content of the eyeball leads to delayed moisture loss, which can result in the collapse of the eye over time. This phenomenon has been particularly observed in tilapia [28]. These visual and chemical alterations are indicative of the progressive loss of fish freshness.

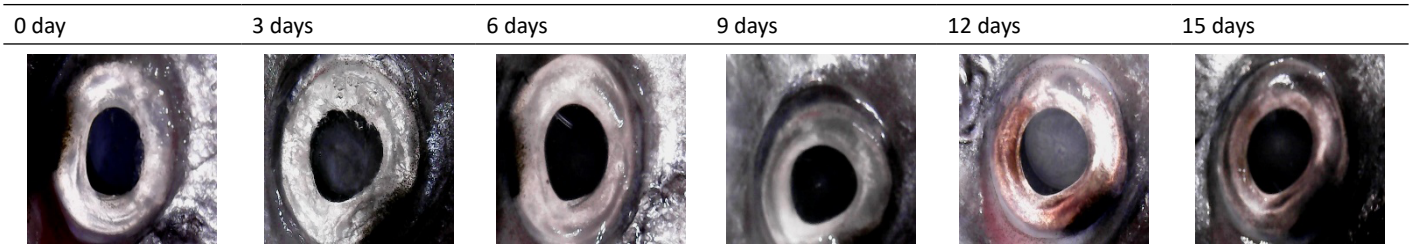

FIGURE 2. Change in the original image of fish eyes during storage

Analysis of fish freshness through colors parameters

The FIG. 3 a shows that with the increase in storage time, there was a steady decline in R, G, and B values, with a noteworthy drop after the sixth d ($P < 0.05$). The simultaneous decrease in chromatic components suggests a loss in eye brightness, likely due to changes in biochemical and structural composition over time. The stabilization of the values from the ninth day onwards indicates that degradation is where pigments responsible for coloring are extensively degraded or oxidized. Such physical changes can be utilized as indicators of fish freshness, in addition to influencing its attractiveness to consumers [29 , 30].

According to FIG 3b, fish freshness was predominantly determined through the measurement of brightness (L*), which is one of the key parameters distinguishing fresh from spoiled fish. As time went on, the value of (L*) significantly decreased, from 88.24 to approximately 33.06 ($P < 0.05$), reflecting a gradual darkening of the eyes. This decrease in brightness can be attributed to one or more factors combined, including air exposure, drying out, and chemical and biochemical breakdown, such as pigment oxidation and cell structure deterioration, compounded by prolonged storage at low temperature [31].

The (b*) value also decreased significantly ($P < 0.05$) up to day six of storage, indicating loss of yellow pigment component, before increasing exponentially on day nine ($P < 0.05$), which could be an indication of an accumulation of secondary pigments related to biochemical breakdown. As a consequence of this increase, (b*) held steady until the final d of the storage time. Regarding the (a*) value, it remained relatively stable during the initial days of storage, then increased sharply around the ninth day, and subsequently remained stable until the final d of the storage period.

The HSI colour model, which is closely related to the physiology of the human eye, characterised by three components (H, S and I) that operate relatively independently. In the HSI colour model, the H component defines the main hue of a colour and is measured as an angle between 0° and 360° in the visible spectrum, where 0° corresponds to red, 60° to yellow, 120° to green and 180° to cyan [32]. During storage (FIG 3c), the H value progressively decreased before stabilising around the twelfth and fifteenth days of storage (≥ 0.05), rendering it ineffective in reflecting changes in freshness over time. The S component represents the degree of colour purity, also known as saturation, based on the spectral distribution of light. Although saturation can fluctuate under different lighting conditions, the S value generally remains stable, ensuring consistency in colour assessment [33]. The S-value of the eye of *Dicentrarchus labrax* gradually increased during storage, indicating a progressive darkening of its original colour. This change intensified the hue and improved its depth, leading to a general darkening of the eye as storage time increased. The I component of the HSI colour space is a subjective parameter that exclusively represents the luminosity of the image; unlike the other components, it contains no colour information and has no influence on colour perception. Its role is therefore limited to evaluating light intensity independently of colour variations [34]. Throughout storage, the I value of the eyes of gilthead sea bream (*Sparus aurata*) decreased significantly, from 139.55 to 73.87. This decrease reflects a progressive reduction in luminosity.

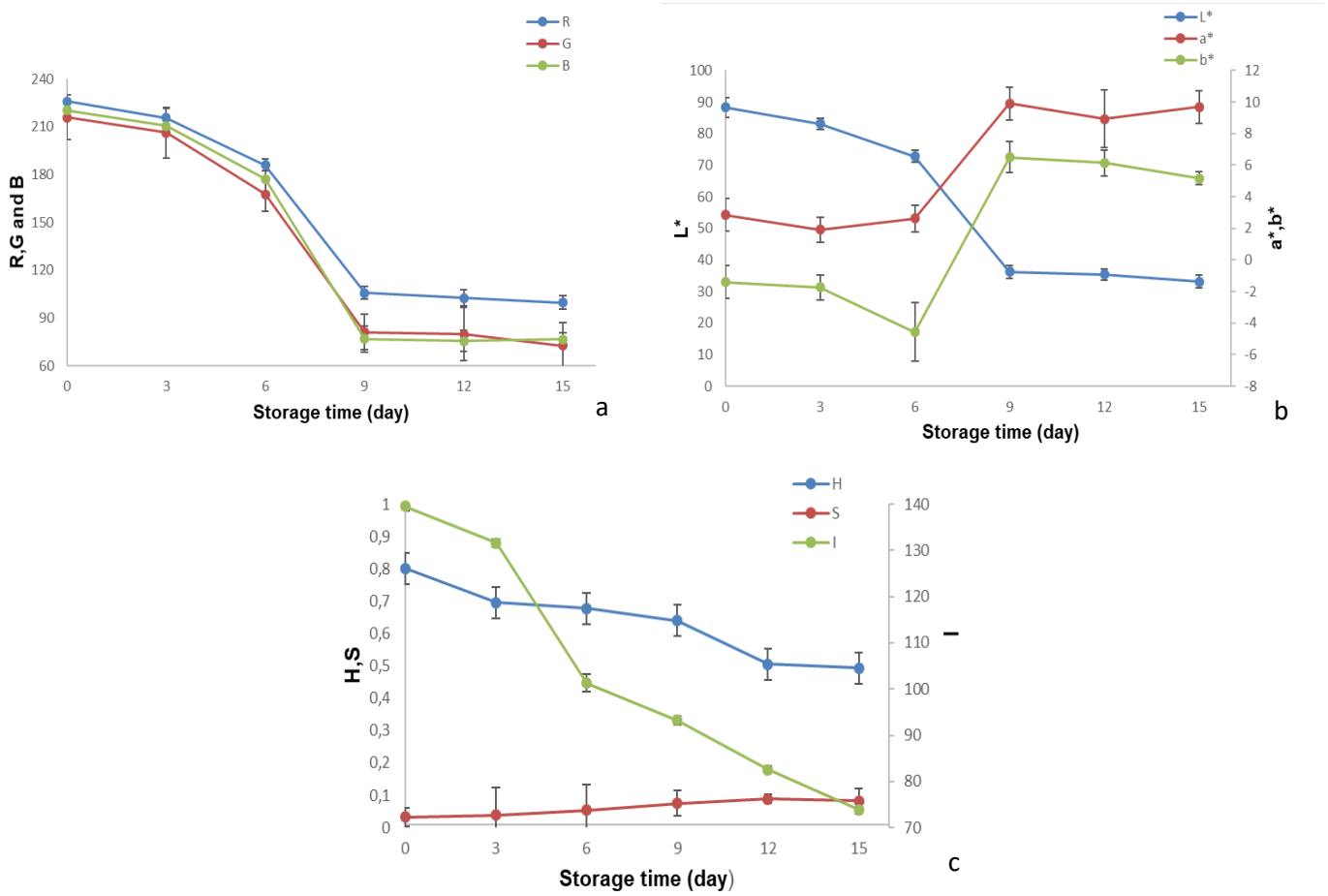

FIGURE 3. Change of color parameters (R, G, B, L*, a*, b*, H, S, I) in fish eyes during storage

Artificial neural network

Designing an artificial neural network (ANN) model requires extra caution in defining its topology, especially in terms of how many neurons there are in the hidden layer [35]. Different architectures were attempted for this work and after a series of comparative experiments, the best configuration selected was a multilayer perceptron (MLP) having 20 neurons in the hidden layer. The symbolic diagram of the final ANN model is given in FIG.4.

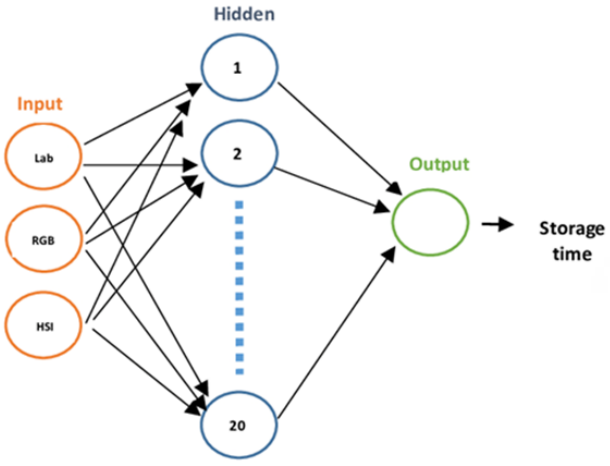

FIGURE 4. Illustration of a typical multi-layer neural network

The number of neurons that provided optimal functionality was determined through rigorous analysis. This analysis was focused on maximising the coefficient of determination (R^2) while minimising the mean squared error (MSE). The results of this analysis are summarised in Table I. It was observed that the R^2 and MSE values exhibited significant variation up to the addition of 18 neurons. The incorporation of an additional 19 neurons, followed by a further 20 neurons, resulted in the stabilisation of R^2 at a high value of 0.98. Concurrently, the MSE values exhibited fluctuations that were not contingent on the number of neurons, with the lowest values being attained with 18 and 19 neurons. Conversely, the use of a single neuron in the hidden layer yielded the highest MSE value (0.190), underscoring the significance of sufficient neuron count to ensure model efficacy (TABLE I).

Despite the main objective of maximizing R^2 and minimizing MSE, the most balanced results were obtained with 18 neurons, this configuration offering a slight improvement in MSE (MSE=0,028825) compared to the 20-neuron configuration. A high correlation coefficient (R^2 = 0.98) confirms the robustness of the model and the relevance of the variables used in its design (FIGS. 5a; 5b). This performance highlights the potential of ANN modeling for practical implementation in freshness prediction systems using non-destructive colorimetric input.

These observations are consistent with results reported in the literature for example, Liu *et al.* [36] showed that the inclusion of six neurons in the hidden layer led to the minimum MSE in an ANN model for rainbow trout fillet quality evolution prediction (*Oncorhynchus mykiss*). In a similar application, Rezende-de-Souza *et al.* [37] developed an ANN model for fish quality evaluation based on colorimetric parameters (CIELab) and total volatile basic nitrogen (TVB-N) and concluded that its performance was best achieved with only three neurons.

TABLE I
The results of the artificial neural network model assessment

Number of the neurons	MSE	R^2	MAE
1	0,195242	0,896824	2.1036
2	0,159423	0,916622	1.7513
3	0,132795	0,931068	1.5681
4	0,114666	0,940776	2.2658
5	0,114502	0,940864	1.8482
6	0,104563	0,946143	1.8103
7	0,09907	0,949049	1.8176
8	0,085285	0,956301	1.7547
9	0,081388	0,958341	2.3661
10	0,075843	0,961236	1.7370
11	0,077278	0,960488	1.9206
12	0,074028	0,962182	1.9699
13	0,061524	0,968674	2.1000
14	0,050462	0,974381	1.9285
15	0,052752	0,973202	2.3769
16	0,043977	0,97771	2.0734
17	0,029439	0,985135	2.3978
18	0,028825	0,985447	4.2540
19	0,034111	0,982755	3.4642
20	0,029932	0,984884	2.7007

MSE: mean squared error
R^2: correlation coefficient
MAE: mean absolute error

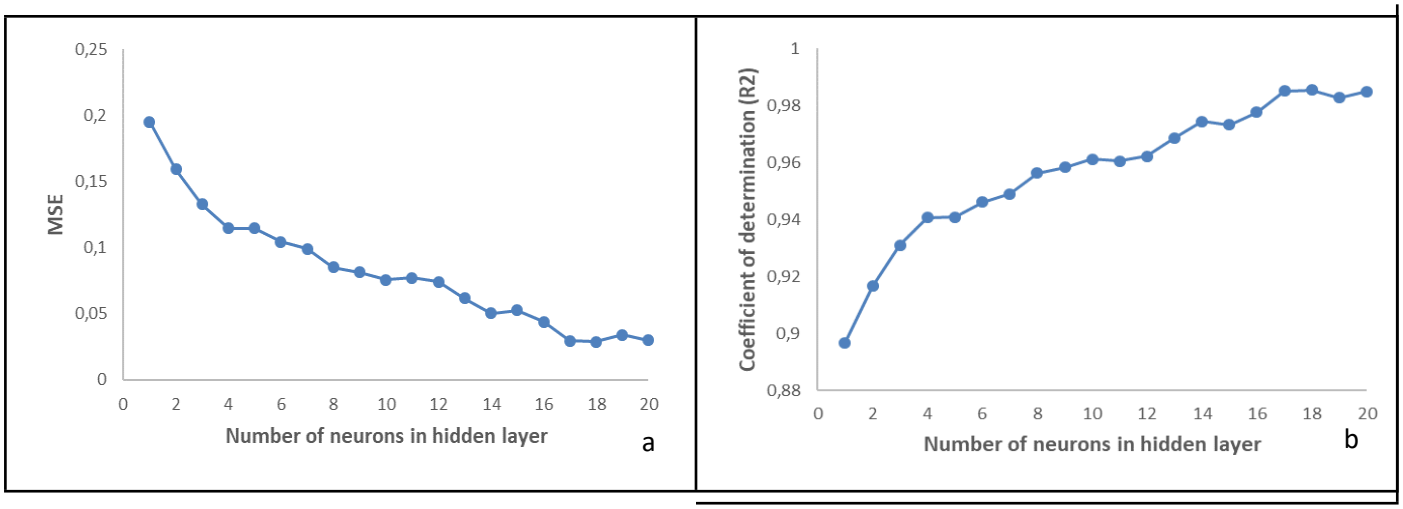

FIGURE 5. The network MSE and R2 values vs the number of neurons in the hidden layer

CONCLUSION

The findings of this study demonstrate that a computer vision system, utilising fisheye analysis, can serve as an effective tool for assessing the freshness of European seabass without resorting to destructive techniques. The approach via artificial neural networks yielded excellent classification precision on the basis of storage days. By using artificial neural networks (ANN), high prediction accuracy was achieved in classifying fish according to storage time, confirming the strong relationship between ocular colour parameters and spoilage progression. Furthermore, it was evident that variations in ocular colouration during storage periods could serve as a uniform criterion for distinguishing between freshness levels. This non-invasive approach eliminates the need for traditional destructive testing, reduces analysis time, and allows for real-time application in industrial settings. This would not only enhance efficiency but also improve the quality control measures employed within the industry. The research findings of this study can be used to develop an automatic and efficient fish sorting system based on freshness.

Conflict of interests

The authors declare no conflict of interest regarding the publication of this manuscript.

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