



A low-cost imaging framework for freshness evaluation from multifocal fish tissues

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ABSTRACT

Fish is one of the most nutritive food products whose quality gets affected along the food supply chain from harvesting to consumption. Freshness of fish, during that time, gets affected owing to the chemical decomposition of focal tissues like gills, eyes and skin. A novel mathematical model, is being proposed in this article, for the computation of a distinct freshness coefficient, Q-score, obtained by fusing the information from relevant focal tissues like gills, eyes, and skin of the fish. The mathematical model was designed by employing a meta-heuristic approach, where computationally optimized weights have been assigned to the features derived from the focal tissues. These multifocal tissues have been thoroughly investigated and assertive efforts have been made to normalize and integrate the extracted features into a single score. Implementation of the framework, provides an accuracy of 98.07%, indicating the efficacy of the proposed work. The proposed method is automatic and rapid for food quality evaluation. Imaging-based framework for the identification of fish freshness makes the proposed approach non-destructive which upholds its capability to be used in real-time situations.

1. Introduction

Fish is consumed as a food source in many regions across the world (Wang et al., 2019). It is rich in healthy protein, vitamins and minerals (Tidwell and Allan, 2001). Consumption of fish is increasing gradually as it offers several human health benefits. The growing advancements and sophistication in the modern food industry makes quality and freshness as the two prime concerns for selection of fish as a source of food (Komlatsky et al., 2019). However, the quality of fish gets affected on chemical decomposition that eventuates along the supply chain, i.e., from harvesting to consumption (Prasad and Murugadas,). A decomposed fish causes adverse effects on human health like cardiac complications, respiratory disorders, severe diarrhea, abdominal cramps, nausea and vomiting (Macagnano et al., 2005). Therefore, there is a need to monitor and control the quality of fish food item at each processing step of supply chain in order to combat serious health issues and can benefit the mankind.

The most popular method in determining fish quality is by the use of traditional laboratory technique employing various spectrophotometers (Esa et al., 2014). Although, such manual methods are accurate but exhibits several limitations like they are time-consuming,

labor-intensive, requires trained manpower and destructive (Wang et al., 2019; Arora et al., 2018). To overcome such shortcomings, various imaging-based approaches have been designed by the researchers that can be used in computer vision technique for fish quality analysis.

The use of computer vision techniques, that can impart rapid, accurate and economical solutions to the real-time situations, is the urge of the present time.

Previous studies show that different machine learning algorithms have been implemented by researchers for analyzing various types of fish. To this context, binary classification has been applied on the different fish image dataset such as *Milk fish*, *round scad* and *short mackerel scad* (Tolentino et al., 2017). The consumption of *Salmon salar* fish has shown to be popularly consumed across the globe whose quality analysis has been performed on the basis of the texture feature extraction (He et al., 2015), the design of prediction model classifies the edibility of *Parabramis pekinensis* fish (Huang et al., 2016), *channa punctatus* (Issac et al., 2019). Analysis has been performed on *Labeo Rohita* fish where high correlation of 92.4% between the machine learning technique and the findings obtained from manual method experts has been reported (Issac et al., 2017); and the classification of images on the basis of wavelet feature extraction was also found to be experimented on

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aforesaid fish type (Dutta et al., 2016a), the implementation of electrochemical impedance method significantly classified healthy and unhealthy *Cyprinus carpio* fish (Sun et al., 2018). Linear discriminant analysis model was designed to classify between *Gadus morhua* and *Melanogrammus aeglefinus* fish type (Grassi et al., 2018).

For determining the quality of fish, its focal tissues are considered as the main region of interest. So, different focal tissues like gills and eyes (Tolentino et al., 2017) have been experimented and analyzed by the researchers for its freshness as well as quality evaluation using computer vision technique. Wavelet transformation technique has been applied on the segmented gill tissues and the wavelet coefficients at different decomposition levels like first, second and third have been analyzed for assessing the freshness of fish (Dutta et al., 2016b). The presence of heavy metal exposed fish has also been reported wherein gill tissue (Singh et al., 2021), was again considered as the most prominent section of fish to be analyzed using the concept of *p*-value determination. Moreover, the presence of harmful metals was also identified by morphing the potential features extracted from eye fish focal tissue (Issac et al., 2019). Also, existing research accounts for the discrimination of pesticides exposed *Labeo Rohita* fish from the normal ones (Sengar et al., 2017) by analyzing the feature extracted from segmented eye focal tissue in spatial domain. The implementation of data fusion technique applied on the skin fish focal tissue (Huang et al., 2016) where back propagation-based prediction model classifies the quality of fish.

Major gaps have been identified from the state of art, which indicates that the identification of fish freshness using computer vision approach has not been explored exhaustively and there still exists scope for research. It has been observed from the existing literature that the fish freshness has been explored either for gill or eye or skin focal tissue, i.e., for a single focal tissue only. None of the computer vision approaches emphasizes on all the focal tissues together. Also, none of the existing methods reports on any pre-processing step that attempts to revoke image artifacts, illumination sources impact and imaging device effect on the acquired fish images. Furthermore, the lack of computation of novel freshness coefficient (Q-score) from multiple focal tissues, i.e. gill, eye, and skin, altogether motivates in finding unparalleled outcomes. It has also been ascertained that advanced imaging approaches like spectral imaging (Cheng et al., 2016; Chen et al., 2021) and advanced deep learning approaches which are commonly used on fish quality analysis (Chhabra et al., 2019; Taheri-Garavand et al., 2020) have been explored in recent researches. Although the aforesaid modern methods have shown convincing results but on the other hand the shortcomings observed in such techniques, like complex system, utilization of large amount of redundant data, and requirement of accelerating device to satisfy rapid acquisition (Li et al., 2013; Wu and Sun, 2013), will hamper the rapidity of detection and accuracy of the proposed model making it unsuitable to be used in real-time scenarios. Unfortunately, the use of spectral imaging makes the model costly whereas to make the proposed research work available in real-time situations, it is required to make it available to cheap cameras so that it can be operable on economical handy devices. Therefore, it has been affirmed from the shortcomings recognized in the previous studies that there still exists a need to design a system for identification of fish freshness using computer vision approach.

The aim of the proposed research work is to design an imaging framework for an automatic computation of novel freshness coefficient (Q-score) from multiple fish focal tissues. The main contribution of this research work is to identify the potential feature for the discrimination of healthy and unhealthy fish (*Labeo Rohita*). In the existing study, chemical decomposition of fish affects its most vulnerable focal tissues such as gills, eyes, and skin. This transition may behave as a biomarker for freshness decay in fish samples. This inherent perceptible change in the focal tissues is statistically converted into a mathematical parametric

quantity and represented in terms of Q-score. This transubstantiation shows exemplary outcomes as it discriminates fresh fish samples from the stale ones accurately and rapidly.

Another contribution of this research work is the appropriate selection of algorithms for the segmentation of focal tissues so that the background can be removed, and more focus can be given on the major region of interest. With the help of segmentation methods, discriminatory statistical features were obtained which was extensively investigated. The comprehensive analysis of extracted features formulates twofold meta-heuristic techniques. First, slope estimation technique for determining most discriminatory focal tissue and statistical feature. Second, support coefficient (SC) technique for computing as well as assigning optimum weights to focal tissues and statistical feature. This estimation scheme seems suitable in discriminating class of fish samples.

Third contribution of this research work is the speculation of rigorous efforts for normalisation of weights of tissues and features, for optimum computation of Q-score. The proposed experimental research work has been meticulously analyzed for the design of a novel model.

The last significant contribution of this research work incorporates validation of designed model with the standard chemical methodology that shows the reliability of the presented research work.

The proposed mathematical method ensures that the process is computationally automatic, efficient, cost-effective and non-destructive that has capability to be integrated with normal camera so that it can be operable by users having affordable devices making it robust to be used in real-time application.

2. Materials and methods

2.1. Fish samples collection

Live *Labeo Rohita* (Rohu) fish were collected from fish farm of National Institute of Abiotic Stress Management (NIASM) located in Baramati, Pune, Maharashtra. The average weight and average length of fish were 90.40 g and 21.60 cm respectively. The depth of the mean sea level was 570 m and their geographical coordinates are 75°32'02.79"E and 17°10'31.71"N from where fish samples were collected for experiment. The collected fish samples were placed in the pond for one day (24 h) before the start of the experiment. Invasion of pathogens and deposits of toxic substance present in water were eradicated.

Routine measurement of toxic substances and detection of freshness protocols were performed in the water for confirmation before proceeding with the experiment procedure. After placing fish samples in water for 24 h, they were immediately placed into ice-cold water for 15-min followed by preserving each fish sample in a thermocol box of dimensions 28 × 18 × 12 cm³. The thermocol box consisted of ice such that ice to fish ratio was maintained at 2:1.

2.2. Chemical analysis using laboratory-based method

The chemical analysis technique used in this paper is a validated method for toxicity assessment (Taneja et al., 2016) which can be referred for the identification of freshness in the fish sample. The actual weight of original solvent volume and salt volumes was of 5 g sample which have been changed here in accordance to the currently available samples.

Multifocal fish tissues like gill, eyes and skin tissues were dissected for chemical analysis and experimentation purpose. The dissected multifocal tissues have been stored at -19 °C temperature. Different sample quantities have been used for multifocal tissues like 2 g (g) for gill focal tissue, 1 g each for eye and skin focal tissue. This analysis was performed with 1.5 g of sodium acetate (C₂H₃NaO₂), 6 g of magnesium sulphate (MgSO₄) along with 2 mL of hexane (C₆H₁₄) in presence of 10

mL acidified acetonitrile which is converted into 1% acetic acid. At -20°C temperature, acetonitrile was extracted, and the fat contents are freezed out. This extraction method was accomplished in 20 min followed by washing with MgSO_4 (150 g) and 100 mgs of calcium chloride (CaCl_2). A dispersive solid phase extraction method was formulated by combining florisil (50 mg), 150 mg of C18 and 50 mg of Primary Secondary Amine (PSA) which was sourced for cleaning the liquid left under the solid residue, known as supernatant. Later, polytetrafluoroethylene membrane filter was used for filtering the supernatant. This filtered supernatant was analyzed using analytical technique of combining GC-MS/MS.

2.3. Spectroscopy method

Gas Chromatograph was attached to triple quadrupole mass spectrometer (GC:7890 A, MS: 700B) comprising of two mass analyzers connected in series. This spectrometer was made up of Agilent Technologies, Alto Palo, United States of America and controlled by Hunter Software of B.05.00.412 version. DB-5MS capillary column (30 m \times 0.25 mm \times 0.25 μm) of Agilent Technologies has been used for analytical separation. In GC, helium was used as a carrier gas which was set at a constant rate of 1 mL/min. The adjustment of the temperature of oven was done in three steps. Firstly, its initial temperature was set at 100°C with 1-min hold. Secondly, 200°C ramping at $50^{\circ}\text{C}/\text{min}$ with 0-min hold and then thirdly at $10^{\circ}\text{C}/\text{min}$ till 310°C for a gold of 3-min. This process was carried till a span of 17 min. The transfer line temperature of the spectrometer was set at 285°C .

The multi-mode inlet (MMI) of GC was used. A Gooseneck split less liner of 78.5 mm \times 6.5 mm \times 4 mm was programmed in 3 steps. Firstly, initial temperature was set at 80°C with 0.1-min hold, secondly, this temperature was raised up to 325°C at 450°C with 5-min hold. Thirdly, $10^{\circ}\text{C}/\text{min}$ raise up to 250°C for 0-min hold. 30 mL/min of purge flow to split vent was set with a pressure set at 7.414 psi for 2 min after injection. The mass spectrometer was driven in MS/MS mode with acquisition commencing at 4.4 min. Source Ionization (SI) temperature was maintained at 280°C and electron ionization was obtained at 70 eV.

2.4. Image acquisition of fish samples

Standard images of the fish samples were acquired under standardized illumination conditions and proper camera placing using the image acquisition set-up as shown in Fig. 1. The illumination sources used for



Fig. 1. Image acquisition set-up.

image acquisition of fish samples consists of four compact fluorescent (CFL) bulbs and four 566 mm long florescent tubes of 20 W which were arranged in a square shape of 32 cm \times 32 cm. The color temperature of CFL bulbs was judiciously selected at 3400 K so that soft light (warm) can be used for appropriate image acquisition of fish samples. These light sources were diffused by a diffuser sheet to develop an even illumination and also prevent from developing hot spots. To nullify further the effect of image artifacts and to revoke shadows while acquisition, diffusive light sources were oriented at 45° . Image acquisition of multifocal fish tissues were obtained out by using 16 mega pixel (MP) NIKON D90 digital camera (imaging device) having auto illumination feature and 26.2×15.3 mm CMOS sensor specification. The imaging device was placed at a height of 42 cm from the sample. The images acquired from digital camera records an image with size of 4920 pixels wide \times 3264 pixels high. This procedure of image acquisition was carried from first day till sixth day. The total number of samples were 96 sample images for each focal tissue, i.e. gill, eye and skin. The fish dataset consisted of 288 (96 images/focal tissue) images.

2.5. Proposed method

An automatic identification method for fish freshness using computer vision is proposed in this research work. The physical appearance of gill, eye and skin focal tissues of fish changes with time. So, the proposed methodology is on pre-processed images of these focal tissues which are referred as Region of Interest (ROI). ROI is the portion of image that requires segmentation in order to extract features (Arora et al., 2018). The fish image dataset is in RGB color format, which is converted into grayscale on segmentation to revoke further computational complexity. Grayscale fish image is the average of R, G, and B component of that image. Feature extraction methodology has been applied on the segmented grayscale image of fish multifocal tissues. Mean and variance were the two statistical features, extracted from the segmented from the multifocal tissues in spatial domain. Statistical feature mean computed the contribution of the individual pixel intensity for the segmented fish focal tissue image and variance feature measured the variation of each pixel of segmented image with respect to its neighboring pixels. The selection of these statistical features was significant in discriminating different class of fish image. Fig. 2 shows computer vision-based proposed model for identification of freshness in segmented fish multifocal tissues.

The detection of fish freshness depends upon two-fold significant parameters, first, on the monotonicity of each statistical feature and second, change in the color pattern of each focal tissue on storage. To accomplish this, weightage of each feature and focal tissue was empirically computed using weightage computation method. Based on the weighted mean and variance of multifocal tissue, normalisation technique was applied in order to compute freshness range of the fish samples.

This model can be summarized concisely as:

- Region of interest (ROI) segmentation
 - Gill segmentation
 - Eye segmentation
 - Skin segmentation
- Estimation of slopes and support coefficients (SC)
- Weight estimation scheme
 - Weight estimation of focal tissues
 - Weight estimation of statistical feature
- Normalisation of extracted feature

2.5.1. ROI segmentation

This section presents the implementation of appropriate algorithms for ROI segmentation.

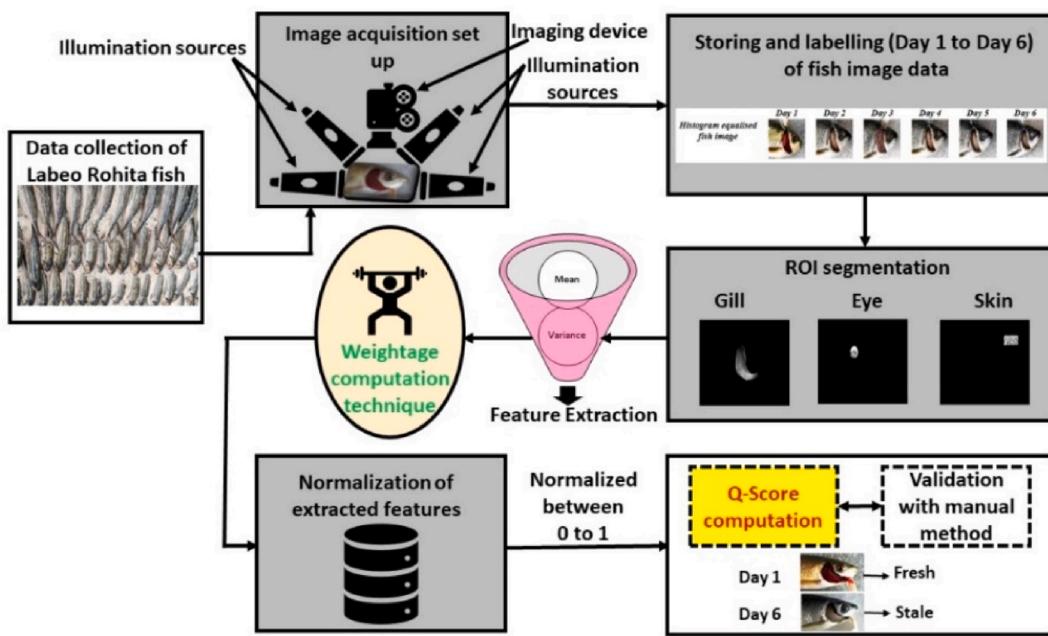


Fig. 2. Block diagram of computer vision-based model.

The results are validated from the analytical laboratory-based method. The computer vision algorithm was performed using MATLAB R2017a (9.2.0.538062) software.

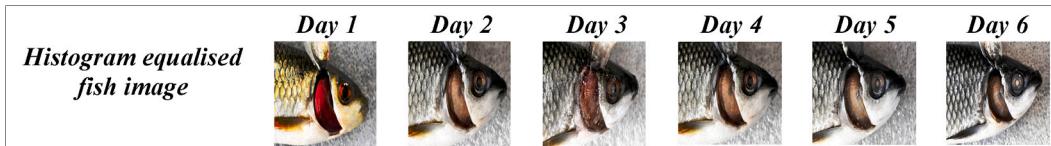


Fig. 3. Pre-processed images of rohu fish obtained from histogram equalisation.

2.5.1.1. Gill segmentation. The original color of gill fish is reddish-brown. Change in the gill color gives the most important perceptible characteristic for the identification of its properties and freshness (Dutta et al., 2016b). The color of the gill tissues fades on storage. Fish was stored for 6 days and images were acquired for all consecutive days. The image acquisition has been done on a normal background. With the use of appropriate image segmentation algorithms, background was removed optimally so as to focus on the fish focal tissues for freshness detection. To remove image artifacts, histogram equalisation was applied, the equalised images have been shown in Fig. 3.

K-means clustering algorithm has been used for the segmentation of gill tissues from the pre-processed fish images. The pre-processed input images were converted from RGB color model into CIE Lab color model because of twofold reasons, first, all the colours perceptible to human vision have been labeled in this colour model. This method expresses the colour into 3 different values, first 'l' will have values from black to white, second, 'a' will have values from green to red and 'b' will express values from blue to yellow. Second reason for applying this transformation was to increase the uniformity in the colour of the acquired image by isolating luminosity. Therefore, this transformation was best suitable for measurement of food colour (Romanillo et al., 2015).

Each colour marker consists of a cluster with nearest pixel which was perceived as mean. The entire cluster was represented by the value of mean. Hence, different colours were grouped together as separate clusters. Assorted clusters were taken as different means. In this paper, three clusters of pre-processed fish images were obtained. The red channel cluster was found to carry the maximum information of the gill properties from the whole image.

Algorithm 1 shows the steps of the segmentation of ROI.

Algorithm 1: Automatic gill segmentation using k-means clustering algorithm

- Step 1:** Input the pre-processed histogram equalised images as shown in Fig. 4 (a)
- Step 2:** Convert input images into CIE Lab color space model. (i) Convert pre-processed RGB model into XYZ model
- (ii) Convert XYZ model to CIE Lab Color Model
- (iii) Coefficients of Segmentation such as L (lightness), color direction a ($-a$: green axis, $+a$: red axis) and color direction b ($-b$: blue axis, $+b$: yellow axis) are shown in Fig. 4(b) and (c), Fig. 4 (d) respectively
- Step 3:** Classification of colours in ' ab ' space of CIE Lab color space by applying k-means clustering.
- Step 4:** Image is segmented into 3 clusters.
- Step 5:** Red channel cluster is selected because it entailed maximum information.

Fig. 5 represents the steps taken during automatic segmentation of gill from histogram equalised fish sample using k-means clustering algorithm where row (a) shows the transformation of CIE Lab color space image of the gill samples. Row (b) shows the image which is labeled by cluster index. For every object in fish input image, an index or a label corresponding to each cluster is returned, which is labeled automatically in CIE Lab color model. Row (c) represents the first cluster. Row (d) represents second cluster. Row (e) represents third cluster. Row (f) shows segmented red channel and background removal. The steps of segmentation have been incorporated row-wise and the results were found influencing.



Fig. 4. (a) Shows pre-processed input RGB color space fish image obtained from histogram equalisation, (b) L coefficient (lightness) of CIE Lab color space, (c) color direction a (-a: green axis, +a: red axis) of CIE Lab color space and (d) color direction b (-b: blue axis, +b: yellow axis) of CIE Lab color space. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Day		Day 1	Day 2	Day 3	Day 4	Day 5	Day 6
Step 1	RGB to CIE Lab color space (a)						
Step 2	Index corresponding to each cluster (b)						
Step 3	First cluster (c)						
Step 4	Second cluster (d)						
Step 5	Third cluster (e)						
Step 6	Segmented gill (f)						

Fig. 5. Automatic segmentation of gill focal tissue from Day 1 to Day 6: Step 1- CIE Lab color space, Step 2- Cluster Index, Step 3- First cluster, Step 4- Second Cluster, Step 5- Third Cluster, Step 6- Segmented gill tissue. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

2.5.1.2. Eye segmentation. Eyes of the fish are circular in shape. It was observed that the eyes of the fish were bulging, clear and shiny when fresh. With the passing day, the shape of the eye was shrunk, and its appearance turned dull and greyish brown. So, the eye focal tissue of fish can be used as an indicator for assessing freshness of the fish sample. Therefore, eye focal tissue was considered as another region of interest which was segmented out in order to extract discriminatory features.

Fig. 6 shows the stepwise illustration for automatic segmentation of eye focal tissue. The proposed method of segmentation process consists of two conversion technique:

- First the histogram equalised input images were transformed into grayscale image. As eye is circular in shape, so circle in the fish image

was found using gradient edge detection technique followed by creation of circular mask for segmenting ROI.

- Second, histogram equalised images were converted into image model. In HSV model, the colours were depicted in three different coordinates where H indicates hue or tints and tones, S indicates saturation or greyish shade and V indicates the value of brightness.

As discussed earlier, the eye of the fish turns greyish in colour if stored for days, so S channel was selected for segmentation purpose because this channel contains maximum information in comparison to other channels. Further, the binary mask created was summed with the selected saturation channel which results in segmented ROI which was the eye focal tissue of the fish sample obtained from histogram equalised image.

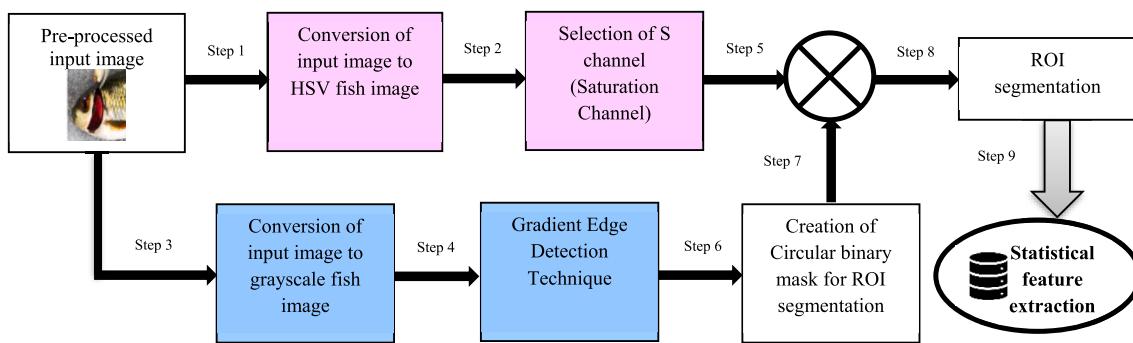


Fig. 6. Stepwise illustration for automatic segmentation of eye focal tissue.

On the pre-processed fish images, Algorithm 2 was applied in order to segment ROI (eye) from the new colour invariant input fish image.

Algorithm 2 shows the steps involved in feature extraction technique from skin focal tissue.

Algorithm 2: Automatic eye segmentation

- Step 1:** Original pre-processed histogram equalised fish images were used as input images (as shown in Fig. 7 (a))
 - Step 2:** Conversion of input images to HSV fish images (as shown in Fig. 7 (b))
 - Step 3:** Selection of S channel from converted HSV image
 - Step 4:** Conversion of input fish Images to grayscale fish Image (as shown in Fig. 7 (c))
 - Step 5:** The circular shape of fish eye circle was detected by using below equation of hough transform method:

$$(m - m_0)^2 + (n - n_0)^2 = R_c^2$$

Where: (m, n) , (m_0, n_0) represents the points of the centre and coordinates of the circle respectively R_c represents the radius of the circle.
 - Step 6:** For creating binary mask, below equation was used:

$$I_{MaskedImage} = I_{grayscale} > 0.5$$

Pixel values, $I_{grayscale} > 0.5$ will be replaced by 1(white) else by 0(black)
 - Step 7:** ROI was segmented by element-wise multiplication of S channel image and binary mask image.
 - Step 8:** Extraction of statistical features from the segmented ROI (as shown in Fig. 7 (d))
- Mean, $\bar{x} = \frac{\sum x}{n}$

$$\text{Variance}, \sigma^2 = \frac{\sum (x - \bar{x})^2}{n}$$

$$\text{Standard Deviation} = \sqrt{\sigma^2}$$

 Where x =measured quantity
 N = number of measured quantity

The steps for segmenting eye focal tissue from whole fish has been shown in Fig. 8 where first column shows histogram equalised image of fish sample followed by grayscale conversion of image on the second column. Third column shows the binary mask which is mapped on the grayscale image to segment the eye focal tissue of input images.

2.5.1.3. Skin segmentation. Skin of the fish have bright, shiny like appearance which turns dull, dark and fades with time. This focal tissue degrades as per succession in their storage days. Therefore, for the

identification of freshness of fish sample, skin of the fish was considered as another parameter of analysis. The steps involved in segmenting ROI and extraction of features from the segmented portion of ROI has been shown in Fig. 9.

Histogram equalised input image of skin focal tissue was converted into HSV model. The skin of fish was segmented in S channel, as shown in Fig. 10, because of its peculiar appearance S channel which makes it more prominent than in any other channel.

Algorithm 3 shows the steps involved in feature extraction technique from skin focal tissue.

Algorithm 3: Automatic skin segmentation

- Step 1:** Input the histogram equalised image (as shown in Fig. 10 (a))
 - Step 2:** Conversion of input image to HSV model
 - Step 3:** Selection of S (saturation) channel from converted HSV image (as shown in Fig. 10 (b))
 - Step 4:** Selection of a rectangular shape and segment the selected region from the image of S channel (as shown in Fig. 10 (c))
 - Step 5:** Extraction of statistical features from the segmented ROI
- Mean, $\bar{x} = \frac{\sum x}{n}$

$$\text{Variance}, \sigma^2 = \frac{\sum (x - \bar{x})^2}{n}$$

$$\text{Standard Deviation} = \sqrt{\sigma^2}$$

 Where x = measured quantity, N = number of measured quantities

ROI in saturation channel.

2.5.2. Estimation of slopes and support coefficients (SC)

Statistical features followed a monotonic discrimination from day 1 to day 6, day 1 having the greatest value of mean and variance which decreases in a monotonic way till day 6. Feature that shows maximum change from day 1 to day 6 contributes more in the identification process and exhibits more weightage. Slopes of mean and variance were calculated by using Eq. (1).

$$m = \frac{\sum_{i=1}^n f_i}{\sum_{i=1}^n f'_i}, \quad m_i = \frac{\sum_{i=1}^n v_i}{\sum_{i=1}^n v'_i} \quad (1)$$

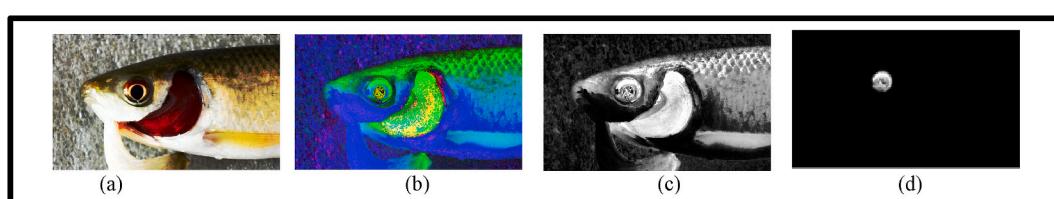


Fig. 7. (a) Shows pre-processed input image obtained from histogram equalisation, (b) represents HSV colour model of input images (c) shows the selection of S channel from HSV fish image, (d) presents the segmented eye focal fish tissue. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

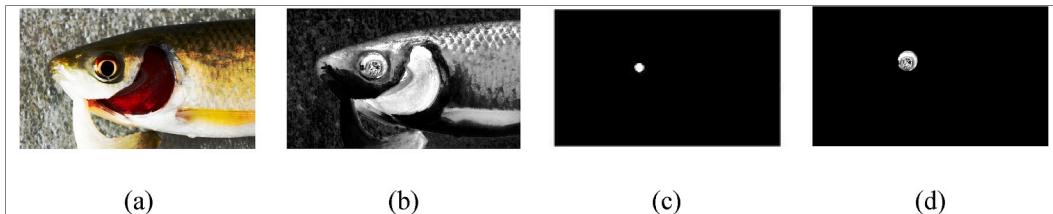


Fig. 8. (a) Input pre-processed image (b) Grayscale image (c) Binary mask (d) Segmented ROI (i.e. eye).

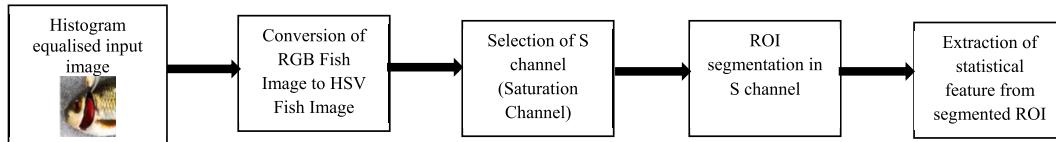


Fig. 9. Block Diagram of automatic segmentation of skin focal tissue.

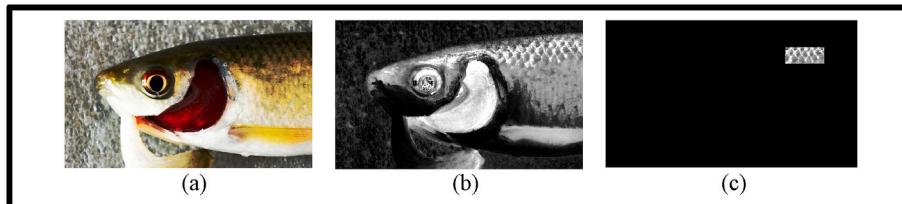


Fig. 10. (a) Shows histogram equalised input image, (b) shows S channel obtained from HSV image model and (c) shows.

$\sum_{i=1}^n f_i$ and $\sum_{i=1}^n f'_i$ are the summation of maximum and minimum mean value respectively. $\sum_{i=1}^n v_i$ and $\sum_{i=1}^n v'_i$ are the summation of maximum and minimum variance value respectively and n is the number of fish.

2.5.3. wt estimation scheme

It has been observed that different focal tissues and their statistical features contribute distinct significance in the identification of freshness in fish focal tissues. Based on this distinction, weightage of each focal tissue and statistical feature were computed. To obtain this, support coefficients (SC), a_{mean} , b_{mean} , $a_{variance}$, and $b_{variance}$ were optimally calculated. SC of mean and variance was empirically calculated by Eq. (2) and Eq. (3) respectively.

$$a_{mean} = \frac{\sum_{j=1}^m t_j + \sum_{i=1}^m t_i}{\sum_{i=1}^m t_i}, \quad b_{mean} = \frac{\sum_{j=1}^m t_j + \sum_{i=1}^m t_i}{\sum_{j=1}^m t_j} \quad (2)$$

$$a_{variance} = \frac{\sum_{j=1}^m t'_j + \sum_{i=1}^m t'_i}{\sum_{i=1}^m t'_i}, \quad b_{variance} = \frac{\sum_{j=1}^m t'_j + \sum_{i=1}^m t'_i}{\sum_{j=1}^m t'_j} \quad (3)$$

where, m = 3; number of focal tissues (gill, eye and skin)

$\sum_{j=1}^m t_j$ and $\sum_{i=1}^m t_i$ is the summation of maximum and minimum value of mean for multifocal tissues respectively

$\sum_{j=1}^m t'_j$ and $\sum_{i=1}^m t'_i$ is the summation of maximum and minimum value of variance for multifocal tissues respectively

2.5.3.1. wt estimation of focal tissue. The estimation of weights of focal tissues can be summarized concisely as:

- Statistical estimation of weight of mean by using their slopes and support coefficients.
- Statistical estimation of weights of variance by using their slopes and support coefficients.
- Averaging of weights.
- Computation of final weight of gill, eye, and skin.

The weight of each focal tissue for mean value was obtained from Eq. (4). The weight of each focal tissue for variance value was obtained from Eq. (5).

$$w_1 = \frac{m}{a_{mean}}, \quad x_1 = \frac{m}{b_{mean}} \quad (4)$$

$$w_2 = \frac{m_i}{a_{variance}}, \quad x_2 = \frac{m_i}{b_{variance}} \quad (5)$$

The average of the weights, w_m and v_v , were calculated for each statistical feature with respect of each focal tissue i.e. gill, eye and skin by using Eq. (6).

$$w_m = \frac{1}{2} \cdot (w_1 + w_2), \quad v_v = \frac{1}{2} \cdot (x_1 + x_2) \quad (6)$$

Eq. (7) shows the final weights obtained for each focal tissue for different statistical feature

$$W = \frac{1}{2} \left(w_m + v_v \right) \quad (7)$$

2.5.3.2. wt estimation of statistical feature. This section describes the method used for computing the weightage of statistical feature. Eq. (8) was used for calculating the weights of each statistical feature where f_{wm} showed the weight of mean and f_{vv} showed the weight of variance.

$$f_{wm} = \frac{1}{2} \cdot \left(\frac{(l_{km}/s_m) + (m_{kn}/s_m)}{2} \right), \quad f_{vv} = \frac{1}{2} \cdot \left(\frac{(l_{kv}/s_v) + (m_{kv}/s_v)}{2} \right) \quad (8)$$

where,

$$l_{km} = \frac{f_1 + f_n}{f_n}, \quad m_{km} = \frac{f_1 + f_n}{f_1}, \quad s_m = \frac{f_1}{f_n}$$

f_1 and f_n is the value of mean for first and nth storage day for different focal tissues respectively,

$$l_{kv} = \frac{f_{1'} + f_{n'}}{f_{n'}}, \quad m_{kv} = \frac{f_{1'} + f_{n'}}{f_{1'}}, \quad s_v = \frac{f_{1'}}{f_{n'}}$$

$f_{1'}$ and $f_{n'}$ is the value of variance for first and nth storage day for different focal tissues respectively.

2.5.4. Normalisation of the extracted features

The extracted features of multifocal tissues have been normalised to obtain the range $\sim 0\text{--}1$ in order to make the result more robust and adaptable. The steps taken to normalize the extracted features are mentioned below:

Step 1: Normalisation of gill tissue feature was obtained by using Eq. (9).

In the proposed research work, the experiment was done for the maximum number of 6 days, so, $n = 6$.

$$N_{gill} = \frac{s_{xy}}{5\eta * \exp(1)} \quad (9)$$

N_{gill} indicates the normalised value of the feature associated with gill focal where s_{xy} is the extracted statistical feature of x th sample for y th day of segmented gill focal tissue and $\eta = (n+1, n+2, \dots, n+y)$, η is the constant value indicating the number of storage days for which the gill focal tissue was under observation.

Step 2: Normalisation of eye tissue feature was obtained by using Eq. (10).

$$N_{eye} = \frac{s_{xy}}{\delta} \quad (10)$$

N_{eye} indicates the normalised value of feature associated with eye focal tissue which was the ratio of s_{xy} (extracted statistical feature of x th sample for y th day of segmented eye focal tissue) to δ (change in normalised factor) which can be evaluated as shown in Eq (11).

$$\delta = p + (m - 1) * d; \quad p = \{50\}, \quad m = \{1, 2, \dots, y\text{th day}\} \quad (11)$$

where d is the deviation in the normalised factor. $d = \{20\}$ in the current experiment.

Step 3: Normalisation of skin tissue feature was obtained by using Eq. (12).

$$N_{skin} = \frac{s_{xy}}{\epsilon} \quad (12)$$

N_{skin} indicates the normalised value of the feature associated with skin focal tissue which was the ratio of s_{xy} (extracted statistical value of x th sample for y th day of segmented skin focal tissue) to ϵ (change in normalised factor) that was evaluated by using Eq. (13).

$$\epsilon = q + (m - 1) * e; \quad q = \{123\}, \quad m = \{1, 2, \dots, y\text{th day}\} \quad (13)$$

where d is the deviation in the normalised factor. $e = \{100\}$ in the proposed experimental work.

Step 4: Normalisation of empirically computed weights.

Normalisation of these weights of focal tissues for statistical feature; mean and variance have been obtained from Eq. (14).

$$W_m = \sum_{i=1}^n W_{m_i}, \quad W_v = \sum_{i=1}^n W_{v_i} \quad (14)$$

Weights of statistical features for multifocal tissues have been previously discussed and shown in Table 4.

$$W'_m = \frac{\sum_{i=1}^n f_{ij}}{W_m} \quad (15)$$

where i = mean value of a focal tissue of a sample; j = sample.

Eq. (15) represents the summation of mean value of multifocal tissues of a particular sample with respect to the normalised weights.

$$W'_v = \frac{\sum_{i=1}^n f'_{ij}}{W_v} \quad (16)$$

where i = mean value of a focal tissue of a sample; j = sample.

Eq. (16) represents the summation of variance value of multifocal tissues of a sample with respect to the normalised weights.

3. Results

This section presents the results obtained for the identification of fish freshness.

3.1. Analysis of extracted features obtained from segmented histogram equalised image

The computational complexity is reduced by, first, converting original RGB color format fish image into grayscale image upon segmentation. The grayscale image returns average of R, G and B components of input fish image. Discriminatory features have been extracted from the segmented fish focal tissue images. Mean returns the average of individual pixel intensity. As discussed in the previous section, the dataset consists of 96 samples/focal tissue, i.e. 96 samples each for gill, eye, and skin. Mean and variance are the two statistical parameters which have been obtained from the segmented fish gill, eye, and skin focal tissues. Mean returns the average of the individual pixel intensity and variance returns the variation of each pixel with respect to its neighboring pixel. Another step applied for improving computational speed is by applying statistical analysis on the features obtained from 288 segmented fish image. The size of extracted features is reduced by taking their average.

To improve the computational speed in assessing the quality of fish, the size of extracted features have been reduced by applying statistical analysis on among the mean and variance values, i.e. by taking their average.

The statistical analysis has been performed, as shown in Table 1, among the mean and variance values determined. The statistical features of gill, eye, and skin is the average of individual mean and variance obtained from 96 samples each for gill, eye, and skin.

Day 1 of all the 96 samples of gill focal tissue for Mean feature has been averaged and is represented under Mean, similarly for Day 2, the average of Mean feature for gill focal tissue has been shown at S.No 2. Similarly, the averaging has been done for other days of gill focal tissue.

Table 1

Statistical analysis obtained from averaging individual mean and variance of gill (96 samples), eye (96 samples), and skin (96 samples) tissues.

Focal tissue	Gill		Eye		Skin	
	Day	Mean	Variance	Mean	Variance	Mean
1. Day 1	95.58	22,078.6	83.53	1537.5	125.12	1865.89
2. Day 2	95.20	19,658.9	78.56	1376.4	108.76	1657.33
3. Day 3	90.67	17,839.6	63.88	1145.3	84.32	1532.6
4. Day 4	83.11	14,879.1	60.57	964.63	73.00	1465.1
5. Day 5	78.56	12,009.0	54.27	850.74	67.56	1357.4
6. Day 6	65.44	10,211.6	35.89	687.94	55.48	1200.67

$$\text{Statistical feature}_{\text{focal tissue}} = \frac{\sum \text{Individual means of 96 samples of focal tissue for Day 1}}{96}$$

$$\text{Statistical feature}_{\text{focal tissue}} = \frac{\sum \text{Individual means of 96 samples of focal tissue for Day 2}}{96}$$

$$\text{Statistical feature}_{\text{focal tissue}} = \frac{\sum \text{Individual means of 96 samples of focal tissue for Day 3}}{96}$$

$$\text{Statistical feature}_{\text{focal tissue}} = \frac{\sum \text{Individual means of 96 samples of focal tissue for Day 6}}{96}$$

In the similar manner, the averaging has been done for all the days for eye as well as skin focal tissues.

Table 1 indicates that the mean and variance for gill, eye, and skin fish tissues decreases monotonically from Day 1 to Day 6, i.e., as they undergo chemical decomposition on storage. This monotonic decrease in the extracted feature shows a discrimination between the stored fish from Day 1 to Day 6. The significance of focal tissue and the extracted feature has been determined by comprehending their extremities. **Table 2** shows the maximum and minimum values of mean and variance for multifocal tissues.

Identification of fish freshness depends upon two occurrences, first, behaviour of each focal tissue and, second, monotonic variation of each extracted feature. So, it becomes important to compute the weightage of each feature and its corresponding focal tissue. To achieve this, slope of each feature and its corresponding focal tissue has been computed and compared as shown in **Table 3**.

Fig. 11 shows the slopes of mean of multifocal tissues for histogram equalised images. It has been observed that the slope of mean of eye focal tissue ($m= 2.383$) was highest in comparison to other focal tissues which infers that mean feature of eye focal tissue carries the most significant information. Hence, eye fish focal tissue was of great importance in identifying freshness content in fish sample in comparison to other focal tissue. **Fig. 12** shows the slopes of variance of multifocal tissues for histogram equalised images. It has been observed that the slope of variance of eye focal tissue ($m= 2.234$) was highest in comparison to other focal tissues which infers that variance feature of eye focal tissue carries the most significant information. Hence, eye fish focal tissue was of great importance in identifying freshness content in fish sample in comparison to other focal tissue. Magnitude of each focal tissue has been empirically computed in order to identify the range of fish freshness.

Based on the above findings, weights of focal tissues and features have been empirically computed.

Table 4 inferences:

1. Eye focal tissue has the highest weightage for statistical feature mean, i.e. 1.191. It infers that mean feature alone for eye focal tissue will give maximum information in fish freshness identification than other focal tissues.
2. Also, eye focal tissue has the highest weightage for statistical feature variance, i.e. 1.117. It infers that variance feature alone for eye focal

Table 2
Minimum and maximum values of mean in segmented channel ROI.

Focal Tissue	Gill		Eye		Skin	
Extreme value	Max	Min	Max	Min	Max	Min
Mean	95.58	65.44	83.53	35.89	125.12	55.48
Variance	22,078.6	10,211.6	1537.5	687.94	1865.89	1200.67

tissue will give maximum information in fish freshness identification than other focal tissues.

Table 5 inferences:

1. The dataset of 288 images (96 samples/focal tissue) was statistically averaged into 4 batches.
2. With help of empirical formula discussed in Eq. (8), weights of mean and variance, fw_m and fv_v , respectively, were computed.
3. For gill focal tissue, weightage of variance is greater than weightage of mean.
4. For eye focal tissue, weightage of mean is greater than weightage of variance.
5. For skin focal tissue, weightage of mean is greater than weightage of variance.

3.2. Freshness coefficient (Q-score)

Based on the optimized values of SC, weights assessment was implemented that was utilized in the computation of Q-score. Q-score of

Table 3
Slope table.

S. No.	Focal Tissue	Slope	Variation of mean values in Segmented channel ROI (m)	Variation of Variance values in Segmented channel ROI (m_i)
1	Gill focal tissue	m_1	1.460	2.162
2	Eye focal tissue	m_2	2.383	2.234
3	Skin focal tissue	m_3	2.255	1.554

Table 4
Weightage of multifocal tissue for statistical feature.

Statistical Feature	w_m	v_v	Average of weights W	Focal tissue
Mean	0.496	0.963	0.730	Gill
	0.810	1.572	1.191	Eye
	0.767	1.488	1.127	Skin
Variance	0.696	1.466	1.081	Gill
	0.719	1.515	1.117	Eye
	0.500	1.054	0.777	Skin

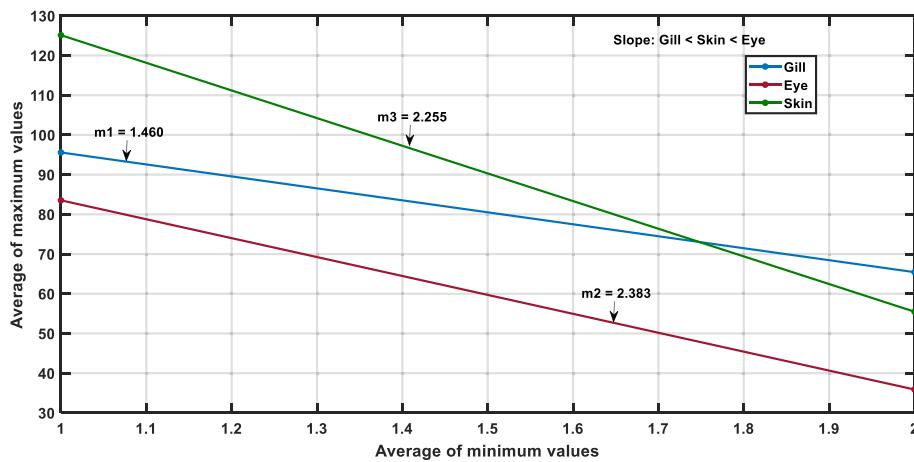


Fig. 11. Slope of mean value of multifocal segmented ROI tissue.

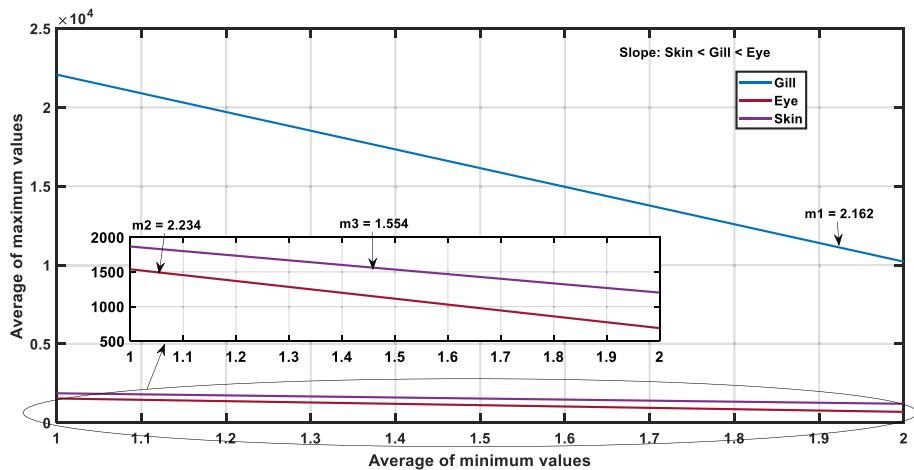


Fig. 12. Slope of variance value of multifocal segmented ROI tissue.

Table 5
Determination of weightage of statistical feature for multifocal tissue.

Focal Tissue	Batch	Mean	Variance	Greater Weightage	Remarks
		Weightage of Mean (f_{w_m})	Weightage of Variance (f_{v_r})		
Gill	1	0.750	0.976	Variance	Variance has
	2	0.731	1.226	Variance	more
	3	0.699	1.144	Variance	weightage in
	4	0.741	1.0213	Variance	comparison to mean.
Eye	1	1.232	1.221	Mean	Mean has more
	2	1.119	1.058	Mean	weightage in
	3	1.186	1.136	Mean	comparison to
	4	1.124	1.055	Mean	variance.
Skin	1	1.164	0.795	Mean	Mean has more
	2	1.077	0.787	Mean	weightage in
	3	1.121	0.760	Mean	comparison to
	4	1.151	0.852	Mean	variance.

the samples for statistical feature mean was computed by using Eq. (17).

$$Q\text{-score of Mean, } FI_m = \frac{\sum_{i=1}^n w_i * t_i}{\sum_{i=1}^n w_i} \quad (17)$$

where n = number of multifocal tissues, w_i is the weight of focal tissue and t_i is the value of focal tissue.

Table 6
Q-score computation.

Q-score	Identification
1.0 to 0.8	Completely fresh fish (F1)
0.8 to 0.6	Moderately fresh fish (F2)
0.6 to 0.4	Less fresh fish (F3)
0.4 to 0	Stale fish (F4)

Q-score of variance has been calculated by using Eq. (18).

$$Q\text{-score of Variance, } FI_v = r_1 * ft_1 + r_2 * ft_2 + r_3 * ft_3 \quad (18)$$

where, r_1, r_2, r_3 are the normalised values of weights.

ft_1, ft_2, ft_3 are the variance values of gill, eye and skin focal tissues respectively

Range of sample has been calculated which was normalised from 0 to 1 using Eq. (10). Table 6 shows the Q-score of multifocal fish tissue in the range 0–1.

The range of fish freshness was calculated by applying optimum weights to the features extracted from, first, the segmented multifocal tissue and, second, by normalising distinct statistical parameters. The decrease in freshness range indicates an increase in toxicity content. Fig. 13 shows a graphical representation of freshness range obtained by using histogram equalised fish images for its freshness identification.

Table 7 shows the validation of computer vision-based result using

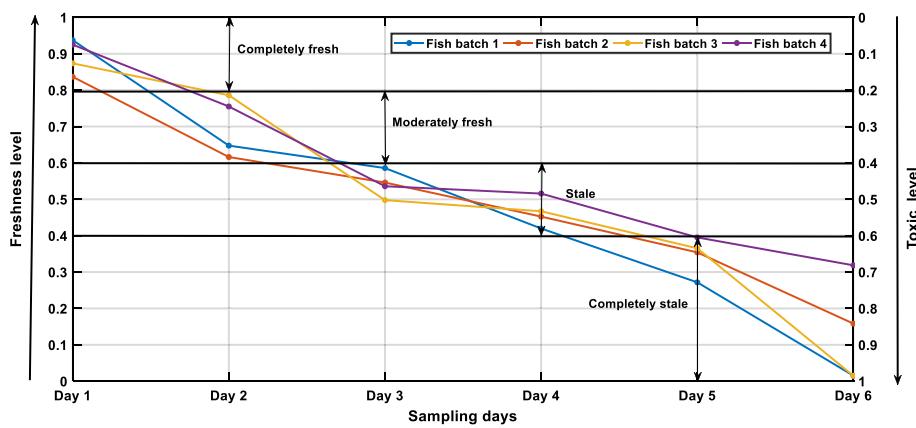


Fig. 13. Freshness range for quality assessment of fish multifocal tissue.

Table 7
Validation of computer vision result with the chemical laboratory.

Sample number	CL	CVS	Result
1	F1	F1	1
2	F1	F1	1
3	F3	F3	1
4	F4	F4	1
5	F4	F4	1
6	F2	F2	1
7	F3	F3	1
8	F4	F4	1
9	F1	F1	1
10	F3	F3	1
11	F3	F3	1
12	F1	F1	1
13	F4	F4	1
14	F3	F3	1
15	F2	F2	1
16	F3	F3	1
17	F4	F4	1
18	F4	F4	1
19	F2	F2	1
20	F1	F1	1
21	F3	F3	1
22	F4	F4	1
23	F4	F4	1
24	F3	F3	1
25	F3	F1	0
26	F1	F1	1
27	F2	F2	1
28	F3	F3	1
29	F2	F2	1
30	F4	F4	1
31	F1	F1	1
32	F2	F2	1
33	F3	F3	1
34	F4	F4	1
35	F2	F2	1
36	F2	F2	1
37	F3	F3	1
38	F4	F4	1
39	F1	F1	1
40	F1	F1	1
41	F2	F2	1
42	F3	F3	1
43	F2	F2	1
44	F4	F4	1
45	F1	F1	1
46	F1	F1	1
47	F2	F2	1
48	F4	F4	1
49	F2	F2	1
50	F1	F1	1
51	F4	F4	1
52	F4	F4	1

Table 8
Comparison between existing methods and proposed research work.

Image dataset	Focal tissue	Algorithm used	Result obtained
(Tolentino et al., 2017) 1680 Sample images	Gill, eye	1. Cropping of original RGB image & Feature extraction 2. SVM classification	Classification accuracy: 98%
(Issac et al., 2019) 116 Sample images	Eye	1. ROI Segmentation & Rim creation 2. Feature Translations	Accuracy not reported Computation time = 1.44 s
(Issac et al., 2017) 24 Sample images	Gill	1. Threshold based image segmentation. 2. Correlation coefficient computed.	Correlation: 92.4%.
(Dutta et al., 2016b) 96 Sample images	Gill	1. ROI segmentation & Feature extraction	Freshness accuracy: 95.8%
(Singh et al., 2021) 116 Sample images	Gill	1. ROI Segmentation 2. Feature extraction 3. p-value determination	82%-92% region covered within receiver operating characteristics. Accuracy not reported
(Sengar et al., 2017) 144 Sample images	Eye	1. Eye segmentation & Feature extraction 2. Comparison between ANN, SVM, Naïve Bayes and Random Forest classification methods.	Classification accuracy: 96.87%
(Alaimahal et al., 2017) 30 Sample images	Gill	1. Statistical feature extraction 2. Implementation of Local binary pattern operator. 3. Classification using KNN Classifier	Classification accuracy: 90%
Proposed research work: 288 Sample images	Gill, eye, and skin	1. Design of new mathematical model for computation of novel Q-score 2. Computation of slopes and SC of all focal tissues 3. Computation of weights of focal tissues and features. 4. Normalisation of weighted parameters 5. Computation of novel Q-score	Classification of fish into four classes, viz., F1, F2, F3 and F4. Accuracy obtained on validation of CVS with CL technique: 98.07%

manual laboratory technique. First column shows the fish samples. Second column shows the result obtained from convention laboratory (CL) technique while third column shows the computer vision (CVS) result. Representation of 1 in the fourth column shows that CL and CVS results matches and 0 shows that there is a mismatch.

3.3. Discussions and final remarks on the experimental results

A mathematical model was designed for computing the Q-score from multifocal fish tissues like gill, eye and skin using computer vision approach in this proposed research work. It was observed from the state of art that the existing computer vision-based methods either focuses on gill (Tolentino et al., 2017; Dutta et al., 2016b; Singh et al., 2021) or on eye (Tolentino et al., 2017; Sengar et al., 2017; Issac et al., 2019) or on body surface focal tissue (Huang et al., 2016). None of the computer vision-based method emphases on all the major focal tissues of fish. Also, existing state of art did not report any computation of freshness coefficient for fish quality identification. Some of the most relevant state of art has been shown in Table 8. The extracted features were investigated exhaustively so as to measure the slopes and support coefficient. Mathematical computation of weighted focal tissues and its features, highlights the discriminatory information that is needed for computing the Q-score. Normalisation of weighted values was worthwhile in calculating the novel Q-score from multifocal fish tissues. On validation of results with standard chemical technique, 98.07% of accuracy was obtained for the Q-score calculation. The proposed mathematical model has the potential that can automatically and accurately determine the edibility of the fish sample under experimentation. Hence, this work opens new dimensions of research in fish quality assessment in real-time situations.

Computer vision-based technique for fish freshness assessment has not been explored comprehensively in the state of art. Therefore, the proposed research work aims to fulfil the gaps and may be considered as a significant contribution towards the assessment of fish quality inspection. The proposed method is more robust, automatic, flexible, and non-destructive in comparison to the existing methods.

4. Conclusion

Fish is consumed as a source of food in many regions of the world. It is rich in nutrients, vitamins, minerals, and proteins. Multiple tissues of fish such as gill, eye and skin decompose with time, which causes a drop in its freshness quality.

Existing imaging-based approaches focussed on single fish focal tissue and unheeded other major focal tissues. Moreover, there exists lack of pre-processing measures that can revoke image artifacts before its analysis. The proposed research work attempts to overcome these shortcomings of prevailing researches by identifying significant fish focal tissues, such as, gills, eyes, and skin, during chemical decomposition of fish along the supply chain from harvesting to consumption. Efforts have been made in the proposed work to nullify the effect of image artifacts, impact of illumination sources and the repercussions of imaging device in order to obtain accurate results. Furthermore, this research work aims to design a mathematical model for the computation of novel freshness coefficient (Q-score), obtained from integrating feature weights and tissue weights. To achieve this, strategic framework has been designed for the mathematical measurement of slopes and support coefficients that made proposed method efficient in discriminating the class of fish sample. Judicious estimation of weights and normalisation of extracted features were significant in determining novel findings and made the proposed model more robust than the existing methods. The validation of the proposed model with the standard laboratory technique showed 98.07% accuracy which indicates that the proposed research work is more superior than the state of art. New dimensions of research in the area of non-destructive quality testing of food items for real-time applications could be explored as this

research work is novel, accurate and non-destructive.

As far as future research aspects are concerned, use of deep learning models, with larger fish image dataset, may prove to be significant in assessing fish quality. The designed model, then, could possibly be integrated with hand-held devices like mobile phones, which will enable the user to take quick decision about the edibility of the fish based on the report generated by the device.

Credit author statement

Monika Arora: Software, Methodology, Writing – original draft. M. Parthasarathi: Validation, Writing – review & editing. Malay Kishore Dutta: Conceptualization, Supervision, Writing – review & editing

References

- Alaimahal, A., Shruthi, S., Vijayalakshmi, M., Vimala, P., 2017. Detection of fish freshness using Image Processing. *Int. J. Eng. Res. Technol.* 5 (9), 1–6. Date: 19 August 2021.
- Arora M, Mangipudi P, Dutta MK, Burget R. Image processing based automatic identification of freshness in fish gill tissues. In2018 International Conference on Advances in Computing, Communication Control and Networking (ICACCCN) 2018 Oct 12 (pp. 1011-1015). IEEE.
- Chen, Z., Wang, Q., Zhang, H., Nie, P., 2021. Hyperspectral imaging (HSI) technology for the non-destructive freshness assessment of pearl gentian grouper under different storage conditions. *Sensors* 21 (2), 583. Jan.
- Cheng JH, Sun DW, Qu JH, Pu HB, Zhang XC, Song Z, Chen X, Zhang H. Developing a multispectral imaging for simultaneous prediction of freshness indicators during chemical spoilage of grass carp fish fillet. *J. Food Eng.*. 2016 Aug 1;182:9-17.
- Chhabra HS, Srivastava AK, Nijhawan R. A hybrid deep learning approach for automatic fish classification. InProceedings of ICETIT 2019 2020 (pp. 427-436). Springer, Cham.
- Dutta MK, Sengar N, Kamble N, Banerjee K, Minhas N, Sarkar B. Image processing based technique for classification of fish quality after cypermethrine exposure. *LWT-Food Science and Technology*. 2016 May 1;68:408-417.DOI: 10.1016/j.lwt.2015.11.05.
- Dutta MK, Issac A, Minhas N, Sarkar B. Image processing based method to assess fish quality and freshness. *J. Food Eng.*. 2016 May 1;177:50-58. DOI:10.1016/j.jfoodeng.2015.12.018.
- Esa SM, Lee KY, Jarmin R. Effect of conditioning time on a novel PVC-based membrane for chemFET sensitive to histamine. InRegion 10 Symposium, 2014 IEEE 2014 Apr 14 (pp. 572-577). IEEE. DOI: 10.1109/TENCONSpring.2014.6863100.
- Grassi S, Casiraghi E, Alamprese C. Fish fillet authentication by image analysis. *J. Food Eng.*. 2018 Oct 1;234:16-23.
- He HJ, Wu D, Sun DW. Nondestructive spectroscopic and imaging techniques for quality evaluation and assessment of fish and fish products. *Crit. Rev. Food Sci. Nutr.*. 2015 May 12;55(6):864-886.DOI: 10.1080/10408398.2012.746638.
- Huang, X., Xu, H., Wu, L., Dai, H., Yao, L., Han, F., 2016. A data fusion detection method for fish freshness based on computer vision and near-infrared spectroscopy. *Analytical Methods* 8 (14), 2929–2935.
- Issac, A., Dutta, M.K., Sarkar, B., 2017. Computer vision based method for quality and freshness check for fish from segmented gills. *Comput. Electron. Agric.* 139, 10–21. <https://doi.org/10.1016/j.compag.2017.05.006>.
- Issac A, Srivastava A, Srivastava A, Dutta MK. An automated computer vision based preliminary study for the identification of a heavy metal (Hg) exposed fish-channa punctatus. *Comput. Biol. Med.*, 2019 Aug 1;111:103326.
- Komlatsky VI, Podoinitsyna TA, Verkhotorov VV, Kozub YA. Automation technologies for fish processing and production of fish products. InJournal of Physics: Conference Series 2019 Dec (Vol. vol. 1399, No. 4, p. 044050). IOP Publishing.
- Li, Q., He, X., Wang, Y., Liu, H., Xu, D., Guo, F., 2013. Review of spectral imaging technology in biomedical engineering: achievements and challenges. *J. Biomed. Opt.* 18 (10), 100901. Oct.
- Macagnano, A., Careche, M., Herrero, A., Paolesse, R., Martinelli, E., Pennazza, G., Carmona, P., D'amico, A., Di Natale, C., 2005 Nov 11. A model to predict fish quality from instrumental features. *Sensor. Actuator. B Chem.* 111, 293–298. <https://doi.org/10.1016/j.snb.2005.06.028>.
- Prasad MM, Murugadas V. Microbial Quality and Safety of Fish and Fishery Waste. ICAR-Central Institute of Fisheries Technology.
- Romanillo, R., Leone, A., Peri, G., 2015 Dec 18. Measurement of food colour in L* a* b* units from RGB digital image using least squares support vector machine regression. *Journal of Agricultural Engineering* 46 (4), 138–143.
- Sengar N, Dutta MK, Sarkar B. Computer vision based technique for identification of fish quality after pesticide exposure. *Int. J. Food Prop.*. 2017 Dec 29;20(Suppl. 2):2192-2206.
- Singh A, Gupta H, Srivastava A, Srivastava A, Joshi RC, Dutta MK. A novel pilot study on imaging-based identification of fish exposed to heavy metal (Hg) contamination. *J. Food Process. Preserv.*. 2021 May 15:e15571.
- Sun J, Zhang R, Zhang Y, Liang Q, Li G, Yang N, Xu P, Guo J. Classifying fish freshness according to the relationship between EIS parameters and spoilage stages. *J. Food Eng.*. 2018 Feb 1;219:101-110.

- Taheri-Garavand A, Nasiri A, Banan A, Zhang YD. Smart deep learning-based approach for non-destructive freshness diagnosis of common carp fish. *J. Food Eng.*. 2020 Aug 1;278:109930.
- Taneja A, Ranjan P, Ujlayan A. An efficient SOM and EM-based intravascular ultrasound blood vessel image segmentation approach. *Int. J. Syst. Assur. Eng. Manag.*. 2016 Dec 1;7(4):442-449.
- Tidwell JH, Allan GL. Fish as food: aquaculture's contribution. *EMBO Rep.*. 2001 Nov 1;2 (11):958-963.
- Tolentino LK, Orillo JW, Aguacito PD, Colango EJ, Malit JR, Marcelino JT, Nadora AC, Odeza AJ. Fish freshness determination through support vector machine. *J. Telecommun. Electron. Comput. Eng.*. 2017 Jun 1;9(2-5):139-143.
- Wang X, Shan J, Han S, Zhao J, Zhang Y. Optimization of fish quality by evaluation of total volatile basic nitrogen (tvb-n) and texture profile analysis (tpa) by near-infrared (nir) hyperspectral imaging. *Anal. Lett.*. 2019 Aug 13;52(12):1845-1859.
- Wu D, Sun DW. Advanced applications of hyperspectral imaging technology for food quality and safety analysis and assessment: a review—Part I: Fundamentals. *Innovat. Food Sci. Emerg. Technol.*. 2013 Jul 1;19:1-4.