FISH FRESHNESS EVALUATION USING U-NET AND KNN CLASSIFIER

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Abstract

Manual inspection of fish quality is often subjective, time-consuming, and prone to inconsistency. This work proposes an ***intelligent fish quality analysis system*** *leveraging* ***computer vision and deep learning*** *to enable automated, accurate, and reproducible evaluation. A* ***U-Net semantic segmentation network*** *is employed to isolate key anatomical regions of fish, including* ***fins, trunk, eye, and jaw****, allowing the extraction of biologically relevant features such as flexibility, rigidity, brightness, and morphological dimensions. These features are then analyzed using a* ***K-Nearest Neighbor (KNN) classifier*** *to categorize fish as* ***Fresh*** *or* ***Infected****, while damage severity is quantified using region-specific metrics. By combining* ***deep learning-based segmentation*** *with* ***feature-based classification,*** *the proposed framework provides a reliable, interpretable, and scalable solution for automated fish quality monitoring. The findings reveal a strong correlation between damage indicators and infection status, validating the effectiveness of the proposed assessment methodology. This approach provides a reliable and practical solution for fish quality evaluation and has potential applications in automated inspection systems, quality control processes, and food safety monitoring.*

Introduction

Ensuring the freshness and quality of fish is a critical concern across the seafood industry, aquaculture, and fisheries. Fish is a highly perishable commodity [1] , and its quality can deteriorate rapidly due to microbial growth, enzymatic activity, mechanical damage during handling, and improper storage conditions. Traditionally, the assessment of fish freshness has relied on manual inspection [2] , including visual examination, tactile evaluation, and organoleptic tests such as smell and texture. While these methods can provide immediate feedback, they are inherently subjective, inconsistent, and labor-intensive. The reliability of manual inspection is influenced by the inspector's experience, fatigue, and environmental conditions, which can lead to variability in quality evaluation. Additionally, manual inspection [3] becomes impractical in large-scale processing or retail operations, where rapid and high-throughput assessment is required.

Recent advancements in computer vision and deep learning provide a transformative approach to fish quality evaluation. Computer vision enables machines to "see" and analyze images or videos of fish[4] , extracting critical visual information such as shape, color, texture, and anatomical features. Deep learning [5] , particularly convolutional neural networks (CNNs), has demonstrated remarkable capability in learning complex hierarchical features from images, enabling automatic recognition of patterns, anomalies, and defects that are difficult to discern manually. When combined, these technologies allow the development of an intelligent, automated system for accurate, consistent, and high-throughput fish quality assessment.

The primary aim of this work is to design an intelligent fish quality analysis system that can evaluate the freshness and health of fish automatically. The system leverages semantic segmentation, feature extraction, and hybrid deep learning–machine learning workflows to provide a comprehensive assessment of fish quality. Specifically, it focuses on segmenting key anatomical regions, including the fins, trunk, eye, and jaw, which are critical indicators of fish freshness and spoilage. Segmenting these regions allows the system to extract region-specific biological features, such as rigidity, flexibility, and signs of tissue deterioration, providing more detailed and interpretable information about fish health.

The extracted features are then used to classify the fish into distinct quality categories, such as Fresh or Infected, using feature-based machine learning techniques. For fish identified as infected or damaged, the system estimates the damage severity using morphological quality indicators, providing a quantitative measure of spoilage. This capability is particularly valuable for processing plants, retailers, and regulatory authorities, enabling them to make informed decisions regarding sorting, processing, storage, or disposal of fish.

The primary goal of this project is to develop an **intelligent fish quality analysis system** capable of automatically segmenting key anatomical regions (fins, trunk, eye, jaw), extracting region-specific biological features, classifying fish as fresh or infected, and estimating damage severity. By employing a **hybrid Deep Learning [6] and Machine Learning workflow**, the system aims to provide quantitative, interpretable, and reliable quality evaluation with minimal human intervention.

The objective of this work is to estimate Damage Severity if any for the fish.

For infected or spoiled fish, the system computes a damage percentage based on morphological quality indicators derived from the segmented regions. This quantitative assessment provides insight into the extent of spoilage and helps in decision-making regarding processing, storage, or disposal. Visualization technique region-specific damage scores are used to present the results intuitively and also to provide a fully automated, reliable, and consistent evaluation system that minimizes human intervention. By standardizing the assessment process, the system eliminates subjectivity, reduces labor costs, and ensures repeatable and accurate quality evaluation across large datasets or operational scales.

This work represents a comprehensive solution for automated fish quality assessment. The system not only classifies freshness but also provides region-specific insights and damage quantification, enhancing transparency and trust in quality evaluation. In the context of modern seafood supply chains, such a system contributes to food safety, reduced wastage, and improved operational efficiency, while supporting sustainable practices in fisheries and aquaculture.

Proposed Methodology

Semantic segmentation is a computer vision task in which each pixel of an image is classified into a predefined category [7] . Unlike simple object detection, which only provides a bounding box around an object, semantic segmentation identifies **precisely which pixels belong to which class**, producing a detailed map of the objects in the image. In the context of fish quality analysis, this allows the system to **accurately isolate different anatomical regions** of a fish, such as the fins, trunk, eye, and jaw.

In this work, U-Net [8] is specifically designed for **semantic segmentation**, where the goal is to assign a class label to every pixel in an image. In the "U-Net" , it consists of **contracting path (encoder)** on the left and an **expanding path (decoder)** on the right. The encoder captures contextual features, while the decoder reconstructs the spatial resolution to produce a detailed segmentation map. A key feature of U-Net is the use of **skip connections**, which transfer features from the encoder to the decoder to retain high-resolution details lost during down sampling.

Encoder (Contracting Path)

The encoder is responsible for **feature extraction.** Its primary purpose is to capture the essential information about objects and their surroundings in the input image while progressively reducing spatial resolution. This reduction allows the network to focus on **high-level context** rather than low-level pixel noise.

Key components of the encoder include:

1. **Convolutional Layers:**
- These layers apply filters (kernels) to the input image to extract features such as edges, textures, shapes, and patterns.
- Each convolution is typically followed by a **Rectified Linear Unit (ReLU)** activation function, introducing non-linearity and helping the network learn complex patterns.

2. **Pooling Layers:**
- **Max pooling or average pooling** layers reduce the spatial dimensions of feature maps, decreasing computation while preserving the most significant features.
- For example, a 2x2 max-pooling operation reduces the width and height of the feature map by half

while retaining the most dominant activations.

3. **Hierarchical Feature Extraction:**

- As the image passes through successive convolution and pooling layers, the network learns increasingly **abstract and high-level features.**
- Early layers capture simple patterns like edges and corners, while deeper layers capture complex structures such as shapes, textures, and patterns specific to the target object.

Key components of the decoder include:

1. **Upsampling Layers:**

- The decoder uses transposed convolution (also called deconvolution) or upsampling layers to increase the spatial dimensions of feature maps.
- Upsampling converts a small, low-resolution feature map into a larger map, preparing it for precise pixel-wise classification.

2. **Skip Connections:**

- Skip connections are a hallmark feature of U-Net. They copy feature maps from the encoder and concatenate them with the corresponding upsampled decoder feature maps.
- This allows the decoder to combine high-level contextual information from the encoder with low-level spatial details, which is critical for precise boundary detection.
- For example, in fish segmentation, skip connections help the network accurately delineate the edge of the fins or the eye against the background.

3. **Convolutional Layers:**

- After upsampling and concatenation, convolutional layers refine the feature maps, improving the network's ability to produce smooth and accurate segmentation boundaries.

Output of the Decoder:

- The final output is a segmentation mask, where each pixel is assigned to a specific class (e.g., fin, trunk, eye, jaw, or background).
- The decoder ensures that this mask aligns with the original image, maintaining both accuracy and fine spatial details.

Results & Discussion

The proposed fish quality analysis system is designed to provide real-time visualization through an intuitive Streamlit interface. This interface allows users to interact with the system easily, displaying not only the original fish images but also the segmentation masks, overlay outputs, and extracted feature values such as trunk flexibility, fin rigidity, eye brightness, and jaw dimensions. The system also presents the classification result—whether the fish is Fresh or Infected—along with the damage percentage for infected specimens.

The segmented classes are given in Table 1.

Table 1. Class Specification in this Study

Class ID	Region	Color
0	Background	White
1	Fins	Green
2	Trunk	Blue
3	Eye	Red
4	Jaw	Yellow

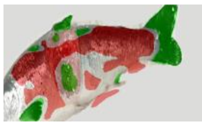
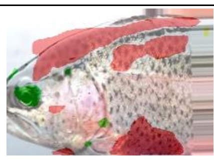
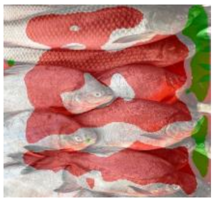
Feature Extraction from Segmented Regions

After completing segmentation, key **features** are extracted from each anatomical region to assess fish health and quality and shown in Table 2. These features provide numerical indicators for classification and damage assessment:

Table 2. Essential features are extracted in this study

Region	Extracted Features
Trunk	Flexibility, Scales Rigidity, Area[9]
Fins	Rigidity, Area
Eye	Brightness, Area[10]
Jaw	Length, Width, Area
Scales	Rigidity

Table 3. Outcome of the Study

S.No	Input	Feature Extraction					Damage segmentation	Remarks
		Trunk Flexibility	Fins Rigidity	Jaw area	Scales rigidity	Eye Brightness		
1.		0.107	0.722	0.5	0.559	0		INFECTED IN THE UPPER BODY OF THE FISH
2.		0.587	0.334	66	0.655	0.21		THE FISH TRUNK IS DAMAGED
3.		0.176	0.745	0.5	0.824	0.77		SOME OF THE FISH SCALES ARE DAMAGED
4.		0.535	0.971	0.2	0.467	0.49		DAMAGE IN THE BOTTOM OF THE BODY

5.		0.897	157	0.9	0.234	0.232		HEAD OF THE FISH IS INFECTED

KNN Classification Process

1. **Distance Measurement:** KNN [11] calculates the similarity between the test fish and all fish in the training dataset using a distance metric, typically **Euclidean distance.**
2. **Neighborhood Selection:** The algorithm identifies the **k closest neighbors** (commonly k=2) based on the computed distances.
3. **Majority Voting:** The class (Fresh or Infected) most frequently represented among the k neighbors is assigned to the test fish.

The extracted features are provided as input to the **K-Nearest Neighbor (KNN) classifier** to determine the fish's quality status. **Fresh fish** are characterized by high trunk flexibility, bright and clear eyes, and well-preserved morphological features. In contrast, **infected fish** exhibit reduced flexibility, dull eyes, stiff fins, or abnormal jaw dimensions, indicating compromised quality and outcome s given in Table 3. Table 3 illustrates how feature extraction and damage segmentation work together to accurately identify the location and severity of fish body damage, supporting effective health monitoring and disease detection. ch sample is analyzed based on five key features—**trunk flexibility, fins rigidity, jaw area, scales rigidity, and eye brightness**—which are critical indicators of fish health. The numerical values obtained from feature extraction represent normalized or quantified measurements derived from image or sensor-based analysis. These values are then interpreted through damage segmentation to identify affected regions, and corresponding remarks summarize the observed condition of each fish.

By integrating deep learning-based semantic segmentation with machine learning classification, the system ensures reliable and accurate assessment of fish quality, reducing the subjectivity inherent in manual inspection. Its real-time functionality makes it suitable for aquaculture operations, fish markets, and food safety applications, where rapid and consistent evaluation is critical. The combination of automation, visualization, and interpretability provides operators with actionable insights, supporting decision-making for storage, processing, and consumption while maintaining high standards of food safety.

Table 4 Damage percentage and health classification of fish samples

S.No	Input	Damage Assessment		Classification Result
		Damage Percentage	Damage Indicators	
1.		49%	Eye Brightness: 0.000 (Low)	INFECTED
2.		49.1%	Trunk Flexibility: 0.345 (Low) Eye Brightness: 0.000 (Low)	INFECTED
3.		34%	Trunk Flexibility: 0.176 (Low) Eye Brightness: 0.000 (Low)	INFECTED
4.		89.5%	Trunk Flexibility: 0.348 (Low) Eye Brightness: 0.000 (Low)	INFECTED
5.		67%	Eye Brightness: 0.000 (Low)	INFECTED
6.		0%	No Damage – Fish is healthy	FRESH

7.		49%	Eye Brightness: 0.000 (Low)	INFECTED
8.		0%	No Damage – Fish is healthy	FRESH
9.		57%	Eye Brightness: 0.000 (Low)	INFECTED
10.		0%	No Damage – Fish is healthy	FRESH

The damage assessment results reveal varying levels of infection and freshness across the analyzed samples in Table 4. Samples 1 to 5 exhibit significant damage percentages ranging from 34% to 89.5%, indicating a high level of deterioration. These samples consistently show low eye brightness values (0.000), which is a key indicator of infection. In addition, samples 2, 3, and 4 demonstrate reduced trunk flexibility values (0.345, 0.176, and 0.348 respectively), further supporting their classification as infected specimens. Sample 4 records the highest damage percentage at 89.5%, suggesting severe degradation.

Sample 7 and sample 9 also display moderate to high damage levels of 49% and 57%, respectively, and are similarly characterized by low eye brightness, confirming their infected status. In contrast, samples 6, 8, and 10 show no observable damage, with damage percentages recorded at 0%. These samples exhibit no adverse indicators and are therefore classified as fresh and healthy fish.

Overall, the assessment highlights a strong correlation between increased damage percentage, low eye brightness, reduced trunk flexibility, and infection status. The presence of zero damage and normal indicators in select samples demonstrates the effectiveness of the assessment method in distinguishing fresh fish from infected ones with clarity and reliability.

Conclusion

The damage assessment analysis effectively differentiates between fresh and infected fish samples using measurable indicators such as eye brightness and trunk flexibility. Samples exhibiting higher damage percentages consistently showed reduced eye brightness and lower trunk flexibility, leading to their classification as infected. In contrast, samples with zero damage demonstrated normal characteristics and were accurately identified as fresh and healthy. The results indicate a strong relationship between physical damage indicators and infection status, confirming the reliability of the proposed assessment approach. Overall, this study highlights the effectiveness of using objective damage parameters to support accurate fish health classification, which can contribute to improved quality control, food safety, and decision-making processes in fish inspection systems.

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