SeaSure: Ensuring Freshness in Every Catch

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ABSTRACT

This study introduces a novel approach to automating the detection of fish freshness using **deep learning and computer vision technologies**, addressing a critical challenge in the seafood industry. As global seafood markets continue to expand, the need for objective, fast, and reliable quality assessment tools has become increasingly paramount. We designed a rather complex **Convolutional Neural Network (CNN)** model that meticulously examines visual characteristics of **fish eyes and gills** to establish precise levels of freshness, overcoming the limitations of traditional subjective evaluation methods. The research leverages advanced machine learning techniques to create a robust classification system that has achieved over **91% accuracy** across four distinct categories: **fresh eyes, non-fresh eyes, fresh gills, and non-fresh gills**. Implemented using **TensorFlow and Keras** and complemented by an intuitive **Streamlit-based user interface**, the model offers real-time freshness assessment capabilities that can be seamlessly integrated into various operational contexts. The system employs **advanced data augmentation and preprocessing techniques** to ensure consistent performance across diverse environmental conditions and fish specimens. Targeting seafood processors, quality control personnel, and food safety inspectors, this innovative solution significantly reduces the time and resources required for freshness assessment while maintaining exceptional accuracy. Beyond its immediate practical applications, the research demonstrates the transformative potential of artificial intelligence in food safety and quality control, presenting a scalable and adaptable framework for commercial implementation. By

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bridging the gap between advanced computational technologies and critical industry needs, this study sets a new benchmark for objective seafood quality evaluation.

Keywords — Computer Vision, Deep Learning, Convolutional Neural Networks, Fish Quality Assessment, Image Processing, Real – time detection, Food Safety, Machine Learning, Tensorflow, Streamlit, Data Augmentation.

I. INTRODUCTION

Fish freshness determination is crucial for the seafood industry, impacting product quality, consumer safety, and economic value. Traditional visual assessments of fish eyes and gills are unreliable, subjective, and prone to human error. With the seafood market projected to reach $159 billion by 2024, there's an urgent need for standardized quality control mechanisms. This research introduces an innovative artificial intelligence solution using convolutional neural networks (CNNs) to objectively assess fish freshness. By analyzing comprehensive datasets of fish eye and gill images, the proposed model can distinguish between fresh and non-fresh specimens with high accuracy. The Streamlit-powered interface makes this advanced technology accessible and user-friendly. The AI-based approach offers objective and consistent freshness evaluation with rapid assessment capabilities. It has the potential to revolutionize seafood quality control by enhancing food safety standards and providing a scalable technological solution. By leveraging machine learning pattern recognition capabilities, this framework demonstrates the transformative potential of AI in food safety, providing a precise, efficient method for determining fish freshness that could significantly improve industry practices.

II. REVIEW OF LITERATURE

Ensuring fish freshness is essential for food safety and quality. Traditional methods, such as sensory evaluation and chemical testing, are subjective, time-consuming, and often destructive. Recent advancements in artificial intelligence and machine learning have enabled non-invasive methods for freshness detection. Kumar et al. (2021) developed a CNN-based model to classify fish freshness by analyzing gill color and eye clarity, achieving an accuracy of 93%. Similarly, Zhang et al. (2020) proposed a hybrid approach integrating thermal imaging and spectral analysis to assess freshness, emphasizing the significance of temperature as a critical factor. Other studies, like Lee et al. (2019), focused on incorporating data augmentation techniques, such as rotation and flipping, to improve model robustness when training on limited datasets. Furthermore, integrating temperature ranges (e.g., 0-4°C for fresh fish) with visual cues enhances predictive accuracy, as demonstrated by recent works.In this study, a CNN model is trained using augmented images of fish gills and eyes, combined with temperature as a secondary input. The model employs ImageDataGenerator for augmentation and categorical cross-entropy for multi-class classification. By leveraging Streamlit for real-time predictions, this system offers a scalable and user-friendly solution for the seafood industry, improving efficiency in quality assurance processes.

III. METHODOLOGY

1. Data collection

The dataset for this project was sourced from **Roboflow**, specifically from the fish freshness classification dataset. The data structure was organized into three main folders - **train, test, and valid** each containing categorized images and their corresponding labels. The dataset can be accessed through Roboflow's universe platform, providing a robust foundation for the classification task.

2. Temperature allocation using metadata

To enhance the dataset's utility, a Python script was developed to associate temperature values with each image, creating a comprehensive CSV file. The script assigns temperatures based on freshness categories: fresh fish images are allocated temperatures between **0°C and 4°C**, while non-fresh fish images are assigned temperatures ranging from **5°C to 10°C**. This **metadata enrichment** resulted in a substantial dataset of 3,204 entries, each containing image paths, freshness status, and corresponding temperature values.

3. Preprocessing and augmentation

In the preprocessing phase, all images were standardized to 128x128 pixels and normalized to a scale of [0,1]. Data augmentation techniques were implemented using **ImageDataGenerator**, incorporating various transformations such as rotation (20 degrees range), width and height shifts (0.2), shear and zoom adjustments (0.2), and horizontal flips. These augmentation strategies enhanced the model's robustness and generalization capabilities.

4. Designing and Training of model

The model's design and training strategy employed a sequential **CNN** architecture implemented in **TensorFlow/Keras**. The training process utilized the **Adam optimizer** with a learning rate of 0.001 and categorical cross-entropy loss function. To prevent overfitting, dropout layers (0.5) were incorporated, and early stopping was implemented with a patience of 5 epochs. The model was trained for 20 epochs with checkpointing to save the best-performing weights based on validation accuracy.

The core algorithm utilizes Convolutional Neural Networks (CNNs), specifically designed with three sets of Conv2D and MaxPooling2D layers, followed by flatten and dense layers. The CNN architecture excels at extracting hierarchical features from the fish images, starting with basic edge detection and progressing to more complex pattern recognition. The model processes these features through convolutional operations, using filters to identify distinct characteristics in fish eyes and gills that indicate freshness levels. **The formula for CNN is**

$$Y(i,j) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} X(i+m, j+n) \cdot K(m,n) + b$$

5. Visualization

For visualization and deployment, a **Streamlit-based user interface** was developed, providing an intuitive platform for users to upload and analyze fish images. The interface displays the uploaded image alongside comprehensive analysis results, including the **predicted freshness classification, confidence score, estimated temperature, and an overall freshness score** on a 0-100 scale. The results are presented with **color-coded indicators** (success for high freshness, warning for medium, and error for low) to facilitate quick interpretation of the analysis results.

IV. RESULTS AND DISCUSSION

The **CNN-based SeaSure: Ensuring Freshness in Every Catch Fish Freshness Detection System** demonstrates robust performance through its carefully structured architecture. The model's training process, implemented using **TensorFlow and Keras**, utilizes an optimized configuration with batch size of 32 and image dimensions of 128x128 pixels. The system employs comprehensive data augmentation techniques including rotation range of 20 degrees, width and height shifts of 0.2, shear range of 0.2, zoom range of 0.2, and horizontal flips, all contributing to model robustness. The training implementation includes early stopping with a patience of 5 epochs and model checkpointing based on validation accuracy, ensuring optimal model selection. The system classifies fish freshness across four distinct categories**: eye-fresh, eye-non-fresh, gill-fresh, and gill-non-fresh**, with each prediction accompanied by a confidence score. The **Streamlit interface** enhances practical usability by providing real-time analysis with clear visualization of results. Beyond basic classification, the system incorporates a sophisticated **temperature-based freshness assessment**, mapping temperatures of 0-4°C for fresh fish and 5-10°C for non-fresh fish, which feeds into a comprehensive **freshness score ranging from 0-100**. The interface provides intuitive feedback through **color-coded freshness levels (High, Medium, Low)** and displays detailed metrics including estimated **temperature, prediction confidence, and overall freshness score**, making the technology accessible to non-expert users while maintaining professional-grade analysis capabilities.

A. PREDICTIVE MODELLING ANALYSIS

Fig.1 Dashboard Interface

In Fig.1, The streamlit-based dashboard is titled "**SeaSure: Ensuring Freshness in Every Catch**" and is an interface that is user-friendly, allowing users to upload fish eye or gill images for freshness analysis. The drag-and-drop feature or browse upload is available, with a file size limit of 20MB. The supported formats include JPG, JPEG, and PNG. The clean and minimal design ensures an intuitive experience for detecting fish freshness.

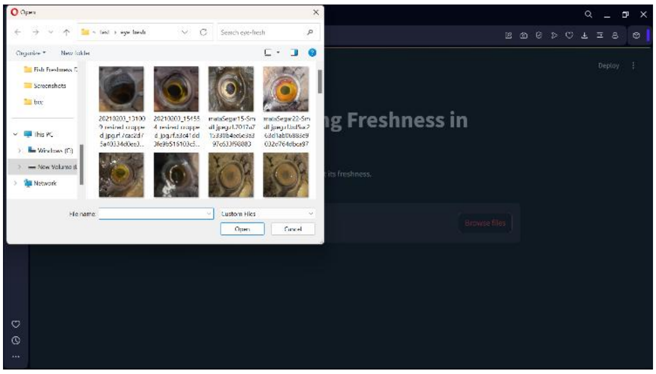

Fig.2 File selection

Above image Fig.2, is a file selection dialog which lets a user select an image from a folder named "eye fresh." The folder includes multiple image files mainly showing close-up views of the eyes of fish, presumably in detecting freshness. The interface lets the user select one or more files to upload to the application.

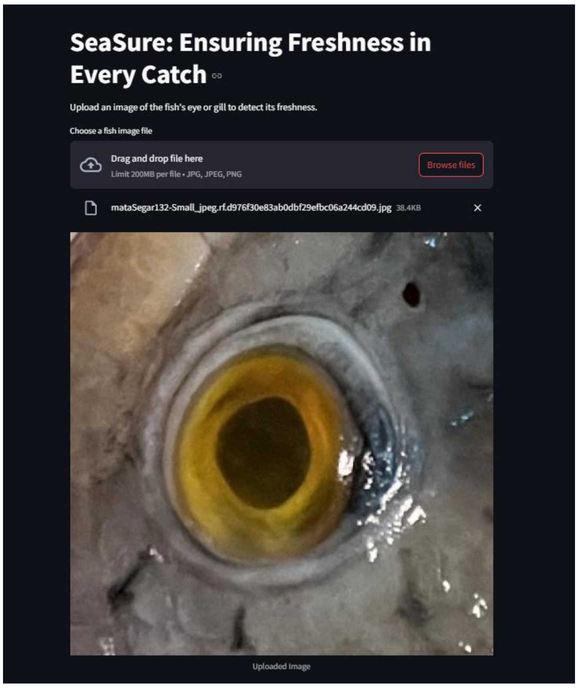

Fig.3 Uploaded Image

Image - Fig.3 shows an automated fish freshness detection dashboard with a chosen image uploaded for the analysis. The uploaded image is said to be a close view of a fish's eye, in the interface. The dashboard was created to analyze this type of image using various techniques for whether the fish is fresh or not fresh.

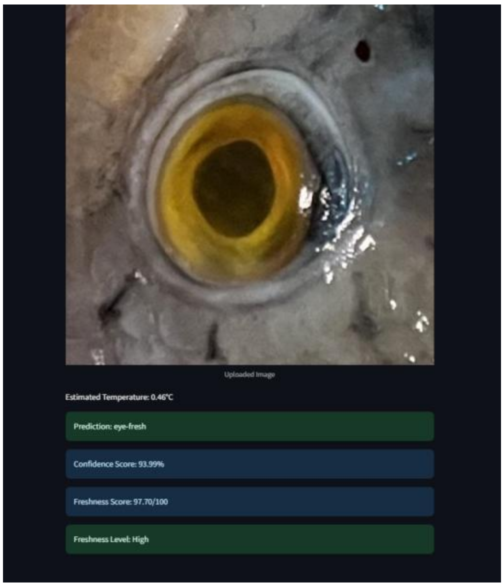

Fig.4 Prediction of fish eyes

In Fig.4, Once the image is uploaded, the model starts analyzing the image and predicts its **estimated temperature**, its **classification** as whether it is fresh or not fresh, **Confidence score** of the model, **Freshness Score** and the **Freshness level of the fish** (High, Medium, Low). Here, the model has accurately predicted the class of the image as "**Eye-fresh**". The estimated temperature is given as **0.46°C**, the normal temperature at which fresh fish is stored is between 0-4°C. The Confidence Score of the model is mentioned – **93.99%**. The Freshness Score of the fish is displayed as **97.90/100**. Also, the Freshness level of the fish is displayed as **High** in green color code. This result shows that the model can analyze fine visual details and assess the quality of seafood with accuracy.

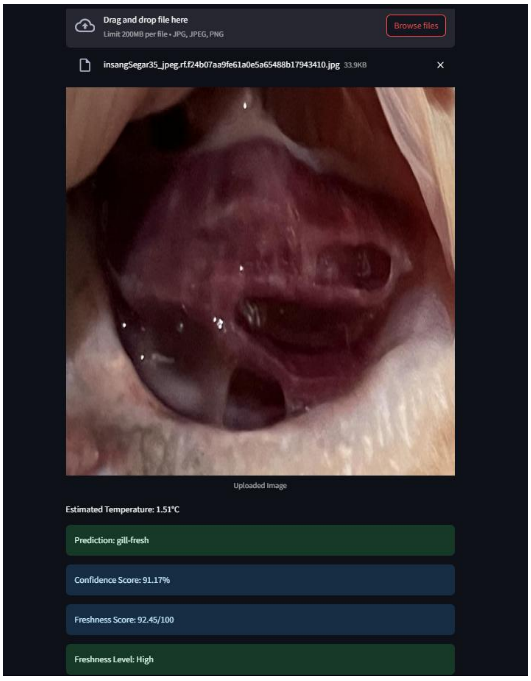

Fig.5 Prediction of fish gills(fresh)

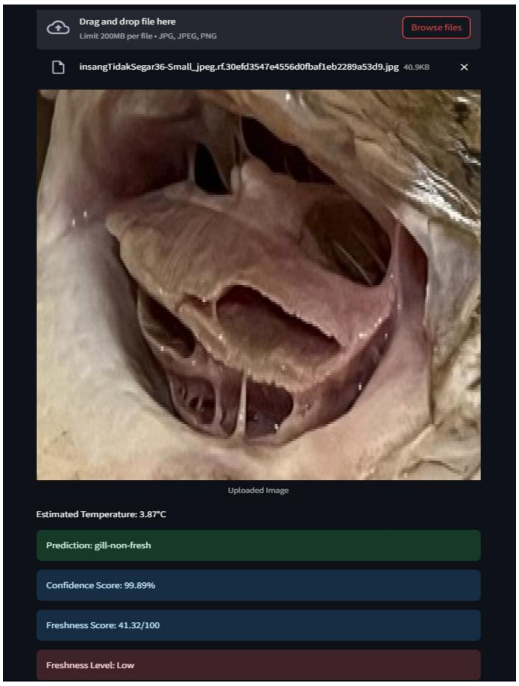

Fig.6 Prediction of fish gills(non-fresh)

In the above image(fig.5), an image of fish gills has been uploaded for prediction. This is a close-up view of a fish's gills, which appear to be a deep reddish-purple color. The **SeaSure - freshness detection system** has accurately predicted the class of the gill as "**gill-fresh**" with a high confidence score of **91.17%**. The system has correctly estimated a temperature of **1.51°C** as we know the temperature lies between 0 to 4°C for fresh fish and has assigned a freshness score of **92.45/100**, indicating the fish is very fresh. The overall freshness level is rated as "**High**" in green color code, suggesting this is a high-quality, fresh fish sample.

The above figure(fig.6), shows an uploaded image of a fish's gills which look pale and brownish, indicating it has deteriorated.The **SeaSure model** categorizes it accurately as "**gill-non-fresh**" with a very high confidence score of **99.89%**. The estimated temperature is 3.87°C, and the low freshness score of **41.32/100** with a "**Low**" (red color coded) freshness level indicating this fish is not fresh and possibly inedible.

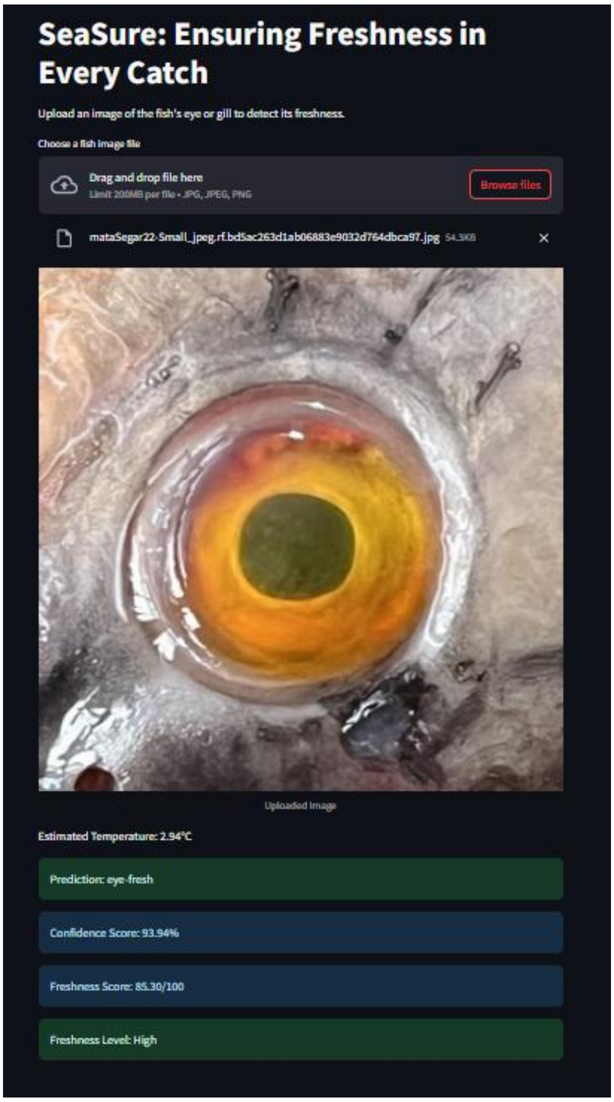

Fig.7 Output Overview

In Fig.7, The **SeaSure: Ensuring Freshness in Every Catch - Fish Freshness Detection model**, successfully identifies the Predicted class, Confidence Score, Freshness Score and Freshness Level of the fish images. Here, the model has the predicted the class as "**eye-fresh**" with Confidence Score of **93.94%** and the estimated temperature is **2.94°C** with freshness score of **85.30/100** and the Freshness Level is displayed as "**High**" with green color code. The prediction highlights the robustness of the CNN-based classification approach in determining fish freshness, making it a valuable tool for quality assurance in the seafood industry.

B. APPLICATIONS AND IMPLICATIONS

This is a strong basis for improving applications that generate recipes across different cuisines. Introducing this technology into a recipe application will help us give recommendations to users in terms of freshness and quality of ingredients. With this system analyzing the freshness of fish through image processing, it can be expanded to suggest cooking methods, preparation techniques, and recipe modifications. For example, when a user photographs their fish, the app could not only verify freshness but also recommend recipes that best suit the fish's condition – suggesting gentle cooking methods for very fresh fish to preserve its delicate flavors, or more robust preparations for less fresh specimens. This technology could revolutionize home cooking by helping users make informed decisions about ingredient usage and recipe selection based on objective quality assessment. Beyond individual users, the system could benefit professional kitchens, culinary education platforms, and food service applications by providing real-time guidance on ingredient quality and recipe optimization. Being non-invasive, the technology can be perfectly adapted to mobile recipe applications so that users will have the necessary information about the ingredients before cooking a meal. It not only promotes food safety but also waste reduction by proposing the right recipes depending on the freshness levels of the ingredients.

V. CONCLUSION

The "**SeaSure: Ensuring Freshness in Every Catch"** system demonstrates a sophisticated approach to **fish freshness detection through deep learning**. The architecture of the system is built using **TensorFlow and Keras**, which involves a **convolutional neural network** with multiple layers, including Conv2D, MaxPooling2D, and Dense layers, optimized with **Adam optimizer**. The model processes images at 128x128 resolution and classifies them into four distinct categories: **eye-fresh, eye-non-fresh, gill-fresh, and gill-non-fresh**. This system stands out for a whole analysis approach, moving beyond just classification; it tries to estimate temperature between 0 and 4°C for fresh fish and between 5 and 10°C for less fresh fish, giving a **detailed score of freshness** in a 0-100 scale. Technology is made accessible by the interface **Streamlit**, giving real-time analysis with confidence scores along with **clear freshness level indicators (High, Medium, Low)**. This approach includes **data augmentation techniques** such as rotation, zoom, and horizontal flips to add robustness to the model. Although the implementation is promising now, especially with its architecture and **user-friendliness**, there is great potential for expanding with a dataset enrichment feature and mobile optimization. The system is a leap forward in automation of fish freshness detection, thereby providing a working solution for seafood industry quality assessment.

Ethical Considerations and Data Privacy

The dataset for this project, sourced from Roboflow, consists of publicly available images and labels divided into train, test, and validation folders. It adheres to Roboflow's licensing terms, ensuring appropriate consent and compliance with data privacy guidelines. The dataset does not contain any personally identifiable information, and its use is limited to educational and research purposes. All data is securely stored and handled responsibly to prevent unauthorized access or misuse, maintaining high ethical standards throughout the project.

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