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Web-Based Deep Learning Model for Tuna Loin Quality Assessment in the Fisheries Processing Industry

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ABSTRACT

The Maluku region recognizes tuna loin as a premier processed commodity derived from capture fisheries resources. This study developed an innovative non-destructive quality prediction model for tuna loin utilizing deep learning technology. Traditionally, quality assessment of tuna meat relies on color and texture evaluation through organoleptic/sensory methods, which demands significant time and specialized expertise. Expanding on prior CNN-based research for tuna treatment classification **(Tupan *et al*., 2025)**; this investigation pioneers the application of Deep Convolutional Neural Networks (DCNN) specifically for tuna grading purposes. The research focused on evaluating the effectiveness of various CNN architectures (ResNet, DenseNet, and Inception) for tuna loin grade classification, while simultaneously developing an integrated prediction system available as both a web-based application and Android mockup. Performance analysis of the multi-architecture CNN algorithms revealed varied accuracy levels across different grade classification schemes. In the three-tier classification system (Alpha, Bravo, and Charley), DenseNet demonstrated superior performance with 94.64% accuracy, while ResNet achieved 91.07% and Inception reached 83.93%. These results highlight the significant potential of deep learning approaches for automated quality assessment in fishery products. The resulting integrated platform features an intuitive user interface that enables tuna loin image uploads for analysis by the dual-classification prediction model. Validation testing confirms the successful implementation of both treatment and grading classification systems, providing the fish processing industry with a comprehensive, efficient tool for real-time quality assessment. The deployed solution addresses critical industry challenges including consistency in quality evaluation and enhanced decision-making capabilities throughout the tuna processing supply chain.

INTRODUCTION

Indonesia's marine ecosystems support approximately 37% of the world's fish species diversity, underscoring the country's significant contribution to global aquatic biodiversity. The nation benefits from an abundance of high-value marine resources, including tuna, shrimp, lobster, reef fish, ornamental species, shellfish, and seaweed, which serve as key economic commodities. The estimated sustainable potential of Indonesia's marine fisheries reaches 12.54 million tons annually, spanning its territorial waters and exclusive economic zone (ZEEI), highlighting its substantial fishing capacity. However, the allowable catch quota (JTB) is limited to 80% of this potential, approximately 10.03 million tons per year, while actual utilization in 2019 accounted for only 69.59% of this limit, with combined marine and inland capture fisheries producing 7.53 million tons. Furthermore, marine microflora and fauna remain largely unexplored, yet they hold considerable potential for future applications in functional food development **(Gustiano *et al*., 2021)**.

The fisheries sector plays a vital role in Maluku Province's economy, serving as a key driver of regional economic growth. Statistical data reveal that between 2016 and 2020, fisheries contributed an average of 12.64% to Maluku's Gross Regional Domestic Product (PDRB). Among the various fisheries commodities, yellowfin tuna has become a leading export product, with production nearly doubling from 15,608 tons in 2015 to 30,804 tons in 2019. However, the outbreak of the COVID-19 pandemic in 2020 led to a sharp decline in production, decreasing by 53% to 14,349 tons. In terms of geographical distribution, Island Cluster 7 recorded the highest tuna production, contributing 48% (12,293 tons) of the total regional output, followed by South Seram Island Cluster 5 with 18% (4,510 tons) and Banda Island Cluster 6 with 12% (3,704 tons) **(Tauda *et al*., 2021)**. The expansion of production capacity has also facilitated an increase in direct tuna exports from Maluku, rising by 11.8% from 1,432 tons in 2019 to 1,601 tons in 2020.

Tuna fisheries in Maluku primarily rely on traditional fishing methods, where fishermen commonly process their catch into loin cuts directly onboard to maximize the limited storage capacity. However, these onboard processing practices often do not adhere to proper sanitation standards, increasing the risk of contamination that may degrade the quality of tuna loins during subsequent distribution and marketing stages **(Suryaningrum *et al*., 2017)**. The quality of fish products is influenced by multiple factors, including safety, sensory attributes, physical characteristics, nutritional content, availability, freshness, and overall product integrity. Various assessment techniques, such as chemical, physical, biochemical, and microbiological methods, are available to evaluate quality. However, these techniques often require significant financial resources, prolonged processing times, and specialized technical expertise **(Kılıçarslan *et al*., 2024)**. Additionally, color evaluation is a crucial quality indicator widely used to assess consumer perception and to determine seafood freshness based on observable visual changes.

The quality of fish products is influenced by various factors, including safety, sensory attributes, nutritional content, freshness, availability, physical characteristics, and overall product integrity. To assess fish quality, several methodologies have been developed, encompassing chemical, physical, biochemical, microbiological, and sensor-based approaches. Although chemical and biochemical techniques are commonly employed to determine freshness levels, these methods often involve high costs, lengthy processing times, and the need for specialized expertise **(Sengar *et al*., 2018)**. Another crucial parameter in quality assessment is color, which serves as a key indicator for evaluating consumer perception and determining seafood freshness based on visual changes. In the fishing industry, manual sorting techniques traditionally used by fishermen can lead to inaccuracies due to visual fatigue, while physical inspection methods may inadvertently cause damage to fish destined for consumption. Extensive research has been conducted on fish freshness evaluation, highlighting the importance of visual attributes such as color, skin texture, and eye clarity, which significantly influence both economic value and consumer preferences. Consumers primarily rely on seafood color as a freshness and quality indicator **(Shi *et al*., 2019)**. However, conventional freshness assessment techniques remain time-intensive and are typically limited to professional evaluators.

Machine vision systems (MVS) have been developed as a solution to address the limitations of traditional assessment methods. This technology integrates data acquisition with image processing techniques specifically designed for seafood evaluation **(Dowlati *et al*., 2012)**. The MVS framework consists of essential components, including an image capture camera, illumination system, and a specialized software for image analysis **(Hong *et al*., 2014)**. The primary applications of MVS technology focus on assessing seafood quality, encompassing morphology evaluation, species identification, and the analysis of various physical and chemical properties during processing and storage **(Dowlati *et al*., 2012)**. Initial studies on MVS applications in seafood quality assessment examined fish freshness by analyzing eye appearance **(Murakoshi *et al*., 2013)** and extracting gill characteristics **(Issac *et al*., 2017)**. These studies consistently highlight the effectiveness of MVS in reflecting seafood quality and predicting freshness. Digital image processing serves as a key approach for extracting relevant information and recognizing objects within images. Furthermore, such techniques are widely utilized in deep learning-based identification methods, a rapidly evolving domain in machine learning with advanced computer vision capabilities. Recent advancements in computer vision, particularly convolutional neural networks (CNNs), have demonstrated high accuracy in tasks such as object detection. Research on fish freshness assessment also includes comparisons of various machine learning algorithms, such as K-Nearest Neighbor **(Prasetyo *et al*., 2024)**.

Studies utilizing tuna loin imagery in conjunction with deep learning models based on convolutional neural networks (CNNs) remain relatively limited. Existing literature indicates that computer vision and machine learning techniques have been employed in evaluating fish meat quality **(Lugatiman *et al*., 2019; Moon *et al*., 2020; Medeiros *et al*., 2021)**. Moreover, artificial intelligence methodologies have been widely explored in fisheries and marine science, particularly for assessing fish freshness. Among these, deep learning with CNN-based algorithms is the most frequently applied approach for predicting freshness **(Priyatman *et al*., 2019; Wu *et al*., 2019; Taheri-Garavand *et al*., 2020; Rayan *et al*., 2021; Yildiz *et al*., 2024)**. Various algorithmic models have been utilized to evaluate prediction performance, including VGG 16 architecture (**Taheri-Garavand *et al*., 2020)**, the YOLOv architecture **(Anas *et al*., 2021)**, and MobileNet architecture **(Prasetyo *et al*., 2021)**. Additionally, some studies have combined multiple architectures such as Xception, MobileNet VI, ResNet 50, and VGG 16 to enhance prediction accuracy **(Prasetyo *et al*., 2021)**. However, there is a notable gap in research exploring hybrid deep learning models integrating CNNs with architectures like DenseNet, ResNet, and Inception, which have the potential to achieve prediction accuracies exceeding 85%.

Considering these factors, a thorough analysis is crucial to assess the quality of tuna loin raw materials while simultaneously advancing automated prediction models based on image processing. These models should incorporate multiple architectural approaches utilizing convolutional neural networks (CNNs) to enable comparative evaluations of prediction accuracy. Such an approach is particularly relevant for optimizing tuna loin quality assessment within the fish processing industry on Ambon Island. This study extends previous research on CNN-based tuna treatment classification **(Tupan *et al*., 2025)** by utilizing the same CNN architectures for a three-class grade prediction model. The results from both treatment and grade classifications are further developed into a web-based prediction system, providing a scalable and efficient solution for real-time tuna loin quality assessment. This approach offers a significant advancement in fishery product evaluation, ensuring consistency, reducing dependency on manual inspections, and improving decision-making processes throughout the tuna supply chain.

MATERIALS AND METHODS

1. Research/system overview

The research flowchart outlines a systematic approach to developing a Convolutional Neural Network (CNN) model for classifying fish meat images. The process begins with collecting a diverse dataset of fish meat images, followed by a pre-processing stage to clean, standardize, and prepare the data for analysis. To enhance the model’s ability to generalize, data augmentation techniques are applied, artificially expanding the dataset. These processed and augmented images are then utilized in the "Modeling" phase, where the CNN model is trained. Once training is complete, the model's performance is assessed by comparing its predictions with actual data. If the model achieves the desired accuracy and effectiveness, it is deemed ready for deployment. However, if the results are unsatisfactory, modifications are made, and the model undergoes re-training. The flowchart illustrates a feedback loop that ensures continuous refinement until optimal performance is reached. Once the model is fully trained and meets the required standards, it is deployed for practical use. The research flowchart is presented below in Fig. (1).

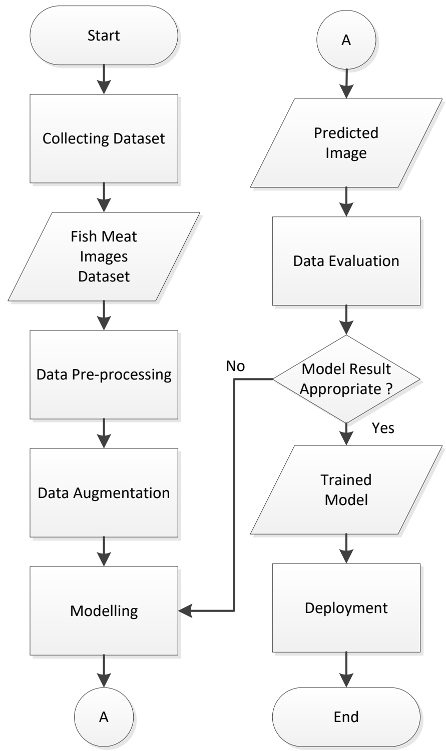

Fig. 1. Flowchart of the research

To serve as a reference, images of tuna loin that had been graded by skilled personnel from the quality assurance division at PT. Maluku Prima Makmur underwent microbiological evaluation. This assessment aimed to verify that the tuna loin's safety and quality complied with the company's national standards, specifically SNI 4104:2015. The microbiological analysis included tests for total plate count (TPC), coliform, *E. coli*, *Salmonella*, and *Staphylococcus*, while histamine levels were assessed through chemical testing. These examinations were conducted within the quality assurance section of PT. Maluku Prima Makmur in Ambon, Maluku, Indonesia, which functioned as the research site. Additionally, the tuna loin samples' color was analyzed to generate a dataset for deep learning-based modeling. This color assessment utilized a Color Reader (Minolta CR-10) and was carried out at the Fisheries Product Technology Laboratory, Faculty of Fisheries and Marine Sciences, Pattimura University, Ambon, Maluku, Indonesia. The recorded color values were subsequently transformed into hue degrees using the formula Hue Degree = $\tan^{-1}$ (b/a) **(Loppies *et al*., 2021)**.

2. Image datasets

The data collection process involved capturing high-resolution images of fish meat to ensure a well-distributed representation across different classification grades. The final dataset consists of 287 images, categorized into three distinct grades: 100 images for

Grade Alpha, 88 images for Grade Bravo, and 99 images for Grade Charley. This dataset serves as the primary foundation for the classification analysis.

To maintain consistency in image quality, all images were captured under controlled lighting conditions and a standardized environment. Table (1) outlines the specific camera settings applied during the image acquisition process, including resolution, exposure time, white balance, and other key parameters. Standardizing these settings helps reduce external variations, ensuring the dataset remains reliable and consistent for classification purposes.

To provide a visual reference for each category, Fig. (2) showcases representative images from each grade: Fig. (2A) corresponds to Grade Alpha, Fig. (2B) represents Grade Bravo, and Fig. (2C) illustrates Grade Charley. These sample images help establish a clear classification framework for the study.

Table 1. Configuration of camera parameters for capturing tuna images **(**Adapted from **Tupan *et al*., 2025)**

Parameter	Specification
Object Distance	10 cm
Grade/Treatment	Tuna loin classification: Alpha, Bravo, and Charley
Image Format	JPEG normal (8.6 MB), [2.3] K resolution (standard quality)
Lens Type	DX VR (AF-P NIKKOR 18-55mm, f/3.5–5.6 G)
Touch Shutter	Disabled
Image Resolution	Large (L)
Shutter Mode	Continuous High-Speed
Autofocus Mode	Single-servo AF (AF-S)
Flash Setting	Automatic
Resolution	6000 × 4000 pixels
ISO image	Automatic ISO-A 6400
Time setting	2–20 s


(a) (b) (c)

Fig. 2. Image for **(a)** Grade Alpha, **(b)** Grade Bravo, **(c)** Grade Charley

Furthermore, preprocessing techniques were implemented to optimize the dataset for model training. Images were resized to 224×224 pixels to enhance computational efficiency while preserving essential details. Rather than analyzing all pixels, segmentation techniques were applied to focus on key features, improving the model's capability to accurately differentiate between classification grades.

3. Image resizing and augmentation

The image dataset underwent dimensional standardization, transforming the original high-resolution captures (6000 × 4000 pixels) to a compact 224 × 224 pixel format the preferred input dimensions for various deep learning architectures including MobileNet, the images underwent a resizing process to reduce their dimensions. This transformation ensured uniformity across the dataset while improving computational efficiency. Standardizing image dimensions was essential for maintaining consistency when handling varying image sizes, allowing for reliable model training and evaluation.

In the enhancement stage, data augmentation procedures were applied to diversify the image collection. The process incorporated multiple transformation techniques rotations, scaling operations, shear distortions, zoom adjustments, width/height modifications, brightness alterations, and both horizontal and vertical flips. These manipulations generated varied representations of source images, significantly improving the model's ability to generalize patterns during the training phase. By producing modified samples that Convolutional Neural Networks process as independent inputs, the augmentation strategy effectively mitigated dataset size constraints while simultaneously increasing sample diversity and strengthening the overall robustness of the training material.

4. Model architecture

DenseNet

DenseNet utilizes identity connections at every layer, enabling the concatenation of residual mappings from all preceding layers. As a result, each layer receives input from the feature maps of all earlier layers while also forwarding its output to subsequent layers. This architecture encourages effective feature reuse throughout the network without substantially increasing computational demands. For this research, the DenseNet-121 variant was chosen based on its common implementation and proven effectiveness in deep learning applications **(Zhou *et al*., 2020)**.

ResNet

ResNet-50 consists of a 50-layer deep convolutional neural network architecture as described by **Nashrullah *et al*. (2020)**. Its principal innovation involves the implementation of shortcut connections, which serve a vital function in convolutional neural networks, particularly within ResNet-50, as indicated by **Elsharif and Abu-Naser (2022)**. These bypass connections, and residual learning frameworks address challenges, such as vanishing and exploding gradients during the training process, as highlighted by **Liu *et al*. (2022)**.

Inception

Inception V3, created by Google for the 2012 ImageNet Large Visual Recognition Challenge, represents an advanced deep convolutional neural network model. In contrast to conventional methods, it implements multiple filters within its convolutional layers and merges their outputs through channel concatenation before advancing to subsequent stages **(Pujiarini & Lenti, 2023)**. The Inception module operates as a multi-scale feature extraction mechanism, integrating outputs from multiple convolutional filters within a unified framework. The resulting features are then organized along the channel dimension for further processing in subsequent layers.

5. Model training and testing

The CNN architectures utilized in this study include ResNet, DenseNet, and Inception, each selected for their unique advantages. ResNet was chosen for its ability to train deep networks effectively using skip connections, DenseNet for its efficient feature reuse through dense connections, and Inception for its multi-scale processing, which captures features at different resolutions.

After data augmentation and segmentation, the processed dataset were used for model training and testing. To ensure a balanced representation across all grades, 80% of the dataset (231 images out of 287) were allocated for training, while 20% (56 images) were reserved for testing.

6. Performance model

To evaluate the effectiveness of the proposed model, four performance metrics (Equations (1)–(4)) were employed **(Carrington *et al*., 2022; Shahi *et al*., 2022, 2023; Sitaula & Shahi, 2022; Tupan *et al*., 2025)**. These metrics are derived from the confusion matrix, which compares actual class labels with predicted outcomes. Correctly classified instances are positioned along the diagonal of the matrix, serving as a key measure of model accuracy.

$$P_a = \frac{TP_a}{TP_a + FP_a} \tag{1}$$

$$R_a = \frac{TP_a}{TP_a + FN_a} \tag{2}$$

$$F1_a = 2 * \frac{P_a \times R_a}{P_a + R_a} \tag{3}$$

$$ACC = \frac{TP_a + TN_a}{TP_a + TN_a + FP_a + FN_a} \tag{4}$$

In this framework, TPa, TNa, FPa, and FNa correspond to the true positive, true negative, false positive, and false negative values for class "a," respectively. Likewise, Pa, Ra, F1a, and ACC denote the precision, recall, F1-score, and accuracy metrics associated with class "a."

7. Implementation

The prediction modeling for tuna loin treatments was implemented in Python using Keras. The hyperparameters used in the modeling process are detailed in Table (2). The dataset was split into training and test sets following an 80:20 ratio, ensuring a balanced distribution across all categories.

Table 2. Detailed hyper-parameters used in research **(**Adapted from **Tupan *et al*., 2025)**

Parameter	Description
Image dimensions	224 × 224 pixels
Color mode	RGB (three-channel color representation)
Class mode	Categorical classification
Defined classes	{“Alpha”: 0, “Bravo”: 1, “Charley”: 2}
Batch size	64 samples per training iteration
Epochs	15 full dataset passes during training
Rotation range	Random rotations up to 90 degrees
Width shift range	Horizontal displacement up to 5% of image width
Height shift range	Vertical displacement up to 5% of image height
Shear range	Shearing transformation up to 5%
Horizontal flip	Enabled for data augmentation
Vertical flip	Enabled for data augmentation
Optimization algorithm	Adam optimizer
Brightness adjustment	Scaled within the range of 0.75 to 1.25
Rescaling factor	Pixel values normalized to [0,1] by dividing by 255
Validation data split	20% of the dataset used for validation
Loss function	Categorical cross-entropy for multi-class classification

RESULTS AND DISCUSSION

This section explores tuna loin quality for dataset and the training procedure of three deep convolutional neural network (DCNN) architectures: ResNet, DenseNet, and Inception. The study evaluates each model's effectiveness in classifying tuna loin grades based on four performance metrics. The assessment is conducted using tuna loin image samples that were not included in the training and validation phases. Additionally, the obtained results are compared against the performance of alternative architectures reported in prior research.

1. Tuna loin quality for dataset

Microbiological and histamine test results for three fresh tuna loin samples, which were captured as images for the dataset, are displayed in Table (3).

Table 3. Microbiological and histamine testing of tuna loin for dataset

Sample	Microbiological test results[1]					Histamine test[2] ppm (mg/Kg)
	TPC (cfu/g)	*Coliform* (cfu/g)	*E-coli* (cfu/g)	*Salmonella* (Neg/g)	*Staphylococcus* (cfu/g)	
Sample 1	800	0	0	Negative	Negative	3 ppm
Sample 2	1500	0	0	Negative	Negative	3 ppm
Sample 3	1200	0	0	Negative	Negative	5 ppm

[1,2] Data sourced from PT. Maluku Prima Makmur Ambon, Maluku, Indonesia (2024)

Based on the test results presented in Table (3), the following analysis can be made:

- Total Plate Count (TPC): The recorded TPC values varied between 800 and 1,200cfu/ g, indicating the total microbial presence in the tuna samples. Although these values are relatively elevated, they remain significantly lower than the 5×10^5cfu/ g threshold set by SNI 4104:2015, which regulates Quality and Food Safety Standards for Frozen Tuna Loin Raw Material. Generally, microbial counts below 100,000cfu/ g are regarded as safe. Therefore, these findings confirm that the samples fall within acceptable safety parameters.
- Coliform and *E. coli*: The analysis confirmed that no coliform or *E. coli* colonies were found in any of the tested samples. This result is an encouraging indication that the tuna products are not contaminated with fecal matter or harmful pathogens.
- *Salmonella*: Every sample examined tested negative for *Salmonella*, a bacterium known to pose a significant foodborne health hazard. The absence of *Salmonella* suggests that the tuna samples meet safety standards and do not present a risk of food poisoning.
- *Staphylococcus*: The test results further indicated that none of the samples contained *Staphylococcus* bacteria. Since this microorganism is capable of producing dangerous

toxins, its absence ensures a minimal risk of contamination and associated health issues.

- Histamine Analysis: The histamine levels detected in the samples ranged between 2 and 5ppm. According to SNI 4104:2015, the upper limit for histamine content in tuna is 100mg/ kg (100ppm). As the recorded histamine levels are significantly below this limit, the results confirm that the tuna products are well within the safety standards.

Additionally, the fresh tuna loin samples that had been tested for microbiological and histamine parameters were then analyzed for color measurement and conversion. The outcomes of this color analysis and conversion are displayed in Table (4).

Table 4. Color measurement using color reader and hue degree conversion

Sample code	LAB Value			Hue degree	Color conversion	Description
	L	a	b			
Sample 1	43.24	20.45	7.62	20.44^0		Approaching Reddish-Orange
Sample 2	42.71	13.62	5.51	22.00^0		Between Red and Orange, leaning towards Orange
Sample 3	38.05	15.68	6.41	22.25^0		Between Red and Orange, leaning towards Orange

The interpretation of the color measurement and conversion results from Table (4) is as follows: Among all samples, Sample 1 exhibited the highest L value (43.24), signifying greater brightness in the meat. Sample 2 had the lowest ‘a’ value (13.62), indicating a weaker red intensity. With a comparatively high ‘b’ value (5.51), the orange tone appears more prominent. In contrast, Sample 3 closely resembled Sample 2, as its ‘a’ (15.68) and ‘b’ (6.41) values are quite similar, suggesting a coloration that is more inclined towards orange than red.

The appearance of fish meat, especially tuna, is a key factor in assessing product quality and attracting consumers. Within the seafood processing sector, meat color is often used as a freshness indicator, significantly affecting buying preferences. The pigmentation of fish meat is strongly associated with myoglobin levels, which play a role in delivering oxygen to muscle tissues. A higher **a*** value in fresh tuna loin samples is linked to superior quality and freshness **(Kristinsson *et al*., 2008)**. Fish exhibiting a deep red hue is typically fresher and considered to be of higher grade.

2. Training model result

ResNet model result

This section presents the training outcomes and performance evaluation of the CNN-based classification model, which was developed and trained using the processed dataset outlined below. Fig. (3) depicts the ResNet model's performance across 15 training epochs, showcasing trends in validation loss, validation accuracy, training loss, and training accuracy. The consistent decline in validation loss suggests effective learning and generalization of the model. However, validation accuracy initially increases but then stagnates, suggesting limited improvement in predicting unseen data. The training loss consistently decreases, reflecting effective learning from the training data. However, its lower value compared to validation loss hints at potential overfitting. Meanwhile, training accuracy increases but then plateaus and slightly declines, further suggesting that the model may be memorizing the training data. Overall, the model demonstrates good performance, but the observed trends indicate overfitting, highlighting the need for further refinement to enhance generalization capability.

Table 5. Model fitting for ResNet architecture

Epoch	Val_loss	Val_accuracy	Train loss	Train accuracy	Description
1/15	1.2211	0.3478	1.4824	0.3405	val_loss improved from inf to 1.22109
2/15	0.9052	0.5870	0.7733	0.6432	val_loss improved from 1.22109 to 0.90518
3/15	0.6780	0.6522	0.7122	0.6324	val_loss improved from 0.90518 to 0.67799
4/15	0.7237	0.6522	0.4257	0.8595	val_loss did not improve from 0.67799
5/15	0.5987	0.6522	0.3945	0.8703	val_loss improved from 0.67799 to 0.59867
6/15	0.6679	0.6522	0.3368	0.8865	val_loss did not improve from 0.59867
7/15	0.5240	0.7391	0.2460	0.9297	val_loss improved from 0.59867 to 0.52405
8/15	0.4029	0.8043	0.2245	0.9297	val_loss improved from 0.52405 to 0.40294
9/15	0.4814	0.7609	0.1870	0.9568	val_loss did not improve from 0.40294
10/15	0.5197	0.6957	0.1639	0.9622	val_loss did not improve from 0.40294
11/15	0.1548	0.8043	0.1548	0.9459	val_loss did not improve from 0.40294
12/15	0.4570	0.7609	0.1373	0.9676	val_loss did not improve from 0.40294
13/15	0.4110	0.7826	0.1235	0.9730	val_loss did not improve from 0.40294
14/15	0.5159	0.7826	0.1379	0.9676	val_loss did not improve from 0.40294
15/15	0.6704	0.6957	0.1266	0.9568	val_loss did not improve from 0.40294

Fig. 3. Training model result for ResNet

DenseNet Model Result

Fig. (4) illustrates the training performance of the DenseNet model over 15 epochs, showing the progression of validation loss, validation accuracy, training loss, and training accuracy. The steady decline in validation loss suggests enhanced model generalization to previously unseen data. Validation accuracy follows an upward trend but eventually stagnates and fluctuates slightly, suggesting that while the model becomes better at predicting on the validation set, the improvement is marginal after reaching a certain point. Training loss decreases throughout the epochs, which is expected as the model learns from the training data. However, the fact that training loss remains lower than validation loss could indicate potential overfitting. Training accuracy continues to rise but, like validation accuracy, it plateaus and exhibits slight variations, possibly signaling that the model is memorizing the training data rather than learning generalizable patterns. Overall, the DenseNet model demonstrates solid performance, but these trends suggest a risk of overfitting, necessitating further adjustments to enhance its generalization ability.

Table 6. Model fitting for DenseNet architecture

Epoch	Val_Loss	Val_Accuracy	Train Loss	Train Accuracy	Description
1/15	0.8632	0.5435	0.8947	0.6054	val_loss improved from inf to 0.86318
2/15	0.8833	0.6739	0.6596	0.7351	val_loss did not improve from 0.86318
3/15	0.5320	0.7174	0.5310	0.7784	val_loss improved from 0.86318 to 0.53198
4/15	0.5331	0.7174	0.4465	0.8216	val_loss did not improve from 0.53198
5/15	0.6370	0.6739	0.3221	0.8649	val_loss did not improve from 0.53198
6/15	0.5100	0.7174	0.3340	0.8162	val_loss improved from 0.53198 to 0.50996
7/15	0.5230	0.7174	0.2812	0.8811	val_loss did not improve from 0.50996
8/15	0.4892	0.7609	0.2397	0.8973	val_loss improved from 0.50996 to 0.48921
9/15	0.4722	0.7174	0.2679	0.8703	val_loss improved from 0.48921 to 0.47223
10/15	0.4041	0.7826	0.1977	0.9297	val_loss improved from 0.47223 to 0.40413
11/15	0.3866	0.8043	0.2147	0.9189	val_loss improved from 0.40413 to 0.38663
12/15	0.3767	0.7609	0.1920	0.9243	val_loss improved from 0.38663 to 0.37675
13/15	0.3970	0.7391	0.1834	0.9189	val_loss did not improve from 0.37675
14/15	0.4706	0.7826	0.1681	0.9459	val_loss did not improve from 0.37675
15/15	0.3173	0.8043	0.1548	0.9405	val_loss improved from 0.37675 to 0.31734

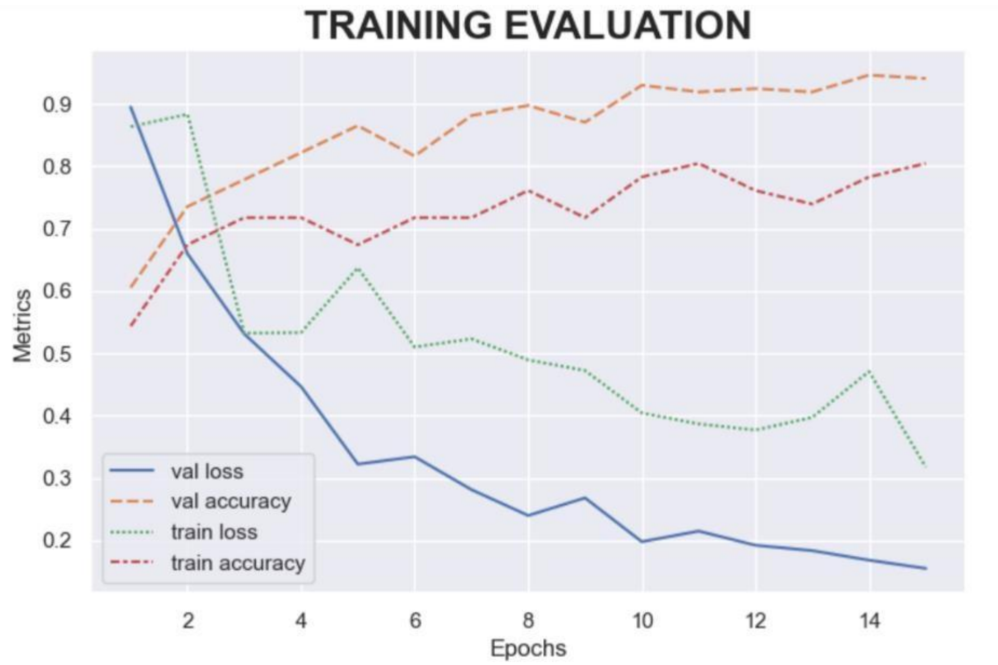

Fig. 4. Training model result for DenseNet

Inception model result

Fig. (5) depicts the training performance of the Inception model over 15 epochs, outlining trends in validation loss, validation accuracy, training loss, and training accuracy. A notable decline in validation loss, particularly during the initial epochs, suggests effective learning and improved model performance on previously unseen data. However, validation accuracy (orange line) stabilizes after an initial increase, suggesting that the model's predictive ability on the validation set reaches a point of diminishing returns. Training loss (green line) also decreases but fluctuates more compared to validation loss, which could indicate instability in learning or noise in the training data. Training accuracy (red line) gradually increases, aligning with validation accuracy, though both remain relatively stable after several epochs. This behavior suggests that the model is not heavily overfitting, as the training and validation metrics follow similar trends. Overall, the model appears to perform well, with decreasing loss and stable accuracy, though minor fluctuations in loss metrics indicate potential room for further optimization.

Table 7. Model fitting for Inception architecture

Epoch	Val_Loss	Val_Accuracy	Train Loss	Train Accuracy	Description
1/15	1.3194	0.3043	3.0939	0.2865	val_loss improved from inf to 1.31939
2/15	1.4525	0.4565	1.6130	0.4324	val_loss did not improve from 1.31939
3/15	0.8357	0.5652	1.1257	0.5568	val_loss improved from 1.31939 to 0.83574
4/15	0.9826	0.4783	0.8351	0.5892	val_loss did not improve from 0.83574
5/15	0.8062	0.5870	0.7673	0.6162	val_loss improved from 0.83574 to 0.80620
6/15	0.8245	0.5652	0.5995	0.7784	val_loss did not improve from 0.80620
7/15	0.6818	0.6522	0.5760	0.7297	val_loss improved from 0.80620 to 0.68184
8/15	0.6293	0.7391	0.4310	0.8541	val_loss improved from 0.68184 to 0.62928
9/15	0.6993	0.6522	0.4159	0.8378	val_loss did not improve from 0.62928
10/15	0.7475	0.6087	0.4058	0.8486	val_loss did not improve from 0.62928
11/15	0.7271	0.6304	0.3639	0.8811	val_loss did not improve from 0.62928
12/15	0.6258	0.7174	0.2875	0.9081	val_loss improved from 0.62928 to 0.62581
13/15	0.6495	0.6957	0.3131	0.8757	val_loss did not improve from 0.62581
14/15	0.6587	0.5870	0.2717	0.8973	val_loss did not improve from 0.62581
15/15	0.7552	0.6522	0.2578	0.8919	val_loss did not improve from 0.62581

Fig. 5. Training model result for Inception

ResNet model evaluation

Fig. (6) displays the confusion matrix illustrating the classification performance of the ResNet model across three categories: Alpha, Bravo, and Charley. The results indicate that the model accurately classifies all 20 instances of Alpha with no misclassifications. For Bravo, 15 out of 17 instances are classified correctly, with one misclassified as Alpha and another as Charley. Similarly, for Charley, 16 out of 19 instances are correctly predicted, while one is misclassified as Alpha and two as Bravo. This matrix provides a clear insight into the model's accuracy and the areas where misclassifications occur, particularly between Bravo and Charley.

Table (8) presents the classification report detailing the model's performance metrics, including accuracy, precision, recall, and F1-score. The overall accuracy of the ResNet model is 91.07%, indicating that the majority of instances are correctly classified across all classes. Precision is high for all categories, with Alpha at 90.91%, Bravo at 88.24%, and Charley at 94.12%, reflecting the model's effectiveness in making accurate positive predictions. Recall is perfect for Alpha at 100% but slightly lower for Bravo (88.24%) and Charley (84.21%), suggesting that while the model excels at identifying Alpha instances, it occasionally misses some Bravo and Charley cases. The F1-score, which balances precision and recall, remains strong across all classes, although Charley shows a slight drop in performance compared to Alpha. Overall, the model demonstrates consistent and reliable classification capabilities.

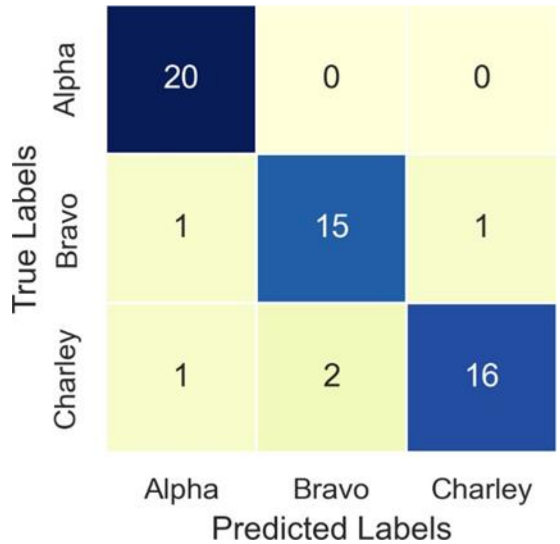

Fig. 6. ResNet model confusion matrix

Table 8. ResNet model classification report

Confusion matrix	Grade Alpha	Grade Bravo	Grade Charley
Accuracy	0.9107	0.9107	0.9107
Precision	0.9091	0.8824	0.9412
Recall	1.0000	0.8824	0.8421
F1 Score	0.9524	0.8824	0.8889

DenseNet model evaluation

Fig. (7) presents the confusion matrix illustrating the performance of the DenseNet model in classifying the Alpha, Bravo, and Charley classes. The model correctly predicts all 20 instances of Alpha without any errors. For Bravo, it accurately classifies 14 out of 17 instances, with the remaining three misclassified as Charley. Notably, the model correctly predicts all 19 instances of Charley, demonstrating strong performance in identifying this class. The confusion matrix highlights that while the model excels in classifying Alpha and Charley, it faces slight challenges in distinguishing some Bravo instances, which are occasionally misclassified as Charley.

Table (9) provides a classification report detailing key performance metrics, including accuracy, precision, recall, and F1-score. The overall accuracy of the model is 94.64%, reflecting a high capability in classifying instances across all classes. Precision is perfect for Alpha and Bravo at 100%, indicating that all positive predictions for these classes are correct. However, precision for Charley is slightly lower at 86.36%, suggesting some misclassifications. Recall is perfect for Alpha and Charley at 100%, but slightly lower for Bravo at 82.35%, meaning the model misses a few Bravo instances. The F1-score, which balances precision and recall, is strong across all classes, with a perfect score for Alpha and slightly lower but still high scores for Bravo (90.32%) and Charley (92.68%). Overall, the model delivers excellent performance with minor areas for improvement in classifying the Bravo class.

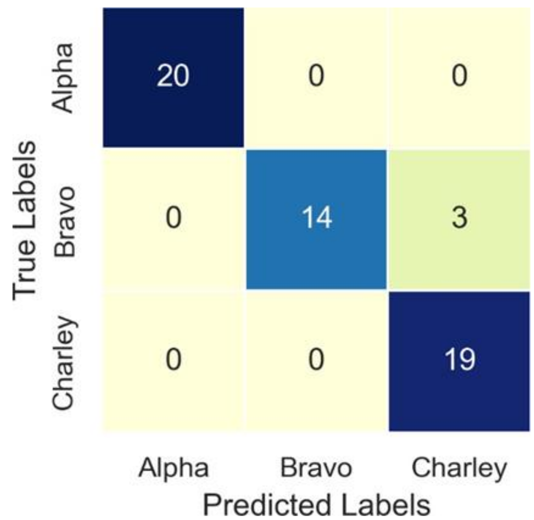

Fig. 7. DenseNet model confusion matrix

Table 9. DenseNet model classification report

Confusion matrix	Grade Alpha	Grade Bravo	Grade Charley
Accuracy	0.9464	0.9464	0.9464
Precision	1.0000	1.0000	0.8636
Recall	1.0000	0.8235	1.0000
F1 Score	1.0000	0.9032	0.9268

Inception model evaluation

Fig. (8) presents the confusion matrix illustrating the performance of the Inception model in classifying the Alpha, Bravo, and Charley classes. The model correctly predicts all 20 instances of Alpha without any misclassification. However, for Bravo, it accurately classifies only 12 out of 17 instances, with 2 misclassified as Alpha and 3 as Charley. Similarly, for Charley, the model correctly predicts 15 out of 19 instances, with 4 misclassified as Bravo. This confusion matrix highlights that while the model performs well in classifying Alpha, it struggles to differentiate between Bravo and Charley, leading to some misclassifications.

Table (10) provides a classification report detailing key performance metrics, including accuracy, precision, recall, and F1-score. The overall accuracy of the model is 83.93%, indicating that while the majority of instances are classified correctly, there is still room for improvement. The highest precision is for Alpha at 90.91%, meaning most of its predictions are correct. Precision for Bravo is lower at 75.00%, reflecting some misclassifications, while Charley achieves a precision of 83.33%. Recall is perfect for Alpha at 100% but lower for Bravo (70.59%) and Charley (78.95%), suggesting that the model misses some instances of these classes. The F1-score, which balances precision and recall, is strong for Alpha (95.24%) but lower for Bravo (72.73%) and Charley (81.08%).

Overall, the Inception model demonstrates strong classification capabilities for Alpha but less consistent performance for Bravo and Charley, indicating areas that require further refinement. Based on these observations, it can be concluded that the model shows a solid ability to classify data into three distinct classes, although improvements are needed to enhance its accuracy for Bravo and Charley.

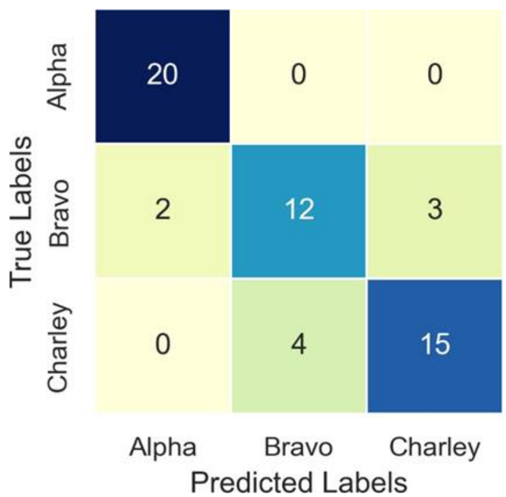

Fig. 8. Inception model confusion matrix

Table 10. Inception model classification report

Confusion matrix	Grade Alpha	Grade Bravo	Grade Charley
Accuracy	0.8393	0.8393	0.8393
Precision	0.9091	0.7500	0.8333
Recall	1.0000	0.7059	0.7895
F1 Score	0.9524	0.7273	0.8108

3. Web-based tuna loin quality prediction application design and mockup

Based on the findings of **Tupan *et al*. (2025)**, deep learning models have demonstrated significant potential in automating the classification of tuna loin quality. This study builds upon that research by utilizing a Model Classification Grade approach to develop a web-based application for real-time tuna loin classification. By leveraging deep learning techniques, the proposed system enables efficient and accurate assessment of tuna loin quality, ensuring consistency in classification while reducing the dependency on manual inspection. To implement this system effectively, a robust deployment strategy is required to integrate the trained model into an accessible and user-friendly application.

Deploying a deep learning model is the final stage in the artificial intelligence development cycle, where a trained and tested model is made available for real-world applications. At this stage, the model is not only executed locally for research purposes but is also implemented in an application that end users can access. The deployment process involves various techniques to ensure that the model runs efficiently and integrates seamlessly into web or mobile-based applications, such as Android.

One of the popular methods for deploying deep learning models is using Streamlit, an open-source framework that enables quick and easy web application development. Streamlit provides a simple interface for integrating deep learning models into web applications. In this context, Streamlit can be used as a platform to develop an application that allows users to upload tuna loin images and receive real-time quality predictions. Streamlit offers several advantages, such as an easy front-end development process without requiring in-depth web programming knowledge. This makes it an ideal choice for deploying deep learning models, especially for users who want to quickly implement their models into widely accessible applications.

In addition, the importance of the user interface (UI) in deploying deep learning models cannot be overlooked. A well-designed UI enables users to interact with the model intuitively and efficiently. In the context of a tuna loin quality assessment application, a user-friendly UI simplifies the process of uploading images, viewing prediction results, and understanding the presented information. Without an effective UI, even the most accurate deep learning model would be difficult for end users to utilize. Therefore, designing a functional and responsive UI is crucial to ensuring that the web- or Android-based tuna loin quality prediction model fulfills its primary goal: providing automated and easily accessible quality assessment.

The application testing results demonstrate the successful implementation of the tuna loin classification model into a simple web-based application. By leveraging Streamlit, the model integrates seamlessly with the web interface, allowing users to upload images and receive instant classification results into two predefined categories. The application operates with consistently accurate classification results, confirming that the model deployment is effective. This makes the website an intuitive and easily accessible tool for real-time tuna loin quality classification.

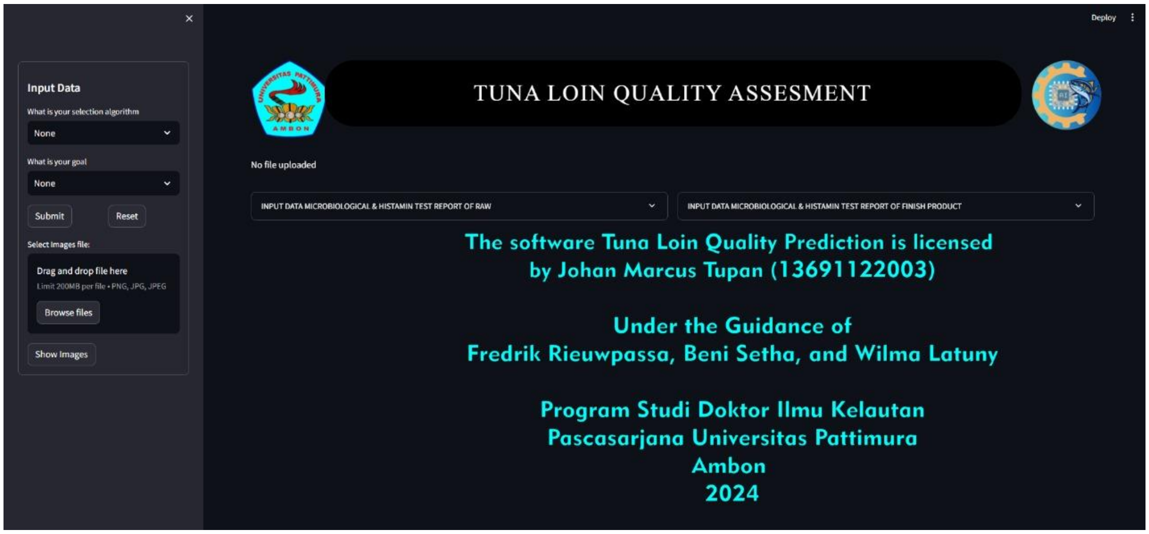

Fig. 10a. User interface design for tuna loin quality assessment application

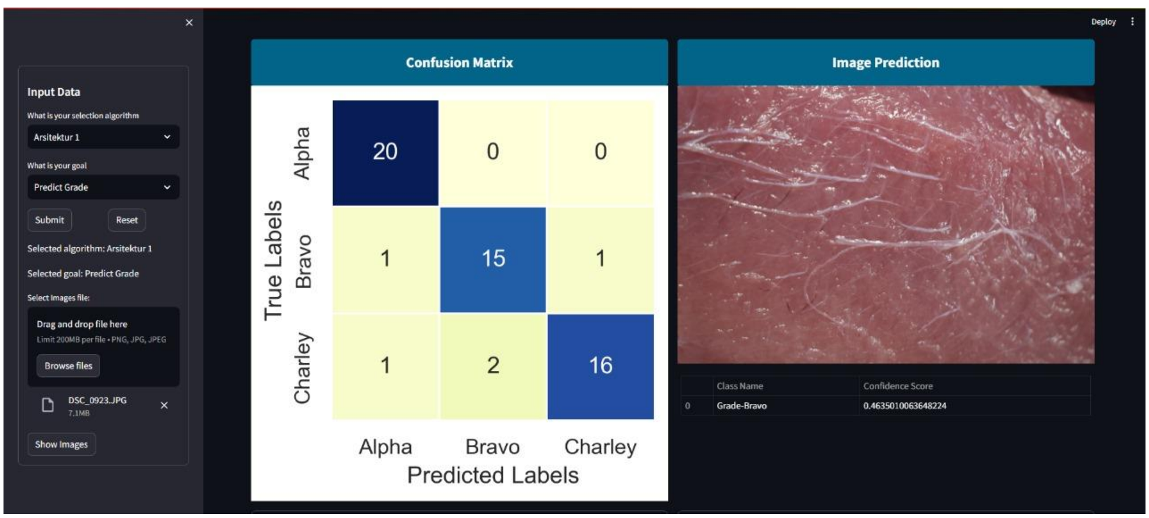

Fig. 10b. Confusion matrix results and image prediction sub-menu

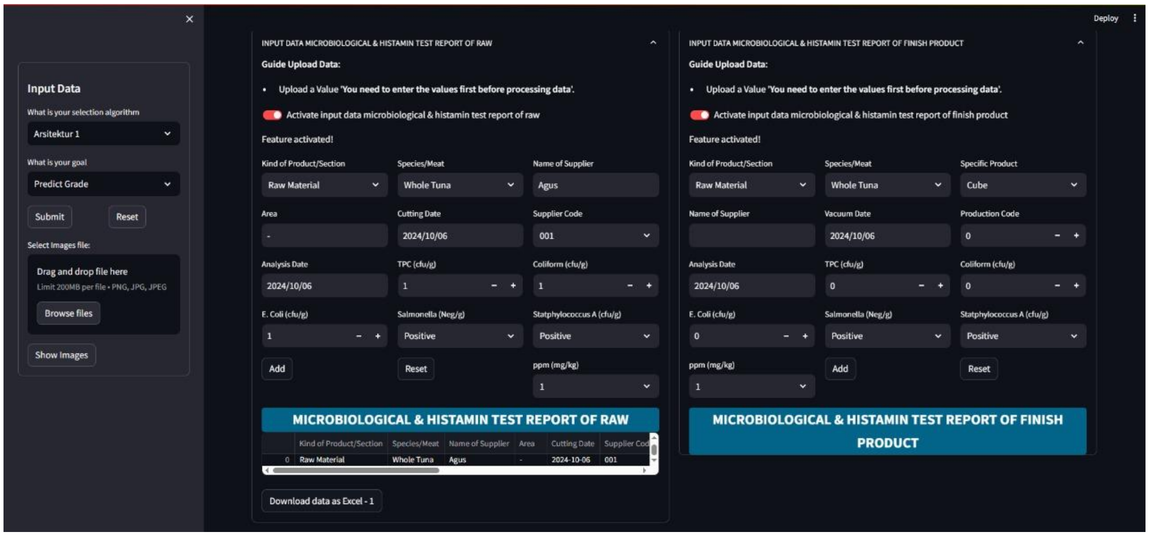

Fig. 10c. Microbiological & histamine test report sub-menu for raw materials and finished products

CONCLUSION

This research successfully developed an AI-powered tuna loin quality assessment system using Deep Convolutional Neural Networks (DCNN), addressing industry challenges in non-destructive grading and treatment classification. Traditional sensory-based methods for assessing tuna quality require significant time and expertise, prompting the need for automated solutions. This study assessed the performance of three CNN architectures ResNet, DenseNet, and Inception in classifying treatments (No-Treatment, CO-Treatment, and CS-Treatment) based on previous research and a three-tier grading system (Alpha, Bravo, and Charley). Among these models, DenseNet demonstrated the highest grading accuracy at 94.64%, surpassing ResNet at 91.07% and Inception at 83.93%. Similarly, for the three-class treatment classification, DenseNet achieved the highest accuracy at 95.54%, followed by ResNet at 93.75% and Inception at 91.07%. The developed system integrates a web-based interface and an Android mockup, enabling users to upload tuna loin images for real-time analysis. Validation testing confirmed the system's reliability in differentiating tuna quality categories, making it a valuable tool for improving quality consistency and decision-making in the fish processing supply chain. While the model performs well, some instances of misclassification indicate areas for improvement. Future work will focus on optimizing data preprocessing, expanding the training dataset through augmentation techniques, and exploring more advanced CNN architectures to enhance classification accuracy. Additionally, full implementation of the mobile platform could further streamline real-time quality control, making AI-driven assessments more accessible and efficient for the seafood industry. With continuous development, this research contributes to advancing

AI-based quality assessment tools in fisheries, offering a scalable and practical solution for modernized tuna processing.

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REFERENCES

Anas, D. F.; Jaya, I. and Nurjanah. (2021). Design and implementation of fish freshness detection algorithm using deep learning. *IOP Conference Series: Earth and Environmental Science, 944*(1). https://doi.org/10.1088/1755-1315/944/1/012007

Carrington, A. M.; Manuel, D. G.; Fieguth, P. W.; Ramsay, T.; Osmani, V.; Wernly, B.; Bennett, C.; Hawken, S.; Magwood, O. and Sheikh, Y. (2022). Deep ROC analysis and AUC as balanced average accuracy, for improved classifier selection, audit and explanation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *45*(1), 329–341.

Dowlati, M.; de la Guardia, M. and Mohtasebi, S.S. (2012). Application MSV of machine-vision techniques to fish-quality assessment. *TrAC Trends in Analytical Chemistry*, *40*, 168–179.

Elsharif, A. A. E. F. and Abu-Naser, S. S. (2022). *Retina diseases diagnosis using deep learning*.

Gustiano, R.; Kurniawan, K. and Haryono, H. (2021). Optimizing the Utilization of Genetic Resources of Indonesian Native Freshwater Fish. *Asian Journal of Conservation Biology*, *10*(2), 189–196. https://doi.org/10.53562/ajcb.67022

Hong, H.; Yang, X.; You, Z. and Cheng, F. (2014). Visual quality detection of aquatic products using machine vision. *Aquacultural Engineering*, *63*, 62–71.

Issac, A.; Dutta, M. K.; and Sarkar, B. (2017). Computer vision based method for quality and freshness check for fish from segmented gills. *Computers and Electronics in Agriculture*, *139*, 10–21.

Kılıçarslan, S.; Hız Çiçekliyurt, M. M. and Kılıçarslan, S. (2024). Fish Freshness Detection Through Artificial Intelligence Approaches: A Comprehensive Study.

Turkish Journal of Agriculture - Food Science and Technology, *12*(2), 290–295. https://doi.org/10.24925/turjaf.v12i2.290-295.6670.

Kristinsson, H.G.; Crynen, S. and Yagiz, Y. (2008). Effect of a filtered wood smoke treatment compared to various gas treatments on aerobic bacteria in yellowfin tuna steaks. *LWT-Food Science and Technology*, 41: 746-750.

Liu, F.; Xu, H.; Qi, M.; Liu, D.; Wang, J. and Kong, J. (2022). Depth-wise separable convolution attention module for garbage image classification. *Sustainability*, *14*(5), 3099.

Loppies, C. R. M.; Apituley, D. A. N.; Sormin, R. B. D. and Setha, B. (2021). Kandungan mioglobin ikan tuna (Thunnus albacares) dengan pemakaian karbon monoksida dan filter smoke selama penyimpanan beku. *Jurnal Teknologi Hasil Perikanan*, 1(1), Januari 2021.

Lugatiman, K.; Fabiana, C.; Echavia, J. and Adtoon, J. J. (2019). Tuna meat freshness classification through computer vision. *2019 IEEE 11th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment, and Management (HNICEM)*, 1–6.

Medeiros, E. C.; Almeida, L. M. and Filho, J. G. de A. T. (2021). Computer vision and machine learning for tuna and salmon meat classification. *Informatics*, *8*(4), 70.

Moon, E. J.; Kim, Y.; Xu, Y.; Na, Y.; Giaccia, A. J. and Lee, J. H. (2020). Evaluation of salmon, tuna, and beef freshness using a portable spectrometer. *Sensors*, *20*(15), 4299.

Murakoshi, T.; Masuda, T.; Utsumi, K.; Tsubota, K. and Wada, Y. (2013). Glossiness and perishable food quality: visual freshness judgment of fish eyes based on luminance distribution. *PLoS One*, *8*(3), e58994.

Nashrullah, F.; Wibowo, S. A. and Budiman, G. (2020). The Investigation of Epoch Parameters in ResNet-50 Architecture for Pornographic Classification: Investigasi Parameter Epoch Pada Arsitektur ResNet-50 Untuk Klasifikasi Pornografi. *Journal of Computer Electronic and Telecommunication*, *1*(1).

Prasetyo, E.; Suciati, N. and Fatichah, C. (2021). Yolov4-tiny and spatial pyramid pooling for detecting head and tail of fish. *2021 International Conference on Artificial Intelligence and Computer Science Technology (ICAICST)*, 157–161.

Prasetyo, E.; Suciati, N.; Fatichah, C. and Pardede, E. (2024). Standardizing the fish freshness class during ice storage using clustering approach. *Ecological Informatics*, *80*, 102533.

Priyatman, H.; Sajid, F. and Haldivany, D. (2019). Klasterisasi Menggunakan Algoritma K-Means Clustering untuk Memprediksi Waktu Kelulusan Mahasiswa. *Jurnal Edukasi Dan Penelitian Informatika (JEPIN)*, *5*(1), 62.

Pujiarini, E. H. and Lenti, F. N. (2023). Convolution Neural Network Untuk Identifikasi Tingkat Kesegaran Ikan Nila Berdasarkan Perubahan Warna Mata. *Jurnal Khatulistiwa Informatika*, *11*(1), 21–25.

Rayan, M. A.; Rahim, A.; Rahman, M. A.; Marjan, M. A. and Ali, U. A. M. E. (2021). Fish freshness classification using combined deep learning model. *2021 International Conference on Automation, Control and Mechatronics for Industry 4.0 (ACMI)*, 1–5.

Sengar, N.; Dutta, M. K. and Travieso, C. M. (2018). Computer vision based technique for identification and quantification of powdery mildew disease in cherry leaves. *Computing*, *100*(11), 1189–1201.

Shahi, T. B.; Sitaula, C.; Neupane, A. and Guo, W. (2022). Fruit classification using attention-based MobileNetV2 for industrial applications. *Plos One*, *17*(2), e0264586.

Shahi, T. B.; Xu, C.-Y.; Neupane, A.; and Guo, W. (2023). Recent advances in crop disease detection using UAV and deep learning techniques. *Remote Sensing*, *15*(9), 2450.

Shi, C.; Qian, J.; Zhu, W.; Liu, H.; Han, S. and Yang, X. (2019). Nondestructive determination of freshness indicators for tilapia fillets stored at various temperatures by hyperspectral imaging coupled with RBF neural networks. *Food Chemistry*, *275*, 497–503.

Sitaula, C. and Shahi, T. B. (2022). Monkeypox virus detection using pre-trained deep learning-based approaches. *Journal of Medical Systems*, *46*(11), 78.

Suryaningrum, T. D.; Ikasari, D. and Octavini, H. (2017). Evaluasi mutu tuna loin segar untuk sashimi yang diolah di atas perahu selama penanganan dan distribusinya di Ambon. *JPB Kelautan dan Perikanan*, 12(2), 165–178.

Taheri-Garavand, A.; Nasiri, A.; Banan, A. and Zhang, Y. D. (2020). Smart deep learning-based approach for non-destructive freshness diagnosis of common carp fish. *Journal of Food Engineering*, *278*, 109930.

Tauda, I.; Hiariey, J.; Lopulalan, Y. and Bawole, D. (2021). Management policy of small-scale tuna fisheries based on island cluster in Maluku. *IOP Conference Series: Earth and Environmental Science*, *777*(1). https://doi.org/10.1088/1755-1315/777/1/012011

Tupan, J. M.; Rieuwpassa, F.; Setha, B.; Latuny, W. and Goesniady, S. (2025). A Deep Learning Approach to Automated Treatment Classification in Tuna Processing: Enhancing Quality Control in Indonesian Fisheries. *Fishes*, *10*(2), 75.

Wu, T.; Yang, L.; Zhou, J.; Lai, D. C. and Zhong, N. (2019). An improved nondestructive measurement method for salmon freshness based on spectral and image information fusion. *Computers and Electronics in Agriculture*, *158*, 11–19.

Yildiz, M.B.; Yasin, E.T. and Koklu, M. (2024). Fisheye freshness detection using common deep learning algorithms and machine learning methods with a developed mobile application. European Food Research and Technology (2024) 250:1919–1932. https://doi.org/10.1007/s00217-024-04493-0

Zhou, X.; Li, C.; Rahaman, M. M.; Yao, Y.; Ai, S.; Sun, C.; Wang, Q.; Zhang, Y.; Li, M. and Li, X. (2020). A comprehensive review for breast histopathology image analysis using classical and deep neural networks. *IEEE Access*, *8*, 90931–90956.