IJCCS (Indonesian Journal of Computing and Cybernetics Systems)
Vol.x, No.x, July xxxx, pp. 1~5
ISSN (print): 1978-1520, ISSN (online): 2460-7258
DOI: 10.22146/ijccs.xxxx

Measurement and Analysis of Detecting Fish Freshness Levels Using Deep Learning Method

Dhea Fajriati Anas*[1], Indra Jaya[2], Yeni Herdiyeni[3]
[1]Master Program of Marine Technology, FPIK IPB University, Bogor, Indonesia
e-mail: *[1]fa13_dhea@apps.ipb.ac.id, [2]indrajaya@apps.ipb.ac.id, [3]yeni.herdiyeni@apps.ipb.ac.id

Abstrak

Uji subjektif dan objektif yang digunakan untuk mengetahui proses kemunduran ikan memerlukan keahlian khusus dan waktu sehingga tidak efektif untuk digunakan masyarakat di pasar. Kualitas produk ikan di pasar tidak selalu terjamin, sehingga konsumen harus menentukan kelayakannya. Deep learning dapat digunakan untuk menganalisis gambar dan mendeteksi tingkat kesegaran ikan secara otomatis dan akurat. Penelitian ini bertujuan untuk mengevaluasi efisiensi model deep learning dalam pendeteksian kesegaran ikan dan mengimplementasikannya ke dalam aplikasi android. Dataset gambar dan uji pH dengan sebagai acuan fase postmortem dikumpulkan selama 24 jam dengan pengecekan setiap jam pada tiga spesies ikan (Rachycentron canadum, Trachinotus blochi, dan Lates calcarifer). Kelas dibagi menjadi tiga yaitu, fase pre-rigor/segar, rigor mortis/agak segar, dan post-rigor/tidak segar. Dataset dibagi menggunakan metode 10-fold cross-validation dan dianalisis menggunakan algoritma YOLOv5 dan Faster R-CNN. Hasil penelitian menunjukkan bahwa YOLOv5 memiliki nilai rata-rata setiap metrik lebih tinggi dibandingkan dengan Faster R-CNN. Dataset 8 pada YOLOv5 menunjukkan nilai precision 99.4%, recall 98.1%, f1-score 98.7%, accuracy 99.3%, dan mAP 99.3%. Model YOLOv5 untuk dataset 8 dipilih untuk implementasi aplikasi Android karena nilai metriknya yang tinggi. Aplikasi ini efektif dalam menyediakan informassi deteksi tingkat kesegaran ikan dan confidence score.

Kata kunci— *Deteksi objek, Tingkat kesegaran ikan, pH, YOLOv5, Faster-RCNN, Aplikasi android*

Abstract

Subjective and objective tests used to determine the fish deterioration process require specialized skills and time, making them inefficient for use by the general public in markets. The quality of fish products in markets is not always guaranteed, so consumers must determine their suitability. Deep learning can be used to analyze images and automatically and accurately detect the freshness of fish. This study aims to evaluate the efficiency of deep learning models in detecting fish freshness and implementing them into an Android application for public use. "Image datasets and pH tests were collected as references for the postmortem phase over a 24-hour period, with hourly checks on three fish species (Rachycentron canadum, Trachinotus blochi, and Lates calcarifer). Data were classified into three classes, pre-rigor/fresh, rigor mortis/semi-fresh, and post-rigor/not fresh. The dataset was divided using the 10-fold cross-validation method and analyzed using YOLOv5 and Faster R-CNN algorithms. The study results showed that YOLOv5 had higher average values for each metric compared to Faster R-CNN. Dataset 8 in YOLOv5 showed precision of 99.4%, recall of 98.1%, f1-score of 98.7%, accuracy of 99.3%, and mAP of 99.3%. The YOLOv5 model for dataset 8 was selected for implementation in the Android application due to its high metric values. This application effectively provides information on fish freshness detection and confidence scores.

Keywords— *Object detection, Fish freshness level, pH, YOLOv5, Faster-RCNN, Android application*

Received June 1st,2012; Revised June 25th, 2012; Accepted July 10th, 2012

1. INTRODUCTION

Fishery products are among the most perishable foods due to their high water and protein content, requiring proper and swift handling to maintain quality (Putri et al. 2023). Fish freshness significantly impacts taste, texture, food safety, and public health. The decline in fish quality is influenced by internal and external factors and is divided into pre-rigor, rigor mortis, and post-rigor phases (Nurilmala et al. 2021; Nurhayati et al. 2019). Tests to determine fish quality, such as organoleptic, TVB, TPC, pH, and enzyme activity, require specific knowledge, skills, and time, making them ineffective for public use in markets. Additionally, some tests are destructive, requiring fish dissection. Public knowledge about fish freshness is limited, and market fish quality is not always guaranteed, leaving consumers to decide the suitability of fish for processing.

Artificial intelligence (AI) can analyze images to detect fish freshness automatically and accurately. Deep learning, a branch of AI, uses neural networks with multiple layers to mimic the human brain (Cui et al. 2020; Santoso and Ariyanto 2018). It has significantly improved in areas like visual object recognition and detection (LeCun et al. 2015). Deep learning's feasibility is supported by high-performance computing and large data management.

Fish freshness can be visually determined by eye condition, with the shine of the eyes being a key indicator (Murakoshi et al. 2013). Fresh fish eyes are clear and transparent, while over time they dry and lose shine, correlating with the eye fluid's refractive index (Murakoshi et al. 2013; Gokoglu and Yerlikaya 2004; Yapar and Yetim 1998).

Previous studies have used AI for fish freshness detection, including Support Vector Machine (SVM), Artificial Neural Network (ANN), random forest, Naïve Bayes, K-Nearesst Neighbors (KNN), wavelet transformation, and fuzzy logic (Tolentino et al. 2017; Sengar et al. 2017; Iswari et al. 2017; Sornam et al. 2017; Navotas et al. 2018; Kumar et al. 2020; Lalabadi et al. 2020). However, these methods require further processing for freshness labeling and lack real-time detection capabilities.

Implementing deep learning models in an Android-based application allows for practical and widespread use of fish freshness detection technology. This ensures high-quality fish for the public while increasing efficiency. You Only Look Once version 5 (YOLOv5) and Faster Region-based Convolutional Neural Network (Faster R-CNN) were chosen for their accuracy and efficiency in object detection (Li et al. 2023; Yashaswini et al. 2022). YOLOv5 offers fast, real-time performance, and is lightweight, while Faster R-CNN provides high accuracy and detection efficiency. These models that implemented in an android-based application can quickly determine fish freshness making the technology accessible for public use.

2. METHODS

2.1 pH Test and Dataset Collection

Dataset collection was conducted by capturing images of the fish eyes and their surroundings, accompanied by pH testing. This process was carried out hourly continuously until the fish spoiled, to capture changes in the condition of the fish eyes from immediately after death to spoilage. Fish eye images were captured using a 108 MP smartphone camera, with various image capture variations shown in Appendix 1. pH testing was performed using a digital pH meter inserted directly into several parts of the fish's body. The pH values in each postmortem phase varied between different fish species but showed insignificant differences among species.

According to Suprayitno (2020), pH values for fish in the pre-rigor phase ranged from 6.9 to 7.2, in rigor mortis phase ranged from 6.2 to 6.6, and in post-rigor phase started to rise towards 7.5 to 8.0 during the spoilage phase. In a study by Roth et al. (2006), initial pH decreased from approximately 6.8 during pre-rigor to around 6.2-6.5 during rigor mortis, and stabilized around 5.8-6.0 after the rigor mortis phase ended. Generally, fish that are no longer fresh have a more alkaline pH compared to fresh fish due to compounds such as ammonia, trimethylamine, and other volatile bases (Nurilmala et al. 2021; Hadiwiyoto 1993). Fish entering the post-rigor or spoilage phase typically exhibit pH values approaching neutral, around 7.5 to 8.0, or higher in cases of severe spoilage (Nurilmala et al. 2021; Moeljanto 1992).

2.2 Dataset Labelling and Division

Dataset labeling involved creating labels by annotating bounding boxes (ground truth boxes) and assigning class names to objects in each image. Image annotation was performed using the LabelImg Tools application. The result of annotation is a dataset containing information on the bounding box positions along with their labels, formatted as *.txt files for YOLOv5 and *.xml files for Faster R-CNN. Subsequently, the dataset was balanced for each label using the synthetic minority over-sampling technique (SMOTE) developed by Chawla et al. (2002). SMOTE generates synthetic samples for minority classes to reduce the model's tendency to overfit on the majority class and to achieve a more balanced representation for all classes, facilitating generalization on previously untested training data (Prananda et al. 2024). The operation of SMOTE is generally illustrated in Figure 1.

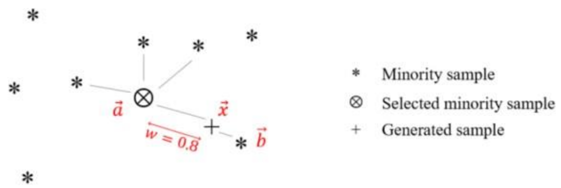


Figure 1 SMOTE operation

$$\vec{x} = \vec{a} + w \times (\vec{b} - \vec{a})$$

SMOTE operates in three steps, first, it randomly selects a vector $\vec{a}$ (minority observation), second it determines the vector $\vec{b}$ by initially setting the constant value of k as the constant value of the desired percentage of the augmentation process; and third, it generates a new sample $\vec{x}$ using the equation shown above, where w is a randomly selected weight (Prananda et al. 2024). The process of labeling and ensuring a balanced dataset is crucial as it will be used in the training process for object recognition.

The method used for dataset division is k-fold cross-validation. This study employs 10-fold cross-validation to evaluate algorithm performance by dividing the data into ten subsets consisting of train and test sets in each fold. During each fold division, one subset is used for training, while the remaining nine are used for testing. This process is repeated ten times with different combinations of train and test sets. An illustration of the 10-fold cross-validation method can be seen in Figure 2. The Python module used to facilitate dataset division with k-fold cross-validation is sklearn.

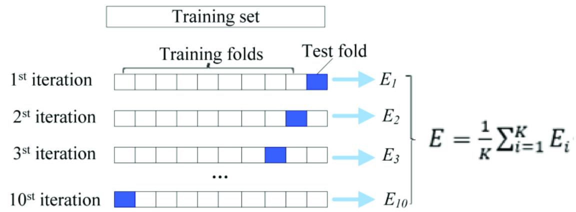


Figure 2 Illustration of Dataset Arrangement with 10-Fold Cross Validation

2.3 Model Architecture

This research uses two algorithm models, namely You Only Look Once version 5 (YOLOv5), and Faster Region-based Convolutional Neural Network (Faster-RCNN). This algorithm was chosen because it has been widely published regarding its good accuracy and computational speed [21]. In general, the object detection architecture compresses the input via a feature extractor (Backbone), then passes it to the object detector (Detection Neck and Detection Head) [10]. The Neck functions as a feature aggregation whose task is to combine and combine the features formed in the Backbone to prepare for the next step, namely, detection in the Head. The head is responsible for carrying out detection including localization and classification for each bounding box. Two-Stage Detector implements these 2 tasks separately and combines the results later (Sparse Detection), while single-stage detector implements them simultaneously (Dense Detection). YOLO is a one-stage detector, while Faster-RCNN is a two-stage detector/multi-stage detector.

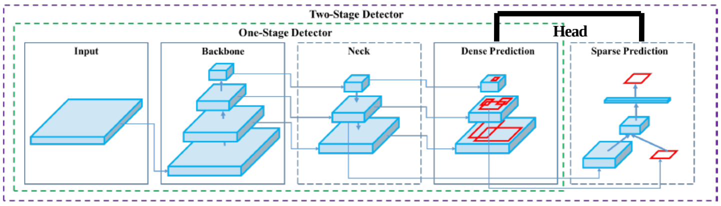


Figure 3 Two concepts of object detection architecture

YOLO applies a single neural network to the entire image by dividing each image into an S x S grid, then each grid predicts B bounding boxes, confidence values in each box and C class probabilities [9]. YOLO is able to carry out real-time detection with a simple architecture in the form of a convolutional neural network.

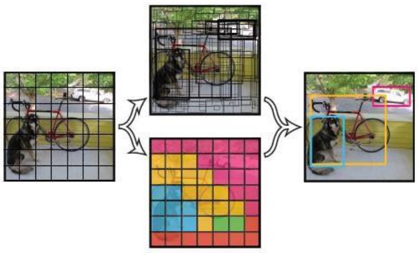


Figure 4 YOLO detection model system

The YOLO network consists of three main parts, namely, backbone, neck, and head. Backbone is a convolutional neural network that combines and forms image features at different granularity, neck is a series of layers to combine image features, then pass them to the prediction stage, and head is to use the features that have been processed at the neck stage to predict boxes and classes.

YOLOv5 uses backbone Cross Stage Partial (CSP) networks, neck Spatial Pyramid Pooling (SPP) and Path Aggregation Network (PAN), as well as head YOLOv3 [10]. The main advantage of YOLOv5 over previous versions, especially version 4, is the improvement in the object detector section. YOLOv5 proposes to integrate the anchor box selection process which can be done automatically according to the dataset. This technique is called adaptive anchor boxes. The advantage is that the network does not consider any dataset to use as input, but can automatically learn the best anchor boxes for a dataset and use them during training [10]. The framework used by YOLOv5 is PyTorch. YOLOv5 is available in four model versions, namely, s (small), m (medium), l (large), and x (extra large).

Faster R-CNN uses a Region Proposal Network (RPN), which is a neural network that replaces the role of selective search to propose regions. The role of selective search is replaced because the process is slow in processing images, which is around 2 seconds/image [20] . The way this algorithm works is that the convolutional layer creates and sends a feature map to the RPN, then the RPN processes the existing feature map and creates a region proposal and creates a bounding box for sections that are considered likely to contain objects. R-CNN classifies the proposals that have been made by RPN and determines whether the objects in the proposal are objects in the model that has been trained and labels the objects [20].

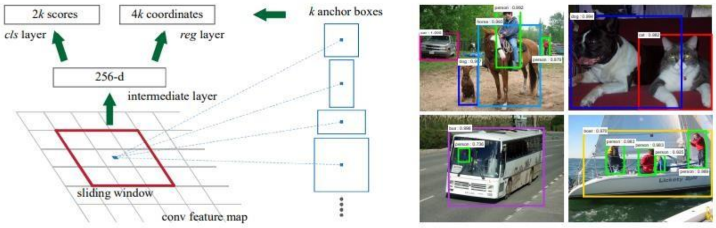


Figure 6 Region Proposal Network (RPN) and example of detection with RPN on PASCAL VOC 2007 data

2. 3 Model Training

Training which aims to train the algorithm to recognize the dataset and form a model based on this training. The training stage consists of feed-forward propagation and back propagation processes. Feed-forward propagation is an algorithm that only calculates the output from the input (feed forward) so that there is no feedback to the input, while back propagation is an algorithm for training (adjusting weights) which consists of feed-forward propagation and feedback (feed-forward propagation). back propagation) to calculate errors/losses [14]. The back propagation process is carried out repeatedly to obtain the smallest error/loss value so that it is hoped that the level of detection accuracy will be better [3]. The process was carried out in Google Colab with a total of five models produced for each algorithm.

2. 3 Model Validation

Validation which aims to recognize the dataset based on the weight values from the training results. The validation stage only consists of a feedforward process. Validation is carried out using several percent of images from the entire dataset for each freshness level that are not included in the training dataset. This was done to find out whether the model that has been trained is able to detect the level of fish freshness, if validated using new data. The validation results are continued with evaluating the performance of the classifier by measuring precision and recall values. Measurements can be made using a predictive confusion matrix. According to Han and Kamber (2011) in Fibrianda and Bhawiyuga (2018), the confusion matrix can be interpreted as a tool that has the function of analyzing whether the classifier is good at recognizing tuples from different classes. The values of true positive and true negative provide information when the classifier is correct in classifying data, while false positive and false negative provide information when the classifier is incorrect in classifying data.

		Predicted class		
		yes	no	Total
Actual class	yes	TP	FN	P
	no	FP	TN	N
	Total	P'	N'	P + N

Figure 7 Confusion matrix displays the total positive and negative tuples

Where,

- True Positive (TP) = the amount of data with a true positive value and positive predictive value
- False Positive (FP) = the amount of data with a negative true value and positive predictive value
- False Negative (FN) = the amount of data with a true positive value and negative predictive value
- True Negative (TN) = the amount of data with negative true values and negative predictive value

Precision is the ratio of correct positive predictions compared to the overall positive predicted results or data taken based on insufficient or wrong or inaccurate information. The following is the formula for precision,

$$Precision = \frac{TP}{TP + FP}$$

Recall/sensitivity is the ratio of true positive predictions compared to all data that is true positive or data that cannot be predicted correctly. The following is the formula for recall.

$$Recall = \frac{TP}{TP + FN}$$

F1-Score is an evaluation metric that describes the balance between precision and recall. The following is the formula for F1-Score,

$$F1\ Score = 2 \times \frac{recall \times precision}{recall + precision}$$

Mean average precision (mAP) is a metric that is commonly used to see the performance of object detection models, namely it is the final value of the average average precision (AP) value. The mAP value also describes how precise the model is in predicting every possibility that exists in the benchmark data or test data. Average precision (AP) is by calculating the area under curve (AUC) of the precision-recall curve in each class.

$$\text{mAP@}\alpha = \frac{1}{n}\sum_{i=1}^{n} \text{AP}_i \quad \text{for n classes}$$

The value a in the formula is the threshold value or IoU confidence limit accepted by the model. Intersection over union (IoU) is a Jaccard Index-based measurement process to evaluate the overlap between two bounding boxes. The threshold used in this research is mAP@50.

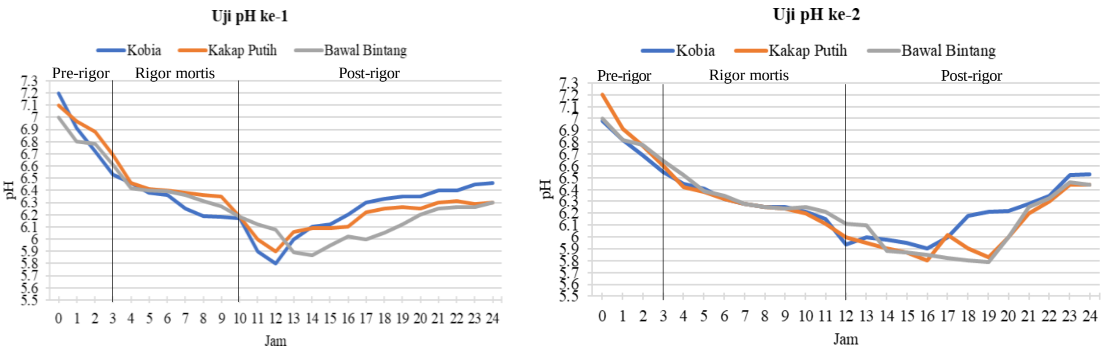
2. 4 Model Implementation

Application creation was carried out in the Android Studio Electric Eel application. The most ideal model will be converted into TorchScripy Lite (*.ptl), then entered into Android Studio for further processing so that it can be used in Android-based applications. TensorFlow Lite enables model results to be run on mobile, IoT, and other devices.

3. RESULTS AND DISCUSSION

3.1 pH Test

The pH test is a quantitative method that can be used as an indicator of the level of fish freshness. The first and second tests were carried out for 24 hours each. pH testing and taking photos were carried out every hour simultaneously by leaving the fish at room temperature right after the fish was killed by pricking it on the head. pH testing in graphic form can be seen in Figure 9 and Figure 11,



(a) (b)

Figure 8 pH result graph of the (a) first experiment, and (b) second experiment

Based on Figure 8(a), the pre-rigor phase lasts very short in the three types of fish, namely one to two hours after the fish dies. The decrease in pH continues to occur over time and is an indicator of entering the rigor mortis phase. The rigor mortis phase lasts for seven to nine hours after the pre-rigor phase, and begins to decrease below six after that, which indicates that the fish is starting to enter the post-rigor phase. The post rigor phase occurs at the eighth and tenth hour after the death of the fish. Based on Figure 8(b), the pre-rigor phase lasts very short in the three types of fish, namely one to three hours after the fish dies. The rigor mortis phase lasts for ten to eleven hours after the pre-rigor phase, and begins to decrease below six after that, which indicates that the fish is starting to enter the post-rigor phase. The post rigor phase occurs at the eighth and tenth hour after the death of the fish.

Changes in pH values in Figures 8(a) and 8(b) exhibit a similar pattern. All types of fish experience a significant decrease in pH from the pre-rigor phase to the rigor mortis phase, followed by an increase in pH during the post-rigor phase, indicating the onset of spoilage. When the fish is killed or in the pre-rigor phase, blood circulation stops, leading to a decrease in oxygen within the fish tissues. This causes muscle cells to switch to anaerobic metabolism to produce energy, involving glycolysis where glycogen is broken down into lactic acid. The accumulation of lactic acid causes a decrease in muscle pH, creating an acidic environment that inhibits the growth of some pathogenic bacteria. During the rigor mortis phase, there is a decline in adenosine triphosphate (ATP), the main energy molecule used by cells for biological processes. After death, ATP reserves decrease due to the lack of new ATP production, causing calcium ions to be released into the muscle cytoplasm, binding to troponin and leading to muscle contraction. As a result, the muscles cannot relax and become stiff. In this phase, lactic acid continues to accumulate, further lowering the pH and temporarily inhibiting proteolytic enzyme activity, thus maintaining muscle rigidity. Once the rigor mortis phase ends, endogenous enzymes like cathepsins and calpains start breaking down muscle proteins, increasing microbial activity which degrades proteins into peptides and amino acids. Enzymes and microbes produce basic compounds such as ammonia, trimethylamine, and other amines, causing the pH to increase towards neutral or slightly alkaline. Protein degradation and the increase in pH result in the muscle texture becoming softer and more tender, while the fish odor changes to an unpleasant one due to the production of volatile compounds by microbes (Daskalova 2019).

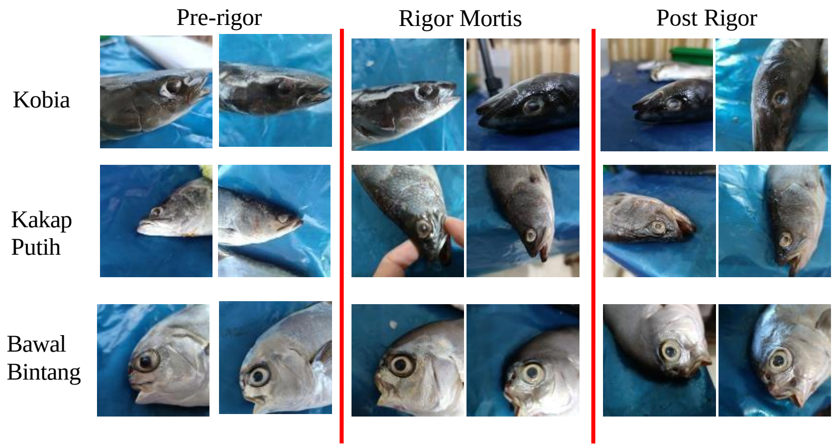


Figure 9 Sample comparison images of the three types of fish

One parameter that can be used to determine the level of freshness of fish is to look at the condition of its eyes. Based on Figure 9, it can be seen that there are changes in the condition of the eye and the surrounding area in each phase. In the pre-rigor phase, the fish is still very fresh with the same characteristics as when the fish was still alive, so that the eyes appear bright, the eyeballs are convex or protruding, and the cornea is still clear. In the rigor mortis phase, the eyes appear slightly bright, the eyeballs are flat, the cornea is slightly cloudy, and the pupils are white. In the post rigor phase, the fish's eyeballs are slightly concave, the pupils and cornea are slightly cloudy, and the pupils turn grayish.

3.2 Evaluation Model

Taking photos focusing on the fish's eye area and surrounding areas is carried out at the same time as the pH test. The results of the pH test table obtained in the previous stage are used as a reference for sorting images based on their level of freshness. Detection is divided into three classes, namely fresh or pre rigor, slightly fresh or rigor mortis, and not fresh or post rigor. The total dataset is 4979. The resulting dataset is not balanced between the three classes for each type of fish. This was overcome by carrying out an oversampling process using the Synthetic Minority Over-sampling Technique (SMOTE) method for classes for each type of fish where data was still lacking. The number of datasets that will be used for train and test is 600 for each class for all types of fish so that the total dataset that will be used is 5400.

The oversampled dataset was then split into training and testing data. The method used was 10-fold cross-validation. This was done to avoid bias arising from the differing characteristics of the images. The evaluation results comparing the two algorithms can be seen in Table 1.

Table 1 Comparison of model accuracy for the Faster R-CNN algorithm, and YOLOv5 with 10-fold cross validation

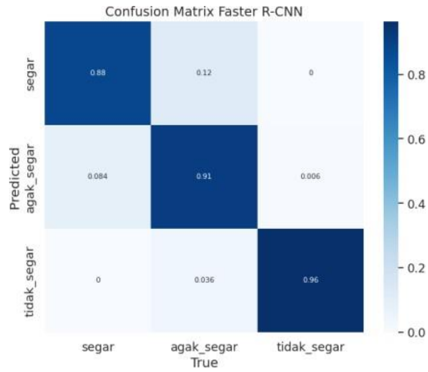
YOLOv5					
Model	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**Accuracy (%)**	**mAP@.5 (%)**
Dataset 1	97.2	100	98.6	98.3	99.4
Dataset 2	97.9	99.4	98.6	99	99.5
Dataset 3	99.3	96.3	97.8	98.3	99.3
Dataset 4	99.4	97.9	98.6	99	99.5
Dataset 5	97.2	99.9	98.5	99	99.4
Dataset 6	99.2	96.2	97.7	99.3	99.4
Dataset 7	96.7	99.8	98.2	99.3	99.4
Dataset 8	99.4	98.1	98.7	99.3	99.3
Dataset 9	99.3	96.6	97.9	98.3	99.3
Dataset 10	99.7	97	98.3	98.3	99.4
Average	**98.53**	**98.12**	**98.29**	**98.81**	**99.39**
Faster R-CNN					
Model	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**Accuracy (%)**	**mAP@.5 (%)**
Dataset 1	92.3	91.8	92.1	91.4	97.4
Dataset 2	77.8	77.6	77.2	76.8	83.1
Dataset 3	87.5	86.4	86.2	86.1	94.4
Dataset 4	82.5	82.1	82	81.8	92.7
Dataset 5	87.9	88.4	88.1	88.1	94.4
Dataset 6	85.8	84.3	84.5	85.4	88.9
Dataset 7	86.6	87	86.8	86.5	94.4
Dataset 8	88.1	88.5	88.2	88	95.3
Dataset 9	82.4	83.4	82.1	82.4	90.2
Dataset 10	83.8	76.8	78.4	79	86
Average	**85.47**	**84.63**	**84.56**	**84.55**	**91.68**

Based on Table 1, the YOLOv5 algorithm has a better average value for each metric, including precision, recall, f1-score, accuracy and mAP, compared to Faster R-CNN. Precision is a metric that describes the accuracy of the requested data with the prediction results produced by the model. In the YOLOv5 algorithm, dataset 10 has the highest precision value of 99.7%, and Faster R-CNN on dataset 1 is 92.3%. Recall is a metric that describes the accuracy of the model's prediction results compared to the total amount of ground truth for a class. In the YOLOv5 algorithm, dataset 1 has the highest recall value of 100%, and Faster R-CNN on dataset 1 is 91.8%. F1-score is a metric that describes the balance between precision and recall. In the YOLOv5 algorithm, the highest f1-score was on dataset 8 at 98.7%, and Faster R-CNN on dataset 1 was 92.1%. Accuracy is a metric that describes how accurately the model correctly classifies the entire prediction dataset. In the YOLOv5 algorithm, the highest accuracy value is from datasets 6, 7, and 8 at 99.3%, and Faster-RCNN on dataset 1 is 91.4%. Mean average precision (mAP) is a metric to see object detection performance by paying attention to the intersection over union (IoU) between ground truth boxes and bounding boxes to obtain values such as TP, FP, and confidence score for each prediction result. In the YOLOv5 algorithm, datasets 2 and 4 have the highest mAP value of 99.5%, and Faster R-CNN on dataset 1 of 97.4%. The best algorithm will be used for implementation into the Android application. In the YOLOv5 algorithm, the model on dataset 8 was chosen because it has quite high values in all metrics.

(a) (b) (c)

Gambar 10 Sampel gambar beberapa kesalahan pendeteksian pada algoritma Faster-RCNN untuk (a) ikan kobia, (b) gabungan ketiga jenis ikan, dan (c) ikan bawal bintang

In Figure 10(a), the algorithm mistakenly identifies the light reflection from the cobia fish skin as the eye of the fish, labeling it as fresh. This occurs because during image capture, an unintended reflection formed, resembling the characteristics of a fish eye. Variations in lighting, camera angle, and resolution are variables that can affect detection. In Figure 10(b), the algorithm also mistakenly identifies the upper mouth of the star pomfret fish as the eye of the fish, labeling it as slightly fresh. When the image is enlarged, it is evident that the upper mouth resembles the characteristics of a fish eye. In Figure 10(c), the algorithm produces two labels for one detection target: fresh and slightly fresh. The correct label for the image is fresh. The algorithm generates two labels because the image depicts a fresh fish in its final hour before transitioning to slightly fresh, resulting in similar visual characteristics such as color, texture, or shine, with very subtle differences that make it difficult for the model to identify.



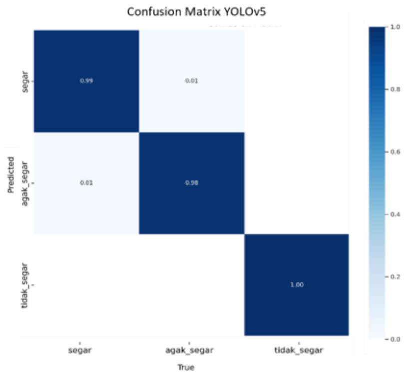
Gambar 11 *Confusion matrix* algoritma Faster R-CNN pada dataset 1

The misclassification presented in Figure 10 is supported by the confusion matrix results in Figure 11. The model correctly classifies 88% of the fresh fish images as fresh, while the remaining 12% are misclassified as slightly fresh. A similar pattern is observed in the slightly fresh class, where the model correctly classifies 91% of the slightly fresh fish images as slightly fresh, while 8.4% are misclassified as fresh and 0.6% as not fresh. For the not fresh class, the model correctly classifies 96% of the not fresh fish images as not fresh, with 3.6% misclassified as slightly fresh. The results indicate that the model does not make significant misclassification errors, such as classifying fresh fish as not fresh or vice versa, since these two classes have distinctly different characteristics. This demonstrates that the model is capable of accurately recognizing the differences between the classes.

(a) (b)

Gambar 12 Sampel gambar beberapa kesalahan pendeteksian pada algoritma YOLOv5 untuk (a) ikan kobia, dan (b) ikan kakap putih

In Figure 12(a), the algorithm mistakenly identifies the circle on the phone tripod as the eye of a fish, labeling it as slightly fresh. This occurs because the detected part resembles a fish eye, being circular and black in color. In Figure 12(b), the algorithm produces two labels for one detection target: fresh and slightly fresh. The correct label for the image is fresh. This happens similarly to the sample in Figure 12(c), where the image depicts a fresh fish in its final hour before transitioning to slightly fresh. Consequently, the visual characteristics such as color, texture, or shine are very similar, with subtle differences that make it difficult for the model to identify.



Gambar 13 *Confusion matrix* algoritma YOLOv5 pada dataset 8

The misclassification presented in Figure 12 is supported by the confusion matrix results in Figure 13. The model correctly classifies 99% of the fresh fish images as fresh, while the remaining 1% are misclassified as slightly fresh. A similar pattern is observed in the slightly fresh class, where the model correctly classifies 98% of the slightly fresh fish images as slightly fresh, while the remaining 1% are misclassified as fresh. For the not fresh class, the model correctly classifies 100% of the not fresh fish images as not fresh. The results indicate that the model does not make significant misclassification errors, such as classifying fresh fish as not fresh or vice versa, since these two classes have distinctly different characteristics. This demonstrates that the model is capable of accurately recognizing the differences between the classes.

3.3 Implementation Model

At this stage, the best model is converted into a TorchScript lite model first before being used in the Android application. The fish freshness level detection application has several ways of taking pictures, including being able to take photos of fish directly from the application, selecting images from the gallery, and being able to carry out real-time detection by pointing the camera at the fish. When detection is carried out, several information will appear, namely the freshness level of the fish and the confidence score. Confidence score is a value that shows how confident the model is in detecting an image. The application display can be seen in Figure 14.

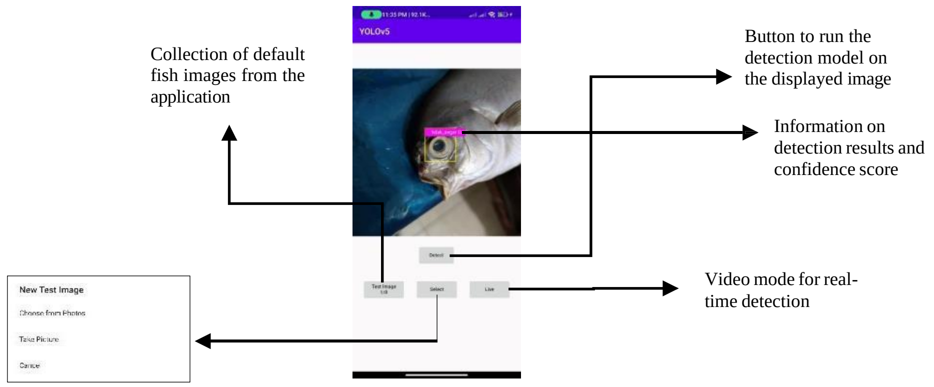


Figure 14 Application display of fish freshness level

4. CONCLUSIONS

Measuring pH and taking pictures of the fish's eyes which were carried out every hour immediately after the fish were killed in clearly captured the process of changes in the condition of the fish's eyes in the three types of fish (*Rachycentron canadum* or cobia fish, *Trachinotus blochii* or pomfret, and *Lates calcarifer* or white snapper). The dataset obtained from this process produces good average values for each metric, both for YOLOv5 and Faster-RCNN. However, YOLOv5 has a higher average value of each metric compared to Faster R-CNN. In the YOLOv5 algorithm, the highest precision value is from dataset 10 at 99.7%, the highest recall value is from dataset 1 at 100%, the highest f1-score is from dataset 8 at 98.7%, the highest accuracy value is from datasets 6, 7, and 8 amounted to 99.3%, and the highest mAP value was from datasets 2 and 4 at 99.5%. In the Faster-RCNN algorithm, the highest precision value is from dataset 1 at 92.3%, the highest recall value is from dataset 1 at 91.8%, the highest f1-score is from dataset 1 at 92.1%, the highest accuracy value is from dataset 1 at 91.4 %, and the highest mAP value is from dataset 1 at 97.4%. The YOLOv5 model for dataset 8 was chosen for the Android application implementation because it has quite high values in all metrics. The implementation in the form of an Android application functions well with several important features and information needed such as fish freshness level results and confidence scores.

REFERENCES

[1] A. Bochkovskiy, C.Y. Wang, and H.Y.M. Liao, “YOLOv4: Optimal speed and accuracy of object detection,” *arXiv*, vol. 2004, pp. 1-17, 2020.

[2] A. Daskalova, “A farmed fish welfare: stress, post-mortem muscle metabolism, and stress-related meat quality changes,” *International Aquatic Research*, vol. 11, pp. 113-124, 2019.

[3] A.R. Prananda, E.L. Frannita, E. Pramitaningrum, A. Hidayat, W.B. Setiawan, N. Purwaningsih, “Klasifikasi jenis cacat kulit menggunakan SMOTE-GoogLeNet,” *Journal Informatic Technology and Communication* vol. 8, no. 1, pp. 23-32, 2024

[4] A. Santoso, and G. Ariyanto, “Implementasi deep learning berbasis keras untuk pengenalan wajah,” *Jurnal Emitor*, vol. 18, no. 1, pp. 15-21, 2018.

[5] B. Anwar, “Penerapan algoritma jaringan syaraf tiruan *backpropagation* dalam memprediksi tingkat suku bunga bank,” *Jurnal SAINTIKOM*, vol. 10, no. 2, pp. 111-123, 2011.

[6] Badan Standarisasi Nasional (BSN). *Ikan Segar SNI 01-2729-2013*¸Jakarta, ID: Badan Standarisasi Nasional (BSN), 2013.

[7] D. Kumar, S. Kumar, and Rajput, “An intelligent system for fish freshness quality assessment using artificial neural network,” *IJCRT (International Journal of Creative Research Thoughts)*, vol. 8, no. 2, pp. 765-958, 2020.

[8] G. Jocher. “YOLOv5”. Ultralytics. https://docs.ultralytics.com/. (accesed on May 10, 2020].

[9] H.M. Lalabadi, M. Sadeghi, and S.A. Mireei, “Fish freshness categorization from eyes and gills color features using multiclass artificial neural network and support vector machines,” *Aquacultural Engineering*, vol. 90, no. 2020, pp. 1-9, 2020.

[10] J. Han, and M. Kamber, *Data Mining: Concepts and Techniques Tutorial*, San Fransisco, USA: Morgan Kaufman Publisher, 2001.

[11] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, “You only look once: unified, real-time object detection,” *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2016.

[12] J. Solawetz. “Yolov5 new version-improvement and evaluation”. Roboflow. https://blog.roboflow.com/yolov5-improvements-and-evaluation/. (accesed on Jan. 10, 2023)

[13] I.C. Navotas, C.N.V. Santos, E.J.M. Balderrama, F.E.B. Candido, A.J.E. Villacanas, and J.S. Velasco, “Fish identification and freshness classification through image processing using artificial neural network,” *(ARPN) Asian Research Publishing Network Journal of Engineering and Applied Sciences*, vol. 13, no. 18, pp. 4912-4922, 2018.

[14] L.K.S. Tolentino, J.W.F. Orillo, P.D. Aguacito, E.J.M. Colango, J.R.H. Malit, J.T.G. Marcelino, A.C. Nadora, and A.J.D. Odeza, “Fish freshness determination through support vector machine,” *Journal of Telecommunication, Electronic, and Computer Engineering*, vol. 9, no. 2-5, pp. 139-143, 2017.

[15] M.F. Fibrianda, and A. Bhawiyuga, “Analisis perbandingan akurasi deteksi serangan pada jaringan komputer dengan metode naïve bayes dan support vector machine (SVM),” *Jurnal Pengembangan Teknologi Informasi dan Ilmu Komputer*, vol. 2, no. 9, pp. 3112-3123, 2018.

[16] M.H. Sazli, “A brief review of feed forward neural networks,” *Commun. Fac. Sci. Univ. Ank. Series A2-A3*, vol. 50, no. 1, pp. 11-17, 2006.

[17] M. Nurilmala, Nurjanah, A. Fatriani, A.R. Indarwati, R.M. Pertiwi “Kemunduran mutu ikan baronang (*Siganus javus*) pada penyimpanan suhu chilling,” *Jurnal Teknologi Perikanan dan Kelautan*, vol. 12, no. 1, pp. 92-101, 2021.

[18] M. Sornam, A. Radhika, and M. Manisha, “Fish freshness classification using wavelet transformation and fuzzy logic technology,” *Asian Journal of Computer Science and Information Technology*, vol. 7, no. 2, pp. 15-21, 2017.

[19] N.M.S. Iswari, Wella, and Ranny, Fish freshness classification method based on fish image using K-Nearest Neighbor. 4th International Conference on New Media Studies, 2017.

[20] N. Sengar, M.K. Dutta, B. Sarkar, “Computer vision based technique for identification of fish quality after pesticide exposure,” *International Joural of Food Properties*, vol. 20, no.s2, pp. 192-205, 2017.

[21] R. Vargas and L. Ruiz, “Deep learning: previous and present applications,” *Journal of Awareness*, vol. 2, no. 3, pp. 11-20, 2018.

[22] S. Cui, Y. Zhou, Y. Wang, and L. Zhai, “Fish detection using deep learning”. *Hindawi*, vol. 2020, pp. 1-13, 2020.

[23] S. Ren, K. He, R. Girshick, and J. Sun, “Faster-RCNN: Towards real-time object detection with region proposal networks,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 39, no. 6, pp. 1137-1149, 2017.

[24] S. Srivastava, A.V. Divekar, C. Anilkumar, I. Naik, V. Kulkarni, and V. Pattabiraman, “Comparative analysis of deep learning image detection algorithms”. *Journal of Big Data*, vol. 8, no. 1, pp. 1-27, 2021.

T. Murakoshi, T. Masuda, K. Utsumi, K. Tsubota, Y. Wada, “Glossiness and perishable food quality: visual freshness judgment of fish eyes based on luminance distribution,” *Plos One*, vol. 8, no.3, pp. 1-5, 2013.

[25] T. Nurhayati, Nurjanah, and R. Nugraha, *Fisiologi, Formasi, dan Degradasi Metabolit Hasil Perairan*, Bogor, ID: IPB Press, 2019.

[26] Y. LeCun, Y. Bengio, and G. Hinton, “Deep learning,” *Nature*, vol. 521, no. 7553, pp. 436-444, 2015.