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LOBSTER AGE DETECTION USING DIGITAL VIDEO-BASED YOLO V8 ALGORITHM

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Abstract

Lobster is an aquatic animal that has high economic value in the fishing industry. Demand for lobster in both domestic and export markets continues to increase thanks to its delicious meat and a variety of desirable dishes. Indonesia, especially Java Island, contributes significantly to the national lobster production. However, the current manual determination of lobster age has limitations such as complexity, time required, and subjectivity in assessment.To overcome this problem, this research proposes the detection of lobster age using the YOLO (You Only Look Once) method, specifically the YOLOv8 version. This algorithm is known to be able to perform image and video recognition quickly and produce high accuracy. YOLOv8 can be run using a GPU, enabling parallel operations that significantly increase the speed of object detection compared to using a CPU alone. The data processing in this study involves several stages, starting from pre-processing in the form of image extraction and bounding from lobster videos. Next, the YOLOv8 algorithm was used to train the model with customized grid and bounding box parameters. The trained model is then validated and tested using lobster image and video data. The results of the test show that the developed YOLOv8 model has a precision of 0.997, recall of 0.998, mAP50 of 0.995, and mAP50-95 of 0.971. This shows that the model is able to detect and determine the age of the lobster with very high accuracy, providing a more efficient and objective solution than the manual method.

Keywords: *Age Detection, Lobster, mAP50, YOLOv8.*

1. INTRODUCTION

Lobsters are a very financially valuable seafood and have very tasty meat. Lobsters are considered one of the most profitable commodities in coastal areas. From a fisheries perspective, detailed details on lobster populations and their relationship with key habitats in deeper fishing grounds are needed for the spatialization of this species. This will help to better assess the impact of fishing and ultimately improve the sustainability of fisheries [1]. During the months of January-August 2023, lobster exports from Indonesia were recorded at 703.67 tons worth US$12.57 million. In 2022, total lobster exports amounted to 1,469.55 tons worth US$25.7 million [2]. From a fisheries standpoint, locating these species requires detailed data on lobster populations and their relationship to key habitats in deeper fishing grounds. This will help to better assess the impact of fishing and ultimately improve sustainability in the fishery [3] [4]. Understanding and monitoring lobster age is an integral part of effective marine resource management. The age of a lobster is an important factor affecting its price and quality, as well as protein sufficiency for growth. Currently, the determination of lobster age is generally done manually by experts through observation of the morphology and physical characteristics of the lobster. This manual method includes observations of shell, body size, and carapace structure [5]. However, this manual method has several limitations, such as complexity, time required, and subjectivity in assessment [6]. Several alternative methods have been tried to determine the age of aquatic animals, such as otolith analysis and chemical tagging, but these methods are often expensive and require specialized equipment [7]. In this study, the authors used bamboo lobster and sand lobster for age detection because both have high economic value and are commonly cultivated species in Indonesia. In addition, the similar size and shape between these two lobster species make manual identification difficult and error-prone [8]. Based on these problems, in this study a lobster age detection was made using the YOLO (You Only Look Once) method. The main focus of the YOLO target detection algorithm is the fast calculation speed and small model size. The structure of the YOLO structure is quite simple. YOLO can use neural networks directly to display the position and category of the bounding box. This is because YOLO only needs to input the image into the network to obtain the final detection result, which allows YOLO to perform video timing detection. YOLO has a strong generalization ability as it can learn very general features that are transferred to other fields [9], [10], [11]. In this study the authors used YOLO Version 8 because YOLOv8 has shown significant improvements in terms of accuracy and speed, making it the right choice for Digital Video-based Lobster age detection. This research presents a Lobster age detection system based on YOLOv8 based on Digital video. The system architecture is described, and experimental results are provided showing its effectiveness in Digital Video-based Lobster age detection [12]. Previous research has been carried out related to the automatic detection of western rock lobster using synthetic data with the YOLOv3 method, This research focuses on developing an automated approach to detect lobsters with underwater imaging. the highest mAP was achieved using 500 synthetic, images in the training set (250 each of antenna and body images). the mAP achieved by including 100 and 250 synthetic images in the training set was also comparable to the highest mAP achieved [13]. Furthermore, previous research used two approaches to detect and manipulate lobsters with a FANUC robotic arm 'FANUC LR Mate 200iD/7L'. The first approach used the iRVision vision system with GPM Locator and CSM Locator, which failed to detect with sufficient accuracy and speed. The second approach used YOLOv4 on Nvidia Jetson NX, which achieved 99.29% precision with a detection time of 0.1806 seconds. These results show that YOLOv4 is superior in accuracy and speed. However, the drawback of this research is the use of YOLOv4, which is an older technology. With the rapid advancement of technology, newer algorithms such as YOLOv8 offer significant improvements in terms of detection speed and accuracy in object detection [14]. In addition, in previous research, various techniques have been used for summarization and object detection in underwater videos, using machine learning models and image processing techniques. The YOLOv3 model was used to detect objects after keyframes extraction with the perceived motion energy (PME) method. Its accuracy is not explicitly mentioned in this study. Underwater videos suffer from blurry and low contrast image problems, which affect the detection quality still needed to improve efficiency [15]. After the training is complete, the trained YOLOv8 model will be tested using previously collected lobster video data. Therefore, this research focuses on developing a method for detecting and estimating the age of lobsters using the YOLOv8 model. By applying the YOLOv8 algorithm to digital videos, the authors hope to identify and estimate the age of lobsters with a high level of accuracy.

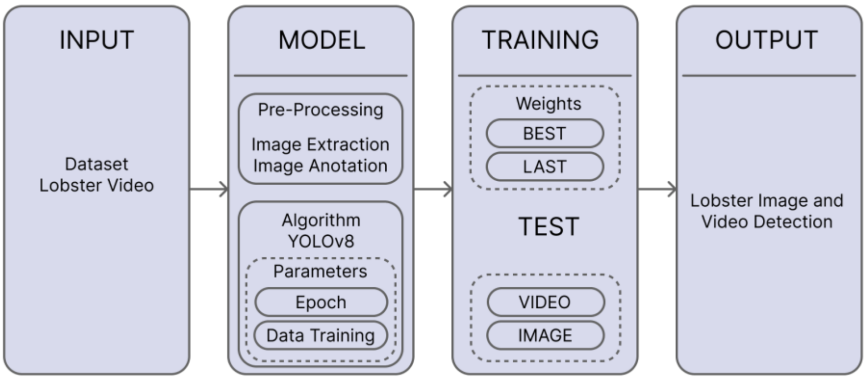

Figure 1 Data processing framework using YOLOv8

2. RESEARCH METHODS

The method used for video detection of Lobster age can be shown in Figure 1 with the YOLOv8 method. The process starts from the input of a lobster video which is then processed in the pre-processing stage. At this stage, images are extracted from the video to 1772 images and given bounding to mark the age of the lobster and there are 3 classes namely Age 2 months, Age 3-4 months, Age 5-6 months. After pre-processing, the bounded images are used to train the object detection model using YOLOv8 algorithm.

The best model weight (BEST) and the last model weight (LAST) are generated during training. The trained model is then tested using video data and lobster images to assess its accuracy and performance. The end result of this process is a model that is able to accurately detect lobsters in images and videos, so as to determine the age of lobsters based on the parameters that have been trained using the YOLOv8 algorithm.

2.1. Data Set

Input data used in this system is lobster video. This video will be processed for image extraction then the bounding process. the process of separating data that has been extracted includes Train set 1551 images, Valid set 147 images, Test set 74 images.

2.2. Preprocessing

In the pre-processing stage, images are extracted from the lobster video using the Roboflow platform.

This process produces static images that will be used in training and testing the model. After extraction, the images are annotated using Roboflow as well [16]. In the bounding process, three age classes, namely Age 2 months, Age 3-4 months, and Age 5-6 months, are used for two types of lobsters, namely Bamboo Lobster and Sand Lobster. In this study, the data or video capture process was carried out with the provision of a distance from the object of 40 cm and ensuring the position of the object was right in the middle during the video capture process. This step is important to ensure the consistency and quality of the data obtained, making it possible to obtain images with optimal resolution for further analysis. This process ensures that the information obtained from each image is of sufficient quality for the lobster detection and age estimation process to be carried out using the YOLOv8 algorithm.

2.3. Method Implemantion

After the pre-processing stage, where images are extracted and annotated, this research uses the YOLOv8 algorithm to train the object detection model [17]. An algorithm was created by the researcher to use YOLOv8 to perform Lobster Age Detection. Later this will be executed according to each code that has been created by the researcher.

2.4. YOLOv8 Method Training

The training process in system development using the YOLOv8 technique involves the execution of developer code as an integral part of the process. In this training, three classes were identified, namely 2-month-old lobsters, 3-4-month-old lobsters, and 5-6-month-old lobsters, which were the focus of the analysis. The training was conducted using 70 epochs, where each epoch represents one iteration through the entire training dataset. Test scores were obtained during the training procedure by processing the collected datasets of the three classes. These test results are a useful source of comparison, referring to previous research relevant to the development of lobster age detection algorithms and models [18].

2.5. YOLOv8 Method Testing

After completing the model training process with the YOLOv8 technique, the performance of the model was tested on two types of data, namely videos and images. The first test was conducted using video recordings of lobster activity and aimed to evaluate the model's ability to detect moving objects. In addition, the model was also tested with lobster images extracted from the video, so that the detection accuracy could be evaluated with still image data. This approach provides a comprehensive evaluation of pattern recognition performance in various contexts, ranging from moving data to static data. This is important to ensure the reliability of the model in providing accurate lobster age estimates in various situations in real environments [19].

2.6. Evaluation

The final step in this research process is evaluation. Mean average precision or mAP is used to evaluate the performance of the model. Mean average accuracy is a parameter used as a measure of the accuracy of a model trained on a particular data set. For this lobster age detection model, the highest mAP value obtained durin training is used as the main indicator of model success [20].

$$mAp = \frac{1}{N}\int_{i=1}^{N} APi \tag{1}$$

Equation (1) in the formula calculates the average of the Average Precision (AP) values for all evaluated classes or objects, providing a measure of the overall accuracy of the model in detecting various classes or Objects.

3. RESULT AND DISCUSSION

Based on the prediction of lobster age detection shown in Figure 2, it can be explained that 2-month-old lobsters have a mAP value of 0.96, 3-4-month-old lobsters have a mAP value of 0.97, and 5-6-month-old lobsters have a mAP value of 0.97. These results show that lobster age detection using YOLOv8 is very accurate and consistent. The model is able to recognize 2-month-old lobsters of small size, 3-4-month-old lobsters of medium size, and 5-6-month-old lobsters of large size that are ready for harvest, which provides important information for determining the optimal harvest time.

Pre-processing per image takes 0.6 ms, while the time required for the YOLOv8 model to perform inference per image is 4.7 ms, and post-processing per image takes 2.6 ms. The high efficiency and accuracy of this model make it a very useful tool for industrial applications in monitoring and managing lobster populations in real-time. With these capabilities, the YOLOv8 model not only improves the productivity and efficiency of lobster fishing operations, but also helps in maintaining the sustainability of the lobster population by ensuring that each age stage of the lobster can be detected and categorized quickly and precisely. This enables better resource management and can contribute to more sustainable and economical lobster fishing practices.

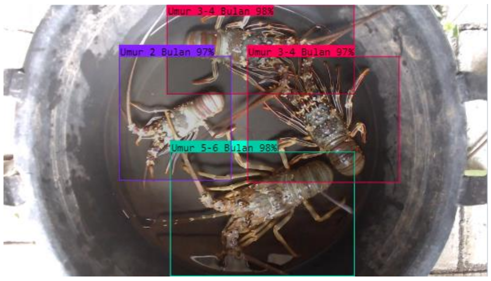

Figure 2 Lobster Age Prediction Results using the YOLOv8 model

Figure 3 shows the training and validation results of the YOLOv8 model for lobster age prediction through various important evaluation metrics. The loss graphs (train/box_loss, train/cls_loss, train/dfl_loss) decrease consistently, indicating improved accuracy in object location and classification during the training process. This consistent decrease reflects the model's improved understanding of important features related to lobster age. Precision (metrics/precision(B)) and recall (metrics/recall(B)) remained high, indicating accurate and consistent detection, meaning the model was able to correctly detect and classify almost all lobsters at various ages.

In the validation data, the loss graphs (val/box_loss, val/cls_loss, val/dfl_loss) show a significant decrease. This indicates that the model learned well from the training data and was able to reduce the error effectively. This graph reflects how the model adjusts its internal parameters to predict more accurately over time. In addition, the high and stable mean Precision (metric/mAP50(B) and metric/mAP50-95(B)) values indicate the excellent performance of the model in detecting the age of lobsters. A high mAP value means that the model can detect lobsters with high precision at various thresholds, from easier (mAP50) to more difficult (mAP50-95), indicating a strong generalization ability of the model to new data.

The efficiency of the model's processing time is also very important. With a preprocessing time of 0.6 milliseconds, inference of 4.7 milliseconds, and postprocessing of 2.6 milliseconds per image, the model demonstrated the ability to process data very quickly. This is critical for real-time applications, such as in industrial environments to efficiently monitor and manage lobster populations. This speed ensures that the model is not only accurate in detecting lobster age, but also fast enough to be used in situations where time is a critical factor. These results confirm that the YOLOv8 model not only has a high level of accuracy, but also the efficiency required for practical applications in the real world.

Detection model was trained and tested using YOLOv8 with lobster image data uploaded to Google Colab. The hardware used includes T4 GPU acceleration with Python 3 runtime environment. For this experiment, a limited and free version of Google Colab was used. Table 1 shows the main results of the training: after 70 training epochs, the values of precision, recall, mAP50 (mean Precision Average at 50% Intersection over Union), and mAP50-95 for different lobster age classes. These values show high levels of precision, recall, and mAP50-95 for each of the lobster age classes.

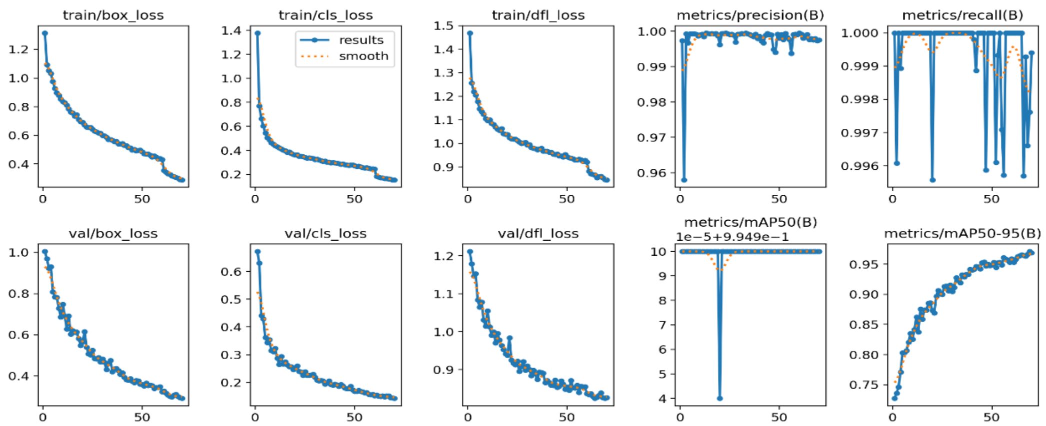

Figure 3 Comparison Chart of Accuracy and Loss of Age Model on Lobster

Table 1 Performance Metrics of YOLOv8 Model for Lobster Age Detection

Class	Intances	Box and Mask		
		Precision	Recall	Map 50-95
All	588	0.997	0.998	0.971
2 months old	147		0.998	0.968
3-4 months old	294	1	1	0.971
5-6 months old	147	1	1	0.974

Table 1 shows the training and testing results of the lobster detection model with the YOLOv8 algorithm. From these results, it can be concluded that the model can effectively identify and classify the age of lobsters with very high accuracy. Consistent mAP50-95 values above 0.97 indicate the model's ability to provide consistent and reliable estimates. In the age group of 2-month-old lobsters, the precision value reached 0.998 and the recall value reached 0.968, indicating the ability of the model to accurately identify 2-month-old lobsters. As for the 3-4 month and 5-6 month age groups, both precision and recall values reached 1.0, indicating that the model was able to classify both classes without error. These results show that the lobster age detection model using YOLOv8 is successful in providing accurate and consistent age estimates, which has broad potential to be used in different contexts.

The graphs shown are the performance evaluation results of the YOLOv8 algorithm for lobster age detection using digital video. These plots consist of a precision-confidence curve, a precision-recall curve, and a recall-confidence curve, each of which gives a different picture of the model's performance. The accuracy-confidence curve shows the relationship between the accuracy and confidence of the model for detecting lobsters of different ages (2 months, 3-4 months, 5-6 months) and all classes [21]. The precision-recall curve depicts the relationship between precision and recall, showing how well the model detects all objects that are expected to be detected with as few errors as possible [22]. The gain versus confidence curve shows the relationship between gain and confidence level and gives an idea of how well the model detects objects with different confidence levels [23]. Overall, these plots show that the YOLOv8 model performs very well in detecting lobster age with high precision and recall at different confidence levels.

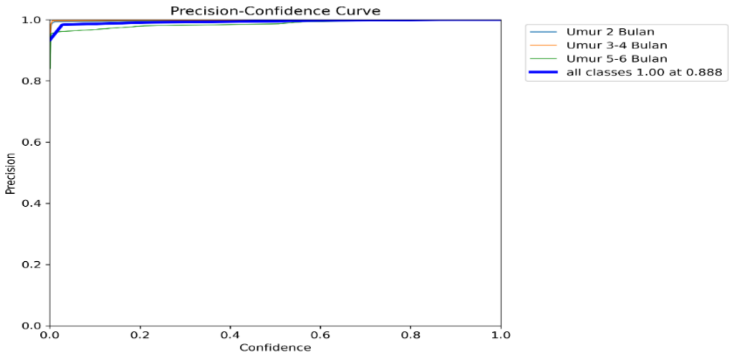

Figure 4 Precision-Confidence Curve

In Figure 4, the graph shows the relationship between precision and confidence for each lobster age class (Age 2 Months, Age 3-4 Months, Age 5-6 Months) and for all classes as a whole. From this graph, it can be seen that all classes have very high precision (>0.9) at various confidence levels, indicating that the YOLOv8 model is very accurate in detecting lobster age at various confidence levels.

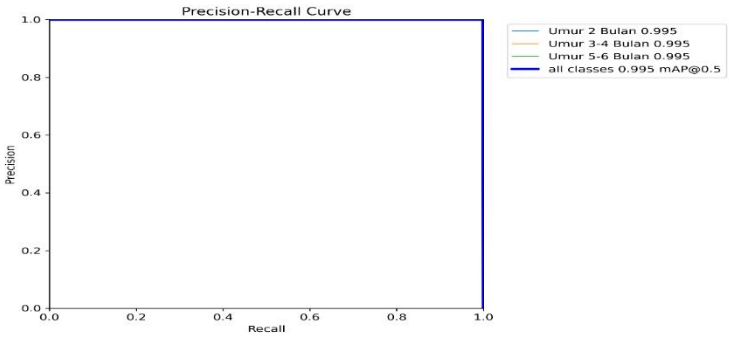

Figure 5 Precision-Recall Curve

Figure 5 presents the relationship between precision and recall for each lobster age class and all classes as a whole. mAP@0.5 (Average Accuracy with IoU Threshold 0.5) measures the average accuracy at intersections that exceed the 0.5 link threshold, which indicates how well the model detects objects of varying difficulty. This plot shows that the precision and gain of all classes are very high (0.995), which indicates that the model not only detects most objects correctly, but also rarely detects errors.

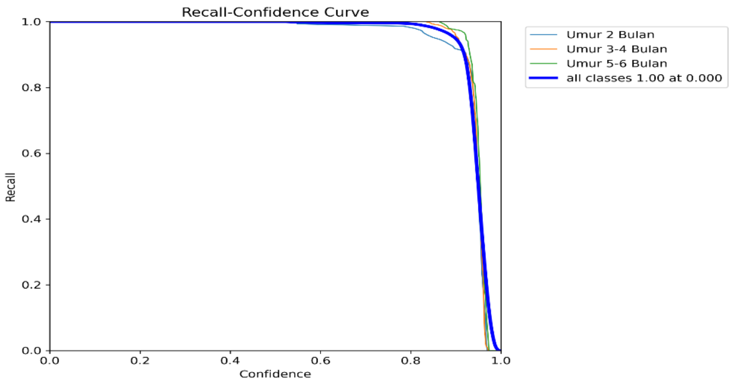

Figure 6 Recall-Confidence Curve

Figure 6 presents the relationship between recall and confidence for each category and for all categories as a whole. This plot gives an idea of how well the model detects all items that should have been detected (returned) at different confidence levels. The graph shows that recall remains high up to a certain confidence level before it starts to drop sharply, indicating that the model is very good at detecting objects with high confidence, but recall starts to drop as confidence decreases.

The study measured the bounding box of each class of lobster and produced a coordinate graph for each class to accurately monitor the growth and size distribution of the lobster. The graph allows researchers to analyze changes in the dimensions and position of the bounding box over time, helping in identifying growth patterns as well as size differences between lobster classes. With this data, researchers can gain greater insight into the factors affecting lobster growth and optimize rearing conditions to achieve better results. The following graphs were generated.

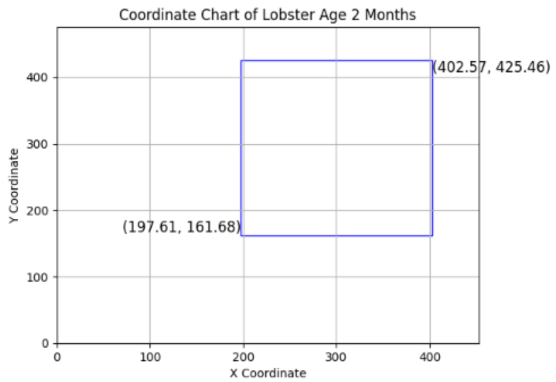

Figure 7 Bounding Box Graph of 2-Month-old Lobster Coordinates

Figure 7 shows the bounding box coordinate graph for a 2-month-old lobster, where the bottom left coordinate is (217.61, 181.68) and the top right coordinate is (402.57, 425.46). From this graph, we can calculate the average width and height of the bounding box, which is a width of 184.96 pixels resulting from the difference in x coordinates (402.57 - 217.61) and a height of 243.79 pixels resulting from the difference in y coordinates (425.46 - 181.68).

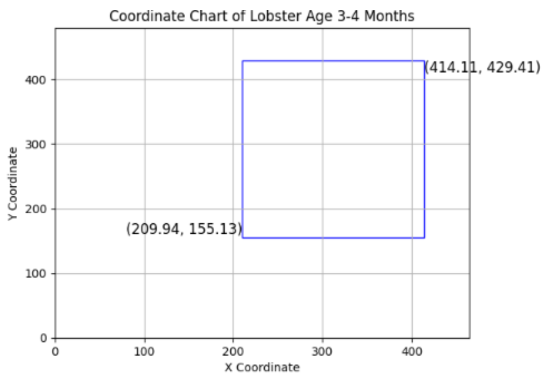

Figure 8 Bounding Box Graph of 3-4 Month-old Lobster Coordinates

Figure 8 shows the bounding box coordinate graph for 3-4 month old lobsters, where the bottom left coordinate is (209.94, 155.13) and the top right coordinate is (414.11, 429.51). From this graph, we can calculate the average width and height of the bounding box, which is a width of 204.16 pixels resulting from the difference in x coordinates (414.11 - 209.94) and a height of 274.28 pixels resulting from the difference in y coordinates (429.51 - 155.13).

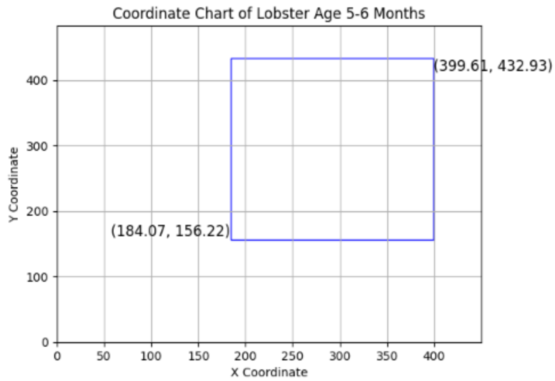

Figure 9 Bounding Box Graph of 5-6 Month-old Lobster Coordinates

Figure 9 shows the bounding box coordinate graph for 5-6 month old lobsters, where the bottom left coordinate is (164.07, 136.22) and the top right coordinate is (399.61, 432.93). From this graph, we can calculate the average width and height of the bounding box, which is a width of 235.55 pixels resulting from the difference in x coordinates (399.61 - 164.07) and a height of 296.72 pixels resulting from the difference in y coordinates (432.93 - 136.22).

Furthermore, the metrics of the training results are measured using two matrices, namely the normalized and non-normalized confusion matrices. The normalized and non-normalized confusion matrices evaluate the performance of the YOLOv8 model in lobster age detection from digital videos. The unnormalized matrix shows the absolute number of correct and incorrect predictions, while the normalized matrix shows the proportion or percentage of correct and incorrect predictions in each category. These two types of matrices give an idea about the accuracy, precision, and gain of the model. The normalized matrix helps to understand the relative efficiency of the model in each category, while the unnormalized matrix gives a concrete picture of the occurrence of errors [24], [25]. Overall, both show that the model has high performance with almost perfect accuracy, thus confirming that the model is highly effective and reliable for the task of lobster age detection. The following confusion matrix is generated:

Figure 10 shows the normalized matrix results, where the matrix describes the proportion or percentage of correct and incorrect predictions in each category. From the matrix, it can be seen that the YOLOv8 model performs very well in lobster age detection. For example, in the "2 months" category, the model successfully classified 99% of the data correctly, and only 1% was misclassified as "5-6 months". The "3-4 months" and "5-6 months" categories showed 100% accuracy, meaning all samples in those categories were correctly classified by the model. In addition, the "background" class also showed 100% accuracy which confirms that the model is very capable of distinguishing lobsters from the background. This normalized matrix helps understand the relative performance of the model in each category, showing that the model is almost perfect for lobster age classification from digital videos.

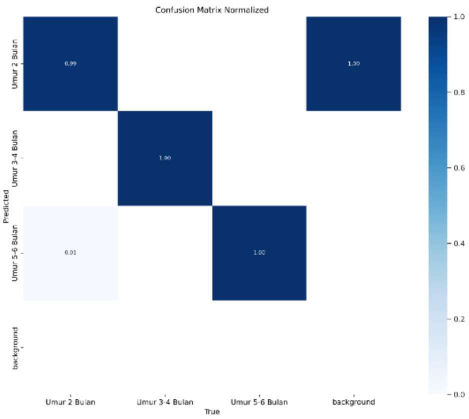

Figure 10 Normalized matrix

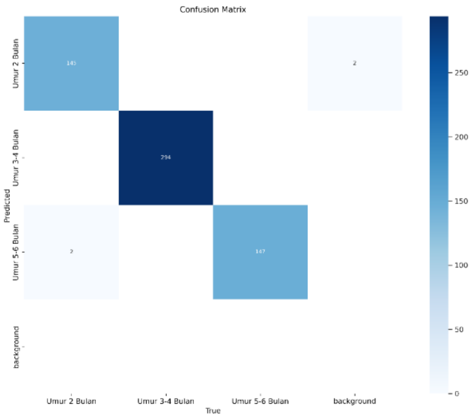

Figure 11 Unnormalized matrix

Figure 11 shows the results of the non-normalized confusion matrix, In this matrix the algorithm successfully predicts the "2 months" category with 145 correct predictions and 2 incorrect predictions, the "3-4 months" category with 294 correct predictions, and the "5-6 months" category with 147 correct predictions and 2 incorrect predictions. There were no significant prediction errors in the "background" category. These results show that the model is quite effective especially in the "3-4 months old" and "5-6 months old" categories, but there are some errors in the "2 months old" category, which may be caused by visual similarity errors between classes, so the parameters should be adjusted to improve the quality and quantity of the model or training data.

Table 2 Comparison of Previous Research Methods with Proposed Method

Research	Method	Object Detection	mAP / Accuracy
[13]	YOLOv3	Western Rock Lobster Detection (Synthetic Data)	Comparable mAP with 100-500 synthetic images (type of lobster 80%)
[14]	iRVision	Western Rock Lobster Detection with FANUC Robotic Arm	Failed in accuracy and speed
[14]	YOLOv4	Western Rock Lobster Detection with FANUC Robotic Arm	99.29% precision, 0.1806s detection time
[15]	YOLOv3	Objects in underwater videos	-
	YOLOv8 (Proposed)	Western Rock Lobster DeteWestern Rock Lobster Detection (Underwater Imaging)ction with FANUC Robotic Arm	Precision: 0.997, Recall: 0.998, mAP50: 0.995, mAP50-95: 0.971

4. DISCUSSION

Table 2 shows the comparison results between previously researched methods and the proposed method. The research mentioned in [13] used computer vision techniques for color-based image recognition and achieved 80% lobster type accuracy. In the cited research [14], YOLOv4 was used to detect lobster age with a FANUC robotic arm and achieved 99.29% accuracy. In the above-mentioned study [15], YOLOv3 was used to detect objects in underwater videos, but the detection accuracy was not reported. The proposed method uses YOLOv8 to detect the age of lobsters and achieves excellent results with precision of 0.997, recall precision of 0.998, mAP50 of 0.995 and mAP50-95 of 0.971.

The author's research uses the YOLOv8 method to determine the age of lobsters, which shows significant advantages over previous methods. Compared to previous studies that used different approaches, such as computer vision for color-based identification (80% accuracy for lobster type) and YOLOv4 on a FANUC robotic arm (99.29% accuracy for lobster age detection), the proposed method achieved an accuracy of 0.997, considering the value of 0.998, mAP50 of 0.995 and mAP50-95 of 0.971. This shows that the accuracy is significantly improved. In addition, the proposed method is based on video processing, which has its own challenges such as blurry and low-contrast images, but still provides excellent recognition results. Although previous studies used YOLOv3 to detect objects in videos without mentioning its detection accuracy, this study shows that YOLOv8 is not only superior in accuracy, but also effective in solving video image quality problems, thus increasing the importance and superiority of the proposed method in real-world applications.

5. CONCLUSION

In this study, the lobster age detection method with the YOLOv8 method successfully demonstrated its ability with very high accuracy. When the mAP50-95 reached 0.971, the model could identify lobsters aged between 2 months and 6 months with consistently high precision and gain. The fast and efficient identification process, combined with the model's ability to process digital video images, makes it a very useful tool for real-time monitoring and management of lobster populations in industrial applications. As such, this research will not only significantly advance the development of lobster detection technology, but also open up new opportunities for more sustainable and sustainable fishing.

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