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DESIGN AND DEVELOPMENT OF A DEEP LEARNING-BASED AUTOMATIC FISHERIES LOGBOOK FILLING TOOL

Rancang Bangun Alat Pengisi Logbook Perikanan Otomatis Berbasis Deep Learning

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ABSTRACT

Filling out a fishery logbook is critical in capturing fisheries to maintain fishery sustainability. However, manual logbook filling often leads to errors in data recording, which can impact the accuracy and quality of fishery data. This study propose the design of an automatic fisheries logbook filling tool based on Deep Learning, called FLOADS (Fisheries Logbook and Detection System). This system consists of instruments placed at the ship's hatch, equipped with a camera capable of detecting fish species, measuring the weight of individual fish passing through, and recording and sending data, along with the ship's position and speed, to a server on land. The development stages of the FLOADS include problem identification, tool design, prototype development, and field testing. The FLOADS prototype consisted of three parts: a fish collection container, a fish sliding area, and an Imaging Box with dimensions of 120 cm × 65 cm × 82 cm. Validation of the YOLOv5 model showed an accuracy rate of 99.07% and an F1-Score of 99.1% for recognizing the Tuna, Cakalang, and Tongkol (TCT) fish species. Field testing was conducted in Palabuhanratu using a 10 GT fishing vessel. The field testing results show that FLOADS performs well on board to detect objects with an accuracy rate of 89.1% and track vessel activities with reasonable accuracy.

Keywords: *Deep Learning, DeepSORT, Fisheries Logbook, Measurable Fishing, TCT.*

ABSTRAK

Pengisian *logbook* perikanan merupakan aktivitas kunci pada perikanan tangkap untuk menjaga keberlanjutan perikanan dan memastikan perikanan yang terukur. Namun, pengisian *logbook* secara manual seringkali menyebabkan kesalahan dalam pencatatan data yang dapat berdampak pada keakuratan dan kualitas data perikanan yang dihasilkan. Untuk mengatasi masalah tersebut pada penelitian ini dilakukan perancangan alat pengisi *logbook* perikanan otomatis berbasis *Deep Learning* yang dinamakan FLOADS (*Fisheries Logbook and Detection System*). Sistem ini terdiri atas instrumen yang ditempatkan di pintu palka kapal dilengkapi dengan kamera yang mampu mendeteksi jenis ikan, mengukur berat individu ikan yang lewat dan merekam serta mengirimkan data tersebut disertai posisi dan kecepatan kapal menuju server di darat. Tahapan pengembangan FLOADS meliputi identifikasi masalah, perancangan alat, pembuatan prototipe, dan pengujian alat. Prototipe FLOADS terdiri dari tiga bagian, yaitu bak pengumpul ikan, tempat meluncur ikan, dan *Imaging Box* dengan dimensi 120 cm x 65 cm x 82 cm. Validasi model YOLOv5 menunjukkan tingkat akurasi sebesar 99,07% dan F1-*Score* sebesar 99,1% untuk pengenalan objek ikan Tuna, Cakalang, dan Tongkol (TCT). Uji coba dilakukan di Palabuhanratu menggunakan kapal nelayan berukuran 10 GT. Hasil uji coba menunjukkan bahwa FLOADS dapat bekerja dengan baik di atas kapal untuk mendeteksi objek dengan tingkat akurasi sebesar 89,1% dan melacak aktivitas kapal dengan akurasi yang baik.

Kata kunci: *Deep Learning, DeepSORT, Logbook* Perikanan, Perikanan Terukur, TCT.

INTRODUCTION

Based on statistical data from the Ministry of Marine Affairs and Fisheries (MMAF), the total production of the Tuna, Cakalang, and Tongkol (TCT) fisheries in 2020 was 1,350,146 (KKP 2022). TCT fisheries play an essential role in the industry for developing main products, such as fresh fish, processed canned fish, and frozen processed products, to meet the demands of the international market (Prasetyo *et al*. 2018). This will undoubtedly increase fishing intensity, which triggers biological overfishing and can lead to overinvestment (economic overfishing) (Irnawati *et al.* 2019).

The measured quota-based policy in capture fisheries management is a government effort to limit fishing based on the number and species of fish, number of vessels, selective fishing gear, fishing season, local human resources, and landing port where the quota is given (Zaini 2021). This policy aims to have a long-term impact on Indonesia's fish stock and ecosystem health (Prameswari 2022). Logbook completion is one of the government's policies for paying attention to and supervising capture fisheries, especially for TCT capture fisheries with a significant market share (Zulham *et al.* 2022).

The need to fill out a logbook to report fishing activities was carried out by the regulations written in Permen KP No. 33 Tahun 2021 concerning Fishing Logbooks. Logging in logbooks has many problems, including misidentification of fish species, input of inappropriate weights and sizes, and a high data manipulation (Kiswanto *et al*. 2020). In another case, the paper is easily wet and torn, and the fishing location’s confidentiality issue causes the logbook to be filled incorrectly (Nugroho *et al.* 2017). To overcome these obstacles, the Ministry of Marine Affairs and Fisheries (MMAF) has developed several e-logbook devices, digital versions of logbooks, or Android applications (Apriliani and Nugroho 2016). However, filling out this e-logbook is still manually, which is still quite troublesome and makes fishers reluctant to fill it out (Fitrianah *et al.* 2015). Some parameters that make it difficult to fill in the logbook are the time and date of the start of the fishing operation, position of the fishing operation, type of fish caught, number and weight of the catch, and time and position of the end of the fishing operation. Therefore, a new solution is required to overcome the complexity of filling in these parameters.

YOLOv5 is an object detection algorithm that has achieved excellent results for fish detection (Liu *et al.* 2021). It uses a one-shot detection approach for efficient fish detection in images or videos. With its high detection speed and accuracy, YOLOv5 can be used in fish population monitoring, illegal fishing surveillance, and fish behavior and habitat analysis (Jan *et al*. 2007). The implementation of YOLOv5 in fish detection makes an essential contribution to the understanding and sustainable management of fishery resources. Fish detection using YOLO has a promising potential in the field of fisheries. This algorithm provides high accuracy and a fast detection speed (Santoso *et al.* 2021). With these capabilities, YOLOv5 can monitor fish populations, control illegal fishing, and further understand fish behavior and habitat (Saleh *et al.* 2022).

Simple online and real-time tracking with a deep association metric (DeepSORT) is a deep-learning technique with a tracking framework to achieve efficient and accurate object tracking (Wojke *et al.* 2017). DeepSORT uses deep neural networks to extract robust features from each detected fish object, making it capable of distinguishing between individual fish, even in complex situations (Xing *et al.* 2022). By combining appearance information and movement cues, DeepSORT can accurately track fish movement over time, even under closed conditions or changes in appearance (Wu *et al.* 2023). This tracking capability allows the system to effectively count the number of fish by continuously monitoring their positions and trajectories.

This study aims to design a prototype fishing logbook instrument that record vessel activities and catches automatically. The system consisted of an instrument placed in a vessel's hatch equipped with a camera capable the type of fish, measuring the weight of individual fish passing by, and recording and transmitting the data along with the position and speed of the vessel to a server on land.

METHOD

Time and Location

This research was conducted over four months, from June to September 2022. Instrument design and development activities were conducted at the Marine Instrumentation and Robotics Workshop, IPB Dramaga Campus, Bogor, West Java. Equipment testing was conducted at PPN Palabuhanratu, West Java, Indonesia, on August 28, 2022.

Tools and Materials

Table 1 lists the main tools and materials used in the FLOADS design process, such as logbooks and object detection.

Research Procedure

The research implementation was divided into three stages: design, production, and testing. The explanation for each stage is as follows:

Design Stage

The tool design was created using 3D SketchUp software. FLOADS consists of several parts, namely the fish holding tank, fish entry lane, and Imaging Box, which contain weight sensors, lights, and a camera on the top facing downwards. FLOADS are sized to fit TCT fishing vessels, which have a size range of 5-30 Gross Tonnage (GT). The electronic design was conducted by creating an electronic schematic consisting of an Arduino Mega, Raspberry Pi 3 B +, camera, three load cell 50 kg weight sensors with an HX711 amplifier, and a NEO6MV2 GPS. The program was design by collecting TCT fish datasets and labeling each fish species.

Production Stage

The tool manufacturing stage involves creating instruments consisting of three parts: the fish storage tank, fish sliding path, and Imaging Box. Inside the Imaging Box were lights so the camera could see the fish. Additionally, there are weight sensors that can directly measure the weight of the fish passing through them. The identification process was conducted using a webcam camera, and an outlet for the fish catch output that led directly to the ship's hold. The assembled components were placed in an electronically sealed box. Program development began by collecting datasets by launching fish into an imaging box and recording them. The dataset collection involves various samples of TCT fish, which are then launched under different conditions to simulate real-life conditions in the field. The recorded results were annotated by converting them into frames. The dataset was then labeled and divided into labeled datasets at a ratio of 90:10 for training and validation (LeCun *et al*. 2015). Subsequently, training was conducted on YOLOv5 and the resulting weights were combined with the DeepSORT algorithm. In addition, a website was created to display the detection results and fish capture locations (Yang *et al*. 2019).

Testing Stage

After designing the FLOADS, the next step was to test and evaluate the results. Testing was conducted in several stages (Liu *et al*. 2021). First, model validation was carried out to ensure the accuracy and performance of the deep learning models used, such as YOLOv5 and DeepSORT, in recognizing and tracking the types of captured fish. The confusion matrix is a table that depicts the classification results of the model by comparing the predictions made by the model with actual labels in the test dataset. This table consists of four main parts (Davis &

Table 1 Main Tools and Materials

No	Tools and Materials	Functions/descriptions
1.	Camera	Captures visual images
2.	HX711 Sensor	Measure the weight of fish
3.	Arduino Mega	Microcontroller and receiving data from the sensor
4.	GY-NEO6MV2 GPS UBLOX Sensor	Determine the location of fish capture
5.	Raspberry Pi 3 Model B	Mini-computer to execute the fish detection algorithm
6.	GSM/GPRS/GNSS/ Bluetooth HAT	Modem to transmit data to the server
7.	Plywood 61 x 122 cm	The main frame on the device
8.	Gravity *Roll*er	Provides a sliding surface for fish

Goadrich2006): True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN). The Confusion Matrix was used to calculate evaluation metrics such as accuracy, precision, recall, and F1-Score.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}\ x\ 100\% \quad ....(1)$$

$$Precision = \frac{TP}{TP+FP}\ x\ 100\% \quad ....(2)$$

$$Recall = \frac{TP}{TP+FN}\ x\ 100\% \quad ....(3)$$

$$F1-score = 2\ \frac{precision \cdot recall}{precision+recall} \quad ....(4)$$

With:
TP: true positive
FP: false positive
TN: true negative
FN: false negative

These metrics provide a more comprehensive overview of the model's performance in recognizing and classifying objects. Higher values obtained for each metric indicate better model performance. Subsequently, based on the validation results, the instruments and models were improved to enhance the performance and efficiency. Improvements were made by considering feedback from previous stage testing, including adjustments to weight sensors, hardware reliability, and interaction between instruments and the system. With these improvements, these instruments can function optimally. Finally, field testing was conducted using the improved instruments. This test was performed in Palabuhanratu, which involves a fishing vessel with a size of 10 Gross Tonnage (GT).

RESULT

Instrument Design

The FLOADS is designed considering the ease of manufacturing and minimizing costs. The design of the FLOADS instrument has a model that can be seen in Figure 1.

The FLOADS was constructed using plywood 120 cm in length, 65 cm in width, and 82 cm in height. The design of the instrument model was tailored to accommodate its use in fishing activities. Weight sensors were placed at the back of the steel roller. The fish output section was adjusted according to the type of fishing vessel. The fish collection and launching components were designed as a knockdown system, facilitating the easy assembly and disassembly of the instrument on the vessel. The installed roller is a passive roller designed to slow down the descent of the fish, allowing the camera to capture the detection results effectively. The fish launching tract is lined with aluminum to prevent damage and protect the fish from plywood contamination (Lahinta *et al*. 2020).

Figure 2 shows the placement of the FLOADS on a ship of size 10 GT. It can be observed that FLOADS can adapt to the shape of the vessel being used. The core part of FLOADS is the Imaging Box for the detecting and weighing of fish, allowing other parts to adjust to the shape of the vessel. FLOADS is positioned in front of the fish hold so that the fish can slide directly into the ship's hold. The test results indicate that the FLOADS can be placed on the ship without disrupting fishing.

Electronic System

The electronic system of the FLOADS consists of several components that play crucial roles in its operation and measurements (Figure 3). These components include the Arduino Mega, Raspberry Pi 3 B +, camera, three load cell weight sensors, HX711 as an amplifier for weight measurement, GSM modem, and GY-NEO6MV2 GPS module to obtain latitude and longitude coordinates.

The Arduino Mega served as the main controller in the FLOADS system. It is responsible for coordinating all the components and running object detection algorithms using deep learning. Raspberry Pi 3 B + is a local server that manages and stores fish capture data. The camera was integrated into the system to capture images or videos of objects passing through the detection path. Three load cell weight sensors were installed on the fish collection tank to measure the weight of fish passing through the detection path, while HX711 acted as an amplifier to convert analog signals into digital signals. The GSM modem was used to automatically send fish capture data to the server on land via a cellular network, ensuring real-time data updates. The GY-NEO6MV2 GPS module helps obtain geographical location information from the vessel, such as latitude and longitude coordinates, so that fish capture data can be associated with precise locations.

An Arduino Mega microcontroller processed the data generated by the sensors as the controller of the entire instrument system.. Subsequently, the circuitry was enclosed in an electronic sealed box designed to protect the components from water splashes. The assembled circuitry was then tested. The GPS sensor test can yield the date, time, longitude, and latitude coordinate values. Meanwhile, testing of the weight sensor begins by calibrating the sensor by placing known weight loads on the load cell. The calibration value of the HX711 sensor was obtained by adjusting the calibration factor until the sensor readings matched the known load weight (Nugraha 2017). The readings from the sensors were then fed into an Arduino program. Figure 4 depicts the linear regression of the weight values from measurements using a digital scale and load cell weight sensor. The weight values from both measurements showed little difference, resulting in a correlation value of 0.98567.

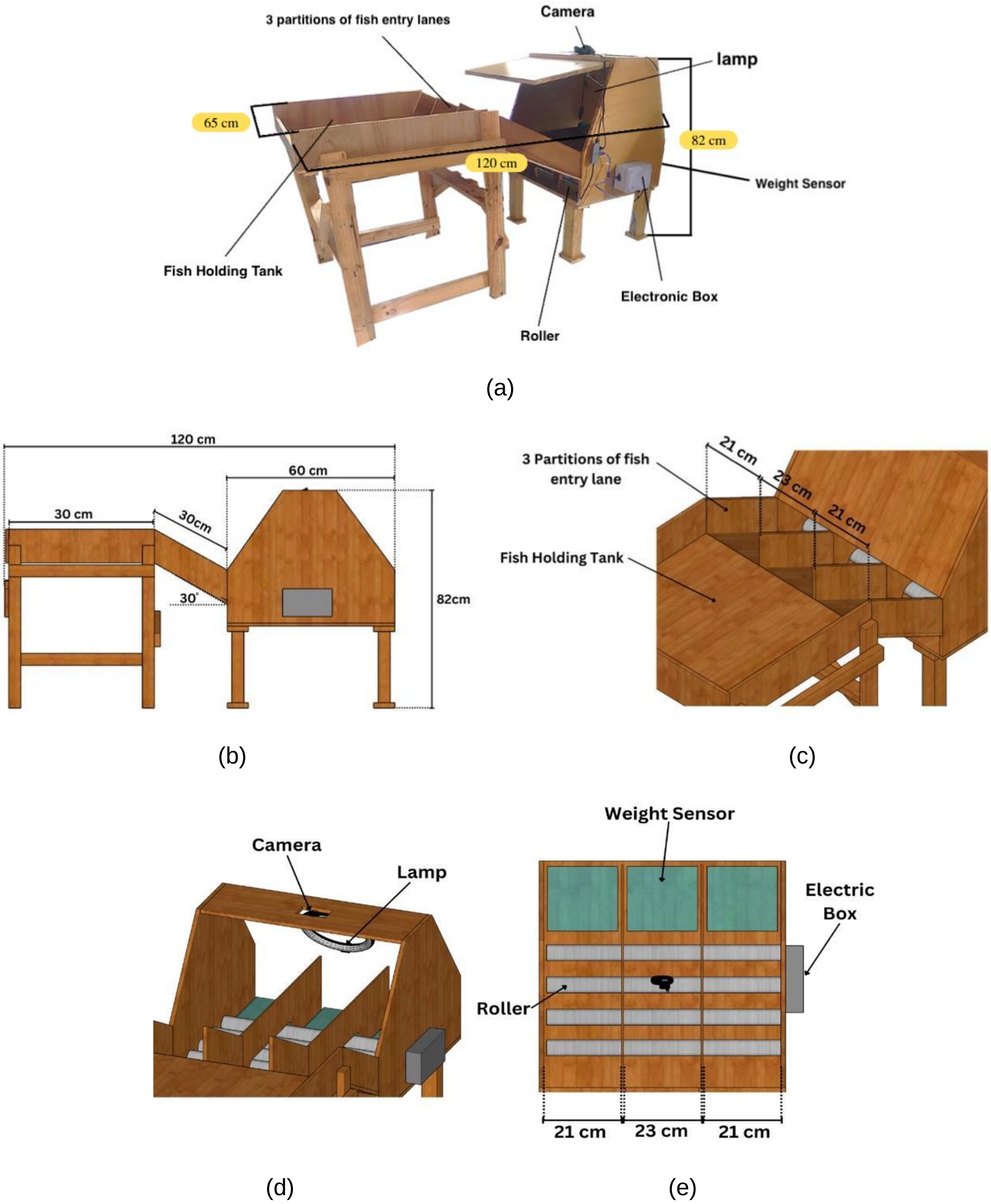


Figure 1 (a) FLOADS Production Results (b) FLOADS Design and Dimensions (c) Entry Lane Dimensions (d) Placement of Camera and Lights (e) Placement of Rollers and Weight Sensors

Figure 2 Installation of FLOADS on the Ship

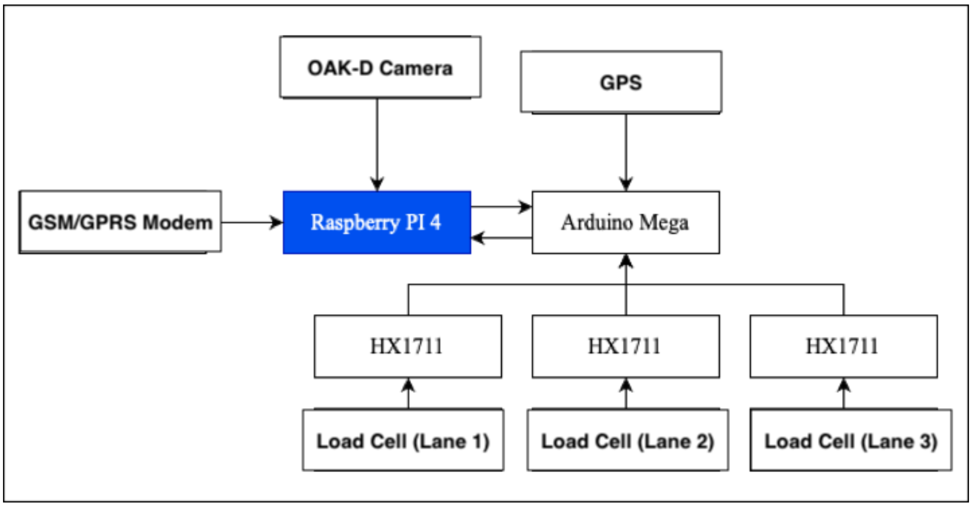


Figure 3 Diagram Blocks of Electronic System

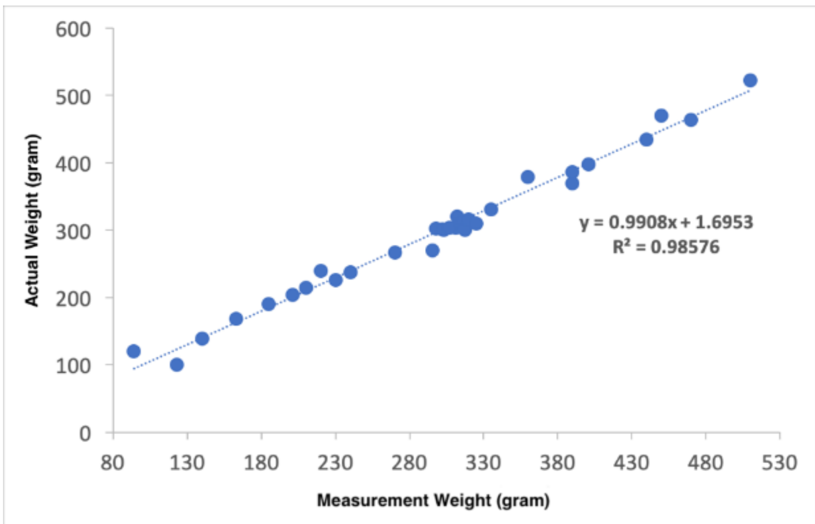


Figure 4 Graph of Load Cell Sensor Testing Results

Training and Evaluation of Detection System Model

Training data for TCT fish were obtained using a dataset collected by recording TCT fish passing through the Imaging Box. In total, 256 datasets were obtained from the recordings. These datasets were then subjected to augmentation or modification of images to enable the training process to learn from various conditions (Shorten and Khoshgoftaar 2019). Augmentation was performed using three treatments: 25% brightness, 25% brightness reduction, and applying a 4px blur.

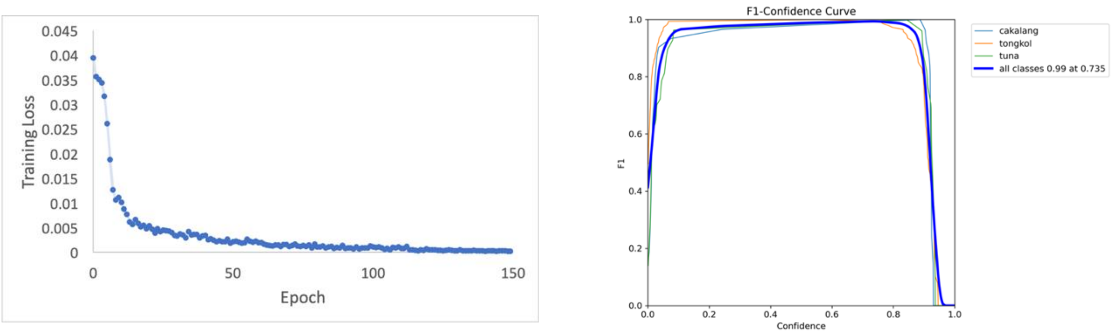
The augmentation process yielded 1024 images. Subsequently, the dataset was divided into training and validation sets at a ratio of 90:10 for the training set and validation set (Azhari *et al*. 2021). The training results were conducted using the program with 150 iterations and a batch size 32.

Based on Figure 5, it can be observed that the training loss values changed in each epoch. The training process produces optimal values when loss decreases (Le *et al*. 2011). The training loss value was 0.04, which improved to 0.003. The F1-Confidence score curve also shows that the model can perform good classification from the beginning, with all three classes reaching high peaks (0.99) at a confidence level of 0.735. The F1-score is the harmonic mean of the precision and recall (Junos *et al*. 2021), indicating that the model has good precision and recall rates.

The correlation value obtained from weight sensor testing is an indicator that describes the linear relationship between the measurement results of the load cell weight sensor and the digital scale. FLOADS produced a correlation value of 0.98567, indicating a very strong linear relationship between the measurement results of the load cell weight sensor and the digital scale. A high correlation value indicates that changes in the measurement results of the load cell weight sensor tend to be consistent with changes in the measurement results of the digital scale (Mamondol 2021). In this context, the greater the weight of the fish passing through the detection path, the greater the weight values produced by both the load cell weight sensor and digital scale.

Figure 6 illustrates the process occurring in the imaging box. The FLOADS was divided into three fish sliding lanes. When passing through the roller, fish are detected using deep learning to obtain object classes such as Tuna, Cakalang, or Tongkol, along with the confidence score of the detection. The fish will then slide towards the load cell weight sensor installed in front of the roller, and the weight of the fish in each lane will be measured. Real-time object detection by Guo *et al*. (2021) showed that the frame rate of the YOLOv3 model reached an average of 28 fps, and YOLOv4 reached an average of 13 fps with high accuracy in detecting objects. The frame rate test of the FLOADS detection system with the YOLOv5 and DeepSORT algorithms obtained a value of 21 fps. This value enables FLOADS to detect fish quickly in real time.

The model was evaluated using a trained model and validated using a validation set. Model evaluation was conducted using TCT images with bounding boxes, classes/categories, and confidence scores. The bounding box is a square line that encompasses the labeling area. The class/category is the name of the metadata containing the TCT. The confidence score represents the Intersection over Union (IoU) or the similarity and diversity values of samples used to evaluate the area between the bounding box and the ground truth box (Khairunnas *et al*. 2021). Model evaluation utilizes the confusion matrix model to display



(a) (b)

Figure 5 (a) Training loss graph with Epoch of 150 (b) The curve of F1-Confidence

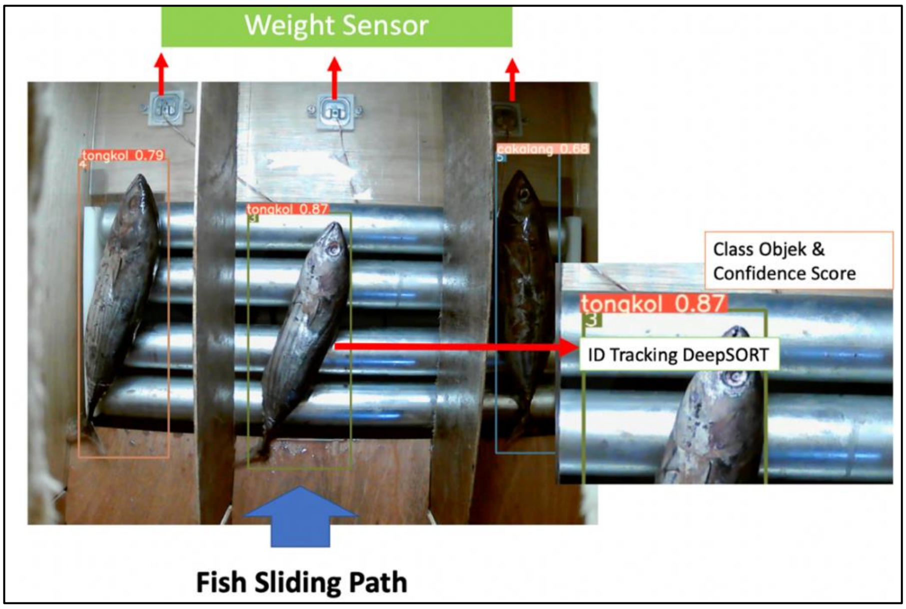


Figure 6 The system for fish detection and weight measurement inside the Imaging Box

Table 2 The precision, recall, and F1-Score values per type of fish.

Fish	*Precision*	*Recall*	F1-*Score*
Tuna	99.0%	98.2%	95.0%
Cakalang	98.9%	97.6%	99.5%
Tongkol	99.3%	99.1%	99.8%

the matrix, prediction, and actual prediction (Mahardhika *et al*. 2016). The confusion matrix results can be used as a reference for calculating the accuracy of the model, namely the accuracy, precision, recall, and F1-Score. The precision, recall, and F1-Score values for each type of fish obtained from the training results are shown in Table 2.

The resulting confusion matrix yielded a total accuracy of 99.07%, precision of 99.3%, recall of 98.3%, and F1-Score of 99.1%. The accuracy value indicated that the model was accurately designed to classify the fish types. Moreover, a higher precision value indicates a good system. Additionally, a recall value indicates the success rate of retrieving information correctly (Azhari *et al*. 2021).

Integrating Website for Monitoring Measurement Result

The website page view in Figure 7 depicts the display of a locally developed server website. In this study, a local server website was created so that fishers could access the data recorded on the vessel directly. The information displayed on the website included recordings of fish entering the Imaging Box. Fish are identified by the system based on their species, and bounding boxes with the detected species name along with confidence score values are displayed. The DeepSORT algorithm also enables each detected fish to have a unique ID, allowing for individual fish counting per species (Wu *et al*. 2023). Other data, such as individual fish weight and capture location, were also displayed on the website.

The workflow of the FLOADS used in this study is shown in Figure 8. The FLOADS instrument was equipped with several important components. First, GPS tracks the vessel's position in real time. With this GPS, information about the fish capture location can be accurately recorded, allowing the obtained geographic data to be used for further analysis related to fishery patterns and fish distribution (Chang 2011). In addition to locally stored data, this instrument includes a GSM Modem that enables direct data transmission to a server on land. Data regarding fish species, catch quantity, fish weight, and other information related to fishing activities can be automatically transmitted in real time via the GSM network. This enables fishers and relevant parties to monitor and access fishery data efficiently.

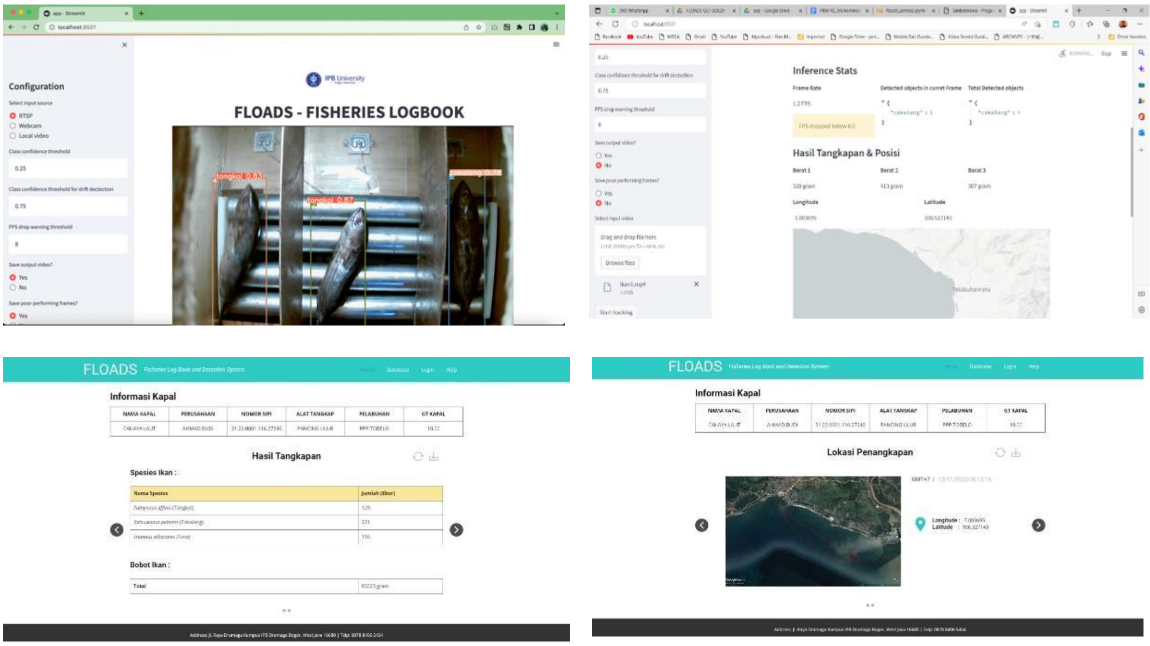


Figure 7 Web Page Dashboard of FLOADS

Furthermore, this instrument is equipped with a weight sensor that is used to measure the weight of the fish passing through the sensing path. This weight sensor enables automatic and accurate fish weight measurement without the need for manual intervention (Nugraha 2017). The fish weight data can then be stored and transmitted to a server on land along with other information. All data collected by this instrument were sent to a server on land to be stored in a database. Data can be accessed through a website. Fishers, researchers, or stakeholders can access this website to view and analyze the collected by the fisheries. This facilitates the monitoring, evaluation, and management of fisheries by using accurate and up-to-date data

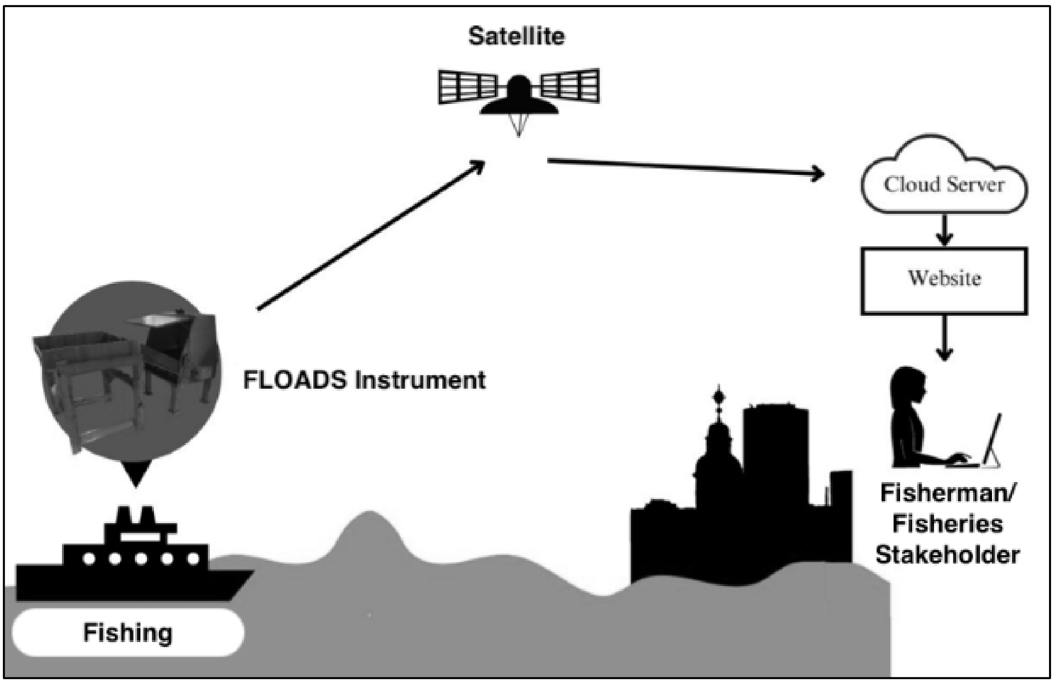


Figure 8 The workflow of FLOADS, an automatic fisheries logbook filling system based on Deep Learning

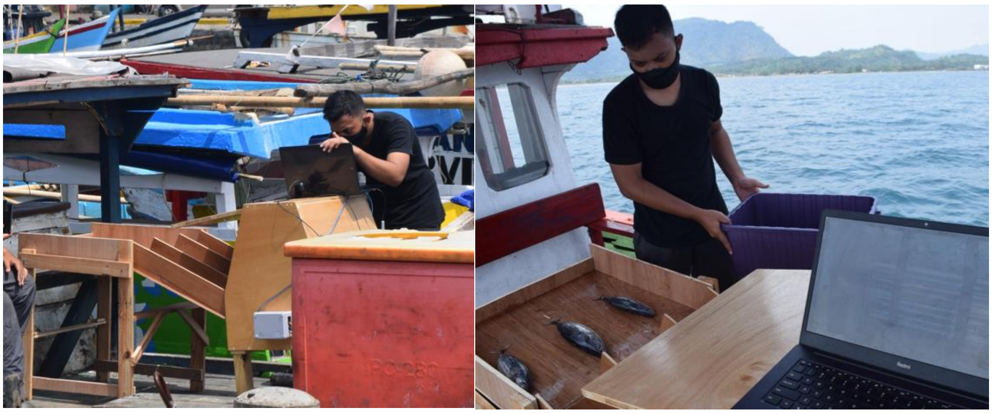
Field Test

Instrument testing in the waters was conducted on August 28, 2022, in Palabuhanratu, Sukabumi Regency, West Java Province. Testing was performed on a 10 GT-sized vessel. This field test aimed to evaluate a fish detection system and weight measurements in real-world environments. The trial used 20 tongkol (bullet tuna), 19 tuna, and 22 skipjack tuna (Appendix 1). The testing results using the K-Fold Cross-Validation technique, where the dataset was repeatedly shuffled five times, yielded an average accuracy of 89.1%, a precision of 100%, a recall of 86.8%, and an F1-Score of 93%. The field test results showed an excellent model performance.

Figure 9 illustrates that FLOADS successfully determined the capture location when the fish entered the Imaging Box. GPS data were used to track the vessel trajectory and determine the fish capture location. Additionally, data recording systems were tested under conditions without GSM signals and with automatic data transmission systems when there was a signal (Appendix 1). The field test results indicated that the fish detection system and weight measurements performed well when tested directly in real-world environments. Furthermore, the data recording and automatic data transmission systems also function well under under no-signal and signal conditions.

DISCUSSION

The design process resulted in several crucial factors that must be considered when designing automatic fish detection instruments. First, the vessel's design must be considered so that the instrument can be adapted to the shape of the vessel being used. This allows the instrument to be optimally placed and function effectively on the vessel. Furthermore, when placing the instrument on the vessel, it is necessary to ensure that the tool does not interfere with fishing operations, thus impeding activities. This is done to maintain the smoothness of the fishing process and increase productivity.



(a)

(b)

Figure 9 (a) Field Test onboard (b) Display of ship trajectory web report during testing.

An important aspect to consider in the design of the FLOADS instrument is the placement of an Imaging Box equipped with rollers and weight sensors. The Imaging Box acted as the core tool for fish detection and weight calculation. The presence of passive rollers in this tool helps to slow down the falling motion of the fish, allowing the camera to obtain clear and accurate images. A weight sensor was placed at the back of the roller iron function to measure the weight. The fish container and slider were designed using a knockdown system. The knockdown system allows these parts to be easily assembled and disassembled in a vessel. With this system, adjustments to the installation of the FLOADS instrument according to the vessel's shape can be performed more flexibly and efficiently. This will greatly help ensure the suitability of the tool for different vessel conditions.

This study used deep learning to train a detection model using the FLOADS instrument. By utilizing deep learning, the algorithm can learn important features from images or videos of fish collected using the FLOADS instrument. This allows the detection system to recognize fish accurately, even in complex and diverse environmental situations. The main advantage of using deep learning in this study is its ability to extract complex features and model more abstract relationships between these features. This enables the detection model to learn complex patterns such as the shape, texture, and context of the captured fish. Consequently, the deep learning algorithm can provide accurate and fast detection results.

Monitoring the measurement results of FLOADS based on a website, where the Deep Learning model that has been created is integrated through the website so that it can store fish capture data in real-time. The design of the website for an automatic fishery logbook-filling instrument involves several important aspects. First, the user interface design must be intuitive and easy for fishermen to use. Second, the information displayed on the website includes relevant fishery data, such as fish species, catch quantity, fish weight, and geographical information related to the capture location. Finally, data visualization and graphics can be used to facilitate understanding and analysis. Additionally, search and filter features can be added to allow users to search for data based on specific criteria, such as fish species or capture dates. These aspects were implemented on a website created to display the measurement results of the FLOADS.

Ultimately, this system could become an alternative in the future to address the inaccuracy of the generated fisheries logbook data. FLOADS is expected to accelerate the fishery logbook filling process, especially in TCT fisheries, thus assisting fishers' work and facilitating the calculation of capture fisheries statistics, fish stock estimation, and fish traceability.

CONCLUSION

FLOADS is a prototype fisheries logbook device based on deep learning that can automatically identify fish species, capture time and location, and measure the weight of individual fish. FLOADS operates using the YOLOv5 algorithm for species identification, DeepSORT for more efficient tracking, and the HX711 sensor to determine the weight of the catch. The generated data can be accessed by fishermen or relevant agencies via a website. The accuracy values obtained from the testing results for all three models were an accuracy of 99.5%, precision of 99.3%, recall of 100%, and F1-Score of 99.6%. Field tests have proven that the designed automatic fishery logbook instrument can function well in real-world environments and assist fishers in monitoring their vessels and catch results.

RECOMMENDATIONS

First, it is important to refine the FLOADS prototype to meet the practical needs in the field. This involves improving the design and overall development of the device by considering factors such as size, weight, and reliability. Second, integrating FLOADS with existing fishery management systems requires attention. For further development, it is crucial to connect FLOADS with existing fisheries management systems so that the data generated by FLOADS can be easily accessed, analyzed, and used by fishers, fisheries management, and other relevant agencies. Moreover, the implementation of FLOADS should also be expanded to various fishing locations to test the system's performance under diverse environmental and fishery conditions. By conducting comprehensive evaluations of the impacts and benefits of using FLOADS, this research can make a significant contribution to more accurate fisheries data collection, sustainable fisheries management, and the improvement of fishers' welfare and operational efficiency.

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Appendix 1 Excerpt of data received during data collection at Palabuhan Ratu Bay (August 28, 2022)

Logging Time (GMT+0)	Receiving Time (GMT+0)	Latitude	Longitude	Fish	Weight (gram)	Delayed
06:34:30	07:42:01	-7.033354	106.347271	Tongkol	325	1
06:34:20	07:41:58	-7.033355	106.347272	Tongkol	400	1
06:34:12	07:41:55	-7.033356	106.347275	Tuna	378	1
06:34:10	07:41:52	-7.033357	106.347275	Cakalang	347	1
06:34:02	07:41:48	-7.033357	106.347274	Cakalang	401	1
06:34:01	07:41:46	-7.033357	106.347275	Tongkol	338	1
06:34:00	07:41:43	-7.033357	106.347275	Cakalang	321	1
06:30:12	07:41:40	-7.033023	106.348113	Cakalang	417	1
06:30:10	07:41:36	-7.033024	106.348114	Cakalang	314	1
06:30:10	07:41:34	-7.033024	106.348119	Tuna	385	1
06:30:10	07:41:31	-7.033023	106.348114	Tongkol	408	1
06:29:55	07:41:27	-7.033026	106.348112	Tongkol	404	1
06:29:50	07:41:25	-7.033028	106.348117	Tongkol	331	1
06:29:41	07:41:21	-7.033028	106.348114	Cakalang	319	1
06:29:40	07:41:19	-7.033024	106.348114	Tuna	334	1
06:29:03	07:41:16	-7.033023	106.348115	Cakalang	370	1
06:29:02	07:41:13	-7.033023	106.348116	Cakalang	306	1
06:29:02	07:41:9	-7.033023	106.348114	Cakalang	370	1
06:29:00	07:41:07	-7.033028	106.348114	Tuna	367	1
06:28:40	07:41:04	-7.033028	106.348117	Tuna	348	1
06:19:33	07:41:01	-7.032355	106.349586	Tuna	421	1
06:19:30	07:40:58	-7.032354	106.349587	Tongkol	412	1
06:19:28	07:40:55	-7.032359	106.349586	Tongkol	392	1
06:19:26	07:40:52	-7.032353	106.349586	Cakalang	413	1
06:19:24	07:40:49	-7.032352	106.349586	Cakalang	307	1
06:19:24	07:40:46	-7.032354	106.349586	Tongkol	362	1
06:19:23	07:40:43	-7.032355	106.349585	Tuna	399	1
05:25:00	05:26:54	-7.029558	106.355453	Cakalang	372	0
05:25:00	05:26:52	-7.029558	106.355453	Tuna	322	0
05:25:00	05:26:47	-7.029556	106.355453	Tuna	384	0
05:25:00	05:26:44	-7.029556	106.355452	Tuna	380	0
05:25:00	05:26:41	-7.029559	106.355452	Tongkol	355	0
05:25:00	05:26:37	-7.029557	106.355453	Tongkol	314	0
05:25:00	05:26:33	-7.029558	106.355453	Tongkol	358	0

Logging Time (GMT+0)	Receiving Time (GMT+0)	Latitude	Longitude	Fish	Weight (gram)	Delayed
05:25:00	05:26:28	-7.029558	106.355456	Cakalang	413	0
05:25:00	05:26:25	-7.029558	106.355457	Cakalang	377	0
05:25:00	05:26:22	-7.029554	106.355453	Cakalang	403	0
05:25:00	05:26:19	-7.029553	106.355452	Cakalang	361	0
04:55:40	05:26:16	-7.028542	106.358536	Cakalang	366	1
04:55:40	05:26:12	-7.028543	106.358536	Tongkol	413	1
04:55:34	05:26:09	-7.028542	106.358538	Tongkol	412	1
04:55:32	05:26:05	-7.028546	106.358536	Tongkol	345	1
04:55:29	05:26.02	-7.028544	106.358536	Tongkol	330	1
04:55:29	05:25:58	-7.028546	106.358539	Tuna	352	1
04:55:28	05:25:55	-7.028543	106.358537	Tuna	407	1
04:54:00	05:25:52	-7.028546	106.358536	Tuna	314	1
04:53:00	05:25:48	-7.028545	106.358536	Tuna	397	1
04:52:40	05:25:45	-7.028542	106.358536	Tuna	372	1
04:52:30	05:25:42	-7.028542	106.358539	Cakalang	373	1
04:52:30	05:25:39	-7.028541	106.358539	Cakalang	378	1
04:07:30	05:25:36	-7.029436	106.347656	Cakalang	371	1
04:07:23	05:25:32	-7.029432	106.347656	Tongkol	361	1
04:07:20	05:25:28	-7.029436	106.347656	Tuna	405	1
04:07:11	05:25:25	-7.029437	106.347653	Tongkol	352	1
04:07:10	05:25:21	-7.029437	106.347654	Tuna	305	1
04:07:02	05:25:17	-7.029437	106.347656	Cakalang	349	1
04:07:02	05:25:13	-7.029434	106.347658	Tuna	307	1
04:07:00	05:25:10	-7.029435	106.347656	Cakalang	351	1
04:07:00	05:25:08	-7.029435	106.347659	Tongkol	338	1
04:06:22	05:25:06	-7.029436	106.347659	Tuna	338	1
04:06:20	05:25:03	-7.029437	106.347656	Tongkol	308	1