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Development Of A CNN-Based Model For Automated Detection And Growth Monitoring Of Catfish (Clarias Gariepinus) In Aquaponics Systems

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Abstract—Food security continues to face challenges from environmental degradation and climate change, and highlighting the need for innovations in sustainable aquaculture. In the Philippines, most systems remain to rely on manual fish and water parameter monitoring, which is labor intensive, not consistent, and tends to stress the fish. Although catfish (Clarias gariepinus) is a significant aquaculture species, growth monitoring is still highly manual and subject to human error. In this study, a YOLOv11 model on Convolutional Neural Networks (CNNs) was developed to facilitate the detection and monitor the growth of catfish in aquaponics systems. Images were taken employing a low-cost webcam with a resolution of 1080p within the greenhouse facility at Central Luzon State University. Images marked with annotations were subsequently run through Python and OpenCV to enhance the resolution and to extract features correctly. The performance of the model was 98% accurate for training and 96.7% for validation with a mean identification accuracy of 80% when it was trained for 50 epochs. Regression outputs indicated strong correlations (R^2 = 0.91 for length; R^2 = 0.82 for weight) with a mean error of ±55 g. Ongoing work is aimed at real-time integrating with IoT-based monitoring to facilitate smarter, more efficient, and sustainable aquaponics systems.

Keywords—Aquaponics, Automated Fish Monitoring, Convolutional Neural Networks, Clarias gariepinus, Growth Estimation.

I. INTRODUCTION

Aquaculture plays a vital role in addressing global food security challenges and has become one of the fastest-growing food production sectors worldwide amid declining capture fisheries and climate-related pressures [1], [2], [3]. The United States of America faces food insecurity, especially the Philippines, which is currently devastated by moderate to severe food insecurity about 44.7% of its population [4]. According to [5], [6], African catfish (Clarias gariepinus) is known as a commercially vital freshwater fish species not only in the Philippines but also in other parts of the world such as in Africa because of its fast growth rate, hardiness, and tolerance to fluctuating conditions of environment. Despite such economic importance, monitoring fish growth and estimating biomass in aquaculture and aquaponics systems still rely on traditional manual sampling of fishes, which includes stressful handling of fish [7]. These traditional techniques, besides stressing the stock, may result in inconsistencies and measurement errors due to estimation of human and varying sampling frequencies as pointed out by [8].

With the rise of digital and smart agriculture and precision-based technologies, increasing attention has been placed on the integration of artificial intelligence (AI) in aquaculture. Computer vision systems and Convolutional Neural Networks (CNNs) allow for visual analysis for detecting, tracking, and measuring aquatic organisms without any physical direct contact [9]. Among these, especially the You Only Look Once (YOLO) family of models has consistently shown exceptional performance in object detection tasks in real-time due to its high accuracy and computational efficiency

[10], [11]. Applications involving YOLO-based approaches have found successful utilization in shrimp, carp, and tilapia monitoring, specifically in counting and analyzing their behavior [12], [13], [14]. However, such CNN-based methods for growth detection and measurement studies in Clarias gariepinus remain limited within the existing literature.

To address this gap, this study proposed a CNN-based model using YOLOv11 that is capable of automatically detecting and estimating catfish growth within an aquaponics environment. This system was developed to be low-cost, non-invasive, and continuous monitoring to eliminate the conventional manual sampling and weighing of fish. Hence, the developed system aimed to: (1) detect the catfish using image-derived object detection, (2) estimate the length and weight through regression analysis based on bounding box dimensions, and (3) evaluate the accuracy and reliability of the proposed system in predicting growth parameters.

The impact of this work will be significant to enhance aquaculture productivity through data-driven monitoring, reduced labor input, and promote animal welfare. Integrating AI, image processing, and aquaponics technology, the proposed system supports ongoing efforts toward sustainable aquaponics, efficient farm management, and the wider transition toward smart agricultural systems in the Philippines. Hence, the study contributes to emerging digital agriculture initiatives, precision agriculture, and provides a basis for future AI–IoT integration targeting real-time decision support in smart aquaponics.

Although aquaponics systems commonly involve hydroponic plant components and aquaculture tanks, the focus in this paper was only on the fish-monitoring component of the system. This phase aimed at the establishment and validation of an automatic CNN-based detection and growth estimation model for Clarias gariepinus, whereas its integration with hydroponics and IoT-based water quality monitoring will be covered under the broader systems architecture, which is ongoing work. A prerequisite to integration into the full aquaponics would be the establishment of a reliable monitoring module for fish growth.

II. RELATED WORKS

Recent advancements in computer vision from 2020 to 2025 have led to accelerated automation of monitoring systems in aquaculture and aquaponics. Convolutional Neural Networks (CNNs) are still the foundation of any image-based detection due to the capability of learning multi-level spatial features adaptable to changes in lighting conditions, water turbidity, and movement of fish. Several studies have shown that CNN-based feature extractors effectively capture contours, textures, and shape cues — even under challenging lighting and turbidity, thereby enabling reliable detection of aquatic organisms [15], [16]. In modern pipelines (e.g., YOLOv8-based, FR-CNN, two-stage R-CNN), these features are then refined via bounding-box regression, IoU-based localization, and NMS (or its variants) to deliver accurate species detection and counting in underwater imagery [17], [18], [19]. Reference [20] presented these principles to support for rapid evolution and new benchmarks of real-time performance by YOLO architectures. Furthermore, the YOLO models from YOLOv4 to YOLOv8—and the emerging YOLOv11—present an increase in both detection precision and speed. According to [21], [22], [23], one of the most critical advantages is its YOLO's single-stage pipeline is advantageous for continuous, non-invasive fish monitoring, which is essential in aquaponics systems where biomass influences nutrient cycling and water quality. References [24], [25] further highlighted that accurate biomass estimation is vital for maintaining aquaponics stability.

Fig. 1. African catfish (Clarias gariepinus).

With the initiatives of digital, precision, and smart agriculture, the application of image processing has also advanced not only in aquaculture but also in aquaponics. Reference [26] defined modern aquaponics as the combination of automation, sensors, and, imaging systems in data-driven ecosystems. The acquisition of image, addressing turbidity and visual noise using preprocessing practices, and CNN-based detection for extracting morphometric features are some of the typical workflows [25]. References [27], [28] showed that it is reliable to estimate fish length and weight using image-derived measurements to promote non-invasive aquaculture and aquaponics operations.

Recent works highlighted significant progress in real-time fish detection and estimation of biomass. Reference [29] achieved robust detection performance in aquaponics tanks under varying illumination. Weight estimation was enhanced by [25] using near-infrared imaging, whereas detection in turbid water was improved by [30]. Another study utilized high-resolution imaging for behavioral stress assessment [31], however, [24] confirmed the growing potential of CNN-based underwater imaging for biomass tracking.

The research into image processing specifically for aquaponics has also expanded. Reference [27] applied computer vision to predict the weight of Nile Tilapia; [32] developed IoT–vision systems for real-time density monitoring; and [33] introduced digital twins for simulation in aquaponics. Despite progress, many of these systems remain species-specific and require controlled conditions when taking images. However, key gaps persist. Most studies focus only on tilapia, carp, or shrimp, with limited work on African catfish (Clarias gariepinus), and no publicly available annotated datasets exist for this species [12], [13], [14], [24]. Some existing systems emphasize water quality monitoring rather than automated growth assessment, and environmental variability also limits the detection accuracy-turbidity, reflections, inconsistent lighting conditions. Locally, Philippine systems still rely on manual monitoring of fish growth [34]. Locally, Philippine aquaponics are still monitored manually. Therefore, there is no study from 2020–2025 has applied YOLOv11 for catfish detection or morphometric estimation in aquaculture and aquaponics environments. These identify the need for species-specific, real-time visual monitoring system, thus motivating the development of a CNN-based YOLOv11 model presented in this study.

III. METHODOLOGY

A. Conceptualization and Design

This research focused on automated detection and fish growth monitoring regarding estimating length and weight of Clarias gariepinus by deploying a computer-vision-based workflow in an aquaponics environment without a hydroponic component. The system was conceptualized to be an end-to-end pipeline that integrates image acquisition, pre-processing, object detection, and biometric estimation.

Fig. 2 depicts the flowchart of the process. A low-cost 1080p USB webcam continuously captured real-time images and video frames from the fish tank. These visual inputs were then transmitted to the data-processing stage where OpenCV was applied to extract and preprocess frames. The cleaned frames then went into a YOLOv11-based detection model for fish localization and feature extraction. Detection outputs, including bounding boxes and instance labels were routed to a web-based interface displaying identified fish and their estimated biometric parameters. The modeling pipeline was consistent with the standardized pipelines of computer visions for monitoring aquaculture, where devices that is low-cost supply visual data that is real-time to lightweight CNN-based sensors installed within digital platforms to support analytics and management [25], [29].

In this study, an experimental-developmental research design was employed to execute the conceptual mode into an operational system. Experimentally, the images of catfish were captured using the webcam directly from the aquaponics tank and were utilized in developing and validating the YOLOv11 model. The system architecture, which includes the scripts of image preprocessing, detection modules, and visualization of output, was iteratively designed and refined in support of potential deployment in real aquaponics operations. This approach ensures that the resulting model and its application can serve as the fundamental component for future integrations with IoT-based aquaponics systems.

B. System Setup

The study was conducted at Central Luzon State University using aquaculture fish tank system containing catfish (Clarias gariepinus), along with a 1080p webcam, and laptop for data processing and visual output. At this stage of the experiment, only the aquarium tank and components of imaging were utilized since no plants or hydroponics elements were included in this investigation. The webcam was installed above the tank to record catfish images and videos continuously (Fig. 3). Precautions were taken to managed environmental conditions and animal welfare to minimize excessive variations in illumination and reflections [30].

C. Sampling

A total number of 2,450 catfish appearances were captured over 14 days. Size categories were small, medium, and large, ranging from 10 cm to 26 cm. The annotated dataset was partitioned using the standard percentages, with 80% allocated for training and the remaining 20% for validation [35]. The summary dataset composition is given in Table I, showing the number of images and total annotations.

D. Data Collection and Preprocessing

Images were captured using Python scripts integrated with OpenCV. The preprocessing procedures included:

- resizing to YOLOv11 input dimensions
- illumination and contrast adjustment
- noise filtering and background reduction
- color-space normalization

These steps enhanced image quality under variable turbidity and lighting conditions [25].

Table I. Summary of the dataset used for model development.

Dataset Split	Number of Images	Number of Annotations
Training Set	3,360	26,480
Validation Set	840	6,620
Total	4,200	33,100

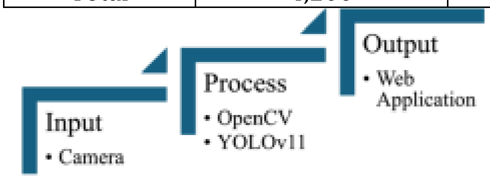

Fig. 2. Process flowchart.

Fig. 3. Automated aquaculture monitoring system setup.

The raw images, as shown in Fig. 4, are first refined into segmentation masks and then processed for contour extraction and individual catfish detection. For better robustness of the model, data augmentation was performed by flipping, brightness adjustment ±20%, Gaussian blur, and slight rotation ±6°. Fig. 5 shows the sample annotated image with bounding box used for training. Overlay of different colors was also done for catfish detection, as shown in Fig. 6.

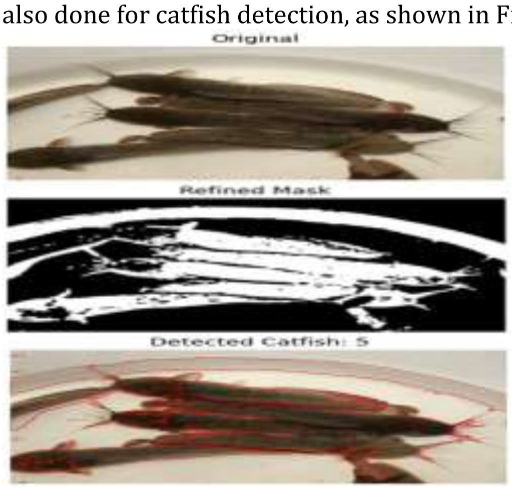

Fig. 4. Image processing (raw picture, segmentation, detection).

Fig. 5. Sample annotated image with bounding box.

E. Model Architecture and Training

A custom detection head YOLOv11-S model was set up in PyTorch 2.1 and trained on an RTX 4060 GPU (8 GB). Training ran for 50 epochs using the Adam optimizer with cosine learning rate scheduling. The dataset was divided into three parts: 70% used for training, 20% for validation, and the remaining 10% was utilized for testing.

Hyperparameters such as learning rate, batch size, and confidence threshold were iteratively tuned (Table II). Training and validation loss curves were recorded for later analysis.

Table II. YOLOv11 training parameters and hyperparameter settings

Parameter / Hyperparameter	Value
Model Architecture	YOLOv11-S
Framework	PyTorch 2.1 (mixed-precision enabled)
Input Image Size	640 × 640
Batch Size	16
Number of Epochs	50
Optimizer	Adam
Learning Rate Schedule	Cosine annealing
Training / Validation / Test Split	70% / 20% / 10%
GPU Hardware	NVIDIA RTX 4060 (8 GB VRAM)
Augmentation Techniques	Flip (H/V), brightness shift (±20%), Gaussian blur (2–4), rotation (±6°)
Loss Components (final)	Obj: 0.34, Class: 0.28, Localization: 0.23
Final Training Accuracy	98%
Final Validation Accuracy	96.7%
Number of Training Images	2,940
Number of Validation Images	840
Number of Test Images	420

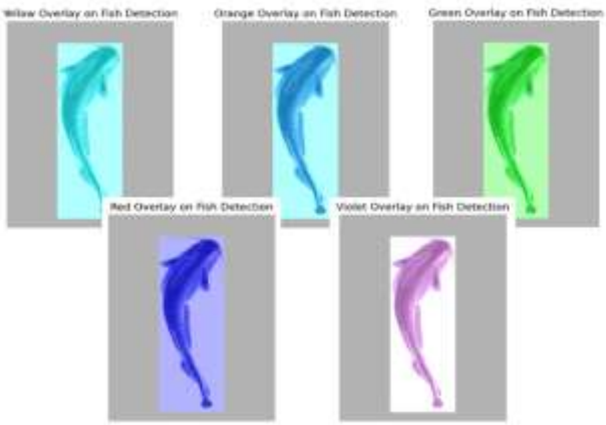

Fig. 6. Color overlays variations for catfish detection

F. Length and Weight Estimation

The bounding boxes computed by YOLO were processed to estimate the pixel-based morphometric measures. Regression models for fish length and weight estimation were developed.

$$l = 0.0178\, h_b + 0.0143\, w_b + 9.37 \qquad (1)$$

Equation 1 is the regression model for estimating catfish length, where l is the predicted length (cm), h_b is the bounding box height (pixels), and w_b is the bounding box width (pixels). In addition, the actual length was used for predicting weight of the catfish.

The formula of estimating weight is demonstrated as:

Estimated weight formula was developed through regression model which is denoted as:

$$w = 0.241\,(l)^2 - 2.16\, l + 17.8 \qquad (2)$$

Equation (2) is a polynomial regression model for the estimation of catfish weight from estimated length, where w is the estimated weight (g) and l is the predicted length (cm). The ground-truth calibration was performed using a standardized measuring board. Final regression performance values (R^2, RMSE) are shown in Results and Discussion section.

G. Ethical Considerations

This study ensures that all procedures avoided invasive handling and minimized fish stress. Image capturing was done without physical direct contant, in line with recommended welfare practices in aquaculture experiments. The researches adhered to CLSU's institutional guidelines for the ethical conduct of aquaculture research,

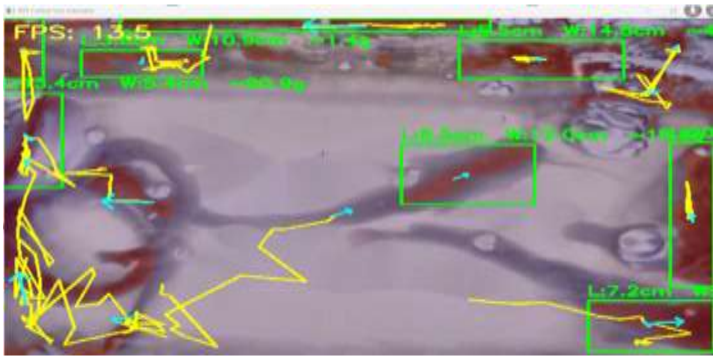

Fig. 7. Length and weight estimation.

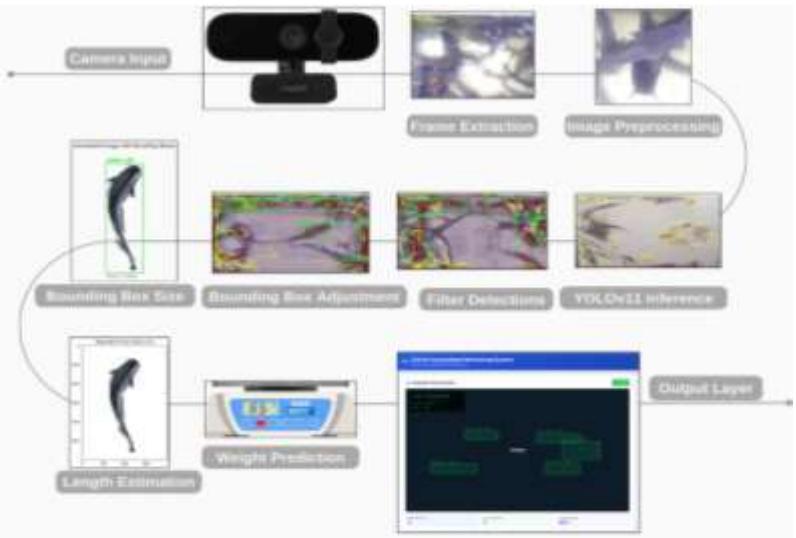

Fig. 8. System flowchart.

IV. RESULTS AND DISCUSION

The YOLOv11 model demonstrated excellent performance during the training phase, achieving a training accuracy of 98% and a validation accuracy of 96.8%. These metrics indicate strong model generalization with minimal overfitting.

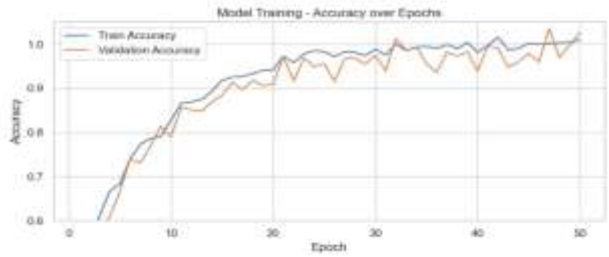

Fig. 9. Training and validation accuracy of the YOLOv11 model.

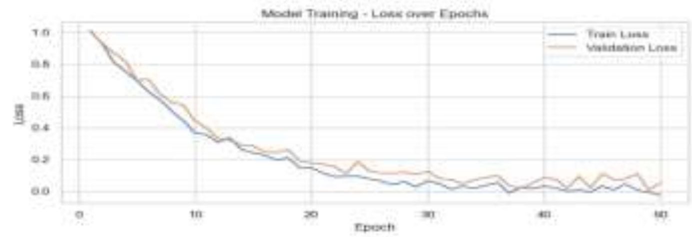

Fig. 10. Training and validation loss curves of the YOLOv11 model.

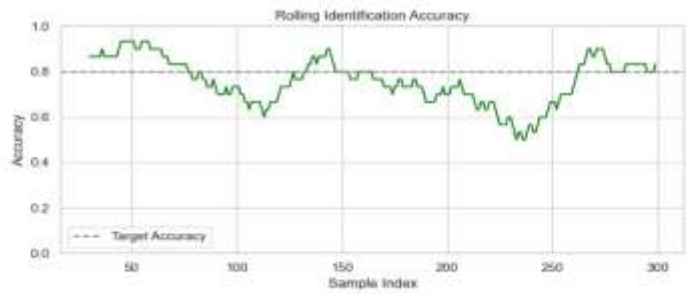

Fig. 11. Rolling identification accuracy of the YOLOv11 model.

Fig. 9 presents the training and validation accuracy curves of the model. Meanwhile, Fig. 10 shows the YOLOv11 model's training and validation loss curves, which shows stable convergence and consistent performance across 50 epochs. The model achieved a mean identification accuracy of 80% when tested on unseen samples which ensures its robustness under different lighting and water clarity conditions (Fig. 11).

Regression analyses were conducted to examine the system's ability to predict growth parameters, such as length and weight, from images. Fig. 12 illustrates the relationship between estimated and actual values for length, whereas Fig. 13 presents the corresponding relationship for weight. The model achieved an R^2 value of 0.91 for length estimation and an R^2 value of 0.82 for weight estimation, with a mean prediction error of approximately ±55 g. These results demonstrate that YOLOv11, combined with regression modeling, can reliably estimate fish growth characteristics (Table III). The slightly lower weight correlation is consistent with established findings that weight estimation is inherently more variable due to body posture, curvature, and depth perception challenges during image capture [29].

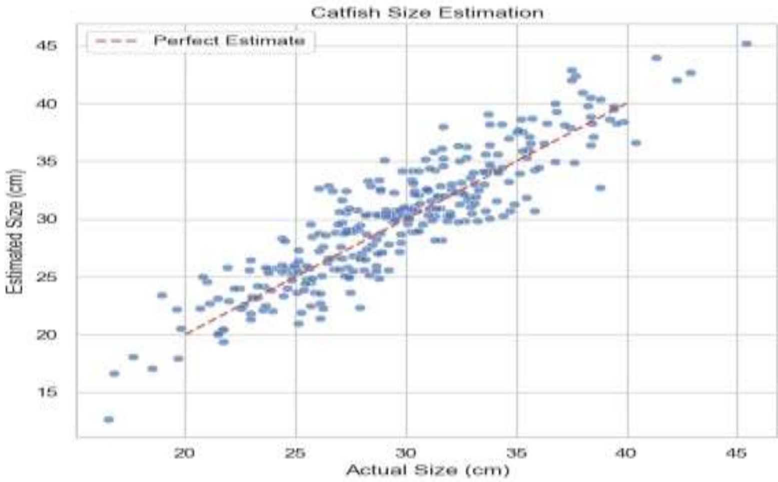

Fig. 12. Regression for catfish growth estimation: estimated size vs. actual size.

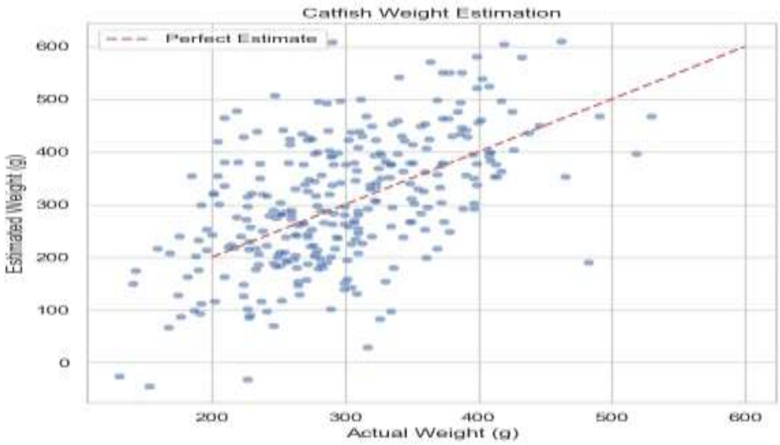

Fig. 13. Regression for catfish growth estimation: estimated weight vs. actual weight.

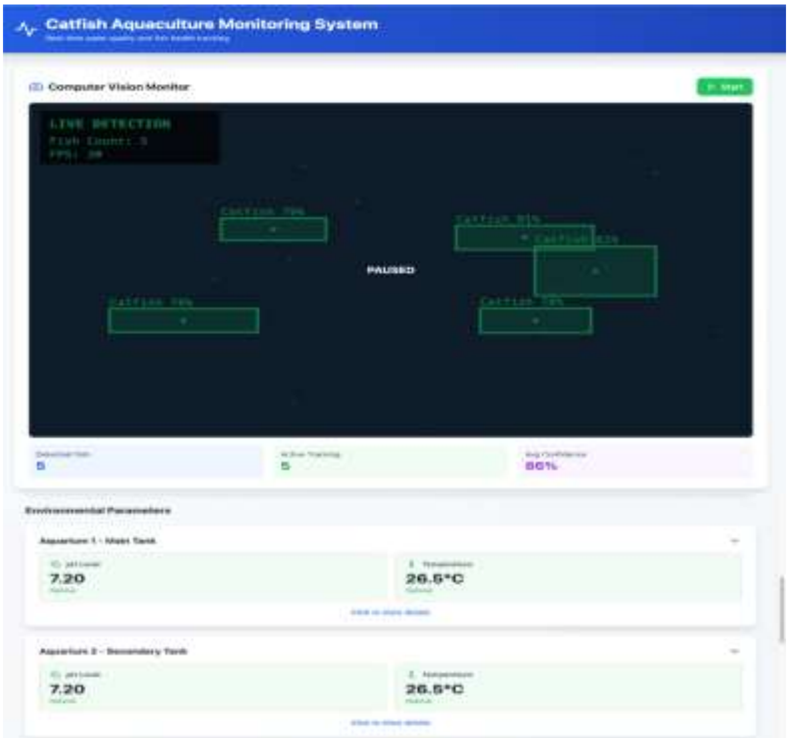

Fig. 14. Web application interface of catfish monitoring system.

Table III. Regression model results.

Parameter	R^2	RMSE	Formula
Length	0.91	±2.6 cm	0.0178h + 0.0143w + 9.37
Weight	0.82	±55 g	$0.241L^2 - 2.16L + 17.8$

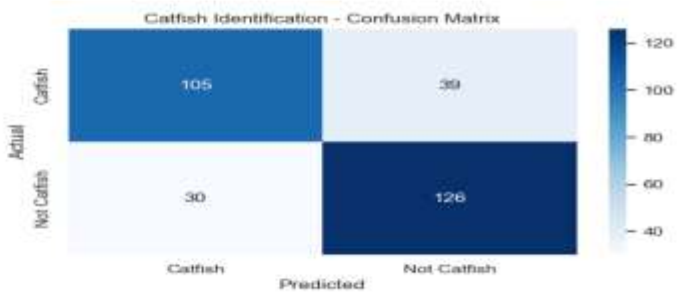

Fig. 15. The confusion matrix.

Table IV. Detection performance metrics.

Metric	Result
Precision	77.8%
Recall	72.9%
Accuracy	77.3%
F1-score	75.2%

Table V. Performance summary of the YOLOv11 detection and regression models.

Metric	Result
Training Accuracy	98%
Validation Accuracy	96.7%
Mean Identification Accuracy	80%
Length Estimation (R^2)	0.91
Weight Estimation (R^2)	0.82
Mean Length Prediction Error	±2.6 cm (RMSE)
Mean Weight Prediction Error	±55g (RMSE)

A screenshot of the deployed web application showing real-time detection results (Fig. 14) illustrates monitoring system usability.
The confusion matrix shown in Fig. 15 summarises the classification behaviour on the test set. The performance metrics of detection were presented in Table IV.
A summary of the key performance metrics of the detection and regression models is presented in Table V, which gives an overview of both the accuracy of the system and the prediction error margins.
Integrating real-time catfish detection into an aquaculture system reveals strong potential for digital and smart aquaponics applications. The accurate detection and growth estimation by the YOLOv11 model promotes automated monitoring of growth and behavior of the fish. These systems can facilitate excellent

dynamic management decisions, such as adjustments to feeding schedules or water parameters when integrated with IoT-based water quality sensors. Similar frameworks for smart aquaculture monitoring have been explored in recent studies [36], underlining the significance and practicality of AI-driven approaches.

Despite its strong performance, the model offers several areas for improvement. Expanding the dataset is a major opportunity, particularly by adding images captured under different turbidity levels, changes in lighting conditions, and a broader range of fish sizes. Enhancing data diversity could further strengthen the model's robustness for operational scenarios. Beyond dataset improvements, temporal image sequences with motion tracking algorithms could improve fish counting and behavioral analysis. Future work may also consider the use of multispectral or depth sensors to further reduce weight estimation errors and enhance consistency in prediction.

To sum it up, the findings confirm the capability of the developed system to accurately identify African catfish and estimate growth parameters within an aquaponics system. The model's reliable detection accuracy, strong regression performance, and real-time processing capacity demonstrate the feasibility of implementing computer vision-based monitoring systems in aquaculture operations. This is one such advancement that fosters a transition toward automated and data-driven fish production, hence, enhancing both efficiency and sustainability.

CONCLUSION

The developed CNN-based YOLOv11 model has achieved automation of detection and growth monitoring of African catfish (Clarias gariepinus) in an aquaponics environment. The system demonstrated great accuracy and precision for individual fish detection, showing a reliable performance that can estimate length and weight through image-derived regression. Results obtained have demonstrated great potential for real-time, non-invasive, continuous monitoring, addressing some of the key limitations of the traditional labor-intensive method of manual sampling in aquaculture.This study also establishes a good foundation for next-generation smart aquaponics technologies. Ongoing work aims at integrating automated detection and growth modelling with IoT-based sensors of water quality parameters into a fully automated monitoring system capable of real-time decision support. Expanding the dataset, detection accuracy, and refining regression models are further improvements. Moreover, applying deep learning on other aquaculture species will extend the present system's impact and will facilitate scalable deployments in various aquaponics settings.Overall, the developed YOLOv11-based framework represents a significant advancement toward intelligent, automated, and welfare-friendly fish monitoring systems for modern aquaculture and aquaponics operations.

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