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Count and location determination of Nile Tilapia (*Oreochromis niloticus*) using convolutional neural network and CLAHE

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Abstract

Fish counting in aquaculture is an important task in fish population estimation. However, it is very challenging because of the diversity of backgrounds, uncertainty of fish motion, and obstruction between objects. To solve this problem, a model using Convolutional Neural Network (CNN) and Contrast Limited Adaptive Histogram Equalization (CLAHE) is proposed to provide an advanced and efficient counting method for aquaculture. The methodology involved image acquisition, CNN implementation, and evaluation. First, images were manually annotated from video frames. Then, a CNN was trained on the training dataset to detect the tilapia and determine its location. Lastly, the performance of the method was evaluated and compared with other assessment methods. The results show that the study gained 95%, 87%, and 91% for precision, recall, and F1-score, respectively. Further, the mean average precision at 0.5 resulted in 94.21%; thus, the study can detect and locate the fish in a tank and be integrated into a feeding management system.

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Introduction

Accurate counting of organisms, such as Nile Tilapia (Oreochronis niloticus), is important for various applications, including fisheries management, environmental monitoring, and aquaculture operations (Li *et al.*, 2020). In the Philippines, tilapia is the second most important cultured species, with approximately 281,111 MT of total production in 2021. In 2020, tilapia made up 20% of the aquaculture production in the country, with Central Luzon as the leading producer. Tilapia is an important commodity for food security and economic development (PCAARRD, n.d.).

The tilapia industry in the Philippines has made notable growth in production from 2002 to 2022, with an increase of 115.58%. This may be attributed to several programs done by the government, such as improving the strain of tilapia and improving the technology in production and culture to sustain industry growth (Bureau of Fisheries and Aquatic Resources, 2022).

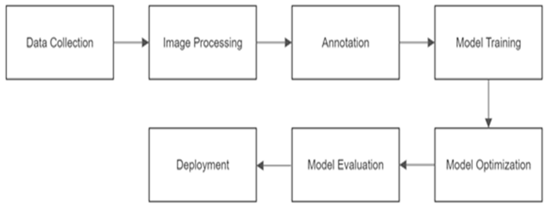
However, despite the progress made in tilapia aquaculture, problems and challenges persist. Pollution-related problems like diseases and water quality management, sources of quality fingerlings, and market competition are among the key challenges faced by farmers (Bureau of Fisheries and Aquatic Resources, 2022). Addressing these challenges and enhancing the efficiency and sustainability of tilapia production is crucial for the industry's continued growth.

In this context, developing an automated methodology for accurate surface tilapia detection using a Convolutional Neural Network (CNN) brings an opportunity to improve tilapia farming practices. Leveraging the capabilities of CNN and Contrast Limited Adaptive Histogram Equalization (CLAHE) aims to develop an approach to determine whether Nile Tilapia are at the surface or submerged. The insights gained from this research can contribute to optimizing feeding strategies, improving management practices, and enhancing tilapia aquaculture's overall productivity.

The paper is presented as follows: Section 1 introduces the motivation for the research. Section 2 concentrated on the related works on image processing, CNN, and CLAHE. The methodology of the research is presented in Section 3. Section 4 presents the Tests and Results. Finally, Section 5 discussed the conclusion and future works.

Materials and methods

This paper used different techniques to count and locate Nile Tilapia. The methodology's block diagram is shown in Fig. 1.



Data Collection

The study gathered a large dataset of images containing Nile Tilapia. This was done by capturing images from a DLSR camera with a resolution of 1920x1080. There were 13000 images selected that served as data for training and validation.

Image Processing

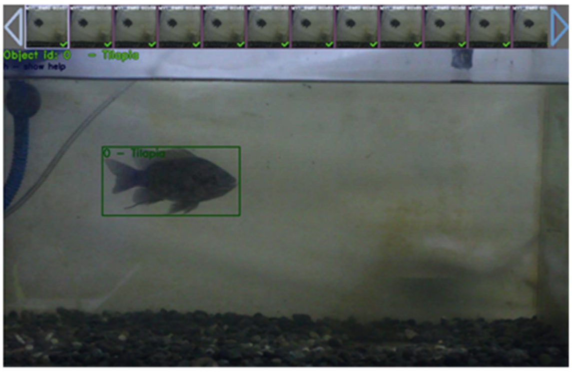
The images were preprocessed to enhance the quality and improve the visibility of the Nile Tilapia. They were converted to lab color, and CLAHE was applied to the L-channel. The clip limit was set to 2.0 and the grid size to (10, 10). Further, the images were resized to 416x416.

The water surface was also detected to determine if the image of tilapia was near the surface. Thresholding using binarization and Otsu was utilized. The edges were detected using Canny and probabilistic Hough line transform to detect straight lines. The y-coordinate of the least disturbed part of the surface identifies the water region.

Annotation

Manual labeling of tilapia images was done to create the ground truth of the datasets shown in Fig. 2.

Each annotation was composed of five values: object class, x-center, y-center, width, and height. In total, there were 108937 labeled images for training and validation.



Model Training

The study utilized a CNN architecture for training a deep learning model on the annotated dataset. There were 78574 images used for training and 30363 for validation. You Only Look Once (YOLOv3) reframes object detection as a single regression problem, straight from image pixels to bounding box coordinates and class probabilities. The YOLO network uses features from the entire image to predict each bounding box. For YOLOv3, a base feature extractor with 53 convolution layers called Darknet-53, see Fig. 3 (Redmon & Farhadi, 2018)

	Type	Filters	Size	Output
	Convolutional	32	3 × 3	256 × 256
	Convolutional	64	3 × 3 / 2	128 × 128
1×	Convolutional	32	1 × 1	
	Convolutional	64	3 × 3	
	Residual			128 × 128
	Convolutional	128	3 × 3 / 2	64 × 64
2×	Convolutional	64	1 × 1	
	Convolutional	128	3 × 3	
	Residual			64 × 64
	Convolutional	256	3 × 3 / 2	32 × 32
8×	Convolutional	128	1 × 1	
	Convolutional	256	3 × 3	
	Residual			32 × 32
	Convolutional	512	3 × 3 / 2	16 × 16
8×	Convolutional	256	1 × 1	
	Convolutional	512	3 × 3	
	Residual			16 × 16
	Convolutional	1024	3 × 3 / 2	8 × 8
4×	Convolutional	512	1 × 1	
	Convolutional	1024	3 × 3	
	Residual			8 × 8
	Avgpool		Global	
	Connected		1000	
	Softmax			

Model Optimization

Some of the notable parameters of the CNN were altered in this study. The batch value was set to 16, and the network size was 416x416. The number of iterations was 13000, and the filters were set to 18.

Model Evaluation

The trained model was evaluated in terms of mean average precision, recall, and f1-score to assess the model's performance in accurately counting and locating Nile tilapia.

Deployment

The trained CNN model was deployed to automatically count and determine the tilapia's location. It was integrated into a software application that accepts images from video and provides the count and location information as output.

Results

CNN Model and CLAHE

There were a total of 108937 images of tilapia for training and validation. The 78754 images were used for training, and 30363 for validation. A sample of the tilapia image is presented in

Fig. 4. Raw image of tilapia.

Fig. 5 shows the image after enhancing using CLAHE. The tilapia in the image was accurately detected. The yellow box indicates that the tilapia is near the It is said to be at the surface of the y-coordinate of the fish intersects with the y-coordinate of the water surface. Further, only the yellow boxes were counted using the toolkit in the YOLOv3.

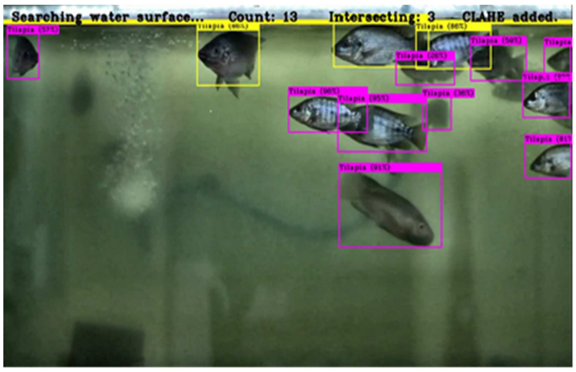


Fig. 5. Tilapia was detected and counted.

Evaluation

The performance of the YOLO was evaluated in terms of average precision, recall, and f1-score. Based on the ground truth and predicted labels, the results gained 25484, 1235, and 3798 for True Positive, False Positive, and False Negative, respectively. Based on the values presented, the performance of the model gained values of 0.95 for precision, 0.87 for recall, and 0.91 for f1-score. Further, the mean average precision of the CNN with CLAHE at Intersection over Union (IoU) value of 50% gained a result of 0.9421.

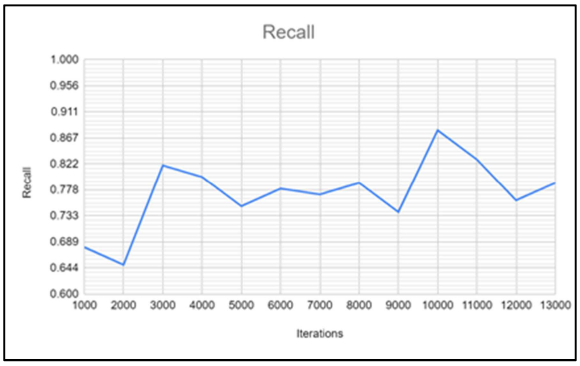


Fig. 6. Recall value of the CNN with CLAHE model.

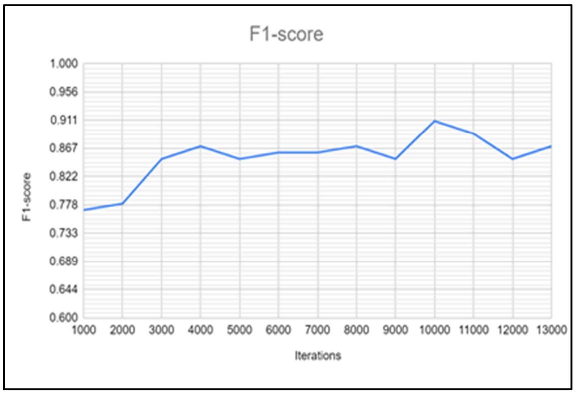


Fig. 7. F1-score value of the CNN with CLAHE model.

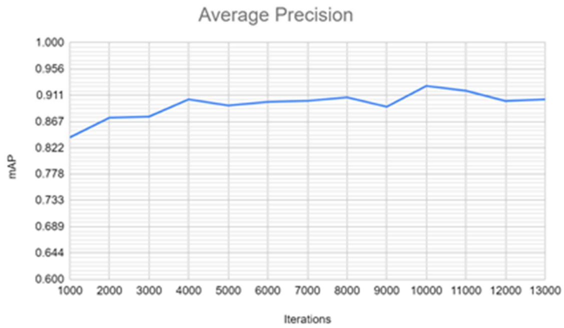


Fig. 8. Average Precision value of the CNN with CLAHE model.

In addition, after 13000 iterations, Fig.s 6,7 and 8 present the results for the recall, f1-score and average precision. Based on the fig.s below, the results 10000 iteration is the best in terms of performance.

Related Works

Previous research studies have explored the application of image processing techniques, CNN, and CLAHE in various fish research (Mandal *et al.*, 2018). The study of (Wang *et al.*, 2022) proposed a real-time detection and tracking of abnormal fish behavior based on improved YOLOV5 and SiamRPN++. This approach combined two approaches to detect precisely and track in real-time the abnormal behavior of individual fish. Similarly, (Muksit *et al.*, 2022) developed a model for fish detection in unconstrained real-world marine environments. Their method demonstrated lightweight and accurate fish detection in underwater environments, contributing to fish recognition and monitoring.

In terms of image enhancement, (Mishra *et al.*, 2018) presented an underwater image enhancement technique using CLAHE. This method improved the visibility of objects in underwater images, making it suitable for further analysis and processing. (Lumauag & Nava, 2019) presented a simple method of tracking and counting fish using image processing. The methodology has a high level of detection and counting accuracy in recognizing objects in a temperate and open environment.

Moreover, (Jose *et al.*, 2022) and (Conrady *et al.*, 2022) employed a CNN-based approach for fish species classification. Their model accurately classifies different fish species and contributes to species identification and monitoring. The study by Saminiano (2020) utilized CNN to classify the feeding behavior of fish, whether to feed or not to feed. Additionally, (Yu *et al*., 2020) proposed a scheme for segmenting fish images and measuring morphological features based on Mask R-CNN. Their approach achieves robustness and high accuracy in segmenting and measuring the fish morphological feature in different backgrounds. These related works demonstrated the diverse applications of image processing, CNN, and CLAHE in fish research. They cover fish detection, tracking, recognition, behavior analysis, species classification, and morphometrics. The findings and methodologies of these studies provide the foundation for the current study, which aims to determine the count and location of Nile Tilapia using the combination of CNN and CLAHE.

Conclusion

This study presented the effectiveness of the Convolutional Neural Network in counting and locating the Nile tilapia. With a high level of detection and accuracy, the model can be integrated into a system for aquaculture, especially for feeding management.

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