Volume XVI Number 2, 2024

Fish-NET: Advancing Aquaculture Management through AI-Enhanced Fish Monitoring and Tracking

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Abstract

This study seeks to enhance aquaculture and fishery management using artificial intelligence, focusing on Nigerian catfish farming. The methodology encompasses a sequence of steps from data collection to validation. A dataset, primarily composed of aerial imagery from catfish ponds and supplemented with additional data from the internet, formed the foundation of this research. By leveraging computer vision and deep learning techniques, the data were processed to assess the potential of the three distinct cutting-edge object detection models. Based on various evaluation metrics to gauge their effectiveness in fish detection tasks, the Faster R-CNN emerged as the optimal model, boasting a superior balance of precision and recall. This model was subsequently integrated with an object-tracking model and deployed as an application, yielding promising results in terms of fish detection and tracking. The findings in this study suggest that AI-driven tools can automate monitoring processes, significantly increasing accuracy and efficiency in resource utilization.

Keywords

Aquaculture, fish detection, AI fish tracking, Nigerian catfish farming, sustainability.

Salako, J., Ojo, F. and Awe, O. O. (2024) "Fish-NET: Advancing Aquaculture Management through AI-Enhanced Fish Monitoring and Tracking", *AGRIS on-line Papers in Economics and Informatics*, Vol. 16, No. 2, pp. 121-131. ISSN 1804-1930. DOI 10.7160/aol.2024.160209.

Introduction

Agriculture, particularly aquaculture, has long been a major source of livelihood in sub-Saharan Africa, sustaining rural households and contributing significantly to the economic landscape. Even within the context of a nation such as Nigeria, where the petroleum industry has substantial economic influence, the pivotal role of agriculture in the country's gross domestic product cannot be overemphasized. Notably, over 70% of Nigeria's population finds employment and sustenance through agriculture, underscoring its enduring significance in the nation's economy (Iyang et al., 2020). Over the past few decades, aquaculture has witnessed exponential growth globally and in Nigeria. The fast-growing aquaculture production in Nigeria, as evidenced by a substantial expansion of 10.3% between 1961 to 2011, showcases the potential and role of fish farming in contributing to the nation's economy (Katampe, 2016). Despite these significant contributions, the Nigerian aquaculture industry is hampered by outdated and manual methods such as traditional fish counting and processing, and the use of underdeveloped techniques like cage, pond, and composite fish cultures (Emmanuel et al., 2014). These methods, while long-standing, are inefficient, difficult to scale, and prone to human error, necessitating innovative approaches for better management. Addressing these challenges, this research explores the integration of advanced artificial intelligence (AI) systems to automate fish detection and tracking, aiming to enhance both the economic and operational efficiency of the aquaculture sector.

Artificial intelligence, a branch of computer science focused on creating machines with human-like intelligence, has already begun transforming the aquaculture industry. The emergence of AI and computer vision technologies has spurred both startups and established businesses to develop applications that address the unique challenges of aquaculture, enhancing research and production (Kacprzyk, 2009). The integration of artificial intelligence and computer vision in aquaculture marks a critical advancement in improving efficiency, scalability, and sustainability (Patel et al., 2022). This digital transformation is essential to meet the growing global seafood demand and enhance the livelihoods of fish farmers, particularly in Nigeria. The 'agro-vision' concept, pivotal in precision agriculture, has significantly advanced aquaculture by employing AI-driven cameras and sensors for continuous monitoring of aquatic life. This technology facilitates early detection of anomalies and diseases, informed by historical data and current environmental conditions, thereby improving the management of feeding schedules, reducing stress, and boosting overall health in aquatic life (Udeogu et al., 2023). Consequently, these insights are instrumental in refining feeding schedules, alleviating stress in aquatic life, and boosting overall health. AI improves precision aquaculture by providing a data-driven understanding of fish behavior, paving the way for resource-efficient and environmentally sustainable practices (An et al., 2021).

The introduction of AI and computer vision has opened new opportunities for enhanced environmental monitoring, community engagement, and efficient fish detection and tracking. Combined with environmental sensors, these technologies offer a robust solution for monitoring key parameters like water quality and temperature, essential for maintaining fish health and habitat (Mandal and Ghosh, 2023). The application of computer vision-based technologies has been identified as a means to enhance the performance and productivity of aquaculture industries, ease the lives of fish farmers, and improve harvest (Shreesha et al., 2020). Moreover, AI-based applications extend to optimizing water quality management, feed optimization, and enhancing environmental monitoring, community engagement, and fish welfare. These advancements not only increase production efficiency using fewer resources but also support sustainable practices essential for meeting global seafood demands and enhancing fish farmers' livelihoods in Nigeria (Lim et al., 2023; Patel et al., 2022).

While AI and computer vision hold the promise of enhancing aquaculture productivity and easing the burden on fish farmers, the success of these technologies depends on deep domain expertise in AI and aquaculture thus making it a multifaceted endeavor. This necessitates collaborative efforts to overcome data and environmental, financial, and expertise-related challenges to fully realize the potential of AI in revolutionizing aquaculture practices, including the development of image processing algorithms for fish monitoring and sizing using computer vision (Rodriguez et al., 2015).

Related Works The application of artificial intelligence in fish farming presents a plethora of opportunities to overcome the inherent limitations associated with traditional aquaculture and fishery management. Among the critical advancements is the use of deep learning, which significantly improves real-time decision-making through applications such as live fish identification, species classification, behavioral analysis, and water quality prediction. Furthermore, diverse local conditions and aquaculture practices across different regions and species require artificial intelligence models to be highly adaptable to meet specific local and species-centric requirements. Fish detection challenges are highlighted as a result of varying illumination, low contrast, and other factors, necessitating robust computer vision models for effective fish detection in unique application scenarios (Yang et al., 2021). Concurrently, the burgeoning issue of overproduction, which frequently leads to environmental imbalance and a decline in aquatic product quality, has been meticulously addressed through AI-driven solutions such as Precision Fish Farming (PFF), which aims to improve the accuracy, precision, and repeatability of farming operations, thereby fostering more sustainable aquaculture practices (Føre et al., 2018). Additionally, the integration of digital twin technology with the Artificial Intelligence Internet of Things (AIoT) has been recognized as a catalyst for intelligent fish farming, providing a nuanced understanding and management of aquaculture ecosystems (Ubina et al., 2023). Furthermore, machine learning algorithms have been extensively explored for their potential to evaluate fish biomass, identify and classify fish, and analyze behavioral patterns, which are integral to efficacious aquaculture management (Zhao et al., 2021).

In the evolving aquaculture landscape, there has been a surge in innovative techniques to improve fish tracking and monitoring. One such advancement is the radio-based fish tracking system, which allows for detailed observations of individual fish movements and behaviors, proving to be an invaluable tool for large-scale aquaculture operations (Martín et al., 2022). Underwater acoustic telemetry has also been recognized as an effective means of overseeing fish activity, especially within expansive water bodies. This modality provides a lens for the continuous nuances of fish behavior and migration trajectories

(Yang et al., 2022). Harshith et al. (2023) demonstrated in their work the implementation of remote aquaculture monitoring using image processing and AI, enabling real-time detection of parametric changes, disease identification in fish, and automated control of aquaculture systems. Moreover, machine vision technologies have been surveyed for target tracking applications in aquaculture, presenting a taxonomy of techniques and analyzing fish detection and tracking methods (Mei et al., 2022). The introduction of environmental DNA analysis offers a promising avenue for determining fish presence and decoding species-specific information within aquaculture systems. Its non-invasive nature is a cornerstone for gauging both fish populations and their genetic diversity (Shu et al., 2020). Diving deeper into individualized fish metrics, the introduction of wearable sensors and bio-logging apparatuses heralds a new era of data collection. These tools are meticulously designed to collect detailed data on fish behavior and physiology, shedding light on gender-specific activity trends and other critical aspects (Kaidarova et al., 2023). Notably, the merging of computer vision with machine learning has ushered in a transformative approach to real-time fish behavior surveillance. There is an unprecedented ability to decipher and understand fish behavior, which in turn augments insights into their holistic well-being and growth trajectories (Sung et al., 2017).

Aquaculture has also seen the development of intuitive mobile applications, granting practitioners the luxury of monitoring and tracing fish dynamics via handheld devices. These applications serve as gateways for instantaneous data retrieval and interpretation (Zhao et al., 2021). Several studies have explored the application of artificial intelligence (AI) in aquaculture, particularly in the identification and management of fish diseases. Yang et al. (2021) demonstrated how AI can analyze fish photos to detect disease indicators such as lesions, odd behavior, and discoloration. Chan et al. (2022) leveraged cameras in fish farms to monitor and identify early symptoms of disease. Early detection through this approach can help farmers mitigate the need for antibiotics and reduce the risk of disease outbreaks, thereby improving treatment outcomes and limiting the spread of infections within fish populations.

Additionally, AI has been utilized to analyze video data from salmon farms to detect behavioral changes indicative of stress or disease. Deep learning algorithms were employed to identify and interpret these behavioral patterns, achieving a high degree of accuracy in early disease detection. Wu et al. (2022) expanded this research by examining four major aspects of deep-sea aquaculture: intelligent feeding, water quality detection, biomass estimation, and underwater inspection. They highlighted the shift from traditional manual practices to mechanized and automated systems, collectively referred to as unmanned intelligent equipment. The adoption of these technologies in various aquaculture fields has been shown to reduce labor costs, mitigate threats, and enhance operational efficiency. Fish activity can be directly impacted by water quality due to their high reliance on the aquatic environment. Lu et al. (2022) introduced a low-cost AI buoy system for real-time water quality monitoring at offshore aquaculture cages, providing data on dissolved oxygen, salinity, water temperature, and velocity. Additionally, by analyzing data from sensors that measure parameters such as temperature, dissolved oxygen, pH, and ammonia levels (Dupont et al., 2018), AI algorithms can detect patterns and anomalies that may indicate problems with water quality (Zhao et al., 2021; Khurshid et al., 2022). This enables farmers to take corrective actions before any harm is done to the fish. AI-powered water quality monitoring systems can continuously monitor multiple parameters in real-time, providing more accurate and timely information than manual monitoring methods (Javaid et al., 2022). This allows for quick responses to changes in water quality, reducing the risk of fish mortality and other negative outcomes.

AI plays a pivotal role in developing predictive models that anticipate changes in water quality before they occur. By analyzing historical data on water quality and other factors such as weather patterns and feeding schedules, AI algorithms can predict the likelihood of changes in water quality and provide early warnings to farmers (Saeed et al., 2022). Gunda et al. (2019) developed an AI-based mobile application platform for monitoring water quality, specifically for bacterial contamination, using a low-cost rapid test kit. These advancements demonstrate the significant potential of AI in enhancing water quality management in aquaculture, ultimately supporting healthier and more sustainable fish farming practices. Dixit et al. (2023) highlighted how AI systems can identify genetic variations associated with specific traits by analyzing vast amounts of genomic data. This information is then used to develop predictive models of fish performance. These models can predict the performance of various fish populations under different environmental conditions and identify the best candidates for breeding to achieve specific goals, such as enhanced disease resistance or improved growth rates. By making breeding operations more targeted and efficient, AI helps save time and resources while ensuring the attainment of desired traits. This approach significantly enhances the productivity and sustainability of fish populations, offering substantial benefits for aquaculture and fisheries management (Mandal and Ghosh, 2023).

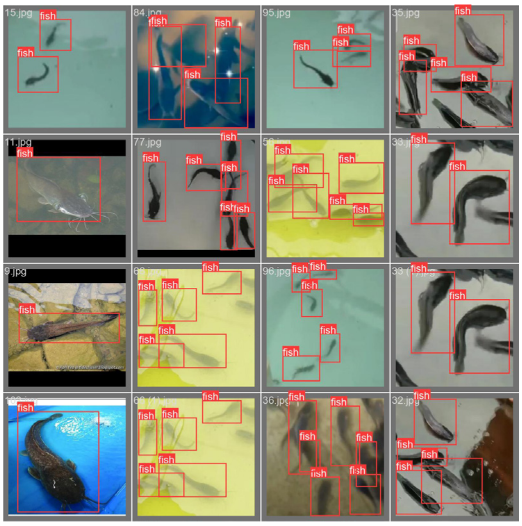
Despite these remarkable advances in harnessing artificial intelligence for aquaculture advancements, a palpable gap remains in the collective understanding of fish monitoring and tracking. To address this lacuna, the present research endeavors to pioneer the realm of aquaculture management by championing the cause of AI-Enhanced Fish Monitoring and Tracking.

Materials and methods

This section describes the methodical approach consisting of several steps that contributed to the development and validation of an AI-driven solution aimed at improving the accuracy, scalability, and efficiency of detecting and tracking fish, with a specific focus on Nigerian catfish farming.

Dataset description

The dataset comprises about 102 catfish images of different sizes, the majority of which were extracted from video footage taken above a fish pond, while the rest were obtained from the Internet. Additional files, such as code and model configurations, are made available here on GitHub.



Source: Authors

Figure 1: A compilation of images from the Nigerian Catfish Image Dataset.

Dataset creation

In this study, a mobile phone camera was used to record fish in the tarpaulin fish pond from an overhead perspective. This perspective was chosen because it is the most economical and efficient, and it minimizes reflection and other potential disturbances, ensuring clearer visibility of the fish. Efforts were made to record the video when fish clustering was minimal to aid in the accurate annotation of images extracted from the footage, given that catfish, like other fish, tend to congregate in one area of the pond to avoid sunlight. Using this method, we were able to obtain approximately 80 images of catfish. To diversify and enrich the dataset, supplementary data were procured from the internet. Figure 1 shows various sizes and orientations of catfish captured from different ponds. Each image extracted from the overhead camera footage contains bounding boxes that indicate the detected catfish for object-detection annotation. The images reflect the diverse datasets obtained from both manual recording and supplementary online sources, processed, and annotated.

Preprocessing and annotation

The dataset used in this study underwent preprocessing to enhance image quality and normalize the images, making them suitable for training. Data cleaning was performed by eliminating unsuitable images. This causes the number of images to decrease from about 150 to 102. They were resized to 320 × 320 and renamed in numerical order, ranging from "1.jpg" to “102.jpg”. Bounding boxes are essential for object-detection tasks. They are rectangular boxes that define the location of the target object (catfish in this case), with each bounding box consisting of the x and y coordinates (xmin-top left, ymin-top left, xmax-bottom right, ymax-bottom right) (Everingham et al., 2010). The annotations for each image of the dataset were created using a free graphical image labeling tool, LabelImg, in both the PASCAL VOC format and the YOLO format (Abedeen et al., 2023).

Modeling experiments and evaluation

This research was modeled as an object detection problem and three models were designed using different architectures: Faster R-CNN, YOLO, and RetinaNet. For this study, the models were trained utilizing the complimentary GPU resources offered by Google Colab. The results of the models were inspected and compared.

Evaluation Metrics Precision is the ratio of correctly classified positive samples to the total number of samples identified as positive, whether accurately or inaccurately. The recall is the ratio of correctly classified positive samples to the total number of actual positive samples. Precision measures the accuracy of the detected objects, while recall measures a model's ability to detect all possible objects. Both precision and recall were used to understand the performance of the object detection models and tune them to achieve better results (Equation 1 and 2).

$$Precision = \frac{TP}{TP + FP} \quad (1)$$

$$Recall = \frac{TP}{TP + FN} \quad (2)$$

Where:

TP - is the number of True Positives,

FP - is the number of False Positives,

FN - is the number of False Negatives.

Higher precision may decrease recall, and vice versa. This trade-off can be visualized and analyzed using a precision–recall curve. A Precision-Recall (PR) curve illustrates the balance between precision and recall at varying thresholds. The average precision (AP) is a single metric that summarizes the area under the precision-recall curve, providing an aggregate measure of a model's performance across a single class (in this case, the fish) and at different thresholds. Higher average precision values indicate better model performance in terms of both precision and recall (Equation 3) (Mercaldo et al., 2023).

$$\mathrm{AP} = \sum_n (R_n - R_{n-1}) P_n \quad (3)$$

Where:

R_n and P_n are the precision and recall at the n^{th} threshold respectively.

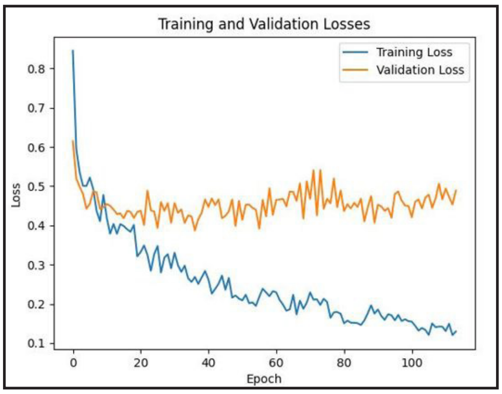
In this study, the Intersection over Union (IoU) metric was used to evaluate the accuracy of the bounding boxes predicted by the object detection models in comparison with the ground truth bounding boxes. This quantitatively measures how well the model can locate and delineate objects within images. The IoU is computed by dividing the intersection area of the two boxes (the predicted bounding box and the ground-truth bounding box) by the area of their union (Rezatofighi et al., 2019). A higher IoU score (close to 1) indicates that the predicted bounding box is very close to the ground truth. In this study, the measure of overlap was evaluated at two levels: 50% overlap (@0.5) and 95% overlap (@0.95).

Data augmentation

For object detection tasks such as this research, data augmentation plays a crucial role in enhancing the performance and generalizability of the models by artificially enlarging the training dataset with diverse variations of the input data. This is desirable because we have a small image dataset. The data augmentation techniques used were horizontal flip, vertical flip, and random rotation. Horizontal flip augmentation mirrors the fish image along its vertical axis, effectively duplicating the dataset and providing additional variations of the object orientations. Similarly, vertical flip augmentation mirrors the image along its horizontal axis, adding variability to the dataset. In the random rotation technique, the image is rotated by a random angle, exposing the model to a variety of rotational variations and assisting it in learning rotation-invariant features.

Object detection using Faster R-CNN

Faster Region-based Convolutional Neural Networks improve upon previous iterations like Fast R-CNN by introducing a Region Proposal Network (RPN) that shares full-image convolutional features with the detection network, thus enabling nearly cost-free region proposals (Ren et al., 2015). The architecture comprises three main components: a ResNet-50 backbone for feature extraction, a Region Proposal Network (RPN) for generating object proposals, and Fast R-CNN for object classification and bounding box regression. The ResNet-50 backbone leverages residual learning to extract hierarchical features from input images (Chen et al., 2021). The RPN uses these features to propose regions of interest, which are then processed by the Fast R-CNN component to classify objects and refine bounding box predictions. In this study, the model was trained for approximately 150 epochs, and its performance was evaluated on a test set. Figure 2 depicts



Source: Authors

Figure 2: Graph depicting the trend of training and validation losses over epochs during Faster R-CNN training progresses.

the trend of training and validation losses over epochs, highlighting the Faster R-CNN model's learning progression.

Object detection using YOLO

You Only Look Once (YOLO) is a state-of-the-art, real-time object detection system that processes an image in a single pass. It treats object detection as a single regression problem, predicting both class labels and bounding box coordinates directly from the image pixels (Redmon et al., 2016). We trained across 150 epochs using the YOLOv8l implementation and annotations in YOLO format. Figure 3 illustrates the training progress of the YOLOv8 model, showing the evolution of losses, precision, recall, and mean average precision (mAP) over time.

Object detection using RetinaNet

RetinaNet addresses the class imbalance problem, which is common in object detection tasks. RetinaNet combines the simplicity of single-stage detectors with a novel loss function called focal loss. Focal loss reduces the loss contribution from easy negatives (background) while focusing more on misclassified positives and hard negatives (Lin et al., 2017).

The focal loss formula (Equation 4) is given by:

$$\mathrm{FL}(p_t) = -\alpha_t(1-p_t)^{\gamma}\log(p_t) \quad (4)$$

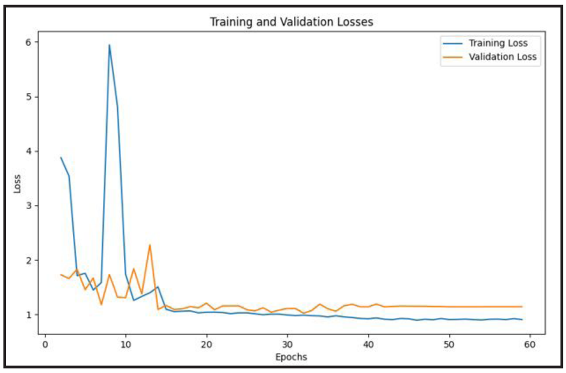
Where:

p_t - is the model's estimated probability for the true class.

α_t - is a balancing factor.

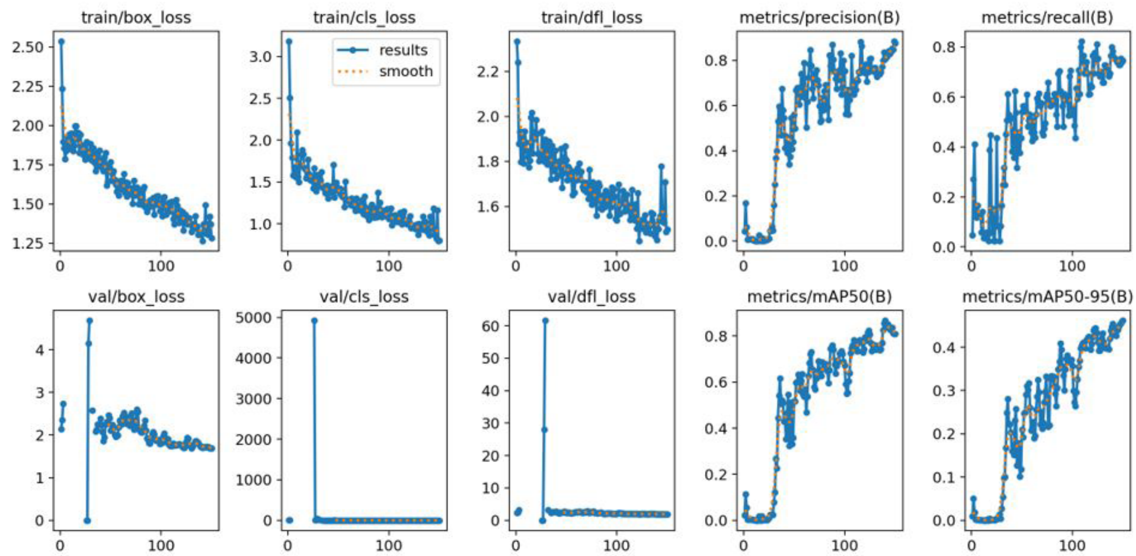
γ - is the focusing parameter (usually set to 2), which helps in reducing the contribution of easy examples to the loss and focusing more on the hard misclassified examples.

RetinaNet's architecture comprises a backbone network for feature extraction and two task-specific subnetworks for classification and bounding box regression. For this research, the backbone network used was ResNet50, The model was trained for approximately 60 epochs, and its performance was evaluated on a test set. Figure 4 illustrates the trend of training and validation losses over epochs, highlighting the RetinaNet model's learning progression.



Source: Authors

Figure 4: Graph depicting the trend of training and validation losses over epochs during RetinaNet training progresses.



Source: Authors

Figure 3: Graph of losses, precision, recall, and mAP as YOLOv8 training progresses.

Results and discussion

The table below presents the evaluation metrics of three different model architectures: Faster R-CNN, YOLO, and RetinaNet when applied to fish detection tasks in the context of Nigerian catfish farming.

Metrics	Faster R-CNN	YOLO	RetinaNet
Precision	0.8575	0.8758	0.1278
Recall	0.6358	0.7469	0.7961
AP: @0.5	0.9222	0.8095	0.2223
AP: @0.95	0.749	0.4619	0.1111

Source: Authors

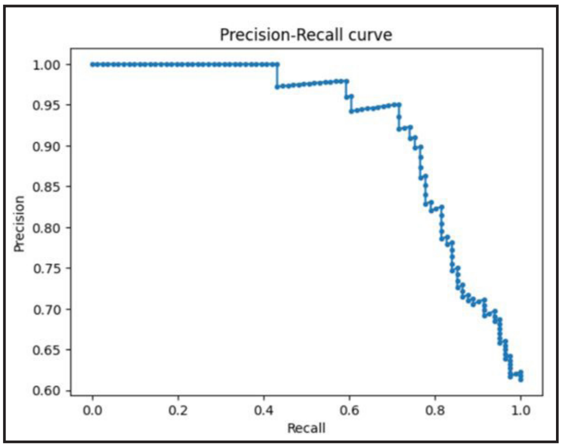
Table 1: Comparison of precision, recall, and AP across the three different models.

Precision Analysis YOLO emerged as the best-performing model as depicted in Table 1, with a precision of 0.8758, closely followed by Faster R-CNN with 0.8575. In contrast, RetinaNet had a significantly lower precision of 0.1278, suggesting a higher rate of false detections.

Recall Analysis RetinaNet outperformed its competitors in this metric, with a recall of 0.7961. YOLO followed with a commendable 0.7469, whereas Faster R-CNN lagged with a recall of 0.6358. This implies that RetinaNet may be better at identifying most fish, but at the expense of more false positives, as evidenced by its low precision.

Average Precision (AP) Analysis Faster R-CNN dominated with an AP of 0.9222 when tested at an IoU threshold of 0.5, indicating superior performance in moderately strict detection criteria. YOLO trailed with 0.8095, whereas RetinaNet's score was significantly lower at 0.2223. However, at a more stringent IoU threshold of 0.95, a Faster R-CNN still led the pack with an AP of 0.749. YOLO's performance dipped to 0.4619, and RetinaNet further lagged by 0.1111. This suggests that Faster R-CNN consistently performs well, even under stricter detection criteria.

Figure 5 displays a Precision-Recall curve, illustrating the trade-off between precision and recall for the Faster R-CNN model, with performance remaining high at the beginning and decreasing as recall increases. Given these results, Faster R-CNN emerges as a balanced model offering both high precision and decent recall, making it suitable for applications where both accuracy and comprehensiveness are paramount. Although YOLO has slightly higher precision, its recall is slightly lower. RetinaNet has a high recall but a low precision, making it less suitable for our specific use case where false positives can be harmful.



Source: Authors

Figure 5: Precision-recall curve for Faster R-CNN fish detection model.

Faster R-CNN's proficient detection capabilities can lead to more accurate and efficient monitoring of fish populations in the context of the study's goal of improving aquaculture and fishery management. Such advancements are pivotal in the automation of monitoring procedures, potentially leading to improved resource utilization and reduced operational costs.

Conclusion

In the dynamic landscape of aquaculture and fishery management, the integration of artificial intelligence represents a beacon of innovation, holding the promise to transform conventional approaches. This study delved deeply into the realm of AI, with a specific focus on Nigerian catfish farming, aiming to leverage its potential to enhance the accuracy, scalability, and efficiency of fish detection. Our robust methodology encompasses a comprehensive process of data collection, data processing, model training, and model evaluation. In our evaluation of three prominent object detection models: Faster R-CNN, YOLO, and RetinaNet, we identified Faster R-CNN as the frontrunner. It struck a balance between precision and recall, rendering it the ideal choice for fish detection in aerial imagery of catfish ponds.

The economic implications of our findings are profound. With Faster R-CNN leading the way, stakeholders in aquaculture can anticipate a future where monitoring processes are not only automated but also remarkably accurate. Such advancements have the potential to significantly reduce manual labor, minimize errors, and optimize resource utilization. Furthermore, the integration of an application that combines fish detection with object tracking enables real-time monitoring and data-driven decision-making, previously unattainable through traditional methods. This AI-enhanced approach promises substantial improvements in operational efficiency and cost-effectiveness for fisheries management by automating fish population monitoring and optimizing resource allocation. Nonetheless, our research merely marks the initial step in a wide array of possibilities. While Faster R-CNN excelled in our dataset, the ever-evolving nature of AI suggests that newer models or techniques may emerge with even greater capabilities. Additionally, exploring data augmentation strategies, model fusion, or the incorporation of other AI paradigms could further enhance the accuracy and efficiency of fish detection.

In conclusion, this study underscores the immense potential of artificial intelligence in reshaping traditional aquaculture and fishery management. By bridging the gap between technology and aquaculture, we not only pave the way for a more sustainable and efficient future but also set the stage for countless innovations in the realm of AI-driven fishery management. The journey has just begun, and the horizon is promising.

Acknowledgements

We wish to express our profound gratitude to Abosede Oloyede for her invaluable assistance in creating the footage, which laid the foundation for the dataset integral to this research. Our appreciation also extends to Google Colab for the generous provision of complementary GPU resources, which markedly accelerated the computational endeavors associated with our research. Finally, OOA appreciates FAPESP Brazil for its support during this research.

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References

[1] Abedeen, I., Rahman, M. A., Prottyasha, F. Z., Ahmed, T., Chowdhury, T. M. and Shatabda, S. (2023) "FracAtlas: A Dataset for Fracture Classification, Localization and Segmentation of Musculoskeletal Radiographs", *Scientific Data*, Vol. 10, No. 1, p. 521. ISSN 2052-4463. DOI 10.1038/s41597-023-02432-4.

[2] An, D., Hao, J., Wei, Y., Wang, Y. and Yu, X. (2021) "Application of computer vision in fish intelligent feeding system—A review", *Aquaculture Research*, Vol. 52, No. 2, pp. 423-437. ISSN 1365-2109. DOI 10.1111/are.14907.

[3] Chan, S. N., Fan, Y. W. and Yao, X. H. (2022) "Mapping of coastal surface chlorophyll-a concentration by multispectral reflectance measurement from unmanned aerial vehicles", *Journal of Hydro-Environment Research*, Vol. 44, pp. 88-101. ISSN 1876-4444. DOI 10.1016/j.jher.2022.08.003.

[4] Chen, Q., Liu, Z., Zhang, Y., Fu, K., Zhao, Q. and Du, H. (2021) "RGB-D salient object detection via 3D convolutional neural networks", *Proceedings of the AAAI conference on artificial intelligence*, Vol. 35, No. 2, pp. 1063-1071. ISSN 2374-3468. DOI 10.1609/aaai.v35i2.16191.

[5] Dixit, S., Kumar, A., Srinivasan, K., Vincent, P. D. R. and Krishnan, N. R. (2023) "Advancing genome editing with artificial intelligence: Opportunities, challenges, and future directions", *Frontiers in Bioengineering and Biotechnology*, Vol. 11. ISSN 2296-4185. DOI 10.3389/fbioe.2023.1335901.

[6] Dupont, C., Cousin, P. and Dupont, S. (2018) "IoT for Aquaculture 4.0 Smart and easy-to-deploy real-time water monitoring with IoT", *22018 Global Internet of Things Summit (GIoTS), Bilbao, Spain, 2018*. pp. 1-5. DOI 10.1109/GIOTS.2018.8534581.

[7] Emmanuel, O., Chinenye, A., Oluwatobi, A. and Kolawole, P. (2014) "Review of aquaculture production and management in Nigeria", *American Journal of Experimental Agriculture*, Vol. 4, No. 10, p. 1137. ISSN 2231-0606. DOI 10.9734/AJEA/2014/8082.

[8] Everingham, M., Van Gool, L., Williams, C. K., Winn, J. and Zisserman, A. (2010) "The Pascal Visual Object Classes (VOC) Challenge", *International Journal of Computer Vision*, Vol. 88, pp. 303-338. ISSN 1573-1405. DOI 10.1007/s11263-009-0275-4.

[9] Føre, M., Frank, K., Norton, T., Svendsen, E., Alfredsen, J. A., Dempster, T., Eguiraun, H., Watson, W., Stahl, A., Sunde, L. M. and Schellewald, C. (2018) "Precision fish farming: A new framework to improve production in aquaculture", *Biosystems Engineering*, Vol. 173, pp. 176-193. ISSN 1537-5129. DOI 10.1016/j.biosystemseng.2017.10.014.

[10] Gunda, N. S. K., Gautam, S. H., and Mitra, S. K. (2019) "Editors' Choice—Artificial Intelligence Based Mobile Application for Water Quality Monitoring", *Journal of The Electrochemical Society*, Vol. 166, No. 9. ISSN 1945-7111. DOI 10.1149/2.0081909jes.

[11] Harshith, D. G., Surve, S., Prasad, S. S., Ganesh, B. V. and Thomas, K. A. (2023) "Remote Aquaculture Monitoring with Image Processing [ML] and AI", *2023 5th International Conference on Bio-engineering for Smart Technologies (BioSMART)*, pp. 1-4. ISSN 2831-4344. DOI 10.1109/BioSMART58455.2023.10162001.

[12] Iyang, N. F., Effiong, U. E. and Okon, J. I. (2020) "Nigeria diversification agenda and economic growth: The role of agriculture", *Social Science and Management International Journal*, Vol. 1, No. 2. pp. 36-51. ISSN 2583-9853.

[13] Javaid, M., Haleem, A., Khan, I. H. and Suman, R. (2022) "Understanding the potential applications of artificial intelligence in agriculture sector", *Advanced Agrochem*, Vol. 2, No. 1, pp. 15-30. ISSN 2773-2371. DOI 10.1016/j.aac.2022.10.001.

[14] Jia, B. B. and Zhang, M. L. (2020) "Multi-dimensional classification via kNN feature augmentation", *Pattern Recognition*, Vol. 33, No. 1, pp. 3975-3982, ISSN 2374-3468. DOI 10.1609/aaai.v33i01.33013975.

[15] Kacprzyk, J. (2009) "Fuzzy Sets Theory, Foundations of", *Encyclopedia of Complexity and Systems Science*, pp. 4059-4080. ISBN 978-0-387-30440-3. DOI 10.1007/978-0-387-30440-3_238.

[16] Kaidarova, A., Geraldi, N. R., Wilson, R. P., Kosel, J., Meekan, M. G., Eguíluz, V. M., Hussain, M. M., Shamim, A., Liao, H., Srivastava, M. and Saha, S. S. (2023) "Wearable sensors for monitoring marine environments and their inhabitants", *Nature Biotechnology*, Vol. 41, No. 9, pp. 1208-1220. ISSN 1546-1696. DOI 10.1038/s41587-023-01827-3.

[17] Katampe, B. (2016) "Overview of aquaculture in Nigeria: prospects and challenges", Seminar Presentation presented to: *5th Postgraduate Research Symposium, Moulton College, Northampton, 15 December 2016.* Available: http://nectar.northampton.ac.uk/id/eprint/9310.

[18] Khurshid, H., Mumtaz, R., Alvi, N., Haque, A., Mumtaz, S., Shafait, F., Ahmed, S., Malik, M. I., and Dengel, A. (2022) "Bacterial prediction using internet of things (IoT) and machine learning", *Environmental Monitoring and Assessment*, Vol. 194, No. 2. ISSN 1573-2959. DOI 10.1007/s10661-021-09698-4.

[19] Lim, L. W. K. (2023) "Implementation of Artificial Intelligence in Aquaculture and Fisheries: Deep Learning, Machine Vision, Big Data, Internet of Things, Robots and Beyond", *Journal of Computational and Cognitive Engineering*, Vol. 3 No. 2, pp. 112-118. ISSN 2810-9503. DOI 10.47852/bonviewJCCE3202803.

[20] Lin, T. Y., Goyal, P., Girshick, R., He, K. and Dollár, P. (2017) "Focal loss for dense object detection", *Proceedings of the IEEE International Conference on Computer Vision*, pp. 2980-2988. E-ISSN 2380-7504. DOI 10.1109/ICCV.2017.324.

[21] Lu, H. Y., Cheng, C. Y., Cheng, S. C., Cheng, Y. H., Lo, W. C., Jiang, W. L., Nan, F. H., Chang, S. H. and Ubina, N. A. (2022) "A low-cost AI buoy system for monitoring water quality at offshore aquaculture cages", *Sensors*, Vol. 22, No. 11. ISSN 1424-8220. DOI 10.3390/s22114078.

[22] Mandal, A. and Ghosh, A. R. (2023) "Role of artificial intelligence (AI) in fish growth and health status monitoring: a review on sustainable aquaculture", *Aquaculture International*, Vol. 32, pp. 1-30. ISSN 2455-8400. DOI 10.1007/s10499-023-01297-z.

[23] Martín, F. F., Rodríguez, A. V., de Quiros, L. B., Martínez, A. L. and Postolache, O. (2022) "An Underwater Radio-Frequency IoT System for the Identification of Fish", *2022 International Symposium on Sensing and Instrumentation in 5G and IoT Era (ISSI),* pp. 127-131. DOI 10.1109/issi55442.2022.9963314.

[24] Mei, Y., Sun, B., Li, D., Yu, H., Qin, H., Liu, H., Yan, N. and Chen, Y. (2022) "Recent advances of target tracking applications in aquaculture with emphasis on fish", *Computers and Electronics in Agriculture*, Vol. 201, p. 107335. ISSN 1872-7107. DOI 10.1016/j.compag.2022.107335.

[25] Mercaldo, F., Brunese, L., Martinelli, F., Santone, A. and Cesarelli, M. (2023) "Object Detection for Brain Cancer Detection and Localization", *Applied Sciences*, Vol. 13, No. 16, p. 9158. ISSN 2523-3971. DOI 10.3390/app13169158.

[26] Patel, N., Patel, S., Parekh, P. and Shah, M. (2022) "Advancing Aquaculture with Artificial Intelligence", In "*Agricultural Biotechnology"*, 1st ed., pp. 189-213. ISBN 9781003268468. DOI 10.1201/9781003268468-10.

[27] Patrício, D. I. and Rieder, R. (2018) "Computer vision and artificial intelligence in precision agriculture for grain crops: A systematic review", *Computers and Electronics in Agriculture*, Vol. 153, pp. 69-81. ISSN 0168-1699. DOI 10.1016/j.compag.2018.08.001.

[28] Redmon, J., Divvala, S., Girshick, R. and Farhadi, A. (2016) "You only look once: Unified, real-time object detection", *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 779-788. E-ISSN 1063-6919. DOI 10.1109/CVPR.2016.91.

[29] Ren, S., He, K., Girshick, R. and Sun, J. (2015) "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks", *Advances in Neural Information Processing Systems*, Vol. 28, No. 6. ISSN 1049-5258. DOI 10.1109/TPAMI.2016.2577031.

[30] Rezatofighi, H., Tsoi, N., Gwak, J., Sadeghian, A., Reid, I. and Savarese, S. (2019) "Generalized intersection over union: A metric and a loss for bounding box regression", *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 658-666. DOI 10.1109/CVPR.2019.00075.

[31] Rodriguez, A., Rico-Diaz, A. J., Rabunal, J. R., Puertas, J. and Pena, L. (2009) "Fish Monitoring and Sizing Using Computer Vision", In: Ferrández V. J., Álvarez-Sánchez, J., de la Paz L. F., Toledo-Moreo, F. and Adeli, H. (eds) *Bioinspired Computation in Artificial Systems. IWINAC 2015. Lecture Notes in Computer Science*, Vol. 9108, Springer, Cham, pp. 419-428. ISBN 978-3-319-18832-4. DOI 10.1007/978-3-319-18833-1_44.

[32] Saeed, R., Zhang, L., Cai, Z., Ajmal, M., Zhang, X., Akhter, M., Hu, J. and Fu, Z. (2022) "Multisensor monitoring and water quality prediction for live ornamental fish transportation based on artificial neural network", *Aquaculture Research*, Vol. 53, No. 7, pp. 2833-2850. ISSN 1365-2109. DOI 10.1111/are.15799.

[33] Shreesha, S., Manohara, P. M., Verma, U. and Pai, R. M. (2020) "Computer Vision Based Fish Tracking and Behaviour Detection System", *2020 IEEE International Conference on Distributed Computing, VLSI, Electrical Circuits and Robotics (DISCOVER)*, pp. 252-257, IEEE. DOI 10.1109/DISCOVER50404.2020.9278101.

[34] Shu, L., Ludwig, A. and Peng, Z. (2020) "Standards for Methods Utilizing Environmental DNA for Detection of Fish Species", *Genes*, Vol. 11, No. 3, p. 296. ISSN 2073-4425. DOI 10.3390/genes11030296.

[35] Sung, M., Yu, S. C. and Girdhar, Y. (2017) "Vision based real-time fish detection using convolutional neural network", *OCEANS 2017-Aberdeen*, IEEE. pp. 1-6. DOI 10.1109/OCEANSE.2017.8084889.

[36] Ubina, N. A., Lan, H. Y., Cheng, S. C., Chang, C. C., Lin, S. S., Zhang, K. X., Lu, H. Y., Cheng, C. Y. and Hsieh, Y. Z. (2023) "Digital twin-based intelligent fish farming with Artificial Intelligence Internet of Things (AIoT)", *Smart Agricultural Technology*, Vol. 5, p. 100285. ISSN 2772-3755. DOI 10.1016/j.atech.2023.100285.

[37] Udeogu, C. U., Nwakanma, C. I., Ayoade, I. A., Amadi, C. S. and Eze, U. F. (2023) "Agro-vision IoT-enabled Crop Pest Recognition System based on VGG-16", *2023 2nd International Conference on Multidisciplinary Engineering and Applied Science (ICMEAS)*, IEEE. pp. 1-5. DOI 10.1109/ICMEAS58693.2023.10429830.

[38] Wu, Y., Duan, Y., Wei, Y., An, D. and Liu, J. (2022) "Application of intelligent and unmanned equipment in aquaculture: A review", *Computers and Electronics in Agriculture*, Vol. 199, p. 107201. ISSN 1872-7107. DOI 10.1016/j.compag.2022.107201.

[39] Yang, L., Liu, Y., Yu, H., Fang, X., Song, L., Li, D. and Chen, Y. (2021) "Computer vision models in intelligent aquaculture with emphasis on fish detection and behavior analysis: A review", *Archives of Computational Methods in Engineering*, Vol. 28, pp. 2785-2816. ISSN 1753-5131. DOI 10.1007/s11831-020-09486-2.

[40] Yang, X., Zhang, S., Liu, J., Gao, Q., Dong, S. and Zhou, C. (2021) "Deep learning for smart fish farming: applications, opportunities and challenges", *Reviews in Aquaculture*, Vol. 13, No. 1, pp. 66-90. ISSN 1753-5131. DOI 10.1111/raq.12464.

[41] Yang, Y., Elsinghorst, R., Martinez, J. J., Hou, H., Lu, J. and Deng, Z. D. (2022) "A real-time underwater acoustic telemetry receiver with edge computing for studying fish behavior and environmental sensing", *IEEE Internet of Things Journal*, Vol. 9, No. 18, pp. 17821-17831. ISSN 2327-4662. DOI 10.1109/JIOT.2022.3164092.

[42] Zhao, S., Zhang, S., Liu, J., Wang, H., Zhu, J., Li, D. and Zhao, R. (2021) "Application of machine learning in intelligent fish aquaculture: A review", *Aquaculture*, Vol. 540, p. 736724. ISSN 1873-5622. DOI 10.1016/j.aquaculture.2021.736724.