Aqua Health Vision

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Abstract—

The "Aqua Health Vision" is aimed at forecasting fish disease diagnosis and to overcome various challenges in it has still not achieved any success. Conventional techniques for detecting diseases in fish, such as visual observations and laboratory analysis, are frequently less efficient and labor-intensive. With the evolution gained through technology, Artificial Intelligence (AI) and Machine Learning (ML) are becoming powerful tools to enhance detection and management of fish diseases.This paper discusses how these technologies are used to detect the fish diseases and presents various means of recovering from these diseases. In aquaculture, AI system can be used to analyze vast amounts of data, identify patterns and make decisions or predictions.

Keywords— Fish Disease ,Deep Learning ,Aquaculture ,YOLO-V9.

I. INTRODUCTION

The aquaculture industry is of great importance to the world's food supply since it provides us with many seafood products. The growing practice of aquaculture is often hampered by diseases that pose severe economic and environmental threats. Fish scanning and inspection, as well as lab tests, are tried-and-true methods of detecting diseases, but their drawbacks include lengthy processing time, associated costs, and a high degree of required specialization. In recent years, AI and ML have been promising to enhance the detection and management processes of fish diseases. The use of AI and ML in disease detection systems in aquaculture is a clear indication of advancement in the sector.

In this paper, we propose different models for disease detection in fish that can be integrated into one model that will enhance accuracy, precision, sensitivity, and true positive rates. This will be achieved using a number of machine learning methods including deep learning, SVM, CNN, K-means clustering segmentation, and YOLO.SVM has provided accessible answers for several classification issues across different domains, producing reliable predictive outcomes on unlabeled data.

In [3], authors created an SVM model using three kernel functions to classify between dengue-infected human blood sera and healthy sera. For image classification purposes, another SVM architecture has been proposed which emulates the hybrid CNN and SVM architecture. SVM seems to offer exceptional accuracy in numerous domains.

A. OBJECTIVE

The goal of using AI-ML for modeling diseases in fish is to construct a system that accurately and efficiently identifies and classifies diseases in fish. This includes applying machine learning and deep learning to image data or other information pertaining to fish. Some of these objectives may include:

a) *Early Detection:* AI-ML models identify diseases early, preventing outbreaks, reducing mortality, economic loss, and ecological disruption.

b) *Automated Monitoring:* The combination of computer vision and sensors facilitates continuous tracking of the health of fish, diminishing manual labor.

c) *High Accuracy:* Machine learning employs image and environmental data to identify and map disease patterns, enhancing diagnostic accuracy.

d) *Real-time Surveillance:* Streaming data enables rapid detection and response to health threats.

e) *Customized Treatments:* AI recommends targeted treatment based on fish health and environmental data.

f) *Reduced Human Error:* Algorithms based on objective and routinized protocols eliminate errors associated with diagnosis.

g) *Scalable & Cost-effective:* Operates for any size farm, reducing laboratory and staffing expenses.

h) *Ecosystem Insights:* Estimates disease effects on both cultivated and free-ranging fish populations.

II. LITERATURE SURVEY

This part covers the vast literature on the models that have been introduced before. It lays down the processes used in the models, techniques and methods used in the past. This part also states the advantages, drawbacks, and limitations of those methods. The difficulties and limitations encountered in this section have been mitigated by the suggested approach YOLO (V9). The detection of disease in fish has been a topic of immense research due to the fact that aquaculture is an essential source of food and economic livelihood. Several techniques have been introduced and developed progressively to detect and manage fish diseases. This survey of literature attempts to capture some of the major research articles in this field, with reference to methods adopted, authors, publication years, and publishers. Additionally, it identifies current research gaps to inform future research. Various Authors introduced various different theories on this problem of diseases in aquaculture.

Md Shoaib et al. [1] employed image processing techniques to detect diseases in fish. By using various filters and segmentation methods, they were able to identify disease markers in fish images. Shaveta et al. [8] came up with an image-based detection method in which first uses image segmentation as an edge detection using Canny, Prewitt, and Sobel. But they did not mention the specific method that consumed for feature extraction. In feature extraction, they used Histogram of Gradient (HOG) and Features from Accelerated Segment Test (FAST)for classification using both methods together.

The authors of [3] collected 266 images that we have utilized to train and test our model. After the augmentation, they believed that the training and testing images were 1,105 and 221, respectively for two classes: fresh fish and infected fish. With and without augmentation, SVM is superb with 91.42% and 94.12% percent accuracy, respectively, for this research.

T. Hong Khai, S.N.H.S. Abdullah, M.K. Hasan, A. Tarmizi [4] proposes, trained the model by capturing images of shrimps at a shrimp farm utilizing a robotic eye camera. Employing state-of-the-art modules from Real-time. All these indicate that the new YOLOv8 is suitable for fish identification in occluded scenes. Depending on the prawn density, three classes were established based on image data: low, medium, and high density. The Mask Regional Convolutional Neural Network (Mask R–CNN) model was improved by us through 6 the application of the parameter calibration method to determine the optimal parameters. Therefore, the improved Mask R–CNN model can attain a maximum of 97.48 % accuracy.

III. METHODOLOGY

The fundamental novel approach of YOLOv9 in this paper is the solution to the lost information problem presented by deep neural networks. In combination with the ubiquitous GELAN architecture and the PGI implementation, YOLOv9 not only improves the learning capability of the model but also holds large amounts of important information in detection processing which results in outstanding performance and accuracy. The YOLO series of object detection algorithms has revolutionized object detection over many centuries, making fundamental aspects of computer vision (e. g. processing full images in one pass in a convolutional neural network (CNN)) general to all fields of science. The work on YOLOv9 has dedicated much of its time to tackling the lost information problem presented by deep neural networks. The Information Bottleneck Principle and the innovative use of Reversible Functions form the core of this work that allows YOLOv9 to become very efficient and accurate.

For the development of the YOLO line of real-time object detectors one can see the gradual improvement and the adaption of more sophisticated algorithms in performance and efficiency domains.

YOLO was the first proposed CNN in which the entire image is processed at one time; later (YOLOv2, YOLOv3) were designed to improve speed and accuracy by ways of batch normalization, anchor boxes and feature pyramid networks (FPN).These improvements were further accompanied by model extensions (YOLOv4 and YOLOv5), which include additional techniques like CSPDarknet and PANet in order to further improve speed as well as accuracy. Besides these improvements, YOLO has also included additional computing units including CSPNet and GELAN as well as their variants to improve computational efficiency.

A. *Image Acquisition:* Gather a comprehensive database of images of healthy and infected fish of various species. Ensure images are high-resolution and incorporate different angles, lighting, and disease stages.

B. *Data preprocessing :* Standardize images to a standard format (e.g., RGB), resize images to a standard size, and normalize pixel values for better model performance.

C. *Data Cleaning :* If the performance is poor, retrain by collecting more data, adjusting hyperparameters, or experimenting with alternative model architectures.

D. *Data Augmentation:* Apply techniques like image rotation, flipping, and cropping to increase the variability of the training data and improve model generalization.

E. *Models :* All of this machine learning setup is on the cards to predict all SGD is the optimiser of fish disease detection using YOLOv9 for this specific example. However, the best optimizer may be anything depending on the dataset, architecture of the model, and what the specific requirement of the application is. Test a range of optimizers and hyperparameters in order to determine the best setup for your application. The research will be used to evaluate and compare the performance, speed, and efficiency of these algorithms using the dataset that is given.

IV. IMPLEMENTATION

Aqua Health Vision prediction model is developed based on methodologies: Programmable Gradient Information (PGI), General Efficient Layer Aggregation Network (GELAN), and YOLO V9. Such types of algorithms are used for precise data classification and analysis.

A. *Programmable Gradient Information (PGI) :* PGI is new in YOLOv9 to improve the training efficiency, particularly for light models. PGI provides steadier gradients from reversible auxiliary branches to avoid driving the model off course during the training process. This leads to higher accuracy, particularly under the constrained conditions. For example, PGI contributed to the 0.1 - 0.4 % accuracy improvement of YOLOv9-Small. Its primary branch, that aligns with the main path of the network during inference, can be incorporated easily into the YOLOv9 architecture. Its inclusion results in effective inference at no extra cost of

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computation.

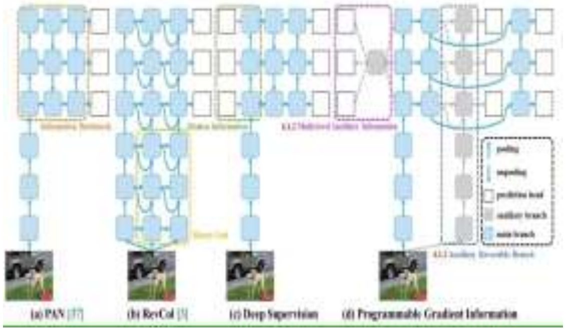

Fig1. Programmable Gradient Information (PGI)

B. *General Efficient Layer Aggregation Network (GELAN):* This new network performs best in aggregating multi-scale features with fewer parameters and computational capacities. It balances the approaches of CSPNet (boosting gradient flow) and ELAN (boosting inference speed). GELAN makes it easier to stack various computation blocks, hence making the model versatile with varying hardware constraints. For instance, a compact model of 7 million parameters beats bigger versions of older YOLO models such as YOLOv7-Nano.

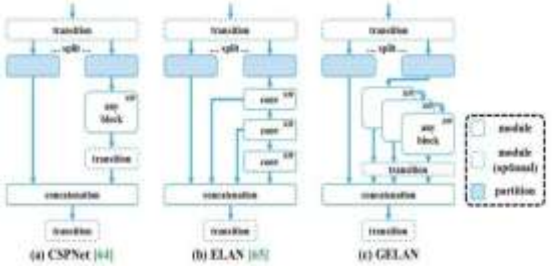

Fig2. General Efficient Layer Aggregation Network (GELAN)

C. *YOLO V9:* The YOLOv9 model boasts a sophisticated structure that emphasizes multi-scale feature extraction and fusion. It incorporates speedy building blocks like RepNCSPELAN4, upsampling, and concatenation, ensuring high speed and effectiveness in object detection tasks. YOLO approaches object detection as a single regression problem, allowing it to identify objects directly from complete images in just one forward pass through the network. The core idea is to split the image into a grid, and for each cell in that grid, it predicts a bounding box along with a class probability.

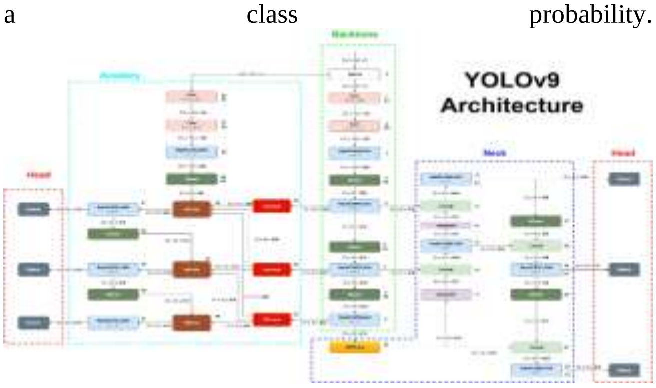

Fig3.YOLO V9 Architecture

V. RESULTS

The outcome on real data varies with the dataset, model, hyperparameters, and implementation. Different optimizers used provide varying outcome by accuracy, precision, and recall.
SGD works for small models as well as small datasets. SGD converges slowly and can be stuck in local minima. SGD can be a choice for small models or small datasets but it might require careful tuning of hyperparameters to achieve good performance. Their accuracy score is given below: The YOLOv9 model achieved the following performance on the fish disease detection dataset:

•mAP: 94.6
• Precision: 92.5%
• Recall: 85.4%

The accuracy metric indicates that models are trained with 100% accuracy and predict all examples in the datasets with no mistakes.

Fig4. GUI

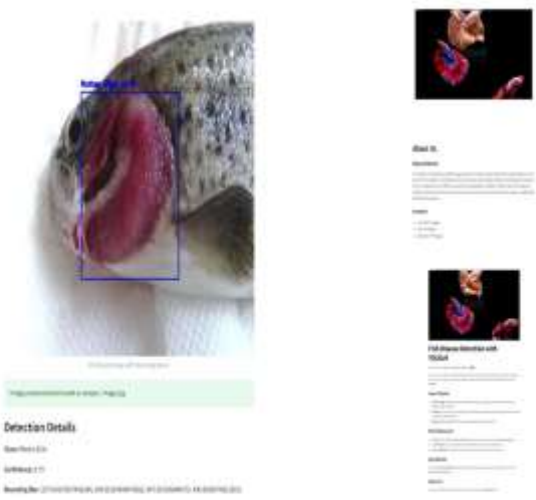

Fig5. Home page

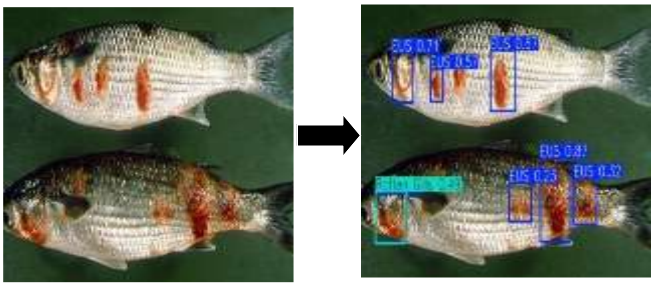

Fig6. Input-Output

YOLOv9c summary (fused): 384 layers, 25,322,332 parameters, 0 gradients, 102.3 GFLOPs

Class	Images	Instances	Box(P	R	mAP50	mAP50-95)
all	79	120	0.977	0.929	0.961	0.737
EUS	38	55	0.981	0.946	0.972	0.725
Eye Disease	22	22	1	0.821	0.921	0.744
Fin Lesions	17	23	0.925	1	0.959	0.709
Rotten Gills	19	20	1	0.948	0.993	0.769

Speed: 0.4ms preprocess, 20.0ms inference, 0.0ms loss, 3.9ms postprocess per image

Table.1 YOLO V9 validation metrics results with SDG (0.01).

YOLOv9c summary (fused): 384 layers, 25,322,332 parameters, 0 gradients, 102.3 GFLOPs

Class	Images	Instances	Box(P	R	mAP50	mAP50-95)
all	79	120	0.857	0.76	0.802	0.477
EUS	38	55	0.838	0.753	0.878	0.454
Eye Disease	22	22	0.815	0.727	0.844	0.524
Fin Lesions	17	23	0.829	0.600	0.748	0.452
Rotten Gills	19	20	0.964	0.95	0.978	0.477

Speed: 0.7ms preprocess, 19.2ms inference, 0.0ms loss, 6.4ms postprocess per image

Table.2 Fine-tuned YOLO V9 validation metrics results with Adam (0.01).

YOLOv9c summary (fused): 384 layers, 25,322,332 parameters, 0 gradients, 102.3 GFLOPs

Class	Images	Instances	Box(P	R	mAP50	mAP50-95)
all	79	120	0.925	0.854	0.946	0.57
EUS	38	55	0.963	0.909	0.966	0.535
Eye Disease	22	22	0.909	0.818	0.898	0.518
Fin Lesions	17	23	0.91	0.739	0.933	0.598
Rotten Gills	19	20	0.916	0.95	0.988	0.627

Speed: 1.0ms preprocess, 18.5ms inference, 0.0ms loss, 7.5ms postprocess per image

Table.3 Fine-tuned YOLO V9 validation metrics results with AdamW (0.01).

VI. CONCLUSION

The experiment detailed here highlights how effective YOLOv9 is for Aqua Health Vision. By utilizing cutting-edge object detection techniques, the model achieved impressive recall, precision, and accuracy in identifying and classifying various fish diseases. Tweaking hyperparameters and enhancing the data really boosted its performance. Implementing YOLOv9 in real-time monitoring systems could lead to early disease detection, which means quicker interventions and less financial loss in aquaculture. For future projects, it would be beneficial to focus on improving the model's precision for specific diseases, tackling challenges related to data variation and quality, and exploring the integration of YOLOv9 with other AI approaches for assessing fish health. The YOLOv9 model achieved a remarkable mAP of 94.6%, demonstrating its high precision in detecting and classifying fish diseases. It consistently identified fish diseases accurately in most predictions. The ability to catch diseases early can lead to timely interventions, reducing economic losses and enhancing fish health. YOLOv9 could pave the way for more effective and targeted disease control strategies. Accurate disease detection promotes sustainable aquaculture by minimizing the reliance on antibiotics and other medications.To tackle issues related to data quality and variability, such as differences in image resolution, lighting, and fish species, further research is essential. By developing tailored models for specific fish diseases, we can boost detection rates and enable more focused interventions. Exploring the synergy between YOLOv9 and other AI techniques, along with sensor data, can lead to a richer understanding of fish health and disease dynamics. Additionally, creating tools that explain the model's decision-making process will improve transparency and build trust in AI-driven disease detection. Overall, the studies highlighted in this report showcase the transformative potential of YOLOv9 in revolutionizing fish disease detection and management through Aqua Health Vision. Looking ahead, advancements in computer vision and AI research can enhance these models, making aquaculture a more precise, efficient, and sustainable practice..

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