Automated disease identification in aquaculture utilizing underwater imaging and YOLOV10 network

Shirinoy Kamolova[1*]; Haydeer Mohamad Abbas[2]; Dadaxon Abdullayev[3]; Chandrasekharan G[4]; Inomjon Matkarimov[5]; Dr. Lalit Sachdeva[6]

Received: 21 March 2025; Revised: 26 April 2025; Accepted: 26 May 2025; Published: 30 June 2025

Abstract

In intense fish farming, continuous identification and surveillance of prevalent infectious diseases are crucial for formulating scientific methods for fish disease avoidance, which may significantly mitigate the death of fish and financial damage. Nonetheless, subpar underwater imagery and poorly identifiable targets pose significant obstacles to detecting infected fish. This research proposes an Automated Disease Identification (ADI) system using Underwater Imaging (UI) and an Improved YOLOV10 Network to address these problems. This work introduces an innovative residual awareness unit referred to as R-AU. This component is included in the main structure of the YOLOv10 model to enhance the system's attention to the intricate aspects of targets in biology during the gathering of features. Using a bilateral feature triangle (BFT) with a dynamic combination of features in the head network augments the amalgamation of contextual data from deeper layers. At the same time, localization signals from shallow levels boost the model's capacity to differentiate objects from their surroundings. Studies conducted at a fishery platform indicated that the enhanced YOLOV10 framework outperformed the baseline YOLOV10, with the mean accuracy rising from 94.36% to 99.75%, reflecting an improvement of 5.39%. The Enhanced YOLO10 system can proficiently identify unhealthy fish and is suitable for large-scale aquaculture.

1*- Jizzakh State Pedagogical University, Uzbekistan. Email: shirin.kamolova.67@mail.ru, ORCID: https://orcid.org/0009-0000-5322-1796

2- Department of Computers Techniques Engineering, College of Technical Engineering, Islamic University in Najaf, Najaf, Iraq; Department of Computers Techniques Engineering, College of Technical Engineering, Islamic University in Najaf of Al Diwaniyah, Al Diwaniyah, Iraq.
Email: iu.tech.eng.haideralabdeli@gmail.com, ORCID: https://orcid.org/0009-0006-2404-4456

3- Urgench State University, Khorezm Region, Uzbekistan. Email: dadaxonabdullayev96@gmail.com, ORCID: https://orcid.org/0009-0009-8583-2538

4- Department of Marine Engineering, AMET University, Kanathur, Tamil Nadu, India.
Email: chandrasekarang@ametuniv.ac.in, ORCID: https://orcid.org/0009-0005-5595-6792

5- Associate Professor, Mamun University, Uzbekistan. Email: inomjon.matkarimov0303@gmail.com, ORCID: https://orcid.org/0000-0002-6783-8591

6- Associate Professor, Department of Management, Kalinga University, Raipur, India.
Email: ku.lalitsachdeva@kalingauniversity.ac.in, ORCID: https://orcid.org/0009-0002-2214-282X

*Corresponding author

DOI: 10.70102/IJARES/V5S1/5-S1-10

Keywords: Automated disease identification, YOLOV10, R-AU, Aquaculture, underwater imaging, Fish disease.

Introduction and Related Works

Naturally caught aquatic creatures constitute a significant proportion of seafood consumed (Zhang, Y., 2022). Excessive fishing driven by the demand for naturally caught aquatic organisms undermines ecology. In aquatic fish farming (FF), introducing fish nutrition or compost enhances FF; however, remaining nutrients, fish excrement, and different waste products can result in aquatic eutrophication, potentially causing ecological disasters like red tides (Freshwater Fish Disease). Consequently, this form of aquatic FF has been prohibited in lakes and rivers. In this environment, the share of large-scale FF will further rise (Mia *et al.*, 2022). One research indicates that advanced FF systems must prevail (Kaur and Chandra, 2024). The high population density and feeding strategy will encounter the increased proliferation of microorganisms, viruses, and fungus, along with the buildup of phosphate and nitrogen, particularly nitrites and ammonia levels, rendering FF more vulnerable to different illnesses. Research indicated that almost fifty percent of productivity declines in FF result from illnesses (Boyd *et al.*, 2020; Sujatha and Mounika, 2023).

Currently, the identification of fish diseases mostly depends on manual techniques. Nevertheless, since light passes from the atmosphere into the aquatic environment, the human eye struggles to assess the well-being of fish, causing delayed medicine delivery or modifications to breeding plans, therefore missing optimal treatment periods and incurring major financial losses (Khan and Taha, 2023). This represents the technological constraint of large-scale FF. Consequently, examining automated systems for fish illness diagnosis and assessment is essential (Ahmed, Aurpa and Azad, 2022).

Advancements in deep learning (DL) technique have led many scholars to suggest methods for identifying animal habits and the exterior features of animals and plants through video image processing, enabling the detection of animals in states of gestation, starvation, and illness, as well as assessing plant maturation and illness, resulting in significant advances in the past few years (Kao *et al.*, 2019; Topalova *et al.*, 2024). The identification technique must possess high real-time capability to mitigate losses from fish-transmissible diseases. The You Only Look Once (YOLO) method is presently in its tenth version. It is the predominant single-stage recognition technique, characterized by high precision and rapid identification speed, and is frequently employed in diverse target recognition applications (Soy and Balkrishna, 2024; Yu *et al.*, 2023).

Fish diseases can potentially cause extensive infections and death rates, representing a major factor in the decline of fish stocks in large-scale FF. Consequently, precise early detection is essential for the timely identification and prevention of disease dissemination (Wright *et al.*, 2023). Currently, many extensive aquaculture operations have used submerged imaging systems.

Nonetheless, overseeing films and physically evaluating fish skin conditions is expensive and difficult to execute in demanding environments. Among the most widespread contemporary tools, computer vision methodologies are widely used to detect fish diseases (Shi *et al.*, 2024).

Visual detection systems provide the benefits of cost-effectiveness and swift analysis while maintaining water quality. Nonetheless, obstacles in fish illness identification persist owing to the intricacies of aquatic ecosystems and the technological constraints in obtaining high-resolution pictures, which now restrict the precision of fish disease diagnoses (Alkaim and Hassan, 2024).

Several preliminary studies have used techniques that process images to detect fish illnesses. Researchers in (Wang *et al.*, 2025) established an image analysis technique for detecting Epizootic Ulcerative Syndrome (EUS) in fish. The pictures underwent initial processing by histogram equalization, which was succeeded by edge detection to isolate relevant data. Subsequently, features were described to obtain image characteristics. The Support Vector Machine (SVM) method was used to identify fish afflicted with EUS, with a detection rate of 84.84% (Kumar *et al.*, 2024). Characteristics were derived from images by clustering using K-mean, followed by classification with the random forest approach, resulting in an accuracy rate of 89.15%. Moreover, Principal Component Analysis (PCA) has been used to diagnose fish diseases (Ina-Salwany *et al.*, 2019).

Nonetheless, these frameworks have restricted adaptation capacity owing to the very simplistic backdrops included in their samples. Furthermore, the identification swiftness and precision of these testing approaches show considerable potential for improvement, limiting their practical usefulness (Das and Ghosh, 2024). The enhanced YOLOv4 framework, which integrates compact depth-wise differentiated convolutions and refines its feature removal and activation processes, has been used in underwater net cage FF observation systems (Giang *et al.*, 2015).

Proposed Method

Dataset

The dataset was generated to develop a DL-based model for fish image disease diagnosis, which may assist aquaculture. The database (Khokher *et al.*, 2022) has a total of seven classes as follows: (1) Aeromoniasis (bacterial illness), (2) Bacterial gill disease, (3) Bacterial Red disease, (4) Saprolegniasis (fungal disease), (5) Healthy fish, (6) Parasitic illnesses and (7) Viral diseases – White tail disease. Figure 1 illustrates the sample healthy UI.

(a) (b) (c)

Figure 1: Sample healthy UI of fish species Khokher *et al.*, 2022.

UI Enhancement

Figure 1 clearly illustrates that the images in the database encounter significant challenges in UI, including poor lighting and color distortion. The adaptive histogram equalization approach enhances individuals with color discrimination and low contrasting issues. The improved image addresses color divergence and poor contrast, dramatically enhancing impression and abundant detail. This is advantageous when learning the target identification framework.

Improved YOLOV10 Network

The YOLOv10 version is more compact, precise, and rapid compared to its predecessors in the YOLO groups, using the Mosaic technique to execute a splitting process on an input UI. It also employs a dynamic scaling technique to enhance the surrounding depth of the UI, hence mitigating excessive fitting during learning. A significant feature of the YOLOv10 framework is the removal of Non-Maximum Suppression (NMS) throughout the learning process. Conventional YOLO models use NMS to eliminate redundant estimates, potentially elevating interpretation delay. Conversely, YOLOv10 eliminates the need for NMS by using an alternate assignment technique, enhancing performance.

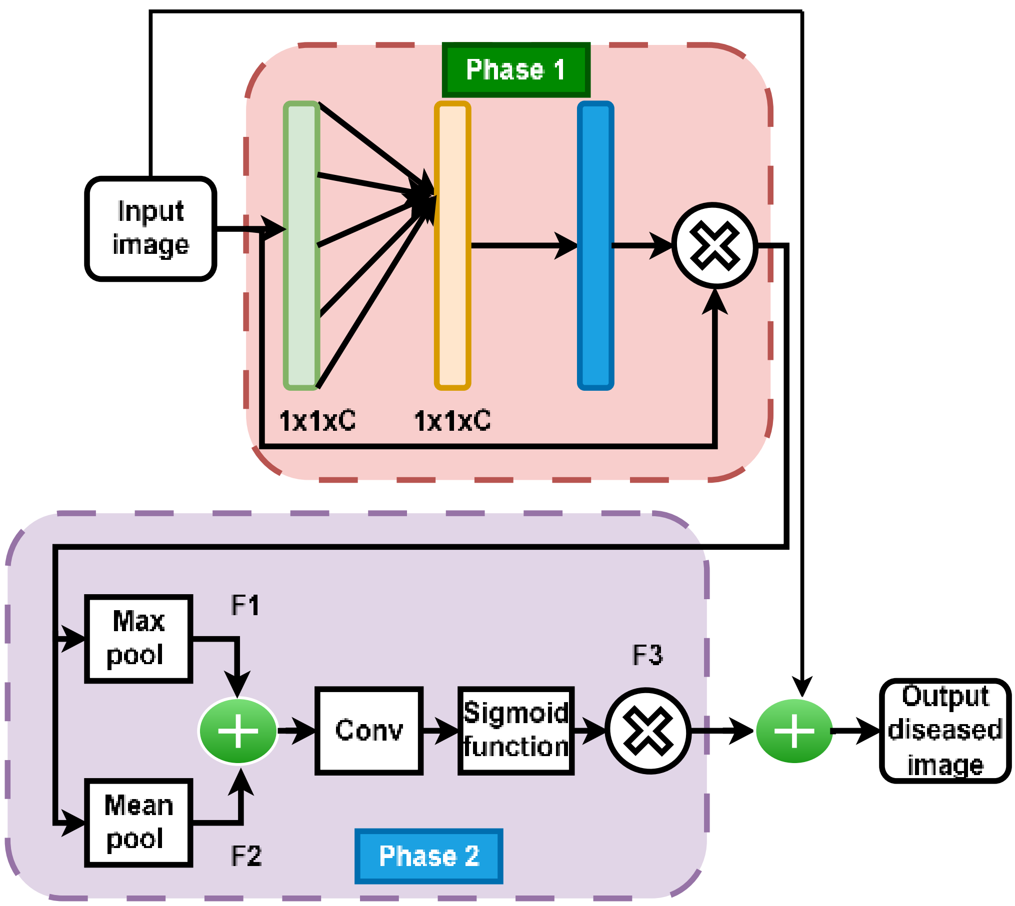

Figure 2: Organization of the R-AU component for ADI.

Attention processes are frequently utilized to focus on certain regions of a UI to enhance effectiveness. A novel R-AU, derived from the fundamental residual blocks, has been suggested. Figure 2 illustrates the organization of the

R-AU component, which integrates attention across geographical and network parameters, creating an orderly progression from networks to landscape. The global average pooling technique produces attention-channel weights via fully linked layers in the first phase. These weights facilitate ranked mixtures of various channels in the feature graph, thereby preventing reduced dimensionality while obtaining inter-channel reliance.

The second phase facilitates the exact identification and weighting of regions of interest (RoI) on the characteristic map, improving accuracy by extracting more distinctive characteristics. Greatest and mean pooling are used on F to get the $F1\ and\ F2$ characteristics, respectively. $F1\ and\ F2$ are later amalgamated and subjected to a convolution process. The geographic focus weights $F3$ are derived by averaging the characteristics produced from convolution processes by applying the sigmoid operator. R-AU utilizes Global Mean Pooling during the initial phase to analyze the characteristic input map F across the channel vector. This procedure produces the mean value for every channel, so condensing the input characteristic map F into an attribute map with size $1 \times 1 \times C$.

After applying a 1D convolutional kernel, the resultant characteristic map is processed via a sigmoid function to provide standardized attention-channel weights. During the second phase, R-AU initially employs maximum pooling and average pooling on the augmented features from the first phase to produce two regional map functions. Subsequently, it executes the combination of features. Ultimately, standardized attention scores are obtained employing the sigmoid function, enabling the amplification of significant areas and the attenuation of the extraneous regions by element-wise amplification. R-AU augments the YOLOv10 framework's ability to concentrate on crucial data about UI organisms by sequential computing of channel and focus in space while preserving minimal computational expenses.

The YOLOv10 approach produces integrated output characteristics by upsampling and slicing several characteristics. However, it neglects the disparate contributions of characteristics at each stage to the integrated output characteristics. An efficient and direct BFT is included in the YOLOv10 framework to resolve this problem. The BFT system employs dual-direction, cross-scale connection to enhance the degree of multiple-scale feature integration.

Results and Discussion

This study assessed the ADI performance of the enhanced algorithm by comparing the proposed YOLOv10 framework with conventional YOLOv10, YOLOv3, and YOLOv4, utilizing Memory size, Recall, and Accuracy as metrics for assessing and contrasting the ADI in aquaculture.

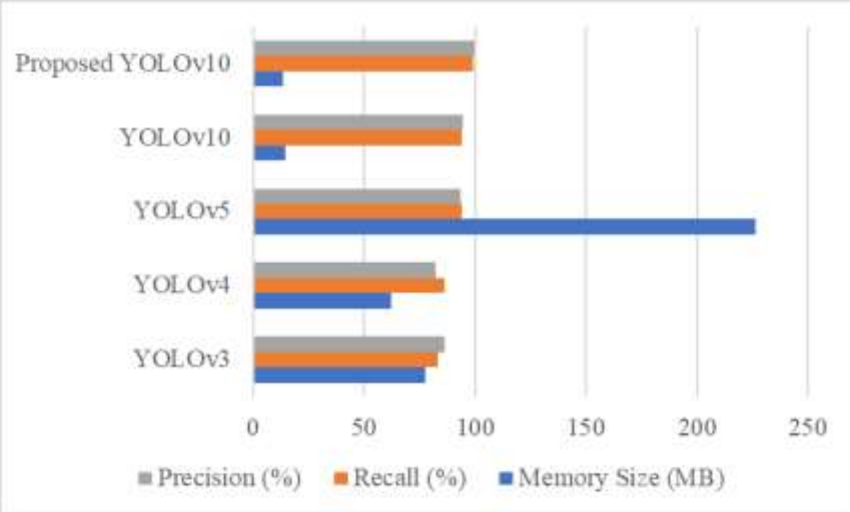

Figure 3: Performance comparison of various methods for ADI in aquaculture with UI.

Figure 3 offers a comparative examination of five object detection models—YOLOv3, YOLOv4, YOLOv5, YOLOv10, and the Proposed YOLOv10—evaluated according to three metrics: precision, recall, and memory size. Among the models, YOLOv5 exhibits the most memory use (~240 MB) while maintaining a recall and accuracy of about 95%, rendering it less suitable for resource-limited settings. Conversely, YOLOv10 and the Proposed YOLOv10 attain comparably good recall and accuracy (~98–99%) with minimum memory consumption, indicating that the proposed YOLOv10 optimally balances efficiency and performance. Among all, the proposed YOLOv10 achieves the highest recall (99.31%) and precision (99.75%) while maintaining the lowest memory footprint (13.6 MB). In contrast, YOLOv5, although exhibiting high recall and precision, demands significantly more memory (226 MB), which can be a limitation for edge computing or real-time systems. This underscores its appropriateness for real-time ADI in aquaculture monitoring systems that need lightweight models with great precision.

Conclusion

This study addresses these issues by proposing an Automated Disease Identification (ADI) system based on Underwater Imaging (UI) and an Improved YOLOV10 Network. This study presents an original residual awareness unit called R-AU. This element is included in the core framework of the YOLOv10 model to improve the system's awareness of the complex characteristics of targets in biology during the feature collecting. While localization signals from shallow levels increase the model's ability to distinguish objects from their surroundings, a BFT with a dynamic combination of features in the head network augments the aggregation of contextual data from deeper levels. With the mean accuracy increase from 94.36% to 99.75%, showing an improvement of 5.39%, studies done at a fisheries platform showed that the upgraded YOLOV10 framework beat the baseline YOLOV10. Large-scale aquaculture is appropriate for the Enhanced YOLO10 system, which can effectively detect diseased fish.

References

Ahmed, M.S., Aurpa, T.T. and Azad, M.A.K., 2022. Fish disease detection using image based machine learning technique in aquaculture. *Journal of King Saud University-Computer and Information Sciences*, *34*(8), pp.5170-5182. https://doi.org/10.1016/j.jksuci.2021.05.003

Alkaim, A. and Hassan, A., 2024. Incorporating Training and Management for Institutional Sustainability: The Worldwide Implementation of Sustainable Development Goals. *Global Perspectives in Management*, *2*(4), pp.26-35.

Boyd, C.E., D'Abramo, L.R., Glencross, B.D., Huyben, D.C., Juarez, L.M., Lockwood, G.S. and Valenti, W.C., 2020. Achieving sustainable aquaculture: Historical and current perspectives and future needs and challenges. *Journal of the World Aquaculture Society*, *51*(3), pp.578-633. https://doi.org/10.1111/jwas.12714

Das, A. and Ghosh, R., 2024. Integration of Pervaporation and Distillation for Efficient Solvent Recovery in Chemical Industries. *Engineering Perspectives in Filtration and Separation*, *2*(2), pp.12-14.

Giang, N.K., Im, J., Kim, D., Jung, M. and Kastner, W., 2015. Integrating the EPCIS and Building Automation System into the Internet of Things: a Lightweight and Interoperable Approach. *Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications*, *6*(1), pp.56-73. https://doi.org/10.22667/JOWUA.2015.03.31.056

https://www.kaggle.com/datasets/subirbiswas19/freshwater-fish-disease-aquaculture-in-south-asia

Ina-Salwany, M.Y., Al-Saari, N., Mohamad, A., Mursidi, F.A., Mohd-Aris, A., Amal, M.N.A., Zamri-Saad, M., 2019. Vibriosis in fish: a review on disease development and prevention. *Journal of Aquatic Animal Health*, *31*(1), pp.3–22. https://doi.org/10.1002/aah.10045

Kao, Y.C., Liu, J.C., Wang, Y.H., Chu, Y.H., Tsai, S.C. and Lin, Y.B., 2019. Automatic Blocking Mechanism for Information Security with SDN. *Journal of Internet Sciences and Information Security*, *9*(1), pp.60-73. https://doi.org/10.22667/JISIS.2019.02.28.060

Kaur, K. and Chandra, G., 2024. Demographic Data Gaps and the Challenges of Population Modeling in Low-resource Settings. *Progression Journal of Human Demography and Anthropology*, *2*(1), pp.13-16.

Khan, M. and Taha, A., 2023. Simulating Complex Structures with Structural Engineering Software. *Association Journal of Interdisciplinary Technics in Engineering Mechanics*, *1*(1), pp.26-37.

Khokher, M.R., Little, L.R., Tuck, G.N., Smith, D.V., Qiao, M., Devine, C. and Wang, D., 2022. Early lessons in deploying cameras and artificial intelligence technology for fisheries catch monitoring: where machine learning meets commercial fishing. *Canadian Journal of Fisheries and Aquatic Sciences*, *79*(2), pp.257-266.

https://doi.org/10.1139/cjfas-2020-044

Kumar, B.S., Karpagavalli, S., Keerthana, K. and Krishnaja, A., 2024. Automatic segmentation of colon cancer using sam AI. *Archives for Technical Sciences*, *2*(31), pp.296–304. https://doi.org/10.70102/afts.2024.1631.296

Mia, M.J., Mahmud, R.B., Sadad, M.S., Al Asad, H. and Hossain, R., 2022. An in-depth automated approach for fish disease recognition. *Journal of King Saud University-Computer and Information Sciences*, *34*(9), pp.7174-7183. https://doi.org/10.1016/j.jksuci.2022.02.023

Shi, S., Caluyo, F., Hernandez, R., Sarmiento, J. and Rosales, C.A., 2024. Automatic Classification and Identification of Plant Disease Identification by Using a Convolutional Neural Network. *Natural and Engineering Sciences*, *9*(2), pp.184-197. https://doi.org/10.28978/nesciences.1569560

Soy, A. and Balkrishna, S.M., 2024. Automated detection of aquatic animals using deep learning techniques. *International Journal of Aquatic Research and Environmental Studies*, *4*(S1), pp.1-6. https://doi.org/10.70102/IJARES/V4S1/1

Sujatha, K. and Mounika, P., 2023, April. Evaluation of ML models for detection and prediction of fish diseases: A case study on epizootic ulcerative syndrome. In *2023 Second International Conference on Electrical, Electronics, Information and Communication Technologies (ICEEICT)* (pp. 1-7). IEEE. https://doi.org/10.1109/ICEEICT56924.2023.10156914

Topalova, I., Lozova, T., Riepnova, T., Dashchenko, N., Chudaieva, L. and Darushyn, O., 2024. Business Process Management in Entrepreneurial Activity Based on a Platform Approach. *Indian Journal of Information Sources and Services*, *14*(2), pp.46-55. https://doi.org/10.51983/ijiss-2024.14.2.08

Wang, D., Wu, M., Zhu, X., Qin, Q., Wang, S., Ye, H., Shi, Y., 2025. Real-time detection and identification of fish skin health in the underwater environment based on improved YOLOv10 model. *Aquaculture Reports*, *42*. https://doi.org/10.1016/j.aqrep.2025.102723

Wright, A., Li, X., Yang, X., Soto, E. and Gross, J., 2023. Disease prevention and mitigation in US finfish aquaculture: A review of current approaches and new strategies. *Reviews in Aquaculture*, *15*(4), pp.1638-1653. https://doi.org/10.1111/raq.12807

Yu, G., Zhang, J., Chen, A. and Wan, R., 2023. Detection and identification of fish skin health status referring to four common diseases based on improved YOLOv4 model. *Fishes*, *8*(4), 186. https://doi.org/10.3390/fishes8040186

Zhang, Y., 2022. Freshwater biodiversity conservation in China: Progress in the Yangtze River basin. *Aquatic Conservation: Marine and Freshwater Ecosystems*, *32*(10), pp.1565-1570. https://doi.org/10.1002/aqc.3861