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Review Article

AI-based Intelligent Aquaculture: Applications in Fish Detection, Smart Feeding, Biomass Estimation and Disease Management

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Aquaculture has grown rapidly in the last 50 years; however, the industry is confronted by several significant operational challenges. These include disease outbreaks, ineffective feeding management, labour shortage, complexity of the supply chain, and environmental degradation. Artificial intelligence offers possibilities for potential to tackle these limitations. It plays an important role in enhancing operational efficiency by integrating advanced technologies such as machine learning, deep learning, computer vision, Internet of Things (IoT), big data analytics, cloud computing, and robotics in aquaculture system. This review brings together evidence from peer-reviewed research and relevant grey literature to provide a comprehensive overview of recent advances in AI for aquaculture, with a particular focus on fish detection, smart feeding, biomass estimation, disease management, and intelligent farm management. An AI-powered system enables more real-time monitoring of fish behaviour, automatic distribution of feed, accurate biomass estimation, clarification of species and early detection of pathogenic threats. Advanced deep learning models (e.g., convolutional neural network (CNN) and YOLO based architectures) have shown high accuracy in fish identification and behaviour analysis. Moreover, sensor-based monitoring of key water quality parameters such as temperature, pH, oxygen, ammonia, nitrite, and salinity optimizes environmental control, enhances fish survival rate and feed conversion efficiency. AI goes beyond the farm level and improves supply chain management through predictive demand forecasting, inventory optimization and advanced traceability. The AI-based intelligent aquaculture systems provide significant improvements to productivity, environmental sustainability and functioning efficiency even with challenges such as high implementation costs and technical complexities. As a result, these systems play a key role in enhancing global food security and responsible aquaculture practices.

(***Key words:*** *Artificial intelligence (AI), Biomass estimation, Demand forecasting, Internet of things (IoT), Machine learning, Robotics*)

The integration of artificial intelligence and advanced computational methods is reshaping aquaculture farm management. These technologies improve the precision and efficiency of management systems by delivering actionable analytics on fish behaviour, enabling earlier disease detection, and optimizing feeding regimes (Sen *et al.,* 2025).

The adoption of artificial intelligence and advanced computational techniques reduces resource waste and lessens environmental harm in aquaculture. By combining machine learning, computer vision, and real time monitoring of physical, chemical, and biological parameters, AI equips farmers with highly accurate, automated decision support tools. Consequently, AI based solutions are driving a more data driven and efficient aquaculture sector, enabling intensive fish production to contribute to future global food security without further degrading the environment (Sen *et al.,* 2025).

AI serves as the "intelligent brain" behind modern robotic and automated equipment, letting systems learn from data, assess complex aquatic conditions, and make independent production decisions. Robotic solutions combine information technology, mechanical engineering, and automation, enabling machines to perform many tasks that once required extensive human labour (Rembold, 1990). These intelligent devices rely on technologies like edge computing, machine vision, autonomous navigation, and precision control (Shi *et al.,* 2016). In addition, IoT, Big Data, 5G, and cloud

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computing make it possible to monitor farms remotely and manage them from centralized platforms (Wang *et al.,* 2021).

Over the last 50 years, scientific advances have played a central role in expanding aquaculture (Burnell and Allan, 2009). Compared with land based farming, aquaculture is more varied in the species farmed, the feeds used, the production systems employed, and the ways diseases are managed (FAO, 2020).

The aquaculture sector is at a pivotal moment: despite facing substantial ecological and operational challenges, it also possesses significant potential for growth. Ecological systems, infrastructure improvements, and smart aquaculture are widely regarded as the foundational pillars for future development (Antonucci and Costa, 2020). Early global initiatives illustrate this shift. For example, ABB proposed a conceptual offshore submerged salmon farm in the Arctic to boost production while maintaining strict quality standards; in this design, net pens are managed remotely from a centralized feed barge and automated sensors continuously record environmental variables weather, currents, dissolved oxygen, temperature, and depth specific pH alongside real time biomass estimates, with data relayed to a cloud platform via wireless networks (Wang *et al.,* 2021). Likewise, the ARTIFEX project seeks to transform inspection, maintenance, and repair for offshore farms through coordinated use of Unmanned Surface Vehicles (USVs), Unmanned Aerial Vehicles (UAVs), and Remotely Operated Vehicles (ROVs) (Wang *et al.,* 2021).

AI operating system and architecture in aquaculture

The fundamental step in implementing an automated process control system in aquaculture is selecting a suitable computing platform and operating

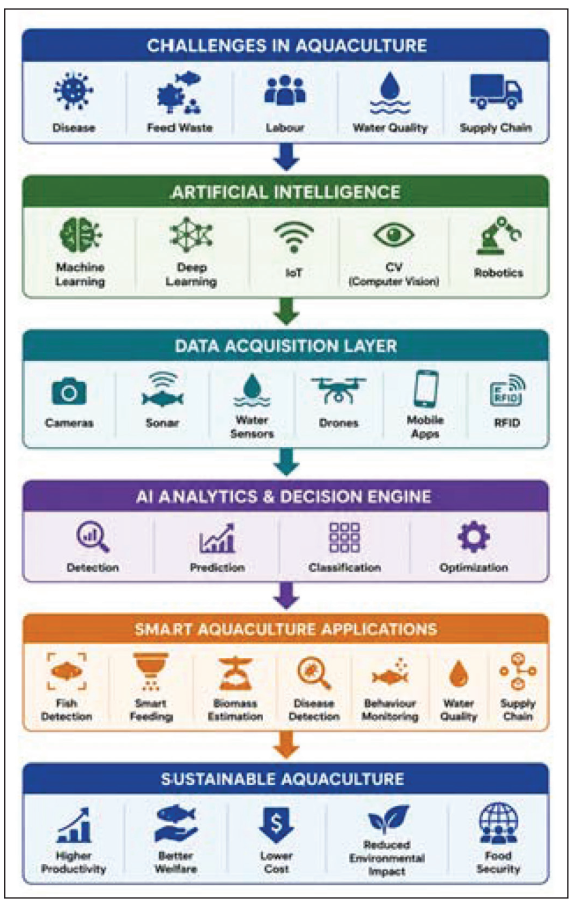

Fig. 1. *AI-driven intelligent aquaculture framework*

architecture. Historically, criteria such as functionality, interconnectivity, architectural expandability, and the price-to-performance ratio have been considered the primary bases for system selection.

While early industrial automation integration relied on traditional operating systems such as UNIX, OS/2, and Windows NT (Labs, 1994; Lee, 2000), modern aquaculture facilities utilize robust, cloud-integrated, and Linux-based platforms capable of effectively processing the massive data streams generated by the Internet of Things (IoT).

System architecture

In aquaculture, automated control systems are generally classified into four major designs:

- Closed-loop controller or data logger system
- Programmable Logic Controller (PLC) systems
- Supervisory Control and Data Acquisition (SCADA) systems
- Supervisory Control and Data Acquisition (SCADA) systems: Microcomputer-based systems that monitor, control, and collect data from aquaculture farm operations and equipments. These systems are considered highly effective for small and medium-scale aquaculture farms and provide a suitable foundation for large-scale expansion (Grenier, 1994).

Modules of artificial system

Modern AI-based aquaculture systems are structured into specialized modular components to ensure operational flexibility, scalability, and ease of maintenance:

- Data Processing Module: The module responsible for collecting, refining, and transforming raw sensor data before algorithmic analysis.
- Model Training & Inference Modules: Modules that use Machine Learning to study historical patterns and provide real-time predictive analysis.
- Computer Vision (CV) Module: A module that allows machines to interpret visual data (images/video) for key tasks such as fish identification, behaviour tracking and biomass estimation.
- Decision-Making & User Interface (UI) Module: This module translates the predicted outcomes into actionable control and optimisation strategies, delivering a centralised and user-friendly dashboard for farm operators (Lee, 2000).

AI for species reconignition and cultivation

The long-term sustainability of global food systems depends largely on the development of aquaculture. The development of intelligent breeding and rearing management systems relies on the use of artificial

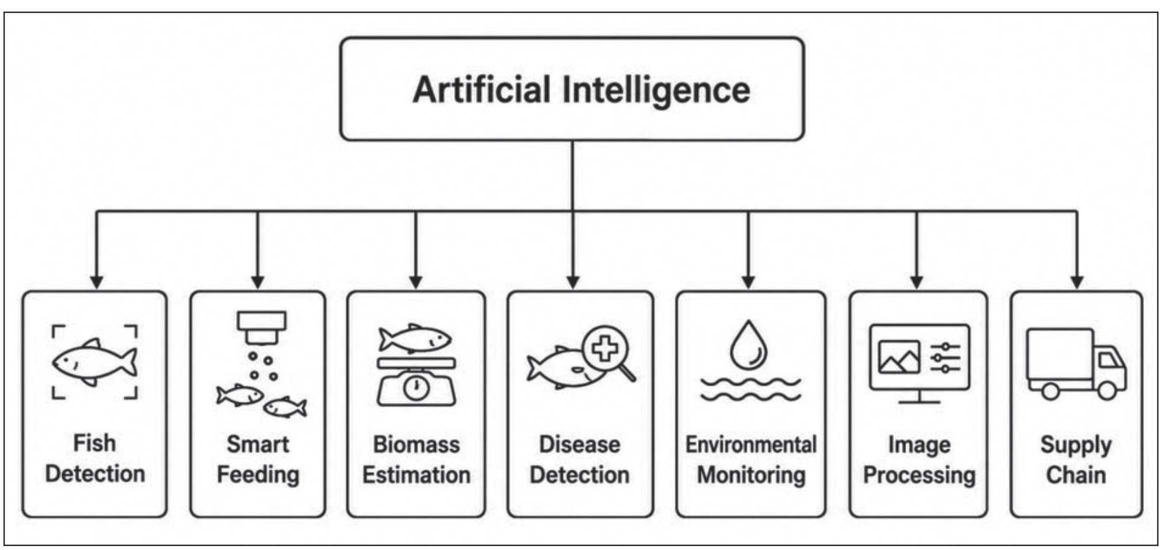

Fig. 2. *Major application areas of artificial intelligence in aquaculture*

intelligence (AI) to enable accurate and autonomous identification of live fish, which in turn provides reliable data for improved production efficiency.

Challenges and methodologies in species identification

Machine vision is an effective system for continuous, non-destructive and non-contact monitoring at a relatively low cost (Hossain *et al.,* 2024; Zhou *et al.,* 2018). However, the aquatic environment presents unique challenges for the analysis of images and videos. Factors such as low light, high background noise, and high-water turbidity can greatly reduce image quality, contrast and resolution (Zhou *et al.,* 2017a). Erratic schooling behaviour of fish leads to problems like visual distortions, occlusions and overlaps (Sunny *et al.,* 2020; Zhou *et al.,* 2017b).

Deep learning and vision-based techniques

In the past, species identification was performed using appearance-based methods considering variations in shape, texture and colour in controlled indoor environments. However, such methods are not applicable in uncontrolled, underwater environments. To overcome challenges such as blurred images and complex backgrounds (Mandal *et al.,* 2018), there has recently been a rapid shift towards deep learning-based techniques.

Deep learning architectures, particularly Convolutional Neural Networks (CNNs), have demonstrated immense potential in species classification and in many instances, have outperformed human experts in terms of accuracy (Yamamoto, 2017). For example, a hybrid deep CNN-KNN architecture has achieved an accuracy of over 98% on extensive visual datasets such as Fish4Knowledge (Deep and Dash, 2019). Furthermore, advanced underwater drones equipped with 360-degree panoramic capabilities powered by models such as AlexNet have been successfully utilized for real-time fish identification in natural lakes and have demonstrated high accuracy (Meng *et al.,* 2018).

Behavioural analysis

Fish exhibit highly specific behavioural responses to even the slightest changes in their environmental conditions. Therefore, behavioural monitoring is considered a key, non-destructive indicator of overall fish health, stress levels, and readiness for harvest (Zion, 2012). By identifying abnormal swimming patterns or aggregation behaviour through continuous AI-based monitoring, aquaculture farmers can develop early warning systems for hypoxia, disease, or predator threats. This enables timely, proactive, and effective adjustments to feeding and capture strategies (Rillahan *et al.,* 2011; Yu *et al.,* 2022).

Smart feeding systems

Feed cost is considered the largest operational expense in aquaculture. In recent years, the combination of machine vision, acoustic sensor technology, and artificial intelligence (AI) has revolutionized feeding protocols (Li *et al.,* 2020).

Computer vision-based automated feeding

Artificial intelligence–driven automated systems dynamically regulate feed distribution by continuously analyzing real time measurements of fish behaviour and biomass. Deep learning models provide fine grained mechanical control, substantially reducing feed loss and improving the feed conversion ratio (FCR). For example, Hu *et al.* (2022) developed a computer vision approach based on the R (2+1) D deep model to evaluate feeding activity from surface turbulence, reporting a classification accuracy of 93.2%. More recently, a ResNet variant augmented with the covolutional block attention module (CBAM) attention mechanism achieved approximately 99.72% accuracy in classifying feeding intensity.

Acoustic-based monitoring

Acoustic monitoring has emerged as a highly effective alternative technique, particularly in turbid water conditions where optical cameras fail to function effectively. Passive acoustic systems establish a direct correlation between the intensity of sounds generated during feeding, such as the noise of pellet mastication and the satiety levels of the fish. Advanced models such as the Audio Spectrum Swin Transformer (ASST) have been employed for the high-accuracy classification of feeding-related acoustic signals. This has enabled real-time adjustments in automated hopper systems, even in the presence of high background noise (Wei *et al.,* 2020; Zeng *et al.,* 2023).

Multimodal data integration

The most advanced smart feeding systems are based on multimodal data fusion. By integrating optical CNN-based image analysis, acoustic signals, and data from implantable check-biologgers or bioggers such as ECG and acceleration metrics, AI frameworks employ methods like Bayesian change-point detection. This enables a comprehensive and highly accurate analysis of food intake behaviour (Shen *et al.,* 2021; Zhou *et al.,* 2019).

Biomass assessment and growth monitoring

Accurate biomass assessment is key to improving feed management and strategic harvests planning. Traditional manual sampling techniques are very labour-intensive and induce considerable physiological stress in fish that may result in higher mortality rates. AI-driven non-invasive techniques, provide a more efficient, accurate, and welfare-friendly approach to biomass estimation.

Optical mass measurement and counting

Additionally, AI has automated the counting of fish fry. Early studies used Back Propagation (BP) neural networks (Newbury *et al.,* 1995); modern systems, however, use more advanced techniques like Fuzzy Artificial Neural Networks and Least Squares Support Vector Machines (LS-SVM). The techniques can successfully identify and count fish in dense and overlapping clusters (Fan and Liu, 2013; Zheng and Zhang, 2010).

Direct biomass estimation via LiDAR

The integration of Light Detection and Ranging (LiDAR) technology with visual machine learning systems allows for direct volumetric scanning of aquatic environments (Dassot *et al.,* 2011). Originally developed to monitor the spatial distribution of flatfish (Duarte *et al.,* 2007), this technology generates rapid surface models of objects through submerged laser scanning, thereby enabling direct mathematical estimation of biomass volume with a minimal margin of error.

Artificial intelligence (AI) in fish health monitoring and disease detection

The early detection of pathogen outbreaks remains one of the most significant challenges in aquaculture, as infectious diseases can rapidly decimate fish stocks and cause severe economic losses. AI-based diagnostic systems are capable of the predictive and proactive disease detection through the analysis of behavioural changes, morphological abnormalities and the waterborne microbiome (Benetti*,* 2025). Machine learning models can identify symptoms such as surface lesions, ulcers, and exophthalmia through sophisticated image processing that used advanced pattern recognition and predictive analysis techniques (Hoel, 2018).

Computer vision-based disease detection

Computer vision technology is being widely used to identify the visual symptoms of fish and shrimp diseases in aquaculture. For example, in Vembarasi *et al.* (2024), an initial identification system of White Spot Syndrome Virus (WSSV) in shrimp has been proposed through image processing techniques. Artificial Neural Network (ANN) was used in this study, in which Canny Edge Detection and Gray-Level Co-occurrence Matrix (GLCM) techniques were adopted for feature extraction. The results revealed that the model was highly effective, achieving 94.71% accuracy, 94.86% sensitivity, and 93.32% specificity. The system was successfully tested using a dataset of healthy and WSSV-infected shrimp and was able to clearly distinguish between healthy and infected individuals.

Water quality-linked disease prediction

Most forecasting models that monitor water quality parameters are capable of classifying changes related to disease risk. In the study by Nayan *et al.* (2021), researchers employed a Gradient Boosting Model (GBM) to predict disease risk based on water quality data. This model achieved 92% accuracy in predicting disease probability by analyzing parameters such as pH, dissolved oxygen (DO), and nitrate levels. Additionally, in the study by Moni *et al.* (2024), water quality parameters analyzed by IoT-enabled sensors were integrated with a Mobile NetV2 CNN-based disease detection system, resulting in 91.5% accuracy.

Image processing technology in disease diagnosis

The diagnosis of specific fish diseases relies primarily on three key image processing procedures: segmentation, feature extraction, and classification. Due to the highly diverse and complex nature of symptoms associated with aquatic diseases, obtaining clear and unobstructed visual data is challenging (Barbedo, 2014). Modern AI protocols employ advanced colour feature extraction and K-means clustering techniques to identify diseased tissues (Chakravorty *et al.,* 2015). For instance, researchers successfully identified Epizootic Ulcerative Syndrome (EUS) in fish by extracting specific visual features using the Histogram of Oriented Gradients (HOG) and Features from accelerated segment test (FAST) algorithms. Subsequently, this data was processed through a neural network to achieve an accurate diagnosis (Kumar *et al.,* 2017; Lyubchenko *et al.,* 2016).

Environmental monitoring systems (iot integration)

Intelligent aquaculture represents a significant shift from traditional, labour-intensive fish farming to highly automated and sensor-based systems. IoT-enabled biosensors continuously collect environmental data and transmit it to centralized systems for AI-based analysis (Li and Li, 2020).

- Temperature sensors: Real-time temperature control based on RTDs and thermocouples protects fish from metabolic shock. An increase of approximately 25% in survival rates has been recorded through IoT-based temperature management in Recirculating Aquaculture Systems (RAS) (Lin *et al.,* 2021; Tamim *et al.,* 2022).

- pH and dissolved oxygen (DO) sensors: Continuous electrochemical pH monitoring helps prevent conditions such as acute acidosis or alkalosis (Muthmainnah *et al.,* 2024). Additionally, optical DO sensors used for automated aerator control have been found effective in reducing hypoxia-induced mortality by 30–50% and improving the feed conversion ratio (FCR) by approximately 22% (Sun *et al.,* 2018; Yuan *et al.,* 2022).

- Ammonia, nitrate, and salinity sensors: Ion-Selective Electrodes (ISEs) are capable of rapidly detecting sharp increases in toxic nitrogen levels, while conductivity-based sensors monitor salinity to ensure an appropriate osmoregulatory environment (Li *et al.,* 2023).

Supply chain optimization and big data

The aquaculture supply chain across hatcheries, grow-out units, processing plants, and international circulation networks is highly fragmented (Nimmagadda *et al.,* 2023). The integration of big data and frameworks like Hadoop has made it possible to analyze vast datasets and derive predictive insights (Li and Li, 2020). AI algorithms optimize logistics by accurately forecasting market demand, managing complex inventory, and ensuring end-to-end organic traceability. Consequently, product safety improves, and post-harvest losses are reduced.

Overview of AI-integrated tools and technologies

A brief overview of the key technical systems driving smart aquaculture, their specific operational applications, and relevant literature is presented in Table 1.

Challenges and future prospects of AI in aquaculture

Although the incorporation of AI offers innovative enhancements in effective productivity, precision and resource optimization, the industry must address several significant challenges to ensure its positive and sustainable impact.

Benefits and prospects

AI distant enhances human capability in continuous data analysis and optimizes farm conditions by rapidly executing complex multivariate calculations. This results in fewer errors, enhanced biosecurity, and a significant reduction in resource wastage. Furthermore, advanced robotic systems enable the expansion of aquaculture into areas previously considered unsuitable, such as highly challenging offshore marine environments.

Technical and socio-economic limitations

However, the widespread use of AI also presents several socio-economic challenges, particularly regarding the potential displacement of traditional labour-based employment in rural aquaculture communities.

Table 1. *AI-integrated tools and technologies in smart aquaculture*

Tool / Technology	Application in aquaculture	Source
Computer vision (optical camera-based system)	Computer vision (optical camera-based system): This advanced technology is used for the identification of fish species, behavioural analysis, non-contact measurement of size and weight, and the automated detection of skin diseases and wounds.	(Hu *et al.,* 2022; Yang *et al.,* 2021; Zion, 2012)
Acoustic sensors (Sonar/ Hydrophones):	Monitoring fish satiety and feeding intensity through the analysis of generated sounds is a highly effective method in turbid or deep waters and in areas with low light.	(Wei *et al.,* 2020; Zeng *et al.,* 2023)
LiDAR (Laser scanning)	A rapid 3D fish surface system for direct volume calculation and efficient biomass estimation, which is non-invasive.	(Dassot *et al.,* 2011; Duarte *et al.,* 2007)
IoT environmental sensors	Water quality sensor system: An advanced system for continuous monitoring of key water parameters such as temperature, pH, dissolved oxygen (DO), and toxic nitrogen compounds.	Lin *et al.,* 2021); Muthmainnah *et al.,* 2024)
Unmanned vehicles (UAVs, USVs, ROVs)	Monitor offshore sea pens, navigate underwater via remote control, oversee operations, and identify fish moving within open-water farms.	(Meng *et al.,* 2018)
Implantable biological data collection devices	Tracking the fish in the area, while continuously monitoring heart rate and accurately identifying feeding patterns.	(Shen *et al.,* 2021)

Furthermore, the establishment and operation of these systems require high initial investment and specialized technical expertise. Over-reliance on automation can also pose serious risks, as software failures, sensor inconsistencies, or cybersecurity issues could lead to the mass loss of aquatic life within just a few hours.

CONCLUSION

Artificial Intelligence (AI) has established itself as a crucial technological tool in modern aquaculture, offering effective solutions to key challenges related to operational productivity, disease management, and ecological sustainability. AI enables continuous, non-invasive, and precise monitoring of fish health and farm environments through the integration of deep learning, computer vision, IoT-based sensor networks, and big data analytics. From precision feeding algorithms to volumetric biomass estimation, advanced automated technologies reduce reliance on manual labour and significantly improve feed efficiency and production forecasting capabilities. Although challenges related to implementation costs and technical expertise persist, their long-term socio-economic and environmental benefits far outweigh these initial difficulties. Ultimately, AI-driven intelligent aquaculture presents a scientific and sustainable development model that plays a crucial role in meeting the growing global demand for aquatic protein while ensuring responsible ecological conservation.

CONFLICTS OF INTEREST

The authors of this article declare that there is no conflict of interest.

REFERENCES

Antonucci, F. and Costa, C. (2020). Precision aquaculture: A short review on engineering innovations. *Aquaculture International* **28**: 41-57.

Barbedo, J.G.A. (2014). Computer-aided disease diagnosis in aquaculture: Current state and perspectives for the future. *Revista Innover* **1**: 19-32.

Benetti, R. (2025). Enhancing sustainable aquaculture: Applications of artificial intelligence in fish farming. *Unpublished Master Thesis*, University of Padova, Padova, Italy.

Burnell, G. and Allan, G. (eds.) (2009). *New Technologies in Aquaculture: Improving Production Efficiency, Quality and Environmental Management*, First edition, Woodhead Publishing. 1224 p.

Chakravorty, H., Paul, R. and Das, P. (2015). Image processing technique to detect fish disease. *International Journal of Computer Science and Security (IJCSS)* **9**: 121-131.

Dassot, M., Constant, T. and Fournier, M. (2011). The use of terrestrial LiDAR technology in forest science: Application fields, benefits and challenges. *Annals of Forest Science* **68**: 959-974.

Deep, B.V. and Dash, R. (2019). Underwater fish species recognition using deep learning techniques. In: *2019 6th International Conference on Signal Processing and Integrated Networks (SPIN)*, IEEE, Noida, India. pp 665-669.

Duarte, O.S., Oca Baradad, J. and Reig Puig, L. (2007). Evaluation of spatial distribution of flatfish by laser scanning. In: *Aquaculture Europe 2007, Competing Claims*, European Aquaculture Society, Istanbul, Turkey. p 157.

FAO. (2020). The State of World Fisheries and Aquaculture 2020: Sustainability in Action. Food and Agriculture Organization of the United Nations, Rome, Italy. 244 p.

Fan, L. and Liu, Y. (2013). Automate fry counting using computer vision and multi-class least squares support vector machine. *Aquaculture* **380**: 91-98.

Grenier, D. (1994). DCSS up product consistency, quality, output. *I&CS-Instrumentation & Control Systems* **67**: 51-58.

Hoel, T. (2018). Data science helps Norway's fish farmers keep salmon populations healthy. *AquaHoy*, September 19, 2018. Available online.

Hossain, B., Sunny, A.R., Gazi, M.M.R.N., Das, A.R., Mohajon, R., Miah, A.T.H. and Rana, M.N.U. (2024). Advancing fish farming through deep learning: Applications, opportunities, challenges, and future directions. *Pathfinder of Research* **2**: 58-80.

Hu, W.C., Chen, L.B., Huang, B.K. and Lin, H.M. (2022). A computer vision-based intelligent fish feeding system using deep learning techniques for aquaculture. *IEEE Sensors Journal* **22**: 7185-7194.

Kumar, T., Malik, S. and Sahoo, A.K. (2017). Fish disease detection using HOG and FAST feature descriptor. *International Journal of Computer Science and Information Security* **15**: 216-221.

Labs, W. (1994). PC operating systems make the most of advanced hardware. *I&CS-Instrumentation and Control Systems* **67**: 45-48.

Lee, P.G. (2000). Process control and artificial intelligence software for aquaculture. *Aquacultural Engineering* **23**: 13-36.

Li, D. and Li,C. (2020). Intelligent aquaculture. *Journal of the World Aquaculture Society* **51**: 808-814.

Li, H., Zhang, J., Ge, X., Chen, S. and Ma, Z. (2023). The effects of short-term exposure to pH reduction on the behavioral and physiological parameters of juvenile black rockfish (*Sebastes schlegelii*). *Biology* **12**: 876.

Lin, J.Y., Tsai, H.L. and Lyu, W.H. (2021). An integrated wireless multi-sensor system for monitoring the water quality of aquaculture. *Sensors* **21**: 8179.

Lyubchenko, V., Matarneh, R., Kobylin, O. and Lyashenko, V. (2016). Digital image processing techniques for detection and diagnosis of fish diseases. *International Journal of Advanced Research in Computer Science and Software Engineering* **6**: 79-83.

Mandal, R., Connolly, R.M., Schlacher, T.A. and Stantic, B. (2018). Assessing fish abundance from underwater video using deep neural networks. Proceedings *2018 International Joint Conference on Neural Networks (IJCNN)*, Institute of Electrical and Electronics Engineers, Rio de Janeiro, Brazil. pp 1-6.

Meng, L., Hirayama, T. and Oyanagi, S. (2018). Underwater-drone with panoramic camera for automatic fish recognition based on deep learning. *IEEE Access* **6**: 17880-17886.

Moni, J., Jacob, P.M., Sudeesh, S., Nair, M.J., George, M.S. and Thomas, M.S. (2024). A smart aquaculture monitoring system with automated fish disease identification. Proceedings *2024 1st International Conference on Trends in engineering systems and technologies (ICTEST)*, Institute of Electrical and Electronics Engineers. pp 1-6.

Muthmainnah, M., Nashirudin, W., Sasmitaninghidayah, N., Chamidah, A., Mulyono, I. and Tazi, I. (2024). The development of an IoT-based automated temperature and pH monitoring system to enhance the management of gourami fish ponds. *ARPN Journal of Engineering and Applied Sciences* **19**: 294-300.

Nayan, A.A., Mozumder, A.N., Saha, J., Mahmud, K.R., Azad, A.K.A. and Kibria, M.G. (2021). A machine learning approach for early detection of fish diseases by analyzing water quality. *Trends in Sciences* **18**: 351.

Newbury, P.F., Culverhouse, P.F. and Pilgrim, D.A. (1995). Automatic fish population counting by artificial neural network. *Aquaculture* **133**: 45-55.

Rembold, U. (1990). Some examples of advanced robot systems. In: *Robot Technology and Applications*, U. Rembold (ed.), Springer, New York, USA. pp 605-668.

Rillahan, C., Chambers, M.D., Howell, W.H. and Watson, W.H. III (2011). The behavior of cod (Gadus morhua) in an offshore aquaculture net pen. *Aquaculture* **310**: 361-368.

Sen, K., Dey, S., Ganguly, A. and Rajak, P. (2026). Artificial intelligence in aquaculture: Advancing sustainable fish farming through AI-driven monitoring, optimization, and disease management. *Aquaculture* **614**: 743602.

Shen, Y., Arablouei, R., De Hoog, F., Xing, H., Malan, J., Sharp, J. and Kusy, B. (2021). In-situ fish heart-rate estimation and feeding event detection using an implantable biologger. *IEEE Transactions on Mobile Computing* **22**: 968-982.

Shi, W., Cao, J., Zhang, Q.,Li,Y. and Xu,L. (2016). Edge computing: Vision and challenges. *IEEE Internet of Things Journal* **3**: 637-646.

Sun, Z.,Cai,C., Guo, F.,Ye,C., Luo, Y.,Ye,S. and Jiang, C. (2018). Oxygen sensitive polymeric nanocapsules for optical dissolved oxygen sensors. *Nanotechnology* **29**: 145704.

Sunny, A. R., Masum, K. M., Islam, N., Rahman, M., Rahman, A., Islam, J. and Prodhan, S. H. (2020). Analyzing livelihood sustainability of climate vulnerable fishers: Insight from Bangladesh. *Journal of Aquaculture Research and Development* **11**: 593.

Tamim, A. T., Begum, H., Shachcho, S. A., Khan, M. M., Yeboah-Akowuah, B., Masud, M. and Al-Amri, J. F. (2022). Development of IoT based fish monitoring system for aquaculture. *Intelligent Automation & Soft Computing* **32**: 55-71.

Vembarasi, K., Thotakura, V.P., Senthilkumar, S., Ramachandran, L., Praba, V.L., Vetriselvi, S. and Chinnadurai, M. (2024). White spot syndrome detection in shrimp using neural network model. Proceedings *2024 11th International Conference on Computing for sustainable global development (INDIACom)*, Institute of Electrical and Electronics Engineers. pp 212-217.

Wang, T., Xu, X., Wang, C., Li, Z. and Li, D. (2021). From smart farming towards unmanned farms: A new mode of agricultural production. *Agriculture* **11**: 145.

Wei, M., Lin, Y., Chen, K., Su, W. and Cheng, E. (2020). Study on feeding activity of *Litopenaeus vannamei* based on passive acoustic detection.

IEEE Access **8**: 156654-156662.

Yamamoto, S. (2017). Enterprise requirements management knowledge towards digital transformation. In: *IT Convergence and Security 2017: Volume 1*, Springer, Singapore. pp 309-317.

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* **28**: 2785-2816.

Yu, X., Wang, Y., An, D. and Wei, Y. (2022). Counting method for cultured fishes based on multi-modules and attention mechanism. *Aquacultural Engineering* **96**: 102215.

Yuan, X.L., Wu, X.Y., He, M., Lai, J.P. and Sun, H. (2022). A ratiometric fiber optic sensor based on CdTe QDs functionalized with glutathione and mercaptopropionic acid for on-site monitoring of antibiotic ciprofloxacin in aquaculture water. *Nanomaterials* **12**: 829.

Zeng, Y., Yang, X., Pan, L., Zhu, W., Wang, D., Zhao, Z. and Zhou, C. (2023). Fish school feeding behavior quantification using acoustic signal and improved Swin Transformer. *Computers and Electronics in Agriculture* **204**: 107580.

Zheng, X. and Zhang, Y. (2010). A fish population counting method using fuzzy artificial neural network. Proceedings *2010 IEEE International Conference on Progress in informatics and computing*, Institute of Electrical and Electronics Engineers. pp 225-228.

Zhou, C., Yang, X., Zhang, B., Lin, K., Xu, D., Guo, Q. and Sun, C. (2017a). An adaptive image enhancement method for a recirculating aquaculture system. *Scientific Reports* **7**: 6243.

Zhou, C., Xu, D., Chen, L., Zhang, S., Sun, C., Yang, X. and Wang, Y. (2019). Evaluation of fish feeding intensity in aquaculture using a convolutional neural network and machine vision. *Aquaculture* **507**: 457-465.

Zhou, C., Xu, D., Lin, K., Sun, C. and Yang, X. (2018). Intelligent feeding control methods in aquaculture with an emphasis on fish: A review. *Reviews in Aquaculture* **10**: 975-993.

Zhou, C., Zhang, B., Lin, K., Xu, D., Chen, C., Yang, X. and Sun, C. (2017b). Near-infrared imaging to quantify the feeding behavior of fish in aquaculture. *Computers and Electronics in Agriculture* **135**: 233-241.

Zion, B. (2012). The use of computer vision technologies in aquaculture–a review. *Computers and Electronics in Agriculture* **88**: 125-132.