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Revolution of AI in Aquaculture and Fish Processing: A Review

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ABSTRACT

The application of Artificial Intelligence (AI) in aquaculture and fish processing remains underexplored and underutilized. This review aims to provide a comprehensive overview of current and emerging AI technologies in these sectors, evaluating their accuracy, practicality, and potential for sustainable and economical implementation. The objective is to highlight AI's transformative role and encourage its adoption among fish farmers, processors, and other stakeholders to improve productivity and operational efficiency. AI is revolutionizing the aquaculture and fish processing industries by enhancing efficiency, reducing labour costs, and promoting sustainable practices. Traditional methods in these fields often demand intensive manual labour, increasing production costs and limiting scalability. The integration of AI technologies enables real-time monitoring, automation, and data-driven decision-making, which significantly reduces labour dependency and enhances precision. In aquaculture, AI applications include fish growth monitoring, disease detection, and environmental control, using machine learning algorithms and IoT-based systems to optimize operations. In fish processing, AI-driven tools support tasks such as sorting, grading, filleting, and packaging, ensuring consistent product quality and safety. These advancements not only streamline production but also reduce waste and improve resource utilization. This review presents recent developments and success stories of AI implementation in aquaculture and fish processing, illustrating its potential to modernize the industry. By fostering smarter and more sustainable practices, AI can contribute significantly to boosting productivity, improving economic outcomes, and supporting food security goals in the fisheries sector.

KEYWORDS: Smart aquaculture, artificial intelligence, machine learning (ML), deep learning (DL)

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1. INTRODUCTION

Artificial Intelligence (AI) is a scientific discipline that focuses on developing computer systems capable of exhibiting intelligent characteristics similar to human cognition and decision-making (Xu et al., 2021). Machine learning is further categorized into four types: supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning (Bose, 2017).

The application of artificial intelligence (AI) in agriculture and allied sectors, including fisheries and aquaculture, plays a crucial role in addressing the growing food demand resulting from population growth over time (Jha et al., 2019). Traditional farming practices may become inadequate in meeting future food requirements. Therefore, automation technologies such as Artificial Intelligence and the Internet of Things (IoT) are potential solutions to mitigate food shortages in the future (Jha et al., 2019).

Among AI advancements, Deep Learning (DL) represents a sophisticated technique used to predict various parameters in aquaculture, including species classification, fish identification, feeding time optimization, fish behavior analysis, and movement tracking (Yang et al., 2020). Due to the increasing global seafood demand, aquaculture plays a key role in meeting this need, while the fish processing industry acts as the other side of the coin by supporting and boosting aquaculture. It processes fish into consumable products, preserves them for a long period, and ensures food safety for consumers by maintaining the quality of fish products (Ngasotter et al., 2020). Adoption of AI with aquaculture and fish processing industries ensuring the sustainability by monitoring water quality, optimizing feeding ratio, predicting fish health and automating the fish processing and quality checking of the fishes (Gladju et al., 2022; Rather et al., 2024). Traditional aquaculture required more labour, and optimizing feeding for fish and shrimp biomass was challenging. For example, if excess feed was given, it increased feed costs and deteriorated water quality. Conversely, if less amount of feed was provided, animal growth was reduced, leading to economic losses and decreased profitability (Chiu et al., 2022). Additionally, the initial diagnosis and detection of diseases in cultured animals were difficult in traditional aquaculture compared to AI-based smart aquaculture. (Zhou et al., 2018; Anusha et al., 2024). In AI-integrated smart aquaculture, labour requirements were reduced and optimized feeding efficiently, preventing economic losses caused by overfeeding while maintaining water quality in an optimal, balanced state (Rather et al., 2024; Chiu et al., 2022). Moreover, AI-enabled systems used underwater cameras and image processing to detect diseases at an early stage, significantly reducing large-scale fish stock losses. (Mandal and Ghosh, 2024). All these AI technologies synergistically worked with the Internet of Things (IoT) and cloud computing to create an optimal solution for the well-being of smart aquaculture (Mustapha et al., 2021). Traditional fish processing plants required numerous labourers for cutting, grading, sorting, gutting fish, and cleaning, peeling, and deveining shrimp and other aquatic animals. In contrast, AI-based smart fish processing plants used automated machine, reducing labour costs (Hassoun et al., 2022). Traditional fish processing industries also had lower optimization of electricity usage. However, AI-based smart fish processing plants achieved higher electricity optimization, promoting sustainability while increasing profitability for the industry (Ghoroghi et al., 2023). Devices such as unmanned aerial vehicles, programmed robots, and drones, incorporated with artificial intelligence including machine learning (ML) and deep learning (DL) helped and supported advanced aquaculture techniques like offshore cage culture. These technologies were highly useful for monitoring and optimizing critical parameters such as feeding, water quality, fish population estimation (Wu et al., 2022; Rather et al., 2024), and the inspection and automated cleaning of cage nets for biofouling (Fu et al., 2024), which were otherwise challenging to manage manually. This review aims to explore recent advancements and applications of Artificial Intelligence in aquaculture and fish processing, focusing on how these technologies enhance productivity, improve sustainability, reduce labour costs, and support the development of smart aquaculture and processing systems.

2. APPLICATION AND IMPLEMENTATION OF ARTIFICIAL INTELLIGENCE

2.1. *In traditional aquaculture*

AI-based models have proved to be highly efficient in assessing water quality parameters such as dissolved oxygen (DO), Biological oxygen demand (BOD), pH, Ammonia, and Chemical oxygen demand (COD), outperforming traditional stochastic models (Elkiran et al., 2019). The primary advantages of AI-based models over conventional approaches included cost-effective monitoring and higher accuracy. Commonly used AI-based models in water quality assessment included Back Propagation Neural Network (BPNN), Support Vector Machine (SVM), Adaptive Neuro-Fuzzy Inference System (ANFIS), and Linear Auto-Regressive Integrated Moving Average (ARIMA), among others (Elkiran et al., 2019). For instance, by utilizing known parameters such as ammonium ion concentration, pH, and water temperature, AI-based models could estimate dissolved oxygen and other water quality variables with high precision and while maintaining low-cost monitoring inputs (Elkiran et al., 2019).

In aquaculture, fish size measurement traditionally required manual sampling, which was labour-intensive and induced stress in fish. AI-based techniques, including computer vision and deep learning algorithms, offered a non-invasive alternative by utilizing sensors for automated fish size measurement (Biswas et al., 2023). For example, in mariculture, the length and weight of grouper fish were predicted using an AI-based system known as Artificial Intelligence Image Recognition Fish Size (AIIRFS) (Chang et al., 2021). Additionally, AI-driven models could predict fish stress levels by analyzing behavioral data through machine learning algorithms, providing early warnings to optimize water quality parameters and minimize stock losses due to extreme stress conditions (Li et al., 2022).

AI also played a crucial role in genomic breeding for aquaculture species. The genomic breeding value of shrimp was assessed using image analysis under machine learning frameworks, offering advantages over traditional breeding programs by reducing inbreeding depression and enhancing genetic gain (Zenger et al., 2019). Similarly, the breeding outcomes of tilapia brooders could be accurately predicted using Genetic Algorithms combined with Deep Neural Networks (DNN), ensuring not only precise breeding predictions but also fostering sustainable aquaculture practices (Tynchenko et al., 2024).

In disease prediction and water quality monitoring, AI techniques such as the Random Forest algorithm have demonstrated high accuracy in detecting early disease outbreaks and identifying key water quality indicators (Kanagachidambaresan et al., 2024). Advanced AI models, including Electromagnetic Field Optimization (EFO) and Multi-Layer Perceptron Neural Network (MLPNN), have been employed to enhance the accuracy of dissolved oxygen (DO) predictions for effective water quality management (Yang, 2023a). Furthermore, the removal of turbidity in aquaculture effluent water has been optimized using a hybrid AI approach that combined Adaptive Neuro-Fuzzy Inference System with Genetic Algorithm (ANFIS-GA), achieving superior turbidity reduction performance (Igwegbe et al., 2023).

Integrating Internet of Things (IoT), Machine Learning (ML), and Quantum Approximate Optimization Algorithm (QAOA) had further improved water quality predictions while simultaneously increasing fish survival rates (Baena-Navarro et al., 2025). These advancements highlighted the transformative potential of AI in aquaculture, enabling precise monitoring, efficient resource utilization, and sustainable management practices.

2.2. Recirculatory aquaculture system

A typical RAS consisted of continuous circulation and filtration of the water to remove waste material (suspended solid, TAN, Organic matter, faeces, etc.) and maintain optimal water quality parameter. However, the production cost for RAS was relatively high due to continuous circulation. Hence, AI-based models such as Machine Learning (gene algorithm support vector machine model), could be used to reduce production cost significantly. The speed of the water flow and aeration could be adjusted based on the input data algorithm like turbidity, Dissolved Oxygen, Total Ammonical Nitrogen (TAN), etc. this would reduce the production cost (Chen et al., 2021). Mortality in RAS was also an important factor in the production system. Monitoring the mortality in RAS required human labour to observe the mortality of fish at every time. AI and IoT based underwater cameras captured the image of the fish in the system and processed the image and then gave the result to the farm manager through cloud system whether the fish mortality occurred or not anytime (Ranjan et al., 2023). So that the human intensification and operational cost would be reduced significantly.

The prediction and optimization of water quality parameters in medium-sized Recirculating Aquaculture Systems was done using combined AI techniques like Convolutional Neural Network (CNN), Gated Recurrent Unit (GRU), and the Attention mechanism (Yang et al., 2023b). The aeration in Recirculating Aquaculture Systems was optimized and controlled using input data such as hypoxia behaviour of fish detected using computer vision and optimized using deep learning techniques helped to reduce the energy usage for aeration in RAS efficiently (Yang et al., 2024). The feeding cost in shrimp farming played a significant role in economic health of shrimp farm. AI techniques such as multiple linear regression, artificial neural networks, and support vector machine (SVM) accurately helped to optimize shrimp feeding in recirculating aquaculture systems by predicting shrimp biomass size with precision. (Chen et al., 2022). The prediction of dissolved oxygen level in recirculating aquaculture system is achieved using integrated variational mode decomposition and deep belief network, which outperformed other AI methods (Ren et al., 2020). The artificial intelligence technique novel reverse understanding convolutional neural network (CNN) prediction models was provided higher accuracy and reliablility compared to traditional back propagation neural networks for the accurate prediction of dissolved oxygen in RAS (Ta and Wei, 2018). CNN (convolutional neural networks), LSTM (long short-term memory) hybrid model demonstrated high effectiveness for predicting most water quality parameters in RAS of red tilapia except pH, which showed comparatively lower accuracy (Jongjaraunsuk et al., 2024). The prediction of important water quality parameters such as ammonia nitrogen and nitrite were done accurately with General Regression Neural Network (GRNN) compared to other AI algorithms (Chen et al., 2024). The feed optimization using heuristic algorithm was completed for the Recirculating Aquaculture Systems (RAS) to reduce the feed cost associated with excess feed (Yang et al., 2021). Zhou et al. (2023) reported that the automatic feeding and optimal feeding of the fishes was done in recirculating aquaculture systems using algorithms like deep vision, fuzzy neural network to increase the profit. Similarily, Soto-Zarazúa et al. (2011) reported that fuzzy logic control technique was used to optimize environmental conditions for rearing intensive tilapia culture in RAS and water saving. The detection of fish mortality in recirculating aquaculture systems (RAS) was done with deep learning methods that used underwater cameras and equipped with YOLOv4-based lightweight backbone, attention mechanisms, and a ReLU-memristor-like activation function (Zhou et al., 2025).

2.3. Micro-algae cultivation

Artificial Intelligence (AI) had significant applications in estimating the growth rate of micro-algae cultivation. AI-based methods, such as Artificial Neural Networks (ANN), were utilized to predict micro-algae production based on key input variables, including nutrient supply, water quality parameters (such as temperature and pH), and solar radiation (Supriyanto et al., 2019). These predictive models enhanced the efficiency and optimization of micro-algae cultivation systems.

2.4. Cage culture

One of the major challenges in cage culture was selecting an optimal location for net cages. AI-powered technologies, such as unmanned aerial vehicle (UAV) systems, facilitate automated site selection through image recognition and deep learning techniques (Liang and Juang, 2022). Additionally, integrating drones with AI and deep learning models enhanced various aspects of cage culture, including fish counting, length estimation, and feeding evaluation, ultimately improving profitability compared to traditional methods (Ubina et al., 2021).

For precise fish monitoring, an underwater televisual system utilizing a stereo camera, coupled with the SSD Mobilenet v3 algorithm and de-hazing water correction, has been developed. This system enabled accurate measurement of free-swimming grouper length in cage culture, delivering high performance metrics and crucial growth data to support sustainable aquaculture practices and enhance production efficiency (Ahmadi et al., 2023). Furthermore, AI-based techniques, combined with UAV systems, facilitate automatic weight estimation of fish using deep learning models, including Convolutional Neural Networks (CNN), Extreme Gradient Boosting (XGBoost), and a Hybrid CNN-XGBoost model (Taparhudee et al., 2024).

2.5. Remote sensing and AI models in Aquaculture

Remote sensing, when integrated with AI models such as Optimal Artificial Neural Networks (ONN), Adaptive Neuro-Fuzzy Inference System (ANFIS), and Coupled Evolutionary Algorithm-Adaptive Neuro-Fuzzy Inference System (EA-ANFIS), aided in identifying optimal cage culture locations in reservoirs. These AI techniques predicted key water quality parameters, including dissolved oxygen, water temperature, and total dissolved solids, to optimize fish farming conditions (Sedighkia and Datta, 2024). Additionally, AI-based vision algorithms employing stereo systems enabled the examination of fish movement in a three-dimensional space within cage systems, allowing for an accurate assessment of fish behavior and activity levels (Davies, 2009).

The integration of AI-driven technologies in micro-algae cultivation and cage culture enhanced precision, efficiency, and sustainability, contributing to the advancement of aquaculture practices.

2.6. Pen culture

In net-pen aquaculture, automated inspection of net damage such as holes, fouling, and vegetation clogging was conducted using underwater image analysis and semantic segmentation techniques, specifically employing the YOLOv8 model (Akram et al., 2024). Additionally, real-time monitoring of seawater quality parameters was achieved through remote-surveillance systems integrating GSM, GPS modules, IoT, and embedded systems, ensuring optimized and sustainable marine net pen aquaculture (Panda et al., 2023). Net integrity assessments were further enhanced in turbid water conditions using autonomous underwater vehicles (AUVs) in combination with convolutional neural networks (CNNs) for accurate image-based analysis (Lee et al., 2022).

2.7. Biofloc technology

AI and IoT technologies had significantly advanced water quality monitoring and management in biofloc aquaculture systems. IoT-based techniques, along with linear regression models, facilitated accurate prediction of water quality indicators such as temperature, dissolved oxygen (DO), and pH in catfish farming (Mufidah and Nuha, 2023). Similarly, IoT combined with decision regression tree models enabled precise water quality parameter predictions, which could be conveniently monitored via mobile applications (Mozumder and Sharifuzzaman Sagar, 2022).

In tilapia biofloc culture systems, fuzzy logic algorithms were utilized for automated pH and water temperature control, as well as for optimizing feeding schedules (Parenreng et al., 2022; Joshna et al., 2024). Additionally, automation-integrated biofloc shrimp farming systems, incorporating sensors, demonstrated superior nutritional efficiency, water quality control, and enhanced growth performance compared to traditional shrimp aquaculture (Sasikumar et al., 2024).

Advanced AI models such as Autoregressive Integrated Moving Average (ARIMA) were used for detailed predictions of water quality indicators, including Total Dissolved Solids (TDS), water temperature, DO, pH, and electrical conductivity in biofloc finfish farming (Bakhit et al., 2022). The measurement of Total Suspended Solids (TSS), traditionally a labour-intensive and costly process, was efficiently predicted using Support Vector Machine (SVM) models, offering an inexpensive and automated alternative for biofloc fish farming (Teramoto et al., 2024).

Decision Support (DS) algorithms facilitated real-time monitoring and alarm notifications for critical water quality parameters such as turbidity, pH, and temperature, ensured precise and timely interventions in biofloc systems (Alam et al., 2023). Additionally, the breeding outcomes of tilapia brooders were accurately predicted using Genetic Algorithms and Deep Neural Networks (DNN), not only enhanced breeding accuracy but also contributed to sustainable aquaculture (Tynchenko et al., 2024). Furthermore, total biomass estimation in tilapia culture has been effectively achieved with high precision through computer vision and machine learning models, specifically using multilayer perceptrons (Ramírez-Coronel et al., 2024).

The integration of AI and IoT technologies in pen culture and biofloc systems enhanced precision aquaculture, optimizing production efficiency, water quality management, and sustainability.

2.8. Feed formulation

The primary goal of aquaculture feed formulation was to develop cost-effective feed compositions while ensuring optimal nutrition. However, manual formulation presented challenges, as it required skilled expertise to balance nutrient content and minimize anti-nutritional factors (ANF) (Siad and Bouzid, 2023). AI-based techniques enabled automated fish feed formulation by utilizing locally available ingredients, optimizing cost efficiency while simultaneously addressing ANF concerns (Siad and Bouzid, 2023; Soong et al., 2022).

One of the major constraints in carnivorous fish culture was the high feed cost, primarily due to its elevated protein content. AI-driven models, such as the Evolutionary Algorithm (EA), facilitated the formulation of cost-effective diets for carnivorous species, helping to mitigate rising production costs while maintaining nutritional adequacy (Soong et al., 2022).

The integration of AI in feed formulation enhanced efficiency, reduced dependency on manual expertise, and promoted sustainable aquaculture by optimizing feed production economics.

2.9. Fish feeding system

Traditionally, fish in aquaculture systems were fed manually, while some farms utilized automatic feeders that dispensed feed at fixed intervals set by the farmer based on biomass estimations (An et al., 2020). However, Artificial Intelligence (AI)-driven intelligent feeding systems offered a more precise approach by monitoring fish behavior and movement through computer vision technology, utilizing underwater cameras to capture and analyze real-time images.

This AI-based feeding system autonomously adjusted feed distribution based on the analyzed fish behavior, ensuring optimal feeding efficiency. A key advantage of this method was the significant reduction in feed loss, leading to improved Food Conversion Ratio (FCR) compared to both manual feeding and conventional automatic feeders (An et al., 2020).

By integrating AI-driven feeding solutions, aquaculture operations could enhance sustainability, optimized feed utilization, and improved overall production efficiency.

2.10. Fish disease management

Monitoring fish diseases in aquaculture presented a significant challenge. However, AI-based Machine Learning algorithms, such as Support Vector Machines (SVM), offered a promising solution for disease detection. These systems captured and processed images of the fish, classifying them to determine whether they were diseased and identified the specific disease affecting them (Ahmed et al., 2022).

AI-based techniques like Deep Learning algorithms also enabled the detection of parasites, such as fish lice, Ichthyophthirius multifilis, and Gyrodactylus species. By uploading numerous images of the parasites into the AI model, it could predict parasitic infections affecting the fish (Li et al., 2023).

In addition to traditional image analysis, fish disease could be detected using smartphone-based AI techniques, such as Random Forest algorithms, which provided a high level of accuracy. This approach was particularly user-friendly for fish farmers, enabling them to identify moribund fish and take timely action (Mia et al., 2022). Several smartphone applications now offered image processing services to detect fish diseases and provide actionable suggestions to farmers (Agossou and Toshiro, 2021).

Furthermore, genomic data, such as single nucleotide polymorphisms (SNP), combined with machine learning and deep learning techniques, could be used to predict disease resistance in fish, aiding in breeding programs for

Table 1: Illustrates the various Artificial intelligence related to aquaculture and fish processing industries with its function

System	Type of AI technology used	Potential use	Reference
Shrimp hatcheries	Random Forest, logistic regression	Optimizing shrimp hatchery productivity	(Panitanarak and Kaowleg, 2024)
Shrimp hatcheries	Blynk application and a real-time counting system (Iot based system)	Automatic counting of shrimp seed (effectively time saving and reduce labour cost)	(Hanis et al., 2024)
Shrimp hatcheries	scaled multilayer feature fusion network along with IoT	Real time shrimp larvae counter	(Hsieh et al., 2024)
Prawn aquaculture	Convulation neural network	Early prediction of disease outbreak in prawn aquaculture	(Aravindhaa et al., 2024)
Shrimp aquaculture	logistic regression	Early detection of Acute Hepatopancreatic Necrosis Disease (AHPND) in shrimp farm	(Khiem et al., 2020)
Ornamental shrimps	image processing and K-means unsupervised machine learning	Automatic counting of ornamental shrimps	(Yeh and Ling, 2021)
Shrimp hatcheries	CNN-based method using density map regression	Accurate Counting of shrimp eggs	(Zhang et al., 2021)
Shrimp culture (biofloc)	Random forest with higher accuracy, adaboost, and deep neural networks	Early prediction of dissolved oxygen (DO) and biofloc amount	(Jasmin et al., 2022)
Shrimp hatcheries	Particle swarm optimization (PSO) and fuzzy analytic hierarchy process (FAHP)	Increasing the survival rate by early optimization of environmental and nutritional factors	(Khan, 2024).
Shrimp disease management	GIS and machine learning (Neural network performs accurately)	Early prediction of shrimp diseases such as acute hepatopancreatic necrosis, white spot syndrome disease, and Enterocytozoon hepatopenaei infection	(Khiem et al., 2022)
Shrimp hatcheries	density map regression and local peak filtering	Automatic counting, location, and sizing of shrimp larvae	(Zhou et al., 2024)
Shrimp aquaculture	Decision tree-based machine learning (ML) and extra tree (ET) model exhibits higher accuracy	Prediction if white spot syndrome virus susceptibility	(Tuyen et al., 2024)
Fish and shellfish hatcheries	convolutional neural network	Automatic counting of different hatching stages of brine shrimp (Artemia biomass)	(Evdokimov et al., 2024)
Shrimp aquaculture	AquaProFAN framework (AquaGent AI-based chatbot)	Helpful in giving guidance to farmer regarding queries related to shrimp aquaculture	(Jasmin et al., 2024)
Shrimp aquaculture	TF-IDF (Term Frequency-Inverse Document Frequency) and Natural Language Processing (NLP)	For classification of various kind of shrimp disease	(Quach et al., 2023)
Shrimp aquaculture	Mask regional convolutional neural network (Mask R-CNN)	Automatic counting of shrimp in shrimp ponds	(Hong et al., 2022)
Finfish aquaculture	multilayer perceptron (MLP) and radial basis function (RBF) neural networks	Autonomous prediction of dissolved oxygen (DO), biological oxygen demand (BOD), and chemical oxygen demand (COD)	(Galezan et al., 2020)

more resilient stock (Vu et al., 2022).

The integration of AI and genomic technologies in disease detection and prevention enhanced fish health management, offering more precise, timely, and user-friendly solutions for aquaculture practitioners.

2.11. Fish freshness assessment

The assessment of fish freshness was crucial in maintaining the quality of seafood. One approach involved measuring the humidity in the surrounding air, as increased humidity was indicative of decreased freshness. AI-based techniques, such as linear algorithms and Linear Discriminant Analysis (LDA) models, used sensors to detect changes in humidity as one of the factors in determining the freshness of fish meat (Musatov et al., 2010). Additionally, sensory attributed such as off-flavor and rancid substances were analyzed using LDA models to further evaluate fish freshness (Baldwin et al., 2011).

2.12. Fish freezing technology

AI models, such as Artificial Neural Networks (ANN) and Support Vector Machines (SVM), were also applied to monitor the freshness of fish stored in ice. These systems captured images of the gills and eyes of the fish using cameras, and AI algorithms processed the images to classify the fish based on its freshness. Based on this classification, the system can adjust the ice storage conditions accordingly (Mohammadi Lalabadi et al., 2020).

A significant issue in frozen fish storage is freezer burn, which could be detected using AI techniques like computer vision combined with machine learning algorithms. These systems could identify freeze burn and adjust freezer airflow and temperature to minimize the damage (Xu and Sun, 2017).

AI was also used to examine imported frozen fish products for quality assurance, utilizing systems like Border Prediction Intelligent (BPI) to ensure food safety and quality (Tu et al., 2024). Furthermore, hyperspectral imaging had proven effective in predicting drip loss in vacuum-packed fish fillets during chilling, freezing, and thawing processes, contributing to more accurate quality control (Anderssen et al., 2020).

Through these AI-based technologies, the seafood industry could enhance the monitoring and preservation of fish quality throughout freezing and storage, improving food safety and reducing waste.

2.13. Fish processing plant

The fish processing industry often experienced a reduction in profit due to high and excessive energy consumption, particularly in cold storage operations (Ghoroghi et al., 2023). Traditionally, temperature control in cold storage was manually predicted based on experience. However, AI-based models, such as Artificial Neural Networks (ANN), offered a more efficient solution by forecasting the required temperature and predicting energy consumption. These models helped optimize air conditioning operation, ensuring that energy usage was not excessive, thus reducing operational costs and improving energy efficiency in fish processing industries (Ghoroghi et al., 2023).

AI technologies like General Regression Neural Networks were also employed to predict the proximate composition of fish, such as moisture content, PUFA, MUFA, and omega-3 and omega-6 fatty acids, using low-frequency nuclear magnetic resonance (LF-NMR). These AI-based predictions yield resulted comparable to conventional chemical analysis, providing an efficient, less labour-intensive alternative (Al-habsi et al., 2024).

In fish cutting, a traditionally labour-intensive and time-consuming process, AI-integrated smart fish cutting machines, utilizing machine vision, significantly reduced both time and labour requirements (Liu et al., 2022). Additionally, AI techniques like computer vision and machine learning were applied to classify the freshness of different fish meats, such as tuna and salmon, ensuring that only the highest-quality products reached consumers (Medeiros et al., 2021). By leveraging AI in these areas, the fish processing industry could reduce costs, increase productivity, and improve the accuracy and efficiency of quality assessments

3. FISH CANNING INDUSTRIES

3.1. In energy consumption

Artificial intelligence (AI) played a vital role in optimizing energy consumption in fish canning industries, particularly in the retort sterilization process. AI models, like the Non-Linear Auto-Regressive Artificial Neural Network (NARX-ANN), predicted the F-value needed for sterilization, ensuring microorganisms in seafood products were killed efficiently. By accurately determining the required sterilization temperature, AI helped minimize energy waste, reducing operational costs and labour requirements (Guldas et al., 2016).

3.2. In Identification of cold spot temperature

In canning, it's crucial to identify the coldest spot (the slowest-heating region) in canned foods, as it was most prone to under-processing. AI-based methods, such as Apparent Position Numerical Solution (APNS), were employed to predict the cold spot temperature using factors like heating lag and heat penetration curves. This approach ensured efficient thermal processing without human intervention, preventing over-processing and improving product quality (Zhu et al., 2022).

3.3. Fish quality assessment

Artificial Intelligence (AI) played a crucial role in assessing the quality of fish, whether farm-harvested or wild-caught, by analyzing various chemical changes that occured in the fish body post-mortem. Techniques such as neural network analysis and Principal Component Analysis (PCA) were used to identify bio-molecules responsible for spoilage and predict the post-mortem time interval (Gil et al., 2008). One such technique involved the use of electrodes to detect fish freshness potentiometrically by measuring the generation of bio-molecules like Inosine Mono Phosphate (IMP), Inosine, and Hypoxanthine (Hx), which accumulate after the fish's death (Gil et al., 2008). Additionally, El Barbri et al. (2008) developed an AI-based electronic nose method to assess fish freshness. This system used a chamber with an electronic nose sensor to detect the odors emitted from the fish during spoilage, driven by microbial activity and other degradation processes.

AI-based machine learning models, such as PCA, self-organized maps, K-nearest neighbors, random forests, and Support Vector Machines (SVM), were employed to classify fish fillets as either fresh or spoiled, and to predict the shelf life and freshness of the product (Kashani Zadeh et al., 2023). Traditional methods of estimating the total viable count (TVC) in fish and fishery products were time-consuming and labour-intensive. However, AI techniques, such as deep learning, have been shown to estimate TVC by analyzing hyperspectral images, significantly reducing labour requirements (Yu et al., 2019). Furthermore, AI models like Artificial Neural Networks (ANN) could predict microbial counts and chemical changes in value-added fish products, such as fish burgers, without the need for traditional methods (Khalafpour and Roomiani, 2022).

AI-based techniques, including Fourier Transform Infrared Spectroscopy (FTIR), PCA, and Linear Discriminant Analysis (LDA), could also be employed to estimate spoilage in fish products stored under Modified Atmosphere Packaging (MAP) (Saraiva et al., 2017). The combination of FTIR and Raman spectroscopy with AI could help detect toxic preservatives, such as formalin, in fish, ensuring food safety and quality control (Benny et al., 2023).

3.4. Fish by-product utilization

Fish by-products, such as trash fish, could be utilized for protein extraction through hydrolysis using enzymes like pepsin and papain. AI-based models, particularly Machine Learning (ML), played a vital role in predicting the optimal amount or degree of hydrolytic enzyme required for efficient protein hydrolysis. This approach helped minimize the overuse of enzymes and reduced operational costs (Verdú et al., 2023). Additionally, the combination of ML with rapid spectroscopic techniques was increasingly used to assess the quality of fish oil, including its authenticity and other quality parameters, ensuring the food safety of consumers (Giese and Fritsche, 2021).

Microalgae harvesting, which typically required significant labour, could be optimized through the use of Artificial Neural Networks (ANN). These models helped optimize and characterize the use of fish bone bioflocculants for more efficient microalgae harvesting, making the process more cost-effective and significantly reducing labour requirements (Suparmaniam et al., 2022).

3.5. Value added fish products

Frying fish could lead to a reduction in its nutritional profile, including the loss of polyunsaturated fatty acids (PUFA) and other essential nutrients (Sadhu et al., 2021). To address this issue, Artificial Neural Network (ANN)-based genetic algorithms and particle swarm optimization (PSO) have been employed to retain the nutritional quality of fried fish to a certain extent. These AI models could predict and recommend the optimal frying parameters-such as temperature, time, and oil amount-to produce fried fish with higher levels of PUFA compared to other combinations (Sadhu et al., 2022).

Color changes in fish fillets could reduce their appeal to consumers. Hyper Spectral Imaging, combined with ANN, has been used to detect and analyze these color changes in fish fillets by processing images automatically, without the need for human intervention (Wang et al., 2022). Additionally, the quality of value-added fish products like surimi was significantly influenced by color and moisture changes during surimi gelation. AI-based models, including Convolutional Neural Networks (CNN), were used to predict these changes and other quality attributes during the gelation process of surimi (Yoon et al., 2023; Ikbal et al., 2022).

3.6. Blockchain management

Shrimp Chain was a hybrid blockchain-based framework developed to improve traceability, transparency, and certification in Bangladesh's shrimp export market. It addressed challenges in the supply chain by enabling data entry through mobile or web applications or IoT devices. This distributed certification system empowered shrimp farmers by enhancing food safety, quality, and compliance, providing them with better control over the market, and incentivizing them to produce high-quality shrimp (Khan et al., 2022).

4. CONCLUSION

Artificial intelligence played a crucial role in the fisheries sector and had a broad range of applications across other sectors, such as agriculture and allied industries.

Traditional aquaculture systems would struggle to meet growing food demands of an increasing global population. AI not only helped increase profits by boosting fish production and reducing human labour, but it also aided in detecting and rectifying environmental impacts caused by anthropogenic activities.

5. REFERENCES

Agossou, B.E., Toshiro, T., 2021. IoT and AI based system for fish farming: case study of Benin. In: Proceedings of the Conference on Information Technology for Social Good. https://doi.org/10.1145/3462203.3475873.

Ahmadi, Y., Jaya, I., Rahmat, A., Iqbal, M., 2023. Fish length estimation of free-swimming grouper in the cage culture using underwater televisual system (UTS), De-haze water correction, and deep learning methods. In: IOP Conference Series on Earth and Environmental Science, IOP Publishing 1251(1), 012037.

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

Akram, W., Bakht, A.B., Din, M.U., Seneviratne, L., Hussain, I., 2024. Detection and semantic segmentation in aquaculture net pens inspection: benchmark and dataset. IEEE Access 13, 3453–3474. https://doi.org/10.1109/ACCESS.2024.3524635.

Alam, T.J., Hayder, A.A.S.B., Apu, A.F., Banna, M.H.A., Rahman, M.S., 2023. IoT based biofloc aquaculture monitoring system. In: Proceedings of the 4th International Conference on Trends in Computational and Cognitive Engineering, TCCE 2022, Singapore, Springer Nature Singapore. 99–112

Al-Habsi, N., Al-Julandani, R., Al-Hadhrami, A., Al-Ruqaishi, H., Al-Sabah, J., Al Attabi, Z., Rahman, S., 2024. Artificial intelligence predictability of moisture, fats and fatty acids composition of fish using low frequency nuclear magnetic resonance (Lf-Nmr) relaxation. Journal of Food Science and Technology 61(11), 2071–2081. https://doi.org/10.1007/s13197-024-05977-3.

An, D., Hao, J., Wei, Y., Wang, Y., Yu, X., 2020. Application of computer vision in fish intelligent feeding system-a review. Aquaculture Research 52(2), 423–437. https://doi.org/10.1111/are.14907.

Anderssen, K.E., Stormo, S.K., Skåra, T., Skjelvareid, M.H., Heia, K., 2020. Predicting liquid loss of frozen and thawed cod from hyperspectral imaging. LWT 133, 110093.

Anusha, M., Jagadeesh, T., Bagde, P., Kumari, P., Rathlavath, S., Prabhakar, P., 2024. Strategies and techniques for enhancing fish health and averting disease outbreaks in aquaculture settings through the use of vaccination: a review. International Journal of Bio-resource and Stress Management 15(9), 01–11. DOI: https://doi.org/10.23910/1.2024.5563.

Aravindhaa, V., Manikanta, K.V.K., Mandula, H., Allamaneni, D., Sangeetha, N., 2024. Applying IoT and machine learning for enhanced efficiency and disease management, advancing sustainability in freshwater prawn farming. In: 3rd International Conference on Artificial Intelligence For Internet of Things (AIIoT), IEEE, 1–6.

Baena-Navarro, R., Carriazo-Regino, Y., Torres-Hoyos, F., Pinedo-López, J., 2025. Intelligent prediction and continuous monitoring of water quality in aquaculture: integration of machine learning and internet of things for sustainable management. Water 17(1), 82. https://doi.org/10.3390/w17010082.

Bakhit, A.A., Jamlos, M.F., Alhaj, N.A., Mamat, R., 2022. Biofloc farming with IoT and machine learning predictive water quality system. In: IEEE International RF and Microwave Conference (RFM), IEEE, 1–4.

Baldwin, E.A., Bai, J., Plotto, A., Dea, S. 2011. Electronic noses and tongues: applications for the food and Pharmaceutical Industries. Sensors 11(5), 4744–4766. https://doi.org/10.3390/s110504744.

Benny, A., Renitta, R.E., Mary, X.A., Dutta, P.K., Karthik, C., El-kenawy, E.S.M., 2023. Machine learning algorithm review for the detection of formalin in fish. In: 7th IET Smart Cities Symposium (SCS 2023), IET, 344–349.

Biswas, R., Mutz, M., George, N., Werth, D., 2023. A study on artificial intelligence techniques for automatic fish-size estimation. In: Science and Information Conference, Cham: Springer Nature Switzerland, 1116–1126.

Bose, B.K., 2017. Artificial intelligence techniques in smart grid and renewable energy systems-some example applications. In: Proceedings of the IEEE 105(11), 2262–2273. https://doi.org/10.1109/jproc.2017.2756596.

Chang, C.H., Weng, J.S., Chiu, P.S., Lien, W.C., Chiu, K., 2021. Artificial intelligence-based image recognition for measuring the size of grouper in mariculture. Journal of the Fisheries Society of Taiwan 48(4), 227–237.

Chen, F., Du, Y., Qiu, T., Xu, Z., Zhou, L., Xu, J., Sun, M., Li, Y., Sun, J., 2021. Design of an intelligent variable-flow recirculating aquaculture system based on machine learning methods. Applied Sciences

11(14), 6546. https://doi.org/10.3390/app11146546.
Chen, F., Qiu, T., Xu, J., Zhang, J., Du, Y., Duan, Y., Zeng, Y., Zhou, L., Sun, J., Sun, M., 2024. Rapid real-time prediction techniques for ammonia and nitrite in high-density shrimp farming in recirculating aquaculture systems. Fishes 9(10), 386. https://doi.org/10.3390/fishes9100386.
Chen, F., Sun, M., Du, Y., Xu, J., Zhou, L., Qiu, T., Sun, J., 2022. Intelligent feeding technique based on predicting shrimp growth in recirculating aquaculture system. Aquaculture Research 53(12), 4401–4413. https://doi.org/10.1111/are.15938.
Chiu, M.C., Yan, W.M., Bhat, S.A., Huang, N.F., 2022. Development of smart aquaculture farm management system using IoT and AI-based surrogate models. Journal of Agriculture and Food Research 9, 100357. https://doi.org/10.1016/j.jafr.2022.100357.
Davies, E.R., 2009. The application of machine vision to food and agriculture: a review. The Imaging Science Journal 57(4), 197–217. https://doi.org/10.1179/174313109x454756.
El Barbri, N., Llobet, E., El Bari, N., Correig, X., Bouchikhi, B., 2008. Application of a portable electronic nose system to assess the freshness of Moroccan sardines. Materials Science and Engineering: C 28(5–6), 666–670. https://doi.org/10.1016/j.msec.2007.10.056.
Elkiran, G., Nourani, V., Abba, S.I., 2019. Multi-step ahead modelling of river water quality parameters using ensemble artificial intelligence-based approach. Journal of Hydrology 577, 123962. https://doi.org/10.1016/j.jhydrol.2019.123962.
Erhan, D., Courville, A., Bengio, Y., Vincent, P., 2010. Why does unsupervised pre-training help deep learning? In: Proceedings of the 13th International Conference on Artificial Intelligence and Statistics (pp.). JMLR Workshop and Conference Proceedings, 201–208.
Evdokimov, I.Y., Malkova, A.V., Irkitova, A.N., Shirmanov, M.V., Dementev, D.V., 2024. Effect of a new probiotic on Artemia cysts determined by a convolutional neural network. Foods and Raw Materials 12(1), 91–100.
Fu, J., Liu, D., He, Y., Cheng, F., 2024. Autonomous net inspection and cleaning in sea-based fish farms: A review. Computers and Electronics in Agriculture 227, 109609. https://doi.org/10.1016/j.compag.2024.109609.
Galezan, F.H., Bayati, M.R., Safari, O., Rohani, A., 2020. Modeling oxygen and organic matter concentration in the intensive rainbow trout (*Oncorhynchus mykiss*) rearing system. Environmental Monitoring and Assessment 192, 1–12.
Ghoroghi, A., Petri, I., Rezgui, Y., Alzahrani, A., 2023. A deep learning approach to predict and optimise energy in fish processing industries. Renewable and Sustainable Energy Reviews 186, 113653. https://doi.org/10.1016/j.rser.2023.113653.
Giese, E., Fritsche, J., 2021. New approaches to detect compositional shifts in fish oils. Oil and Oilseed Processing, 81–101. https://doi.org/10.1002/9781119575313.ch5.
Gil, L., Barat, J.M., Garcia-Breijo, E., Ibañez, J., Martínez-Manez, R., Soto, J., Llobet, E., Brezmes, J., Aristoy, M.C., Toldrá, F., 2008. Fish freshness analysis using metallic potentiometric electrodes. Sensors and Actuators B: Chemical 131(2), 362–370. https://doi.org/10.1016/j.snb.2007.11.052.
Gladju, J., Kamalam, B.S., Kanagaraj, A., 2022. Applications of data mining and machine learning framework in aquaculture and fisheries: a review. Smart Agricultural Technology 2, 100061. https://doi.org/10.1016/j.atech.2022.100061.
Guldas, M., Kurtulmus, F., Gurbuz, O., 2016. Prediction of lethality by nonlinear artificial neural network modeling. Journal of Food Process Engineering 40(3). https://doi.org/10.1111/jfpe.12457.
Hanis, H.M., Muslim, H.H., Reigen, R., Wahyuni, E.S., 2024. Automatic shrimp seed counting device based on internet of things (IoT) and Artificial Intelligence (AI) to support precision sustainable farming. In: 13th International Innovation, Invention and Design Competition (INDES 2024), 31–34.
Hassoun, A., Siddiqui, S.A., Smaoui, S., Ucak, I., Arshad, R.N., Garcia-Oliveira, P., Prieto, M.A., Ait-Kaddour, A., Perestrelo, R., Camara, J.S., Bono, G., 2022. Seafood processing, preservation, and analytical techniques in the age of Industry 4.0. Applied Sciences 12(3), 1703. https://doi.org/10.3390/app12031703.
Hong Khai, T., Abdullah, S.N.H.S., Hasan, M.K., Tarmizi, A., 2022. Underwater fish detection and counting using mask regional convolutional neural network. Water 14(2), 222. https://doi.org/10.3390/w14020222.
Hsieh, Y.K., Hsieh, J.W., Hu, W.C., Tseng, Y.C., 2024. AIoT-based shrimp larvae counting system using scaled multilayer feature fusion network. IEEE Internet of Things Journal 11(22), 36438–36451. https://doi.org/10.1109/JIOT.2024.3410539.
Igwegbe, C.A., Obi, C.C., Ohale, P.E., Ahmadi, S., Onukwuli, O.D., Nwabanne, J.T., Białowiec, A., 2023. Modelling and optimisation of electrocoagulation/flocculation recovery of effluent from land-based aquaculture by artificial intelligence (AI) approaches. Environmental Science and Pollution Research

30(27), 70897–70917. https://doi.org/10.1007/s11356-023-27387-2.

Ikbal, A., Chowdhury, S., Murmu, P., Dora, K.C., Nath, S., Roy, S., Saklani, P., 2022. Surimi powder inclusion with semolina-based pasta product-A potential method of protein fortification. International Journal of Bio-resource and Stress Management 13(2), 144–154. DOI: https://doi.org/10.23910/1.2022.2435.

Jasmin, A., Ramesh, P., Tanveer, M., 2024. Development of artificial intelligence-based chatbot for smart aquafarm practices. Expert Systems 41(6), e13123.

Jasmin, S.A., Ramesh, P., Tanveer, M., 2022. An intelligent framework for prediction and forecasting of dissolved oxygen level and biofloc amount in a shrimp culture system using machine learning techniques. Expert Systems with Applications 199, 117160.

Jha, K., Doshi, A., Patel, P., Shah, M., 2019. A comprehensive review on automation in agriculture using artificial intelligence. Artificial Intelligence in Agriculture 2, 1–12. https://doi.org/10.1016/j.aiia.2019.05.004.

Jongjaraunsuk, R., Taparhudee, W., Suwannasing, P., 2024. Comparison of water quality prediction for red tilapia aquaculture in an outdoor recirculation system using deep learning and a hybrid model. Water 16(6), 907. https://doi.org/10.3390/w16060907.

Joshna, M., Ahilan, B., Antony, C., Ravaneswaran, K., Chidambaram, P., Uma, A., Ruby, P., 2024. Polyculture of genetically improved farmed tilapia (GIF Tilapia) and penaeus vannamei using biofloc technology-a review. International Journal of Bio-resource and Stress Management 15(7), 01–20. DOI: HTTPS://DOI.ORG/10.23910/1.2024.5396.

Kanagachidambaresan, G.R., Rohini, P., Muralidhar, M., Durairaj, T.S., 2024. Performance analysis of ML algorithms for disease prediction using water quality parameters. In: 15th International Conference on Computing Communication and Networking Technologies (ICCCNT), IEEE, 1–7.

Kashani Zadeh, H., Hardy, M., Sueker, M., Li, Y., Tzouchas, A., MacKinnon, N., Bearman, G., Haughey, S.A., Akhbardeh, A., Baek, I., Hwang, C., Qin, J., Tabb, A.M., Hellberg, R.S., Ismail, S., Reza, H., Vasefi, F., Kim, M., Tavakolian, K., Elliott, C.T., 2023. Rapid assessment of fish freshness for multiple supply-chain nodes using multi-mode spectroscopy and fusion-based artificial intelligence. Sensors 23(11), 5149. https://doi.org/10.3390/s23115149.

Khalafpour, M.J., Roomiani, L., 2022. Investigation of microbial, chemical and color changes of fish burgers in different storage conditions using Artificial Neural Network. Research and Innovation in Food Science and Technology 11(1), 67–82.

Khan, M.A., Hossain, M.E., Shahaab, A., Khan, I., 2022. Shrimp chain: a blockchain-based transparent and traceable framework to enhance the export potentiality of Bangladeshi shrimp. Smart Agricultural Technology 2, 100041.

Khiem, N.M., Takahashi, Y., Oanh, D.T.H., Hai, T.N., Yasuma, H., Kimura, N., 2020. The use of machine learning to predict acute hepatopancreatic necrosis disease (AHPND) in shrimp farmed on the east coast of the Mekong Delta of Vietnam. Fisheries Science 86, 673–683.

Khiem, N.M., Takahashi, Y., Yasuma, H., Oanh, D.T. H., Hai, T.N., Ut Ngoc, V., Kimura, N., 2022. Use of GIS and machine learning to predict disease in shrimp farmed on the east coast of the Mekong Delta, Vietnam. Fisheries Science, 1–13.

Lee, H., Jeong, D., Yu, H., Ryu, J., 2022. Autonomous underwater vehicle control for fishnet inspection in turbid water environments. International Journal of Control, Automation and Systems 20(10), 3383–3392.

Li, D., Wang, G., Du, L., Zheng, Y., Wang, Z., 2022. Recent advances in intelligent recognition methods for fish stress behavior. Aquacultural Engineering 96, 102222.

Li, J., Lian, Z., Wu, Z., Zeng, L., Mu, L., Yuan, Y., Bai, H., Guo, Z., Mai, K., Tu, X., Ye, J., 2023. Artificial Intelligence-based method for the rapid detection of fish parasites (*Ichthyophthirius multifiliis*, *Gyrodactylus kobayashii*, and *Argulus japonicus*). Aquaculture 563, 738790. https://doi.org/10.1016/j.aquaculture.2022.738790.

Liang, W.Y., Juang, J.G., 2022. Application of image identification to UAV control for cage culture. Science Progress 105(4), 00368504221135450.

Liu, W., Lyu, J., Wu, D., Cao, Y., Ma, Q., Lu, Y., Zhang, X., 2022. Cutting techniques in the fish industry: a critical review. Foods 11(20), 3206.

Mandal, A., Ghosh, A.R., 2024. Role of artificial intelligence (AI) in fish growth and health status monitoring: a review on sustainable aquaculture. Aquaculture International 32(3), 2791–2820. https://doi.org/10.1007/s10499-023-01297-z.

Medeiros, E.C., Almeida, L.M., Filho, J.G.D.A.T., 2021. Computer vision and machine learning for tuna and salmon meat classification. Informatics 8(4), 70.

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

Mohammadi Lalabadi, H., Sadeghi, M., Mireei, S.A., 2020. Fish freshness categorization from eyes and gills color features using multi-class artificial neural network and support vector machines. Aquacultural Engineering 90, 102076. https://doi.org/10.1016/j.aquaeng.2020.102076.

Mozumder, S.A., Sharifuzzaman Sagar, A.S.M., 2022. Smart IoT biofloc water management system using decision regression tree. In: Proceedings of International Conference on 4th Industrial Revolution and Beyond 2021, (pp.). Singapore: Springer Nature Singapore, 229–241.

Mufidah, N.F., Nuha, H.H., 2023. Monitoring and prediction of water quality in catfish biofloc ponds at SEIN farm using iot and linear regression. In: International Conference on Artificial Intelligence, Blockchain, Cloud Computing, and Data Analytics (ICoABCD), IEEE, 13–18.

Musatov, V. Yu., Sysoev, V.V., Sommer, M., Kiselev, I., 2010. Assessment of meat freshness with metal oxide sensor microarray electronic nose: A practical approach. Sensors and Actuators B: Chemical 144(1), 99–103. https://doi.org/10.1016/j.snb.2009.10.040.

Mustapha, U.F., Alhassan, A.W., Jiang, D.N., Li, G.L., 2021. Sustainable aquaculture development: a review on the roles of cloud computing, internet of things and artificial intelligence (CIA). Reviews in Aquaculture 13(4), 2076–2091. https://doi.org/10.1111/raq.12559.

Ngasotter, S., Panda, S.P., Mohanty, U., Akter, S., Mukherjee, S., Waikhom, D., Devi, L.S., 2020. Current scenario of fisheries and aquaculture in India with special reference to Odisha: a review on its status, issues and prospects for sustainable development. International Journal of Bio-resource and Stress Management 11(4), 370–380. DOI: https://doi.org/10.23910/1.2020.2126a.

Niehaus, S., Hartwig, M., Rosen, P.H., Wischniewski, S., 2022. An occupational safety and health perspective on human in control and AI. Frontiers in Artificial Intelligence 5, 868382. https://doi.org/10.3389/frai.2022.868382.

Panda, S., Narayanamoorthi, R., Dhanalakshmi, S., 2023. Advanced real-time monitoring system for marine net pens: integrating sensors, GPRS, GPS, and IoT with Embedded Systems. In: International Conference on Micro-Electronics and Telecommunication Engineering, Singapore: Springer Nature Singapore, 419–435.

Panitanarak, T., Kaowleg, B., 2024. Machine learning for increasing productivity in shrimp hatchery. In: 28th International Computer Science and Engineering Conference (ICSEC), IEEE, 1–6.

Parenreng, J.M., Syahrul, S., Wahid, A., Sary, D.W., 2022. Modern farming biofloc ponds for tilapia aquaculture based on the internet of things use a fuzzy logic algorithm. Internet of Things and Artificial Intelligence Journal 2(4), 233–247.

Quach, L.D., Quynh, A.N., Khang, N.Q., Thu, A.N.T., 2023. Using the term frequency-inverse document frequency for the problem of identifying shrimp diseases with state description text. International Journal of Advanced Computer Science and Applications 14(5).

Ramírez-Coronel, F.J., Rodríguez-Elías, O.M., Esquer-Miranda, E., Pérez-Patricio, M., Pérez-Báez, A.J., Hinojosa-Palafox, E.A., 2024. Non-invasive fish biometrics for enhancing precision and understanding of aquaculture farming through statistical morphology analysis and machine learning. Animals 14(13), 1850. https://doi.org/10.3390/ani14131850.

Ranjan, R., Sharrer, K., Tsukuda, S., Good, C., 2023. MORTCAM: An artificial intelligence-aided fish mortality detection and alert system for recirculating aquaculture. Aquacultural Engineering 102, 102341. https://doi.org/10.1016/j.aquaeng.2023.102341.

Rather, M.A., Ahmad, I., Shah, A., Hajam, Y.A., Amin, A., Khursheed, S., Ahmad, I., Rasool, S., 2024. Exploring opportunities of artificial intelligence in aquaculture to meet increasing food demand. Food Chemistry: X 22, 101309. https://doi.org/10.1016/j.fochx.2024.101309.

Ren, Q., Wang, X., Li, W., Wei, Y., An, D., 2020. Research of dissolved oxygen prediction in recirculating aquaculture systems based on deep belief network. Aquacultural Engineering 90, 102085. https://doi.org/10.1016/j.aquaeng.2020.102085.

Sadhu, T., Banerjee, I., Lahiri, S.K., Chakrabarty, J., 2021. Enhancement of nutritional value of fried fish using an artificial intelligence approach. Environmental Science and Pollution Research 29(14), 20048–20063. https://doi.org/10.1007/s11356-021-13548-8.

Sadhu, T., Lahiri, S.K., Bhattacharjee, A., Chakrabarty, J., 2022. Application of artificial neural network with metaheuristic optimization for improving the nutritive value of fried fish. Journal of Food Processing and Preservation 46(12). https://doi.org/10.1111/jfpp.17190.

Saraiva, C., Vasconcelos, H., de Almeida, J.M., 2017. A chemometrics approach applied to Fourier transform infrared spectroscopy (FTIR) for monitoring the spoilage of fresh salmon (Salmo salar) stored under modified atmospheres. International Journal of Food Microbiology 241, 331–339.

Sasikumar, R., Lincy, L.L., Saranya, S., Roja, B., Thamanna, L., Sreekutty, V.P., Chellapandi, P., 2024. Field trial evaluation of sensor-based aquaculture automation for improved biofloc shrimp culture. Journal of Water Process Engineering 64, 105661.

Sedighkia, M., Datta, B., 2024. Suitability assessment of cage fish farming location in reservoirs through neural networks-based remote sensing analysis. Remote Sensing 16(2), 236.

Siad, O., Bouzid, C., 2023. Biotech meets artificial intelligence to enhance the value of by-products in animal nutrition. Biological Sciences 03(01). https://doi.org/10.55006/biolsciences.2023.03012.

Soong, C.J., Rahman, R.A., Ramli, R., Manaf, M.S., Ting, C.C., 2022. An evolutionary algorithm: An enhancement of binary tournament selection for fish feed formulation. Complexity 2022, 1–15. https://doi.org/10.1155/2022/7796633.

Soto-Zarazua, G.M., Peniche-Vera, R., Rico-García, E., Toledano-Ayala, M., Ocampo-Velázquez, R., Herrera-Ruiz, G., 2011. An automated recirculation aquaculture system based on fuzzy logic control for aquaculture production of tilapia (*Oreochromis niloticus*). Aquaculture International 19(4), 797–808. https://doi.org/10.1007/s10499-010-9397-5.

Suparmaniam, U., Shaik, N.B., Lam, M.K., Lim, J.W., Uemura, Y., Shuit, S.H., Lee, K.T., 2022. Valorization of fish bone waste as novel bioflocculant for rapid microalgae harvesting: experimental evaluation and modelling using back propagation artificial neural network. Journal of Water Process Engineering 47, 102808.

Supriyanto, Noguchi, R., Ahamed, T., Rani, D.S., Sakurai, K., Nasution, M.A., Wibawa, D.S., Demura, M., Watanabe, M.M., 2019. Artificial neural networks model for estimating growth of polyculture microalgae in an open raceway pond. Biosystems Engineering 177, 122–129. https://doi.org/10.1016/j.biosystemseng.2018.10.002.

Ta, X., Wei, Y., 2018. Research on a dissolved oxygen prediction method for recirculating aquaculture systems based on a convolution neural network. Computers and Electronics in Agriculture 145, 302–310. https://doi.org/10.1016/j.compag.2017.12.037.

Taparhudee, W., Jongjaraunsuk, R., Nimitkul, S., Suwannasing, P., Mathurossuwan, W., 2024. Optimizing convolutional neural networks, XGBoost, and hybrid CNN-XGBoost for precise red tilapia (*Oreochromis niloticus* Linn.) weight estimation in river cage culture with aerial imagery. Agri Engineering 6(2), 1235–1251. https://doi.org/10.3390/agriengineering6020070.

Teramoto, E.T., Wasielesky, W., Krummenauer, D., Bueno, G.W., Proença, D.C., Gaona, C.A.P., 2024. Appling machine learning for estimating total suspended solids in BFT aquaculture system. Aquacultural Engineering 106, 102439.

Tu, W.C., Tsai, W.L., Lee, C.H., Tsai, C.F., Wei, J.T., Lin, K.F., Weng, Y.M., 2024. Application and effectiveness of artificial intelligence for the border management of imported frozen fish in Taiwan. Journal of Food and Drug Analysis 32(1), 21.

Tuyen, T.T., Al-Ansari, N., Nguyen, D.D., Le, H.M., Phan, T.N.Q., Prakash, I., Pham, B.T., 2024. Prediction of white spot disease susceptibility in shrimps using decision trees based machine learning models. Applied Water Science 14(1), 2.

Tynchenko, V., Kukartseva, O., Tynchenko, Y., Kukartsev, V., Panfilova, T., Kravtsov, K., Malashin, I., 2024. Predicting tilapia productivity in geothermal ponds: a genetic algorithm approach for sustainable aquaculture practices. Sustainability 16(21), 9276.

Ubina, N.A., Cheng, S.C., Chen, H.Y., Chang, C.C., Lan, H.Y., 2021. A visual aquaculture system using a cloud-based autonomous drones. Drones 5(4), 109. https://doi.org/10.3390/drones5040109.

Verdú, S., Fuentes, C., Fuentes, A., Pérez, A.J., Barat, J.M., Grau, R., 2023. Predicting fish by-product proteolysis status by RGB laser-scattering imaging combined with machine learning procedures. Journal of Food Engineering 358, 111660.

Vu, N.T., Phuc, T.H., Oanh, K.T.P., Sang, N.V., Trang, T.T., Nguyen, N.H., 2022. Accuracies of genomic predictions for disease resistance of striped catfish to Edwardsiella ictaluri using artificial intelligence algorithms G3 Genes|Genomes|Genetics 12(1), jkab361, https://doi.org/10.1093/g3journal/jkab361.

Wang, S., Das, A.K., Pang, J., Liang, P., 2022. Real-time monitoring the color changes of large yellow croaker (*Larimichthys crocea*) fillets based on hyperspectral imaging empowered with artificial intelligence. Food Chemistry 382, 132343. https://doi.org/10.1016/j.foodchem.2022.132343.

Wu, Y., Duan, Y., Wei, Y., An, D., Liu, J., 2022. Application of intelligent and unmanned equipment in aquaculture: a review. Computers and Electronics in Agriculture 199, 107201. https://doi.org/10.1016/j.compag.2022.107201.

Xu, J.L., Sun, D.W., 2017. Identification of freezer burn on frozen salmon surface using hyperspectral imaging and computer vision combined with machine learning algorithm. International Journal of Refrigeration 74, 151–164. https://doi.org/10.1016/j.ijrefrig.2016.10.014.

Xu, L.D., Lu, Y., Li, L., 2021. Embedding blockchain technology into IOT for security: a survey. IEEE

Internet of Things Journal 8(13), 10452–10473. https://doi.org/10.1109/jiot.2021.3060508.
Yang, J., 2023. Predicting water quality through daily concentration of dissolved oxygen using improved artificial intelligence. Scientific Reports 13(1), 20370.
Yang, J., Jia, L., Guo, Z., Shen, Y., Li, X., Mou, Z., Lin, J.C.W., 2023. Prediction and control of water quality in Recirculating Aquaculture System based on hybrid neural network. Engineering Applications of Artificial Intelligence 121, 106002. https://doi.org/10.1016/j.engappai.2023.106002.
Yang, J., Wu, H., Yang, J., Zhou, Y., Shen, Y., 2021. Intelligent feeding algorithm for recirculating aquaculture system based on deep learning. In: International Conference on Computing, Control and Industrial Engineering, Singapore: Springer Nature Singapore, 397–408. https://doi.org/10.1007/978-981-19-3927-339.
Yang, J., Zhou, Y., Guo, Z., Zhou, Y., Shen, Y., 2024. Deep learning-based intelligent precise aeration strategy for factory recirculating aquaculture systems. Artificial Intelligence in Agriculture 12, 57–71. https://doi.org/10.1016/j.aiia.2024.04.001.
Yang, X., Zhang, S., Liu, J., Gao, Q., Dong, S., Zhou, C., 2020. Deep learning for smart fish farming: Applications, opportunities and challenges. Reviews in Aquaculture 13(1), 66–90. https://doi.org/10.1111/raq.12464.
Yeh, C.T., Ling, M.S., 2021. Portable device for ornamental shrimp counting using unsupervised machine learning. Sensors and Materials 33(9), 3027–3036. https://doi.org/10.18494/SAM.2021.3240.
Yoon, W.B., Oyinloye, T.M., Kim, J., 2023. Classification of quality characteristics of surimi gels from different species using images and convolutional neural network. Processes 11(10), 2864. https://doi.org/10.3390/pr11102864.
Yu, X., Yu, X., Wen, S., Yang, J., Wang, J., 2019. Using deep learning and hyperspectral imaging to predict total viable count (TVC) in peeled Pacific white shrimp. Journal of Food Measurement and Characterization 13, 2082–2094.
Zenger, K.R., Khatkar, M.S., Jones, D.B., Khalilisamani, N., Jerry, D.R., Raadsma, H.W., 2019. Genomic selection in aquaculture: application, limitations and opportunities with special reference to marine shrimp and pearl oysters. Frontiers in Genetics 9, 693.
Zhang, J., Yang, G., Sun, L., Zhou, C., Zhou, X., Li, Q., Guo, J., 2021. Shrimp egg counting with fully convolutional regression network and generative adversarial network. Aquacultural Engineering 94, 102175.
Zhou, C., Lin, K., Xu, D., Chen, L., Guo, Q., Sun, C., Yang, X., 2018. Near infrared computer vision and neuro-fuzzy model-based feeding decision system for fish in aquaculture. Computers and electronics in agriculture 146, 114–124. https://doi.org/10.1016/j.compag.2018.02.006.
Zhou, C., Wang, C., Sun, D., Hu, J., Ye, H., 2025. An automated lightweight approach for detecting dead fish in a recirculating aquaculture system. Aquaculture 594, 741433. https://doi.org/10.1016/j.aquaculture.2024.741433.
Zhou, C., Yang, G., Sun, L., Wang, S., Song, W., Guo, J., 2024. Counting, locating, and sizing of shrimp larvae based on density map regression. Aquaculture International 32(3), 3147–3168.
Zhou, Y., Zhang, Q., Zhang, H., Yang, J., Guo, Z., Bulugu, I., Shen, Y., 2023. A deep vision sensing-based fuzzy control scheme for smart feeding in the industrial recirculating aquaculture systems. Electronics Letters 59(2), e12727. https://doi.org/10.1049/ell2.12727.
Zhu, S., Li, B., Chen, G., 2022. Improving prediction of temperature profiles of packaged food during retort processing. Journal of Food Engineering 313, 110758. https://doi.org/10.1016/j.jfoodeng.2021.110758.