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THE FUTURE OF AQUACULTURE: INTEGRATING ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING FOR SUSTAINABLE PRODUCTIVITY

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Aim. This study aimed to evaluate the potential of Artificial Intelligence (AI) and Machine Learning (ML) in improving aquaculture production systems through enhanced monitoring, automation, and data-driven decision-making.

Methods. The study was conducted through a comprehensive analysis of recent experimental and field-based reports integrating AI-driven technologies in aquaculture. Models such as convolutional neural networks, recurrent neural networks, and AIoT-based digital twins were reviewed for their applications in monitoring fish growth, detecting disease, and controlling water quality. Various aquatic species, including tilapia, salmon, and carp, were referenced as model organisms in these studies to evaluate performance accuracy and operational efficiency.

Results. The findings revealed that AI-enabled image recognition models successfully detected fish health anomalies and feeding behaviours with high precision. Sensor-based water quality systems linked to AI algorithms improved environmental stability and reduced mortalities. Automated feeding and real-time decision-support frameworks minimized resource wastage, while predictive models optimized growth rates and harvesting schedules. Collectively, these advancements improved productivity and reduced operational costs while maintaining ecological balance.

Conclusion. Artificial Intelligence and Machine Learning have demonstrated transformative potential for advancing aquaculture toward greater sustainability, profitability, and environmental stewardship. Their integration supports intelligent farm management and resilience against climate and resource challenges.

Key words: aquaculture, artificial intelligence (AI), machine learning (ML), smart fish farming, sustainability.

Aquaculture is considered an important industry that provides a substantial protein source for human consumption and offers other health benefits [1, 2]. As the global population continues to expand, the need for sustainable and effective aquaculture techniques becomes increasingly crucial, meeting rising demand and minimizing environmental impact [1, 2]. But aquaculture, like other industrial sectors worldwide, faces a series of critical challenges that threaten its sustainability and long-term stability. Among the most pressing concerns is the progressive decline in suitable aquaculture zones, primarily driven by urban expansion, environmental degradation, and climate-induced habitat alterations. The industry also suffers from the scarcity of genetically superior and disease-resistant varieties, which significantly restricts production efficiency and genetic improvement programs. In

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addition, the Intensive aquaculture method has emerged in recent years as a contemporary, rapidly evolving approach to aquatic farming, gaining attention in numerous nations for its high output, adaptability, reduced feed requirements, and efficient use of water and other renewable energy resources [3]. However, this type of aquaculture system is highly labour-intensive, typically requiring substantial human involvement and manual operation of machinery [4]. These approaches are not only costly due to escalating labour costs and shortages of the skilled workforce but also inefficient in managing water resources and responding promptly to environmental fluctuations [4]. Widespread aquatic pollution resulting from anthropogenic activities further exacerbates production risks by deteriorating water quality and fostering disease outbreaks. The degradation of germplasm resources, owing to indiscriminate breeding practices and inadequate conservation measures, undermines genetic diversity and resilience. Moreover, the excessive and often indiscriminate use of antibiotics, hormones, and other chemotherapeutic agents has resulted in the accumulation of harmful residues in aquatic organisms, raising concerns about food safety and public health. Finally, the sector continues to grapple with technological inadequacies, including limited adoption of advanced farming systems, diagnostic tools, and automation, all of which constrain its ability to meet global demand efficiently [5]. To address these difficulties, the sector is shifting towards advanced process control technologies and intelligent fish-farming practices. The cultivation of aquatic species in a intelligent way encompasses a diverse array of technological applications, including the Artificial Intelligence (AI), Automation, Machine Learning (ML) and Internet of Things (IoT), aimed at enhancing resource efficiency and promoting sustainable development within the aquaculture sector [2, 6, 7]. Specifically, AI and ML are two trendsetting technologies that can be applied to transform the pisciculture sector [1]. Their utilization in aquaculture can allow for the streamlining and automation of various procedures, culminating in improved efficiency and increased yields [1]. By incorporating AI and ML, the sector can make notable progress in monitoring, feeding, disease identification and environmental regulation, ultimately resulting in greater sustainability and productive fish farming practices.

We emphasized the newly developed intelligent technologies in fish farming, such as AI, Automation, ML, and IoT, which are increasingly being adopted to enhance efficiency, optimize resource utilization, and promote sustainability in aquaculture. The present study employed a comprehensive analytical and comparative approach to examine the integration of AI and ML technologies in modern aquaculture systems. To achieve this, experimental data and model-based applications reported in recent scientific literature were systematically reviewed and synthesized. Emphasis was placed on AI-driven systems for precision aquaculture-covering automated feeding, water quality monitoring, behavioural analysis, and predictive management.

The Role of AI and ML in Advancing Aquaculture AI, unlike human and animal intelligence, represents the intelligence showcased by machines [6]. Essentially, AI involves logical, automated procedures primarily guided by algorithms, proficient at carrying out well-defined tasks [8–10]. The field covers theories and methodologies for creating sophisticated computer programs that can replicate specific aspects of human intelligence [11–15]. AI is presently being investigated and integrated into sectors such as healthcare, agriculture, finance, and aquaculture [16].

AI along with ML has a wide array of applications across diverse sectors and industries, including aquaculture, presenting potential solutions for enhancing various aspects of aquaculture (Figure 1) [2, 17]. The utilization of cutting-edge technologies such as AI along with ML shows promise in realizing sustainable fish and production, enhancing welfare and alleviating the environmental impacts linked with aquatic species farming [17]. AI is expected to address existing limitations in aquaculture by enabling automated operations of tasks, such as machine and tool control, without human intervention [2]. By integrating AI and ML into aquaculture operations, meaningful exploration of data becomes viable, delivering continuous analytical insights into how fish growth reacts to various farming inputs and conditions.

AI-Driven Insights for Improved Fish Growth in Aquaculture

The growth performance of fish and other aquaculture species is shaped by multiple factors, including water quality, feed management, and overall environmental conditions. AI and ML approaches have shown considerable potential in forecasting growth patterns based on these parameters. For example, Convolutional Neural Networks (CNNs) can analyze underwater images and videos to identify and measure individual fish, enabling accurate growth predictions when trained on large datasets of annotated images [18]. Similarly, real-time sensors can record critical water-quality parameters, including temperature, pH, and dissolved oxygen, while Recurrent Neural Networks (RNNs) process this time-series information to detect trends and forecast growth outcomes [19]. In addition, acoustic signals generated by fish during feeding can be analyzed using deep learning frameworks to assess feeding intensity and appetite, thereby supporting demand-driven feeding practices that enhance growth efficiency [20]. Furthermore, digital twin technology allows the creation of virtual models that integrate feeding regimes, water quality, and environmental conditions, enabling farmers to simulate alternative management strategies and select those most likely to optimize fish growth [21]. A detailed summary of different AI/ML models applied to detect fish growth and survival rates is presented in Table 1, which can enhance aquaculture production.

Combatting. Disease Outbreaks in Aquaculture with AI and ML: Disease outbreaks are one of the most critical challenges faced by aquaculture, severely undermining productivity, profitability, and sustainability [25]. Fish pathogens spread rapidly in high-density farming conditions, causing massive stock mortalities and financial losses [29]. The situation is further aggravated by farmers' limited ability to diagnose and respond quickly to sudden outbreaks, making

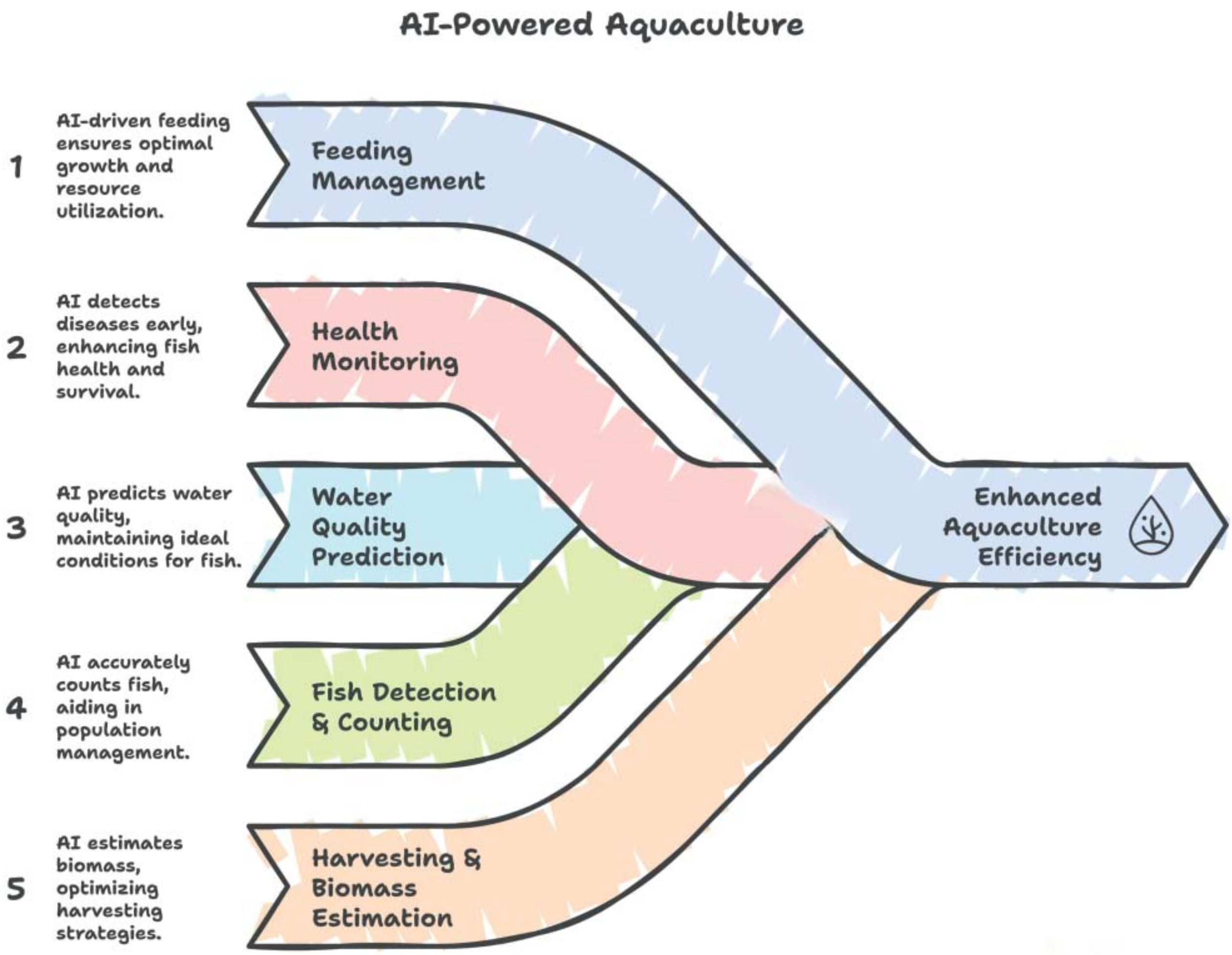

Fig. 1. **Conceptual framework illustrating the incorporation of AI in different aspects of aquaculture management**

***Table 1*. Summary of recent advancements in AI- and ML-driven systems for monitoring fish growth and productivity enhancement in aquaculture**

AI Application	Description	Benefits
AIoT-based Smart Cage System [22]	Integration of underwater cameras, sensors, and AI algorithms to non-invasively estimate fish size, weight, and growth in real time.	Provides continuous monitoring of fish growth, reduces manual labor, improves feeding efficiency, and lowers stress on fish.
Deep Learning Image Analysis (YOLOv3, Faster R-CNN) [23]	Use of object detection algorithms (YOLOv3, Faster R-CNN) to identify fish in underwater images and calculate body length and weight.	Application of ML models to forecast fish growth patterns by analyzing environmental factors, feeding rates, and historical growth records
ML for Growth Prediction [24]	Application of ML models to forecast fish growth patterns by analyzing environmental factors, feeding rates, and historical growth records	Supports decision-making in aquaculture by forecasting growth patterns, optimizing feed schedules and improving productivity.
XperCount Device by XpertSea [25]	An AI-powered device (XperCount) that uses ML and camera technology to rapidly weigh, count, image, and measure shrimp within seconds. The data is analyzed to monitor stock health and growth trends.	Provides rapid, non-invasive assessment of cultured shrimp, reduces manual labor, and enables better health monitoring and yield prediction.
Machine Learning–Ultrasonic Monitoring System (YOLOv4) [26]	A system combining ultrasound imaging with a YOLOv4 deep learning algorithm to monitor shrimp behavior, positioning, and length with high accuracy. Data augmentation techniques reduced overfitting and improved reliability.	Achieves accurate monitoring of shrimp health and growth, improves real-time aquaculture management, and minimizes errors in quantity and size detection.
ML-based Growth Rate Prediction (Environmental Parameters) [27]	Application of machine learning models trained on fish growth datasets to predict growth rates using environmental parameters such as temperature, pH, and dissolved oxygen.	Helps optimize feeding schedules, enhance resource use efficiency, and determine optimal harvest times to maximize production.
Support Vector Machine (SVM) Model for Tilapia Growth Prediction [28]	An ML model based on the Support Vector Machine (SVM) algorithm was developed to predict tilapia growth rate, achieving up to 85% accuracy.	Provides reliable growth forecasts, assists farmers in optimizing feeding strategies, and enables the determination of optimal harvest times to maximize yield and efficiency.

timely treatment difficult [29]. Consequently, the integration of AI, computer vision, and ML into aquaculture disease surveillance has received increasing attention.

Disease Outbreaks in Aquaculture with AI and ML

Disease outbreaks are among the most critical challenges faced by aquaculture, severely undermining productivity, profitability, and sustainability [25]. Fish pathogens spread rapidly in high-density farming conditions, causing massive stock mortalities and financial losses [29]. The situation is further aggravated by farmers' limited ability to diagnose and respond quickly to sudden outbreaks, making timely treatment difficult [29]. Consequently, the integration of AI, computer vision, and ML into aquaculture disease surveillance has received increasing attention.

[30] demonstrated the use of computer vision and deep learning models by combining FlowNet2 with 3D CNNs to analyze RGB and optical flow data for fish behavior recognition, achieving an impressive accuracy of 95.79%. Such approaches highlight how behavior-based monitoring can serve as an early indicator of disease onset. Similarly, AI programs that compare programmed reference datasets with real-time inputs from aquaculture sites have shown promise in detecting anomalies before outbreaks escalate [25, 31]. ML-based approaches, such as integrating Principal Component Analysis (PCA) with Artificial Neural Networks (ANN), have been employed to diagnose epizootic ulcerative syndrome (EUS), improving detection accuracy [32]. In shrimp aquaculture, decision-tree algorithms have been successfully applied to detect white spot disease, achieving satisfactory accuracy levels [33].

Machine vision has been a game-changer in disease monitoring, enabling rapid, automated recognition of infected fish through imaging [34]. Images captured by underwater cameras or sensors can be uploaded to cloud platforms, where AI-driven models process and classify disease symptoms, thus empowering farmers with timely management solutions [35, 36]. For example, Aquaconnect, an Indian aquaculture start-up, developed FarmMOJO, a mobile-based app for shrimp farmers that predicts potential outbreaks by analyzing water quality and disease images contributed by farmers [25]. Norway's Aquacloud, launched in 2017, is another successful case of a cloud-based surveillance program that monitors sea lice infestations, significantly reducing mortality and treatment costs [25].

Contemporary advances in deep learning architectures have further enhanced disease detection. Huang and Khabusi (2023) proposed a CNN-OSELM multilayer fusion model with an attention mechanism, achieving 94.28% accuracy in disease recognition amid demanding underwater environments [37]. Similarly, [36] developed an AI-driven surveillance system capable of continuous optical monitoring of cultured fish, detecting early signs of disease and alerting stakeholders in real time. Other studies have incorporated hybrid systems, such as combining acoustic technology with computer vision [38] or using YOLOv7 for mortality detection [39].

Collectively, these studies and other studies described in Table 2 illustrate the transformative role of AI and ML in aquaculture disease management. By integrating advanced imaging, big data analytics, and predictive modeling, these tools enable proactive disease prevention, reduce farmer dependency on reactive treatments, and significantly enhance aquaculture sustainability.

The Role of AI Technologies for Optimized Fish Feeding. In an aquaculture system, feed costs nearly 60% of the total investment. Insufficient or excessive feeding can cause several issues in containment [25]. Reduced feeding may lower muscle conversion and, in severe cases (e.g., in shrimp), can trigger cannibalism and aggressive interactions [25]. Excessive feeding leads to feed loss and negatively affects water quality. Although freshwater aquaculture allows cultivators to stay close to the farm, feeding the fish can be time-consuming. Farmers can sometimes forget to feed the fish or may be unavailable for some reason [6]. This is where AI can be invaluable, stepping into the cultivators' shoes using automated feeding systems. AI is instrumental in assessing fish appetite and optimizing the feeding process by analyzing their behavior, feeding patterns, and environmental conditions. In developed nations such as Norway, Japan, and the United States, these systems have advanced to practical implementation, enabling precise management of feed distribution, storage, and supply chains [31].

For example, a Norwegian aquaculture equipment company has developed an automated net-cage feeding system comprising a management platform, an online monitoring system, and a feeding module [31, 43]. The monitoring system continuously tracks key water quality parameters, such as pH, temperature, dissolved oxygen (DO), and transmits this data to the management system, which then automatically adjusts feeding accordingly.

The Finnish company Arvo-Tec has developed an advanced robotic feeding control system that enables remote feed management, enhances water quality, and allows precise feeding through a web interface [44]. Its command module, WOLF, integrates feeding, measurement, light regulation (photoperiod), and alarm functions, and estimates fish growth based on the feed conversion ratio

An Indonesian aquaculture intelligence company, 'eFishery,' has designed a comparable platform that detects fish feeding demand by analyzing vibration signals [25]. Adoption of this technology has resulted in yield increases of over 35% and substantial improvements in profitability. At present, such systems are gaining widespread application in regions including China, Egypt, Indonesia, and the United Arab Emirates.

In Singapore and Japan, an aquaculture technology company called 'Umitron Cell' produces a bright fish feeder that integrates IoT, machine learning, and satellite remote sensing, with its initial deployment in Ainan City, Ehime, Japan [25]. t is a data-driven decision-support system designed to help farmers optimize feeding schedules by analyzing real-time data on fish behavior, environmental conditions, and feed utilization, thereby enhancing growth efficiency and reducing waste.

[45] proposed a hybrid approach utilizing the ResNet34-CBAM model to detect feeding behavior in tilapia within aquaculture systems. The research involved comparing various

Table 2. **Descriptive Summary Table of AI/ML Applications in Aquaculture Disease Monitoring**

Technology/Model	Application	Key Features / Outcomes
Aquaconnect (FarmMOJO) Mobile app with ML integration [25]	Shrimp disease prediction	Predicts disease outbreaks using water quality data and uploaded images
Aquacloud (Norway, 2017) Cloud-based monitoring system [25]	Sea lice prevention	Reduced fish mortality and minimized costly treatments
FlowNet2 + 3D CNN (RGB + optical flow) [30]	Fish behavior analysis for disease monitoring	Achieved 95.79% accuracy in fish behavior identification; supports early disease detection
PCA + ANN classification [32]	Fish disease (EUS) detection	Enhanced accuracy and efficiency in detecting EUS
Decision tree ML algorithm [33]	Shrimp disease (White spot) detection	Achieved satisfactory accuracy in disease diagnosis
AI-based optical monitoring system [36]	Real-time disease surveillance	Detects disease onset and alerts stakeholders instantly
CNN-OSELM fusion network with attention mechanism [37]	Fish disease recognition	94.28% accuracy in disease detection under underwater conditions
Acoustic technology + computer vision [38]	Real-time monitoring	Prototype system for continuous fish health and environment monitoring
MortCam + YOLOv7 [39]	Mortality detection	Real-time mortality detection from annotated image datasets
Imaging system + computer vision [40]	Fish health monitoring	Automated recognition of diseased fish from captured images
Knowledge distillation + GhostNet + ResNeXt101 [41]	Stress-state recognition	Lightweight model for fish stress detection via interclass information transfer
GMMs + KNN regression [42]	Fish weight estimation	Estimated fish weight from standard length features

classification models and enhancing the ResNet34 architecture for improved precision. To reduce extended training durations, the study employed transfer learning techniques. The optimized model achieved 99.72% accuracy, with performance assessed via image-based validation and retraining as needed.

Similarly, [46] utilized the YOLOv4-Tiny-ECA deep learning model to analyze underwater images of feeding activity. Their system captured both fish behavior and floating uneaten pellets, processed the images to reduce noise, and extracted key features that effectively reflected feeding patterns. This combination of computer vision with robust deep learning models highlights the growing efficiency of automated feeding management in aquaculture.

The Critical Role of AI in Ensuring Optimal Water Quality for Aquaculture

Water quality is a key determinant of fish health and growth, directly influencing their physiological well-being and overall development. Thus, adequate water quality monitoring is crucial for the success and sustainability of aquaculture operations [47]. AI/ML-based systems, that analyze sensor data can monitor pH, temperature, and ammonia levels in real time, enabling early detection of abnormalities that can be detrimental to fish health [48]. Among the monitored parameters, dissolved oxygen (DO) is critical, and its predictive capabilities support informed decision-making in aquaculture, helping to mitigate associated risks [49]. To enhance aquaculture management and enable precise, convenient pond monitoring, a water-quality monitoring system using narrowband Internet of

Things (NB-IoT) technology has been developed [50].

Scientists developed “SHOAL,” a robotic fish, part of the EU’s Seventh Framework Programme (FP7), designed to detect pollution around farm sites (Fig. 2) [25]. The SHOAL project represents a breakthrough in biomimetic robotics, where a swarm of robotic fish was engineered to monitor and detect pollutants in marine environments. These robots are designed to mimic the swimming patterns of real fish, using a flexible tail-fin propulsion system that ensures smooth manoeuvrability while minimizing disturbance to surrounding marine life. At the core of SHOAL’s functionality is a suite of advanced chemical sensors embedded in each robotic fish. These sensors can measure pollutants such as nitrates and heavy metals, as well as general water-quality indicators such as salinity and dissolved oxygen concentration. Instead of relying on labour-intensive sample collection by divers, the robots continuously collect and analyze data in situ, allowing for real-time monitoring. Artificial intelligence drives the navigation and decision-making processes of these robotic fish. Equipped with sonar, they detect obstacles, map their surroundings, and autonomously adjust their swimming paths to ensure safe operation in confined, dynamic port environments. One of SHOAL’s defining features is swarm communication. Using underwater acoustic signals, the robotic fish communicate with one another to coordinate movements and share collected data. This creates a cooperative “shoal,” much like a school of real fish, where information is transmitted within the group and relayed wirelessly to shore-based stations for immediate analysis by authorities. This real-time, coordinated monitoring system enables rapid detection and response to pollution events, providing comprehensive coverage of large, complex aquatic areas. The modular design further enhances its adaptability: sensors can be swapped to meet specific

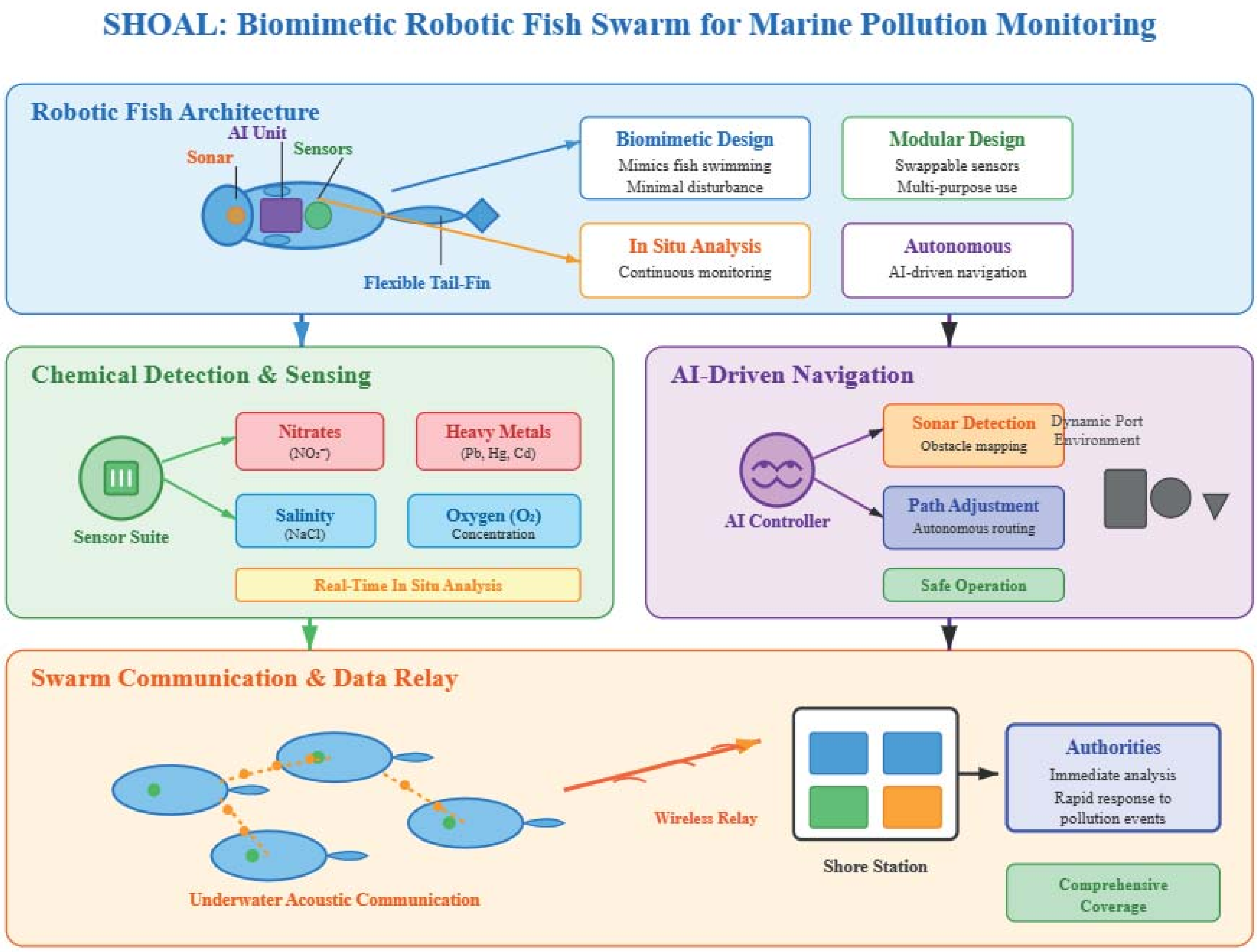

Fig. 2. **Overview of the SHOAL biomimetic robotic fish swarm for marine pollution monitoring**

monitoring needs, whether for pollution detection, search-and-rescue operations, or port security. SHOAL demonstrated the potential of robotic swarms to replace slower, costlier, and less effective traditional monitoring methods. Its success underscores how bio-inspired robotics, powered by AI and communication technologies, can transform marine environmental management and future aquaculture monitoring.

Moreover, AI algorithms can assist farmers in optimizing water quality parameters according to the specific requirements of the farmed fish species [51, 52] developed advanced AI algorithms for predicting the Water Quality Index (WQI) and classifying water quality levels. Their models, including nonlinear autoregressive neural networks (NARNET) and long short-term memory (LSTM) algorithms, along with support vector machine (SVM), K-nearest neighbor (K-NN), and Naive Bayes, accurately predicted WQI and classified water quality with superior robustness.

A study by Chen, Xu, and Deng (2022) introduced a computer vision-based system designed to monitor aquaculture ponds by analyzing water color and detecting phytoplankton [53]. This Water Colour Identification System was developed to help maintain optimal aquatic conditions for aquaculture. The algorithm implemented in the system was capable of recognizing 19 distinct water colour types that are significant for aquaculture management.

Uncrewed aerial vehicles (UAVs) are among the most widely adopted AI-driven tools in aquaculture, particularly for assessing water quality in fish farms. [54] designed a UAV-based system integrated with satellite remote sensing that can collect georeferenced data such as electrical conductivity, turbidity, water depth, pH, sensor depth, temperature, nitrate concentration, chlorophyll-a levels, and dissolved oxygen from a 1.1-hectare agricultural pond. A key drawback of this approach is its limited flight duration, though advancements in battery technology are expected to overcome this constraint.

AI is instrumental in creating predictive models that forecast changes in water quality. A study by [55] analyzes historical water quality data, along with factors such as weather patterns and feeding schedules, to predict potential changes and provide early warnings to farmers.

Temperature is a vital factor in aquaculture, directly influencing the health, metabolism, and growth of aquatic organisms [56]. AI algorithms can continuously analyze data from temperature sensors to monitor water temperature in real time, identifying patterns and anomalies and providing real-time alerts if temperatures deviate from optimal ranges [57]. This enables farmers to maintain optimal environmental conditions, promoting fish health and growth [51, 58]. Continuous temperature monitoring by AI also provides insights into how environmental fluctuations affect fish, helping to avert potential issues [59].

Intelligent monitoring and harvesting in Aquaculture

The final component of aquaculture is the intelligent harvesting mechanism. Before that, however, to evaluate the condition and well-being of fish assemblages, information on species composition, health status, abundance, and distribution remains essential. One significant concern highlighted in the literature is the unsustainable availability of fish [31]. To address this, automation in smart fisheries must be employed, particularly for classifying, identifying, and detecting aquatic resources to estimate stock quantity reliably.

Several studies have proposed advanced monitoring systems to support innovative aquaculture. [60] introduced a cost-effective, cloud-integrated autonomous drone system integrated with advanced computer vision, combined with deep learning models, providing scalability for diverse aquaculture operations. Their framework not only monitored aquaculture sites but also identified potential threats such as ships and human intrusions using RGB imagery. Planned extensions of this system include simultaneous multi-surveillance, fish behavioral tracking, ship plate-number recognition systems, and big data analytics for efficient data processing and management.

Satellite-based monitoring has also been explored to assess aquaculture activities. [61] applied a combination of machine learning approaches—including Random Forest (RF) and Support Vector Machine (SVM)—along with GIS tools to extract geospatial information about aquaculture site distribution and extent. These methods enhance visualization and enable precise site-level analysis. [62] further extended remote-sensing applications by developing a multi-input/single-output convolutional neural network (ConvNet) that integrates multi-band imagery to monitor vessel activity and offshore energy infrastructure, demonstrating applicability beyond traditional aquaculture.

Table 3. **Applications of computer vision and deep learning in aquaculture monitoring**

Application Area	Approach/Technique	Key Methods/Models Used
Wild fish monitoring at aquaculture sites[63]	Underwater video monitoring combined with automatic fish detection techniques.	Deep learning approach using **yolov4** to detect fish as a single class, without specifying species.
Underwater fish detection[64]	Wireless sensor network integrated with image analysis for fish monitoring.	Mask R-CNN for fish detection; Gaussian Mixture Model (GMM) for background subtraction.
Counting crustacean larvae[65]	Computer vision algorithms and image processing for larval detection and quantification.	Two computer vision systems were developed using the YOLOv5s algorithm for accurate detection and counting of larvae.
Counting fish [66]	Enhanced computer vision pipeline for identifying individual fish.	Improved YOLOv5 integrated with a Transformer module (TRH-YOLOv5) to detect lateral line scales for fish counting.
Fish biomass estimation[67]	Integration of deep learning techniques with stereo vision technology enables real-time monitoring of fish behavior and population dynamicы.	Target detection algorithm (DL-YOLO) based on YOLOv5n, applied to detect and extract high-quality moving fish images.
Fish weight estimation[67]	Computer vision and deep learning combined with regression models for weight prediction.	Mask Recurrent-CNN trained for detection and dimension extraction; regression learning applied to estimate fish weight.

Beyond these approaches, several deep learning and computer vision-based models have been used for detection, counting, and biomass estimation in aquaculture. A summary of recent applications is provided in Table 3, highlighting how these methods are tailored to specific monitoring needs, ranging from wild fish detection to larval counting and weight estimation.

Conclusions

The implementation of AI and ML in aquaculture has the potentiality to revolutionize the industry. These innovative technologies provide solutions to enhance various aspects of aquaculture, including growth prediction, disease detection, feeding strategies, water quality management, and efficient harvesting. From AI mechanisms that monitor the welfare of cultivable species to computer vision systems for disease detection, these technologies are proving their worth in practical applications. By employing automated feeding mechanisms and smart water-quality monitoring, farmers can sustain ideal conditions for fish growth, thereby reducing costs and lessening their ecological footprint. The insights driven by AI empower farmers to execute informed decisions based on data, thereby amplifying productivity and sustainability.

Nevertheless, despite its benefits, analysis of current review work reveals several key trends and gaps in the application of AI in aquaculture. Machine learning approaches have been effectively applied to several tasks, yielding notable gains in efficiency and productivity across aquaculture systems. However, there remains a need to improve model accuracy and robustness by using more diverse datasets, particularly those that represent various geographical regions. Another major limitation is the limitations in standardized data collection protocols, which hamper cross-study comparisons and knowledge exchange. Moreover, most existing studies focus on isolated applications of AI, such as either disease management or feeding optimization, rather than an integrated approach. There is a noticeable gap in research on the holistic integration of multiple AI techniques to manage the interrelated components of aquaculture systems, as integrating AI into aquaculture systems faces challenges such as high upfront investment requirements and ongoing maintenance costs.

In conclusion, AI is indispensable for the future growth and sustainability of the aquaculture industry. By enhancing resource efficiency, reducing environmental impact, and improving operational accuracy, AI can significantly help meet global demand for fish while promoting environmental stewardship. However, it is crucial to balance technological advancements with considerations for economic and social impacts, ensuring that the benefits of AI are accessible and equitable. Because the potential of AI to diminish the need for manual labour may raise socio-economic conflicts, particularly for societies that depend on fisheries-related jobs.

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Authors' Contribution

Arnab Chatterjee: Conceptualization, writing-original draft, review, and editing.

Dr. Sutapa Sanyal: Supervision, guidance, and critical review of the manuscript.

Declarations

Ethical Approval: Not applicable.

Competing Interests

The authors declare no competing interests.

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Ethics and Consent to Participate declarations

Not applicable

Consent for Publication

Not applicable. This article does not contain any individual person's data in any form.

Data availability

Not applicable. No new data were generated or analyzed in this study, as it is a review of existing literature. All referenced data are available in the cited publications.

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МАЙБУТНЄ АКВАКУЛЬТУРИ: ІНТЕГРАЦІЯ ШТУЧНОГО ІНТЕЛЕКТУ ТА МАШИННОГО НАВЧАННЯ ДЛЯ СТАЛОГО ВИРОБНИЦТВА

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Мета. Дослідження спрямовано на оцінку потенціалу штучного інтелекту (ШІ) та машинного навчання (МН) у вдосконаленні систем аквакультури шляхом покращеного моніторингу, автоматизації та прийняття рішень на основі даних.

Методи. Дослідження проведено на основі всебічного аналізу сучасних експериментальних і польових звітів, що описують інтеграцію технологій, керованих ШІ, у сфері аквакультури. Було розглянуто моделі, такі як згорткові нейронні мережі, рекурентні нейронні мережі та цифрові двійники на основі AIoT, для їх застосування у моніторингу росту риби, виявленні захворювань і контролі якості води. У дослідженнях розглядалися різні водні види, включаючи тилапію, лосося та коропа, як модельні організми для оцінювання точності та ефективності роботи систем.

Результати. Результати показали, що моделі розпізнавання зображень, керовані ШІ, успішно виявляють аномалії у здоров'ї риб та їхній поведінці з високою точністю. Системи контролю якості води на основі сенсорів, пов'язані з алгоритмами ШІ, підвищували стабільність середовища та зменшували смертність. Автоматизоване годування та системи підтримки прийняття рішень у режимі реального часу зменшували втрати ресурсів, тоді як прогнозні моделі оптимізували темпи росту та графіки збору врожаю. Сукупно ці досягнення підвищили продуктивність і зменшили операційні витрати, водночас підтримуючи екологічну рівновагу.

Висновок. Штучний інтелект і машинне навчання демонструють трансформаційний потенціал у просуванні аквакультури до більшої сталості, прибутковості та екологічної відповідальності. Їх інтеграція підтримує інтелектуальне управління господарствами та підвищує стійкість до кліматичних і ресурсних викликів.

Ключові слова: аквакультура, штучний інтелект, машинне навчання, розумне рибне господарство, сталість.

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