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Exploring opportunities of Artificial Intelligence in aquaculture to meet increasing food demand

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ABSTRACT

The increasing global population drives a rising demand for food, particularly fish as a preferred protein source, straining capture fisheries. Overfishing has depleted wild stocks, emphasizing the need for advanced aquaculture technologies. Unlike agriculture, aquaculture has not seen substantial technological advancements. Artificial Intelligence (AI) tools like Internet of Things (IoT), machine learning, cameras, and algorithms offer solutions to reduce human intervention, enhance productivity, and monitor fish health, feed optimization, and water resource management. However, challenges such as data collection, standardization, model accuracy, interpretability, and integration with existing aquaculture systems persist. This review explores the adoption of AI techniques and tools to advance the aquaculture industry and bridge the gap between food supply and demand.

Introduction

Since the 21th century, the global population has experienced rapid growth. Despite efforts in the agriculture sector to keep up with the demand of food, the pace of population growth has outstripped agricultural production (Ahmed et al., 2024). Consequently, this imbalance has resulted in an uneven distribution of essential nutrients such as protein, fat and calories in the diet consumed by the people (Pradhan et al., 2019). According to United Nation's estimates, there are over 900 million malnourished people worldwide with one fourth of them being children under the age group of four or five. These young children are particularly vulnerable to the adverse effects of severe protein and energy malnutrition (PEM). The primary cause of inadequate access to nutritious remains a significant factor contributing to under-nutrition, especially among children in many developing countries (UN, 2010).

Over the past few decades, fish has emerged as a significant protein source in many developing countries (Ahmed and Ahmad, 2020; FAO, 2020; Ahmad et al., 2021. Ahmad et al., 2021a, b; Ahmad et al., 2022). The nutritional value of fish is unquestionable as it is rich in high-quality protein, essential micronutrients and omega-3 unsaturated fatty acids. Notably, fish exhibits more pronounced satiating effects compared to terrestrial animal proteins like beef and chicken meat (Uhe et al., 1992). Around 60 % of people in developing countries heavily depend on fish for at least 30 % of their animal protein intake, while nearly 80 % of the population in most developed countries obtain less than 20 % of the animal protein from fish (FAO, 2022). However, some Asian countries show a relatively higher reliance on fish (Delgado, 2003). Despite fish plays a crucial role in sustaining a significant segment of the global population, with a major portion of the diet consisting of fish and fishery related products (Minar et al., 2012; Chakraborty et al., 2015; Gandotra et al., 2017). It's availability is being compromised by unsustainable fishing practices in natural water bodies. This management is contributing to a deficiency in providing nutritionally adequate food for the populations of developing countries.

Worldwide total catch of fisheries production in 2016 was around 91 million tons, involving about 79 million tons from marine waters and only 12 million tons from inland waters (FAO, 2018). By 2030, an extra quantity or quantum of 37 million tons of fish for each year will be needed to meet the demand of current degrees of fish utilization for an extended world population. As capture fisheries is showing the

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indications of nearly stagnation for last one decade, there is a dire need to tap extra sources of resources that can be achieved through the mobilization of water bodies. Aquaculture emerges as a viable solution to this challenge, offering the potential to significantly augment overall fish production (Allan, 2004; Khursheed et al., 2023). To address the growing disparity between demand and supply on a global scale, advanced aquaculture technologies represent the sole viable recourse.

Although different traditional techniques have already been employed in aquaculture, but recent technological advancements promise to reduce human intervention and enhance aquaculture productivity. Notably, AI stands out as a transformative force in the aquaculture industry (Mustapha et al., 2021). AI technologies are actively employed in monitoring and managing fish health and growth, leading to improved feed, diminished risk of disease outbreaks, and enhanced overall farm productivity. Geetha and Bhanu (2018) reported that the involvement of developmental algorithms and models in AI, enabling that conventially necessitate human intelligence, such as learning, reasoning and problem-solving. In the realm of aquaculture, AI facilitates the analysis of data derived from sensors and cameras to monitor fish behaviour, detect signs of disease or stress, employ automatic sensors for measuring fish length and weight, and optimize feeding regimes (Barreto et al., 2022; Føre et al., 2018; Tonachella et al., 2022). By analyzing this data using AI algorithms, researchers can develop predictive models that can identify the early signs of disease or stress in fish (Gladju et al., 2022). Sharma and Kumar (2021) emphasize the role of integrated sensors, biosensors, and AI in minimizing the reliance on antibiotics and other medications. Furthermore, AI contributes to the formulation of personalized feeding programs tailored to meet the nutritional requirements of individual fish, optimizing growth rates and fostering improved overall health and well-being (Kaur et al., 2021). It can also help to improve the management of fish reproduction, by developing predictive models that can identify the optimal conditions for spawning and egg production (Chapman et al., 2014; Migaud et al., 2013). This review comprehensively synthesis the application of AI to enhance the efficiency and sustainability of the aquaculture industry, particularly in the domains of fish reproduction, feeding, and growth. A compilation of prior studies on AI applications is presented in Tables 1 and 2. Moreover, this paper aims to delve into the myriad applications of AI in aquaculture elucidating potential benefits and addressing the challenges and limitations that must be surmounted to fully exploit its potential.

Table 1
An overview of some studies related to Artificial Intelligence (AI) in aquaculture.

S. No.	Area of Research	Outcome	Reference
1.	AI in aquaculture	Effectiveness in traceability, feeding, disease detection, growth prediction, environmental monitoring, market information, and others is key to increasing aquaculture productivity and sustainability.	Mustapha et al., 2021
2.	Deep learning techniques	InceptionV3 pre-trained model for classifying three different types of abnormal appearance of grouper can reach average 98.94 % accuracy in phase II task.	Chen et al., 2022
3.	AI based disease detection	Covers periodical optical monitoring of the fishes in the farm, detecting the onset of any disease, with a minimum time lag.	Darapaneni et al., 2022
4.	Intelligent feeding technique	To calculate the shrimp biomass and determine the appropriate feeding amount by reading the sensors in real time.	Chen et al., 2022
5.	Intelligent feeding	Intelligent equipment can replace people, reduce labor intensity, reduce risk, and improve work efficiency.	Wu et al., 2022
6.	Internet of Things (IoT) systems in aquaculture	Maintaining water quality and other parameters within the acceptable ranges.	Rastergari et al., 2023

Overview of Artificial intelligence (AI)

AI refers to the simulation or approximation of human intelligence in machines. The aim of AI includes computer-enhanced learning, reasoning and perception (Xu et al., 2021). In recent years, AI has grown an importance in aquaculture research and production, with both start-ups and established corporations developing new AI-based applications for the industry (The Lutz Report, 2023). Data mining and machine learning are two closely related techniques that are commonly used in the field of AI to analyze large amounts of data and extract useful insights and knowledge. While they share some similarities, there are also few differences between the two techniques (Sarker, 2022). Data mining refers to the process of extracting patterns and relationships from large datasets. It involves using a variety of statistical and computational techniques to identify trends, associations, and anomalies in the data. Data mining techniques can be used to explore the data, identify patterns and relationships, and develop predictive models that can be used to make

Table 2
Use of Artificial Intelligence (AI) in aquaculture.

Area of application	Examples of AI techniques	Benefits
Breeding	Machine learning algorithms, genetic algorithms, neural networks	Improved accuracy in selecting breeding pairs, faster genetic improvement, reduced cost and time of breeding programs, increased disease resistance
Feeding optimization	Neural networks, fuzzy logic, decision trees, genetic algorithms	Reduced feed wastage, improved growth rates, lower costs, improved sustainability, identification of optimal feeding regimes for different fish species
Disease detection and management	Machine learning algorithms, image recognition, natural language processing	Early detection and diagnosis of diseases, improved accuracy in diagnosis, reduced treatment costs, improved disease management
Water quality management	Expert systems, fuzzy logic, neural networks	Improved water quality management, reduced use of chemicals and antibiotics, improved disease prevention and control, reduced mortality rates
Environmental monitoring	Artificial neural networks, machine learning algorithms, acoustic sensors	Improved understanding of the impact of environmental factors on fish behavior and growth, improved sustainability
Harvesting and processing	Robotics, computer vision, machine learning algorithms	Improved efficiency, reduced labor costs, improved accuracy in grading and sorting fish, reduced waste
Supply chain management	Blockchain, artificial intelligence algorithms	Improved traceability, reduced fraud, increased transparency, improved efficiency
Energy optimization	Artificial neural networks, fuzzy logic, genetic algorithms	Reduced energy consumption, improved sustainability, reduced costs
Aquatic vegetation management	Machine learning algorithms, artificial neural networks	Improved understanding of the impact of aquatic vegetation on fish growth, identification of optimal vegetation management strategies
Aquaponics	Machine learning algorithms, expert systems, genetic algorithms	Improved efficiency, reduced labor costs, improved sustainability, increased crop yields

decisions based on the data (Wu et al., 2021).

Machine learning, on the other hand is a subfield of AI that involves the development of algorithms and models that can learn from data and make predictions or decisions based on that learning (Sarker, 2021). Machine learning algorithms are designed to identify patterns and relationships in data, and then use those patterns to make predictions or decisions about new data (Choudhury et al., 2021). There are several different types of machine learning algorithms, including supervised learning, unsupervised learning, and reinforcement learning (Mahesh, 2020). Supervised learning algorithms are trained on labelled data, where the correct answers are known, and are used to make predictions or decisions about new data learning (Mahesh, 2020). Unsupervised learning algorithms, on the other hand, are trained on unlabelled data, where the correct answers are not known, and are used to identify patterns and relationships in the data (Patel, 2019). Reinforcement learning algorithms are used to train agents to take actions in an environment in order to maximize a reward. Both data mining and machine learning techniques are widely used in a variety of industries and applications, including finance, healthcare, marketing, and more (Sarker, 2021). They are particularly useful in fields where large amounts of data are available, and where there is a need to extract insights and knowledge from that data in order to make informed decisions. An overview of some studies related to AI in aquaculture is presented in Table 1. Considering the revolutionary of AI and machine learning, present review has been designed to summarize the role, importance and future perspectives of AI in aquaculture.

Types of AI

AI refers to the simulation of human intelligence in machines that are programmed to perform tasks that would typically require human intelligence, such as perception, reasoning, learning, and decision-making (Xu et al., 2021). AI is a broad field that encompasses various subfields and applications, and there are several types of AI (Fig. 1).

Based on functionalities, types of AI are as below;

Reactive AI: This type of AI is programmed to react to specific situations or inputs but cannot learn from past experiences or make predictions about the future (Sarker., 2022).

Limited Memory AI: This type of AI can learn from past experiences and make decisions based on that knowledge, but it has limited memory and cannot consider a large amount of data (Xu et al., 2021).

Theory of Mind AI: This type of AI can understand the beliefs, emotions, and intentions of other agents, making it useful for applications such as social robotics.

Self-Aware AI: This type of AI has a sense of self and can understand its own capabilities and limitations.

Based on Capabilities following are types of AI;

Narrow AI: Weak AI, commonly referred to as narrow AI, is limited to performing a single narrow task. It advances along the spectrum of a single subset of cognitive talents. As machine learning and deep learning techniques advance, specialised AI applications are appearing more frequently in our daily lives (Sarker., 2022).

General AI: General AI, also known as strong AI, is capable of understanding and learning any intellectual task that a human being is capable of. It enables a machine to apply knowledge and skills in a variety of contexts. So far, AI researchers have not been able to achieve strong AI. They have to figure out how to make machines conscious, programming a full set of cognitive abilities.

Super AI: Outperforms human intelligence and is capable of performing any task better than a human. Artificial super intelligence envisions AI evolving to be so similar to human sentiments and experiences that it not only understands them, but also elicits emotions, needs, beliefs, and desires of its own. Its existence is still speculative. Thinking, solving puzzles, making judgements, and making decisions on its own are some of the critical characteristics of super AI (Xu et al., 2021; Sarker, 2022).

Potential applications of artificial intelligence in aquaculture

Aquaculture stands as a rapidly expanding industry that demands significant technological advancements to improve farming practises. To enhance productivity, the development of novel farming methods is imperative and AI emerges as a key in many ways. Nowadays, AI gadgets are accessible to provide a more stable environment for the stock. Although there are several applications of AI in aquaculture, but here we discuss few of them in detail as below:

1. Use of AI in monitoring water quality.

Effective water quality monitoring is paramount for the success of

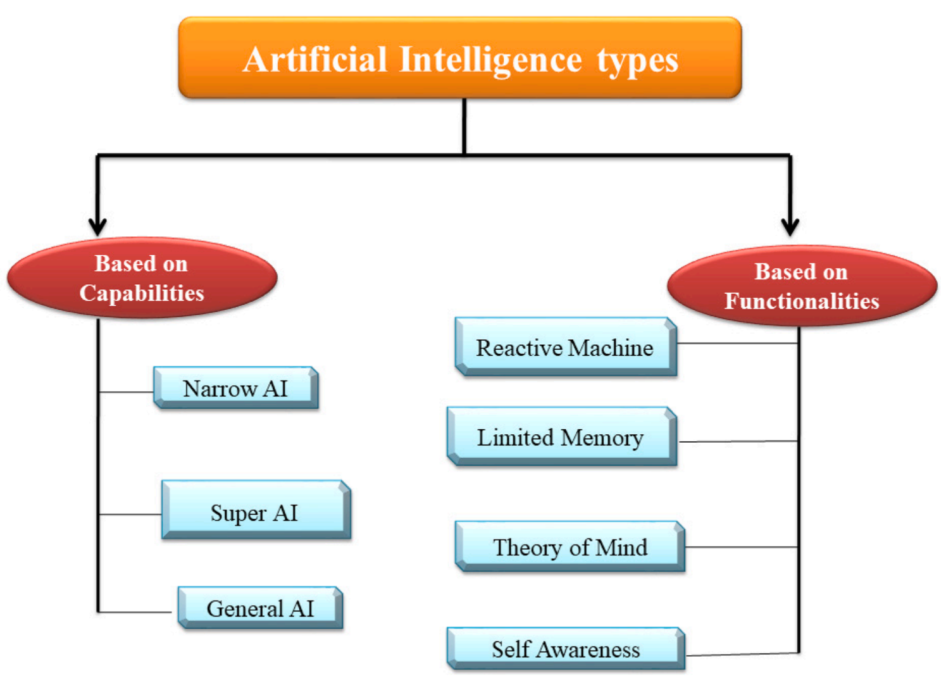

Fig. 1. Artificial Intelligence (AI) and its types.

aquaculture operations (Lindholm-Lehto, 2023), given the multifaceted factors influencing it. Some of them are necessary to keep water at least as sustainable as possible. Fish activity can be directly impacted by the water quality due to the fish's high reliance on the aquatic environment. Monitoring water quality is therefore a crucial problem to take into account, particularly in the fish farming industry (Arafat et al., 2020) and AI is increasingly being used to help in this area (Lu et al., 2022). This section aims to elucidate how AI can be effectively employed in monitoring water quality within aquaculture systems. By analyzing data from sensors that measure parameters such as temperature, dissolved oxygen, pH and ammonia levels (Dupont et al., 2018), AI algorithms can detect patterns and anomalies that may indicate problems with the water quality (Zhao et al., 2021; Khurshid et al., 2022). This can help farmers to take corrective actions before any harm is done to the fish. AI-powered water quality monitoring systems can continuously monitor multiple parameters in real-time, which can provide more accurate and timely information than manual monitoring methods (Javaid et al., 2022). This allows farmers to respond quickly to any changes in water quality, reducing the risk of fish mortality and other negative outcomes.

AI assumes a pivotal role in developing predictive models that anticipate changes in water quality before they occur. It can be helpful in analyzing the historical data on water quality and other factors such as weather patterns and feeding schedules (Saeed et al., 2022). Besides, AI algorithms can predict the likelihood of changes in water quality and provide early warnings to farmers. Gunda et al. (2018) have developed an AI-based mobile application platform for water quality monitoring for bacterial contamination, where they have used a low-cost rapid test kit i.e., Mobile water kit for detecting the water quality for bacterial contamination. Moreover, AI algorithms can help farmers to optimize water quality parameters based on the specific needs of the fish species being farmed (Chiu et al., 2022). Aldhyani et al. (2020) developed advanced AI algorithms to predict water quality index (WQI) and water quality classification (WQC). For the WQI prediction, artificial neural network models, namely nonlinear autoregressive neural network (NARNET) and long short-term memory (LSTM) deep learning algorithm have been developed. In addition to this, three machine learning algorithms, namely, support vector machine (SVM), K-nearest neighbour (K-NN) and Naive Bayes have been used for the WQC forecasting. Their results revealed that the proposed models can accurately predict WQI and classify the water quality according to superior robustness.

Moreover, temperature is a critical factor in aquaculture, as it directly affects the health and growth of aquatic organisms (Mugwanya et al., 2022). AI algorithms can analyze data from temperature sensors in fish farms to monitor water temperature continuously. By this technique, the system can identify patterns and anomalies in the temperature data and provide real-time alerts to farmers if the temperature deviates from the optimal range for the specific fish species being farmed (Yang et al., 2021). This will allow farmers to detect changes in temperature quickly and take appropriate actions to maintain optimal conditions for the health and growth of the fish (Mustafa et al., 2016; Joseph et al., 2019; Chiu et al., 2022). By continuously monitoring the temperature, AI algorithms can also provide valuable insights to farmers on the impact of environmental changes on the fish and help to prevent potential problems that may arise due to changes in temperature (Føre et al., 2018). Besides this, AI algorithms can identify trends and patterns in the data, which can indicate potential risks to the health and growth of the fish (Manoj et al., 2022). This might be explained that when temperature increases rapidly, it may indicate a problem with the cooling system, which could lead to higher mortality rates for the fish (FAO, 2018).

AI algorithms can also analyze data from other environmental factors such as water quality, feed management and weather patterns to provide a holistic view of the fish farm's conditions (Lafont et al., 2019). By integrating this data, AI algorithms can provide more accurate and comprehensive insights to farmers on how different environmental factors can impact the health and growth of the fish (Niloofar et al., 2021). This can help farmers make more informed decisions on how to optimize their fish farm operations and prevent potential problems that may arise due to changes in temperature or other environmental factors (Gladju et al., 2022). Considering the findings of these studies, it can be inferred that AI algorithms can provide valuable insights to fish farmers.

2. Use of AI in disease detection and prevention

A pivotal application of AI in bolstering the health and well-being of fish within aquaculture system revolves around disease identification and control. Numerous studies have focused on the use of AI for disease detection and management, optimization of feeding regimes and management of fish reproduction (Fig. 2). In the realm of aquaculture operations, the increasing utilization of AI is notably evident in the identification and treatment of fish infections (Li et al., 2023). AI can be used in analyzing the data from sensors and cameras to find indicators of illness or stress in fish. Cameras, for instance, can be used to observe fish behaviour and spot alterations that can point to stress or disease, such decreased activity levels or unusual swimming behaviour. Chen et al. (2022) reported that advanced disease identification based on fish behaviour and external appearance has been identified as a promising field for AI use. In addition, this detection system is based on underwater cameras or sensors to capture images that are sent through the cloud to the processing unit and scoring system. This gives artisanal farmers considerably more time to seek for management solutions (Darapaneni et al., 2022).

Analyzing fish photos for disease indicators is another method of applying AI to the identification of disease in fish (Yang et al., 2021). It can detect disease symptoms like lesions, odd behaviour, or discolouration by examining fish photos captured by cameras in the fish farm (Nik Zad, 2013; Chan et al., 2022). This can help farmers in early disease detection and treatment, limiting the demand for antibiotics and the risk of outbreaks. This method can assist aquaculturists in identifying fish infections sooner, which can enhance treatment results and lessen the disease's ability to spread to other fish populations. Analyzing water quality data for disease indicators is another method of employing AI for fish disease identification (Setiyowati et al., 2022). Temperature, pH, and dissolved oxygen levels are a few examples of water quality variables that can have an impact on fish health and reveal the existence of specific diseases. AI programmes can be used to examine data on water quality and spot trends that can point out the presence of disease (Nayan et al., 2021). AI algorithms can, for instance, assess environmental information like temperature, precipitation, and nutrition levels to forecast when and where disease outbreaks are likely to occur (Elavarasan et al., 2018). This can assist aquaculturists in taking proactive steps to stop the spread of disease and lower the possibility of suffering financial losses (Rajitha et al., 2007). Besides, the use of antibiotics and other pharmaceuticals may be decreased by using AI tools and techniques to perform early interventions, such as modifying water quality indicators or delivering tailored therapies (Holmes et al., 2016).

Furthermore, several studies explored the use of AI to analyze the video data from salmon farms to detect changes in behaviour that may indicate stress or disease. The researchers used a deep learning algorithm to identify behavioural patterns in the fish, and were able to detect early signs of disease with a high degree of accuracy. Wu et al. (2022) studied four major aspects of deep-sea aquaculture including intelligent feeding, water quality detection, biomass estimation, and underwater inspection. This transitional development has changed the traditional manual way to mechanization, then to automation, hence named as unmanned intelligent equipment. Use of these intelligent equipment in various fields of aquaculture can reduce labour cost, reduce threats and can increase working potential. Lee et al. (2000) used fuzzy logic-based control system for denitrification in a closed recirculation system. They developed a computer-control denitrifying bioreactor for a system housing squid for biomedical research. This Fuzzy logic can be used to process real-time inputs from sensors used to measure dissolved oxygen, oxidation–reduction potential and pH and in turn controls the pumping rates and addition carbon feed to the bioreactor.

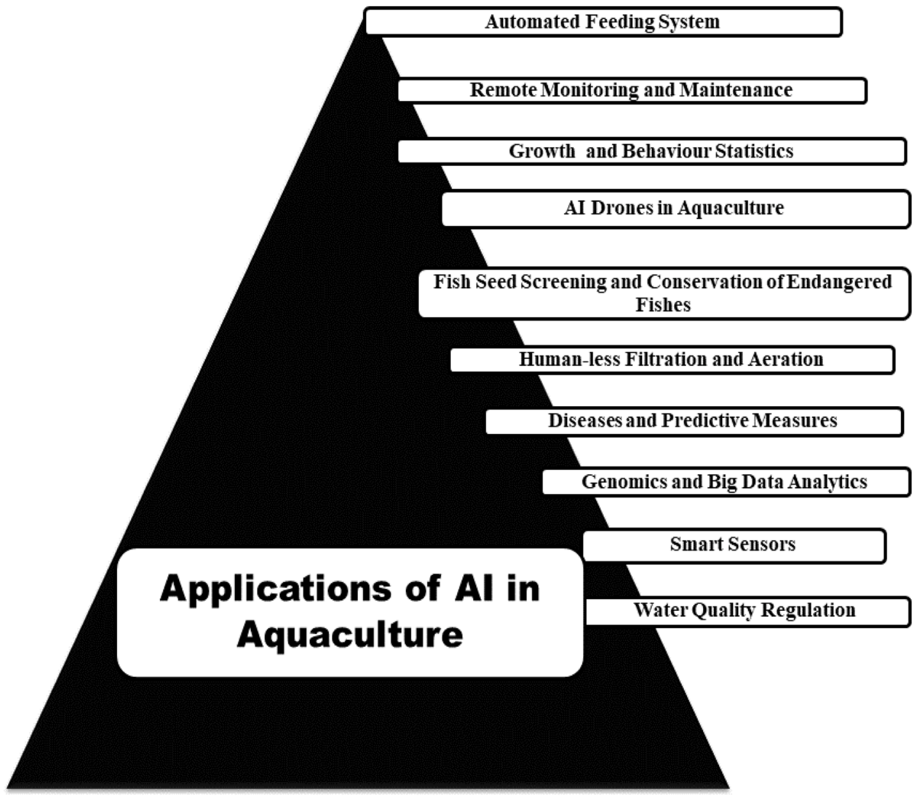

Fig. 2. Applications of Artificial Intelligence (AI) in aquaculture.

Overall, the use of AI to fish disease detection has the potential to dramatically enhance the health and wellbeing of fish populations raised in aquaculture. Table 3 shows some techniques which are being used in disease detection. However, further research is needed to explore the full range of applications of AI in aquaculture, and to develop more advanced and sophisticated AI algorithms and models.

3. Use of AI in biomass monitoring.

For determining fish health and growth rate during the growing stage, biomass is one of the most crucial factors (Li et al., 2020). The manual procedure for estimating biomass entails sampling using a fishing net or tray, catching each fish, weighing them individually, and then calculating the biomass (Martinez-de et al., 2003). It is a time-consuming and labor-intensive process, which makes it difficult to estimate a larger number of samples for precise biomass estimation (Cai et al., 2020). Additionally, it shows a higher level of measurement errors brought on by human error. This procedure stresses the fish, which may have negative consequences like growth retardation, nerve damage, and even death. Manually handling dead fish during post-processing for biomass estimation also compromises the texture and quality of the product (Zion, 2012). As a result, extensive research has been done to investigate alternative techniques for estimating biomass (Li et al., 2020). The use of AI offers new opportunities for modern aquaculture. Meanwhile, combining machine learning and vision can more precisely estimate fish's size, weight, number, and other biological data.

Machine learning and computer vision have emerged as powerful tools in various domains and their application in estimating the weight of fish showcases their potential in fisheries management and environmental monitoring (Monkman et al., 2019). Several studies and research projects have explored the use of machine learning algorithms to more accurately estimate the weight of fish. One notable approach involves utilizing computer vision techniques to analyze images of fish and extract relevant features for weight prediction. Bravata et al. (2020) highlights the implementation of convolutional neural networks (CNNs) to process images of fish and predict their weight with high accuracy. The study demonstrates the effectiveness of deep learning in capturing intricate patterns and characteristics that contribute to weight variations among different fish species. Another study by Lopez-Tejeida et al. (2020) improved a method to obtain fish weight using machine learning and NIR camera with Haar Cascade Classifier. They reported that by the implementation of hardware and software adds an infrared light and pass band filter for the camera successfully, the fish was detected automatically, and the fish weight and length were calculated moreover the future weight was estimated.

a. Size estimates: Body lengths of harvested fish are key indices for marine resource management. Some fisheries management organizations require fishing vessels to report the lengths of harvested fish (Tseng et al., 2020). Conventionally, body lengths of fish are measured manually using rulers or tape measures. Such methods are, however, time consuming, labour intensive, and subjective. Several researchers have used the ImageNet dataset and the Atlantic fish dataset to conduct algorithmic research on estimates of fish size. For estimating the length of European bass under various architectures, Monkman et al. (2019) suggested the R-CNN model. In addition, the author used OpenCV to calculate the image and increase accuracy in light of the image distortion. According to the findings, the typical deviation percentage was 2.2 %.

b. Age determination: One of the main methods of fish age discrimination used presently is the automatic interpretation and recognition of fish age using fish otolith images (Bermejo et al., 2007). Machine learning has been successfully used for tasks like object recognition and other types of image analysis, and it is essential for otolith image-based age estimation. In order to determine the age of fish, Moen et al. (2018) used deep learning to automatically interpret otolith images and converted ImageNet pre-trained parameters to the trained CNN model through transfer learning. The experimental outcomes showed that the model performed well and could be used to compare the accuracy of artificial experts. The model was unable to accurately predict the youngest fish age area, which resulted in low prediction

Table 3
Use of Artificial Intelligence (AI) in disease detection.

S. No	Disease diagnosis	Technique/tool	Detection Accuracy	Reference
	Fish parasites (Ichthyophthirius multifiliis, Gyrodactylus kobayashii, and Argulus japonicus)	Deep learning algorithm YOLOv4 through python	95.41 %	Li et al., 2023
	Difference between Infected fish and fresh fish	Support Vector Machine (SVM) algorithm	91.42 % without augmentation 94.12 % with augmentation	Ahmed et al., 2022
	WSSV (White Spot Syndrome Virus	Artificial Neural network, Fuzzy Algorithm	90 %	Fabregas et al., 2018
	EUS (Epizootic Ulcerative Syndrome)	Machine learning algorithims Principal Component Analysis (PCA) and Histogram of Oriented Gradients (HOG)	86 %	Malik et al., 2017
	EUS (Epizootic Ulcerative Syndrome)	Principal Component Analysis (PCA) and K-menas Algorithm	90 %	Chakravorty et al., 2015
	Red Spot and White spot	Convolutional Neural Network (CNN)	91.67 % for white spot 94.44 % for red spot	Hassan et al. 2022
	EUS, Red Spot, Argulus, Tail and Fin Rot, Broken antennae rostrum and Bacterial Gill rot.	C-means Fuzzy logic and K-means clustering	96.48 % for K-means clustering 97.90 % for C-means Fuzzy logic	Sikder et al., 2021

accuracy for specific ages.

c. Sex determination: For the identification of the sex of fish, biological methods were used in the past (Du et al., 2017; Yarmohammadi et al., 2017; Webb et al., 2019). These methods had high detection errors and caused fish trauma. The machine learning method for identifying fish sex does not rely on the quality or age of the fish, but rather on the relative morphological parameters of the fish. In parallel, machine vision technology can effectively obtain the morphological parameters of the fish. For these reasons, the method of combining machine vision and machine learning can obviously identify the sex of fish in an effective manner (Barulin, 2017). Barulin (2019) conducted a study on Sex identification of starlet sturgeon based on based on scute structure using Boruta algorithm/Random forest algorithm. The experimental results showed that this approach performs well, and they also offer a positive outlook for using AI to determine a species sex.

4. Use of AI in fish feeding.

The cost of feeding fish accounts for 40–50 % of the total operational cost of aquaculture (Ogunlela and Adebayo, 2016), while 60 % of the feed that is dispensed into the aquarium becomes particulates (Srivastava and Liu, 2015). These accumulated particles pollute the water, which uses oxygen to break them down and release ammonia, nitrogen, and other noxious substances that can stunt the growth of fish. While measuring the amount of fish feed intake remains a significant challenge, the amount of feed dispensed to match fish appetite levels plays a significant role in increasing fish productivity.

AI can also help to optimize feeding of fish and AI software can calculate the ideal feeding schedule and serving size. This could improve feed use, reduce waste, and foster fish growth and health. One important area where AI can have a significant impact on fish behaviour, appetite, and growth rates is aquaculture feeding optimization. By taking into account elements like water temperature, dissolved oxygen levels, and the nutritional content of feed, AI may be used to develop prediction models that determine the ideal feeding schedule and quantity for a certain fish population. Through waste and the chance of overfeeding, this can have a detrimental effect on the environment by resulting in contaminated water. By reading the sensors in real-time, an optimal model for artificial intelligence may be employed to determine the shrimp biomass and determine the proper amount (Chen et al., 2022).

AI can also be used to assess fish behaviour and hunger in real-time in addition to optimising feeding schedules. It has been reported that cameras and sensors can be used to keep an eye on activities like feeding, swimming, and other signs of stress or hunger (Barreto et al., 2022). Fish will then receive the ideal quantity of nutrition to support their growth and development by using this information to change feeding schedules and amounts in real-time (Lafont et al., 2022). Studies have reported that AI can also be used to develop individualised feeding plans for each fish, taking into account their genetic make-up, age, and body weight (Reyed, 2023). Precision aquaculture is a method for maximising growth rates and minimising the overall environmental effect of aquaculture operations (O'Donncha and Grant, 2019). Using AI for feeding optimization can significantly increase fish growth rates, appetite, and behaviour in aquaculture while lowering waste and having a minimally detrimental environmental impact (Føre et al., 2018).

5. Use of AI in promoting growth rates.

The optimal temperature for the growth of fish varies, depends on the species of fish reared. Maintenance of the optimal temperature, fish farmers can promote faster growth rates and larger fish (Uddin et al., 2022). However, if the temperature rises too high or too low, it can negatively impact growth rates (Sivri et al., 2007). There are several ways in which growth rates, aquaculture, and AI are interconnected. Foremost factor is to monitor growth rate. The growth rates of these organisms are critical to the success of the aquaculture industry. AI can be used to monitor and manage the growth rates of these organisms, ensuring optimal conditions for growth and maximizing production.

In the current era modern and innovative and technical instrumental devices are using stereoscopic observations to measure the size, observe the shape, position and behaviour of fish and shrimps. It has been reported that "Sonar cameras" converts sound echoes into video images to use them in dark or turbid environments (Li et al., 2020). Studies have reported that water quality can be monitored in three dimensional in cages and large tanks by using autonomous vehicles that lift and lowers the sensor to develop 3-D data profiles (Edan et al., 2009). Whereas indoor recirculatory aquaculture system and underwater net-pen production environment were found more stable (Using sonar to help farmers solve the biomass problem, 2022).

Moreover, AI can be used to develop predictive models that can forecast the growth rates of aquatic organisms (Hmoud Al-Adhaileh & Waselallah Alsaade, 2021). To effectively estimate growth rates, these models can take into account a variety of environmental variables, including water temperature, oxygen concentrations, and nutrition availability (Ansari et al., 2021). This can help farmers in reducing waste and streamlining their production processes. Based on a fish species' development rate, water temperature, and other environmental conditions, a prediction model can be used to establish the ideal feeding rate for that species (Ghandar et al., 2021). In order to help farmers organise their operations more efficiently, the model may also forecast the anticipated yield and the date of harvest. Predictive models can not only increase manufacturing efficiency but also help stop disease outbreaks. Predictive models can identify early indications of stress or disease in aquatic species through environmental monitoring, enabling farmers to take preventative action and lessen the effect on production (Bell et al., 2022). Predictive modelling is a useful tool for farmers who want to maximise output while minimising environmental effect since it can boost growth rates, efficiency, and sustainability in aquaculture (Das et al., 2022). Another study examined the use of AI to optimize feeding regimes for salmon. They use machine learning algorithms to develop personalized feeding programs based on individual fish characteristics, and were able to achieve significant improvements in growth rates and feed conversion ratios (Barreto et al., 2022). AI algorithms may create individualised feeding schedules that satisfy each fish's unique nutritional needs and maximise growth rates by accessing data on feeding behaviour and development rates (Metcalfe, 2019).

6. Use of AI in sustainability, efficiency and behaviour of fish.

Aquaculture has the potential to be a sustainable food supply, but it needs to be carefully managed to prevent harm to the environment. It has been reported that AI can be employed to keep an eye on environmental factors like water quality, fertiliser levels, waste reduction, and productivity (Krishnan et al., 2021). The use of AI in aquaculture has the potential to boost productivity, promote sustainability, reduce disease outbreaks, and improve growth rates, making aquaculture a more viable and long-term source of food (Mandal and Ghosh, 2023). Fish feeding habits, activity levels, and social relationships can all be affected by temperature conditions. Certain fish species have been found to grow more aggressive in warmer temperatures. Some fish species are known to become more aggressive in warmer temperatures. Well-known examples are tilapia, a common freshwater fish raised for food that has been demonstrated to become more aggressive in warmer temperatures. This is thought to be caused by changes in their metabolism, which can have an impact on how they behave. Popular sport fish, largemouth bass have been seen to become more hostile in warmer water temperatures. This is assumed to be caused by changes in their food habits and increased metabolic activity.

The behavior of various fish species in response to temperature changes is a fascinating area of study. Bluegills, a popular freshwater sunfish, exhibit increased aggression in warmer water likely due to heightened competition for resources such as food and habitat (Barber, 2007). Similarly, Atlantic salmon have been found to become more aggressive in warmer climates, which can lead to higher stress levels and increased succeptibility to diseases, potentially impacting their overall health and productivity (Portz et al., 2006; Svenning et al., 2022).). Coldwater fish called yellow perch have been seen to grow more aggressive in warmer weather (Stasko et al., 2012). Their feeding habits may vary as a result, and there may be more competition for few resources. Depending on the species and the particular environmental factors, the effect of rising temperatures on fish aggression may differ. Nonetheless, it is widely acknowledged that variations in water temperature can significantly affect fish behaviour as well as their general health and wellbeing.

Several fish species become less active as a result of their slowed metabolisms and the need to conserve energy to keep their bodies warm in colder climates (Reeve et al., 2022). Which include a few fish species that slowdown in cooler weather (Power et al., 1999). Coldwater fish like trout become less active when the temperature drops. In order to save energy, they are known to seek out warmer water, such as at the surface or close to a warm tributary's outflow (Heggenes et al., 2021). Another fish species that slows down in cooler weather is the catfish. As the water temperature is more consistent and they can preserve energy, they are known to go to deeper parts of a body of water. Freshwater fish with a wide tolerance for temperature variation include carp. However, they are known to become less active in colder temperatures and will often move to deeper areas of a body of water to conserve energy (Ficke et al., 2007). Pike are a type of predatory fishes that slowdown in cooler weather. They are known to travel to warmer water in deeper parts of a body of water where they can conserve energy. Besides, popular sport fish, walleye, become less active in cooler weather. In order to preserve energy, they are known to seek out warmer water, for example, close to a warm tributary's outflow.

This shows that depending on the species and the particular environmental conditions, the effects of cooler temperatures on fish activity might differ (Huntingford et al., 2006). Nonetheless, it is widely acknowledged that variations in water temperature can significantly affect fish behaviour as well as their general health and wellbeing. Consequently, fish producers can encourage healthy behaviours that produce fish with better health by maximising the temperature circumstances (Craig et al., 2017). The Tokyo-based Umitron Corporation created the Umitron's system, a system for tracking swimmer behaviour, using AI technology. This system makes decisions about when and how much feed should be supplied in each fish cage based on real-time observation of swimming behaviour. This approach significantly reduces trash production, transportation and logistical needs compared to daily feeding as well as feed transformation efficiency. The fish are sold under the name "AI Sumagastsuo" in Tokyo (Umitron launches feed optimisation and mortality estimation software, 2022).

7. Use of AI in reproduction

The study of reproductive mechanisms is crucial across various organisms, including, humans, animals, and plants, each with unique reproductive processes. Temperature plays a significant role in fish reproduction as certain species require specific temperature ranges for successful spawning. Fishermen can encourage effective reproduction and increase the number of fish in their farm by adjusting the temperature conditions. Freshwater or saltwater habitats can be used for aquaculture, which can use a variety of techniques include tank-based systems, net-pen systems, and integrated multi-trophic aquaculture. It has been studied that in aquaculture, AI can be used to enhance feeding and water quality, regulate fish populations, and prevent disease outbreaks (Prapti et al., 2022). Research on reproduction can be used in aquaculture to create fresh breeding plans that will boost the wellbeing and output of populations of farmed fish. In addition, there have been several studies exploring the use of AI for the management of fish reproduction. For example, one of the studies developed a predictive model to identify the optimal conditions for egg production in striped bass. Moreover, previous literature suggests that the use of AI in aquaculture has significant potential to improve the efficiency and sustainability of the industry. By enabling more effective management of fish reproduction, feeding, and growth (Mustapha et al., 2021), AI can lead to improved fish health and well-being, as well as increased productivity and profitability for fish farmers (Ubina and Cheng, 2022; Khan et al., 2018).

8. Use of AI in breeding programs.

Based on genomic data, AI can be used to create prediction models of fish performance, allowing for more effective and focused breeding programmes for qualities like disease resistance and growth rate. AI systems may find genetic differences associated with particular features by analysing vast amounts of genomic data, and they can then utilise this knowledge to create prediction models of fish performance (Dixit et al., 2023). The performance of various fish populations under various environmental situations may thus be predicted using these models, as well as the top candidates for breeding to achieve particular objectives like disease resistance or growth rate. AI enables breeding operations to be more targeted and effective, which saves time and money while achieving desired features. By increasing the productivity and sustainability of fish populations, this can have a large positive impact on aquaculture and fisheries management (Mandal and Ghosh, 2023). Therefore, the use of AI and breeding programmes together has great potential to advance the fields of aquaculture and fisheries management as well as genetic quality and performance of fish populations.

9. Use of AI in conservation genetics.

AI can be used to analyze genetic data from endangered or threatened fish species, enabling better understanding of their genetic diversity and potential for conservation. The conservation of these species is important for maintaining healthy aquatic ecosystems and preserving the biodiversity of our planet. Endangered or threatened fish species face many challenges, including overfishing, habitat loss, pollution, and climate change. In order to overcome these problems, conservation genetics can play a crucial role in understanding and addressing these challenges.

Analysis of genetic data using AI algorithms, researchers can identify distinct populations within a species, as well as the genetic diversity within and among these populations (Vilhekar and Rawekar, 2024).This information can be used to develop more effective conservation strategies, such as targeting conservation efforts to areas with high genetic diversity or prioritizing the protection of distinct populations that may be more vulnerable to extinction (Vilhekar and Rawekar, 2024). Researchers can use AI to track alterations in the genetic diversity of fish populations that are at danger of extinction. They can also evaluate the success of conservation methods and spot possible dangers to the long-term survival of a species by monitoring changes in genetic diversity. AI can also assist researchers in finding genetic markers linked to characteristics like disease resistance or successful reproduction that are crucial for the survival and procreation of fish species (Palaiokostas, 2021).. Using this knowledge, breeding strategies may be created that put an emphasis on maintaining certain qualities and support the species long-term survival. In general, the application of AI to conservation genetics can assist us in understanding and preserving fish species that are in danger of extinction and are crucial to the health of our aquatic ecosystems and the lives of those who depend on them.

Conservation genetics is an important field that aims to understand and preserve the genetic diversity of endangered or threatened species. AI can be a valuable tool in this field, as it can help researchers analyze large amounts of genetic data more efficiently and accurately than traditional methods (Xu et al., 2021). By analyzing genetic data using AI algorithms, researchers can identify patterns of genetic diversity within a species, such as the presence of unique or rare alleles. This information can then be used to develop effective conservation strategies, such as targeted breeding programs or the establishment of protected habitats. Additionally, AI can help researchers identify potential threats to the genetic diversity of endangered species, such as the introduction of invasive species or habitat destruction (Branco et al., 2023). By identifying these threats early on, conservationists can take action to mitigate their impact and preserve the genetic diversity of vulnerable species. Overall, the use of AI in conservation genetics has the potential to greatly enhance our understanding of endangered and threatened species and help ensure their long-term survival. Overall, AI holds the promise of revolutionising the research of fish genomes and opening up new possibilities for aquaculture, fishery management, and environmental conservation. The ethical ramifications of genetic tools based on AI, though, are also a source of worry, and it's important to make sure they're used sustainably and responsibly. As a result, it's critical to carefully weigh the possible advantages and disadvantages of AI in fish genome analysis and to make sure it's applied in a way that's advantageous to both people and the environment.

Hence, AI has the potential to change the aquaculture sector by enabling more profitable, efficient, and sustainable production techniques. Yet, there are also worries about the price and availability of AI technology, as well as potential moral dilemmas with the treatment of animals and the environment. To ensure that AI is utilised responsibly and sustainably, it is crucial to thoroughly weigh the potential advantages and hazards of its usage in aquaculture.

10. Use of AI in fish genome.

AI has the potential to revolutionise the study of fish genomes by enabling a speedier and more precise analysis of genetic data and accelerating the development of new genetic tools for use in aquaculture and fisheries management (Song et al., 2023). Fish genome research is one area where AI has showed considerable potential (Ditria et al., 2022). AI can assist researchers in swiftly and accurately analysing enormous amounts of genetic data due to the growing complexity of data analysis techniques and the availability of genomic data (De Alwis et al., 2022). In order to detect genetic variations and comprehend the activities of particular genes, it can be incredibly helpful for AI algorithms to learn from enormous amounts of data in order to recognise patterns and make predictions.

By detecting desirable genetic features and enabling the selection of the best candidates for breeding, AI can assist in aquaculture and fisheries management to improve the breeding of fish species. By examining genetic diversity and locating genetic markers that can be used to follow fish movements and population changes, it can also assist in the monitoring of fish populations. AI can also be utilised to create novel genetic tools that can be used to improve the health and production of fish, such as gene editing technology (Rasal and Sundaray, 2020). AI has the potential to significantly advance the study of fish genomes, leading to important breakthroughs in aquaculture and fisheries management. Some of the potential applications of AI in fish genome analysis include:

11. Use of AI in genome sequencing and editing.

Large volumes of genomic data may be analysed using AI, allowing for quicker and more precise genome sequencing and assembly. AI can speed up the process of genome sequencing, a critical tool for determining the genetic makeup of fish species (Ruppert et al., 2019). AI algorithms can assist researchers in finding the most pertinent and instructive regions of the genome and speed up the synthesis of high-quality genome sequences by processing enormous amounts of genomic data. This can be very advantageous for fish breeding and selection in aquaculture. For instance, researchers can find desired features like disease resistance, rapid growth, and environmental adaptation by sequencing the genomes of several fish populations and examining genetic variants. Researchers can choose the best candidates for breeding with the use of AI, which can make the process much quicker and more precise than conventional techniques (Xue et al., 2023). This will ultimately increase the productivity and sustainability of aquaculture operations. In order to advance the research of fish genomes and enhance aquaculture techniques, AI and genome sequencing hold immense potential.

In order to change fish genomes more effectively and precisely for purposes like increased growth and disease resistance, AI can be used to design and refine genome editing technologies like CRISPR-Cas9 (Ferdous et al., 2022). The science of genome editing, which makes use of instruments like CRISPR-Cas9, holds great promise for enhancing features in fish species including disease resistance and growth (Houston et al., 2020). Unfortunately, developing and refining genome editing technologies can take a lot of time and resources. By anticipating the most efficient target areas for genome editing and refining the CRISPR-Cas9 system's design for optimum effectiveness and precision, AI can speed up this process (Jones and Wilson, 2022). AI systems can discover potential off-target effects and reduce the danger of unintentional modifications to the genome by evaluating vast volumes of genetic data. Researchers can create more effective and precise genome editing tools for use in aquaculture and fisheries management with the aid of AI. For instance, CRISPR-Cas9 can be used to change existing features to better fit changing environmental conditions or to introduce desired genetic traits such as disease resistance or increased growth into fish populations (Roy et al., 2022). Overall, the development of new genetic tools and interventions that can improve the health and resilience of fish populations is made possible by the combination of AI and genome editing technologies, which has enormous potential for improving the productivity and sustainability of aquaculture and fisheries management.

Major challenges

One problem is the absence of clear data and data sharing guidelines. A large amount of high-quality data is required to develop effective AI models and algorithms. There is currently a lack of common data formats and protocols to facilitate data sharing across different aquaculture enterprises and research institutions. This limits the application of AI in aquaculture and creates difficulties in collecting and analysing large amounts of data.

Mustapha et al. (2021) reported that, there are various limitations and challenges that may hinder the extensive adoption of AI in aquaculture. One of them is security concerns associated with many levels of the interconnected systems and networks that will be required. It requires complex data acquisition to convert it into meaningfully capture the complexity and biological interactions found in many production systems. Deep learning AI requires large amounts of training data, which is typically difficult to come by. For some applications, this is further compounded by the turbidity and bio-fouling associated with many culture systems. Finally, cost-benefit considerations will largely determine the extent and pace of AI adoption. But the long term trends for adoption are increasingly apparent.

In order to develop effective AI algorithms and models, large amounts of high-quality data are required. However, there is currently a lack of standardized data formats and protocols for sharing data across different aquaculture operations and research institutions. This makes it difficult to collect and analyze large amounts of data, and limits the effectiveness of AI in aquaculture. Aquaculture operations involve a wide range of variables, such as water quality, temperature, and feed inputs, that can interact in complex ways to affect fish health and growth. Developing AI algorithms and models that can effectively capture and analyze these complex interactions is a major challenge that will require continued research and development. Developing and implementing AI systems in aquaculture can be expensive, particularly for smaller-scale operations. There may be a need for investment in infrastructure and technology to support the implementation of AI in aquaculture. As AI systems rely on large amounts of sensitive data, there is a need to ensure that data is securely stored and transmitted, and that data privacy is maintained.

Skill and knowledge gaps

Data analysis, software development, and aquaculture domain knowledge are just a few of the abilities needed to build and implement AI systems in aquaculture. Programs for education and training might be required to fill in skill and knowledge gaps. These challenges need to be addressed if aquaculture is to completely benefit from AI. By creating effective AI models and algorithms, addressing concerns with data sharing, complexity, cost, privacy, and data security, AI can help aquaculture operations become more sustainable and efficient while also providing a stable and secure supply of high-quality seafood for the growing global population. It can also help close skill and knowledge gaps. Another issue is the creation of sophisticated AI models and algorithms that can account for the intricate and dynamic structure of aquaculture systems. A few of the several variables that can interact intimately in aquaculture operations to affect fish health and growth are temperature, feed inputs, and water quality. It will take ongoing research and development to create AI models and algorithms that can successfully record and evaluate these intricate interactions.

Conclusion

Because AI makes it possible to regulate fish growth, feeding, and reproduction more effectively and over the long term, the aquaculture industry could undergo a total transformation. AI can improve decision-making speed and accuracy, decrease the need for antibiotics, and lower the negative environmental effects of aquaculture operations. However, there are a number of challenges that need to be solved before aquaculture can completely benefit from AI. Some of them include the lack of standardized data and data communication protocols, as well as the need for advanced AI models and algorithms that can account for the complex and dynamic nature of aquaculture systems. Notwithstanding these challenges, the future of aquaculture AI looks bright. The aquaculture industry will likely see an increase in the use of AI as technology grows. Thanks to AI, fish production can be managed more effectively and sustainably, providing a consistent and safe supply of premium seafood for the world’s growing population.

Future recommendations

Despite these difficulties, aquaculture AI has a promising future. The advancements in sensor technology and data collection techniques have made it easier to collect and share high-quality data. Additionally, the progress in machine learning and deep learning algorithms allows for more sophisticated analysis of large datasets. As these technologies continue to evolve in the aquaculture sector, AI is expected to play a more significant role in the effective and sustainable management of fish production, as well as in improving the overall health and well-being of farmed fish. The following suggestions for upcoming research and development will help aquaculture fully reap the potential advantages of AI:

Standardization of data and data sharing protocols

Standardized data formats and protocols must be established in order to facilitate data exchange among various aquaculture companies and research institutes. This will make it possible to gather and evaluate vast volumes of high-quality data and will speed up the creation of efficient AI models and algorithms. AI algorithms and models need to be developed that can effectively capture and analyze the complex interactions between variables in aquaculture operations, such as water quality, temperature, and feed inputs. AI systems need to be integrated with existing aquaculture technologies, such as sensors and cameras, to enable real-time monitoring and decision-making. There is a need to develop low-cost AI systems that are accessible to smaller-scale aquaculture operations, and that can help to improve the efficiency and sustainability of these operations. AI can be used to develop predictive models that can forecast fish growth, feed requirements, and disease outbreaks, enabling more effective and efficient management of aquaculture operations. Collaboration between the aquaculture industry and academia can help to bridge skill and knowledge gaps, and facilitate the development and implementation of AI systems in aquaculture.

By addressing these recommendations, AI can help to improve the efficiency and sustainability of aquaculture operations, and ensure a reliable and secure source of high-quality seafood for the growing global population.

CRediT authorship contribution statement

Mohd Ashraf Rather: Writing – review & editing, Visualization, Resources, Project administration, Conceptualization. **Ishtiyaq Ahmad:** Writing – review & editing, Writing – original draft, Validation, Resources, Methodology, Formal analysis, Data curation, Conceptualization. **Azra Shah:** Writing – review & editing, Visualization, Resources, Data curation. **Younis Ahmad Hajam:** Writing – original draft, Visualization, Resources, Formal analysis, Data curation. **Adnan Amin:** Writing – review & editing, Visualization, Resources, Formal analysis, Data curation. **Saba Khursheed:** Writing – review & editing, Visualization, Resources, Formal analysis, Data curation. **Irfan Ahmad:** Writing – review & editing, Validation, Supervision, Project administration. **Showkat Rasool:** Writing – review & editing, Visualization, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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No data was used for the research described in the article.

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