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Charting the aquaculture internet of things impact: Key applications, challenges, and future trend

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ABSTRACT

Aquaculture plays a pivotal role in global food production, grappling with distinct hurdles in water quality, feeding operation, and disease control. Efficient management of these core aquaculture operations has been acknowledged as a fundamental measure, yet remains unattainable through traditional methodologies. The advent of the Internet of Things (IoT) has opened up transformative avenues for real-time aquaculture operations. IoT solutions have emerged as a potent toolset, facilitating prompt monitoring, data collection, analysis, and control within aquatic environments. Notwithstanding its remarkable advantages, the technology is not devoid of limitations and areas requiring advancement. This paper examines the diverse applications of IoT in aquaculture, encompassing water quality monitoring, feeding strategies, and intelligent health inspection. Aquaculture challenges like sensor corrosion, data fusion limits, environmental impacts on transmission, and more have been thoroughly discussed. It also highlights IoT's potential in aquaculture, focusing on sensor advancements, artificial intelligent (AI) integration, and increased productivity. Presenting the IoT-aquaculture trajectory, this paper highlights IoT's potential in aquaculture while stressing the need to balance benefits with challenges.

1. Introduction

Aquaculture, the cultivation of aquatic organisms like fish and crustaceans, is vital for global food security and a key protein source (Boyd et al., 2022). As the global population grows, sustainable expansion in aquaculture is urgently needed. The FAO (2022) report analyzes global aquaculture trends, highlighting its dynamic growth (Fig. 1). Global aquaculture production rose from under 8 million tonnes in 1980 to over 105 million tonnes in 2018, led by seaweeds, carp, bivalves, tilapia, and catfish. Asia, especially China, dominates, contributing over 80 % of production volume and leading in species diversity. Since 1980, China has been the top aquaculture producer, significantly boosting global output. FAO projects the Americas will see a 29 % increase in aquaculture by 2020, with Africa's production expected to exceed 2.8 million tonnes by 2030, driven by Egypt.

Asian countries are expected to maintain their dominance in the aquaculture sector, comprising over 88 % of global production by 2030. Based on the recent trends in aquaculture, American and European advancements in modern aquaculture technology consolidate sustainability and operational efficiency (Boyd et al., 2022, 2020; Little et al., 2018; Kumar et al., 2018). This includes improvements in feed, genetics, and farming practices, as well as farming systems like Recirculating Aquaculture Systems (RAS) (Rastegari et al., 2023).

Implementing technological tools helps alleviate identified challenges and enhances the sustainability and competitiveness of aquaculture practices. Commonly employed technologies, as per FAO (2020), include high-resolution satellite images, automatic identification systems (AIS), in-situ cameras and sensors. Genetic and deoxyribonucleic

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acid (DNA) profiling, block-chain, Internet of Things (IoT), big data analytics, AI, and machine learning are also trending. IC technologies like IoT-AI are particularly utilized for monitoring, controlling, correcting, and predicting critical parameters throughout the fish production chain. IoT tools are also deployed for water and feed administration in aquaculture. The IoT technology allows adjusting dosages based on behavioural patterns, thereby minimizing costs and waste production. These tools also aid in identifying fish pathologies affecting phenotype. IoT enables tracking of every stage of aquaculture, monitoring water parameters or other variables. Sensors within the cage or RAS systems generate alerts if parameters deviate from desirable ranges.

This expansion in production are driven by the growing demand for seafood while adhering to the principles of resource conservation (Naylor et al., 2021; Freitas et al., 2020). IoT-based technology has emerged as a transformative force, poised to reshape numerous operations in aquaculture industries. IoT in aquaculture leverages intelligent sensors, sophisticated data analytics, automation, and robust connectivity solutions. By ingeniously incorporating IoT technology into aquaculture devices, real-time data collection and actuation become possible. Resulting in precise task execution with remarkable efficiency (Hang et al., 2020). This transition mitigates the labour-intensive and feed-waste nature of traditional aquaculture. It also prevents potential undesirable consequences, such as the introduction of pathogenic organisms like bacteria, viruses and pollution (Bentzon-Tilia et al., 2016; Sanches-Fernandes et al., 2022). Particularly, in more advanced places like America and Europe, the impact of IoT-AI-based technology has significantly transformed aquaculture practices (Wang et al., 2021a). This approach ensures the safety and robust growth of aquatic life. Researchers have used IoT for real-time monitoring of aquaculture water quality, optimizing feeding, and tracking fish health (Mahamuni and Goud, 2023). These applications have overcome traditional challenges like irregular water assessments, high labor demands, data inaccuracies, and poor data representation (Prapti et al., 2021).

The modern IoT technology has recorded a significant advancement in aquaculture, it is essential to acknowledge its limitations. Foremost among these constraints are the significant initial costs and the susceptibility of sensors to corrosion (Ni, 2020). Tziortzioti et al. (2019) have highlighted that implementing IoT infrastructure, comprising sensors, data analytics platforms, and connectivity solutions, often requires a substantial upfront investment. This financial burden often acts as a barrier, particularly for smaller aquaculture operations in developing regions. Furthermore, Reddy et al. (2021) reported that sensors deployed in aquatic environments face harsh conditions, including exposure to saltwater, leading to corrosion and long-term malfunction.

Consequently, this escalation in running costs in conjunction with the diminution in the sensor detection further undermines the reliability of the collected data (Murray et al., 2014). Ishita (2019) reported that remote aquaculture locations often face IoT connectivity issues, leading to data gaps and disruptions. Also, Fu et al. (2022) reviewed the important role of employing deep learning technology in water quality management in real-time. The study suggested employing deep learning technology in addressing water demand forecasting, leakage detection, and sewer defect assessment. This suggests a lack of practical adoption reported in real-world management scenarios. Maintaining detailed records of IoT advancements and gaps will provide a strong foundation for future research and solutions.

Several IoT-related reviews exist, like Jan et al. (2021), which covers WSN technology in leak detection but overlooks aquaculture aspects such as water quality monitoring and feeding optimization. Similarly, Manoj et al. (2022) focus on environmental monitoring with an emphasis on water quality but concentrate on traditional WSN technology, overlooking recent IoT developments. In another context, Ahmed et al. (2020) focus on water quality monitoring, including WSN, but do not cover broader aquaculture practices like health and disease inspection. Geetha and Gouthami (2016) specialize in real-time smart water quality monitoring using IoT techniques, while Banna et al.

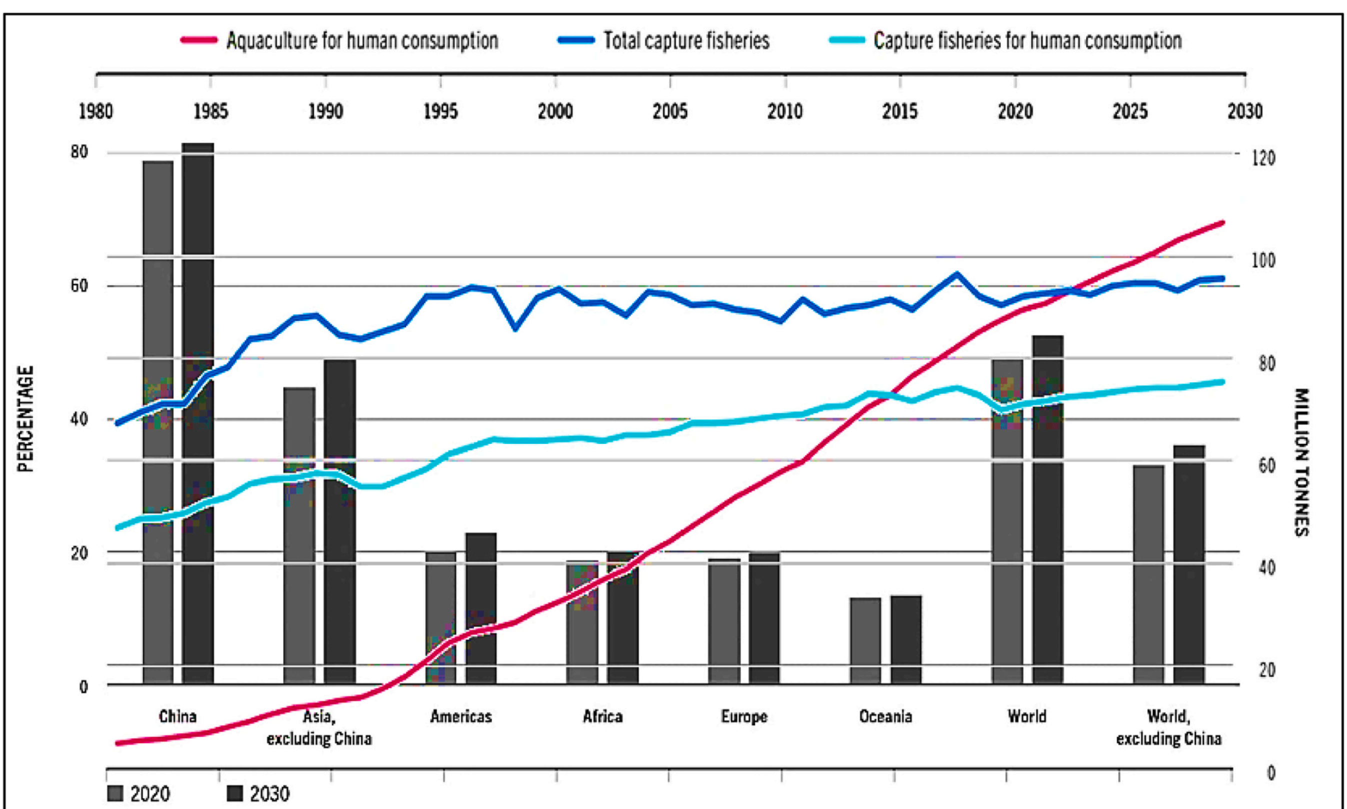

Fig. 1. Trajectory of Global Aquaculture Production over Time [FAO, 2022].

(2014) survey sensor technologies for water monitoring but have limited coverage of other aquaculture dimensions. Thus, most existing reviews focus on specific aquaculture aspects, leaving a gap for a comprehensive synthesis.

This paper reviews IoT advancements in aquaculture, offering a comprehensive analysis of its applications across various operations. it explore advanced IoT technology in conjunction with sensors, machine learning and deep learning within the realm of aquaculture operations. The paper's structure unfolds as follows: Section 1.0 entails the introduction that gives a concise background of this review paper. Section 2.0 offers an encompassing overview of IoT technology and its functionality. Moving on to Section 3.0, we critically review key applications. This includes water quality monitoring, feeding optimization, health management, delving into hyperparameter tuning techniques and optimization strategies employed by previous researchers. This section critically discusses the IoT platform, operational challenges, and future perspectives in aquaculture. Finally, Section 4 encapsulates the paper with a conclusion.

2. Overview of IOT

IoT-technology involves an interconnected network of devices and systems through the Internet, facilitating the collection, exchange, and sharing of data (Čolaković and Hadžialić, 2018). Its goal is to enhance efficiency by enabling seamless communication between physical and digital realms (Ali et al., 2019). IoT in aquaculture management improves carrying capacity by integrating operational algorithms, actuators, smart indicators, and decision-making (Weitzman and Filgueira, 2020). The network of devices enables communication, data analysis, and decision-making without direct human intervention (Atlam et al., 2018; Ghosh et al., 2018). This setup enables seamless data collection, efficient transmission, multitasking, and system control with minimal manual intervention (Shammar and Zahary, 2020).

Basically, the overview of IoT application encompasses six major aspects, namely devices and sensors (1); connectivity (2); data processing (3); cloud servers and data storage (4); application and actuation (5); and task execution (6), as depicted in Fig. 2 (Shammar and Zahary, 2020; Chamara et al., 2022). Each aquaculture operation, like water quality monitoring, requires distinct devices and sensors for data capture (Bórquez López et al., 2020).

Many IoT sensor devices are available for aquaculture, but careful selection is essential for compatibility with microcontrollers and connectivity components (Ni, 2020). As reported by Miller et al. (2023), most IoT sensors and devices have unique specifications ensuring compatibility, data collection, and transmission. Strategically placed sensors assess water parameters and control environmental conditions, diseases, and feeding behavior (Kumar et al., 2019). Gateway devices are crucial for connectivity, acting as bidirectional data transceivers that enable communication between sensor nodes and the IoT system (Atalla et al., 2023). Fig. 2 highlights the essential role of gateway devices (such

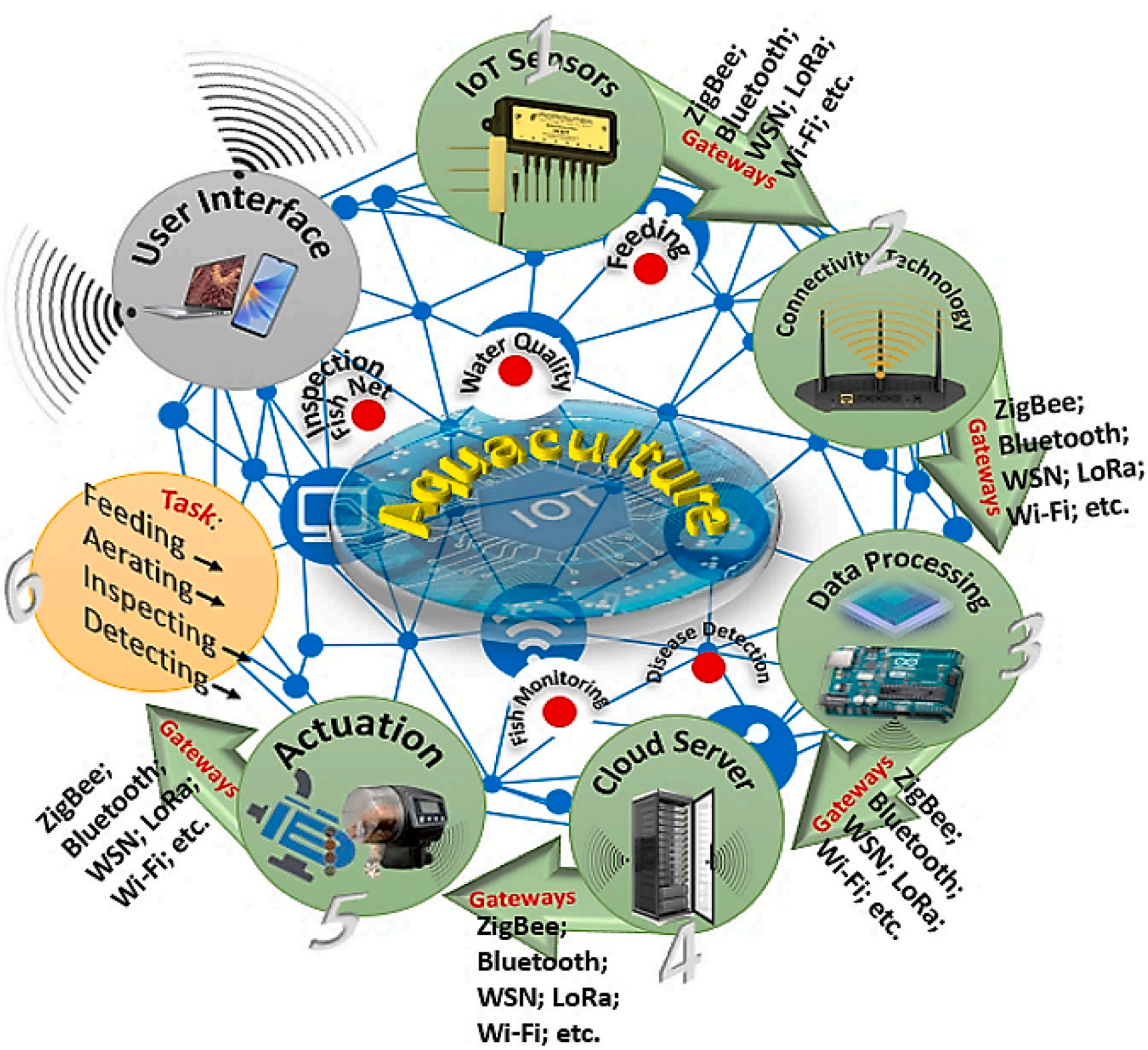

Fig. 2. Overview of IoT Applications in Aquaculture.

as Zigbee) in ensuring reliable connectivity and data transmission within the IoT layout (Kumar et al., 2019; Atalla et al., 2023).

According to Kabanov and Kramar (2022), IoT devices employ a variety of gateway communication technologies for internet-device connectivity. Commonly utilized connectivity devices include wireless fidelity (Wi-Fi), cellular networks, Bluetooth, Zigbee, and LoRa Wireless Access Network (LoRaWAN) devices. However, the selection of the appropriate connectivity mechanism depends on factors such as range, power consumption, and data transfer speed. Subsequently, the transmitted data requires efficient processing. IoT has the capacity to generate and manage vast volumes of data from diverse sources (Kumar et al., 2019). Data is processed and analyzed using analytics, machine learning, and AI to provide insights for real-time decision-making and automation (Mahdavinejad et al., 2018). This underscores the significance of aligning data processing methodologies with the preset objectives of smart aquaculture. Thus, researchers have consistently integrated various architectural configurations with cloud-based or edge servers to enhance data processing capabilities (Hamdan et al., 2020).

Modern IoT devices like the HQ30D pH Sensor and DS18B20 Temperature Sensor have computational capabilities, but some systems delegate tasks to local servers (Sethi and Sarangi, 2017). These features ensure local edge computation by the devices even in the absence of internet connectivity (offline). Furthermore, Mtowe and Kim (2023) reported that edge computing significantly reduces latency, ensuring critical real-time response. However, for enhanced flexibility and a robust system, IoT layouts commonly leverage cloud platforms to store, process, and manage data, (Fig. 2). Interestingly, cloud services offer scalability, storage, and computational power required to manage the substantial data volume generated by these devices (Pons et al., 2023).

The results of cloud computations determine the subsequent actions and device actuation or operation, as illustrated in Fig. 2. To facilitate convenience and seamless interactions, researchers have employed several user interfaces enabling easy data assessment, monitoring, control, and device actuation (e.g., pumps, and aerators). Popular IoT user interfaces include Virtuino (Zaidi Farouk et al., 2023), Blynk (Taha et al., 2022), Adafruit (Anwar and Li, 2020), and Thingspeak (Taha et al., 2022). These devices, sensors, and IoT platforms are linked through a unique application programming interface (API) key. The API key fosters diverse interoperability, enabling synergistic collaboration among various IoT devices and platforms. The interoperability of IoT devices, coupled with internet connectivity and user-friendly interfaces (UI), ensures real-time monitoring, control, and task execution (such as "feeding," “WQP”, "aeration," "inspection" as depicted in Fig. 2), (Zaidi Farouk et al., 2023).

3. Methodology

3.1. Applications of IoT in aquaculture

IoT technology in aquaculture relies on sensors, actuators, internet platforms, data analysis techniques, and data storage (Ighalo et al., 2021; Gubbi et al., 2013). IoT technology enables remote monitoring and control, enhancing interoperability for managing water quality, optimizing feeding, and monitoring fish health. This technology boosts aquaculture productivity, sustainability, and profitability by providing real-time data and enabling remote monitoring and control This remark is per the researchers’ reports (Mahamuni and Goud, 2023; Pons et al., 2023; Almetwally et al., 2020), which have undergone rigorous critical review in the subsequent sections that follow.

3.1.1. Water quality management

As per Manoj et al.’s findings (Manoj et al., 2022), the quality of water holds a pivotal role in aquaculture, directly influencing the well-being and growth of aquatic organisms. Table 1 presents the key water quality parameters alongside their recommended threshold ranges. Adhering to the recommended threshold limits is crucial for ensuring sustainable cultivation and maximizing productivity (Boyd et al., 2022). However, aquaculture activities, especially feeding and egestion, often degrade water quality (Maulini et al., 2021). Timely measures are thus necessary to maintain these parameters within the recommended threshold for sustainable fish production (Bentzon-Tilia et al., 2016). Even slight deviations from the water quality limits can have dire consequences. For instance, exceeding the threshold limits for Ammonia can result in fish mortality, while low nitrite levels can cause "Brown-Blood Disease. Nitrate concentrations up to 100 mg/L, however, are deemed safe (Goddek,). Deviation in pH can significantly impact aquaculture, affecting reproduction and overall health of aquatic organisms (Yep and Zheng, 2019). Temperature fluctuations can influence nitrification processes and contribute to the prevalence of fish diseases (Goddek,). Maintaining dissolved oxygen levels above 4–5 mg/L is critical for successful fish cultivation. Electrical conductivity (EC) in nutrient solutions aids in optimizing nutrient utilization (Stone and Thomforde,; Fern and Esteban, 2006) but variations in the concentration impact water quality thus the fish morphology (Rocha et al., 2022).

Table 1
Literature Information on Water Quality Parameter (WQP) Sensors and Their Threshold Limits.

References	Water Parameter	Threshold range	Sensor Module
(Goddek,)	Dissolve Oxygen (DO)	Greater than 4 mgL^{-1}	DFROBOT-SEN0237; Atlas DO probe
(Stone and Thomforde,)	EC	30–5000 uS/cm	DFROBOT-SKU: DFR0300-H
(Goddek,)	Temperature	17–34 °C	DFROBOT-DS18B20 mon
(Yep and Zheng, 2019)	pH	6.5–8.0	DFROBOT-SKU: SEN0169; B&C Electronics–SZ 1093 model; OMEGA PHE−45 P pH sensor; Orion 3 Star pH meter
(Rocha et al., 2022)	Salinity	0–2 ppt $CaCO_3$	DFROBOT-SKU: DFR0300-H
(Rocha et al., 2022)	Turbidity	Less than 1000 mgL^{-1}	DFROBOT-Analog TDS sensor
(Goddek,)	Nitrates	50–100 ppm	WINSEN-MQ−137
(Rocha et al., 2022)	Nitrites	0.25–1 mgL^{-1}	Apure-NO_2−201 sensor
(Stone and Thomforde,)	Humidity	60–80 %	DFROBOT-SKU: DFR0300-H
(Stone and Thomforde,)	Water level	0.02 kgL^{-1}	Omron K8AK-LS1; HC-SR04 ultrasonic sensor; BC546 NPN transistor circuit
(Fern and Esteban, 2006)	Light intensity	600–900 PPFD	BH1750
(Goddek,)	CO_2	340–1300 ppm	MG−811 Sensor
(Goddek,)	Air Temperature	18–30 °C	DHT11

Hence, real-time monitoring of these crucial parameters is indispensable (Akhter et al., 2021a). IoT water quality and environmental sensors are crucial for continuously monitoring and optimizing essential parameters This approach uses IoT, sensors, and data analytics for real-time, remote monitoring of critical water quality factors like temperature, dissolved oxygen, pH, and ammonia. Strategically positioned within aquaculture systems, these IoT-enabled sensors continually collect and transmit data to centralized servers or cloud platforms. Subsequent analysis of this data helps in identifying trends, anomalies, and potential issues. IoT-based real-time monitoring addresses immediate concerns and enables predictive maintenance and precise adjustments for effective aquaculture management (Akhter et al., 2021a).

Table 2 provides a comprehensive overview of literature related to aquaculture water quality monitoring using IoT systems. One noteworthy example is the IoT-based prototype developed by Encinas et al. (2017). An Arduino board, a hub of sensors, a cloud database, internet

Table 2
Summary of Literature on IoT-Based Technology for Monitoring Water Quality in Aquaculture.

Parameter(s) and sensors models	Threshold limit	Major Components	Connectivity	Data Processing & Database	Significant outcome	Deduced remark	Reference
pH; T; DO	NR	Sensors; microcontroller; internet connectivity	UATR; Zigbee (10–250kbps); X-bee transmitter (2.4 GHz);	Arduino UNO; MySQL;	low cost, low power consumption, scalable	Need for a comprehensive evaluation & validation	(Encinas et al., 2017)
DO (D−6800, 0–20 mg/L), pH (DFORBOT-pH, 0–14), T (LM35, 55°C to 150°C) WL (HC-SR04 Ultra sonic, 2–400 cm), NH3 (TIA−2100, 0.0125–0.02), and WO (MQ4-sensor), Aerator; water pump; pH-Controller	DO<4–10 ppm oC); pH= 7.0–7.2	Sensors, actuators, microcontroller, internet	Wi-Fi Modem; GSM Modem	Arduino as a processor, web server and data storage device (NS)	Readings outside the threshold limit result in the activation of the relay to maintain the commended limits	Detailed validation results have been reported	(Abinaya et al., 2019)
DO, NH3, pH, T, Salinity, Nitrate and Carbonates	DO= 4–10 ppm; NH3=0–0.1 ppm; pH= 7.5–8.5; Salinity= 0–2 ppt; alkalinity= 20–40 ppm	Solar power, microcontroller, sensors	inbuilt Wi-Fi module, Python program for collecting sensor data	Rasbery pi3 module, MySQL	The Aqua farmer mobile App developed	Less 24 h reading reported. The report does not include system validation	(Raju and Varma, 2017)
DO, NH3, pH (SEN0161, 0–14), T (DFR0198, −10°C to +85°C), EC (DS18B20),	T = 20–30 oC; pH= 6.5–9; conductivity = 60–2000 uS/cm; colour= G-B	Sensors, Raspberry pi, Arduino UNO, cloud	Inbuilt Wi-Fi; internet	php; MySQL database	Fish Culture Monitoring (FCM); python program for extracts the RGB value.	Blurred imaging and unstable Internet undermine performance	(Saha et al., 2018)
DO, salinity Temperature, Valves, pump	DO>4 mg/L; salinity<33ppt; temp 17–30 oC	ANN, Arduino; sensors	Internet, CDMA Module (InRouter210C)	Remote monitoring platform; MyEclipse 3.2, MySQL 5.1, Apache Tomcat 5.5.	average pH of 7.943; forecasting ANNs model developed, 95.2 % accuracy, suitable for long distance	The analysis is based on the WQP	(Zhu et al., 2010)
Temp, DO, pH, TSS, EC	hydraulic loading rate (HLR) of 600 mm/day	Arduino and wireless mesh sensors	Internet connectivity	Arduino; local database	WQP monitoring and RAS established	Large footprint as it involves 4–5 series of connected ponds, requires manual computation	(Zhang et al., 2011)
PH, DO, EC and Temperature	pH=6–8.5; DO=20 mg/l; EC=200 µs/cm; T=34 oC	Wireless Mesh Sensor Node; Waspmote;	Wireless Mesh Sensor network, Zigbee; GPRS; WiFi	Waspmote embedded systems platform; local database or remote web serve	wireless mesh sensor network IoT system designed & implemented	A lab-scale and the multiple gate requirement could be a drawback	(Odey, 2013)
T; pH, DO, EC, and salinity	pH=6.5–8.5; DO=20 mg/l; EC=150 µs/cm; T=30 oC	Sensors, ESP Module as a microcontroller, ThingSpeak cloud	ESP 32 Wi-Fi module; Wi-Fi network; Wi-Fi access point (AP)	ESP32; ThingSpeak IoT platform; Thing-View APP		Suitable for fresh water aquaculture. The scope of brackish aquaculture is not considered	(Lin et al., 2021)
T, pH, DO		Sensors, PICNIC 2.0 Microcontroller, cloud	Arduino ATMega	ZeeBee	LabVIEW		(Simbeye et al., 2014)
T, pH, DO, ORP, salinity	multiple sensor nodes and sensor/server node hybrid	Sensors, rasp-microcontroller, cloud	Raspberry Pi	ThingSpeak, WiFi/CDMA			(Saparudin et al., 2019)
T, pH, DO, ORP		Sensors, Embedded MCU, cloud	RoLa/WiFi	Embedded MCU/ ThingSpeak			(Danh et al., 2020)
T; EC; salinity; pressure; DO	temperature sensors (for different depths), a conductivity and salinity sensor, a pressure sensor and a dissolved oxygen (DO) sensor	A3 buoy is a 3 m rope; n internal data logger and lithium batteries		HOBO software (‘convert R to S)	buoy system is useful even in a high algal concentration	The exposed sensor can become corroded	(Schmidt et al., 2018)
Temperature (∘C) Turbidity (NTU) pH	integrating sensors with wireless sensor networks (WSNs)		Deep Learning and Traditional Learning Mode	data fusion (DF) deep reinforcement learning (DRL) and Deep Learning	accuracy percentage (92.15–95.75, %)	Requires dataset	(Gao et al., 2019; Kaur et al., 2023; Flores et al., 2023)

NR=not reported; UATR= Universal Attenuated Total Reflectance; MySQL=Structured Query Language connectivity, a mobile application, and a desktop application were employed. The system utilizes sensors; the pH probe, analogue temperature probe sensor, and digital DO sensor, to transmit data via Zigbee protocol. Processed data is subsequently stored in a MySQL cloud database. this prototype demonstrates the potential for real-time monitoring, but further evaluation is required. Another notable contribution comes from Abinaya et al. (2019). The authors designed an IoT system capable of monitoring and controlling an array of water parameters (including DO, pH, water level, ammonia, and water odour). This system uses a modem Global System for Mobile (GSM) modem for data transmission and sending alerts to relevant personnel. It also includes a buzzer system that activates when detected data exceeds predetermined thresholds, initiating appropriate regulatory actions. In a study reported by Raju and Varma (2017), a solar-powered IoT system for water monitoring was developed. The system's architecture uniquely includes a power module along with standard components like internet connectivity, cloud storage, sensors, and a microcontroller. A Raspberry Pi-3 with built-in Wi-Fi serves as the central data processing unit. It receives signals from various sensors and devices, processing them, and transmitting the data to the cloud.

Similarly, Saha et al., 2018 employed a Raspberry Pi-3 as the central data processing unit in an IoT-based aquaculture water quality monitoring system. In this setup, the Arduino board (ATmega328P) directly acquires data from the sensors before transmitting it to the central unit. Notably, this system monitors the colour profile of aquaculture water in addition to other parameters, including temperature, pH, and EC. The system employs preset-threshold limits and a Python-program, facilitating the exchange of captured. The script analysis data through the Android Media Transfer Protocol (MTP), thereby providing insights into water quality and recommended actions. Zhu et al., 2010 showcased an online system for monitoring water quality under intensive culturing conditions. This system included sensors for pH, temperature, DO, and EC. They also developed a DO forecast model with half-hour predictions using an artificial-neural-network (ANN) and the stochastic-gradient-descent (SGDM) algorithm. Zhang et al., 2011 employed an Orion 5-Star Portable multi-sensors (pH, ORP, DO and EC) device to monitor the water quality of a land-based fish farming system. The system was enhanced by integrating with a constructed wetland for effective recirculating aquaculture (RAS). They implemented a smart wireless Aqua-Mesh sensor, equipped with temperature, pH, DO, and EC sensors, to enhance aquaculture monitoring. Odey, 2013 developed the Aqua-Mesh system for aquaculture, incorporating wireless sensors for temperature, pH, DO, and EC monitoring. The Waspmote platform dynamic wireless mesh sensor network allows continuous monitoring of aquaculture parameters and triggering alerts when thresholds are surpassed (Hang et al., 2020). Multiple gates (WiFI and General Packet Radio Service, GPRS) were used to facilitate good connectivity and SMS alerts to the farmer or operator. Simbeye et al., 2014 employed a distinct LabVIEW to develop a smart water quality monitoring and control system. The LabVIEW net-gate operates synergistically with the WiFi sensor to read temperature, pH, DO, and EC levels.

In addition, the system could auto-control pH levels by actuating the water pumps when out of the threshold limit (Rastegari et al., 2023). Collectively, the multiple net-gates improve connectivity but it can significantly increase the overall infrastructure cost. Schmidt et al., 2018 presented a cost-effective, unmanned water quality monitoring buoy system designed for coastal aquaculture. The system used pressure, temperature, and DO sensors to collect data, which was stored in an internal data logger. The logged data were manually offloaded and displayed using SOHO software. Saparudin et al., 2019 developed a wireless IoT water quality monitoring system for a high stocked fish pond. In this study, only the water temperature was the primary monitoring parameter. A similar study has been reported by a number of researchers and the summary of the findings is presented in Table 2 (Danh et al., 2020; Huan et al., 2020; Sanya et al., 2022). The authors established an IoT-based system for monitoring aquaculture water, though the parameters considered in each of the studies vary (Table 2).

Besides the WiFi IoT-based system, Sung et al., 2023 employed a Wireless Sensor Network (WSN) for real-time data collection and analysis has been reported. Simbeye et al., 2014 implemented a WSN-based monitoring and control. The system alerts the farmers via GSM when irregularities in critical parameters (such as temperature, dissolved oxygen, pH, and water levels). Similarly, Max et al., 2007 developed Smart Coast, a WSN system with user-friendly sensors and low-power communication for real-time internet data access. The IoT system uses a microcontroller to process data from multiple sensors, applying encrypted limits to perform tasks or control actuators (Sethi and Sarangi, 2017). Restricting data use to actuator triggers and not fully exploiting its potential limits its value (Ahmid and Kazar, 2023). Given the dynamic nature of aquaculture activities, the use of preset IoT-multi sensors may not suffice for predictive purposes (Zhang and Gui, 2023). This underscores the necessity for integrating IoT with AI computational systems to establish a more robust water quality monitoring approach (Rahu et al., 2023).

The rise of IoT-driven AI computational systems, especially those with GPU-embedded processors, has become essential for modern computer-integrated intelligence applications.

This led to deep learning methods, using artificial neural networks for dynamic water quality analysis (Hou et al., 2023). When optimized, these methods have proven highly valuable for various tasks, particularly aquaculture water quality monitoring (Gao et al., 2019). More so, the technology excels in feature extraction and end-to-end decision--making. This enables anticipating water quality changes and implementing proactive measures to protect inhabitants (Chen et al., 2020). For instance, Miao et al., 2010, successfully combined neural networks and genetic algorithms to develop a model for water DO level projection. An IoT-based aquaculture system used deep neural networks and Long-term and Short-term Memory (LSTM) algorithms to model parameters like water temperature, pH, and salinity (Kaur et al., 2023). Both studies implemented the models in a microcontroller for comprehensive system control. Mehra et al., 2018 utilized an artificial neural network incorporating multiple environmental factors for monitoring, controlling and predicting WQPs. In this study, both Arduino Uno and Raspberry PI were used to allow Machine-Machine interaction and effective control of the key parameters (such as Temperature). Cody et al. [2020] employed an integrated convolutional neural network (CNN) with an auto-encoder technique to enhance monitoring operations along the water supply-lines. Besides, Gao et al., 2019 reported an IoT-AI smart fish farming water monitoring system and it uses a predictive method for automated WQ management. The local outlier factor (LOF) algorithm, a density-based outlier detection technique, was used for point data segmentation. An LOF > 1 indicates an outlier, while values close to 1 suggest normal points. Overall, the IoT-AI WQP system's predictions and inferences are based on the fixed initial dataset used for training (Flores et al., 2023). However, considering the dynamic nature of the aquatic lives, the prediction may not be completely reliable or accurate (Jan et al., 2022).

In recap, the IoT application for monitoring aquaculture water quality involves four main steps: (1) Hardware selection, (2) Layout and Connectivity planning, (3) Software development, and (4) Application deployment, (Fig. 3) (Zulkifli et al., 2022). Key water quality parameters monitored include temperature, NH3, pH, DO, EC, and salinity due to their impact on aquatic life and management Then, identify the suitable and compatible sensors and devices to monitor and control these parameters. The next step is designing the circuit layout and selecting connectivity systems like Zigbee, Wi-Fi, ESP8266, and mobile data (GPRS/3 G, 4 G, 5 G). As WSN technology advances, incorporating 5 G technology and integrating multiple sensors with AI is expected to lead to notable improvements in IoT applications. This advancement reduces latency in detecting, processing, and transmitting water quality data by leveraging AI and 5 G technology.

o ensure smooth integration, software must include instruction codes

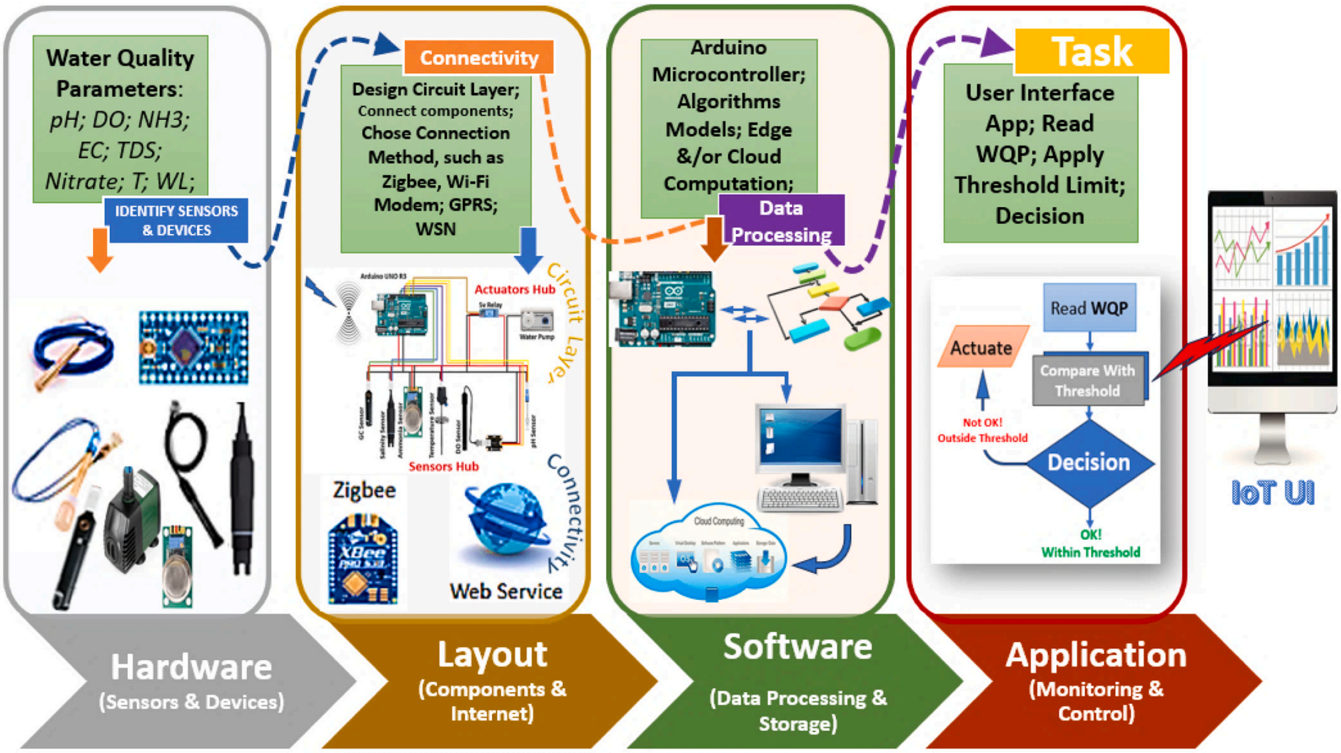

Fig. 3. Flow of IoT Implementation for Managing Water Quality in Aquaculture.

for processing, storage, and controlling systems like cloud databases, Arduino boards, Raspberry Pi, and ESP32 boards. These devices operate based on the encrypted instructions and threshold limits set for each water quality parameter in the software. Lastly, the literature highlights the importance of the IoT user interface (UI) for visualization and operability. Commonly used open-access apps for developing water quality monitoring and control include ThingSpeak, Blynk, and MySQL.

3.1.2. Feeding optimization

In the realm of aquaculture, the key determinant of efficiency and expenses lies in the optimal provision of feed (Chiu et al., 2022). Therefore, understanding the ideal moment to cease feeding is crucial for optimizing efficiency. To date, most aqua farmers rely on manual feeding, a process known for its time-consuming and labour-intensive (Wu et al., 2022). Recently, the focus has shifted to IoT-based feeding management that adapts to behavior and growth changes, driven by its economic value (Mahamuni and Goud, 2023; Silalahi et al., 2023). Fernández Sánchez et al. (2023) conducted an economic assessment for implementing IoT technology in aquaculture. The study focused on automating feeding operations for the production of European sea-bass in the Mediterranean Sea. An economic algorithms-IoT-based approach was implemented to accommodate a typical farm with different production volumes. This study shows that IoT-based automated feeders are a sound economic choice for sea bass farms of any size. This strategy encompasses diverse techniques along with monitoring and responsive apparatus, enabling the automated assessment of the dietary requirements of fish (Munguti et al., 2020). Thus, the advances in IoT based feeder are discussed under the following sub-captions;

3.1.2.1. Feeding system based on timing. This system relies on electronic programmable timers or digital timers to dispense feed according to predefined user-set timings and schedules. This technique requires some manual input, like adjusting the feeding schedule to meet food requirements (Dada et al., 2018). Digital timers and programmable timing represent the primary methods commonly utilized in developing semi-automatic fish-feeding systems. Ogunlela and Adebayo (2014) proposed an automated fish feeder using a digital timer with monostable and stable modes for precise timing and delay control. The monostable mode uses a capacitor network and external resistor to regulate time intervals, while the astable mode generates a single pulse within 1–10 seconds. Osueke et al. (2018) designed a 24-hour fish feeder using a digital timer as the central control for regulating operation duration. The 60-minute experiment using 4 mm local and foreign feeder pellets distributed 85.5 kg of feed to the aquarium, with less than 3 % feed loss. This indicates an efficiency of approximately 86.9 % in preserving and managing feed under controlled conditions.

Noor et al. (2012) introduced an innovative fish feeder based on a PIC microcontroller, optimizing pellet distribution efficiency. Their system allows manual adjustment of the feeding cycle and motor speed, making it adaptable to different pond sizes and pellet distribution needs. In a related study, Abdallah and Elmessery (2014) proposed an advanced automatic fish feeder system specifically tailored for intensive mirror carp production. Their system has two control mechanisms. One uses the AT89c51 controller for scheduled feed dosage, while the other adjusts dosage based on real-time water temperature, fish weight, and oxygen consumption. More recently, Niswar et al. (2017) developed an automated feeding system targeting soft shell crabs, integrating a precision microcontroller unit. Their innovative approach involves dispensing 5 % of the crab's body weight during each feeding cycle, effectively minimizing food wastage. Although this demonstrates promising results, the existing feeding systems predominantly rely on fixed schedules, which may lead to inefficiencies. Ignoring fluctuations in fish appetite due to growth, age, size, and environmental changes can lead to overfeeding. This can cause water pollution, stunted fish growth, and reduced productivity (Volkoff and Rønnestad, 2020; Craig et al., 2017). Therefore, an alternative to the timed-based feeders is critical.

3.1.2.2. IoT Auto-feeder based on multiple sensors technology (IoT-MST). Numerous researchers have harnessed the potential of multi-sensor systems in the development of IoT-based automatic fish feeders. This technological leap has transformed the way we manage and optimize the process of feeding fish. In this document, we delve into the pivotal role played by multi-sensor systems in the creation of automated fish feeders. We draw upon pertinent literature to underscore their significance and the diverse range of applications they offer. Table 3 presents a critical overview of the existing literature on IoT-based multi-sensor fish feeders. For instance, Riansyah et al. (2020) achieved success in crafting an IoT smart feeder. They employed an array of sensors to detect feed levels, while an Arduino Uno processed the received signals to dispense feed. The study developed a user-friendly app using Blynk. The programmable Wem-D1R1 module ensured timely feeding by maintaining schedules. A similar study by Hardyanto et al. (2018) utilized an ATMega controller to process sensor data. Meanwhile, Michael Angello Handoko Putra used a servo motor for the feed metering system, diverging from the usual stepper or DC motors. However, it's notable that these studies primarily relied on time-based feeding schedules, with the dispensing rate not being a central focus.

Luo et al. (2015) introduced a comprehensive multi-sensor fusion algorithm consisting of four critical components: estimation, classification, inference, and artificial intelligence techniques. This versatile approach enhances automation and decision-making, especially in determining the right amount of feed to dispense. Rubio et al. (2004) developed a modified version of a multi-sensor feeder tailored for feeding sea bass. String sensors were employed under varying empirical conditions, enabling feed dispensing through a bit and pull trigger mechanism. This design accommodated both trained and non-trained fish populations. Notable advantages included quicker experiment completion, the ability to feed at night, and immunity to accidental activations caused by external factors. Additionally, the system proved to be cost-effective and facilitated rapid component replacement. However, this system suited trained fish better, as non-trained fish needed a longer adaptation period and sensors corroded over time (Coppola et al., 2023). As an improvement to the feeder, Parra et al., 2018 introduced a long-term fish-feeding monitoring system based on sensor data from individual fish triggers. Their results showed a 100 % success rate in trigger registrations, ensuring high accuracy, minimal feed wastage, and reduced sensor corrosion. The system's adaptability allowed researchers to fine-tune trigger-activating individuals, optimizing feeding practices. This approach prioritized the welfare of individual fish over assessing collective growth rates, emphasizing the importance of growth uniformity.

Similarly, Millot et al., 2008 explored the impact of individual fish behaviour on growth rates using the concept of a demand-feeding system. Interestingly, the study found no significant difference in final body weights between higher- and lower-triggering fish samples, challenging conventional assumptions. Garcia et al., 2011 researched a fish feeding sensor system that uses multiple sensor measurements for informed decision-making. Expanding upon this, Zhang et al., 2013 introduced a multi-metric learning algorithm that integrates various sensors with shared or distinct classifications to enhance performance. Both studies demonstrated substantial improvements in accuracy when compared to manual feeding record-keeping.

The integration of multi-sensor systems has revolutionized IoT-based automatic fish feeders, significantly enhancing the efficiency and precision of feeding practices. However, the susceptibility of the sensors to corrosion underscores its critical role thereby relegating the overall system reliability (Malla et al., 2023).

3.1.2.3. IoT feeder based on sensors and acoustic technology (IoT-SAT). Prior research has shown that acoustic signal strength within certain frequency ranges correlates with the intensity of fish feeding activity (Lin et al., 2023). Implying that acoustic intensity has a direct linear correlation with the fish's feeding requirements and hunger levels (Yuan et al., 2023). Compared to light and electromagnetic waves, acoustic waves experience minimal signal loss in water, enabling them to cover significant distances (Ubina et al., 2021a). This makes the acoustic system one of the most effective methods for detecting and identifying small objects beneath the water's surface (Horne, 2000). In previous studies, the fusion of IoT-based passive acoustics with machine learning techniques has been applied for smart fish feeding (Li et al., 2022), species identification (Li et al., 2020; Zeng et al., 2023) and counting (Puig-Pons et al., 2019). Utilizing high-speed cameras, technology based on feeding acoustics feedback has been developed, as well (Saberioon et al., 2017). This technology enables the simultaneous monitoring of the feeding acoustics and movements of various aquatic organisms. Furthermore, the distinctive signals produced during feeding within specific frequency bands can be harnessed to estimate the amount of feed consumed (Zeng et al., 2023). Hence, the acoustic signals emitted during fish feeding offer a crucial foundation for evaluating the intensity of their feeding behaviour.

For instance, Tahir et al., 2020 developed a simple feed dispenser based on the IoT acoustic reflection technology. The HC-SR04 sensor features an ultrasonic transmitter and receiver module, which emit and receive sound waves at specific frequencies. In another study reported by Llorens et al., 2017, an acoustic underwater feeder was developed to dispense pellets for fish. The feeder was equipped with an ultrasonic echo system for detection of the uneaten feed. This system provides a piece of useful feedback information for adjusting and optimizing feeding rates and schedules. Similarly, Yuan et al., 2023 and Terayama et al., 2019 employed IoT acoustic-based sonar feeding systems, while Chang et al., 2022 reported a modified acoustic AIoT feeding system. The main challenge with this system was depth limitation, which affected wave transmission and undermined reliability and performance efficiency. In addition, the associated low monochrome and the blurred imaging influence the accuracy of the data processing (Hu et al., 2021a). Due to these limitations, researchers suggest that an acoustic feeding system may not be suitable for large or commercial-scale applications (Terayama et al., 2019; Saleh et al., 2022a). Hassan et al., 2019 aimed to improve efficacy by using a high-frequency acoustic sensor system, which is less susceptible to disturbances, to monitor feeding behavior. This study uniquely used a multiple acoustic sonar system to extend signal range and reduce losses.

In addition, Acker and Burczynski, 2002 observed fish feeding and the identification of pellets by employing a powerful digital sonar scanning (DSS) system. The DSS-acoustic signal exhibited a strong signal-to-noise ratio, enabling them to detect pellets up to 25-meters away from the unoccupied pen. However, adding an acoustic system increases costs and, despite success in feed monitoring, it faced challenges in accurately detecting pellets (Li et al., 2017). Particularly, when small fish were in proximity to the pellets, causing the system to struggle in recognizing the pellets.

Besides, researchers have attempted to combine a camera with an acoustic system to improve feeding efficacy (Yang et al., 2021a). Fundamentally, the images yield valuable insights into fish feeding behaviour and growth, enabling the scheduling of feeding operations. Reports show that split beam sonar imaging methods provide detailed insights into fish feeding behavior and maintain accurate tracking and positioning records (Yang et al., 2021a). Also, dual-frequency identification sonar, akin to optical images, holds promise for fish-feeding behaviour detection (Connolly et al., 2022). Additionally, multi-frequency digital scanning sonar imaging has been applied to gather information about fish behaviour during feeding (Huy et al., 2023). Parra et al., 2018 developed an integrated IoT-acoustic system incorporated with a camera to monitor and control the eating behaviour of fish. In France, Artero et al., 2021 employed a similar concept to optimize the feeding operation of fishery production. Both studies used Arduino, acoustic motion detection sensors, cameras, and internet connectivity for image capture, analysis, and logical feed dispensing decisions. Furthermore, Garcia et al., 2011 and Wang et al., 2020 employed IoT sensor-based feeders in marine fishing farms. The major components of the system include an underwater camera,

Table 3
Summary of IoT-Based Feeding Systems in Aquaculture.

Technology	Major components	Operating principles	Connectivity	Data process	Database	Main result	Deduced Remark	Reference
IoT+ MST	Sensors (pH, TDS), Arduino Uno R3; Wemos D1R1 (feeding controller); ESP8266 module, feed dispenser (servo)	The programmable Wem-D1R1 module keeps the feeding schedule dispensed twice per day	Wi-Fi, ESP8266 Wi-Fi connection; Blynk App to provide UI	Arduino UNO R3	A dedicated data storage system	The system allows monitoring of pH, TDS and feeding	Requires adjustment from time to time to give the required feed	(Riansyah et al., 2020)
IoT+ MST	Sensors (WL, light, humidity), relays, Arduino ATMega 328, feed dispenser, ESP8266 module	sensors send data to the microcontroller, which directs the feeder. ESP8266 module sends the WQP online to the U	Internet, Wi-Fi, ESP8266, UI app (also serves as the switch)	Arduino ATMega	NM	web-based interface; a prototype	A Suitable database is not considered	(Hardyanto et al., 2018)
IoT+AI	Underwater ESP32-EYE; Microprocessor (pi), feed dispenser	Video capturing of the feeding and un-feeding condition	Spatial network + 3D convolutional motion network + LSTM recurrent classification network	Cloud data processing	NM	Over 80 % prediction accuracy	The result is promising, but a longer study duration will confirm consistency in the prediction accuracy	(Måløy et al., 2019)
IoT+ MST	RTC DS3231 module, sensors, Arduino UNO, and feed dispenser (servo)	The RTC module syncs time for the Arduino to handle feeding thrice daily.	Internet is not required to operate	Arduino Uno	Database not included	Feeding scheduling	No data logging, necessitating frequent feeding adjustments.	(Handoko Putra et al., 2023)
IoT+ SAT	Sensors (pH 6.5–7.5, ultrasonic-HC-SR04), servo motor, Arduino board	The feeder uses 3-level sound waves for scheduled feeding, converting them to distance.	Wi-Fi for data transmission; Blynk app	Arduino UNO with integrated ultrasonic emitter and receiver module	NM	prototype feeder ultrasonic	The inference of the sound wave influence result	(Tahir et al., 2020)
IoT+ SAT	Arduino board, sensors and motor driver, relay, Ultrasonic Level Sensor; Buzzer Alarm System; Servo Motor Driver;	Arduino gauges feed level with the ultrasonic sensor and controls the servo for dispensing	Wi-Fi; friendly UI	Arduino ATMega + Algorithms Proportional-Integral (PI) loop	NM	A prototype	It has a UI but lacks a database.	(Karningsih et al., 2021)
IoT+SIT	Hopper, feed dispenser, accelerometer, gyroscope, magnetometer	Utilizes ANN models for behavioural analysis. Key parameters: acceleration, angular velocity, and DFT for decision-making.	Wi-Fi,	Autoregressive Moving Average (ARMA) model	Personal computer (PC)	developed model using FD+CD gave 100 % accuracy	angular velocity accuracy swan around 35.60 %.	(Adegboye et al., 2020)
IoT+MST	Solar power system, relays, sensors (Proximity;),	Solar power system with LM2596 regulates servo-based dispensing.	Wi-Fi + LoRa TTGO SX1276	ESP32 Microcontroller	Web cayenne platform + PC	Developed a LoRa-based smart feeder with nearly 100 % dispensing efficiency.	Associated battery overheating	Silalahi et al., (2023)
	Microcontroller, sensors, servo motor (dispenser);	Microcontroller directs servo for encrypted feed scheduling.	wireless communication + Bluetooth (HC−05 module)	Arduino UNO, mobile app	PC	An IoT prototype feeder developed	Short data recording system	(Tejaswini et al., 2022)
IoT+ SAT	Storage and Dispatch Module; Wi-Fi Module; Graphical User Interface; Arduino Uno magnetometer, an accelerometer, GPS module, MPU−6050 Gyro metre, RTC chips, SD card screen displays, relay, RTC module; stepper motor	Automated fish feeder dispenses food via stepper motors. GUI module enables user control. Ultrasonic sensor monitors and triggers automatic food transfer when levels are low.	Wi-Fi router + Internet	Microcontroller NodeMCU + mobile application	Web server+ PC	The feeder system efficiently dispenses feed with minimal human intervention		(Malla et al., 2023)
IoT+ SAT	microcontroller board; NodeMCU ESP8266; ultrasonic sensor; 2x servo motors	Ultrasonic sensor detects food levels and waterproof sensor identifies fish.	R4.0 system connected online and mobile apps	ThingSpeak platform by using Blynk to collect data collections from all sensors		developed a prototype of a dynamic fish feeder based		Kassim et al., (2021)

(*continued on next page*)

Table 3 (*continued*)

Technology	Major components	Operating principles	Connectivity	Data process	Database	Main result	Deduced Remark	Reference
						on fish existence		
IoT+ SAT	Arduino UNO, ultrasonic sensor, Stepper motor Nema 17, Node MCU, Stepper motor-MAS 95 R 0028 M, L298 Motor Driver Module	Smart Feeder Monitoring automates fish feeding with user-set schedules and manual options.	Wifi; ESP8266; Internet	Arduino UNO;	Firebase	A smart feeder with 20.9 % efficiency	Require optimization to improve the efficiency	Abdullah et al., (2019)

microcontroller, behaviours detecting sensors, an internet connector and a mechanical feed dispenser. Besides the successful application dispensing of the feed, this setting allows visualization in real-time. However, sensor corrosion over time distorted data capture and affected the entire feeding operation.

The literature indicates that hungry fish rise to the surface and then descend as their appetite decreases (Nienhaus,). This shows that fish behaviour and positions at a particular time correlate with their hunger levels. Analyzing fish location and density can provide key data for developing a remote app to control feeding devices. In addition, the sonar-imaging technique is well-suited for estimating fish biomass at the deep underwater compared to optical imaging (Pargi et al., 2022). Sonar imaging systems can be costly, especially for small-scale fish farmers. Reducing costs is essential to meet the demands of the growing population.

3.1.2.4. IoT feeder based on sensors and Intelligent Technology (IoT-SIT). Skøien and Alfredsen, 2015 introduced an intelligent fish-feeding system to optimize aquaculture production profitability. The system adjusts feed quantities based on fish behavior in densely populated tanks. It monitors feed consumption by detecting residual feed on the water surface using correlation filtering and computer vision. Meanwhile, Livanos et al., 2018 developed a Fuzzy Logic Controller (FLC) system for managing sea bream larval feeding. Similarly, Soto-Zarazúa et al., 2010 utilized a fuzzy logic control algorithm based on fish age, dissolved oxygen, temperature, and body weight to regulate tilapia feeding. These approaches yielded comparable growth rates and significantly reduced feed consumption and water pollution compared to timed-based feeders. Rana et al., 2017 used a similar fuzzy logic- MATLAB-based control system for freshwater aquariums, integrating temperature, dissolved oxygen, and conductivity measurements. However, incorporating additional factors such as dissolved ammonia, waste feed, and carbon dioxide could enhance accuracy. Considering real-time techniques for assessing actual feeding behaviour could be pivotal in developing an efficient aquaculture feeding regime.

Recently, the combined use of IoT devices, AI, and computer vision hybrid systems in feeding operations has gained significant attention (Hu et al., 2022; Mustapha et al., 2021). This shift is due to the cost-effectiveness compared to traditional multi-sensor and acoustic feeders and the non-invasive nature of biomass data capture (Pribadi et al., 2020). Furthermore, advancements in image preprocessing and enhancement algorithms have made computer vision technology a viable solution in this context (Li et al., 2020; Zhou et al., 2018a). One noteworthy development in this field is the integrated feeding system devised by Fuentes and Tongson, 2021, which seamlessly combines IoT-AI technologies. This system employs an Arduino board for data processing, correlation filters, and a vector machine-algorithm to classify fish-feeding behaviour efficiently. This approach not only reduces the time delay in detecting feeding activities, also ensures real-time data processing, transmission, and dispensing.

Hu et al., 2021a introduced a straightforward yet effective adaptive threshold segmentation technique for identifying uneaten fish feed in underwater images. Leveraging internet-based computer vision technology, this method accurately measures the temporal and spatial distribution of food particles within fish cages. It also calculates food particle volume and transmits data via an internet connection while preventing fish interference through enclosure mechanisms. This method boasts fast detection, precise quantification, and a minimal detection error rate of just 1.3 %. Another notable innovation is presented by Zhou et al., 2018a. The study implemented an internet-based Adaptive Network-based Fuzzy Inference System (ANFIS) to automate fish feeding operations. This approach achieved a remarkable feeding decision accuracy rate of 98 %. Thus, amounting to a substantial improvement in the feed conversion ratio (FCR) compared to conventional feeding methods. However, the recent hybrid IoT deep learning technology surpassed traditional sensors IoT systems in terms of accuracy and feeding optimization (F. Directions, 2023). This technology has found widespread application in tasks such as analysing fish behaviour and optimizing feeding schedules. Example, Hu et al., 2022 introduced a method for quantifying salmon feeding activity based on IoT-generated frame intensities correlated with fish movement. This system yielded a computer-based visual feeding activity index (CVFAI) highly correlated with the manual observation feeding activity index (MOFAI).

Furthermore, the evolution of Convolutional Neural Networks (CNN) has been remarkable. For instance, LeNet5, one of the more succinct 7-layer CNN models, has exhibited an impressive accuracy rate (>90 %) (Zeng et al., 2023). Current research in the application of CNN primarily revolves around enhancing features and models. Such as the report of Wang et al., 2021b, it explored spatiotemporal models, while others used a fusion of optical features and convolution techniques for feeding behavior analysis. Ubina et al., 2021b introduced an intelligent system for evaluating fish feeding intensity in aquaculture. The system utilizes CNN with a 95 % accuracy rate. In Norway, Måløy et al., 2019 employed a spatiotemporal recurrent network to develop a smart system for underwater feeding of salmon fish. A Dual-Stream Recurrent Network (DSRN) was used to study salmon swimming behaviour. It combines spatial and motion-temporal data using three different networks: a spatial network, a 3D-convolutional motion network, and an LSTM recurrent classification network. The model prediction of Feeding and Non-Feeding behaviour has 80 % accuracy. Adegboye et al., 2020 assessed feeding behavior using Noda and Gleiss's dataset. They achieved 100 % accuracy with a Fourier descriptor threshold of 0.5, demonstrating precise fish feeding capabilities. Furthermore, there are models capable of handling both feeding activity classification and feed pellet counting tasks (Albrektsen et al., 2022) through the utilization of improved networks like Efficientnet-B2 (Zhou et al., 2018b), graph convolution networks (Huang et al., 2022), and lightweight 3D ResNet-GloRe (Feng et al., 2022), along with multi-task networks. Besides, Muñoz-Benavent et al., 2018 demonstrated that biomass data may be a basis for estimating feeding dispensing quantity. In this study, a non-invasive automatic feeder which works stereoscopic vision system and a deformable model for estimating the fish length were used. The required amount of the feed is dispensed based on the magnitude of the biomass data. Fig. 4 depicts the insight into the state of the art on

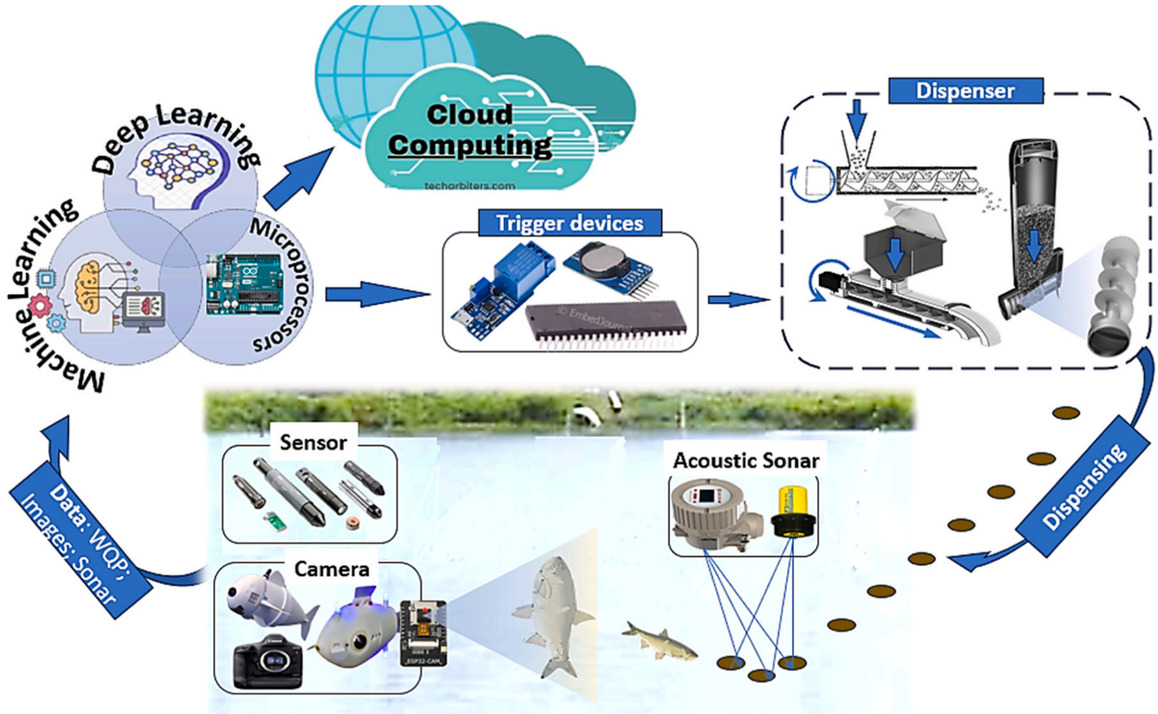

Fig. 4. Schematic Diagram of IoT-Based Technology for Aquaculture Feeding Operations.

IoT-based feeding systems for fish culturing. This figure shows that integrating IoT, AI, computer vision, and deep learning is revolutionizing fish-feeding operations. It provides cost-effective, non-invasive, and highly accurate solutions for monitoring and optimizing feeding activities. These advancements hold great promise for improving aquaculture practices.

One main limitation of deep learning technology (such as CNN) in fish feeding systems and biomass estimation is its heavy reliance on extensive labeled data for training (Yang et al., 2021b; Saleh et al., 2022b). Deep learning models require large and diverse datasets to learn and generalize effectively (Sarker, 2021). In the case of fish behaviour recognition and biomass estimation, acquiring such comprehensive labeled datasets can be challenging and time-consuming. Additionally, annotating data for complex behaviours and precise biomass estimation can be labour-intensive and costly (Abinaya et al., 2022). This limitation can hinder the practical application and scalability of deep learning-based approaches in the fish farming industry.

3.1.3. *Fish health monitoring*

Traditional disease detection requires farmers to constantly monitor fish stocks to identify outbreaks and prevent disease spread, potentially avoiding significant losses (Subasinghe et al., 2023). In traditional health management approaches for aquatic ecosystems, several strategies are typically employed. These strategies encompass water replacement, aeration to enhance dissolved oxygen levels, isolation of infected species, and the administration of manual medications (Bohara et al., 2023; Rigos et al., 2023). It's worth noting that the method of manual medication application can vary depending on the specific administration procedure. For example, when applying manual vaccination through the mouth, direct contact is required (Mutoloki et al., 2015). However, this direct contact can lead to increased stress in the fish and potentially result in mortality. Besides the challenge of manual medication application, another significant limitation of traditional health management lies in the prompt diagnosis of diseases. This untimeliness limitation hampers the ability to swiftly identify and address health issues in aquatic environments (Opiyo et al., 2018).

Conversely, IoT-based disease detection systems provide farmers with timely notifications. This eliminate the need for continuous manual surveillance of the fish farm (Agossou et al., 2021). Thus, improves farmers' work-life balance and allows integration with automated treatment systems. It streamlines comprehensive disease management on the fish farm. Effective fish husbandry plays a pivotal role in ensuring the success of aquaculture enterprises. A successful aquaculture operation depends on maintaining healthy fish stocks with minimal mortality and a favorable food-conversion ratio (FCR). It also requires addressing eutrophication issues and optimizing productivity (Philis et al., 2019). Research shows that compromised fish health often indicates disease, leading to higher mortality rates and shorter lifespans among fish populations. While experienced fish keepers can sometimes visually identify diseases, this method lacks absolute accuracy (Huq et al., 2012).

It is crucial to emphasize that early detection of ill-health in fish serves a dual purpose. Firstly, it minimizes further harm to afflicted fish. Secondly, it also prevents the potential transmission of diseases to healthy individuals (Darapaneni et al., 2022). It is well-documented that many instances of fish diseases stem from fluctuations in water parameters, including DO, salinity, ammonia levels, pH, and temperature. Such variations may arise from improper feeding practices (under or overfeeding). The absence of aquatic plants, inappropriate species combinations, and incorrect stocking densities are other possible factors. Therefore, continuously monitoring and controlling water parameters within the recommended threshold limit in real-time is critical (Fazio, 2019). This proactive approach is essential for averting or mitigating the severity of diseases that can afflict fish populations.

3.1.3.1. *Factors impacting fish health.*

Opiyo et al., 2018 studied factors affecting fish health, identifying pathogens like bacteria, fungi, and viruses, as well as unfavorable environmental conditions such as poor water quality. The study indicated that bacterial infections in fish typically result from parasitic infestations, physical injuries, or abrasions. However, they can also emerge due to prolonged exposure to suboptimal WQP and improper feeding practices. These infections manifest as symptoms such as ulcerations or sores. Fungal infections, on the other hand, often appear as white cottony growths on the external surfaces of fish. However, they can also affect internal tissues. Causes of fungal infections encompass poor water quality, contaminated food, and open wounds, among other factors (Ziarati et al., 2022). Viruses are microscopic pathogens that infiltrate fish cells and replicate within them. Visual diagnosis of these potential pathogens is often inaccurate due to human limitation such as misdiagnosis, thus compromising overall fish health (Hernández-Cabanyero and Amaro, 2020).

In 2019, over 50 % of fish production loss was recorded in Malaysia due to diseases and associated improper practices (Dewi et al., 2022). Thus, an annual loss of revenues that year reached up to 6 billion US dollars. Similarly, in Chile, infectious salmon anaemia alone costs 2 billion US dollars and causes 20000 workers to lose their jobs (Assefa and Abunna, 2018a). China is one of the leading countries in aquaculture production but between the years 2010–2020, a 15 % a loss was recorded due to diseases (Hu et al., 2021b; Li et al., 2011). Therefore, the imperative for a dependable, more precise and timely fish health monitoring system becomes undeniable. Such a system is crucial to ensure the well-being and productivity of fish populations (Grandgirard et al., 2002).

3.1.3.2. Intervention of IoT-Based Fish Health Monitoring System. The adoption of IoT-based and AI systems for comprehensive health management in aquaculture has not been widely explored. This is evident from the limited number of reported studies.literature indicated that IoT devices can effectively support continuous monitoring of fish health, enabling early disease detection and reducing mortality (Mahamuni and Goud, 2023; Xiao et al., 2020). For instance, Clawson et al., 2022 reported that using IoT devices for real-time mapping of aquatic life is an efficient approach for rapid early diagnosis of infections. Fish diseases often manifest as skin colour changes and unusual movement patterns. These making it challenging for traditional fish management to provide real-time notifications (Cermakova et al., 2023). This stresses the need for IoT and deep learning systems for automated fish detection and health monitoring, involving real-time video streaming or aquatic ecosystem imaging (Liu et al., 2023). The integrated IoT-advanced Deep Learning techniques, (such as CNNs) system extracts the image features through a segmentation and classification process (Taha et al., 2022). Achieving this demands models capable of extensive preprocessing, post-processing, and optimization.

Example, Ranaweera et al., 2022 introduced AquaScanner, a multifaceted system that combines image processing and IoT technology for fish disease detection and prevention. This innovative IoT-based system incorporates CNN which assists in detecting fish diseases and then provides essential information and medication recommendations. Besides, the system continuously monitors and regulates the feed dispenser. It also tracks key water quality parameters, such as ammonia levels, to ensure a safe environment for various fish species. An AquaScanner mobile app allows remote control and real-time monitoring capabilities for both fish health and water quality. Khai et al., 2022 developed a CNN model that successfully detected two fish diseases, white spot and red spot, with 94.44 % accuracy. A multi-step procedure for classifying tuna fish was developed by integrating image processing with Mask R-CNN and ResNet50V2. This approach achieved a classification accuracy of 70 % (Lekunberri et al., 2022). Lu et al., 2020 developed an innovative IoT-driven fish disease detection system using image analysis. This system harnesses machine learning methods to process captured images for disease identification. The image processing algorithms executed preliminary noise through preprocessing and segmentation techniques. The Support Vector Machine (SVM) algorithm, combined with kernel functions, was used to classify and characterize various fish illnesses effectively In 2021, Ubina et al., 2021c introduced an advanced IoT-AI system designed for monitoring fish well-being and various aquaculture activities, including feeding and water quality. This innovative system is constituted of IoT sensors, devices, AI algorithms, and cloud computing technology. the embedded sensors and actuators within sorting machines are designed to gather and transmit data regarding key health indicators of the fish. These indicators encompass metrics like swimming speed, movement patterns, and feeding behaviour. The collected data is seamlessly transferred to the cloud through wireless communication networks, enabling real-time and remote monitoring. This data is then analyzed to provide concise insights into the fish's overall health, mortality rates, and potential disease occurrences. More so, Agossou et al., 2021 used image processing and machine learning to accurately identify salmon diseases, boosting disease prevention and food security. A review paper highlighted that integrating PLC (Programmable Logic Controller) and ICT can address power failures and streamline fish farm monitoring and management (Basnet and Bang, 2018). This technology enhances disease detection which works based on water quality parameters, and overall aquaculture management.

Furthermore, Darapaneni et al., 2022 employ an underwater ESP32 camera equipped with illumination to capture images at predetermined intervals. The captured images are then processed and classified through the Azure Cognitive Cloud platform. This procedure enables real-time health predictions for aquatic life and identifies appropriate treatments when readings exceed thresholds. Furthermore, Patel et al., 2022 reported that an underwater camera can captures images at regular intervals, encrypting the data. These images are then processed and classified using Azure Cognitive Cloud to provide real-time health information and recommend treatment measures.

Based on the available literature, Fig. 5 highlights various methods researchers have used to diagnose fish health in real-time with IoT-based technology. In this figure, health diagnosis can be achieved through algorithmic analysis of input data or pre-processed WQ and EC data. Additionally, deep learning models like CNN, LSTM, AANet, or machine learning algorithms such as logistic regression and K-Mean can be employed. Regardless of the technique chosen, they all require initial input data or signals. The data can be captured through sensors, cameras, or direct actuation via potentiometers or a combination of these methods (Darapaneni et al., 2022). In the case of the integrated WQP + EC diagnosis, microcontrollers are used for pre-analysis before the algorithmic processes (Hou et al., 2023). The processed results then form the basis for the next step which depends on the specific tasks of the system. The specific task may include WQP monitoring and control, data processing and intelligent control. The later tasks often require algorithms for efficient segmentation, classification, and decision-making, as reported earlier. The output of the algorithms entails recommended actions or tasks to be taken in order to arrest the detected health-related issue (Li et al., 2022). Thus, establishing the basis for actuating or recommending operations such as aeration, water recycling, vaccination, or quarantine of infected fish (Bentzon-Tilia et al., 2016; Mahamuni and Goud, 2023; Assefa and Abunna, 2018b).

The operational pattern of the integrated IoT deep learning technique is similar to the WQP+EC method. However, the key difference lies in the algorithms and input data used (Mukonza and Chiang, 2023). Deep learning systems, (such as F-CNN, R-CNN, ANN, and LSTM), use camera detection to capture images of fish and monitor their movements periodically. These algorithms then compute biomass and classify health information based on the dataset (Muñoz-Benavent et al., 2022). The IoT-Machine Learning approach relies on models or algorithms trained with datasets. It often incorporates motion detection data and images for analysis (Mahdavinejad et al., 2018). All of this data is synergistically analysed to predict health-related information and measures. Fig. 5 shows that the predicted health status of the fish can be accessed through user interaction platforms. These platforms are developed using apps such as Virtuino, Blynk, and ThingSpeak (Papanikolaou et al., 2022).

3.2. User Interaction Platform

Fig. 6 presents a detailed schematic representation of the IoT-based user interaction platform for aquaculture management. Establishing a

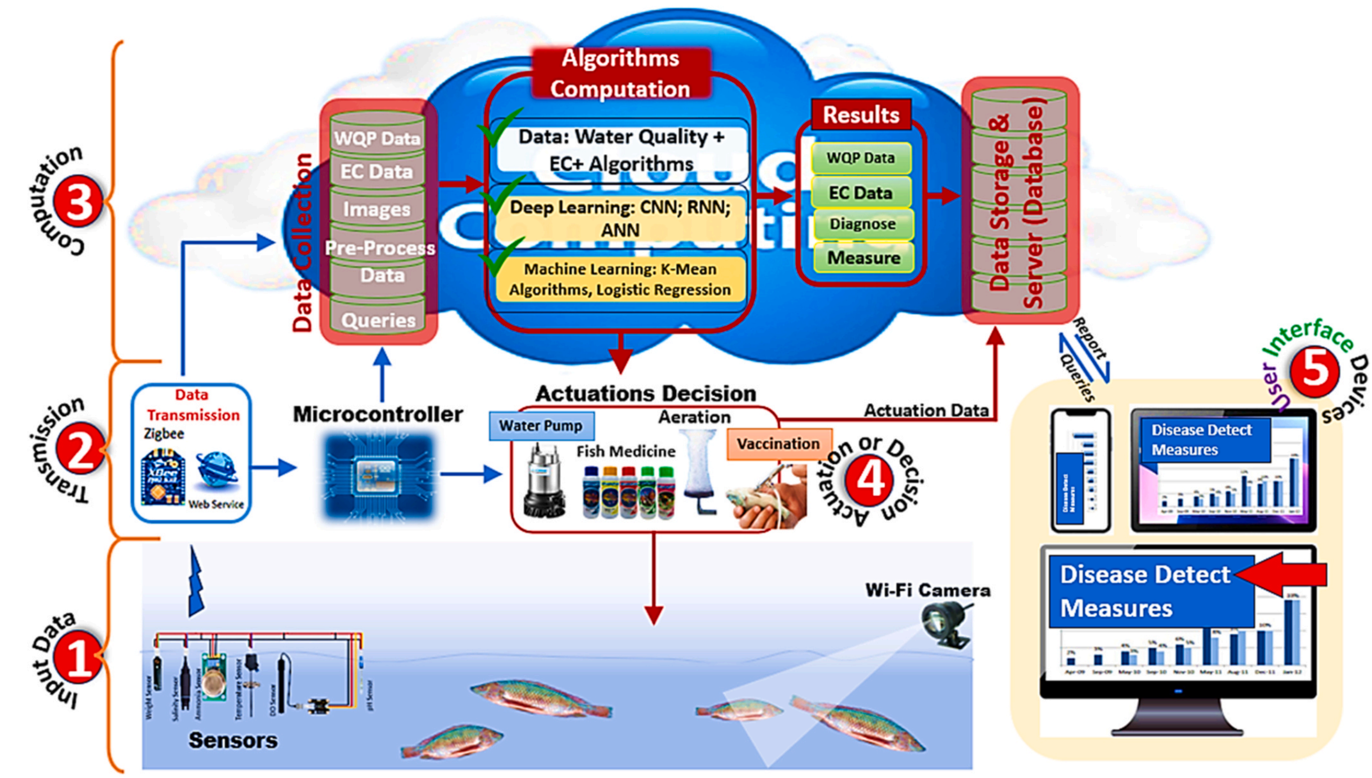

Fig. 5. Schematic Diagram of IoT-Based Technology for Health and Disease Monitoring.

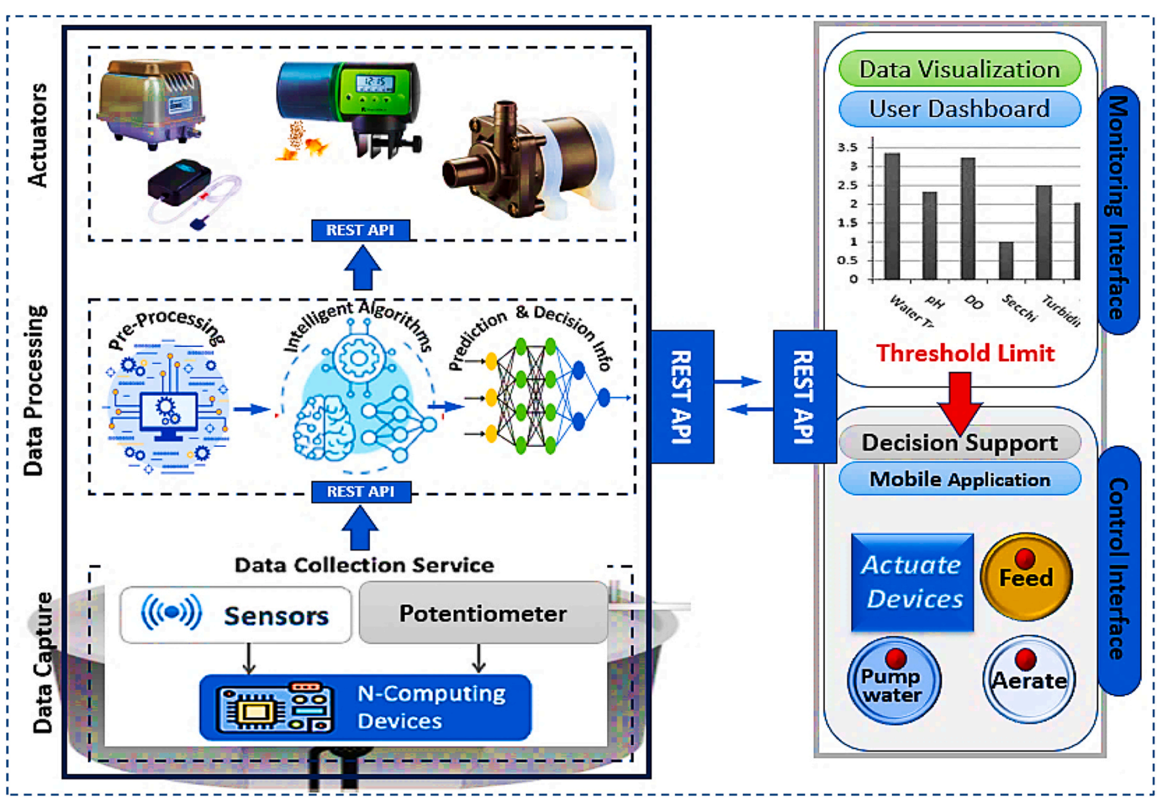

Fig. 6. Schematic Diagram of the Remote Platform.

user-friendly interaction platform is as crucial as the aquaculture IoT system itself. This platform facilitates seamless data and signal exchanges among interconnected devices and sensors. It enables comprehensive real-time management of aquaculture activities, including water quality, feeding, disease detection, and environmental monitoring (Sanya et al., 2022; Lin et al., 2021). Key components of this system are sensors, actuators, and data processing and analytics. It also includes communication and connectivity, control and automation, and a remote user interface with decision support tools Data capturing, processing, actuators, and user application components communicate securely using encrypted REST API keys (Lin et al., 2021). A REST API defines protocols for how sensors, devices, and applications connect and interact with each other (Adu-Manu et al., 2017).

The remote user interface allows farmers to monitor real-time data, gain insights, and make informed decisions. This optimizes resource allocation and ensures the sustainability of aquaculture operations (Ranaweera et al., 2022). The most commonly used interface apps include iOS (Drenoyanis et al., 2019; Nie et al., 2020), Blynk (Kassim et al., 2021; Shahiran and Salimin, 2021; D.K. V et al., 2023), Thing-Speak (Mahamuni and Goud, 2023; Lin et al., 2021), and Cayenne IoT Project Builder (Silalahi et al., 2023). These platforms can serve as a foundation for developing mobile applications tailored to IoT-based aquaculture water quality monitoring and control systems.

This approach enhances overall efficiency, productivity, and sustainability. It promotes responsible management of aquatic resources and supports the growth of the aquaculture industry. In addition, the Integration of 4 G and 5 G technologies improves connectivity capacity, making IoT applications more viable (Wang et al., 2021a; Pons et al., 2023; Taha et al., 2022). The convergence of AI-IoT and 5 G underscores the importance of early warnings and remote monitoring through autonomous wireless sensing systems (Pons et al., 2023).

3.2.1. Remote monitoring interface

In aquaculture, parameter-monitoring systems use IoT and microcontrollers. The collected data is transmitted to web-based platforms for real-time visualization on graphical user interfaces (GUI) (Simbeye et al., 2014; Malla et al., 2023). Taha et al., 2022 recently reported on the development of an iOS app. This app enables continuous real-time monitoring of aquatic conditions using sensor and microcontroller data. This GUI significantly consolidates the shift toward a more reliable interacting platform that ensures real-time information accessibility. The iOS allows both web interfaces and mobile applications. Additionally, a remote monitoring system was developed combining IoT and CNN for greenhouse environments. This system provides real-time anomaly alerts through an Android mobile application using an A6 GSM module (Castañeda-Miranda and Castaño-Meneses, 2020). Continuous monitoring of these parameters aims to create a healthier environment for fish and plants. It also significantly reduces water consumption compared to traditional farming methods.

3.2.2. Remote Control Interface

Remote control pertains to the capability of sending signals to operators, allowing them to interact with and alter environmental parameters. This potential spans beyond mere monitoring, extending to control systems and actuator management. Alselek et al., 2022 integrated an Intelligent Voice Control System (IVCS) with a signal alerting system and IoT technology to monitor and regulate aqua parameters. This implies that remote monitoring and control use various communication technologies (e.g., WSN, Zigbee) and microcontrollers (e.g., Arduino, Raspberry Pi). These components facilitate data processing and communication among connected devices. These systems use various protocols and platforms for real-time operations. They enable farmers to manage actuators and receive alerts when measurements fall outside specified ranges (Nie et al., 2020; Mohanty and Pindoo, 2023). These systems utilize a range of technologies, from traditional methods to advanced techniques like CNN for complex predictions (Wai et al., 2022). A cloud data storage system facilitated the collection, storage, and analysis of information. This setup enabled trend analysis and automated decision-making for efficient aquaponic management.

3.3. Critical deductions

3.3.1. Deduced Drawbacks: IoT in aquaculture

the adoption of the IoT in aquaculture holds immense promise, it is not devoid challenges and drawbacks. The analysis of existing literature revealed certain limitations, with key aspects that require further exploration. Therefore, more research is needed to provide operators and practitioners with a comprehensive understanding of IoT's diverse impacts on aquaculture practices. As aquaculture operations scales-up, reliance on more efficient and less physical human involvement becomes imperative (Vo et al., 2021).

Table 4 presents the summary of the limitations deduced from the existing literature. Developing aquaculture monitoring and control systems that exhibit a high degree of adaptability is crucial. The complex interactions between parameters, such as how water temperature changes affect DO and pH, often make prediction and understanding challenging. Consequently, a flexible control system is required to monitor and regulate a wide range of actuators and sensors. Integrating robust control systems such as Supervisory Control and Data Acquisition (SCADA) along with Programmable Logic Controls (PLC) with IoT technologies improve decision-making. This combination fosters advancements in the industry by enhancing monitoring and control capabilities (Drenoyanis et al., 2019; Nie et al., 2020). PLC systems demonstrate considerable flexibility when dealing with varied combinations of actuators (e.g., water recycling pumps, air aerators etc.) and sensors. The machine-learning-based algorithms are already widely used for real-time information processing, they are bound by certain operational limitations.

Many approaches are predominantly trained in a supervised manner based on static data (Graham et al., 2022; Conrady et al., 2022). This implies that the model must have been exposed to representative data from all growth stages accessible within the culturing system (Ubina et al., 2021a; Conrady et al., 2022). Implementing more dynamic approaches would allow for more effective adaptation to the organisms' development. This includes exploring reinforcement learning, active learning, and edge computing. These approaches aim to integrate algorithm retraining directly on microcontrollers This highlights that IoT, AI, computer vision, and deep learning in aquaculture need extensive labeled and annotated data. This is essential for effective implementation and analysis (Ubina et al., 2021a; Chang et al., 2022; Conrady et al., 2022). To tackle these, strategies like data augmentation, semi-supervised learning, and automated annotation tools can be implemented (Zhou et al., 2019). Additionally, collaborative data-sharing initiatives and crowd-sourcing can help in acquiring comprehensive labeled datasets for accurate fish biomass estimation. Using transfer learning and improving data preprocessing can mitigate the need for large datasets, enhancing the effectiveness of deep learning models. Addressing these challenges will help the aquaculture sector fully leverage these technologies, optimizing fish feeding and biomass estimation for more sustainable practices (Rastegari et al., 2023).

3.3.2. Deduced Limitations and Future Perspective

The literature highlights that while IoT technology has advanced in aquaculture, further research and development are still crucial. The rapid evolution of IoT, Machine Learning, and AI integration makes ongoing review essential to enhance system operability. This is essential for critically assessing the merits, drawbacks, limitations, and areas needing further improvement in this dynamic landscape. Therefore, fostering collaboration among researchers, industry specialists, and technology innovators becomes vital for propelling the field forward. Resilient data fusion techniques and refined monitoring systems, including clearer image capture, are crucial for the aquaculture sector. Developing advanced technologies for optimal feed application, water monitoring, and disease detection is also essential for progress Fig. 7 encapsulates the future outlook and advances of IoT technology in aquaculture, and is elucidated as follows:

Table 4
Identified Limitations in IoT Aquaculture and Recommended Solutions.

SN	Operation	Limitation	Deduced Suggestions	References
1	WQ; Feeding; Health	Complex parameter interactions hinder prediction accuracy (Drenoyanis et al., 2019) and comprehension.	Develop adaptive control systems that can monitor and regulate a diverse range of actuators and sensors in aquaculture. Implement SCADA and PLC systems along with IoT technologies for enhanced decision-making.	(Drenoyanis et al., 2019; Nie et al., 2020; Guo et al., 2022)
2	WQ; Feeding; Health	Machine learning algorithms are often trained in a supervised manner using static data. E.g., existing images	Explore dynamic approaches for machine learning algorithms to adapt to the organisms' development stage using integrated reinforcement learning and edge computing.	(Ubina et al., 2021a; Graham et al., 2022)
3	WQ; Feeding	Systems lack adaptability to organism growth stages.	Implement adaptive monitoring systems that can adjust and recalibrate in response to the changing requirements of the system.	(Silalahi et al., 2023; Tejaswini et al., 2022; Yeoh et al., 2010)
4	Feeding; health	Inadequate real-time adaptation of algorithms on microcontrollers limits the responsiveness of the system.	Introduce edge computing capabilities to facilitate real-time adaptation of algorithms on microcontrollers. Utilize edge computing resources for on-site data processing and decision-making to enhance the system's responsiveness.	(Ghosh et al., 2018; O'Donncha and Grant, 2020)
5	Feeding	Most commonly used feeders work based on a fixed schedule, which may not dispense adequate feed required	Implement an IoT-based auto-feeder with multi-sensor technology and SCADA for real-time monitoring, in conjunction with predictive algorithms for anticipating changes in fish appetites using data captured by the dynamic sensor	(Riansyah et al., 2020; Karimanzira and Rauschenbach, 2019)
6	WQ; Feeding; Health	Sensor reliability is compromised by susceptibility to corrosion.	Enhance sensor durability with corrosion-resistant materials and regular maintenance.	(Reddy et al., 2021; Maraveas and Bartzanas, 2021; Luan et al., 2020)
7	WQ; Feeding	Need for an advanced time-based feeding system and also improve limits precision of the existing AI feeder	A multifaceted data analysis system is encouraged. These involve employing advanced sensor technologies with self-diagnostic capabilities, and deployment of demand-based systems using multi-sensor fusion for precise feed dispensing. Integrate machine learning for adaptive feeding based on fish behaviour. Analyze real-time data to adjust feeding quantities and schedules.	(Føre et al., 2011; Gavrilescu et al., 2015)
8	WQ; Feeding; Health	Depth limitations affecting wave transmission and system reliability.	- Utilize high-frequency acoustic sensor systems to improve performance and transmission range. - Implement multiple acoustic sonar systems to complement signal transmission over longer distances.	(Hamdan et al., 2020; de Lima et al., 2020)
9	Feeding; health	Low monochrome and blurred imaging affect data processing accuracy.	- Integrate camera systems with acoustic technologies to enhance feeding efficacy and data processing. - Explore advanced imaging-sonar techniques like split-beam sonar imaging and dual-frequency identification sonar for improved feeding behaviour detection.	(Terayama et al., 2019; Baseca et al., 2019)
10	Feeding; health	Increased costs associated with integrating additional acoustic systems.	- Optimize costs by developing cost-effective and efficient acoustic systems suitable for commercial-scale applications. - Incorporate intelligent technology to enhance the operability of IoT systems for aquaculture management.	(Sung et al., 2023; Akhter et al., 2021b)
11	WQ; Feeding; Health	Corrosion of sensors leads to distorted data capture and feeding operation.	Implement robust corrosion-resistant materials for sensor longevity and data accuracy. - Develop regular maintenance protocols for sensor cleaning and upkeep to ensure reliable data capture	(Reddy et al., 2021)
12	Feeding; Health	Reliance on extensive labeled data for deep learning models.	- Develop strategies for efficient and cost-effective acquisition of diverse labeled datasets for training deep learning models. - Implement data augmentation techniques to expand the labeled dataset	(Ubina et al., 2021a; Jimeno-Sáez et al., 2020)
13	Feeding; Health	costly data annotation for complex fish behaviours.	- Explore semi-supervised and active learning methods to reduce the labour intensity of data annotation. - Develop automated annotation tools for precise and efficient labeling of complex behaviours.	(Jan et al., 2021; Hassan et al., 2016)
14	WQ; Feeding; Health	Challenging acquisition of comprehensive labeled datasets for fish biomass estimation.	- Establish collaborative data-sharing platforms among aquaculture research institutions to build comprehensive datasets. - Utilize crowd-sourcing and data-sharing initiatives to create diverse and extensive datasets for accurate biomass estimation	(Wu et al., 2022)
15	Feeding; Health	Heavy reliance on large and diverse datasets for effective generalization in deep learning models.	- Employ transfer learning techniques to leverage pre-trained models and optimize the utilization of available data. - Enhance data preprocessing methods to ensure efficient data utilization in training deep learning models.	(Anwar and Li, 2020)
16	Health	Limited health-related dataset and focus on IoT-based and AI systems for comprehensive health management in aquaculture.	Emphasize collaborative data sharing and crowd-sourcing for acquiring labeled datasets.	(Taha et al., 2022; Nasir and Mumtazah, 2020)
17	Feeding; Health	Requirement for extensive preprocessing, post-processing, and optimization in integrated IoT-advanced Deep Learning.	– Implement strategies such as data augmentation and semi-supervised learning to address the challenges related to labeled data and its annotation. – Utilize transfer learning techniques and refine data preprocessing methods to enhance the generalization in deep learning models. – Develop user interfaces using platforms like Virtuino, Blynk, and ThingSpeak to facilitate easy access to the predicted fish health status and recommendations.	(Yoerger et al., 2021)

i. **Promote Aquaculture Ecosystem Monitoring (AEM):** This necessitates the development of IoT-driven systems that seamlessly integrate corrosion-resistant sensor networks, real-time data analytics, and AI-driven decision-making algorithms (Reddy et al., 2021). These systems should monitor various parameters, including water quality, environmental conditions, fish feeding behavior, and disease detection. This ensures a comprehensive approach to aquaculture management (Fig. 7). Utilizing highly sensitive and durable sensors, along with IoT measuring meters, is crucial for accurate data collection in

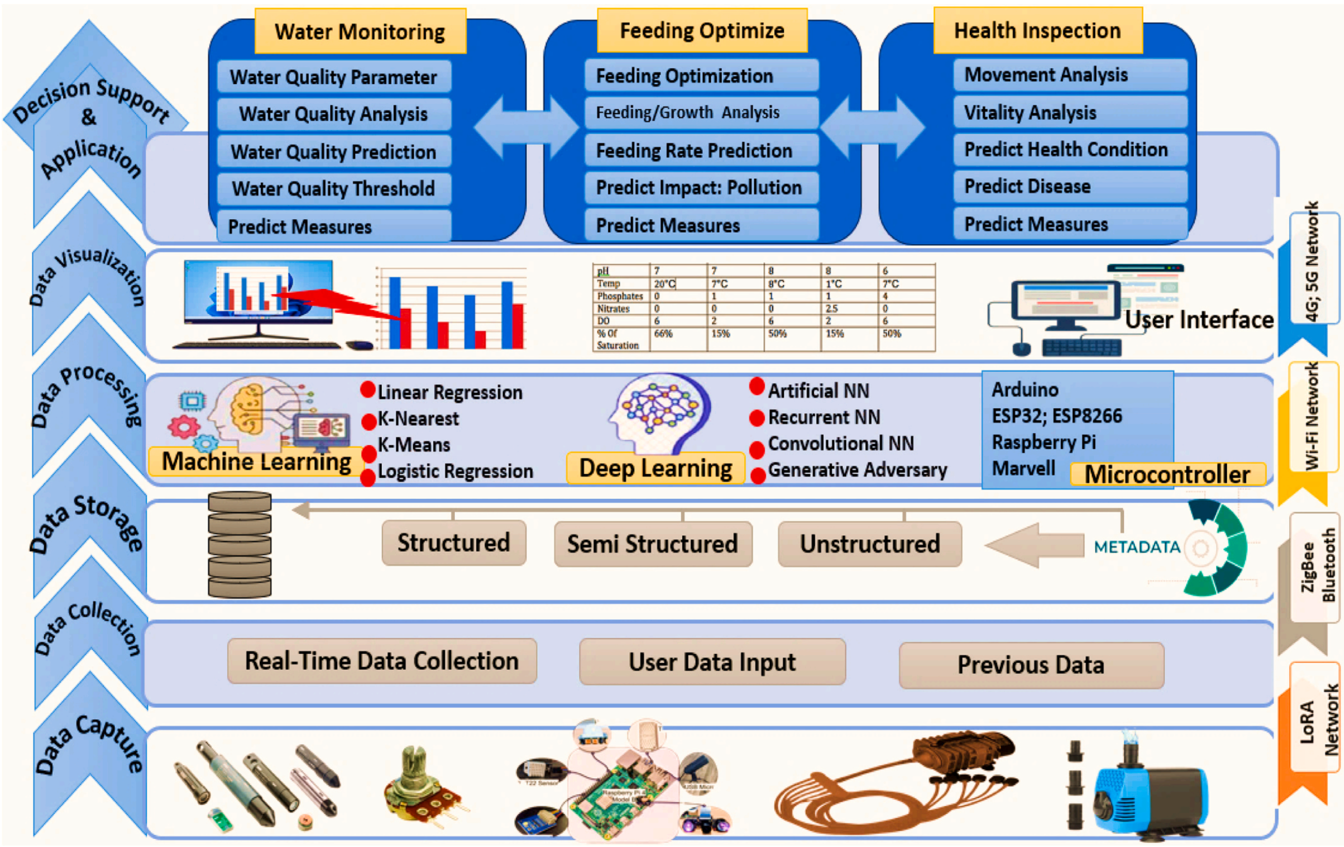

Fig. 7. Integrated IoT System for Enhanced and Intelligent Aquaculture.

diverse aquatic environments. This is essential for establishing a robust Aquaculture Environmental Monitoring (AEM) system (Reddy et al., 2021; Maraveas and Bartzanas, 2021; Luan et al., 2020). Efficient use of data collection devices requires integrating data processing techniques. This ensures reliable and timely information for effective decision-making in aquaculture management (Nie et al., 2020; Guo et al., 2022). This underscores the necessity of exploring compatible advanced data analytics, predictive models, and automation in aquaculture processes. It is essential to accentuate the integration of AI-driven algorithms to regulate water quality parameters, and optimize feeding schedules as well (Drenoyanis et al., 2019; Nie et al., 2020; Guo et al., 2022).

ii. **Enhancing Feeding Efficiency and Waste Management (FEWM)**: The literature review highlights significant advancements in feeding operations. However, further exploration of advanced strategies, such as precision and smart feeding technologies, is essential to minimize feed wastage. Investigating real-time monitoring systems and automated feeders is crucial. This may require robust algorithms to accurately identify appetite patterns (Fig. 7). Moreover, considering the continuous egestion activities of fish directly into the surrounding water, efficient and intelligent wastewater management is imperative. This approach enhances fish welfare and boosts overall productivity. Researchers agree that excessive food wastage in aquaculture leads to pollution and disease among aquatic organisms (Terayama et al., 2019; Baseca et al., 2019). To address this challenge, advanced strategies and technologies are essential. Emphasizing information fusion techniques can effectively tackle feed wastage issues (Fig. 7) (Ghosh et al., 2018; Riansyah et al., 2020; O'Donncha and Grant, 2020; Karimanzira and Rauschenbach, 2019).

iii. **Health Management and Disease Detection (HMDD)**: Despite the critical role of the IoT, the health aspect of aquaculture management remains relatively underexplored. There is a pressing need to stimulate further research on the smart detection of fish diseases and health status. Advancing the development of integrated IoT-based systems for fish health management and disease detection is imperative. This recommendation involves using computer vision, image processing, and machine learning algorithms to detect subtle changes in fish behavior, feeding patterns, and physical characteristics (Taha et al., 2022; Nasir and Mumtazah, 2020; Yoerger et al., 2021) (Fig. 7). This approach facilitates early disease detection and timely intervention measures, thereby reducing mortality rates, enhancing growth rates, and bolstering overall productivity.

4. Conclusion

This paper present a comprehensive overview of IoT technology in fish cultivation, highlighting its benefits and limitations. Our analysis from 2000 to 2023 shows a need for an integrated IoT system in aquaculture. This system should offer comprehensive data and a holistic approach, rather than focusing on isolated operational insights A fundamental IoT setup involves securing compatible devices such as sensors and actuators and designing circuits. It also includes selecting appropriate gateways, encrypting instructions, coding models and algorithms, and creating a user-friendly interface. Our initial cross-study analysis of aquaculture water quality (WQ) monitoring shows that IoT has effectively tackled the challenge of timely WQ management and control. Currently, IoT-based WQ monitoring heavily relies on sensors for primary data capture, followed by subsequent processing based on a predefined architecture. Data processing can be accomplished through edge computing using microcontrollers or computers, while cloud computation is recommended for remote purposes. In terms of feeding, various methods have been explored, including timed feeding schedules, integration of multiple sensors, and hybrid IoT-sensor-AI.

However, timed feeding falls short of accommodating the dynamic changes in fish biomass and the required amount of feed. the susceptibility of multiple sensors to corrosion often hinders the accurate estimation of the feeding schedule and quantity. This justifies the implementation of the hybrid IoT-sensors-AI feeder, which incorporates intelligent algorithms or models (e.g., CNN, LSTM, AANet, ANN). The algorithms analyzes the dynamic feeding requirements and dispensation timing.The main limitation is the reliance on an initial training dataset for decision-making. This may be unreliable due to the dynamic nature of fish cultivation. For health management, researchers use hybrid IoT-sensor-AI systems for disease detection and prediction. These systems rely on real-time environmental conditions captured by multiple sensors. Health diagnosis based on integrated sensors and deep learning predictive models (such as R-CNN and AANet) has shown promise, particularly through the analysis of fish colour and movement speed. Overall, IoT-based technology has had a positive impact on aquaculture by facilitating real-time management. Improvements are needed in enhancing sensor resistance to corrosion and integrating data fusion for better decision-making. Additionally, expanding IoT-based ichthyology to cover a broader range of fish diseases is essential. An integrated IoT-based sensor resistant to corrosion, combined with AI algorithms for processing complex data, could effectively address these challenges and advance aquaculture.

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CRediT authorship contribution statement

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Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used Grammarly in order to improve the English Language. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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.

Data availability

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

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