Intelligent fish farm—the future of aquaculture

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Abstract

With the continuous expansion of aquaculture scale and density, contemporary aquaculture methods have been forced to overproduce resulting in the accelerated imbalance rate of water environment, the frequent occurrence of fish diseases, and the decline of aquatic product quality. Moreover, due to the fact that the average age profile of agricultural workers in many parts of the world are on the higher side, fishery production will face the dilemma of shortage of labor, and aquaculture methods are in urgent need of change. Modern information technology has gradually penetrated into various fields of agriculture, and the concept of intelligent fish farm has also begun to take shape. The intelligent fish farm tries to deal with the precise work of increasing oxygen, optimizing feeding, reducing disease incidences, and accurately harvesting through the idea of "replacing human with machine," so as to liberate the manpower completely and realize the green and sustainable aquaculture. This paper reviews the application of fishery intelligent equipment, IoT, edge computing, 5G, and artificial intelligence algorithms in modern aquaculture, and analyzes the existing problems and future development prospects. Meanwhile, based on different business requirements, the design frameworks for key functional modules in the construction of intelligent fish farm are proposed.

Keywords Artificial intelligence · Internet of Things · Intelligent equipment · Machine vision · Unmanned boat

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Introduction

Fishery products play a central role in food security and nutrition strategies at all levels. It is estimated that the global fish production in 2018 was about 179 million tons, of which 82 million tons came from aquaculture. From 1961 to 2017, the average annual growth rate of global consumption of fish for food was 3.1%, which was almost twice the average annual growth rate of the world population during the same period, the rate was also higher than that of other animal protein foods (meat, dairy products, milk, etc.) with an annual growth rate of 2.1% (FAO 2020). Fish will have great potential to become an important substitute for livestock and poultry protein. The key reason for this is better quality cheap protein present in fish (Gopalakrishnan et al. 2017), and there are no epidemic problems such as avian influenza in aquaculture. Due to the impact of restrictions on travel and entry-exit caused by COVID-19, fisheries in the world have encountered difficulties in securing migrant labor. Furthermore, the agricultural labor force engaged in fishery production is gradually entering the aging stage, and labor shortage makes it difficult to guarantee the normal supply of global aquatic products. Over fishing, backward aquaculture method, human activities, industrial pollution and other reasons make the aquaculture water quality worse (Sarma et al. 2013; Peters and Meybeck 2000), aquatic ecosystems is damaged, and aquatic products diseases occur frequently. Several major aquaculture production areas in the world are facing the problems of tightening domestic environmental protection policies and aggravating aquatic biological diseases (Vatsos and Angelidis 2017). Meanwhile, the suitable aquaculture zones will be reduced year by year, and the profit income per unit area is declining. The scientific and technological innovation and engineering technical support of the whole fishery industry chain are insufficient. There is a lack of basic research and basic theory related to biological environment interaction and engineering process integration. The development of aquaculture engineering, mechanization and information technology and equipment construction are seriously lagging behind. Some breeding enterprises in underdeveloped areas are restricted by breeding technology and environmental conditions, breeding germplasm is degraded, enterprises lack good varieties, and aquatic products are of low quality (Brugère et al. 2019). Besides, the use of various antibiotics, hormones and high-residue chemical drugs in aquaculture production is no longer an individual phenomenon (Mateo-Sagasta et al. 2017), and irregular and unscientific use of drugs has made the problem of drug residues in aquatic products become the focus of attention.

Aquaculture is facing huge challenges, but there is also a bigger opportunity. Ecological, facility, industrial, and intelligent are the future development directions of aquaculture (Francesca et al. 2020; Martin et al. 2018). In order to improve Norway's salmon production and ensure high standards of quality, ABB as a global leader in automation technology is building the first new concept offshore submersible fish farm in the Arctic Ocean (ABB 2019). The fish pens will be remotely controlled by a feed barge. Environmental data including meteorological conditions, ocean current, dissolved oxygen (DO), water temperature, pH value of different water layers, and net cage biomass are collected by automatic equipment and uploaded to ABB Ability™ using wireless communication. The ballast water system in fish pens can resist fierce weather and wave conditions. The whole industrial electrical system has high robustness, but it is not involved in the task of fish behavior analysis, intelligent feeding and adult fish harvesting. Some organizations have begun to build various types of intelligent fish farm. ARTIFEX project attempts to carry out inspection, maintenance and repair operations at sea-based fish farms through

the cooperation between unmanned ship, unmanned aerial vehicle and remotely controlled underwater robot (Artifex 2018). In addition to being used as a take-off and landing platform for aerial drones, the unmanned ship can also be used as a base station for underwater robots. The unmanned aerial vehicle is responsible for checking the integrity of surface facilities and monitoring the feeding process of fish. The underwater robot should not only complete the underwater inspection task, but also clean and repair the fishing net. These intelligent equipment will provide technical support for the rapid deployment of intelligent fish farm. The key technologies of the above projects include the hardware design of unmanned ship, aircraft and underwater vehicle and the software development of autonomous control system. The difficulty of these projects is that these advanced technologies should work together accurately. As an advanced stage of aquaculture development, intelligent fish farm will apply intelligent machines to replace manual labor and optimize the deployment of fishery resources in a data-driven way to achieve efficient, green and smart aquaculture.

This paper introduces the latest integrated application of edge computing and 5G technology in the construction of intelligent fish farm, and puts forward the architecture of intelligent fish farm ecosystem for the first time. Then, according to the hardware configuration of the system, the key intelligent equipment of the intelligent fish farm is listed, and its technical characteristics are analyzed. Aiming at the top-level design of intelligent fish farm, the latest research status at home and abroad is summarized from the aspects of water quality early warning and control, intelligent feeding, fish behavior monitoring, biomass estimation, fish disease diagnosis and equipment fault diagnosis, and the design scheme of relevant business modules of intelligent fish farm is proposed. Finally, this paper summarizes the challenges and research hotspots in the development of intelligent fish farm, and tries to provide aquaculture professionals with the latest, complete and referential ideas about future fishery construction.

Definition and system framework of intelligent fish farm

The authors believe that the intelligent fish farm is an all-weather, full-process and full-space automated production mode, that is, in the case of workers not entering the fish farm, the new generation of information technology such as IoT, big data, artificial intelligence (AI), 5G, cloud computing and robots are used for remote measurement and control of fish farm or robot independent control of fishery facilities, equipment, machinery, so as to complete all production and management operations of the fish farm. Finally, intelligent fish farms rely on digital and intelligent technology to solve the problems of aquaculture labor shortage, water pollution, high risk and low efficiency. Intelligent fish farm is the industrial transformation of fishery production mode and the development direction of fishery in the future. Intelligent fish farm can be divided into four categories according to different culture environments: pond-type intelligent fish farm, land based factory-type intelligent fish farm, cage-type intelligent fish farm and intelligent marine ranch.

Pond-type intelligent fish farm collects water quality information using sensors in real time, and unmanned aerial vehicle patrols to obtain the water surface activities of fish. The growth status and feeding process of fish are observed by bionic fish. The water quality is regulated by fertilizing and spraying chemicals on unmanned boat. Bait is transported by unmanned vehicle. DO is accurately controlled by intelligent aeration system. The

intelligent bait feeder realizes accurate and automatic feeding. Intelligent harvesting is carried out by automatic trawl machine and fish distributor. Only when all systems work together in an orderly manner can the reliable operations of the pond-type intelligent fish farm be guaranteed.

Land based factory-type intelligent fish farm mainly realizes automated recirculating aquaculture (RAS). This fish farm mainly integrates micro-filters, biological filters, intelligent feeding machines, aquaculture tail water purification and utilization devices, as well as advanced model and intelligent equipment technologies to construct a fish circulation three-dimensional aquaculture model. Based on the deep study of the relationship between the basic requirements of aquaculture biology and the operation parameters of RAS system, scientific decision-making on the optimal culture density, appropriate water environment demand and efficient aquaculture management strategy of benthic fish under the recycling aquaculture mode are carried out by extensively collecting production data and integrating big data analysis technology. By integrating high quality seed production and selection technologies, the fish farm establishes a supporting technology of good breeding methods suitable for circulating aquaculture, and realizes the whole process of parent fish mating, egg hatching, fry cultivation, adult fish breeding, sales, and packaging.

Cage-type intelligent fish farm obtains seawater quality and ocean current information using sensors, and obtains fish movement and feeding information using machine vision and sonar. The feed barge can deliver bait accurately according to water quality, fish biomass and feeding behavior. The underwater net is cleaned autonomously by the net washing robot. The automatic fish catching work are realized using the automatic net lifting system and the fish pump. The emergency control of water quality is realized by light supplement and emergency oxygen system. The fish farm is divided into floating type and fixed type. It will form a three-dimensional aquaculture mode according to the water layer where different aquaculture objects live. The bait, energy and other production materials will be transported from the land-based warehouse to the breeding area by unmanned vessels. Cage-type intelligent fish farm can relieve the pressure of offshore resources and effectively solve the problem of land-based aquaculture occupying a lot of space.

Intelligent marine ranches usually use high-definition surface cameras and underwater robots to collect the video information of the ranch in real time, and then transmit the video to the data server in the shore-based information control center using the transmission network for the purpose of biological identification, behavior analysis, and biomass estimation. By installing Doppler sensors, underwater cameras and sonars the ranch obtains the ocean current data and the distribution of plants and animals near artificial reefs. The ranch uses water quality monitoring buoys, weather monitoring stations, management boats, radar and other underwater mobile monitoring equipment to realize the automated all-round monitoring of the marine ranch. Using satellite remote sensing technology (SRS), marine ranches can evaluate the fish stock variability in different space and time scales (George 2014). Based on the interaction between microwave and sea surface micro scale structure, synthetic aperture radar remote sensing technology can remotely sense ocean current, cyclone and other fishery related marine environment information. The feeding method in ranch can choose to use unmanned aerial vehicle to spread bait in the air, or choose to use unmanned boats to close the water surface for autonomous feeding. The material supply for marine ranch is usually transported by unmanned boat in the way of land-sea relay.

The key technologies involved in intelligent fish farm are shown in Fig. 1. In addition to the specific fishery infrastructure, the four types of intelligent fish farm all include above and under water environment monitoring system, water quality and feeding control system,
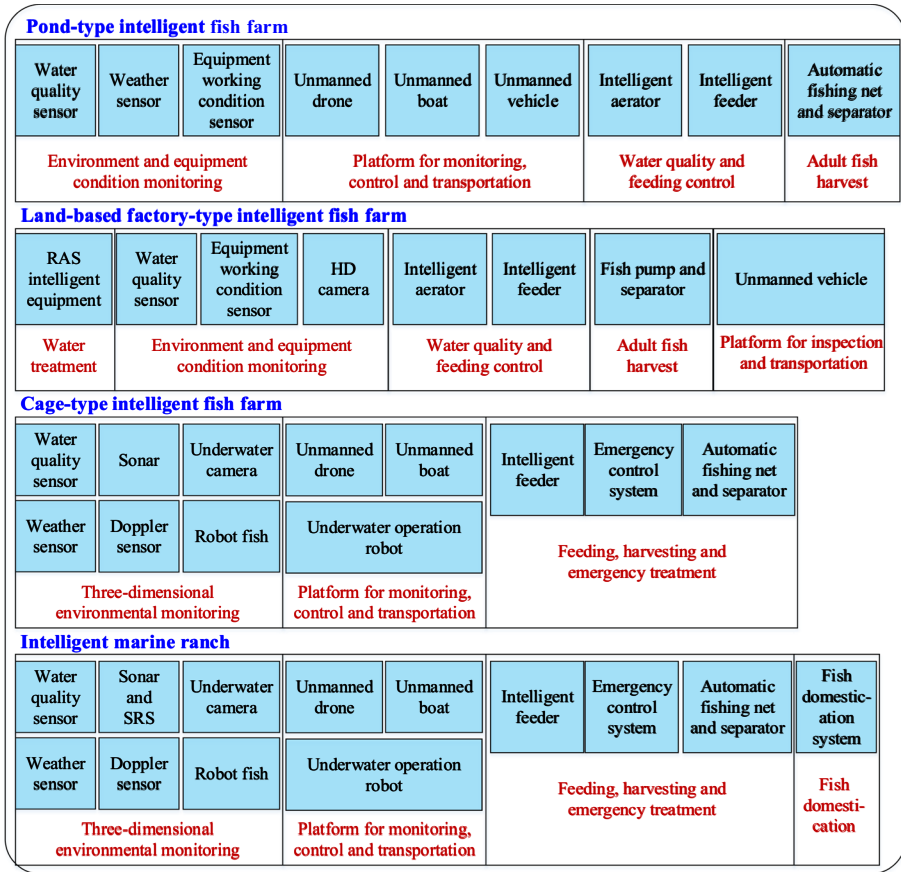
Fig. 1 The involved key technologies in intelligent fish farm

unmanned vehicle platform for auxiliary monitoring, control and transportation tasks, and adult fish harvesting system. In the future, the intelligent fish farm can flexibly select hardware platform according to different aquaculture requirements. The cooperation between equipment is done based on the Internet of Things (IoT) and 5G. The precise control of equipment completely depends on the accurate calculation of intelligent algorithms. The key technologies involved in the intelligent fish farm will be introduced in the rest of the article.

Advance information technology in intelligent fish farm

The traditional aquaculture IoT system is a high integration of cloud technology and Internet of things technology (Huan et al. 2020). It adopts three-tier structure: device layer, network layer and cloud service layer. The device layer is composed of sensing equipment, control equipment and data acquisition terminal. The sensing equipment is responsible for collecting the environmental data such as DO, pH, temperature, salinity, ammonia nitrogen, nitrite, water level, etc., as well as the working status of the device and aquaculture

video image information. The control equipment includes aerator (oxygen cone), feeder, pump valve and other aquaculture equipment. The data acquisition terminal is responsible for the upward transmission of sensor data and the reception of control instructions. The network layer generally adopts wireless network, such as Bluetooth, Wi-Fi, 3G/4G, Lo-Ra, NB-IoT, and other wireless transmission technologies, which is responsible for the data transmission between the device layer and cloud service layer. The cloud service layer includes cloud platform and smartphone app, which are mainly used to store and process aquaculture data and provide various aquaculture information services.

Although the aquaculture IoT system has the advantages of simple equipment access and rapid system construction (Al-Hussaini et al. 2018), it is difficult to solve the following problems in the face of explosive growth of equipment and data due to the unified upload and centralized processing of data by cloud computing model. Sensors continuously collect various sensing data, and the data is usually stable or with little change. Uploading all the data to the cloud for processing will consume a lot of network resources and cloud resources. When the network is unstable, it is impossible to process data and control equipment in time. All sensor data and control data need to be transmitted using the network, and there are risks of information eavesdropping, tampering, deception, and illegal operation of equipment. These problems will increase the cost of the IoT system (communication flow, information storage, computing cost), reduce system stability and availability, and it is difficult to realize automatic production, especially in the application of large-scale industrialized aquaculture. In addition, the non-standardization of sensing and control devices, and their own resource limitations about computing and storage capabilities have brought certain obstacles to equipment access and linkage control. Therefore, to develop intelligent fish farm, it is necessary to study and solve the above problems.

Edge computing provides intelligent services on the edge of the network close to the source of things or data, so that each edge of the IoT has data collection, analysis and calculation, communication and intelligent processing capabilities, and can process data, filter data, and analyze data nearby (O'Grady et al. 2019). Local decision-making and event processing can meet the key requirements of network capacity limitations, data timeliness, resource limitations, and security and privacy challenges. Previously, machine learning and even deep learning could only be done on high-performance hardware using edge training and inference performed by gateways, edge servers, or data centers. Nowadays, microcontrollers used to execute machine learning at the edge have become a very popular area of research and development (TinyML 2020). Existing water quality sensors have hardly any self-confirmation of their working status, that is, they have always been considered that the sensors are working normally. In this way, once the sensor fails, the output result will seriously deviate from the actual situation, which may cause false alarms and reduce the credibility of the detection results. In order to solve this problem, Zhao et al. (2011) first applied edge computing to sensor fault diagnosis and data repair methods. The multiple classifiers expanded from binary classifier based on relevance vector machine are obtained to carry out the fault diagnosis of the pH, temperature, and salinity sensors. The relativity of multi-parameters in water quality monitoring is used sufficiently to achieve the data recovery of multi-function self-validating sensor under the condition of a small number of nonlinear training sets.

With the advent of the 5G network era, intelligent fish farm also has higher requirements for network performance. Compared with the 4G network, the capability index of the 5G network has been significantly enhanced. The delay must be no more than 1 ms, the peak data rate can reach 10 Gbit/s, the connection density can

reach 10 terminals/km, and the user experience rate can reach 100Mbit/s. It is difficult for the current network architecture to meet these requirements. And now massive amounts of IoT device data are stored in the cloud service center, and the real-time interaction between user and the cloud center requires high speed transmission rate, which will cause huge traffic pressures on the network in high mobility areas. For businesses with high real-time requirements, end-to-end millisecond-level low latency is required, but it is difficult for ordinary cloud computing models to meet the above tasks. Therefore, this research introduces Edge computing and 5G into the aquaculture IoT system to improve the standardization, stability and usability of the system. The conceptual design for intelligent fish farm is shown in Fig. 2. Things and cloud services are distributed, and key applications and basic process control should be deployed at the edge layer. Web services or data analysis applications can be deployed on the network/cloud. The communication layer and the edge layer integrate resources and make them interoperable.

The work of fishery informatization will produce a large number of multidimensional data. Big data technology is a kind of high-speed processing and multi-dimensional deep mining of massive data to obtain valuable information. It includes big data acquisition, big data preprocessing, big data storage and big data analysis. By simulating human thinking and intelligent behavior, AI can learn the massive information provided by the IoT and big data, analyze and judge the problems, finally complete the decision-making task, and realize the accurate operation of the fish farm. Compared with traditional technology, AI technology focuses on the calculation, processing, analysis, prediction and planning of problems. The IoT, edge computing, 5G, Big data and AI complement each other and deeply integrate to provide technical support for the construction of intelligent fish farm.
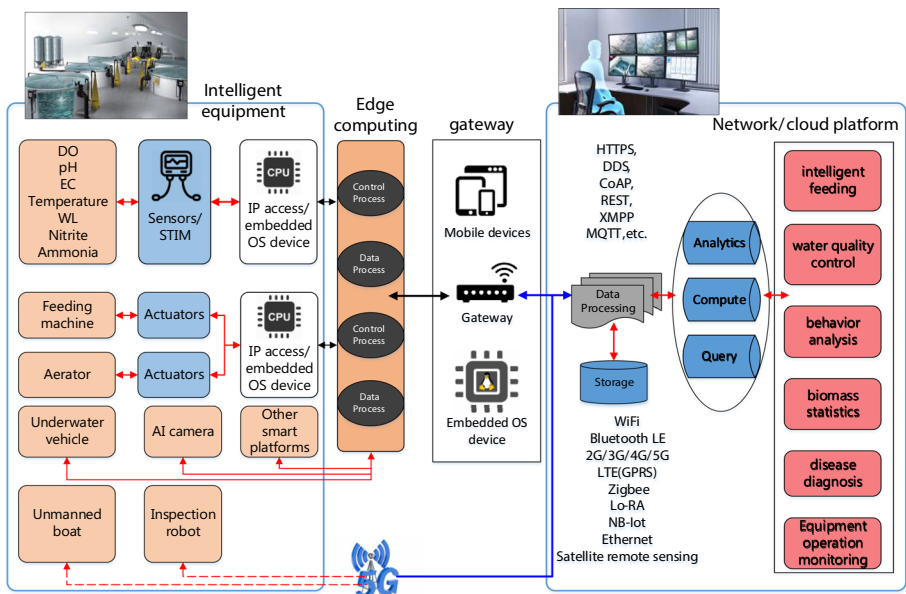

Fig. 2 Conceptual design of IoT ecosystem in intelligent fish farm

Intelligent equipment and robots in intelligent fish farm

Traditional aquaculture basically relies on personal experience with low efficiency, high cost and low automation. Nowadays, day-to-day tasks on fish farm facilities, such as fish welfare monitoring, facility inspections, control of feed rationing and lice counting, are currently conducted by several crews on board service vessels (Baird 2017). In the future, autonomous and remotely operated system could play a major role in conducting different tasks at fish farm facilities, being that the working conditions in aquaculture are very complicated and change frequently and sharply, particularly in marine cage culture. Intelligent equipment and robots will integrate advanced sensors, big data and AI, so that they can effectively adapt to the complex operation environment and realize the independent operation of intelligent fish farm. They can also greatly reduce the labor intensity and cost, and improve the fishery production efficiency. In addition, intelligent equipment and robots can autonomously perceive the massive data of intelligent fish farm and transmit these data to the cloud platform as the data basis for big data analysis (Mustapha et al. 2021).

AI serves intelligent equipment and robots, and endows intelligent equipment and robots with "intelligent brains," which can learn, judge and make decisions independently in fishery production. Robot technology is the effective combination of information technology, machinery and automation technology. It can enable all kinds of machines to participate in the whole process of fishery production like human (Rembold 2020). In addition, intelligent equipment and robots also need the support of edge computing, machine vision, navigation and precise control technology in order to meet the demand of machines replacing humans (Shi et al. 2016).

Intelligent equipment based on the traditional fishery equipment use modern information technology and intelligent manufacturing technology for digital transformation, so as to carry out the precision operations in intelligent fish farm. Intelligent equipment and robots of farm can be divided into mobile equipment and fixed equipment. Mobile equipment refer to the equipment that need to be moved to complete autonomous operation, mainly including unmanned ground vehicle (UGV), unmanned aerial vehicle (UAV), unmanned ship or unmanned surface vessel (USV) and unoccupied underwater robot (ROV). Fixed equipment include water quality monitoring and control equipment, feeding equipment and oxygen equipment, as well as harvesting equipment such as fish suction pump and classification equipment.

Intelligent hardware for measure and control

Water environment ecological monitoring refers to the use of sensors and cameras carried by unmanned ships or surface buoys to automatically collect water quality parameters (DO, temperature, chlorophyll, turbidity, ammonia nitrogen and pH), aquaculture biological pictures and video information, and then store, transmit, analyze and predict data. Long time accurate detection of aquaculture water quality parameters provides a reliable data source for automatic control and intelligent decision-making of intelligent fish farm. At present, the detection of DO mainly includes Clark electrode method and fluorescence quenching method (Tai et al. 2016). Optical dissolved oxygen sensors need no calibration and have some advantages of fast response time, stable measurement result, strong anti-interference ability and low maintenance. In the future, the membrane-free DO sensors based on fluorescence and the sensors based on nanocomposite modified electrode will be the focus of

future research. pH online measurement in aquaculture is mainly realized by digital differential electrode or composite electrode (Lee et al. 2017). Digital differential electrode uses three-electrode system instead of traditional double-electrode technology, which has excellent accuracy and reliability. The detection of ammonia nitrogen, nitrate nitrogen and nitrite nitrogen in aquaculture usually only adopts the method of online water quality analyzers, which deploys all the laboratory chemical analysis process to a shore based detection box. The automatic analyzer includes water sample pretreatment module, chemical digester, titrator, optical sample pool, peristaltic pump and electronic detection unit. The equipment supports linkage control, fully automatic operation, maintenance free, and can realize automatic zero adjustment, automatic calibration and automatic cleaning. The analysis results can be sent to the data center by fieldbus or wireless transmission. In the near future, unmanned boats and underwater robots equipped with aquaculture environment dynamic monitoring system can not only automatically cruise the intelligent fish farm, but also carry out the omni-directional, real-time and multi-point water quality monitoring tasks, which will greatly improve the informatization, automation and intelligent level of intelligent fish farm.

Intelligent aeration system refers to the equipment that can accurately measure and control the DO in water, which is composed of various sensors, network transmission module and IOT actuator (Huan et al. 2020). The intelligent aerator can monitor water temperature, air humidity, air pressure and DO in real time. At the same time, it can record scene information by means of video monitoring, and uploads this information to the cloud platform which can realize the precise control of the aerator. In addition, the intelligent aerator can predict the DO content in a short time.

Recirculating aquaculture system (RAS) can recycle the wastewater produced in aquaculture pond after treatment using a series of water treatment units (Xiao et al. 2018). RAS integrates advanced technologies such as environmental engineering, civil engineering, modern biology, nano engineering (Moges et al. 2019) and electronic information to remove harmful pollutants such as feces, ammonia nitrogen and nitrite nitrogen from aquaculture water. The system mainly consists of protein separator, microfiltration machine, biofiltration system, degassing system, temperature control system, sterilization system, water quality monitoring and oxygenation system. Rapid removal of ammonia nitrogen and rapid increase of DO in commercial RAS are the core issues of system design. Based on the theory of material balance, some researchers (Pedersen et al. 2020; Wik et al. 2009) have optimized the design parameters of the system, such as the amount of water supply, oxygen supply, circulation amount, circulation times, effective volume of biofilter, by dynamically simulating the process of fish growth, waste generation and water treatment cycle. Computer aided dynamic simulation will become an effective tool for RAS design. Special data collector will collect the working current, working voltage, vibration amplitude and surface temperature of the motor to monitor the operation status of the circulating pump in real time. These data will serve as the evidence for fault diagnosis of aquaculture water treatment system.

Intelligent hardware for precision self-feeding

Automatic feeding system has been widely used in industrial recirculating aquaculture, including automatic feeding system with multi monomer centralized control and automatic feeding robot system. Automatic feeding system in some developed countries such as Norway, Japan, and the United States has entered the application stage, which has achieved

accurate control in the links of feed transport, storage and delivery. The net cage automatic feeding system developed by Norwegian fishery equipment enterprise consists of management system, online monitoring system and feeding module. The management system directly controls the fan and feeder, and adjusts the feeding in real time. At the same time, the online monitoring system can monitor several of parameters of aquaculture water such as the pH, DO and temperature in real time, and transmit the feedback data to the management system, so as to realize the automatic feeding of bait (Wang et al. 2021). The robot feeding control system developed by Finland's Arvo-Tec company can realize remote control of feeding, water quality improvement, and precise feeding using the web interface (Arvotec 2021). The Arvo-Tec control unit WOLF is a fully integrated feeding, measurement, light control (photo period) and alarm system. The system takes water temperature, oxygen content, biomass and other environmental parameters as the initial data, and carries out the feeding control according to energy demand model. In addition, the system estimates fish growth based on feed conversion ratio. In the pond-type intelligent fish farm, intelligent bait-dropping equipment should be deployed on unmanned boats or UAV, and the UAV will be responsible for the independent transportation and loading of bait.

Unmanned patrol system

The patrol equipment in the intelligent fish farm includes UAV, USV and robot fish. The patrol equipment can realize the daily underwater management, video information collection, behavior monitoring of breeding objects and ecological environment monitoring of aquaculture. The flight attitude control module can complete the hovering, vertical motion, rotation, and pitch of UAV by using PID and fuzzy control algorithm (Bonadies et al. 2018). Using GNSS, machine vision and 5G, the automatic navigation system can determine the speed, course, height, position and distance of the patrol UAV, and realize the operation path planning and intelligent obstacle avoidance, so as to ensure the high precision positioning and navigation of the patrol UAV in the complex environment of intelligent fish farm. The monitoring system is equipped with cameras, hyperspectral sensors and remote sensing equipment using machine vision to realize the omni-directional perception of environmental ecological information and feeding information of fish in intelligent fish farm. Particularly in Open-Pen Sea Cage Aquaculture, 5G will be used for high-throughput HD video transmission and monitoring that can well solve the problem of high cost and difficulty of optical cable laying. In the future, UAV using AI algorithm will be equipped with powerful airborne edge computing module to realize the functions of autonomous takeoff, autonomous landing, autonomous cruise and monitoring. In addition, the UAV used in the inspection of intelligent fish farm will also be equipped with an automatic charging controller module to realize real autonomous operation.

The speed, course, position and operation path planning of unmanned vessels can be realized using GPS or Beidou navigation system. Unmanned boat can carry underwater monitoring sonar to realize the tracking of fish stocks and the estimation of biomass. It also performs task by interacting with ROV. Unmanned boat can also be used as the carrying platform of other aquaculture equipment, such as aerator, bait feeder, harvesting equipment, especially as the launching platform of UAV and biomimetic robot fish.

Biomimetic robot fish can realize three-dimensional monitoring and automatic inspection of underwater aquaculture environment (Ravalli et al. 2017). Underwater acoustic system includes sonar equipment and multi beam detection equipment, which can realize underwater positioning, automatic obstacle avoidance, object tracking and biomass

estimation. Biomimetic robot fish carries a variety of sensors to automatically monitor the water quality and the operation status of key equipment. Biomimetic robot fish can also monitor the feeding rule of fish based on computer vision technology, and analyze relevant data to provide a basis for optimizing the feeding strategy.

The inspection robot based on the deep learning, computer vision and positioning technology can detect the position of sick and dead fish, and use the automatic manipulator to pick up the dead fish combined with the optical and acoustic system. Underwater robot in cage culture can also locate the damaged and contaminated positions of the net clothes, and use tool to clean and repair the net clothes. Orbital robot can inspect the circulating water pipe network, oxygenation equipment and feeding equipment in the recirculating aquaculture workshop according to the predetermined inspection route. In the future, all inspection works in intelligent fish farm will be completed by cloud platform and intelligent equipment. USV, UAV and ROV will work together to realize the three-dimensional monitoring of water environment, land environment and air environment.

Intelligent harvesting system

Intelligent harvesting system is the last module for fish farm to complete the breeding cycle. Using this system, the breeding objects will enter the market through the transportation with or without water. At present, trawling is the most efficient way of fishing. The system in intelligent fish farm uses sonar, underwater camera and net positioning instrument to achieve precision fishing. The participation of unmanned vehicles and unmanned ships in the transportation of aquatic products will greatly improve the efficiency of fishery production. This will help to achieve the goals of high efficiency and energy saving, while reducing the labor intensity of fishermen. Sea cucumber catching robot uses Doppler-GPS integrated navigation, computer vision and mechanical servo-drive technology to automatically pick sea cucumber. The navigation system of sea cucumber catching robot is responsible for collecting the position information of underwater robot, planning the navigation route and controlling the movement of the robot. The machine vision system is responsible for collecting the sea cucumber images, preprocessing the sea cucumber images, recognizing the sea cucumber and calculating the relative coordinates of the sea cucumber (Qiao et al. 2017). The actuator can control the pressure pump and manipulator to pick sea cucumber.

Intelligent equipment and robots are the key that will liberate aquaculture manpower and achieve automated production. They are supported by modern information technology such as comprehensive perception, intelligent processing, intelligent navigation and automatic control technology, combined with the improvement of traditional aquaculture equipment to realize the unmanned production, environmental information monitoring, optimization control and precise operation. Robots, unmanned vehicles, unmanned boats and robotic fish will play an important role in intelligent fish farm.

Data-driven decision-making

The key objective of intelligent aquaculture is moving beyond data toward decision. In order to realize the intelligent aquaculture, it is necessary to carry out all-round fine control on the various elements of aquaculture, such as intelligent feeding, water quality control, behavior analysis, biomass estimation, fish disease diagnosis, equipment working condition

monitoring and fault warning. AI is a technological science that studies and develops new theories, new methods, new technologies and new application systems for simulating and expanding human intelligence. It is inevitable to promote the deep cross-border integration of AI and aquaculture. The following will review a variety of applications of AI technology in aquaculture, and explore the feasibility of integrating these methods in the construction of intelligent fish farm.

Water quality soft measurement and control method

Aquaculture water quality greatly affects the growth rate, health status and feed intake efficiency of fish. A single water quality parameter in aquaculture water is easily affected by other water quality parameters, which increases the difficulty of detection by a single detection method, and also provides the possibility for the application of soft measurement. The basic idea of soft measurement technology is to infer or estimate important parameters that are difficult to observe with the help of some easily observed variables. For soft measurement technology, the feature extraction and soft measurement model are the key. The current soft sensor modeling methods are mainly divided into process mechanism models, machine learning models based on statistical analysis and gray box models. Traditional water quality prediction methods have slow convergence speed and low prediction accuracy. They are not suitable for modeling with high dimensionality, small sample data sets and parameter optimization influenced by subjective factors. Liu et al. (2013a, b) put forward two nonlinear aquaculture DO prediction methods based on ACO-LSSVR and IPSO-LSSVR. The ACO-LSSVR method improves the ant colony optimization algorithm using the local fine search based on the idea of "detection" and the idea of dynamic update of pheromone, realizes the automatic acquisition of the best parameters of the LSSVR model, and builds a DO nonlinear prediction model based on ACO and LSSVR. Compared with BPNN, the RMSE and running time t of this method are reduced by 67.9% and 2.3464 s, respectively. The IPSO-LSSVR method improves the particle swarm optimization algorithm (IPSO) using the adaptive dynamic update strategy of inertial weights, realizes the fine search in the optimization process of LSSVR model combination parameters, and constructs the DO nonlinear prediction model of IPSO fusion LSSVR. Compared with the traditional LSSVR, the RMSE and MAE of this method are reduced by 29.36% and 67.46%, respectively. The changes in water quality parameters of cage aquaculture are usually non-linear, dynamic, changeable and complex. Hu et al. (2019) constructed a water quality prediction model based on a long short-term memory (LSTM) deep learning network, which repaired, corrected, and removed noise water quality data using linear interpolation, smoothing, and moving average filtering techniques, and used Pearson's correlation coefficient to obtain correlation priors between pH, water temperature, and other water quality parameters. Experimental results show that in the short-term prediction, the prediction accuracy of pH value and water temperature can reach 98.56% and 98.97%, and the prediction time is 0.273 s and 0.257 s, respectively. In the long-term prediction, the prediction accuracy of pH value and water temperature reached 95.76% and 96.88%, respectively.

There are many factors affecting the content of ammonia nitrogen in pond culture, which are interrelated and nonlinear. It is difficult to accurately predict the ammonia nitrogen content by using mathematical methods and traditional neural networks, because there are some problems such as local convergence and low computational efficiency in the process of data training. Chen et al. (2019) used the PCA method to screen the main factors affecting the change of ammonia nitrogen content, used the wavelet threshold method

to achieve noise elimination, and proposed an ammonia nitrogen prediction model based on particle swarm optimization (PSO) algorithm and multi-variable deep belief network (MDBN). Compared with the traditional LSSVM and BPNN, the MAPE of this method are reduced by 28.59% and 21.46%, respectively. Wang et al. analyzed the production and nitrification process of ammonia nitrogen in marine aquaculture water, selected water temperature, salinity, pH value, DO as auxiliary variables, and established a soft measurement model of ammonia nitrogen concentration based on stochastic configuration networks (SCN) with high convergence speed and strong generalization ability. The RMSE of SCN method is less than 0.064 mg/L, and the prediction time is less than 1.32 s. Yu et al. (2020) proposed a soft measurement method of ammonia nitrogen based on empirical mode particle swarm optimization extreme learning machine (EMD-IPSO-ELM). This method uses the empirical mode method to decompose the ammonia nitrogen inherently to obtain the number of hidden layer nodes of the extreme learning machine, and then uses the particle swarm algorithm to select the input layer weights and biases of the extreme learning machine. On-line measurement of water quality and meteorological parameters enables the estimation of ammonia nitrogen content. Rahim et al.(2020) chose to use time series of the physicochemical water quality variables including pH, ORP, water temperature and electrical conductivity in the Small Prespa Lake in Greece to build deep learning (CNN, LSTM, CNN-LSTM) and traditional machine learning models (support-vector regression-SVR, decision tree-DT) for predicting DO and chlorophyll-a concentrations. The hybrid CNN-LSTM model has the strengths of both standalone deep learning models; it decreased the RMAE for DO prediction by 0.24% and 1.45% (for chlorophyll-a prediction by 6.41% and 6.48%) in the testing period compared to CNN and LSTM models.

Ocean satellite remote sensing has the characteristics of wide observation range, short repetition period and high temporal and spatial resolution. It can image the global ocean in a short time, observe the sea areas that are not easy to reach by ships, and observe the parameters that are not easy to measure by ordinary methods. Large-scale farms can use the existing and forecasted data sets on satellite remote-sensing to evaluate the environmental information such as chlorophyll-a, sea surface temperature, surface organic pollution, and ocean current (George 2014).

The soft measurement is predicted by model and the input variables of the auxiliary sensor. If a sensor fails, it will directly lead to the deviation or even failure of the soft measurement prediction. Therefore, it is necessary to verify the effectiveness of the input sensors before the soft sensors perform model prediction. A soft-sensing model based on self-confirmation technology (SEVA) will be developed in the intelligent fish farm. The basic principle of soft measurement model is shown in Fig. 3. The model will output five kinds of information, including probability interval output, model state (fault state, reconstruction state and loss state), uncertainty, fault information and verification output value. It will reconstruct and repair the data of the failed input sensor to achieve the purpose of model self-checking and self-diagnosis.

Success in designing affordable automated control systems for aquaculture will be widely applicable because it will enhance water management. In order to better carry out distributed measurement, intelligent control, and centralized management of DO for a large-scale aquaculture pond, Ma et al. (2015) designed a pond DO cascade control system based on a variable universe fuzzy PID controller and an aerator speed PID controller. PID controller parameters were tuned online by a variable universe fuzzy control unit to realize the purpose for DO adaptive control. According to the change trend of the DO measurement sequences, a combined grey dissolved oxygen forecasting model is constructed based on gray theory and weights. The predicted value is used as the feedback value of
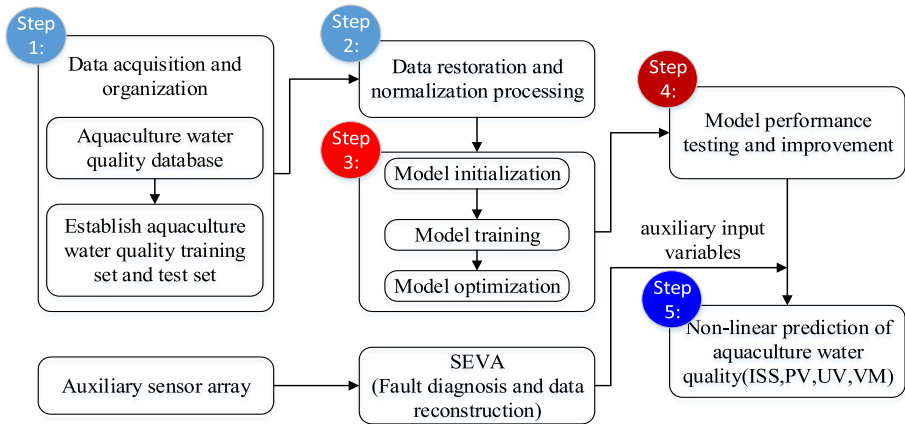
Fig. 3 The basic principle of self-confirming soft measurement model

the variable universe fuzzy PID controller to realize the predictive control and advanced regulation of DO. Another predictive controller was developed for hourly control DO to improve the production of whiteleg shrimp and minimize costs; Marcos et al. (2017) first established a DO dynamic model by analyzing the process of DO production and consumption in shrimp ponds and the growth rate of shrimp. Then, the Nonlinear Extended Prediction Self Adaptive Control (NEPSAC) algorithm is applied to the dynamic model to optimize the use of the aeration system. The NEPSAC algorithm can be easily embedded into RaspberryPi or Beaglebone to realize edge computing control. Peng et al. (2018) combined the differential evolution (DE) algorithm with a fuzzy controller to construct a parallel joint control FLC model for the DO, ammonia nitrogen, and pH value of aquaculture water. The DE algorithm was used to adjust the fuzzy rules of FLC. The FLC-DE model was applied to verify the water quality control of a shrimp breeding pond in Zhanjiang, China. The results show that the control accuracy of DO and pH was within ± 0.25 mg/L and ± 0.23, respectively.

Model predictive control (MPC) is a kind of computational intelligence algorithm based on predictive model, which continuously scrolls and optimizes in a limited time domain, and achieves the optimal control of target by real-time feedback (Vrecko et al. 2011). The basic principle of MPC is shown in Fig. 4. Since the Dynamic Matrix Control (DMC) model predictive control algorithm is based on the nonlinear second-order rolling
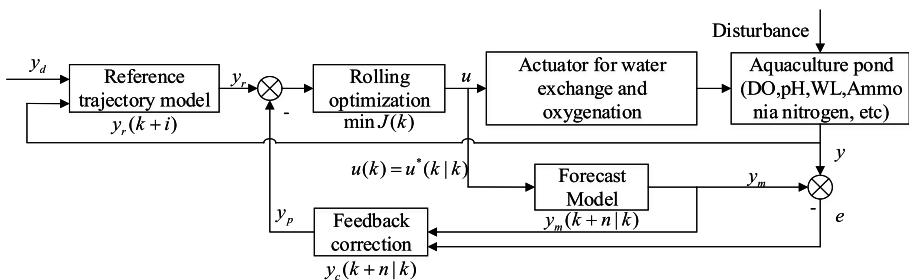

Fig. 4 The basic principle of MPC

optimization, the amount of online calculation is not large, and it is more conducive to embedding into the local controller. The author can refer to the more mature model predictive control algorithm ideas in the industrial field to deal with complex production control, and by improving the predictive method, looking for the optimal parameters of the rolling optimization link and feedback link, construct a Quadratic Dynamic Matrix Control (QDMC) model of DO in aquaculture water to achieve precise control of water quality in intelligent fish farm.

Intelligent feeding strategy

Among the various costs of aquaculture, the cost of bait accounts for up to 80% of the total cost. How to reduce the cost of feed is the key to maximize the profit of aquaculture. At present, the bait delivery method is basically based on the growth conditions of the fish and the breeding experience, which cannot achieve accurate bait feeding, and it is very easy to cause insufficient feeding of the fish, the waste of bait and water pollution. The existing bait-casting machines lack information feedback on the feeding situation of the fish. Feeding back the evaluation results of bait-feeding effect to the control system will help to adjust the feeding amount in real time. The artificial experience model is usually based on a large amount of observation experience in aquaculture, and a regression fitting analysis method is used to establish a mathematical equation related to the nutrient requirements of fish growth and the amount of feed. The feed requirement is determined by the ratio of the body mass or body length of the fish (Sun et al. 2016). The complexity and variability of the breeding environment bring multiple disturbances to the artificial experience prediction model. In order to automatically establish the mapping relationship between fish intake and environmental factors, Chen et al. (2020) proposed a feed intake prediction model for group fish using the MEA-BP neural network in intensive aquaculture. In their research, the four variables of water temperature, DO, average fish weight and fish number were used as the input of BPNN, and then GA(Genetic Algorithm) and MEA(mind evolution algorithm) algorithms were used to optimize the initial weights and thresholds of BPNN to improve the matching accuracy. The linear correlation coefficient between the predicted value of the trained model and the measured value is 96%, and the RMSE and MAPE was 6.89 and 0.04, respectively. The single morphological characteristics of fish body are not accurate in estimating the feed demand of fish. Some researchers use the biological energy of fish body combined with the breeding environment to scientifically predict the feed demand of fish. The dietary requirement of fish at different growth stages is determined by digestive energy. Liu et al. (2018) estimated the digestible energy of Carassius auratus gibelio by calculating the summation of expected energy gain, basic metabolic energy, heat increment of feeding and metabolic energy of urine and gill, and constructed bioenergy model to predict feed intake. The FCR value (1.47) predicted by this model was consistent with the observed value (1.51) throughout the production cycle.

In recent years advanced technologies such as machine vision, acoustic technology and sensor data fusion have been gradually applied to large-scale and refined aquaculture (Li et al. 2020a, b; Wu et al. 2015). In order to accurately control and judge the reasonable feeding time, and improve the efficiency of feeding, Wang et al. (2015) proposed a method of using machine vision technology to obtain the feeding parameters of the ingested fish to realize the accurate feeding of fish in aquaculture. This method first uses the interframe difference method to effectively detect the fish point set in the target area in the image sequence, and then optimizes the fish point set to improve the efficiency of the least

squares ellipse fitting algorithm, and then obtains the target fish area parameter value, and finally uses the change curve of parameter value to calculate the maximum value of the area parameter. When the parameter value changes below the set threshold, the bait-casting machine is automatically turned off to realize intelligent control of fishery bait. Liu et al. (2014) applied a machine vision system to observe the feeding activity of Atlantic salmon. The system adopted the inter-frame difference method to eliminate the effects of superimposed reflections on the surface of the water body, and evaluated the feeding intensity with the feeding activity index (CVFAI). The established mapping relationship model between the CVFAI and the manual observation feeding index (MOFAI) is used as the basis for starting and stopping the automatic feeding machine. Some researchers (Hu et al. 2015; Zhou et al. 2019) used machine vision technology to collect the aggregation degree of the fish and the water spray as the feature area of the image to describe the characteristic parameters of the feeding regularity, and proposed a variety of fish intake calculation models based on the change curve of the feeding regularity over time. However, with the extension of the fish gathering time and the increase in the number of fish overlaps, the accuracy of the feeding model may be affected. Zhou et al. (2018) used near-infrared machine vision to monitor the movement trajectory of fish after feeding. Based on fuzzy control rules, they established an adaptive network-based fuzzy inference system (ANFIS) with feeding behavior parameters (FIFFB and SIFFB) as input variables to achieve automatically on-demand feeding (Zhou et al. 2017a, b). The ANFIS model can get 98% of the feeding decision accuracy. In addition, some researchers take the amount of uneaten fish food pellets as the control index for the start and stop of feeding machine to realize the feeding control strategy with fish as the main body. Foster et al. (1995) used a light-compensating camera (Panasonic WV-B400 black and white CCD) to detect and count feed pellets in a sea cage during a feeding event. An automatic pellet counting algorithm using recorded image sequences was developed and tested. The average counting accuracy error is about 10%. Using the same process in a large glass-made water tank Liu et al. (2015) developed an adaptive method for detection and recognition of uneaten fish food pellets based on Otsu Thresholding and a linear-time component labeling algorithm. The accuracy of the proposed algorithm for figuring out the number of fish food pellets is greater than 92%, and it is also effective in handling non-uniform lighting conditions. Machine vision is susceptible to the impact of the target environment during the image collection process, such as water surface reflections, fluctuations and vibration noise. It is necessary to equip sensors with error correction function in the design of feeding equipment to improve the monitoring accuracy and make the image signal reflect the real-time feeding behavior more truly.

Sonar imaging technology has been successfully applied to marine fish monitoring (Peixoto et al. 2020). The swimming position of the fish reflects the hungry degree of the fish. The underwater acoustic sensor is used to monitor the 3D movement trajectory of the fish and decide whether to stop feeding or not according to the detected fish position density. This theory has been proven and used in practice (Zhou et al. 2017a, b). Compared with the use of underwater machine vision technology to detect fish foraging behavior, sonar imaging technology does not need to consider the impact of light. However, the use of underwater sonar is susceptible to environmental noise. In the production process of a fish farm, environmental noise at the feeding area is usually distributed periodically, while the feeding signals are random signals. Therefore, removing the environmental noise by the digital signal processing method can help improve the decision-making accuracy of this method.

The decision-making system for feeding fish in intelligent fish farm should comprehensively consider the relationship between the physiological and behavioral characteristics

of fish, the water quality conditions of the breeding environment, the feed formula, the operation method of the feeding equipment and the growth rate of fish. It is a more accurate method to establish fish feeding decision-making system based on dynamic balance models. It is recommended that the system adopts the multi-source data fusion method to establish the mapping relationship between feed intake and the quantity of feed on offer. Combined with high-efficiency intelligent control algorithms, the system can realize adaptive feedback control for real-time decision-making of the feeding system. The construction idea of intelligent feeding system is shown in Fig. 5. For different scenarios of intelligent fish farm, different configurations of information fusion can be selected.

Behavior analysis of raised species

Stress response in fish involves the comprehensive effects of sensory system, nervous system, immune system and metabolic system. It is affected by many factors such as fish species, poison type and exposure environment. The research on fish behavior can provide important theoretical data for aquaculture (Niu et al. 2018; Saberioon et al. 2016). In the process of aquaculture the main concerns of fish behavior are swimming behavior, feeding behavior, reproductive behavior, aggression and carnivorous behavior.

Fish bioassay is one of the earliest biological monitoring methods, especially used to investigate the impact of pollution fluctuation on fish behavior. Up to now, the indicators used to monitor and evaluate water quality mainly include movement behavior (speed, height, turning times and wagging frequency), respiratory behavior (gill cover movement frequency, respiratory rate, breathing depth and cough frequency) and group behavior (dispersion, communication, average distance and regional distribution). Kang et al. (2009) used Bio Fish Meter Lab equipment (Dual camera stereo cross distribution) record three-dimensional (3D) data on the movement of Oryzias latipes, and successfully solved the problem of signal plane crossing in video tracking technology. The abnormal behaviors
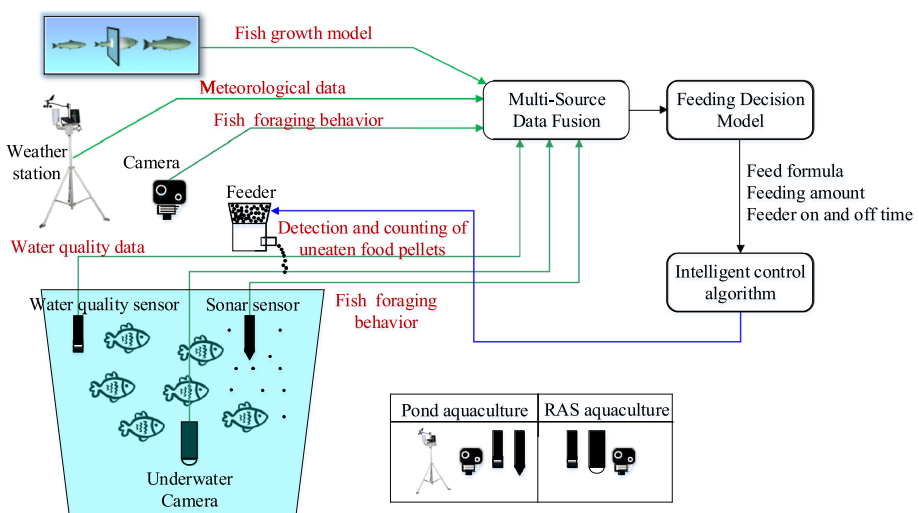

Fig. 5 Intelligent feeding system based on multi-source data fusion

such as rapid swimming and surfacing behavior were taken as the basis to judge whether the water quality was safe or not. Chew et al. (2009) developed a fully automatic system to monitor the behavior of fish in real time, using machine vision collection and image analysis technology to investigate the activity levels of fish, the density of trajectory curves, avoidance behaviors, and social interactions within fish before and after water pollution, combined with individual abnormal monitoring indicators such as balanced loss rate, irregular turns, etc., to achieve comprehensive evaluation and early warning of breeding water pollution. The combination of heuristic algorithm and Markov model can be used to analyze the swimming behavior of fish before and after stress stimulation. Liu et al. (2011) used self-organizing map (SOM) algorithm to classify six kinds of movement states of zebrafish before and after adding formaldehyde, and then used hidden Markov model (HMM) to evaluate the Markov process of different motion states. The early warning signal established based on this method has an accuracy rate of 70.1–81.2% for the estimation of stress response behavior. In general image processing systems, it is usually difficult to track the movement patterns of a shoal of fish with a small size. The fractal dimension is used to quantify the behavioral states of moving targets in a compressed manner to obtain results consistent with the analysis of individual behavior. Characteristic data describing different motion trajectories, such as speed, Y-axis coordinates, stop time, stop number, turning rate, meander, are used to train Multi-Layer Perceptron (MLP). The MLP method can reveal the local information in a specific movement patterns and respond sensitively to the observation of stress response (Ji et al. 2006). Fish's ventilation frequency, cough rate, and heart rate can be obtained by some non-contact bioelectric field technology. Rapid hypoxia decreased the heart rate and increased the respiratory amplitude and frequency of Acipenser baeri and Scophthalmus maximus.

The study on the feeding behavior of fish can provide guidance information for precise feeding, water quality management, development and domestication of artificial compound bait, so as to improve the utilization rate of fish feed, reduce the cost of fish feed and reduce the pollution level of water environment. Using computer vision technology to monitor fish behavior and obtain fish hunger levels can improve ability and accuracy of image processing, and provide a theoretical basis for intelligent feeding. The corresponding cases have been mentioned many times in the above content. Grasping the law of reproductive behavior of fish and studying the behavior development of larval fish can accurately guide artificial reproduction and improve the survival rate and quality of artificial reproduction. At present, artificial method is usually used to identify the sex of specific fish. This method is a labor-intensive work, and the evaluation result is subjective. Deep Convolutional Neural Networks (DCNNs) and SVM are two kinds of machine learning methods for automatic sex classification of zebrafish based on fish appearance texture and caudal fin color (Hosseini et al. 2019). The sex ratio identified by the DCNNs algorithm is highly consistent with the sex ratio of the actual control group ($\varphi = 0.97$), which is especially suitable for temperature induction process experiments ($\varphi = 1.0$), whereas the results of the SVM method are slightly lower. The results show that high ambient temperature can reduce the color intensity of male zebrafish, and the color of male caudal fin is positively correlated with body weight and body length. Many fish produce sounds for many reasons, such as courtship and mating, navigation, and environmental stress. Some groupers produce species-related courtship sounds during spawning and gathering. By placing a HD video camera in the water and using audio separation and recording software (Adobe Audition) to extract features of the audio signal of the grouper spawning gathering area (Michelle et al. 2014), it can be statistically analyzed that the peak frequency range of the black grouper's courtship sound is between 67 and 96 Hz. Compared with underwater audio monitoring

by camera, passive acoustic technology has higher monitoring accuracy and can be used to observe the reproductive cycle of fish. The combination of discrete wavelet transform (DWT) and deep learning (such as CNN, RNN, LSTM) in underwater sonar signal denoising (Ibrahim et al. 2018), feature extraction and automatic classification is the future trend of underwater acoustic research.

Fish like other animals often protect their food and territory. Aggressive behavior can cause injuries to the skin and fins of fish, which makes them susceptible to disease and death. Aggressive behavior also consumes energy for growth, resulting in loss of aquaculture production, reduction of food conversion efficiency and slow growth. In order to screen drugs to reduce zebrafish aggression, Gutiérrez et al. (2018) developed a novel device for automatic monitoring and behavior quantification of zebrafish aggression based on computer vision technology. Through drug treatment and mirror-induced aggression experiment, ZebraLab software real-time calculated the "ratio" and "angle" of aggressive behavior, and the intensity of zebrafish aggressive behavior was quantified by H index ($H = $ angle*log(ratio)/2). The photoperiod, light intensity, individual differences, different growth stages, adequacy and palatability of food, rearing density, temperature, and bottom quality have an impact on the intensity of fish cannibalism. Domesticated bait, adequate and evenly distributed food pellets, appropriate rearing density and timely grading can reduce the mutual cannibalization of carnivorous fish.

Deep learning is the most advanced machine learning method at present. It comes from the research of artificial neural network architecture which has a large number of hidden layers and millions of parameters. Deep learning combines low-level features to form more abstract high-level representation attribute categories or features, so as to find the distributed feature representation of data. Deep learning has achieved remarkable results in many fields such as image understanding, video and audio analysis. Intelligent fish farm tries to combine machine vision (3D observation structure), sonar detection and deep learning
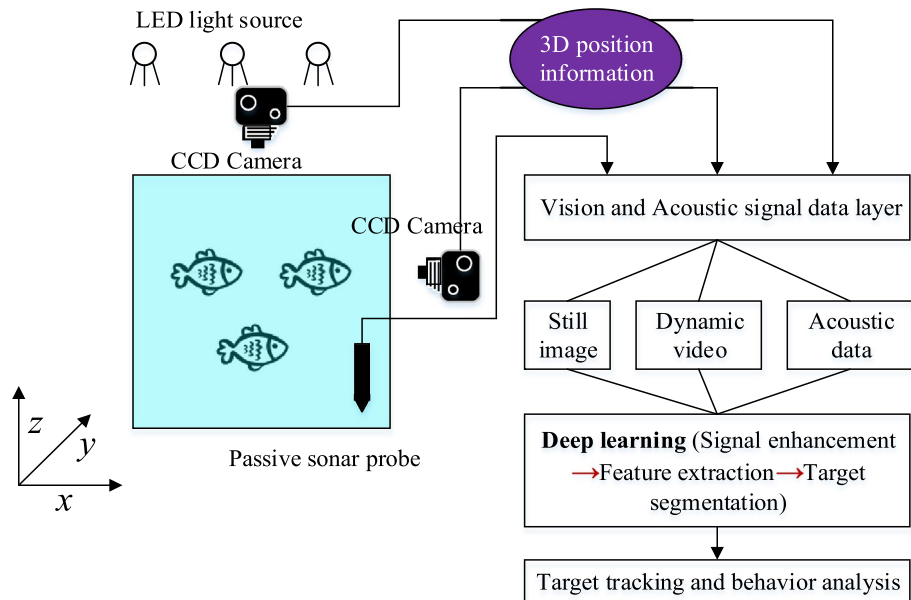

Fig. 6 Design of fish behavior monitoring and analysis platform

technology to realize behavior analysis of cultured animals in real time. The design of fish behavior monitoring platform is shown in Fig. 6.

Biomass statistics

The biomass statistics is crucial to support the fish farmers' decisions such as fish food dosage, drug consumption and fish loss. It is usually used to collect subsamples from the culture pond, weigh them, and finally calculate the biomass of the whole pond. This method has great error and is also a labor-intensive work, which will bring great stress response and high mortality to fish. With the rapid development of sensor and intelligent computing technology, machine vision has emerged many results in the field of online non-destructive biomass estimation in aquaculture (Li et al. 2019; Dios et al. 2003; Li et al. 2020a, b). The length, width, area and circumference of fish in different growth periods are closely related to their weight (Shi et al. 2020). These parameters will be used as an important basis for the estimation of fish biomass. Viazzi et al. (2015) estimated the mass of Jade perch *Scortum barcoo* by 2D computer vision technique, a set of fish samples with different sizes were photographed out of the water. The image processing algorithm was used to extract the length, area and contour information of the fish in the sequence photos. A linear model with area, length and width as input variables and weight as output was constructed by regression analysis. Single factor regression equation using fish area without considering fin tail can accurately determine the weight of Jade perch, and correlation coefficient R^2 of model determination is 0.99. The binocular stereo vision system generally obtains two digital images of the measured object simultaneously from different angles by dual cameras, and restores the 3D geometric information of the object based on the principle of parallax, and reconstructs the 3D contour and position of the object. A deformable adaptive computer vision algorithm can automatically fit Bluefin Tuna ventral silhouette in the swimming state. Pau et al. (2018) used local thresholding technology to implement image segmentation for extracting a single Bluefin Tuna object from the video frame acquired by the stereo vision system. The deformable tuna model is defined as a vector of 6 parameters, which contains the position information of 18 vertebral points and 35 profile points from the fish mouth to the end of the caudal peduncle keel. Euclidean distance, snout fork length and five widths in different sections of the fish silhouette were used to study the fattening evolution. Although the machine vision methods have the advantages of remote non-interference operation in monitoring fish biomass, the detection accuracy of the methods suffer from poor visibility, illumination change, distance and relative direction changes between camera and fish, swimming speed and rearing density in aquaculture. In recent years, Fast R-CNN and Faster R-CNN have gained excellent research performance in object detection(Yang et al. 2020), but these algorithms require a very complex execution pipeline to perform recognition tasks with less Frames Per Second (FPS) and accuracy. To obtain better results for detecting different fish, Raza et al. (2020) set the detection scale of YOLOv3 to 4, applied K-means clustering to increase the anchor box, developed a novel transfer learning technique and improved the loss function. The average accuracy of the improved YOLOv3 model is 91.30%, which is better than Faster R-CNN, YOLOv2 and original YOLOv3. Detection speed of the method is faster than R-CNN around 1000 times and faster than Fast R-CNN 100 times. The improved YOLOv3 model can even be used for real-time object detection.

Laser scanning technology is another noninvasive monitoring technology that can be used to estimate fish biomass in real time. The total biomass of fish is generally estimated

by the product of the density (ρ) and volume (V) of the fish. Almansa et al. (2015) tested a laser scanning method for estimating the total biomass of Senegalese sole using the volume of all the Senegalese sole in the culture pond. The digital camera and structured light in the laser scanning system can move synchronously, and the distance and inclination angle remain unchanged during the moving process. The digital camera captures the laser line reflected from the surface of fish body as modeling data. The fish layer thickness at each point was characterized by comparing the height difference of laser beam in spatial coordinates. The ratio of fish biomass to fish layer volume (FB/FLV) was very close to 1 under the condition of medium and high stocking density with large fish. This method requires that the interstitial water content is very small when the monitoring objects are overlapped, so it is especially suitable for the benthic and relatively inactive species, such as turbot family and tongue sole family. When the laser scanner performs automatic image analysis, uneven illumination and unnecessary noise may cause image distortion, it can be handled for on-site biomass estimation by allowing regular and frequent repeated operations to discard bad images to improve scanning accuracy.

Compared with the limited penetration ability of light in water, the attenuation of sound wave in water is much smaller. Identification sonar is a kind of multi-beam system which uses acoustic lens to transmit independent beam. It can generate high-definition image which is almost equal to optical image in dark or turbid water area, so as to recognize target. The biomass in Gilthead sea bream and sea bass cages with different rearing densities and individual sizes can be estimated by installing an echosounder with two floating split-beam transducers. Using this platform, Djemali et al. (2017) performed fish biomass assessment by fish counting, rather than echo integration. Methane gas bubbles and fish behavior in deep sea cages may affect the assessment of fish abundance. In addition, seasons and photoperiods have important reference values for the formulation of acoustic sampling strategies. Dual frequency recognition sonar (DIDSON) and real-time image processing algorithm can be used to track and count the moving fish. Jing et al. (2017) obtained single fish target using depth first search algorithm, and then combined with extended Kalman filter algorithm and nearest neighbor algorithm filtering to track fish. The huge randomness of the dense target's motion leads to 16% of the statistical error of fish numbers.

Modern advanced remote sensing technology using satellite remote sensing images and relevant professional software to analyze the marine fishery resources can accurately obtain the position of fish stock, which greatly improves the accuracy and quantity of fishing. Visible light remote sensing technology uses the visible spectrum band to telemeter the water color change characteristics of the fish farms, quickly estimates the concentration of chlorophyll-a in the sea water, and then evaluates the distribution of marine fish stock fed on zooplankton and phytoplankton (George 2014). Thermal infrared remote sensing technology uses sea surface temperature (SST) data sets to study the aggregation and migration of fish, and can be used to evaluate the health status of coral reef (Mahendra et al. 2010). Sea surface height remote sensing technology is a microwave remote sensing method that uses satellite altimeter to telemeter sea surface height abnormal information and then analyzes the fish farm environment. According to the principle that marine life like to gather along oceanic frontal regions, the position information of the oceanic frontal regions is retrieved from altimeter data to detect fish stock (Digby et al. 1999).

The assessment of fish resources in intelligent fish farm is an automatic, nondestructive and rapid analysis process. Machine vision, sonar and satellite remote sensing technology can play a role. Since video sensors are used, the external morphometry of fish can easily be done (Aguzzi et al. 2009). This can help in identifying and counting the presence

of species in a farmed area using deep learning techniques such as R-CNN, YOLO and SSD (Yang et al. 2021). The basic design idea of the platform is the same as that in Fig. 6. In addition, the system can appropriately add satellite remote sensing monitoring sensors to obtain large-scale, high-frequency, continuous and objective data sets. In view of the problems of dense underwater targets and complex environment, the software implementation methods for machine vision need to be optimized from image preprocessing, target recognition, multi-target tracking algorithm and counting rules. Coupling satellite remote sensing technology with models helps to manage fishery resources on an ecosystem scale.

Diagnosis of fish diseases

With the intensive and large-scale development of aquaculture, fish diseases are becoming more and more serious, showing the characteristics of multiple disease types, wide incidence range, long duration, high mortality and difficulty in prevention and control. Fish disease has gradually become one of the bottleneck factors restricting the sustainable development of aquaculture. Traditional diagnostic methods for fish diseases mainly depend on eye observation by aquaculture technicians. They finally determine the type and severity of the disease according to experience combined with comprehensive analysis of epidemiological characteristics and ecological environment. This method for identifying diseases is highly subjective and slow. Especially in areas where experts and technicians are scarce, fish diseases cannot be detected and diagnosed in time. Once the disease breaks out, it will cause immeasurable loss. The fast processing method of sick fish images based on machine vision is to use computers instead of human eyes to automatically and intelligently handle and recognize sick fish images (Barbedo et al. 2014). After a healthy fish gets sick, it is usually accompanied by changes in the color and texture of the body surface. The surface color of the healthy carp usually appears black and bright on the back, and the part near the belly is white with clear texture, while the surface color of the sick fish generally shows red bloodshot, swelling or plaque, and the surface texture of the fish changed significantly in the early stage of the disease. Since different fish suffer from the same disease with different symptoms, the first step in studying fish diseases is to identify the type of fish by analyzing the sub-images of the sick fish body and extracting its features including the color feature and texture feature based on the statistical method and the wavelet method. Through LIBSVM training and prediction experiments, the optimal feature combination for fish species identification is obtained (Hu et al. 2012). Image segmentation is the basis of image recognition. Only by accurately segmenting the disease spots on fish can the diseased parts be marked and then identified.

In order to automatically identify and diagnose fish diseases with Epizootic Ulcerative syndrome, Malik et al. (2017) performed morphological operations on the fish disease images collected by machine vision system, so as to enhance the image and detect the edge of the image. A corner detection algorithm (Features from Accelerated Segment Test, FAST) was used to extract the features of the fish disease images after preprocessing. For increasing diagnosis accuracy and speed, the principal component analysis (PCA) method was selected to reduce the dimension of the data set. Finally, the neural network classifier based on machine learning is constructed to judge whether the detection object is infected or not. The diagnosis accuracy of PCA-FAST-NN is 86%. Some approaches used the Raspberry Pi kit to control the camera to obtain the video data of the fish in the culture pond (Waleed et al. 2019). The image preprocessing stage built a data set of three color spaces (RGB, Ycbcr, XYZ). The Ycbcr color space was used for image segmentation. Different

convolutional neural network structures (ResNet18, ResNet50, ResNet101 and Alex-Net) executed feature extraction and classification of XYZ color space image data for automatic recognition of fish diseases such as Epizootic ulcerative syndrome, Ichthyophthirius, and Columnaris. The technology of fish image detection and recognition based on machine vision is not yet very mature. The main reason is that the living environment of fish is complex. If plants or debris in the water block the view, the swimming posture of the fish changes too fast, the water quality becomes turbid and the light becomes dark, these factors often make the fish body image difficult to obtain. Current researches on fish images are limited to obtaining excellent recognition and detection results under certain conditions. To improve the accuracy and sensitivity of the automatic fish disease diagnosis system in the intelligent fish farm, it is an effective way to add water quality analysis, fish behavior analysis and meteorological data analysis as the correction input of the deep learning method. The hardware platform is designed by adding access support for environmental sensors such as water quality and weather sensors on the basis of Fig. 6.

Fault diagnosis of equipment

Abnormal working environment will reduce the availability and integrity of aquaculture IoT measurement & control cluster system, and lead to fatal accidents in aquaculture. When a fault occurs, if there is no diagnostic information, it will be difficult to determine the type, degree and location of the fault. It is often necessary to power off and shut down for disassembly and inspection, which will delay the production process. The diagnosis information based on mathematical models can be obtained from the working condition data, so that the faults can be identified and located without powering off and disassembly for inspection. In view of the complexity of multivariate combination feature extraction, strong autocorrelation of variables and significant nonstationarity of fault conditions, a fault feature extraction method based on DPCA-VMD-SVD is proposed (Yang et al. 2017). Based on the dynamic principal component analysis (DPCA), the basic matrix of the sample is mapped into the dynamic principal component space, and 31 dynamic principal components are selected according to the proportion of cumulative variance. Then, each dynamic principal component matrix is decomposed into three intrinsic mode functions (IMF) by variational mode decomposition (VMD). Finally, the IMF matrix of each principal component is compressed into a vector composed of singular values based on singular value decomposition (SVD), and a 3×31 sample feature matrix is extracted from a 30×21 sample basis matrix. In order to solve the problem of small sample size, diverse categories, inseparable linearity and classification conflicts in the aquaculture IoT, the researchers further applied the cross-correlation of pattern classes to set up 24 sets of SVM two-class classifiers. Multi-objective parameter optimization was carried out based on the swarm intelligence optimization algorithms, and finally the classification conflict was eliminated based on the D-S evidence theory, which effectively improved the classification accuracy by 2.5 to 4.4 percentage points. The computer monitoring system must consider the reliability of the system to prevent the occurrence of fish deaths caused by the serious excess of certain environmental factors due to the failure of the control system. The fault tree analysis (FTA) is an important method of system reliability analysis. The undesirable events of the system are taken as the analysis targets to find out the logical correlation between possible component failures, software defects, human errors and system failures, which are represented by an inverted tree diagram. The fusion of FTA and fuzzy neural network (FNN) methods can perform intelligent fault diagnosis in aquaculture IoT system (Chen et al. 2017). By identifying the weak links

of the system, the optimization of the system design was done to ensure the normal operation in aquaculture. The fault tree shown the cause of fault events and their logical relationship, and the FNN was used to train the relationship mapping between the fault symptoms and faults. An expert system that used machine vision and surveillance cameras to detect anomalies in aerators has the characteristics of low cost, easy promotion and high automation (Liu et al. 2020). Using a three-step operation involving maximum contour detection, candidate region detection and object region detection, it is possible to detect long-distance aerator targets from different positions. In the working state detection module, the Kanade-Lucas-Tomasi (RF-KLT) algorithm based on the idea of region construction and corner matching can extract robust motion features in a fixed area, which expands the application scope of traditional optical flow methods and breaks through the limitation of adjacent frames. When the system performs all-weather monitoring, infrared cameras and improved machine vision processing algorithms appear very necessary.

In the intelligent fish farm, modern mechanical equipment is developing towards automation, complexity, high efficiency and intelligence. The cluster system for monitoring and diagnosis presents the characteristics of large scale, multiple measuring points and high sampling frequency. The measurement data come from the coupling effects of multiple physical quantities in different periods of various parts within the monitored object. Mechanical equipment is in normal working condition for a long time, and abnormal conditions only account for a very small part. Machine condition monitoring and fault diagnosis need to be fast and accurate to avoid equipment damage or production crisis caused by abnormal data loss. Therefore, the fault diagnosis methods based on traditional feature extraction and pattern recognition can no longer meet its application requirements. As a breakthrough in the field of modern AI, deep learning can automatically learn valuable features from the original feature set or even raw data, which means that deep learning can largely get rid of the dependence on advanced signal processing technology, artificial feature extraction and cumbersome feature selection technology. The fault diagnosis methods developed based on the deep learning framework will undoubtedly become the development trend of mechanical equipment fault diagnosis in intelligent fish farm.

An intelligent fault diagnosis framework for aquaculture IoT is shown in Fig. 7. The diagnosis process is divided into two steps. Firstly, all data need to be preprocessed, the feature parameters which can represent the fault symptoms are extracted based on deep learning, and a certain number of sample sets are selected to train the neural network to get the expected diagnosis network and classifier. Secondly, according to the trained neural network and classifier, the online data of the system is diagnosed.

Challenges

According to the advanced level of information technology, the intelligent fish farm can be roughly divided into three stages: In the primary stage, most of the work in fish farm relies on aquaculture experts to operate and control remotely with experience. In the intermediate stage, people no longer need to remotely operate the equipment in the monitoring room for 24 h, and the IoT system can operate autonomously, but it still requires a small number of people to participate in command executing and production decision-making, which is called the unattended fish farm. In the advanced stage, the production of the fish farm does not require human participation at all, all operations and management businesses are independently planned and decided by the cloud management platform, and robots
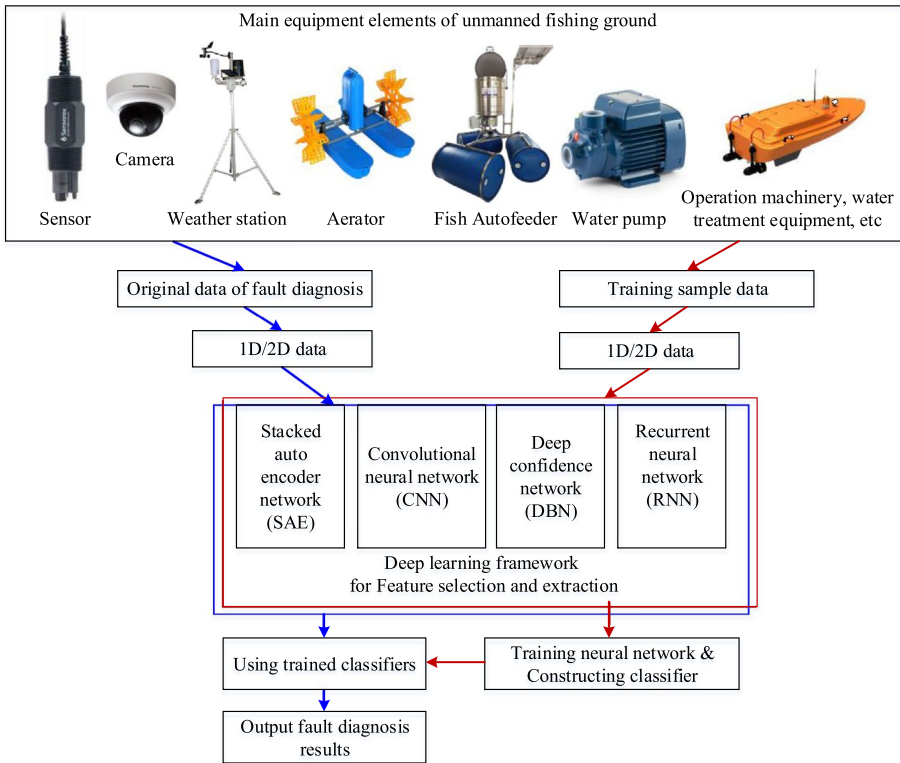
Fig. 7 Deep learning fault diagnosis based on multi-source heterogeneous data fusion

and intelligent equipment operate autonomously, that is a completely unmanned fish farm. The intelligent fish farm can adopt intelligent digital technologies to solve the problems of aquaculture labor shortage, water pollution, high risk and low efficiency of aquaculture, but there are still some technical details to be considered.

With the deep integration of agricultural technology and advanced information technology such as IoT, cloud computing, big data and AI, agricultural robots as a new generation of intelligent agricultural machinery will break through innovation bottlenecks and be widely used. The future fish farm will need a lot of agricultural robots. Research on new technologies of agricultural robots includes deep learning, new materials, human–computer integration and haptic feedback. Because of the complex and changeable working environment in intelligent fish farm, the variety of cultured species and their different growth states, aquaculture robots are facing great challenges in the aspects of optimization of target identification and positioning algorithm, optimization of navigation and path planning algorithm and optimization of operation object sorting and monitoring algorithm. IoT technology plays an important role in the collaborative work of various production factors in intelligent fish farm. In order to achieve sustainable development, aquaculture IoT needs to overcome the three problems. Water quality sensors are susceptible to surface attachment of the biological elements and have poor reliability of online measurement. The sensors show short life-span and low intelligence. The environmental complexity of intelligent fish farm and the low power consumption of sensors have put forward higher requirements

for agricultural IoT data transmission. There is still a certain gap compared with the industrial process measurement and control in terms of network transmission security technology, anti-interference technology and automatic dynamic networking technology under low power consumption. The instability of network transmission brings certain difficulties to the back-end data processing and intelligent data analysis. The standards for supporting agricultural IoT are lagging behind, and the construction of sensor network architecture in fish farm is lack of unified guidance and specification document. Designers of IoT devices usually define private data transfer protocols. There is no uniform standard to follow for the application of sensor data fusion and the design of upper application system, which is not conducive to the development of industrial technology.

In the aspect of aquaculture big data, the biodiversity of aquatic animals and the complexity of their growing environment in intelligent fish farm pose challenges to data acquisition. At present, many researches are conducted in laboratory environment. Traditional video image acquisition used to monitor the occurrence of fish diseases and abnormal behavior of fish under natural environmental conditions gets low accuracy, which has always been the bottleneck of accurate acquisition of aquaculture big data. The combination of big data technology and aquaculture only simply and directly applies the existing intelligent methods, but pays little attention to the characteristics of aquaculture, which leads to the practicability of aquaculture big data analysis lagging behind the market demand. To improve the degree of intelligence in the aquaculture industry, it is also necessary to make breakthroughs in key intelligence technologies and increase the depth and breadth of applications of deep learning, knowledge computing, swarm intelligence and hybrid-augmented intelligence in aquaculture. In addition, the current research on aquaculture big data only focuses on a single or partial production process, lacks horizontal and vertical relevance and has no solution for the whole aquaculture industry.

The breakthrough point of AI in intelligent fish farm is deep learning. Compared with traditional machine learning, deep learning can better extract the features of agricultural images and structured data, and effectively combine with agricultural machinery to better support the development of aquaculture intelligent equipment. It is found that there are still some deficiencies in the application of deep learning in aquaculture as follows: Firstly, deep learning needs large data sets for model training, verification and testing, which requires the construction of cameras or sensor equipment to collect data information in different environments. The ambiguity and instability of underwater imaging systems and the high-frequency disturbance and drift of sensors increase the design complexity of deep learning algorithm. Secondly, most of the aquaculture problems based on deep learning are supervised learning, and the corresponding sample data need to be labeled. Generally, more professionals are required to participate and manually mark target category. Finally, although deep learning can learn the features of training data sets well, it cannot be generalized beyond the expression ability of data set, which means the migration of deep learning algorithm needs further consideration.

Conclusions

In view of the practical problems such as the degradation of offshore fish stocks, marine pollution (Sarma et al. 2013), higher average age of agricultural workers and the reduction of employees engaged in aquaculture, it is imperative for the aquaculture revolution to change from the traditional experience aquaculture to the digital intelligent aquaculture.

Modern emerging technologies such as AI, big data, IoT, sensors, machine vision and robots will gradually participate in the whole process of aquaculture production for liberating traditional labor force completely, and finally realize multi-scene all-weather real-time monitoring of production environment, big data analysis based on cloud platform and real-time intelligent decision-making.

In this paper, a new concept of the intelligent fish farm is first proposed, and the application of new generation information technology in aquaculture is briefly reviewed. Then, the application of intelligent measurement and control, feeding, inspection and harvesting equipment in intelligent fish farm is introduced in detail. Based on the analysis and summary of the core application layer of the intelligent fish farm, some subsystems integration schemes are proposed. The proposal and construction of intelligent fish farm has certain reference value and guiding significance of application for the digital, intelligent and unmanned development of aquaculture in the future. The construction of intelligent fish farm is much more complex than other intelligent farm projects. The reliability and service life of sensors, the robustness and accuracy of analysis and decision-making models, the reliability of data transmission based on IoT technology, and the cooperation efficiency among various aquaculture intelligent equipment also need to be further solved.

In the future, the rapid development of intelligent fish farm is inseparable from sound infrastructure construction and rich government policy support. The government should encourage potential aquaculture enterprises to upgrade first, introduce advanced agricultural technology and high-tech talents, and at the same time, ensure the healthy and green operation of intelligent fish farm by regulating the requirements of aquaculture sustainability indicators.

Declarations

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