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REVIEW

Information fusion in aquaculture: a state-of the art review

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Abstract Efficient fish feeding is currently one of biggest challenges in aquaculture to enhance the production of fish quality and quantity. In this review, an information fusion approach was used to integrate multi-sensor and computer vision techniques to make fish feeding more efficient and accurate. Information fusion is a well-known technology that has been used in different fields of artificial intelligence, robotics, image processing, computer vision, sensors and wireless sensor networks. Information fusion in aquaculture is a growing field of research that is used to enhance the performance of an "industrialized" ecosystem. This review study surveys different fish feeding systems using multi-sensor data fusion, computer vision technology, and different food intake models. In addition, different fish behavior monitoring techniques are discussed, and the parameters of water, pH, dissolved oxygen, turbidity, temperature etc., necessary for the fish feeding process, are examined. Moreover, the different waste management and fish disease diagnosis techniques using different technologies, expert systems and modeling are also reviewed.

Keywords aquaculture, computer vision, information fusion, modeling, sensor

1 Introduction

Combining and transforming information from different sources to make a decision is called information fusion[1]. Information fusion is commonly used in almost every field of artificial intelligence[2], robotics[3], image processing[4], computer vision[5] and multi-sensors[6]. However, it is not commonly used in aquaculture. To make aquaculture more productive and beneficial, it is necessary to increase the efficiency of several processes, such as water quality, fish feeding, fish behavior, fish disease diagnosis and waste management. Furthermore, the accurate measurement of the physical, chemical and biological parameters is important in aquaculture, especially for the feeding process. There are many publications on fish feeding regarding technologies[7], such as image processing[8], data fusion, multi-sensors[9] and different modeling techniques[10,11]. Due to wide range of flexibility in using wireless sensor networks in any environment[12,13], it can be helpful for solving fusion problems as well.

This review describes the different efforts of researchers to increase the productivity of aquaculture. Each technology presents a limitation, and information fusion is a powerful method of integrating information from different sources and accounting for the conflicts of combined sources and information source interdependence[14].

In fish feeding, water quality measurement is important. The environmental conditions, required for various types of fishes are not uniform, and the ideal values for temperature, pH, turbidity and dissolved oxygen are different for each fish type[15,16]. There are different devices, hardware and software used for measuring water parameters to define water quality[17,18]. The efficiency of fish feeding is a critical problem. A total of 60% of the cost of fish is spent on feeding, but a considerable part of food is wasted, which results in a large loss in revenue. An appropriate feeding strategy can improve the aggression and competition in fish culture[19,20]. Fish feeding, food intake and feeding time are important but the estimation of food lost during the feeding is more important than other

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factors. Lloret et al.[21] proposed an underwater wireless group-based sensor network in order to quantify and to monitor the accurate amount of pollution that deposits on the seabed. The timely diagnosis of fish diseases is also important, both for production and for reduction of waste output, which are beneficial for aquaculture[22]. This review describes the art of fusion technology using sensors, computer vision technologies and modeling techniques. Various fusion based publications, expert systems, and model-based research are presented in this paper. Many applications, methods and assessments relating to aquaculture components are identified.

The objective of this review is to present a new strategy for various subsystems of aquaculture. Recently, Zion et al.[23] described the various features including counting, size and mass estimation, gender identification, quality assessment, species and stock identification, based on computer vision technology but did not mention water quality, which is an important factor. In this review, we addressed fish feed modeling, fish behavior, fish harvesting, water quality and food waste management using various technologies. There are many in depth studies in this field, but we hope that this review will present new possibilities.

2 Water quality monitoring

Currently, sensor and computer vision technology are common tools used to monitor water quality, supporting immediate action when problems arise. To improve the system and increase efficiency, new technologies should be introduced to improve water quality monitoring. Information fusion can be used in water quality monitoring to assess water quality and its different parameters. We can monitor water quality only when we calculate and fuse the parameters efficiently to make an effective decision. In fish farming, water quality measurement is a key factor in aquaculture. In fish culture, fish behavior changes with respect to changes in the environment. The aquatic environment also effects the growth of the fish, which is the main objective of the fish farming. Water quality can be measured using the different physical and chemical tests and by monitoring the movement and feeding behavior of the organisms. In this section, we describe the different technologies and methodologies used in the last few years and in the last section we present ideas regarding the integration of these methods to attain maximum results and accuracy. Combining these technologies with modeling techniques we can monitor and measure the results more accurately.

A summary of previous work related to water quality monitoring in aquaculture is presented in Fig. 1 to show information fusion based on multiple sensors, computer vision technology and modeling techniques, with fusion at different levels[24,25].

2.1 Use of computer vision and sensor technology

To make water quality monitoring effective, it is necessary to automate the classical water monitoring processes, such as the accurate measurement of pH, dissolved oxygen, salinity and turbidity.

Buentello et al.[15] mentioned that suitable temperature and dissolved oxygen levels are important for productive fish farming. In aquaculture, the use of underwater sensors for environmental monitoring is increasing. The turbidity measurement of the underwater environment is important because it directly affects the feeding process, because a slight change in turbidity can affect fish behavior.

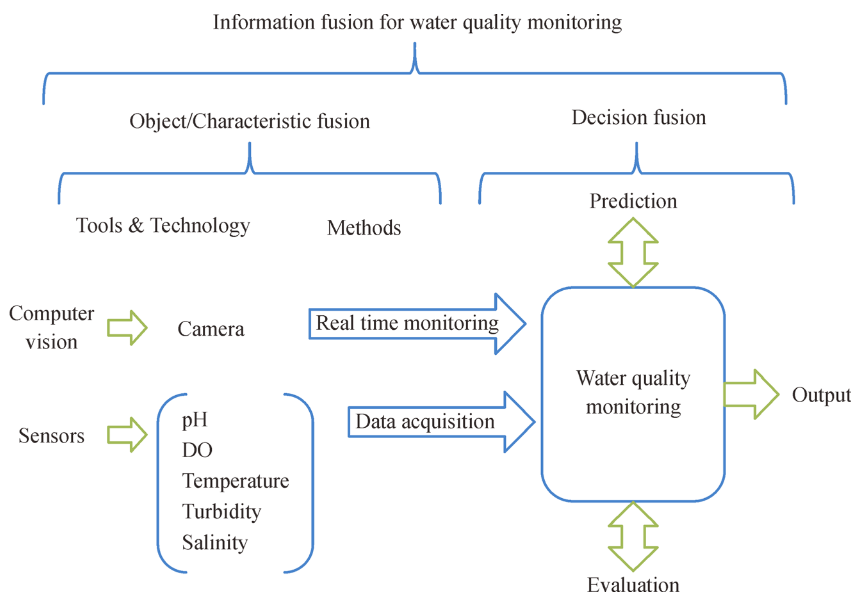

Fig. 1 Information fusion approach for water quality monitoring in aquaculture

Toran et al.[26] designed a virtual instrument for water quality monitoring in which they measured the various variables of water quality, as well as automating the classical water quality monitoring process. In their design, they divide the system into three parts: a data acquisition and measurement unit, a control access unit and remote access. Another report[27] concerned efforts to assess the water quality from the swimming pattern of the fish. This study used a video monitoring method to analyze the behavior of fish in transparent and contaminated water. This research introduced novel descriptors based on a recurrence plot representation used to discriminate the fish patterns in clean and polluted water.

In a recent study, Garcia et al.[28] proposed a sensor network to monitor and control the feeding system, where water quality parameters such as pH, temperature, dissolved oxygen, salinity and turbidity were measured using different sensors.

Tai et al.[29] proposed a smart, sensor-based water quality monitoring system for multi-environments. Using this system, water quality parameters are measured and monitored accurately without manual intervention. Additionally, this method is cost effective and energy efficient, because it uses solar energy.

Zhu et al.[14] demonstrated real time online monitoring of water quality with good precision and high efficiency using multi-parameter sensors to monitor water quality parameters such as pH, dissolved oxygen, water level, etc. To ensure the accuracy of the system, the STM8L152 device was chosen.

Recently, Lambrou et al.[30] developed an inexpensive sensor for turbidity measurement. However, a device that is cost effective and can be used by unskilled workers is urgently needed.

2.2 Water quality using models

Surface water quality is a sensitive and critical parameter, and its careful measurement is required. Different factors are involved in surface water contamination; therefore, it is necessary to monitor the water quality and make estimations for the surface water, based on the water quality index (WQI), which relates to surface water classification according to different categories. In the WQI, the quality of water is denoted by a number that describes the level of water quality. For each parameter, a range from one to one hundred is used to define its characteristics and a weighting factor is applied according to its importance.

Sánchez et al.[31] indicated that a low water quality index represents watershed pollution and oxygen deficiency. There are many advantages to this method, because it is simple, inexpensive and fast. However, water quality is affected differentially due to the change in climate conditions during the summer and winter.

dos Santos Simoes et al.[32] reported how aquatic organisms are influenced by the WQI. They compared three WQI; WQInfs with nine parameters, WQImoc with three parameters, and WQImin, which has a minimum operator concept. In this comparison, the authors showed that WQImin can monitor the operation of aquaculture better than WQInfs and WQImoc.

In another study, Akkoyunlu et al.[33] evaluated pollution, using water quality indices. In this case study, the authors compared various parameters of water quality in North America (CCME-WQI, OWQI, and NSF-WQI), and provided an improved method for choosing a suitable index and parameters, according to the environmental conditions. The greatest drawback in this study was the weighting factor for the parameters.

Later on, Koçer et al.[34] presented the environmental effect on the assessment of water quality indices in a land-based trout farm. In this study, the authors compared the result of WQI using 24 parameters. However, although probably phosphorus might be another contamination, successful classification results were achieved. A major benefit of this method is the time and cost savings, which is a key aspect of water quality management.

The studies of Akkoyunlu et al.[33] and Koçer et al.[34] had same weak points in the use of the weighting factor. Currently, artificial intelligence technology is commonly used to solve environmental problems. Lermontov et al.[35]. presented a fuzzy WQI (FWQI) analysis, which relies on FWQI and fuzzy logic. FWQI is computed using a fuzzy inference tool and artificial intelligence based on fuzzy logic. In this study, the authors were unable to achieve the required objective, due to lack of knowledge about the fuzzy logic and the complex rules. Although the results in this study were poor, this idea could potentially be used as an alternative environmental index.

In intensive fish farm management, monitoring and prediction about water quality is key. In previous studies, Koçer et al.[34] monitored water quality using a remote wireless system. In this article, a wireless sensing network with an IPEC based virtual private network and a CDMA service were fused with the forecasting model in which an artificial neural network was used. The results were satisfactory, with a few drawbacks, but the system measured the different parameters of water and temperature continuously.

This system provided 81.4% percent accuracy using a forecast model with 100% accuracy of the alarm. Although the forecast model provided good results, it could be improved by focusing more on the data set. However, its applications are still limited due to its time consuming, expensive, and complex structure.

To classify the underlying area, it is better to combine neuro-fuzzy modeling with GIS, which has the benefit of incorporating expert scientific knowledge with a geospatial model. Lermontov et al.[35] presented a spatial model using a GIS-based neuro-fuzzy technique for the marine finfish aquaculture environment. The neuro-fuzzy model provided a good idea of the final classification, using the Kruskal–Wallis and Spearman rank correlation method by accurately showing the level of the nitrogen concentration. Therefore, the neuro-fuzzy model was a beneficial tool for the selection of a suitable environment for a marine culture.

Navas et al.[36] introduced a signal processing technique to predict and assess the quality of water on the basis of environment pattern processing and the negative impact on ecology that affects production and growth of organism by calculating the deviation and frequency at specific levels, using a Gamma classifier. A WQI index was used to compare, analyze, and predict the signal with good results. Although this system was a better decision support system, it had some limitations because only a small number of parameters were used to analyze water quality.

To evaluate the water quality in fish culture, it is important to assess the quality by its biological, chemical and physical parameters, through toxicological tests to protect the organisms.

Hernández et al.[37] proposed a reasoning process based on fuzzy inference systems to assess the water quality immediately. In the proposed solution, the authors divided the assessment of parameters on daily and weekly bases with the fuzzy logic, by identifying the status of water quality and negative effects. This system showed effective results for immediate water quality assessment.

In aquaculture, especially for fish culture, it is important to select a suitable environment for the organism that is less critical and more effective for the production of the species. Carbajal-Hernández et al.[38] presented the fusion of a 3D hydrodynamic and particle tracking model for managing a better environment for finfish culture. The fusion of these two models is encouraged for site selection in aquaculture. In future perspectives, it would be possible to fuse the other models with the 3D hydrodynamic model for the benefit of aquaculture environmental management.

Ferreira et al.[39] introduced a management tool for marine culture through the fusion of hydrological and water quality indices. In shrimp farming, it is import to generate the water quality indices using the proper measurement parameters. WQI data can be interpreted quickly and easily, and it is a better choice for the management of water quality and production in aquaculture fish farming.

Charef et al.[40] investigated a smart sensing system in which the fusion approach was used by integrating the multi-sensor fusion and artificial neural network. Impressive results were achieved regarding pollution parameters, particularly for chemical oxygen demand. The method used in this system is simple and attractive for measuring and controlling production. This system is cost effective and fast, and it can be further improved by adding and measuring of other parameters.

3 Fish feeding in aquaculture

Fish feeding not only provides food to fish but also involves various factors that are important to the feeding process. Efficient integration of these factors will be beneficial for this process. For this purpose, the introduction of fusion methodology is considered in this article. Pixel, characteristic, and decision level fusions are three levels of information fusion[41]. This article introduces a method that uses computer imaging and sensor technology to characterize the aquatic environment and presents a model for making decisions based on this characterization.

In Fig. 2 Information fusion, based on multi sensor and computer vision summaries different work related to fish feeding in aquaculture. The various methods can be fused with feed intake models following the different levels of fusion, which can be used in any field[25,41].

3.1 Use of computer vision technology

Fish feeding is a key component of aquaculture. Researchers have made many efforts to increase the efficiency and effectiveness of fish feeding. The best way is to use a technology for studying the method and necessary components. In a recent study, Zion et al.[23] described the necessary components related to fish culture in the aquaculture environment, which can be beneficial for the future development of fisheries. Although the Zion [23] review described the different necessary components, it did not examine water quality. Water quality affects the feeding and growth rate in fish cultures. In this review, the different parameters of water quality important for fish feeding and growth are discussed. Using different case studies these components of fish feeding will be examined, using computer vision and sensor technology. Additionally, we will examine how these components can be integrated to make fish feeding productive for aquaculture.

With the development of science and technology, the use of computer vision technology is common in aquaculture. Zion et al.[42] used image processing technology as a movement invariant method for underwater live fish harvesting. Zion used a sorting method to distinguish the fish that were ready for harvesting. Although the accuracy of this research is acceptable, it can be improved with fusion technology. Cubitt et al.[43] identified the hunger state of fish (fed and fasted fish) with an 85% success rate using a pattern recognition and support vector machine. Currently, the use of web technology is popular in most fields, although it has not been widely used in aquaculture. Yao et al.[44] reviewed the state of the art of web information fusion, in which ontology, semantic web and web support systems were discussed. Gümüş et al.[45] presented the overall structure of computer vision, measurement ability, and error detection of different methods of machine vision technology for aquatic food

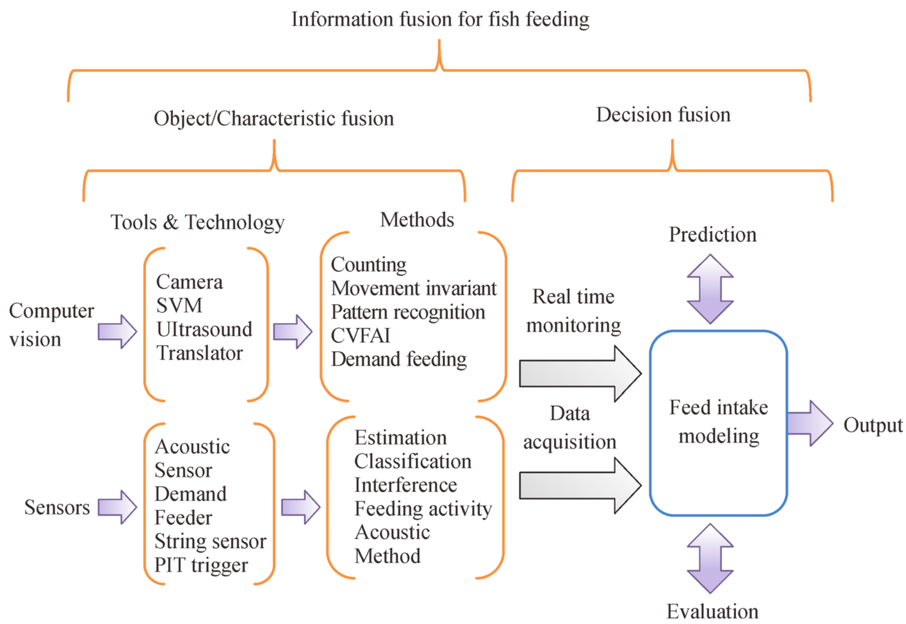

Fig. 2 The information fusion approach for fish feeding in aquaculture

in aquaculture, and described the benefits and drawbacks of computer vision technology.

Recently, Polonschii et al.[46] reported that remote real-time bio-monitoring using ultrasound transducers, was an advanced, less expensive and more effective solution for monitoring fish behavior. Estimating efficiency of fish feeding is not possible before the intake (appetite) of food by the fish has been defined, while the intake and fasting behavior of fish varies under different conditions. Lee et al.[47] presented a sustainable fish feeding system by using machine vision technology on the basis of counting the number of fishes. The feeding decision has been made on the basis of information, acquired from the different resources and integrated, resulting in an algorithm using computer vision technology. Recently, Liu et al.[7] proposed a computer vision system based on the feeding activity of fish in a re-circulating aquaculture system. In this experiment, a CCD camera was used to monitor the fish behavior. Then, a computer vision-based feeding activity index (CVFAI) method was proposed; to make this method accessible, and a manual feeding activity index was measured for each type of activity. If the CVFAI provides small or large values, then the stress behavior of the fish can be predicted.

3.2 Use of a multi-sensor

The trend of using multi-sensor fusion in aquaculture is a growing approach in this field. The proper selection of the fusion method can help to achieve the maximum benefits and efficiency. It is common to control production costs by improved feeding, and the use of sensors is becoming more common day by day.

Garcia et al.[48] highlighted the food lost during fish feeding in aquaculture. The author explained how the aquatic environment is disturbed due to wastage of food and proposed a feeding control system based on the groups of sensor controlling the feeding.

Azzaydi et al.[49] proposed a comparison of the effect of automatic *ad libitum* demand feeding and time restricted demand feeding strategies on the growth and feeding rhythm of sea bass (*Dicentrarchuslabrax* L.). This comparison showed inferior results for automatic feeding. The most important factor in the improvement of growth and efficiency is the time of feeding and how the feeding occurs. One of large problems in demand feeding is that only a few fish in a group are able to activate or pull the trigger. In addition, sometimes the feed cost cannot be estimated. Restricted demand feeding shows the best results because fish can predict the feeding time, which is beneficial for optimization. Luo et al.[25] reported that a multi-sensor fusion algorithm method was divided into four parts: the estimation, classification, inference, and artificial intelligence methods, which can be applicable in any field. The authors explained computer vision and sensor technology to best fit the classification method. In the aquaculture environment, feeding is effective only when sufficient feed is provided and feed waste is very low. One of most widely used techniques is manual feeding, but this method is labor-intensive. By using restricted feed availability, the feed conversion rate can be increased in some species, such as trout. Mallekh et al.[50] proposed a solution for these problems by using an acoustic detector for feeding activity. The authors used an acoustic method, which was directed by sound emitted by fish during the feeding period, using an acoustic sensor and processing system. For future use, the acoustic sensor is highly preferred for use in farming systems. Rubio et al.[51] proposed a self-feeding system for sea bass using a string sensor under different empirical conditions. In this system, the authors used among others the bit and pull trigger for the group of trained and non-trained fish in three experiments. There where many advantages of the system, including the short time needed to complete the experiment, the fish were able to be fed at night, no accidental triggering activations by waves, wind or fish, no feed wastage, the low cost, and the ease and speed of component replacement. Although growth rate results were beneficial and sufficient for system efficiency, this system is more suitable for trained fish. However, for non-trained fish, such results may not be achieved, especially because the time required would be longer than expected.

Covès et al.[52] presented a long-term fish feeding monitoring system, based on individual fish triggering. The trigger registrations in these experiments were 100%. The accuracy of the experiment was 95%, and the feed wastage rate was low, because, as found with the previous system, only a few individuals were used to activate the trigger. The results can be altered if the most trigger-activating individuals are moved to a different container. These practices provide an effective benefit for the fish. In most studies of demand feeding systems, the growth rate of the group of fish was monitored. Only in a few studies have the individual growth rates been measured. Millot et al.[53] presented the effect of individual behavior on the growth rate and health of sea bass juveniles using a demand feeding system. In these experiments, the authors showed that although the growth rate of higher triggering individuals was greater than the other zero or nonzero triggering individuals, the final bodyweight was not greater than the other individuals. In their concluding remarks, the authors state that the measurement of feed consumption and feed demand was more important than the individual growth rate.

In aquaculture, to achieve better production and growth, food and feeding methods present a major challenge. For this reason, it is important to know about fish appetite (one of the key ways to reduce food waste), turbidity and higher stocking density. These parameters are the main contributing factors that create problems in visualizing fish behavior, and to learn more about fish food intake (appetite), and what causes environmental pollution. Noble et al.[54] presented the effect of three self-feeding regimes on behavior, growth and damage of rainbow trout in a group. Flood et al.[11] used a self-feeding system to examine the daily feeding of amago salmon (*Oncorhynchus masou macrostomus*) while feeding rhythms, feed waste, and variability in feed demand were studied. The results of this work showed that the maximum consumption of food occurred at mid-day, suggesting the optimization of the daily feeding during the day.

Garcia et al.[12] investigated a monitoring and control sensor system for fish feeding, where the fusion method used to make decisions was based on the various sensor measurements. Subsequently, Zhang et al.[11] proposed a multi-metric learning algorithm. In that article, the authors integrated different sensors with similar or different joint classification characteristics to achieve better results. Currently, sensor technology is widely used in underwater environmental monitoring and control, especially in the demand feeding system. Self-feeders are used more than the interactive feedback system, in which a passive integrated trigger is used to actuate the availability of food pellets. Multiple self-feeders can be more effective in meeting nutrition needs. In the demand feeding system, the computer vision and sensor technologies are integrated to improve the production and efficiency of the system[54].

3.3 Feed intake modeling

In fish feeding, consumption and growth of the aquatic animal is important for production. The most important and difficult task is the creation of a model according to the requirements for estimating the feed and growth rate. Decision level fusion (modeling) is one of best solutions to meet the requirements. However, there is no perfect proposed model that meets all the requirements because of the different environments and behaviors of aquatic animals. In aquaculture, the results are mostly empirically based[55]. In the last few decades, different models have been presented under various conditions to meet the requirements. One of the most important tasks in developing a model that is able to define parameters of the system is complicated by the fact that every system has different conditions, requirements and needs, and the parameters vary according to the conditions. There are many publications in which different models are presented, but every model has unique limitations. Pauly et al.[56] carried out experiments based on estimations regarding food consumption and growth rate, but the parameters about energy intake and growth rate were not suitable to meet the expected results. Later, Pauly et al.[57] used ecosystem models to estimate food consumption. A few hypotheses about temperature and different types of species were presented in this article. Some of the predictions showed better results and correlations, but most of the predictions were not accurate. It is important to identify the relative parameters that are necessary for meeting the requirements, and in this case, there was a lack estimation of parameters, so the food consumption ratio was low.

Tudor et al.[58] estimated food consumption rate of mercury by fish using a mass balance model. The model generated quite accurate results with minor differences of 1%–2%. This model has advantages over the bioenergetics model and over the model based on stomach contents. In this article, assumptions about food consumption in females were found to correlate with how much energy is required and displayed. Richter et al.[59] present a MAXIMS fish feeding model in which the calculated parameters of daily evacuation rate, ingestion and feeding period were used. Predictions about some other models were also presented in this study, such as the inversely dependent model, and the constant model. The results of these predictions were shown statistically using the *F*-test. However, the MAXIMS model is not suitable for more than 40 parameters. Because it is difficult to measure the food intake time for aquatic animals, a fuzzy logic control for feeding can be helpful in an automatic feeding device using computer-based models[60]. Due to the lack of knowledge, regarding the feeding and parameters of a system in which fuzzy logic is used, a neural network may provide better results. Mcdermot et al.[61] presented an individual based model for different species with various conditions and tracked the feeding, growth rate, and movement behavior of multiple generations of different species. This study also examined environmental effects and considered different parameters. The authors compared the effects of different models and individual models showed better results under various conditions and time dependency.

Trudel et al.[62] predicted the mercury concentration using a mercury mass balance model and then used this model to find the suitable mercury concentration. They also showed that to obtain the best value from the mercury mass balance model, it was necessary to accurately estimate the feeding rate and the consumption rate, and the bioenergetics model was not suitable. Tudor et al.[58] proposed an impulse-input model, which showed good results in the random process of food ingestion, but it was not sufficiently reliable for the food consumption. Cho et al.[63] presented a computational model based on nutritional need, to estimate the waste and determine the feeding regulation. In addition, the Fish-PrFEQ program introduced in this article predicted the live weight gain, growth rate and estimated the required nutritional components. However, some of the predictions regarding the feed requirements and waste load were inaccurate because of unrelated coefficients, used in this program. Therefore, it is important to use the necessary and related coefficients to achieve the best results. Alanärä et al.[19] proposed a daily feed requirement model for five parameters. In this work there was no temperature effect on digestible energy need.

Nunes et al.[61] presented a simple model for ingestion rate and food consumption. Although this model satisfied the simple conditions, it did not meet the requirements because environmental effects such as water quality variables (pH, temperature, dissolved oxygen and turbidity) were not included. Later, Canale et al.[64] validated a bioenergetics model in which the net energy consumption was equal to the net weight and the temperature effect on the body.

Árnason et al.[65] showed the effect of temperature and bodyweight on feed conversion and growth rate of turbot (*Scophthalmus maximus*), and the growth model showed good results. However, at a certain temperature, the model showed unpredictable results due to limitations in the weight range or the short period of time of the experiments. Chowdhury et al.[66] determined the feed requirement and water output under actual farming conditions. Almost all body consumption components were developed under the actual environmental conditions. As mentioned earlier, there are certain limitations in every model, according to environmental and parametric variation, and better results can be produced by integrating the models on a common basis. An attempt at integration was made by Ferriss et al.[9] to improve the consumption rate by combining mercury mass balance with bioenergetics model. A statistical approach was used in this experiment, provided the maximum estimates for swimming and mercury concentration. However, due to some uncertainty in the parameters, it failed to meet the requirement for the mercury data. Although the integrated model is not perfect due the uncertainties, it can be applied for different feeding strategies of common conditions.

4 Fish behavior monitoring

In aquaculture, monitoring and tracking fish behavior are important in fish feeding, growth and production. In the last few decades, technologies (especially the underwater cameras, telemetry, acoustic Doppler velocity and passive integrated transponders) have been largely incorporated into aquaculture to monitor the behavior of fish individually, or on a group basis. Underwater video monitoring is based on tracking, counting or recognizing the pattern of fish behavior in fish feeding, and also monitoring the water quality. Acoustic and radio-telemetry are used to monitor the muscle activity, feeding demand, movements, physiology and behavior of free swimming fish in different environments and under certain conditions[9].

The acoustic Doppler velocity technique has been used to measure the swimming behavior of fish, and the passive integrated transponder (PIT) has widely been used in aquaculture because it is portable, less expensive, and easy to integrate in any environment. Although the portable system has some limitation over the stationary system, it is easy to use. Currently, stationary and portable systems are fused together to monitor fish at higher and temporal resolution. In PIT, the selection between the full duplex and half duplex technology is an important question from the point of view of speed and consumption[67].

In Fig. 3 various computer vision methods are shown, such as multi tracking, feature extraction, motion pattern and image processing for monitoring the fish behavior. Moreover different sensors like PIT, telemetry and ADV

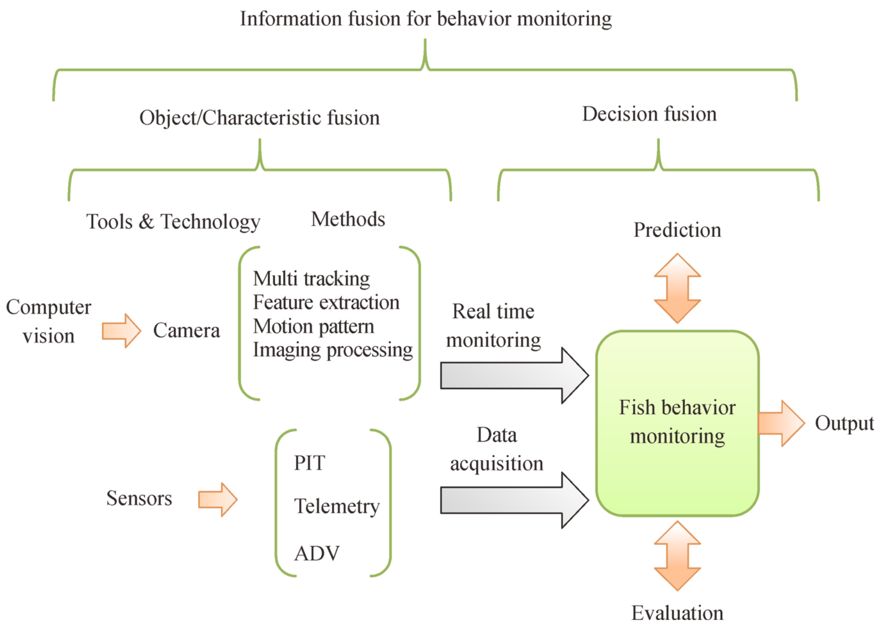

Fig. 3 Information fusion approach for fish behavior monitoring in aquaculture

can be used for data acquisition, and these technologies for fish behavior monitoring incorporated in the subsequent levels of fusion[25,41].

4.1 Use of computer vision technology

Spampinato et al.[68] presented a counting-based machine vision system using underwater cameras (with low quality images). Although the authors show 85% accuracy, this accuracy can be improved by integrating with an algorithm for the best processing time and video utilization. Furthermore, the authors developed a multi-tracking video system to quantify the behavior of fish, individually, among 100 fishes. Although this effort shows a result of more than 99% tracking success for individual fish, the statistical tracking method did not show good results and caused an error when an occlusion occurred between fishes. It is difficult to track the occlusion between every neighboring fish, and this can be ignored on the basis of speed of an individual.

Spampinato et al.[69] made a combined effort to automatically classify the underwater species and to understand their behavior, based on the integration of invariant shape and texture features, which provided a 90% classification result. Although this method showed a more acceptable result, it can be improved by adding the different fish features and smooth texture fusing of the behavior of fish. Amer et al.[8] used underwater cameras to monitor the fish motion pattern by fine-grained categorization and used the detection, tracking and feature extraction techniques to successfully identify the six distinct patterns of fish movement. For the video classification, they used the random forest method with the categorized histograms of fish displacement. One major problem in monitoring of fish is the detection and tracking processes[70]. And these authors used image acquisition and feature extraction to detect and track the fish, respectively. Although the experimental results were suitable for real time applications, they were not suitable for detecting fish in mutable conditions because of the moving objects. Recently, Pornpanomchai et al.[71] developed an image recognition system by integrating five subsystems: image acquisition, image preprocessing, feature extraction, image recognition and results presentation. In this system, although the neural network technique of image recognition subsystem provides a higher precision of 99%, it consumes more time than the Euclidean distance method. In the future, we can increase the species and extract more features of fish in the real environment with the client server computerized system.

4.2 Use of sensor technology

Armstrong et al.[72] used an individual spatial strategy for Atlantic salmon by monitoring the behavior and integrating a PIT and video camera. Although, because of the PIT and video monitoring they achieved better signal and vision, the territorial mosaic model was not suitable due to overlapping at large scales in home ranges. Greenberg et al.[73] measured the habitat-based continuous data of individual fish using different levels of spaces, intrusiveness and temporal resolution with PIT and described the depth of the pool, the sex of the individual, the time of day and the growth rate. The study of the swimming activity showed a reasonable value for productive fish feeding (acoustical Doppler velocity techniques were used for this purpose). David et al.[74] used radio-telemetry to remote monitoring of the continuous fish activity in a given range. In this method, the activity of fish was monitored by obtaining a signal from the antenna at any position in the water, and the whole system was able to be dismantled in a few minutes. However, this method is not suitable for high temporal resolution to acquire the direct observations where there is typically a lack of proper light. If we integrate the temporal resolution properties with this method, it could provide a better result under different conditions.

David et al.[75] conducted an experiment to measure the swimming behavior of cultured fish using acoustic telemetry. The authors used the stocking density factor to create differences in the activity variables, i.e., activity rhythm, space utilization and trajectory complexity. The results showed the quantifiable effect of stocking density on these three variables, but in true aquaculture conditions it is difficult to measure these alterations. Masaló et al.[76] measured the turbulence at different densities and quantified the swimming behavior. Although ADV is reliable for measuring the quantitative results of turbulence, it eliminates some measurements because fish larger than 48 g are of a higher density. Thida et al.[77] detected the abnormality by analyzing fish behavior in fresh and chemically contaminated water, and based the conclusion on pattern extraction, trajectory presentation and abnormal detection; the results showed accuracy of 90%. From the behavior of the fish, we can detect the chemicals in water, so we can generate warning signals. In addition, Yan et al.[78] proposed a simple and accurate tracking marker method and a fish mathematical kinematics model to measure the two different locomotion types of swimming. Johnston et al.[67] monitored fish behavior continuously in a natural stream using a flatbed passive integrated transponder, and then combined the individual behavior and the empirical data from the PIT at different scales and time frames. This method can be more useful for monitoring of biotic interaction, habitat and fish movements.

The Kalman filter is a well-known method, also for fish culture. Pinkiewicz et al.[79] explained the behavior of fish using the Kalman filter model and fish tracking method. In this paper, the authors successfully concluded that the speed and direction change on a daily basis, and the system also has an alarm ability in unusual conditions. The behavior of the fish varies with respect to the environment, but it also depends on the number of fish in the cage or pond.

Aquatic animals change their movements according to changes in the environment, and other factors also affect their behavior. Pinkiewicz et al.[79] analyzed the behavior of fish using stock density, as a stress factor. Although the various studies analyzed fish behavior, the main difference is the frame loss, because each frame saves a separate file, and it takes a long time to integrate this information, and also problems can occur from lost frames. In this method, the authors saved all of the frames into one file, which show a minimal time for frame loss (about 0.333 s). They also concluded that stocking density had a specific role in the growth and behavior of fish.

In another report, Cha et al.[80] presented a simple method for quantifying behavior using different frames. In this experiment, the authors differentiated the attraction of fish toward two lights (blue and white) and concluded that the blue light attracts more fish. Although this composite image method is useful for the relative study of fish and light, it has two drawbacks: (1) different frames are overlapped and the correct speed of the fish is not measured properly, and (2) the algorithm is not sufficiently efficient for the movement of fish at different depths because it only corrects the refraction at the bottom of the water.

5 Fish disease diagnosis

Sustainable development of aquaculture is effected by many factors, and fish disease is one of these factors. Different species often show different symptoms of the same disease; therefore, it is better first to classify the species prior to the disease diagnosis.

In Fig. 4 information fusion is based on various technologies and methods, such as image comparison and biosensor techniques for real-time monitoring and expert system analysis followed by fusion at different levels[25,41].

5.1 Use of computer vision technology

In the last few years, efforts have been made by different researchers and aqua-culture experts to improve the diagnosis and treatment of fish diseases. However, disease outbreaks occur due to misdiagnosis or mistreatment. Georgiadis et al.[81] presented an epidemiological approach to prevent, diagnose and control fish disease. The authors concluded that it was necessary to understand the epidemiological factors to overcome infectious diseases in aquaculture, and direct interaction between the aquaculture experts, epidemiologist and fish health specialist can assist in managing of fish diseases.

Li et al.[24] developed a web based intelligent diagnosis system called Fish Expert to diagnose fish diseases. In this system, different images related to diseases are saved in the database, which can be compared with an image of the current problem. Then, the system is able to suggest a solution (this entire process is web-based). The advantages of this system are the following: the system is easy to access, diagnosis using image comparison is simple, the system has a user feedback facility, and it provides information regarding diseases and medicine. One drawback of the system is that it is not user friendly. Wang

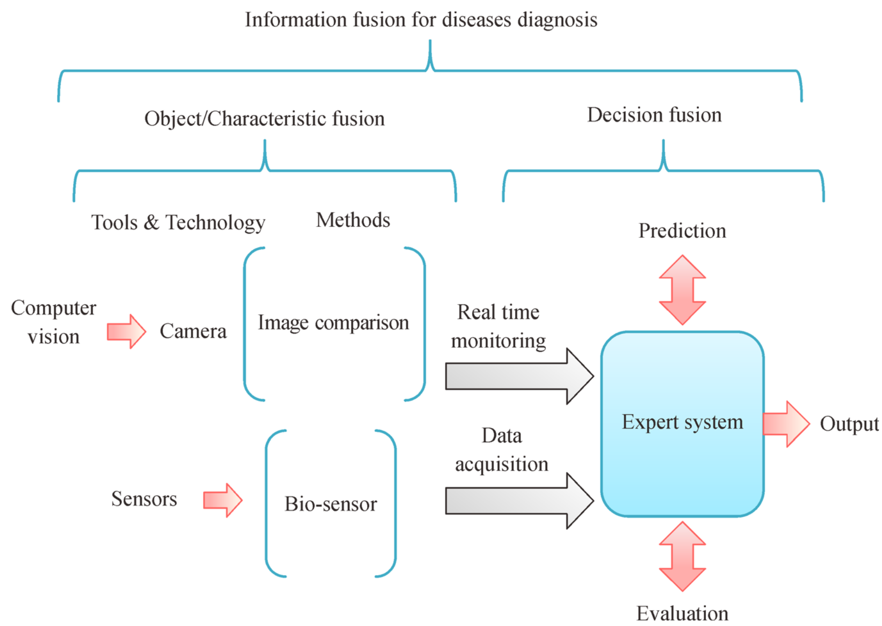

Fig. 4 Information fusion approach for fish disease diagnosis in aquaculture

et al.[41] designed a short message service (SMS)-based expert system to diagnose fish disease. In this system, a short message is sent to an expert to exchange the information automatically. The accuracy of the system was 93.5%, but it is also limited by the amount of data that can be sent. Nan et al.[82] developed a fish disease early warning system based on water quality management (EWS-FDWQ). This is a knowledge based system in which water quality management is described using a mathematical model. EWS-FDWQ is less labor intensive, effective in decreasing economic losses, more useful for industrial application, and has an early estimation, so the disease can be predicted, and it is less expensive. Although there are many advantages of this system, the expert response to the system was average because of the lack of time and certain system limitations. In this system, only water quality was examined, although fish feed and behavior are also important parts of aquaculture. In addition, there are different factors involved in each environment, and this study was based on only one facility. A case-based reasoning would be more effective in producing the early warning system.

Zhang et al.[83] proposed a model by integrating two prototype models, as follows: the first was to identify and understand the problem in the initial version, and the second to practically ascertain the feedbacks and drawbacks using a rapid throw away prototype with another model to revise and improve the drawbacks of the first version. Finally, a web-based system was developed. This system incorporated the integrated form of the user requirement, knowledge engineering and information technology. This system diagnoses fish disease and provides an expert enterprise facility, integrating various models and a data set to facilitate fish diagnosis. This system also provides water quality management and safety management. This system also faces some challenges, however, including a delay of feedback from the user, an unstable support team, and a limited system boundary. In the future, the fusion technique can be applied by combining and adding more components and variables to make the system more reliable and efficient.

Hu et al.[84] classified species using computer vision techniques. The authors proposed a unique and easy method for acquiring images using a smart phone, and sub-image features to make a six feature group. The authors used the LIBSVM software for a feature selection procedure, and two multi-class support vector machines were constructed to classify the images. The authors concluded that the integration of the Bior4.4 wavelet filter and the DAGSVM classifier produced the best classification model of species recognition.

5.2 Use of sensor technology in fish disease diagnosis

Hong et al.[85] developed a biosensor (QCM DNA) for the diagnosis of fish viruses. The purpose of the QCM DNA biosensor was to detect the G protein in fish infection using a DNA probe. A comparison experiment was performed to maximize the sensitivity of the sensor in which an immobilization method using avidin–biotin interaction provides the maximum sensitivity to detect the target DNA. The authors concluded that the QCM biosensor is quick and more efficient in detecting viral RNA compared to RT-PCR methods.

6 Feed waste management

Feed waste management in aquaculture is necessary to reduce the environmental impact and to achieve good production and there is a great need to improve the accuracy of feed waste measurement. For this purpose, Lloret et al.[21] determined the wasted feed, based on a wireless sensor network.

Cho et al.[86] concluded that biological and chemical waste output could be reduced by combining the strategies used for solid waste, including suspended solid and dissolved waste.

In Fig. 5, the works related to waste management in aquaculture can be summarized as follows: the first level of fusion, involves pellet detection, solid wastes and dissolved oxygen measurements by computer vision and signal/noise detection sensors; the second level of fusion involves modeling techniques according to the different levels of fusion[25,41].

In the last few decades, different strategies have been used to minimize feed waste by estimating waste output through diet formulation, reducing solid waste, as well as reducing dissolved nitrogen and phosphorous from waste and by proper feeding strategies[87].

The author concluded that using less waste-producing feed, using proper ingredients to balance feed, and reducing the ratio of protein to energy reduced the nitrogen waste. Phosphorous waste was reduced by using the optimum level and fish culture operations that minimized wastage. Thus, the estimation of feed wastage in aquaculture can improve profitability and production, as well as decrease environmental pollution.

Cripps et al.[88] presented a review of solid waste management and removal from the aquaculture production system. The authors concluded that fusion methodology can be useful for optimizing the aquaculture environment, which comprises feed management, feed quality, disposal management, and the pre-treatment quality of water. They also concluded that the different strategies of Europe and North America, regarding a high flow rate through the farm and a slow flow rate for the water quality requirement must be integrated together to achieve better results in future.

Foster et al.[89] presented a computer vision-based analysis of uneaten food pellets in a sea cage, using a detection and counting method, and they used a light-compensating video camera for monitoring pellet detection. Although the results in this experiment were satisfactory, detection error was not adequate for good results because there was an unpredictable fluctuation in low or high detection, and the object classification algorithm did not perform well because it could not identify the pellets correctly. In this experiment there was insufficient light to provide the best results and the blocking of light led to incorrect pellet detection. This can be improved by using a transparent shield around the camera or digital camera and improved lighting in the experiment.

Azzaydi et al.[49] presented a new approach to fish feeding rhythms by continuously monitoring uneaten pellets. In this approach, the authors used a collector and decanter for uneaten pellet detection and collection, respectively, with the help of a sensor and an integrated demand feeding approach. They concluded that feeding is effective during the day because the number of uneaten pellets is fewer than at night, and devices are useful for integrating demand feeding for the optimization and benefit of the aquaculture environment.

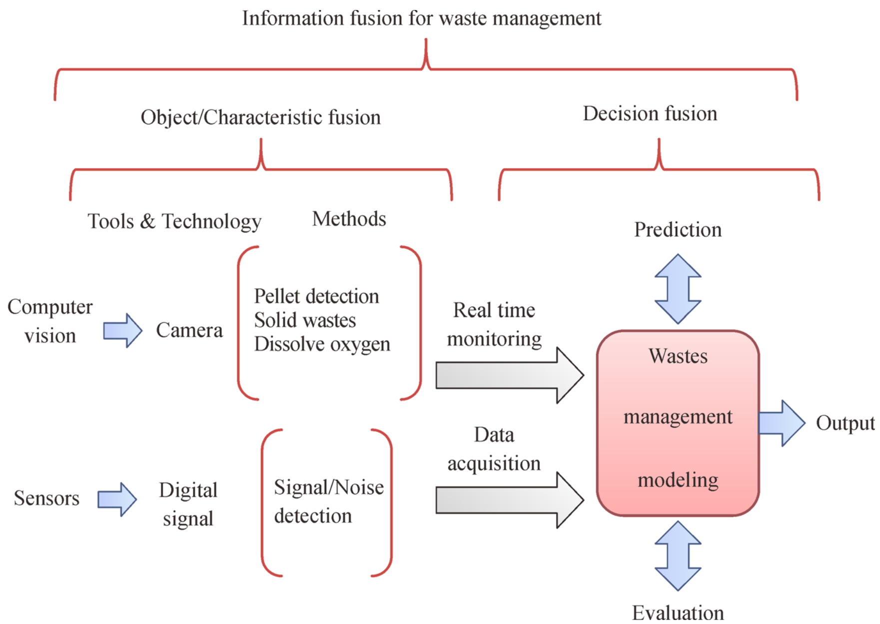

Fig. 5 Information fusion approach for waste management in aquaculture

Dudley et al.[90] proposed a solution of net-pen aquaculture waste transport using a modeling strategy. The authors integrated the finite difference model (Duchess)[91], which is used for the two dimensional deluge tidal computation and transport model[90]. The models were used to develop an aquaculture waste transport simulator model (AWATS). It was concluded from this integration that AWATS is a combination of information regarding velocity variation and provides the overall status of the waste distribution. Although this model provides the complete picture of flow field, it is not reliable for the calibration of the flow model to display the field data. In the future, oxygen demand for carbonaceous material of the sediment can be integrated with this model to achieve better results.

Ang et al.[92] examined pellet wastage using different feeding strategies for salmonids in sea cage farming. The authors concluded that to achieve the best results for feed wastage control and for satiation of every fish in surface and subsurface feeding strategies, changes to feeding and environmental should be considered to improve system performance. Subsequently, Parsonage et al.[93] measured the accuracy of pellet detection, using a machine vision system in which the feed waste and response time of the system was identified. According to the authors, the system can be effective if the sampling rate is two frames per second, the camera is properly maintained, the response time is reduced to change the position of the camera, and an alarm is used to detect food wastage. Acker et al.[94] monitored fish feeding and the detection of pellets using digital scanning sonar and used the acoustic signal method to obtain a high signal/noise ratio to detect the pellet under the unoccupied pen within 25 m. Although the system showed good results, with reliable feed monitoring, it showed an error with pellet detection, because when small fish are near the pellet the system cannot recognize the pellet. This problem can be solved by integrating fuzzy logic and artificial neural network, which can be used for distinguishing pellets.

Chamberlain et al.[95] proposed a waste model for simulating the effect of uncertainty of different parameters in finfish aquaculture. The waste model (DEPOMOD) is the integration of four different sub-modules of grid generation, particle tracking, re-suspension, and a benthic impact model. In this model, the authors predicted the carbon flux, the uncertainty of waste feed, carbon concentration of feed and fecal material. The assessment combined the relative uncertainty with the contribution of fecal material and the waste component and Chamberlain et al.[95] reviewed the application of modeling waste dispersion and the velocities of settling uneaten food pellets from sea cage aquaculture.

The author concluded that pellet size, settling velocity and the distribution of the associated percentage of mass should be considered in a realistic model.

7 Conclusions and future perspectives

This review has presented developments in aquaculture over the past 35 years, including sensor, computer vision technology and different modeling techniques. Less than a tenth of the literature typically used fusion methods to integrate the technologies and models. However, many papers utilized sensors, computer vision technologies and different models for specific aquaculture processes such as fish feeding, water quality monitoring, fish behavior monitoring, fish disease diagnosis and waste management.

Monitoring water quality in aquaculture is generally solved by classical techniques, while using sensors or by monitoring the behavior of the organisms with underwater cameras, combined with various algorithms to improve the accuracy and efficiency of the data from these technologies. Nevertheless, there is great need to fuse these technologies and use the acquired data for transforming them into a comprehensive form and to obtain maximum efficiency and better results for the benefit of aquaculture.

Various systems and techniques have been used to make fish feeding more efficient, but further reductions in feed waste need to be achieved. Given that feed waste is one of the biggest problems in aquaculture, different sensors and underwater vision technologies have been developed. However, these technologies require further improvement.

Currently, there are different automatic demand feeders and online monitoring systems available to improve the accuracy of the feeding process, but an adequate technology is still not available. Some fusion technologies have been used and provided better results. However, the accuracy of fish feeding will not be sufficient until the appetite time and amount of feed required are more clearly identified. In the future, considerable effort should be made to overcome these problems to make feeding more productive.

Continuous monitoring of the behavior of aquaculture organisms can make a difference for productive aquaculture. Different approaches using sensor technology and underwater cameras for monitoring fish behavior and patterns have been developed in the last few years, but there is still a need to integrate these technologies and transform the information to achieve better results. Using sensors and computer vision technology, fish behavior can be monitored and decisions about water quality and different fish movement patterns can be made more and more accurate. There is a great need to use an efficient algorithm to manage these technologies to achieve better and more efficient systems for the aquaculture environment.

The diagnosis of fish disease is a critical problem in aquaculture, because many fish die, resulting in major production loss and pollution. The research in diagnosing fish diseases has only produced moderate advances, which is a major limitation. Only a few researchers have used the vision technology based expert system to overcome the diagnosis problems. However, the technology is not mature enough for use in productive aquaculture, and there is a great need to find new ways for fish disease diagnosis by proper integration of the available resources, which would be beneficial to the industry.

Both improved welfare of fishes and improved productivity are needed can be achieved by improving management of waste in aquaculture, because the high rate of food waste causes pollution and disease in aquatic organisms. To overcome the food waste problem, different strategies and technologies have been used in recent years, but feed loss remains one of the biggest challenges in aquaculture. Only a few diet strategies and computer vision monitoring techniques have been used to overcome this problem. From our knowledge and perspective, information fusion techniques remain underutilized in solving this problem and could be used (with additional research) to more intensively overcome the feed waste problems.

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This article is a review and does not contain any studies with human or animal subjects performed by any of the authors.

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