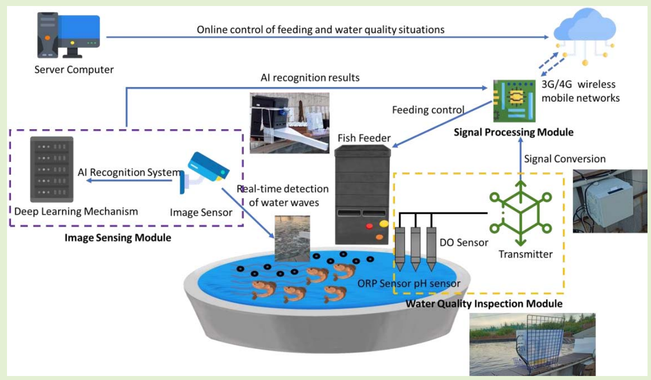
A Computer Vision-Based Intelligent Fish Feeding System Using Deep Learning Techniques for Aquaculture

Wu-Chih Hu, Liang-Bi Chen, *Senior Member, IEEE*, Bo-Kai Huang, and Hong-Ming Lin

***Abstract*—The decisions made regarding traditional fish feeding systems mainly depend on experience and simple time control. Most previous works have focused on image-based analysis of the leftover feed at the bottom of the pond to determine whether to continue or to stop feeding. However, the feasibility of such a method in an actual outdoor aquaculture pond is low. The main reason for this is that real outdoor aquaculture ponds have turbid water quality, small feed targets, interference from intense fish activity, overlapping images of fish and feed, etc. Therefore, image-based recognition is not easy to implement in actual outdoor aquaculture. To overcome this problem, this article proposes an automatic fish feeding system based on deep learning computer vision technology. In contrast to traditional computer-vision-based systems for recognizing fish feed underwater, the proposed system uses deep learning technology to recognize the size of the waves caused by fish eating feed to determine whether to continue or to stop feeding. Furthermore, several water quality sensors are adopted to assist in feeding decisions. As a result, the proposed system uses deep learning technology to recognize the size of the water waves caused by fish eating feed to determine whether to continue to cast feed or to stop feeding. Experimental results show that an accuracy of up to 93.2% can be achieved.**



***Index Terms*—Aquaculture, computer vision, deep learning, fish feeding systems, image recognition, image sensor application, intelligent systems, smart fish farming.**

I. Introduction

AT PRESENT, as the global population continues to grow, the demand for food supply is also increasing. With the intensification of worldwide greenhouse warming, because of the reduction in global land resources and desertification, substantial food shortages are expected. Therefore, the food crisis is one of the major issues facing the world today.

As the global area available for crop cultivation and animal husbandry continues to decrease, protein remains an indispensable primary source of nutrition for humanity. Because it is relatively easy to catch aquatic fish and shrimp, which constitute a food source that is rich in protein, humanity's utilization of fishing resources is increasing daily.

In brief, the food crisis is an important issue that the world must face today. Aquatic fish, shrimp, crabs, and shellfish are sources of high-quality protein in food. Aquaculture produces two-thirds of the world's marine products [1], [2]. Therefore, aquaculture has been recognized as an essential strategy for ensuring global food security.

According to the 2016 annual report titled The State of World Fisheries and Aquaculture (SOFIA) issued by the Food and Agriculture Organization (FAO) of the United Nations [3], since 1990, global natural fishing production has remained at approximately 90 million metric tons, while global aquaculture production has increased rapidly. It is estimated that by 2025, global aquaculture production will reach more than 100 million tons, and aquaculture already greatly contributes to global fishing resources, with its share increasing from 25.7% in 2000 to 46.8% in 2016 [4].

Nevertheless, the current aquaculture industry faces challenges, such as extreme climate conditions, an aging population, a lack of labor, high breeding costs, and unstable

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breeding rates. The traditional aquaculture industry has relied on labor and experience since ancient times. Various issues, such as climate change and the threat of an aging population, have been hindering the development of the aquaculture industry.

In the last few years, countries worldwide have introduced information and communication technology (ICT) into agricultural development using the Internet of Things (IoT) and artificial intelligence (AI) technology to solve the current difficulties faced by agriculture.

The application of related technologies is driving the advancement of new agricultural policies to further promote the transformation of the overall agricultural industrial structure, including transforming the aquaculture industry into intelligent agriculture. IoT technology is also being introduced into aquaculture applications to construct smart aquaculture systems based on artificial intelligence over the Internet of Things (AIoT).

An AIoT-based aquaculture system can provide 24-hour, year-round water quality monitoring, microclimate sensing and warning functions, while extending the early warning and response time, which can be linked to an intelligent electric box to automatically control water wheels, pump motors, feed machines and use other equipment. In addition, the sensed values and feeding records in such an AIoT system can be used to further assist farmers in making science-based judgments and decisions to carry out accurate and intelligent aquaculture and to achieve labor savings, stable water quality, energy savings, and accurate feeding. It can also reduce major risks of disaster and damage, thereby increasing the production rate of aquatic species and maximizing the benefits of aquaculture.

Among the various influencing factors, feeding is the main factor that determines the production cost and water quality in aquaculture. To adapt to large-scale fish farming, most farmers currently use automatic feeding machines. The feeding frequencies and feeding amounts of these machines are generally set in accordance with the experience of the farmers.

Because of the limited flexibility of actual fish feeding behavior, fish feeding is generally carried out with automatic feeding machines. However, the use of automatic feeding opportunities may often lead to overfeeding or underfeeding. The level of fish feeding technology also directly determines the production efficiency and feeding cost [5], [6].

In actual aquaculture, fish feeding costs may even account for more than 60% of the total cost in some cases [7]–[9]. Thus, it is clear that unreasonable feeding reduces production efficiency, and insufficient feeding affects fish growth. Overfeeding also reduces the efficiency of feed conversion, and the remaining feed pollutes the environment.

Therefore, by optimizing the feeding process, great economic benefits can be obtained [1]. Moreover, as the demand for high-quality aquatic products continues to increase, more attention is being paid to the health of fish during aquaculture. Excess feed that is not eaten consumes oxygen and produce ammonia and other toxic substances, and thus, affect the health and growth of the fish [5]–[7].

Feed deposited on the bottom of a fish pond decomposes to produce ammonia, nitrogen, and harmful nitrate compounds, which affect the healthy growth of fish [8], [9]. Previous related studies [9], [10] have further noted that an increase in ammonia concentration may lead to physiological disorders related to the blood chemistry, osmotic adjustment capacity, oxygen consumption, oxidative stress, and antioxidant status of farmed fish. This can then lead to changes in feeding behavior, decreased growth and immunity, or even death.

The decisions made in traditional fish feeding systems mainly depend on experience and simple time control. Currently, most studies focus on image-based analysis of the leftover feed at the bottom of the pond to determine whether to continue or to stop feeding.

However, the feasibility of such a method in actual outdoor aquaculture ponds is low. The main reason for this is that real outdoor aquaculture ponds have turbid water quality, small feed targets, interference from intense fish activity, overlapping images of fish and feed, etc. Therefore, image-based recognition is not easy to implement in an actual outdoor aquaculture.

This article proposes an automatic fish feeding system based on deep learning technology to overcome the above-mentioned problems. The proposed system is different from traditional computer-vision-based systems for recognizing fish feed underwater. Instead, the proposed system uses deep learning technology to recognize the size of the waves caused by fish eating feed to determine whether to continue or to stop feeding. Moreover, several water quality sensors are adopted to assist in making feeding decisions.

The remainder of this article is organized as follows: Section II reviews and discusses previous works. Section III introduces the proposed system. Section IV demonstrates the prototype of the proposed system and presents experimental results. Finally, Section V concludes this work and discusses possible further research directions.

II. Previous Works

In the last few years, many previous studies [1], [2], [6], [9]–[14] have reviewed and discussed the introduction of related ICT-, IoT-, and AI-based schemes into aquaculture to achieve intelligent aquaculture. As a result, real-time detection and monitoring of uneaten fish feed can effectively reduce the occurrence of overfeeding, thereby reducing costs and considerably improving water quality, which is of practical importance and benefits the aquaculture industry. However, many issues must be faced in detecting and monitoring underwater fish feed, such as small targets, complex backgrounds, and fish interference, which present great challenges for recognizing underwater fish feed particles.

In early studies, acoustic technology was mainly used to detect underwater feed pellets. For example, Llorens *et al.* [15] quantified the number of uneaten feed pellets dropped by means of an ultrasonic echo method. Juell [16] used echo integration to estimate bunches of feed pellets falling underwater. However, acoustic-based automated schemes still require an acoustic characterization of feed pellets and their conditions [17], such as the backscatter energy per unit volume or the average backscatter cross section of a single scatterer.

Additionally, Zhao *et al.* [1] and Terayama *et al.* [18] claimed that although acoustic-based sonar systems can be used at night, their practical application is limited by monochrome and low-quality images. Furthermore, acoustic technology is expensive and susceptible to noise interference. Therefore, the shortcomings of acoustic-based systems might limit their application in actual aquaculture production.

In addition to optical and acoustic technologies, much research has been published on the use of various sensors based on different parameters to monitor, identify and evaluate fish feeding behavior. Horie *et al.* [19] found that the feeding behavior of most fish caused characteristic changes in acceleration that differ from normal movement. Parra *et al.* [20] designed and deployed a sensor device to measure such characteristic shifts in acceleration to study eating behavior in detail.

Garcia *et al.* [21] deployed a sensor system to monitor and control fish feeding in marine fish farms. Chiang and Chang [22] also designed sensors to monitor the calibrated salinity of the marine environment and aquaculture salinity. Fish foraging at the water surface can also cause water surface fluctuations. Subakti *et al.* [23] used sensors suspended on the water surface to monitor fish feeding behavior and the feeding time on the surface.

In recent years, computer vision technology has undergone rapid development due to its low cost, ease of development, and nondestructive nature. At the same time, many specific image preprocessing and enhancement algorithms have been developed, making methods based on computer vision technology feasible solutions.

For example, Atoum *et al.* [24] used correlation filters to detect underwater feed particles. They also used a support vector machine classifier to classify different feeding behaviors to determine whether fish were actively eating. In addition, this system was also designed as a feed detector for real-time monitoring of excess food particles on the water surface.

Li *et al.* [25] proposed an adaptive threshold segmentation method to detect uneaten feed in underwater images. The proposed method is simple and easy to deploy, having achieved good results in practical applications. Ballester-Moltó *et al.* [26] also reported that when the number of uneaten particles in the area detected by the computer reached a certain threshold, this indirectly indicated that the overall feeding amount of the fish was decreasing. Then, corresponding feedback could be directed to a controller to reduce or to stop supplying the feed.

Skoien *et al.* [27] developed a particle detector based on computer vision technology to accurately quantify the temporal and spatial distribution of food particles in a cage. The underwater camera in the device detected and calculated the volume of food particles that sank through the funnel. The top and sides of the camera were closed to prevent any influence from the fish. In addition, this work used image processing algorithms to recognize the size and speed of sedimentation materials and to filter out any interfering substances. As a result, this detector had a fast detection speed, accurate quantification capabilities, and a detection error of 1.3%.

Zhou *et al.* [28] adopted an adaptive network-based fuzzy inference system (ANFIS) to realize automatic feeding. The results showed that the feed decision accuracy rate of the ANFIS model was 98%, and the feed conversion ratio (FCR) was reduced by 10.77% when compared with a feed table.

Recently, deep learning technology has enabled substantial advances because it can automatically extract high-dimensional features from massive amounts of information. Deep learning technology has achieved an accuracy rate much higher than that of traditional machine learning [29]. Accordingly, deep learning technology has been widely used in intelligent aquaculture tasks, such as water quality prediction, fish identification, and behavior analysis [6].

For instance, Liu *et al.* [30] proposed a method of measuring salmon feeding activity. This method was based on the sum of different frame intensities caused by fish movement. An overlap coefficient was defined to correct the calculation error caused by fish overlapping in an image to determine the computer-based visual feeding activity index (CVFAI), which had a correlation coefficient with the manual observation feeding activity index (MOFAI) of 0.9195.

Chen *et al.* [31] combined the area method and a texture-based approach to study fish feeding behavior in fish schools. That study analyzed four texture features: inverse moment, correlation, energy, and contrast. The results showed that the contrast and intensity of the activity of the fish population reached 0.8942. However, that study did not consider the interference caused by wave splashing and overlapping of individuals during the feeding process.

Although many previous works have achieved successful detection of uneaten feed pellets underwater, underwater feed pellet detection also faces many challenges, such as the difficulties presented by image blurring, small targets, high particle density, and blurred motion.

Therefore, the detection accuracy of uneaten feed pellets in the actual field still needs to be improved. In particular, problems arise due to turbid water quality in real outdoor aquaculture farms. Consequently, the abovementioned computer-vision-based methods may not be applicable in real outdoor aquaculture farms. In addition, in dark or turbid water, acoustic imaging has obvious advantages over computer vision.

To address this issue, in this article, we propose a computer-vision-based intelligent fish feeding system that aims to identify the size of the waves caused by fish feeding. The proposed system analyzes images of the feeding fish and uses deep learning techniques to characterize the fish feeding situation to determine whether the rate of dispensing fish feed needs to be increased or decreased. Thus, the purpose of this is to achieve intelligent feeding to reduce the manual workload and feed waste.

III. The Proposed Fish Feeding System

A. System Architecture

Fig. 1 shows the system architecture of the proposed intelligent fish feeding system, which consists of an image sensing

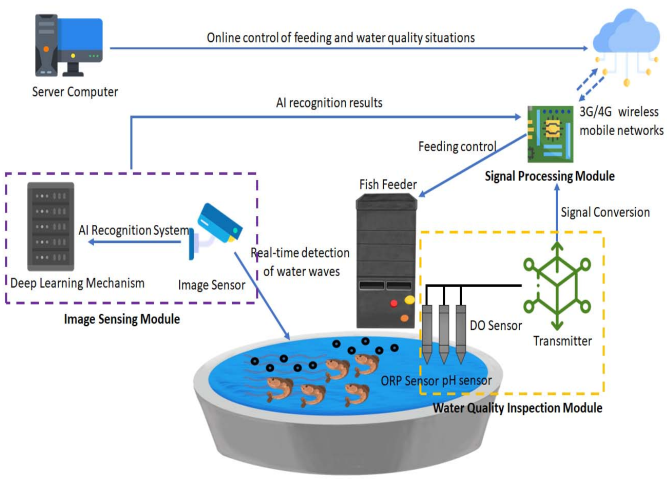

Fig. 1. The architecture of the proposed intelligent fish feeding system.

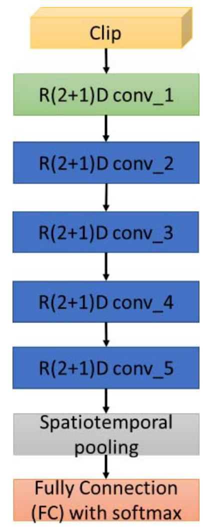

Fig. 2. The architecture of the R(2+1)D network.

module, a water quality inspection module, a fish feeder, a signal processing module, and a server computer.

The image sensing module is composed of an image sensor (camera) and a deep learning mechanism. The water quality inspection module includes an oxidation–reduction potential (ORP) sensor, a dissolved oxygen (DO) sensor, a pH sensor, and an intelligent industrial transmitter.

The signal processing module consists of a microcontroller (MCU) module and a relay module. The server computer is responsible for online control of the feeding situation and water conditions. Moreover, related data are monitored and recorded by the server computer. Below, the details of the components of the proposed intelligent fish feeding system are introduced sequentially.

B. Image Sensing Module

1) Image Sensor: We adopt a white light image sensor (camera) that is specially designed for offshore aquaculture. This camera achieves a full HD 1080p resolution with a highly sensitive 2-million-pixel complementary metal–oxide–semiconductor (CMOS) Sony image sensor.

This camera has a digital wide dynamic range and is capable of fog penetration, strong light suppression, and strengthening abnormal environmental light sources. Moreover, the adopted camera has 18 built-in infrared (IR) light-emitting diodes (LEDs), which can achieve a projection distance of up to 20 meters. Furthermore, the adopted camera also has anti-ultraviolet and anti-salt properties.

2) Deep Learning Mechanism: The deep learning mechanism receives the images captured by the image sensor. The purpose of the proposed deep learning mechanism is to detect ripples on the water's surface to determine the fish feeding state.

The deep neural network (DNN) architecture of the developed deep learning mechanism is based on R(2+1)D [38]. A complete 3D convolution can be approximated by a 2D convolution and a 1D convolution. Accordingly, spatial and temporal modeling is decomposed into two separate steps to design the R(2+1)D architecture. The architecture of the R(2+1)D network is shown in Fig. 2, and Table I demonstrates the detailed network architecture of R(2+1)D, where L is the number of frames.

TABLE I
DETAILED NETWORK ARCHITECTURE OF R(2+1)D

Layer name	Output size	R(2+1)D	Stride
Conv_1	L*56*56	1*7*7 3*1*1	1*2*2
Conv_2	L*56*56	$\begin{bmatrix} 1*3*3 \\ 3*1*1 \\ 1*3*3 \\ 3*1*1 \end{bmatrix}$*2	1*1*1
Conv_3	$\frac{L}{2}*28*28$	$\begin{bmatrix} 1*3*3 \\ 3*1*1 \\ 1*3*3 \\ 3*1*1 \end{bmatrix}$*2	2*2*2
Conv_4	$\frac{L}{4}*14*14$	$\begin{bmatrix} 1*3*3 \\ 3*1*1 \\ 1*3*3 \\ 3*1*1 \end{bmatrix}$*2	2*2*2
Conv_5	$\frac{L}{8}*7*7$	$\begin{bmatrix} 1*3*3 \\ 3*1*1 \\ 1*3*3 \\ 3*1*1 \end{bmatrix}$*2	2*2*2
	1*1*1	spatiotemporal pooling, fc layer with softmax	

Furthermore, Fig. 3 shows a diagram of the convolutional splitting architecture. Supposing that the number of channels in the i-th layer is N_i, N_i 3D convolutions are replaced by N_i 2D convolution kernels and M_i 1D time-dimension convolutions. M_i determines the dimensionality of the intermediate subspace and makes the number of parameters of R(2+1)D similar to that of R3D.

Adam [39] is selected as the optimizer for the proposed deep learning mechanism. Although most of the literature uses stochastic gradient descent (SGD) as the optimizer, most test results indicate that Adam performs better. However, the faster convergence speed of SGD would be more suitable for

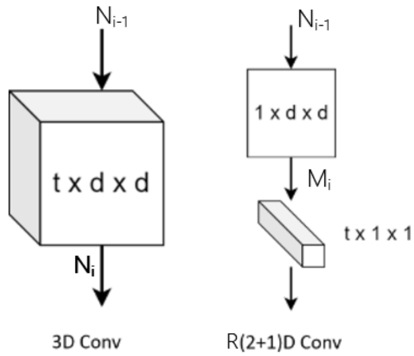

Fig. 3. The architecture of convolutional splitting.

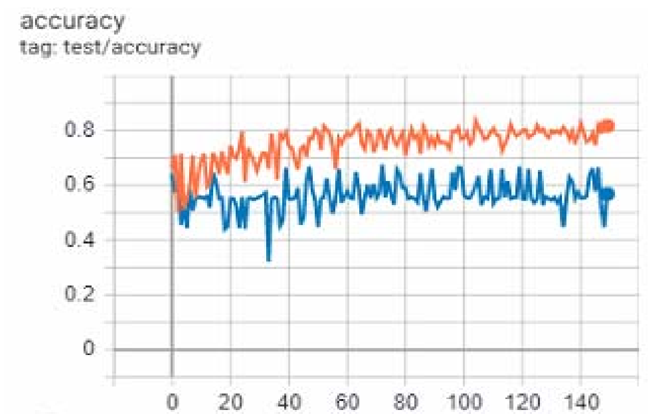

Fig. 4. Comparison of the test accuracy curves of the original R(2+1)D model trained with Adam and AdamW+AMSGrad.

the proposed system. Nevertheless, when Adam is selected as the optimizer, a lower learning rate can be set in the middle, as well as later stages of training to speed up model convergence without affecting the accuracy or loss value. As a result, the learning rate is set to 0.001, and the number of training periods (epochs) is set to 150.

Furthermore, the improved version of Adam, known as AdamW [39], is also tested to compare the performance of the two optimizers, and because the dataset used in this work is small, AdamW is used in combination with AMSGrad [40] during training to further improve the model convergence. For comparison, Fig. 4 shows the curves of the test accuracy of the original R(2+1)D model achieved with Adam and AdamW+AMSGrad. In this figure, the orange line corresponds to AdamW+AMSGrad, and the blue line corresponds to Adam alone. The accuracy of the model trained with Adam alone is only 66%, while the model accuracy achieved through AdamW+AMSGrad training increases to 83%.

The original R(2+1)D network architecture decomposes a 3D space-time convolution into a 2D space convolution and a 1D time convolution, increasing the number of channels of the 2D convolution. By increasing the number of channels, the number of parameters of the resulting R(2+1)D model is made similar to that of the corresponding 3D model. To determine the channel amplification, (1) is used to calculate the number of channels of the 2D convolution.

TABLE II
Detailed Network Architecture of the Proposed R(2+1)D* Model

Layer name	Output size	R(2+1)D*	Stride
Conv_1	L*56*56	1*7*7;64*0.5 3*1*1;64*0.5	1*2*2
Conv_2	L*56*56	$\begin{bmatrix}1*3*3;64*0.5\\3*1*1;64*0.5\\1*3*3;64*0.5\\3*1*1;64*0.5\end{bmatrix}*2$	1*1*1
Conv_3	$\frac{L}{2}*28*28$	$\begin{bmatrix}1*3*3;128*0.5\\3*1*1;128*0.5\\1*3*3;128*0.5\\3*1*1;128*0.5\end{bmatrix}*2$	2*2*2
Conv_4	$\frac{L}{4}*14*14$	$\begin{bmatrix}1*3*3;256*0.5\\3*1*1;256*0.5\\1*3*3;256*0.5\\3*1*1;256*0.5\end{bmatrix}*2$	2*2*2
Conv_5	$\frac{L}{8}*7*7$	$\begin{bmatrix}1*3*3;512*0.5\\3*1*1;512*0.5\\1*3*3;512*0.5\\3*1*1;512*0.5\end{bmatrix}*2$	2*2*2
	1*1*1	spatiotemporal pooling, fc layer with softmax	

Please note that t is the time range of the time filter, and d represents the 2D width and the height of the convolution space. N_{i} represents the number of channels convolved in the i-th layer. In the experiments conducted in this research, because 16 consecutive frames are used, t is 16, which can be seen as follows:

$$M_i = \left\lfloor \frac{td^2 N_{i-1} N_i}{d^2 N_{i-1} + t N_i} \right\rfloor \tag{1}$$

Compared with the typical training set, our data volume is tiny. Consequently, the number of channels after amplification is too large for our training set, resulting in insufficient data volume to support the model calculations. Therefore, when the original R(2+1)D model is used in this work, the channel amplification in D is changed to maintain the original channel number to reduce the number of features required for the calculation.

Fortunately, the model does not converge too early. Nevertheless, the effect is not as good as expected; therefore, we refer to the expansion factor used in wide residual networks (WRNs) [41] and add it to the model. This parameter controls the number of channels in the model. In this work, the expansion factor is set to 0.5, meaning that the number of channels is halved and the model depth is set to 18.

Thus, we use a shallower model to reduce the difficulty of optimization to achieve better training results, while effectively reducing the numbers of calculations and parameters for model training. In addition, AdamW+AMSGrad is used to improve the R(2+1)D model. The architecture of the improved R(2+1)D model, named R(2+1)D*, is summarized in Table II. The numbers of parameters and calculations before and after reducing the number of channels are shown in Table III. The data calculations are performed using the ptflops tool [42].

C. Water Quality Inspection Module

Whether it is for fish or other organisms, water quality is crucial for aquaculture. Therefore, we use the critical

TABLE III
COMPUTATIONAL COMPLEXITY (IN MULTIPLY–ACCUMULATE OPERATIONS, MACS) AND PARAMETERS OF R(2+1)D AND THE PROPOSED R(2+1)D* MODEL

Model name	Computational complexity (MACs)	Parameters
R(2+1)D	41,307,727,596	33,159,163
R(2+1)D*	**19,802,360,832**	**15,375,554**

TABLE IV
THE SPECIFICATION OF THE ADOPTED ORP SENSOR

Item	Description
Measuring range	± 2000 mV
Operating temperature range	5 to 70°C
Resolution	±10mV at 25°C
Response time	≦20 s
Connector	BNC connector
Size	40 mm×27 mm

parameters of water quality to illustrate that the general temperature will drop by approximately 20-25 °C, and a temperature of the growth environment of the fish that is too low (<9.5 °C) or too high (>29°C) is not suitable for the growth of fish. It will also arouse the appetite of the fish. Continued feeding of the fish that lack an appetite will also cause bait waste and water pollution. As a result, water quality control is essential. Fish are well-suited to slightly alkaline water. Too much acid can cause uneven growth and restricted activity in fish. The suitable range of pH is 7.5-8.5. The suitable range of oxygen content is more than 6 ml, and dissolved oxygen was added. The faster the growth rate of low-salt fish is, the better the quality. Hence, water quality inspection is essential in aquaculture.

In this work, the water quality inspection module aims to assist in determining whether the current water quality is suitable for feeding. Three types of water quality sensors are adopted in the water quality inspection module, which is explained as follows.

1) ORP Sensor: An ORP sensor measures an index representing the oxidation-reduction ability, which characterizes the relative degree of oxidation or reduction and is expressed in units of mV. The higher the oxidation-reduction potential is, the stronger the oxidation, and the lower this potential is, the weaker the oxidation.

A positive potential indicates that the medium shows a certain degree of oxidation, and a negative potential suggests that the medium offers a certain degree of reducibility. The specifications of the adopted ORP sensor can be seen in Table IV.

2) DO Sensor: A DO sensor measures the conductivity value of an aqueous solution as a means of evaluating the water quality. Such sensors are often used in hydroponics, aquaculture, and environmental water monitoring. The specifications [44] of the adopted DO sensor can be seen in Table V.

TABLE V
THE SPECIFICATION OF THE ADOPTED DO SENSOR

Item	Description
Type	Galvanic Probe
Detection range	0 to 20 mg/L
Response time	Up to 98% full response, ≦ 90 s
Pressure range	0 to 50 PSI
Connector	BNC connector
Size	42 mm×27 mm

TABLE VI
THE SPECIFICATION OF THE ADOPTED pH SENSOR

Item	Description
Measuring range	pH 0-14
Measuring temperature range	0 to 100°C
Working current	5 to 10 mA
Response time	≦ 5 s
Stability time	≦ 60 s
Power consumption	≦ 0.5 W
Working temperature	-10 to 50°C (Nominal Temp. 20°C)
Working humidity	95%RH (Nominal 65%RH)
Size	42 mm×32 mm×20 mm
Weight	25 g
Temperature sensor	Built-in LM35 and DS18B20 dual temperature compensation

3) pH Sensor: A pH sensor measures the pH value of an aqueous solution. The pH value of the solution is calculated from the potential difference measured between the pH electrode and the reference electrode. The specifications of the adopted pH sensor can be seen in Table VI.

4) Intelligent Industrial Transmitter: The function of the intelligent industrial transmitter is to read the current measured values of the ORP, DO and pH sensors and perform an analog or digital signal conversion for the signal processing module.

D. Signal Processing Module

The purpose of the signal processing module is to control feeding actions. Fig. 5 shows the flow chart of the fish feeding actions. The signal processing module receives signals from the intelligent industrial transmitter of the proposed water quality inspection module and AI recognition results from the deep learning mechanism of the proposed image sensing module. First, the feeding start time is triggered. Water quality conditions are a priority consideration. When the current water quality conditions are suitable for feeding, fish feeding is performed.

The feeding control signal is sent to the feeder to provide feed. The proposed deep learning mechanism continuously recognizes the size of the water waves caused by the fish eating the feed to determine whether to continue or to stop feeding the fish. The server computer can remotely perform online control and monitoring of the feeding situation and water quality conditions according to the signal processing module via a 3G/4G wireless mobile network. Related feeding and water

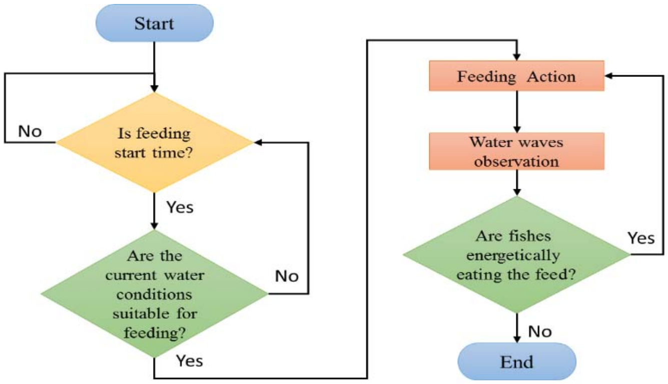

Fig. 5. The flow chart of the fish feeding actions.

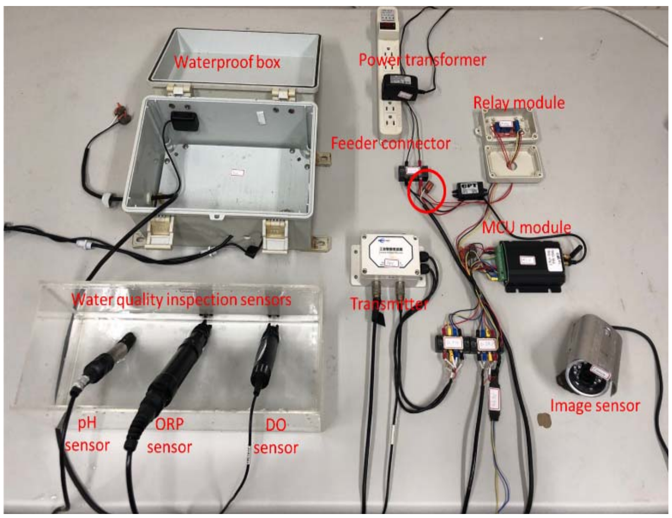

Fig. 6. Photograph of the proposed intelligent fish feeding system.

quality records can also be transmitted to the server computer by the signal processing module via the 3G/4G wireless mobile network for data storage and for further analysis.

IV. System Prototype and Experimental Results

This section demonstrates the prototype of the proposed intelligent fish feeding system and discusses the experimental results. The proposed system has been successfully installed and tested in the outdoor black porgy pond of the Department of Aquaculture at the National Penghu University of Science and Technology, Magong, Penghu, Taiwan.

A. System Prototype

Fig. 6 shows a photograph of the proposed intelligent fish feeding system. Figs. 7 and 8 depict the system as it is installed in the actual experimental outdoor black porgy pond. The MCU module, the intelligent industrial transmitter, the relay module, and various connectors are housed inside a waterproof box for outdoor water protection, as shown in Fig. 7 (b).

B. Experimental Results

1) Dataset: The dataset used in this work is obtained from actual captured videos of the water in the fish pond from the splash to the end of the entire film. The obtained

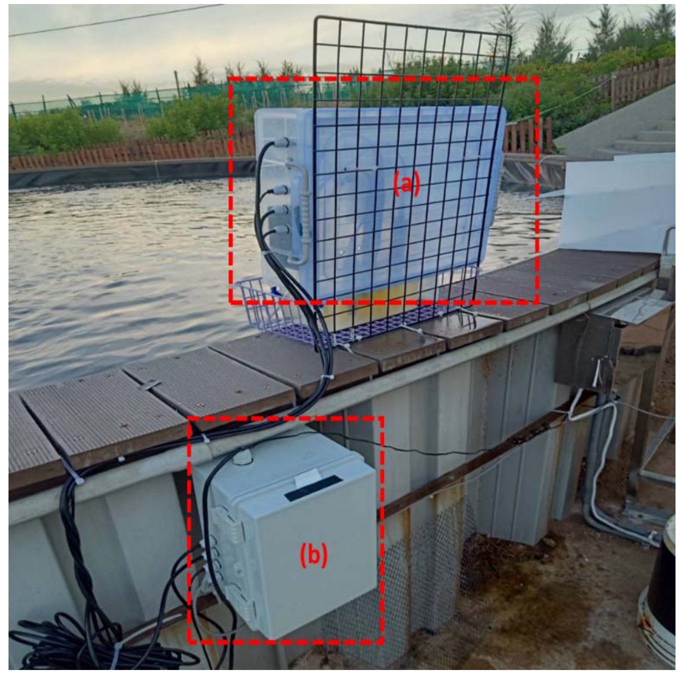

Fig. 7. Photograph of the proposed intelligent fish feeding system installed in the actual experimental outdoor black porgy pond field. (a) Water quality inspection module (b) Waterproof box.

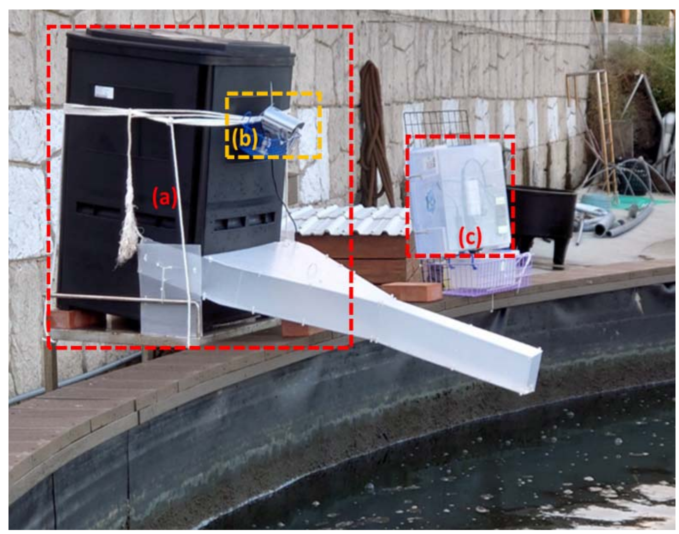

Fig. 8. Photograph of the proposed intelligent fish feeding system installed in the actual experimental outdoor black porgy pond field. (a) Fish feeder. (b) Camera. (c) Water quality inspection module.

videos are further edited into clips of 2 seconds in length (approximately 60 frames).

To obtain samples, 16 consecutive frames are randomly selected from a clip to form a picture group, and this picture group is then subjected to brightness adjustment and data augmentation processing. Hence, the final dataset includes 792 large water wave picture groups and 984 small water wave picture groups. Furthermore, the final dataset is divided into a training group and a verification group at a ratio of 8:2 [29].

2) Data Preprocessing: For data preprocessing, each original image with a size of 540*960 is first center cropped to a size of 540*540, retaining only the splash in the middle of

TABLE VII
ACCURACY TEST RESULTS OF EACH OPTIMIZED MODEL

Model name	Accuracy
R(2+1)D	67.1%
R(2+1)D*	93.2%

the image. Then, random cropping is applied to crop each splash image to a size of 405*405 to expand the data, and finally, each cropped image is scaled to 112*112 to input into the model.

3) Experiments: The proposed intelligent fish feeding system uses a computer-vision-based deep learning technique to recognize water wave images of aquaculture ponds. The main reason for adopting water wave images is that the surface of the aquaculture pond fluctuates greatly when the fish are feeding, and thus, such images are suitable for determining whether the fish are full.

In this study, two feedings are performed per day, at 7 AM and 5 PM. In the aquaculture pond, manual feeding is first used, and the fish are trained to feed at a fixed point. The training period is approximately 2 to 3 weeks and subsequently. The feeder is used for regular and quantitative feeding instead of manual feeding. The behavior during the period of manual feeding is used as the basis for determining the timing and feed quantities for automatic feeding by the feeder.

We set the time for automatic feeding by connecting the MCU module to the feeder with a relay module in the middle. When the computer server sends a command, the MCU module activates the relay to trigger the feeder to start dispensing feed. At the same time, water wave (splash) image data of the fish feeding behavior is used for the training and testing of the deep learning network architecture.

Table VII shows the test accuracy results of each optimized model. We find that after the adjustment of the parameter settings and the adoption of the AdamW optimizer in combination with the ASMGrad learning strategy, the proposed R(2+1)D* model is more accurate than the R(2+1)D model.

Fig. 9 further compares the results of the R(2+1)D model and the proposed R(2+1)D* model. In Fig. 9 (a), it can be found that for the R(2+1)D model, the learning rate during the training process is low, resulting in an incomplete convergence of the trained model.

Fig. 9 (b) shows that the loss of the R(2+1)D model decreases at a lower rate, while the adjustment range of the learning rate for the proposed R(2+1)D* model is sufficient, enabling the model to fully converge.

In Fig. 9 (c), it can be seen that the proposed R(2+1)D* model is considerably superior to the R(2+1)D model in terms of verification accuracy. In Fig. 9 (d), the model verification loss results show that the loss of the R(2+1)D model fluctuates substantially due to insufficient model convergence.

The proposed R(2+1)D* model is implemented in the proposed deep learning mechanism and is successfully applied to control the fish feeder of the proposed fish intelligent feeding system in the outdoor black porgy pond, as depicted in Fig. 10.

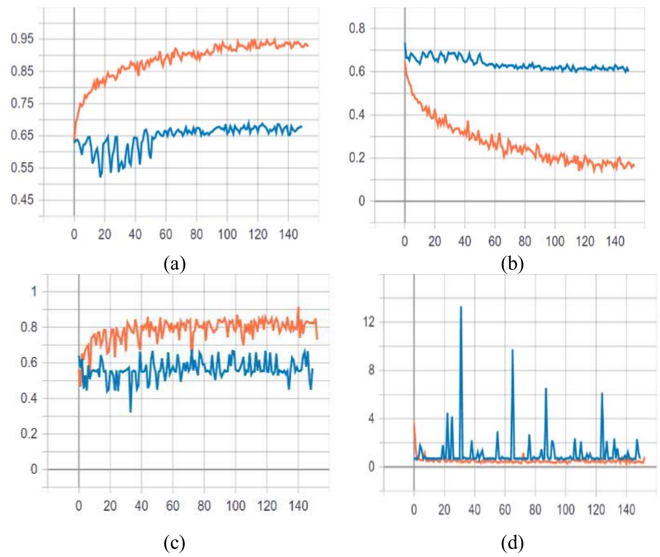

Fig. 9. Comparison of the test curves of the R(2+1)D model and the proposed R(2+1)D* model. (a) Model training accuracy. (b) Model training loss. (c) Model verification accuracy. (d) Model verification loss.

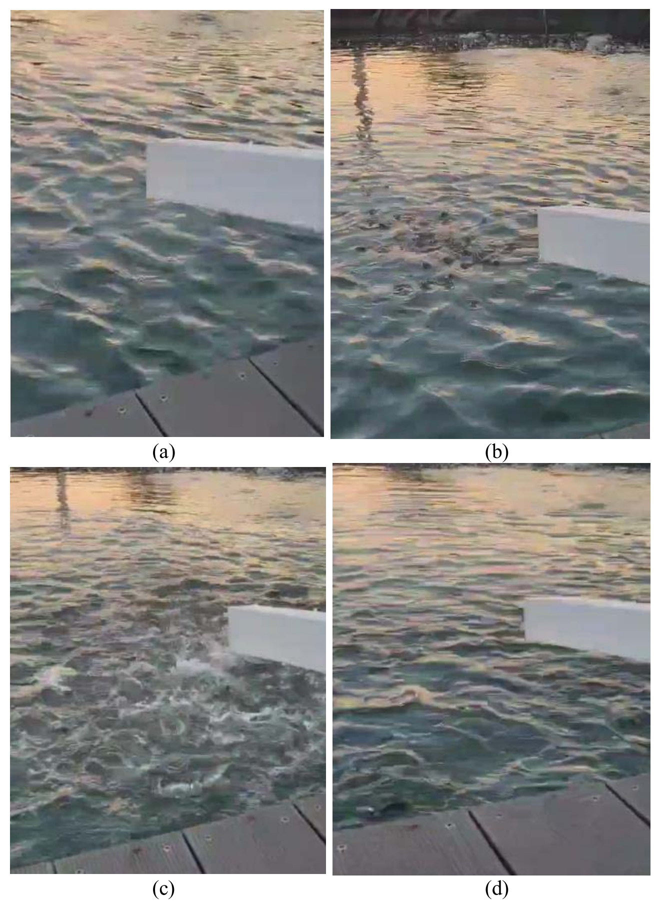

Fig. 10. Real feeding situation. (a) Before feeding. (b) Casting feed. (c) Fish energetically eating the feed. (d) Completion of feeding.

V. CONCLUSION

In this article, a computer-vision-based intelligent fish feeding system using deep learning techniques for aquaculture is proposed. The proposed system is composed of an image sensing module, a water quality inspection module, a fish feeder, a signal processing module, and a server computer.

In contrast to traditional computer-vision-based systems for recognizing fish feed underwater, the proposed intelligent fish feeding system adopts deep learning technology to recognize the size of the waves caused by fish eating feed to determine whether to continue or to stop feeding the fish. Furthermore, we improve the R(2+1)D model. The experimental results show that the accuracy of the proposed R(2+1)D* model is better than that of the R(2+1)D model, reaching 93.2%. The proposed intelligent fish feeding system is successfully installed and verified in the outdoor black porgy pond of the Department of Aquaculture at the National Penghu University of Science and Technology, Magong, Penghu, Taiwan.

In future work, more sensors and actuators should be evaluated and considered for integration with the proposed intelligent fish feeding system to achieve an advanced and efficient intelligent aquaculture system to improve aquaculture. The web could-based platform will be evaluated and developed to assist further decisions and big data analysis. In addition, the proposed deep learning mechanism should be evaluated for implementation on for an AI edge computing platform.

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References

[1] C. Zhou, D. Xu, K. Lin, C. Sun, and X. Yang, "Intelligent feeding control methods in aquaculture with an emphasis on fish: A review," *Rev. Aquaculture*, vol. 10, no. 4, pp. 975–993, 2018.

[2] Y. Wei, Q. Wei, and D. An, "Intelligent monitoring and control technologies of open sea cage culture: A review," *Comput. Electron. Agricult.*, vol. 169, Feb. 2020, Art. no. 105119.

[3] Food and Agriculture Organization (FAO). *The State of World Fisheries and Aquaculture (SOFIA)*. (2016). [Online]. Available: http://www.fao.org/3/i5555e/i5555e.pdf

[4] Food and Agriculture Organization (FAO). *The State of World Fisheries and Aquaculture (SOFIA)*. (2018). [Online]. Available: http://www.fao.org/documents/card/en/c/I9540EN/

[5] L. Chen, X. Yang, C. Sun, Y. Wang, D. Xu, and C. Zhou, "Feed intake prediction model for group fish using the MEA-BP neural network in intensive aquaculture," *Inf. Process. Agricult.*, vol. 7, no. 2, pp. 261–271, Jun. 2020.

[6] X. Yang, S. Zhang, J. Liu, Q. Gao, S. Dong, and C. Zhou, "Deep learning for smart fish farming: Applications, opportunities and challenges," *Rev. Aquaculture*, vol. 13, no. 1, pp. 66–90, Jan. 2021.

[7] T.-H. Wu, Y.-I. Huang, and J.-M. Chen, "Development of an adaptive neural-based fuzzy inference system for feeding decision-making assessment in silver perch (Bidyanus bidyanus) culture," *Aquacultural Eng.*, vol. 66, pp. 41–51, May 2015.

[8] M. Føre *et al.*, "Modelling growth performance and feeding behaviour of Atlantic salmon (Salmo salar L.) in commercial-size aquaculture net pens: Model details and validation through full-scale experiments," *Aquaculture*, vol. 464, pp. 268–278, Nov. 2016.

[9] H. Verdal *et al.*, "Improving feed efficiency in fish using selective breeding: A review," *Rev. Aquaculture*, vol. 10, no. 4, pp. 833–851, Dec. 2018.

[10] X. Hu *et al.*, "Real-time detection of uneaten feed pellets in underwater images for aquaculture using an improved YOLO-V4 network," *Comput. Electron. Agricult.*, vol. 185, Jun. 2021, Art. no. 106135.

[11] S. Honarmand Ebrahimi, M. Ossewaarde, and A. Need, "Smart fishery: A systematic review and research agenda for sustainable fisheries in the age of AI," *Sustainability*, vol. 13, no. 11, p. 6037, May 2021, doi: 10.3390/su13116037.

[12] Y. Wei, W. Li, D. An, D. Li, Y. Jiao, and Q. Wei, "Equipment and intelligent control system in aquaponics: A review," *IEEE Access*, vol. 7, pp. 169306–169326, 2019.

[13] D. Li, Z. Wang, S. Wu, Z. Miao, L. Du, and Y. Duan, "Automatic recognition methods of fish feeding behavior in aquaculture: A review," *Aquaculture*, vol. 528, May 2020, Art. no. 735508.

[14] L. Parra, G. Lloret, J. Lloret, and M. Rodilla, "Physical sensors for precision aquaculture: A review," *IEEE Sensors J.*, vol. 18, no. 10, pp. 3915–3923, May 2018.

[15] S. Llorens, I. Pérez-Arjona, E. Soliveres, and V. Espinosa, "Detection and target strength measurements of uneaten feed pellets with a single beam echosounder," *Aquacultural Eng.*, vol. 78, pp. 216–220, Aug. 2017.

[16] J.-E. Juell, "Hydroacoustic detection of food waste—A method to estimate maximum food intake of fish populations in sea cages," *Aquacultural Eng.*, vol. 10, no. 3, pp. 207–217, Jan. 1991.

[17] J. Simmonds and D. MacLennan, *Fisheries Acoustics: Theory and Practice, Second Edition*. Hoboken, NJ, USA: Blackwell Publishing, 2005.

[18] K. Terayama, K. Shin, K. Mizuno, and K. Tsuda, "Integration of sonar and optical camera images using deep neural network for fish monitoring," *Aquacultural Eng.*, vol. 86, Aug. 2019, Art. no. 102000.

[19] J. Horie *et al.*, "Development of a pinger for classification of feeding behavior of fish based on axis-free acceleration data," in *Proc. Techno-Ocean*, 2016, pp. 268–271.

[20] L. Parra, S. Sendra, L. García, and J. Lloret, "Design and deployment of low-cost sensors for monitoring the water quality and fish behavior in aquaculture tanks during the feeding process," *Sensors*, vol. 18, no. 3, p. 750, Mar. 2018.

[21] M. Garcia, S. Sendra, G. Lloret, and J. Lloret, "Monitoring and control sensor system for fish feeding in marine fish farms," *IET Commun.*, vol. 5, no. 12, pp. 1682–1690, Aug. 2011.

[22] C.-T. Chiang and C.-W. Chang, "Design of a calibrated salinity sensor transducer for monitoring salinity of ocean environment and aquaculture," *IEEE Sensors J.*, vol. 15, no. 9, pp. 5151–5157, Sep. 2015.

[23] A. Subakti, Z. F. Khotimah, and F. M. Darozat, "Preliminary study of acceleration based sensor to record Nile tilapia (*Oreochromis niloticus*) feeding behavior at water surface," *J. Phys., Conf. Ser.*, vol. 795, Jan. 2017, Art. no. 012060.

[24] Y. Atoum, S. Srivastava, and X. Liu, "Automatic feeding control for dense aquaculture fish tanks," *IEEE Signal Process. Lett.*, vol. 22, no. 8, pp. 1089–1093, Aug. 2015.

[25] D. Li, L. Xu, and H. Liu, "Detection of uneaten fish food pellets in underwater images for aquaculture," *Aquacultural Eng.*, vol. 78, pp. 85–94, Aug. 2017.

[26] M. Ballester-Moltó, P. Sanchez-Jerez, J. Cerezo-Valverde, and F. Aguado-Giménez, "Particulate waste outflow from fish-farming cages. How much is uneaten feed?" *Mar. Pollut. Bull.*, vol. 119, no. 1, pp. 23–30, Jun. 2017.

[27] K. R. Skoien, M. O. Alver, and J. A. Alfredsen, "A computer vision approach for detection and quantification of feed particles in marine fish farms," in *Proc. IEEE Int. Conf. Image Process. (ICIP)*, Oct. 2014, pp. 1648–1652.

[28] C. Zhou *et al.*, "Near infrared computer vision and neuro-fuzzy model-based feeding decision system for fish in aquaculture," *Comput. Electron. Agricult.*, vol. 146, pp. 114–124, Mar. 2018.

[29] W.-C. Wang, L.-B. Chen, and W.-J. Chang, "Development and experimental evaluation of machine-learning techniques for an intelligent hairy scalp detection system," *Appl. Sci.*, vol. 8, no. 6, p. 853, May 2018.

[30] Z. Liu, X. Li, L. Fan, H. Lu, L. Liu, and Y. Liu, "Measuring feeding activity of fish in RAS using computer vision," *Aquacultural Eng.*, vol. 60, pp. 20–27, May 2014.

[31] C. Chen, Y. Du, and C. Sun, "Evaluation of feeding activity of fishes based on image texture," *Trans. Chin. Soc. Agricult. Eng.*, vol. 33, no. 5, pp. 232–237, Mar. 2017.

[32] W. Hassan, M. Fore, M. O. Pedersen, and J. A. Alfredsen, "A new method for measuring free-ranging fish swimming speed in commercial marine farms using Doppler principle," *IEEE Sensors J.*, vol. 20, no. 17, pp. 10220–10227, Sep. 2020.

[33] H. Kim *et al.*, "Image-based monitoring of jellyfish using deep learning architecture," *IEEE Sensors J.*, vol. 16, no. 8, pp. 2215–2216, Apr. 2016.

[34] Z. Zhao, Y. Liu, X. Sun, J. Liu, X. Yang, and C. Zhou, "Composited FishNet: Fish detection and species recognition from low-quality underwater videos," *IEEE Trans. Image Process.*, vol. 30, pp. 4719–4734, 2021, doi: 10.1109/TIP.2021.3074738.

[35] J. van Beijnen and G. Yan. *A Practical Guide to Using AI in Aquaculture*. (Jan. 2020). [Online]. Available: https://thefishsite.com/articles/a-practical-guide-to-using-ai-in-aquaculture

[36] Y.-B. Lin and H.-C. Tseng, "FishTalk: An IoT-based mini aquarium system," *IEEE Access*, vol. 7, pp. 35457–35469, 2019.

[37] B. Ouyang *et al.*, "Initial development of the hybrid aerial underwater robotic system (HAUCS): Internet of Things (IoT) for aquaculture farms," *IEEE Internet Things J.*, vol. 8, no. 18, pp. 14013–14027, Sep. 2021, doi: 10.1109/JIOT.2021.3068571.

[38] D. Tran, H. Wang, L. Torresani, J. Ray, Y. LeCun, and M. Paluri, "A closer look at spatiotemporal convolutions for action recognition," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit.*, Jun. 2018, pp. 6450–6459.

[39] I. Loshchilov and F. Hutter, "Decoupled weight decay regularization," 2017, *arXiv:1711.05101*.

[40] S. J. Reddi, S. Kale, and S. Kumar, "On the convergence of Adam and beyond," in *Proc. 6th Int. Conf. Learn. Represent.*, 2018, pp. 1–23.

[41] S. Zagoruyko and N. Komodakis, "Wide residual networks," 2016, *arXiv:1605.07146*.

[42] *Flops Counter for Convolutional Networks in PyTorch Framework*. Accessed: Apr. 18, 2021. [Online]. Available: https://github.com/sovrasov/flops-counter.pytorch

[43] W.-C. Hu, H.-T. Wu, J.-W. Zhan, and P.-H. Hsieh, "Developing intelligent feeding systems based on deep learning," in *Proc. ACM Int. Conf. Intell. Comput. Emerg. Appl.*, Dec. 2020, pp. 1–2.

[44] *Gravity: Analog Dissolved Oxygen Sensor/Meter Kit for Arduino*. Accessed: Jun. 26, 2021. [Online]. Available: https://www.dfrobot.com/product-1628.html

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