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Article

Development of an Edge Computing-Based Intelligent Feeding System for Observing Depth-Specific Feeding Behavior in Red Seabream

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Abstract: The supply of feed has a significant effect on fish growth and operation costs, making it a critical factor in aquaculture. Owing to the repetitive nature of feed supply, feeding techniques have undergone a shift from manual feeding to systems allowing operators to set feed quantities and timing, reducing labor efforts. However, unlike manual feeding, automatic systems cannot adjust the amount of feed supplied according to the feeding activities of fish, potentially resulting in overfeeding or underfeeding. Such overfeeding causes marine pollution and increases operational costs, whereas underfeeding hinders fish growth. In this study, we present an intelligent feeding system that observes the depth-specific feeding behavior of red seabream during the feeding process and determines whether feed supply must be continued. The performance of the feeding algorithm is evaluated by comparing the feed loss rate measured during a feeding experiment at a red seabream sea cage farm with that of the traditional manual feeding method. The results reveal that the feed supply per unit time of the manual method and the developed intelligent feed supply system is at an equivalent level. Moreover, the difference in the average feed loss rate is a negligible 1.16%, confirming that the new system is slightly more advantageous.

Keywords: aquaculture; automatic feeder; edge computing; feeding; monitoring; red seabream

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1. Introduction

The Food and Agriculture Organization has projected that aquaculture products will account for 53% of the global seafood consumption by 2030 [1]. With an increase in the significance of the aquaculture industry, several countries are now striving to develop it into a vital national sector [2]. Consequently, the traditional labor-intensive aquaculture industry is rapidly evolving into a technology-intensive industry driven by advances in automation, water treatment, and biotechnology. With this, technologies automating the aquaculture process are increasingly being developed to save labor, stabilize aquaculture production, and reduce operating costs [3].

A representative example of such technology is automatic feeding. Feeding is a repetitive task in aquaculture that is labor intensive and exerts a direct impact on the growth of aquaculture organisms. Moreover, considering that the cost of feed procurement accounts for a large proportion of the operational costs, it is crucial to supply the appropriate amount of feed according to growth stages and feeding activities of fish to prevent feed loss [4,5]. In particular, in land-based tank farming, excessive feeding can increase mortality rates owing to water pollution caused by increased excreta and feed loss [6]. In cage farming, lost feed contributes to marine environmental pollution [7,8].

Previous studies have developed methods to supply appropriate amounts of feed by analyzing feeding behavior; these methods employ mathematical models and image processing techniques to address existing problems in the feeding process [9]. Moreover, image processing techniques are increasingly being applied to determine the amount of feed supply based on quantifications of fish feeding activities in recirculating aquaculture systems [10]. However, assessing the fish feeding activity using images presents challenges owing to the low-light conditions inside farms and complex backgrounds of the objects to be observed. Therefore, recent research has attempted to recognize feeding behavior using underwater acoustics and deep learning technology [11–13].

In this study, we present an edge computing-based intelligent feeding system that observes the depth-specific feeding behavior of red seabream to automate feeding. The feeding algorithm is designed to observe the depth-specific feeding behavior of red seabream during the feeding process and determine whether the feed supply must be continued. We evaluate the performance of the intelligent feeding system by analyzing the feeding quantity and speed according to the feed diameter. To compare the feeding algorithm with the traditional manual feeding method, we analyzed the feed loss rate based on the total amount of feed supplied and the amount of lost feed measured in a feeding experiment conducted at a red seabream sea cage farm.

2. Materials and Methods

2.1. Design of the Intelligent Feeding System

The intelligent feeding system was developed for use in a sea cage farm. The developed intelligent feeding system is designed to supply feed using the wind force generated by a blower, as shown in Figure 1. The system consists of a hopper, blower, quantitative feeder, and programmable logic controller (PLC) that controls each component. The quantitative feeder comprises a feed measuring disk and motor that rotates the disk. The feed measuring disk is designed with circular grooves (diameter: 79.49 mm, height: 79.20 mm) with the same volume at 90° intervals to ensure that the feed is evenly loaded. Moreover, the quantitative feeder is designed to measure the rotation of the feed measuring groove. This is achieved by installing a bracket with protrusions along the same direction as the measuring groove on the motor shaft, enabling the rotating protrusion to be detected by the proximity sensor.

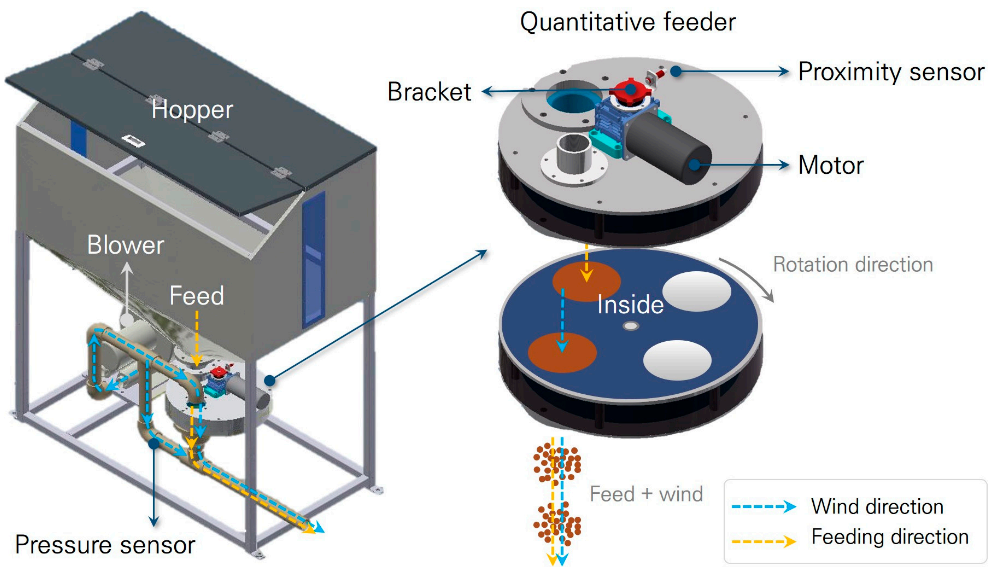

Figure 1. Intelligent feeding system.

The feeding amount (W_t) can be calculated using the volume (V_t, mm^3) of the feed measuring groove, density (D, g/mm^3) of the feed, and rotation count (n) of the feed measuring groove, as expressed in Equation (1).

However, the feeding quantity varies owing to the empty space between feed grains, depending on the diameter of the feed loaded into the feed measuring groove. Therefore, the feeding quantity must be calculated by considering the volume rate (C), which is represented by the volume (V_c) of the empty space in the volume of the measuring groove, as expressed in Equation (2). Equations (1) and (2) are as follows:

$$\text{Feeding quantity } (W_t) = V_t \times D \times n \times C \quad (1)$$

$$C = 1 - \frac{V_c}{V_t} \quad (2)$$

2.2. Edge Computing System

As shown in Figure 2, the hardware of the edge computing system is composed of a CruzPro fishfinder (PCFF80) transducer and interface box, a mini PC, and a Wi-Fi router to observe the depth-specific feeding behavior of red seabream and establish a link with the intelligent feeding system. The Internet network of the sea cage farm was composed of a wireless bridge.

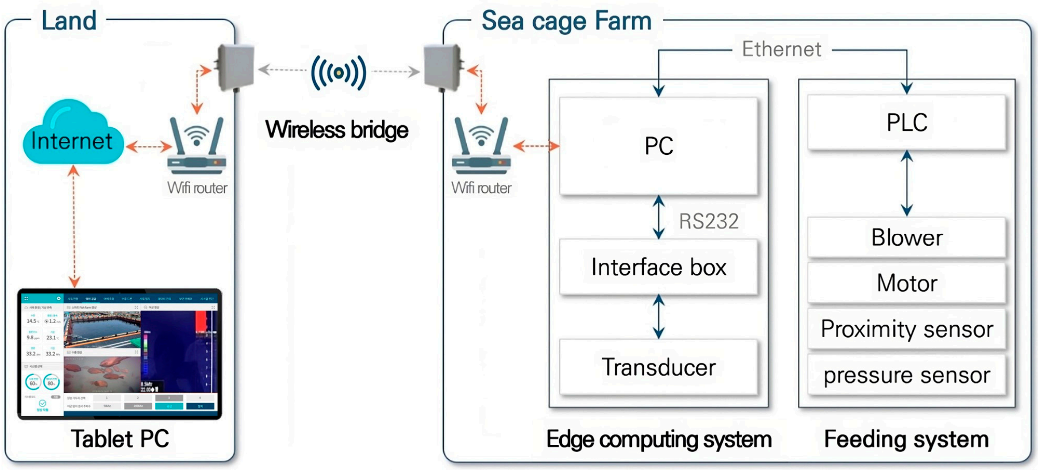

Figure 2. Configuration of the intelligent feeding system based on edge computing and an Internet network.

The specifications of the fishfinder are listed in Table 1. The fishfinder and PC use the RS232 communication method, and the PLC of the intelligent feeding system communicates with the PC via the Ethernet.

Table 1. Specifications of the fishfinder.

Frequency	Depth Capability	Operating Supply	Communication Interface
200/50 kHz	Minimum: 3 feet, 1000 feet or more at 200 kHz, 2500 feet or more at 50 kHz for both shallow and deep-water high resolution	9.5–16.0 VDC, 0.05 A nominal, 4.7 A peak at max power	RS232, 115,200 bps, serial data USB 1.1 and 2.0 compatible (comes with both USB and RS232)

Additionally, an app for mobile devices based on the Android operating system was developed to remotely set the feeding time of the intelligent feeding system, monitor the swimming depth of the fish school, and check the operating status. The developed app was designed to control the PLC by accessing the PC of intelligent feeding system installed in a remote place through the Internet network.

The PC software of the edge computing system was designed to collect and analyze the data output in ASCII code from the fishfinder, reflecting the target strength (TS), i.e., the reflected signal (Ir) from the target according to the incident signal (Ii), at different depths, as expressed in Equation (3). The data processing flow of the PC software is illustrated in Figure 3. To visualize the swimming depth of the fish school, the PC software was designed to convert the ASCII code of the fishfinder into 8 bits, divide it into 16 sections, and then map the color information of each section to reconstruct it into a pixel line format. Equation (3) is as follows:

$$TS = 10\log(Ir/Ii) \quad (3)$$

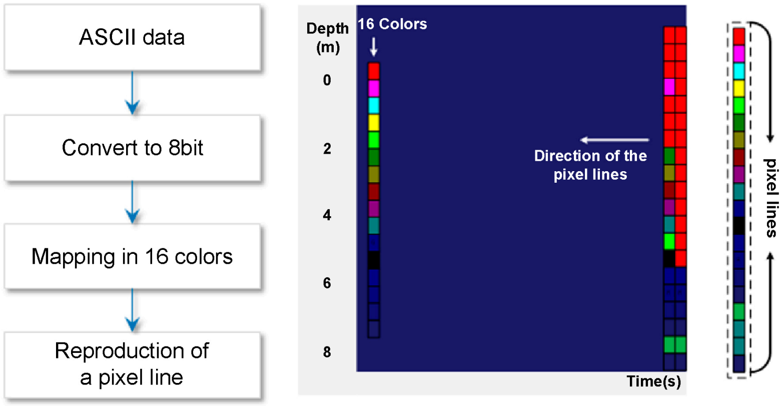

Figure 3. Process of the PC software based on edge computing.

2.3. Feeding Algorithm

Generally, the feeding behavior of red seabream being farmed in sea cages involves the movement of the fish from deeper waters to the surface of the sea when feed is supplied, consuming sufficient feed in a school, followed by their movement back to deeper waters. Utilizing this characteristic, we developed a feeding algorithm that determines whether the feed supply must be continued based on the depth-specific feeding behavior observations of the red seabream from the feed supply time, as illustrated in Figure 4.

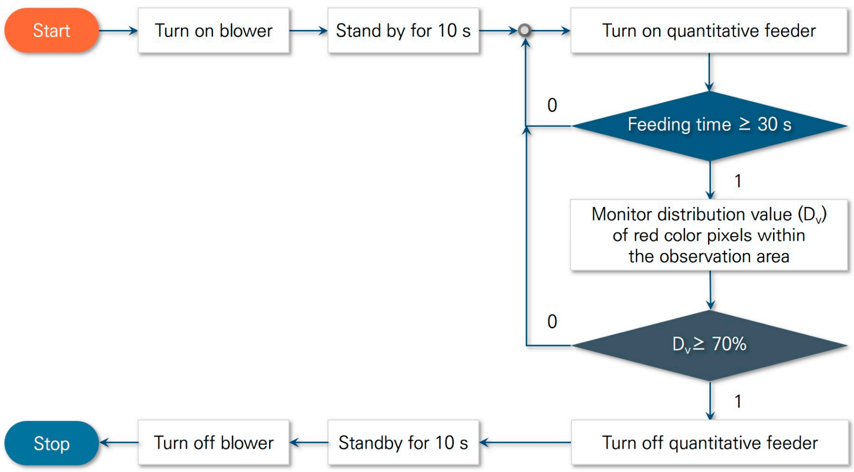

Figure 4. Feeding algorithm based on observations of red seabream feeding behavior.

The observation results of the depth-specific feeding behavior of red seabream are illustrated by the number of pixels shown in red in Figure 3, which represents the acoustic intensity value of the fish school in the set observation area. The system determines whether the feed supply must be continued by observing the proportion (D_v) of red pixels in the set observation area from the time feed is supplied. However, the proportion of red pixels in the set observation area is high in both cases, i.e., when the red seabream school rises to the sea surface to consume feed and when it descends to deeper waters after adequate feed consumption. Therefore, the feeding algorithm was designed to stand by for the duration of time in which the red seabream ascend to the sea surface from the time feed is supplied and to cease feed supply upon detecting their descent after sufficient feed consumption. The standby time from the time feed is supplied until the red seabream ascends to the sea surface, and the distribution value of red pixels (D_V) in the observation area were set to 30 s and 70%, respectively, reflecting the field experiment results.

2.4. Performance Evaluation Method

The performance of the intelligent feeding system was evaluated by measuring and analyzing the difference in feeding quantity according to the diameter of the feed and the maximum feeding speed. The difference in feeding quantity was analyzed through 50 repeated experiments that involved measuring the weight of the feed filled to the brim in the measuring grooves of the quantitative feeder according to the diameter of the feed. The maximum feeding speed was determined based on the feeding time and quantity. The feeding time was measured based on the pressure signals from the pressure gauge during feed spray and time, and the feeding quantity was determined by referring to the weight data of the feeding amount according to the diameter. For the experimental conditions, the inverter of the motor designed with a reduction ratio of 100:1 was set to the maximum speed of 60 Hz, and the diameter of the feed was selected as 7 mm, suitable for the growth stage of red seabream under breeding and management as an experimental subject.

The performance of the feeding algorithm was evaluated by comparing its results with those of the traditional manual feeding method in a feeding experiment at a red seabream sea cage farm. In the feeding experiment, we categorized the traditional manual method and the feeding algorithm as the control group and experimental group, respectively. Table 2 presents the aquaculture information. The sea cage farm sizes (12 × 12 × 6 m) of the control and experimental groups are identical.

Table 2. Aquaculture information on the experimental fish species.

Group	Feeding Method	Average Weight (g)	Number of Fish	Fish Density (kg/m^3)	Diameter of Feed (mm)
Control	Manual	538.2 ± 19.0	~28,000	17.8	7
Experimental	Algorithm	506.2 ± 20.2	~25,000	15.0	7

For the sea cage farm of the experimental group, we fixed the fishfinder transducer and the developed edge computing-based intelligent feeding system by creating an installation flange, as shown in Figure 5a,b. The transducer was installed at the exact center of the cage where the feed was sprayed. Additionally, the transducer was installed to face the bottom of the ocean from the surface, making it easier to observe the depth-specific feeding activity of the red seabream. The developed edge computing system and intelligent feeding system are shown in Figure 5c,d, respectively. The fishfinder was set to the maximum depth of 5 m, which is the height of the cage net as shown in Table 3.

Table 3. Fishfinder settings.

Frequency	Beam Width	Fixed Analog Gain	Depth Range
200 kHz	11°	10	0~5 m

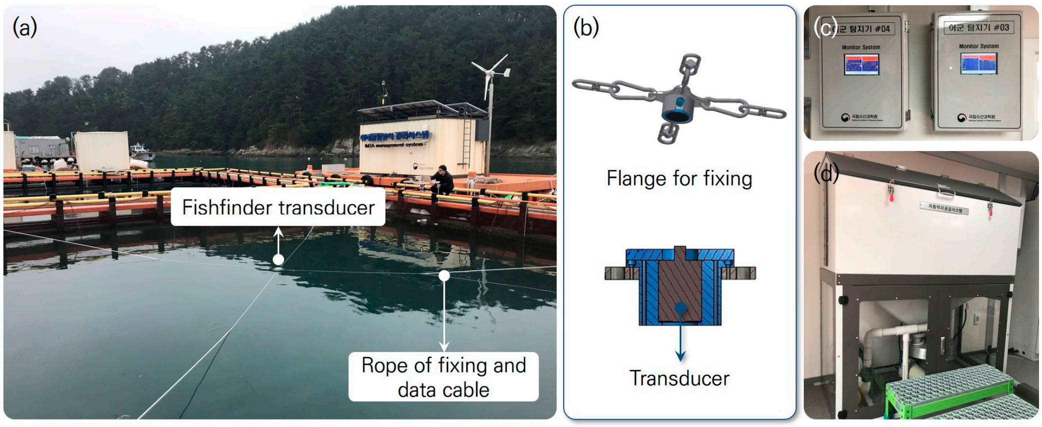

Figure 5. (**a**) Red seabream sea cage farm; (**b**) installation flange for fishfinder transducer; (**c**) edge computing system based on fishfinder interface box; (**d**) intelligent feeding system.

The performance of the feeding algorithm was evaluated by conducting a comparative analysis of the results of 30 repeated feeding experiments involving both the control and experimental groups. The evaluation considered the total feeding time, amount of feed supplied, amount of feed lost, and loss rate. Here, the lost feed refers to the amount of feed that the red seabream did not consume and was subsequently lost. The weight of the lost feed was measured by installing a feed collection net (size: 1.5 × 2.0 × 0.200 m, mesh size: 2 mm) under the point where feed was supplied and collecting it, as shown in Figure 6. Lost feed was collected 5 min after the end of feeding.

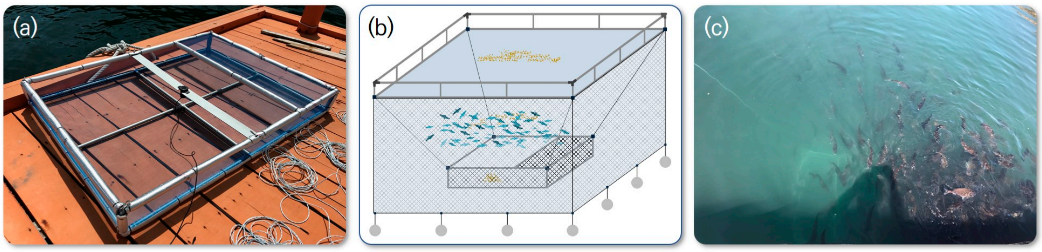

Figure 6. (**a**) Installation of feed collection net; (**b**) collection method for lost feed; (**c**) scene of capturing lost feed with feed collection net.

The feed loss rate can be calculated using Equation (4), which uses the total weight (W_t) of the feed supplied in the feeding experiment and the weight (W_l) of the feed collected by the feed collection net. Here, W_t and W_l mean the day and wet weights, respectively, and the wet weight was measured after air drying for about an hour. Equation (4) is as follows:

$$\text{Feed Loss Rate}(\%) = \frac{W_l}{W_t} \times 100 \tag{4}$$

3. Results and Discussion

3.1. Feeding Behavior Characteristics of Red Seabream

The feeding behavior characteristics of the red seabream were identified by observing the swimming depth of the fish school using the fishfinder while manually supplying the feed, as depicted in Figure 7. These observations demonstrated that when feed is supplied, the red seabream rises from the net at the bottom of the sea cage to the sea surface to consume the feed, and once they have consumed enough feed, they descend back to the net at the bottom of the sea cage. Notably, this phenomenon was consistent for adult fish rather than juveniles and when the water temperature was at least 11 °C.

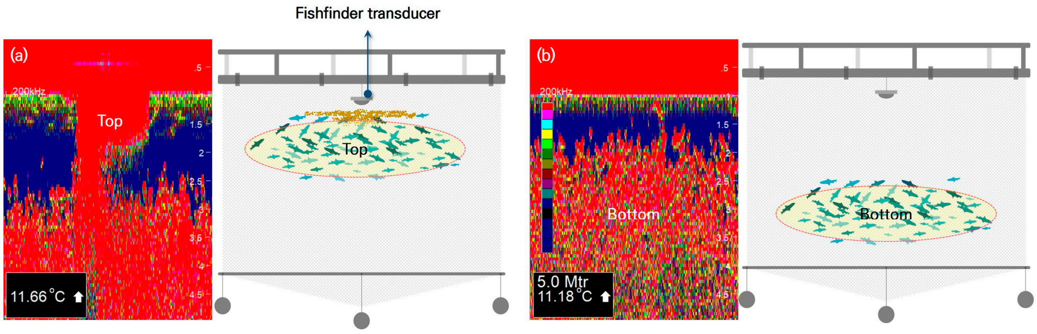

Figure 7. Depth-specific feeding behavior characteristics of red seabream recorded using fishfinder: (**a**) start and (**b**) end of feeding.

3.2. Performance of the Intelligent Feeding System

The size of the feed is adjusted according to the growth of the red seabream, and in general, as the red seabream grows, feed with a larger feed diameter is supplied. Therefore, in this study, the average weight of feed supplied was measured according to the diameter of the feed (Sajo DongA One Co., Ltd., Seoul, Republic of Korea, New solution), as shown in Figure 8. From the experimental results, it can be observed that the weight of the feed supplied by the intelligent feeding system differs owing to the volume of the empty space based on the diameter of the feed. The regression analysis results listed in Table 4 indicate that as the diameter of the feed increases, the supply amount decreases as a power function [14].

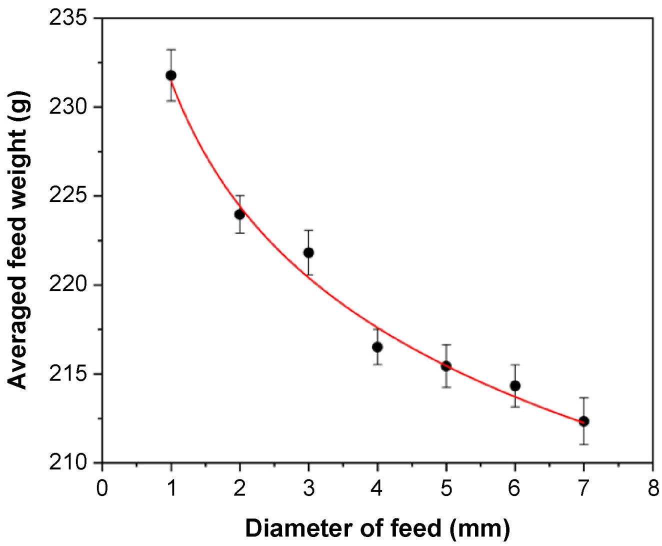

Figure 8. Change in weight of feed supplied according to the diameter of feed.

Table 4. Regression analysis results.

Equation	a	b	R^2
$y = a \cdot x^b$	231.41	−0.043	0.986

In the feeding experiment, the maximum supply distance and feeding speed were analyzed by measuring the spray pressure of the feed and the rotation count and time of the feed measuring grooves using a proximity sensor.

According to the experimental results, as shown in Figure 9, the feed was sprayed up to approximately 8.1 m, which is the central position of the sea cage, with a maximum pressure of 1300 mmAq at 1 s intervals. Therefore, the maximum feeding speed is determined by the time per second, and the average weight of the feed is determined by its diameter, as shown in Figure 8. When using feed with a diameter of 7 mm, as in this feeding experiment, the maximum supply speed averages out at 213.21 g/s.

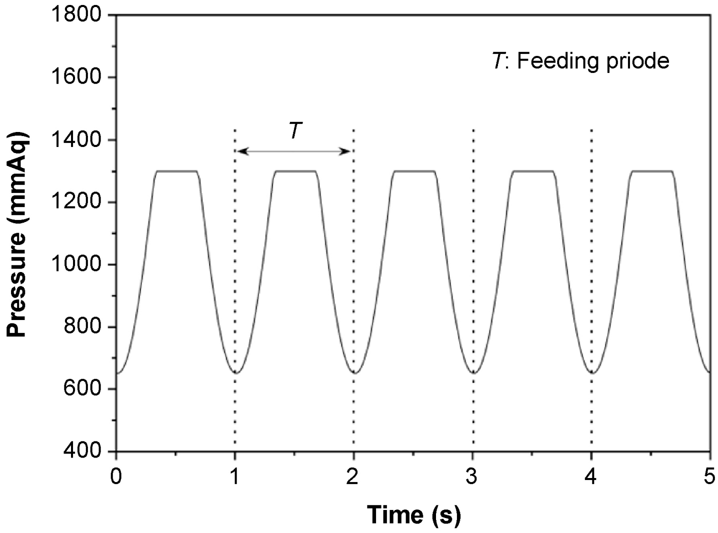

Figure 9. Feed spray pressure, rotation count, and time of feed measuring groove.

In addition to this observed performance, the developed intelligent feeding system allows intermittent feeding, unlike the traditional continuous feeding system, as the feeding rate and waiting time can be set separately. This advantage is expected to reduce the amount of feed loss and contribute to the even growth of fish by providing sufficient time for fish to consume feed [15,16].

3.3. Analysis of the Feed Loss Rate

We performed experiments in designated areas divided into the control and experimental groups, each using the manual method and feeding algorithm, respectively. In the experimental group, feed with a diameter of 7 mm was supplied at an average rate of 213.21 g per session at 3 s intervals. To facilitate a fair comparison, the control group was also supplied with feed under the same conditions.

The feeding time was recorded from the time that feed was supplied. The control group was analyzed until the termination of feeding activity as a result of the red seabream adequately consuming the feed, while the experimental group was analyzed until feeding was automatically stopped by the algorithm. The amount of feed supplied was calculated by weight as the total amount of feed supplied during the feeding time.

Figure 10 illustrates the total feeding amount and time measured during the 30 repetitions of the feeding experiment, for each feeding method of the control and experimental groups. Table 5 presents the sum of the measured feeding amount and supply time during the feeding experiment period, the value converted to the feeding amount per unit time, and the results of the regression analysis.

As a result of the experiment, the amount of food supplied was higher in the control group than in the experimental group, and it took a long time to supply the feed [17]. This is because the breeding density of the control group is relatively higher than that of the experimental group. In addition, the difference in feed supply can be caused by complex causes, such as changes in the breeding environment, such as water temperature and dissolved oxygen, and stimulation by external stress [18,19]. As such, although there was a difference in feed supply according to breeding density, it was found that there was no difference in feed supply per unit time. Additionally, the regression analysis shows that the supply amount relative to supply time has a linear relationship, (a) the slopes of the control and experimental groups are the same, and (b) the error in the feeding amount is negligible.

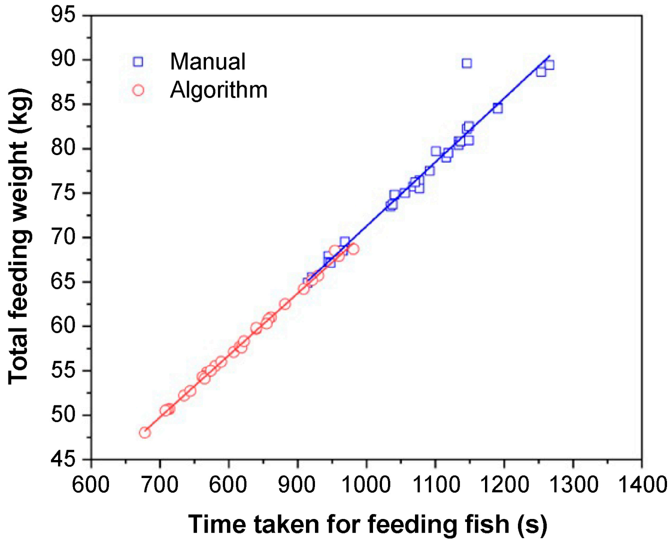

Figure 10. Supply amount and supply time according to the feeding method.

Table 5. Total feeding amount and time and regression analysis results by feeding method.

	Total Feeding Weight (kg)	Time Taken for Feeding Fish (s)	Feed Weight Per Second (kg/s)	Equation: y = a·x + b		
				a	b	R^2
Manual	2311.4	3239.7	0.071	0.070	−0.814	0.948
Algorithm	1743.6	24588	0.070	0.070	0.927	0.997

Feed loss according to the feeding method was measured by collecting the feed from the feed collection net installed for the control and experimental groups after feeding was stopped, and then weighing the feed using a digital scale. Figure 11 shows the feed loss rate measured through 30 repeated trials of feed supply experiments, each conducted using different feed supply methods in the control and experimental groups. The feed loss rate was calculated as the proportion of the lost feed amount to the total feed supplied, as expressed in Equation (3).

The experimental results indicate that the average feed loss rates of the control and experimental groups are 4.91% and 6.07%, respectively. A *t*-test was conducted to compare the averages between the two groups. The resulting *p*-value was significantly below the threshold at 0.0027 ($p < 0.05$), demonstrating a 1.16% difference in the average feed loss rates between the control and experimental groups.

The difference in feed loss between the control and experimental groups was negligible, and we found that the control group with less feed loss performed better. However, the feed loss rate may vary depending on the amount of feed lost due to the flow rate of algae during the feed capture process. Therefore, in order to accurately compare the feeding performance of the control group and the experimental group, it is judged that it is necessary to measure the marine environment, such as flow speed and flow direction, and to prepare a plan to fully measure the feed lost underwater [20,21].

As a result of comparing the feeding performance of the control group and the experimental group in this study, it was found that the feeding amount per unit time was at the same level, but the amount of feed lost in the experimental group was slightly higher, indicating that the performance of the developed intelligent feeding system needs to be improved. In particular, to improve the performance of the feeding algorithm, it is necessary to conduct research and continuous field experiments to methodologically optimize the setting criteria of the range of the observation area and the percentage of red-colored pixels (D_v) that affect the decision to continue feeding. On the functional side of the feeding system, it is necessary to develop technologies to cope with system failures. In addition, the feeding system needs to be improved to be more durable for marine use and to be easier to install and maintain for fishermen, since it is used at sea.

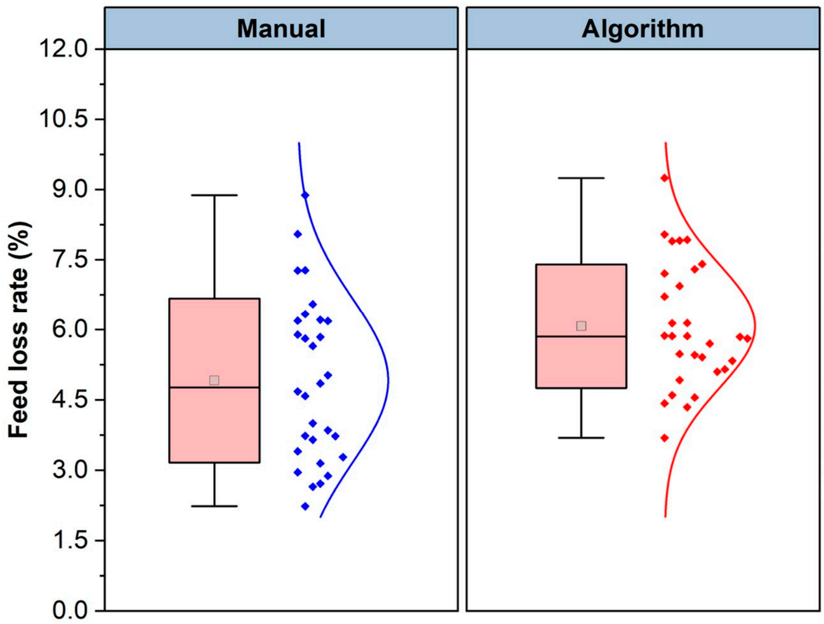

Figure 11. Feed loss rate according to the feeding method.

In the future, an intelligent feeding system that reflects these improvements will be developed, and a study will be conducted to analyze the relationship between the breeding environment, such as water temperature and dissolved oxygen, and the feeding behavior data of red seabream by depth to supply the appropriate amount of feed.

Such research is expected to help improve the operating environment of aquaculture sites, ensure appropriate feed supply, stabilize fish production, ensure the health of fish, and reduce overall operational costs. Moreover, we expect that the developed system can contribute to shifting from traditional labor-intensive farming methods to a technology-intensive aquaculture industry by automating the farming process using intelligent techniques.

4. Conclusions

In this study, we developed an intelligent feeding system based on edge computing to automate feeding by observing the feeding behavior of red seabream by depth. The feeding performance was compared with the traditional manual feeding method through field experiments on the feeding amount and loss rate per unit time.

For the performance test of the developed system, red seabream raised at a depth of 5 m in a sea cage farm were used. The performance test condition of the system was set to feed the feed (diameter: 7 mm) at the set time, wait 30 s, and then stop feeding if the red-colored pixel distribution value was 70% or more in the fish observation area on the edge computing system, and to stop feeding if was is less than that.

From the experimental results, the feeding rates per unit time of the manual method and the intelligent feeding system were comparable. On the other hand, the feed loss rate was 1.16% higher when feeding with the intelligent feeding system than the manual method, indicating that performance improvement is necessary. However, the difference in feed loss was insignificant, confirming the feasibility and effectiveness of the feeding system through observing the feeding behavior of red seabream by depth.

Author Contributions: Conceptualization, D.L.; methodology, D.L. and K.L.; software, D.L.; validation, D.L. and K.L.; formal analysis, D.L. and J.B.; investigation, D.L. and K.L.; resources, D.L.; data curation, D.L. and K.L.; writing—original draft preparation, D.L.; writing—review and editing, D.L., K.L., and J.B.; visualization, D.L.; supervision, D.L.; project administration, D.L.; funding acquisition, J.B. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare no conflict of interest.

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