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Digital Twin Architecture Evaluation for Intelligent Fish Farm Management Using Modified Analytic Hierarchy Process

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Abstract: Precision aquaculture deploys multi-mode sensors on a fish farm to collect fish and environmental data and form a big collection of datasets to pre-train data-driven prediction models to fully understand the aquaculture environment and fish farm conditions. These prediction models empower fish farmers for intelligent decisions, thereby providing objective information to monitor and control factors of automatic aquaculture machines and maximize farm production. This paper analyzes the requirements of a digital transformation infrastructure consisting of five-layered digital twins using extensive literature reviews. Thus, the results help realize our goal of providing efficient management and remote monitoring of aquaculture farms. The system embeds cloud-based digital twins using machine learning and computer vision, together with sensors and artificial intelligence-based Internet of Things (AIoT) technologies, to monitor fish feeding behavior, disease, and growth. However, few discussions in the literature concerning the functionality of a cost-effective digital twin architecture for aquaculture transformation are available. Therefore, this study uses the modified analytical hierarchical analysis to define the user requirements and the strategies for deploying digital twins to achieve the goal of intelligent fish farm management. Based on the requirement analysis, the constructed prototype of the cloud-based digital twin system effectively improves the efficiency of traditional fish farm management.

Keywords: digital twin; digital transformation; AIoT technology; machine learning; big data analytics in aquaculture; analytic hierarchical process

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1. Introduction

The primary aims of fish farm management include operation cost reduction, profit maximization, fish quality augmentation, and harvest efficiency optimization. To achieve these goals, large and modern aquaculture farms incorporate technological innovations to maximize fish production and minimize fish food, action prediction to optimize the control factors of aquaculture machines, and order management based on the optimal harvest policy. The core functionality of intelligent fish farming is to monitor the status of fishes' life stages, from brood-stock/eggs to fully-grown adults [1]. However, one of the challenges is the different environments for each stage of fish farming. For example, indoor tanks under controlled conditions are typical environments in the hatchery phase to minimize the risk of external factors affecting the fish. For the final growing phase, they are transferred to outdoor ponds or sea cages and grown up until their marketable size. Since the volume water requirement of the fish is often proportional to its size, there is a need to monitor their crowding population during different growth stages. The fish schools' density cannot be too high when the fish are of greater sizes. Otherwise, the possibility of depleted oxygen intake due to overcrowding will be a significant risk to their health.

Outdoor ponds or sea cage farming can quickly fulfill these requirements compared with indoor tanks. However, in this environment, fish are exposed to natural fluctuations, which are essential factors in the production environment, e.g., water flow, temperature, salinity, and light intensity. However, with these exposures, additional challenges burden the farmers to control the production conditions because sea-based farming increases the chance of stressors such as pollutants, pathogens, and parasites in the population [1]. This study then analyzes the key requirement factors of intelligent fish farming to guide the production process and fully understand the aquaculture farm's environmental and fish conditions.

The first step to the digital transformation of fish farm management is to deploy sensors on fish ponds or offshore sea cages to collect fish and environmental data to establish data-driven prediction models. The digital transformation of aquaculture is also defined as Aquaculture 4.0, which follows the concept of Industry 4.0 technologies [2,3] to achieve the goal of precision aquaculture by supporting decision-making based on the utilization of artificial intelligence (AI) and the Internet of Things (IoT) [1,4]. AI technologies, such as information-based management with big data and models, guide the production process and fully understand aquaculture farms' environmental and fish conditions. On the other hand, IoT technologies characterize intelligent fish farms with surveillance cameras, water inspecting devices, and working sensors to store and serve data to a fog or cloud system through interconnection networks. This digital transformation of aquaculture based on the implementation of the AIoT system facilitates fish farms to optimize operations of a precision aquaculture framework. Therefore, including sensor deployment, cloud big data management, and AI analytics in this framework enables real-time, data-driven decision-making [5].

In industrialized aquaculture, where many farms are situated on open seas, regular visits to the site for monitoring pose a big challenge, especially in its cost and the time requirement and safety of the workers. Traditional data collection approaches involve using pen and paper to manually write the observations made by the workers and farm owners on their observations of the current status and welfare of the aquatic animals on the site. These written observation data are then transferred to spreadsheet applications for data analysis. However, such a mechanism is often incomplete, inconsistent, and poorly formatted. The presence of big data and big data analytics infrastructure transformed the aquaculture industry for data-driven decision-making. More and more aquaculture farmers are turning to data to support their farm management and operation procedures. Many are now investing in new technologies for sustainability and to increase profitability. With these influences, automatic collection, processing, and the advanced analysis of data can be translated into an accessible and readable format that the fish farmers can understand. Low-cost sensors allow them to collect data remotely from far and hard-to-reach locations. Unlimited data acquisition can now be sent via wireless network technologies to the cloud for storage and data analytics. Such mechanisms provide automatic and higher-quality data collection.

Intelligent fish farm management aims to optimize and automate the fish farm computerization by the intelligent networking of smart sensors, aquaculture machines, and AI processes using an AIoT system. The implementation of an AIoT system integrates previously existing concepts such as the Internet of things (IoT), cloud computing, artificial intelligence (AI), machine learning (ML), big data analytics, and cognitive services and applies them to fish production. Figure 1 shows the AIoT system design for intelligent fish farming based on the fusion of three vital design principles, i.e., interconnection, information transparency, and decentralized decisions. The underlying IoT system facilitates the interconnection among machines, devices, sensors, and people so they can communicate via the Internet. Information transparency's relevance relies on implementing an AI-empowering cloud system that can automatically collect, manage, and organize the vast amount of data from connected machines, devices, and sensors. These virtualized technologies represent the physical objects of the AIoT system as logical objects or digital twins (DTs). Each object is described as a formal digital representation of some asset, process, or system that captures attributes and behaviors of that entity suitable for communication, storage, interpretation, or processing within a specific context [6]. The AIoT system is also required to incorporate AI and ML farm operations to meet the requirements of decentralized decisions. Thus, it facilitates DTs to provide intelligent services, enabling better decision-making and increasing automation and overall productivity. DTs with enhanced capabilities are called cognitive twins (CT) [7].

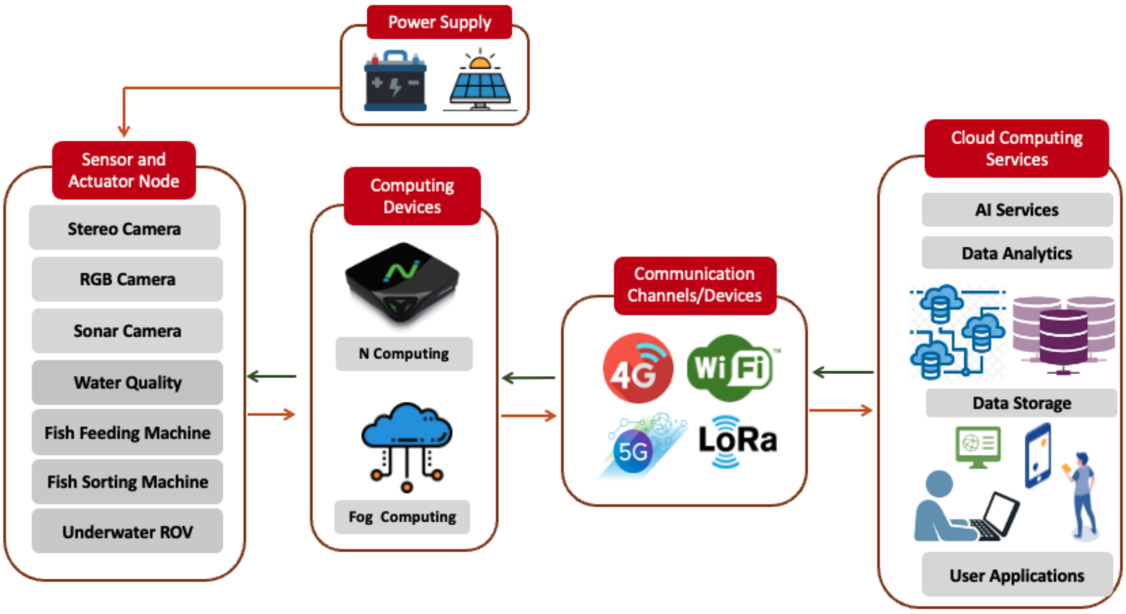

Figure 1. Schematic view of the proposed AIoT system for intelligent fish farming [8].

This study aims to construct an AIoT system that addresses all the key operations of fish farm management. As shown in Figure 2, the system's functionality can be implemented using a five-layer digital twin architecture to facilitate the digital transformation for precision aquaculture. The first step of the digital transformation of fish farm management is the virtualization of physical sensors, machinery controllers, and fish ponds or offshore cages. In this phase, every physical object is transformed into the corresponding logic object, also defined as a digital twin. The features, states, prediction models, and action sequences of the physical object are stored in this stage. However, the characteristics of individual physical objects might be very different and thus very difficult to be represented by a generic digital twin template. For instance, both the optical and the sonar cameras could be used to automatically acquire environmental or fish data for monitoring the status of the fish. However, different machine learning tools are often used to analyze their respective captured videos. Next, these logic objects send sensor data which are often fused and integrated into the cloud. The cloud is equipped with machine learning or deep learning prediction models to offer basic services, including water quality prediction models, fish metrics estimation models, and fish food requirements for daily feeding. The basic services provide AI functions to transform unstructured sensor data into structured fish farm information, which is further inputted into the succeeding decision-making processes to establish fish farm data applications. In this system, the fish farm manager uses web interfaces to connect to these data applications for precision aquaculture. Advanced technologies integrating IoT and cloud virtualization techniques facilitate the construction of an AIoT system based on digital twin modeling. Despite this development, the existing industrially available sensors are insufficient to address the issues of low power consumption, high bandwidth networking, waterproofing, and end-computing AI functions. These physical sensors need further improvement before implementing the corresponding logic objects.

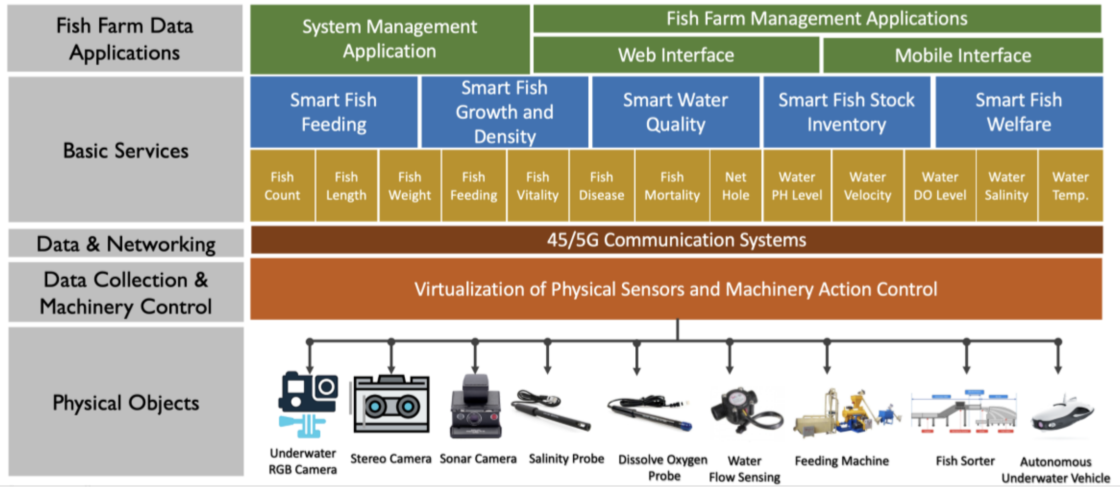

Figure 2. Digital aquaculture architecture based on Digital Twins [8].

Moreover, the knowledge management of conventional fish farming is the core technology for aquaculture transformation using emerging AIoT technologies. In this study, we exploit the effective knowledge management methodology by representing the knowledge of traditional fish farming as a set of digital twins using the modified analytical hierarchical process [9,10]. Based on the analysis results, we constructed an AIoT prototype system to verify the effectiveness of intelligent fish farming.

The remainder of this paper is organized as follows. Section 2 presents the literature reviews of intelligent fish farming. Section 3 presents the research methodology. The empirical results and discussions of our research findings in comparison with previous studies are detailed in Section 4. Finally, the conclusions and future work for the digital transformation based on digital twins are presented in Section 5.

2. Literature Reviews

Digital twins for intelligent fish farming involve a variety of sensors to extract essential features of the farm environment for decision-making to optimize fish health, growth, and economic return and reduce risk to the environment. However, the cost to establish a complete digital twin platform that solves all intelligent fish farming management concerns is too high for small-scale fish farms. Instead, we can focus on studying how a digital twin behaves under specific conditions. Despite its complexity, the application-oriented fish farming system is easier to develop with controllable costs. Jones et al. performed a systematic literature review to characterize the benefits of using digital twins [11]. The said study divided the previous digital twins to support smart manufacturing to reduce costs [12–15], risks [15], and complexity [16]. At the same time, it can improve after-sales service [17,18], efficiency [19], maintenance decisions [20], security [21], safety and reliability [22], manufacturing processes [23,24], enhance flexibility and competitiveness [23], and foster innovation [12]. Although the digital twin behavior for intelligent fish farming is more challenging, following a similar approach to define the key factors of fish farm management for the corresponding digital twins to implement is possible.

Digital twins facilitate the implementation of digital aquaculture employing smart technologies to perform data acquisition, analysis, and complex decision-making from fish ponds or sea cages [25,26]. As the fusion of big data, real-time information from the individual farm, and AI, digital twins enhance the efficiency of fish farming, maximize production, reduce cost, and optimize the decision-making process. Furthermore, the AIoT tools facilitate intelligent farm management, improve aquaculture operation efficiency, control production quality, and link with the food supply chain and decision support tools [27]. Underwater cameras or sonar imaging devices are essential sensors to capture underwater images, inputted to specific AI functions, and big data analytics to extract management knowledge from fish farms [28–32]. For instance, fish health, growth, and behavior detection can be monitored and controlled using advanced AI and deep learning techniques [33,34]. Data-driven approaches augment on-farm decision-making capabilities, improve fish production, and reduce losses, benefiting farmers. The IoT and wireless technologies enable real-time data transmission and monitoring in digital farming [35,36]. The cloud-based IoT systems facilitate communication between software platforms, sensors, farmers, and aquaculture machinery in digital farming. However, cameras for data collection on fish ponds in rural areas or offshore cages contain large amounts of data, causing a high load on the wireless networks and increasing the latency of data communication. Because of this, the subsequent decision-making process's response time becomes unreliable due to the delay in transmission. Such limitations can be addressed by a recent smart farming approach, such as edge computing, to enable computation or processing at the network's edge [36] by reducing the network load and supporting real-time data processing. However, the power supply demand of sensors and edge systems is always a severe issue in digital aquaculture, especially for offshore cages. Although cyber-physical systems have been widely introduced in smart farming systems to develop hardware and software to improve the adaptability, safety, and security of computer-based algorithms and systems [37], only very few digital aquaculture systems are discussed in the literature [38]. With this inadequacy, further studies of how to architect digital twins that support the adaptability, practicality, security, and safety of collected information for better management of aquaculture farms are necessary.

In 2019, Garner, a well-known global research and advisory institution, listed DTs as one of the top ten strategic technology trends impacting modern society [38,39]. The proposed AIoT architecture can be considered the container of DTs, each corresponding to a physical sensor, a statistic model, a user, or an aquaculture machine. The digital transformation of fish farm management based on the use case analyses of the AIoT software system is to transform the expertise of precision aquaculture into multiple key models that implement individual intelligent aquaculture operators. In this paper, we prioritize these key models based on the planning, execution, and results of a systematic mapping study on architecting DTs. First, the study captures crucial factors of intelligent fish farm management for specifying the required digital twins tailored to their specific needs of precision aquaculture. Starting from an initial set of potentially relevant 1630 peer-reviewed publications, we selected 140 primary studies of smart and precision aquaculture. Then, we analyzed the various primary studies using thorough data extraction, analysis, and key factors extraction. Finally, to compensate for single method limitations and reduce possible threats to conclusion validity, we discussed the results of our study with experts in the aquaculture community following the approach of the well-known analytical hierarchy process [40]. Hence, the systematic mapping constructs use cases of the AIoT system by architecting DTs based on the evaluating results of AHP. The field of software architecture for digital twins is lively, and an increasing number of architectural solutions are being proposed. Although there is a lack of widely accepted reference architectural solutions for digital twins, most are built using a combination of layered and service-oriented patterns and address maintainability, performance efficiency, and compatibility quality attributes. To the best of our knowledge, this study is the first case to analyze the user requirements of a complete AIoT system for precision aquaculture based on the digital twin concept.

3. Methodology

This study aims to create an analysis framework based on the Industrial Internet of Things (IIoT) [41] analysis for aquaculture transformation by providing a means of characterizing entities described as digital twins. The following questions should be answered through the literature reviews: (a) What major functions should be included in managing a fish farm? (b) What necessary physical objects should be designed to support intelligent fish farming? (c) What functional components can support fish farming operators in the digital twin? (d) What are the typical digital twins for intelligent fish farming? We adopted a two-phase approach to address the research questions, as mentioned earlier. The first phase focuses on questions (a), (b), and (c), seeking to obtain an overview of relevant existing literature that reviewed and/or characterized digital twins for intelligent fish farming. The second phase focused on question (d), exploring relevant literature related to the priority evaluation of the architectures of digital twins using the modified AHP.

3.1. Architecting Digital Twins Using Literature Reviews

User requirement analysis of digital aquaculture is the first step to achieving the digital transformation of fish farm management goals. In this subsection, the software system's key use cases that enable intelligent fish farming are extracted by an extensive review of published literature. However, each of these published digital twin solutions only focuses on a specific aquaculture operation and is far from providing a complete system for intelligent fish farming. Therefore, we consider the digital twin solution sufficiently discussed by published literature to be an important key factor supporting digital aquaculture. Next, these key requirements and their details are presented to aquaculture researchers, fish farmers, and experts from the fish agency in Taiwan to specify the importance of these factors.

In seeking the answer to questions (a), (b), and (c) regarding the major components of intelligent fish farming, 1630 potentially relevant peer-reviewed publications were analyzed, and eight were selected for architecture comparison. The common characteristics of these papers suggest that the usage of AIoT technology is the key to successfully achieving the goal of precision aquaculture or intelligent fish farming. However, the presented physical objects and prediction models to construct individual AIoT solutions are very different. Most of the sensors and types of machinery for operating fish farms are far from being highly reliable or cost-effective, mainly when applied to operate an offshore cage. Moreover, the power-supply problem often results in severe challenges, though these can be solved by setting a set of batteries that is rechargeable by a solar panel. For each physical object or digital twin service, we also use two indexes, the Importance (I) and the Easiness (E), which are normalized to be within the interval [0,1]. The higher index value signifies the digital twin's higher importance. If a digital twin is mentioned in a reviewed paper, the importance of the object will be set regarding the paper's impact factor (IF). Thus, the definition of the importance index I of an object O is

$$I(O) = \frac{\sum_{j \in \Omega_O} IF(j)}{\sum_{i \in \Omega} IF(i)} \tag{1}$$

where Ω and Ω_O are the set of all the reviewed papers and the set of papers that mentioned object O, respectively.

Similarly, the value of the easiness index of an object O is computed as

$$E(O) = 1 - (c - c_{min})/(c_{max} - c_{min}) \tag{2}$$

where c, c_{max}, and c_{min} are the cost of object O, which is the maximal cost value among all the objects and the minimal cost value among all the objects. The cost to implement an object affects the easiness of a fish farm to invest in the digital twin. Furthermore, the cost to construct an object is defined based on the development experiments of our AIoT systems for intelligent fish farming. It is difficult to obtain the correct values of these two indexes for an object because few fish farms in Taiwan have adopted AIoT systems to manage fish production.

Tables 1–4 summarize the values of the importance and easiness indexes regarding the sensors, machinery, aquaculture environments, data-driven prediction models, and decision-making models, which are the major entities used to construct our five-layered AIoT models for intelligent fish farming. The literature reviews give the initial values of these two indexes for all the components. These analyses are based on the results of the selected 12 reviews of intelligent fish farming. Furthermore, these initial values are then quantized by being presented to the expert team comprising nine cross-discipline researchers: three have expertise in big data analytics, one is an expert in the field of data visualization, three are experts in designing aquaculture machines, sensor networking, and power-supply systems, two are experts from the aquaculture field, and one has a rich experiment background in fish farm management. The resulting importance and easiness indexes for each component are then used to compute the corresponding importance and easiness of individual criteria of the analytic hierarchy that specifies the key factors to construct an AIoT information system for intelligent fish farming.

Table 1. Layer 1 physical objects used in fish farm management and their feasibility evaluation in terms of indexes *I* and *E*.

Layer 1: Physical Object		***I***	***E***
Data collection (D)	D1. water quality	0.8	0.8
	D2. optical RGB camera	0.8	0.8
	D3. sonar camera	0.8	0.6
	D4. acoustic sensor	0.6	0.8
	D5. climate open data	0.5	0.8
Machinery (M)	M1. fish feeding machine	0.8	0.2
	M2. net cleaner	0.6	0.2
	M3. sorting machine	0.5	0.2
	M4. heater/colder	0.8	0.5
	M5. oxygen pump	0.8	0.5
	M6. drone	0.5	0.2
	M7. underwater drone	0.4	0.2
Environment (E)	E1. indoor fish pond	0.8	0.8
	E2. outdoor fish pond	0.8	0.7
	E3. offshore cage	0.8	0.3

Table 2. Layers 2 and 3 of the Digital Twins send sensor data to the cloud storage or execute actions defined by decision-making models.

Layers 2 and 3: End-System Digital Twin		**Network Communications**	***I***	***E***
Data networking (N)	N1. water quality	LoRa, NB-IoT	0.8	0.8
	N2. optical RGB camera	4G/5G/WiFi	0.8	0.7
	N3. sonar camera	4G/5G/WiFi	0.8	0.7
	N4. acoustic sensor	4G/5G/WiFi	0.8	0.7
	N5. climate open data	4G/5G/WiFi	0.8	0.8
Action Execution (A)	A1. fish feeding	LoRa, NB-IoT	0.8	0.8
	A2. food usage	LoRa, NB-IoT	0.8	0.8
	A3. net cleaning	LoRa, NB-IoT	0.8	0.8
	A4. fish sorting	LoRa, NB-IoT	0.8	0.8
	A5. heater	LoRa, NB-IoT	0.8	0.8
	A6. air pumper	LoRa, NB-IoT	0.8	0.8

Table 3. Layer 4 of the Digital Twins as a basic services provider.

Layer 4: Basic Service Digital Twin		**Deep Learning Model**	***I***	***E***
Environmental conditions prediction (C)	C1. water quality prediction	LSTM [42]	0.8	0.8
	C2. climate prediction	LSTM [42]	0.8	0.8
	C3. net hole detection	YoLoV4 [43]	0.8	0.8
	C4. aquatic plants detection	YoLoV4 [43]	0.8	0.8
Fish metrics estimation (F)	F1. fish length/height/weight estimation	Mask-RCNN [44], U-Net [45]	0.8	0.8
	F2. fish classification	YoLoV4 [42]	0.8	0.8
	F3. fish count estimation	ANN regression [46]	0.8	0.8
	F4. fish density estimation	U-Net [45]	0.8	0.8
Fish behavior recognition (B)	B1. fish feeding intensity	Activity recognition CNN [32],	0.8	0.8
	B2. fish vitality recognition	Optical flow detection CNN [32]	0.8	0.8
	B3. fish diseases detection	DBSCAN [47]	0.8	0.8

Table 4. Layer 5 of the Digital Twins as a provider of fish farm data applications based on the associated user interface.

Layer 5: Data Application Digital Twin	**Component Functions**	***I***	***E***
Water quality prediction (WQP)	D1, D5, N1, N5, E1, E2	0.8	0.6
Underwater video surveillance (UVS)	D2, D3, D5, N2, N3, N5, F1, F2, F3, F4, B1, B2, B3	0.8	0.6
Water surface monitoring (WSM)	D2, D3, N2, N3	0.8	0.6
Fish food prediction (FFP)	WQM, UVS, A2	0.8	0.8
Smart fish feeding (SFF)	FFP, WSM, UVS, M1, B1, A1, A2	0.8	0.5
Fish growth model (FGM)	WQM, UVS, A2	0.8	0.8
Weight conversion ratio (WCR)	UVS, A2	0.8	0.6
Fish food tracking (FFT)	FFP, A2	0.8	0.6
Water quality alarming (WQA)	E1, E2	0.8	0.6
Fish disease detection (FDD)	WQM, UVS	0.8	0.6
Fish feeding policy evaluation (FFP)	FGM, Q-learning [48], FFP	0.8	0.6
Fish pond scheduling (FPS)	UVS	0.8	0.8
Fish in-stock evaluation (FIE)	UVS	0.8	0.8
Fish harvest scheduling (FHS)	UVS, SFF	0.8	0.8

Next, the virtualization technique is applied to implement physical objects as end-system digital twins, which take the responsibility of sending sensor data to the cloud storage or executing actions defined by decision-making models. The cloud plays a vital role in managing the collected big datasets and performing embedded AI functions to determine the feedback actions for operating aquaculture tasks, e.g., fish feeding processes. Table 2 shows the importance and easiness evaluation results for the digital twins (logic objects) in Layers 2 and 3.

The fourth layer of our AIoT model is the basic services that use pre-trained machine learning or deep learning models to analyze the sensor data for predicting environmental conditions, fish metrics estimation, and fish behavior recognition. Again, the cloud architecture facilitates the implementation of plug-in services because all the AI functions are maintained at the server site. Furthermore, such a mechanism increases the possibility of offering on-the-fly services when the farm manager sends a new requirement. Table 3 shows the digital twins for basic services and their AI functions.

Finally, the last layer of the fish farm data applications is the user interface. The fish farmer can use the user interface to access the decision-making results to efficiently and effectively manage the fish farm. Individual decision-making models access different results of basic services to optimize the action sequence for a specific aquaculture management task. Figure 3 shows the proposed reinforcement learning-based digital twin for controlling the smart feeding machine to minimize fish food usage. With the water velocity, temperature, fish weight, and fish count as the inputs, the digital twin generates the daily food amount, which is an action for our automatic feeding machine to execute.

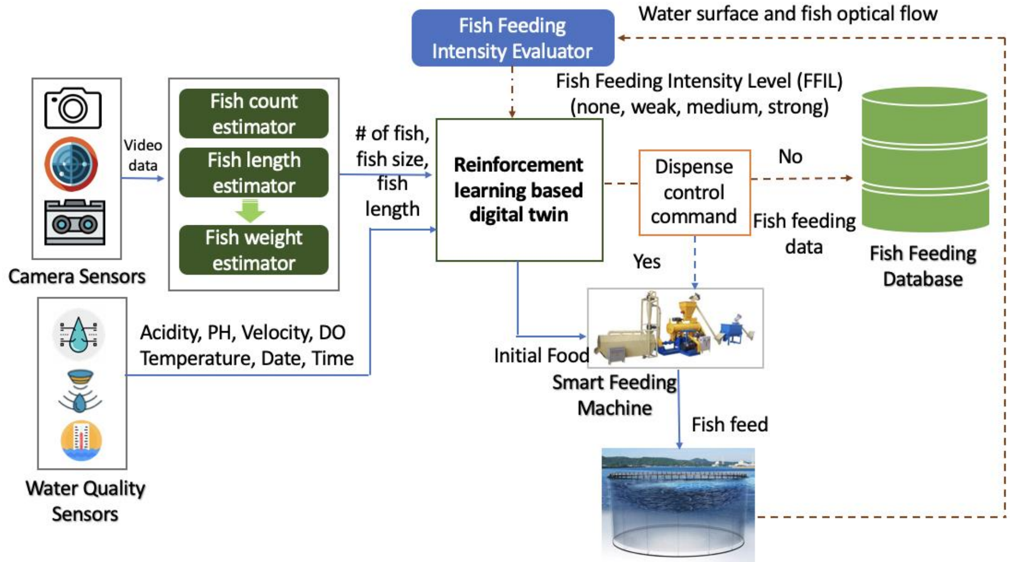

Figure 3. The reinforcement learning-based digital twin for controlling the smart feeding machine to minimize the usage of fish food.

Furthermore, the amount of fish food can be separated into multiple actions executed by our automatic fish-feeding machine. For each action execution, the fish feeding intensity evaluation function (B1) is also used to simultaneously observe the fish feeding status. If the current feeding status is 'weak', the remaining actions will be skipped to avoid overfeeding. Table 4 shows the summaries of the digital twins belonging to Layer 5.

3.2. Digital Twin Architecture Evaluation Using Modified AHP

As shown in Figure 4, the individual physical operation of a physical farm would have a corresponding logical object in the virtual farm based on the digital twin concept. A logical object (digital twin) is a virtualization of a physical object consisting of a sensor to capture data and a wireless communication end system to send data to a fog, an end, or a cloud system for further fish or environment status detection. The logical object also uses a prediction model to make a decision that enables an action sequence to control the machinery and bring benefits to the farmer. For example, as seen in Figure 4, our logical object for smart feeding scheduling uses multiple logical sub-objects to predict the amount of fish food for daily feeding. Thus, the smart fish-feeding digital twin might contain several sub-objects to prevent the fish from over-feeding or underfeeding.

To achieve the goal of intelligent fish farming, this study analyzes the user requirements of the cloud-based information system, comprising six sub-systems to manage the sensors, aquaculture machinery and fish ponds, end system management, live data monitoring, production planning, and value-added services. These sub-systems form the first-tier key factors of the analytic hierarchy. As mentioned in the previous sub-section, we use the digital twins to implement each sub-system. The resulting analytic hierarchy is thus of two tiers, as shown in Figure 5. Although all the sub-systems should be included to address the issues of intelligent fish farming, the digital twins supporting individual fish farms could be very different due to the limitation of resource investment.

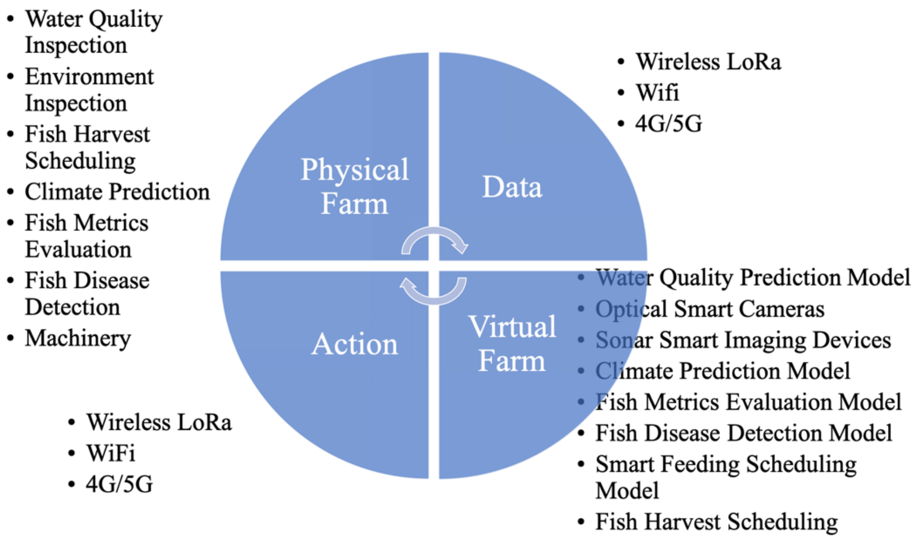

Figure 4. User requirement analysis of intelligent fish farming using digital twins [9].

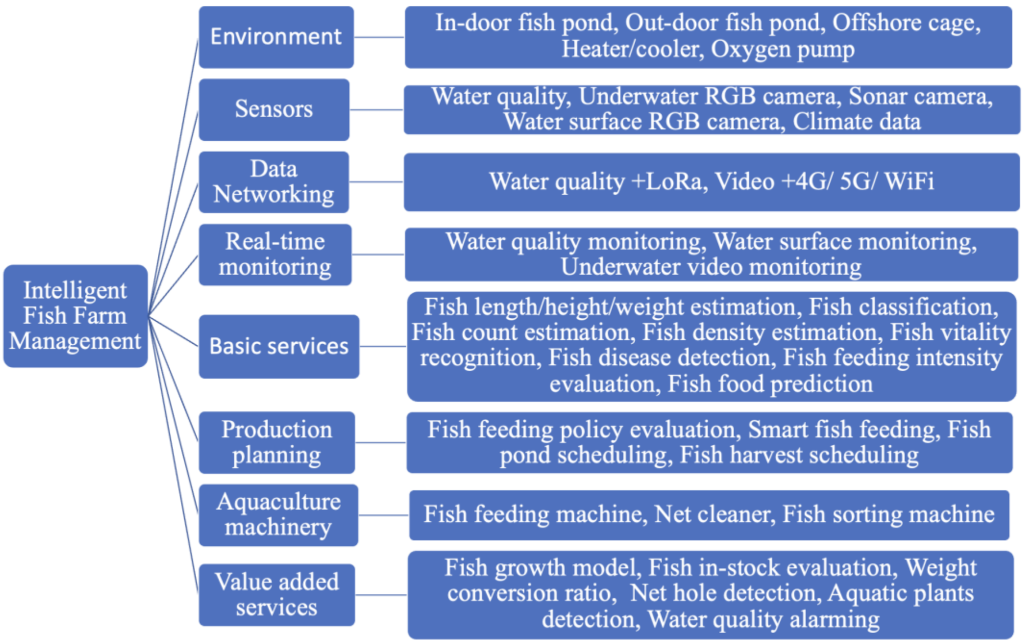

Figure 5. Hierarchy of digital twin architecture related to the AIoT system for intelligent fish farm management.

Consequently, the analytic hierarchy process (AHP) could be adopted to locate each digital twin's important weight (priority) in the AIoT information system. The hierarchical network also represents the decision problem of our intelligent fish farming. The overall objective, with the details defined by the next two lower levels, represents the criteria and sub-criteria. With comparative judgments, users are requested to set up a comparison matrix at each hierarchy by comparing pairs of criteria or sub-criteria. Generally, AHP uses a scale of values ranging from 1 (indifference) to 9 (extreme preference) to express the user's preference. Finally, in the synthesis of the priority stage, each comparison matrix is solved by an eigenvector method for determining the criteria importance.

In this study, the AHP should be modified for two reasons. First, the number of the second-tier criteria is often larger than 9; thus, it exceeds the limits of the AHP. Second, it is difficult to construct the comparison matrices using questionnaire surveys since real-world fish farm managers have very few experiences operating an intelligent fish farming management system. To deal with these two difficulties, in this study, we use the importance and easiness indexes defined in Equations (1) and (2), respectively, to synthesize the importance and easiness of all the criteria of the analytic hierarchy.

Figure 6 shows the workflow of the AIoT system for intelligent fish farming. The first step is the design of the fish production environment, such as an indoor fish pond, outdoor fish pond, or offshore cage, which might also be equipped with devices for quality improvement. Next, the sensors set in the aquaculture environment captures sensor data which are then automatically uploaded to the cloud system for storage using a data networking end system. Once the cloud detects the newly arrived data, the orchestration module triggers the pre-trained AI prediction models to estimate fish metrics or detect abnormal environmental events. Note that the method to process the sensor data depends on the data type.

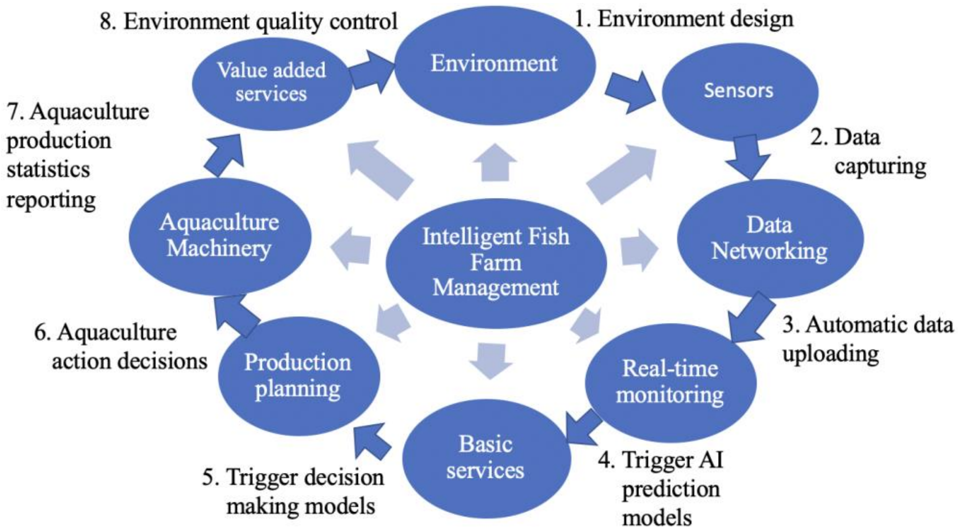

Figure 6. The automatic workflow of the AIoT information system for intelligent fish farm management.

Furthermore, the sensor-specific AI function is vital in transforming the non-structured sensor data into well-organized structured information often stored and managed by a relational database system. This essential information is then inputted into the decision-making models to generate optimal actions for controlling the aquaculture machines, which increases the automation degree of routine work to improve the efficiency of fish farm management. Moreover, the decision-making models for detecting the issues of the aquaculture environment activate the environmental improvement devices to decrease the risk of an aquaculture operation. Finally, the value-added services facilitate an understanding of the states of fish farms which might initiate abnormal event handling to minimize the risk of the aquaculture operation. Basically, all the sub-systems are equally important in achieving the goal of reducing the aquaculture risk based on the information system for intelligent fish farm management. Although there exists a few alternative AIoT solutions that address partial user requirements suggested by the analyses in the literature, it is difficult to evaluate the priorities of these suggested alternative solutions since the risk levels introduced by the individual solutions are very different. Moreover, to the authors' best knowledge, the literature reviewers lack complexity analyses of the physical objects, including sensors, aquaculture machines, fish ponds, and offshore cages, which are the core IoT devices to construct the AIoT information system. The priority evaluation of the physical objects, the corresponding digital twins, and decision-making models using our modified AHP spans a new systematic methodology for designing a cost-effective AIoT system based on the requirements of a fish farm.

Level 1 reciprocal matrices $\left[M_1^I \in \mathbb{R}^{8\times 8}, M_1^E \in \mathbb{R}^{8\times 8}\right]$ for judging the relative importance of the seven sub-systems in terms of importance and easiness indexes are computed as

$$[M_1^I, M_1^E] = \left[\begin{bmatrix} I_1^I/I_1^I & \cdots & I_1^I/I_6^I \\ \vdots & \ddots & \vdots \\ I_6^I/I_1^I & \cdots & I_6^I/I_6^I \end{bmatrix}, \begin{bmatrix} I_1^E/I_1^E & \cdots & I_1^E/I_6^E \\ \vdots & \ddots & \vdots \\ I_6^E/I_1^E & \cdots & I_6^E/I_6^E \end{bmatrix}\right] \tag{3}$$

where I_i^I and I_i^E are the important and easiness indexes of the i-th sub-system, respectively. The values of these two indexes are defined as

$$[I_i^I, I_i^E] = \left[\frac{1}{|NC_i|}\sum\nolimits_{j\in NC_i} I_j^I, \frac{1}{|NC_i|}\sum\nolimits_{j\in NC_i} I_j^E\right] \tag{4}$$

where NC_i is the set of objects (physical or logical) selected to implement the i-th criterion; $|NC_i|$ is the cardinality of NC_i. The underlying concept of (4) is to represent the importance and easiness indexes of a composite object by the averages of those of the next-level sub-objects. Level 1 weightings of the eight digital twin architectures are then obtained from M_1^I and M_1^E.

Without loss of generality, let m and n be the number of Level 1 criteria and the number of Level 2 criteria for each Level 1 criterion, respectively. For each row of Level 1 reciprocal matrices M_1^I and M_1^E, we can define weighting measurements as

$$\left[r_i^{I,1}, r_i^{E,1}\right] = \left[\sqrt[m]{\frac{a_i^{I,1}}{a_1^{I,1}} \times \frac{a_i^{I,1}}{a_2^{I,1}} \times \cdots \times \frac{a_i^{I,1}}{a_m^{I,1}}}, \sqrt[m]{\frac{a_i^{E,1}}{a_1^{E,1}} \times \frac{a_i^{E,1}}{a_2^{E,1}} \times \cdots \times \frac{w_i^{E,1}}{w_m^{E,1}}}\right], \ i = 1, \ldots, m \tag{5}$$

where $a_i^{I,1}$ ($a_i^{E,1}$) is the relative importance (easiness) value of the i-th Level 1 criterion. Then, Level 1 weightings are determined by

$$w_i^1 = \frac{1}{2}\left(r_i^{I,1}/\sum\nolimits_{j=1}^m r_j^{I,1} + r_i^{E,1}/\sum\nolimits_{j=1}^m r_j^{E,1}\right), \ i = 1, \ldots, m \tag{6}$$

Similarly, we can compute Level 2 weightings $w_{i,j}^2, j = 1, \ldots, n$ for the i-th Level 1 criterion. Finally, the resulting weighting of the p-th leave node of the analytic hierarchy is computed as

$$w_{p=(i-1)\times m+j} = w_i^1 \times w_{i,j}^2 \tag{7}$$

4. Experimental Results and Discussion

As mentioned above, the proposed methodology consists of two phases. In the first phase, each component's values of importance and easiness are obtained using the literature reviews of intelligent fish farming and related topics. The expert team also validated the results shown in Tables 1–4. Then, they are inputted into the modified AHP for the weighting computing of each criterion in the analytic hierarchy. Table 5 shows the evaluation results of Level 1 criteria. Accordingly, the software criteria, including real-time monitoring, basic services, production planning, and value-added services, have the highest global weighting values because these are AI functions that are repeatable and easy to maintain on the server site. On the contrary, the aquaculture machinery criterion has the lowest weighting values because the cost of the automatic machines used for the performance improvement of fish farm management is often very expensive. Thus, the cost reduction issues of aquaculture machines are significant considerations in applying the system on a small fish farm.

Table 5. The priority evaluation of Level 1 criteria using the modified AHP.

Level 1 Criteria	Importance (I)	Easiness (E)	Relative Importance		Local Weighting	Global Weighting
			I	E		
Environment	0.8	0.6	0.12887679	0.10411144	0.116494114	0.116494114
Sensors	0.74	0.74	0.11921103	0.12966155	0.124436288	0.124436288
Data networking	0.8	0.77	0.12887679	0.13033199	0.129604392	0.129604392
Real-time monitoring	0.8	0.8	0.12887679	0.13881525	0.13384602	0.13384602
Basic services	0.8	0.8	0.12887679	0.13881525	0.13384602	0.13384602
Production planning	0.8	0.8	0.12887679	0.13881525	0.13384602	0.13384602
Aquaculture machinery	0.67	0.43	0.11035358	0.08063402	0.095493802	0.095493802
Value added services	0.8	0.8	0.12605144	0.13881525	0.132433345	0.132433345

Tables 6–13 show the priority evaluation results of Level 2 criteria for individual Level 1 criteria using the modified AHP. All the types of fish farms are important, according to the evaluation results shown in Table 5. The sonar imaging device is of smaller weighting value than other sensors since the cost and the power supply requirement of a sonar device for image capturing are more expensive than other devices. However, the sonar device monitors the fish farm even when the events of water turbidity happen. In our system, the end systems upload the sensor data to the cloud storage and are further processed by the big data analytics in the cloud. Since the LoRa data communication consumes low power, the battery set and the sonar panel can supply sufficient power to the water quality sensing devices, offering real-time water quality minoring. The camera is shot off as an additional power-saving mechanism when no specific underlying events happen. Therefore, our system can provide live data monitoring to help the fish farmers understand the real-time status of the fish and the farm environment. The evaluation results are shown in Table 9. Tables 10–13 show that all the AI functions, including 'Basic Services', 'Production Planning', and 'Value Added Services' as equally important to complete the functionality of the AIoT information system for precision aquaculture.

Table 6. Level 2 priority evaluation results for Level 1 'environment' criterion using the modified AHP.

Level 1 Criterion	Level 2 Criterion	Local Weighting	Global Weighting
Environment	Indoor fish pond	0.38888889	0.04530327
	Outdoor fish pond	0.36111111	0.04206732
	Offshore cage	0.25	0.02912353

Table 7. Level 2 priority evaluation results for Level 1 'sensors' criterion using the modified AHP.

Level 1 Criterion	Level 2 Criterion	Local Weighting	Global Weighting
Sensors	Water quality	0.21337127	0.02655113
	Underwater RGB camera	0.21337127	0.02655113
	Sonar camera	0.18705548	0.02327649
	Water surface RGB camera	0.21337127	0.21337127
	Climate open data	0.17283073	0.17283073

Table 8. Level 2 priority evaluation results for Level 1 'data networking' criterion using the modified AHP.

Level 1 Criterion	Level 2 Criterion	Local Weighting	Global Weighting
Data networking	Water quality + LoRa	0.34291493	0.04444328
	Video + 4G/5G/WiFi	0.31417014	0.04071783
	Climate data + 4G/5G/WiFi	0.34291493	0.04444328

Table 9. Level 2 priority evaluation results for Level 1 'real-time monitoring' criterion using the modified AHP.

Level 1 Criterion	Level 2 Criterion	Local Weighting	Global Weighting
Real-time monitoring	Water quality	0.33333333	0.04461534
	Climate data	0.33333333	0.04461534
	Underwater video	0.33333333	0.04461534

Table 10. Level 2 priority evaluation results for Level 1 basic services criterion using the modified AHP.

Level 1 Criterion	Level 2 Criterion	Local Weighting	Global Weighting
Basic services	Fish length/height/ weight estimation	0.125	0.016730753
	Fish classification	0.125	0.016730753
	Fish count estimation	0.125	0.016730753
	Fish density estimation	0.125	0.016730753
	Fish vitality recognition	0.125	0.016730753
	Fish disease detection	0.125	0.016730753
	Fish feeding intensity evaluation	0.125	0.016730753
	Fish food prediction	0.125	0.016730753

Table 11. Level 2 priority evaluation results for the Level 1 'production planning' criterion using the modified AHP.

Level 1 Criterion	Level 2 Criterion	Local Weighting	Global Weighting
Production planning	Fish feeding policy evaluation	0.225	0.03011535
	Smart fish feeding	0.25833333	0.03457689
	Fish pond scheduling	0.25833333	0.03457689
	Fish harvest scheduling	0.25833333	0.03457689

Table 12. Level 2 criteria priority evaluation results for Level 1 'aquaculture machinery' criterion using the modified AHP.

Level 1 Criterion	Level 2 Criterion	Local Weighting	Global Weighting
Aquaculture machinery	Fish feeding machine	0.39230769	0.03746295
	Net cleaner	0.34230769	0.03268826
	Fish sorting machine	0.26538462	0.02534259

Table 13. Level 2 criteria priority evaluation results for Level 1 'value added services' criterion using the modified AHP.

Level 1 Criterion	Level 2 Criterion	Local Weighting	Global Weighting
Value added services	Fish growth model	0.16666667	0.02207222
	Fish in-stock evaluation	0.16666667	0.02207222
	Weight conversion ratio	0.16666667	0.02207222
	Net hole detection	0.16666667	0.02207222
	Aquatic plants detection	0.16666667	0.02207222
	Water quality alarming	0.16666667	0.02207222

Different solutions to improve fish farm management each have an appropriate set of modules or functionalities with a priority value. The computed priority value of each module determines its level of importance, wherein the higher the value, the higher the importance attributed to it, which reflects the necessity of its inclusion in the digital twin component. To determine the impact of the variables used in the requirement analysis for fish farm management, we use our current results to provide function-specific fish farm management, such as the fish feed prediction as an example. This solution can add or integrate multiple functionalities by integrating water quality inspection, the camera system (sonar or RGB camera), and the cloud system. We build a function for the fish feed prediction for each component, and each module has a priority value based on the analysis result. Since there are different solutions for different functions for intelligent fish farm management, their priority value may differ. For example, if all modules were included in the system, the priority should be 1, where the priority is the sum of the underlying modules. Basically, the results of our analysis provide suggestions, solutions, or architecture on what kind of system features should be constructed as part of the physical objects in the cloud to provide function-specific fish farm management. Higher priorities are given higher regard or inclusion into the system.

Although we only have a prototype in terms of implementation, we were able to test the transmission speed and several of our sensors in one of our aquaculture farm sites in Penghu, Taiwan. Our transmission speed depends on the services or capacity of our mobile network. Using 4G (5G is prioritized if available), the camera sensors can perform image transmissions with an uplink bandwidth of 8 megabits per second. For complete video surveillance, half an hour of video is required, and it will take around 30 min to transmit the data from the aquaculture site to the cloud. The architecture for the wireless communication network depends solely on the commercially available network in the aquaculture site. In our case, a 4G communication network is utilized, which uses a standard communication network to send data packets, which is Internet Protocol (IP) based.

Our system followed the event-driven type of monitoring. Our land-based monitoring system sends a command to activate our sensors (e.g., RGB or sonar camera devices) to perform surveillance by enabling our camera sensor device, primarily if we perform fish feeding, metric estimation, environment monitoring, or if the temperature is beyond the specified threshold to make sure that the fish are still at their best or have good vitality. The event-driven type is adopted due to two reasons. First, aquaculture farms located offshore don't have an unlimited or continuous power supply, and they solely depend on battery packs as their power source. Therefore, performing surveillance when only needed is a form of power-saving mechanism. Second, the transmission system depends most of the time on the 4G network, and it will take time to transmit data, especially video surveillance data, to the cloud. Although for water quality monitoring, users can specify the interval of sending the water quality data to the cloud since it does not require a large amount of data to be transmitted over the network; thus, periodical data sending can be scheduled any time of the day.

The architecture of the DT-based intelligent fish farm management system that fulfills the requirements of precision aquaculture is shown in Figure 7. The system has been divided into three sections: (1) Fish Farm Information, (2) Real-time Cage Monitoring, and (3) Data Analysis and Decision Making. The AIoT system has been integrated and utilized for offshore cage monitoring at Pingtung and Penghu in Taiwan. However, our proposed digital twin architecture is enriched with information that is difficult for human senses to accurately or objectively judge or assess (e.g., water quality sensors in terms of PH level and salinity). Therefore, even the data provided by the fish farmers and workers is not sufficient to optimize farm production.

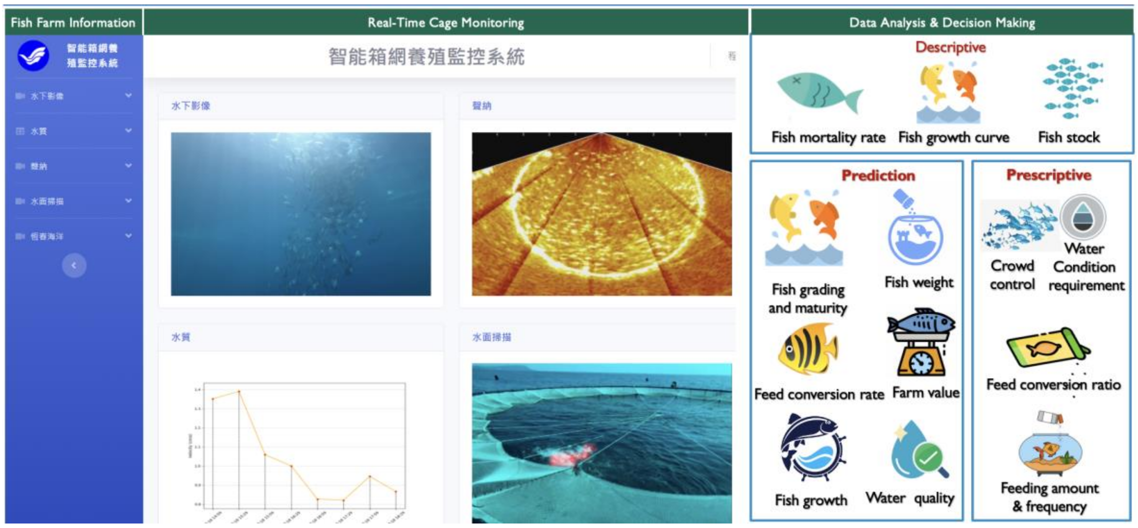

Figure 7. The web-based user interface for fish farm managers offering intelligent fish farming is based on our AIoT prototype system [8]. The Chinese titles "箱網養殖監控系統," "水下影像," "聲納," "水質," "水面掃描," and "恆春海洋" are "Aquaculture cage monitoring system," "Underwater image," "Sonar image," "Water quality," "Water surface scanning", and "Ever Spring Marine Co., Ltd.".

A prototype has been devised for the AIoT system. We tested the accuracy of some of the digital twin objects to ensure that the system was reliable and accurate. The fish feeding machine is integrated to ensure that feeding is optimized and the cost of the feeding is reduced. Based on our experiment conducted in the Hengchun aquaculture farm, integrating the smart feeding machine as part of the feeding process can save about 20–27% of feed cost. For workforce reduction, we can reduce one-third of the workforce requirement. Table 14 shows our prototype system's evaluation results of various digital twin objects.

Table 14. Evaluation results of various digital twin objects.

Digital Twin Object	Error Percentage Results
Fish vitality evaluation	5%
Fish count estimation	3.44%
Fish weight estimation	8.7%
Body length estimation	5.1%
Body height estimation	8.9%
Fish disease detection	15%
Water quality inspection	1%
Net hole detection	2%
Net hole prediction	17.3%
Fish net cleaner	Less than 20%
Sorting machine	Less than 10%
Feeding amount prediction	8.3%
Fish size grading	10%

Table 15 shows the characteristics of the IoT devices, data communication systems, and aquaculture machinery to achieve the goal of precision aquaculture based on the AIoT system. Our AIoT prototype system meets the requirements of intelligent fish farming compared with these reviewed system models.

Table 15. Summary of findings regarding the construction of the AIoT for intelligent fish farming with columns (a) physical objects; (b) network communication; (c) basic service model; (d) fish farm data application; (e) user interface; (f) number of readers; (g) number of papers reviewed.

Source	AIoT Requirements Analysis Parameters						
	(a)	(b)	(c)	(d)	(e)	(f)	(g)
Agossou and Toshiro [49]	Water quality inspection	LoRa	Issues detection and alerting	Fish diseases detection	Web-based dashboard	198	16
Chiu et al. [50]	Water Quality inspection	Wifi	Issues detection and alerting	Fish growth status	Web-based dashboard	16	34
Chen et al. [51]	Water quality inspection	LoRa	Issues detection and alerting	x	Web-based dashboard	673	26
Wang et al. [3]	Multi-mode sensors suggestion	LoRA/4G/5G	Live data monitoring	Production planning	Data visualization	1	77
Zhao et al. [52]	Underwater camera	x	Computer vision-based fish behavior analysis	x	x	5	183
Sun et al. [53]	Water quality sensors, RGB Camera	x	Deep l earning-based fish behavior analysis	x	x	40	117
O'Donncha and Grant [4]	Multi-mode sensor data	x	Fish behavior analysis	Production planning	Visualization, dashboard	28	14
Føre et al. [1]	Sonar, acoustic data, optical camera, ROV	x	Machine Learning-based models	Models for farm operation	Visualization, dashboard	267	71

5. Conclusions

In this study, we have proposed a systematical way to analyze the user requirements of the AIoT information system for intelligent fish farming. Furthermore, the techniques to represent physical objects as digital twins have been discussed. The contributions of this work are (1) we proposed a methodology of a DT-based AIoT system design for precision aquaculture; (2) we integrated the proposed modified AHP as the evaluation methodology of DT architectures comprising the AIoT information system; (3) we implemented and applied the prototype system to monitor fish farms; (4) we designed the power supply and data communication system for offshore cages; and (5) we implemented the cloud-based AI functions to solve the issues of smart caging. Further studies would focus on risk management by implementing more decision-making and alarm functionalities.

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