

Koi Care Robots: A Framework and Practical Applications

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Abstract. This study proposes a robotic framework for intelligent koi pond management, aimed at enhancing the care and well-being of koi in controlled aquatic environments. The robotic platform is designed with multiple integrated subsystems, including a water filtration unit, real-time koi monitoring, water quality sensing and analysis, joystick-enabled manual operation, and automated navigation. The prototype integrates several sensing components, including a 9-axis inertial measurement unit (IMU), an underwater distance sensor, an underwater camera, and a 2D LiDAR system. The IMU supplies continuous feedback on orientation and dynamic stability, supporting precise navigation and control performance. The underwater distance sensor facilitates real-time detection of submerged obstructions to ensure safe underwater operation. Visual data acquired by the underwater camera are processed using deep learning-based classification algorithms for object recognition. Additionally, the 2D LiDAR sensor detects and maps above-water obstacles, supporting reliable navigation and environmental awareness. The robotic framework is implemented using ROS2, which manages system integration, communication, and control. Real-time water quality evaluation is achieved through deep learning-based analysis and classification of underwater imagery. Furthermore, the system is integrated with an automated feeding machine that dispenses floating pellets using deep learning. The robot is powered by a solar energy system, enabling autonomous and sustainable operation. Experimental results demonstrate the robustness and reliability of the framework in real-world conditions.

Keywords: Kois, Ros, Robots, Water quality, Koi Care, Koi feeding, Pet Care.

1 Introduction

Kois (*Cyprinus carpio* var. *koi*) are selectively bred ornamental carp renowned for their vivid coloration, unique patterning, refined body conformation, and graceful locomotion. Owing to their visual appeal and symbolic significance, they are widely cultivated in garden ponds and ornamental water features across the globe.

Successful cultivation of *Kois* requires maintaining optimal water quality, including stable temperature, appropriate pH, high dissolved oxygen, and minimal ammonia and nitrite levels [1,2,3,4]. Adequate pond space, effective filtration, and proper aeration are essential to support healthy development. A balanced, high-protein diet administered in controlled portions promotes growth, while low stocking density and regular health monitoring help reduce stress and prevent disease. Together, proper environmental management, nutrition, and husbandry practices ensure healthy and efficient koi growth. Effective koi cultivation depends on skilled expertise and proper management practices. AIoT (Artificial Intelligence of Things)-based systems provide a promising approach to assist growers [5-17]. Chumchu and Patil proposed an animal feeding machine in a Thailand patent registration [14]. Chumchu et al. developed an intelligent feeding system for koi using a five-minute feeding method [15]. Chumchu and Patil [16] also proposed a pond-cleaning robot in a Thailand patent registration. Additionally, Chumchu et al. [17] proposed a real-time water classification system using deep learning.

Conventional AIoT systems are generally limited to monitoring and operating within specific areas of a pond. Expanding coverage to the entire pond requires deploying multiple IoT sensors and actuators, which significantly increases installation and maintenance costs. As an alternative, a mobile koi care robot can transport sensors throughout the pond, enabling comprehensive monitoring of both koi behavior and water quality while reducing overall system cost. Furthermore, periodic interaction and environmental enrichment provided by the robotic system may enhance koi welfare and potentially promote improved growth performance.

Robots used for pet care refer to robotic systems designed to assist with feeding, monitoring, cleaning, companionship, and overall health management of pets, helping improve convenience for owners and well-being for animals. There are many research studies focused on designing robots for pet care [18-27]

To the best of our knowledge, there is no existing research on Koi care robots. In this paper, a Koi care robot framework is proposed. The framework is designed to monitor water quality parameters and optimize feeding regimens. In addition, it provides functionalities for pond cleaning, manual control, and autonomous navigation using the Robot Operating System (ROS). Practical experiments have been conducted in three ponds containing more than 70 Kois, ranging in Koi size from 20 to 80 centimeters in length. The experimental results demonstrate that the proposed framework performs effectively under real-world conditions. The prototype of the proposed framework provides automatic feeding, water filtration, water quality monitoring, and efficient mobility.

2 The proposed koi care robot framework

2.1 Overview of the proposed framework

The proposed framework is illustrated in Fig. 1. The system comprises a robotic platform, robot sensing modules, water sensing modules, control units, an automated feeding mechanism, a power supply subsystem and a remote-control unit. The mechanical structure of the robot is specifically engineered to support both aquatic mobility and water-cleaning operations [16]. Movement and water suction are accomplished using four integrated pump units, as shown and labeled (1)–(4) in Fig. 2.

The robot's sensing system includes an Inertial Measurement Unit (IMU) (MPU-6050) for estimating motion and orientation, a GY-271 compass sensor for heading determination, an underwater distance sensor (MB7060) for underwater obstacle detection, a LiDAR unit (RPLIDAR A1) for environmental mapping, and an underwater camera (GoPro Hero 13 Black) for visual monitoring and data collection.

Water sensing modules are used to measure temperature, pH (potential of hydrogen), and dissolved oxygen (DO). Temperature and pH are measured using the YIERYI BLE-YC01 sensor, which can be placed anywhere within the tested pond. The sensed data are transmitted to the robot via Bluetooth communication. Dissolved oxygen is measured using the DO9100 sensor, which also uses Bluetooth communication, allowing flexible placement within the pond.

Two controllers are used because the Raspberry Pi Zero 2W handles communication with the GoPro and forwards the data to the NVIDIA Jetson Nano Developer Kit, which then transmits it to a router for delivery to the remote-control unit or other hosts for further processing. The GoPro cannot transmit data directly to ground computers because Wi-Fi signals do not propagate effectively over long distances underwater.

The intelligent feeding system [14] is shown in Fig. 3. The feeding machine employs a horizontal-plane shaking mechanism for feed dispensing, which improves energy efficiency and reduces power consumption. In addition, it employs deep learning techniques informed by the experience of Koi growers. The proposed system consists of a home-use CCTV camera and a fish feeding machine [15]. The koi feeding process is conducted using the five-minute feeding method. The feeding machine initiates feeding for a short, predefined duration. The system then detects uneaten pellets every minute. If the number of uneaten pellet clusters is lower than a predefined threshold, the feeding machine will bestow feed again. This process continues until the number of uneaten pellet groups falls below a predefined threshold within a five-minute period. The feeding process can be scheduled for specific durations and set feeding times on any day via the mobile or web application.

The power subsystem shown in Fig. 4 is built around a 50 W, 12 V battery, which can be recharged via a conventional household power supply or a solar charging system, supporting flexible and sustainable operation. The voltage is stepped down to 5 V to supply the control units. The solar charger used is the ST-S1210 SUOER (12 V, 10 A max), and the solar panel is a flexible mono PV panel rated at 50 W ($630 \times 540 \times 3$ mm).

The remote-control unit is based on a Raspberry Pi 5, integrated with a Raspberry Pi Touch Screen and either a Wi-Fi connectivity joystick or a USB joystick. It is used for manual control of the robot's movement as well as for configuring automatic navigation.

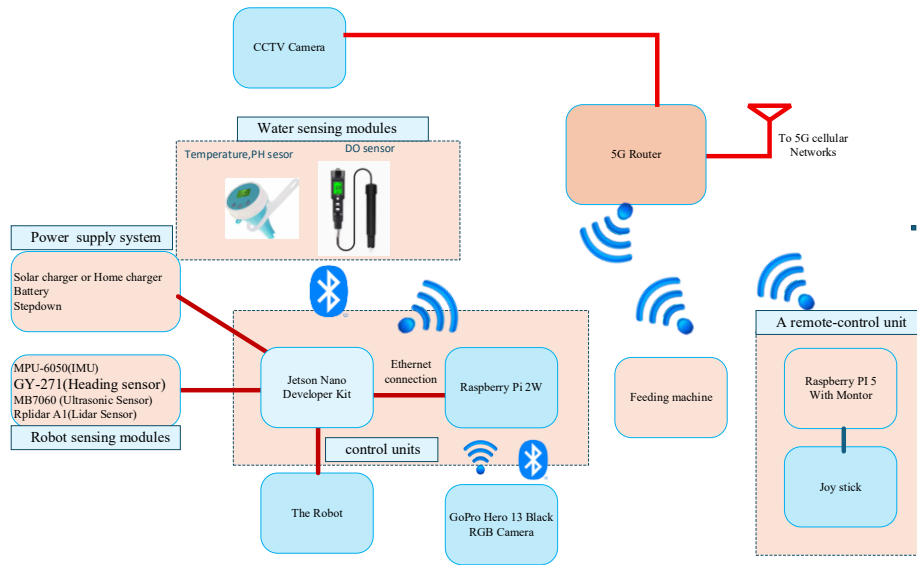


Fig. 1. Overview of the proposed framework.

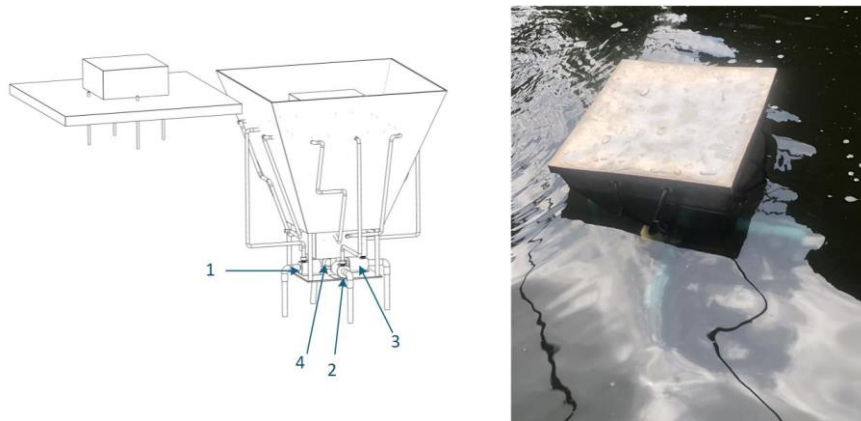


Fig. 2. The robot structure [16].

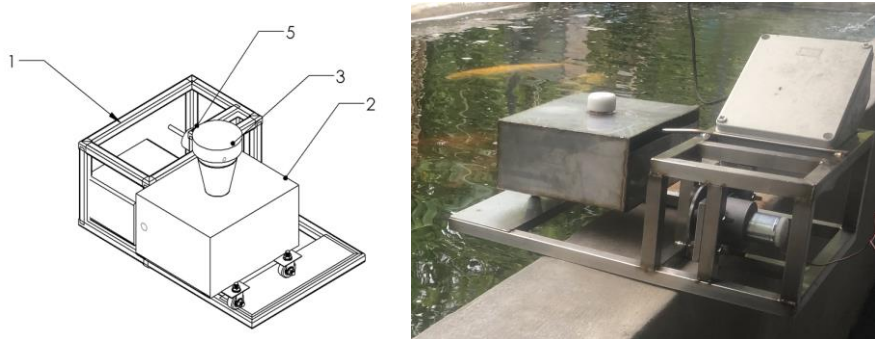


Fig. 3. The feeding machine structure [14].

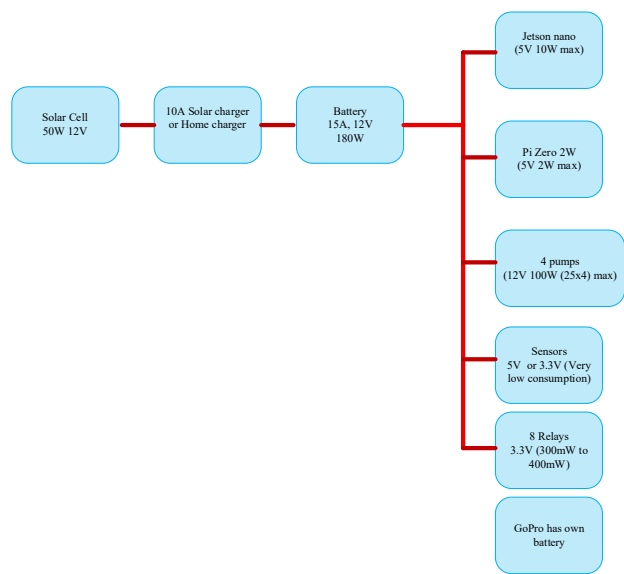


Fig. 4. Power Source for the robot.

2.2 Ros2 (The Robot Operating System)

In this framework, Robot Operating System 2 (ROS 2) is adopted because it supports both Python and C++, enabling flexible and high-performance robotic system development. The ROS 2 navigation architecture is illustrated in Fig. 5. It consists of a Waypoint Follower, a Behavior Tree (BT) Navigation Server, a Recovery Server, a Controller Server, and a Planner Server.

The input information is obtained from the Behavior Tree, TF transforms, map data, and sensor data. The Behavior Tree can be programmed using XML. TF transforms are published through TF messages, while map information is provided via `nav_msgs`. Sensor data are collected from various sensors, such as IMU sensors, distance sensors, LiDAR, and camera sensors.

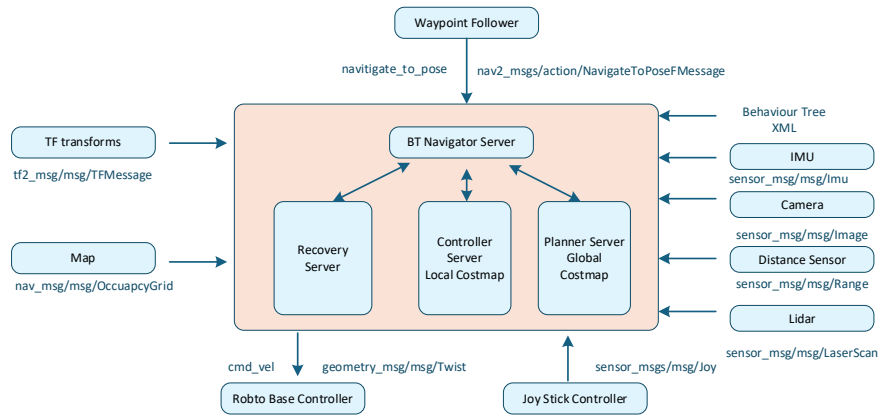


Fig. 5. ROS2 navigation.

2.3 Manual Navigation

Manual navigation is controlled using a wireless or USB joystick connected to a Raspberry Pi 5 with a touchscreen. A joystick node running on the Raspberry Pi processes input commands and sends them to the robot. The robot then interprets these commands to operate four pumps and eight relays, enabling navigation and water filtration functions. Additionally, joysticks can be used to capture photos with the GoPro.

2.4 Automated Navigation

Automated Navigation is the ability of a robot to move from one location to another autonomously without human control. Using sensors, maps, and algorithms, the robot can determine its position, plan a path to a target, and avoid obstacles while moving. In ROS 2 robotics systems, automatic navigation is commonly implemented using the Navigation2 stack, which integrates mapping, localization, path planning, and obstacle avoidance to guide the robot safely to its destination.

From **Fig. 5**, Sensor data come from a 6-axis MPU-6050 IMU, GY-271 compass module for heading sensors, an underwater GoPro hero 13 black camera, a 2-D Rplidar A1 lidar and an MB7060 XL-MaxSonar underwater sensor distance. ROS2 is installed in Jeson nano development kit. In this prototype, the Cartographer node is used to generate maps of three experimental ponds, which are then utilized for autonomous navigation. To produce odometry (Odom) data, a LiDAR-based odometry approach [29] is implemented, since the robot—operating like a boat—cannot directly provide reliable odometry on its own. Sensor fusion is performed using an Extended Kalman Filter (EKF), which integrates LiDAR-based odometry and IMU sensor data. Autonomous navigation is route-based and operates on a pre-built map generated using Cartographer. The navigation goal is implemented using QT in Raspberry PI 5.

2.5 Deep learning applications

This proposed framework supports a wide range of deep learning applications for Koi growing. For example, it can be used for water quality classification, intelligent feeding systems powered by deep learning, fish health monitoring, Koi behavior detection, and precise underwater positioning using Wi-Fi signals.

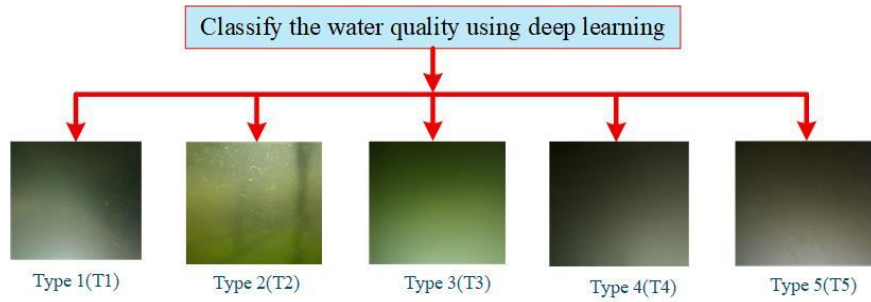


Fig. 6. Under water captured images and water classification.

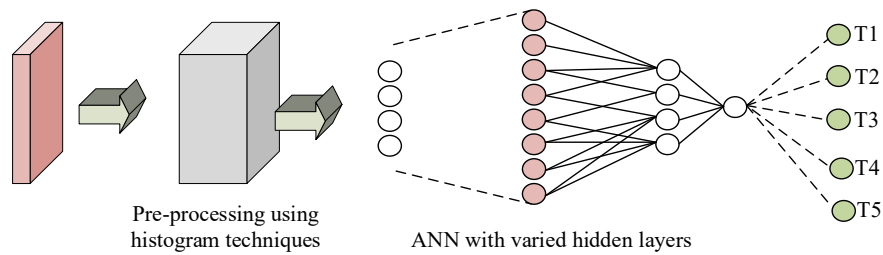


Fig. 7. Artificial Neural Network (ANN) model employed in the framework prototype.

Within this prototype of the proposed framework, in addition, a deep learning-based application is integrated to control Koi feeding [15] and water quality classification

[17] is utilized for real-time monitoring of pond conditions. The automation Koi feeding is the process of Koi feeding based on the five-minute feeding method shown in Fig. 3. The feeding machine initiates feeding for a short, predefined duration. The system then detects uneaten pellets every minute. If the number of uneaten pellet clusters is lower than a predefined threshold, the feeding machine will grant feed again. This process continues until the number of uneaten pellet groups is not lower than the predefined threshold within a five-minute duration. The feeding process can be scheduled for specific pre-defined durations and feeding time on any day through the mobile or web application.

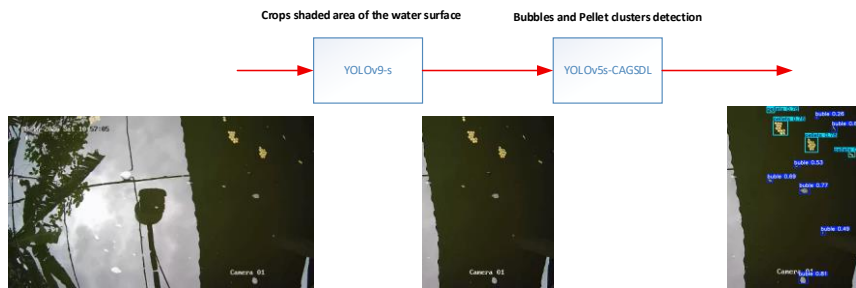


Fig. 8. Artificial Neural Network (ANN) model employed in the framework prototype.

Water quality classification is used to classify 5 types of water shown in Fig. 6 which is labeled T1, T2, T3, T4, and T5. T1: Images of fresh water recently supplied by a local freshwater provider for the 4-cubic-meter Koi pond, T2: Images from the 15-cubic-meter Koi pond containing 12 large Koi fish, each approximately 60-80 cm in length. Water in this pond is quite clear but there are some floating algae. T3: Images from the 35-cubic-meter Koi pond with 18 large Koi fish, each approximately 60-70 cm in length. The pond water is clean, with a light green coloration that lies within the optimal range for fish growth. T4: Images of brown-colored water taken from a wastewater treatment pond. T5: Images of brown-colored water collected from the filter system of the 35-cubic-meter pond, containing waste produced by Kois.

In addition, the proposed frame supports for extensible deep learning applications in area of health status assessment, disease detection using deep learning-based image analysis, behavioral pattern analysis, and AI-driven fish recognition and interaction. Additionally, the framework supports the implementation and control of water filtration and quality regulation subsystems, ensuring optimal aquatic environmental conditions. Furthermore, telemedicine can be an important tool in the care of koi fish.

3 Results and Discussion

3.1 Experimental Results

Figure 9 illustrates the prototype of the proposed framework. It consists of a control station and a robot. The control station includes a wireless joystick or USB joystick and a Raspberry Pi 5 connected to a touch screen monitor. The robot is equipped with four pumps, eight solenoid valves, a GoPro Hero 13 Black camera, an RPLIDAR sensor, an MPU6050 module, a GY-271 module, an MB7060 ultrasonic sensor, and a solar power system.

Figure 10 and Figure 11 present the accuracy and loss comparisons between the implemented model and the pre-trained models, namely the Inception V3 model and the Xception model. The dataset used for evaluation is shown in Table 1.

Figure 12 presents the confusion matrix for water classification and water quality inference using ANN models with 6 hidden layers and 32 neuron each. The results demonstrate that the proposed framework can be integrated with our previously developed real-time water quality system [16].

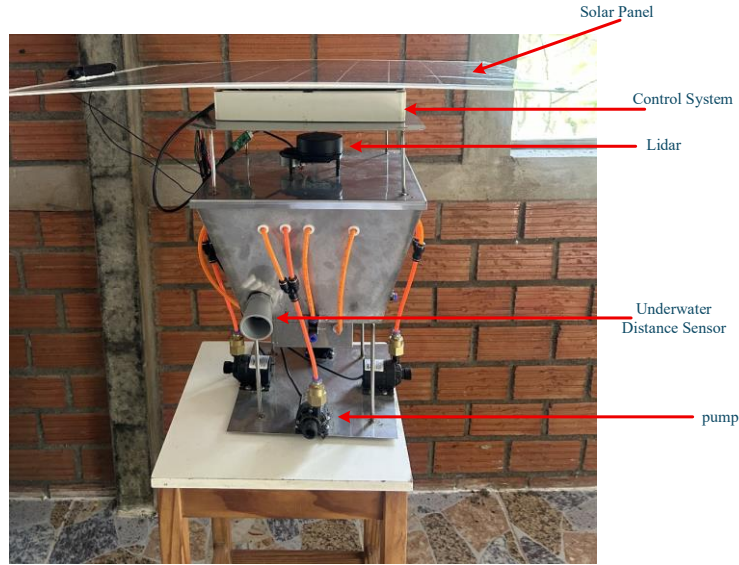
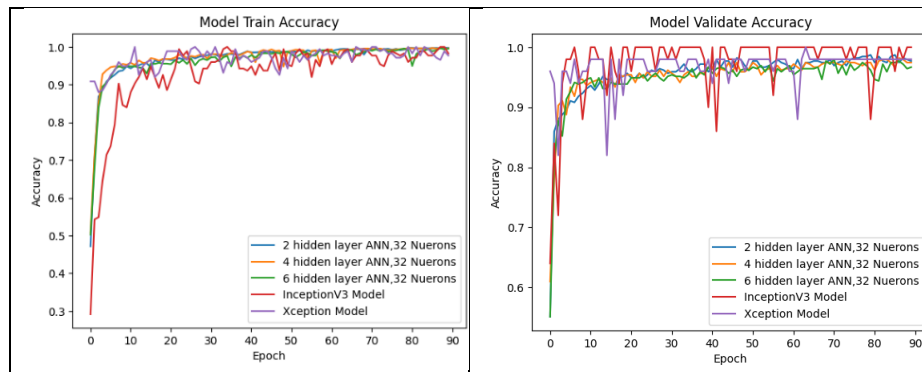
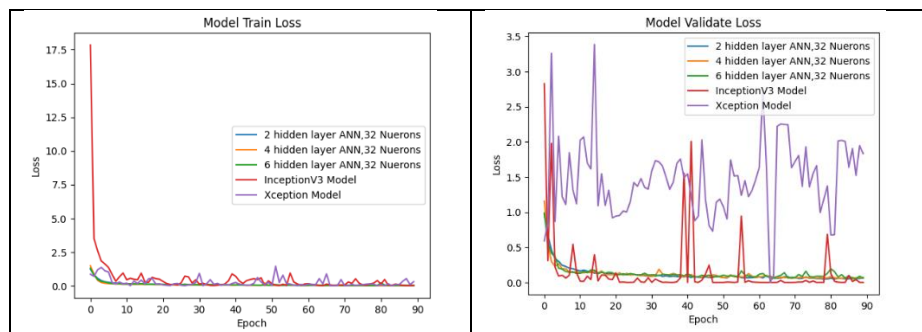


Fig. 9. The prototype of the proposed robot framework

Table 1. Dataset image distribution across classes and experimental splits.

Class Index	Labels of	Amount of	Train- ing	Valida- tion	Test 10%
0	T1	289	202	57	30
1	T2	611	427	122	62
2	T3	414	289	82	43
3	T4	488	341	97	50
4	T5	320	224	64	32

**Fig. 10.** Assessment of water classification accuracy in both training and validation phases.**Fig. 11.** Assessment of water classification loss in both training and validation phases.

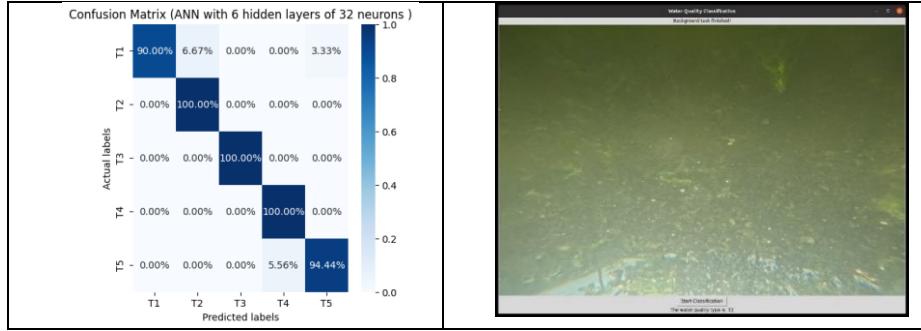


Fig. 12. Confusion matrix and real-time water classification results.

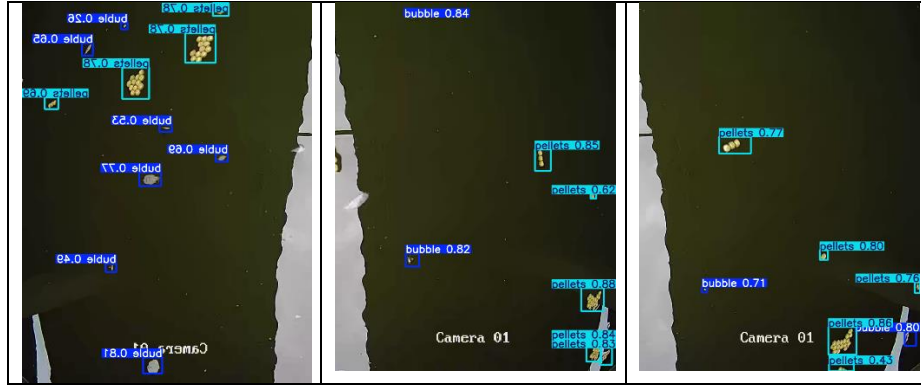


Fig. 13. Remaining pellet detection was implemented in this prototype for automated feeding.

Figure 13 demonstrates the testing of the remaining pellet detection in this prototype. The results show that the detection system performs effectively and can be used to control the feeding machine based on a five-minute feeding process.

Figure 14 illustrates the pre-built map of the 15-cubic pond generated using the Cartographer node in ROS2. The resulting map closely matches the actual layout of the pond. This map is then utilized to enable autonomous navigation within the pond environment.

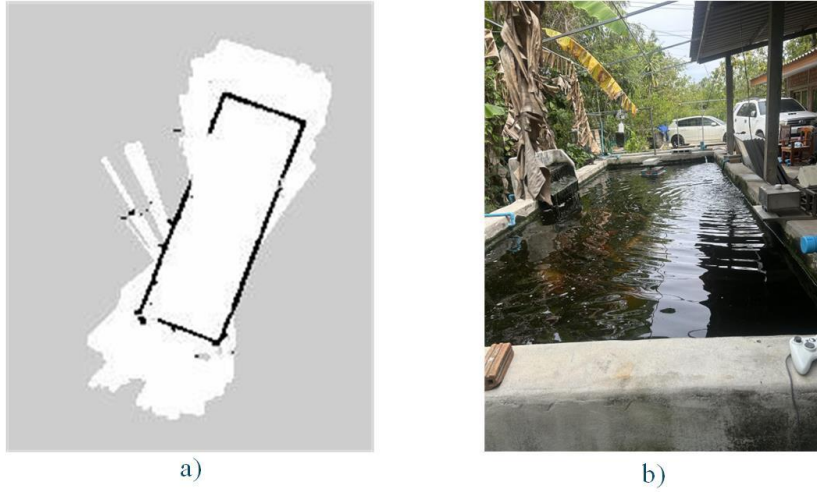


Fig. 14. (a) 15 m³ pond map generated using Cartographer and (b) the 15 m³ pond.

Figure 15 illustrates underwater images in the 15 m³ pond captured by the prototype. Figure 15(a) shows the bottom of the pond, where a significant amount of algae can be observed. This condition is typical in koi ponds that have been in long-term operation. Figure 15(b) shows the pond wall, which is similarly covered with a considerable amount of algae. Figures 15(c) and 15(d) present images of koi fish within the pond.

Figure 16 illustrates underwater images in the 35 m³ pond captured by the prototype. Figures 16(a) and 16(b) show two views of the 35 m³ pond, which has a length of 33 meters. Figure 16(c) presents the bottom of the pond, where the GoPro camera provides clear image quality. Figures 16(d) and 16(e) show images of koi fish. From Figures 15 and 16, it can be observed that the underwater image quality is sufficient for developing deep learning-based systems for koi monitoring and care.

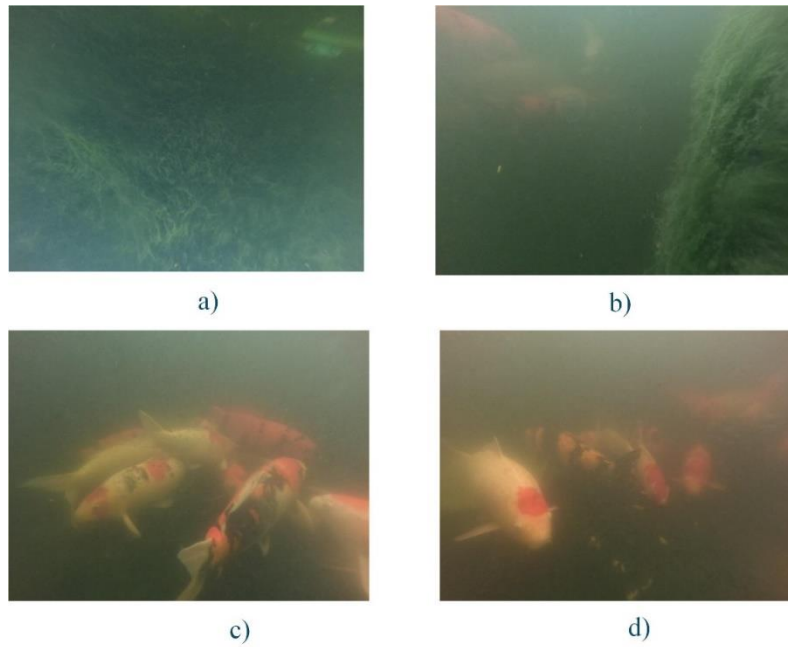


Fig. 15. Underwater images captured by the prototype in the 15 m³ pond .

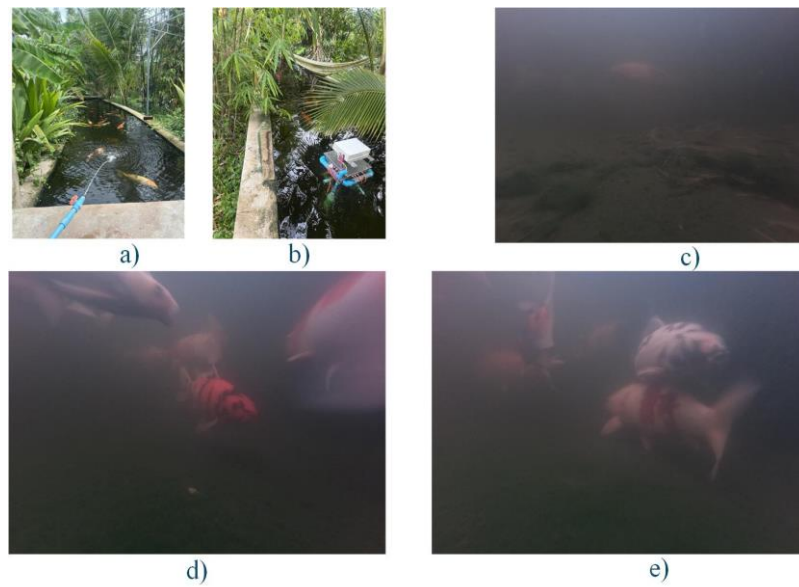


Fig. 16. 35 m³ pond images.

4 Conclusion and Future works

Effective koi aquaculture requires continuous monitoring and specialized management, typically provided by professional koi breeders, which results in substantial operational costs. To address this limitation, this study proposes a modular robotic framework for automated koi care. The proposed system integrates core functionalities, including automated feeding control, autonomous pond cleaning, and real-time environmental and fish monitoring.

The architecture is designed to be extensible, enabling the integration of advanced intelligent modules such as health status assessment, disease detection using deep learning-based image analysis, behavioral pattern analysis, and AI-driven fish recognition and interaction. Additionally, the framework supports the implementation and control of water filtration and quality regulation subsystems, ensuring optimal aquatic environmental conditions. Furthermore, telemedicine can be an important tool in the care of koi fish. By embracing these innovations in Koi care robot technology, owners can significantly enhance the well-being of their Kois while deepening the bond they share.

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