Sistema basado en IoT y visión por computadora para monitoreo en acuacultura

Low-cost IoT and computer vision-based aquaculture monitoring system

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Eiriku Yamao[1]

Abstract

Securing a reliable source of food for the ever-growing population is one of the big challenges for humanity. Demand for aquatic foods will continue to grow and production process in aquaculture needs improvement. A low-cost Internet of Things based system for monitoring hatching and growth of Rainbow trout (*Oncorhynchus mykiss*) is designed and implemented in a rural area in Peru. Three-layer architecture with sensors and underwater camera based on raspberry pi, Wi-Fi and satellite connection to Internet sends data to cloud services for storage and analysis. The system reduced drastically the manual and time-consuming monitoring tasks related to traditional aquaculture and the data collected will be used to establish optimal growth conditions parameters and future growth predictions.

Keywords: Aquaculture, Internet of Things, Computer Vision, Underwater Image Recognition

Resumen

Asegurar una fuente segura de alimentos para la población mundial en constante crecimiento es uno de los grandes retos de la humanidad. La demanda de los alimentos acuáticos continuará aumentando en los próximos años y los procesos de producción requieren mejoras. Un sistema de bajo costo basado en internet de las cosas para monitorear el crecimiento de alevines de trucha arcoíris (*Oncorhynchus mykiss*) fue diseñado e implementado en una zona rural de Perú. Una arquitectura de tres capas con sensores y una cámara submarina, conexión Wi-Fi e internet satelital, permiten enviar datos hacia servicios en nube para su almacenamiento y posterior análisis. El sistema redujo drásticamente el tiempo de ejecución de las tareas de monitoreo y la data recolectada servirá para establecer los parámetros de las condiciones óptimas de crecimiento y su predicción en el futuro.

Palabras clave: Acuacultura, Internet de las cosas, visión por computadora, Reconocimiento de imágenes bajo el agua

1 Universidad de San Martín de Porres, La Molina, Lima - Perú

Autor de correspondencia:
eyamao@usmp.pe

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Introduction

Advances in Information Technology, Artificial Intelligence and Data Science drive forward technological improvements and automatization of aquaculture processes such as water quality control, feed optimization, biomass monitoring and growth control (Gladju et al., 2022).

Modern aquaculture technologically supported by Internet of Things (IoT) is intensive, productive and automated via smart sensors and smart camera systems that monitor all aspects of production for a smart and sustainable aquaculture with intelligent prediction, early warning and forecasting, and precision feeding (Maksimovic, 2018).

Challenges associated with the implementation of IoT are: Sensors accuracy drop due to permanent contact with water, lack of reliable network/internet connection, lack of reliable electrical connections, energy consumption optimization, data inaccuracy, lack of policies to ease adoption and high cost of IoT systems (Rastegari et al., 2023).

Conventional fish detection by catching and taking samples requires more energy, cost and time(Asri et al., 2022)Manual data collection leads to human errors and missing values. A smart data acquisition system can automate the real time sampling process to support decision making in aquaculture. Combining smart camera devices with ML and DL algorithms has been used for biomass estimation, species classification, gender detection and quality inspection (Biazi & Marques, 2023).

Image processing techniques have been used in many fields to automate or enhance manual tasks. In aquaculture, image processing is used for classification, counting, size and weight measurement, disease detection, determine freshness (Awalludin et al., 2020). Recent studies focus on improving image processing in low-light or turbid water conditions (Yuan et al., 2022). Properly configured systems can produce accurate estimates of population mean length with a mean error in the order of 1% (Risholm et al., 2022).

The findings and challenges of computer vision models for fish detection in aquaculture are that the data acquisition is critical. Many studies have conducted their testing using open-source dataset or in an ideal/controlled condition but in real-life conditions surface reflection, poor lighting conditions, sudden changes in illumination (E.g. a cloud passing by) and such is usually not considered in public open-source datasets (Yang et al., 2021)

In less developed countries, adoption of these new technologies has been slow due to the cost of system implementation and technically skilled manpower (Gladju et al., 2022). To improve the aquaculture and fishery sector, to satisfy the increasing demand for food, low-cost, low-energy, widespread and easy-to-use IoT equipment is required (Maksimovic, 2018). This paper presents the experiences of developing and implementing a low-cost smart aquaculture system in a production environment in Peru.

Methodology

The fish farm is located in an off the grid, rural area in the mountain area in southern Peru. The facility is located next to a natural water spring that is directed towards the fish tanks. Hatching and growth monitoring of rainbow trout - *Oncorhynchus mykiss* is the primary task on this site. The Key challenges include the lack of electricity and internet access. Solar panels and a satellite dish have been installed to overcome this.

The diagram of the system architecture is shown in Figure 1. It uses a three-layer structure: perception layer, networking layer, and application layer (Kumar & Mallick, 2018). The perception layer includes the sensors, underwater camera, and a PC for temporal data storage. Salmonid are subject to problems of reduced growth, reduced condition factor and nephrocalcinosis when they are exposed to high concentration of dissolved carbon dioxide (Biazi & Marques, 2023), sensors collect data such as Dissolved Oxygen, pH, temperature, salinity, and others.

The Underwater camera is shown in Figure 2. It is based on a Raspberry Pi with the Pi camera and a high-grade camera lens all inside a water-proof casing. The camera is mounted on a frame which secures the passage of fish samples at the same distance. Data collected is also sent to a local PC that works as temporal data storage to prevent data loss due to network instability. Networking layer includes Wi-Fi and internet connection via satellite. Cloud layer includes cloud platform services for data storage and processing.

Figure 1
System Architecture

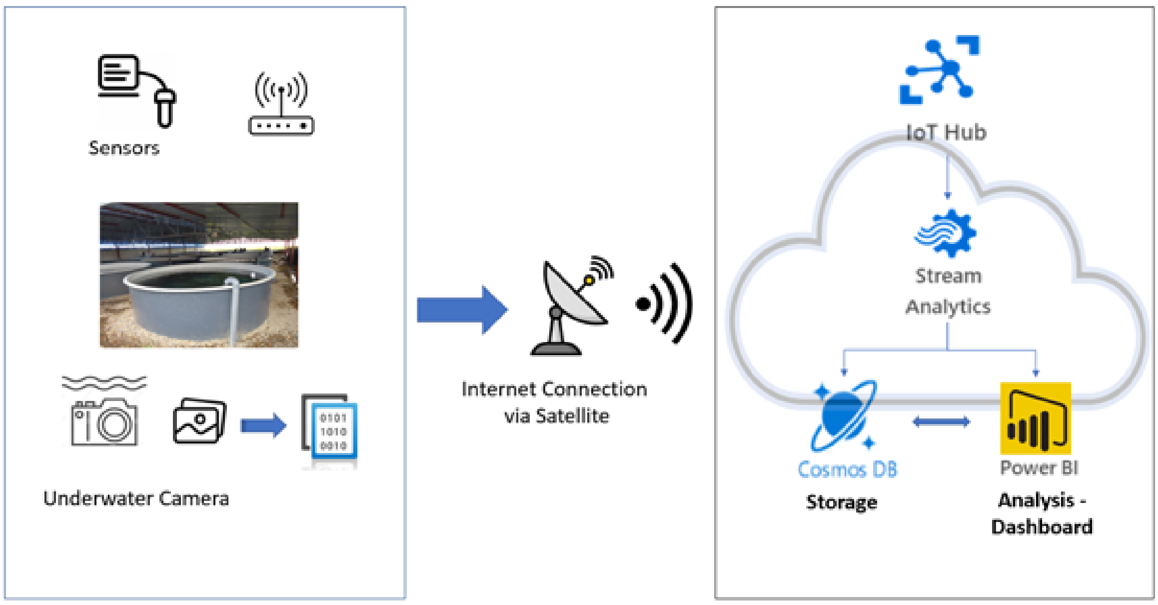
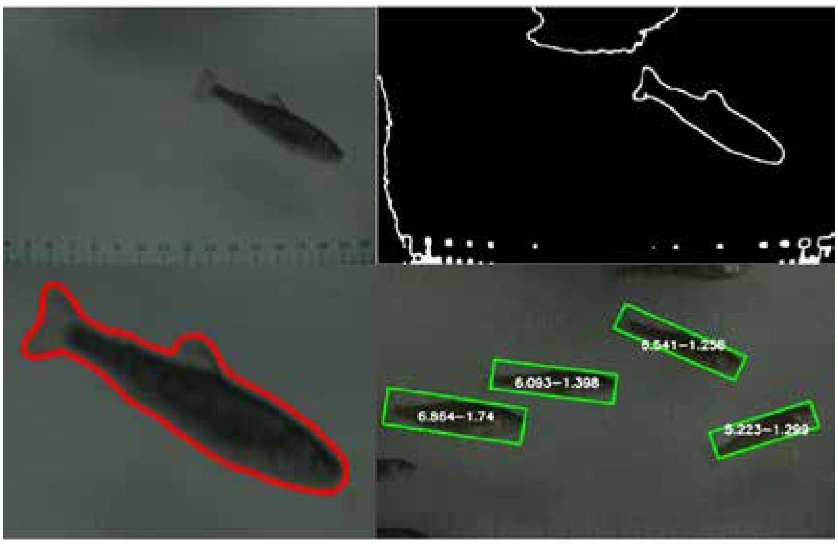


Figure 2
Underwater camera

DATA PIPELINE

The pipeline uses the following steps. First, the image taken by the camera goes through image preprocessing to improve contrast and brightness, to reduce noise generated by sunlight or shade, given that the fish tanks are located outdoors. Second, the fish segmentation part applies canny edge detection and Otsu thresholding which erodes and dilates the images until finding the contours of each fish present in the image. Next, estimation of length is made by calculating the Pixel per Metric Ratio from a calibration image taken first with a ruler in the background. This establishes the total length of the image and its equivalent in pixels. The length and height of the contour are converted to cm using this ratio. The steps taken and intermediate results are as seen in Figure 3

Figure 3
Image processing



Finally, weight is calculated using the formula:

$$W = (p^2 * L) / 800$$

Where W is the weight, p is the perimeter, L is the length and 800 is the curvature coefficient, which depends on the species. For rainbow trout, the value is between 700 and 900. The formula is based on measures in the American system (weight in pounds and length in inches) it has been converted to the international system used in Peru (weight in grams and length in centimeters).

Once the weight is calculated, it can be used to calculate other values, such as Fulton's condition factor (K) to measure the growth condition of the trout using the formula:

$$K = 100 * \frac{W}{L^3}$$

W is the weight calculated in the previous step and L is the measured length. The formula represents in a value close to 1 the conditions in which the fish is growing. A value of *K* close or equal to 1 indicates a normal or OK condition; value can go to 1.2 or 1.5 in a very well-grown fish at the higher end and values of 0.8 or lower for suboptimal conditions.

Results and Discussion

Traditional aquaculture is laborious, with intensive manual tasks to monitor and care for the optimal growth conditions of fish. The IoT system implemented in this paper has dramatically reduced the time and personnel required for such tasks. Also, data availability was an issue given that the production center is in a rural area. All data is now stored in a cloud platform which is constantly updated. Decision makers can now dashboards from anywhere in the world, facilitating their tasks.

Underwater camera system removes the need for manual sampling and measuring of fish growth, which is usually an invasive, time-consuming, and inaccurate task (Li et al., 2020)Image segmentation techniques for computer vision can correctly identify and measure most fish samples present in an image with a small percentage of errors (less than 5%) due to two or more fishes appearing close to each other and shadows with enough contrast from the background. Stability in underwater condition is hard to achieve (Biazi & Marques, 2023). Multiple image preprocessing techniques exist but none is optimized for the constantly changing conditions of underwater images, such as water turbidness, increased brightness from sunlight, shadows created by clouds, objects, people, and many others. Improve image detection in non-optimal water conditions (Yuan et al., 2022) is important for ease of use and mass adaptation of underwater cameras in aquaculture.

Conclusion and future work

Aquatic food consumption will continue to grow towards 2030, with most of them expected to be from aquaculture and open sea harvest. Modernization and optimization of aquaculture processes must be a priority for industry and government entities alike (Biazi & Marques, 2023). A proper monitoring system for growth and behavior of fish improves productivity and profitability, and also reduces risk of failure, spinal deformity and mortality rate (Li et al., 2022).

The implementation of the IoT system allows data collection from the sensors and camera to create models of growth parameters, establish the optimal conditions and propose prediction models in the future.

Aspects not considered for this paper are long-term reliability and maintenance costs due to time restrictions and use of Deep Learning models due to hardware restrictions. Usage of a DL framework to automate feature extraction process of underwater images (Li et al., 2022) is proposed as future improvement.

References

Asri, S. D., Jaya, I., Buono, A., & Wijaya, S. H. (2022). Fish Detection in Seagrass Ecosystem using Masked-Otsu in HSV Color Space. *International Journal of Advanced Computer Science and Applications*, *13*(12). https://doi.org/10.14569/IJACSA.2022.0131253

Awalludin, E. A., Arsad, T. N. T., & Wan Yussof, W. N. J. H. (2020). A Review on Image Processing Techniques for Fisheries Application. *Journal of Physics: Conference Series*, *1529*(5), 052031. https://doi.org/10.1088/1742-6596/1529/5/052031

Biazi, V., & Marques, C. (2023). Industry 4.0-based smart systems in aquaculture: A comprehensive review. *Aquacultural Engineering*, 102360. https://doi.org/10.1016/j.aquaeng.2023.102360

Gladju, J., Kamalam, B. S., & Kanagaraj, A. (2022). Applications of data mining and machine learning framework in aquaculture and fisheries: A review. *Smart Agricultural Technology*, *2*, 100061. https://doi.org/10.1016/j.atech.2022.100061

Kumar, N. M., & Mallick, P. K. (2018). The Internet of Things: Insights into the building blocks, component interactions, and architecture layers. *Procedia Computer Science*, *132*, 109–117. https://doi.org/10.1016/j.procs.2018.05.170

Li, D., Hao, Y., & Duan, Y. (2020). Nonintrusive methods for biomass estimation in aquaculture with emphasis on fish: A review. *Reviews in Aquaculture*, *12*(3), 1390–1411. https://doi.org/10.1111/raq.12388

Li, D., Wang, Q., Li, X., Niu, M., Wang, H., & Liu, C. (2022). Recent advances of machine vision technology in fish classification. *ICES Journal of Marine Science*, *79*(2), 263–284. https://doi.org/10.1093/icesjms/fsab264

Maksimovic, M. (2018). Greening the Future: Green Internet of Things (G-IoT) as a Key Technological Enabler of Sustainable Development. In N. Dey, A. E. Hassanien, C. Bhatt, A. S. Ashour, & S. C. Satapathy (Eds.), *Internet of Things and Big Data Analytics Toward Next-Generation*

Intelligence (pp. 283–313). Springer International Publishing. https://doi.org/10.1007/978-3-319-60435-0_12

Rastegari, H., Nadi, F., Lam, S. S., Ikhwanuddin, M., Kasan, N. A., Rahmat, R. F., & Mahari, W. A. W. (2023). Internet of Things in aquaculture: A review of the challenges and potential solutions based on current and future trends. *Smart Agricultural Technology*, *4*, 100187. https://doi.org/10.1016/j.atech.2023.100187

Risholm, P., Mohammed, A., Kirkhus, T., Clausen, S., Vasilyev, L., Folkedal, O., Johnsen, Ø., Haugholt, K. H., & Thielemann, J. (2022). Automatic length estimation of free-swimming fish using an underwater 3D range-gated camera. *Aquacultural Engineering*, *97*, 102227. https://doi.org/10.1016/j.aquaeng.2022.102227

Yang, L., Liu, Y., Yu, H., Fang, X., Song, L., Li, D., & Chen, Y. (2021). Computer Vision Models in Intelligent Aquaculture with Emphasis on Fish Detection and Behavior Analysis: A Review. *Archives of Computational Methods in Engineering*, *28*(4), 2785–2816. https://doi.org/10.1007/s11831-020-09486-2

Yuan, X., Guo, L., Luo, C., Zhou, X., & Yu, C. (2022). A Survey of Target Detection and Recognition Methods in Underwater Turbid Areas. *Applied Sciences*, *12*(10), 4898. https://doi.org/10.3390/app12104898