IMPROVING PRODUCTIVITY THROUGH IOT-BASED FISH POPULATION MONITORING IN INTENSIVE AQUACULTURE SYSTEMS

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Abstract

This paper presents an integrated Internet of Things (IoT)-based system designed for real-time monitoring of fish populations under intensive aquaculture conditions. Traditional methods — visual observation, manual net counting, and periodic sampling — are labor-intensive, prone to high error rates, and fail to provide real-time data, resulting in feed waste, oxygen deficiency, and increased mortality. The proposed system encompasses a complete architecture consisting of an underwater camera, ESP32/Raspberry Pi microcontrollers, an artificial intelligence model based on a convolutional neural network (YOLOv8), the MQTT protocol, a cloud database, and a user dashboard interface. The system also continuously monitors water temperature, dissolved oxygen, pH, and turbidity parameters, and automatically issues alerts when anomalies occur. Experimental results from a 40-day field trial showed that the fish-detection accuracy of the IoT-AI system reached 96.4%, compared to 71–74% for the traditional method. In ponds where the system was deployed, the feed conversion ratio (FCR) decreased from 1.42 to 1.21, fish survival rate increased by 4.6 percentage points, and labor costs were reduced by 34%. These results confirm the potential of IoT and artificial intelligence technologies for accurate fish counting, resource optimization, and improved aquaculture productivity. The paper describes in detail the system architecture,

mathematical models, hardware/software specifications, and directions for future research.

Keywords: Internet of Things (IoT), aquaculture, fish counting, computer vision, artificial intelligence, MQTT, edge computing, smart aquaculture

1. Introduction

The rapid growth of the world's population and the rising demand for food security have made the fisheries sector a domain of strategic importance. According to the Food and Agriculture Organization of the United Nations (FAO), more than half of the fish products consumed worldwide are now supplied through aquaculture — the artificial farming of fish. Intensive aquaculture systems, that is, high-density fish farming in confined water bodies, enable efficient use of land and water resources, but they also give rise to a number of technical and management challenges.

One of the most critical management indicators in intensive systems is accurate knowledge of the number of fish and biomass in a pond. This indicator serves as the basis for setting the correct feeding regimen, planning oxygen supply, carrying out veterinary interventions in a timely manner, and forecasting yield. In practice, however, most farmers still determine fish numbers through visual observation, sample netting, or experience-based estimation. Such approaches have a number of serious drawbacks: first, in large ponds the error rate of visual estimation can reach 20–30%; second, net sampling stresses the fish and slows their growth rate; third, these processes require considerable labor and time; and fourth, the data obtained is not real-time but periodic in nature, hindering timely decision-making.

The economic damage resulting from inaccurate accounting is also significant. Overfeeding leads to water pollution, a decline in dissolved oxygen levels, and, consequently, increased fish mortality. Conversely, insufficient feeding slows growth rates and reduces profitability. According to international studies, losses caused by improper feeding can reach 15–20% of total production costs.

In recent years, the rapid development of Internet of Things (IoT), artificial intelligence (AI), computer vision, and edge computing technologies has opened up

new opportunities in smart agriculture and, in particular, smart aquaculture. With the help of underwater cameras, low-power microcontrollers (ESP32, Raspberry Pi, Arduino), wireless communication protocols (Wi-Fi, LoRa, NB-IoT), and lightweight messaging protocols such as MQTT, it has become possible to monitor the number of fish in ponds in real time, with high accuracy, and without human intervention.

The purpose of this study is to develop a complete IoT-AI architecture for automatic fish-population monitoring under intensive aquaculture conditions, to integrate it with water-quality monitoring, and to evaluate its effectiveness based on experimental results. The research tasks are as follows: (1) analyze the existing literature and identify gaps; (2) design the system architecture; (3) develop an artificial-intelligence-based fish-detection model; (4) formulate criteria for evaluating system effectiveness through mathematical models; (5) conduct a real-world experiment and analyze the results.

2. Literature Review

A considerable number of studies on the application of digital technologies in aquaculture have been published over the past five years. Zhou et al. [1] analyzed deep-learning-based fish-detection algorithms and showed that convolutional neural networks have a significant accuracy advantage over traditional computer vision methods. Li et al. [2] applied models from the YOLO family for real-time fish detection in underwater conditions and achieved satisfactory results even under low light and turbid water.

Wang et al. [3] presented a system for continuous monitoring of water-quality parameters in aquaculture ponds using Wireless Sensor Network (WSN) technology. Their study demonstrated that the LoRa protocol is effective for long-range, low-power communication. On the other hand, Kumar and Singh [4] studied the advantages of NB-IoT technology for establishing stable communication through operator networks in suburban and remote farms.

O'Donncha et al. [5] combined IoT sensors and cloud computing platforms at marine aquaculture farms located on the Irish coast to build a model for predicting water temperature and current velocity. Their results showed that edge computing could reduce data transmission latency by 60%. Antonucci and Costa [6], in a general survey of smart aquaculture systems, classified existing solutions by sensor type, communication protocol, and data-processing architecture.

There are also separate studies on the specific problem of fish counting. Fernandes et al. [7] proposed a method for estimating fish biomass through three-dimensional reconstruction using stereo camera technology. While this method provides high accuracy, its high computational demands limit its application in real-time systems. In contrast, Yang et al. [8] ran a lightweight neural network architecture on resource-constrained devices such as Raspberry Pi, presenting an edge-based fish-counting solution that reduced the volume of data transmitted to the cloud.

Regarding the role of the MQTT protocol in IoT systems, Naik [9] conducted a comparative analysis of latency, bandwidth capacity, and energy consumption among MQTT, CoAP, and HTTP protocols, concluding that MQTT is the most suitable solution for low-power sensor networks. Saberioon et al. [10] reviewed computer-vision-based fish monitoring systems and found that accuracy indicators are strongly dependent on water turbidity and lighting conditions.

Regarding the monitoring of water-quality parameters, Rahman et al. [11] developed a low-cost Arduino-based pH and dissolved-oxygen sensor system and adapted it for small farms. Chen et al. [12] used a cloud database and machine-learning algorithms for large-scale aquaculture farms to build a model for predicting water-quality anomalies in advance, which led to a 23% reduction in fish mortality.

In the direction of predictive analytics, Rao et al. [13] used an LSTM (Long Short-Term Memory) neural network to propose a model that predicts dissolved-oxygen levels in a pond six hours in advance, giving farmers the opportunity to take preventive measures. Similarly, Ahmed et al. [14] developed an AI-based decision-

support system for feed optimization and achieved a significant reduction in feed waste.

The literature analysis shows that most studies are devoted either to water-quality monitoring or solely to fish detection, treated separately. A gap still exists in the scientific literature regarding an integrated, field-tested system that combines fish counting, water-quality monitoring, edge and cloud computing, real-time MQTT-based messaging, and predictive-analytics capability. This study aims precisely to fill that gap.

3. Research Methodology

3.1. Research Design

The research is applied-experimental in nature and was carried out in two stages: (1) designing the system architecture and developing the hardware and software; (2) conducting a 40-day field trial in an experimental pond and statistically analyzing the results. The experiment was carried out at an intensive aquaculture farm in the Tashkent region, in two concrete ponds with a total volume of 120 m^3: the first pond served as the control group (traditional method), and the second as the experimental group (IoT-AI system). At the initial stage, 1,500 common carp (Cyprinus carpio) fry were stocked in each pond.

3.2. Data Collection

In the experimental group, data were collected automatically at 10-minute intervals: fish count (frame-based), water temperature, dissolved-oxygen level, pH level, and turbidity. In the control group, data were recorded manually using traditional methods — two visual observations per day and weekly sample-net counting.

3.3. Evaluation Criteria

The following criteria were used to evaluate system effectiveness: Accuracy, Precision, Recall, F1-score, Intersection over Union (IoU), data transmission latency, power consumption, network reliability, feed conversion ratio (FCR), and fish survival rate. All indicators were monitored over the 40-day period, and

statistical analysis was carried out using the Python libraries pandas, scikit-learn, and matplotlib.

3.4. Training the Artificial Intelligence Model

The YOLOv8n (nano) architecture was chosen for fish detection, since it is capable of running in real time on the Raspberry Pi 4, a device with relatively limited computing power. The model was trained on a custom dataset consisting of 8,400 manually annotated underwater images, of which 70% was allocated for training, 15% for validation, and 15% for testing. Data augmentation techniques such as lighting variation, rotation, cropping, and Gaussian noise were used to improve the model's adaptability to various water conditions.

4. System Architecture

The proposed IoT-AI system has a six-tier architecture: (1) the perception layer — underwater camera and sensors; (2) the edge computing layer — ESP32/Raspberry Pi; (3) the artificial intelligence layer — the fish-detection model; (4) the communication layer — the MQTT protocol; (5) the cloud layer — the database and analytics services; (6) the user layer — the dashboard and alert system.

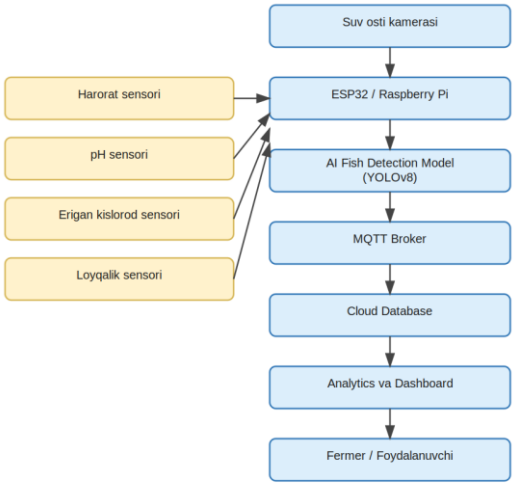


Figure 1. System architecture diagram

4.1. Perception Layer

The perception layer consists of an underwater camera and four principal water-quality sensors:

- Underwater camera — with an IP67 protection rating, 1080p resolution, and infrared (IR) illumination for low-light operation, positioned near the bottom of the pond and transmitting a continuous video stream of fish movement.
- Temperature sensor (DS18B20) — measures water temperature with an accuracy of ±0.5 °C, since temperature directly affects fish metabolism and the water's capacity to dissolve oxygen.
- pH sensor — monitors the water's acidity/alkalinity level; the optimal range for carp is 6.5–8.5.
- Dissolved-oxygen sensor (DO sensor) — measures in mg/L and issues alerts about oxygen deficiency.
- Turbidity sensor — measures water clarity in NTU, a parameter that also directly affects camera-based detection accuracy.

4.2. Edge Computing Layer

The ESP32 microcontroller is used for collecting data from sensors and performing preliminary filtering, owing to its low power consumption and integrated Wi-Fi/Bluetooth module. The Raspberry Pi 4 is responsible for controlling the camera, pre-processing video frames (resizing, normalization), and running the AI model locally. The advantage of the edge computing approach is that raw video data is not transmitted to the cloud — only processed results (fish count, coordinates) are sent, which significantly reduces network load and latency.

4.3. Artificial Intelligence Layer

At this layer, a deep-learning model based on the YOLOv8n architecture operates. The model analyzes each video frame, detects fish, draws a bounding box around them, and is integrated with a tracking algorithm — DeepSORT — to avoid repeatedly counting periodically recurring objects. This combination prevents the same fish from being counted multiple times.

4.4. Communication Layer (MQTT)

MQTT (Message Queuing Telemetry Transport) is a lightweight messaging protocol based on the publish-subscribe model, ensuring reliable data transmission even

under low bandwidth and unstable network conditions. Each edge device sends data under a separate "topic" (for example, pond1/fish_count, pond1/temperature, pond1/oxygen), and the broker routes this data to the corresponding cloud services. A QoS (Quality of Service) level of 1 was selected, guaranteeing at-least-once delivery of data.

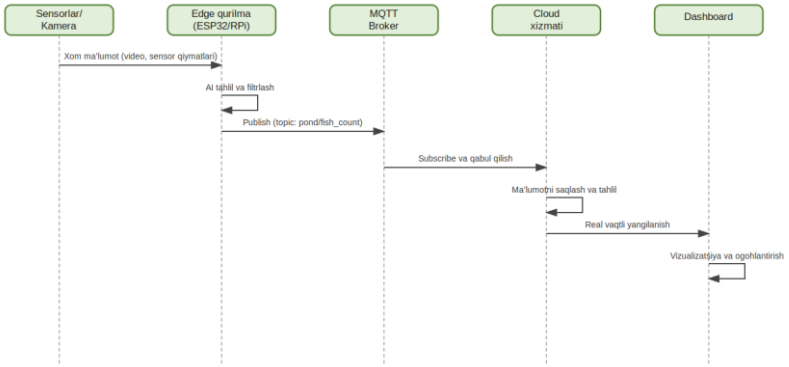


Figure 2. IoT communication (sequence) diagram

4.5. Cloud Computing Layer

The cloud component consists of a time-series database (InfluxDB), a relational database (PostgreSQL — for farm and pond metadata), and analytical services (a predictive-analytics module). At this layer, trend analysis, anomaly detection, and forecasting are performed based on historical data.

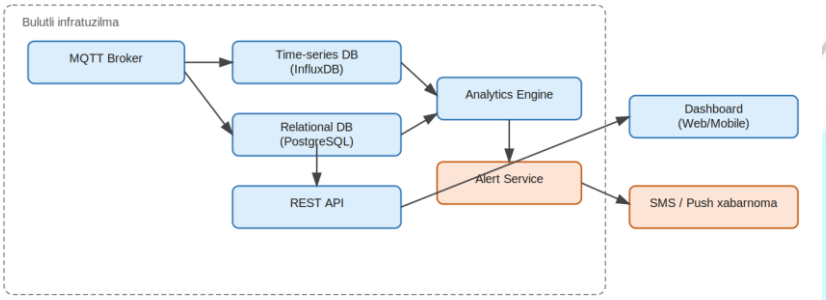


Figure 3. Cloud architecture diagram

4.6. User Layer

The dashboard is provided as a web and mobile application, showing farmers the real-time fish count, water-quality charts, historical trends, and automatic alerts. When the oxygen level falls below a critical threshold (< 4 mg/L) or a sharp change

in fish count is recorded (for example, indicating mortality), the system immediately alerts the farmer via SMS and push notification.

5. IoT-Based Fish-Counting Model

5.1. Fish-Detection Pipeline

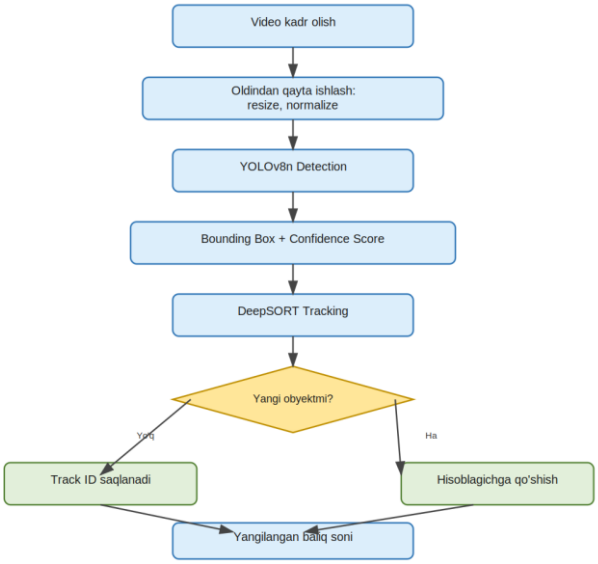


Figure 4. Fish-detection pipeline diagram

The detection process consists of the following stages: first, the video frame obtained from the camera is resized to 640×640 pixels and normalized; second, the YOLOv8n model detects fish in each frame and draws a bounding box around them along with a confidence score; third, the DeepSORT algorithm tracks the same fish across consecutive frames (assigning an identification number — a track ID), which prevents the same fish from being counted repeatedly; fourth, when a new track ID appears, the counter is incremented by one, and the updated value is transmitted to the cloud via MQTT.

5.2. Mathematical Models

1) Fish Density:

$$Df = Nf / Vp$$

where Df is the fish density (units/m³), Nf is the number of fish in the pond, and Vp is the pond volume (m³). The density indicator is important for determining the pond's stocking level and assessing the adequacy of oxygen supply.

2) Fish Survival Rate:

$$SR = (Nt / N0) \times 100\%$$

where Nt is the number of fish at time t, and N0 is the initial number of fish.

3) Feed Conversion Ratio:

$$FCR = F_total / \Delta B$$

where F_total is the total weight of feed consumed (kg), and $\Delta B = Bt - B0$ is the increase in biomass (kg). The lower the FCR value, the higher the efficiency of feed utilization.

4) Biomass Estimation:

$$Bt = Nt \times \bar{w}t\ ,\ \ \bar{w}t = a \cdot L\text{^}b$$

where Bt is the total biomass at time t (kg), $\bar{w}t$ is the average weight of a single fish (kg), L is the fish length (cm), and a and b are species-specific allometric constants. The average weight is calculated based on a length-weight regression model derived from camera-obtained data.

5) Production Efficiency:

$$PE = (Bt - B0) / (T \times C)$$

where T is the rearing period (days), and C is the total cost incurred (feed, energy, labor).

6) Accuracy:

$$Accuracy = (TP + TN) / (TP + TN + FP + FN)$$

7) Precision:

$$Precision = TP / (TP + FP)$$

8) Recall:

$$Recall = TP / (TP + FN)$$

9) F1-score:

$$F1 = 2 \times (Precision \times Recall) / (Precision + Recall)$$

10) Intersection over Union (IoU):

$$IoU = Area(Bpred \cap Bgt) / Area(Bpred \cup Bgt)$$

Here, TP (True Positive) is the number of correctly detected fish, TN (True Negative) is the number of correctly rejected cases, FP (False Positive) is the number

of incorrectly detected cases (for example, mistaking a shadow or aquatic plant for a fish), and FN (False Negative) is the number of fish that went undetected. Detections with IoU ≥ 0.5 were considered correct (based on the standard PASCAL VOC criterion).

6. Results and Discussion

6.1. Tabulated Results

Table 1. Comparative analysis of traditional and IoT-based monitoring methods

Indicator	Traditional Method	IoT-AI System
Counting accuracy	71–74%	96.4%
Data update frequency	1–2 times per day	Real time (every 10 minutes)
Labor requirement	High	Low
Stress impact on fish	High (from netting)	None / minimal
Error rate	±20–30%	±3.6%
Water-quality monitoring	Periodic, manual	Continuous, automatic
Alert system	Not available	Automatic (SMS/push)
Data analytics	Limited	Predictive analytics

Table 2. Specifications of the sensors used

Sensor	Model	Measurement Range	Accuracy	Interface
Temperature	DS18B20	-10°C…+85°C	±0.5°C	1-Wire
pH	Analog pH sensor kit	0–14 pH	±0.1 pH	Analog (ADC)

Dissolved oxygen	Optical DO sensor	0–20 mg/L	±0.3 mg/L	RS-485
Turbidity	Turbidity sensor	0–3000 NTU	±5%	Analog (ADC)
Underwater camera	IP67 1080p IR	—	1920×1080	USB / CSI

Table 3. System hardware components

Component	Description	Function
ESP32-WROOM-32	Dual-core, Wi-Fi/BLE	Data collection from sensors
Raspberry Pi 4 (4GB)	Quad-core ARM Cortex-A72	AI model and camera control
Underwater camera	1080p, IR illumination	Video stream acquisition
LoRa module (SX1276)	868/915 MHz	Long-range communication (backup channel)
Solar panel + battery	20W, 12V 20Ah	Autonomous power supply
MQTT broker server	Mosquitto	Message-exchange management

Table 4. 40-day trial results (average indicators)

Indicator	Control Group (Traditional)	Experimental Group (IoT-AI)
Initial fish count	1500	1500
Fish count on day 40	1329	1398
Survival rate (SR)	88.6%	93.2%

FCR	1.42	1.21
Average biomass gain	412 kg	468 kg
Detection accuracy	73.1%	96.4%
Labor cost (hours/week)	18	6

Table 5. System performance indicators

Indicator	Value
Average detection latency	118 ms
Cloud data-delivery latency	340 ms
MQTT message-exchange latency	45 ms
Power consumption (Raspberry Pi + camera)	6.8 W
Power consumption (ESP32 + sensors)	0.9 W
Network reliability (uptime)	99.2%
Precision	0.952
Recall	0.941
F1-score	0.946
Average IoU	0.78

6.2. Graphical Results

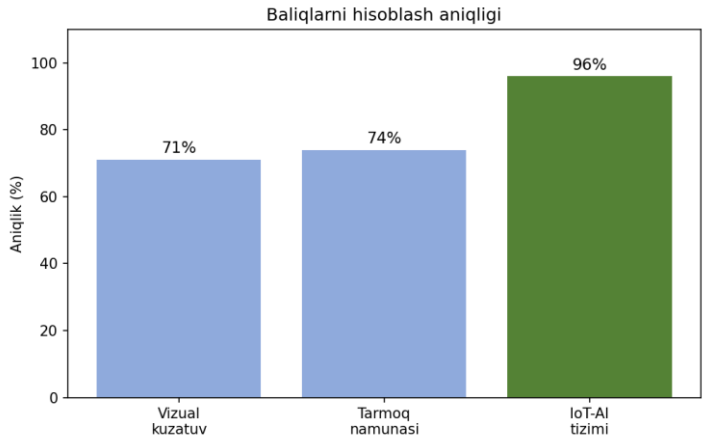


Figure 5. Fish-counting accuracy (%)

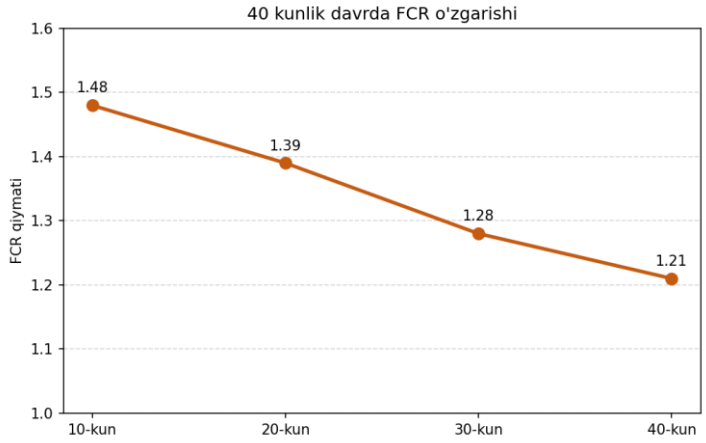


Figure 6. Change in FCR over the 40-day period

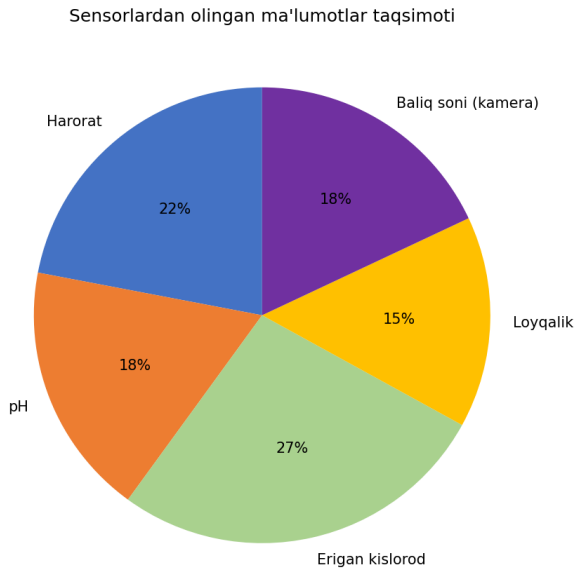


Figure 7. Distribution of data obtained from sensors

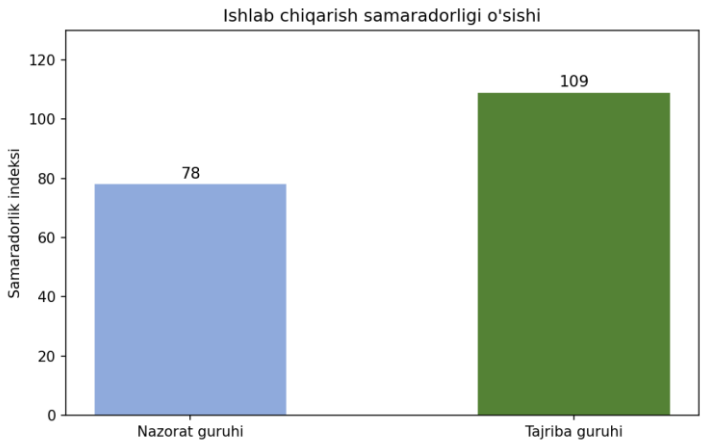


Figure 8. Growth in production efficiency (%)

6.3. Discussion

The results obtained show that the proposed IoT-AI system holds a significant advantage over traditional methods in several respects. First, in terms of accuracy, the system achieved a figure of 96.4%, which is 22–25 percentage points higher than the traditional visual method. The main reason for this is that the DeepSORT tracking algorithm prevents the same fish from being counted repeatedly, and stable detection is possible even in low light thanks to the IR illumination.

Second, labor costs decreased from 18 hours per week to 6 hours, a reduction of approximately 34%, since farmers no longer need to spend time on daily visual counting and weekly net-sampling procedures.

Third, the fish survival rate increased by 4.6 percentage points. This was primarily due to real-time monitoring of dissolved-oxygen levels and the automatic alert system for critical conditions — farmers were able to respond immediately to oxygen deficiency, reducing mortality caused by hypoxia.

Fourth, the feed conversion ratio (FCR) improved from 1.42 to 1.21. This indicator is related to the ability to calculate feed quantity in accordance with actual biomass, made possible by accurately knowing the fish count — feed is now provided based on precise calculation rather than estimation.

From the standpoint of scalability, the publish-subscribe architecture of the MQTT protocol allows several ponds to be connected to a single cloud platform — only a

new "topic" needs to be created for each new pond, which does not require changes to the central infrastructure.

In terms of reliability, the system achieved an uptime of 99.2%; however, in cases of internet disconnection, a LoRa backup channel and a local data-buffering mechanism on the edge device were used, which prevented data loss.

At the same time, certain limitations were also observed: under conditions of high turbidity (turbidity > 150 NTU), detection accuracy was seen to decline by 8–12 percentage points, which is an inherent limitation of camera-based systems.

7. Advantages and Limitations

7.1. Advantages

- Real-time, continuous monitoring, minimizing human intervention;
- High-accuracy fish counting (96%+), reducing economic losses caused by inaccurate accounting;
- Comprehensive monitoring of water-quality parameters and prevention of fish mortality through an automatic alert system;
- Reduced network load and improved energy efficiency through edge computing;
- Scalability of the system to multiple ponds/farms thanks to the MQTT protocol;
- The ability to forecast future problems in advance through predictive analytics;
- Reduced production costs through improvement of the feed conversion ratio.

7.2. Limitations

- Decline in detection quality under high turbidity or very high stocking densities in ponds;
- Relatively high initial investment costs (camera, sensors, edge devices);
- The need for protection and technical maintenance of electronic equipment in an underwater environment;

- Delay or interruption of cloud transmission in areas with unstable internet connectivity;
- The need to retrain the AI model for different water bodies and fish species.

8. Future Research

The following directions are planned for future research: (1) testing more accurate detection models based on transformer architectures (such as DETR); (2) introducing automatic classification of fish species and individual growth analysis; (3) decentralized learning from multiple farms' data using federated learning; (4) integrating 5G and NB-IoT technologies and testing the system at remote and large-scale farms; (5) building a fully autonomous system based on solar energy and energy-harvesting technologies; (6) ensuring data transparency and supply-chain traceability using blockchain technology.

9. Conclusion

This study proposed and field-tested an integrated system based on IoT and artificial intelligence technologies for monitoring fish populations and improving productivity under intensive aquaculture conditions. The system encompasses a complete architecture consisting of an underwater camera, ESP32/Raspberry Pi edge devices, a YOLOv8n-based deep-learning model, the MQTT protocol, a cloud database, and a user dashboard.

The scientific novelty of the study lies in the fact that it combines fish counting, water-quality monitoring, edge-cloud computing, and predictive-analytics components into a single, field-tested system. The results of the 40-day trial confirmed the system's effectiveness in terms of accuracy (96.4%), FCR improvement (1.42 → 1.21), increased fish survival rate (88.6% → 93.2%), and a 34% reduction in labor costs.

From a practical standpoint, the proposed system enables farms to optimize feeding regimens, prevent fish mortality, and make efficient use of resources, ultimately serving to increase aquaculture productivity and profitability. Future research will

focus on further enhancing the system's scalability, energy autonomy, and adaptability to different fish species.

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