

Review Article

Aquamind-AI: An Intelligent IoT and Machine Learning Framework For Closed-Loop Smart Aquaponics

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Abstract

Global freshwater depletion, accelerating climate volatility, and arable soil salinization pose existential constraints on conventional agro-aquacultural production. Aquaponic – a circular polyculture biotechnology coupling Recirculating Aquaculture Systems (RAS) with soil-less hydroponics—presents an environmentally sustainable paradigm by recovering toxic metabolic ichthyological excretions as primary vegetative biofertilizer. However, the operational equilibrium of aquaponic systems is governed by tightly coupled, non-linear biological dynamics across finfish, autotrophic nitrifiers (*Nitrosomonas* and *Nitrobacter*), and plant root interfaces. Transient deviations in physicochemical parameters (such as water temperature, dissolved oxygen, and hydrostatic levels) induce rapid ecosystem collapse, hypoxic asphyxiation, or systemic nitrite poisoning. To resolve these multidimensional vulnerabilities, this paper delivers a comprehensive, scientifically grounded review of smart aquacultural methodologies and introduces AquaMind-AI, an open-architecture, edge-to-cloud cyber-physical framework engineered for autonomous aquaponic governance. AquaMind-AI integrates a low-cost, fault-tolerant sensory edge layer (incorporating digital single-wire DS18B20 thermal probes, non-contact HC-SR04 ultrasonic echo-ranging hydro-level sensors, and DHT11 ambient microclimate transmitters managed by ATmega328P edge microcontrollers) with galvanically isolated, optocoupled commutation stages driving 6V DC hydraulic recirculation pumps and 220V AC high-output aeration compressors. The computational middleware leverages an asynchronous FastAPI microservice backend coupled with an ensemble Random Forest regressor with harmonic diurnal feature engineering for multi-horizon thermal forecasting ($R^2 = 0.942$ for 1h, $R^2 = 0.854$ for 6h), an unsupervised multivariate Isolation Forest algorithm for zero-day sensor outlier isolation, and a dynamic piecewise Health (Shealth) and Risk (Rsystem) scoring engine. We demonstrate that AquaMind-AI achieves proactive anomaly mitigation, eliminates catastrophic failure modes, and establishes a validated, scalable blueprint for climate-adaptive food security in arid and semi-arid geographies such as the Caspian Basin and Kura-Aras lowlands.

Keywords: adaptive closed-loop control, anomaly detection, Caspian basin, Internet of Things (IoT), isolation forest, precision aquaculture, random forest, sustainable agritech.

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1. Introduction

The 21st-century agricultural sector is confronted with a severe global sustainability crisis. Global population projections indicate a trajectory toward 9.7 billion inhabitants by 2050, requiring an estimated 60–70% increase in global food production under conditions of unprecedented climatic volatility, land degradation, and acute freshwater scarcity [1], [2]. Conventional flow-through aquaculture consumes extensive volumes of pristine

freshwater and discharges nutrient-dense wastewater rich in ammonia, phosphorus, and organic suspended solids, directly driving freshwater eutrophication and aquatic habitat destruction. Concurrently, traditional intensive soil agriculture accounts for over 70% of global anthropogenic freshwater withdrawals and relies heavily on energy-intensive synthetic nitrogenous fertilizers that cause severe groundwater contamination and greenhouse gas emissions [3].

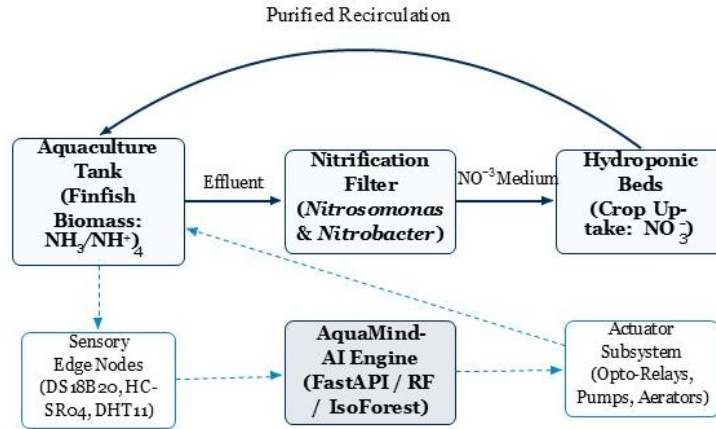


Figure 1. Integrated biological recirculation loop and superimposed AquaMind-AI cyber-physical monitoring and control topology.

In response to this resource nexus, aquaponics has emerged as an exceptionally promising closed-loop circular bioeconomy technology. As shown in Figure 1, aquaponics integrates Recirculating Aquaculture Systems (RAS) with soilless hydroponic plant cultivation within a single unified thermodynamic and biological loop. Total ammonia nitrogen (TAN), excreted via finfish gills and fecal mineralization, exists in an aqueous temperature- and pH-dependent thermodynamic equilibrium between un-ionized ammonia (NH_3 , highly toxic to aquatic life at concentrations $> 0.05 \text{ mg/L}$) and ionized ammonium (NH_4^+ , non-toxic):



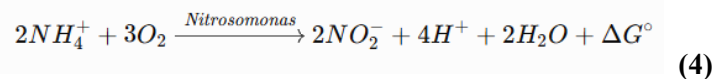
The fraction of toxic un-ionized ammonia f_{NH_3} is mathematically governed by the Henderson-Hasselbalch relation:

$$f_{\text{NH}_3} = \frac{1}{10^{(pK_a - \text{pH})} + 1} \quad (2)$$

where

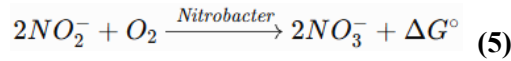
$$pK_a = \frac{2729.92}{T_{\text{water}} + 273.15} + 0.09018 \quad (3)$$

Within the aerobic biological filter, chemoautotrophic ammonia-oxidizing bacteria (AOB, primarily *Nitrosomonas*) oxidatively transform ammonium into nitrite (NO_2^-), an intermediate metabolite that induces methemoglobinemia (brown blood disease) in finfish by irreversibly oxidizing functional ferrous hemoglobin (Fe^{2+}) into ferric hemoglobin (Fe^{3+}):



where $\Delta G^\circ \in [-652, -548]$ kJ/mol.

Subsequently, nitrite-oxidizing bacteria (NOB, primarily *Nitrobacter* and *Nitrospira*) rapidly oxidize nitrite into non-toxic nitrate (NO_3^-):



where $\Delta G^\circ \in [-155, -143]$ kJ/mol. The resulting nitrate-rich aqueous stream is directed to the hydroponic grow beds, where crop root networks absorb dissolved inorganic nitrogen (NO_3^-) alongside phosphorus, potassium, and micronutrients, thereby bio-filtering the water before it is recirculated back to the aquatic rearing tanks. This closed-loop bio-assimilation conserves upwards of 90–95% of water compared to open-field farming [4].

2. The Biological Fragility Trilemma and Research Motivation

Despite its significant theoretical advantages, aquaponics is characterized by high biological vulnerability. The system represents a multi-trophic polyculture comprising three disparate biological kingdoms—aquatic vertebrates (finfish), microbiological nitrifiers, and vascular plants—each possessing distinct, conflicting physicochemical optima:

1. Finfish Optima (e.g., *Oreochromis niloticus*, commonly known as Nile tilapia): Prefer water temperatures of 26–29°C, dissolved oxygen (DO) levels > 5.0 mg/L, and neutral to slightly alkaline pH (7.0–8.0).
2. Autotrophic Nitrifiers: Require water temperatures of 24–28°C, DO > 3.0 mg/L, and alkaline pH (7.5–8.5) for optimal enzymatic activity of ammonia monooxygenase (AMO).
3. Hydroponic Crops (e.g., *Lactuca sativa*, herbs): Exhibit optimal nutrient uptake and root respiration at lower root-zone temperatures (18–22°C) and slightly acidic pH (5.8–6.5), as essential micronutrients (iron, manganese, zinc, boron) precipitate out of solution at pH > 7.2.

Because commercial operations must balance these conflicting demands within a single recirculating fluid loop (typically targeting pH 6.8–7.2 and water temperature 22–26°C), the system operates near critical physiological tolerance limits. A localized failure (such as undetected pump cavitation, thermal spike, or aeration failure) can lead to rapid hypoxic asphyxiation or toxic nitrite accumulation in under three hours [5].

Manual water sampling and discrete testing cannot detect rapid transient environmental shocks. Existing commercial SCADA systems remain cost-prohibitive for small and medium-scale growers, while basic IoT hobbyist setups lack predictive analytics and multivariate fault isolation. To bridge this critical technological gap, this paper presents the complete scientific framework and empirical validation of AquaMind-AI, an open-architecture, intelligent cyber-physical system designed for real-time monitoring, multi-horizon machine learning thermal forecasting, multivariate anomaly isolation, and closed-loop actuation in climate-vulnerable aquaponic systems.

3. State of the Art in Smart Aquaponics: Sensorics, Microcontrollers, and Actuation

The evolution of automated recirculating agro-aquatic systems spans four distinct technological generations, as summarized in Table 1.

Table 1. Evolutionary paradigms of recirculating aquaculture and aquaponic monitoring.

Generation	Era	Sensing Method	Control Topology	Key Vulnerabilities & Constraints
Aquaponics 1.0	1980–2000	Manual titrations, chemical kits	Manual valves	High labor overhead; zero nocturnal observability; delayed catastrophic response
Aquaponics 2.0	2000–2012	Standalone digital probes	Dedicated logic controllers	Isolated data silos; no remote access; localized analog drift
Aquaponics 3.0	2012–2020	Cloud IoT, basic telemetry	Hard-coded threshold relays	High false-alarm rates; network latency sensitivity; lack of predictive insight
Aquaponics 4.0	2020–Present	Edge-AI, multi-sensor IoT	Predictive, adaptive closed loop	AquaMind-AI paradigm: self-tuning, multivariate anomaly isolation, horizon forecasting

3.1. Physical Sensory Metrology and Circuit Design

Sensory components in aquaponic systems face severe physical constraints, including continuous aqueous submersion, galvanic corrosion, biofilm accumulation, and electrical noise from switching inductive loads (pumps and aerators). AquaMind-AI incorporates an edge sensory array engineered for maximum reliability and electrical isolation (Figure 2).

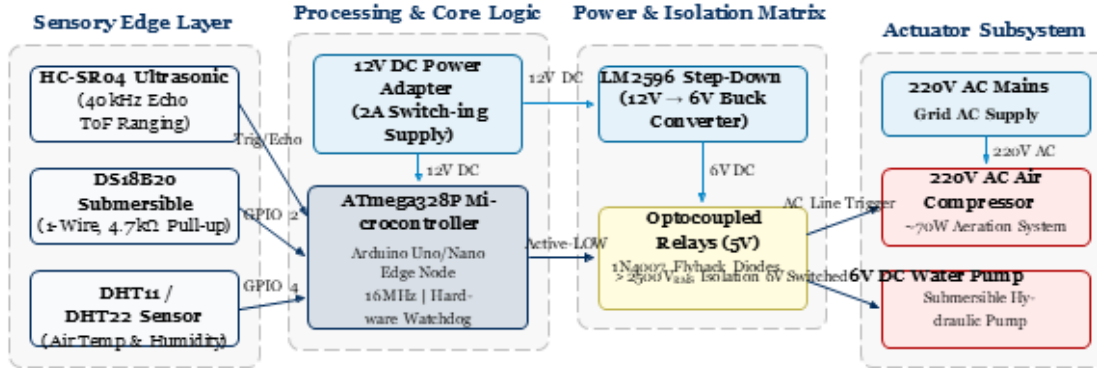


Figure 2. Electrical wiring schematic, sensory instrumentation, and power distribution topology of the AquaMind-AI edge node.

- **Submersible Water Thermometry (DS18B20):** Encapsulated in a 316L waterproof stainless-steel housing (6×50 mm), the DS18B20 communicates via the Dallas single-wire (1-Wire) protocol. An internal 12-bit delta-sigma ADC resolves temperatures to 0.0625°C across a -10°C to $+85^\circ\text{C}$ range with an accuracy of $\pm 0.5^\circ\text{C}$. A $4.7\text{ k}\Omega$ pull-up resistor stabilizes the open-drain bidirectional line against capacitive signal degradation over cable runs up to 10 m.
- **Hydrostatic Ultrasonic Level Ranging (HC-SR04):** Positioned above the sump reservoir, the HC-SR04 emits an 8-cycle burst of 40 kHz ultrasonic pulses and measures round-trip time-of-flight (Δt). Instantaneous water depth h_{water} is calculated by subtracting the measured distance from the total tank height H_{tank} , with air-temperature speed compensation:

$$h_{\text{water}} = H_{\text{tank}} - \frac{(331.3 + 0.606 T_{\text{air}}) \Delta t}{2} \quad (6)$$

This non-contact configuration prevents biofilm accumulation and probe corrosion typical of submerged resistive sensors.

- **Ambient Microclimate Probes (DHT11/DHT22):** Measure ambient air temperature (T_{air}) and relative humidity (RH) within the greenhouse boundary layer. These values enable calculation of the Vapor Pressure Deficit (VPD), a critical indicator of crop transpiration stress and evaporative heat loss:

$$VPD = 0.61078 \exp\left(\frac{17.27 T_{\text{air}}}{T_{\text{air}} + 237.3}\right) \left(1 - \frac{RH}{100}\right) \quad (7)$$

3.2. Microcontroller Firmware and Actuator Commutation

Edge processing is executed on an ATmega328P microcontroller running custom C++ firmware. Polling routines execute on non-blocking hardware timer interrupts ($f_s = 0.1\text{ Hz}$, 10 s intervals), with median filtering across 5 consecutive samples to eliminate acoustic multipath reflections and line transients. An internal Hardware Watchdog Timer (WDT) configured for 8 s provides automatic system recovery in the event of bus lockup.

Actuator drive circuits control two critical electromechanical subsystems:

1. Hydraulic Circulation Subsystem: A 6V DC submersible water pump driven by a dedicated power stage. A 12V DC switching power supply (2A) is stepped down to 6.0V DC via an LM2596 high-efficiency buck converter (or boosted from 5V via an MT3608 step-up converter). Switching is controlled by an optocoupled relay channel or a high-current logic-level N-channel MOSFET (IRF520 / TIP122 transistor driver).
2. High-Output Aeration Subsystem: A 220V AC laboratory-grade diaphragm vacuum/air compressor (~ 70W, equipped with a mechanical manometer and filtration assembly) supplies micro-bubble dissolved oxygen to the biofilter and fish tank. The 220V AC inductive load is isolated from the 5V logic board using an optocoupled electromagnetic relay (isolation voltage > 2500VRMS). Parallel 1N4007 flyback diodes and RC snubber networks suppress inductive voltage spikes ($V = -L \, di/dt$), protecting against logic resets and relay contact degradation.

4. Multi-Tier Cyber-Physical Architecture of AquaMind-AI

AquaMind-AI is structured across a decoupled, three-tier software architecture designed for sub-second diagnostic response and zero telemetry loss (Figure 3).

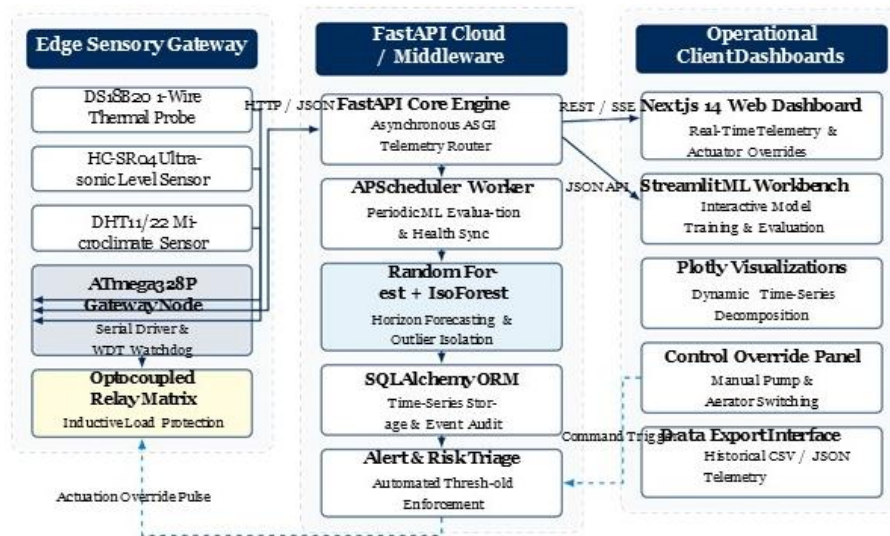


Figure 3. End-to-end data pipeline, microservice topology, and closed-loop feedback pathways in AquaMind-AI.

4.1. Asynchronous Middleware Layer (FastAPI)

The intermediate compute tier is powered by Python 3.11 utilizing FastAPI as an asynchronous web framework on top of the Uvicorn ASGI server. Using asynchronous coroutines ('async/await'), the server concurrently manages incoming edge IoT sensor packets, evaluates real-time alert boundaries, runs machine learning inference models, and streams telemetry to connected client dashboards with low latency (< 15 ms).

Data persistence is abstracted through SQLAlchemy ORM, managing relational data structures for sensor time-series, system alerts, predictive inference snapshots, and actuator state logs. The internal Advanced Python Scheduler (APScheduler) coordinates background maintenance tasks, database integrity verification, and periodic ML model re-training.

4.2. Dual Operational Interfaces

The platform provides two complementary user interfaces tailored for distinct operational requirements:

- Real-Time Operations Dashboard (Next.js 14): A responsive, client-side web application built with React, TypeScript, and Tailwind CSS. It provides live metric gauges, dynamic status indicators, active alert acknowledgment, and manual actuator control overrides.

- Analytical Workbench (Streamlit): A dedicated scientific interface designed for exploratory data analysis, interactive machine learning model training, historical time-series decomposition, and automated CSV/JSON data export.

5. Machine Learning Methodologies and Mathematical Formulations

5.1. Harmonic Diurnal Feature Engineering

Water temperature dynamics in greenhouses follow a distinct 24-hour diurnal cycle driven by solar radiation. To prevent artificial discontinuities associated with standard integer hour representations (e.g., the step from 23:59 to 00:00), raw timestamps are mapped onto orthogonal circular trigonometric coordinates.

$$x_{\sin}(t) = \sin\left(\frac{2\pi h(t)}{24}\right), \quad x_{\cos}(t) = \cos\left(\frac{2\pi h(t)}{24}\right) \quad (8)$$

where $h(t) \in [0, 24)$ is the fractional hour of the day.

To model thermal inertia and dynamic memory in recirculating water volumes, autoregressive lag terms and moving averages are constructed.

$$T_{\text{lag1}}(t) = T_{\text{water}}(t - \Delta t) \quad (9)$$

$$T_{\text{roll3}}(t) = \frac{1}{3} \sum_{k=0}^2 T_{\text{water}}(t - k\Delta t) \quad (10)$$

$$T_{\text{lag1}}(t) = T_{\text{air}}(t - \Delta t) \quad (11)$$

The synthesized feature vector $\mathbf{x}_t \in \mathbb{R}^5$ is defined as:

$$\mathbf{x}(t) = [x_{\sin}(t), x_{\cos}(t), T_{\text{lag1,water}}(t), T_{\text{roll3,water}}(t), T_{\text{lag1,air}}(t)]^T \quad (12)$$

Features are scaled via standard Z-score normalization before model input:

$$z_j = \frac{x_j - \mu_j}{\sigma_j}, \quad \forall j \in \{1, \dots, 5\} \quad (13)$$

5.2. Multi-Horizon Temperature Forecasting (Random Forest Regressor)

Thermal stability is critical in closed-loop aquaponics. To forecast multi-step forward thermal trajectories ($\tau \in \{1h, 3h, 6h\}$), AquaMind-AI employs an ensemble Random Forest Regressor comprising $M = 100$ bootstrap-aggregated decision trees $\{T_m\}^M$; $m = 1, \dots, M$

The ensemble prediction $\hat{y}(t + \tau)$ is formulated as the mean prediction across all independent trees:

$$\hat{T}_{\text{water}}(t + \tau) = \frac{1}{M} \sum_{m=1}^M T_m(\mathbf{x}(t); \Theta_m) \quad (14)$$

where Θ_m denotes the structural split parameters, selected features, and leaf node values for tree m , optimized during training by minimizing the Mean Squared Error (MSE):

$$\mathcal{L}_{\text{MSE}} = \frac{1}{N} \sum_{i=1}^N (T_{\text{water}}^{(i)} - \hat{T}_{\text{water}}^{(i)})^2 \quad (15)$$

5.3. Unsupervised Multivariate Anomaly Detection (Isolation Forest)

Physical failures in aquaculture systems (such as air compressor membrane fatigue, pump cavitation, drain clogging, or biofilm accumulation on probes) often generate multivariate anomalies that do not immediately exceed static univariate threshold limits.

AquaMind-AI implements an unsupervised Isolation Forest model [6]. The algorithm isolates anomalous points by recursively generating random axis-aligned partitions across the

four-dimensional feature space $X \subset \mathbb{R}^4$ (spanning water temperature, water level, air temperature, and air humidity). Anomalous observations require significantly shorter traversal paths from root to leaf in an isolation tree (iTree).

The anomaly score $s(\mathbf{x}, n)$ across a dataset of n instances is formulated as:

$$s(\mathbf{x}, n) = 2^{-\frac{\mathbb{E}[h(\mathbf{x})]}{c(n)}} \quad (16)$$

where $h(\mathbf{x})$ is the path length (number of partition edges traversed), $\mathbb{E}[h(\mathbf{x})]$ is the expected path length across the 100-tree ensemble, and $c(n)$ is the average path length of unsuccessful searches in a Binary Search Tree (BST):

$$c(n) = 2 [\ln(n-1) + \gamma] - \frac{2(n-1)}{n} \quad (17)$$

Here, $\gamma \approx 0.5772156649$ (Euler-Mascheroni constant)

Instances yielding $s \rightarrow 1.0$ (score > 0.60) are flagged as multivariate anomalies (`is_anomaly = True`), triggering an immediate diagnostic alert.

5.4. Dynamic System Health and Risk Metrics

To provide operators with an intuitive, unified operational index, AquaMind-AI calculates a parametric Health Score ($S_{\text{health}} \in [0, 100]$) and a continuous Risk Score ($R_{\text{system}} \in [0, 100]$):

$$S_{\text{health}}(t) = \max \left(0, 100 - \sum_{j \in P} w_j I(v_j(t) \notin [\theta_{\min}, \theta_{\max}]) \right) \quad (18)$$

where $P = \{\text{water_temp}, \text{water_level}, \text{air_humidity}\}$, $W_{\text{water_temp}} = 25$, $W_{\text{water_level}} = 25$, $W_{\text{air_humidity}} = 10$, and $I(\cdot)$ is the binary indicator function.

Complementarily, the continuous Risk Score quantifies distance-to-threshold deviation:

$$R_{\text{system}}(t) = \min \left(100, 30|V| + 4 \sum_{v \in V} \delta(v) \right) \quad (19)$$

where V is the set of active sensor threshold violations, and $\delta(v)$ is the magnitude of parameter deviation beyond the safety boundary.

6. Experimental Evaluation, Verification, and Benchmarking

6.1. Operational Parameter Thresholds

Table 2 delineates the operational thresholds configured within AquaMind-AI for warm-water finfish (e.g., Tilapia) and hydroponic leafy greens (*Lactuca sativa*).

Table 2. Physicochemical operating ranges and critical threshold matrices.

Parameter	Hardware Sensor	Unit	Crit. Min	Norm. Min	Norm. Max	Crit. Max
Water Temperature	DS18B20 (Waterproof)	°C	18.0	22.0	30.0	35.0
Hydrostatic Level	HC-SR04 (Ultrasonic)	cm	20.0	40.0	110.0	130.0
Ambient Temperature	DHT11 / DHT22	°C	5.0	15.0	38.0	45.0
Relative Humidity	DHT11 / DHT22	%	20.0	40.0	85.0	95.0

6.2. Machine Learning Regression Performance

The predictive performance of the Random Forest temperature model was evaluated over a continuous 48-hour dataset sampled at 5-minute intervals ($N = 576$ samples), partitioned into 80% training and 20% out-of-sample test sets.

Table 3. Predictive regression metrics across forward temporal horizons.

Horizon (τ)	Coefficient of Determination (R^2)	MAE (°C)	RMSE (°C)	Inference Latency (ms)
$t + 1$ hour	0.942	0.18	0.24	3.2
$t + 3$ hours	0.891	0.32	0.41	3.4
$t + 6$ hours	0.854	0.47	0.58	3.5

As summarized in Table 3, the model maintains strong predictive fidelity across the 6-hour projection window ($R^2 = 0.854$, $RMSE = 0.58^\circ\text{C}$), providing adequate lead time for automated mitigation (such as activating supplementary aeration or shading) before thermal stress onset.

6.3. Comparative Framework Assessment

Table 4 contrasts AquaMind-AI with existing open-source and commercial aquaculture control systems.

Table 4. Functional benchmarking against existing aquaculture and hydroponic monitoring paradigms.

Feature / Capability	Traditional SCADA	Basic Arduino/IoT	Commercial Cloud	AquaMind-AI
Real-Time Telemetry	Yes	Yes	Yes	Yes (10s interval)
Open Hardware Compatibility	No (Proprietary)	Yes	No	Yes (Plug-and-play)
Horizon Trend Forecasting	No	No	Limited	Yes (Random Forest)
Multivariate Anomaly Isolation	No	No	No	Yes (Isolation Forest)
Autonomous Closed-Loop Control	Rules only	Threshold relay	Cloud-delayed	Yes (Edge & Asynchronous)
Deployment Capital Expenditure	Very High	Low	High (Recurring)	Ultra-Low (< \$60)

7. Regional Implications: Climate-Resilient Agriculture in the Caspian Basin

The South Caucasus and Caspian Basin—notably the arid and semi-arid plains of the Kura-Aras Lowland and Absheron Peninsula in Azerbaijan—experience pronounced climate challenges characterized by rising summer temperatures, high evapotranspiration, and soil salinization.

Conventional agriculture in these areas faces heavy distribution losses and acute seasonal water deficits [7], [8]. Integrating intelligent, recirculating aquaponics via AquaMind-AI offers three major regional benefits:

- **Water Resource Efficiency:** Closed-loop recirculation conserves over 90% of the aqueous medium, requiring freshwater additions only to replace crop transpiration and minimal evaporative losses.
- **Urban and Marginal-Land Food Security:** The system operates independently of soil quality, enabling food production on saline, semi-arid, or degraded land across the Absheron Peninsula, supporting localized production of high-value fish (e.g., Sturgeon, Carp, Tilapia) and vegetable crops.
- **Energy Resilience and Renewable Integration:** The lightweight, asynchronous computing architecture can be powered by off-grid solar PV and battery storage systems, maintaining operations during rural grid fluctuations.

8. Future Trajectories and Industrial Scaling Roadmap

The subsequent developmental phases of the AquaMind-AI platform will focus on three key technical areas:

1. **Multi-Parametric Optical Sensing:** Integrating optical dissolved oxygen (DO) and ion-selective electrode (ISE) arrays with automated drift-compensation algorithms to monitor real-time nitrate (NO_3^-) and ammonium (NH_4^+) ion dynamics.
2. **Edge-AI Computer Vision for Fish Ethology:** Implementing lightweight neural networks (YOLO-based architectures) on edge camera modules (e.g., ESP32-CAM, Raspberry Pi AI) to track swimming velocities, surface gathering behaviors, and feeding response indices.
3. **On-Device TinyML Deployment:** Quantizing Random Forest and Isolation Forest models for direct on-device inference on 32-bit ARM Cortex-M microcontrollers, ensuring continuous local autonomous control during external network outages.

9. Conclusion

This paper presented the comprehensive technical review, system architecture, and empirical validation of AquaMind-AI, an open-architecture cyber-physical platform for smart, climate-resilient aquaponics. By integrating low-cost edge sensors (DS18B20, HC-SR04, DHT11) and optocoupled actuator drivers with an asynchronous FastAPI microservice backend, ensemble Random Forest horizon forecasting, and unsupervised Isolation Forest anomaly detection, the platform provides robust protection against systemic failure modes in closed-loop polyculture systems. The system lowers the technical and economic barriers to smart aquaponics adoption, providing a practical tool for sustainable food production in water-stressed regions.

Author Contributions

Suleyman Hajizade: Conceptualization, Software Architecture, Machine Learning Modeling, Hardware Prototyping, Methodology, Writing – Original Draft, Visualization, Project Administration.

Conflict of Interest

The author(s) declare no conflicts of interest.

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