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IoT-Enabled Smart Aquaculture Monitoring System for Sustainable Freshwater Fish Farming in Telangana: A Field-Informed Framework

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ABSTRACT

Freshwater aquaculture yield depends on water quality, stocking practices, feeding management, and timely identification of environmental stress. Conventional sporadic measurements may not capture short-term fluctuations in dissolved oxygen, pH, temperature, and ammonia that affect fish health. This paper presents a field-informed Internet of Things (IoT) framework for freshwater aquaculture monitoring in Karimnagar district, Telangana, India. The system requirements were derived from a structured farm valuation reported for 15 ponds. The proposed architecture separates the sensing layer, communication layer, cloud-storage layer sensor-interface and edge-processing layer, analytics layer, and farmer-interface layer. The framework is designed to monitor dissolved oxygen, pH, temperature, total ammonia nitrogen, turbidity, and water level, while maintaining related records of stocking, disease observations, feeding, and harvest. Wi-Fi, cellular communication, or LoRa-based transmission can be selected based on the farm connectivity and deployment requirements. The methodology incorporates data-quality checks, threshold-based alerts, historical visualization, local buffering, and a authentication methodology based on reference-instrument comparison. The planned assessment methods include mean absolute error, root mean square error, packet-delivery ratio, data completeness, Bland–Altman agreement alert latency, and system availability. The involvement of this study is a regionally informed system architecture and an integrated data model linking environmental monitoring with farm-management information. This work provides a basis for prototype implementation and empirical evaluation under freshwater aquaculture conditions.

1. Introduction

Aquaculture is the fastest-growing food-production sector globally, contributing approximately 49% of total fish and shellfish consumed by humans [1]. In India, total fish production rose from 14.16 million tonnes in 2019–20 to an estimated 19.78 million tonnes in 2024–25—a 38% increase—driven largely by freshwater culture [2]. Telangana state has witnessed commensurate growth in pond-based freshwater farming, with rohu

(Labeo rohita), catla (Catla catla), and common carp (Cyprinus carpio) as principal species. Despite this expansion, farm productivity remains constrained by sub-optimal water-quality management, disease incidence, and limited access to real-time environmental data.

Water quality parameters, particularly dissolved oxygen (DO), pH, temperature, and un-ionized ammonia (NH_3-N), are primary determinants of fish health and growth rate [3]. DO is the most operationally critical variable: concentrations below 3 mg L^{-1} induce stress and feeding cessation, while values below 1 mg L^{-1} can cause mass mortality within hours [4]. Ammonia toxicity is species- and stage-dependent and must be interpreted as the fraction of un-ionized NH_3 calculated from total ammonia nitrogen (TAN), pH, and temperature [5]. Conventional management—periodic spot measurements and farmer experience—cannot detect rapid nocturnal DO depletion, post-feeding ammonia spikes, or sensor drift, all of which are common in intensively stocked ponds.

The Internet of Things (IoT) offers a pathway to continuous, automated, and remotely accessible monitoring. Recent work has validated multi-sensor IoT platforms for aquaculture water quality measurement, demonstrated dissolved-oxygen prediction using ensemble machine learning, and identified sensor maintenance and rural connectivity as persistent operational challenges [6–10]. However, most deployed systems focus on sensor data streams in isolation, without integrating farm-management events (stocking, feeding, disease, harvest) that are essential for productivity attribution and predictive modelling. Furthermore, published evidence from freshwater farms in peninsular India, particularly in Telangana and Andhra Pradesh, remains sparse.

This paper addresses these gaps with three primary contributions: (i) a field-informed IoT architecture derived from systematic assessment of 15 Karimnagar district farms; (ii) an integrated data model combining environmental sensor streams with farm-management records; and (iii) a detailed end-to-end validation protocol spanning bench calibration, laboratory comparison, and multi-site farm deployment. The framework is designed for practical deployment by resource-limited smallholder farmers, with emphasis on low-power operation, rural-grade connectivity, and an actionable alert interface.

2. Literature Review and Research Gap

The application of IoT to aquaculture water-quality monitoring has grown substantially over the past decade. Shete et al. [6] developed an IoT-enabled aquaculture monitoring method using Arduino-based boards with temperature, pH, and DO sensors, explicitly incorporating calibration protocols and cross-validation against manual measurements—establishing a methodological baseline for sensor accuracy assessment. A 2025 systematic review by Flores-Iwasaki et al. [7] analysed 217 Scopus-indexed studies (2020–2024) and found that pH, temperature, and DO are the most frequently monitored parameters, while sensor maintenance, power supply, and rural operability remain unresolved challenges across all deployment contexts.

Zuhaer et al. [8] demonstrated a comprehensive multi-parameter IoT system incorporating DO, ammonia, turbidity, pH, temperature, and TDS with an Android cloud interface for real-time remote access. Their system directly confirms the feasibility of integrating the parameter set proposed in the present study. Feng et al. [9] applied an ensemble machine-learning approach—combining gradient boosting and Random Forest—to IoT-acquired dissolved-oxygen time-series from commercial aquaculture, achieving RMSE values of 0.32–0.47 mg L^{-1} and demonstrating the viability of data-driven predictive modelling from continuous sensor streams. Baena-Navarro et al. [10] further integrated IoT sensing with ML models including Random Forest (R^2 = 0.999, RMSE = 0.0998 mg L^{-1}) and the Quantum Approximate Optimization Algorithm for water-quality prediction in aquaculture, illustrating the trajectory toward intelligent, closed-loop management systems.

At the edge-computing frontier, a recent study deployed Multiple Linear Regression and Random Forest models directly on ESP32 microcontrollers for real-time DO and pH prediction in tilapia aquaculture [11], demonstrating that meaningful analytics can execute without continuous cloud dependency—a critical design requirement for farms with intermittent connectivity. Parallel advances include LoRaWAN-based long-range sensor networks for rural aquaculture [12], low-cost pH sensors with temperature compensation and electronic calibration [13], and LSTM-based hypoxia prediction systems that provide early warning of critical DO depletion [14].[19][20] illustrates an IoT acquisition-to-cloud-to-alert pipeline in a different application domain; your contribution is its adaptation to aquaculture monitoring and integration with farm-management records.

For India specifically, the Quantum LSTM framework of Arepalli and Naik [15] for DO monitoring in Andhra Pradesh ponds represents the most geographically proximate prior work, yet it focuses on a single parameter and lacks integration of farm-management data. Biazi and Marques [16] provided a comprehensive Industry 4.0 review of smart systems in aquaculture, confirming that full integration of production management data with environmental sensing—enabling productivity attribution and harvest prediction—remains an open problem.

2.1 Identified Research Gaps

A synthesis of the literature reveals four specific gaps that the present work addresses:

Gap 1 – Regional evidence: No peer-reviewed IoT aquaculture study has been grounded in a structured farm assessment from Telangana or the Karimnagar district specifically, leaving local species–parameter–management context unaddressed.

Gap 2 – Integrated data model: Existing systems capture environmental parameters but omit co-synchronised farm-management records (stocking density, feed quantity, disease events, harvest weights), which are essential for yield attribution and predictive modelling.

Gap 3 – End-to-end validation: Few studies specify a complete validation protocol from bench sensor calibration through reference-instrument comparison, communication-reliability testing, and multi-farm operational evaluation.

Gap 4 – Farmer-centric actionability: Most deployed platforms remain research prototypes without explicit attention to usability, technology acceptance, and alert design for low-literacy or technology-naïve farmer users.

The literature review identifies four research gaps. The relationship between each research gap, the proposed methodological response, and the evidence required to validate the contribution is summarized in Table 1. The role of the present study is therefore threefold: (i) derivation of monitoring requirements from a regional farm assessment; (ii) requirement of an architecture that integrates water-quality observations with production-management records; and (iii) definition of a reproducible validation mechanism for evaluating sensor accuracy, communication reliability, and farmer-oriented functionality.

Table 1. Research Gap Analysis

Research gap	Methodological response	Evidence required
Gap 1: Limited region-specific evidence from Telangana freshwater aquaculture	Conduct a structured assessment of farm characteristics, management practices, water-quality observations, and yield	Verified farm-level survey records, sampling dates, pond count, and descriptive statistics
Gap 2: Limited integration of environmental readings with farm-management records	Develop a common data model linking sensor observations with stocking, feeding, disease, and harvest records	Database schema, sample records, and evidence that records can be linked by farm and pond identifiers
Gap 3: Incomplete end-to-end validation procedures	Define sensor calibration, reference comparison, communication testing, data-quality assessment, and field evaluation procedures	Calibration records, paired sensor/reference readings, communication logs, and test results
Gap 4: Limited farmer-oriented monitoring and actionability	Design a mobile-accessible interface with understandable alerts, trend displays, and farm-record entry	Interface screenshots, alert tests, and farmer usability feedback, when collected

3. Research Objectives

The specific objectives of this research are:

O1. To conduct a structured field assessment of water-quality constraints, management practices, and technology readiness across freshwater aquaculture farms in Karimnagar district, Telangana.

O2. To derive sensor and system requirements directly from field evidence and to specify a six-layer IoT architecture suited to the regional deployment context.

O3. To design an integrated data model that co-acquires environmental sensor streams and farm-management records for subsequent productivity analysis.

O4. To develop and bench-validate a multi-sensor prototype incorporating DO, pH, temperature, ammonia, turbidity, and water-level sensors with ESP32 edge processing and multi-modal wireless communication.

O5. To specify and execute an end-to-end validation protocol covering sensor accuracy, system reliability, alert latency, and farmer-response metrics across pilot farm deployments.

O6. To establish the structured dataset and analytical pipeline necessary for future predictive modelling using Random Forest, Support Vector Regression, and LSTM approaches.

4. Proposed System Architecture

The proposed system consists of six functional layers. The separation of the sensing layer from the edge/controller layer distinguishes physical measurement from signal acquisition, processing, and communication.

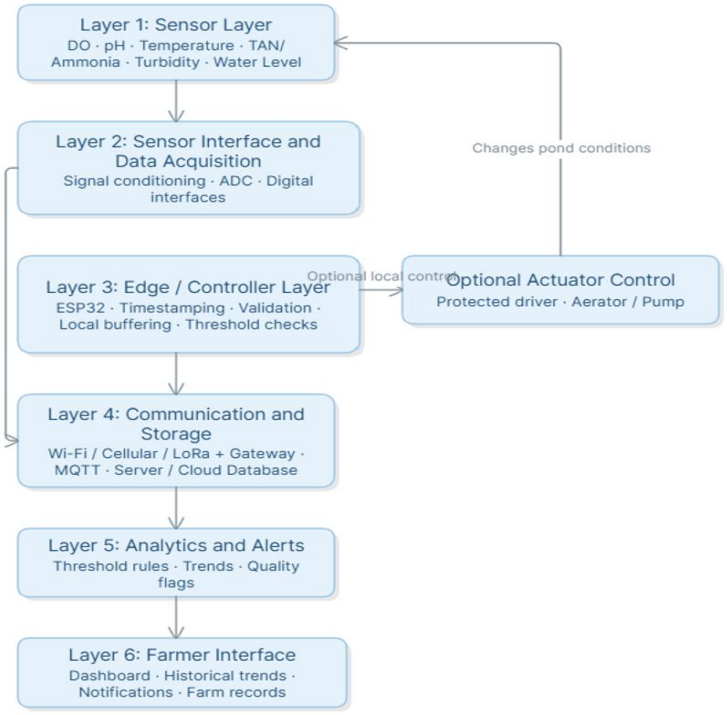


Fig. 1. Proposed System Architecture

4.1 Layer 1 – Sensor layer

Submersible sensors deployed at fixed depths within each pond continuously measure six parameters: DO (electrochemical Clark cell or optical fluorescence), pH (solid-state ion-selective electrode with temperature compensation), water temperature (thermistor or PT100), total ammonia nitrogen (ion-selective electrode, with pH/temperature correction for un-ionized NH_3 fraction per Boyd and Tucker [5]), turbidity (optical nephelometric), and water level (ultrasonic or pressure transducer). Sensor selection criteria include measurement range, accuracy, IP68 waterproofing, response time, calibration interval, power draw, and regional field availability.

4.2 Layer 2 – Sensor interface and data acquisition

Analogue signals from sensors are conditioned via low-pass filtering and amplification before analogue-to-digital conversion. Digital sensors communicate via I^2C, SPI, or UART. This layer performs initial range checking to flag implausible values (e.g., DO > 20 mg L^{-1}, pH < 4 or > 11) before transmission, reducing spurious cloud writes and alert false-positives.

4.3 Layer 3 – Edge /Controller layer

An ESP32-class microcontroller (dual-core Xtensa LX6, 240 MHz, 520 KB SRAM) serves as the edge node. It executes local data validation, applies species- and stage-specific threshold logic for immediate pump or aerator actuation, packages data records per the defined schema, and manages communication. Firmware supports over-the-air (OTA) updates and local micro-SD card buffering to prevent data loss during connectivity outages—an essential feature for rural deployments where network availability may be intermittent.

4.4 Layer 4 – Communication and Storage

Communication mode is selected based on farm location and infrastructure: Wi-Fi (802.11 b/g/n) for farms with router access; 4G LTE (SIM800/SIM7600 modem) as primary or fallback for farms with cellular coverage; LoRa/LoRaWAN at 865–867 MHz (Indian sub-GHz ISM band) for remote farms with poor cellular signals, providing range of 2–15 km at low data rates. MQTT over TLS is used as the messaging protocol, with AWS IoT Core, Azure IoT Hub, or an open-source broker (Mosquito) as the cloud endpoint. Time-series data are stored in an InfluxDB instance with Grafana for visualisation, or an equivalent open-source stack.

4.5 Layer 5 – Analytics and Alerts

The analytics layer performs three functions in increasing order of sophistication: (i) static threshold comparison with species- and life-stage-specific limits for real-time alerts; (ii) trend detection using rolling-window statistical tests to identify deteriorating conditions before thresholds are breached; and (iii) predictive modelling using Random Forest and LSTM models trained on accumulated longitudinal data to forecast DO, pH, and ammonia 30–120 minutes ahead. Alert severity levels are defined as: Advisory (parameter approaching limit), Warning (limit crossed), Critical (acute risk to fish), and Sensor Fault / Communication Failure (data integrity compromised).

4.6 Layer 6 – Farmer Interface

The farmer-facing application is delivered as a mobile-optimised web dashboard (responsive HTML5/Progressive Web App) accessible on Android smartphones—the dominant device type among Telangana smallholder farmers. The interface presents: current parameter values with colour-coded status indicators; 24-hour, 7-day, and 30-day trend charts; alert notifications via push message and SMS fallback; and entry forms for farm-management records (stocking date and density, daily feed quantity, disease or mortality observations, harvest weight). The dual capture of sensor and management data is the architectural innovation that distinguishes this framework from single-stream monitoring systems.

5. Field Assessment and System Requirements Derivation

5.1 Assessment Methodology

A structured farm assessment was conducted across 15 freshwater aquaculture farms in Karimnagar district, Telangana, using a pre-tested questionnaire administered in person. Data collected included farm coordinates, pond area, water source, stocking species and density, feed type and quantity, observed disease incidents, mortality rates, current technology use, culture duration, and harvest yields. Water samples were collected from each pond and analysed for DO, pH, temperature, TAN, and turbidity using calibrated portable instruments (YSI Pro30 and Hanna HI9829). The assessment was approved by the institutional review process and farmer consent was obtained in the local language (Telugu).

5.2 Key Findings

Table 2 summarises the baseline descriptive statistics from the 15-farm assessment dataset. Mean pond area was 1.86 ± 0.63 acres, stocking density 4,440 ± 606 fish acre^{-1}, and observed yield 2,457 ± 408 kg acre^{-1}. Mean DO was 5.14 ± 0.82 mg L^{-1}, which, while above the acute stress threshold, indicates that morning minima—not captured by the midday assessment—may routinely reach critical levels. Mean TAN was 0.07 ± 0.04 mg L^{-1}; at mean pH 7.63 and typical summer temperatures (28–34°C), this corresponds to un-ionized NH_3 fractions approaching 0.08–0.15 mg L^{-1}, near the chronic toxicity threshold for catla and rohu [5].

Table 2. Baseline descriptive statistics from farm assessment (n = 15 ponds, Karimnagar district).

Parameter	Mean	SD	Min	Max
Pond area (acres)	1.86	0.63	0.75	3.20
Stocking density (fish acre^{-1})	4,440	606	3,000	5,500
Water temperature (°C)	29.4	2.1	26.1	33.8
pH	7.63	0.35	7.05	8.32
Dissolved Oxygen (mg L^{-1})	5.14	0.82	3.80	6.90
TAN (mg L^{-1})	0.07	0.04	0.02	0.18
Turbidity (NTU)	28.3	11.6	9.5	58.2

Yield (kg acre^{-1})	2,457	408	1,680	3,290

Key constraints identified through farmer interviews included: absence of aeration timers (12 of 15 farms); reactive rather than preventive disease management (11 of 15); and no digital record-keeping (15 of 15). Only 3 farms owned portable DO meters. These findings directly justify continuous automated monitoring and structured digital record capture as the primary system requirements.

5.3 Technical Requirements

From the field evidence, the following primary system requirements were derived: (R1) DO measurement range 0–20 mg L^{-1}, accuracy ±0.2 mg L^{-1}, sampling interval ≤5 min; (R2) pH range 0–14, accuracy ±0.1 pH, with temperature compensation; (R3) temperature range 5–50°C, accuracy ±0.3°C; (R4) TAN range 0–5 mg L^{-1}, with on-device correction for un-ionized NH_3; (R5) turbidity range 0–1000 NTU; (R6) data transmission interval 5–15 min; (R7) alert delivery latency <2 min from threshold breach; (R8) system uptime >95%; (R9) data completeness >98% per 24-hour period; (R10) battery autonomy ≥48 h with solar charging; (R11) IP68 enclosure for all submerged components; and (R12) farmer dashboard operable on a 4G Android handset.

6. Hardware Design and Sensor Specification

Table 3 lists the selected sensor modules with their operational specifications aligned to the requirements in Section 5.3. Sensor selection prioritised accuracy, calibration interval, and regional availability through authorised Indian distributors.

Table 3. Sensor specifications for the prototype system.

Parameter	Sensor / Module	Range	Accuracy	Calibration Interval	Interface
Dissolved Oxygen	Atlas Scientific DO EZO or optical fluorescence probe	0–20 mg L^{-1}	±0.05 mg L^{-1}	Monthly check / annual replacement	UART / I^2C
pH	Atlas Scientific pH EZO + low-cost ISE or ISFET with temp comp.	0–14	±0.002 pH	2-point buffer, monthly	UART / I^2C
Temperature	DS18B20 waterproof (±0.5°C) or PT100 RTD	–55 to +85°C	±0.3°C	Annual	1-Wire / Analogue
TAN / Ammonia	Ion-selective electrode (ISE) or colorimetric mini-analyser	0–5 mg L^{-1}	±0.1 mg L^{-1}	Weekly electrode conditioning	Analogue / UART
Turbidity	DFRobot Gravity turbidity (NTU) or Hach 2100P OTU	0–1000 NTU	±5% FS	Formazin standard, monthly	Analogue
Water Level	Ultrasonic (JSN-SR04T) or submersible pressure transducer	0–4 m	±1 cm	Annual	Analogue / Serial

The edge controller board integrates the ESP32 module with a real-time clock (DS3231 RTC) for accurate timestamping, micro-SD card slot for local data buffering, solar charge controller (MPPT, 10 A), and switchable 4G/LoRa communication modules. All electronics are housed in a IP65-rated fibreglass enclosure mounted on the pond bund, with sensor probes on armoured cables to the pond interior.

7. Data Acquisition, Quality Control, and Alert Specification

7.1 Experimental Setup and Instrumentation

The projected experimental setup consists of a multi-parameter water-quality sensing unit, an edge controller, a communication interface and a cloud-based monitoring dashboard. The parameters considered for monitoring are dissolved oxygen (DO), total ammonia nitrogen (TAN) pH, water temperature, and water level. Turbidity may be included as an additional parameter where appropriate instrumentation is available.

The sensing unit interfaces with the edge controller, which records timestamped measurements, checks data validity and transfers the observations to the monitoring platform using the selected communication

protocol. The recording of the pond identifier, sensor identifier, timestamp, measured value, measurement unit and sensor-status information is carried out by data acquisition procedure.

Each sensor must be calibrated according to the manufacturer's instructions and checked against an appropriate reference instrument. The experimental record should document the sensor model, measurement range, sampling interval, transmission interval, stated accuracy, calibration procedure, reference instrument, monitoring duration and pond conditions.

Finally, the experimental configuration and its performance must be reported using the hardware and measurements actually used.

Each transmitted record includes the fields: FarmID, PondID, SensorNodeID, Timestamp (ISO 8601 UTC), ParameterCode, Value, Unit, QualityFlag, SensorStatus, BatteryVoltage, SignalStrength, and AcquisitionMode (live / buffered). The QualityFlag field encodes: 0 = valid, 1 = out-of-range, 2 = sensor disconnected, 3 = sudden unrealistic step change (>3σ from 5-point rolling mean), 4 = calibration overdue.

7.2 Farm Management Records

Farm events are entered through the dashboard interface: StockingRecord (date, species, quantity, source pond, estimated weight), FeedRecord (date, feed type, quantity kg, method), DiseaseRecord (date, symptoms, pond area affected, veterinary action), HarvestRecord (date, species, weight kg, mean individual weight, destination). These records share FarmID and PondID keys, enabling time-aligned joining with sensor streams for productivity analysis.

7.3 Alert Thresholds

Table 4 specifies operational alert thresholds for Indian major carps at the post-fingerling production stage, based on Boyd and Tucker [5] and FAO guidelines [3,4]. Un-ionized NH_3 is computed on-device from measured TAN, pH, and temperature using the equilibrium formula of Emerson et al. [5], ensuring species-relevant toxicity assessment rather than relying on TAN alone.

Table 4. Alert threshold specification for Indian major carps (Labeo rohita, Catla catla, Cyprinus carpio) – production stage.

Parameter	Advisory (approach)	Warning (threshold breached)	Critical (acute risk)
DO (mg L^{-1})	< 5.0	< 3.5	< 1.5
pH	< 6.5 or > 9.0	< 6.0 or > 9.5	< 5.5 or > 10.0
Temperature (°C)	> 33 or < 18	> 35 or < 15	> 38 or < 12
Un-ionized NH_3 (mg L^{-1})	> 0.05	> 0.10	> 0.20
Turbidity (NTU)	> 150	> 250	> 400
Water Level	> 10% drop / 24 h	> 20% drop / 24 h	> 30% drop / 24 h

8. Validation Protocol

8.1 Phase 1 – 8.1 Sensor Accuracy and Agreement Metrics

The accuracy of the sensors is evaluated by comparing each IoT sensor measurement with a corresponding measurement obtained using a calibrated reference instrument under comparable conditions. Let (x_i) represent the reference measurement and (y_i) represent the IoT sensor measurement for the ith paired observation, with (n) denoting the number of valid pairs.

The mean absolute error (MAE) quantifies the average absolute difference between sensor and reference readings:

$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - x_i|$

The root mean square error (RMSE) quantifies the magnitude of measurement errors while assigning greater weight to larger deviations:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - x_i)^2}$$

The mean bias is calculated to assess systematic overestimation or underestimation:

$$Bias = \frac{1}{n}\sum_{i=1}^{n}(y_i - x_i)$$

Bland–Altman analysis is used to assess agreement between the two measurement methods. The mean difference and the limits of agreement, calculated as the mean difference plus or minus 1.96 times the standard deviation of the paired differences, will be reported where the assumptions and sample size support interpretation. These metrics require paired observations from the IoT sensors and reference instruments.

8.2 Phase 2 – Communication and System Performance Metrics

The communication system is evaluated using packet delivery ratio (PDR), data completeness, end-to-end transmission latency, alert latency and system availability. The power consumption will also be measured where the instrumentation permits reliable recording.

PDR is calculated as the percentage of transmitted data packets successfully received by the monitoring platform. Data completeness will be calculated as the proportion of expected measurement records successfully stored. Alert latency will be measured as the time between detection of a threshold violation and generation or delivery of the corresponding alert, with the measurement endpoints clearly specified.

This evaluation documents the test duration, expected sampling and transmission frequency, network interruptions, missing records, number of packets transmitted and received, alert events and power measurements. Numerical performance results will be reported only from system logs collected during actual testing.

8.3 Phase 3 – Farm Deployment and Farmer Evaluation

The validated prototype is deployed on 3–4 pilot farms representing variation in pond size (0.5–3.5 acres), species composition, stocking density, and water source (canal, borewell, rain-fed). Farm-level metrics monitored over the deployment period (minimum 60 days) include: DO exceedance frequency and duration; system uptime and DCR; sensor fouling rate and calibration drift; farmer alert-response time (time from alert notification to corrective action); and management record completeness. User acceptance is assessed using the Technology Acceptance Model (TAM) questionnaire in Telugu, covering perceived usefulness, ease of use, and intention to continue use. A structured interview explores barriers to adoption and feature-improvement requirements.

8.4 Phase 4 – Productivity Association Analysis

After sufficient longitudinal data are collected (target ≥3 complete production cycles per farm), Spearman rank correlations and multiple linear regression will be used to test associations between DO time-under-threshold, temperature exceedance events, ammonia exposure episodes, and observed yield (kg acre^{-1}).

9. Limitations and Future Work

The present study has the following acknowledged limitations. First, the pilot scale (3–4 farms) limits the statistical power of farm-level evaluation; generalisation to the broader Telangana freshwater farming population requires expanded multi-season deployment. Second, ammonia measurement via ion-selective electrode requires more frequent maintenance than optical sensors and may exhibit drift in turbid pond water; a comparative evaluation of ammonia measurement technologies is warranted. Third, communication reliability in highly rural areas with no cellular coverage requires LoRa gateway infrastructure that may not be farmer-deployable independently. Fourth, power supply stability during monsoon cloud cover represents a recognised constraint for solar-dependent systems in peninsular India.

Future work will: (i) expand deployment to ≥15 farms across at least three districts of Telangana for representativeness; (ii) investigate edge-AI implementations of Random Forest and linear regression on ESP32 for offline DO and pH prediction following the approach of [11]; (iii) develop LSTM models for 30–120 min ahead DO forecasting when sufficient longitudinal data (≥2 full production cycles per farm) are available; (iv) conduct formal usability and technology acceptance evaluation using validated TAM instruments in Telugu; and (v) explore integration with government fisheries databases for district-level production benchmarking.

10. Conclusion

This paper has presented a field-informed, six-layer IoT framework for real-time water quality monitoring and farm management data capture in freshwater aquaculture systems of Telangana, India. The framework

was designed from structured evidence gathered across 15 farms in Karimnagar district, ensuring that the system architecture directly addresses documented regional constraints rather than adapting generic prototypes. The proposed system advances the state of practice in three principal respects: the co-acquisition of environmental sensor streams and farm-management records in a single integrated data model; explicit specification of un-ionized ammonia computation from TAN, pH, and temperature for species-relevant toxicity alerting; and a four-phase validation protocol that encompasses bench calibration, reference-instrument comparison, system reliability testing, and farmer-response evaluation. The evidence base assembled through the field assessment confirms that the absence of continuous DO monitoring, the lack of structured record-keeping, and reactive disease management are primary constraints limiting productivity in Karimnagar district farms. The proposed framework, once validated at pilot scale and expanded to multi-season multi-farm deployment, has the potential to enable the data-driven aquaculture management that has been identified as a national priority under the Pradhan Mantri Matsya Sampada Yojana. The structured longitudinal dataset generated by the system will provide the empirical foundation for subsequent predictive modelling dissolved-oxygen forecasting, yield prediction, and early disease detection that represents the next frontier of smart aquaculture research in India.

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