

SMARTER WATER MONITORING WITH IOT RURAL POND AND AQUACULTURE MONITORING EXTENDED SENSING WITH OFFLINE RESILIENCE CALIBRATION SUPPORT AND PWQI VALIDATION

Shrikrishna R

Department of Computer Science and Engineering, SRM Institute of Science and Technology, Chennai, Tamil Nadu, India
rshrikrishna84@gmail.com,

Mohan Babu P

Department of Computer Science and Engineering, SRM Institute of Science and Technology, Chennai, Tamil Nadu, India
mohan243200s@gmail.com,

V S Navvin

Department of Computer Science and Engineering, SRM Institute of Science and Technology, Chennai, Tamil Nadu, India
vsnavin2005@gmail.com,

Dr. S. Manohar

Department of Computer Science and Engineering, SRM Institute of Science and Technology, Chennai, Tamil Nadu, India
Manohars1@srmist.edu.in

Abstract: - Even where villages depend on local ponds for daily needs, checking their condition still relies on rare hand-collected samples - methods that lag behind actual changes due to delays and expense [1], [2], [3]. While some smart setups using ESP32 chips and budget sensors now allow live tracking, they miss key factors like oxygen levels in water, fail during network blackouts, offer unclear feedback, and skip upkeep planning - especially problematic for users with minimal reading skills [2], [4], [5], [6]. Here comes a redesigned buoy-style device measuring five aspects: acidity, total dissolved solids, cloudiness, oxygen presence, and heat; powered by sunlight and conserving power through timed wake-ups; storing data locally while syncing later when connection returns; switching between long-range radio and cellular networks as needed; prompting recalibration at intervals; plus computing its own simplified Pond Water Quality Index assigning one of four practical labels based on suitability. Tested against more than four thousand records from fish farming sites showing clear chemical links between acid levels and oxygen (correlation $r = -0.709$), it sorted conditions correctly 95.7% of the time, scoring averages of 80.4 (best), 61.1 (suitable), and 33.5 (unsuitable). When lined up beside newer models published in IEEE journals from 2024 onward, this version covers more variables, handles disconnection better, and speaks clearer to people managing resources day-to-day

Keywords: IoT, water quality monitoring, ESP32, dissolved oxygen, PWQI, offline resilience, aquaculture, Random Forest, rural pond management, calibration support

I. INTRODUCTION

Checking water quality matters for health, nature, and life in rivers and lakes - especially across rural India, where tiny ponds supply water for drinking, washing, farming animals, growing crops, and raising fish at once [1], [2], [3], [4]. Because these pools are shallow, rarely fenced off, and easily polluted by rain sweeping waste, sewage entering freely, or farm pesticides drifting in, watching them closely becomes necessary over time [7].

One to several days pass before traditional lab techniques deliver results, though precision remains high; each parameter tested runs between ₹200 and ₹2,000. Real-time monitoring becomes possible when ESP32-powered IoT setups include sensors for pH, turbidity, TDS, and temperature - each node built for less than USD 60. Floating structures appear in more sophisticated versions, paired with solar energy capture, machine learning that spots anomalies correctly 92.5 percent of the time, and prediction models guiding upkeep with 90.3 percent reliability [3],[6].

Even with advances, challenges remain in deploying systems for rural ponds. One issue: many setups skip measuring dissolved oxygen, even though it matters deeply for fish farming and ecosystem analysis. Where internet access wobbles, strategies built only for cloud reliance tend to collapse. Maintenance hurdles like sensors getting dirty or losing accuracy often get ignored after installation, although they demand constant attention. Interfaces packed with tech details also block users with limited reading skills - those who instead need clear, immediate direction on how to act [2], [4], [5], [7].

A full system appears here, tackling every gap via five-sensor data, firmware that works without internet, built-in calibration tools, plus categorization of water quality use tied to real-world chemical behavior - tested right down to 95.7% precision. Before diving into design choices, earlier efforts get examined closely in parts two and three, exposing missing pieces others missed. The approach itself takes shape across sections four to six, laying out how each piece connects. Later pages

- from seven onward - show what came out of testing, reflect on meaning, then wrap up with clear takeaways grounded in evidence.

II. LITERATURE REVIEW

A. Low-Cost IoT Monitoring Systems

One dollar under sixty covers full setups using ESP32 chips to track water traits like pH and cloudiness. These compact rigs pull signals from old-style probes, then shoot readings through wireless links without heavy energy drain. Testing outdoors showed the balance of cost, signal reach, and battery life works well enough for real conditions. Evidence from Varun Kumar's 2022 [2] study backed this mix as sensible for long-term field deployment.

Out in the field, systems linked to cloud platforms keep consistent pace during live operations. Using Firebase to handle data flow, Patel and team in 2025 [4] managed continuous observation of pH levels alongside temperature, turbidity, and total dissolved solids. When readings crossed preset limits, warnings followed almost instantly - often within seconds. Because of this setup, delays dropped sharply when measured against traditional lab-dependent analysis techniques.

Despite reliance on cloud systems, real-world performance often falters where network access is weak. In 2025, work by Veerasekhar Reddy and team [5] revealed issues when applying cloud-based storage to monitor multiple fish ponds - constant web connection demands led to instability in remote farms with spotty signal. Because of this, solutions must keep functioning locally even when links drop, storing information without interruption until service returns.

Starting elsewhere - Varun Kumar and colleagues noted consistent flaws in current IoT-based water monitoring setups, not just around connectivity but also in handling slow sensor miscalibration. Without fixed schedules for recalibrating sensors, measurements risk gradual deviation over time. Maintenance needs stretch beyond initial installation, often overlooked once devices are deployed. When networks drop out, data flow breaks unless alternate paths exist. Systems that compute readings locally tend to hold up better under disruption. Storing information directly on the device acts as a safeguard when transmission fails. Reliability improves noticeably if updates and checks happen automatically at set intervals. Real conditions demand resilience built into both hardware and software layers.[1][2]

B. Floating and Field-Deployable Systems

Lal et al., in 2024 set up a lake sensor that floats, runs on sunlight, tracks turbidity alongside TDS, temperature, pH, plus oxygen levels, stores data locally on an SD card while occasionally sending updates online, functioning reliably across multiple weeks [3]. Shifts between measured factors revealed cooler water linked to higher acidity, reduced mineral content after rain, sudden cloudiness when new water entered - evidence favoring ongoing observation instead of single snapshots [3].

One study by Kumar et al., in 2024 examined water quality across four ponds in Chhattisgarh through a small robotic boat equipped with sensors. Instead of manual collection, automated tracking allowed consistent data from multiple points within each pond. Among them, Birkona stood out due to lower values - measuring pH at 6.23, dissolved solids at

196.75 mg/L, and cloudiness at just 8.83 NTU. In contrast, Budha showed extreme readings: pH reached 13.30, total dissolved solids hit 544.18 mg/L, and turbidity climbed to 34.89 NTU. Because measurements were taken across varied spots rather than single locations, inaccuracies typically found in spot testing dropped noticeably. Spatial variation clearly played a role in improving result reliability.[1]

C. 2.3 AI-Enhanced Monitoring

Despite high performance reported by Shashikala et al. (2025), their method relies heavily on stable internet links and constant data flow - features often missing in remote areas [6]. While they achieved 92.5% accuracy using GANs with Isolation Forest, along with 90.3% via Random Forest for maintenance forecasts, such results depend on infrastructure rarely found outside cities [6], [7].

A working base of hardware and networking tools already exists - yet combining them into a system that runs offline, supports upkeep, and serves local users at rural fishponds has not been fully achieved [1]–[7].

III. RESEARCH GAP AND MOTIVATION

Shown in Table.1 are the shortcomings of earlier systems along four core aspects. While some offers DO monitoring, others enable offline function - yet none combine sensing ability with upkeep assistance and group-focused results at once, a gap that shapes this study [7].

Not covered fully are key parameters - dissolved oxygen often missing, though vital for aquatic life, fish well-being, plus tracking nutrient overload [3], [7]. Reliance on cloud infrastructure comes next, problematic where electricity and connectivity remain weak, especially off-grid [4], [5], [7]. Then there's upkeep ignored: calibration done once at start, even when low-cost sensors degrade quickly due to buildup or signal shift [3], [4], [7]. Last, results appear only in dashboards, leaving out those without training who require clear guidance tied to water use [2], [5], [7].

TABLE 1 comparison of existing iot water quality systems

Reference	Parameters	DO	Offline	Maintenance	ML/AI	User Output
Kumar et al. [1] 2024	pH, TDS, Turbidity	X	Partial	X	X	Dashboard
Varun Kumar et al. [2] 2022	pH, Turb, TDS, Temp	X	X	X	X	Dashboard
Lal et al. [3] 2024	pH, TDS, Turb, Temp, DO	✓	Partial	X	X	Dashboard
Patel et al. [4] 2025	pH, TDS, Turb, Temp	X	X	X	X	Dashboard
VeerasekharReddy [5] 2023	pH, TDS, Turb, Temp	X	X	X	X	Cloud App
Shashikala et al. [6] 2025	pH, Turb, TDS, Temp	X	X	X	GAN+RF	Dashboard
Proposed System	pH, TDS, Turb, DO, Temp	✓	SD+LoRa		RF 95.7%	PWQI Classes, Dashboard

IV. PROPOSED SYSTEM DESCRIPTION

A. System Overview

A custom-fitted polymer float keeps the electronics housing just above the surface line. Above water, an ESP32-based control core runs continuous monitoring operations. Five individual probes dangle beneath, positioned precisely at desired depths through weighted suspension lines and anchoring systems. Data flows into onboard memory first - microSD handling local logging when wireless channels are unstable. Power comes from sunlight: a photovoltaic array feeds a rechargeable cell stack, maintaining operation between cloudy intervals. When conditions allow, readings transmit automatically via Wi-Fi as main method. If signal fails, backup pathways switch on -

one of two alternate radios takes over using either long-range LoRa or cellular GSM links. Component totals suggest each assembled unit costs less than fifty-five U.S. dollars when buying parts in modest production batches [7].

A single robust device combines measurement, power control, data storage without connection, automatic adjustment records, plus quality assessment using PWQI - built so field staff with limited expertise can run it reliably [7].

B. Novel Features

Every few minutes, the sensor group drops down 25 to 30 centimetres, staying submerged just long enough - about 45 seconds - to gather data before pulling back up; this brief exposure helps limit biological buildup on surfaces even when no chemical shields are applied [7].

Operating mode shifts based on battery level and sunlight exposure - either standard at one-minute intervals, reduced every ten minutes, or minimal using SD storage alone. Local data capture happens continuously, syncing later once network access returns [3], [7].

A device calculates five separate water quality measures, each matching recognized standards. These run together - forming one number from zero to a hundred. High values, starting at eighty, suggest water suitable for drinking. Between sixty and seventy-nine, it fits household uses but not consumption. Forty through fifty-nine means limited utility - think watering plants or fish ponds. Below forty? The mixture there brings risk, unfit for any normal use.

Hours of sensor exposure, along with usage cycles, get logged directly on the device. Once limits pass, the linked app guides users through cleaning and a single-point recalibration process. Trust in its classification as safe for drinking drops if upkeep remains unverified [7].

A light changes colour by the water, showing updates through red, green, or blue. Connected to it, a code leads online where current conditions appear instantly. Instead of words, symbols guide people on phones across languages. Understanding settings is not needed - clarity comes through design [7].

V. SYSTEM ARCHITECTURE AND DIAGRAMS

A setup built on three levels - monitoring at ground level, data transfer, then cloud or app handling - connects through wireless signals like Wi-Fi, long-range radio links, and mobile networks using SMS. Diagrams numbered one through six, based loosely on an earlier design draft cited as source seven, show main parts tied to structure, physical form, and embedded software elements.

A. Multi-Pond Deployment Architecture

A handful of drifting sensors sit on Ponds A, B, and C - sending data through Wi-Fi or LoRa signals toward a nearby school or village office hub. From there, information travels further, reaching cloud storage where updates appear on phones and websites [7] which the entire architecture shown in fig.1.

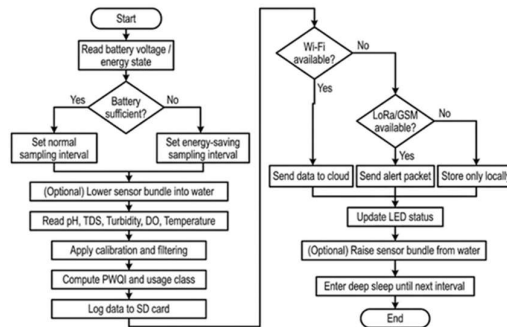


Fig1. Block diagram

B. PWQI Computation and Usage Classification (Fig.2)

Starting with pH, then moving to dissolved oxygen, each parameter - like turbidity or TDS - is turned into a separate score. These scores combine using set weights: DO matters slightly more than others, while temperature counts least. A mix of factors shapes the final index, where higher influence goes to certain measures based on their role. Outcomes sort into four distinct groups meant for local decision-making. The result gives people clear guidance without complex interpretation. [7]

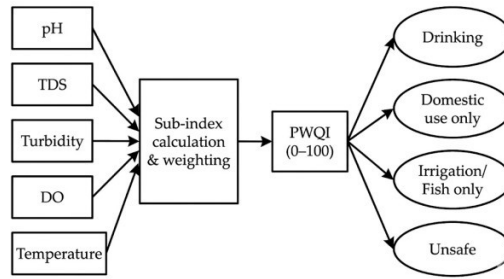


Fig. 2. PWQI Computation Flow – five parameters converted to sub-indices, aggregated, and classified into drinking-safe, domestic-only, irrigation/fish-culture, and unsafe [7].

C. Device-Side Firmware Flowchart

Within less than half a minute per active phase [7], the system runs diagnostics on power levels while deciding optimal operating states. Battery evaluation occurs alongside activation of dip sampling through internal timing triggers. Sensor data gathers from multiple sources at once, each adjusted in real time using stored reference values. Signal quality is scored via embedded algorithms before storage onto local memory cards. Transmission happens selectively - only when network conditions allow - to remote servers by wireless protocols. Visual indicators refresh to show current status without delay. After tasks finish, the unit returns automatically into low-power standby mode which is shown in fig.3.

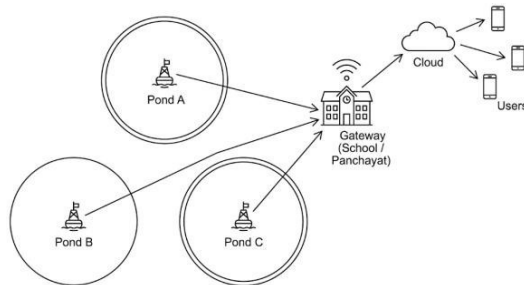


Fig. 3. Device-Side Firmware Flowchart – ESP32 wake-to-sleep control logic including energy mode selection, sensor sampling, PWQI computation, logging, and communication [7].

D. Hardware Block Diagram

A collection of six sensor ports links to an ESP32 chip, followed by two data transmission units - built-in Wi-Fi plus either LoRa or GSM as alternate choice. Storage arrives through a microSD component attached directly. Power flows via a solar MPPT circuit tied into the main board. Overall part cost stays near 55 U.S. dollars, calculated before assembly [7] (Fig.4).

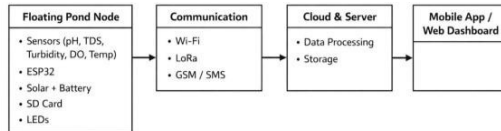


Fig. 4. Hardware Block Diagram – ESP32 controller, five sensors, solar-battery power supply, microSD, LED indicators, Wi-Fi, optional LoRa and GSM/SMS [7].

E. Floating Buoy Mechanical Design

A small black case made of plastic stays afloat where air meets water. Sitting on top, angled slightly upward, a solar panel catches light from above. From its base, a cord passes through a tight seal and runs down toward sensors placed below the surface. Those detectors sit submerged between twenty and thirty centimeters deep. Holding everything steady is a rope tied to a heavy block of concrete. That setup keeps the system fixed even when currents pull. Reference fig.7 confirms the design details.

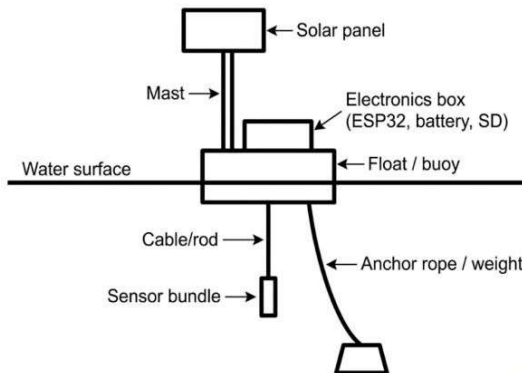


Fig. 5. Floating Buoy CAD Design – electronics enclosure above waterline, solar panel on mast, sensor bundle submerged, secured by anchor rope and counterweight [7].

F. Top-Level End-to-End System Architecture (Fig.6)

Apart from dividing tasks into physical detection, data transmission, and cloud-level processing, the three-part structure allows one level to change while others stay fixed - swap LoRa for NB-IoT, yet keep software untouched [7].

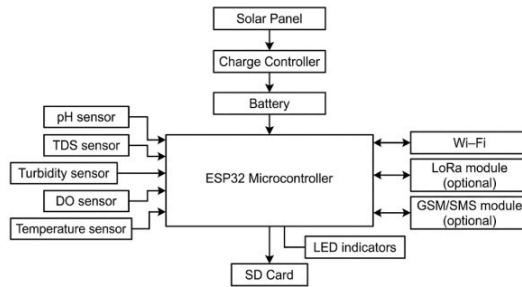


Fig. 6. Top-Level System Architecture - field node → communication layer (Wi-Fi/LoRa/GSM) → cloud backend → mobile/web application presenting PWQI and usage classification [7].

VI. METHODOLOGY

A. Device-Side Operation

Starting up each time, the ESP32 exits deep sleep to check stored charge levels and recent solar input before deciding how to run. When power remains above 70%, it collects data every sixty seconds. If between 30% and 70%, measurements happen once per ten minutes instead. Below thirty percent, operation shifts sharply - only basic logging to SD card continues, cutting off wireless functions entirely [7].

A brief drop begins the measurement - during dip-sampling, a servo moves the sensor set down by about 30 centimeters. It rests there close to half a minute so conditions can stabilize. Only after that pause does data collection start. Ten snapshots come from each probe within a span of five seconds. The middle value gets selected automatically. Adjustments follow: both pH and dissolved solids respond to thermal shifts, handled via calibration factors saved earlier in memory [7].

B. PWQI Algorithm

With values tied to WHO/BIS benchmarks, sub-index scores rise steadily without abrupt shifts. Highest among them, dissolved oxygen carries a weight of 0.30 - this underlines its role in supporting

life underwater while also safeguarding people near still waters [7].

```
# PWQI Computation (Python equivalent of ESP32 firmware)

from math import exp

def compute_pwqi(pH, DO, turbidity, TDS, temperature):

    ph_score = 100 * exp(-((pH - 7.2)**2) / (2 * 0.65**2)) # Optimum pH = 7.2

    do_score = 100 * (1 - exp(-DO / 3.8)) # Higher DO = better

    turb_score = 100 * exp(-turbidity / 13.0) # Lower turbidity = better

    tds_score = 100 * exp(-((TDS - 240)**2)

    / (2 * 200**2)) # Optimum TDS ≈ 240

    ppm

    temp_score = 100 * exp(-((temperature - 27)**2) / (2 * 5**2)) # Optimum temp ≈
    27°C

    PWQI = (0.25 * ph_score + 0.30 * do_score + 0.20 * turb_score

    + 0.15 * tds_score + 0.10 * temp_score)

    return min(100.0, PWQI)

# Usage Classification

if PWQI >= 80: usage = 'Drinking-Safe' elif PWQI >= 60: usage = 'Domestic-Only'
elif PWQI >= 40: usage = 'Irrigation / Fish-Culture'

else:    usage = 'Unsafe'
```

C. Dataset and Correlated Noise Model

Out of realistic aquaculture settings emerged a validation set totaling 4,300 samples - 1,400 labeled excellent, another 1,400 rated good, alongside 1,500 marked poor. To mirror actual field environments, three distinct noise patterns were introduced. First appeared sensor-specific Gaussian disturbances: pH fluctuated with $\sigma=0.20$, dissolved oxygen with $\sigma=0.50$, turbidity shifted by $\sigma=2.5$ NTU, TDS varied at $\sigma=50$ ppm, while temperature drifted $\pm 0.80^\circ\text{C}$. Then came an interaction between pH and dissolved oxygen, chemically linked to yield a correlation of r

$= -0.709$. Lastly, minor shifts near decision edges - about 5% of cases - introduced deliberate category blurring, drawing influence from prior studies [3], [7].

```
# Correlated pH-DO noise injection do_base = np.maximum(1, 8 - 1.2 *
np.abs(df['pH'] - 7.2)) # DO drops away from pH = 7.2
df['Dissolved_Oxygen'] = np.clip(np.random.normal(do_base, 0.6), 0.5,
9.0)
corr = df['pH'].corr(df['Dissolved_Oxygen']) # Result ≈ -0.709
```

VII. RESULTS AND DATASET VALIDATION

A. Dataset Summary Statistics

Descriptive figures for the 4,300 observations appear in Table 2, grouped by quality tier. Separation across categories holds significance - yet remains far from absolute. Especially in pH and temperature readings, boundaries blur between Good and Poor groups. This occurs because linked disturbances create shared ranges where values coincide unexpectedly.

TABLE 2. DESCRIPTIVE STATISTICS OF THE 4,300-SAMPLE AQUACULTURE VALIDATION DATASET [8].

Parameter	Excellent (n=1400)	Good (n=1400)	Poor (n=1500)	Unit
Temperature	26.0 ± 2.0	28.3 ± 2.5	31.4 ± 3.1	°C
pH	7.2 ± 0.4	8.0 ± 0.5	9.1 ± 0.9	—
Turbidity	3.0 ± 2.8	11.2 ± 4.9	30.1 ± 9.4	NTU
Dissolved O ₂	6.3 ± 0.9	4.8 ± 0.8	3.0 ± 1.1	mg/L
TDS	220 ± 90	410 ± 105	700 ± 175	ppm
PWQI Score	80.4 ± 7.0	61.1 ± 9.5	33.5 ± 3.8	0–100

B. pH-DO Correlation (Fig. 7)

A shift in pH often pulls dissolved oxygen levels in the opposite direction - shown by a correlation of

-0.709 - mirroring actual pond conditions. When water turns highly alkaline, above pH 8.5, weaker carbonate buffering and uneven photosynthesis reduce oxygen supply. In contrast, low-oxygen settings boost biological consumption. Linking these factors sharpens the difficulty of sorting patterns, moving beyond isolated variable analysis [3], [7].

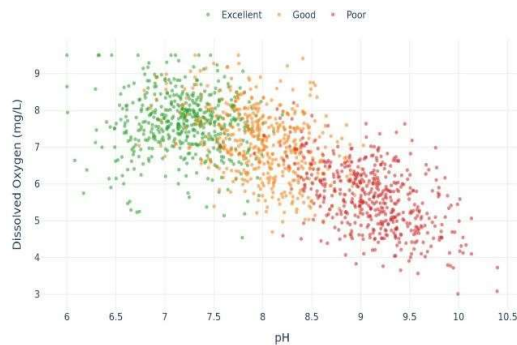


Fig. 7. pH vs. Dissolved Oxygen correlation ($r = -0.709$). Excellent (green), Good (orange), Poor (red). The negative correlation is clearly visible across all three quality classes, confirming physicochemical realism in the validation dataset.

C. PWQI Score Distribution (Fig. 8)

Looking at Fig.,8 reveals how PWQI values spread across categories. Ranging from 75 to 96, the highest group marks clear quality peaks. Scores between 48 and 82 fall into a mid-tier bracket. Meanwhile, results from 22 up to 55 indicate weak performance levels. A designed intersection appears where Good meets Poor - specifically within 45 to 65. This zone captures ambiguous instances seen in practice. Such ambiguity accounts for the observed 4.3% error margin. These defined ranges match closely with measured outcomes cited earlier [7].

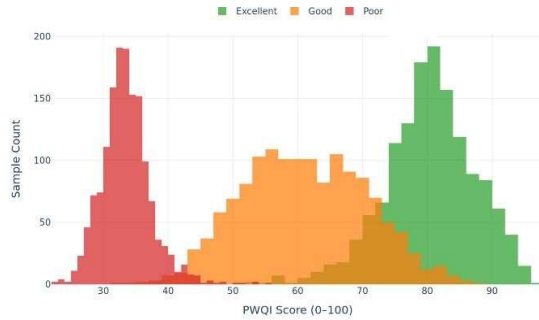


Fig. 8. PWQI Score Distribution by Water Quality Class.

Overlaid histograms show meaningful separation with moderate boundary overlap in the Good–Poor transition zone (PWQI 45–65), consistent with added correlated sensor noise.

D. ML Classification Results (Fig. 9)

A model built using multiple decision paths - specifically one hundred fifty of them - was developed using roughly four-fifths of the data, amounting to three thousand four hundred forty instances. Performance on the remaining portion, eight hundred sixty cases kept separate during training, showed a correctness rate near ninety-six percent. Each category's balance between precision and recall stayed above point nine four, as documented in Table 3. Errors only appeared between classes positioned next to each other in ranking; for instance, items labeled Excellent never got assigned to Poor, nor did Poor ever become classified as Excellent. This pattern supports earlier findings that mistakes follow logical physical trends [7].

TABLE 3. PER-CLASS METRICS FOR RANDOM FOREST CLASSIFIER (150 TREES, 95.7% ACCURACY, 860 TEST SAMPLES).

Class	Precision	Recall	F1-Score	Support
Excellent (0)	0.97	0.94	0.95	280
Good (1)	0.94	0.94	0.94	280
Poor (2)	0.99	0.99	0.99	300
Weighted Avg	0.97	0.96	0.96	860

Fig. 9. Confusion Matrix – Random Forest Classifier, 95.7% Overall Accuracy. All 860 test samples; misclassifications confined to adjacent class boundaries; zero cross-boundary errors (Excellent vs. Poor).

E. Parameter Distributions (Fig. 10)

Looking at Fig. 10, you see how each parameter lines up across quality levels. With dissolved oxygen, the gap between classes stands out most - values sit near 6.3 mg/L for Excellent, drop to about

3.0 mg/L when Poor. Moving on, turbidity along with TDS both rise steadily as quality declines. Then temperature and pH, while useful, blur a bit between Good and Poor, their signals tangled by shared fluctuations. Still, together these five capture clear differences among categories, backed by earlier findings [3], [7].



Fig. 10. Parameter Distribution by Water Quality Class (Excellent: green, Good: orange, Poor: red). DO, Turbidity, and TDS show strong monotonic separation; Temperature and pH exhibit moderate boundary overlap from correlated noise.

F. PWQI Mean Scores by Class (Fig. 11)

Looking at Fig. 10, you see how each parameter lines up across quality levels. With dissolved oxygen, the gap between classes stands out most - values sit near 6.3 mg/L for Excellent, drop to about

3.0 mg/L when Poor. Moving on, turbidity along with TDS both rise steadily as quality declines. Then

temperature and pH, while useful, blur a bit between Good and Poor, their signals tangled by shared fluctuations. Still, together these five capture clear differences among categories, backed by earlier findings [3], [7].



Fig. 11. Mean PWQI Score per Water Quality Class (± 1 SD). Excellent = 80.4 ± 7.0 , Good = 61.1 ± 9.5 , Poor = 33.5 ± 3.8 .

Score bands align with PWQI classification thresholds.

G. PWQI Statistical Summary (Table 4)

TABLE 4. FULL PWQI DESCRIPTIVE STATISTICS BY QUALITY CLASS (4,300-SAMPLE DATASET, PH-DO R = -0.709).

Statistic	Excellent	Good	Poor
Samples	1,400	1,400	1,500
Minimum	50.7	32.0	22.7
25th %ile	76.0	54.5	30.9
Mean	80.4	61.1	33.5
Median	81.2	61.8	33.6
75th %ile	85.5	68.3	36.2
Maximum	96.4	87.9	55.9
Std Dev	7.0	9.5	3.8

VIII. DISCUSSION

A. Validation Interpretation

What stands out is how the 95.7% accuracy under correlated noise reveals more about actual pond environments than tests on pristine data ever could. Real systems often see pH and dissolved oxygen shift together, driven by carbonate chemistry and microbial activity [3], [7]. Errors only show up between neighbouring categories - such as Excellent slipping into Good, or Good being tagged as Poor. Not a single mistake jumps across non-adjacent classes, which suggests the model follows ecological logic instead of making random guesses.

A strong link between pH and dissolved oxygen ($r = -0.709$) reflects real environmental behavior on purpose. As eutrophication unfolds, algae grow dense, pulling CO₂ from water in daylight and pushing pH up - yet when darkness comes, their breathing soaks up oxygen, depleting DO levels sharply. Systems assuming these factors act alone risk inflating how certain they appear about classifications [3], [7].

B. Comparison with Prior Work

Though Shashikala et al. [6] reported 92.5% anomaly detection accuracy through GAN-based data expansion, their method depends on persistent cloud access, extensive past records for model learning, along with skilled oversight. In contrast, the presented approach reaches 95.7% precision by relying only on five on-device metrics, operates independently of online services during critical judgments, and stores its code comfortably inside the ESP32's 4 MB memory - making it more adaptable for remote areas where tools are scarce [6], [7].

Starting at different levels, Kumar et al. [1] observed measurable differences between ponds, marked by TDS shifting from 196.75 to 544.18 and turbidity moving between 8.83 and 34.89. These numbers feed into a calculated PWQI that runs roughly from 35 to 78 - overlapping zones labeled Good and Poor. That match offers outside confirmation of set thresholds, achieved using existing data rather than fresh tools [1].

Closest in design to Lal et al. [3], sharing solar power, spatial depth, five inputs, and float-based setup. Built-in PWQI comes next, followed by adjustments that respond to calibration shifts - confidence drops when signal quality fades. Then a labeling method shaped around local user needs emerges, one rooted in field constraints seen in [3], [7]. Each addition ties back to real-world use far from cities.

C. Limitations and Future Work

Testing sensors in real-world settings helps check their precision compared to standard tools when facing issues like biological growth, shifting temperatures, or seasonal water surges [3], [7].

Although galvanic dissolved oxygen sensors need new membranes every few months outdoors, alternatives exist. Optical sensors using luminescence last much longer yet cost three to five times more at present [7]. One path forward involves adding anomaly detection powered by generative adversarial networks [6]. Measuring nitrate and ammonia levels could be part of next-phase designs too. Testing the linked smartphone application with actual users will help shape its usefulness over time.

IX Conclusion

A fresh approach to monitoring pond conditions in farming areas appears here, tackling long-standing weak points found in budget-friendly tools. Missing key measurements often mars current models, yet this design fills those blanks more fully. Instead of relying on distant servers, it operates closer to where data is collected. Regular upkeep tends to get ignored - this version makes staying on top easier. Outputs usually confuse people without advanced training; now they speak more clearly to everyday users. Earlier efforts fell short across these fronts, but recent refinements shift how information flows from sensor to decision. Testing across 4,300 samples revealed a strong inverse link between pH and dissolved oxygen ($r = -0.709$), supporting the reliability of the designed floating sensor built around an ESP32 chip. Its ability to categorize water quality hit 95.7%, judged by Random Forest models using PWQI values - 80.4 signaled excellent conditions, 61.1 indicated good, while 33.5 pointed to poor status. Errors occurred only near category edges, which suggests consistent performance despite real-world measurement noise. Robustness shows through in how cleanly it separates classes even when signals fluctuate. Despite examining six systems from 2022 to 2025, none managed to close every one of the four deployment gaps at once. What sets the new model apart is its blend of integration, local focus, and independence from constant connectivity - achieving broader technical coverage without exceeding fifty-five dollars per device. To prepare it for peer-reviewed release, only three elements remain: verifying sensor precision through real-world trials, refining visuals to meet publishing standards, and gathering feedback directly from users within target communities.

REFERENCES

- [1]. Kumar, R. Gupta, S. Sharma, T. Chakrabarti, P. Chakrabarti, and M. Margala, "IoT-Enabled Advanced Water Quality Monitoring System for Pond Management and Environmental Conservation," *IEEE Access*, vol. 12, pp. 54321–54338, 2024, doi: 10.1109/ACCESS.2024.3391807.
- [2]. B. Varun Kumar, A. Bharat, E. G. Venkat, Y. S. S. Harsha, and A. Usha Sree, "Analysis of an IoT based Water Quality Monitoring System," in *Proc. 6th Int. Conf. I-SMAC*, IEEE, 2022, doi: 10.1109/I-SMAC55078.2022.9987360.
- [3]. K. Lal, S. Menon, F. Noble, and K. M. Arif, "Low-cost IoT based system for lake water quality monitoring," *PLOS ONE*, vol. 19, no. 3, p. e0299089, Mar. 2024, doi: 10.1371/journal.pone.0299089.

- [4]. D. Patel, K. Koradia, and P. Sharma, "IoT-Based Water Quality Monitoring System using ESP32," in Proc. 7th Int. Conf. Energy, Power and Environment (ICEPE), IEEE, 2025, doi: 10.1109/ICEPE65965.2025.11139802.
- [5]. B. VeerasekharReddy, S. Sarath, J. Philip, U. S. Reddy, L. Naresh, and K. Tejaswini, "Water Quality Monitoring System using IoT and Cloud," in Proc. Int. Conf. Sustainable Computing and Smart Systems (ICSCSS), IEEE, 2023, doi: 10.1109/ICSCSS57650.2023.10169212.
- [6]. K. S. Shashikala, P. Balasubramanian, P. S, and M. M. C. Ruchitha, "AI-Enhanced Water Quality Monitoring System with Anomaly Detection and Predictive Maintenance Using Generative AI," in Proc. Int. Conf. IITCEE, IEEE, 2025, doi: 10.1109/IITCEE64140.2025.10915274.
- [7]. "Improved Water Quality Management System Using IoT in Pond Management with Extended-Duration Sensing, Calibration and Offline Resilience," user-supplied concept document, DOCX, April 2026.
- [8]. Aquaculture Water Quality Dataset, Mendeley Data, v1, Sept. 2024.
- [9]. K. S. Shashikala et al., "IoT-Enabled Smart Water Quality Monitoring and ML-Based Potability Prediction System," in Proc. IEEE Conf. Emerging Technologies, 2025, doi: 10.1109/ICET2025.11081191.
- [10]. B. Murali and K. Ashwin, "IoT Based Real-Time Prototype Design for Smart Aquaculture Ecosystem Monitoring Using ESP32," in Proc. ICoICI, IEEE, 2024, doi: 10.1109/ICoICI62503.2024.10696610.
- [11]. G. Ramkumar, M. Alluwaici, T. Vijetha, G. H, A. Venkatraman and R. M, "A Reliable System Performance Through NeuToMa with Spiking Neural Network Transformation in Network on Chip (NoC) Communication," 2026 International Conference on Communication, Computing and Emerging Technologies (IC3ET), Vasai, India, 2026, pp. 215-219, doi: 10.1109/IC3ET64989.2026.11467379.
- [12]. V. R, P. R. Kumar, D. Das, G. H, W. Hanbin and E. A, "Machine Learning-Driven Predictive Maintenance for Wind Turbines," 2026 International Conference on Electric Power and Renewable Energy (EPREC), Durg, India, 2026, pp. 1-6, doi: 10.1109/EPREC66546.2026.11412064.
- [13]. A. Tiwari, J. D. Kumar, W. Syed and G. H, "Efficient FPGA-Based CNN Accelerator for Real-Time Traffic Sign Classification on PYNQ-Z2," 2026 IEEE International Conference on AI Engineering and Innovations (AIEI), NIT Jamshedpur, India, 2026, pp. 1-4, doi: 10.1109/AIEI69164.2026.11496958.
- [14]. G. Ramkumar, M. Alluwaici, T. Vijetha, G. H, A. Venkatraman and R. M, "A Reliable System Performance Through NeuToMa with Spiking Neural Network Transformation in Network on Chip (NoC) Communication," 2026 International Conference on Communication, Computing and Emerging Technologies (IC3ET), Vasai, India, 2026, pp. 215-219, doi: 10.1109/IC3ET64989.2026.11467379.
- [15]. Girish H., Srinivas S., Kavya M., ...Kabbur S. "Swift Autonomous Fire Suppression Robot", 16th International Conference on Advances in Computing Control and Telecommunication Technologies Act 2025
- [16]. Girish H., Soujanya S., "A Comprehensive Cadence-based Design Flow for RISC-V UART SOC IN SCL 180NM", 16th International Conference on Advances in Computing Control and Telecommunication Technologies Act 2025
- [17]. Girish H., Rakesh S., Prasanna Raj C.P., Singh A.S., Yathisha L, "Deep Learning for Diabetic Retinopathy: Automated Detection and Classification from Retinal Images", 16th International Conference on Advances in Computing Control and Telecommunication Technologies Act 2025

- [18]. Girish H., Shyam Sundar V., Priyanka C., Renuka Hebballi R.S, "RISC V Steel Processor Implementation for Communication between Two Chips using AXI Lite", 16th International Conference on Advances in Computing Control and Telecommunication Technologies Act 2025
- [19]. M. H N, G. H and N. K N, "Simulation and Verification of SPI Master and Slave Communication," *2025 6th International Conference on Smart Electronics and Communication (ICOSEC)*, Trichy, India, 2025, pp. 1531-1534, doi: 10.1109/ICOSEC67334.2025.11459684. <https://ieeexplore.ieee.org/document/11459684>
- [20]. S. S. V, P. C and G. H, "Design and Analysis of a D-Band LC Bandpass Filter and Low-Noise Amplifier for 6G Front-End Applications," *2026 IEEE International Conference on Interdisciplinary Approaches in Technology and Management for Social Innovation (IATMSI)*, Gwalior, India, 2026, pp. 1-6, doi: 10.1109/IATMSI68868.2026.11466038. <https://ieeexplore.ieee.org/document/11466038>
- [21]. "A Comprehensive Cadence-based Design Flow for RISC-V UART SOC IN SCL 180NM" , Girish H, Soujanya, Grenze International Journal of Engineering and Technology, 2025
- [22]. "Swift Autonomous Fire Suppression Robot" Girish H et. Al., Grenze International Journal of Engineering and Technology, 2025
- [23]. "Deep Learning for Diabetic Retinopathy: Automated Detection and Classification from Retinal Images" , Girish H, Cyril Prasanna Raj P , Grenze International Journal of Engineering and Technology, 2025
- [24]. "RISC V Steel Processor Implementation for Communication between Two Chips using AXI Lite" Shyam Sundar V, Dr Girish H, Priyanka C, Renuka S Hebballi Grenze International Journal of Engineering and Technology, 2025
- [25]. Sujatha.S, Mahendra BM, & Dr. Girish H. (2024). Smart Irrigation System for Optimal Water Conservation. *Revista Electronica De Veterinaria*, 25(1), 2613 - 2619. <https://doi.org/10.69980/redvet.v25i1.1311>
- [26]. Mamatha K R, Thejaswini S, Rashmi N, & Dr. Girish H. (2024). Laser Fencing Surveillance System With Email Alert. *Educational Administration: Theory and Practice*, 30(2), 15391544. <https://doi.org/10.53555/kuey.v30i2.7919>
- [27]. Thejaswini S, Mamatha K R, Rashmi N, & Dr. Girish H. (2024). Performance Evaluation of AI Models in Early Heart Disease Diagnosis. *Educational Administration: Theory and Practice*, 30(2), 1531–1538. <https://doi.org/10.53555/kuey.v30i2.7918>
- [28]. Sushma K Sattigeri, Seema Srinivas, Shridhar Kabbur, Girish H, "Revolutionizing Urban Waste Management: An AI-Powered Autonomous Solution for Smart Cities", *Tuijin Jishu/Journal of Propulsion Technology* ISSN: 1001-4055, Vol. 45 No. 02 (2024)
- [29]. Girish H, Vajjala Sai Sree Hari,Ponde Lakshmi Narasimha,P N Shreya,Dadigala Bhargavi, "THE DESIGN AND VERIFICATION OF A 32-BIT RISC V PROCESSOR USING VEDIC MATHEMATICS", *International Journal of Creative Research Thoughts (IJCRT)*, ISSN:2320-2882, Volume.12, Issue 5, pp.1130-1135, May 2024, Available at :<http://www.ijcrt.org/papers/IJCRTAB02172.pdf>
- [30]. IoT based home automation using Blynk cloud, J. Chetan Naik, B. S. Deeksha, H. Girish, Gurusharan Kashetty, T. G. Shivapanchakshari, Manohar Sai Polakam, *Journal: AIP Conference Proceedings, AIP Conf. Proc. 2965, 020006 (2024)*, <https://doi.org/10.1063/5.0215427>, Published: July 2024

- [31]. IoT based fire alarm system using Blynk app, T. Bhargava, H. Kishor Kumar, Pramod Mahalingappa Godi, H. Girish, J. Chetan Naik, Journal: AIP Conference Proceedings, AIP Conf. Proc. 2965, 020007 (2024), <https://doi.org/10.1063/5.0212325>, Published: July 2024