

Smart-Bandeng: Internet of Things-Based Water-Quality Monitoring for Community Milkfish Aquaculture in Ujungpangkah

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Abstract

Milkfish farmers in Pangkahwetan, Ujungpangkah, Gresik, commonly rely on visual observations and reactive responses to assess pond-water conditions, underscoring the need for accessible real-time monitoring. This community service programme introduced and demonstrated the Smart-Bandeng System, an Internet of Things (IoT)-based platform that integrates temperature, pH, and turbidity sensors with a web-based monitoring interface and a K-Nearest Neighbors (KNN) classification component. The programme involved the Pangkahwetan Pond Farmers Association, comprising 30 farmers who manage approximately three hectares of ponds. Activities included socialisation, operator training, device installation, field demonstration, mentoring, and follow-up planning. During a documented two-hour field test, sensor readings were transmitted at five-second intervals. The available dataset recorded temperatures of approximately 28.00–28.19 °C and turbidity values of 29–30 NTU. pH was initially 7.03, rose abruptly to 12.68–13.08, and subsequently returned to 7.00. Because this rapid fluctuation was not verified using a calibrated reference instrument, it is interpreted cautiously as a possible sensor, calibration, electrical, or local sampling artefact rather than a confirmed pond-wide change. Programme documentation did not report sensor models, calibration accuracy, participant pretest-posttest outcomes, harvest effects, or validated KNN performance metrics. The primary documented achievement was therefore the successful deployment and real-time demonstration of a community-oriented monitoring prototype, rather than evidence of reduced harvest failure or improved production. Future implementation should prioritise sensor validation, verification of water-quality thresholds, model-performance assessment, operator competency evaluation, and longitudinal monitoring of technology adoption, pond management, and production outcomes before wider operational deployment.

Keywords: aquaculture monitoring; Internet of Things; milkfish; water quality; community technology

Abstrak

Petambak bandeng di Pangkahwetan, Ujungpangkah, Gresik, masih banyak mengandalkan pengamatan visual dan respons reaktif terhadap kondisi air tambak sehingga membutuhkan sistem pemantauan waktu nyata yang mudah digunakan. Program pengabdian kepada masyarakat ini bertujuan memperkenalkan dan mendemonstrasikan Smart-Bandeng System, yaitu platform berbasis Internet of Things yang mengintegrasikan sensor suhu, pH, dan kekeruhan dengan pemantauan berbasis web serta komponen klasifikasi K-Nearest Neighbors. Mitra program adalah Persatuan Tani Tambak Pangkahwetan yang terdiri atas 30 petambak dan mengelola sekitar tiga hektare tambak. Pelaksanaan mencakup sosialisasi, pelatihan operasional, pemasangan perangkat, demonstrasi lapangan, pendampingan, dan rencana evaluasi lanjutan. Pada uji lapangan selama dua jam, data sensor dikirim setiap lima detik. Data yang terdokumentasi menunjukkan suhu sekitar 28,0–28,19 derajat Celsius dan kekeruhan 29–

30 NTU, sedangkan pH awal 7,03 kemudian meningkat sangat cepat menjadi 12,68-13,08 sebelum kembali menjadi 7,00. Karena perubahan pH tersebut tidak divalidasi dengan instrumen acuan terkalibrasi, hasil ini ditafsirkan secara hati-hati sebagai kemungkinan artefak sensor, kalibrasi, gangguan listrik, atau sampling, bukan perubahan kondisi tambak yang telah terkonfirmasi. Laporan sumber belum menyediakan model sensor, akurasi kalibrasi, hasil pretest-posttest peserta, dampak panen, maupun metrik validasi model K-Nearest Neighbors. Dengan demikian, capaian yang dapat dipastikan adalah keberhasilan penerapan dan demonstrasi prototipe pemantauan waktu nyata. Implementasi berikutnya perlu memprioritaskan validasi sensor, verifikasi ambang mutu air, validasi model, kompetensi operator, adopsi teknologi, dan luaran produksi jangka panjang.

Kata kunci: budidaya bandeng; Internet of Things; kualitas air; monitoring; teknologi komunitas

INTRODUCTION

Gresik Regency is one of East Java's major brackish-water aquaculture areas, with milkfish (*Chanos chanos*) among its leading commodities. Programme background documentation, citing the Directorate General of Aquaculture (2022), reports approximately 28,000 hectares of ponds, annual milkfish production of about 87,000 tonnes, and an estimated economic value of IDR 1.4 trillion. These figures underscore the local importance of pond aquaculture and the need to protect production from environmental instability. Water quality is a critical determinant of aquaculture performance because temperature, dissolved oxygen, pH, salinity, turbidity, nitrogen compounds, and other physicochemical parameters influence fish physiology, feeding, growth, and susceptibility to disease (Prapti et al., 2022; Zhao et al., 2021).

Pangkahwetan Village, Ujungpangkah District, is a coastal aquaculture area where many farmers continue to assess pond-water conditions primarily through visual cues such as colour, odour, and surface appearance. The programme partner, the Pangkahwetan Pond Farmers Association, comprises 30 farmers managing approximately three hectares of ponds. The needs assessment identified four priority concerns: the absence of quantified real-time water-quality information, limited familiarity with digital production-management tools, predominantly reactive decision-making, and the risk of delayed detection of abnormal pond conditions. These constraints are particularly relevant in ponds affected by tidal exchange, rainfall, river inflow, and anthropogenic pollution.

Real-time sensing has become an important component of smart aquaculture. A review of IoT-based aquaculture systems found that temperature, dissolved oxygen, and pH were among the most frequently monitored parameters and that real-time monitoring was the dominant application (Prapti et al., 2022). More recent reviews have further documented the rapid expansion of IoT sensor applications in aquaculture and highlighted their potential for early anomaly detection, remote access, and data-informed management. At the same time, these studies emphasise persistent practical challenges, including sensor fouling, corrosion, calibration drift, communication reliability, and maintenance under rural field conditions (Abdullah et al., 2024; Flores-Iwasaki et al., 2025).

Machine learning can extend sensor-based systems beyond data visualisation to classification, prediction, and decision support. Zhao et al. (2021) reviewed machine-learning

applications in fish aquaculture, including water-quality prediction and intelligent management. However, predictive performance cannot be evaluated meaningfully without transparent reporting of the training data, class labels, preprocessing procedures, hyperparameters, validation strategy, and performance metrics. Systematic reviews of smart aquaculture and aquaponics likewise indicate that monitoring prototypes are common, whereas rigorous stakeholder-centred evaluation and long-term performance validation remain comparatively limited (Anila & Daramola, 2025; Chandramenon et al., 2024).

The Smart-Bandeng System was introduced as an appropriate-technology intervention for community-based pond aquaculture. The prototype integrates an ESP32 microcontroller; temperature, pH, and turbidity sensors; wireless data transmission; a web-based monitoring dashboard; and a K-Nearest Neighbors component intended to classify water conditions. Its community-service contribution lies in combining field deployment with farmer training and mentoring rather than treating the system solely as an engineering prototype. Available programme records, however, provide substantially more information on the technical demonstration than on community-level outcomes. The present article therefore distinguishes between system functions that were demonstrated in the field and outcomes that were not measured or validated.

Accordingly, this community service programme aimed to deploy and demonstrate the Smart-Bandeng prototype with the Pangkahwetan Pond Farmers Association and to establish a practical pathway for real-time water-quality monitoring. The documented outputs included device deployment, real-time data acquisition, dashboard visualisation, and field use of the monitoring interface. Because programme records do not provide validated pretest-posttest measures of farmer competency, technology adoption, harvest performance, mortality, economic outcomes, or machine-learning accuracy, the programme is not interpreted as evidence that harvest failure was reduced, yield increased, or predictive accuracy was achieved.

METHODS

The programme employed a participatory technology-deployment and mentoring approach rather than a controlled effectiveness design. Activities comprised socialisation, operator training, field installation, technology demonstration, mentoring, evaluation planning, and sustainability planning. No independent control group or participant-level pretest-posttest dataset was available; consequently, the programme is evaluated as a field implementation and feasibility activity rather than a quasi-experimental effectiveness study.

The programme was implemented in the aquaculture area of Pangkahwetan Village, Ujungpangkah District, Gresik Regency, East Java, Indonesia. Programme records document a two-hour field data-collection session dated 07/06/2026; however, the date format is ambiguous, and the complete programme start and end dates were not consistently recorded. Mentoring was planned to continue for approximately two to three months following deployment.

The community partner was the Pangkahwetan Pond Farmers Association, consisting of 30 farmers who collectively manage approximately three hectares of pond area. Farmers

participated as beneficiaries and field operators, provided the installation site, attended operational training, and were expected to contribute to routine sensor maintenance, data observation, and pond-management decisions. Detailed participant characteristics, recruitment criteria, session-specific attendance, and baseline digital-literacy measures were not available in the programme records.

The Smart-Bandeng prototype used an ESP32 microcontroller connected to temperature, pH, and turbidity sensors. Sensor readings were transmitted wirelessly to a database and displayed through a web-based interface. Implementation included an explanation of the monitoring concept, operator training, field installation and demonstration, real-time observation, troubleshooting, and planned mentoring. Technical documentation did not specify the sensor manufacturers or models, measurement ranges, stated precision, calibration procedures, deployment depth, number of deployed devices, or maintenance schedule. These details should be documented in subsequent technical evaluations to support reproducibility and performance assessment.

The documented technical outputs comprised real-time data acquisition, data transmission at five-second intervals, database storage, web-dashboard visualisation, and operation of a K-Nearest Neighbors classification component. The programme plan also proposed evaluating partner understanding, operational skills, application use, sensor functionality, and harvest productivity through observation, interviews, questionnaires, and yield analysis. However, corresponding quantitative community-outcome data were not available. These indicators are therefore treated as intended evaluation targets rather than achieved outcomes.

Programme documentation used reference ranges of 28-32 °C for temperature, pH 7.0-8.5, and 20-30 NTU for turbidity and attributed them to SNI 01-6148-1999. The cited BSN reference identifies SNI 01-6148-1999 as a standard for milkfish parent stock rather than a general pond-water monitoring guideline. The present article therefore retains these thresholds as programme reference values but does not present them as independently verified universal SNI limits for pond-water quality. The applicable standard and parameter definitions should be verified before final operational use.

The K-Nearest Neighbors component was intended to classify whether observed water conditions fell within predefined reference ranges. Programme records did not include the training-dataset size, class distribution, feature scaling, selected k value, distance metric, train-test split, cross-validation procedure, confusion matrix, accuracy, precision, recall, F1 score, or external validation. Accordingly, KNN is reported as an implemented analytical component of the prototype, not as a validated predictive model.

The available technical dataset was analysed descriptively. The field sample consisted of measurements recorded at five-second intervals. Inferential statistical analysis was not undertaken because the programme did not include repeated independent experimental units, participant-level outcome data, or validated model-performance outputs.

Programme documentation did not include a formal ethics-committee approval number, an institutional-permission identifier, or a written participant-consent procedure. No

identifiable participant photographs are included in this publication-ready version. The authors should ensure that all applicable institutional permission and consent requirements are documented in accordance with journal policy before publication.

Sustainability planning included farmer operator training, provision of a Smart-Bandeng guidebook, routine maintenance, continued mentoring, and potential collaboration with local government and neighbouring pond communities. Long-term sustainability should be evaluated using measurable indicators such as device uptime, calibration frequency, independent farmer operation, response to alerts, maintenance costs, and changes in pond-management practices.

RESULTS

The Smart-Bandeng prototype was assembled and deployed in the field with the Pangkahwetan Pond Farmers Association. During the documented test, the system acquired temperature, pH, and turbidity readings, transmitted data at five-second intervals, stored the measurements in a database, and displayed current values through a web-based dashboard. These findings demonstrate the feasibility of real-time field data acquisition under the observed test conditions; however, they do not establish sensor accuracy, improved farmer competency, or effects on aquaculture production.

Table 1. Partner profile and Smart-Bandeng implementation characteristics

Characteristic	Description	Reported value/status
Community partner	Pangkahwetan Pond Farmers Association	30 farmers
Managed pond area	Approximate partner-managed pond area	3 hectares
Measured parameters	Temperature, pH, turbidity	3 parameters
Controller	ESP32 microcontroller	ESP32-based prototype
Transmission interval	Real-time sensor upload	Every 5 seconds
Field-test duration	Continuous field data collection	2 hours
Dashboard	Web-based monitoring interface	Operational demonstration
Machine-learning component	K-Nearest Neighbors	Implemented; validation metrics not reported

Table 2. Five-second field readings recorded during the field test

Time	Temperature (°C)	Turbidity (NTU)	pH
08:53:20	28.00	29	7.03
08:53:25	28.00	29	7.03
08:53:30	28.00	29	7.03
08:53:35	28.00	29	7.03
08:53:40	28.00	29	7.03
08:53:45	28.00	29	7.03

Time	Temperature (°C)	Turbidity (NTU)	pH
08:53:50	28.00	29	7.03
08:53:55	28.00	29	7.03
08:54:00	28.19	30	12.68
08:54:05	28.19	30	12.68
08:54:10	28.19	30	12.68
08:54:15	28.19	29	13.08
08:54:20	28.19	29	13.01
08:54:25	28.00	29	13.04
08:54:30	28.00	29	7.00

Across the displayed 70-second interval, temperature and turbidity remained relatively stable, whereas pH changed abruptly from 7.03 to 12.68-13.08 before returning to 7.00. Programme documentation interpreted this sequence as an actual pond-water event followed by rapid correction after the addition of peat and fresh water. This interpretation requires caution because a pond-wide pH shift of this magnitude within seconds would need independent confirmation. In the absence of simultaneous measurements from a calibrated reference instrument, documented calibration data, and information on sensor placement and water mixing, the observed fluctuation may reflect sensor drift, electrical interference, probe fouling, a transient local sampling condition, or another measurement artefact.

An interface example in the programme documentation displayed pH 13.3, temperature 24.6 °C, turbidity 55 NTU, and an overall classification of unsuitable water. These values are reported only to describe the prototype interface and should not be interpreted as validated field measurements because no calibration or reference-instrument confirmation was provided for that display.

Table 3. Water-quality reference ranges applied in the programme

Parameter	Programme reference range	Interpretive note
Temperature	28-32 °C	Used as an SNI-linked reference in the programme; the applicable standard should be verified
pH	7.0-8.5	Used as an SNI-linked reference in the programme; the applicable standard should be verified
Turbidity	20-30 NTU	Used in the programme; the appropriate turbidity/clarity definition and standard should be verified

The K-Nearest Neighbors component was used to generate a water-suitability classification based on the programmed reference ranges. Because no model-development or

validation results were reported, the available evidence does not support claims of predictive accuracy. The defensible technical conclusion is limited to successful integration of the KNN component into the prototype workflow and its use in displaying a classification output.

DISCUSSION

The Smart-Bandeng programme addresses a practical community need for timely information when pond conditions change. IoT-based water-quality monitoring is increasingly used in aquaculture because continuous sensing can shorten the interval between environmental change and management response. Prapti et al. (2022) identified real-time monitoring as one of the most common functions of IoT-based aquaculture systems, while Abdullah et al. (2024) and Flores-Iwasaki et al. (2025) highlighted the value of remote monitoring alongside persistent challenges in sensor durability, maintenance, calibration, and data reliability. The present field demonstration is therefore consistent with current smart-aquaculture development, particularly as a community-oriented prototype.

An ESP32-based architecture is potentially suitable for low-cost community deployment, but technical reporting must be sufficiently detailed to support reproducibility and safe operational use. Sensor model, measurement range, stated precision, calibration frequency, deployment depth, fouling protection, power supply, network reliability, and replacement cost are all relevant to field adoption. Reviews of smart aquaculture consistently identify calibration drift, biofouling, corrosion, and environmental exposure as major limitations of long-term sensing (Abdullah et al., 2024; Flores-Iwasaki et al., 2025). In the absence of these specifications, Smart-Bandeng can be described as operationally demonstrated but not yet technically validated.

The abrupt pH sequence is the most important technical issue in the available field dataset. A rise from approximately pH 7 to above pH 12, followed by a return to pH 7 within seconds, is sufficiently extreme that measurement error should be excluded before biological or management interpretations are made. pH probes can be affected by calibration error, electrical noise, contamination, local chemical gradients, fouling, or inadequate stabilisation time. Although programme notes associate the decline with the addition of peat and fresh water, the short interval and absence of an independent reference measurement prevent a causal conclusion. The sequence is therefore best treated as an anomalous signal requiring investigation rather than evidence of an immediate pond-wide chemical correction.

The three monitored parameters provide useful information but do not constitute a complete aquaculture water-quality profile. Reviews identify temperature, pH, and dissolved oxygen as particularly important in aquaculture monitoring, with ammonia, salinity, conductivity, nitrite, nitrate, and turbidity also relevant depending on the culture system (Prapti et al., 2022; Anila & Daramola, 2025; Chandramenon et al., 2024). Dissolved oxygen and salinity were not documented in the present prototype, although both may be important in brackish-water milkfish ponds. Any future expansion should therefore be guided by local management needs, affordability, maintenance capacity, and the specific decisions that each additional sensor is intended to support.

The machine-learning component also requires substantially stronger validation. Machine learning is increasingly applied to aquaculture water-quality prediction and decision support (Zhao et al., 2021), but a KNN classifier cannot be described as accurate without transparent performance evaluation. At minimum, future reporting should specify the training-set size, input features, class labels, selected *k* value, distance metric, preprocessing procedures, train-test partition, confusion matrix, accuracy, precision, recall, F1 score, and preferably cross-validation results. If classification is primarily determined by fixed water-quality thresholds, the added value of KNN relative to a direct rule-based system should also be explained.

From a community-development perspective, technical deployment represents only one dimension of empowerment. The programme plan included observation, interviews, questionnaires, skills assessment, and harvest-yield analysis, yet quantitative results for these outcomes were not reported. Claims of improved empowerment, technology adoption, or reduced harvest risk therefore remain unsupported by the available evidence. A stronger community evaluation should measure baseline and follow-up operator competency, independent dashboard use, correct responses to alerts, sensor-maintenance ability, perceived usefulness, frequency of adoption, and whether farmers changed pond-management decisions in response to system information.

The water-quality reference ranges embedded in the dashboard also require verification. Programme documentation attributes temperature 28–32 °C, pH 7.0–8.5, and turbidity 20–30 NTU to SNI 01-6148-1999. The cited BSN reference identifies SNI 01-6148-1999 as a parent-stock standard for milkfish, so the authors should confirm whether these thresholds are derived from the appropriate clause, another production standard, or a different aquaculture guideline. This is particularly important for turbidity because water clarity, total suspended solids, and turbidity may be reported in different units and have different management implications. Until verified, these values should be regarded as programme reference ranges rather than universal operational thresholds.

The long-term value of Smart-Bandeng will depend on whether the prototype remains functional and useful after the service team withdraws. Reviews of smart aquaculture note that many systems are evaluated only as short-term prototypes, while stakeholder-centred assessment, maintenance planning, and long-term field validation remain less common (Anila & Daramola, 2025; Flores-Iwasaki et al., 2025). For Pangkahwetan, sustainability should therefore be monitored through device uptime, calibration and maintenance records, farmer-led troubleshooting, connectivity and data costs, frequency of independent system use, and the pond-management actions taken in response to alerts.

This community service programme has two clear strengths: it responds to a locally identified monitoring need and places a functioning digital prototype directly within a farmer-operated aquaculture setting. Its limitations are equally important: the absence of a control group and farmer pretest-posttest outcomes, incomplete sensor specifications and calibration records, unvalidated KNN performance, uncertainty surrounding the extreme pH sequence, and the absence of documented harvest or economic outcomes. These limitations do not negate the value of the field demonstration; rather, they define the evidence required before

stronger claims can be made regarding technical accuracy, farmer empowerment, operational effectiveness, or production benefits.

CONCLUSION

The Smart-Bandeng programme demonstrated real-time acquisition and web-based visualisation of temperature, pH, and turbidity data for the Pangkahwetan Pond Farmers Association. The prototype transmitted readings at five-second intervals and incorporated a K-Nearest Neighbors classification component. At this stage, however, the available evidence does not establish sensor accuracy, validated machine-learning performance, improved farmer competency, reduced harvest failure, or increased production. The abrupt pH sequence from approximately 7 to above 12 and back to 7 requires calibration and confirmation with a reference instrument before it can be interpreted as a genuine pond-water event. Smart-Bandeng should therefore be regarded as a promising technical and community-deployment pilot. Further implementation should verify applicable water-quality standards, document sensor calibration and KNN validation, assess farmer adoption and competency, and evaluate longer-term pond-management and production outcomes.

RECOMMENDATIONS

Within the next 1-3 months, the service team and farmer operators should calibrate all sensors against appropriate reference instruments, document sensor specifications and maintenance procedures, and verify the applicable water-quality standards for milkfish aquaculture. The KNN component should be evaluated using a clearly described labelled dataset and transparent performance metrics. Over the subsequent 3-6 months, follow-up should assess farmer competency, independent system use, responses to alerts, device uptime, maintenance costs, changes in pond-management practices, mortality, harvest yield, and production economics. Dissolved oxygen and salinity should be considered for future integration where local management needs and maintenance capacity justify their inclusion.

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