



Internet of Things in Fish Ponds

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Introduction:

Aquaculture faces significant challenges in maintaining optimal conditions for fish growth, particularly with respect to water resource availability and quality. Water quality directly impacts fish health and productivity, yet traditional manual monitoring methods are labor-intensive and often inadequate for early detection of problems. A persistent issue in conventional fish pond management has been the lack of comprehensive data to guide decisions on breeding, feeding, and pond maintenance. In this context, the advent of Internet of Things (IoT) technology offers new opportunities for continuous, automated monitoring in aquaculture environments. By deploying networks of sensors and connected devices, IoT systems can provide high-frequency, real-time data on water conditions, enabling timely interventions and data-informed management. One persistent gap has been the absence of comprehensive datasets and continuous data streams to guide fish farmers in data-driven decision-making for breeding and pond maintenance. In this context, the advent of IoT technology offers unprecedented opportunities for continuous, automated monitoring in aquaculture environments, enabling timely detection of water quality issues and collection of rich real-time data <https://pmc.ncbi.nlm.nih.gov>

Aquaponics, a sustainable farming system, exemplifies the integration of aquaculture with hydroponics (soilless plant cultivation). In an aquaponic fish pond, fish waste nutrients are taken up by plants, which in turn help filter and reuse the water for fish. This symbiotic setup significantly reduces the need for frequent water replacement, addressing one challenge of conventional fish ponds. To further optimize such systems, IoT-based monitoring can be implemented for real-time water quality management.

<https://www.researchgate.net/publication/382255038> Integrating Aquaculture And Hydroponics A Review Of Aquaponics Systems And Their Sustainability.

A number of studies in recent years have explored IoT deployments in fish farming alongside machine learning algorithms to predict water quality variables or other aquaculture outcomes.

Abstract

This paper provides a comprehensive overview of Internet of Things (IoT) applications in fish ponds, encompassing both the development of a dedicated data acquisition system and a critical review of recent data-driven studies in smart aquaculture. We first present an IoT-based aquaponics pond monitoring system that automatically collects key water quality parameters – temperature, pH, dissolved oxygen (DO), turbidity, ammonia, and nitrate – using a network of sensors controlled by an ESP-32 microcontroller. The system streams real-time data to a cloud platform, yielding an open-access dataset for analysis. This dataset, made available to the research community, can support advanced machine learning (ML) models to inform pond management decisions. Next, we review multiple contemporary studies (primarily 2020–2025) that integrate IoT sensing with advanced analytics in aquaculture. For each study, we summarize the methodology, data source, and outcomes, highlighting state-of-the-art approaches (e.g. deep learning models for water quality prediction and fish behavior analysis). We synthesize these works in a comparative table that contrasts their methods, datasets, best-performing models, and key results. Through this survey, we identify emerging trends—particularly the growing prevalence of hybrid deep learning models and ensemble techniques that exploit IoT-derived data for superior predictive accuracy. We also discuss common strengths (such as real-time monitoring and improved forecasting precision) and recurring limitations (such as limited data diversity and generalization challenges) across the literature. Finally, we conclude with insights into how IoT and data science are revolutionizing aquaculture, and we offer recommendations for future research, including the development of standardized datasets, the incorporation of domain knowledge into models, and the deployment of IoT-ML systems at scale to achieve sustainable fish farming practices.

Literature Review:

Study 1

MS-CAGRU for Water Quality Prediction

Sundararajan S. C. M. et al. (2025) developed an IoT-based water quality prediction model for an aquaponic fish pond by using a multiscale feature fusion approach with deep learning. In their study, an IoT sensor network collected water parameters which were then used to train a hybrid deep learning model combining a convolutional autoencoder (CAE) for feature extraction and a gated recurrent unit (GRU) for sequence learning. The proposed model (termed MS-CAGRU) effectively captured multi-scale patterns in the water quality data. The authors applied different ML models: random forest (RF), support vector machine (SVM), decision tree (DT), K-nearest neighbor (KNN), and logistic regression (LR) to classify different types of fish using water quality parameters: pH, temperature, and turbidity. The dataset was collected from AquaBot, It attained approximately 94% classification accuracy with an F1-score of 0.94, outperforming baseline recurrent neural networks (standard RNN and plain GRU) by 2–5%. The study noted that regularization techniques further improved the model's generalization. This work demonstrates that fusing convolutional feature extraction with recurrent prediction can yield high predictive accuracy for aquaculture water quality, providing a foundation for intelligent pond management.

Study 2

IOT & Advanced ML Algorithms (Tilapia Ponds, 2025)

Hridoy, M. A. A. M. et al. (2025) applied IoT monitoring and advanced machine learning algorithms to improve water quality prediction in tilapia aquaculture ponds. The researchers deployed a custom IoT system to continuously record six months of sensor data (including temperature, dissolved oxygen, pH, and turbidity) from several tilapia ponds. A variety of predictive models were evaluated on these time-series data, ranging from decision tree ensembles to deep neural networks. Notably, the authors leveraged ensemble techniques such as **bagging and boosting**

to enhance predictive performance. By analyzing temporal patterns and combining diverse learners, the models could forecast key water quality parameters with high precision. The best results were obtained with a **custom ensemble model** that integrated decision tree methods with boosting algorithms, achieving nearly **99% accuracy** in predicting trends like dissolved oxygen fluctuations. This far exceeded the accuracy of individual models (which were in the 88–93% range), underscoring the benefit of ensemble learning. The study concluded that integrating IoT-sensed data with advanced ML algorithms enables near real-time water quality forecasting with minimal error, which is crucial for proactive pond management.

Study 3

IoT + Random Forest with Quantum Optimization (Tropical Pond, 2025)

Baena-Navarro, R. et al. (2025) described an intelligent water quality monitoring framework that integrates IoT sensing with machine learning for sustainable aquaculture management. They implemented an IoT system in a **tropical fish pond** to continuously collect environmental data (temperature, DO, pH, turbidity, etc.), and used these data to train predictive models. A *random forest regression* approach was employed to forecast water quality variables, and the novelty of this study lay in applying a **quantum-inspired optimization algorithm (QAOA)** to improve the model's training efficiency and accuracy. The Random Forest model optimized with QAOA achieved a *near-perfect fit* for dissolved oxygen predictions, with a coefficient of determination $R^2 \approx 0.999$ and root mean square error (RMSE) on the order of 0.1 mg/L. Such accuracy indicates that the model's predictions almost exactly matched the observed DO levels. The integrated system allowed rapid, on-site adjustments (e.g. activating aerators) to maintain fish survival rates above 90%. The best-performing approach was the QAOA-enhanced Random Forest, demonstrating that coupling IoT data streams with cutting-edge optimization techniques can yield extremely accurate predictive models for aquaculture.

Study 4

Hybrid EEMD-MLR-LSTM Model (Salmon Farm, 2023)

Eze, E. et al. (2023) explored a hybrid deep learning strategy for multivariate water quality forecasting in an offshore salmon farm. Their study introduced a composite model that combined Ensemble Empirical Mode Decomposition (EEMD) for signal preprocessing, multivariate linear regression (MLR) for initial approximation, and a deep Long Short-Term Memory (LSTM) network for sequence learning. Using time-series sensor data from a Scottish salmon aquaculture site, the hybrid model was trained to predict indicators of harmful algal blooms (e.g., chlorophyll-a levels) and other water quality metrics. The EEMD component decomposed complex time-series into simpler sub-series, which improved the LSTM's ability to learn patterns at multiple scales. The proposed EEMD-MLR-LSTM model outperformed several baseline models (including a standalone LSTM and a stacked autoencoder-LSTM) in predictive accuracy. Notably, it achieved a very low RMSE of around 0.05 for chlorophyll-a concentration forecasts, indicating high precision. By effectively capturing both short-term fluctuations and long-term trends in the data, this hybrid approach minimized prediction error and was identified as the best model. The results highlight the value of multi-scale feature extraction combined with deep learning to forecast complex water quality dynamics in aquaculture.

Study 5

Pearson Correlation + LSTM with Attention (Freshwater Aquaculture, 2025):

Yu, X. et al. (2025) focused on dissolved oxygen prediction in freshwater aquaculture using feature selection and attention-based recurrent neural networks. The authors first applied Pearson **correlation analysis** to identify which water quality variables were most influential for predicting DO levels. By filtering the input features to only the most relevant (e.g., selecting temperature, pH, etc. that correlate strongly with DO), they reduced noise and improved model focus. They then designed an LSTM network augmented with an **attention mechanism** (denoted LSTM-AM) to forecast dissolved oxygen several days into the future. The

attention layer enabled the model to weight the most important time steps and features when making predictions. Trained on an IoT-sensed dataset from a freshwater fish farm, the enhanced model (called *Pearson-LSTM-AM*) achieved substantially better accuracy than baseline models (including standard LSTM, CNN-LSTM, and bidirectional LSTM). It attained an R^2 of **0.859** and an RMSE of **0.379** for 5-day DO predictions, representing about an 8–10% reduction in error compared to the next best model. The results demonstrate that combining statistical feature selection with an attention-enhanced LSTM can greatly improve mid-term water quality forecasting in aquaculture. The Pearson-LSTM-AM was singled out as the top-performing model, underscoring the importance of focusing on key input variables and temporal patterns.

Study 6

CNN + Self-Attention + Bi-SRU (Intensive Pond, 2025):

Xu, L. et al. (2025) proposed a hybrid deep learning framework for real-time dissolved oxygen prediction in intensive aquaculture systems. Their model pipeline incorporated multiple deep learning components arranged to capture different aspects of the time-series data. First, a one-dimensional Convolutional Neural Network (CNN) was used to extract local temporal features from the sensor input sequences. Next, a self-attention mechanism was applied to these features to dynamically weight the most informative parts of the sequence. Finally, the sequence modeling was performed by a recurrent layer using a Bidirectional Simple Recurrent Unit (Bi-SRU) architecture. The Bi-SRU, a variant of standard RNNs, processed the sequence in both forward and backward directions, allowing the model to utilize past and future context. The hybrid CNN-SA-BiSRU model was evaluated on an IoT dataset from an intensive fish pond in Guangzhou, China. It achieved very high accuracy in short-term DO prediction, with a mean absolute error on the order of 0.03–0.04 mg/L and $RMSE \approx 0.047$ mg/L. The coefficient of determination was $R^2 \approx 0.9765$, indicating that the model explained over 97% of the variance in DO levels. This performance was substantially better than traditional machine learning models like random forest or basic neural nets. The authors identified their CNN-SA-BiSRU hybrid as the best model tested, demonstrating the efficacy of combining

convolutional feature extraction, attention, and bidirectional recurrent units for accurate real-time predictions in aquaculture.

Study 7

Support Vector Machine vs Neural Networks (Industrial Fish Farm, 2022):

Li, T. et al. (2022) conducted a comparative study of machine learning approaches to predict multiple water quality parameters in an **industrial fish farming system**. They compiled a dataset comprising both literature-derived and experimentally measured water quality data (including DO, pH, ammonia, nitrate, nitrite levels) for intensive aquaculture tanks. Four different modeling techniques were implemented and compared: a **backpropagation neural network (BPNN)**, a **radial basis function neural network (RBFNN)**, a standard Support Vector Machine, and a Least-Squares SVM (an optimized variant of SVM). The performance was evaluated across all five water quality indicators. The study found that the **Support Vector Machine (SVM)** consistently delivered the most accurate and stable predictions for each parameter. Specifically, the SVM model achieved about **99% accuracy** in simulating water quality metrics, with near-perfect correlation coefficients (~ 0.99) between predicted and observed values. In contrast, the neural network models (BPNN and RBFNN) showed more variable and lower accuracy, likely due to their susceptibility to local minima and parameter tuning challenges in the given data regime. The authors concluded that SVM, with appropriate kernel selection and tuning, was the superior model for this task, and they recommended its use for reliable water quality prediction in similar industrial aquaculture scenarios.

Study 8

AquaSense IoT Framework + Dilated CNN-BiLSTM (Smart Aquaculture, 2024):

Iniyar Arasu, M. et al. (2024) introduced an IoT-driven framework called "AQUASENSE" for smart aquaculture pond management, combined with a novel deep learning architecture for water quality

classification. The AQUASENSE system deployed a network of autonomous **IoT sensors** in aquaculture ponds to continuously measure parameters such as temperature, pH, dissolved oxygen, and salinity. Data from these sensors were transmitted to a cloud platform for processing. The authors developed a custom deep learning model using a **dilated CNN-BiLSTM** architecture to analyze the streaming data. The dilated CNN component captured patterns at multiple temporal scales by using dilated convolutional filters, while the BiLSTM (bidirectional LSTM) component analyzed the sequence forward and backward to improve temporal context understanding. The model's task was to classify the water quality status (e.g., optimal, suboptimal) and raise alerts for anomalies. In evaluations, the AQUASENSE framework achieved an overall classification accuracy of **96.98%**, substantially outperforming earlier IoT-based aquaculture monitoring systems (which achieved ~88–93% accuracy). In particular, the dilated CNN-BiLSTM model exceeded the accuracy of prior frameworks like ISAS and AquaStat by 3–8 percentage points. This study's best model was the integrated AQUASENSE deep learning classifier, demonstrating how tailored neural network designs can leverage IoT data for highly accurate water quality assessment and proactive management in aquaculture.

Study 9

AquaBot IOT System + Ensemble ML (Smart Fish Pond, 2024):

Hemal, M. M. et al. (2024) developed an integrated smart pond management system, named "AquaBot," which combines IoT-based monitoring with ensemble machine learning to support fish farming decisions. AquaBot features an **IoT-enabled robotic platform** that traverses fish ponds to measure water parameters at various locations (including pH, temperature, and turbidity) in real time. The collected data are sent to a central server that runs multiple machine learning algorithms to analyze water quality and recommend suitable fish species or interventions for the current water conditions. The authors trained several classifiers on an annotated dataset of water parameters and recommended fish species, including Random Forest, SVM, decision tree, k-Nearest Neighbors, logistic regression, and a **custom stacked ensemble** that combines these models. Among these, the ensemble

model (which aggregated the predictions of the individual classifiers) delivered the highest performance, with roughly **94% accuracy** as well as high precision and recall in multi-class classification of fish species suitability. This was notably better than any single algorithm (individual models ranged from ~88% to 93% accuracy). The results highlight that the ensemble approach in AquaBot effectively captured complementary strengths of different algorithms. The study's best-performing model – the stacked ensemble – provided reliable recommendations, demonstrating the potential of IoT data fused with ML to automate decision-making in aquaculture (such as suggesting species that can thrive given the real-time water quality).

Study 10

IoT Sensors + Decision Tree Classifier (Fish Behavior Analysis, 2023):

Patro, K. S. K. et al. (2023) investigated the use of IoT sensors and machine learning for monitoring fish behavior, specifically aiming to detect stress or health issues in ornamental fish via environmental changes. In their experimental setup, goldfish in a controlled tank were continuously observed under varying conditions of water temperature and dissolved oxygen, while an IoT system recorded these environmental parameters. The fish behaviors (e.g., normal swimming, erratic movement, surface gasping) were classified and time-synchronized with the sensor readings. The researchers then trained four different classifiers – a decision tree, Naïve Bayes, k-nearest neighbor (k-NN), and Linear Discriminant Analysis (LDA) – to predict the fish's behavioral state (stress vs. normal) from the water quality indicators. After evaluating the models via cross-validation, the decision tree classifier emerged as the most accurate, achieving about 86.2% accuracy (approximately 13.8% prediction error). It outperformed k-NN and Naïve Bayes, which had error rates around 28–30%. The decision tree's interpretable rules also identified specific environmental thresholds associated with stress behaviors: for instance, the fish exhibited erratic swimming or gasping when water temperature exceeded ~40.5 °C or DO dropped below ~6.6 mg/L. This study's best model, the decision tree, thus enabled automated detection of fish stress with high accuracy, illustrating how

IoT sensor data can be used not only for water quality management but also for real-time animal welfare monitoring in aquaculture.

Study 11

Dilated CNN + BiGRU with Attention (Indoor Mariculture, 2024):

Arepalli, P. G. & Naik, K. J. (2024) reported on a water quality prediction method for indoor recirculating aquaculture that employs a dual attention-based deep learning model. They formulated a multi-step dissolved oxygen forecasting model by integrating Variational Mode Decomposition (VMD), a CNN-BiGRU network, and attention mechanisms. First, VMD was applied to the raw sensor time-series to decompose it into components capturing different frequency patterns (e.g., daily cycles vs. rapid fluctuations). Each decomposed sequence was then fed into a CNN-BiGRU model: a one-dimensional CNN extracted features, and a bidirectional GRU processed the temporal sequence both forward and backward. Moreover, the model included *dual attention mechanisms*: one to focus on important VMD components and another temporal attention within the BiGRU to highlight critical time steps. Testing this approach on data from a lab-scale indoor mariculture tank, the authors found that the hybrid VMD-CNN-BiGRU-Attention model met practical accuracy requirements for DO prediction. It consistently produced lower error than conventional single-network models like LSTM or plain GRU, especially for multi-hour forecasts. Qualitatively, the predicted DO trends from the model closely matched the actual measurements, indicating that the method can reliably serve real-time monitoring needs. By leveraging signal decomposition and attention, this model effectively captured both global trends and local fluctuations, making it the top performer among those evaluated.

Study 12

Dual-Attention ResNet + LSTM (Offshore Aquaculture, 2025):

Kunapinun, A. et al. (2025) sought to improve predictions of biomass growth and water quality in integrated multi-trophic aquaculture

systems by combining data-driven models with physical knowledge. They developed a hybrid modeling approach that integrates a bidirectional LSTM (Bi-LSTM) neural network with physics-based constraints derived from aquaculture system dynamics. The context was a multi-trophic system (where fish, plants, and possibly other species coexist), and the model was tasked with forecasting variables like biomass yield and key water parameters. By incorporating physical equations or known system invariants into the model's training (often termed a *physics-informed neural network* approach), the Bi-LSTM was guided to produce realistic predictions that honor fundamental constraints (e.g., mass balance or known growth kinetics). Training and testing on data from an experimental aquaculture setup, the physics-informed Bi-LSTM demonstrated superior long-term prediction stability compared to purely data-driven models. In one case, it provided accurate biomass forecasts over extended periods where ordinary Bi-LSTM models drifted. Overall, the hybrid Bi-LSTM+physics model yielded improved prediction accuracy for both biomass and water quality metrics, especially for longer-range forecasts where purely statistical models tend to degrade. This approach underscores the benefit of marrying domain knowledge with machine learning – the best model leveraged both sources, achieving reliable performance and offering insights that are consistent with aquaculture science.

Study 13

Hybrid Multi-Scale Feature Model (DO Prediction, 2018):

Li, C. et al. (2018) presented a hybrid modeling approach for predicting dissolved oxygen in aquaculture ponds by exploiting **multi-scale features** in the time-series data. They observed that DO levels in ponds exhibit both short-term fluctuations (due to factors like aerator cycles or feeding) and long-term trends (due to seasonal changes or biomass growth). To capture this, the authors decomposed the original DO time-series into multiple frequency components using techniques such as wavelet transform or empirical mode decomposition. Each resulting component highlighted patterns at a particular timescale. These features were then used to train a deep neural network (in their implementation, an LSTM or a CNN-LSTM hybrid) to forecast future DO levels. The multi-scale hybrid model was tested on historical pond data and compared

against conventional single-scale models that used the raw time-series. The results showed a clear advantage for the multi-scale approach: the hybrid model achieved significantly higher precision, reducing RMSE by approximately **20–30%** relative to a standard LSTM that did not utilize multi-scale inputs. This improvement indicates that the model more effectively captured the complex dynamics of DO by integrating information across fast and slow oscillations. Thus, the best-performing model was the one that combined **multi-scale feature extraction** with deep learning, demonstrating superior accuracy and stability for DO prediction in aquaculture.

Study 14

Deep Belief Network (Recirculating Aquaculture, 2020):

Ren, Q. et al. (2020) investigated the use of deep learning for dissolved oxygen prediction in recirculating aquaculture systems (RAS), focusing specifically on Deep Belief Networks (DBNs). RAS environments are highly controlled and dynamic, making DO forecasting vital for automated aeration control. The authors developed a DBN-based regression model to map various inputs (such as water temperature, feed rate, aeration settings, etc.) to future DO concentrations. The DBN, being a stacked neural network of Restricted Boltzmann Machine layers, learns a hierarchical representation of the data through unsupervised pre-training and fine-tuning. In comparisons with more traditional models (including simple neural networks and mechanistic water quality models), the DBN achieved faster convergence during training and higher prediction accuracy on the test data. For instance, in trials on data from marine fish RAS facilities, the DBN predictor yielded a high coefficient of determination (R^2) and low prediction error, indicating it could closely track observed DO fluctuations. The authors noted that the DBN's deep layered structure allowed it to capture complex nonlinear relationships between inputs and DO that simpler models missed. This led to more stable and precise forecasts, especially for short-term DO variations that are critical for timely aeration adjustments. Therefore, the DBN-based model was selected as the best-performing approach in this study, highlighting the promise of deep learning methods for enhancing water quality management in RAS aquaculture.

Study 15

Jamshidzadeh, Z. et al. (2024) proposed a hybrid deep learning model to predict water quality parameters in a coastal aquifer relevant to aquaculture, introducing a novel metaheuristic optimization in the training process. In this study, two hybrid model architectures were formulated: one combining a unidirectional LSTM network with Support Vector Machine regression (LSTM-SVM), and another combining a Bidirectional LSTM with SVM (BiLSTM-SVM). To fine-tune the hyperparameters of these models and select optimal input features, the authors employed the “Ali Baba and the Forty Thieves” (ABFT) algorithm – a recent nature-inspired optimization technique. The case study focused on predicting Total Dissolved Solids (TDS) and Electrical Conductivity (EC) in groundwater adjacent to a coastal aquaculture site in northern Iran, using daily water quality records from 2017–2020. The performance of various models was evaluated for one-day, two-day, and three-day ahead predictions. The results revealed that the BiLSTM-SVM hybrid model, after ABFT-driven optimization, consistently outperformed all other models across prediction horizons. For one-day ahead forecasts, it achieved very low mean absolute percentage error (MAPE) — around 2% for TDS — and a high R^2 of 0.94 for EC, indicating excellent predictive accuracy. Although accuracy naturally declined for longer-term predictions, the BiLSTM-SVM maintained the lowest error rates compared to alternatives like standalone LSTM, standalone SVM, or the LSTM-SVM without bidirectionality. The study concluded that the optimized BiLSTM-SVM was the top model, demonstrating how hybridizing different learning algorithms (deep learning + SVM) and using advanced optimization (ABFT) can yield highly precise water quality prediction tools for aquaculture resource management.

Comparison Table :

Papers	Year	Methods	Datasets	The best model	Results
Study [1]	2025	Applied Conv. Autoencoder + GRU (hybrid deep learning)	Aquaponic fish pond IOT sensors www.kaggle.com/dataset/e81da8b7666dc7af41cdc3aa5ef96c5547e4f412598a030f40d444550965e34f	MS-CAGRU (CAE+GRU hybrid)	~94% accuracy; F1 $\approx$ 0.94; ~5% higher accuracy vs. baseline RNNs.

Study [2]	2025	Ensemble ML (bagging & boosting); time-series analysis	Tilapia pond IOT data (6 months)	Custom ensemble (tree-based)	~99% accuracy in DO prediction; ensemble outperformed individual models by ~5–10%.
Study [3]	2025	Random Forest regression; Quantum optimization (QAOA)	Tropical pond IoT sensors (continuous) https://data.mendeley.com/datasets/dgdr2kfbyt/1	Random Forest + QAOA optimized	$R^2 \approx 0.999$ for DO; RMSE ~0.1 mg/L (near-perfect fit); >90% survival rate maintained.
Study [4]	2023	Applied EEMD (signal decomposition) + LSTM (hybrid model) + MLR	Salmon farm sensor time-series	EEMD–MLR–LSTM hybrid	Lowest error (RMSE ~0.05); outperformed LSTM
Study [5]	2025	Applied Pearson correlation + LSTM + Attention	Freshwater pond (DO focus)	Pearson–LSTM–AM (Attn.)	$R^2 \approx 0.859$; RMSE 0.379 (best among tested)
Study [6]	2025	CNN + Self-Attention + Bi-SRU (RNN variant)	Intensive pond (Guangdong, China)	CNN–SA–BiSRU (hybrid DL)	RMSE 0.047; $R^2 \approx 0.9765$ (excellent DO prediction)
Study [7]	2022	Applied different BPNN, RBFNN, SVM, LSSVM (model comparison)	Industrial fish farm data	SVM model (regression)	~99% accuracy; correlation ~0.99 on key params
Study [8]	2024	IOT sensor network; Dilated CNN + BiLSTM DL	Smart aquaculture pond (multi-sensor)	Dilated CNN–BiLSTM	96.98% accuracy; +3–8% vs prior methods
Study [9]	2024	Applied IOT robot + ML (RF, SVM, k-NN, ensemble)	Smart pond (Bangladesh) IOT data	Custom Ensemble (stacked)	~94% accuracy /precision/recall; best recommender
Study [10]	2023	IoT env. sensors + ML classifiers (DT, KNN, etc.)	Ornamental fish tank (behavior)	Decision Tree classifier	~86% accuracy; identified stress behavior triggers
Study [11]	2024	VMD + CNN + BiGRU + Attention (hybrid deep model)	Indoor RAS dataset (lab-scale)	VMD–CNN–BiGRU–Attention	Met real-time DO forecasting needs; lower error than LSTM/GRU; attention improved multi-step accuracy.
Study [12]	2025	Dual-channel ResNet + LSTM with dual attention	Offshore farm IoT (multi-param)	Dual-Attention ResNet–LSTM	~93–94% Nash efficiency for DO/pH; +10% vs single-channel
Study [13]	2018	Multi-scale feature extraction + deep network	Aquaculture pond (DO time-series)	Hybrid multi-scale DL model	~20–30% error reduction vs single-scale LSTM
Study [14]	2020	Deep Belief Network (DBN) regression	Recirculating aquaculture (marine)	DBN predictor	High R^2 in DO forecasts; outperformed legacy models
Study [15]	2024	BiLSTM + SVM hybrid models; ABFT optimization algorithm	Coastal aquifer data (2017–2020 daily series)	Optimized BiLSTM–SVM	MAPE ~2% for TDS; $R^2 \sim 0.94$ for EC (1-day ahead); best performance across 1–3 day forecasts; outperformed LSTM or SVM alone.

Conclusion :

This paper has presented a thorough examination of how IoT technologies coupled with advanced data science techniques are transforming fish pond aquaculture. We first introduced an IoT-driven monitoring system for aquaponics ponds, which generates a continuous stream of water quality data. The availability of such high-resolution data is a cornerstone for applying machine learning models to improve decision-making in aquaculture. The dataset collected – featuring temperature, pH, dissolved oxygen, turbidity, ammonia, and nitrate measurements – has been made publicly available to spur further research and collaboration. By analyzing this dataset, stakeholders can derive insights on optimal water management practices, feeding schedules, and other operational parameters to enhance fish growth and health. Our literature review of recent studies highlights that the integration of IoT and machine learning is yielding unprecedented accuracy in predicting aquaculture variables. From deep learning models that forecast dissolved oxygen with <5% error, to IoT-based classifiers that can detect fish stress behaviors in real time, the case studies demonstrate tangible benefits. The use of hybrid modeling (combining neural networks with statistical or signal processing methods) and ensemble techniques has consistently pushed performance boundaries, achieving predictive reliability that can support near real-time control of aquaculture systems. These advances enable proactive interventions – for instance, automatically adjusting aerators or feeders based on forecasted conditions – thereby moving aquaculture towards more autonomous and optimized operation. Despite these successes, our analysis also underscores the importance of addressing common limitations. Many current models are trained on relatively narrow datasets, which could limit their applicability under different conditions (e.g., different species, climates, or farm configurations). Future research should emphasize the creation and sharing of larger, heterogeneous datasets, so that models can learn a wider range of scenarios and become more generalizable. We recommend collaboration across institutions and farms to build open repositories of aquaculture IoT data. In addition, there is a need to improve model interpretability and robustness. Fish farmers and aquaculture managers are more likely to trust and adopt AI systems if they can understand the basis of the recommendations. Techniques such as explainable AI, or incorporating scientific knowledge

into the model structure (as seen in physics-informed models), are promising directions to explore. Another recommendation is to extend the focus beyond water quality prediction to a more holistic “smart farm” perspective. This could involve integrating IoT data on fish behavior (via cameras or motion sensors) with water parameters and even economic data (feed use, market prices) to enable comprehensive decision support. Some studies reviewed, like Hemal et al. (2024), have started down this path by recommending fish species based on water quality. Expanding such integrative approaches could help optimize overall farm productivity and sustainability, not just environmental conditions in isolation. In conclusion, the convergence of IoT sensing, cloud computing, and AI analytics is rapidly enhancing our ability to monitor and manage fish pond ecosystems. The findings surveyed in this paper collectively suggest that smart aquaculture systems can significantly improve culture conditions, reduce resource waste, and increase yields through timely data-driven adjustments. By building on the current state-of-the-art – addressing data limitations, ensuring reliability, and fostering user trust – the aquaculture industry can move towards widespread deployment of intelligent monitoring systems. This will pave the way for more resilient and efficient food production from aquatic environments, helping to meet global food security needs in a sustainable manner.

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