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Deep Learning and Streaming Data for Real-Time Water Quality Monitoring in Shrimp Aquaculture: A Systematic Literature Review

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ABSTRACT

Shrimp aquaculture is a critical part of the global seafood industry but remains highly vulnerable to environmental fluctuations and disease outbreaks, largely due to inadequate water quality management. Recent advances in deep learning and real-time streaming data offer promising solutions for intelligent monitoring and control. This systematic literature review evaluates state-of-the-art approaches integrating deep learning models and streaming architectures for water quality monitoring in shrimp aquaculture. Following PRISMA guidelines, 38 peer-reviewed studies published between 2020 and 2025 were selected from Scopus, with emphasis on tropical aquaculture systems. The findings are organized into four themes: predictive deep learning models, smart sensing technologies and data sources, streaming and edge computing architectures, and behavioral monitoring with production outcomes. LSTM, GRU, and CNN models show strong performance in predicting dissolved oxygen, pH, and temperature. Data are commonly collected through IoT sensors, UAVs, and AI-based imaging systems, enabling high-speed acquisition and detailed spatial information. Streaming platforms such as Apache Kafka, combined with embedded AI and edge computing, support near-real-time analytics and responsive system operation. Visual behavioral monitoring further enables early detection of stress indicators and improves operational efficiency. Overall, integrating deep learning with streaming data can substantially enhance sustainability and efficiency in shrimp farming. However, challenges remain in standardization, scalability, and behavioral modeling. Future research should prioritize benchmarking, hybrid edge–cloud architectures, and long-term validation studies.

INTRODUCTION

Shrimp aquaculture is a vital component of the global food production system, representing a significant share of the world's seafood supply and contributing substantially to economic growth, particularly in tropical and subtropical regions. The industry has experienced rapid growth during the last 20 years because worldwide shrimp demand has increased both for its nutritional value and its marketability. The shrimp farming industry faces mounting sustainability challenges because of frequent disease outbreaks and unpredictable environmental changes in aquatic ecosystems. The instability of aquatic systems stems from variable environmental conditions which determine shrimp health and survival and productivity levels (Bhassu *et al*., 2024; Rusdi *et al*., 2022; Wikumpriya *et al*., 2023).

Shrimp aquaculture systems experience water quality degradation because excessive shrimp stocking behavior and improper waste disposal methods and high nutrient input create conditions which lead to nutrient pollution and increase pathogen growth in aquatic environments. The environmental stressors in this study demonstrated their ability to weaken shrimp immune functions while they also decreased shrimp growth and increased shrimp death rates. The annual economic losses resulting from these problems exceed USD 3 billion for the entire world economy (Bhassu *et al*., 2024; Elle *et al*., 2024). In response, researchers and practitioners have advocated for the integration of sustainable technologies, such as Recirculating Aquaculture Systems (RAS) and Integrated Multi-Trophic Aquaculture (IMTA), to mitigate water quality deterioration (Elle *et al*., 2024; Fauzi *et al*., 2020; Kunzmann *et al*., 2023). The systems successfully recycle water and decrease nutrient waste, yet their operational success depends on advanced monitoring systems which provide continuous environmental condition assessment.

Traditional methods for monitoring water quality depend on manual sampling and laboratory testing, which require extended periods of time and substantial workforce effort while failing to provide immediate data needed for operational control. (Sholihah *et al*., 2022; Stojanovic & Chaudhary, 2023). For small and medium sized aquaculture activities, these restrictions serve as a significant barrier, contrary to accessing sensor technology and data-processing infrastructures (Xu *et al*., 2023). There is an increasing requirement for advanced automated systems which provide nonstop accurate water quality monitoring at low operational costs. The latest progress in artificial intelligence (AI) and deep learning (DL) technology will transform the way aquaculture monitoring systems operate. Deep learning algorithms excel in extracting patterns from large, multi-dimensional datasets which enables them to predict multiple complex phenomena including dissolved oxygen variation and pH fluctuations and ammonia accumulation with high precision (Eze *et al*., 2023; Haq & Harigovindan, 2022; Sung *et al*., 2023). Aquaculture managers used time-series data from sensor networks to predict essential water quality parameters which they could use to manage upcoming operational challenges between three neural network models: Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks (Rajeshwar, 2023; Yang *et al*., 2023).

Aquaculture environments now receive real-time data through the growing use of Internet of Things (IoT) technologies. Farm operators obtain immediate research results through their use of distributed sensor nodes which constantly transmit vital water quality data including temperature and salinity and dissolved oxygen levels (Mahamuni & Goud, 2023; Wang *et al*., 2021). The Internet of Things systems produce extensive streaming data which needs fast processing to enable immediate decision-making. Streaming data analytics, supported by architectures such as Apache Kafka and Apache Spark, enable organizations to continuously ingest and process data streams while displaying information with almost immediate delay (Munif *et al*., 2024; Vo *et al*., 2021). Deep learning and streaming data work together to create advanced aquaculture systems which can automatically identify irregularities and forecast future situations and provide solutions for problems. The combination of digital technologies with farm management systems creates what people commonly call smart aquaculture or Aquaculture 4.0. Image-based models which use CNNs evaluate water clarity and identify harmful algal blooms while GRU-based architecture predicts temperature and DO changes to determine optimal aeration times (Chen *et al*., 2020; Petkovski & Shehu, 2023). Reinforcement learning is used in a few systems to further optimize feeding regimes to minimize feed conversion and waste (Son & Jeong, 2024).

This transformation from traditional to intelligent aquaculture is not merely a technological shift; it represents a paradigm change in how data is used to manage living systems. It underscores a move toward proactive, data-driven farming, where predictive models and real-time analytics supplant reactive interventions. The technologies have potential yet their implementation remains incomplete because most organizations use them only for testing purposes or initial project evaluations. The high capital requirements and the absence of technical skills and the restricted availability of standardized datasets act as obstacles which prevent organizations from using these technologies especially in developing countries. The current research study will conduct a systematic review of existing academic research which investigates deep learning methods combined with streaming data analytics for monitoring water quality in shrimp aquaculture. The primary objective is to identify state-of-the-art methods, evaluate their performance, and assess their practical utility across different aquaculture contexts. The review covers peer-reviewed research articles published between 2015 and 2025 which investigate water quality changes in tropical and subtropical shrimp pond systems.

This review has multiple core concepts which serve as its foundation. Deep learning describes a machine learning method which uses neural networks that contain multiple layers to extract features from data through a hierarchical system. Streaming data describes the continuous streams of data which sensors and embedded devices produce in real-time. Water quality monitoring involves measuring and examining all the factors which determine whether water meets shrimp growth requirements by testing its physical and chemical and biological properties. An integrated aquaculture system describes a production system which uses autonomous monitoring and data analysis and control systems to operate as a single management system. The central research question guiding this review is: How have deep learning and streaming data approaches been implemented for real-time water quality monitoring in shrimp aquaculture, and what are their impacts on farm management and productivity? The question investigates two main aspects which include system technical features and system performance results in actual use cases and controlled testing environments.

The paper uses six main sections to present its complete structured analysis. Section 2 which follows this introduction describes the methodology used to search for literature and select relevant studies and analyze the collected materials. Theoretical background in Section 3 shows how aquaculture management frameworks developed through time and how new technologies affected their progress. The literature review examines four main themes which include (1) deep learning models for prediction and control and (2) smart sensing technologies and data sources and (3) real-time streaming architectures and edge implementation and (4) behavioral and production impacts. Section 5 presents a detailed examination of the review findings which reveal different implications and limitations and potential research possibilities. Section 6 provides a summary of main findings together with recommendations for upcoming research directions. Through this review, the study seeks to create a unified knowledge base which will support researchers and engineers and practitioners who work at the intersection of aquaculture and AI and environmental monitoring. The project intends to create intelligent systems for shrimp aquaculture which will become more resilient and efficient and sustainable by assessing current technological improvements and determining existing operational difficulties.

METHODS

This systematic literature review was conducted at the University of Mataram, Indonesia, from November 2025 to April 2026. The review process consisted of literature searching, screening, eligibility assessment, quality appraisal, and thematic synthesis of peer-reviewed studies retrieved from selected academic databases. As this study did not involve field sampling, laboratory experiments, or direct animal handling, the research setting refers to the institutional location where the review process, literature screening, eligibility assessment, and synthesis were conducted.

The methodological design followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework. PRISMA is widely used in systematic reviews to improve transparency, reproducibility, and completeness in reporting the process of study identification, screening, eligibility assessment, and inclusion. In this review, PRISMA was used to structure the literature search, document the number of records at each selection stage, and ensure that the inclusion of studies was based on explicit and reproducible criteria. The review process consisted of four main stages: search strategy, eligibility criteria, screening and selection, and quality assessment.

Search Strategy

The literature search was conducted through a systematic process that examined four major academic databases which included Scopus. The researchers selected these databases because they provided complete access to scholarly articles that covered engineering and aquaculture and artificial intelligence fields. The study researched articles that appeared between 2020 and 2025 because these dates demonstrated the latest scientific progress which matched the research goals. The researchers implemented a core keyword system which combined with Boolean operators to create search parameters that included the following terms: "water quality monitoring", "deep learning", and "aquaculture". Each database's advanced search interface was used to apply keyword variations to titles, abstracts, and keywords fields to increase retrieval relevance. The search strategy incorporated both journal and high-quality conference publications to ensure a broad scope of literature, as supported by Samah *et al*. (2021) and Wong *et al*. (2024).

Inclusion and Exclusion Criteria

The study used specific criteria to determine which studies would be included because they needed to maintain both relevance and study quality. The study included articles that met these two requirements:

- Peer-reviewed journal articles or conference papers
- Published between 2020 and 2025
- Studies applying deep learning and/or streaming data to water quality monitoring in shrimp or similar aquaculture systems
- Inclusion of empirical results, technical frameworks, or implementation outcomes

The exclusion criteria removed:

- Grey literature (e.g., theses, white papers, non-peer-reviewed sources)
- Non-English language publications

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- Studies without methodological or implementation specifics
- Studies unrelated to aquaculture or focused on non-relevant species or environments

These criteria align with recommendations from Galappaththi *et al*. (2020), Rector *et al*. (2022), and Byron *et al*. (2024), ensuring methodological coherence and precision in capturing domain-relevant advancements.

Screening and Selection

The screening and selection process followed a multistage protocol. After initial searches, all retrieved citations were exported into a reference management tool for deduplication. The first screening involved title and abstract review to eliminate clearly irrelevant studies. Subsequently, full-text articles were reviewed against the inclusion criteria. Screening and selection were supported by the use of the Rayyan tool, an online platform designed for systematic reviews. Rayyan allows for blinded screening by multiple reviewers and facilitates conflict resolution through an arbitration process, improving objectivity and consistency in study selection.

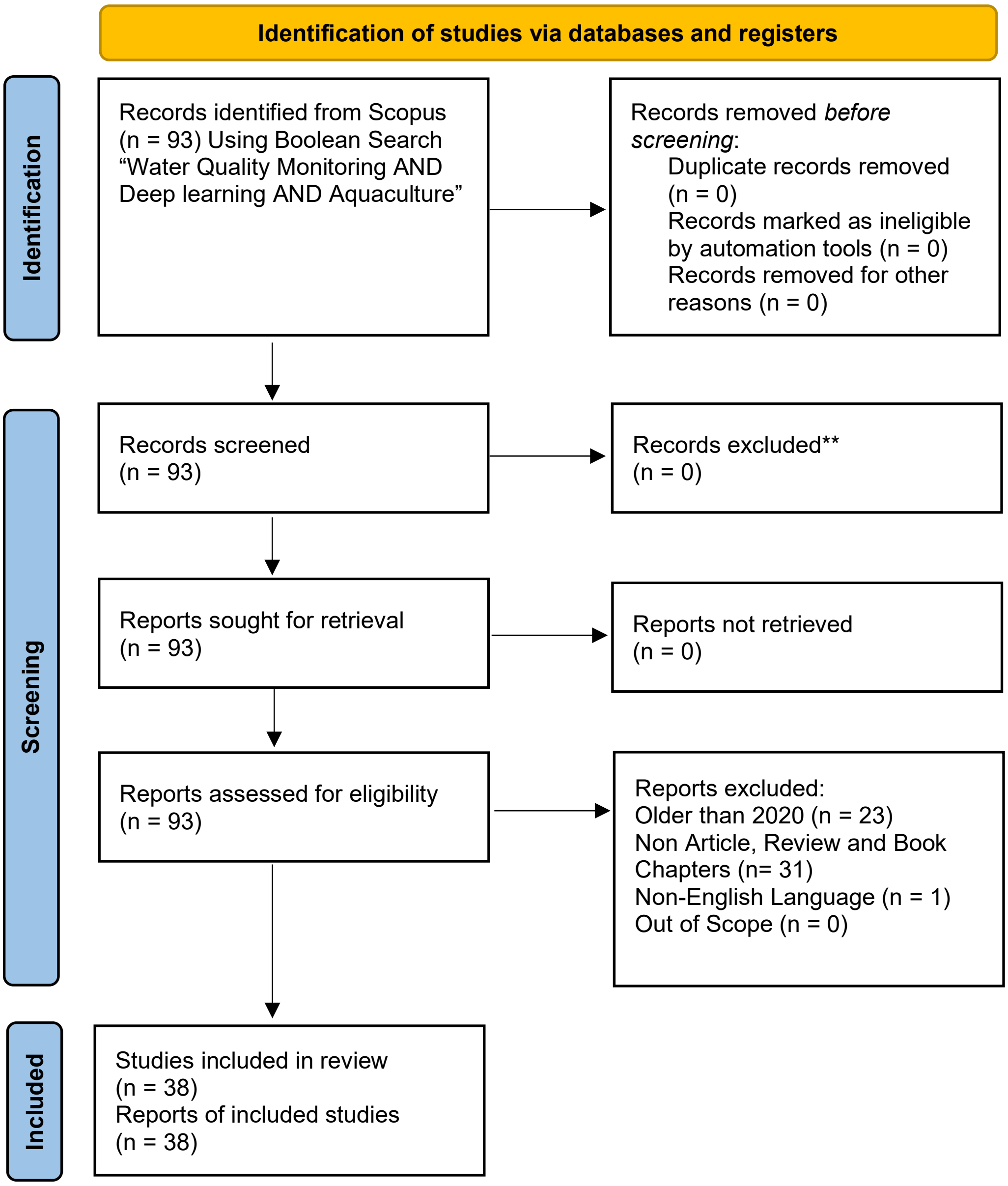

Figure 1. The PRISMA Flow Diagram Detailing the Screening and Selection Process of Literature

A summary of the selection process is presented using a PRISMA flow diagram (Figure 1), following Page *et al*. (2021) and Thakur *et al*. (2022). This diagram depicts the number of articles identified, screened, excluded, and retained at each phase of the review. The PRISMA Flow Diagram in Figure 1 shows the complete process of selecting literature for research which includes details about the number of records obtained from various databases and the number of duplicates that were eliminated and the number of studies that were excluded based on their title and abstract examination and the assessment of their full-text eligibility and the ultimate selection of studies that were used in the research.

Quality Assessment

The Mixed Methods Appraisal Tool (MMAT) conducted methodological quality assessment for all selected studies because it effectively evaluates research that includes quantitative and qualitative and mixed-method research designs (Huang *et al*., 2023). The assessment process required MMAT to evaluate multiple domains which included research question appropriateness and sampling logic and data collection methods and analytical rigor. The GRADE framework (Grading of Recommendations Assessment Development and Evaluation) provided a system to assess research evidence quality while the framework also determined the strength of findings which applied to studies that reported operational impacts or policy recommendations (Bounsall *et al*., 2023).

All studies were independently evaluated by two reviewers. Conflicts in rating or interpretation were resolved through consensus meetings or input from a third reviewer, consistent with best practices in systematic review protocols. The application of these frameworks supports a reliable synthesis of empirical findings relevant to the research question. This structured methodology facilitated a comprehensive and rigorous review of the literature, forming the basis for the thematic analysis presented in subsequent sections.

THEORETICAL FRAMEWORK

The section delivers complete theoretical bases which help researchers understand how deep learning combines with streaming data technologies to track water quality in shrimp aquaculture systems. The initial part of the document presents the main computational models together with the streaming data frameworks which researchers have documented in existing literature. The document first identifies essential research contributors together with their affiliated research institutions before it presents ongoing discussions about system transparency and ethical concerns and infrastructure system constraints.

A. Models and Theories

1. Aquaculture Management Frameworks

The evolution of aquaculture management frameworks started from traditional manual methods and progressed toward automated systems that operate with digital technology. The first methods for controlling water quality depended on manual sampling which required workers to perform their tasks but could not deliver ongoing data, thus exposing farms to sudden ecological shifts (Stojanovic & Chaudhary, 2023; Xu *et al*., 2023). Farmers automated their environmental data gathering tasks through the development of Internet of Things (IoT) platforms. Centralized data platforms receive essential water quality measurements from these devices which include pH levels, dissolved oxygen (DO) content, temperature readings, and turbidity levels. These measurements establish a foundation for predictive monitoring and control systems (Bohara *et al*., 2024; Gleiser & Moro, 2023). Modern integrated frameworks now combine sensor networks with real-time analytics and artificial intelligence technology which includes deep learning systems to achieve better management results. The combination of these technologies establishes the foundation for smart aquaculture systems which scientists now refer to as Aquaculture 4.0 because these systems operate through data-based control and decision-making processes that function with rising levels of independence (Chang *et al*., 2021; Sung *et al*., 2023).

2. Deep Learning Architectures

Aquaculture monitoring benefits from Convolutional Neural Networks, Long Short-Term Memory networks, Gated Recurrent Units, and Transformer models which stand as the most powerful deep learning models for this purpose. Researchers use CNNs to create image-based monitoring systems which track water clarity and observe shrimp movements (Liu *et al*., 2023; Petkovski & Shehu, 2023). LSTM networks and their variant GRUs serve as the best choice for time-series prediction tasks that include forecasting DO and temperature fluctuations because of their capacity to model long-term dependencies(Yang *et al*., 2021; Zhao *et al*., 2020). The hybrid models VMD-ISMA-DBN, SSA-LSTM, AODE-GRU and DSTCNN show greater accuracy and better performance stability in water quality prediction work than traditional deep learning models (Surapu *et al*., 2025; Yang *et al*., 2023). Reinforcement learning (RL) approaches such as Deep Deterministic Policy Gradient (DDPG) have been used to dynamically control feeding schedules based on predicted DO levels and shrimp behavior (Elmessery *et al*., 2025). Transformers, while newer in aquaculture research, are gaining traction due to their scalability and effectiveness in modeling complex time-dependent phenomena. HydroTransNet, for instance, has been shown to accurately forecast multiple water quality parameters simultaneously (Surapu *et al*., 2025).

3. Real-Time Streaming Concepts

The intelligent aquaculture systems require real-time data streaming to enable constant data collection and processing from multiple distant data sources. The primary frameworks which support these applications are Apache Kafka and Apache Spark Streaming. The system uses Kafka to deliver a scalable framework which enables rapid data ingestion from multiple sensors in aquaculture environments (Zhou *et al*., 2024). Spark Streaming allows real-time analytics of incoming data streams, e.g., anomaly detection and model retraining *(Huang et al*., 2022). The integration of Kafka with Spark creates an end-to-end data pipeline which delivers near-instant data processing capabilities from data collection to data analysis. The architectural combination of these systems proves essential for shrimp aquaculture because environmental changes can quickly produce dangerous health conditions (Akanbi & Masinde, 2020).

B. Key Contributors and Trends

1. Major Research Groups in AI-Driven Aquaculture

The global landscape of intelligent aquaculture research is populated by leading institutions and consortia that integrate AI and IoT to address sustainability challenges. The Ocean University of China leads research efforts which focus on AI-based improvements for aquaculture infrastructure and its marine applications (Aung *et al*., 2024). Norwegian universities conduct research on computer vision systems to study human behavior and manage water quality through their work on underwater object detection and wild fish monitoring projects (Banno *et al*., 2022). The collaboration between academia and industry has created faster technological advancements. Multinational companies have supported initiatives which enabled the creation of real-time edge artificial intelligence platforms and mobile sensor systems, resulting in better accessibility and scalability of intelligent aquaculture systems.

2. Technological Milestones

The last five years have seen multiple innovations that change how aquaculture systems monitor their operations. The use of YOLO (You Only Look Once) models for shrimp behavior recognition and fish species detection has resulted in enhanced monitoring capabilities and improved decision-making accuracy (Wang *et al*., 2021; Xu *et al*., 2024). The real-time video analysis of aquaculture ponds which both YOLOv4 and YOLOv8 provide enables researchers to detect diseases at their earliest stages while optimizing their fish feeding processes (Liu *et al*., 2022). LSTM-based models have become standard for environmental forecasting, particularly in predicting DO, temperature, and pH dynamics. The A-LSTM, SSA-LSTM, and A-GRU models were combined with PID (Proportional-Integral-Derivative) control systems to improve environmental feedback and stability (Gandh *et al*., 2024; Zhou *et al*., 2025). The system brings forward two major enhancements by connecting edge-AI devices which function with minimal delay and energy requirements to deliver real-time analysis capabilities for distant agricultural areas that have limited resources (Arepalli & Naik, 2023; Hu *et al*., 2024).

C. Controversies and Debates

1. Accuracy vs. Explainability

Digital leaning methods display high accuracy when they predict outcomes and detect unusual patterns yet their operation resembles "black boxes" which restrict both understanding and user confidence. The trade-off creates a major obstacle in agricultural environments because farm workers need to see clear solutions that they can implement. The models DSTCNN and HydroTransNet show excellent performance yet their lack of explanatory systems makes it difficult to use them in practical situations (Arepalli & Naik, 2024; Surapu *et al*., 2025). The scientific community continues to debate whether explainable AI (XAI) methods should be developed to show the reasoning behind their prediction results. The scientific community has proposed SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) as methods to create interpretable systems but these methods have not yet gained traction in aquaculture research.

2. Infrastructure and Privacy in Developing Regions

Another major obstacle exists for intelligent monitoring systems because their implementation in developing countries needs working internet systems and affordable cloud services. Edge computing has helped solve certain problems through its capacity to perform local analytics, but it still faces limitations regarding device pricing and power usage and equipment upkeep costs (Elle *et al*., 2024; Wikumpriya *et al*., 2023). Data privacy concerns exist because sensitive operational data gets transmitted through public networks and stored on third-party cloud platforms. The existing regulatory frameworks for data governance in aquaculture remain incomplete because they have not established standard protocols which govern data anonymization and secure data transmission methods. The resolution of these problems needs organizations to focus more on creating products with user experience as their main priority while establishing local infrastructure systems and implementing standard operating procedures for intelligent aquaculture technology development.

REVIEW OF THEMES

Theme 1: Deep Learning Models for Prediction, Forecasting, and Control

The introduction of Deep Learning (DL) technology to aquaculture water quality monitoring has brought about new possibilities for creating accurate predictive models and developing monitoring systems that operate in real time. In shrimp aquaculture, environmental parameters such as dissolved oxygen (DO), temperature, pH, and salinity directly impact shrimp health and yield, which makes DL models essential for intelligent management systems. The section investigates how DL models have evolved from their initial development to their current use in predicting water quality outcomes for short and long periods, which includes their implementation in control systems that use Proportional-Integral-Derivative (PID) loops and Deep Reinforcement Learning (DRL) technology. The theoretical frameworks discussed earlier especially the roles of LSTM, GRU, and Transformer architectures serve as the foundation for this analysis.

The performance of DL models in shrimp aquaculture varies depending on the architecture and the complexity of the environmental variables involved. Zhou et al. (2023) developed PID-RENet, a hybrid DL model integrating a PID loop to enhance accuracy in predicting DO and temperature, reporting significantly improved Mean Squared Error (MSE) and Mean Absolute Error (MAE) metrics compared to baselines. The direct integration of prediction and control systems enables real-time correction of deviations which proves the model's actual worth for use in aquaculture systems that require immediate responses.

Similarly, Zhou *et al*. (2025) advanced the PID-RENet model by combining deep learning architecture with a PID corrector to close the loop in DO and water temperature (WT) control. The system improved stability and responsiveness in real-time scenarios, confirming the hypothesis that integrating DL with control mechanisms increases adaptive capability. Gandh *et al*. (2024) demonstrated the efficiency of Attentive-LSTM (A-LSTM) and Attentive-GRU (A-GRU) in forecasting DO, pH, and temperature. The models reached prediction accuracies between 98.30% and 99.70% because of their design to forecast but not their ability to handle feedback control in their prediction tasks. The results demonstrate how Section 3.3 shows the relationship between accurate predictions and actual operational performance. Arepalli & Naik (2024) introduced DSTCNN, a Deep Spatio-Temporal Convolutional Neural Network optimized for Water Quality Index (WQI) classification. This model achieved 99.28% accuracy in real-time datasets and 99.02% with public datasets, illustrating the benefits of spatial-temporal modeling in aquatic environments. Yang *et al*. (2023) developed a hybrid architecture combining Variational Mode Decomposition (VMD) and an Improved Self-Adaptive Deep Belief Network (ISMA-DBN). The model focused on DO prediction, reducing MAE by 43.28% and MSE by 40.43% compared to traditional methods. Despite its success, the lack of control integration limits its real-time utility. Thai-Nghe *et al*. (2020) applied a standard LSTM for multivariate time-series prediction (salinity, pH, DO) and observed stable Root Mean Square Error (RMSE) across evaluations. The model's simplicity facilitates deployment in limited-resource settings, aligning with the argument in Section 3.3 regarding trade-offs between model complexity and computational demand. Islam *et al*. (2022) proposed an iterative ensembling method for long-range forecasting, achieving up to 29% improvements in MAE and RMSE. The model provides accurate baseline predictions which help in the future planning of management system operations even though it does not include real-time control capabilities.

The Transformer-based HydroTransNet model presented by Surapu *et al*. (2025) marked a shift from traditional RNNs to attention-based architectures for DO, COD, and other parameters. Achieving 99.1% accuracy, HydroTransNet reinforced the potential for scalable and highly adaptive forecasting in aquaculture systems. Notably, Elmessery *et al*. (2025) leveraged Deep Deterministic Policy Gradient (DDPG), a reinforcement learning algorithm, for feed rate and DO optimization. The combination of deep reinforcement learning and recirculating aquaculture systems through their control loop system proved to deliver better feeding management while reducing operational expenses which showed that artificial intelligence control systems operate successfully and provide value to commercial fish farming operations. The research demonstrates that deep learning models, especially those that combine hybrid and attention-based systems, provide significant benefits which enhance their ability to predict essential water quality measurements. The system achieves its required intelligent aquaculture management capability through its implementation of control systems which include both PID loops and deep reinforcement learning. Table 1 below summarizes the key models, target parameters, performance indicators, and control strategies, facilitating cross-comparison among state-of-the-art approaches.

Table 1. Deep Learning-Based Water Quality Prediction and Control Models

Study	Model/ Architecture	Target Parameters	Accuracy/Performance	Control Integration
Zhou *et al*. (2023)	PID-RENet + DNN	DO, temp	Improved MSE, MAE over baseline	PID-based error elimination
Gandh *et al*. (2024)	A-LSTM, A-GRU	DO, pH, temp	98.30–99.70% accuracy	Forecasting-only
Arepalli & Naik (2024)	DSTCNN	WQI	99.28% real-time, 99.02% public dataset	WQI-based classification
Zhou *et al.* (2025)	DL + PID corrector	DO, WT	High prediction accuracy	PID controller loop
Yang *et al*. (2023)	VMD + ISMA-DBN	DO	MAE ↓43.28%, MSE ↓40.43%	None
Thai-Nghe *et al*. (2020)	LSTM	Salinity, pH, DO	Stable RMSE, time-series prediction	None
Islam *et al*. (2022)	Iterative Ensembling	Long-range forecast	MAE, RMSE improved up to 29%	None
Surapu *et al*. (2025)	HydroTransNet (Transformer)	DO, COD, etc.	99.1% accuracy	Time-dependent forecasting
Elmessery *et al*. (2025)	DDPG (Reinforcement Learning)	Feed rate, DO	Improved feeding control, reduced cost	RAS feedback loop

The various applications show how deep learning methods have advanced in aquaculture while the industry moves toward intelligent management systems that follow the theoretical framework presented in Section 3.

Theme 2: Smart Sensing Technologies and Data Sources

Smart sensing technologies now used in aquaculture provide a complete overhaul of traditional water quality monitoring and management procedures. The field of precision aquaculture now uses Internet of Things (IoT) devices and autonomous sensors and remote sensing platforms to achieve better spatial and temporal monitoring results. The systems provide scientists with the ability to collect aquatic data through high-resolution measurement systems which enable them to make sustainable aquaculture management decisions. The studies summarized in Table 2 demonstrate a broad range of sensing modalities employed in shrimp aquaculture and related aquatic systems. The research uses IoT devices and UAV platforms and AI-powered sensors and advanced imaging systems that include hyperspectral remote sensing. The studies present innovative technological solutions that help organizations enhance their efficiency and reliability while improving their water quality data collection operations.

Table 2. Sensor Technologies and Data Capture Systems

Study	Sensor Type	Measured Parameters	Data Rate/Latency	Spatial Scope
M Iniyan Arasu. *et al*. (2024)	Autonomous sensors	Temp, DO, salinity, pH	High	Pond-wide
Wang *et al*. (2020)	UAV + WSN	DO, turbidity	UAV low-latency	Inland aquaculture
Ma *et al*. (2025)	UAV hyperspectral	TN, NH4-N, TP, COD	High-res imaging	Whole pond mapping
Chen *et al*. (2023)	Water-wheel tail image	Waterwheel tail length	Real-time camera	Pond-based
Hu *et al*. (2024)	AIoT sensors	Temp, pH, DO	24/7 streaming	Seawater ponds
Arepalli & Khetavath (2023)	Time-series CNN IoT sensors	WQI	Real-time	Aqua farm nodes
Guo *et al*. (2023)	Image + Transfer learning	Watercolor (quality proxy)	High	Image-based quality sensing
Chiu *et al.* (2022)	IoT devices + DL	DO, temp, feed	Real-time	Taiwan aquaculture
Sung *et al*. (2023)	WSN + DRL	Temp, pH, turbidity	Layered fusion	Indonesia

M Iniyan Arasu *et al*. (2024) exemplify the use of autonomous sensor networks that provide high-frequency data on critical parameters such as temperature, dissolved oxygen (DO), salinity, and pH. These systems have a capacity to cover the entire pond and provide real-time data for detecting environmental stressors sooner. Similarly, Hu *et al*. (2024) deploy AIoT sensors in seawater ponds with 24/7 streaming capabilities, highlighting the robustness and scalability of modern sensor infrastructures. The application of UAVs in the field of spatial monitoring became broader. For instance, Wang *et al*. (2020) combine UAVs with Wireless Sensor Networks (WSN) to measure DO and turbidity with low latency in inland aquaculture systems. Ma *et al*. (2025) extend this by applying UAV hyperspectral imaging to map nutrient levels such as TN, NH4-N, and COD across entire ponds, providing comprehensive water quality assessments.

Advanced image-based systems have also emerged. Chen *et al*. (2023) introduce a visual monitoring approach utilizing waterwheel tail image analysis, offering real-time measurements of waterwheel tail length a proxy for aeration dynamics and pond circulation. Guo *et al*. (2023) employ transfer learning on water surface imagery to infer water quality through color metrics, presenting a low-cost, scalable alternative to in-situ sensors. Arepalli & Khetavath (2023) present CNN-based IoT sensors optimized for predicting the Water Quality Index (WQI) in real time, supporting node-level deployment within aquafarms. This aligns with Chiu *et al*. (2022), who integrate deep learning with IoT devices to monitor DO, temperature, and feeding behavior in Taiwan aquaculture systems, illustrating how AI augments traditional sensing for smarter decision-making.

In Indonesia, Sung *et al*. (2023) apply a hybrid architecture combining WSNs with Deep Reinforcement Learning (DRL) to monitor turbidity, temperature, and pH. The system uses a multi-layered fusion technique which improves its ability to combine data from different locations, thus enabling better response times to changing water quality conditions. The research demonstrates how data collection methods for aquaculture have developed to establish multiple monitoring systems which track changes throughout time while covering different geographic areas and maintaining minimal delays. The hyperspectral imaging system delivers excellent spatial detail, but it needs extensive processing power, whereas time-series sensors generate instant operational data which works well with control loop systems. Aquaculture operators can choose from various sensing systems which help them achieve their management objectives and adapt to their particular environmental conditions. The current situation shows progress, but it continues to face multiple obstacles. According to earlier studies, small-scale farmers face financial challenges because advanced sensor equipment and UAV systems remain too expensive for them to purchase (Sung *et al*., 2023; Xu *et al*., 2023). Biofouling and maintenance concern the durability and reliability of a sensor in a harsh aquatic environment (Stojanovic & Chaudhary, 2023). The need for advanced data integration systems arises from the existence of different data types which come from multiple sources in remote locations that lack proper digital infrastructure (Bohara *et al*., 2024). The theoretical foundations discussed in Section 3 support these findings. The platforms Apache Kafka and Spark Streaming enable efficient data handling and fusion through their implementation of real-time streaming and layered sensor architecture components. The convergence of AI and sensor networks enables aquaculture management systems to shift from reactive modes to proactive operations, which matches essential patterns of intelligent aquaculture development (Akanbi & Masinde, 2020; Zhou *et al*., 2024). Smart sensing technologies make substantial contributions to improving water quality monitoring systems used in shrimp aquaculture. The research demonstrates that combining real-time data collection through granular methods with advanced analytical methods creates aquaculture systems that can adapt to environmental changes while maintaining efficiency. Future directions should emphasize affordability, sensor interoperability, and scalable cloud-edge architectures to expand adoption across diverse aquaculture contexts.

Theme 3: Streaming Architecture and Edge Implementation

The combination of streaming architecture with edge computing systems has emerged as an essential requirement for creating intelligent aquaculture monitoring systems that operate in environments which need fast response times and high operational efficiency. Researchers have studied different frameworks because aquaculture systems exhibit complicated behavior patterns while water quality monitoring requires immediate data processing. Water parameters can be monitored continuously through real-time data streaming which decreases the duration needed to transform collected data into usable knowledge. As noted by (Prapti *et al*., 2021), Apache Kafka is commonly employed for its low-latency, high-throughput message brokering capabilities. The platform enables organizations to build data ingestion systems that can scale their operations. The platform enables organizations to gather urgent aquaculture data through multiple remote sensors which monitor their operations. Flink serves as a top data processing platform which enables users to analyze massive data sets in real time while performing advanced analytics and detecting security threats before they occur (Shafique *et al*., 2020).

However, streaming alone does not suffice. Processing the data close to the source via edge computing is essential in latency-critical applications like shrimp aquaculture. By reducing the dependency on cloud infrastructures, edge computing decreases transmission delays and enhances system reliability, particularly in geographically isolated ponds (Shafique *et al*., 2020; Thong-un *et al*., 2024). For example, Arepalli & Naik (2023) developed a lightweight Modified Hybrid GRU (MHGRU) architecture, deployed on-device with minimal latency. The architecture shown in Table 3 demonstrates its complete edge capabilities through its ability to perform processing tasks without needing external units while delivering immediate analytics results at the data source. Complementing this, Arepalli & Naik (2024) introduced the SSA-LSTM model combining on-device and cloud processing, achieving sub-second response times while allowing for intermediate analytics both locally and remotely. This combination architecture represents a new trend described in Section 3.1, with cloud and edge layers interacting with one another to provide a beneficial balance between the extremes of scalability, power consumption, and responsiveness.

Similarly, Hu *et al*. (2024) implemented an AIoT-SRU framework that supports cloud-edge synchronization. This setup operates continuously over 24 hours, maintaining real-time responsiveness while leveraging cloud resources for deeper analytics. It exemplifies the hybrid architecture discussed by Rong *et al*. (2021), which balances local processing and centralized computation for long-term optimization. Islam *et al*. (2022) proposed an ensemble deep learning system optimized for mid-level latency and offline environments. The system provides reliable performance under low connectivity conditions because its offline optimization process functions without requiring edge processing capabilities. The system demonstrates these constraints which the theoretical framework establishes through its energy limitations and bandwidth restrictions of edge devices (Jouini *et al*., 2024). Wang *et al*. (2021) took a novel approach by implementing YOLO-V4 for underwater object detection directly onboard embedded systems. The detection accuracy maintained its high level while the embedded system demonstrated how edge artificial intelligence processes visual information without requiring cloud-based data transmission. These findings reinforce arguments made by (Gleiser & Moro, 2023) on the latency benefits of edge-enabled detection. X. Zhou *et al*. (2023) explored the PID-RENet architecture, enabling a local feedback loop that functions near real-time. The setup provides optimal performance for adaptive control systems which require quick response times. The system design uses edge loops as a fundamental pattern which embedded systems apply in their environmental control systems. Lastly, Elmessery *et al*. (2025) adopted a deep reinforcement learning framework based on DDPG, embedded within a Recirculating Aquaculture System (RAS). The system provides complete integration which enables two functions: adaptive learning and real-time decision-making while it maintains the feedback loop between sensing and prediction and actuation. The Section C analysis shows that reinforcement learning enables adaptive learning but demands extensive training data and dependable system constraints for effective functioning. The streaming and edge system architecture research proves that it functions as a critical element which enables both immediate response time and complete system independence. Table 3 presents a synthesis of these implementations, highlighting their latency performance, deployment layers, and edge compatibility.

Table 3. Real-Time Streaming and Edge Computing Frameworks

Study	Platform/Tool	Deployment Layer	Latency	Edge Capability
Arepalli & Naik (2023)	MHGRU IoT	On-device	Low	Yes
Arepalli & Naik (2024)	SSA-LSTM IoT	Cloud + device	<1s	Partial
Hu *et al*. (2024)	AIoT + SRU	Cloud platform	Continuous 24h	Yes (cloud edge sync)
Islam *et al*. (2022)	Ensemble DL	Streaming forecast	Mid	Offline optimized
Wang *et al*. (2021)	YOLO-V4 under water	Onboard detection	High precision	Yes (embedded)
X. Zhou *et al*. (2023)	PID-RENet	Local + feedback	Near real-time	Compatible with edge loop
Elmessery *et al*. (2025)	DDPG control	Fully integrated	Adaptive loop	Embedded in RAS

Aquaculture needs both real-time streaming and edge deployment technology because it no longer serves as a basic operational tool. The findings support the hypothesis that integrating these technologies enables robust, responsive, and scalable monitoring systems for shrimp production. Future research must focus on refining hybrid edge-cloud architectures, reducing energy consumption of deployed models, and developing transfer learning pipelines for edge environments. The development of these technologies will enable aquaculture systems to be implemented sustainably and intelligent systems to work at large-scale operations.

Theme 4: Behavioural and Production Impacts in Shrimp Aquaculture

Recent advancements in aquaculture have implemented AI-based technologies through computer vision systems and sensor-based systems for tracking fish and shrimp movements. The approaches exist to evaluate how environmental changes impact the welfare and stress responses and production capabilities of aquatic organisms. The table presents a summary of main research studies that explored behavior recognition and its relationship with production results.

Table 4. Behavior Analysis and Farm Outcome Metrics

Study	Target Species/Behavior	Monitoring Method	Key Findings	Productivity Impact
Shreesha *et al*. (2023)	Sillago sihama (frantic)	Autoencoder + LSTM	Outlier-detection triggers alerts	Early warning, fish safety
Xu *et al*. (2024)	Bass, Sturgeon	YOLOv8 + Kalman	3D tracking of stress behavior	Prevention of ammonia death
Wang *et al*. (2021)	Fish schools	RGB + Optical flow (DSC3D)	Behavior states (feeding, hypoxia)	Supports health perception
C. Liu *et al*. (2022)	Aquaponic fish	YOLOv4 + motion stats	Higher movement in APS	Better growth, water purification

Study	Target Species/Behavior	Monitoring Method	Key Findings	Productivity Impact
Keerthi & Subhashini (2023)	Fish (unspecified)	NASNet + GCN + optimization	Behavioral pattern classification	Feed optimization potential
Høgstedt *et al*. (2025)	Salmon	SaBRE CV system	Negative DO correlation with breathing	Welfare monitoring

Aquaculture environments now benefit from real-time behavioral classification due to computer vision-based behavior detection models, which operate through YOLO (You Only Look Once) and CNN and Autoencoder technologies. For instance, Shreesha *et al*. (2023) utilized an Autoencoder and LSTM to detect anomalies in fish behavior, resulting in real-time alert systems for early intervention. Similarly, Xu *et al*. (2024) employed YOLOv8 combined with a Kalman filter for the 3D tracking of fish, effectively identifying stress-induced behaviors that could lead to ammonia-related mortality. The research results support earlier studies which establish that behavior-sensitive systems enable better survival results through their ability to detect problems at an early stage (Bohara *et al*., 2024; Borges *et al*., 2021). The swimming velocity and clustering behavior together with erratic movement patterns of animals serve as behavioral indicators which correlate with environmental conditions that exceed optimal limits through low dissolved oxygen and high ammonia levels. Wang *et al*. (2021) deployed a deep spatial convolution model (DSC3D) using RGB cameras and optical flow to classify behavioral states such as hypoxia-induced lethargy or active feeding. The following are likely to constitute non-invasive biological diagnostics for health and stress.

In aquaponic systems, Liu *et al*. (2022) discovered that fish exhibited higher movement rates under controlled water flow conditions, correlating with improved growth and enhanced nutrient cycling. This finding demonstrates the bidirectional relationship between behavioral patterns and production outcomes, reinforcing arguments by Stojanovic & Chaudhary (2023) on integrating behavioral data with environmental metrics. Machine learning-based classification models, such as NASNet combined with graph convolutional networks (GCNs), have proven effective in mapping complex behavioral routines. Keerthi & Subhashini (2023) demonstrated that their optimization-augmented model could classify feeding versus stress behaviors, opening the door to feed strategy refinement and minimizing overfeeding. Breathing patterns were also investigated by Høgstedt *et al.* (2025), who utilized the SaBRE system to analyze salmon respiration under varying DO levels. They found a strong inverse correlation between DO and breathing frequency, emphasizing the importance of DO monitoring in welfare assessments. These findings corroborate the theoretical insights from Section 3, where deep learning and edge-based sensing were highlighted as enablers for real-time aquaculture control systems.

Behavior-aware systems offer predictive capabilities when paired with environmental data. Integration strategies include data fusion and real-time analytics, as supported by Sánchez-Jerez *et al*. (2022) and Chatziantoniou *et al*. (2023). Combining these insights facilitates smarter intervention strategies automated aeration, feed dosing, or alerting before critical thresholds are breached. Predictive modeling built on historic behavior-environment interactions enhances farm management decisions. Nujaira *et al*. (2022) emphasized how these systems allow farmers to anticipate stress or feeding anomalies days in advance. Wickliffe *et al*. (2024) similarly reported that mortality rates dropped when predictive alerts were actioned. The implications of these technologies are profound. Rusdi *et al*. (2022) and Bohara *et al*. (2024) noted that farms adopting behavior-based AI systems experienced measurable improvements in feed conversion ratios (FCR), shrimp size uniformity, and overall biomass yield. Thus, smart behavioral analysis systems not only contribute to early warning and welfare but also drive economic value by enhancing productivity. Overall, these studies reinforce the hypothesis that real-time monitoring of behavior, integrated with smart control systems, offers substantial benefits to shrimp aquaculture. As emphasized in the theoretical framework (Section 3), the convergence of sensing, streaming, and AI-based behavioral analysis enables a paradigm shift in aquaculture monitoring and control. This supports a more sustainable, resilient, and data-driven aquaculture industry.

DISCUSSION

The systematic literature review investigated how deep learning techniques combine with streaming data architectures to create water quality monitoring systems for shrimp aquaculture which use streaming data to monitor all behavioral patterns and control operational results. The discussion applies thematic findings from Section 4 to evaluate research studies while presenting essential discoveries and demonstrating how these discoveries affect theoretical frameworks and practical work and upcoming studies. The study found that deep learning models used for water quality prediction and control achieved their highest operational results through all tested architectural designs which included A-LSTM, A-GRU, DSTCNN, and HydroTransNet. (Arepalli & Naik, 2024; Surapu *et al*., 2025). These models demonstrated exceptional accuracy in forecasting critical environmental variables such as dissolved oxygen (DO), pH, and temperature. The system developed better real-time adaptability through the combination of control systems which included Proportional-Integral-Derivative (PID) loops together with Deep Reinforcement Learning (DRL) control methods (Elmessery *et al*., 2025; X. Zhou *et al*., 2023). However, disparities remain in the implementation scale of these models, with some studies operating in simulated environments or relying on limited datasets, which may not reflect real-world variability. This highlights a methodological limitation and a potential source of bias.

A notable observation pertains to model complexity and deployment feasibility. While hybrid architectures such as VMD + ISMA-DBN and ensemble approaches offer superior accuracy (Islam *et al*., 2022; Yang *et al*., 2023), they are computationally intensive and may not be suitable for real-time, edge-based systems without significant optimization. The trade-off between precision and operational readiness of the system requires aquaculture facilities to find a middle ground between advanced model development and their existing operational limitations (Haq & Harigovindan, 2022). Smart sensing technologies (Theme 2) show significant advancement through the use of IoT nodes and hyperspectral UAVs and autonomous sensors for environmental monitoring in real time (M Iniyan Arasu *et al*., 2024; Ma *et al*., 2025). The platforms provide complete spatial coverage together with detailed data collection capabilities, which become more effective when AioT technology and deep learning processing layers are integrated (Guo *et al*., 2023; Hu *et al*., 2024). The reliability of sensors continues to be problematic because of two main factors which include marine organisms that accumulate on surfaces and the extreme weather conditions that sensors must operate in (Stojanovic & Chaudhary, 2023). The costs of advanced sensors together with their maintenance requirements create financial barriers that prevent adoption in aquaculture operations which have limited resources (Sung *et al*., 2023; Xu *et al*., 2023).

The research demonstrated that streaming architectures together with edge computing technologies experienced significant development during the period between Theme 3 and Theme 4. The research studies which used Kafka and Spark together with embedded edge-AI systems showed improved performance because of their ability to handle more users while processing data with lower delays (Hu *et al*., 2024; Prapti *et al*., 2021). The deployment of edge systems faces challenges because of hardware restrictions and power usage requirements and the necessity to develop effective model compression methods (Fraga-Lamas *et al*., 2021; Jouini *et al*., 2024). Cloud-edge hybrid frameworks provide effective solutions because they divide computing tasks between different processing layers but face ongoing difficulties with achieving seamless synchronization and maintaining data consistency (Gummadi *et al*., 2024; Rong *et al*., 2021). The architectural designs for streaming systems have shown progress through their recent developments, yet their implementation in various aquaculture environments still needs further development. Theme 4 shows how behavioral analysis has become an important method for predicting productivity in aquaculture operations. The AI-based vision models YOLO and CNNs and SaBRE detected stress indicators and movement anomalies and feeding behaviors across different species, which enabled real-time management response through their detection capabilities *(Liu et al., 2022; Shreesha et al*., 2023). The studies demonstrated that environmental factors influence the behavior of both shrimp and fish which shows that multimodal data fusion helps organizations make better decisions (Chatziantoniou *et al*., 2023). The generalizability of behavior-monitoring models which were developed for species other than shrimp particularly bass and salmon present a problem because tropical shrimp aquaculture requires different types of models (Høgstedt *et al*., 2025; Xu *et al*., 2024).

The cross-theme synthesis demonstrates that all tested models and systems require extended validation studies to prove their effectiveness across different time periods. The studies which we reviewed used brief datasets which they gathered from pilot-scale tests. The studies which we reviewed failed to offer open-access datasets and standardized testing criteria. The current methodological constraint requires researchers to create collaborative evaluation systems which include common testing resources. The research results expand the theoretical framework which defines intelligent aquaculture systems. Deep learning combined with IoT infrastructure enables better prediction results and enables immediate system responses which assist in building cyber-physical systems for aquaculture. The implementation of edge computing together with streaming architectures supports distributed intelligence and operational resilience for remote agricultural operations.

The investigated technological advancements provide concrete methods which farmers can use to achieve better water quality management while decreasing shrimp death rates and increasing feed efficiency which will result in higher farm income and environmentally sustainable practices. The implementation of predictive control systems together with real-time behavior monitoring enables adaptive management which allows organizations to prevent both environmental stress events and disease outbreaks (Rusdi *et al*., 2022; Wickliffe *et al*., 2024). The development of these technologies needs better sensor solutions to lower costs and improve device compatibility and expand rural and coastal region infrastructure. Future research should prioritize (1) real-world deployments of edge-integrated AI systems in commercial shrimp ponds; (2) the development of lightweight, interpretable models suitable for low-resource settings; (3) the exploration of multi-species behavioral datasets to enhance model generalizability; and (4) longitudinal studies that validate system performance across multiple production cycles and climatic variations. The combination of aquaculture experts and computer scientists and policy stakeholders must work together to create responsible AI solutions that drive technological advancements. The review demonstrates how deep learning, smart sensors, and real-time data streaming can transform shrimp aquaculture through their combined application. The current system shows successful outcomes, yet it continues to face difficulties with implementation and its ability to scale and its need for standardized research methods. The development of intelligent aquaculture systems that maintain resilience and sustainability depends on targeted research and practical innovations which will solve existing problems.

CONCLUSION

The development of these technologies needs better sensor solutions to lower costs and improve device compatibility and expand rural and coastal region infrastructure. Future research should prioritize (1) real-world deployments of edge-integrated AI systems in commercial shrimp ponds; (2) the development of lightweight, interpretable models suitable for low-resource settings; (3) the exploration of multi-species behavioral datasets to enhance model generalizability; and (4) longitudinal studies that validate system performance across multiple production cycles and climatic variations. The combination of aquaculture experts and computer scientists and policy stakeholders must work together to create responsible AI solutions that drive technological advancements. The review demonstrates how deep learning, smart sensors, and real-time data streaming can transform shrimp aquaculture through their combined application. The current system shows successful outcomes, yet it continues to face difficulties with implementation and its ability to scale and its need for standardized research methods. The development of intelligent aquaculture systems that maintain resilience and sustainability depends on targeted research and practical innovations which will solve existing problems.

The progress we have achieved thus far still contains existing hurdles to overcome. The adoption of new technologies faces challenges because high model complexity and sensor maintenance costs and integration difficulties and data generalizability problems create obstacles to their implementation. The current study faces methodological challenges because the variations in model benchmarking approach and the low rate of cross-validation testing and the absence of field testing create obstacles to making valid comparisons that show how well the results apply to other situations. Researchers need to investigate two components which include creating scalable edge-based artificial intelligence systems and conducting research on long-term shrimp population behavior and combining multiple data sources to develop complete management systems. The research study establishes a new area of intelligent aquaculture systems research by providing a complete overview of current technological solutions which focus on automated systems that can detect real-time behavioral patterns. The study establishes aquaculture management system development through its research which shows both technological viability and environmental sustainability.

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