

deployment, especially when models are expected to operate across different farms and culture systems. Deep-learning models face an additional bottleneck because they often require large labeled datasets that are difficult to obtain in aquatic environments, where turbidity, occlusion, and biofouling reduce image quality and complicate annotation (Rather et al., 2024).

A second limitation is that many current models remain difficult to generalize, scale, or interpret in real production settings. Recent reviews note that traditional machine-learning approaches show limited semantic understanding and insufficient scalability in high-dimensional environments, while deep-learning systems still struggle with real-time performance, cross-domain adaptability, and robustness under changing field conditions (Wu et al., 2025). These technical issues are compounded by practical barriers such as high setup costs, computational demands, and the risk of over-automation in systems that still require human observation and judgment, particularly in small or resource-constrained farms (Ratan et al., 2026).

### 7.2 Future development of ai and data-driven aquaculture technologies

Future development in computational aquaculture is moving toward more integrated and adaptive digital systems rather than isolated prediction models. Emerging reviews emphasize multimodal data fusion, lightweight and edge-deployable models, synthetic data generation, and digital twin-based virtual farming platforms as key next steps for improving model adaptability and operational use (Wu et al., 2025; Ratan et al., 2026). In parallel, integrated frameworks that combine IoT sensing, AI analytics, and blockchain-supported traceability are being positioned as a pathway toward more resilient, transparent, and scalable aquaculture data infrastructures.

The next generation of systems is also likely to depend on distributed and resource-aware computing architectures that can work beyond high-bandwidth commercial farms. Edge-cloud and federated-learning approaches are being developed to reduce latency, protect farm-level data privacy, and enable local processing for real-time monitoring and growth estimation without continuous cloud dependence (Cheng et al., 2022). At the same time, IoT-ML platforms designed for constrained environments suggest that low-cost sensing, local processing, and more efficient training pipelines can make predictive aquaculture more accessible in rural settings rather than restricting advanced analytics to technologically intensive operations (Baena-Navarro et al., 2025).

### 7.3 Potential contributions to sustainable aquaculture development

The main long-term contribution of computational aquaculture is its potential to improve sustainability by increasing production efficiency while reducing waste and environmental pressure. Reviews of sustainable aquaculture technologies consistently report that AI-supported feeding, growth prediction, and environmental monitoring can reduce human intervention, improve resource utilization, and strengthen traceability and production control across the aquaculture value chain (Yang et al., 2025). These gains matter because improved production efficiency is already recognized as a core pathway toward lower carbon footprint, better feed management, and more sustainable intensive aquaculture systems.

Computational systems may also contribute to sustainability through more proactive management of water quality, pollution, and system resilience. Integrated IoT and machine-learning monitoring has been associated with substantial reductions in losses from water-quality problems and can support survival above 90% under tropical production conditions, showing the practical value of continuous predictive control (Baena-Navarro et al., 2025). Beyond production efficiency alone, AI-enabled precision feeding and effluent-treatment frameworks are increasingly framed as tools for pollution reduction and green fisheries development, provided that implementation economics and system-coupling challenges are addressed.

## 8. Conclusions

A major advance in computational aquaculture is the shift from descriptive monitoring to integrated prediction of growth, feeding, health, and environmental conditions. Recent reviews show that deep learning and broader AI methods now support growth prediction, intelligent feeding, water-quality forecasting, biomass estimation, and behavioral analysis within the same digital framework, which marks a clear expansion beyond single-purpose