

7 Integration of Statistical Models into Precision Shrimp Aquaculture Management

7.1 Development of data-driven aquaculture decision systems

Data-driven aquaculture decision systems increasingly combine continuous environmental sensing, predictive analytics, and user-facing dashboards to support faster and more consistent farm management. A real-time shrimp monitoring system in Bangladesh integrated IoT devices, cloud services, machine learning models, and web applications to track pH, temperature, total dissolved solids, electrical conductivity, and salinity, while also issuing alerts when parameters moved outside optimal ranges (Ahmed et al., 2024). A broader decision-support framework similarly proposed a multi-source data hub that merges environmental, trading, and internet-derived data into a common platform, with modules for environmental monitoring, equipment sharing, cost-profit calculation, and price prediction (Le et al., 2024).

These systems are valuable because they replace fragmented manual observation with structured, stage-specific decision support. Bayesian belief network work in rice-shrimp farming showed that environmental conditions, stocking density, and fertilizer use can be encoded into a decision model that identifies action sets reducing the probability of crop failure, and that systematic interrogation across crop stages helps farmers make timely choices. More recent anomaly-detection research in commercial shrimp ponds also found that routine measurements of salinity, alkalinity, hardness, and inorganic nitrogen can reliably distinguish acceptable from residual water status, supporting low-cost operational warning signals in data-limited settings (Villamar-Barros et al., 2026).

7.2 Application of artificial intelligence and big-data analytics

Artificial intelligence is now used in shrimp aquaculture not only for water-quality prediction but also for feeding, biomass estimation, reproduction management, and production classification. In recirculating systems for *Litopenaeus vannamei*, a data-driven biomass model built from water-quality and management variables showed that support vector machines achieved the best predictive performance, and the resulting model was used to determine appropriate feeding amounts in real time (Chen et al., 2024). In broodstock management for *Penaeus monodon*, a two-stage machine-learning framework predicted both molting and ovarian maturation, with random forest reaching 88.5% accuracy and 94.3% AUC, indicating that AI can also support precision control of reproductive timing (Yang et al., 2025).

Big-data analytics has also expanded into computer vision and multiyear industrial modeling. Deep-learning shrimp counting in industrial recirculating farms outperformed manual counting, and the best model achieved 5.97% error at densities below 200 shrimp per image, bringing automated stock estimation close to deployment thresholds. In industrial-scale outdoor white shrimp farming, five years of data from 12 ponds showed that ensemble machine learning predicted body weight with $R^2 = 0.829$, while explainability analysis indicated that days of culture, stocking density, and cumulative feed ranked above temperature, pH, and dissolved oxygen in predictive importance.

7.3 Future perspectives for sustainable shrimp production

Future precision shrimp aquaculture appears to depend on integrating AI with streaming data architectures, edge computing, and accessible decision-support systems. A recent systematic review found that LSTM, GRU, and CNN models perform strongly for predicting dissolved oxygen, pH, and temperature, while IoT sensors, UAVs, and AI-based imaging systems enable high-speed environmental and behavioral monitoring; however, the same review identified persistent challenges in standardization, scalability, and long-term validation. A broader review of AI for sustainable aquaculture likewise concluded that predictive modeling and decision-support systems are central to precision production, but adoption is still limited by data heterogeneity, sensor reliability, and the socio-economic digital divide between high-tech and small-scale systems.

Sustainable implementation will therefore require not only better models, but also more inclusive innovation systems, farmer training, and governance structures. Reviews focused on shrimp-sector technology emphasize that AI-enabled monitoring, automation, alternative feeds, and microbial approaches can improve productivity, animal health, and environmental performance, yet uptake remains constrained by capital cost, technical complexity, and uneven access to digital tools. Complementary work on digital sustainability in Indonesia further suggests that end-