# Artificial Intelligence in Gut Health Management and Monitoring in Fishes

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**ABSTRACT**

As global aquaculture expands to meet rising food security demands, managing fish health—especially gut health—has become vital for industry sustainability and financial success. For fish, the gastrointestinal tract acts as the control centre for nutrient absorption, immune regulation, and generally boosts performance. However, traditional methods of monitoring gut health, such as histological analysis, necropsy, or visual inspection of mortality events, are inherently reactive, invasive, and often not timely. This paper examines the transformative potential of artificial intelligence (AI) and machine learning (ML) in shifting intestine health management from a reactive approach to a proactive, real-time, precision-based method. Advanced convolutional neural networks (CNNs) are proposed for the automatic, real-time assessment of faecal waste characteristics—such as buoyancy, color, and viscosity—immediately in the water column, serving as instant indicators of digestive function and dysbiosis. Additionally, the paper highlights how AI can analyse complex, high-throughput sequencing data from the fish intestine microbiome. By employing deep learning algorithms to interpret metagenomic data, researchers can now detect early microbial biomarkers of strain or pathogen intrusion well before clinical symptoms emerge.

## INTRODUCTION

The integration of AI-driven equipment with Internet of Things (IoT) sensors creates a comprehensive "virtual dual" of the aquaculture environment, enabling correlation of water-quality parameters (e.g., pH, temperature, dissolved oxygen) with gut-health metrics. This supports predictive modelling that can forecast outbreaks of enteric diseases, optimise feed formulations for specific gut health effects, and significantly reduce reliance on antibiotics. This states that AI-involved intestine health tracking is a essential aspect of "Precision Aquaculture 4.0," which is a way for creating improved feed conversion ratios, minimising environmental impact, and enhancing animal welfare standards in commercial fish farming. The intestinal microbiome of fish is a complicated environment that consists of bacteria, archaea, fungi, viruses, and protozoa. These microbes are essential for digestion, nutrient absorption, immune regulation, metabolism, pressure resistance, and disease prevention (Luan *et al.*, 2023; Kanika *et al.*, 2025). The traditional microbiological strategies are based on culture-based strategies, in which only a small portion of the microbial range is considered. With the appearance of next-generation Sequencing (NGS) and metagenomics (Luan *et al.*, 2023), researchers can now profile whole microbial groups. However, these techniques produce large datasets that can be difficult to interpret manually, and this is where artificial Intelligence (AI) and machine learning emerge as a powerful tool for evaluating the fish gut microbiome.

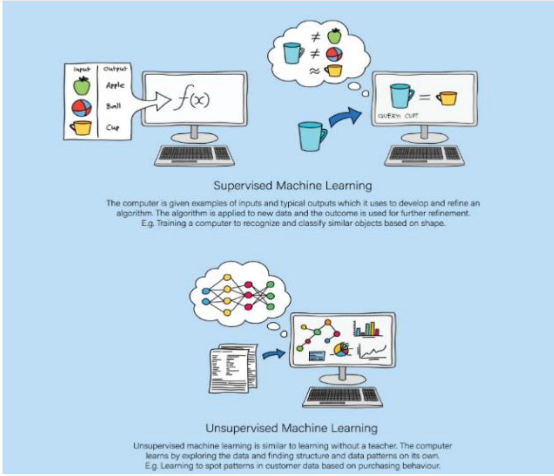

Fig. 1: About supervised and unsupervised learning

## 1. AI IN FISH GUT MICROBIOME ANALYSIS

### 1.1 SUPERVISED LEARNING

What is Supervised Learning?

Supervised learning uses labelled datasets, which means the outcome (label) is already known, such as Group 1 = Healthy fish and Group 2 = Diseased fish. The algorithm is a process or set of rules used in calculations or other problem-solving tasks, especially by a computer, that learns patterns in microbial composition that differentiate these groups and then predicts outcomes for new samples. Common algorithms include Random Forest, Support Vector Machine (SVM), Logistic Regression, and Gradient Boosting (Huang *et al.*, 2025; Gladju *et al.*, 2022).

#### 1.1.1 DISEASE PREDICTION

The disease is predicted as follows: first, gut microbiome samples are collected from healthy and infected fish (e.g., fish infected with Vibrio species). Next, there will be Sequencing, where 16S rRNA sequencing or metagenomics generates microbial abundance data, and, further, the Feature Matrix Creation is performed in such a way that the Rows indicate the Fish samples and the Columns are Microbial taxa abundance (e.g., Lactobacillus, Aeromonas, Vibrio) (Gladju *et al*., 2022; Najafpour *et al*., 2025). Subsequently, the data is converted into a Model Training Dataset. This supervised model learns how the pathogenic microbes increase in diseased fish and how the beneficial microbes decrease. Finally, for a new fish sample, the model predicts the Probability of disease and the Risk score.

#### 1.1.2 FEED RESPONSE CLASSIFICATION

Fish respond differently to feeds depending on their ingredients and how they are incorporated, such as probiotics, prebiotics, plant-based diets, and high-protein diets. Label fish by feed type or growth performance, and calculate high- and low-FCR efficiency. It also trains the model to identify microbial patterns associated with improved digestion, nutrient absorption, and SCFA production, and to predict which feed formulation is optimal based on the gut microbiome profile (Calcagnile *et al*., 2024; Mohammed *et al*., 2025). From this, we can develop Personalised nutrition in aquaculture and microbiome-optimised feeds.

#### 1.1.3 ANTIBIOTIC IMPACT ANALYSIS

This analyses how antibiotics change the gut microbial diversity through the pre-treatment and the post-treatment of the microbiome profile. The sample is labelled as before and after antibiotic treatment, and the model learns the effects of antibiotics and infers outcomes (Singh *et al*., 2024; Tay *et al*., 2025), such as which beneficial microbes are lost, which opportunistic pathogens proliferate, and long-term microbiome recovery patterns. So, it helps in monitoring antibiotic resistance risk, designing probiotic recovery strategies and minimising ecological damage

### 2.2 UNSUPERVISED LEARNING

#### WHAT IS UNSUPERVISED LEARNING?

When there are no predefined labels, the algorithm automatically detects hidden patterns. Common methods include K-means clustering, hierarchical clustering, Principal Component Analysis (PCA), and t-SNE/UMAP. In clustering similar microbial communities, the AI groups fish samples based on microbial composition similarity. For example, fish raised in freshwater, brackish water, or under different temperature conditions may be clustered into distinct microbial community groups by the model. The results are shown as dendrograms, heatmaps, and microbial similarity networks, aiming to identify environmental effects on the microbiome, understand stress-induced changes, and compare farm systems.

#### 2.2.1 DISCOVERING NOVEL MICROBIAL ASSOCIATIONS

Unsupervised algorithms can detect symbiotic microbes, competitive interactions among microbes, and keystone species such as Lactobacillus and Bacillus, which are consistently found together in healthy fish. The AI identifies this association without any prior instruction. This supports probiotic formulation, understanding microbial growth and its environment, and the discovery of novel symbiotic interactions, and also informs the development of immunostimulants.

### 3.1 DEEP LEARNING

Deep learning uses multi- layered neural networks to model complex, nonlinear biological relationships. Unlike traditional machine learning, this approach automatically extracts results from large datasets by integrating multi-omics, categorised as Metagenomics, Transcriptomics, Metabolomics, and Host genome data. Convolutional Neural Networks (CNNs) automatically detect lesions in histological slides and can quantify villus length, inflammatory infiltration, and goblet cell depletion (Gladju *et al*., 2022; Huang *et al*., 2025) Deep learning reduces observer bias and enhances high- throughput evaluation in dietary and toxicological research. Combining microbiome data with metabolomics and transcriptomics enables comprehensive profiling of intestinal health (Tay *et al*., 2025). Machine learning links microbial taxa to metabolic outputs such as short- chain fatty acids and bile acids, thereby enabling the prediction of feed performance and immune responses. Real- time AI monitoring allows early detection of environmental stressors, disease outbreaks, and water quality issues before visible signs appear in fish. Gadget-based studying models continuously process sensor data streams to detect abnormal trends, like sudden drops in dissolved oxygen or spikes in ammonia levels, and immediately notify farmers. This predictive ability reduces mortality, improves feed efficiency, and minimises economic losses. In species like Labeo rohita and Oreochromis niloticus, real-time AI systems can correlate environmental parameters with feeding behaviour, intestinal health indicators, and growth rates, supporting precision aquaculture practices. Advanced AI models also integrate microbiome data, feeding schedules, and historical farm performance to generate predictive models for disease risk and feed optimisation. For instance, if AI detects environmental stressors that usually lead to microbial dysbiosis, it could recommend preventive actions, such as aeration adjustments or probiotic supplementation. Additionally, automated management systems for IoT devices can regulate aerators, (Flores-Iwasaki *et al*., 2025; Shete *et al*., 2024) and water distribution mechanisms without manual input. This automation promotes sustainability by reducing excessive feed use, preventing antibiotic overuse, and lowering energy consumption.

## 4. IOT AND REAL-TIME AI MONITORING

The integration of the Internet of Things (IoT) with Artificial Intelligence (AI) has advanced aquaculture by enabling real- time monitoring and predictive analytics. IoT consists of a network of interconnected sensors and devices that continuously gather environmental and biological data from aquaculture systems (Flores-Iwasaki *et al*., 2025; Shete *et al*., 2024). These sensors measure essential water-quality parameters, including temperature, pH, dissolved oxygen, ammonia, salinity, turbidity, and nitrate, which are vital for maintaining fish health and optimising growth rates. The collected data are transmitted and stored in cloud- based systems, where AI algorithms analyse trends and generate actionable insights. Real- time AI tracking allows for early detection of environmental stress, disease outbreaks, and water quality deterioration before visible symptoms appear in fish (Huang *et al*., 2025; Zuhaer *et al*., 2025). Studying these patterns: systems continuously monitor sensor data streams to identify anomalous behaviours (e. g., sudden drops in dissolved oxygen or spikes in ammonia levels) and promptly send alerts to farmers. This predictive capability reduces mortality rates, enhances feed efficiency, and minimises financial losses. In species such as Labeo rohita and Oreochromis niloticus, real- time AI systems can correlate environmental parameters with feeding behaviour, gut health indicators, and increases in faecal output, enabling precise aquaculture management (Shete *et al*., 2024). Advanced AI systems also incorporate microbiome data, feeding schedules, and historical farm performance records to develop predictive models for disease outbreaks, hazards, and feed optimisation. For example, if AI detects environmental stressors that typically precede microbial dysbiosis, it will recommend preventive actions, such as aeration adjustments or probiotic supplementation. Additionally, automated control systems connected to IoT devices can regulate aerators, feeders, and water exchange mechanisms automatically. This automation supports sustainability by reducing feed waste, limiting antibiotic overuse, and lowering electricity consumption.

## 5. AI-GUIDED MICROBIOME ENGINEERING

AI-guided microbiome engineering represents a transformative approach in aquaculture, in which artificial intelligence is used to design and optimise gut microbial communities to improve fish health and productivity. Historically, probiotic selection in fish farming relied heavily on empirical trial-and-error strategies, in which candidate bacterial strains were evaluated experimentally with limited knowledge of their complex interactions within the gut microbiome. However, the fish gut microbiome is a dynamic, interconnected network in which microbial species compete, cooperate, and influence host body structure through metabolite production and immune modulation. AI enables researchers to move beyond conventional procedures by modelling complex microbial interactions and predicting how specific probiotic strains will behave within an existing microbial network. AI supports rational probiotic selection and microbiome engineering by using computational models to examine, predict, and simulate how microorganisms interact with one another and with the fish host (Hoseinifar *et al*., 2024; Mohammed *et al*., 2025). The technique begins with the collection of intestinal microbiome data and the use of sequencing methods, such as 16S rRNA gene sequencing or metagenomics. Those techniques identify which microbial species are present in the fish gut and their relative abundance. AI algorithms then decompose this large dataset into simpler patterns and relationships among specific microbes and host fitness indicators, including growth rate, immune response, disease resistance, and feed efficiency. For instance, AI can identify beneficial microorganisms such as Lactobacillus or Bacillus, which are consistently associated with healthy fish, whereas pathogenic bacteria, including Vibrio, are linked to disease (Hoseinifar *et al*., 2024.

Once those associations are recognised, AI uses predictive modelling to simulate microbial interactions within the gut ecosystem. The intestinal microbiome is a complex community in which microbes compete for nutrients, produce metabolites, and influence one another's survival. AI systems, including device learning and network-based simulations, can predict how introducing a new probiotic strain will affect this microbial balance. For instance, the model may also predict whether the probiotic will successfully colonise the gut, suppress pathogenic bacteria, or enhance beneficial metabolic activities, such as enzyme production or short-chain fatty acid synthesis. AI can also be expected to elicit the host's physiological response, including enhanced digestion, improved immune function, and reduced infection. Moreover, AI integrates a couple of factors, which include fish species, their diet, environmental conditions, and stress range, to suggest the most suitable probiotic strains or microbial combos. Instead of counting on traditional trial-and-error experiments, which can be time-consuming and expensive, AI provides evidence-based tips for microbiome engineering (Huang *et al*., 2025). This allows researchers and aquaculture practitioners to design targeted probiotic formulations that enhance intestinal health, improve disease resistance, and optimise overall growth performance. standard, AI makes microbiome engineering more particular, efficient, and scientifically guided with the aid of predicting results earlier than actual application.

## CONCLUSION

Artificial Intelligence (AI) is emerging as a transformative tool for tracking and managing gut health in fish, enabling a shift from conventional reactive strategies to advanced predictive and precision-based aquaculture practices. By integrating microbiome analysis, sensor-based environmental tracking, imaging techniques, and machine learning algorithms, AI enables continuous, real-time assessment of intestinal health and overall fish physiology (Huang *et al*., 2025; Gladju *et al*., 2022). These technologies can detect subtle changes in microbial composition, feeding behaviour, and environmental conditions that may indicate early signs of stress, dysbiosis, or disorder. Early detection enables timely intervention through dietary modifications, probiotic supplementation, or environmental modifications, thereby preventing disease outbreaks, reducing mortality, and enhancing productivity. AI reduces the dependence on antibiotics by promoting precautionary measures, which contribute to minimising antimicrobial resistance and support environmentally sustainable aquaculture practices (Luan *et al*., 2023; Hoseinifar *et al*., 2024). The integration of IoT-enabled sensors and automated monitoring systems similarly strengthens AI-based gut fitness control by providing frequent environmental and physiological statistics. This enables farmers to predict the culture system, reduce operational costs, and enhance average farm efficiency. However, a successful AI implementation can also foster interdisciplinary collaboration among aquaculture scientists, microbiologists, engineers, and records analysts to ensure accurate model development and practical applicability.

In conclusion, AI-driven gut health monitoring supports the development of smarter, more sustainable, and efficient aquaculture. By early disease prediction, improving feed utilisation, and assisting preventive fitness management, AI has the potential to enhance fish fitness tracking. As technological advancements continue and accessibility improves, AI will play a crucial role in ensuring sustainable aquaculture production, improved fish welfare, and long-term food safety.

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