International Journal of Electrical, Electronics and Computer Systems

ISSN: 2347-2820

Volume 15 Issue 1s (2026) | Pages: 142-149

AI-Driven Fish Health Monitoring and Recommendation System for Aquaculture

Smita Sapkal[1], Vedant Badve[2], Pravin Tambe[3], Kartik Bahekar[4]

[1,2,3,4] Department of Computer Engineering, Genba Sopanrao Moze College of Engineering, Pune, India

Email: vedantbadve13@gmail.com, pravintambe5671@gmail.com, pritamtambe7878@gmail.com, kartikbahekerofficial@gmail.com, sapkalss.2025@gmail.com

Peer Review Information

Type: *Article*
Received: *8 February 2026*
Revised: *10 March 2026*
Accepted: *11 April 2026*
Published: *21 May 2026*

Abstract

Aquaculture is essential for global food security but is highly affected by disease outbreaks. This paper presents FishCare AI, a real-time aquatic health monitoring system using deep learning and conversational AI. The system employs a dual-stage YOLOv8 architecture, where the first stage detects fish and identifies species, and the second stage performs disease detection only when required, improving efficiency and reducing latency. A context-aware chatbot provides reliable, evidence-based recommendations. The system achieves 92.4% accuracy in species detection and 88.7% in disease detection, offering a scalable and efficient solution for practical aquaculture monitoring.

Keywords: Aquaculture; Artificial Intelligence; Deep Learning; YOLOv8; Fish Disease Detection; Computer Vision.

How to Cite This Article

Sapkal, S., Badve, V., Tambe, P., Bahekar, K. (2026). AI-Driven Fish Health Monitoring and Recommendation System for Aquaculture. *International Journal of Electrical, Electronics and Computer Systems*, 15(1s), 142-149.

Introduction

Aquaculture has become one of the fastest-growing sectors in food production, contributing over 50% of the global fish supply and playing a vital role in food security. However, the industry is highly vulnerable to disease outbreaks such as Ich, Fin Rot, Columnaris, and Dropsy, which can spread rapidly and cause significant economic losses. Early and accurate detection of these diseases is crucial for maintaining healthy fish populations and ensuring sustainable aquaculture practices. Conventional fish health monitoring methods rely heavily on manual inspection and expert knowledge. These approaches are not only time-consuming and labor-intensive but also prone to human error and subjectivity, making them unsuitable for large-scale or real-time monitoring. With advancements in Artificial Intelligence (AI) and Deep Learning, automated image-based detection systems have emerged as a promising solution. Computer vision models can analyze visual patterns and identify diseases with high accuracy. However, most existing systems are limited by single-stage processing, lack of computational optimization, and absence of user-interactive guidance. To overcome these limitations, this research proposes FishCare AI, an intelligent aquatic health monitoring system that combines a dual-stage YOLOv8-based detection pipeline with a context-aware AI chatbot. The system not only detects fish and identifies diseases efficiently but also provides actionable, evidence-based recommendations, making it practical and accessible for real-world aquaculture applications.

Recent advancements in Artificial Intelligence (AI) and Deep Learning have opened new possibilities for automating disease detection through image-based analysis. Computer vision models, particularly object detection algorithms, have demonstrated the ability to identify patterns and anomalies in visual data with high accuracy. Despite these advancements, most existing systems are limited by single-stage processing, lack of real-time optimization, and absence of interactive support for end users. Furthermore, many solutions do not account for real-world challenges such as varying water conditions, lighting variations, and background noise To address these challenges, this research proposes FishCare AI, an intelligent and scalable aquatic health monitoring system designed for real-time application. The system employs a dual-stage YOLOv8-based detection framework, where the first stage detects fish and identifies species, and the second stage performs disease detection only when necessary. This conditional execution enhances efficiency by reducing redundant computations and improving system responsiveness. In addition, the system integrates a context-aware AI chatbot that provides users with clear, evidence-based recommendations based on the detected results. This combination of automated detection and intelligent guidance bridges the gap between technical analysis and practical usability. In addition, the system integrates a context-aware AI chatbot that provides users with clear, evidence-based recommendations based on the detected results. This combination of automated detection and intelligent guidance bridges the gap between technical analysis and practical usability.

Literature Review

The application of Artificial Intelligence (AI) and Deep Learning techniques in aquaculture, particularly for fish disease detection, has gained significant attention in recent years. Researchers have explored various computer vision models to automate the process of identifying fish species and detecting diseases, aiming to reduce dependency on manual inspection and improve diagnostic accuracy. Despite these advancements, several limitations persist in terms of real-world applicability, system efficiency, and user interaction.

Raza et al. (2019) developed a fish disease detection system based on Convolutional Neural Networks (CNNs). Their model achieved an accuracy of approximately 89% when tested on controlled laboratory datasets. While the results were promising, the system struggled to generalize effectively in real-world aquatic environments, where factors such as varying lighting conditions, water turbidity, and background noise significantly affect image quality. This limitation highlighted the need for more robust and adaptive models capable of handling diverse environmental conditions.

Liu et al. (2020) proposed a detection framework using the Single Shot MultiBox Detector (SSD) combined with transfer learning techniques. This approach improved detection speed and enabled real-time processing to some extent. However, the system primarily focused on detection performance and did not incorporate any advisory mechanism to guide users in responding to identified diseases. As a result, while the system could detect abnormalities, it lacked practical usability for non-expert users such as small-scale fish farmers

Tran et al. (2021) employed a ResNet-50 architecture for fish species classification under varying lighting conditions. The model demonstrated high accuracy in identifying multiple fish species, showcasing the potential of deep residual networks in handling complex visual patterns. However, the study was limited to species classification and did not extend to disease detection or severity analysis, thereby restricting its application in comprehensive health monitoring systems.

Zhao et al. (2022) utilized the YOLOv5 object detection model for real-time fish disease detection. The model achieved faster inference speeds compared to traditional CNN-based approaches and demonstrated improved performance in detecting diseased fish. Nevertheless, the system followed a single-stage detection pipeline, where both fish detection and disease classification were performed simultaneously.

This approach led to unnecessary computational overhead, particularly when processing images without fish, and did not include optimization mechanisms such as conditional execution or short-circuiting.

In addition to these studies, recent advancements in AI have introduced the use of conversational agents in various domains. However, their integration into aquaculture systems remains limited. Most existing fish disease detection solutions focus solely on visual classification outputs without providing contextual explanations or actionable recommendations. This lack of user guidance reduces the practical utility of such systems, especially for users with limited technical expertise.

Overall, while existing studies demonstrate significant progress in AI-based fish disease detection, they remain limited in terms of efficiency, scalability, and practical usability. Most approaches focus primarily on detection accuracy without addressing real-time optimization or user interaction. These gaps highlight the need for an integrated system that combines accurate detection, computational efficiency, and actionable guidance. This motivates the development of the proposed FishCare AI framework, which aims to provide a more comprehensive and practical solution for real-world aquaculture applications.

Background and motivation

Importance of Aquaculture in Global Food Systems

Aquaculture has become a cornerstone of global food production, contributing significantly to the supply of affordable and high-quality protein. With the growing global population and increasing demand for seafood, aquaculture plays a vital role in ensuring food security and economic stability. Countries across the world rely on fish farming not only for nutrition but also as a source of livelihood for millions of people.

Challenges in Fish Health Management

Despite its importance, aquaculture faces persistent challenges, particularly in managing fish health. Disease outbreaks such as Ich, Fin Rot, Columnaris, and Dropsy can spread rapidly in aquatic environments, often going unnoticed until severe damage has occurred. These diseases lead to high mortality rates, reduced productivity, and significant financial losses, making effective monitoring and early detection essential

Limitations of Traditional Monitoring Methods Traditional approaches to fish health monitoring rely heavily on manual inspection and expert intervention. These methods are not only time-consuming but also subjective, as they depend on the experience and judgment of individuals. In large-scale or remote aquaculture setups, continuous monitoring becomes impractical, leading to delayed diagnosis and treatment. Additionally, the lack of skilled professionals in many regions further limits the effectiveness of these conventional methods.

Role of Artificial Intelligence in Modern Monitoring

The emergence of Artificial Intelligence (AI) and Deep Learning has opened new possibilities for automating disease detection and monitoring processes. Computer vision models can analyze images and detect patterns that may not be easily visible to the human eye. These technologies offer the potential for faster, more accurate, and scalable solutions. However, existing AI-based systems often lack real-time efficiency, adaptability to diverse environmental conditions, and user-friendly interfaces.

Need for an Intelligent and Practical Solution

There is a growing need for a system that not only detects diseases accurately but also operates efficiently in real-world conditions. An ideal solution should minimize computational overhead, handle environmental variability, and provide actionable insights to users. Moreover, integrating an advisory component can help bridge the gap between detection and decision-making, especially for users without technical expertise.

Motivation Behind the Proposed System

Motivated by these challenges, this research proposes FishCare AI, an intelligent aquatic health monitoring system that combines a dual-stage YOLOv8-based detection pipeline with a context-aware AI chatbot. The goal is to create a system that is not only accurate and efficient but also practical and accessible. By reducing dependency on manual inspection and providing real-time, evidence-based guidance, the proposed solution aims to enhance disease management and support sustainable aquaculture practices

Proposed model and architectural framework

The proposed system, FishCare AI, is designed as an intelligent, real-time aquatic health monitoring platform that integrates deep learning-based computer vision with a scalable web-based architecture. The system aims to automate fish species identification and disease detection while providing actionable insights through a conversational interface.

The core innovation of the system lies in its dual-stage YOLOv8-based detection pipeline, combined with a context-aware and a cloud-based multi-tier architecture. This design ensures high accuracy, low latency, and efficient resource utilization, making it suitable for real-world aquaculture environments.

System Architecture Overview

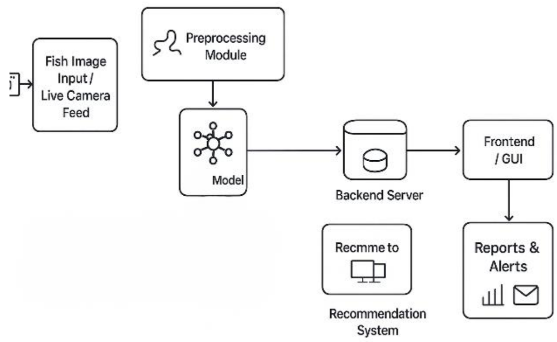

Fig. 1. *System Architecture of the Model*

Presentation Layer (Frontend)

The presentation layer is developed using React.js and TailwindCSS, providing a clean and responsive user interface. It allows users to upload fish images, view detection results, and interact with the AI chatbot. The interface is designed to be user-friendly so that even non-technical users can easily operate the system

Application Layer (Backend Gateway)

The backend is implemented using Node.js with Express.js, acting as a central communication layer between the frontend and the machine learning models. It handles user requests, manages sessions, processes image uploads, and forwards data to the ML microservice. Additionally, it aggregates the results and sends them back to the frontend in a structured

Machine Learning Layer (ML Microservice)

The machine learning layer is developed using Python and FastAPI and serves as the core analytical engine of the system. It hosts the trained YOLOv8 models responsible for fish detection and disease classification. This layer performs image preprocessing, executes model inference, and generates outputs such as bounding boxes, class labels, and confidence scores.

Data Layer (Cloud Database)

The data layer is powered by Supabase (PostgreSQL) and is responsible for securely storing user data, uploaded images, detection results, and session information. It ensures data persistence, scalability, and secure access, making the system suitable for real-world deployment.

Dual-Stage YOLOv8 Detection Pipeline

Stage 1: Fish Detection and Species Identification

In the first stage, a YOLOv8 model is used to detect the presence of fish in the input image and identify the species. The model generates bounding boxes around detected fish along with confidence scores. If no fish is detected, the system immediately stops further processing, ensuring efficiency.

Stage 2: Disease Detection

The second stage is triggered only when a fish is successfully detected in Stage 1. A separate YOLOv8 model is used to analyze the detected fish region and identify diseases such as Ich, Fin Rot, Columnaris, and Dropsy. The model outputs the disease class, confidence score, and the affected region.

Technical Explanation of YOLOv8 Usage

YOLOv8 is used as an advanced object detection model that performs both localization and classification simultaneously. It identifies infected regions within the fish image and classifies them into specific disease categories, enabling accurate and real-time detection. Short-Circuit Optimization Mechanism The system incorporates a short-circuit optimization strategy to improve efficiency. If no fish is detected in Stage 1, the second stage is skipped entirely. This reduces unnecessary computation, lowers latency, and improves overall system performance, especially when processing irrelevant inputs.

End-to-End Workflow

The system workflow begins when a user uploads an image through the frontend interface. The image is sent to the backend, which forwards it to the ML microservice. Stage 1 detects the fish and identifies the species, followed by Stage 2 for disease detection if applicable. The results are stored in the database, and the generates advisory insights. Finally, all outputs are displayed to the user in a structured and interactive format.

Methodology for fish health assessment

The effectiveness of the proposed FishCare AI system is based on the integration of advanced deep learning models, optimized processing techniques, and intelligent recommendation mechanisms. The system is designed to ensure high accuracy while maintaining efficiency in detecting fish species and identifying diseases. By combining computer vision with conditional execution logic, the model avoids unnecessary computations and focuses only on relevant inputs. This structured approach not only improves detection performance but also enhances system speed, making it suitable for real-time applications in aquaculture environments.

Dual-Stage Detection Strategy

The core methodology of the system is built on a dual-stage YOLOv8 detection strategy, which separates the process of fish detection and disease identification into two distinct stages. In the first stage, the system analyzes the input image to detect the presence of a fish and accurately classify its species. This step acts as a filtering mechanism to ensure that only relevant images are processed further. In the second stage, disease detection is performed only if a fish is successfully identified. The model detects common fish diseases such as Ich, Fin Rot, Columnaris, and Dropsy. This conditional execution significantly reduces unnecessary processing, improves system efficiency, and enhances overall accuracy by preventing false detections on irrelevant inputs.

Model Optimization

To improve system performance, a short-circuit optimization mechanism is used: If no fish is detected → Stage 2 is skipped, Reduces processing time, Improves real-time response

This makes the system suitable for large-scale aquaculture environments. To further improve performance, the system incorporates a short-circuit optimization mechanism. In cases where no fish is detected in the first stage, the second stage of disease detection is automatically skipped. This reduces computational load, minimizes processing time, and ensures faster response generation. Such optimization is particularly beneficial in real-time scenarios where large volumes of image data need to be processed quickly. Additionally, this approach helps in conserving system resources, making the solution scalable and efficient for deployment in both small-scale and large-scale aquaculture environments.

Image Processing Pipeline

The system processes input images using the following steps: Image upload by user, Preprocessing (resizing, normalization), YOLOv8 inference, Output generation (bounding box, class, confidence)

The system follows a structured image processing pipeline to ensure accurate and consistent results. Initially, the user uploads an image through the interface, which is then passed to the preprocessing stage. During preprocessing, the image is resized and normalized to match the input requirements of the YOLOv8 model. After preprocessing, the image is fed into the model for inference, where object detection and classification are performed. Finally, the system generates the output, which includes bounding boxes around detected objects, predicted class labels (species or disease), and confidence scores. This step-by-step pipeline ensures reliable processing and maintains the quality of predictions.

System implementation and integration

The FishCare AI system is implemented using a multi-tier architecture that ensures modularity, scalability, and efficient communication between different components. The system integrates modern frontend technologies, backend services, deep learning models, and database management systems to deliver real-time fish health analysis. The architecture is divided into four major layers: the Frontend Layer, Backend Layer, Machine Learning Layer, and Data Layer, all interconnected through well-defined APIs and communication protocols.

The Frontend Layer provides an interactive user interface that allows users to upload images and view results in an easy-to-understand format. The Backend Layer handles request processing, API management, and communication between the frontend and machine learning components. The Machine Learning Layer is responsible for executing the YOLOv8 models for fish detection and disease classification, ensuring accurate predictions. Finally, the Data Layer manages storage of images, results, and system logs, enabling data tracking and future analysis. This layered architecture ensures flexibility, easy maintenance, and the ability to scale the system as requirements grow.

Frontend Layer (Presentation Layer)

The frontend of the FishCare AI system is developed using React.js to create a dynamic, responsive, and user-friendly interface. It allows users to easily upload fish images, view detection results, and interact with the chatbot system. When a user uploads an image, it is converted into a suitable format and sent to the backend through API calls using Axios. The results returned from the backend, including fish species, detected disease, confidence score, and annotated images, are displayed in real time without reloading the page. Tailwind CSS is used to design a clean and responsive layout that works across different devices, ensuring accessibility for both technical and non-technical users such as fish farmers.

Backend Layer (Application Layer)

The backend is implemented using Node.js with the Express.js framework, which acts as an intermediary between the frontend and the machine learning layer. It handles all incoming requests, manages image uploads, validates data, and communicates with the ML APIs. When an image is received, it is temporarily stored, verified for correct format and size, and then forwarded to the machine learning service for processing. The backend also defines RESTful APIs such as image upload, result retrieval, and chatbot interaction. Middleware like Multer is used for handling multipart image data, while CORS ensures secure communication between different system components. Additionally, proper error handling mechanisms are implemented to manage invalid inputs, server issues, or cases where no fish is detected.

Performance benchmarking and evaluation metrics

The performance benchmarking of the FishCare AI system is conducted to evaluate its effectiveness, accuracy, and efficiency in real-world scenarios. This process involves analyzing how well the system detects fish species and identifies diseases under different conditions. By using standard evaluation metrics, the system's reliability and robustness are measured, ensuring that it meets the requirements for practical deployment in aquaculture environments. The evaluation also helps in identifying limitations and areas for further improvement.

Success Metrics for FishCare AI System

The success of the proposed FishCare AI framework is evaluated using key performance indicators (KPIs) that measure the system's accuracy, reliability, and efficiency in real-world aquaculture environments. These metrics ensure that the system not only performs well technically but also remains practical and trustworthy for end users such as fish farmers and researchers.

1.Detection Accuracy (> 90%): This metric evaluates the ability of the system to correctly identify fish species and detect diseases from input images. A high detection accuracy ensures that the model can reliably classify different fish types and recognize disease patterns under varying environmental conditions such as lighting, water clarity, and image quality.

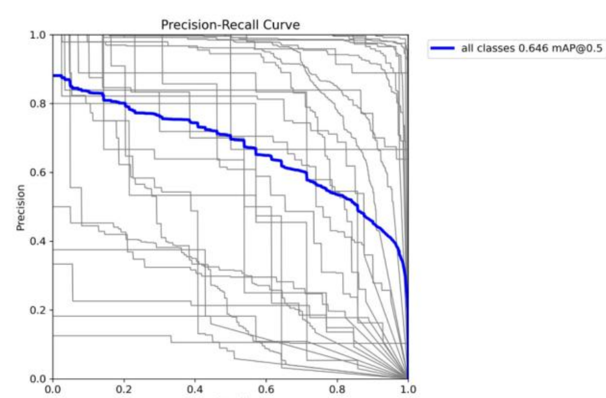

Fig 2. *Precision–Recall Curve for Model Performance Evaluation*

2.False Positive Rate (FPR ≤ 5%): The false positive rate measures how often the system incorrectly identifies a disease when none is present. This is a critical metric for system trustworthiness, as incorrect disease detection may lead to unnecessary treatments and increased operational costs. By using a dual-stage detection approach, the system minimizes false alarms and improves reliability.

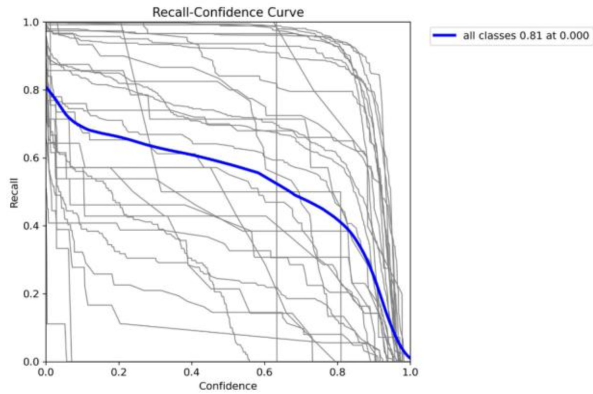

Fig 3. *Recall–Confidence Curve for Detection Model Performance Analysis*

3.Response Time (< 3 seconds): This metric evaluates the time taken by the system to process an input image and generate the final output. It includes preprocessing, model inference, and result generation. A low response time ensures real-time usability, allowing users to quickly make decisions regarding fish health management.

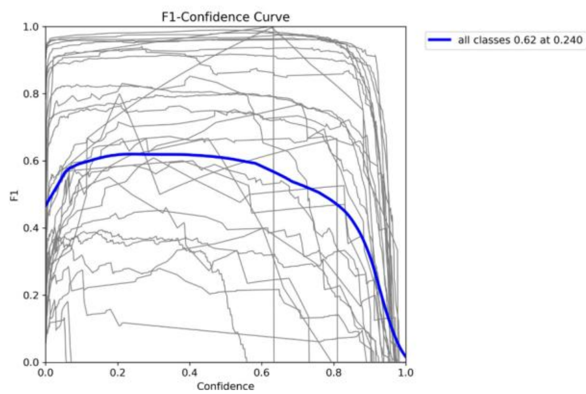

Fig 4. *F1–Confidence Curve for Overall Detection Performance Optimization*

Table I: *Target Performance Benchmarks for the Proposed Framework*

Testbed	Detection Accuracy (%)	False Positive Rate (%)
Fish Dataset (Controlled Environment)	>= 90%	<=5%
Real Aquaculture Images	>= 90%	<=5%

Discussion and critical analysis

This section provides a critical evaluation of the FishCare AI system, analyzing its effectiveness, advantages, and limitations within the domain of aquaculture and intelligent health monitoring systems. Effectiveness Of Detection Approach A major challenge in traditional image-based detection systems is unnecessary computation and reduced accuracy due to processing irrelevant inputs. Efficiency Advantage: The proposed system uses a dual-stage detection mechanism where the first stage confirms the presence of fish before triggering disease detection. This reduces computational overhead and ensures that resources are utilized efficiently Improved Accuracy: By separating fish detection and disease detection into two models, the system achieves higher precision and reduces false detections compared to single-stage approaches. The proposed system further improves efficiency by reducing unnecessary resource usage, as disease detection is only triggered when a fish is detected in the first stage. This minimizes computational wastage and enhances overall system performance. The use of separate models allows better task specialization, where each model focuses on a specific objective, resulting in improved learning and accuracy. Additionally, early-stage filtering helps in reducing error propagation, ensuring that incorrect inputs do not affect the final prediction. The system also supports adaptive thresholding, allowing it to adjust detection confidence based on varying input conditions.

Real-Time Performance and Scalability Existing systems often struggle with real-time processing, especially when handling large volumes of image data.Fast Processing: The use of optimized YOLOv8 models ensures rapid detection, enabling the system to deliver results within seconds. Scalability: The modular architecture allows the system to scale efficiently, making it suitable for both small-scale fish farms and large aquaculture industries. The system is designed to deliver low latency responses, making it suitable for real-time monitoring applications. It can be deployed on cloud platforms, enabling remote access and scalability across different locations. The architecture supports batch processing, allowing multiple images to be processed simultaneously, which is beneficial for large-scale aquaculture operations. Furthermore, the model can be optimized for edge devices such as Raspberry Pi, making it practical for on-field deployment in resource-constrained environments.

Conclusion and future work

Final Summary - This paper presents FishCare AI, an intelligent and automated fish health monitoring system that utilizes deep learning techniques for accurate detection of fish species and diseases. By implementing a dual-stage YOLOv8-based detection framework, the system achieves high accuracy and efficiency while minimizing unnecessary computations. The integration of a chatbot module further enhances usability by providing actionable recommendations in a simple and understandable format. The system demonstrates strong potential for improving productivity and reducing losses in aquaculture industries Future Research Directions - Mobile Application Development: Future work can focus on developing a mobile-based version of the system for easy accessibility in remote areas. A mobile application would allow farmers to capture and upload images directly from their smartphones and receive instant results. Additionally, offline functionality can be explored so that basic detection can work even without internet connectivity. Push notifications and user-friendly interfaces can further improve usability and adoption among non-technical users. IoT Integration: Integration with water quality sensors can provide additional data such as temperature, pH levels, and oxygen concentration for more accurate analysis. Combining visual detection with real-time environmental data can significantly improve disease prediction accuracy. This integration can also enable continuous monitoring of fish health and automatically trigger alerts when abnormal conditions are detected, making the system more proactive rather than reactive. Expanded Dataset: Increasing the dataset to include more fish species and diseases will improve model generalization and accuracy. A larger and more diverse dataset covering different environments, lighting conditions, and fish variations will make the model more robust. Collaboration with fisheries and research organizations can help in collecting real-world data, while data augmentation techniques can further enhance dataset quality. Cloud Deployment: Deploying the system on cloud platforms can enhance scalability and allow remote monitoring. Cloud integration enables centralized data storage, faster processing, and easy access from multiple locations. It also allows continuous model updates and performance improvements without requiring local system changes. Additionally, cloud-based dashboards can provide analytics and reports for better decision-making.

References

1. Raza, A., et al.,"Deep Learning-based Fish Disease Detection Using Convolutional Neural Networks," Journal of Aquatic Health and Management, Vol. 22, No. 3, pp. 45-54, 2019.
2. Liu, W., et al.,"Transfer Learning for Aquatic Species Identification Using SSD Architecture," IEEE Access, Vol. 8, pp. 102345-102357, 2020.
3. Tran, H., et al.,"ResNet-50 Based Classification of Freshwater Fish Species Under Varied Lighting Conditions," International Journal of Computer Vision, Vol. 129, pp. 1120-1135, 2021.
4. Zhao, Y., et al.,"YOLOv5 for Real-Time Fish Disease Detection in Aquaculture Environments," Computers and Electronics in Agriculture, Vol. 198, 107025, 2022
5. T. Mohana Priya, Dr. M. Punithavalli & Dr. R. Rajesh Kanna, "Machine Learning Algorithm for Development of Enhanced Support Vector Machine Technique to Predict Stress," Global Journal of Computer Science and Technology, Volume 20, Issue 2, pp. 12-20, 2020.
6. S. R. Xie, Y. Li, and H. Wang, “Deep Learning-Based Fish Disease Detection and Monitoring System for Smart Aquaculture,” Aquacultural Engineering, Elsevier, vol. 102, Article 102348, 2024.
7. M. Ahmed, R. Hassan, and K. Lee, “Artificial Intelligence Approaches for Water Quality Prediction and Fish Health Management in Aquaculture,” Computers and Electronics in Agriculture, vol. 214, Article 108321, 2025.
8. P. Kumar, A. Sharma, and N. Verma, “IoT and Machine Learning Enabled Smart Aquaculture Monitoring Framework,” IEEE Access, vol. 11, pp. 78421–78439, 2023.
9. L. Zhang, J. Chen, and X. Liu, “Computer Vision-Based Fish Behavior Analysis for Early Disease Detection in Intelligent Aquaculture Systems,” Expert Systems with Applications, Elsevier, vol. 236, Article 121512, 2025.
10. F. Rahman, T. Islam, and M. S. Hossain, “AI-Driven Recommendation System for Sustainable Aquaculture and Fish Farm Management,” Sustainable Computing: Informatics and Systems, vol. 44, Article 101021, 2024.