LEVERAGING ARTIFICIAL INTELLIGENCE AND IMAGE PROCESSING FOR PISCINE DISEASE DIAGNOSTICS IN AQUACULTURE: A COMPREHENSIVE REVIEW

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Abstract

The aquaculture industry faces significant challenges from fish diseases, which result in substantial economic losses and pose a threat to global food security. Traditional diagnostic methods that rely on manual inspection and expert knowledge are often inefficient, subjective, and unsuitable for early detection. This comprehensive review examines how image processing techniques, combined with artificial intelligence, are revolutionising the diagnosis of fish diseases in aquaculture. We systematically examine the technical parts of these systems, including image capture, preprocessing, segmentation, feature extraction, and classification algorithms. The use of deep learning architectures, especially convolutional neural networks (CNNs), has shown impressive diagnostic accuracy, sometimes exceeding 95%, greatly surpassing traditional methods. Despite these advancements, there are still challenges in applying these technologies broadly, such as data standardisation, model adaptation across different species, and computational needs. This review highlights emerging trends like mobile-based diagnostics, multimodal data integration, and real-time monitoring systems that could make aquaculture more predictive and precise. The findings suggest that AI-driven image processing marks a major shift in aquatic health management, potentially reducing disease outbreaks by up to 50% and greatly decreasing chemical treatments through targeted interventions.

Keywords: fish disease diagnosis, aquaculture health monitoring, computer vision, image segmentation, machine learning, deep learning

1. Introduction

Aquaculture has become a vital protein source for billions of people worldwide, with production volumes exceeding capture fisheries in many regions (Tacon et al., 2025; Sidiq et al., 2025). However, the economic viability of this industry is continually threatened by infectious diseases that can spread rapidly in dense farming environments. Traditional methods of disease detection rely on visual inspections by experienced farmers or laboratory-based pathological analysis, both of which have significant limitations (Dhavale et al., 2025; Shi et al., 2025a; Isinkaye et al., 2024). Manual diagnosis is inherently subjective, highly variable, and often ineffective for early detection, when interventions are most crucial (Mamud-Meroni et al., 2025). Laboratory techniques, although more precise, are time-consuming, require specialised expertise, and are often inaccessible to small-scale farmers in remote areas. The advent of computer vision and artificial intelligence technologies presents unprecedented opportunities to overcome these challenges. Image processing techniques facilitate objective, quick, and increasingly accurate disease diagnosis through analysing visual signs on fish specimens (Kulkarni and Bansal, 2024; Khaleel et al., 2024; Deeba et al., 2025; Yilmaz et al., 2025; Gill et al., 2025). Demonstrating significant potential, recent breakthroughs in deep learning, specifically convolutional neural networks (CNNs), have revealed a remarkable capacity to detect subtle pathological patterns that may elude human observers (Iqbal and Kaushik, 2025). These technologies are progressively implemented in various applications, from smartphone-based expert systems for small-scale farmers to integrated monitoring systems in commercial operations (Tina et al., 2025).

This review systematically examines the current state of image processing techniques for fish disease diagnosis in aquaculture. We analyse the technical foundations of these systems, evaluate their performance across various applications, identify implementation challenges, and highlight emerging trends. By synthesising findings from recent studies and commercial implementations, this review aims to provide researchers, technologists, and aquaculture professionals with a comprehensive understanding of how computer vision and AI are transforming aquatic health management.

2. Diagnostic methods vs. AI-based approaches

2.1. Limitations of conventional diagnosis

Traditional fish disease diagnosis primarily relies on visual assessment by experienced farmers who identify abnormalities based on historical knowledge and pattern recognition. The efficacy of this approach is inherently constrained by the limits of human perception, especially in identifying early-stage or subtle symptoms that are not apparent without magnification (Song et al., 2025). More advanced traditional methods include microscopic examination of skin and gill samples, bacterial culture, and molecular techniques such as PCR (Das, 2025). While these laboratory methods offer improved accuracy, they require substantial time (24–72 hours for culture results), specialised equipment, and technical expertise resources often unavailable to small-scale operators in developing regions where aquaculture is increasingly important for food security and livelihoods (Kumar et al., 2025a, b; Sahu et al., 2025; Vargas-González et al., 2025).

The subjectivity of visual diagnosis introduces significant variability, as different observers may interpret the same symptoms differently. Furthermore, many diseases present with similar visual manifestations initially (e.g., lethargy, loss of appetite, colour changes), making differential diagnosis challenging without laboratory confirmation (Deng et al., 2025; Ahmed et al., 2025a). These limitations become particularly problematic during early disease stages when interventions are most effective, but symptoms are least visible (Tamut et al., 2025). The consequences of misdiagnosis include ineffective treatments, preventable mortality, and unnecessary chemical use that contributes to antimicrobial resistance and environmental pollution

3. Artificial intelligence in aquaculture

Artificial Intelligence (AI) represents a transformative approach to fish disease diagnosis in aquaculture, enabling computers to simulate human-like intelligence and make data-driven decisions (Hussain et al., 2025). The capacity of AI systems, specifically those utilising deep learning to learn intricate patterns from vast amounts of data facilitates the creation of advanced algorithms capable of solving complex diagnostic problems (Mohapatra, 2025). The ability to process unstructured data such as images, text, and audio is vital for these systems, as it allows them to analyse the visual symptoms critical for assessing fish health.

Table 1. AI applications and technologies in aquaculture

Area of operation	Specific application	AI technology used	Key function and benefits	Reference
Feeding management	Precision feeding	Computer vision, reinforcement learning	Analyses real-time fish appetite and behaviour to adjust feed distribution, minimising waste and improving feed conversion ratio (FCR).	(Liyanage et al., 2025)
	Feed optimisation	Machine learning, predictive modelling	Analyses historical data on growth, health, and environment to recommend optimal feed composition and scheduling.	(Filho et al., 2025)
Health and welfare monitoring	Early disease detection	Computer vision, deep learning (CNNs)	Automatically monitors for visual signs of disease, such as skin lesions, gill health, and sea lice, enabling early intervention.	(Reppas Chrysovitsinos et al., 2025)
	Biomass estimation and growth tracking	Computer vision, 3D stereo imaging	Provides non-invasive counting, sizing, and weight estimation of fish populations to track growth and manage inventory.	(Aung et al., 2025)
	Stress detection	Behavioural analytics, computer vision	Identifies behavioural changes in swimming patterns that indicate stress from poor water quality or overcrowding.	(Ramesh, 2025)
Environmental monitoring and control	Water quality prediction	IoT sensor fusion, time-series machine learning	Forecasts adverse changes in parameters like dissolved oxygen, allowing for pre-emptive action to avoid fish stress.	(Chen et al., 2025a)
	Automated system control	AI-powered control systems	Integrates and automates aerators, pumps, and feeders to maintain optimal environmental conditions 24/7.	(Tina et al., 2025)
Farm operations and infrastructure	Predator deterrence	Computer vision, audio analytics	Identifies predators like seals and birds to trigger targeted deterrent systems and prevent stock loss.	(Hridoy et al., 2025)
	Net cleaning and inspection	Computer vision (on ROVs)	Automates the inspection of nets for biofouling, holes, and damage to ensure integrity and prevent escapes.	(Huang and Khabusi, 2025)
Genetics and breeding	Selective breeding programmes	Machine learning, genomic analysis	Accelerates genetic gain by analysing genetic markers and phenotypic data to select superior broodstock.	(Tina et al., 2025)
Supply chain and economics	Harvest timing optimisation	Predictive analytics, machine learning	Predicts the most profitable harvest time by modelling growth rates against market prices and operational costs.	(Tierney et al., 2025)
Sustainability and ecosystem management	Faecal waste mapping	AI modelling, sensor data integration	Models the dispersion of waste from farms to assess and minimise the environmental impact on the benthic ecosystem.	(Elmezain et al., 2025)
Data integration and platform	Farm management software	Cloud computing, data analytics, AI	Centralises all farm data into a single platform to provide actionable insights, predictions, and operational alerts.	(Le et al., 2025)

The implementation of AI in aquaculture has shifted the paradigm from reactive treatment to predictive prevention, significantly enhancing early detection capabilities and reducing economic losses caused by disease outbreaks (Ma et al., 2025; Chen et al., 2025b; Carlino-Costa and de Andrade Belo, 2025; Habib et al., 2025).

In aquaculture applications, AI-driven systems function as intelligent decision-support tools that bridge the expertise gap in remote or underserved regions. These systems integrate multiple data sources, including image data from smartphones or specialised cameras, water quality parameters, and behavioural metrics, to provide comprehensive diagnostic assessments (Miller et al., 2025a; Akkaş et al., 2025; Hramov et al., 2025). For instance, AI algorithms can analyse market trends and predict disease risks based on environmental conditions, while computer vision systems automate quality control processes by inspecting fish for pathological manifestations with remarkable accuracy (Huang and Khabusi, 2025). AI scalability and flexibility enable it to handle diverse tasks and datasets autonomously, eliminating the need for extensive manual feature engineering and thereby increasing its accessibility for the aquaculture industry.

4. Machine learning for disease detection

Machine learning (ML), a subset of artificial intelligence, provides computational methods that enable systems to automatically learn and improve from experience without being explicitly programmed (Mohapatra, 2025; Swain, 2025; Fernandes and Dmello, 2025). In aquaculture disease detection, ML algorithms analyse labelled datasets to identify discriminative patterns that correlate visual features with specific diseases, often achieving superior accuracy compared to human experts (Wu et al., 2025). These methods include various approaches such as decision trees, random forests, support vector machines (SVM), and Bayesian networks, which can process both structured and unstructured data to identify complex relationships between environmental factors and disease prevalence (Haddad and Mohammed, 2025). Research demonstrates that SVM algorithms achieve 91.42% to 94.12% accuracy in classifying fish diseases when combined with appropriate image enhancement techniques, providing a reliable alternative to traditional diagnostic methods (Suleiman et al., 2025).

The application of ML in aquaculture extends beyond basic classification to encompass predictive analytics and risk assessment capabilities. By processing historical data on water quality parameters (pH, temperature and dissolved oxygen) alongside visual symptoms, ML models can forecast disease outbreaks with significant lead time, enabling preventive measures before clinical symptoms appear (Hridoy et al., 2025; Roja et al., 2025; Huang and Khabusi, 2025; Malvi et al., 2025; Etin-Osa and Isitua, 2025; Ahmed et al., 2025a). For example, integrated learning frameworks that combine image analysis with environmental monitoring have demonstrated an 85% accuracy in predicting disease risks, particularly when specific thresholds are crossed (water temperature exceeding 28°C with pH <6.5 increasing risk by 3.2 times). This capability for continuous learning and improvement allows ML systems to adapt to evolving data patterns and emerging diseases, making them increasingly valuable for sustainable aquaculture management (Wu et al., 2025).

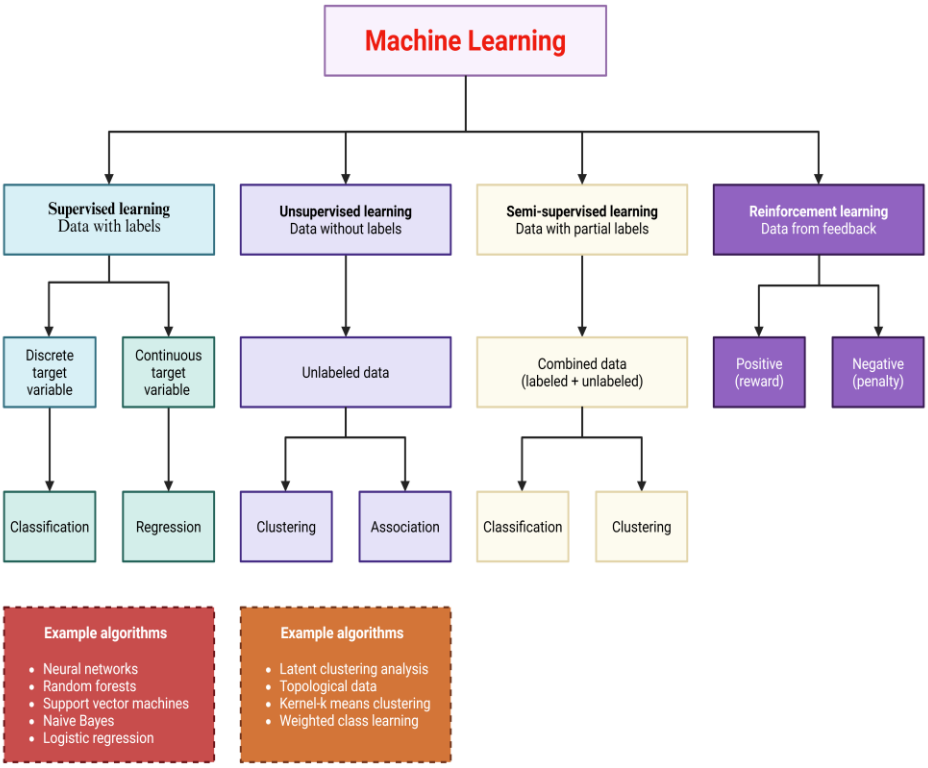

Figure 1. A hierarchical taxonomy of machine learning methodologies based on data annotation characteristics. The diagram categorises approaches into four core paradigms: supervised learning (utilising fully labelled data for classification or regression tasks), unsupervised learning (extracting patterns from unlabelled data via clustering or association), semi-supervised learning (leveraging partially labelled datasets), and rReinforcement learning (learning through environmental feedback with reward/penalty mechanisms). Representative algorithms are enumerated for each subcategory, providing a systematic reference for methodological selection in applied research

5. Deep learning architectures

Deep learning (DL), an advanced subset of machine learning, utilises multi-layered neural networks to model complex patterns and representations directly from raw image data without requiring manual feature engineering (Haldorai et al., 2024; Elbasi et al., 2022). In aquaculture diagnostics, convolutional neural networks (CNNs) have demonstrated exceptional performance in analysing fish images for disease symptoms, with architectures like MobileNetv2, DenseNet121, and VGG16 achieving individual accuracies between 93.43% and 99.71% in controlled studies (Tamut et al., 2025). These networks automatically learn hierarchical feature representations through multiple processing layers, enabling them to identify subtle pathological patterns that might escape human observation, such as early-stage parasites or minor discolourations indicative of bacterial infections. The ensemble approaches that combine multiple deep learning models further enhance diagnostic reliability, reaching 99.14% accuracy in experimental conditions and significantly outperforming traditional computer vision methods that rely on handcrafted features (Asif et al., 2025; Rane et al., 2024).

Beyond standard CNNs, more specialised deep learning architectures have been adapted for aquaculture applications. YOLO (You Only Look Once) variants enable real-time detection and classification of parasites in video streams, achieving high accuracy in identifying challenging targets like *Ichthyophthirius multifiliis* (0.3 mm) and *Gyrodactylus kobayashii* (0.3 mm) despite their minute size (Vijayalakshmi and Sasithradevi, 2025; Li and Du, 2022; Wu et al., 2025; Sarker et al., 2023; Balasubramaniam et al., 2025). Recurrent neural networks (RNNs) analyse temporal sequences of behavioural data to detect anomalies in swimming patterns or feeding responses that often precede clinical disease symptoms. For improving model generalisation across diverse aquaculture conditions, generative adversarial networks (GANs) offer a powerful solution to data scarcity by generating synthetic images to augment limited datasets (Min et al., 2025). These advanced architectures facilitate continuous learning and adaptation to new disease patterns, making deep learning particularly valuable for evolving aquaculture environments where novel pathogens may emerge.

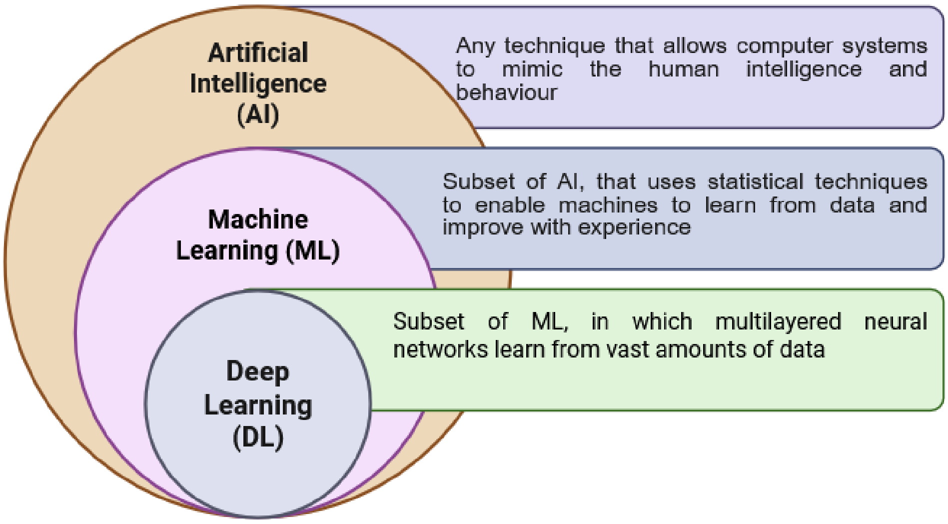

Figure 2. The relationship between artificial intelligence (AI), machine learning (ML), and deep learning (DL). AI is defined as any technique enabling computers to mimic human intelligence. ML is a subset of AI that uses statistical methods to learn from data. DL is a further subset of ML that employs multi-layered neural networks to learn from large datasets

6. The AI paradigm shift

Artificial intelligence, particularly machine learning and deep learning approaches, represents a fundamental shift in diagnostic methodology. Rather than relying on human experts to identify predefined visual features, AI systems learn discriminative patterns directly from labelled image data. This allows them to detect subtle, multivariate patterns that often elude human perception and defy easy description (Somayaji, 2025; Huntingford et al., 2006). The most significant advantage of AI systems is their ability to process vast datasets and identify subtle correlations between visual features and specific diseases, often achieving superior accuracy compared to human experts (Mandal and Ghosh, 2024; Islam et al., 2024). AI-based diagnosis offers several distinct advantages over traditional methods: objectivity (consistent application of decision criteria), scalability (ability to process thousands of images hourly), sensitivity (identification of subtle pre-clinical changes), and accessibility (deployment via mobile devices in remote areas) (Hussain et al., 2025). These systems act as decision-support tools for farmers without specialised training, bridging the expertise gap in underserved regions. Moreover, unlike human experts, they enter a self-reinforcing learning cycle, continuously improving their diagnostic accuracy as more data becomes available.

7. Technical components of AI-based diagnosis systems

7.1. Image acquisition and preprocessing

The foundation of any image-based diagnostic system is high-quality image data that captures relevant pathological manifestations. Acquisition methods vary from smartphone cameras to specialised imaging systems, including hyperspectral imaging, thermal cameras, and microscopy systems (Mukhtar et al., 2025; Baker et al., 2025; Shi et al., 2025b). Image quality is paramount, with resolution requirements depending on the target features. Macroscopic symptoms (lesions, discolouration) may require 5–10 megapixels, while microscopic features (parasites, cellular changes) demand much higher resolutions. Consistent lighting conditions and background control are essential for reducing variability, though advanced algorithms can now compensate for some environmental inconsistencies (Wu et al., 2025). Preprocessing techniques prepare images for analysis by enhancing relevant features and reducing noise (Alrikabi et al., 2025; Setiawan et al., 2025). Common operations include colour normalisation (correcting for lighting variations), contrast enhancement (improving visibility of subtle features), image sharpening (emphasising edges and details), and noise reduction (removing artefacts from water particles or camera sensors (Gagniuc, 2025). Some systems employ background subtraction to isolate the fish from its environment, while others use image segmentation to separate different regions of interest (body, fins, gills) (Hwang et al., 2025).

These preprocessing steps significantly improve the performance of subsequent feature extraction and classification algorithms.

7.2. Image segmentation and feature extraction

Image segmentation is a process that partitions images into structurally or pathologically distinct regions, which is particularly important for localising diseases to specific anatomical structures (Ouyang et al., 2025). Threshold-based methods separate regions based on colour or intensity values, while edge detection algorithms identify boundaries based on abrupt changes in image properties. More advanced approaches include region-growing algorithms that start from seed points and expand to include similar neighbouring pixels, and convolutional neural networks that learn optimal segmentation strategies directly from data (Wang et al., 2025; Kumar et al., 2025a). Accurate segmentation in aquatic environments is challenging due to light refraction, water turbidity, and complex backgrounds. However, recent deep learning approaches have significantly improved performance under these conditions (Naveen, 2025).

Feature extraction converts raw pixel data into quantitatively discriminative representations that can differentiate pathological states. Traditional computer vision approaches use handcrafted features, including colour features (histograms, colour moments), texture features (Gabor filters, Haralick features), morphological features (shape descriptors, area/perimeter ratios), and spatial features (relative positions of lesions) (Gupta and Mishra, 2025). However, deep learning approaches have increasingly replaced handcrafted features with learned representations that automatically optimise for diagnostic discrimination (Panahi, 2025). These learned features often capture subtle patterns that are diagnostically relevant but may not be obvious to human observers designing feature extraction algorithms (Alfahaid et al., 2025).

7.3. Classification algorithms and architectural frameworks

Classification algorithms form the decision-making core of diagnostic systems, mapping extracted features to disease categories (Yasruddin et al., 2025; Zakaria et al., 2025a). Traditional machine learning approaches include support vector machines (effective in high-dimensional spaces), random forests (robust against overfitting), and k-nearest neighbours (simple implementation) (Setiawan et al., 2025). However, deep learning architectures, particularly convolutional neural networks (CNNs), have demonstrated superior performance for image-based diagnosis due to their ability to learn hierarchical feature representations directly from raw pixels. Popular architectures include ResNet (addresses vanishing gradient problems with skip connections), Inception (computationally efficient through factorised convolutions), and YOLO (for real-time object detection and classification) (Memon et al., 2025).

The most effective systems often employ ensemble approaches that combine predictions from multiple models to improve overall accuracy and robustness (Sakib et al., 2025). Architectural frameworks increasingly leverage transfer learning, where models pre-trained on large natural image datasets (e.g., ImageNet) are fine-tuned with smaller medical image collections. This approach is particularly valuable in aquaculture applications where labelled data may be limited (Cui et al., 2025). Recent advances include multimodal architectures that integrate image data with non-visual information such as water quality parameters, behavioural metrics, and environmental conditions to improve diagnostic accuracy through data fusion.

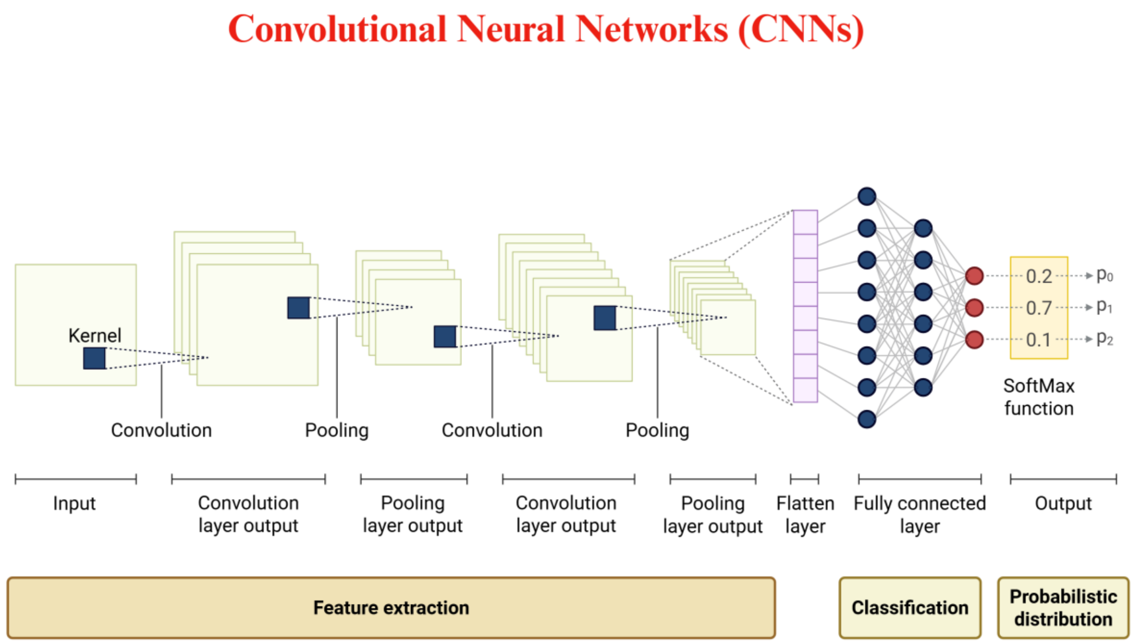

Figure 3. Architectural overview of a standard convolutional neural network (CNN). The model processes an input image through sequential feature extraction (convolution and pooling layers) followed by classification (flattening, fully connected layers, and a SoftMax output layer for probabilistic prediction)

8. Performance metrics and efficacy evaluation

8.1. Accuracy and reliability benchmarks

The performance of AI-based diagnostic systems is typically evaluated using standard classification metrics, including accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC) (Bellal et al., 2025). Studies report impressive results, with random forest algorithms achieving 88.87% accuracy in classifying multiple disease conditions, while deep learning approaches consistently exceed 90% accuracy and, in some applications, reach 95% accuracy or higher (Rahman et al., 2023; Guang, 2025; Ankalaki et al., 2024). These figures represent a substantial improvement over traditional visual diagnosis, which typically shows 70–75% accuracy in field conditions due to human perceptual limitations and subjective interpretation.

Beyond raw accuracy, reliability across diverse conditions is crucial for practical application. Performance varies significantly based on image quality, water clarity, fish species, and disease prevalence. The most robust systems maintain high performance across these variables, though performance typically declines for rare diseases with limited training examples (Nguyen, 2024). The real-world efficacy of these systems is demonstrated by reduced disease outbreaks, earlier interventions, and decreased mortality rates. For instance, the commercial implementation of Guangzhou LaoMi Technology's "Yuxin Yunlian" system reports a 50% improvement in diagnostic efficiency, leading to a 50% reduction in disease outbreaks through early detection and intervention

Table 2. Performance comparison of AI diagnostic approaches for fish diseases

Methodology	**Reported accuracy**	**Key advantages**	**Limitations**
Traditional CNN	90–93%	Established architecture, widely implemented	Requires large datasets, computational intensity
Enhanced CNN (ResNet, Inception)	94–96%	Improved feature learning, better gradient flow	Increased complexity, longer training times
Random forest with handcrafted features	87–89%	Interpretability, works with small datasets	Feature engineering expertise required
YOLO for real-time detection	88–92%	Extremely fast inference, suitable for video	Lower accuracy for small lesions
Multimodal data fusion	95–97%	Incorporates environmental context, higher accuracy	Data acquisition complexity, integration challenges

9. Implementation challenges and limitations

9.1. Technical and computational constraints

Despite promising results, several technical challenges impede the widespread adoption of image-based diagnostic systems. Computational requirements for training deep learning models are substantial, often requiring GPUs or cloud-based resources that may be inaccessible in remote aquaculture operations (Panduranga et al., 2024; Cheng et al., 2024; Cui et al., 2025). While edge computing devices can perform inference locally after cloud-based training, they still represent additional infrastructure investments (Trigka and Dritsas, 2025). Data scarcity presents another significant constraint, as acquiring sufficiently large and diverse labelled datasets for training robust models remains challenging, particularly for rare diseases or less common species.

Model generalisation across diverse environmental conditions and species variants remains problematic (Miller et al., 2025b). Systems trained on one species under specific conditions often experience performance degradation when applied to different species or environments due to phenomena known as “domain shift”. Water quality variables, including turbidity, algae blooms, and light penetration, significantly affect image quality and, consequently, diagnostic performance. While data augmentation techniques and domain adaptation approaches can mitigate these issues, they remain active research challenges without universally effective solutions

9.2. Practical implementation barriers

Beyond technical challenges, practical implementation barriers significantly affect real-world adoption. Cost considerations are paramount, particularly for small-scale operations with limited capital (Zhang et al., 2025). While smartphone-based solutions reduce hardware costs, comprehensive systems with specialised cameras, computing infrastructure, and integration with farm management systems represent substantial investments. User interface design and usability critically affect adoption, as systems must be intuitive for farmers with varying levels of technical expertise (Chakraborty, 2025; da Costa, 2025). Multilingual support is essential in many regions where aquaculture is a prominent system that must work with standard farming practices without requiring disruptive changes. Regulatory approval and validation protocols for AI-based diagnostics are still evolving, creating uncertainty about certification requirements. Perhaps most importantly, farmer trust in automated systems must be developed through transparent operation, interpretable results, and demonstrated reliability across seasons and conditions (Oyeniran et al., 2025). Building this trust requires time and consistent performance, particularly among farmers who have relied on traditional methods for generations.

10. Future directions and emerging trends

10.1. Technological advancements

Several technological advancements promise to address current limitations and expand the capabilities of image-based diagnostic systems. Federated learning approaches enable model training across distributed datasets without sharing sensitive farm data, addressing both privacy concerns and data scarcity issues while improving model generalisation (Aderemi et al., 2025). Explainable AI techniques make black-box models more interpretable by highlighting which image regions most influenced diagnostic decisions, building user trust, and providing learning opportunities for farmers,

Advanced sensor technologies, including hyperspectral imaging and 3D photogrammetry, capture information beyond conventional RGB images, providing additional data dimensions for improved discrimination (Cui et al., 2025; Xu et al., 2025). Video analysis capabilities enable assessment of behavioural markers, including swimming patterns, feeding responses, and social interactions, that provide valuable diagnostic information beyond static visual features (Ficili et al., 2025; Zakaria et al., 2025b). Edge AI chipsets are becoming increasingly powerful and energy-efficient, enabling real-time analysis without continuous cloud connectivity particularly important in remote aquaculture operations with limited internet infrastructure.

10.2. Integrated farming systems

The future of AI-based diagnostics lies not in isolated applications but as components of comprehensive digital farming systems. These integrated platforms combine diagnostic capabilities with environmental monitoring (water quality sensors, weather stations), operational automation (smart feeders, aeration control), and farm management software (inventory, growth tracking, financial planning). This integration enables predictive disease modelling that forecasts outbreaks based on environmental precursors and early warnings, shifting from reactive treatment to preventive management. Blockchain technology is increasingly integrated with AI diagnostics to create verifiable traceability systems that track disease status throughout the production cycle, a valuable feature for certification and premium markets. Decision support systems are evolving toward prescriptive analytics that recommend specific treatment protocols, dosage calculations, and intervention timing based on diagnostic results integrated with environmental and biological data. These advanced systems increasingly support precision treatment approaches such as automated selective removal of infected individuals, targeted medication delivery, and individualised care protocols that minimise chemical usage while maximising treatment efficacy

11. Conclusion

Image processing techniques powered by artificial intelligence are fundamentally transforming fish disease diagnosis in aquaculture, addressing critical limitations of traditional methods through objective assessment, early detection, and democratised expertise. The integration of convolutional neural networks and deep learning architectures has demonstrated remarkable diagnostic capabilities, with accuracy rates exceeding 95% in controlled conditions and showing continuous improvement as algorithms mature and datasets expand. These technologies offer not merely incremental improvement but rather a paradigm shift in aquatic health management, moving from reactive treatment to predictive prevention and from generalised interventions to precision therapies. Despite significant progress, important challenges remain in data standardisation, model generalisation, computational requirements, and real-world integration. Addressing these limitations requires collaborative efforts between computer scientists, aquaculture professionals, biologists, and farmers to develop solutions, both technically sophisticated and practically implementable. The most promising near-term applications likely combine human expertise with AI capabilities, creating collaborative intelligence systems that leverage the strengths of both approaches as technology continues to advance; we anticipate increasingly sophisticated diagnostic systems that integrate multimodal data streams, operate in real time under challenging conditions, and provide not just diagnostic labels but interpretable insights and actionable recommendations. These systems have the potential to significantly reduce the economic and environmental impacts of fish diseases while supporting aquaculture's critical role in global food security. Future research should focus on developing more efficient architectures requiring less labelled data, improving generalisation across species and environments, and creating more intuitive interfaces for diverse user groups. Through continued innovation and thoughtful implementation, AI-driven image processing promises to make aquaculture more productive, sustainable, and resilient against disease threats.

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