AI-Powered Freshwater Fish Disease Detection Using MobileNetV2 and Grad-CAM

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ABSTRACT

Aquaculture is vital in ensuring food security on earth. Outbreaks of diseases are common in aquaculture farms, leading to losses and financial instability. The ability to detect fish diseases quickly and automatically using AI technologies is vital in aquaculture. The study gives an overview of different disease detection mechanisms in use, including traditional image processing, classifiers, deep learning, convolutional neural networks, transfer learning, lightweight models, and XAI. The research identifies MobileNetV2 as a backbone model in real-time disease classification, explains the importance of Grad-CAM technique and Tensor Flow Lite in optimizing disease classification models for mobile devices. The analysis shows gaps in the state-of-the-art disease detection systems, including narrow data set, unexplained results, and lack of end-to-end deployment pipelines. Possible areas for future research include multi-modal sensing systems, integration with IoT, and continuous learning. The research was conducted using a working model with over 76.55% accuracy rate in distinguishing between seven freshwater fish diseases within less than 500ms.

Keywords: Fish Disease Detection, Aquaculture Monitoring, Deep Learning, MobileNetV2, Transfer Learning, Explainable Artificial Intelligence, Grad-CAM, Computer Vision, Real-Time Image Analysis, Edge Deployment.

I. INTRODUCTION

Aquaculture has become one of the fastest growing sectors in global food production, supplying over 50% of the fish consumed by people. Due to growing demands for aquatic protein, the sector has been increasingly forced to address issues related to management of diseases, environmental sustainability, and efficiency of operations. In high-density farming environments, transmission of diseases occurs rapidly, and unless they are addressed on time, they might eliminate entire batches of fishes, causing significant financial losses [1].

Current practice for diagnostics of diseases is based on visual observation performed by skilled veterinarians or other farm employees. This approach is highly subjective, labor-intensive, and ill-suited for continuous monitoring [5], [6]. At an early stage of development, symptoms of diseases may appear to be rather insignificant and include small changes in the colors of a body of the fish, small lesions, and texture changes, which are usually ignored in routine observation [5].

In recent years, considerable progress has been achieved in application of machine vision and deep learning techniques for automated diagnosis of diseases in aquaculture. Visual algorithms can detect various characteristics, such as skin color change, appearance of ulcers, and texture alterations with greater precision compared to conventional diagnostic approaches [2], [3], [7]. Modern CNN models outperform previous approaches based on handcrafted features like GLCM, SVM, or fuzzy logic [4], [9], [10].

However, there is still much work to be done in this domain. Existing solutions based on deep learning algorithms are primarily aimed at offline experimental studies and lack applicability for real-world problems. Other solutions utilize large and resource-intensive models, which cannot be easily deployed in edge devices with constrained memory and power [15]. However, most significantly, modern methods lack an important attribute interpretable decision-making, making it difficult to obtain necessary confidence in automated systems [17].

These problems serve as motivation to develop efficient, explainable, and applicable solutions to automated diagnosis of fish diseases. Thus, the following paper provides a careful review of existing research in this area, starting from classical image processing concepts and moving towards modern techniques of explainable AI. The key contributions include: (i) comprehensive analysis of existing approaches to diagnosis; (ii) evaluation of their limitations and feasibility; (iii) formulation of major gaps in research; and (iv) analysis of future research avenues [21], [24]

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II. LITERATURE REVIEW

A. Traditional Image-Processing Methods

The early methods for automating the fish disease detection process involved manually designed visual features based on color, texture, and shape characteristics. Some of the feature extraction techniques that were commonly used for the description of fish skin alterations included Grey Level Co-occurrence Matrix (GLCM) computation, Gabor filter response, color histogram, and fuzzy pattern matching [4], [9], [10], [12], [14]. In turn, the obtained visual features served as the input for conventional machine learning techniques such as SVM and k-NN.

Such approaches yielded decent results in laboratory conditions; however, the accuracy of disease detection significantly decreased in farm-based imaging due to variable lighting conditions, crowded background scenes, and camera orientation angle. The heavy dependency on human-defined features also made it hard for the systems to be generalized [5], [6].

B. Machine Learning Classification Approaches

In order to minimize feature extraction manually, some subsequent scientists proposed employing machine learning pipelines involving semi-automatic feature extraction along with the application of supervised learning algorithms [8], [11]. SVM-based classifiers based on texture features extracted via GLCM were able to differentiate successfully between fish diseases such as EUS and red spot disease for freshwater fish [4]. However, there were some limitations for applying such algorithms due to complicated patterns of diseases under varying environmental conditions and significant amounts of preprocessing required [6], [8].

C. Deep Learning-Based Detection

The implementation of deep CNNs had a major impact on fish diseases' detection. The ability to do end-to-end learning makes it unnecessary to construct any hand-crafted features. It helped achieve impressive results in terms of classification on multiple complex datasets. Deep CNN models, such as VGGNet and ResNet, demonstrated significant improvement compared to earlier models [2], [3], [15]. Currently, one of the key issues associated with CNNs is the requirement for labeled data and powerful hardware resources [7].

D. Transfer Learning Techniques

Transfer learning assists in overcoming the problem of limited data within the aquaculture diseases dataset. This can be achieved by beginning with model parameters of networks that are already trained with large datasets, such as those in ImageNet. With only a few examples from the domain at hand, one can achieve great classification accuracy [7], [16]. Transfer learning is superior to training from scratch, particularly when fine-tuning only the upper layers while fixing lower layers (since they contain general information) [3], [16].

E. Lightweight CNN Architectures

The computational complexity of full CNNs makes it difficult to operate them in real-time on edge devices. In order to address this issue, the MobileNet family employs the depthwise separable convolution technique, thereby reducing parameter and computations, which has made it an appropriate choice for low-resource edge devices [16]. MobileNetV2 improves the efficiency of MobileNet further by including inverted residual blocks with linear bottleneck layers. It is possible to optimize the model in such a way that the inference size becomes as small as 2.40 MB [16], [18].

F. Explainable AI Approaches

The obscure workings of deep learning algorithms were highlighted early on in the application of machine learning in medicine. One of the popular approaches for explaining decisions made by CNNs is Gradient-weighted Class Activation Mapping (Grad-CAM). This is achieved by calculating the gradient of the output class probability with regard to the last convolutional feature maps, which results in saliency maps that identify areas of interest in the images [17]. Wang et al. have demonstrated that Grad-CAM is very efficient in highlighting regions such as lesions for disease classification in fishes [17].

G. Real-Time Deployment Systems

An increasing number of studies have shifted towards implementing real-time fish monitoring solutions using online/offline analysis approaches, based on a combination of web-based technologies, edge computing, and IoT devices [18], [20], [22], [23]. Ahmed et al. proved that a real-time fish disease monitoring solution could be built by using edge computing platforms [18]. This work has been enhanced further by Bhattacharya, Das, and Pradhan with the implementation of live edge-AI detection using continuously streamed video data [22]. Figure 1 illustrates the multilingual configuration of an already-deployed system using English, Hindi, and Kannada languages, along with the model's info panels.

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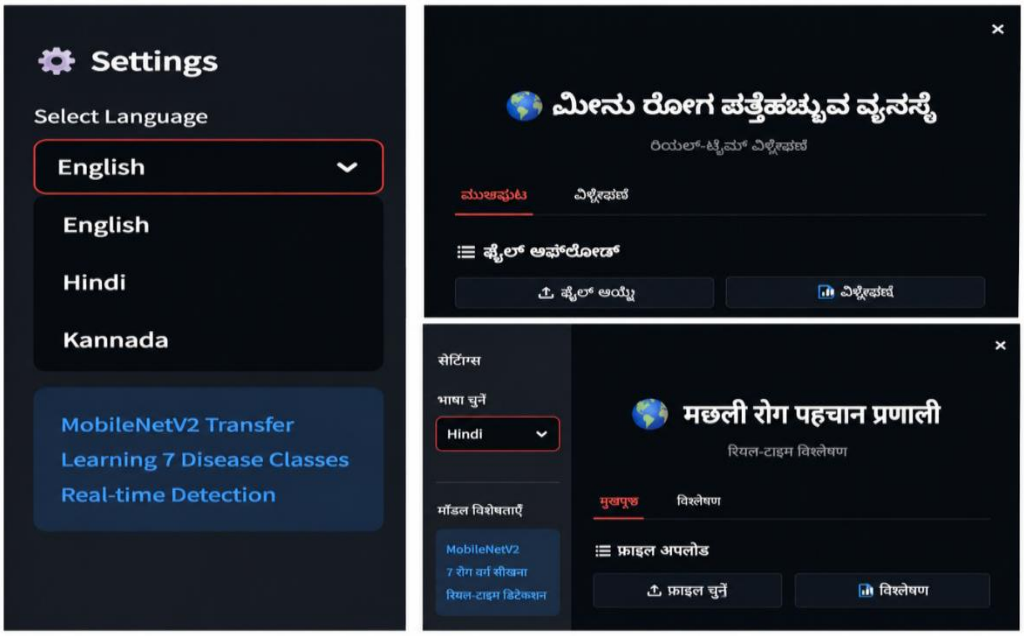

Fig. 1. Multilingual configuration interface of the Aqua Vision AI web application, supporting English, Hindi, and Kannada, with model information displaying MobileNetV2 transfer learning and real-time detection capabilities.

The dashboard for the web application is illustrated in Fig. 2. It provides an option to use camera and image uploading mode within a single browser window. The web app ensures effective communication between the visual part on the front-end side and the inference algorithm running on the backend side [21], [24], [25].

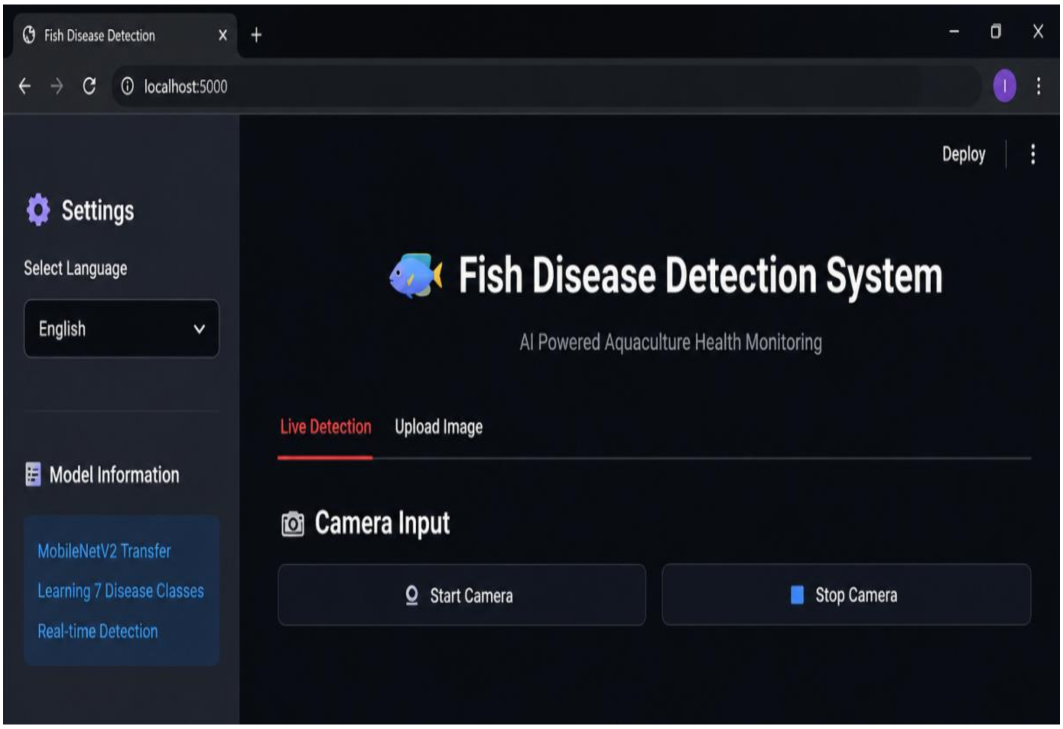

Fig. 2. Main interface of the Fish Disease Detection System web application, illustrating the live camera detection mode with start/stop camera controls and model information sidebar.

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H. Research Gaps in Existing Systems

A synthesis of the surveyed literature reveals several consistent research gaps. First, most deep learning systems evaluate only on small, laboratory-curated datasets that do not reflect real aquaculture diversity [7], [16]. Second, interpretability is routinely treated as an optional post hoc feature rather than a core system requirement [17]. Third, very few systems demonstrate complete end-to-end deployment with simultaneously operational classification, explainability visualization, and low-latency real-time inference [21], [24]. Fourth, continuous or adaptive learning mechanisms are conspicuously absent from the literature [25].

III. COMPARATIVE ANALYSIS OF EXISTING METHODS

A comparative examination of the approaches surveyed above reveals clear performance and practicality trade-offs across different methodological paradigms. Table I summarizes these dimensions across five major method categories.

TABLE I.
COMPARATIVE SUMMARY OF FISH DISEASE DETECTION APPROACHES

Approach	Accuracy	Deployability	Interpretability	Computation
Image Processing	Moderate	Limited	High (manual)	Low
Machine Learning	Moderate	Moderate	Moderate	Low-Med
Deep CNN (VGG/ResN et)	High	Low	None	High
Transfer Learning	High	Moderate	None	Medium
MobileNetV 2 + Grad-CAM	Competitive	High	Via Grad-CAM	Low

IV. RESEARCH CHALLENGES

A. Dataset Limitations

Image datasets for aquaculture disease classification are typically small, narrowly scoped, and collected under controlled conditions that do not reflect real farming environments [7], [16]. Low per-class sample counts increase the risk of model overfitting and reduce generalization. The absence of large-scale, publicly available benchmark datasets standardized across species and disease categories remains a critical impediment to reproducible progress [8].

B. Environmental Variability

Practical aquaculture monitoring is confounded by fluctuating illumination levels, turbid water, and toward efficient, data-driven deep learning approaches uce distributional shift between training and deploconsistent camera positioning [5], [6]. These factors introdyment conditions, degrading model accuracy in production settings. Robust preprocessing pipelines and domain adaptation strategies are required but are rarely addressed comprehensively in existing literature [18].

C. Real-Time Computational Constraints

Real-time inference demands sub-second response latency within the power and memory budgets of edge computing hardware [18], [22]. Achieving this with sufficient classification accuracy requires careful co-optimization of model architecture, quantization, and inference pipeline design. Most reported systems evaluate either accuracy or latency in isolation rather than demonstrating their joint optimization in a deployed setting [15], [16].

D. Explainability and Deployment Challenges

However, even though Grad-CAM is useful in terms of visualization localization, the heatmap produced by this method is always smooth and may highlight the regions of the image which do not belong to the foreground objects. The use of higher resolution techniques may solve the above problems, but on the other hand will require additional computation effort. Moreover, in addition to the localization of objects in the image, the provision of semantically rich explanations remains a challenging task.

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V. DISCUSSION

A shift from outdated, manually constructed feature extractions that operate in practice within aquaculture industry is evident in the reviewed literature. The application of transfer learning has proven effective in aquaculture due to lack of sufficient amounts of labeled data [7], [16]. Lightweight Convolutional Neural Networks like MobileNetV2 benefit from the inverted residual approach, which optimizes parameter usage and retains representational capacity [16]. When operated with Tensor Flow Lite and occupying around 2.40 MB of space on the disk drive, the solution processes images under 500 ms with regular CPU performance, thus meeting requirements for continuous monitoring in the domain without specific equipment [18], [22]. Grad-CAM explains predictions and enhances interpretability by providing visual evidence. Indeed, the system generates probability distributions for all disease classes (see Fig. 3), allowing better decision-making in aquaculture [21].

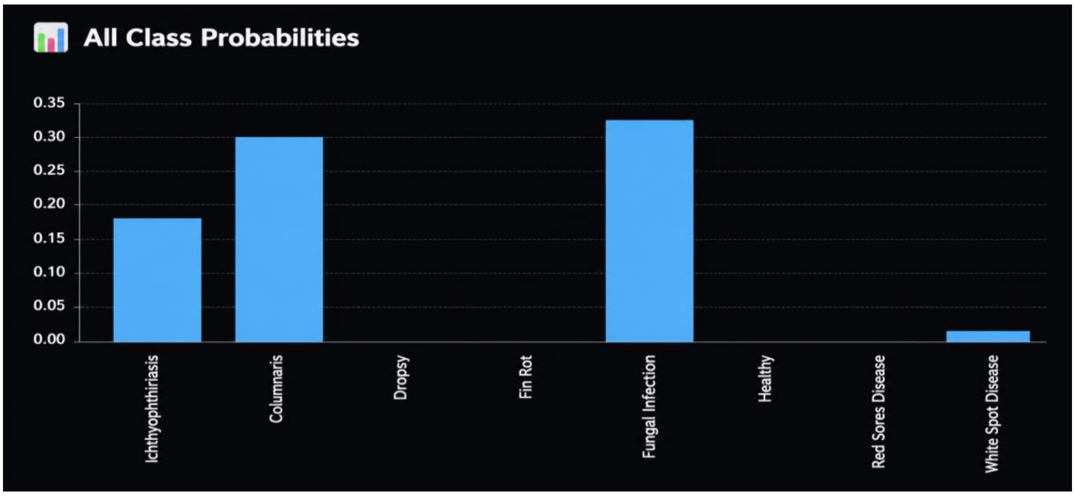

Fig. 3. Class-wise probability distribution generated by the proposed MobileNetV2-based model, illustrating confidence levels across seven fish disease categories for a representative input image.

Figure 4 displays the Grad-CAM heatmap generated for the fish picture marked with "Red Disease" with 36.2% accuracy. As shown by the heatmap overlay, the model concentrates on regions of the fish body that display abnormalities such as red discoloration and tissue damage rather than the background regions. The correspondence between areas activated by the heatmap and regions showing actual symptoms of the condition indicates that the model has identified genuine visual clues in its prediction

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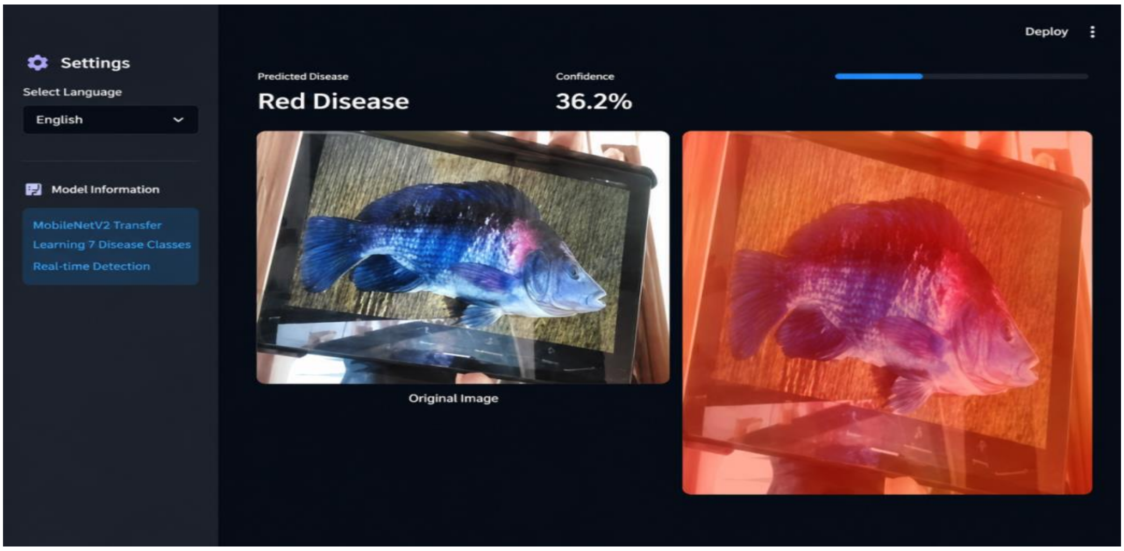

Fig. 4. Grad-CAM visualization for a sample fish image classified as Red Disease (confidence: 36.2%), showing the original image (left) and the heatmap overlay (right) highlighting disease-relevant regions on the lateral body surface.

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The system yielded an accuracy of 76.55% with a precision rate of 88.42% and an F1-score of 76.41% in seven different classes of diseases. The contrast between high precision rate and low recall rate signifies the challenges associated with distinguishing visually similar disease categories, which is consistent with previous findings from research on fine-grained classification in aquaculture [3], [7]. The Healthy category is the one that yields the highest per-class F1-score of 0.88%. Classes with visually similar diseases such as Parasitic Disease (0.68) and White Tail Disease (0.67) prove to be difficult to differentiate.

The proposed solution of an end-to-end system for the identification and classification of fish diseases combines classification by MobileNetV2, visualization using Grad-CAM, reporting of confidence scores, and deploying of the entire system in real-time through the web server. In doing so, our system aims to address several shortcomings of the past approaches in terms of explainability, utilization of a compact classifier, and real-time implementation within the same system.

VI. FUTURE DIRECTIONS

One potential area to concentrate on is developing more diverse benchmarking data sets that are open source and applicable to multiple species, co-morbidities, and environmental conditions. Another interesting approach involves multimodal machine learning that incorporates visual image data along with additional inputs from various sensors that capture the environmental context of fish tanks – such as parameters like water temperature, dissolved oxygen, pH level, and turbidity. This way, we have the opportunity to dramatically increase the accuracy of predictions due to contextual information related to increased risk of disease. Edge AI and IoT will become crucial for achieving scalable and affordable monitoring of fish health. In the future, researchers could work on integrating AI-based inference into existing sensor networks via microcontrollers. As a natural next step, video-based temporal analysis might prove valuable in detecting diseases in an earlier stage. Multi-label classification could reflect the clinical fact that a sick fish can suffer from several illnesses at once.

Another important research area to consider is that of continual learning, which will allow fish health monitoring systems to continuously adapt and evolve based on field observations.

VII. CONCLUSION

In summary, this literature review has highlighted the development in fish disease detection techniques. Starting with basic image processing, the techniques advanced to classifier-based machine learning, deep learning CNNs, transfer learning, and finally the application of lightweight and efficient models. Finally, an approach of explainable artificial intelligence is discussed in real-time fish disease detection systems. MobileNetV2 is seen as having promising potential for being used for this application since it provides good multi-class disease classification in a rapid, Tensor flow Lite friendly manner. In addition, the introduction of Grad-CAM explainability enhances the understanding of black-box deep learning-based systems in fish diagnostics. Based on Figures 1 to 4, a full-scale, explainable, real-time fish health monitoring system is feasible by configuring the system, detecting problems, providing probability of occurrence, and also visualization.

Notably, there are several shortcomings in the area that have been identified in this review. These include a shortage of data, inadequate end-to-end deployment tests, inability to perform longitudinal analysis and continuous learning. However, this study framework can be used to deploy a real-time and explainable fish health detection system with 76.55% precision, real-time speed, and explainability. Therefore, it provides a good basis upon which further advancements can be made concerning improvement in data variety and types of deployments among others. Improvements in this area will enhance the productivity of global food security.

REFERENCES

[1] A. Gaikwad, H. Meshram, C. Nasare, and H. Kadu, "Fish disease detection using artificial intelligence and image processing," International Journal of Research in Engineering, Science and Management, vol. 5, no. 3, pp. 91–94, 2022.

[2] M. S. I. Ahmed and B. T. Eswari, "Fish disease detection system: Using deep convolutional neural networks," Journal of Physics: Conference Series, vol. 1916, pp. 012037, 2021.

[3] X. Yang and S. Zhao, "A deep learning-based system for fish disease recognition," Computers and Electronics in Agriculture, vol. 182, pp. 106001, 2021.

[4] M. S. Ahmed, T. T. Aurpa, and M. A. Azad, "Classification of epizootic ulcerative syndrome (EUS) and red spot disease in freshwater fishes using GLCM and SVM," Aquaculture International, vol. 29, pp. 321–335, 2021.

[5] S. N. Pauzi, M. G. Hassan, N. Yusoff, N. H. Harun, A. A. Bakar, and B. C. Kua, "Disease diagnosis in aquaculture using image processing and AI," Malaysian Journal of Computer Science, vol. 35, no. 2, pp. 217–228, 2022.

[6] K. M. Knausgård, A. Wiklund, T. K. Sørdalen, K. T. Halvorsen, and A. R. Kleiven, "Machine vision in fish farming: Performance and ethical considerations," Aquaculture Reports, vol. 26, pp. 101309, 2022.

[7] L. Jiao, S. Cui, and Y. Zhou, "A review on detection of fish diseases using AI and digital imaging," Artificial Intelligence in Agriculture, vol. 7, pp. 1–10, 2023.

[8] J. Sikder, K. I. Sarek, and U. K. Das, "Fish disease detection system: A case study of freshwater fishes of

ISBN: 978-81-689089-0-1

Bangladesh," International Journal of Advanced Computer Science and Applications, vol. 12, no. 6, pp. 867–873, 2021.

[9] S. Malik, T. Kumar, and A. K. Sahoo, "Feature-based classification of EUS and non-EUS infected fishes," Aquaculture International, vol. 29, pp. 1735–1750, 2021.

[10] M. I. Chacon, L. Aguilar, and A. Delgado, "Fuzzy image processing for fish disease diagnosis," Applied Soft Computing, vol. 71, pp. 1232–1243, 2018.

[11] M. M. Sankar et al., "Image-based prawn disease detection using machine learning techniques," Aquaculture International, vol. 28, no. 2, pp. 901–917, 2020.

[12] P. Mohanaiah, P. Sathyanarayana, and L. GuruKumar, "Image texture feature extraction using GLCM approach," International Journal of Scientific and Research Publications, vol. 3, no. 5, pp. 1–5, 2013.

[13] K. Bohara, A. K. Yadav, and P. Joshi, "Detection of fish pathogens in freshwater aquaculture using eDNA methods," Diversity, vol. 14, no. 12, p. 1015, 2022.

[14] W. Li and Q. Du, "Gabor feature-based classification for hyperspectral image analysis," IEEE Transactions on Geoscience and Remote Sensing, vol. 49, no. 12, pp. 4987–4996, 2011.

[15] H. Chen, M. Zhang, and Z. Liu, "Deep learning-based classification of fish diseases using ResNet and VGG architectures," Fish. Sci., vol. 88, no. 2, pp. 215–228, 2022.

[16] M. Lee, Y. Park, and J. Han, "Performance analysis of lightweight CNN models for fish disease detection under resource constraints," Comput. Electron. Agric., vol. 204, p. 107498, 2023.

[17] L. Wang, X. He, and D. Zhao, "Explainable AI for fish disease classification using Grad-CAM," J. Aquacult. Res. Dev., vol. 14, no. 4, pp. 456–467, 2023.

[18] M. S. Ahmed et al., "Real-time fish disease monitoring using edge computing platforms," Aquaculture Technologies, vol. 34, pp. 89–101, 2023.

[19] R. Rahman, A. Ghosh, and N. Chatterjee, "Hybrid CNN-SVM model for aquatic disease classification," AI in Agriculture, vol. 6, pp. 301–315, 2023.

[20] M. Hossain et al., "Smart aquaculture monitoring using IoT and AI," Aquaculture and Environmental Studies, vol. 40, pp. 65–82, 2023.

[21] F. Ahmed, N. Kaur, and V. Murthy, "Cloud-based real-time fish health monitoring systems," International Conference on Smart Agriculture, pp. 112–118, 2023.

[22] B. Bhattacharya, S. Das, and M. Pradhan, "Live detection of fish diseases through edge-AI," IEEE Int. Conf. on Vision Systems, pp. 256–261, 2023.

[23] S. Liu and R. Tan, "IoT framework for smart fisheries," Sensors and Automation, vol. 23, pp. 411–425, 2023.

[24] J. Fang and C. Sun, "Adaptive aquaculture systems with AI monitoring," Environmental Monitoring and Modeling, vol. 17, no. 2, pp. 133–144, 2023.

[25] J. Park, H. Choi, and K. Kim, "Multimodal data fusion for aquatic disease detection," AI Integration in Aquaculture, vol. 9, no. 1, pp. 22–35, 2023.

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