Real-Time Epizootic Monitoring with Inception Deep Neural Network for Maritime Applications

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This study explores the integration of artificial intelligence in aquaculture to differentiate healthy fish from those afflicted with diseases, aiming to establish a real-time, automated epizootic monitoring system. Utilizing the “Inception v3” convolutional neural network, we examined the model's efficacy in classifying fish based on their health status across two experiments focusing on data augmentation variability. Initial results without augmentation showed diseased fish detection with 86.7% accuracy and healthy fish detection with 86.9% accuracy. However, employing diverse augmentation techniques significantly enhanced detection accuracy to 96.9% for diseased fish and 96.7% for healthy specimens. These findings underscore the potential of computer vision technologies in revolutionizing epizootic monitoring in aquaculture by providing a non-invasive, accurate, and scalable solution to fish health management. The successful application of AI in this context could significantly contribute to the sustainability and productivity of aquaculture operations, underscoring a pivotal shift towards more advanced and humane practices in the industry.

KEYWORDS
~ Computer vision
~ Epizootic monitoring
~ Deep learning
~ Artificial intelligence
~ Fish detection
~ Fish diseases

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doi: 10.7225/toms.v14.n01.002

Received: 9 Jun 2024 / Revised: 24. Nov 2024 / Accepted: 22 Dec 2024 / Published: 20 Apr 2025

1. INTRODUCTION

Aquaculture has a key role in ensuring food security and economic stability in many countries worldwide. It provides a consistent and sustainable source of high-quality protein, essential for human nutrition. Notably, fisheries and aquaculture supply approximately 17% of the world's animal protein (Ababouch and Fipi, 2015). This statistic emphasizes the vital contribution of aquaculture to global food supplies, especially in regions where other protein sources may be scarce (Naylor et al., 2023; Youn et al., 2014). Furthermore, the economic relevance of aquaculture extends to creating jobs, developing rural areas, and generating income. In numerous coastal and inland communities, aquaculture operations are a source of livelihood for thousands of people. The expansion of the aquaculture sector stimulates economic growth, which is particularly critical in developing regions (Bennett et al., 2021).

Many countries have had a rapid growth in aquaculture production in recent years. For instance, in the Russian Federation, over the past five years, the efficiency of aquaculture has increased by more than 50%, amounting to 353 thousand tons in 2021 (Bartley et al., 2015; Vasilyeva et al., 2019). Growing fish consumption is currently a trend in both developed and developing countries, due to the significant growth in the world's population. According to estimations (Kobayashi et al., 2015), global production will increase to 186 million tons by 2030.

Healthy aquaculture practices are closely linked to environmental sustainability. Sustainable aquaculture is essential for maintaining the environmental balance of aquatic ecosystems (Cribb, 2010; Frankic and Hershner, 2003; Neori, 2009). Well-managed aquaculture operations can help lower the pressure on overexploited wild fisheries, thereby contributing to the preservation of marine biodiversity (Walker and Mohan, 2009).

However, given that aquaculture minimizes the environmental impact of fish farming, its environmental potential can not be underestimated. Ensuring the health of aquatic organisms is of utmost importance in the prevention of the spread of diseases and pathogens to wild populations (Oidtmann et al., 2011). Disease outbreaks in aquaculture can have devastating consequences, including the loss of valuable fish stocks, the spread of pathogens to natural habitats, and detrimental impacts on the broader ecosystem (Naylor et al., 2005).

Traditional methods of monitoring fish diseases in aquaculture often entail visual inspection and manual assessment, which have various limitations (Hong et al., 2014; Purcell et al., 2014). These limitations include the labor-intensive and time-consuming nature of visual inspections, as they require significant human resources and can cause delays in disease detection and response (Macaulay et al., 2021). Additionally, human assessment is subjective and prone to variations between individuals, leading to inconsistent results. These methods may also fail to detect subtle signs of disease in the early stages (Føre et al., 2018; Li and Du, 2022). Furthermore, the handling and close examination of fish characteristic of traditional monitoring methods can induce stress in aquatic organisms, which is detrimental to their health and overall growth (Lushchak, 2011). This stress factor poses a significant challenge, as reducing stress is vital for optimal aquaculture production. Moreover, traditional monitoring methods are often not scalable, particularly in the context of large-scale industrial-type aquaculture farms with extensive fish populations (Arlinghaus et al., 2002; Hook et al., 2014). The limitations of these techniques highlight the need for innovative approaches, such as computer vision and artificial intelligence, capable of addressing these challenges and changing the way we monitor fish health in aquaculture settings.

Given these challenges, the integration of artificial intelligence and neural networks into aquaculture monitoring emerges as a compelling solution (Føre et al., 2018). AI-based approaches, such as the use of deep neural networks, like the Inception model, have the potential to change disease detection in aquaculture (Cui et al., 2020). By automating the monitoring process, AI reduces labor requirements, minimizes stress on aquatic organisms, and enhances the accuracy and speed of disease detection. This technology addresses the limitations of current methods and aligns with the goals of efficient, sustainable, and environmentally responsible aquaculture practices (Li and Du, 2022).

Recently, due to the development of artificial intelligence technologies, an approach based on replacing human assessment with a trained model for detecting various objects using neural networks is gaining popularity (Ahmed et al., 2021; Krivoguz, 2020; Krivoguz and Borovskaya, 2021). This method of epizootic fish monitoring minimizes handling and thermal stress of aquatic organisms.

Advancements in artificial intelligence have ushered in a new era of epizootic monitoring, offering a powerful tool to enhance our understanding of animal health and well-being (Hu et al., 2021). Computer vision, a subset of AI, has gained significant importance due to its ability to replace human assessments with trained models, particularly in the context of detecting various objects, including animals, using neural networks. This transformative approach has wide-reaching implications for epizootic monitoring, with a particular emphasis on fish health in aquaculture (Li et al., 2002). Computer vision leverages the capability of machines to “see” and interpret visual information, making it an ideal candidate for monitoring animals in their natural or captive environments (Ahmed et al., 2021; Ciaburri et al., 2020; Sikder et al., 2021).

While the application of computer vision spans various fields, including agriculture, wildlife conservation, and livestock management, its role in epizootic monitoring is hugely important (Sun et al., 2021). The key elements of computer vision for epizootic monitoring include several critical aspects. First, computer vision relies on automated object detection, which has been transformed by neural networks, particularly convolutional neural networks (CNNs). These advanced algorithms outperform at object detection and can discern and classify animals, including fish, in images or video streams with exceptional accuracy. Another key aspect is real-time monitoring. Computer vision systems equipped with neural networks have real-time capabilities, enabling immediate response to potential disease outbreaks or deviations in animal behavior. This rapid response is irreplaceable for effective disease management, as it allows for timely intervention and mitigation.

Additionally, computer vision-based monitoring stands out for its non-intrusive surveillance capabilities. In contrast to traditional methods that often needs physical contact with animals, computer vision operates without direct impact. This non-intrusive method minimizes the need for handling and reduces thermal stress to aquatic organisms, thereby supporting their overall health and well-being. In the context of aquaculture, where the health and well-being of fish are of great importance, the application of computer vision offers several advantages. These advantages are instrumental in enhancing the efficiency, sustainability, and overall management of fish farming operations. Foremost among these advantages is early disease detection. Computer vision algorithms have the capability to identify subtle and early signs of disease in fish, often before any visible symptoms. This early detection is key to timely intervention and disease management, reducing the risk of widespread outbreaks and potential economic losses. Additionally, computer vision offers high throughput capabilities. AI-driven systems can swiftly and accurately process high volumes of visual data, rendering them highly suitable for deployment in industrial-scale aquaculture farms with extensive fish populations. This efficiency ensures that monitoring efforts can scale up to meet the demands of large operations.

One of the features of computer vision is its capacity for continuous monitoring. Unlike human-centric monitoring, computer vision operates 24/7 without interruption, ensuring that no potential issues or deviations in fish behavior are overlooked (Wu et al., 2022). This continuous vigilance extends to nighttime and adverse weather conditions, providing a comprehensive view of the aquaculture environment (Cheng and Sun, 2014).

Furthermore, computer vision-generated data give important information on the various aspects of fish behavior, stress levels, and habitat preferences. This data-driven approach contributes significantly to the improvement of aquaculture practices, enabling farmers to make informed decisions based on a deeper understanding of their fish populations (Cheng et al., 2015). This knowledge can optimize feeding regimes, reduce stress on fish, and improve environmental management in aquaculture facilities (Biazi and Marques, 2023). Despite these advancements, the application of computer vision in disease monitoring in aquaculture remains underexplored. Current practices in the field have yet to fully leverage AI's potential to improve fish health monitoring by enabling early detection of diseases, reducing reliance on manual inspections, and facilitating scalable, non-invasive monitoring techniques.

This study seeks to bridge this critical gap by examining the application of computer vision, coupled with deep neural networks for real-time, accurate detection of diseased fish in the aquaculture environment. This research is poised at the frontier of integrating AI technologies with aquaculture management practices, aiming to validate the efficacy of these tools in enhancing disease detection capabilities. By focusing on the development and testing of an AI-based monitoring system, this paper addresses the need for innovative solutions that can provide early warning of health issues in aquaculture operations, thereby mitigating potential economic losses and supporting the sustainability of the industry. The significance of this research lies in its potential to set a new standard for fish health monitoring, moving beyond the constraints of traditional methods towards a more efficient, accurate, and scalable approach. By leveraging the latest advancements in AI and machine learning, this study not only contributes to the field of aquaculture management but also opens new areas for the application of technologies capable of supporting sustainable practices in the area.

In this research, our primary objective was to explore the potential to distinguish between diseased and healthy fish. This exploration serves as the foundation for the long-term vision of establishing an autonomous, real-time epizootic monitoring system created for use in industrial-type aquaculture farms utilizing pond-based fish cultivation.

The paper has the following structure. The second chapter, "Previous and related papers", gives an overview of prior research on the use of neural networks to recognize underwater objects and classify them by fish species. The third chapter, "Model overview", is an in-depth examination of the model utilized, specifically Inception v3, and gives a comprehensive analysis of its key elements and methodologies used to train and assess its performance. Chapter Four, "Model validation", describes the process of model validation using k-fold cross-validation. Chapter Five, "Data description and preprocessing", outlines the methodology of the collection and preparation of data used to train and test the model. It places special emphasis on the role of data augmentation techniques and their effect on model performance and accuracy. Chapter Six, "Fish disease detection using convolution neural network concepts", discusses the two stages of system development and implementation for epizootic fish monitoring: the build phase and the deployment phase. It describes key processes, including image processing, image embedding, and the use of neural networks for classification. Chapter "Results" presents the findings of two experiments, one conducted with and one without data augmentation. It also discusses the performance metrics obtained in each case. Chapter "Discussion" contextualizes the results of this study within the broader research area and compares them to similar work in the field.

2. PREVIOUS AND RELATED PAPERS

In our previous paper (Sobolev et al., 2022), we demonstrated that it was possible to detect underwater objects in real time. In this case, the YOLO v4 Darknet architecture was used, as well as a set of data we collected on five types of underwater objects in the Sea of Azov – “Jellyfish”, *Liza haematocheilus* adults and juveniles, “Neogobius” and “Syngnathus”. The trained model delivered satisfactory real-time underwater object detection results, with 85-100% mAP accuracy and average 11.3 FPS. Despite its high detection accuracy, low FPS does not justify the full use of this model in real-time underwater object detection and classification; therefore, we intend to use a more lightweight YOLO v5 tiny model in the future. Nevertheless, the task of recognizing underwater objects is not new and currently has a large basis of research. For example, paper (Park and Kang, 2020) considers the recognition of fish, in order to distinguish them from the total mass of invasive species that can cause significant harm to existing ecosystems, because, in their opinion, manual classification and counting are quite complex and resource consuming. The authors attempted to address the issue by using YOLO architecture, which has a good level of accuracy in real-time object recognition by splitting streaming video into separate frames and identifying objects on each of the received frames, to later merge them into a new video file. As a result, having trained a model with the YOLO architecture, they managed to achieve object classification accuracy of 93% and 97% for Bluegill and Largemouth, respectively. Another good example is (Cui et al., 2020) where a convolutional neural network was used to detect fish using an Autonomous Underwater Vehicle (AUV). The dataset collected in the Gulf of Mexico was augmented to increase the number of training objects and the variety of potential fish positions in the camera frame. In addition to augmentation, the authors also applied approaches to simplify and increase the speed of the neural network training process to optimize system speed in real time.

The classification of fish by epizootic status has also been considered in a number of papers by various authors who used different approaches. For example, (Ahmed et al., 2021) consider the use of the Support Vector Machine with kernel function to determine salmon infestation through the application of augmented and non-augmented datasets. As a result, the authors managed to achieve classification accuracy levels of 94% and 91%, respectively. Another example is (Sikder et al., 2021), where the Multi-Support Vector Machine (M-SVM) and k-means clustering in the MATLAB environment were used for the automated detection and recognition of infected fish in the Rangamati Kaptai Lake in Bangladesh. The algorithms achieved 96% and 98% accuracy, respectively, allowing the trained system to detect infected fish at an early stage and administer timely treatment.

3. MODEL OVERVIEW

The “Inception v3” model is a convolution neural network, developed by Google for object recognition in images (Szegedy et al., 2016). In December 2015 the third version of “Inception” was published, where the method of package normalization was used. This method is based on calculating the average and standard deviation for all feature distribution maps in the output layer and its normalization using these values. The last layer of the “Inception” model is a pooling layer with the “softmax” function.

One of the requirements for training a new dataset on the “Inception” model is to set the resolution of the input images to 299x299 pixels using, for example, cubic interpolation. This convolution neural network architecture, according to its developers, is promising and can be used to perform a large number of different tasks, as confirmed by different benchmarks and tests (Szegedy et al., 2015).

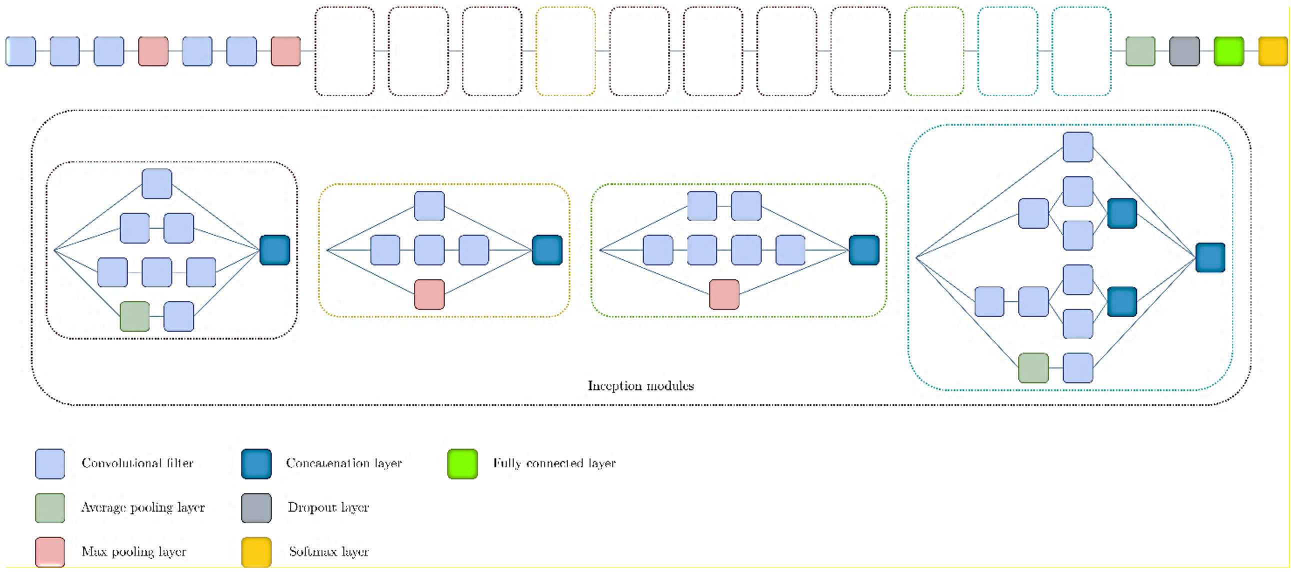

Figure 1. Conceptual scheme of Inception v3 model architecture

4. MODEL VALIDATION

K-fold cross-validation is a procedure that mitigates the limitations of working with limited datasets (Wong and Yeh, 2020). It involves partitioning the dataset into "k" equally sized subsets, where "k" represents the number of groups or "folds" into which the data are divided (Fushiki, 2011; Jung, 2018). In our study, k-fold cross-validation was used to rigorously evaluate the performance of our model's predictions.

K-fold cross-validation is instrumental in assessing the robustness and generalization ability of a model. By partitioning the data into multiple subsets and iteratively training and evaluating the model on different subsets, we mitigated the risk of overfitting or underfitting. This approach provides a more accurate estimate of the model's performance on unseen data, which is vital for its real-world applicability.

Within the context of k-fold cross-validation, several performance metrics were meticulously assessed to gauge the model's effectiveness in distinguishing between diseased and healthy fish:

1. AUC (Area Under Curve). AUC quantifies the overall discriminative power of the model. It represents the probability that the model will correctly rank a randomly chosen positive instance higher than a randomly chosen negative instance. A higher AUC indicates better discrimination (Sokolova et al., 2006; Tuzcu et al., 2019).
2. Classification Accuracy. This metric calculates the ratio of correctly classified instances and the total number of instances. It provides a straightforward measure of overall prediction accuracy (Krivoguz et al., 2022).
3. F-score. The F-score is the harmonic mean of precision and recall. It provides a balanced evaluation of the model's ability to correctly classify both positive and negative instances, particularly valuable when dealing with imbalanced datasets (Sokolova et al., 2006).
4. Precision. Precision measures the proportion of true positive predictions among all positive predictions made by the model. It signifies the accuracy of positive predictions (Goutte and Gaussier, 2005).
5. Recall. Recall, also known as sensitivity or true positive rate, quantifies the model's ability to correctly identify all positive instances among the actual positive instances (Goutte and Gaussier, 2005).

5. DATA DESCRIPTION AND PREPROCESSING

This study utilizes the "Inception v3" convolutional neural network to classify fish into healthy and diseased categories based on visual cues. The dataset comprising images of various fish species in different health states from publicly available sources was collected (Sikder et al., 2021). The dataset included 153 images, with 72 depicting infected fish and 81 healthy specimens (Fig.2). Each image was reviewed and labeled by veterinary experts in aquatic health to ensure accuracy in the health status classification.

Figure 2. Examples of healthy and infected fish in the dataset

Given the input specifications of the “Inception v3” model, all images were resized to 299x299 pixels using cubic interpolation to maintain image quality. To augment the dataset and simulate a variety of environmental conditions that might affect visibility underwater, several augmentation techniques, including rotation, mirroring, and brightness and contrast adjustments were applied. This process aimed to enhance the model's robustness by training it on images that reflect the diverse and dynamic conditions encountered in aquaculture settings.

The key step in dataset preparation involved the categorization of fish images into two distinct classes – “infected” and “healthy”. This binary classification is essential for training and testing the model's ability to distinguish between the two states.

Model training was initialized using the pre-trained “Inception v3” weights, leveraging transfer learning to adapt the model to the specific task. The dataset was split into training (70%), validation (10%), and test (20%) sets. This distribution allowed to train and fine-tune the model while evaluating its performance on unseen data. The k-fold cross-validation with k=5 to ensure the reliability of results was used, mitigating the potential for overfitting and ensuring that the model's performance accurately reflects its generalizability.

To evaluate the model's efficacy in accurately classifying fish health status, several key performance metrics were calculated: Area Under the Curve (AUC), classification accuracy, precision, recall, and F1 score. These metrics provided a comprehensive overview of the model's predictive capabilities, with a particular focus on its ability to balance sensitivity and specificity in disease detection.

All statistical analyses were conducted using Python's SciPy and NumPy libraries. The chi-squared test was used to assess the significance of differences between the model's performance on the augmented versus non-augmented dataset, setting the significance level of $p<0.05$.

6. FISH DISEASE DETECTION USING CONVOLUTION NEURAL NETWORK CONCEPTS

In perspective, the development and deployment of a real-time system for the recognition and detection of infected fish can be divided into two distinct stages: the “building stage” and the “deployment stage” (Figure 3). This comprehensive approach ensures the system's effectiveness and reliability in practical aquaculture applications.

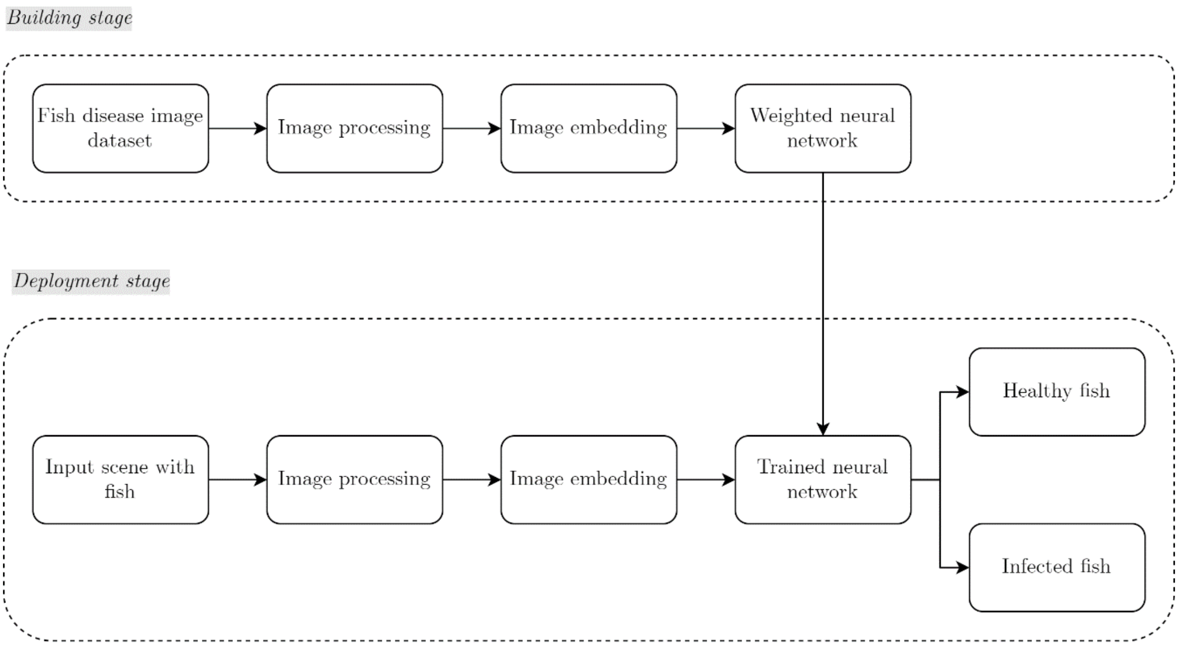

Figure 3. System architecture for fish disease detection using the convolution neural network.

The basis of this system is laid in the building stage, where 70% of the total images from the fish dataset were used for training purposes. This initial stage involves critical processes preparing the model for robust performance. Data pre-processing takes the forefront, encompassing techniques such as data augmentation, rotation, mirroring, conversion to grayscale, and brightness and contrast adjustments. These modifications contribute to the dataset's diversity and ensure that the model is exposed to various scenarios. Subsequently, the pre-processed dataset is converted into digital format suitable for further processing by the neural network model. The training stage follows during which the model learns and adapts through the weighted adjustment of its neurons. Concurrently, meticulous accuracy checks are conducted to ascertain the model's proficiency.

Transitioning to the deployment stage, the system is installed directly at the fish growing pond, where real-time monitoring is crucial. The process begins with the obtainment of images directly from the aquaculture environment. As with the building stage, data pre-processing steps are executed to ensure the suitability of incoming images for analysis. This involves the transformation of the data obtained into a digital format compatible with the trained neural network model. Subsequently, the transformed data are input into the neural network model, which has already been trained rigorously in the building stage. At this point, the classification process unfolds, with the system making real-time determinations, classifying each image as either “healthy fish” or “infected fish”. Notably, the system also has the prediction accuracy visualization option, allowing operators to gauge the confidence level of the classification.

7. RESULTS

An ASUS laptop with Intel i7-11370H (4 cores, 3.30 GHz) CPU, 16 GB DDR4 memory and NVIDIA GeForce RTX 3050 (4 GB) graphic card was used for calculation. The dataset was divided as follows: 70% training data, 10% validation data, and 20% test data.

The primary objective of this paper was to assess the learning capabilities of the model that would allow it to recognize and classify fish based on their epizootic status. To accomplish this, the pre-trained “Inception v3” model was used, known for its deep learning capabilities. For the practical implementation and testing of the model, Python, a versatile and widely adopted platform for machine learning and deep learning tasks was used. Python provides a rich ecosystem of libraries and tools, making it an ideal choice for research. The power of several key libraries and frameworks was used, namely, the TensorFlow framework, a leading open-source machine learning library that seamlessly integrates with Python. TensorFlow served as the backbone for model development and training, offering a robust foundation for deep neural network architectures. In addition to TensorFlow, other Python libraries for data manipulation, image processing, and evaluation were used extensively. These included NumPy for efficient numerical operations, OpenCV for image pre-processing, and scikit-learn for various machine learning applications. The combination of these libraries facilitated data preparation, model training, and result evaluation in a coherent and efficient manner.

The system was tested using two experiments differing mainly in data augmentation. An overview of data preparation and augmentation carried out by the authors in the first and second experiment is given in Table 1.

Image modification	1st experiment	2nd experiment
Auto-orient	Applied	Applied
Isolate objects	Applied	-
Static crop	25-75% horizontal region	-
Resize	Stretch to 299x299 pixels	Stretch to 299x299 pixels
Grayscale	Applied	-
Tile	2 rows x 2 columns	-
Flip	Horizontal	Horizontal
90* rotate	Clockwise, Counter-Clockwise, Upside Down	-

Table 1. Data preprocessing and augmentation settings used in both experiments on fish detection and classification based on their epizootic status

In the first experiment, an attempt was made to increase the number of potential variations of physical-optical conditions in the aquatic environment, as well as of fish behavior under such conditions, which, in our opinion, should significantly increase the accuracy of detection and classification of fish infected with diseases. In the second experiment, we tried to keep the standard conditions which the infected fish were in at the time of their capture.

The model training in both experiments showed that more accurate results are obtained when using an augmented data set (Table 2).

	AUC	Classification accuracy	F-score	Precision	Recall
Data without augmentation	0.889	0.877	0.868	0.877	0.877
Data with augmentation	0.993	0.957	0.957	0.957	0.957

Table 2. Training results for the 1st and 2nd experiment

This is mainly due to the greater variability of the initial data and, accordingly, many different potential conditions in which the infected fish can be. But it should also be noted that the level of accuracy of the models in both experiments is not significant; therefore, in this case it is more worth focusing on speed and cost indicators used for learning to deploy the trained model in practice.

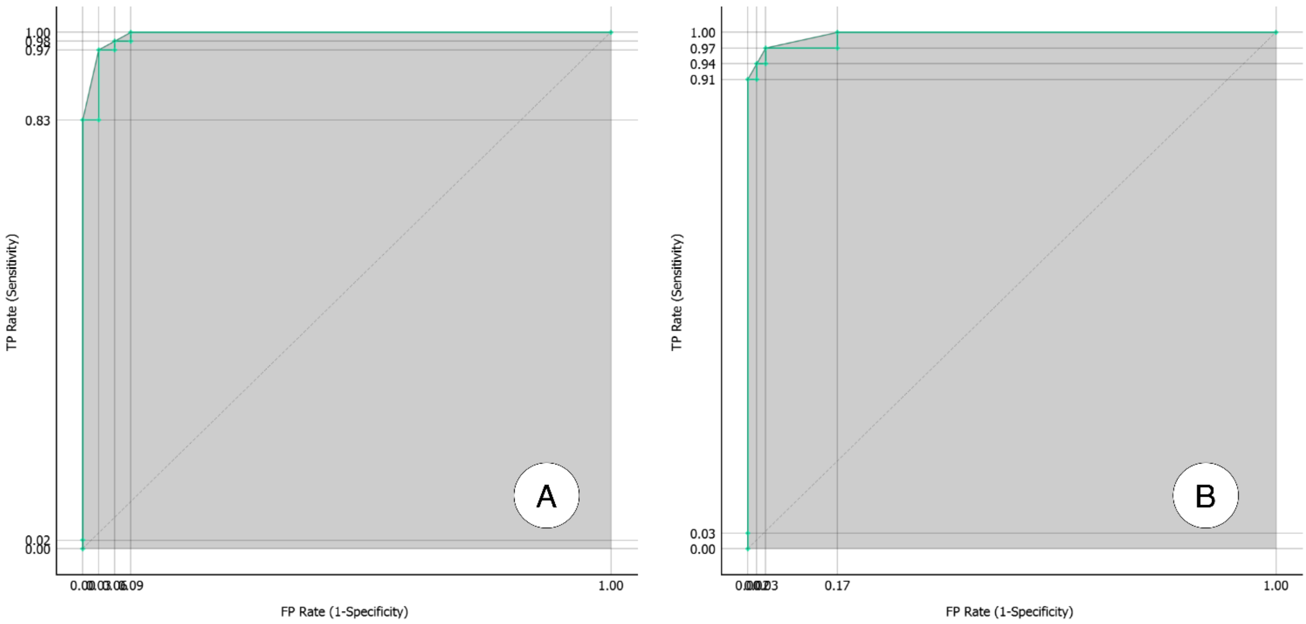

Figure 4. ROC-curves for A – infected class and B – healthy class on data with augmentation

Classification results, presented in the confusion matrix form, also indicate the need to use augmentation to detect infected fish in the ponds (Fig.5.)

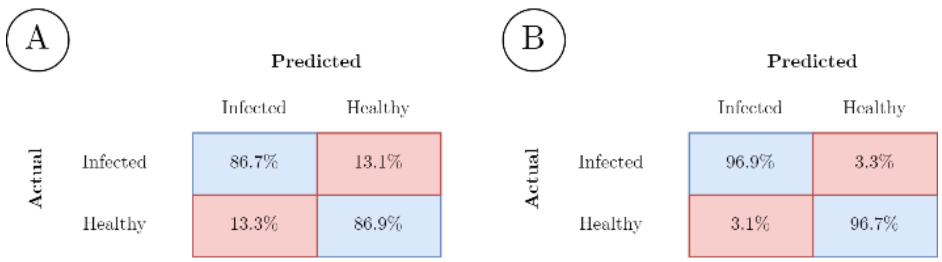

Figure 5. Confusion matrices for training without augmentation (A) and with augmentation (B)

A	Infected	Healthy
Infected	86.7%	13.1%
Healthy	13.3%	86.9%
B	**Infected**	**Healthy**
Infected	96.9%	3.3%
Healthy	3.1%	96.7%

Table 3. Model parameters

Thus, in the original dataset, only 86.7% of images for the infected class and 86.9% for healthy fish were correctly classified. At the same time, the use of various augmentation tools significantly increased detection accuracy up to 96.9% for infected and 96.7% for healthy fish. This suggests that in both experiments, the images of healthy specimens were recognized with higher accuracy than those of diseased fish, which might be explained by barely discernable visual manifestations of diseases in some cases, given that in the initial stages of infection the disease occurs within the organism, without causing significant external changes in scale color or any other physiological features of the fish (Tab.3).

8. DISCUSSION

This research applied computer vision methodologies within the framework of an aquaculture disease monitoring system, using the Inception v3 convolutional neural network to differentiate between infected and healthy fish. The incorporation of this methodology in combination with data augmentation has resulted in improved classification accuracy, reaching a success rate of 96.7% and 96.9% for healthy fish and infected fish, respectively. The outcomes of this study not only demonstrate the efficacy of these methodologies but also stress the importance of data augmentation in simulating diverse scenarios that reflect the natural environment of the subjects, which is essential when working with limited data sets.

This study clarifies the potential for significant transformative advancements in the field of aquaculture through the implementation of computer vision, which is a substantial improvement of traditional monitoring methodologies. The integration of computer vision algorithms facilitates noninvasive, real-time monitoring of aquatic organisms, considerably improving disease management and operational efficiency. The implementation of this technology allows the identification of disease in inception stages, frequently preceding the manifestation of observable symptoms, thereby allowing fast intervention. This capacity for early detection, as evidenced by the high accuracy metrics recorded in the model, proves the efficacy of computer vision systems in detecting subtle indicators of illness that human observers might otherwise neglect.

Traditional monitoring techniques, which primarily rely on manual and visual inspection, are deficient in several aspects. These methods require a substantial amount of labor, are prone to human error, and are fundamentally restricted with respect to scalability and sensitivity. Moreover, such traditional techniques may induce stress in fish, potentially adversely affecting their health and behavior. By contrast, computer vision offers a scalable, precise, and non-stressful alternative, capable of processing significant quantities of visual data swiftly and with minimal human intervention. This advancement not only decreases the dependency on manual labor but also reduces the risk of human-induced stress on fish, thereby promoting healthier and more stable aquaculture environments.

The findings of this study highly correlate with those of similar research in the field of computer vision, which have sought to detect a range of infectious pathologies in fish. For instance, in the Azhar (Azhar et al., 2024) study, the GoogleNet convolutional neural network architecture was used instead of the Inception v3 architecture to diagnose white spot protozoal disease. The resulting model had the accuracy of approximately 90%, which is notable given the complexity of the disease. Another noteworthy example of the application of computer vision in epizootic control is the work of Yaoyi Cai (Cai et al., 2024), in which the NAM-YOLO v7 model demonstrated a 95% accuracy and 93.8% recall rate at the processing speed of 0.18 seconds per image. The main distinction and benefit of this paper compared to this study is the capacity to detect fish condition in real time, which significantly increases the practical value of this approach. Additionally worthy of attention is Hasan's study (Hasan et al., 2022), where CNN was used to diagnose white and red spots. The authors achieved the accuracy of 94.4% using a limited dataset of 90 images, demonstrating the key role of data augmentation in instances where the initial data are insufficient and there is an urgent need to augment them. Augmentation clearly improves model accuracy.

While this study affirms the effectiveness of data augmentation in improving model performance, it simultaneously recognizes certain potential limitations inherent in the approach used. One such limitation is the dependence on a predetermined set of augmentation techniques, which may not sufficiently cover the extensive range of environmental conditions encountered in aquaculture contexts. Future research would benefit from exploring more advanced and diverse augmentation strategies, potentially integrating generative models like generative adversarial networks to produce highly realistic and varied training images. Additionally, an examination of the impact of augmentation on different categories of neural network architectures could yield findings that optimize model selection for specific aquaculture applications. Moreover, further research in real-time data augmentation, where modifications are made in real-time in response to existing environmental conditions, holds significant promise for advancing the field. Such advancements not only address the shortcomings of current methodologies, but also promote the development of more robust, precise, and adaptable disease monitoring solutions in aquaculture.

The practical applications of this technology in real-life aquaculture settings are diverse and have the potential to transform disease management practices. The integration of AI-driven monitoring systems allows aquaculture operations to transition from a reactive to a proactive approach to fish health management. This allows the early detection of signs of disease, preventing the development of visible symptoms or the spread of disease. This capability has the potential to significantly reduce mortality rates associated with late-stage disease intervention and minimize the need for broad-spectrum antibiotic treatments, thereby enhancing the sustainability of aquaculture practices. Furthermore, the implementation of such AI technologies has the potential to significantly reduce economic losses associated with disease outbreaks. By limiting the spread of disease at an early stage, farms can ensure higher survival rates, maintain productivity, and sustain revenue. Furthermore, the data gathered by these AI systems can offer priceless information on disease prevalence, risk factors, and treatment efficacy, thereby contributing to a more comprehensive understanding of aquaculture health management and supporting evidence-based decision-making.

9. CONCLUSION

This research uses computer vision integrated with the Inception v3 neural network to assess fish health in aquaculture environments. The findings from two experiments demonstrate the potential of AI to improve disease detection in fish farming. Computer vision technologies exhibit proficiency in accurately identifying diseased fish and enhancing monitoring methodologies. The first experiment, which used comprehensive data augmentation techniques, had the AUC accuracy of 99%, illustrating the model's proficiency in differentiating between healthy and diseased fish. The outcomes of the experiments clearly show that computer vision can improve fish health monitoring practices in aquaculture facilities. Additionally, the findings emphasize the critical role of data augmentation in enhancing the model to imitate the different and unpredictable conditions in aquaculture environments. They also demonstrate that data augmentation is important for addressing the diverse and complicated conditions typical of aquaculture. This study provides an efficient, and minimally intrusive approach to the development of more sustainable fish farming methodologies. Computer vision offers a solution for aquaculture to detect diseases with expediency and precision. AI-driven monitoring systems could facilitate disease management, mitigate economic losses, and enhance the sustainability of aquaculture practices.

FUNDING

The research is partially funded by the Ministry of Science and Higher Education of the Russian Federation as part of the World-class Research Center program: Advanced Digital Technologies (contract No. 075-15-2022-312 dated 20 April 2022).

CONFLICT OF INTEREST

The authors have declared no potential conflicts of interest with respect to the research, authorship, and publication of this article.

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