A Review Paper on Underwater Fish Detection Technology

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Abstract

Aquaculture plays a vital role in the economy, but fish disease poses a significant challenge, leading to productivity and economic losses. Unhealthy fish identification relies on labor-intensive visual inspection, necessitating the development of smart intelligence systems for fish disease detection and monitoring. This review paper focuses on the first step of fish detection in underwater images/videos, which is crucial for automated pipelines in fish health analysis. The complex underwater environment, characterized by variable lighting, water turbulence, and occlusion, makes fish detection challenging. The literature review highlights the effectiveness of deep learning-based techniques, such as convolutional neural networks (CNNs) and object detection algorithms, for accurate fish detection. Several studies have demonstrated high detection accuracies ranging from 90% to 99%. Methodologies including image preprocessing, feature extraction, and data augmentation have been employed to improve detection performance. The review emphasizes the potential of computer vision in intelligent aquaculture and its impact on fish health analysis. The findings provide valuable insights into the current state of fish detection and highlight the need for efficient and time-effective algorithms that strike a balance between performance and complexity. Developing accurate fish detection algorithms can significantly enhance the productivity of the aquaculture industry, facilitating vision-based fish health analysis.

Keywords: aquaculture, fish disease, fish detection, underwater images/videos object detection algorithms, detection accuracies, image preprocessing, feature extraction, data augmentation, computer vision, intelligent aquaculture, fish health analysis.

Introduction

Efficient monitoring and management of fish populations in aquaculture settings are essential for ensuring their well-being and productivity. However, traditional methods of fish surveillance, such as manual inspection and visual observation, are labor-intensive, time-consuming, and prone to human error. In recent years, the emergence of computer vision and deep learning techniques has offered promising avenues for automating fish detection and monitoring processes.

Underwater environments present unique challenges for fish detection due to factors like variable lighting conditions, water turbulence, and occlusion caused by vegetation or other objects. Overcoming these challenges necessitates robust algorithms capable of accurately identifying fish species, detecting unhealthy individuals, and precisely localizing fish in images and videos. Deep learning techniques, particularly convolutional neural networks (CNNs), have demonstrated remarkable effectiveness in image classification tasks and have been successfully applied to fish detection in underwater environments.

This review aims to provide an objective analysis of the current state of the art in deep learning-based fish detection in underwater images and videos. It will examine the effectiveness of various deep learning techniques, explore the integration of object detection algorithms for precise localization, and discuss the implications of these advancements for aquaculture productivity. Additionally, it will identify key challenges and potential future research directions in this field.

The review will commence by discussing the existing literature on deep learning techniques applied to fish detection, highlighting the methodologies and algorithms employed. It will present a synthesis of reported accuracies and performance metrics achieved by different models, emphasizing the strengths and limitations of each approach. Subsequently, the challenges specific to underwater fish detection and the strategies employed to mitigate them, including preprocessing techniques and data augmentation, will be explored.

The integration of object detection algorithms into fish detection pipelines will be examined, focusing on popular algorithms such as Faster R-CNN, YOLO, and SSD. The review will investigate how these algorithms enhance the accuracy and efficiency of fish detection by providing precise bounding box coordinates. Furthermore, it will discuss the implications of these advancements for aquaculture productivity, including early disease detection, reduced mortality rates, and improved fish health management.

While deep learning techniques have shown significant promise in fish detection, it is crucial to strike a balance between performance and complexity. The review will analyze the computational requirements of state-of-the-art models and discuss the feasibility of deploying them in resource-constrained environments. Moreover, it will explore the potential for vision-based fish health

analysis by integrating fish detection with other analysis techniques, such as disease recognition and image classification.

Lastly, the review will identify future research directions and opportunities in this field. It will highlight the need for robust algorithms capable of handling challenging underwater conditions, the potential for transfer learning to overcome data scarcity, and the integration of multi-modal data sources for a comprehensive understanding of fish health and behavior.

By offering an objective analysis of deep learning-based fish detection in underwater environments, this review aims to contribute to the advancement of intelligent aquaculture practices and facilitate the development of efficient and accurate fish monitoring systems. The findings of this review will have implications for the aquaculture industry, improving fish health management, reducing economic losses, and promoting sustainable fish production.

The Problem Statement

Aquaculture is important to the economy of our country in this blue era. One of the major problems that affects aquaculture farms of all sizes, from small-scale businesses to enormous corporations, is fish sickness. Industry specialists can spot ill fish by looking for abnormal behavior, which adds to the workload. As a result, the aquaculture industry needs a smart intelligence system to prevent the development of fish disease and promote fish wellbeing. In order to monitor fish health, intelligent systems need to automatically and accurately identify fish in underwater photos and videos. In order to diagnose fish diseases automatically, the initial step (fish detection) must maintain a better trade-off between performance and time complexity, which is the subject of this research. Due to the complex and dynamic underwater environment with varying lighting conditions, water turbulence, and occlusion from other objects, the recognition of fish from underwater photographs is quite difficult. As the first step in vision-based fish health analysis, developing an efficient fish detection algorithm can have a substantial impact on the productivity of the aquaculture business.

Literature Review

A paper by Yang et al. (2021) provides a comprehensive review of the use of computer vision in intelligent aquaculture, with a focus on fish detection and behavior analysis. The review covers various computer vision techniques, such as deep learning, convolutional neural networks, and object detection algorithms, and their performance parameters, including accuracy, precision, and recall. The study highlights that deep learning-based techniques have shown superior performance in fish detection and behavior analysis, with accuracy ranging from 90% to 99%. The paper also discusses the methodologies used in the studies reviewed, such as image pre-processing, feature extraction, and data augmentation. Overall, the review provides valuable insights into the current state of computer vision in intelligent aquaculture and its potential for future developments. [1]

Jalal et al. (2020) proposed a deep learning-based approach for fish detection and species classification in underwater environments. The study used convolutional neural networks (CNNs) and long short-term memory networks (LSTMs) to incorporate temporal information and achieved an accuracy of 94.4% for fish detection and 89.2% for species classification. The paper also discusses the methodology used for data acquisition, annotation, and preprocessing, including data augmentation and normalization. Overall, the study highlights the potential of using deep learning and temporal information for accurate fish detection and species classification in underwater environments. [2]

Cui et al. (2020) proposed a deep learning-based approach for fish detection. The study used a convolutional neural network (CNN) architecture called Faster R-CNN and achieved an accuracy of 99.4% for fish detection. The paper also discusses the methodology used for data collection, pre-processing, and augmentation. The study demonstrates the effectiveness of using deep learning and Faster R-CNN for accurate fish detection in underwater environments. [3]

Salman et al. (2020) proposed a deep neural network-based approach for automatic fish detection in underwater videos. The study used a hybrid motion learning system that combines two deep neural networks, one for motion detection and the other for fish detection and achieved an accuracy of 94.9% for fish detection. The paper also discusses the methodology used for data acquisition, pre-processing, and augmentation. The study demonstrates the effectiveness of using a hybrid motion learning system for accurate fish detection in underwater videos. [4]

Linfeng et al. 2020, This paper presents a method called GLHDF to enhance the quality of real-world and low-light underwater images. GLHDF involves four stages, namely, Pixel intensity center regionalization, Global Equalization of Histogram, Local Equalization of Histogram, and Dual-image multi-scale fusion. The method aims to remove noise, correct color, improve contrast, and enhance the overall image quality of underwater images. The first step involves using a multi-scale Gaussian filter to smooth the image, followed by a global equalization of histogram strategy to correct color in the second step. The third step uses a dual-interval histogram based on the average of peak and mean values to improve the contrast of the color-corrected image. Finally, the enhanced image is obtained using a dual-image multi-scale fusion strategy to integrate the color-

corrected and contrast-enhanced images. The method enhances images with good visibility, natural color, high contrast, and sharp texture, and outperforms other state-of-the-art techniques in both qualitative and quantitative evaluations. The proposed method also performs well on low-light, natural, foggy, sandy, and underwater images captured by different specialized cameras. However, GLHDF has limitations, such as the inability to achieve consistent background color for underwater images captured by different cameras, potential computational complexity due to the selection of an average threshold, and the lack of studying underwater images taken at different levels of turbidity. [5]

Salman et al. (2019) proposed a real-time fish detection approach using probabilistic background modeling. The study achieved an accuracy of 95.2% for fish detection in complex backgrounds. The paper also discusses the methodology used for data acquisition, preprocessing, and feature extraction. The study highlights the effectiveness of using probabilistic background modeling for real-time fish detection in complex underwater environments. [6]

Nan, Haiyong, and Bing 2017, The study proposes an image restoration method for enhancing the contrast and correcting color distortion of underwater images. The proposed algorithm uses the maximum map of the red channel to derive the depth map and estimate the overall background light. The transmission map is estimated separately for R, G, and B colors using the simplified light propagation model. The proposed method is tested on natural underwater scenes and calibration board images, and it performs well in terms of contrast enhancement and color correction. However, the method's assumption that the red channel light attenuates fastest may not adapt to certain special conditions, such as a diver wearing a black diving suit, leading to distorted processing results. Nonetheless, the proposed method can work well for most instances in the colorful underwater world. [7]

Boudhane and Nsiri (2016) proposed an underwater image processing method for fish localization and detection in a submarine environment. The paper discusses the methodology of using a combination of image processing techniques such as image enhancement, segmentation, and feature extraction. The study achieved an accuracy of 93% for fish detection using a Support Vector Machine (SVM) classifier. The study highlights the effectiveness of combining different image processing techniques for accurate fish detection in an underwater environment. [8]

Li et al. (2016) proposed a fish detection and recognition system using a Convolutional Neural Network (CNN) with objectness learning to improve speed and accuracy. The study shared CNNs with objectness learning between different species, achieving a detection accuracy of 97.7% and a recognition accuracy of 93.3%. The proposed system significantly reduced the computational cost and achieved real-time fish detection and recognition in an underwater environment. [9]

Wageeh et al presented a fish detection and tracking system for aquaculture using YOLOv3 object detection and Euclidean distance tracking algorithms. The proposed method achieves an accuracy of 93.5% and a mean average precision (mAP) of 84.8% in fish detection. The system also provides

real-time tracking and monitoring of fish in aquaculture farms. The methodology involves pre-processing of video frames, object detection, and tracking using Euclidean distance, and final post-processing to generate the output video. [10]

Han et al proposed a deep Convolutional Neural Network (CNN) method for underwater image processing and object detection. The proposed approach is evaluated on two underwater image datasets and achieves an accuracy of 93.33% and 90.50%, respectively. The methodology involves preprocessing of the images, followed by the use of a deep CNN to classify and detect the objects in the images. The study demonstrates the effectiveness of the proposed method in underwater object detection. [11]

Li et al. proposed a method for enhancing underwater images by using dehazing and color correction techniques. The proposed approach consists of transmission map estimation, color correction, and image fusion. The results demonstrated the effectiveness of the proposed method compared to state-of-the-art approaches. [12]

Pei and Chen proposed a revised underwater image formation model for enhancing the quality of underwater images. The model includes the effects of light attenuation, scattering, and water surface reflection. The proposed method outperformed existing methods in terms of objective evaluation metrics and visual quality. [13]

Kewei et al. proposed a new approach for fish detection and counting in real breeding farms by combining YOLOv3 with MobileNetv1. Existing fish counting methods are manual, time-consuming, and error-prone. RGB imaging is a preferred solution due to its ease of operation, lightweight system, and no harm to fish. Lidar and sonar-based techniques have high accuracy but are bulky and expensive. The feature maps of MobileNet are optimized based on their receptive fields to improve fish detection. The optimized feature map selection based on receptive field analysis and the use of a smaller dataset for pre-training the backbone network results in high accuracy fish detection. A dataset of fish images from breeding farms is used to evaluate the proposed method, which achieves high accuracy. Additionally, a smaller dataset of 16 fish species is used for backbone network pretraining instead of ImageNet, which further improves detection. The proposed method can be used for multiple classes of fish detection and determining fish length and weight. Future work involves implementing the algorithm online and expanding its applicability. [14]

Wang et al. conducted an experimental-based review of various image enhancement and restoration techniques for underwater imaging. They analyzed and compared the performance of different methods based on various evaluation criteria. The review provides a comprehensive overview of the existing methods and their effectiveness. [15]

Zhu et al. proposed a convolutional neural network (CNN)-based approach for enhancing underwater images by performing color balance and dehazing. The proposed method used a fusion strategy to combine the output of the color balance and dehazing modules. The results showed significant improvements in image quality compared to state-of-the-art methods. [16]

Boudhane etal. 2016, In this paper, the authors present a novel method for fish localization and detection in underwater images based on a Poisson-Gauss theory. Object detection is an important process in computer vision, especially in marine environments where cameras are widely used due to the limitations of human access. The proposed approach includes denoising and image restoration, region splitting using mean shift algorithm, and statistical estimation for object combination and detection. The proposed approach outperforms existing state-of-the-art methods under various underwater conditions. As underwater visibility is limited, image processing and computer vision algorithms have become increasingly important for monitoring and tracking marine environments. The proposed method can be adapted to different noise models, making it versatile and practical for various underwater applications. The approach can be used without prior knowledge of the environment and does not require user interaction. In conclusion, the proposed approach has the potential to be applied in various applications such as marine conservation, fisheries management, and underwater exploration. The proposed method has potential applications in underwater fish detection and other computer vision tasks.[17]

Li et al.2016, this paper presents an approach for Automatic object detection and recognition is in great demand for underwater imagery analysis and marine environment surveillance due to the increasing volume of underwater visual data. The paper presents an approach for accelerating underwater object detection and recognition using a region proposal network based on Faster R-CNN. The proposed system achieved a real-time frame rate of 9.8 ftps and 15.1% higher Mean Average Precision (mAP) than the Deformable Parts Model (DPM) baseline on a fish dataset with 12 classes. The use of region proposal networks generated high-quality proposals, improving segmentation performance and fish detection precision. Sharing convolutional features reduces the cost of proposal generation in the fish detection and recognition process. However, video analysis presents a more pressing problem for deep-sea observation systems, which requires further research. The proposed system demonstrates the potential of convolutional networks in underwater image processing.[18]

Wageeh et al. 2020, this paper proposed method aims to address the challenges of manually monitoring fish farms, which is time-consuming and costly. This paper presents a method for improving fish detection and tracking in fish farms by combining an image enhancement algorithm based on retinex with an object detection algorithm. The object detection algorithm used in this study is YOLO. The experiment setup involved a temporary fish tank and a web camera. A dataset of 2000 images was created for the YOLO model to detect fish. Two experiments were conducted. the experiment setup and dataset used for two experiments were presented. The fish tank used for

testing was built in a controlled environment, and a web camera was placed above it to capture videos and images. A dataset of 2000 images of golden fish was collected for YOLO model detection. The first experiment aimed to enhance unclear water images and determine the best camera location for accurate detection. The results showed that there was no significant change in underwater image detection before and after enhancement, and the camera was settled above the pond. The enhanced images improved detection accuracy, confirming the usefulness of the enhancement algorithm. Overall, the experiment setup and dataset were effective in testing and validating the algorithm's performance in fish detection. two methods for drawing fish trajectories and tracking their movements were compared. The first method combined YOLO and optical flow, while the second method utilized a trajectories extraction method. The trajectories extraction method was found to be more accurate than the optical flow method, producing clearer trajectory lines with fewer scattered and wrongly drawn lines. The results showed that the enhanced images had better accuracy in detecting fish. The trajectory extraction method was found to be better than the optical flow method in accurately tracking fish movements. This method can improve fish farm management and reduce costs. Clustering could be used in the future to detect and cluster different fish behaviors. Overall, this method has the potential to improve fish farming efficiency and reduce costs associated with manual monitoring.[19]

W. Zhang et al. 2021, This paper proposes a new algorithm for enhancing underwater images. The algorithm compensates for lower color channels, applies an adaptive contrast enhancement algorithm, and a sharpening technique to produce background-stretched and foreground-stretched images. The proposed algorithm outperforms existing algorithms by at least 5% in all metric scores. The paper also discusses the limitations of existing underwater image enhancement techniques, which can be categorized into image restoration and image enhancement algorithms. Enhancement algorithms have shown to be simple and effective in improving visibility without considering the underwater optical imaging model. [20]

Han et al. 2020, this paper proposes a method for enhancing underwater vision and detecting marine organisms using a deep CNN. This paper proposes a combination of max-RGB and shades of gray methods for enhancing underwater vision, followed by a CNN method to solve weakly illuminated problems and perform detection and classification of marine organisms. Two improved schemes were proposed to modify the deep CNN structure and scheme 2 was found to be better in detecting underwater objects with a detection speed of about 50 FPS and mAP of about 90%. The proposed method was tested on an underwater robot and was found to be accurate and fast enough to assist with underwater working operations. The effectiveness and capability of the proposed method were verified by qualitative and quantitative evaluations, although some objects were missed. Further improvements could be made by using a more complicated algorithm to reconstruct the network. Overall, this method is suitable for detecting objects in underwater environments and outperforms typical methods for this dataset.[21]

Wang et al. 2017, this paper proposes an end-to-end CNN-based framework called UIE-Net for underwater image enhancement. which includes two subnetworks: CC-Net and HR-Net. CC-Net is used to correct color distortion and HR-Net enhances the contrast of underwater images. The framework is trained with two tasks, color correction and haze removal, and utilizes a pixel

disrupting strategy to improve convergent speed and accuracy. The UIE-Net is evaluated on benchmark underwater images for cross-scenes and achieves superior performance over existing methods in terms of entropy and PCQI. The proposed method is robust and effective in enhancing contrast and preserving details. The adaptability of the UIE-Net on cross-scenes is demonstrated through its application on underwater video frames. The framework contains two subnetworks, CC-Net and HR-Net, which output color absorption coefficients and transmission maps for enhancing underwater images. The paper proposes future work to improve the efficiency of the approach by using a fully-CNN implementation. [22]

Han et al. 2020, this research proposes a deep convolutional neural network for detecting and classifying marine organisms in underwater environments. The development of underwater robots for collecting marine products has become a feasible solution to the dangers faced by humans in seabed fishing. One key technique is the detection and location of the main target from underwater vision. This paper proposes a deep convolutional neural network (CNN) based on faster RCNN and the modified method of hyper net for target recognition in underwater vision. The dataset was prepared using an underwater video obtained from a sea cucumber fishing ROV. The dataset used for training and testing is obtained from ROVs and the Underwater Robot Picking Contest. The method proposed in this paper shows good performance of recall and object detection accuracy, with a mean average precision (mAP) of over 90% when the IoU is set to 0.7. The detection runs at a speed of 17 fps on a GPU, which is suitable for real-time processing. The detection time is 58 ms on a GTX 1080ti GPU, which is suitable for real-time processing. This approach has the potential to reduce the dangers associated with seabed fishing by replacing human divers with underwater robots for marine product collection. The modified framework is also applicable in the Underwater Robot Picking Contest. The proposed method is feasible to be applied in underwater vision detection and can be used in real-time for marine organism detection. Further development and testing could lead to a safer and more efficient fishing industry. [23]

Liu et al. 2020, Underwater images often suffer from low visibility and color casts due to light scattering and attenuation, making them unsuitable for computer vision systems. This paper presents a large-scale real-world benchmark, the Real-world Underwater Image Enhancement (RUIE) data set, consisting of three subsets that target image visibility quality, color casts, and higher-level detection/classification. The study evaluates the effectiveness and limitations of various algorithms to enhance visibility and correct color casts on images with hierarchical categories of degradation. The object detection performance on enhanced images is also used as a task-specific evaluation criterion. The findings suggest new directions for visibility enhancement, color correction, and object detection on real-world underwater images. [24]

Dataset details

A collection of images of different types of Indian cultivated fish that have text annotations in YOLOV5 format.

Parameters Considered	Description
Type of Image	Low resolution RGB underwater images
Number of images	8,500
Modality of Dataset	Extracted images from 60fps videos
Split-up of Dataset	70:15:15 (train:test1:test2)
Augmentation	Resizing
Obstacles considered	Water absorption and scattering losses Color Distortion Turbulence Lighting Conditions Depth and pressure
Resolution	640p at 60fps

Results and Discussion:

1. Effectiveness of Deep Learning Techniques:

The review of literature reveals that deep learning techniques, particularly convolutional neural networks (CNNs), have shown remarkable effectiveness in fish detection in underwater images and videos. CNNs have the ability to learn and extract complex features from images, enabling accurate identification of fish species and detection of unhealthy individuals. Several studies have reported high detection accuracies ranging from 90% to 99%, demonstrating the potential of deep learning for fish detection.

2. Challenges in Underwater Fish Detection:

The underwater environment presents numerous challenges for fish detection algorithms. Variable lighting conditions, water turbulence, and occlusion caused by vegetation or other objects hinder accurate fish identification. Researchers have addressed these challenges by employing various strategies. Preprocessing techniques, such as color correction and contrast enhancement, have been used to improve image quality and reduce the impact of lighting variations. Additionally, data augmentation techniques, such as rotation, scaling, and flipping, have been applied to enhance the robustness of the detection models.

3. Integration of Object Detection Algorithms:

To enable precise localization of fish in images and videos, object detection algorithms have been integrated into the fish detection pipelines. These algorithms, such as Faster R-CNN, YOLO (You Only Look Once), and SSD (Single Shot Multibook Detector), have shown promising results in accurately detecting fish and providing bounding box coordinates. By combining object detection with deep learning techniques, researchers have achieved higher accuracy in fish detection tasks, enabling efficient monitoring of fish health.

4. Impact on Aquaculture Productivity:

The development of accurate fish detection algorithms has significant implications for the aquaculture industry. Timely identification of unhealthy fish can help prevent the spread of diseases, reduce mortality rates, and improve overall fish health. Automated fish detection systems can provide real-time monitoring of fish populations, enabling early intervention and appropriate disease management strategies. This not only enhances the productivity of aquaculture operations but also minimizes economic losses associated with disease outbreaks.

5. Balance between Performance and Complexity:

While deep learning-based fish detection algorithms have shown promising results, it is important to strike a balance between performance and complexity. Some state-of-the-art models may require

significant computational resources, making them less feasible for deployment on low-power devices or in resource-constrained environments. Therefore, future research should focus on developing efficient and lightweight algorithms that can achieve high detection accuracies while minimizing computational requirements.

6. Potential for Vision-Based Fish Health Analysis:

The findings of this review highlight the potential of computer vision in advancing fish health analysis. Automated fish detection systems can be integrated with other analysis techniques, such as image classification and disease recognition, to provide a comprehensive assessment of fish health status. This can facilitate early disease diagnosis, treatment optimization, and targeted interventions. Furthermore, the availability of large-scale fish health data, combined with advanced machine learning techniques, opens up avenues for predictive modeling and risk assessment in aquaculture.

7. Future Directions:

Despite the significant progress made in fish detection, several areas warrant further investigation. The development of robust algorithms that can handle challenging underwater conditions, such as poor visibility and occlusion, remains a priority. Additionally, the application of transfer learning, where pre-trained models are fine-tuned on fish detection tasks, can help overcome data scarcity and improve detection performance. Furthermore, the integration of multi-modal data sources, such as underwater acoustics and environmental parameters, can provide a more comprehensive understanding of fish health and behavior.

In conclusion, this review highlights the effectiveness of deep learning techniques, particularly CNNs and object detection algorithms, in fish detection in underwater images and videos. The findings underscore the potential of computer vision in intelligent aquaculture and its impact on fish health analysis. The development of accurate and efficient fish detection algorithms can significantly enhance the productivity of the aquaculture industry, enabling timely

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A Review Paper on Underwater Fish Detection Technology
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Abstract
Aquaculture plays a vital role in the economy, but fish disease poses a significant challenge, leading to productivity and economic losses. Unhealthy fish identification relies on labor-intensive visual inspection, necessitating the development of smart intelligence systems for fish disease detection and monitoring. This review paper focuses on the first step of fish detection in underwater images/videos, which is crucial for automated pipelines in fish health analysis. The complex underwater environment, characterized by variable lighting, water turbulence, and occlusion, makes fish detection challenging. The literature review highlights the effectiveness of deep learning-based techniques, such as convolutional neural networks (CNNs) and object detection algorithms, for accurate fish detection. Several studies have demonstrated high detection accuracies ranging from 90% to 99%. Methodologies including image preprocessing, feature extraction, and data augmentation have been employed to improve detection performance. The review emphasizes the potential of computer vision in intelligent aquaculture and its impact on fish health analysis. The findings provide valuable insights into the current state of fish detection and highlight the need for efficient and time-effective algorithms that strike a balance between performance and complexity. Developing accurate fish detection algorithms can significantly enhance the productivity of the aquaculture industry, facilitating vision-based fish health analysis.
Keywords: aquaculture, fish disease, fish detection, underwater images/videos object detection algorithms, detection accuracies, image preprocessing, feature extraction, data augmentation, computer vision, intelligent aquaculture, fish health analysis.

Introduction
Efficient monitoring and management of fish populations in aquaculture settings are essential for ensuring their well-being and productivity. However, traditional methods of fish surveillance, such as manual inspection and visual observation, are labor-intensive, time-consuming, and prone to human error. In recent years, the emergence of computer vision and deep learning techniques has offered promising avenues for automating fish detection and monitoring processes.
Underwater environments present unique challenges for fish detection due to factors like variable lighting conditions, water turbulence, and occlusion caused by vegetation or other objects. Overcoming these challenges necessitates robust algorithms capable of accurately identifying fish species, detecting unhealthy individuals, and precisely localizing fish in images and videos. Deep learning techniques, particularly convolutional neural networks (CNNs), have demonstrated remarkable effectiveness in image classification tasks and have been successfully applied to fish detection in underwater environments.
This review aims to provide an objective analysis of the current state of the art in deep learning-based fish detection in underwater images and videos. It will examine the effectiveness of various deep learning techniques, explore the integration of object detection algorithms for precise localization, and discuss the implications of these advancements for aquaculture productivity. Additionally, it will identify key challenges and potential future research directions in this field.
The review will commence by discussing the existing literature on deep learning techniques applied to fish detection, highlighting the methodologies and algorithms employed. It will present a synthesis of reported

accuracies and performance metrics achieved by different models, emphasizing the strengths and limitations of each approach. Subsequently, the challenges specific to underwater fish detection and the strategies employed to mitigate them, including preprocessing techniques and data augmentation, will be explored.

The integration of object detection algorithms into fish detection pipelines will be examined, focusing on popular algorithms such as Faster R-CNN, YOLO, and SSD. The review will investigate how these algorithms enhance the accuracy and efficiency of fish detection by providing precise bounding box coordinates. Furthermore, it will discuss the implications of these advancements for aquaculture productivity, including early disease detection, reduced mortality rates, and improved fish health management.

While deep learning techniques have shown significant promise in fish detection, it is crucial to strike a balance between performance and complexity. The review will analyze the computational requirements of state-of-the-art models and discuss the feasibility of deploying them in resource-constrained environments. Moreover, it will explore the potential for vision-based fish health analysis by integrating fish detection with other analysis techniques, such as disease recognition and image classification.

Lastly, the review will identify future research directions and opportunities in this field. It will highlight the need for robust algorithms capable of handling challenging underwater conditions, the potential for transfer learning to overcome data scarcity, and the integration of multi-modal data sources for a comprehensive understanding of fish health and behavior.

By offering an objective analysis of deep learning-based fish detection in underwater environments, this review aims to contribute to the advancement of intelligent aquaculture practices and facilitate the development of efficient and accurate fish monitoring systems. The findings of this review will have implications for the aquaculture industry, improving fish health management, reducing economic losses, and promoting sustainable fish production.

The Problem Statement

Aquaculture is important to the economy of our country in this blue era. One of the major problems that affects aquaculture farms of all sizes, from small-scale businesses to enormous corporations, is fish sickness. Industry specialists can spot ill fish by looking for abnormal behavior, which adds to the workload. As a result, the aquaculture industry needs a smart intelligence system to prevent the development of fish disease and promote fish wellbeing. In order to monitor fish health, intelligent systems need to automatically and accurately identify fish in underwater photos and videos. In order to diagnose fish diseases automatically, the initial step (fish detection) must maintain a better trade-off between performance and time complexity, which is the subject of this research. Due to the complex and dynamic underwater environment with varying lighting conditions, water turbulence, and occlusion from other objects, the recognition of fish from underwater photographs is quite difficult. As the first step in vision-based fish health analysis, developing an efficient fish detection algorithm can have a substantial impact on the productivity of the aquaculture business.

Literature Review

A paper by Yang et al. (2021) provides a comprehensive review of the use of computer vision in intelligent aquaculture, with a focus on fish detection and behavior analysis. The review covers various computer vision techniques, such as deep learning, convolutional neural networks, and object detection algorithms, and their performance parameters, including accuracy, precision, and recall. The study highlights that deep learning-based techniques have shown superior performance in fish detection and behavior analysis, with accuracy ranging from 90% to 99%. The paper also discusses the methodologies used in the studies reviewed, such as image pre-processing, feature extraction, and data augmentation. Overall, the review provides valuable insights into the current state of computer vision in intelligent aquaculture and its potential for future developments. [1]

Jalal et al. (2020) proposed a deep learning-based approach for fish detection and species classification in underwater environments. The study used convolutional neural networks (CNNs) and long short-term memory networks (LSTMs) to incorporate temporal information and achieved an accuracy of 94.4% for fish detection and 89.2% for species classification. The paper also discusses the methodology used for data acquisition, annotation, and preprocessing, including data augmentation and normalization. Overall, the study highlights the potential of using deep learning and temporal information for accurate fish detection and species classification in underwater environments. [2]

Cui et al. (2020) proposed a deep learning-based approach for fish detection. The study used a convolutional neural network (CNN) architecture called Faster R-CNN and achieved an accuracy of 99.4% for fish detection. The paper also discusses the methodology used for data collection, pre-processing, and augmentation. The study demonstrates the effectiveness of using deep learning and Faster R-CNN for accurate fish detection in underwater environments. [3]

Salman et al. (2020) proposed a deep neural network-based approach for automatic fish detection in underwater videos. The study used a hybrid motion learning system that combines two deep neural networks, one for motion detection and the other for fish detection and achieved an accuracy of 94.9% for fish detection. The paper also discusses the methodology used for data acquisition, pre-processing, and augmentation. The study demonstrates the effectiveness of using a hybrid motion learning system for accurate fish detection in underwater videos. [4]

Linfeng et al. 2020, This paper presents a method called GLHDF to enhance the quality of real-world and low-light underwater images. GLHDF involves four stages, namely, Pixel intensity center regionalization, Global Equalization of Histogram, Local Equalization of Histogram, and Dual-image multi-scale fusion. The method aims to remove noise, correct color, improve contrast, and enhance the overall image quality of underwater images. The first step involves using a multi-scale Gaussian filter to smooth the image, followed by a global equalization of histogram strategy to correct color in the second step. The third step uses a dual-interval histogram based on the average of peak and mean values to improve the contrast of the color-corrected image. Finally, the enhanced image is obtained using a dual-image multi-scale fusion strategy to integrate the color-corrected and contrast-enhanced images. The method enhances images with good visibility, natural color, high contrast, and sharp texture, and outperforms other state-of-the-art techniques in both qualitative and quantitative evaluations. The proposed method also performs well on low-light, natural, foggy, sandy, and underwater images captured by different specialized cameras. However, GLHDF has limitations, such as the inability to achieve consistent background color for underwater images captured by different cameras, potential computational complexity due to the selection of an average threshold, and the lack of studying underwater images taken at different levels of turbidity. [5]

Salman et al. (2019) proposed a real-time fish detection approach using probabilistic background modeling. The study achieved an accuracy of 95.2% for fish detection in complex backgrounds. The paper also discusses the methodology used for data acquisition, preprocessing, and feature extraction. The study highlights the effectiveness of using probabilistic background modeling for real-time fish detection in complex underwater environments. [6]

Nan, Haiyong, and Bing 2017, The study proposes an image restoration method for enhancing the contrast and correcting color distortion of underwater images. The proposed algorithm uses the maximum map of the red channel to derive the depth map and estimate the overall background light. The transmission map is estimated separately for R, G, and B colors using the simplified light propagation model. The proposed method is tested on natural underwater scenes and calibration board images, and it performs well in terms of contrast enhancement and color correction. However, the method's assumption that the red channel light attenuates fastest may not adapt to certain special conditions, such as a diver wearing a black diving suit, leading to distorted processing results. Nonetheless, the proposed method can work well for most instances in the colorful underwater world. [7]

Boudhane and Nsiri (2016) proposed an underwater image processing method for fish localization and detection in a submarine environment. The paper discusses the methodology of using a combination of image processing techniques such as image enhancement, segmentation, and feature extraction. The study achieved an accuracy of 93% for fish detection using a Support Vector Machine (SVM) classifier. The study highlights the effectiveness of combining different image processing techniques for accurate fish detection in an underwater environment. [8]

Li et al. (2016) proposed a fish detection and recognition system using a Convolutional Neural Network (CNN) with objectness learning to improve speed and accuracy. The study shared CNNs with objectness learning between different species, achieving a detection accuracy of 97.7% and a recognition accuracy of 93.3%. The proposed system significantly reduced the computational cost and achieved real-time fish detection and recognition in an underwater environment. [9]

Wageeh et al presented a fish detection and tracking system for aquaculture using YOLOv3 object detection and Euclidean distance tracking algorithms. The proposed method achieves an accuracy of 93.5% and a mean average precision (mAP) of 84.8% in fish detection. The system also provides real-time tracking and monitoring of fish in aquaculture farms. The methodology involves pre-processing of video frames, object detection, and tracking using Euclidean distance, and final post-processing to generate the output video. [10]

Han et al proposed a deep Convolutional Neural Network (CNN) method for underwater image processing and object detection. The proposed approach is evaluated on two underwater image datasets and achieves an accuracy of 93.33% and 90.50%, respectively. The methodology involves preprocessing of the images, followed by the use of a deep CNN to classify and detect the objects in the images. The study demonstrates the effectiveness of the proposed method in underwater object detection. [11]

Li et al. proposed a method for enhancing underwater images by using dehazing and color correction techniques. The proposed approach consists of transmission map estimation, color correction, and image fusion. The results demonstrated the effectiveness of the proposed method compared to state-of-the-art approaches. [12]

Pei and Chen proposed a revised underwater image formation model for enhancing the quality of underwater images. The model includes the effects of light attenuation, scattering, and water surface reflection. The proposed method outperformed existing methods in terms of objective evaluation metrics and visual quality. [13]

Kewei et al. proposed a new approach for fish detection and counting in real breeding farms by combining YOLOv3 with MobileNetv1. Existing fish counting methods are manual, time-consuming, and error-prone. RGB imaging is a preferred solution due to its ease of operation, lightweight system, and no harm to fish. Lidar and sonar-based techniques have high accuracy but are bulky and expensive. The feature maps of MobileNet are optimized based on their receptive fields to improve fish detection. The optimized feature map selection based on receptive field analysis and the use of a smaller dataset for pre-training the

backbone network results in high accuracy fish detection. A dataset of fish images from breeding farms is used to evaluate the proposed method, which achieves high accuracy. Additionally, a smaller dataset of 16 fish species is used for backbone network pretraining instead of ImageNet, which further improves detection. The proposed method can be used for multiple classes of fish detection and determining fish length and weight. Future work involves implementing the algorithm online and expanding its applicability. [14]

Wang et al. conducted an experimental-based review of various image enhancement and restoration techniques for underwater imaging. They analyzed and compared the performance of different methods based on various evaluation criteria. The review provides a comprehensive overview of the existing methods and their effectiveness. [15]

Zhu et al. proposed a convolutional neural network (CNN)-based approach for enhancing underwater images by performing color balance and dehazing. The proposed method used a fusion strategy to combine the output of the color balance and dehazing modules. The results showed significant improvements in image quality compared to state-of-the-art methods. [16]

Boudhane etal. 2016, In this paper, the authors present a novel method for fish localization and detection in underwater images based on a Poisson-Gauss theory. Object detection is an important process in computer vision, especially in marine environments where cameras are widely used due to the limitations of human access. The proposed approach includes denoising and image restoration, region splitting using mean shift algorithm, and statistical estimation for object combination and detection. The proposed approach outperforms existing state-of-the-art methods under various underwater conditions. As underwater visibility is limited, image processing and computer vision algorithms have become increasingly important for monitoring and tracking marine environments. The proposed method can be adapted to different noise models, making it versatile and practical for various underwater applications. The approach can be used without prior knowledge of the environment and does not require user interaction. In conclusion, the proposed approach has the potential to be applied in various applications such as marine conservation, fisheries management, and underwater exploration. The proposed method has potential applications in underwater fish detection and other computer vision tasks.[17]

Li et al.2016, this paper presents an approach for Automatic object detection and recognition is in great demand for underwater imagery analysis and marine environment surveillance due to the increasing volume of underwater visual data. The paper presents an approach for accelerating underwater object detection and recognition using a region proposal network based on Faster R-CNN. The proposed system achieved a real-time frame rate of 9.8 ftps and 15.1% higher Mean Average Precision (mAP) than the Deformable Parts Model (DPM) baseline on a fish dataset with 12 classes. The use of region proposal networks generated high-quality proposals, improving segmentation performance and fish detection precision. Sharing convolutional features reduces the cost of proposal generation in the fish detection and recognition process. However, video analysis presents a more pressing problem for deep-sea observation systems, which requires further research. The proposed system demonstrates the potential of convolutional networks in underwater image processing.[18]

Wageeh et al. 2020, this paper proposed method aims to address the challenges of manually monitoring fish farms, which is time-consuming and costly. This paper presents a method for improving fish detection and tracking in fish farms by combining an image enhancement algorithm based on retinex with an object detection algorithm. The object detection algorithm used in this study is YOLO. The experiment setup involved a temporary fish tank and a web camera. A dataset of 2000 images was created for the YOLO model to detect fish. Two experiments were conducted. the experiment setup and dataset used for two experiments were presented. The fish tank used for testing was built in a controlled environment, and a web camera was placed above it to capture videos and images. A dataset of 2000 images of golden fish was collected for YOLO model detection. The first experiment aimed to enhance unclear water images and determine the best camera location for accurate detection. The results showed that there was no significant change in underwater image detection before and after enhancement, and the camera was settled above the pond. The enhanced images improved detection accuracy, confirming the usefulness of the enhancement algorithm. Overall, the experiment setup and dataset were effective in testing and validating the algorithm's performance in fish detection. two methods for drawing fish trajectories and tracking their movements were compared. The first method combined YOLO and optical flow, while the second method utilized a trajectories extraction method. The trajectories extraction method was found to be more accurate than the optical flow method, producing clearer trajectory lines with fewer scattered and wrongly drawn lines. The results showed that the enhanced images had better accuracy in detecting fish. The trajectory extraction method was found to be better than the optical flow method in accurately tracking fish movements. This method can improve fish farm management and reduce costs. Clustering could be used in the future to detect and cluster different fish behaviors. Overall, this method has the potential to improve fish farming efficiency and reduce costs associated with manual monitoring.[19]

W. Zhang et al. 2021, This paper proposes a new algorithm for enhancing underwater images. The algorithm compensates for lower color channels, applies an adaptive contrast enhancement algorithm, and a sharpening technique to produce background-stretched and foreground-stretched images. The proposed algorithm outperforms existing algorithms by at least 5% in all metric scores. The paper also discusses the limitations of existing underwater image enhancement techniques, which can be categorized into image restoration and image enhancement algorithms. Enhancement algorithms have

shown to be simple and effective in improving visibility without considering the underwater optical imaging model. [20]

Han et al. 2020, this paper proposes a method for enhancing underwater vision and detecting marine organisms using a deep CNN. This paper proposes a combination of max-RGB and shades of gray methods for enhancing underwater vision, followed by a CNN method to solve weakly illuminated problems and perform detection and classification of marine organisms. Two improved schemes were proposed to modify the deep CNN structure and scheme 2 was found to be better in detecting underwater objects with a detection speed of about 50 FPS and mAP of about 90%. The proposed method was tested on an underwater robot and was found to be accurate and fast enough to assist with underwater working operations. The effectiveness and capability of the proposed method were verified by qualitative and quantitative evaluations, although some objects were missed. Further improvements could be made by using a more complicated algorithm to reconstruct the network. Overall, this method is suitable for detecting objects in underwater environments and outperforms typical methods for this dataset.[21]

Wang et al. 2017, this paper proposes an end-to-end CNN-based framework called UIE-Net for underwater image enhancement. which includes two subnetworks: CC-Net and HR-Net. CC-Net is used to correct color distortion and HR-Net enhances the contrast of underwater images. The framework is trained with two tasks, color correction and haze removal, and utilizes a pixel disrupting strategy to improve convergent speed and accuracy. The UIE-Net is evaluated on benchmark underwater images for cross-scenes and achieves superior performance over existing methods in terms of entropy and PCQI. The proposed method is robust and effective in enhancing contrast and preserving details. The adaptability of the UIE-Net on cross-scenes is demonstrated through its application on underwater video frames. The framework contains two subnetworks, CC-Net and HR-Net, which output color absorption coefficients and transmission maps for enhancing underwater images. The paper proposes future work to improve the efficiency of the approach by using a fully-CNN implementation. [22]

Han et al. 2020, this research proposes a deep convolutional neural network for detecting and classifying marine organisms in underwater environments. The development of underwater robots for collecting marine products has become a feasible solution to the dangers faced by humans in seabed fishing. One key technique is the detection and location of the main target from underwater vision. This paper proposes a deep convolutional neural network (CNN) based on faster RCNN and the modified method of hyper net for target recognition in underwater vision. The dataset was prepared using an underwater video obtained from a sea cucumber fishing ROV. The dataset used for training and testing is obtained from ROVs and the Underwater Robot Picking Contest. The method proposed in this paper shows good performance of recall and object detection accuracy, with a mean average precision (mAP) of over 90% when the IoU is set to 0.7. The detection runs at a speed of 17 fps on a GPU, which is suitable for real-time processing. The detection time is 58 ms on a GTX 1080ti GPU, which is suitable for real-time processing. This approach has the potential to reduce the dangers associated with seabed fishing by replacing human divers with underwater robots for marine product collection. The modified framework is also applicable in the Underwater Robot Picking Contest. The proposed method is feasible to be applied in underwater vision detection and can be used in real-time for marine organism detection. Further development and testing could lead to a safer and more efficient fishing industry. [23]

Liu et al. 2020, Underwater images often suffer from low visibility and color casts due to light scattering and attenuation, making them unsuitable for computer vision systems. This paper presents a large-scale real-world benchmark, the Real-world Underwater Image Enhancement (RUIE) data set, consisting of three subsets that target image visibility quality, color casts, and higher-level detection/classification. The study evaluates the effectiveness and limitations of various algorithms to enhance visibility and correct color casts on images with hierarchical categories of degradation. The object detection performance on enhanced images is also used as a task-specific evaluation criterion. The findings suggest new directions for visibility enhancement, color correction, and object detection on real-world underwater images. [24]

Results and Discussion:

1. Effectiveness of Deep Learning Techniques:

The review of literature reveals that deep learning techniques, particularly convolutional neural networks (CNNs), have shown remarkable effectiveness in fish detection in underwater images and videos. CNNs have the ability to learn and extract complex features from images, enabling accurate identification of fish species and detection of unhealthy individuals. Several studies have reported high detection accuracies ranging from 90% to 99%, demonstrating the potential of deep learning for fish detection.

2. Challenges in Underwater Fish Detection:

The underwater environment presents numerous challenges for fish detection algorithms. Variable lighting conditions, water turbulence, and occlusion caused by vegetation or other objects hinder accurate fish identification. Researchers have addressed these challenges by employing various strategies. Preprocessing techniques, such as color correction and contrast enhancement, have been used to improve image quality and reduce the impact of lighting variations. Additionally, data augmentation techniques, such as rotation, scaling, and flipping, have been applied to enhance the robustness of the detection models.

3. Integration of Object Detection Algorithms:

To enable precise localization of fish in images and videos, object detection algorithms have been

integrated into the fish detection pipelines. These algorithms, such as Faster R-CNN, YOLO (You Only Look Once), and SSD (Single Shot Multibook Detector), have shown promising results in accurately detecting fish and providing bounding box coordinates. By combining object detection with deep learning techniques, researchers have achieved higher accuracy in fish detection tasks, enabling efficient monitoring of fish health.

4. Impact on Aquaculture Productivity:

The development of accurate fish detection algorithms has significant implications for the aquaculture industry. Timely identification of unhealthy fish can help prevent the spread of diseases, reduce mortality rates, and improve overall fish health. Automated fish detection systems can provide real-time monitoring of fish populations, enabling early intervention and appropriate disease management strategies. This not only enhances the productivity of aquaculture operations but also minimizes economic losses associated with disease outbreaks.

5. Balance between Performance and Complexity:

While deep learning-based fish detection algorithms have shown promising results, it is important to strike a balance between performance and complexity. Some state-of-the-art models may require significant computational resources, making them less feasible for deployment on low-power devices or in resource-constrained environments. Therefore, future research should focus on developing efficient and lightweight algorithms that can achieve high detection accuracies while minimizing computational requirements.

6. Potential for Vision-Based Fish Health Analysis:

The findings of this review highlight the potential of computer vision in advancing fish health analysis. Automated fish detection systems can be integrated with other analysis techniques, such as image classification and disease recognition, to provide a comprehensive assessment of fish health status. This can facilitate early disease diagnosis, treatment optimization, and targeted interventions. Furthermore, the availability of large-scale fish health data, combined with advanced machine learning techniques, opens up avenues for predictive modeling and risk assessment in aquaculture.

7. Future Directions:

Despite the significant progress made in fish detection, several areas warrant further investigation. The development of robust algorithms that can handle challenging underwater conditions, such as poor visibility and occlusion, remains a priority. Additionally, the application of transfer learning, where pre-trained models are fine-tuned on fish detection tasks, can help overcome data scarcity and improve detection performance. Furthermore, the integration of multi-modal data sources, such as underwater acoustics and environmental parameters, can provide a more comprehensive understanding of fish health and behavior.

In conclusion, this review highlights the effectiveness of deep learning techniques, particularly CNNs and object detection algorithms, in fish detection in underwater images and videos. The findings underscore the potential of computer vision in intelligent aquaculture and its impact on fish health analysis. The development of accurate and efficient fish detection algorithms can significantly enhance the productivity of the aquaculture industry, enabling timely