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Internet of Things-Based Smart Fish Farming: Application of Smart Sensors and Computer Vision to Provide Real-Time Monitoring and Diagnosis in Aquaculture

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ABSTRACT
The frequent occurrence of disease outbreaks in fish farming presents a significant challenge, leading to substantial economic losses and threatening food security, thus hindering the progress toward sustainable development goals (SDGs). In aquaculture, disease prevention relies on early detection of changes in water quality, abnormal fish behavior, and physical deformities, tasks typically handled by skilled fisheries experts, who are in short supply in Nigeria. Traditional manual disease detection methods are often costly and unreliable. This study proposes a computer vision-based solution utilizing Faster Region-based Convolutional Neural Network (FasterR-CNN) with Detectron2 for improved disease detection in fish farming. A dataset of 500 images was collected, pre-processed, and divided into training (70%), validation (15%), and testing (15%) sets. Three Faster R-CNN models (X101, R100, and R50) were trained and evaluated, with the X101 model achieving the highest accuracy of 98%. The results underscore the potential of deep learning techniques for accurate and efficient disease detection, offering a scalable solution to enhance fish health management. This approach provides a reliable and cost-effective alternative to traditional methods, contributing to the sustainability and growth of the aquaculture industry while addressing the need for timely interventions in fish disease control.

Keywords:
Aquaculture,
Fish Farming,
Computer Vision,
Faster RCNN,
Injury Detection

INTRODUCTION

Aquaculture is recognized as the fastest-growing food-producing sector globally. In Nigeria, aquaculture production has experienced significant growth, increasing from less than 50,000 tonnes in the 1990s to over 300,000 tonnes in 2016 (Dauda et al., 2018). However, in recent years, a decline in production has been observed, with the exception of 2021, where output reached 275.6 thousand tonnes, slightly higher than the 261.7 thousand tonnes recorded in 2020, the lowest production level in the past decade (FAO, 2023). Several factors have contributed to this decline, including the rising cost of fish feed, climate change-induced variations in water quality, and an increase in disease outbreaks (Subasinghe et al., 2021).

Nigeria possesses vast potential for aquaculture development due to its abundant inland and coastal water resources, as well as a large population that could be actively engaged in fish farming. Despite these advantages, the country remains a net importer of fish and fish products (Dauda et al., 2018). The aquaculture industry faces numerous challenges that hinder small- and medium-scale fish farmers from competing effectively in the global market, thereby limiting the sector's overall growth. These challenges include disease outbreaks (Ogunsanwo et al., 2020), the high cost of fish feed, inadequate water quality management, and a lack of expertise in fish health management among farm owners and managers (Dauda et al., 2015).

Among these challenges, disease outbreaks remain one of the most significant factors contributing to economic losses in the aquaculture sector. These outbreaks not only impact fish production but also threaten food security and hinder progress toward Nigeria's sustainable development goals (SDGs) (Mukaila et al., 2023). The prevention of disease outbreaks in fish farming relies on the early detection of abnormal fish behavior and physical deformities. However, this process requires experienced farm managers or fisheries scientists, who are in limited supply in Nigeria, as most fish farms are managed by individuals with little or no formal training in fisheries and related fields (Dauda et al., 2017).

Currently, fish health management is predominantly conducted through visual observation, which is often unreliable and fails to provide timely or accurate detection of abnormalities. Many farm owners only take corrective measures after a disease outbreak has already occurred, leading to substantial economic losses due to increased production costs and stunted fish growth, even after successful treatment (Dauda, 2020; Abdelrahman et al., 2023). Therefore, ensuring sustainable aquaculture production requires proactive monitoring mechanisms and early warning systems to detect abnormalities within fish culture systems before widespread disease outbreaks occur.

This study aims to develop a computer vision-based model using Faster R-CNN for real-time fish health monitoring and disease detection. The implementation of this model provides a much-needed local solution for improving aquaculture management practices. A diverse dataset of fish images was collected and preprocessed using advanced image processing techniques, including image inpainting for data cleaning, pixelation for resizing, and image augmentation to enhance model robustness and generalization. By leveraging deep learning techniques, this research seeks to enhance early disease detection, minimize economic losses, and promote sustainable aquaculture development in Nigeria.

Aquaculture plays a crucial role in ensuring food security, creating employment opportunities, and driving economic growth, particularly in developing nations (FAO, 2021; Yakubu *et al.* 2024). As global demand for fish continues to rise, aquaculture is becoming an increasingly significant component of the world's food production system. According to the Food and Agriculture Organization (FAO, 2023), global aquaculture production reached an all-time high of 126 million tonnes in 2021, accounting for 49.9% of total fish production. While this global trend indicates continuous growth, the situation in Nigeria is paradoxically different.

Nigeria is one of Africa's largest fish producers and has a rapidly expanding aquaculture sector, which holds immense potential for economic development and food security (Afolabi et al. (2020). Despite this, the country has been experiencing a decline in aquaculture production in recent years. Nigeria ranks second in aquaculture production in Africa, behind Egypt, which contributes 67.9% of the region's total aquaculture output, with Nigeria accounting for 11.9% as of 2021 (FAO, 2023). The decline in production can be attributed to a variety of challenges, including the high cost of fish feed, frequent disease outbreaks, environmental pollution, inadequate water quality management, and limited access to technical expertise (Dauda et al., 2018; Dauda, 2020).Among these challenges, disease outbreaks represent one of the most significant threats to Nigeria's aquaculture industry, often leading to substantial economic losses and jeopardizing the livelihoods of many fish farmers (Abdelrahman et al., 2023; Mukaila et al., 2023). Managing and preventing these outbreaks remains a critical issue that requires urgent and innovative solutions.

Disease outbreaks are among the leading causes of fish mortality in aquaculture. In Nigeria, infectious diseases are particularly prevalent and costly, affecting both small- and large-scale fish farms (Mukaila et al., 2023). The spread of diseases in fish farming systems can be attributed to multiple factors, including poor water quality, high stocking densities, inadequate nutrition, and climate-induced stress (Dauda et al., 2015; Adewolu, 2021). Diseases in aquaculture often result in high mortality rates, reduced fish growth, and economic losses. Infected fish may exhibit symptoms such as skin lesions, abnormal swimming patterns, decreased appetite, and changes in body coloration. In some cases, diseases can spread rapidly, wiping out entire fish stocks within a short period. Given the increasing frequency of disease outbreaks, there is an urgent need for effective early detection and monitoring strategies to mitigate losses and improve overall fish health (Afolabi et al. (2020).

Historically, disease detection in aquaculture has relied on manual inspection methods. Farmers and aquaculture specialists visually assess fish for signs of illness, such as external lesions, erratic swimming behavior, and changes in color (FAO, 2021). While these methods have been widely used, they are often time-consuming, labor-intensive, and prone to human error (Oca et al., 2020). The accuracy of manual disease detection largely depends on the expertise of the observer, and in many cases, symptoms may not be easily noticeable until the disease has progressed significantly (Ji et al, (2021). Additionally, small-scale fish farmers, who make up the majority of Nigeria's aquaculture sector, often lack the technical expertise required to accurately diagnose and manage fish diseases (Dauda et al., 2017). This knowledge gap, combined with limited access to veterinary services and diagnostic laboratories, makes disease management a daunting task for many fish farmers.

To address these limitations, researchers and aquaculture experts are turning to advanced technological solutions, particularly computer vision and artificial intelligence-driven approaches, to enhance disease detection and monitoring in fish farms. Computer vision is an AI-powered technology that enables machines to interpret and analyze visual data (Chen et al., 2020). In the field of aquaculture, computer vision systems can be used to process images of fish and identify patterns or abnormalities that may indicate disease (Oca et al., 2020). These systems leverage deep learning algorithms to detect subtle changes in fish behavior, color, and morphology, enabling early diagnosis of potential health issues.

One of the primary advantages of computer vision systems is their ability to provide real-time, automated monitoring of fish health. Unlike manual inspections, which require human intervention, computer vision systems can continuously analyze video feeds or images captured by underwater cameras and smart sensors (Chen et al., 2020). This allows for rapid and accurate disease detection, minimizing response times and preventing disease outbreaks before they escalate. Deep learning models, such as Convolutional Neural Networks and Faster R-CNN, have demonstrated impressive accuracy in classifying fish diseases based on image datasets (Oca et al., 2020). These models can be trained on large datasets containing images of healthy and diseased fish, enabling them to recognize visual markers of infection with high precision.

In addition to computer vision, smart sensor technology plays a crucial role in fish health monitoring. Sensors embedded in aquaculture systems can collect real-time data on key environmental parameters such as water temperature, pH levels, dissolved oxygen concentration, and ammonia levels (Liu et al., 2021). For example, color sensors can detect changes in fish pigmentation, which may indicate stress or illness. Similarly, water quality sensors help identify unfavorable conditions that could contribute to disease outbreaks (Liu et al., 2021). By integrating sensor data with AI-powered analytics, fish farmers can gain actionable insights into their aquaculture systems, allowing for timely interventions and improved disease prevention strategies.

Despite the promising potential of computer vision and AI-driven disease detection, several challenges must be addressed before these technologies can be widely adopted in Nigeria’s aquaculture industry. AI-based disease detection models require extensive training on large datasets to achieve high accuracy. However, most existing datasets used for fish disease classification are derived from foreign aquaculture environments (Chen et al., 2020). To deploy these models effectively in Nigeria, there is a need to develop locally trained datasets that reflect the country’s unique fish species, environmental conditions, and disease patterns.

The cost of implementing AI-driven systems and smart sensors remains a significant barrier, particularly for small-scale fish farmers (Oca et al., 2020). Many fish farmers operate on tight budgets and may not have the financial resources to invest in sophisticated monitoring technologies. However, recent advancements in microcontroller technology and edge computing have made it possible to develop cost-effective solutions that can be deployed in resource-limited settings (Chen et al., 2020).The successful implementation of computer vision and AI in aquaculture requires a workforce with technical expertise in machine learning, image processing, and sensor integration. Training programs and capacity-building initiatives will be essential to equip fish farmers and aquaculture professionals with the necessary skills to utilize these technologies effectively.

This research focuses on developing a computer vision model utilizing Faster R-CNN to enable real-time monitoring of fish health and early disease detection. The proposed model offers a locally adapted solution to enhance aquaculture management practices. To achieve this, a diverse collection of fish images was gathered and processed using advanced image processing methods, such as image inpainting for noise reduction, pixelation for resizing, and image augmentation to improve the model’s accuracy and adaptability. By applying deep learning techniques, this study aims to facilitate early diagnosis of fish diseases, reduce economic losses, and support the sustainable growth of aquaculture in Nigeria.

Research Gap

Current research on AI-based disease detection in aquaculture lacks locally trained datasets tailored to Nigeria's unique fish species and environmental conditions, limiting model effectiveness. High implementation costs and the need for technical expertise further hinder adoption among small-scale fish farmers, who still rely on manual, error-prone disease detection methods. Additionally, there is limited research on integrating deep learning models with real-time monitoring systems suited for local farming conditions. This study aims to bridge these gaps by developing a cost-effective Faster R-CNN computer vision model trained on Nigerian aquaculture data to enhance real-time fish health monitoring and early disease detection.

MATERIALS AND METHODS

This section outlines the approach taken to develop the fish injury detection system. The methodology encompasses dataset preparation, model selection, training, and evaluation to ensure accurate and efficient detection of fish injuries. The Faster R-CNN model was implemented using Detectron2, leveraging pre-trained weights for transfer learning to improve detection accuracy and reduce training time.

A diverse dataset of fish images (see figure 1) was collected from multiple sources, including aquaculture farms and online repositories. Various preprocessing techniques were applied to enhance image quality and optimize the dataset for model training. These techniques included image inpainting for restoring or reconstructing missing or damaged parts of an image, pixelation for resizing, contrast adjustment to improve visibility, and data augmentation methods such as flipping, rotation, and scaling to increase model robustness.

The dataset was then split into training, validation, and testing sets in a 70:15:15 ratio to ensure an unbiased evaluation of the model’s performance, this process is shown in Figure 2. The Faster R-CNN architecture was fine-tuned by adjusting hyperparameters such as learning rate, batch size, and number of iterations to optimize detection accuracy. The model underwent multiple training cycles, where performance metrics, including mean Average Precision (mAP), precision, recall, and F1-score, were monitored to assess its effectiveness.

After training, the model was tested on unseen images to evaluate its real-world applicability. Comparative analysis with other object detection models was also conducted to validate its efficiency. The final model was integrated into a prototype system for real-time fish health monitoring, providing a practical solution for early injury detection and improved aquaculture management.

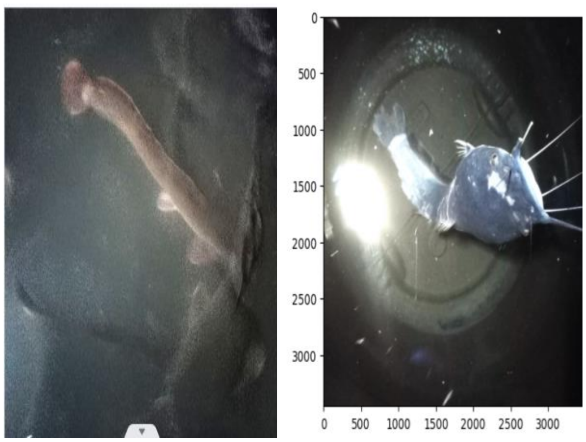

Figure 1: Sample of dataset

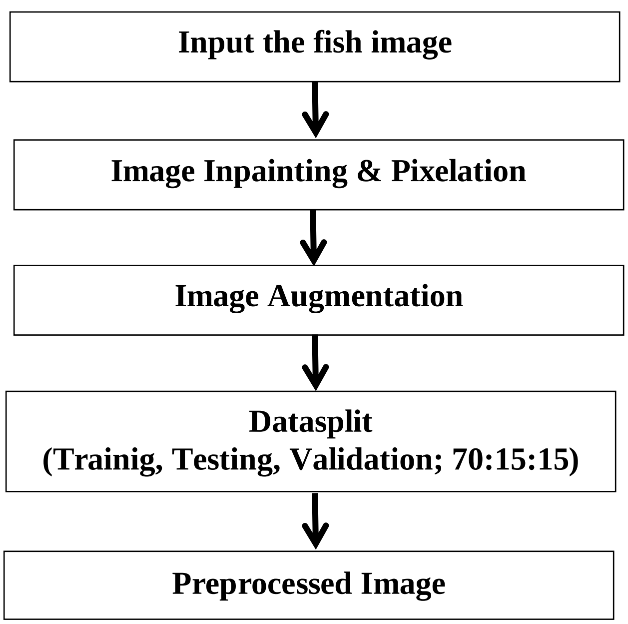

Figure 2: Data preprocessing workflow

Model Architecture

Faster R-CNN, incorporating ResNet-based backbones such as X101, R100, and R50, has emerged as one of the most widely adopted deep learning models for object detection due to its capability to efficiently generate region proposals while maintaining high classification accuracy (Sani et al., 2024). These models were selected for the study based on their demonstrated effectiveness in detecting small objects with high precision, making it well-suited for fish injury detection in aquaculture settings.

The models training was conducted using the Detectron2 framework, utilizing pre-trained COCO weights for transfer learning to enhance detection performance. To ensure an optimal balance between computational efficiency and detection accuracy, hyperparameters such as learning rate, batch size, and number of iterations were systematically fine-tuned. This optimization process aimed to improve model convergence and enhance its robustness in detecting fish injuries across diverse image conditions.

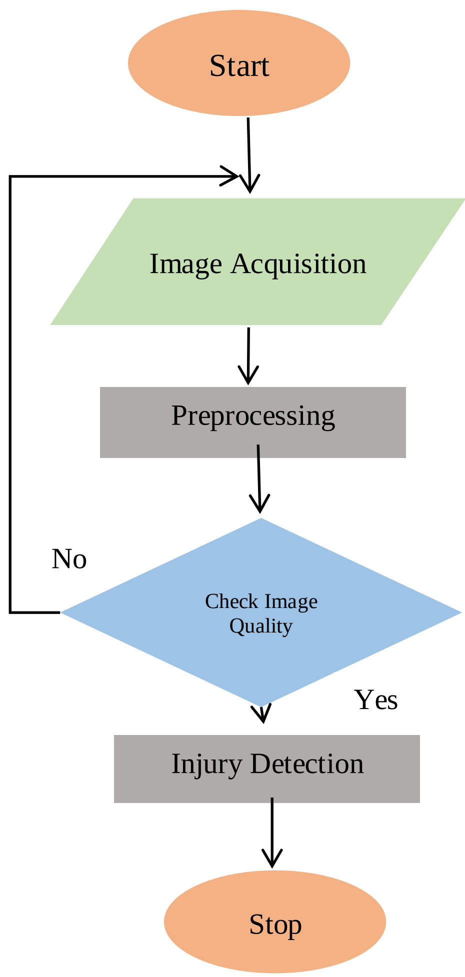

Figure 3: Faster R-CNN Model Architecture

The flowchart in Figure 3 represents an **injury detection process** based on image processing. The process begins with **Image Acquisition**, where an image is captured using a smart phoe camera. The acquired image then undergoes **Preprocessing**, which involve noise reduction, contrast enhancement, grayscale conversion, resizing, and data augmentation to improve image quality. Next, the system performs a **Check Image Quality** assessment. If the image quality is poor (**No**), the process loops back to **Image Acquisition** for a better image. If the quality is sufficient (**Yes**), the system proceeds to **Injury Detection**, where the three selected computer vision models analyze the image for injuries. Finally, the process reaches the **Stop** stage, marking the end of the workflow. This structured approach ensures accuracy by iterating until a high-quality image is available, making it efficient for **automated injury detection** in medical or surveillance applications.

Theoretical Description of Faster R-CNN (X101, R100, and R50)

Faster R-CNN is a two-stage object detection framework that integrates a Region Proposal Network (RPN) with a deep convolutional neural network (CNN) backbone for feature extraction and classification. The architecture variations of X101, R100, and R50refer to different ResNet-based backbones used for feature extraction.

ResNet-50 (R50) is a widely used backbone with 50 layers, providing a balance between computational efficiency and accuracy. It utilizes residual connections to mitigate the vanishing gradient problem, making it effective for deep learning tasks while maintaining a relatively lower computational cost (Cohen & Willing, 2016).

ResNet-100 (R100) extends this architecture to 100 layers, allowing for deeper feature extraction and improved representation of complex patterns. This added depth enhances the model's performance, particularly in scenarios requiring detailed object detection, though it comes with increased computational demands.

ResNeXt-101 (X101) is an extension of ResNet-101 that incorporates grouped convolutions, improving feature representation while maintaining computational efficiency. By using cardinality (grouped convolutions), X101 enhances the learning capacity of the network without significantly increasing the number of parameters. This architecture is particularly well-suited for detecting small and intricate objects, making it the most robust among the three models for high-precision image analysis.

Detectron2

Facebook AI Research (FAIR) developed Detectron2, a cutting-edge open-source platform designed for object detection. The latest version, Detectron2, offers a flexible framework powered by Torch, enabling researchers to implement advanced computer vision methodologies in accordance with standardized protocols (Sani, et al., 2023; Sani, et al., 2024). This system incorporates the Faster R-CNN object detector, recognized for its high precision in identifying objects across various sizes, making it a robust tool for diverse computer vision applications.

Training and Evaluation

In this study, we employed CUDA version 11.3 and Torch version 1.10 for model training. The training process was conducted on a high-performance workstation configured with an NVIDIA T550 graphics card featuring 4GB of DDR6 memory. The system also included 16GB of RAM and a 512GB SSD for efficient storage and processing. Additionally, it was powered by an Intel Core 12th Generation i7 processor and operated on the Windows 11 Pro 64-bit platform, ensuring a stable and optimized environment for deep learning tasks.

RESULTS AND DISCUSSION

The performance of the three Faster R-CNN models was analyzed, with Faster R-CNN X101 achieving the highest accuracy. Results are presented in Table 1.

Table 1: Models Performance Analysis

Models	Accuracy	Precision	Recall	F1-score	No: of trainable parameter
Faster_rcnn_X101	98%	86%	96%	92%	120,500
Faster_rcnn_R100	96%	88%	95%	89%	121,800
Faster_rcnn_R50	94%	84%	89%	87%	124,700

The Faster R-CNN X101 model demonstrated superior performance compared to the other models, primarily due to its deeper architecture and advanced feature extraction capabilities. However, this improved accuracy came at the cost of higher computational demands. On the other hand, the Faster R-CNN R50 model, though slightly less accurate, offered faster inference speeds, making it a more practical choice for real-time applications where efficiency is a priority.

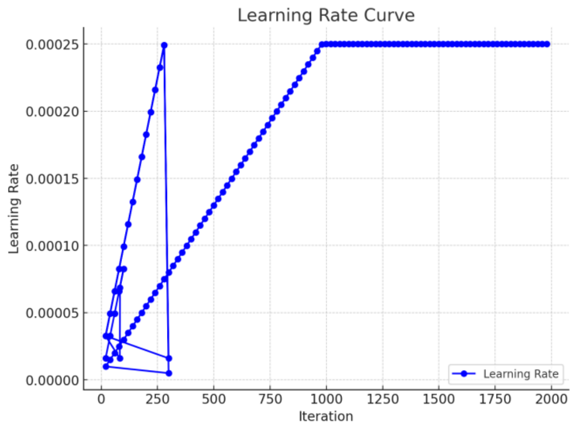

Figure 4: Faster RCNN_50 learning curve

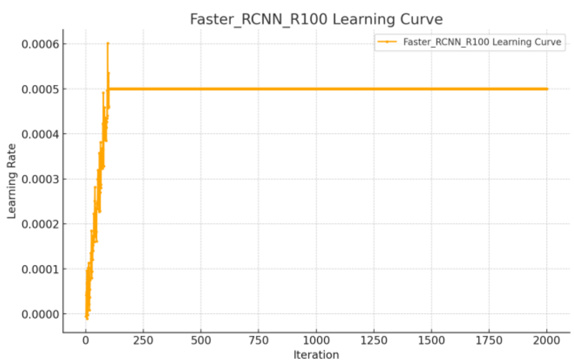

Figure 5: Faster RCNN_R100 Learning curve

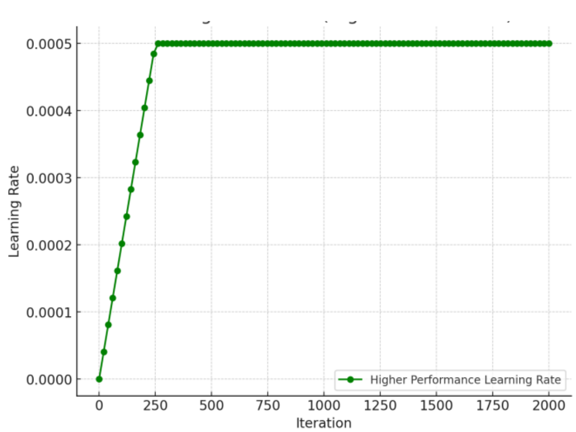

Figure 6: Faster RCNN_X101 Learning curve

Comparison Analysis

The performance evaluation of the Faster R-CNN models revealed significant differences in their effectiveness for object detection. Faster R-CNN X101 demonstrated superior accuracy at 98% and recall at 96%, attributed to its deeper architecture and enhanced feature extraction capabilities. However, its precision was slightly lower at 86%, leading to a higher false positive rate. As shown in Figure 6, the learning curve of X101 indicated rapid and stable convergence, confirming well-optimized training. Despite its high accuracy, this model required more computational resources, making it less suitable for real-time applications.

Faster R-CNN R100 provided a balanced performance, achieving 96% accuracy, 88% precision, and 95% recall. Its learning curve from Figure 5 showed faster convergence, making it a strong alternative for applications that prioritize fewer misclassifications. This model effectively balanced precision and recall, offering a reliable choice for tasks where both factors are equally important.

Faster R-CNN R50 from Figure 4, while being the fastest in inference, recorded the lowest accuracy at 94%, with 84% precision and 89% recall. Despite having the highest number of trainable parameters, its loss curve indicated weaker optimization, suggesting that increased complexity does not always result in better accuracy. Additionally, R50 exhibited instability in learning rate convergence, negatively affecting its overall performance.

The stability of the learning rate played a crucial role in model performance, with X101 and R100 converging efficiently, while R50 showed signs of instability. Overall, X101 remains the most effective choice for high-accuracy detection, R100 provides an optimal balance between precision and recall, and R50, despite its computational efficiency, unperformed compared to the other models.

CONCLUSION

This study developed an automated fish disease detection system utilizing Faster R-CNN within the Detectron2 framework. Among the evaluated models, Faster R-CNN X101 achieved the highest accuracy at 98%, making it the most effective for precise disease identification. Faster R-CNN R100 demonstrated a balanced performance with 96% accuracy, offering an optimal trade-off between precision and recall. While Faster R-CNN R50 provided the fastest inference time, its accuracy of 94% and weaker optimization made it less reliable for highly accurate detections. These findings confirm the effectiveness of deep learning models in enhancing fish disease detection, enabling early intervention and contributing to the sustainability of fish farming practices.

Recommendation

Future research should aim to enhance fish disease detection by refining the deep learning models and expanding dataset diversity. Given that Faster R-CNN X101 achieved the highest accuracy (98%) but required significant computational resources, future studies could explore optimizing its performance through model pruning, quantization, or knowledge distillation to improve efficiency without compromising accuracy. Additionally, Faster R-CNN R100, which demonstrated a balance of precision and recall at 96% accuracy, could be further refined to enhance misclassification rates. Expanding the datasets to include more diverse fish species, varying environmental conditions, and different stages of disease progression will improve model generalization. Incorporating real-time video analysis alongside static images would allow for continuous monitoring, providing early detection of disease outbreaks. Furthermore, alternative object detection models such as YOLO, EfficientDet, or SSD should be explored to determine if they can offer faster inference while maintaining high accuracy. By implementing these strategies, future research can improve the scalability, adaptability, and real-time applicability of automated fish disease detection, contributing to more sustainable aquaculture practices.

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