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Video-Based Disease Detection in Vannamei Shrimp Using YOLOv8 Architecture

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ABSTRACT

Vannamei shrimp (*Litopenaeus vannamei*) is a high-value aquaculture commodity that significantly contributes to the fisheries sector. However, shrimp farming faces a high risk of disease outbreak to mass mortality and substantial economic losses. Conventional health detection methods rely on manual observation, which is subjective, inefficient, and requires expert knowledge. Therefore, this study proposes an automated shrimp health detection system based on video imagery using Convolutional Neural Networks (CNN) implemented through the YOLOv8 algorithm.The dataset consists of 2,000 images extracted from video frames of vannamei shrimp and categorized into healthy and diseased classes. The research methodology includes data preprocessing, augmentation, model training, and evaluation using performance metrics such as precision, recall, and mean Average Precision (mAP). The trained model is deployed in a web-based system using FastAPI and OpenCV to enable real-time detection. Experimental results show that the proposed CNN-based model achieves an mAP@0.5 of approximately 0.92 (92%), with precision and recall values of approximately 0.85 and 0.90, respectively. These results indicate strong detection performance under real-world conditions. The system is capable of automatically identifying shrimp health conditions and provides higher efficiency compared to manual inspection. This study demonstrates that deep learning-based computer vision has strong potential for early disease detection and can support sustainable aquaculture management.

INTRODUCTION

Vannamei shrimp (*Litopenaeus vannamei*) is widely recognized as one of the most valuable aquaculture commodities due to its high economic value and increasing market demand (Agustin & Sari, 2023); (Bosman et al., 2022) (Macusi et al., 2022). In Indonesia, shrimp production plays a significant role in national economic development, particularly in coastal regions such as Aceh (Nur & Irfannur, 2024) (Salim et al., 2025). However, shrimp farming is frequently affected by disease outbreaks, which can lead to decreased productivity and significant financial losses (Asmild et al., 2024).

Traditional shrimp health monitoring typically relies on visual observation conducted by farmers, This is often subjective, inconsistent, and time-consuming (Zhao et al., 2021) As a result, diseases are frequently detected at later stages, reducing the effectiveness of mitigation efforts. Recent advancements in artificial intelligence, particularly in computer vision, provide opportunities to develop automated detection systems. Convolutional Neural Networks (CNN) have demonstrated high performance in image classification and object detection tasks due to their ability to automatically extract hierarchical features from complex datasets (Mienye et al., 2025).

Previous studies have applied conventional machine learning methods such as K-Nearest Neighbor (KNN), Support Vector Machine (SVM), and Random Forest combined with manual feature extraction techniques. However, these methods often struggle in real-world conditions due to variations in lighting, water turbidity, and object complexity (Delfino et al., 2024).

However, most existing studies focus on static image datasets and controlled experimental environments, which limit their applicability in real-world aquaculture conditions. Therefore, this study proposes a video-based detection approach using CNN with the YOLOv8 algorithm to automatically identify shrimp health conditions. Video-based analysis provides temporal and dynamic information that can improve object detection performance and enable real-time monitoring compared to static image-based approaches (Kovačovič et al., 2026). Furthermore, the implementation of YOLOv8 offers advantages in terms of detection accuracy, computational efficiency, and real-time processing capabilities, making it suitable for practical deployment in aquaculture environments. The proposed system is expected to support early disease detection, reduce the risk of disease outbreaks, minimize economic losses, and contribute to the development of sustainable and intelligent aquaculture management systems.

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LITERATURE REVIEW

Vannamei Shrimp and Diseases

Vannamei shrimp are marine organisms belonging to the Crustacea group within the Animalia kingdom. Vannamei shrimp (Litopenaeus vannamei) are classified into the phylum Arthropoda, class Crustacea, order Decapoda, family Penaeidae, genus Litopenaeus, and species Litopenaeus vannamei. They are characterized by a segmented body structure and undergo periodic moulting as part of their growth process (Guenard, 2021) (Supono et al., 2024). Vannamei shrimp are one of the leading commodities in the aquaculture sector due to their high economic value and increasing export demand. In Indonesia, vannamei shrimp have been widely cultivated since 2001 as a replacement for tiger shrimp (Penaeus monodon), which experienced a decline in productivity and seed quality (Juliastoro et al., 2021).

Despite its high economic potential, vannamei shrimp aquaculture faces several challenges, particularly disease outbreaks that can result in significant economic losses. Major diseases affecting vanname shrimp include White Spot Syndrome Virus (WSSV), Infectious Myonecrosis Virus (IMNV), and Taura Syndrome Virus (TSV) (Guo et al., 2021). These diseases can cause physical changes in shrimp, such as the appearance of white spots, muscle tissue damage, as well as reduced activity and appetite. In addition to pathogenic factors, environmental conditions such as water quality, temperature, and stocking density also play a significant role in increasing shrimp susceptibility to diseases. Suboptimal environmental conditions can weaken the shrimp immune system, making them more vulnerable to infections.

Therefore, early detection of shrimp health conditions is essential to prevent the widespread transmission of diseases. With the advancement of technology, image-based and artificial intelligence approaches have been increasingly developed to support automated shrimp health monitoring systems. These approaches are expected to improve the accuracy and efficiency of detecting shrimp conditions compared to conventional manual observation methods. Recent developments in smart aquaculture systems have integrated artificial intelligence and Internet of Things (IoT) technologies to enhance monitoring efficiency and disease detection.

Deep Learning and Convolutional Neural Networks in Image Analysis

CNN has become one of the most widely used methods in image analysis because it can automatically learn important visual features from data without manual feature extraction. It is widely used in image processing to detect relevant features and differentiate between visual patterns ("Penerapan Convolutional Neural Network Pada Klasifikasi Jenis Ras Kucing Menggunakan ResNet50V2 | JIEET (Journal of Information Engineering and Educational Technology)," n.d.) A typical CNN architecture includes convolutional, pooling, activation, and fully connected layers, which collectively enable the model to learn complex representations from image data (He & Chien, 2023).

In recent years, CNN has achieved remarkable performance in a wide range of applications, including image classification, object detection, and video analysis. This success is primarily driven by its ability to automatically extract hierarchical features from complex datasets. Moreover, CNN has been extensively applied in real-time object detection frameworks such as YOLO and SSD, which provide efficient and accurate object recognition in video (Abdullahi,et all, 2024).

Nevertheless, CNN models still exhibit several limitations, including the requirement for large amounts of training data and sensitivity to environmental variations. Therefore, ongoing improvements and optimizations are necessary to enhance their performance and generalization in real-world scenarios.

Previous Research

Previous studies have explored various approaches for shrimp health detection using image processing and artificial intelligence techniques. Early research mainly relied on feature extraction methods such as Gray Level Co-occurrence Matrix (GLCM) combined with traditional classifiers like K-Nearest Neighbor (KNN) and Support Vector Machine (SVM). These methods achieved moderate accuracy, typically ranging from 70% to 85%, under controlled experimental conditions. However, their dependence on handcrafted features limits their robustness when applied to real-world aquaculture environments with varying lighting and water quality. With the advancement of deep learning, Convolutional Neural Network (CNN) has been widely adopted to improve classification performance. Several studies reported accuracy exceeding 90% using CNN-based models for shrimp disease detection. Furthermore, real-time object detection algorithms such as YOLO have been introduced to enhance detection speed and efficiency. Recent studies utilizing YOLOv8 demonstrated high performance, with mean Average Precision (mAP) values above 90% in controlled datasets. Despite these promising results, most existing studies are conducted using static image datasets captured under controlled conditions. Such approaches are limited in their ability to represent real-world aquaculture environments, where factors such as water turbidity, lighting variation, and object movement significantly affect detection performance. In addition, models achieving high accuracy often involve complex architectures that require substantial computational resources, limiting their practical deployment.

In contrast, this study proposes a video-based shrimp health detection approach using CNN with the YOLOv8 algorithm. By utilizing video data, the proposed method captures both spatial and temporal information, including shrimp movement patterns and behavioral changes, which are important indicators of health conditions. Although the performance obtained in this study is lower compared to some previous works, it reflects the increased complexity of

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real-world conditions and demonstrates the feasibility of applying deep learning models for practical and real-time aquaculture monitoring.

Research Gap and Contribution

Based on the reviewed literature, it is evident that although deep learning approaches have significantly improved shrimp health detection, there is still a lack of research focusing on video-based analysis that captures both spatial and temporal information in real-world conditions. Most existing methods either rely on static images or employ complex models that are not optimized for practical implementation. Several recent studies have demonstrated the effectiveness of convolutional neural networks (CNN) and object detection models for aquaculture monitoring; however, they predominantly focus on image-based datasets and controlled environments (Zhang et al., 2022). Furthermore, real-time monitoring systems that integrate temporal behavioral analysis remain limited, despite their importance for early disease detection and precision aquaculture (Mohammad Manzurul Islam et al., 2025) (Journal & Shin, n.d.).

Therefore, this study proposes a CNN-based approach using the YOLOv8 algorithm for shrimp health detection from video imagery. By leveraging video data, the proposed method aims to capture dynamic behavioral patterns in addition to visual features, enabling more comprehensive and real-time health assessment. The use of YOLOv8 is motivated by its improved accuracy and efficiency in real-time object detection tasks compared to previous versions (Reis et al., 2023) (Hussain, 2024). Moreover, the system is designed to be deployed in a web-based environment, enhancing its applicability for practical aquaculture monitoring. This contribution addresses the existing gap by integrating spatial-temporal analysis with a lightweight and deployable system suitable for real-world implementation.

METHOD

This research uses a deep learning approach based on Convolutional Neural Networks (CNN) implemented with the YOLOv8 algorithm. The system processes video input and extracts frames to be used as image data.

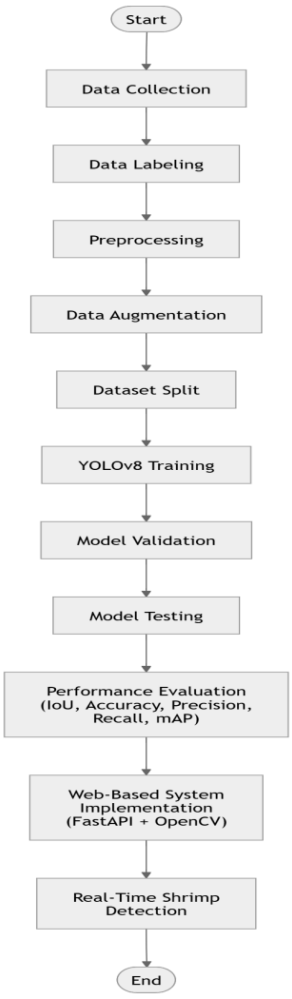

Figure 1. Research Methodology Flowchart

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Data Collection

The dataset used in this study consists of 2,000 images extracted from video recordings of vanname shrimp in aquaculture environments. The proposed system adopts a two-stage classification approach. In the first stage, the model performs binary classification to detect whether shrimp are healthy or diseased. In the second stage, images identified as diseased are further classified into specific disease categories, including White Spot Syndrome Virus (WSSV), Infectious Myonecrosis Virus (IMNV), and Taura Syndrome Virus (TSV).

The data were collected under varying environmental conditions, including differences in lighting, water turbidity, and shrimp movement, to better represent real-world scenarios. Each image was manually annotated to ensure accurate labeling.

The dataset was divided into training (70%), validation (20%), and testing (10%) sets. Before training, preprocessing steps such as image resizing and normalization were applied to standardize the input data.

Data Labeling

The dataset labeling process in this study consists of four main classes: healthy shrimp and three disease categories, namely White Spot Syndrome Virus (WSSV), Infectious Myonecrosis Virus (IMNV), and Taura Syndrome Virus (TSV). Each image in the dataset is annotated according to its corresponding class label:

Figure. 2 Dataset Labels

The labeling process is performed by organizing the dataset into structured directories based on class categories, allowing the system to automatically recognize labels during the training phase. In addition, object annotations are applied to identify shrimp regions within the images, enabling the model to learn relevant visual features effectively. This structured labeling approach ensures consistency in data organization and improves the performance of the classification and detection process. Furthermore, it facilitates automated data loading and reduces errors during model training.

Preprocessing Data

Preprocessing was conducted to improve image quality before training. This process includes image resizing, normalization, and noise reduction to enhance feature clarity. These steps ensure that the input data is consistent and suitable for model training, thereby improving detection performance.

Data Augmentation

Data augmentation was applied to increase the size and diversity of the dataset, thereby improving the model's generalization capability. Several augmentation techniques were implemented, including horizontal flip, vertical flip, and image rotation. The rotation transformation was applied at multiple angles, including 90°, 180°, and 270°, to simulate different object orientations. These transformations allow the model to learn invariant features under various viewing angles and positions.

Each original image generates multiple augmented samples, significantly increasing the total dataset size. This approach helps reduce overfitting and improves the robustness of the model in detecting shrimp health conditions under varying environmental conditions.

Model Training

The model training process was conducted using the YOLOv8 architecture, which is based on CNN to perform object detection and classification tasks. The model is designed to detect shrimp objects and classify their health conditions into four categories: healthy, WSSV, IMNV, and TSV. Before training, all input images were resized to a fixed resolution of 640×640 pixels to ensure consistency. The training process was performed using a batch size of 16 over 100 epochs. The model parameters were optimized using the Adam optimizer, which adjusts the learning rate adaptively to improve convergence.

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During training, the model performs forward propagation to generate predictions, followed by loss calculation to measure the difference between predicted and actual labels. Backpropagation is then applied to update the network weights iteratively, minimizing the loss function and improving model accuracy. The model learns to extract relevant visual features such as shrimp morphology, texture patterns, and disease-related abnormalities from the input images. These features enable the model to distinguish between healthy and diseased shrimp under varying environmental conditions, including changes in lighting and water turbidity.

To prevent overfitting and improve generalization, the training process incorporates data augmentation techniques and validation monitoring. The best-performing model is selected based on validation performance metrics, ensuring optimal detection capability.

The computational training process for the YOLOv8 model was executed on an NVIDIA GeForce RTX 3060 GPU with 12 GB VRAM and 16 GB of system RAM, implemented within a Python environment leveraging the PyTorch framework.

Evaluation Metric: Intersection over Union (IoU)

The performance of the object detection model is evaluated using Intersection over Union (IoU), which quantifies the degree of overlap between the predicted bounding box and the corresponding ground truth bounding box. IoU is formally defined as the ratio between the area of intersection and the area of union of the two bounding boxes. An IoU threshold of 0.5 is adopted in this study to determine correct detections. A predicted bounding box is considered a true positive when the IoU value exceeds the predefined threshold; otherwise, it is categorized as a false positive. This threshold follows standard evaluation practices in object detection tasks.

Furthermore, IoU serves as the fundamental basis for calculating mean Average Precision (mAP), which is used as the primary evaluation metric in this study. Specifically, mAP@0.5 is computed using a fixed IoU threshold of 0.5, while mAP@0.5:0.95 is also evaluated by averaging performance across multiple IoU thresholds ranging from 0.5 to 0.95. The use of IoU-based evaluation ensures that both localization accuracy and classification performance are rigorously assessed, providing a comprehensive measurement of the model's detection capability in real-world scenarios.

Testing and Evaluation

The performance of the proposed model is evaluated using several standard metrics, including accuracy, precision, recall, and mean Average Precision (mAP). Accuracy measures the overall correctness of the model predictions, while precision evaluates the proportion of correctly identified positive samples among all predicted positives. Recall measures the ability of the model to correctly identify all relevant samples. In addition, mean Average Precision (mAP) is used as the primary evaluation metric to assess the object detection performance of the model. This metric considers both localization and classification accuracy, providing a comprehensive evaluation of the model's effectiveness. The evaluation is conducted on the testing dataset to ensure unbiased performance measurement.

System Implementation

The trained model is implemented in a web-based system to enable real-time shrimp health detection. The system is developed using FastAPI as the backend framework, which provides efficient API handling and fast response times. For real-time video processing and image handling, the system integrates OpenCV, which is used to capture video streams, extract frames, and perform preprocessing before feeding the data into the model.

The integration of the YOLOv8 model with FastAPI allows the system to process incoming video data and generate detection results in real time. The output includes bounding boxes and classification labels indicating the health condition of the shrimp. This implementation enables practical deployment in aquaculture environments for continuous monitoring and early disease detection.

RESULT

The experimental results of the proposed YOLOv8-based model are presented in this section to evaluate its performance in detecting shrimp health conditions.

Training and Validation Performance

The training process demonstrates a consistent decrease in loss values, including box loss, classification loss, and distribution focal loss (DFL), as the number of epochs increases. This indicates that the model successfully learns meaningful features from the dataset.

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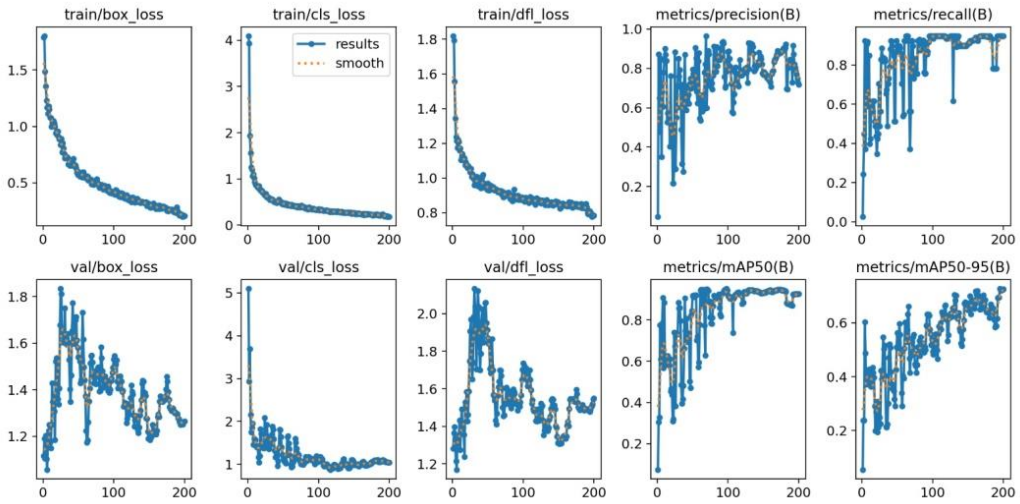

Figure 3 Training and validation performance

As shown in Fig. 2, the training and validation curves exhibit stable convergence without significant divergence, indicating that the model does not suffer from severe overfitting.

In terms of evaluation metrics, the model achieves a precision of approximately 0.85 and a recall of around 0.90, indicating a strong ability to correctly detect shrimp objects while maintaining a high detection rate. Furthermore, the model attains an mAP@0.5 of approximately 0.92 and an mAP@0.5:0.95 of around 0.70, demonstrating robust detection performance under both standard and stricter evaluation conditions.

System Implementation

The system allows users to upload images or capture data directly from a camera for shrimp health detection. The input image is processed by the trained YOLOv8 model, which performs object detection and classification in real time.

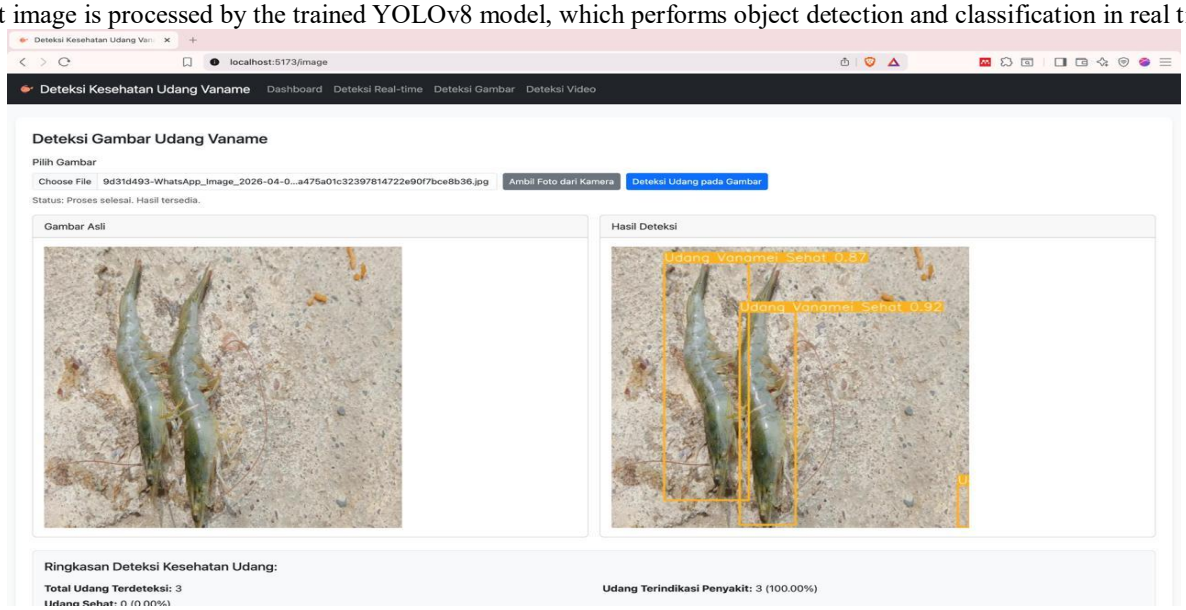

Figure 4. Web-based shrimp health detection system interface

The output includes bounding boxes and confidence scores indicating the detected shrimp and their health conditions. Additionally, the system provides a summary of detection results, including the total number of detected shrimp and their classification status. This implementation demonstrates the practical applicability of the proposed model for real-world aquaculture monitoring and supports real-time decision-making in shrimp farming environments.

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Confusion Matrix Analysis

The normalized confusion matrix presented in Figure 5 illustrates the classification performance of the proposed model across all shrimp health categories. The diagonal elements represent correct classifications, while the off-diagonal elements indicate misclassifications between classes.

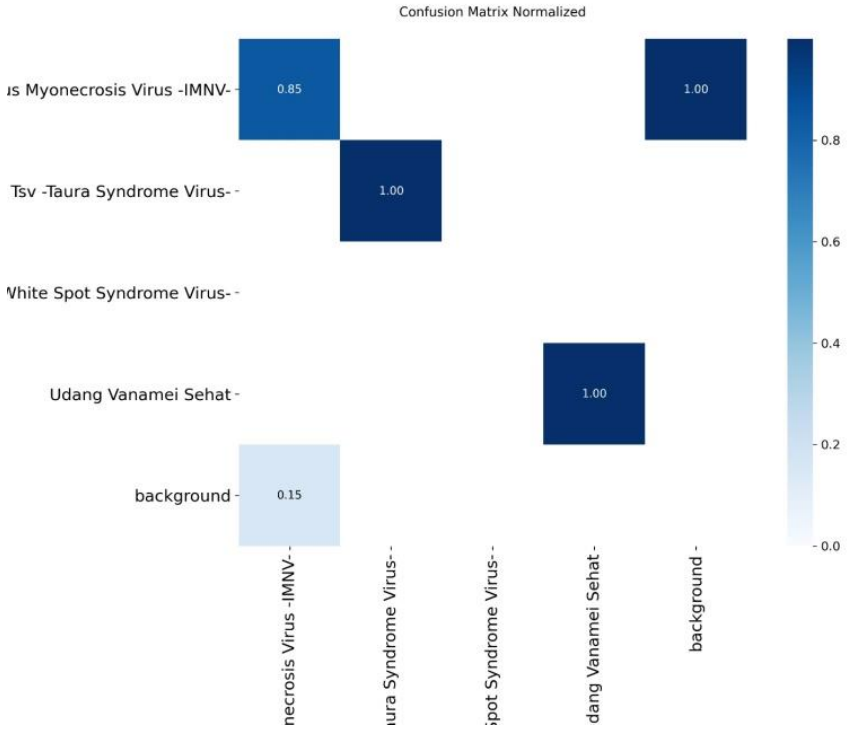

Figure. 5 Confusion Matrix Analysis

The results show that the model achieves excellent classification performance for most classes. The Taura Syndrome Virus (TSV) and healthy shrimp classes reach perfect classification accuracy with values of 1.00, indicating that all samples in these classes are correctly identified without any misclassification. For the Infectious Myonecrosis Virus (IMNV) class, the model achieves an accuracy of approximately 0.85, meaning that 85% of the samples are correctly classified. However, around 15% of IMNV samples are misclassified as background, indicating that some disease characteristics may not be sufficiently distinctive under certain conditions.

Meanwhile, the background class shows minor confusion with the IMNV class, which suggests that environmental noise or visual similarity between shrimp and background elements may affect the detection performance. Overall, the confusion matrix demonstrates that the proposed model has strong classification capability, with only minor misclassification occurring in specific challenging cases

DISCUSSION

The results obtained in this study demonstrate that the proposed YOLOv8-based model achieves strong performance in detecting shrimp health conditions from video-based data. The model achieved an mAP@0.5 of approximately 0.92 (92%), indicating a high level of detection accuracy under the standard IoU threshold. In addition, the mAP@0.5:0.95 value of around 0.70 suggests that the model maintains robust performance even under stricter evaluation conditions. The precision and recall values, which reach approximately 0.85 and 0.90, further confirm that the model is capable of accurately identifying shrimp objects while minimizing missed detections.

The consistent decrease in training and validation loss, along with stable convergence patterns, indicates that the model successfully learns meaningful features from the dataset without experiencing severe overfitting. This suggests that the applied preprocessing and data augmentation techniques effectively improve the model's generalization capability in handling variations in lighting, water turbidity, and object movement.

Compared to previous studies that primarily rely on static image datasets, the proposed video-based approach provides a significant advantage by capturing both spatial and temporal information. Unlike previous studies that rely on controlled datasets, this research focuses on real-world aquaculture conditions, where factors such as water turbidity, lighting variation, and shrimp movement significantly affect detection performance.

These findings highlight that real-world aquaculture environments present unique challenges that are often not captured in controlled experimental settings. This allows the model to learn not only visual features such as texture and shape but also dynamic patterns such as shrimp movement and behavior. As a result, the system is better suited for real-

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world aquaculture environments, where conditions are often unpredictable and complex. Although several prior studies have reported high accuracy values exceeding 90% using CNN-based methods, many of these experiments were conducted under controlled conditions with limited environmental variability. In contrast, this study utilizes video data collected from real aquaculture environments, which introduces additional challenges such as noise, lighting variation, and background complexity. Therefore, the achieved performance reflects a more realistic evaluation scenario and demonstrates the practical feasibility of the proposed approach.

The confusion matrix analysis further supports these findings, showing that the model achieves perfect classification performance for certain classes such as TSV and healthy shrimp. However, minor misclassification is observed in the IMNV class, where some samples are incorrectly identified as background. This limitation may be caused by similarities in visual features or insufficient representation of certain disease patterns in the dataset. Despite these promising results, this study still has several limitations. The dataset size is relatively limited, and the model performance may be further improved by incorporating a larger and more diverse dataset. In addition, the current system focuses on frame-based detection without explicitly modeling temporal sequences. Future research may explore the integration of temporal deep learning models, such as LSTM or 3D CNN, to better capture motion patterns and improve detection accuracy.

Overall, the findings indicate that the proposed YOLOv8-based CNN model, combined with a video-based approach, provides an effective and practical solution for real-time shrimp health detection. This approach has strong potential to support early disease diagnosis and improve decision-making processes in aquaculture management.

CONCLUSION

This study successfully develops a video-based shrimp health detection system using YOLOv8. The model achieves high detection accuracy and demonstrates strong potential for real-time monitoring in aquaculture. The findings demonstrate that video-based analysis enables the extraction of both spatial and temporal information, which provides a more comprehensive understanding of shrimp health compared to static image-based approaches.

This indicates that practical deployment in real aquaculture environments requires not only high accuracy but also robustness to environmental variability.

Although the performance is still limited, the results highlight the challenges of applying deep learning models in dynamic and uncontrolled environments. Future work should focus on improving dataset quality, increasing training data, and optimizing model parameters to enhance detection accuracy.

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