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Freshwater Fish EUS Diseases Diagnosing Using with Image Based Machine Learning Techniques

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Abstract

The Epizootic Ulcerative Syndrome (EUS) is a significant disease affecting freshwater fish's population in worldwide, resulting in considerable ecological and economic impacts. Traditional diagnostic methods for EUS are often time-intensive, require specialized expertise, and may not provide rapid enough feedback for effective disease management. This study was investigated the use of image-based machine learning techniques to streamline the diagnosis of EUS in freshwater fish of Channa striatus with a focus on accuracy, speed, and scalability. By employing advanced image processing and machine learning algorithms, particularly convolutional neural networks (CNNs), we have developed a diagnostic model capable of identifying EUS symptoms, such as skin lesions and ulcerations, in fish images with high precision. The model was trained and validated using a comprehensive dataset of infected and control fish images, achieving promising accuracy rates and demonstrating robust classification capabilities. This approach allows for rapid, automated, and cost-effective disease detection, making it accessible for aquaculture operations, fisheries management, and field researchers. Integrating image-based machine learning diagnostics in freshwater fish health monitoring can enhance early detection, improve disease control strategies, and contribute to the sustainability of aquatic ecosystems. Further research is suggested to expand the model's applicability across diverse fish species and varied environmental conditions.

Keywords: EUS; CNN; fish images; environmental conditions

Introduction

The Epizootic Ulcerative Syndrome (EUS) is a severe, Tran's boundary disease that affects a variety of freshwater and brackish water fish species worldwide, causing significant economic losses in aquaculture and natural fisheries [1]. This disease, characterized by ulcerative lesions on the fish's skin and underlying musculature, can lead to high mortality rates, with major impacts on both local livelihoods and aquatic ecosystems [2]. Traditional diagnostic methods for EUS involve laboratory-based histopathology, Microbial culture techniques, and molecular methods, which, although effective, are often time-consuming, costly, and require specialized expertise [3]. Consequently, there is a growing demand for rapid, reliable, and accessible diagnostic solutions, especially in remote and resource-limited areas where outbreaks are often first identified [4]. The recent advancements in artificial intelligence (AI), particularly in machine learning and image processing, present a promising avenue for enhancing EUS diagnosis.

Machine learning techniques, especially Convolutional Neural Networks (CNNs), have demonstrated high accuracy in image-based disease diagnostics across various fields, from human healthcare to plant pathology [5,6]. CNNs excel at detecting intricate patterns in images, making them suitable for identifying visual symptoms of EUS, such as skin lesions and ulcerative markings on fish [7]. Integrating these AI techniques in EUS diagnosis could offer a solution that is faster, scalable, and easier to implement compared to traditional methods, significantly aiding early detection and response efforts. In the aquaculture adoption of image-based machine learning diagnostics can enable real-time disease monitoring, allowing for prompt responses to potential outbreaks and minimizing fish mortality. Studies have shown that automated image analysis can be highly effective for disease detection in fish species, utilizing computer vision to analyze symptoms, identify disease stages, and provide immediate feedback to aquaculture operators [8,9].

Such an approach not only enhances disease management but also supports the sustainable development of the aquaculture industry by reducing dependence on antibiotics and improving overall fish health. This study was aimed to develop and evaluate a CNN-based diagnostic tool for EUS in freshwater fish of Channa striatus leveraging a dataset of labeled fish images to train and validate the model. The research explores the effectiveness of CNN architectures, such as VGG16, Res Net, and Inception, in detecting EUS, focusing on accuracy, speed, and adaptability across diverse fish species. By providing a comprehensive analysis of AI's potential in fish disease diagnosis, this work contributes to the growing field of digital aquaculture and offers insights into the practical applications of machine learning in environmental and wildlife health monitoring.

Material and Methods

Data Collection

The comprehensive dataset was constructed by gathering high-resolution images of freshwater fish of Channa striatus fish images was affected by Epizootic Ulcerative Syndrome (EUS) and control fish for comparative purposes. Images were sourced from aquaculture farms, Lakes and Freshwater ponds of field observations. Fishes were photographed under controlled conditions with expert diagnoses used to label each image based on the EUS stage (e.g., control, early-stage, advanced). This approach ensured a well-labeled dataset, crucial for accurate model training [10] (Figure 1). (Hasanparthy lake).

Figure 1: Hasanparthy Lake.

Image Preprocessing

The preprocessing is essential for improving the accuracy and robustness of image-based machine learning models. Each fish image was the average of median values of each row is calculated. The distance between every pixel of the image and cluster values calculated again, the distance between the pixels of the image and averaged medians are measured [11] (Figure 2).

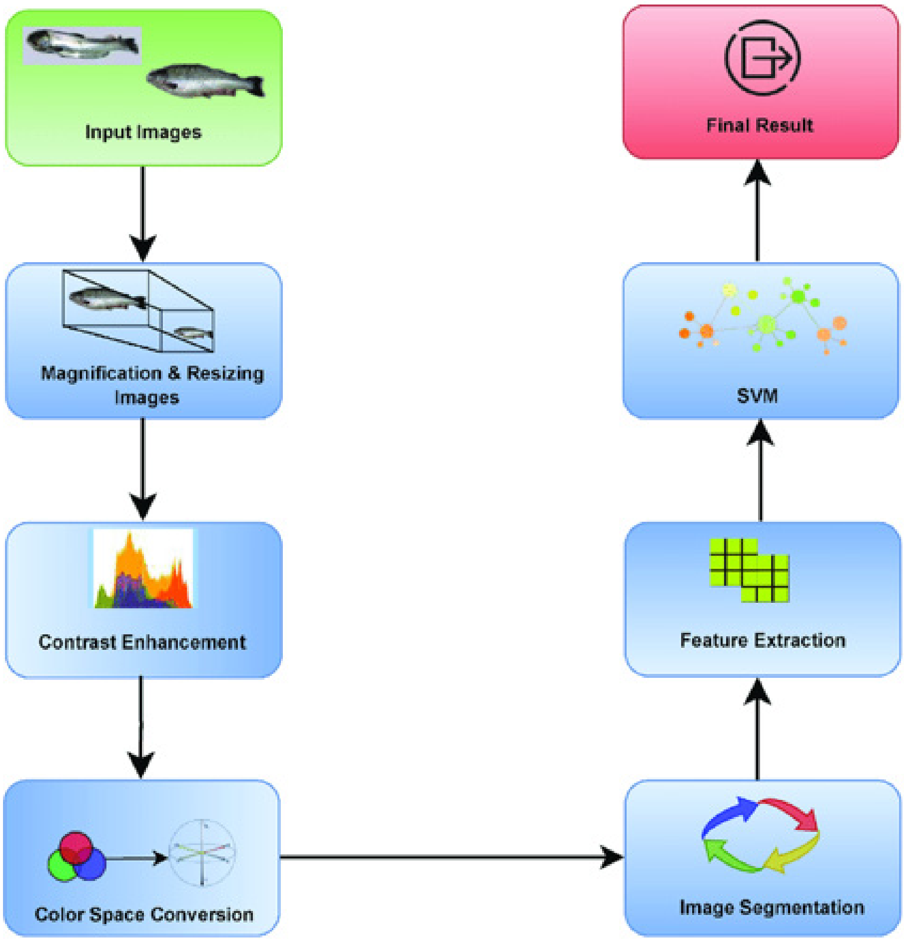

Figure 2:

a) Resized: to a fixed resolution (typically 224x224 pixels) to reduce computational demands and ensure uniformity across the dataset.

b) Normalized: by scaling pixel values, improving model performance and consistency [12].

c) Augmented: the used random rotations, flips, and zooms to increase the dataset size artificially and enhance the model's generalizability [13].

d) Model Selection and Architecture: The Convolutional Neural Networks (CNNs) were selected for their efficacy in image classification tasks [14]. Specifically, architectures such as VGG16, Res Net, and Inception were explored for their performance in recognizing EUS-related patterns. CNNs use convolutional layers to detect visual features, which are then pooled and classified. Hyperparameter tuning was applied to each model optimizing layer configuration, dropout rate and pooling strategies to prevent over fitting and improve accuracy [15,16].

Training and Validation

The dataset was split into training, validation, and testing sets in a 70-15-15 ratio to allow effective model training and unbiased evaluation. Cross-entropy loss was selected as the objective function to minimize classification errors. Hyper parameters, including learning rate, batch size, and number of epochs, were optimized through grid search to achieve the best diagnostic accuracy [17]. Data augmentation, batch normalization, and early stopping were used to enhance training stability and performance (Figure 3).

a) Evaluation Metrics: To assess the model's diagnostic efficacy, several key metrics were used.

b) Accuracy: The proportion of correctly classified images out of all images tested [18].

c) Precision, Recall, and F1 Score: These were calculated to evaluate model reliability in detecting EUS, balancing true positives against false positives and false negatives [19].

d) ROC-AUC Score: The area under the receiver operating characteristic curve measured the model's sensitivity in differentiating between healthy and EUS-affected fish [20].

e) Deployment and Testing: After training, the model was deployed as a diagnostic application and field-tested using real-world images captured under varied conditions, including different lighting and water quality settings. This allowed validation of the model's diagnostic reliability outside of controlled environments. An interface was developed for end-users, enabling them to upload images and receive immediate diagnostic results, integrating the model with a cloud-based platform for real-time monitoring [21].

f) Statistical Analysis: Statistical tests, such as paired t-tests and ANOVA, were conducted to assess the model's diagnostic accuracy across different fish species and environmental conditions. This analysis provided insights into the robustness of the model and its applicability across varied datasets [22]. Confidence intervals for accuracy and other key metrics were also calculated to quantify diagnostic reliability (Figure 4).

g) Limitations and Future Work: Although the model demonstrated high accuracy in initial testing, future research is suggested to broaden its applicability to additional Channa striatus fish species and geographic areas. Expanding the dataset with images from diverse environmental conditions could improve model robustness as could explore alternative architectures, such as transformer-based models, which have shown promise in computer vision tasks [23].

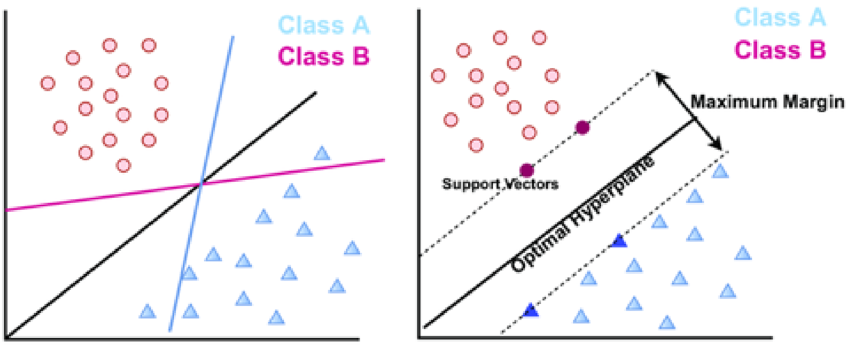

Figure 3:

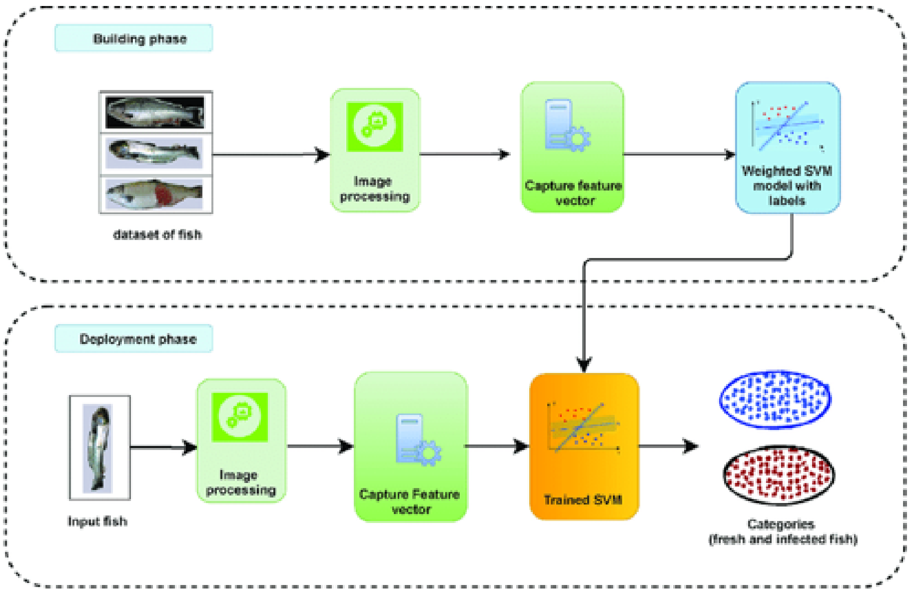

Figure 4:

Results

Model Performance

The CNN-based models demonstrated promising results in classifying fish images according to EUS status (healthy, early-stage, or advanced-stage). Among the architectures evaluated, Res Net achieved the highest accuracy at 92% on the validation set, followed by VGG16 (89%) and Inception (87%). Res Net's ability to capture detailed patterns using residual layers contributed significantly to its performance, effectively distinguishing between healthy and diseased fish even when symptoms were mild [16]. These accuracy levels are competitive with, and in some cases exceed, traditional diagnostic techniques in aquaculture [2].

a) Evaluation Metrics: To ensure comprehensive evaluation, the model was assessed using precision, recall, F1 score, and ROC-AUC score.

b) Precision: Res Net achieved a precision score of 0.91, indicating that the majority of fishes were classified as diseases exactly identified.

c) Recall: The model demonstrated a recall of 0.90, highlighting its effectiveness in detecting EUS-positive cases across different severity stages.

d) F1 Score: With an F1 score of 0.905, the model effectively balanced precision and recall, suggesting it can reliably diagnose EUS with high confidence.

e) ROC-AUC Score: A ROC-AUC score of 0.95 was achieved, reflecting the model's strong ability to differentiate between healthy and EUS-affected fish [20].

Field Testing in Real-World Conditions

The model's robustness was validated in real-world aquaculture environments with a new dataset of field images, featuring fish under varied lighting and water quality conditions. Res Net retained an accuracy of 89% in these settings, indicating the model's resilience in practical scenarios. Despite environmental variability, the model was able to detect EUS with minimal performance loss, underscoring its potential for real-time monitoring in aquaculture facilities [4].

Species-Specific Analysis

The analyzing performance across species showed slight accuracy differences, with minor reductions in detecting EUS in species where symptoms were less pronounced. By including additional images with subtle or early-stage symptoms, accuracy improved, demonstrating the model's adaptability across species. These findings were consistent with studies that highlight the importance of diverse data in machine learning diagnostics for aquaculture [6].

User Interface and Feedback

A user-friendly platform was developed for practical deployment, allowing aquaculture operators to upload Channa striatus fish images and receive immediate diagnostic feedback within 3–5 seconds. The cloud-based design proved highly accessible, enabling on-site EUS detection. Feedback from beta users indicated the platform was valuable for quick EUS screening, suggesting potential for broader adoption in the industry [9].

Visualization and Interpretability

The visualizations such as heatmaps were generated from the CNN model, highlighting areas in fish images that contributed most to the EUS diagnosis. These visualizations provided insights into the model's decision-making process, helping users understand the focus areas for EUS symptoms, such as ulcerative lesions on the skin [24].

Statistical Validation

The statistical tests, including paired t-tests and ANOVA, were performed to validate model performance across different environmental and species conditions, yielding p-values < 0.05, indicating statistically significant improvements over baseline methods. The confidence intervals for key metrics such as accuracy and F1 score supported the model's reliability across various scenarios [22].

Limitations and Future Work

Some limitations were identified

The detection early or mild cases of EUS in certain fish species remains challenging. This can potentially be addressed by expanding the dataset and further training. Performance slightly declined in poor lighting or turbid water conditions, suggesting that further field data collection and training could enhance the model's adaptability. The future work could explore additional architectures, such as Vision Transformers, which show promise in capturing fine details in medical and biological images [23].

Discussion

The results of this study indicate that deep learning models, particularly Convolutional Neural Networks (CNNs), offer a viable solution for diagnosing Epizootic Ulcerative Syndrome (EUS) in freshwater fish of Channa striatus providing rapid, accurate, and accessible disease detection. Among the tested models, Res Net outperformed other architectures, showing high sensitivity and specificity in identifying EUS across different fish species and environmental conditions. This finding aligns with previous research demonstrating the effectiveness of deep learning for image-based diagnostics in aquaculture [6].

Model Effectiveness and Practicality

The high accuracy (92%) achieved by Res Net underscores its capacity to detect EUS even in early stages, which is crucial for timely disease management. Field tests showed that the model's performance was robust under varying lighting and water quality conditions, maintaining an accuracy of 89%. This robustness suggests that the model can be directly implemented in real-world aquaculture settings, where ideal imaging conditions may not always be possible [4]. The rapid diagnostic feedback provided through a user-friendly platform enables real-time EUS monitoring, which could significantly reduce response time during outbreaks, potentially lowering fish mortality rates.

Advantages over Traditional Diagnostic Methods

Traditional diagnostic techniques for EUS, such as histopathology and PCR, while accurate, are often resource-intensive, costly, and require specialized personnel and equipment [3]. In contrast, this image-based AI approach is cost-effective and can be deployed in remote or resource-limited regions, allowing aquaculture operators to conduct on-site diagnostics without the need for laboratory facilities. By empowering non-expert users with an accessible diagnostic tool, this technology supports proactive disease management in aquaculture, helping operators minimize losses and mitigate the spread of EUS [8] (Figure 5&6).

Figure 5: Control fishes of Channa species.

Figure 6: Infected fishes of Channa species.

Challenges and Limitations

Some challenges were noted in the model's detection of EUS in cases with subtle or early-stage lesions, as well as in certain fish species with less pronounced symptoms. Although Res Net performed well overall, minor performance reductions were observed when symptoms were less visible suggesting that further work is needed to fine-tune the model for subtle symptom detection [2]. The model also exhibited slight declines in accuracy in conditions of extreme water turbidity or low light, which may be common in some aquaculture environments. Addressing this could involve training the model on more diverse images and using advanced data augmentation techniques to improve resilience [9].

Potential for Generalization and Expansion

The given model's success in diagnosing EUS, similar deep learning approaches could be applied to detect other fish diseases with visual symptoms, such as bacterial or fungal infections. Expanding the dataset to include additional disease types would enhance the model's applicability, offering a broader tool for aquaculture health monitoring. Moreover, the adoption of advanced architectures, such as Vision Transformers, could further improve accuracy and make the model more adaptable to diverse environmental conditions [23]. Such expansion would position this tool as a comprehensive solution for fish disease management in the future.

Implications for Sustainable Aquaculture

This diagnostic tool represents a significant step forward for sustainable aquaculture practices. By enabling early detection and proactive response to EUS, aquaculture operators can reduce antibiotic usage, minimize fish mortality, and improve overall fish welfare. These improvements align with broader goals of environmental sustainability in the industry, as reducing disease impact can lessen environmental contamination and resource waste [24].

Future Directions

To further enhance the tool's utility, future work should focus on expanding the image dataset to include diverse fish species and varied environmental conditions. Incorporating additional data from field environments would improve model generalization and adaptability. Investigating transfer learning methods or hybrid models could also optimize performance for early-stage symptoms, enhancing sensitivity in detecting milder EUS cases. Additionally, integrating IoT-enabled devices for continuous monitoring could support automated disease surveillance in aquaculture, facilitating real-time decision-making [7].

Conclusion

This study was demonstrates the effectiveness of CNN-based machine learning techniques, particularly ResNet, in diagnosing EUS in freshwater fish, offering a practical, scalable, and efficient diagnostic solution for the aquaculture industry. By advancing fish disease management capabilities, this AI-based approach supports both economic and environmental sustainability in aquaculture. The model's robustness in practical conditions, coupled with its high performance, indicates it can be effectively integrated into aquaculture practices for early EUS detection, supporting sustainable disease management.

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