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Hybrid Transfer–Ensemble Learning Framework for Sustainable Aquaculture Disease Management

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Abstract

Globally, aquaculture contributes to over 182 million tonnes of fish production annually, accounting for nearly 57% of total aquatic yield, and the sector is projected to reach USD 421 billion by 2030. However, fish disease outbreaks are responsible for an estimated 35% annual loss in global aquaculture productivity, posing a major threat to sustainability and food security. Existing manual disease detection methods rely heavily on human observation, visual inspection, and laboratory analysis—processes that are time-consuming, inconsistent, and limited in scalability for large aquaculture farms. These traditional approaches are prone to human fatigue, subjective interpretation, and poor accuracy under variable underwater conditions such as turbidity and lighting fluctuations. To overcome these challenges, the proposed method introduces a hybrid fish disease classification framework integrating the Visual Geometry Group 19 (VGG19) deep learning model with a Random Forest Classifier (RFC) for intelligent, automated disease detection. The system begins with preprocessing fish images using OpenCV and Scikit-Image to normalize resolution, enhance contrast, and eliminate noise. The pre-processed images are fed into the VGG19 network, which extracts hierarchical visual features ranging from low-level colour and texture patterns to high-level disease-specific abstractions such as lesions, fin deformities, or discoloration. These extracted feature vectors are then passed to the RFC, which performs efficient ensemble-based classification across multiple disease categories with improved interpretability and reduced overfitting. Evaluation metrics including accuracy, precision, recall, and F1-score demonstrate that the proposed hybrid approach significantly enhances disease detection reliability compared to manual or standalone deep learning models. Ultimately, this intelligent system offers a robust, scalable, and cost-effective solution for real-time fish health monitoring, supporting sustainable aquaculture management and global food security.

Keywords: Aquaculture, Fish Disease Detection, Fish Health Monitoring, Image Processing, Deep Learning, Machine Learning.

1. Introduction

The rapid expansion of aquaculture and fisheries worldwide has introduced both economic growth and operational challenges. According to the Food and Agriculture Organization (FAO), global fish production surpassed 182 million tonnes in 2023, with aquaculture accounting for nearly 57% of total output. Figure 1 shows the practical ways to control fish disease. This growth reflects a significant reliance on technological integration for monitoring fish health, optimizing yield, and maintaining environmental sustainability. The global aquaculture market is projected to reach USD 421 billion by 2030, driven by advancements in computer vision technologies that assist in automating fish detection, disease identification, and species classification. Conventional monitoring systems depend heavily on manual inspection, which is time-consuming, inconsistent, and often leads to misdiagnosis due to human error. Studies have reported that over 35% of fish yield losses annually are attributed to delayed

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disease detection and improper species management. The emergence of AI-enabled systems has therefore become critical in automating image-based detection and analysis, offering real-time insights that can transform aquaculture management into a data-driven, precision-based operation.

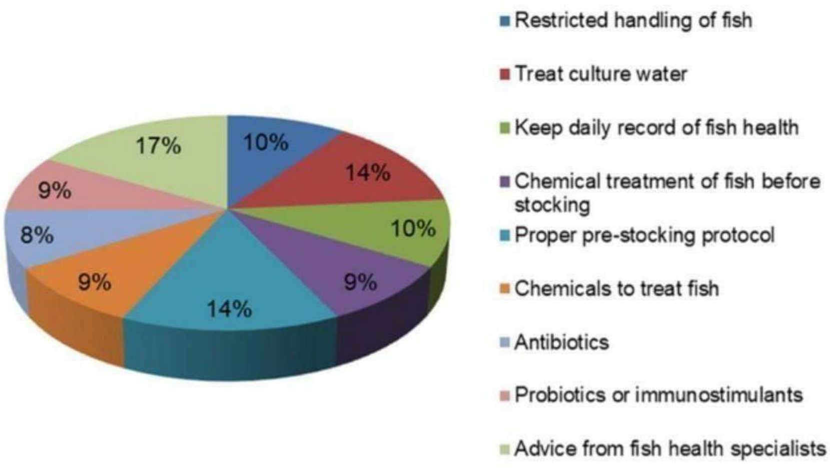

Figure 1: Practical ways to control fish disease

Additionally, the integration of Internet of Things (IoT) devices and smart sensors with AI frameworks has enabled real-time data acquisition from underwater environments. These advancements allow consistent monitoring of water quality, fish behaviour, and disease prevalence with reduced human intervention. The combination of AI, IoT, and computer vision has not only enhanced operational efficiency but also contributed to environmental preservation by promoting sustainable farming practices. Consequently, intelligent automation in aquaculture stands as a cornerstone for ensuring food security, economic growth, and ecological balance in modern aquatic ecosystems.

2. Literature Survey

Haddad, Mihaira H., et al. [6] proposed a Convolutional Neural Network (CNN)-based model for precise detection of fish diseases in aquaculture environments. The methodology incorporated image preprocessing through histogram equalization to enhance feature clarity, followed by convolutional layers for spatial feature extraction. A rectified linear unit activation function was used to introduce non-linearity and improve convergence. The system employed max-pooling layers to minimize dimensionality while preserving essential disease features. Fully connected layers performed classification of multiple fish disease categories based on learned patterns. A SoftMax layer generated probabilistic outputs for final disease identification. However, the model required a large, annotated dataset to maintain classification accuracy, which limited its adaptability to unseen species and rare disease conditions. Pati, Natasha, et al. [7] developed an Explainable Artificial Intelligence (XAI)-based fish disease detection framework that integrated multi-feature extraction across diverse color spaces. The system utilized Red-Green-Blue (RGB), Hue-Saturation-Value (HSV), and CIELAB color domains to capture complementary spatial and chromatic characteristics of diseased regions. A combination of texture descriptors and edge-based segmentation enhanced the precision of lesion localization. The extracted multi-domain features were fused using a weighted aggregation mechanism to improve the classifier's discriminative capacity. Gradient-weighted Class Activation Mapping (Grad-CAM) visualization ensured interpretability of decisions. Nevertheless, the computational complexity of multi-space feature extraction led to extended training durations and limited real-time applicability. Kumar, Saravana, et al. [8] proposed a pseudo-Hamiltonian Neural Network optimized using the Philippine Eagle Optimization Algorithm (PEOA) for intelligent detection of aquaculture fish diseases. The pseudo-Hamiltonian network structure modeled nonlinear relationships between disease parameters with high accuracy. The PEOA optimization improved network parameter tuning and prevented local minima entrapment. The system integrated spectral-spatial features to strengthen decision boundaries between healthy and infected samples. Adaptive learning rates enhanced convergence efficiency, while dropout regularization minimized overfitting. The experimental validation on aquaculture datasets demonstrated robust classification under diverse aquatic conditions. However, the algorithm exhibited sensitivity to initial hyperparameter settings, requiring extensive tuning for consistent outcomes.

Rao, Podeti Koteshwar [9] introduced an Artificial Intelligence (AI) and Machine Learning (ML)-based framework for detecting fungal diseases in freshwater fish. The proposed model utilized advanced feature extraction from digital microscopic images to isolate fungal infection patterns. A supervised ML pipeline, incorporating Decision Tree and Support Vector Machine classifiers, performed disease categorization based on morphological and texture attributes. Image normalization and enhancement techniques ensured noise reduction and uniform lighting conditions. A hybrid ensemble fusion improved classification accuracy across multiple disease types. Despite its effectiveness, the framework lacked adaptability for cross-domain datasets and required manual intervention for dataset labeling. Ergün, Ebru [10] proposed SwinFishNet, a Swin Transformer-based approach for automatic classification of fish species through transfer learning. The methodology employed hierarchical vision transformers that segmented input images into non-overlapping patches to capture local and global dependencies efficiently. A pre-trained backbone on large-scale datasets accelerated model convergence and improved generalization. Positional encoding facilitated spatial awareness across multi-level transformer blocks. Fine-tuning of dense layers enabled domain-specific learning for fish species differentiation. Layer normalization and dropout mechanisms-maintained model stability during training. However, the system's heavy dependency on computational resources limited its deployment in resource-constrained aquaculture monitoring systems.

Nawaz, Umair, et al. [11] conducted a comprehensive survey on the applications of Artificial Intelligence (AI) and Deep Learning (DL) in agriculture, focusing on crops, fisheries, and livestock. The study systematically reviewed convolutional, recurrent, and transformer-based models used for yield prediction, disease diagnosis, and species identification in aquaculture. A taxonomy of existing DL architectures was presented, categorizing them by application type and data modality, including image, sensor, and spectral data. The research emphasized the importance of transfer learning and data augmentation for domain adaptation in fisheries. Furthermore, it explored the integration of Internet of Things (IoT) sensors and AI models for precision aquaculture management. However, the authors identified that limited annotated datasets and lack of model generalization remained key challenges in scaling AI solutions across different agricultural sectors. Bhuria, Ruchika [12] proposed a fine-tuned Residual Network-50 (ResNet50) model for precision fish disease detection and sustainable aquaculture health management. The methodology began with pre-processing underwater fish images using histogram equalization and Gaussian filtering to enhance visibility and reduce noise. The ResNet50 backbone was fine-tuned with modified residual blocks to adapt to domain-specific disease features. Data augmentation through rotation and reflection expanded dataset diversity to prevent overfitting. The final classification layer utilized SoftMax activation for multi-class disease prediction. The system demonstrated strong performance in early disease identification under varying water clarity. Nonetheless, its dependency on transfer learning made it less efficient for species not represented in the pre-trained dataset. Wang, Duanrui, et al. [13] developed an improved You Only Look Once version 10 (YOLOv10) model for real-time underwater fish skin health detection and identification. The proposed framework introduced adaptive anchor box scaling and an enhanced backbone structure with cross-

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stage partial connections for efficient feature reuse. A multi-scale attention mechanism refined detection accuracy under complex lighting and motion conditions. Real-time inference was achieved through optimized network pruning and mixed-precision training. The system effectively identified lesions, infections, and abnormalities on fish skin surfaces. However, despite its real-time capability, the model exhibited reduced accuracy when applied to low-resolution or occluded image samples. Peries, R. F. S., et al. [14] presented an AI-driven solution for automated fish freshness classification using Convolutional Neural Network (CNN) architectures. The method utilized image datasets capturing fish under various freshness stages, processed through contrast normalization and color channel decomposition. Multiple CNN models, including VGG16 and DenseNet variants, were tested, and the most optimal configuration was selected based on accuracy and inference time. The system leveraged layer-wise feature extraction to identify subtle color and texture variations indicating spoilage. A SoftMax classifier provided freshness grading across predefined categories. Despite achieving high accuracy, the framework was constrained by its requirement for controlled lighting during data acquisition.

4. Proposed System

The flowchart illustrates the pipeline for an AI-powered fish disease classification system as shown in Figure. 2. It begins with collecting a fish disease dataset, followed by preprocessing and splitting it into training and testing sets. Features are extracted using the VGG19 model, and a Bagging- Random Forest classifier is applied for classification. The system outputs the fish disease type and evaluates performance. Additionally, the system accepts a test input image directly, extracts its features, classifies the disease, and provides suitable medicine suggestions accordingly.

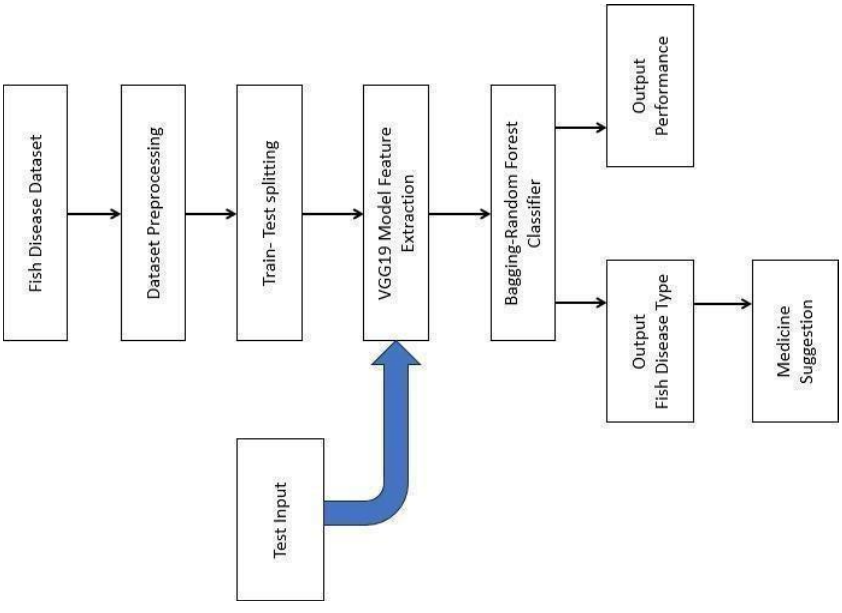

Figure 2: Proposed System Architecture

Fish Disease Dataset: This initial step collects the raw visual data used to train and evaluate the system: labeled fish images covering healthy specimens and multiple disease categories (e.g., Argulus, Redspot, EUS, Tail & Fin Rot). The dataset should include varied lighting, viewpoints, and water conditions to reflect real aquaculture environments. Good practice is to store metadata (species, capture conditions, timestamps) and maintain balanced class representation or plan for later balancing.

Dataset Preprocessing: Raw images are normalized and cleaned to improve downstream learning. Typical preprocessing uses OpenCV and scikit-image to resize images to the VGG19 input size, correct color space, apply histogram equalization/contrast enhancement, denoise (median/Gaussian filters), and remove background clutter when possible. Additional steps include data augmentation (rotation, flipping, cropping, brightness jitter) to increase robustness against turbidity and lighting variability and to mitiate overfitting.

Train–Test Splitting: The preprocessed dataset is partitioned into training, validation (optional), and testing subsets—commonly 70–80% for training and the remainder for testing/validation. Splitting should be stratified by class to preserve label distribution. This separation ensures that model evaluation reflects generalization to unseen fish images and prevents information leakage during feature extraction and classifier training.

VGG19 Model Feature Extraction: A pretrained VGG19 convolutional neural network (transfer learning) processes images to extract hierarchical visual features. Early layers capture low-level cues (edges, color gradients); deeper layers encode disease-specific patterns (lesions, fin deformities, discoloration). The network can be used as a fixed feature extractor (freeze convolutional weights) or fine-tuned on domain images. The result is a vector representation for each image that compactly encodes discriminative visual information.

Bagging – Random Forest Classifier: Extracted VGG19 feature vectors become inputs to an ensemble Random Forest Classifier trained with bagging. Bagging trains many decision trees on bootstrap samples and aggregates their outputs, improving robustness and reducing variance versus a single tree. Using RFC on learned deep features combines the representational power of CNNs with the interpretability and ensemble stability of tree-based models, helping reduce overfitting and improving multi-class discrimination.

Test Input (Inference Flow): At runtime, a new (test) image follows the same preprocessing pipeline, then flows into the VGG19 feature extractor to produce a feature vector. That vector is fed to the trained Random Forest ensemble, which outputs predicted class probabilities or a hard label. The diagram's blue arrow emphasizes that the inference path mirrors the training pipeline, ensuring consistent preprocessing and feature extraction.

Output — Fish Disease Type: The primary system output is the predicted disease label (or "healthy") for the input fish image. If the RFC returns class probabilities, the system can present the top-k predictions with confidence scores to help aquaculture managers judge borderline cases. This label can trigger alerts or logging for traceability in large farms.

Output — Performance: Alongside predictions, the system records evaluation metrics computed on the test set and optionally on batches of operational data. Displaying or logging these performance indicators helps monitor model drift and identify classes needing more data or retraining—crucial for maintaining reliability in changing pond conditions.

Medicine Suggestion: Once a disease is identified, the pipeline can map the predicted disease to recommended treatment actions or medicinal suggestions (standardized interventions, quarantine advice, or referral to veterinary diagnostics). This module should present recommendations carefully—ideally as guidance rather than prescriptions—and include confidence thresholds or an option to consult an expert when confidence is low.

3.1 VGG 19 Feature Extraction

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The VGG19 architecture as shown in Figure 3, developed by the Visual Geometry Group at the University of Oxford, is a deep convolutional neural network composed of 19 weighted layers (16 convolutional, 3 fully connected). When applied to fish disease feature extraction as shown in Figure 3, the network systematically learns hierarchical representations of fish images—ranging from low-level texture details to high-level disease-specific patterns such as lesions, color changes, or fin degradation. The model's simplicity and uniform layer design make it particularly effective in identifying subtle visual cues in underwater images where lighting, clarity, and color distortions often complicate manual observation.

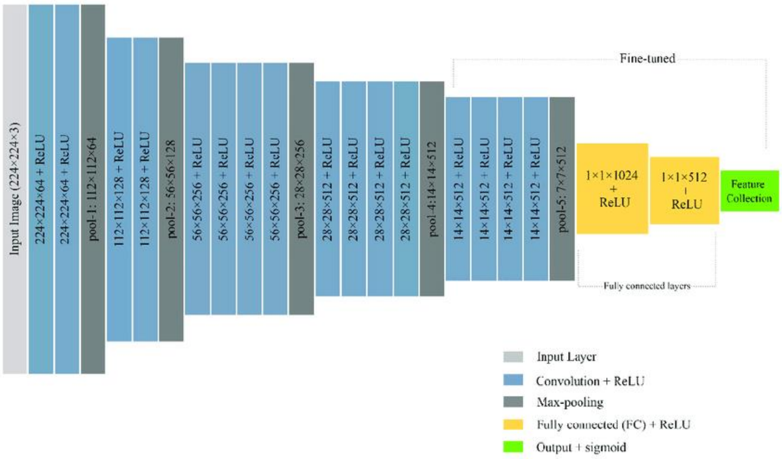

Figure 3: VGG 19 CNN Model

4. Results and Discussion

Figure 4 presents the confusion matrix of the proposed VGG19 with RFC model, demonstrating highly accurate and consistent classification performance across all fish disease categories. The model correctly classified all 55 Argulus samples, achieving a perfect match without any misclassification. Similarly, it accurately identified all 14 samples of Broken Antennae and Rostrum, and achieved full precision for 48 EUS samples with no errors. The model also performed exceptionally well for Healthy Fish, correctly predicting 57 samples, and for Redspot, accurately classifying all 72 instances. Tail and Fin Rot showed only a single misclassification, where 1 sample was incorrectly labeled, while 24 samples were correctly classified. The classifier also achieved complete accuracy for The Bacterial Gill Rot, correctly predicting all 18 samples. Further, the strong diagonal dominance in the confusion matrix highlights the effectiveness of the VGG19–RFC hybrid framework, demonstrating superior discriminative capability and near-perfect prediction accuracy as shown in Figure 6.9 across multiple disease types, with only one minor misclassification recorded in the entire dataset.

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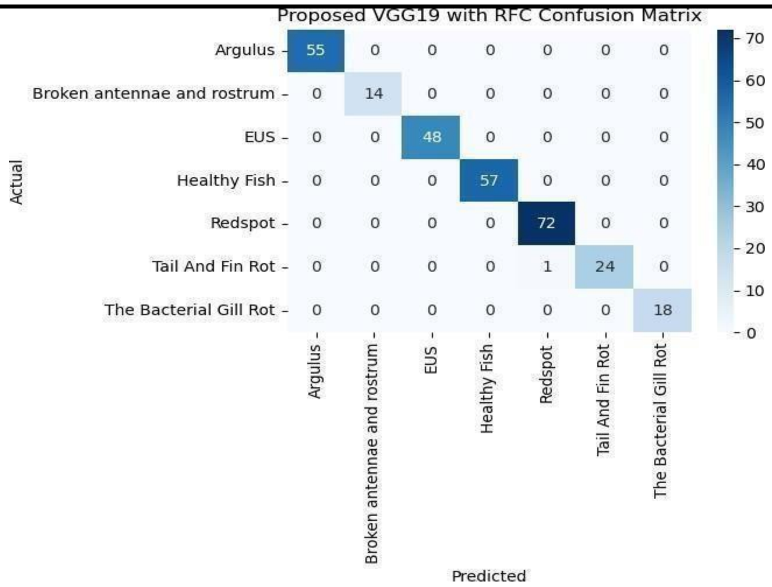

Figure 4: Proposed VGG19 with RFC Confusion Matrix

Figure 5 illustrates the predicted output results generated by the AI-enabled fish disease classification system for different fish health conditions. The system successfully identifies and classifies multiple disease categories including Argulus, Broken Antennae and Rostrum, Healthy Fish, and Redspot based on the uploaded fish image samples. For each test image, the classification interface displays the detected disease label along with the corresponding medicine or pesticide recommendation generated by the trained prediction model. The results demonstrate that the system can effectively distinguish between infected and healthy fish conditions by analyzing visible symptoms present on the fish body surface. The graphical interface also provides a user-friendly environment for image uploading, disease prediction, and treatment recommendation, making the system suitable for practical aquaculture monitoring applications. The predicted outputs validate the effectiveness of the intelligent classification framework in supporting rapid disease identification, reducing manual inspection effort, and assisting fish farmers in taking timely preventive and treatment measures for improved aquaculture management.

(a) Argulus

(b) Broken Antennae and Rostrum

(c) Healthy Fish

(d) Redspot

Figure 5: Predicted Output images

4.1 Comparative Analysis

The performance comparison table presented in table 1, where Logistic Regression Classifier (LRC), Naïve Bayes Classifier (NBC), and the proposed VGG19 with RFC—was compared. LRC achieved 77.51% accuracy, showing balanced metrics but struggled with "Broken Antennae and Rostrum" and "Argulus." NBC had a slightly lower accuracy of 74.05%, excelling in "Broken Antennae and Rostrum" but underperforming in other categories. The VGG19 with RFC model achieved a perfect 100% accuracy to capture complex patterns for fish disease classification.

Table 1. Performance Comparison Table

Model	Accuracy	Precision	Recall	F1 Score
Existing LRC	0.7751	0.7750	0.7751	0.7720
Existing NBC	0.7405	0.7463	0.7405	0.7398
Proposed VGG19 With RFC	1.0000	1.0000	1.0000	1.0000

5. Conclusion

This research introduces an AI-powered automatic fish disease classification and medicine suggestion system, integrating deep learning and machine learning techniques to enhance smart aquaculture. Leveraging VGG19-based feature extraction, the system generates meaningful representations from fish images and employs multiple classifiers, including LRC, NBC, and RFC, to accurately classify various fish diseases. The incorporation of RFC with AME loss optimization significantly improves prediction accuracy while reducing misclassification errors. Designed with a user-friendly GUI built using Tkinter, the system enables both administrators and end- users to efficiently manage datasets, train models, and perform real-time disease classification. Administrative functionalities include dataset processing, feature extraction, and model training, whereas user functionalities facilitate instant image classification and medicine recommendations, while visualizing results through confusion matrices for better interpretability. By automating disease detection and treatment suggestions, this system minimizes reliance on expert fish pathologists, enabling early disease identification and preventive actions in aquaculture. Ultimately, it helps in reducing economic losses, improving fish health, and promoting sustainable fish farming practices, making it a valuable tool for modern aquaculture management.

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