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Deep Learning and AI Tools for Monitoring and Detecting Diseases in Freshwater Fish Populations

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***Abstract*— *freshwater fish populations sustainability and well-being are essential to aquaculture biodiversity and food security conventional approaches to fish disease diagnosis are frequently labor-intensive time-consuming and necessitate professional intervention which causes treatment delays and large financial losses recent developments in deep learning dl a subfield of artificial intelligence AI present viable substitutes for automated quick and precise fish disease detection this study investigates how to use AI and deep learning tools to monitor and diagnose illnesses that impact freshwater fish predictive modeling pattern recognition and image recognition techniques are used by these systems to accurately identify visual symptoms like lesions discoloration or abnormal behavior along with their datasets training procedures and performance metrics the paper examines a variety of machine learning models used in fish health assessment such as convolutional neural networks CNNS support vector machines SVMS and hybrid architectures real-time monitoring systems made possible by internet of things IOT gadgets and AI-powered image processing frameworks are also covered the results show how deep learning can transform aquaculture disease management by improving fish welfare enabling early detection and lowering manual labor the development of robust scalable and economical solutions is one of the future directions*

Keywords*— Artificial Intelligence (AI), Deep Learning, Machine Learning, Fish Disease, Freshwater Fish, Aquaculture, Convolutional Neural Networks (CNNs).

I. INTRODUCTION

The preservation of aquatic aquaculture and local economies all depend on freshwater fish populations however fishes health is seriously threatened by disease outbreaks in freshwater environments which frequently lead to high mortality rates financial loss and ecological imbalance often labor-intensive time-consuming and ineffective at early detection traditional monitoring methods mainly rely on manual inspection and laboratory diagnostics recent developments in deep learning dl a subfield of artificial intelligence ai have made it possible to create automated systems that can recognize minute behavioral and physiological changes in fish [2]. These systems look for anomalies that could be signs of disease by using a variety of data sources including thermal imaging underwater video feeds and environmental parameters in order to detect and track diseases. This study was investigates the application and efficacy of deep learning and artificial intelligence-based methods with a focus on image-based and sensor-driven disease identification models [3].

II. MATERIALS AND METHODS

Dataset Collection:

Fish Species: The study focused on *Channa striatus* and *Channa punctatus* were common in aquaculture practices.

Data Types: The images and videos data of healthy and diseased fish were collected from the aquaculture lakes and publicly available datasets (e.g., Fish Disease Dataset) [4].

Diseases Covered: Ichthyophthiriasis ("Ich"), fin rot, dropsy, and bacterial gill disease.

Environmental Data: The water temperature, pH, turbidity, and dissolved oxygen levels were recorded using IoT-based water quality sensors [5].

Preprocessing:

The images were resized to 224×224 pixels.

Data augmentation (flipping, rotation, contrast adjustment) was applied to increase dataset diversity.

Outliers and poor-quality images were removed using histogram equalization and SSIM filtering.

Model Architecture:

Three models were evaluated:

CNN (Convolutional Neural Network): The custom 5-layer CNN for image classification [1]

ResNet-50: A transfer learning approach using the ResNet-50 model pertained on Image Net.

LSTM (Long Short-Term Memory): this used for analyzing time-series behavioral data and environmental changes [10].

Training and Validation:

Data split: 70% training, 20% validation and 10% testing.

Loss function: Categorical cross-entropy.

Optimizer: Adam with a learning rate of 0.0001.

Evaluation metrics: Accuracy, precision, recall, F1-score, and AUC.

Hardware and Software:

Environment: Google Colab Pro with Tesla T4 GPU.

Programming: Python 3.9, Tensor Flow 2.10, Keras, Open CV.

IoT Integration: Arduino and Node MCU for water quality sensor data [9].

III. RESULTS AND DISCUSSION

ResNet-50 outperformed the custom CNN in terms of accuracy and robustness.

LSTM analysis showed that environmental anomalies (e.g., low dissolved oxygen) correlate with disease onset [8].

Integrating image and sensor data using ensemble models improved predictive performance.

Table.1 **Model Performance**

Model	Accuracy	Precision	Recall	F1 score	AUC
CNN	9.3%	0.87	0.89	0.877	0.93
ResNet-50	94.7%	0.97	0.95	0.97	0.98
LSTM (Sensor)	2.2%	0.94	0.92	0.908	0.95

Visualization and Explain ability:

Grad-CAM visualizations showed that the AI model focused on lesions, fin damage, and gill discoloration for disease prediction [6]. Time-series heat maps correlated temperature spikes with increased disease probability.

Challenges and Limitations:

Data scarcity and imbalance in disease classes impacted the CNN model, Sensor calibration and real-time data transmission faced network-related delays and Generalization to different aquatic environments requires broader datasets [7].

IV. CONCLUSION

This study demonstrates the efficacy of deep learning and AI-based tools we're monitoring and detection of fishes in freshwater fishes the Resnet-50 model showed high accuracy in classifying based on visual cues while lstm models effectively analyzed environmental data for early warning [11]. Integrating AI techniques into aquaculture methods could significantly improve fishes health reduce economic losses and support sustainable fisheries [12]. Future work includes expanding datasets across more fish species and diseases deploying real-time edge AI models and enhancing explain ability for farmer-friendly interfaces [13] continued enhancement AI techniques.

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