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Smart Aquaculture: A Real-Time Fish Disease Detection System

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Abstract: *The role of aquaculture in food security holds a large number and supports the economic value of the country, but fish disease detection is a complex task in present times and requires a huge amount of continuous monitoring. If fish diseases are not detected at an early stage, they can spread throughout the fish farm, which leads to heavy losses for farm owners, especially in large or remote farms where detecting or identifying diseases in fishes completely depends upon manual work and may not result in good accuracy. To overcome these limitations, this research paper proposes a smart aquaculture system for real-time fish disease detection using computer vision and deep learning along with Raspberry Pi integrated with a camera module, where a YOLO model is used for automatic detection of diseases such as fin damage and EUS. When a disease is detected, the system automatically sends an alert to the farm owner through notifications and activates a buzzer and displays the information on a display unit, which helps farmers take quick action and reduces disease-related losses.*

Key Words: *Smart aquaculture, fish disease detection, deep learning, YOLO, computer vision.*

I. INTRODUCTION

Aquaculture in present life is one of the fast-growing sectors and supports the economic value of the country by providing large-scale employment [1]. Aquaculture is increasing day by day, producing food items like fish and some seafood, which are rich in protein and nutrition and support food security and international trade through export and import activities [2], [3]. However, nowadays aquaculture is facing many problems such as improper maintenance of farm water, water levels, temperature, and sudden changes in water pH levels, which bring a lot of fish diseases and cause major damage in aqua life, especially when high-cost fish breeds are affected [4], [5]. If a small disease occurs in one fish, it rapidly spreads to the entire fish farm, causing heavy losses [8]. Traditional fish disease detection depends on manual observation or laboratory-based diagnosis, which are time-taking processes and may not result in good accuracy, making them unsuitable for large or remote fish farms [9], [10]. Implementing artificial intelligence in aquaculture reduces losses and human monitoring farms throughout the day [11]. With the help of deep learning models like YOLO and IoT technology, fish diseases can be identified without manual involvement [12]. In this work, a smart fish disease detection system called "Smart Aquaculture" is proposed using deep learning and IoT technology with Raspberry Pi, which monitors fishes in real time, detects diseases at early stages, and delivers quick alerts to farmers through cloud communication and local indicators, helping to minimize economic losses and support sustainable aquaculture practices.

II. LITERATURE SURVEY

The previous researches on fish disease are based on traditional image processing and machine learning methods [1], [8]. Malik et al. employed image preprocessing, edge detection, feature extraction using HOG and FAST descriptors, and PCA-based classification to detect Epizootic Ulcerative Syndrome (EUS) in fish [1]. This methodology generated reasonable accuracy, but they are limited to single disease identification and no live monitoring. Later studies used clustering-based segmentation techniques to upgrade disease localization. Sikder et al. proposed a fish disease detection system using k-means and fuzzy C-means clustering combined along with texture features and multi-class SVM classification [8]. The output of the system showed acceptable accuracy on fish datasets, but this system did not address real-time deployment in functional fish farms.

A deep learning model, CNN (Convolutional Neural Networks), was used by Waleed et al., who explored CNN-based classification using multiple color spaces to spot fish diseases in aquaculture [4]. Their work showed better performance compared with traditional methods; the system works with only a small number of disease classes and was not suitable for deployment. Recent studies adopted transfer learning and ensemble strategies to generate high accuracy. Biswas et al. An ensemble-based framework for fish disease detection was introduced, which integrates features extracted from multiple pre-trained convolutional neural network (CNN) models and employs a Support Vector Machine (SVM) classifier to make the final prediction. This approach showed very high classification accuracy on selected datasets, but performance depends on large labeled datasets.

Object detection methodologies were developed to permit live tracking. YOLO-based models were used to track physical disease symptoms directly from fish images and videos, offering faster detection compared to classification-based CNN models. However, many YOLO-based solutions focus on offline analysis or require complex hardware resources and high cost, and they are not integrated with alert mechanisms or real-time deployment. Overall, existing literature discusses automated fish disease detection using image processing and deep learning. Many challenges in these approaches include restricted disease coverage, no live tracking, high computational needs, lack of deployment, and no real-time alerting.

III. PROPOSED METHODOLOGY

The developed system consists of computer vision, deep learning, and embedded hardware for live detection of fish diseases, enabling continuous monitoring, automated disease recognition, and quick automatic alert generation. Figure 1 presents the complete workflow of the smart aquaculture real-time fish disease detection system. The process starts with fish image capturing using a Pi/USB camera, where the camera continuously observes fishes. Disease-affected fish undergo data preprocessing, where frames are resized and normalized to fulfill the input requirements of the deep learning model, and performing these steps helps in increasing the detection rate.

The hardware and image recording are constructed using a Raspberry Pi setup. An SD card is inserted into the Raspberry Pi for storage, while regulated power is supplied for functioning. The Raspberry Pi acts as the central processing unit and has built-in Wi-Fi connectivity, which supports communication with cloud services.

Once the disease is identified, the system starts the alert mechanism. The local alert system uses a 16×2 LCD display and a buzzer connected to the Raspberry Pi to produce alert sounds and enable aqua farmers to take required precautions. A cloud-based alert system uses Telegram to send alerts through a bot integrated to deliver notifications. Overall, the detected information enables monitoring and is managed by farmers to take decisions at the right time. Automation of disease tracking and alert generating systems reduces manual checks, shortens response time, and supports operations of all scales.

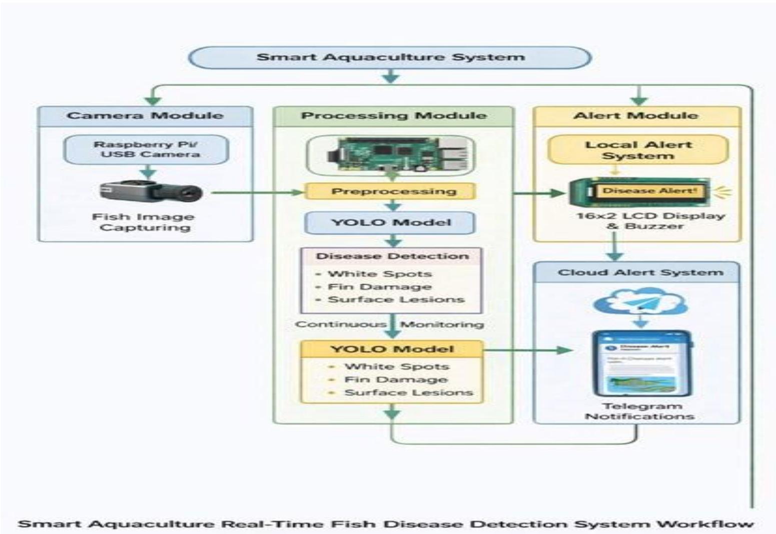

Fig-1: Workflow of YOLO-based fish disease detection

A. YOLO Architecture

YOLO performs single-stage object detection, enabling fast and accurate tracking of fish diseases such as lymphocystis fin damage, and bronchitis. The model intakes each frame and outputs disease class labels along with bounding boxes.

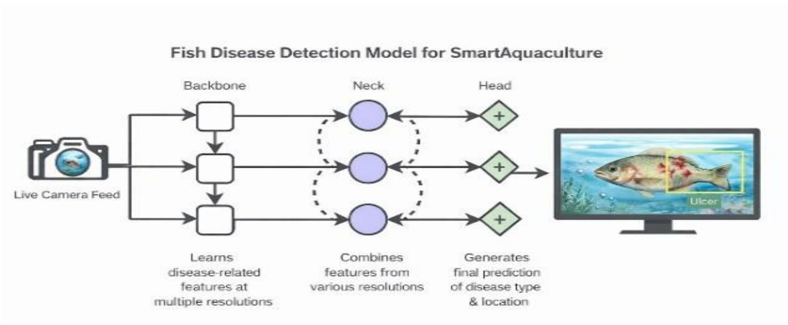

Fig-1: YOLO-based Smart Aquaculture fish disease detection architecture.

In our **Smart Aquaculture fish disease detection model**, the YOLO architecture is used in three main parts: **1) Backbone, 2) Neck, and 3) Head**. The **backbone** learns important visual patterns from the live camera image of fish, such as skin texture, color changes, spots, wounds, fin damage, and ulcer-like regions. It extracts features at different sizes so the model can understand both the full fish body and small disease symptoms. The **neck** combines the features coming from multiple resolutions and connects them, so disease signs are not missed even when they are small or appear in different positions on the fish. This helps the system detect symptoms on small fish, medium fish, or large fish, and also works better when the fish is moving in water. The head gives the final output by predicting the disease type (class) and the exact infected area location (bounding box) on the fish. After detection, the system triggers the SmartAquaculture pipeline, where the detected disease result is shown on the display and an alert is sent to the farmer through the cloud/notification, along with local indicators like buzzer, supporting real-time monitoring and early action.

IV. RESULTS

The smart aquaculture fish disease detection system was tested using fish images captured through a Pi/USB camera. The camera continuously monitored the fishes in the fish farm. When a fish was affected by disease, the system detected the disease automatically using the YOLO model without any manual checking.

The system detected fish diseases in real time. After the image was captured, disease detection happened immediately, which helped in identifying diseases at early stages. Compared to manual observation, this system worked faster and reduced human effort.

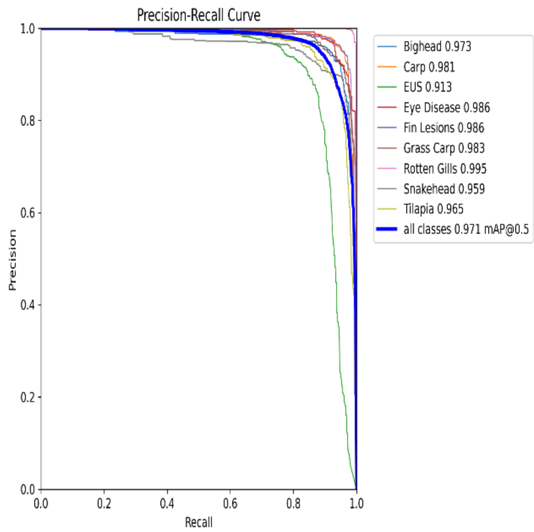

Fig-1: Precision-Recall curve

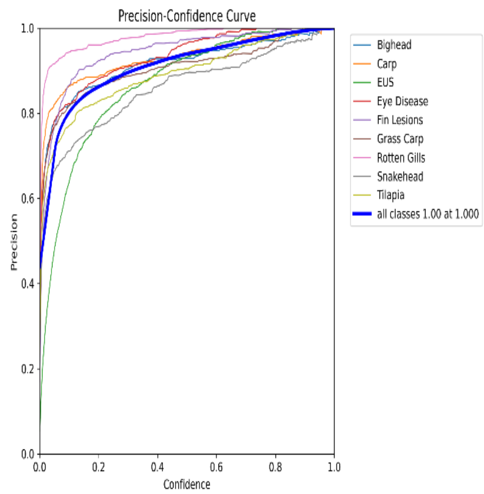

Fig 2: Precision-Confidence curve

In Fig 2 the Precision–Confidence curve indicates that precision steadily increases as the confidence threshold goes up, so it produces fewer false positives when it is more certain about its predictions.

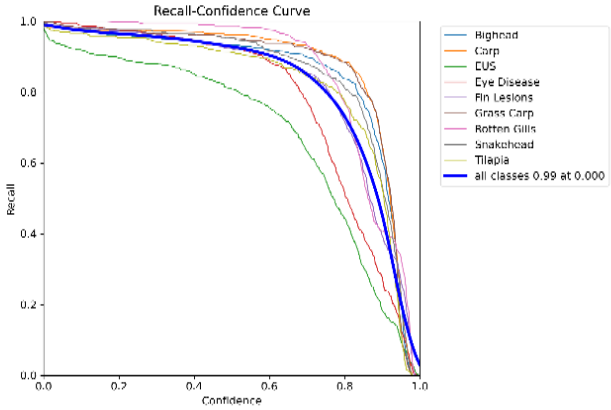

Fig 3: Recall-Confidence curve

In Fig 3 as expected, the Recall–Confidence curve drops as confidence increases. This reflects the usual trade-off: when the model becomes stricter about what it accepts as a detection, it misses a few more true cases, so recall goes down.

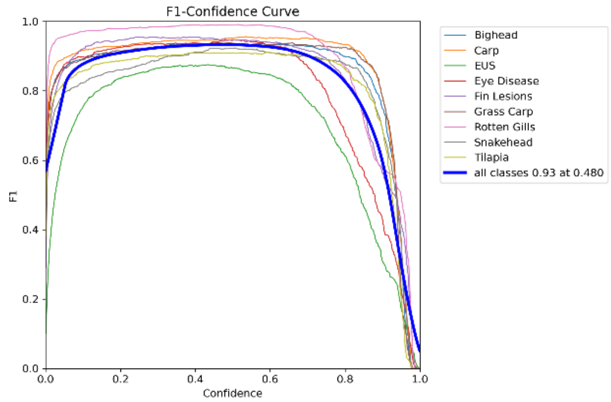

Fig 4: F1 Confidence Curve

In Fig 4 the F1–Confidence curve reaches its peak value of 0.93 at around a 0.52 confidence threshold, which shows a good balance between precision and recall and is therefore a strong candidate for real-time deployment.

The normalized confusion matrix shows strong values along the diagonal, indicating a high rate of correct classifications for each class, with relatively few misclassifications.

Overall, the results indicate that the model is suitable Figure 4.5 shows the disease detection output of the proposed system, where fish diseases such as red spots and fin damage are identified using bounding boxes. This visual output clearly represents how the system highlights the disease-affected regions on the fish body during real-time monitoring.

When a disease was detected, the alert system worked properly. The buzzer was activated, and the disease information was displayed on the LCD display. At the same time, alert messages were sent to the farmer through Telegram. This helped the farmer to know the problem immediately and take action. These results show that the proposed system works effectively for real-time fish disease detection and is suitable for smart aquaculture applications

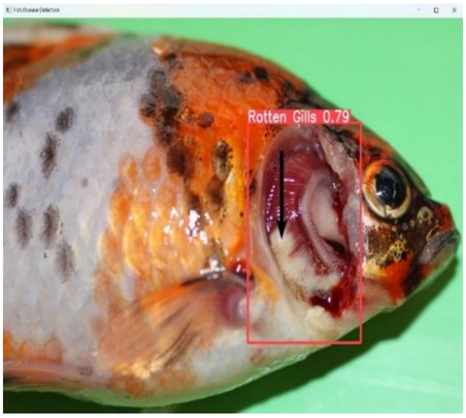

Fig 5: Fish disease detection output generated by the proposed smart aquaculture system using YOLO

A. Comparison of Existing Methods and Proposed Method for Fish Disease Detection:

The comparison table shows the accuracy metrics of existing fish disease detection methods and the accuracy achieved by the proposed project. It clearly highlights the performance improvement of the proposed Smart Aquaculture system compared to earlier approaches.

Paper Title	Approach Used	Performance Metric
Image Processing Techniques for Identification of Fish Disease (2017)	Machine Learning	Accuracy = 86%
Fish Disease Detection System: A Case Study of Freshwater Fishes of Bangladesh (2021)	Machine Learning	Accuracy = 97.90%
Detection of Fish Disease Using Machine Learning Techniques (2021)	Machine Learning	Accuracy = 94.12%
Fish Type & Disease Classification Using Customized CNN with ResNet-50 (2024)	Deep Learning	Accuracy = 87.46%
Smart Aqua Culture: Real time fish disease detection system, (Our Proposed Method)	Deep Learning	mAP@0.5 = 97%

Comparision Table

V.DISCUSSION

From the results, it is clear that the proposed smart aquaculture system works properly for fish disease detection. The system was able to detect fish diseases automatically using the YOLO model. Compared to old methods like manual observation, this system reduced human work and saved time.

The output images clearly show the detected diseases using bounding boxes. Along with this, the alert system also worked correctly. When a disease was detected, the buzzer and LCD display gave alerts, and Telegram notifications were sent to the farmer. This helped the farmer to know the problem immediately and take action without delay. Overall, the proposed system supports continuous monitoring in fish farms. It helps in early disease detection and prevents the disease from spreading to other fishes. This system is useful for smart aquaculture and helps in reducing losses in fish farming. Analytical accuracy is decreased while the excellent of scientific records is imperfect. Also, nearby diseases have a few particular traits in special regions, which could weaken the prediction of disease outbreaks. But existing works are in particular structured to recall data. There are not any suitable methods for processing semi-established and unstructured records. The machine can have the cause of accounting for each structured and unstructured records. Analysis accuracy is increased by way of deep mastering algorithms.

VI.CONCLUSION

The smart aquaculture fish disease detection system was developed to monitor fishes in real time. The system used a camera and Raspberry Pi to capture fish images and detect diseases automatically using the YOLO model. This helped in identifying fish diseases without manual checking.

The system worked continuously and detected diseases at early stages. Compared to old methods like manual observation, this system saved time and reduced human effort. The alert system also worked properly by giving alerts through buzzer, LCD display, and Telegram messages.

Overall, the proposed system is useful for fish farms. It helps farmers to take action quickly and prevent disease spread. This system supports smart aquaculture and can be used for real-time fish disease detection.

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