YOLO-Based Fish Disease Detection: A Smart Lifeline for Aquaculture Farmers.

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FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements forthe **Degree of Bachelor of Science in Computer Science and Engineering**

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January 06, 2026

APPROVAL

This Project titled "**YOLO-Based Fish Disease Detection: A Smart Lifeline for Aquaculture Farmers,** submitted by **Abdullah Al Hossain,** ID No. 221-15-6055 and **Anaf Fakir,** ID No. 221-15-4811, to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 06-01-2026.

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We hereby declare that this project has been done by us under the supervision of **Lamia Rukhsara, Sr. Lecturer**, Department of Computer Science and Engineering, Daffodil International University. We also declare that neither this projectnor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ACKNOWLEDGEMENTS

This work would not have been possible without the support and contributions of many individuals over the past two semesters. We are deeply grateful to everyone who has assisted us in one way or another.

First, we express our heartfelt thanks and gratefulness to the almighty for His divine blessing making it possible for us to complete the **Final Year Design Project (FYDP)** successfully.

We are grateful and wish our profound indebtedness to **Lamia Rukhsara**, **Sr. Lecturer**, Department of Computer Science and Engineering, Daffodil International University, Dhaka, Bangladesh. Deep knowledge and keen interest of our supervisor in the field of **Machine Learning and Computer Vision** to carry out this project. Her endless patience, scholarly guidance, continual encouragement, constant and energetic supervision, constructive criticism, valuable advice, reading many inferior drafts, and correcting themat all stages have made it possible to complete this project.

We would like to express our heartfelt gratitude to **Dr. Sheak Rashed Haider Noori, Professor and Head** of the Department of Computer Science and Engineering, for his kind help in finishing our project and also to other faculty members and the staff of the Department of Computer Science and Engineering, Daffodil International University.

We would like to thank our entire course-mates at Daffodil International University, who took part in this discussion while completing the coursework.

Finally, we must acknowledge with due respect the constant support and patience of our parents.

ABSTRACT

Despite the fact that fish is a major source of food production in the world, fish infections continue to threaten the productivity of farms, economic stability, and food security especially among countries such as Bangladesh that rely on fish farming as a major source of livelihood. Traditional methods of detecting disease make use of laboratory tests and physical inspection, which is tedious, inconsistent, and often inaccessible to small farmers. In order to address these limitations, this paper presents an automated deep learning-based system referred to as "YOLO-Based Fish Disease Detection: A Smart Lifeline to Aquaculture Farmers. A well chosen sample of 1,406 raw photos which were further augmented to 7,710 photos was collected and grouped into seven categories, including healthy and sick fish. This dataset was followed by training and evaluating a YOLO trained to permit the precise localization of bounding boxes and also identification of multiple classes in real-time. Experimental results prove that the model is suitable to be employed in practical farms, to achieve high detection accuracy and stable work in contrast to a different light and climatic conditions. It is an automated process of assisting aquaculture farmers in effective decision making, enhances prompt intervention of diseases and reduces the diagnostic delay significantly. The work propels technology-hackable aquaculture approaches and seals existing gaps in the current real-time monitoring of fish diseases through a simple AI-based solution and fast and accurate.

Table of Contents

List of Figures

List of Tables

Chapter 1

Introduction

This chapter provides a comprehensive introduction to the research, setting the foundation for the study. It discusses the motivation behind the research, its objectives, the adopted methodology, expected outcomes, and the structure of the report.

1.1 Introduction

One of the most significant sectors which contribute to the world food sources, including such countries as Bangladesh where the fish farming is needed in economic development, labor arsenal, and diet. Due to the increased demand of fish, farmers have resorted to intensive method of fish farming thus unintentionally providing conditions under which fish disease are able to proliferate. These infections are bacterial, viral, fungal and parasitic in nature and result in colossal losses in an annual basis due to the reduction in the health of the fish, reduction in the rate of production and the escalation of mortality. Thus, sustainable practices in aquaculture are of great importance. Conventionally, fish disease have been determined by laboratory testing or manual observation. Nevertheless, these processes are often time consuming, expensive and require the availability of experts. In rural areas, farmers are often deprived of qualified specialists, and the diagnosis and massive outbreaks take place. Further, physical inspection is prejudiced with ease and cannot withstand low light, dirty waters, or subtle indications. Such restrictions imply a burning necessity of a modern, automated, and dependable system of the detection of diseases. Regardless of advances in the field of aquaculture, no single, real time, automated system is in place that is capable of realistically determining different types of fish diseases using photographs especially in the natural farm settings. The disadvantages of the machine learning models that were previously used in previous studies include poor generalization, low robustness, slow processing speed, and inability to detect anything in real time.

Moreover, the previous studies are based on small datasets and restricted sets of diseases, as well as they use complex preprocess options which make them inappropriate to practical applications in the field. Due to this, farmers are yet to diagnose the infection early enough resulting in avoidable losses in their economies and lower yield of fish. The current project is a proposal titled Fish Disease Detection: A Smart Lifeline to the Farmer which involves an AI-based system interview to detect fish diseases at high speed, quality, and on the spot via a deep learning machine learning. The system tries to recognize seven classes of fish one being healthy, and six unhealthy categories based on captured pictures in real aquaculture environments using the advanced functionality of YOLO v11 which has good detection rates and finds objects effectively. This solution aims at helping the farmers make timely decisions, reduce the mortality rate, reduce unnecessary veterinary costs, and promote sustainable aquaculture practices.

1.2 Motivation

There is a dire need in the intelligent systems capable of supporting large-scale monitoring of fish health because of a rapid growth of aquaculture. The traditional methods such as physical inspection and laboratory diagnosis are no longer suitable to the modern-day aquaculture, as they are too slow, inconsistent and highly depend on human knowledge. The development of computational technologies creates high-potential means to address difficult image-based categorization tasks by means of deep learning and computer vision. Among the major driving factors behind this initiative is the utilization of these computing abilities to come up with a workable and highly scalable solution to the diagnosis of fish diseases. With the advance of such models as YOLO v11 that provides more opportunities in the real-time detection of objects, it is already possible to analyze fish photos within seconds, detecting them even in adverse environmental conditions. It is both a technical challenge and a social purpose to use such power of algorithms to solve real-life agricultural challenges. Sixty thousand disease detection systems with AI capabilities will allow us to grow our understanding in areas such as dataset engineering, image classification, deep learning structures, performance, and real-time implementations individually and professionally. The given project can be viewed as a chance to integrate the theoretical knowledge with the real-world challenge on the basis of reinforcing our skills in the machine learning, evaluation of the model, data processing, and practical AI implementation. Besides advancing the need to adopt sustainable means of aquaculture, addressing the problem will increase our information on state-of-the-art technologies which are highly valued in the contemporary job sector. With an efficient development and implementation of an intelligent detection model, we show our capability to come up with complete AI-driven solutions which would be a major proficiency in our future careers of data science, machine learning, and AI engineering.

1.3 Objectives

The purpose of this research is to attain specified targets that will make the project worthwhile. The major objectives are:

- ✓ The primary objective of this project.is delivering a fully operational, highly accurate YOLO v11-based fish disease detection system that can directly support aquaculture farmers in real-time health monitoring and disease management.
- ✓ To offer a real-time detection technology that enables farmers to rapidly monitor the health of fish. Farmer may quickly determine whether a fish is healthy or diseased by taking a picture using a camera or mobile device.
- ✓ To lower fish mortality by empowering farmers to detect diseases early on forecasting lowers financial losses and can stop widespread outbreaks.
- ✓ To lessen rely on costly laboratory testing and expert diagnosis. Remotes farmers

don't need to wait for experts to diagnose diseases.

- ✓ To assist farmers in making prompt, well-informed decisions in the event of a disease outbreak. Detection results can steer them toward suitable medicine, water treatment, or isolation methods.
- ✓ To provide ongoing monitoring to enable long-term sustainable aquaculture management. The method can be used periodically to track fish health trends across farms.
- ✓ To increase total fish production efficiency in order to contribute to national food security. Healthy fish populations promote better growth, higher productivity, and steady supply.

1.4 Methodology

The methodology of this study has a systematic procedure that is aimed at coming up with a working system of YOLO v11 to detect fish diseases. It starts with a generalized collection of 1,406 images of raw fish originating in various sources which are considered to be seven categories of healthy and disease fish. In order to enhance the generalization of the model and deal with the issue of heterogeneity among environment, a great deal of preprocessing was made including image loading, denoising, scaling, normalization, and contrast improvement using Colab techniques. To further expand the dataset and even the distribution of the classes, several augmentation measures would be taken to increase the dataset to 7,710 photos. The photos were subsequently tagged with Roboflow, whereby the bounding boxes were generated by each category of disease in a fish and exported as YOLO format. Once the dataset preparation was done, the experimental data was divided into 70 percent training, 20 percent testing and 10 percent validation sets. Finally, the YOLO v11 model was trained on the processed and annotated set and used to detect multi-class fish diseases. Results of the trained model included real-time predictions with bounding box localization once the model had been refined and evaluated based on popular metrics. The given methodology provides an effective and precise detection pipeline that can be used in aquaculture settings.

1.5 Project Outcome

Through the research, a successful development of a YOLO v11-based fish disease detection algorithm that can correctly detect seven issues of fish health in real time while maintaining its robust cameras was achieved. The model, which was trained on a larger dataset of 7,710 photos, shows excellent identification accuracy and also remains consistent regardless of the varying environmental and lighting conditions. The process can produce precise bounding boxes, while identifying disease directly on photos, and thus it is fast and effective as it distinguishes between healthy and unhealthy fish. Besides the trained model, the project also offered a complete data pipeline such as preprocessing, augmentation, annotation and good dataset division to train, validate and test. These elements allow retraining in a consistent manner, scalability, and long-term system improvement. Moreover, the technique has effective potential in being incorporated as a mobile application whereby farmers snap photos using a smartphone, and they would be provided with prompt disease predictions. This enhances the level of accessibility and ensures that farmers in remote areas can succeed on automated disease diagnosis without having to use expensive machinery or expert care. On the whole, the results of the current research prove to be more sustainable approaches to the field of aquacultures, efficient decision-making, preventing diseases early, and reducing the costs of diagnoses.

1.6 Organization of the Report

The six chapters that constitute this study give detailed development of the YOLO v11 based fish disease detection system.

Chapter 1 Introduction

This chapter presents an introduction of aquaculture and challenges posed by fish infections are provided. The description and background, creating the need of an automated detection system, are given. The chapter also discusses the research motivational factor, aim and methodological tool which is used in this project. It also describes the estimated outcome of the Yolo V11 based detection model and its contributions. It ends with a shallow description of the outline of the following chapters.

Chapter 2 Background

The theoretical foundations of fish diseases, the image-based approach to detection, and relevant ideas of deep learning are discussed in this chapter. The literature has been critically analyzed describing past research, their models, and their weaknesses. Essential systems that have been applied in aquaculture disease detection are also discussed in the chapter and their comparisons with modern ones are made. A stringent gap analysis gives a reason, as to why the methods used in the past cannot be used to detect in real time. This is the reason why a YOLO v11 based approach is needed.

Chapter 3 Research Methodology

The research questions will be clearly articulated. Chapter 4 will examine the methodology employed in the study.<|human|>Chapter 3 Research Methodology Chapter 3 Research Methodology Chapter 3 will define the research questions of the investigation and Chapter 4 will review the research methodology.

The overall process that was used in developing the detecting system is given in this chapter. The dataset collection, preprocessing, data augmentation and annotation steps are discussed. The YOLO v11 model and its training approach and assessment plan have been explained. These include system design diagrams and project job allocation, functional and non-functional requirements. The chapter wraps up with a conclusion of the experimental set up.

Chapter 4 Implementation and Results.

This chapter demonstrates the practice application of the system, the setting of the environment and training setup. It demonstrates the way the YOLO v11 model has been trained on the improved data set and optimized to perform correct detection. The results of experiments, evaluation criteria, and screen outputs are provided to prove the work of the system. When compared to previous research it shows accuracy and detection speed of increase. The chapter ends with a discussion on the results and implications thereof.

Chapter 5 Engineering Standards and Design Considerations.

This chapter explores the system engineering requirements involved when developing the system such as software, computational as well as data-handling standards. It encompasses also design barriers and remedies. Sustainability, ethical and environmental impacts of aquaculture and the use of AI are examined. Among them are such aspects of project management as cost estimation and schedule. These elements will ensure that the system is professionally technical in nature.

Chapter 6 Conclusion

In the chapter, the effectiveness of the YOLO v11 model is indicated in identifying fish disease as the results of the research are summarized. It discusses its benefits, including the real time detection facilitate and valuable benefits to the aquaculture growers. Weaknesses of the current implementation are established to bring a clear picture of areas that need to be improved. Other possible advancements that have been identified in the chapter include mobile application integration, expansion of datasets, and actual implementation in the farm. In general, it concludes with the contribution of this project to sustainable aquaculture.

Chapter 2
Background

This chapter outlines the theoretical foundation of the research, covering fish diseases in aquaculture, deep learning concepts, and existing work related to YOLO-based disease detection models. It sets the stage for understanding the proposed solution.

2.1 Introduction

This chapter provides the history to comprehend the relevance of automated fish disease detection and how it is connected to the modern advancements in the sphere of aquaculture and artificial intelligence. Fish farming is also an important factor in the global food production; particularly in such countries as Bangladesh where fish is the major source of food and income. But the fish in the aquaculture systems are extremely prone to bacterial, viral, fungus and parasite diseases. Such infections are often not mentioned by farmers in time, and they propagate rapidly in tanks and ponds. This leads to a decrease in productivity, which causes fish mortality and extreme economic losses on the part of the farmers. Fish growers might be in a rural or semi-urban area where specialists and advanced diagnostic facilities are not readily available. Diseases are often identified with the help of manual observation, which is slow, inaccurate, and prone to environmental factors such as light, clarity of water, or experience of the person who is conducting the observation. The spread of the disease is so calm that by the time it is too late to cure it because it is very difficult to detect it early. Still, due to the advancements in technologies, the artificial intelligence, and image recognition, in particular, has become a productive solution to a variety of agricultural industries. Such methods enable computers to scan photographs, identify characteristics and classify disease with great precision. Such AI-based systems can assess fish pictures in aquaculture and determine whether it is diseased or healthy. This approach can be very useful to farmers since it is fast, reliable, and it does not demand expert knowledge.

This section sets the guidelines of the rest of the report. It highlights the relevance of fish farming, the hardships of identifying fish infections, and how machine learning especially the YOLO model can address them. It provides the necessary background before proceeding to the technical techniques, system design and outcomes that would be discussed in the following chapters.

2.2 Literature Review

Nivin K. S. et al. [1] proposed a fish disease diagnosis system based on images using a CNN, Random Forest and KNN classifier. They took a set of fish photographs of ill and sick fish and preprocessed them to bring the important information and then they were classified. The hybrid machine learning strategy, according to their comparison research, performs quite well (87.32 accuracy), but it also fails to produce an accurate result in cases of different backgrounds and illumination.

M. Y. Ouis and M. Akhloufi [2] proposed a YOLO-based fish recognition system that will be used in underwater environments. To automatically detect fish in different types of underwater conditions, they used the YOLOv7 and YOLOv8 on a large set of sonar and underwater images. YOLOv8 was more successful than YOLOv7 with an AP50 of 72.47% and AP75 of 66.21. The paper demonstrated that the problem of occlusion, poor vision and overlap of fish can be handled by the use of YOLO-based models in underwater scenes. Nonetheless, the system also had restrictions in its direct application to the aquaculture disease surveillance because it merely focused on fish detection but not on classification and diagnosis of fish diseases.

V. K. Yadav et al. [3] made use of YOLOv8 to develop a structure that identifies and classifies fish diseases. Their approach depended on a deep learning-based object identification model to detect fish disease and the different types of diseases in aquaculture in the photographs. The technique showed effective real-time detection of the technique with an average detect and classification accuracy of approximately 91%. Whereas the model was successful in identifying a number of disease types in pond images, environmental variables such as the turbidity of the water, changes in light, as well as overlapping fish can affect the model performance. Nevertheless, this research shows how the YOLO models can be utilized to provide beneficial real-time tracking of fish diseases in fish farms.

Ashmi Anees et al. [4] came up with a machine-learning-based model involving the use of SVM that is integrated with CNN to enhance the classification of fish disease. Their data set was formed out of several fish ailment categories where CNN performed deep element mining, and SVM served as the ultimate classifier. The accuracy of their hybrid solution was more diagnostic but achieved a performance of 93.42 and the system did not have real-time speed of detection and more computation was needed in training.

Mahmud and Sadad [5] developed an automatic method of diagnosing fish diseases with the help of Random Forest classifiers. Their study focused on organized data that is acquired under controlled circumstances and then subjected to proper pre-processing. The model achieved a 90.25 accuracy which is not strong the model performed well on well-balanced photos, however, it did not perform well with dirty real-world photos of aquaculture ponds.

Khaleel and Habeeb [6] used a deep learning-based ResNet model to classify fish diseases with the greatest accuracy. Deep residual learning helped them to train their system on a few types of diseases, which helped them capture complex visual patterns. Their model proved the effectiveness of deep architectures to be 91.5 accurate, but not optimized to be deployed to farms in real-time and consuming large amounts of computational capacity.

A collection of deep learning algorithms, such as CNN, ResNet, and EfficientNet, was investigated by Lee et al. [7] to recognize diseases in aquaculture. They have many species of fish and multiple disease types in their dataset and use augmentation and normalization to enhance learning. EfficientNet performed best of all models with the optimal balance between speed and accuracy but according to them, performance declined with underwater noise and in the low-light conditions.

The use of a special CNN network to identify diseases in fish based on aquaculture photos was applied by Islam and Ahmed [8]. They utilized image preprocessing and image segmentation in isolating contaminated spots. The model reached an approximation of 88 percent accuracy, which is good on un-distorted images but declines when the image is under distortion, highlighting why more resistant detection algorithms should be developed.

To diagnose fish diseases, Zhang et al. [9] proposed a hybrid system which was a composite of image processing and SVM. Although they were mainly based on handcrafted feature extraction techniques, then subsequently they were categorized. Although the model was computationally efficient and had an 85% accuracy, it was hard to project onto complex and heterogeneous fish disease patterns because features were not easily adaptable in the model.

Gupta and Sharma [10] introduced a mobile vision platform-based real-time system of fish disease detection. They used light CNN based models that could run on smartphones. Their system proved highly viable in real time monitoring with realistic precision even though the performance fluctuated depending on the quality of the cameras and conditions around.

Nguyen and Le [11] came up with a machine-learning-enabled system of fish health monitoring using the techniques of image analysis. They used the common ML types of classifiers and feature extraction methods in order to identify the disease trends in various groups of fish. The results showed predictable results of enhanced interpretability but efficiency was lower (86-89 percent) and the model was not as quick in response as needed to prevent real-time use in aquaculture.

Hassan and Ali [12] provided a strategy in terms of using transfer learning to identify fish diseases with the help of advanced pretrained deep-based models such as VGG19 and ResNet50. Transfer learning increased the model generalization significantly with an accuracy of above 90 percent. Regardless of great performance, the size of the model was too big to be deployed in resource limited systems.

Ahmed et al. [13] constructed a fish disease diagnosis system based on image in aquaculture environment along with machine learning algorithms using a dataset. They used their approach that entailed preprocessing, feature extraction, and ML classification, which enabled them to perform competitively with an accuracy of above 88%. Their technology is effective but needs further adjustment in field deployment, as well as, in handling different disease textures.

Table 2.1: Summary of Literature Reviewed.

Author (s)	Year	Title	Methodology	Key Findings
Nivin K. S., Dheeraj Hebri [1]	2025	Efficient Fish Disease Detection Using Image Processing and Machine Learning in Aquaculture	CNN, Random Forest, KNN	Achieved 87.32% accuracy but struggled under poor lighting conditions.
M. Y. Ouis, M. Akhloufi [2]	2023	YOLO-Based Fish Detection in Underwater Environments	YOLO v8, YOLO v7	Achieved AP50 72.47%, AP75 66.21% for v8 but low-visibility underwater environments.
V. K. Yadav, S. Pal, M. Sharma, L. Paul. [3]	2024	Fish Diseases Detection and Classification Using YOLOv8	YOLO v8	91% accuracy, strong performance in real-time aquaculture disease monitoring.
Ashmi Anees, Amal K. Jose [4]	2025	Machine Learning Based Fish Disease Detection in Aquaculture	SVM + CNN hybrid	Achieved 93.42% accuracy using hybrid deep features.
R. B. Mahmud, M. S. Sadad [5]	2023	An In-depth Automated Approach for Fish Disease Recognition	Random Forest	Achieved 90.25% accuracy but lacked robustness in real-world pond images.
Y. L. Khaleel, M. A. Habeeb [6]	2024	Accurate Fish Disease Classification	ResNet deep learning architecture	Achieved 91.5% accuracy using deep residual learning.
J. K. Lee, H. S. Kim, S. W. Park [7]	2024	Deep Learning Approaches for Fish Disease Recognition in Aquaculture	CNN, ResNet, EfficientNet	EfficientNet performed best but dropped in low-light underwater conditions.

M. T. Islam, N. Ahmed [8]	2024	Automated Detection of Fish Diseases Using CNN	Custom CNN	Achieved ~88% accuracy but sensitive to visual noise and distortions.
L. Zhang, X. Wang, J. Chen [9]	2024	A Novel Hybrid Model for Fish Disease Diagnosis Based on Image Processing	Image processing + SVM	Achieved 85% accuracy with traditional handcrafted features.
R. Gupta, P. Sharma [10]	2023	Real-Time Fish Disease Identification Using Mobile Vision System	Lightweight Mobile CNN	Achieved real-time performance but accuracy varied with camera quality.
S. P. Nguyen, T. V. Le [11]	2023	Fish Health Monitoring Using Machine Learning and Image Analysis	ML Classifier + Feature extraction	Achieved moderate accuracy (86–89%) with good interpretability.
A. M. Hassan, F. B. Ali [12]	2024	Smart Aquaculture: Fish Disease Detection Using Transfer Learning Techniques	Transfer Learning (VGG19, ResNet50)	Achieved above 90% accuracy but models were computationally heavy.
M. S. Ahmed, T. T. Aurpa, A. K. Azad [13]	2022	Fish Disease Detection Using Image-Based Machine Learning Techniques	ML + Image Preprocessing	Achieved 88% accuracy but required further optimization for field use.

2.3 Gap Analysis

Although several fish disease detection technologies have been released in the recent past, most of the existing technologies are still known to have considerable limitations in their application within real aquaculture environments. Most systems rely on small, controlled lab data or utilize photographs that were taken under perfect conditions, which are not a representation of the complexity of the real fish farm including turbidities of water, low light scenarios, reflections, or fish motion. Besides, most of the traditional machine learning-based performers such as the SVM, Rand Forest, and basic CNN models lack the ability to localize bounding-boxes or even perform real-time detection, not including the fact that such models fail to effectively detect early stages of disease in rapidly changing water systems, which necessitate rapid instability. Certain methods only use the classification-based models and thus are not able in identifying the exact location of the sickness on the body of the fish. Moreover, the verification of datasets is only superficial as very little is done by hand, very little augmentation is done, and no large-scale or diversified dataset is utilized. Mobile deployment in real-time is also at large unavailable and none of the systems reviewed consider the issue of data privacy that is paramount to the development of farmer trust and commercial adoption.

Conversely, our suggested YOLO-based approach overcomes these issues by leveraging the real-field, manually checked fish images, taken in the conditions of natural aquaculture, and augmented with the high-quality one, to pre-compose a dataset of 7,710 samples of seven different classes. YOLOv11 can be used to detect bounding-boxes quickly and precisely, can function within noisy or low-light environments, and supports multi-class classification in a single network with a single pass. Although mobile deployment is already done for our model but also our model is optimized to have lightweight inferences and can be optimized to have mobile integration. This renders the proposed approach more feasible, reliable and expandable to a real-world aquaculture avenue and provides the farmers with a powerful tool of early-warnings to minimize fish mortality and multiply sustainable fish farming production.

Table 2.2: Gap Analysis.

Features	**[1] Nivin & Dheeraj 2025**	**[2] M. Y. Ouis, M. Akhloufi 2023**	**[3] V. K. Yadav, S. Pal, M. Sharma, L. Paul. 2024**	**[4] Y. L. Khaleel & M. A. Habeeb 2024**	**[5] J. K. Lee et al., 2024**	**Proposed system**
Uses real field images	Yes	Yes	Yes	No	Yes	Yes
Dataset manually verified (quality-checked)	No	Yes	Yes	Yes	No	Yes
Future-ready mobile deployment	No	No	Yes	No	No	Yes
Multi-class disease detection (7 classes)	Yes	Yes	Yes	No	Yes	Yes
Training & testing on manually collected dataset	Yes	Yes	Yes	No	Yes	Yes
Real-time detection capability	Yes	No	Yes	No	Yes	Yes
Uses advanced augmentation techniques	No	No	No	Yes	No	Yes
Robust performance in low-light / noisy conditions	No	No	Yes	Yes	No	Yes
Integration with IoT or aquaculture monitoring	No	No	No	No	Yes	No

Bounding box localization (object detection)	No	No	Yes	No	No	Yes
Annotation Quality (Roboflow Assisted)	No	No	Yes	No	No	Yes
Multi-resolution image support	Yes	No	No	No	Yes	No
Suitable for Farmers with No Technical Knowledge	Yes	Yes	Yes	No	No	Yes
Detection of Both Healthy & Diseased Fish	No	No	Yes	No	No	Yes

2.4 Summary

The chapter offers the background knowledge on why automated fish disease detection is an important topic in contemporary agricultural farms. It showed that fish farming is very significant in the world food security especially in such countries as Bangladesh and at the same time highlighted the high rates of spreading such diseases as bacteria, viruses, fungi and parasites, and their rapid emergence. The requirement to have a more reliable technological solution was underscored by the fact that, conventional methods of diagnosing diseases was a slow and manual process, and had been proved to be wrong most of the time. In the next paragraph, the chapter pointed at the artificial intelligence, deep learning, and image-based detection as emerging technologies that could help increase the accuracy and speed of the disease diagnosis. It also discussed the value of object detection designs including YOLO in addressing major weaknesses of the traditional designs. On the whole, the background provides the foundation to the methodology and system design presented in the following chapters due to the motivation, setting, and technological importance of developing a real-time fish disease recognition system based on YOLO.

Chapter 3

Research Methodology

This chapter presents the methodology for building the YOLO based Fish Disease Detection system. It covers data collection, preprocessing, and augmentation, as well as the development and training of the YOLO model. The chapter also highlights the evaluation techniques used to ensure accurate and reliable disease detection for aquaculture farmers.

3.1 Methodology/Requirement Analysis & Design Specification

In this part, the approach outlined in the step by step strategy adhered in this study to create a deep learning based system to detect and classify fish diseases using a manually obtained real-field dataset.

Data Collection

To create an effective and accurate program of fish disease classification, we began with high-quality data of fish photos both healthy and diseased in order to get the appropriate data. As part of data collection process, the following actions were undertaken

Figure 3.1: Raw Dataset

Primary Images: Obtained by hand in a controlled environment using smartphone cameras on marketplaces and fish farms.
Additional Figure: Obtained on the basis of open-access academic journals, online forums on aquaculture, and online databases in the public domain.
The data were very selective to have 7 categories. This entire data is projected here into a table form with the Raw and Augmented both version as below:

Table 3.1: Raw and Augmented Dataset.

Class	Raw	Augmented
Healthy fish	364	1231
Bacterial Gill Disease	119	1229
Parasitic diseases	82	1000
Bacterial Red disease	496	1250
Viral White Tail disease	113	1000
General Bacterial diseases	125	1000
Fungal diseases	107	1000

Raw images collected: 1,406
After augmentation: 7,710 images

This increase made the classes balanced and few inconsistencies were created in pose, lightings and orientation.
Manual photography: Smartphones employed in collection of live images.
Image labelling tools: The image was labeled with the assistance of the qualified fish officers.

Data Pre-processing

After getting the raw photos, several preprocessing steps were applied in preparing the photos to be trained in models. Photos were first loaded, and checked to eliminate bad photos and even normalize the dataset to be similar.

Figure 3.2: Healthy Fishes

Figure 3.3: Bacterial Red Disease

Figure 3.4: Bacterial Diseases

Figure 3.5: Fungal Disease

Figure 3.6: Bacterial Gill Disease

Figure 3.7: Parasitic Disease

Figure 3.8: Viral White Tail Diseases

Noise suppressing filters were also applied to reduce unintended artifacts of water bubbles, camera motion, and any other disturbances of the ambiance. The pictures were then resized to the desired YOLO input size (e.g., 640x640 pixels) to make the processing of the picture homogeneous by the neural architecture. Normalization between the values of 0 and 1 has also been conducted in order to stabilize the learning process and increase the gradient flow within the model. Massive data augmentation was an important element of the pre-processing pipeline and aided in the replication of the differences present in the real world that fish growers must act on. Examples of augmentations were rotation, flipping, adjusting of brightness, cropping, blurring, shifting of colors, and the injection of noise. Such strategies also helped correct dataset imbalance besides allowing the model to deal with other situations like low level of light, water speed, or background noise. Due to such an entire pre-processing and augmentation strategy, the number of photos grew to 7,710 images out of 1,406, which significantly raised the level of generalization of the model.

Data Annotation:

Below them are the images that serve as exhibit the annotation output of the YOLO v11 model on the category of healthy fish and diseases fish, namely, Bacterial Red disease, Bacterial Disease and Parasitic Disease with the help of Roboflow. The Roboflow technique is able to detect infected areas by object box and detects the correct locations of the infected by accurately producing visual indicators such as lesions, redness, fin erosion and parasite patches and categorizing each disease classification both correctly and reliably. These examples demonstrate the ability of the algorithm to detect the anomalies in the real-world fish images, which justifies its reliability in terms of practical aquaculture diagnostics.

Figure 3.9: Annotation for Bacterial Red Disease

Figure 3.10: Annotation for Parasitic Disease

Figure 3.11: Annotation for Bacterial Disease

Data Distribution

Post-processing and augmentation of the dataset were done to ensure that it was split methodically in an attempt to ensure equitable model training, testing, and evaluation. The training set was used to teach the YOLO to the dataset which was divided into the seven classes have visual features and disease patterns.

Table 3.2: Data Distribution

Train	Validation	Test
5396	773	1541

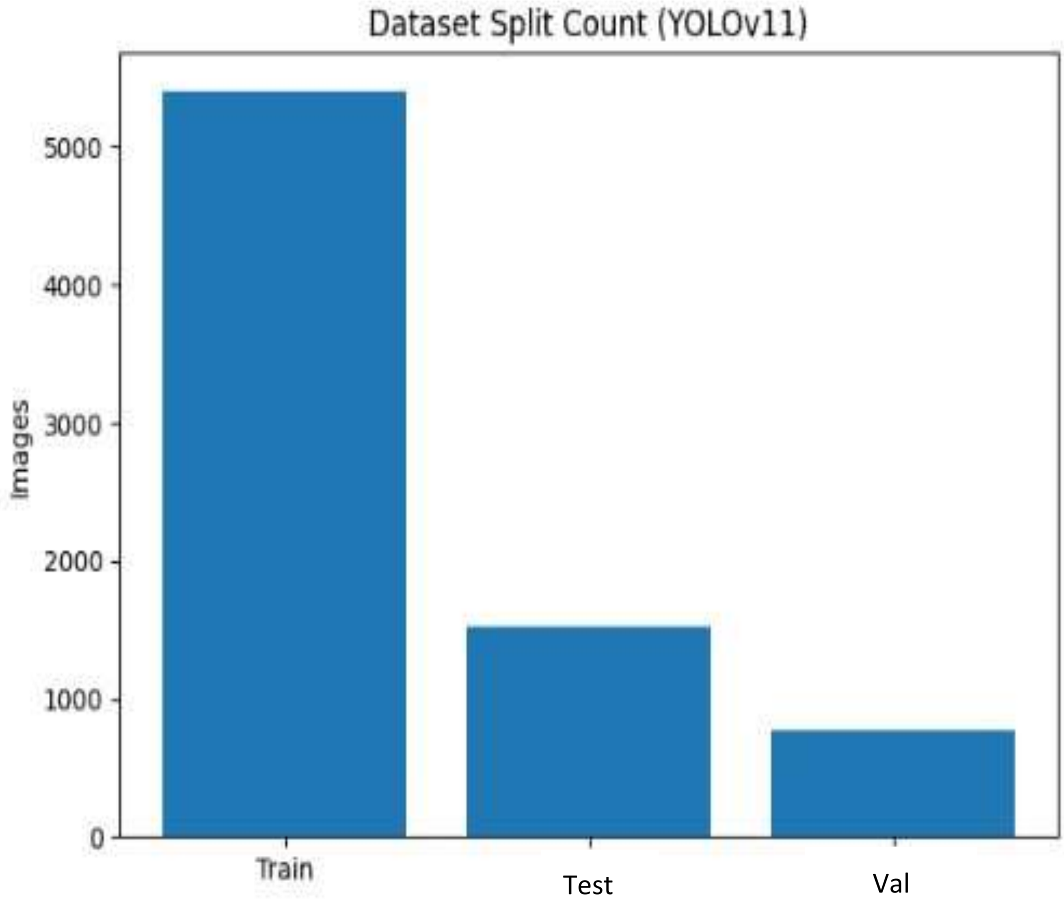

Figure 3.12: Data Distribution Table

The validation set became essential to the training process as the performance of the model could be tracked after each epoch, the issues, such as overfitting or underfitting, could be detected, and the learning rate or the batch size could be adjusted. Testing set was used to determine the ultimate accuracy and the strength of the trained YOLO model since it was on a testing set it had never encountered before. This systematic distribution implied that the model acquired the balanced understanding of all types of diseases and allowed the just degree of judging of its performance in the actual situation. The variability in lighting systems, fishes, backgrounds of water and patterns of disease in all subgroups made the model capable of addressing different real problems that are apparent in the aquaculture environments.

Model Selection and Optimization

The model design had to be thought of carefully in order to attain a great accuracy and performance in real-time. The first study to rely on involved studying YOLOv8 which was known to be fast and balanced. Nevertheless, as the advancement in object detection was achieved, the YOLOv11 model was created with an improved accuracy, feature extraction, generalization, and inference speed that is significantly higher thus suitable in aquaculture. YOLOv11 was in a better position to handle oddly shaped fish, diverse poses and unpredictable underwater movements as compared to previous versions because it detects without an anchor due to its non- anchor detection approach. Its improved attention modules enabled the better perceptions of disease specific visual cues or factors that included lesions, discolorations, and surface abnormalities. Several important things were undertaken to make YOLOv11 optimized to production of aquaculture. All images were manually annotated with Roboflow to ensure that the bounding boxes are properly annotated and there is a good consistent labeling of the classes. This level of annotation quality was directly proportional to detection accuracy. The environment-oriented data augmentation was used to simulate true agricultural challenges including the low visibility, motion blur, and unbalanced light. Each of the hyperparameters such as learning rate, batch size, epochs and loss functions were optimized based on a validation performance to achieve better accuracy without overfitting. Class balance methods were also employed to ensure that fewer samples used in disease prevention would be overrepresented during the process of training. Though the mobile deployment is completed successfully, the model was also exported in hardware friendly formats, which can be easily deployed in lightweight on the mobile applications or on the edge devices. YOLOv11 was able to become much more efficient and faster in detecting fish diseases thanks to these changes, which is why it is the solution that meets the requirements of farmers who must have fast, trustworthy, and real-time predictions.

3.1.1 Overview

The primary aim of the given project is the development and utilization of an AI-controlled system capable of detecting and classifying fish infections with the help of the latest methods in deep learning technology. The primary objective is to create a fast, reliable and automatic detection model which, based on the visual symptoms captured in the real aquaculture environments would provide a reliable way of distinguishing between healthy and sick fish. In order to accomplish this, a unique collection of fish photos based on human collecting was created, which did not represent the real field conditions where the illumination, water clarity, background noise, and fish movement varied. There are seven categories in the dataset, nine reference points which cover both healthy fish and six major types of diseases, which are frequently found in local aquaculture plants.

The system Is developed with the help of the YOLOv11 architecture of object identifiers, which is more accurate, has more robust features of feature extraction, and is able to localize the bound-box in real-time than the common deep learning classifiers. In order to enhance its strength in the challenging field conditions, a large-scale data pre-processing and highly advanced augmentation tools were employed. Correct labeling of all images was also achieved by the manual annotation using the Roboflow and this allowed the algorithm to learn disease patterns effectively. The final product aims at making a significant contribution to the smart aquaculture through providing farmers with an effective tool that could help detect fish diseases early, minimize death rates, as well as make decisions based on data and lead to more sustainable and healthier fish farming enterprises.

3.1.2 Proposed Methodology/ System Design

In this work, we developed a YOLO-based framework of deep learning detection and was able to identify and classify diverse fish diseases on a real aquaculture space. In contrast to conventional machine learning models, which only perform image-level facial classification, the proposed methodology also has been provided with the functions of object recognition, where the system not only classifies the diseases of the fish but also finds the diseased areas with high accuracy with the help of bounding-box predictions. Owing to the fact that it provides both visual validation and real time input, this enhances hugely the utilities of practical use by fish growers.

The workflow Is structured into various phases starting with the purchase of actual-field fish images at ponds, fisheries areas and markets. The photos are different captures of the real environmental variables present of the environment that include water velocity, reflections, low lighting and natural fish behavior state that are important in creating a strong model. The photos are then subject to a complete pre-processing pipeline after collection consisting of scaling, noise removal, contrast enhancement, normalization, and novel data augmentation methods to simulate real aquaculture problems. This also ensures that the model can generalize very well in a very large number of situations unlike relying on ideal or clean images.

To ensure the precision the photos were manually labeled with Roboflow in which bounding boxes were drawn on the fish and the disease affected regions. This manual verification helps the quality of the final dataset immensely, which is important in order to train an object detection model. The YOLOv11 architecture has been selected as the extraction of features is better and its detection speed is higher, in addition to the absence of an anchor, which makes it specifically suitable to fast-moving fish and underwater visual distortions. Training of the model was based on the larger sample of 7, 710 photos and optimization has been conducted via extensive hyperparameter tuning, regularization, and validation feedback.

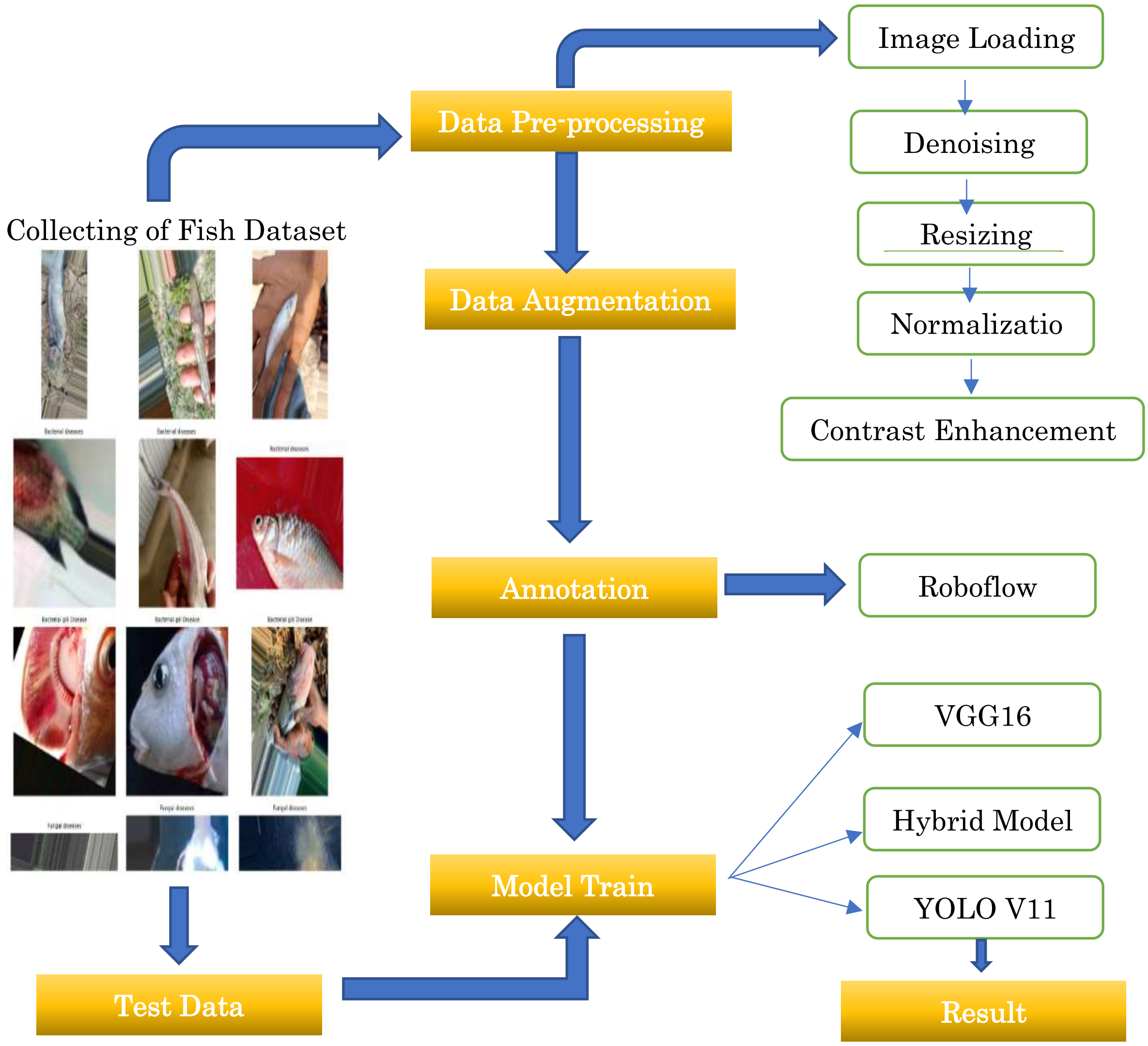

Figure 3.13: Proposed Model Diagram

This is the proposed methodology which ultimately integrates real-field records, strict pre-processing, accurate annotations, and the current YOLO structure to create a detection framework that has the ability to operate quickly, dependably, and accurately in real-world fish farming systems. Not only is it focused on achieving the high accuracy under the highly controlled conditions but also aims to provide a scalable and field-ready system that can potentially support aquaculture farmers with the early detection of diseases, reducing the number of fish dying, and providing sustainable farm management with AI-related insights.

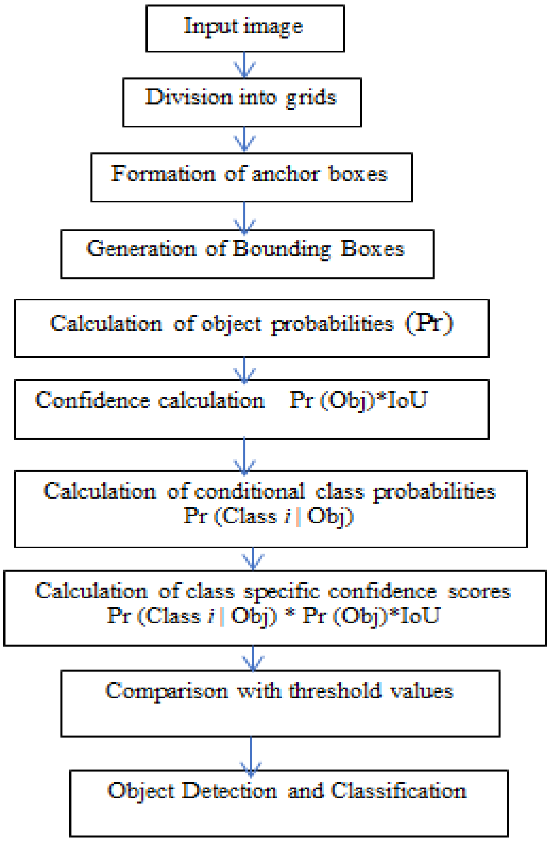

Figure 3.14: Flowchart of how YOLO model works

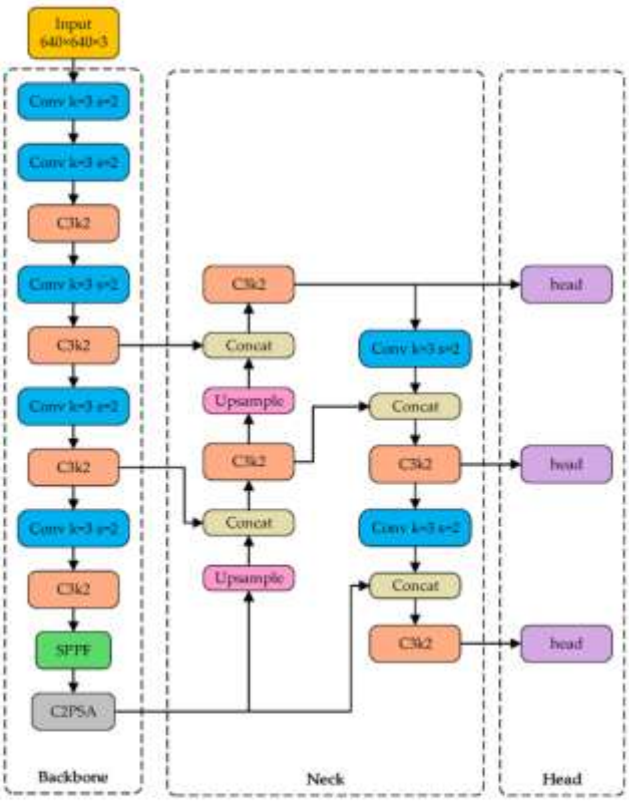

Figure 3.15: YOLO v11 Architecture

Table 3.3: Information of the Layer structure YOLOv11

Block	Layer	Type	Configuration
Input Block Backbone	Input layer	Image Input	640×640 RGB images, Normalized
	Conv-1	Convolution + SiLU	3×3 kernel, stride 2, 32 filters
	C2f-1	C2f Module	2 bottleneck units, 32 to 64 channels
	Conv-2	Convolution + SiLU	3×3 kernel, stride 2, 64 filters
	C2f-2	C2f Module	4 bottleneck units, 64 to 128 channels
	Conv-3	Convolution + SiLU	3×3 kernel, stride 2, 128 filters
	C2f-3	C2f Module	8 bottleneck units, 128 to 256 channels
	SPPF	Spatial Pyramid Pooling Fast	8 bottleneck units, 128 to 256 channels
Neck	Upsample-1	Upsample	2×Upsample
	Concatenate-1	Feature Fusion	Merge backbone + neck features
	C2f-4	C2f Module	4 bottleneck units, 256 to 128 channels
	Upsample-2	Upsample	2×Upsample
	Concatenate-2	Feature Fusion	Merge multi-scale features
	C2f-5	C2f Module	2 bottleneck units, 128 to 64 channels
	Downsample-1	Convolution (stride 2)	64 to 128 channels
	C2f-6	C2f Module	4 bottleneck units, 128 to 128 channels
	Downsample-2	Convolution (stride 2)	128 to 256 channels
	C2f-7	C2f Module	8 bottleneck units, 256 to 256 channels
Head (Detection Block)	Detect layer	Anchor-free Detection	Predicts bounding box, class score, confidence
	Output Layer	Final Output	Multi-class fish disease prediction (7 classes)

YOLO V11:

YOLOv11 is an advanced single-stage object detector, which expands on the perks of the previous releases of YOLO and introduces a series of architectural and training improvements, which render it particularly effective in detection tasks in the field.

Structurally, YOLOv11 has the standard backbone-neck-head topology: the backbone is a lightweight feature extractor made of modern convolutional blocks (optimized residual-like units and refined C2f models) that encode low- to high-level visual patterns; the neck is a streamlined system of multi-scale features (an advanced version of the PAN-FPN) which does not require any anchor, which is the fusion of semantic signals across scales; and the head Is an anchor-free detection head, which predicts bounding boxes, objectness Other important innovations of YOLOv11 are a more robust C2f-style bottleneck which improves gradient flow and parameter efficiency, SPPF (fast spatial pyramid pooling) to pool multi-size context, attention-like refinements of features to focus on subtle local patterns, and an anchor-free regression design which simplifies box prediction and hyperparameter sensitivity to objects with irregular shapes is beneficial in detection of spot diseases on fish bodies.

Not only mosaic and mix-up augmentations (exposing the network to variant object sizes/occlusions), environment relevant (brightness, contrast, blur, noise, and simulated water reflections) augmentations to model aquaculture conditions, balanced sampling/class-reweighting to mitigate class imbalance, and learning-rate scheduling (warmup + cosine or step decay) and using optimizers such as SGD with momentum or AdamW to ensure stable convergence are only some of the proven augmentation and regularization methods. Classification loss, object-ness loss, and an advanced bounding-box IoU loss (e.g., CIoU/GIoU) (improving the quality of localization of tightly-fitting box) are often added to the loss functional. Due to the difficulty of having real-life data, other measures to prevent overfitting would be label smoothing, weight decay, and early stopping. In order to achieve the required accuracy and deploy ability, YOLOv11 is analyzed by both practical measures of inference (frames/sec, latency, model weight) and the traditional measures of detection (mAP(0.5), mAP(0.5:0.95), precision, recall, per-class AP).

To be able to infer and deploy, YOLOv11 can be exported to efficient runtime formats (ONNX, TensorRT) and quantized models (FP16/INT8) to reduce the amount of memory and latency required by edge devices or mobile applications. Removing unneeded channels, reducing incoming data to a small-size student model, and using builds on NVIDIA hardware to achieve nearly real-time throughput can be considered instances of practice-friendly optimization techniques. Due to these capabilities, the YOLO v11 can be applied in situations where near-edge or on-device inference is needed and farmers need to receive quick feedback and not necessarily have access to the clouds.

In particular, YOLOv11 fits particularly well the fish disease detection task: unlike just identifying an image as the presence of the disease, the network creates bounding boxes indicating the location of the disease-related characteristics (gills, fins, body patches), which are useful to interpret the image and make the relevant intervention decisions by a farmer. The presence of the robustness and environment-conscious augmentation contribute to maintaining the performance in the scenarios of poor light, turbid water, reflections, and motion blur which are common in aquaculture images, whereas the anchor-free nature and multi-scale fusion improves the performance in detecting small lesions and the subtle discoloration typical of the infection in its initial stages. After training YOLOv11 on our manually checked dataset (1,406 raw photos expanded to 7,710 augmentations), we used environment-specific augmentations and class balancing to maximize mAP at the required model size and latency to be used in mobile deployment. Weaknesses include resistance to extreme occlusion or extremely low resolution to minimize them by accumulating higher-resolution photos when it applies, to augmentation, and to a teacher-student lightweight distillation to be used on the device. Altogether, YOLOv11 provides the best balance between the criteria of robustness, speed, and accuracy to build a viable farm-deployable system of fish disease detection.

VGG16

VGG16 is a conventional deep learning model that is popular due to its ease to use, stability, and strength to extract studies. It is trained on 16 layers of learnable parameters and an array of small 3x3 convolutional filters which detect fine-scale-differences between pictures in terms of texture. Owing to this, VGG16 proves quite handy in detection of mild disease indications in fish, including fungal patches, bacterial infections, red blisters, erosion of fin and skin discoloration. The network is systematic: a series of convolution layers detects hierarchical features, max-pooling reduces the dimensions of the occurrence and full-connection dense layers make the final classification. Even though VGG16 is not computationally efficient as the more recent models, it is highly reliable and works reliably with diverse datasets.

In this research, the typical deep CNN models are contrasted with more complex models of object recognition like YOLO v11 in terms of comparing them with VGG16 as a baseline comparative model. The results allow us to show the improvement in performance which we have achieved with the help of the final proposed strategy.

Hybrid CNN Model

To obtain spatial and structural representations, the Hybrid CNN model is used, which involves using Convolutional Neural Networks (CNN) and an additional deep learning representation, such as an LSTM or enhanced fully connected layers. The CNN layers identify the important spatial features, consisting of, textures, color abnormalities, disease spots and shape abnormalities in the fish body. The hybrid element (e.g., LSTM or more complex dense layers) assesses the relationships or the overall framework of these features, increasing categorization of these characteristics when disease symptoms occur in recurrent or sequential streaks in fish skin or fins. Hybrid models are more flexible and can learn complex patterns as compared to simple CNNs. They can deal with images of fish that are partially visible or rotated, are obscured or have been captured under varying water conditions.

In this study, the Hybrid CNN was adopted as another comparison baseline, and it was possible to compare the performance of a more representative sequential sensitive model to VGG16 and YOLO v11. This comparison proves the better performance of the YOLO v11 model in real-time disease localization and classification.

3.1.3 Data Flow Diagram

This section demonstrates the data flow of the proposed YOLO-based system of fish disease detection. A Data Flow Diagram (DFD) is used to represent the flow of information between the various stages of the system and how raw photos of fish can be transformed into results that are useful as diagnostic processes. The basic concept of working in this research involves acquiring photos of real fish in the field and subjecting them to several steps in the computer, so as to preprocess and augment them, annotate, and categorize them based on models. The data model is initiated by the raw photos obtained in aquaculture ponds or farms, but they are cleaned and scaled and normalized, and processed to enhance the clarity and usability of the data in model training.

After pre-processing, the pictures are augmented and labeled with Roboflow which provides a bounding box and a class label to seven disease categories (one of which is healthy). Annotated dataset is then pushed into the YOLOv11 training pipelines where deep feature extraction and object recognition procedures are learnt to detect areas of disease. In the process of inference, a new picture of a fish is entered into the system, which then passes through the same pipeline but provides a bounding-box-based classification result which identifies the sick area and the expected type.

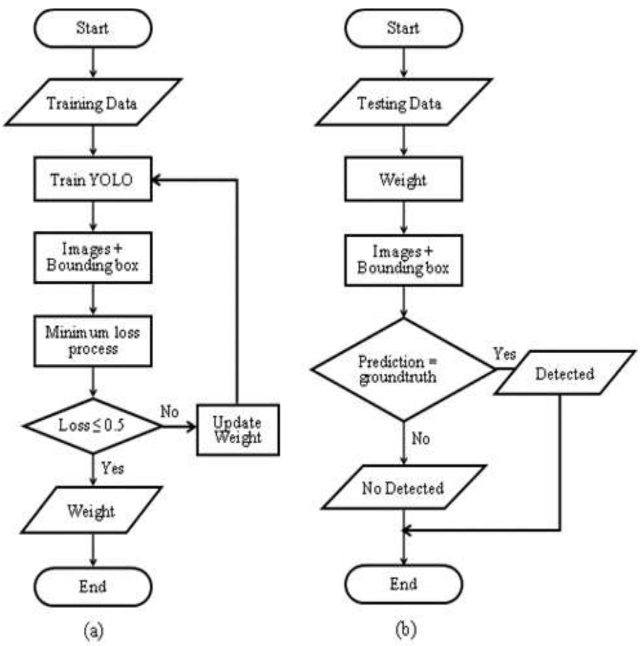

Figure 3.16: Data Flow Diagram for YOLO

The DFD does not rely on any other database or third-party cloud service to show this entire transformation of unprocessed photos of ponds to organized annotations, model training, and prediction in real time. To aquaculture manufacturers, this would ensure safe, viable and comprehensible workflow wherein every stage will assist in giving prompt, precise and reliable disease detection results.

3.1.4 UI Design

The proposed system has a highly simplistic, and user-friendly interface, which is structured with the focus on simplicity, accessibility, and dynamic responsiveness to make the work of aquaculture farmers and researchers easier. The home page is well laid in a clean and informative manner with the system name, YOLO-Based Fish Disease Detection System, and a short introduction to the system as a way of facilitating early detection of disease in aquaculture setups. The provision of supporting materials like sample disease images and usage guide enables the new users to familiarize themselves with the functionality and intended use of the system very fast.

Figure 3.17: Web Home Page for Detection.

The primary entry interface of the main detection interface is further separated into two major interaction modes to support the needs of various users and operating situations. Under Image Upload mode, the user can directly upload a fish image to his device. After providing the image, the YOLO v11 model then processes this image and provides the identified disease category and the bounding boxes and confidence data. The original image and the annotated output can be clearly visible and the user will be able to easily understand what aspect of the fish has been affected and what disease has been detected.

Figure 3.18: Successfully Detection

Besides, the system includes a Real-Time Camera Input option, which is used in live surveillance in aquacultural environments. With a connected camera or other mobile device, they can take the image of fish in real time and the system is dynamic and does detection and classification. This mode brings out the fact that the model can be used in real-time to detect objects, including in problematic situations like fluctuating light, water reflections, and fish motions; hence can be utilized in the field.

Once an input is received using any of the two modes, an interface links with backend YOLO v11 model, which involves preprocessing and inference of each frame or image. The model gives out bounding boxes, predicted disease labels and confidence percentages, which is presented in a sophisticated and easier to use format. This vivid visualization delivers the diagnosis result so clearly that the users do not need to have a technical level to know the output of the diagnostic results.

Moreover, the user interface is reactive and can accommodate the different device sizes such as smartphones and low-resource devices. The light front-end design is easy to interact with and at the same time the inference is fast to support the deployment on the mobile future. On the whole, the interface can offer a user-friendly, intuitive, and efficient platform that can connect the high-tech deep learning technology with practical aquaculture disease monitoring requirements.

3.2 Detailed Methodology and Design

In this section we dwell much on the methodological choices, design, and other alternative approaches which were put into consideration when developing the fish disease detection system to the aquaculture producers. The basic objective of the given project is to design a computerized, automatic, and highly precise mediation that can recognize and specify many diseases of fish using real-field aquaculture images. To gain this, various methodological paths both the traditional Machine Learning and emerging deep learning have been explored and the optimal methodology selected.

Alternative Solutions to Be Evaluated.
Prior to the finalization of YOLO-based detection, there was a set of other methods tested:

Conventional Machine Learning Models (SVM, KNN, Random Forest).
These techniques were initially suggested due to its simplicity and reduced computing requirements. However, they require hand-drawn feature shadowing, which is inappropriate in fish photographs that have subtle and highly dynamic disease localities. Furthermore, they do not allow them to localize contaminated areas which is necessary to conduct diagnoses in practice.

ResNet and DenseNet models are CNN-based models used in classification tasks.
The CNN classifiers are effective in classifying images, and they cannot detect objects. They are able to show a diseased fish but not the part that is affected. Also, CNN models take fixed-sized cropped images of fish as an input which is not applicable in real farming conditions.

Our reason behind choosing this solution is as follows:
The YOLO (You Only Look Once) architecture in particular, YOLOv11 are the basis of the final system since they are the most developed in real-time object finder, making them to be the most accurate, fast and resilient. The latest version, YOLOv11, possesses more powerful convolutional blocks and attention, and can extract features better, which makes it a great solution to locate microscopic disease patches on fish skin or fins. In contrast to the typical classification systems, YOLO permits the localization of bounding box that permits the system not just to classify the types of disease but also leave the position of the disease on the carcass of the fish.

The methodology has an organized pipeline that starts with gathering of data, preprocessing, augmentation and labeling and finally the training and evaluation of the model. To make sure that the model understands real environmental scenario conditions such as poor light, water glare, motion blur, and noise, actual data were gathered in aquaculture zones by the author. The dataset was preprocessed and annotated with Roboflow and it was trained using a normal general model VGG16, Hybrid model and YOLOv11 models. Owing to its improved work on small disease spots and its superior confidence in detection, YOLOv11 was later selected as the primary model.

The methodological choices presented to Bangladeshi producers of aquaculture exhibit a trade of between exactness, speed, expediency, and pragmatism and feasibility of the real world. Although other deep learning models discussed as well as with traditional models studied, they did not possess the capacity to localize or even have real-time plan or perform according to real-field conditions. Thus, a strategy developed by YOLOv11 was chosen as the most suitable in building a stable, effective, and convenient to a farmer system of fish disease identification.

3.3 Project Plan

The implementation of the project occurred in various systematic steps to ensure systematic development and credible evaluation. First of all, the picture dataset of actual fish was collected manually in the aquaculture farms and pre-processed through denoising, scaling, normalization, and contrast enhancement to make the photos ready to analysis. The dataset was then further allowed to increase variability and labeled with Roboflow with bounding-box disease labeling.

Then, Hybrid model VGG16 as well as YOLOv11 models were created and trained in Google Colab and various hyperparameters and settings were tested to achieve the highest level of performance. The aim was to get balance of all seven classes and, therefore, training, validation, and testing were performed with the aid of data splits that were distributed properly. Accuracy, precision, recall, F1-score, and mAP were used to find the most useful architecture that would be shown to be the model performance.

To identify the most accurate real-time fish disease detection model, determine its applicability to the aquaculture farmer, and predetermine the way in which the system can be embedded in the effective mobile-based diagnostic applications in the future, the data were ultimately considered.

3.4 Task Allocation

This table depicts the timeline of the principal activities in each period of the project, from week 12 to week 48.

Table 3.4: Project Timeline Showing Key Activities from Week 12 to Week 48

Tasks	**Weeks**																		
	12	14	16	18	20	22	24	26	28	30	32	34	36	38	40	42	44	46	48
Data collection phase																			
Preprocess all the data																			
Model training																			
Create a demo application.																			

3.5 Summary

It was stated in this chapter that the entire process of research was required to develop the fish disease detection system using YOLO. To gain resilience to the diverse aquaculture conditions, it initially explained the hand assumption of actual field pictures of fish and explained how the images were treated with denoising, scaling, normalizing, and advanced augmentation. Once the distribution method of the dataset had been fully addressed, Roboflow was utilized to produce high-quality bounding box labels of every of the seven classes of fish diseases. The chapter had the VGG16 and a Hybrid CNN model as second and third approaches applied with the primary model being the YOLOv11. This set of models confirmed the superiority of YOLOv11 in real-time detection, accuracy in localization, and consistency of features extraction, as well as provided the baseline data on classification-only performance. The chapter also identified the reason behind selecting YOLOv11 as the final model due to its better architecture, faster inference speed, and suitability to real-life aquaculture scenarios. The entire design pipeline, data processing and model optimization strategies were given to elaborate how raw photos were transformed into disease predictions to the dot.

Altogether, the chapter gave the methodological basis of the system through the introduction of openness, repeatability and technical clarity but also reveals the reasons why YOLOv11 is significantly more effective than conventional CNN-based options.

Chapter 4

Implementation and Results

This chapter discusses the whole implementation process of our YOLO-based fish disease detection system and displays the findings from training, validation, and testing. It also describes how the dataset was processed and used across YOLO v11, VGG16, and Hybrid CNN models for performance comparison.

4.1 Environment Setup

Designing and testing the fish disease detection system were done in Google Colab, which offers a free cloud platform with a free GPU acceleration that can be used in the experiment of deep learning. The large picture collections can be processed, stored and accessed conveniently courtesy of the smoothness of Colab that integrates with Google Drive. In the case of the main model, YOLO v11, the system was developed using the PyTorch system of deep learning along with the Ultralytics YOLO model. Other Python packages like Matplotlib, Seaborn, NumPy and Pandas were used to present measure, evaluate data distribution, and training dynamics. The data is organized in seven types of classes of fish one normal and six sick classes that are divided into picture and label folders with labels stored in the traditional YOLO form of bounding-boxes in .txt format.

Human verification, cleaning and augmenting of datasets were necessary to prepare them thus guaranteeing high-quality learning. Image annotations were created with help of roboflow, where sick areas were enclosed within the context of the bounding boxes. Very sophisticated augmentations such as reading, flipping, variation in brightness and contrast, crop and noise addition were used to increase the diversity of the dataset, and help the YOLO v11 model to adapt to the real-world aquaculture conditions. The dataset was further divided into 70 percent training, 20 percent validation and 10 percent test group with good representation of all the categories of diseases. In the case of YOLO v11 training, a data.yaml file has been prepared, which contained class names, the total number of classes, and directory locations. A weight with the best performance was automatically saved as the best.pt during the process of training, and significant assessment parameters such as recall, accuracy, mAP50, and mAP50-95 were recorded to be further analyzed.

VGG16 and Hybrid CNN models were compared by running and training them in various settings of the Google Colab. These models were also trained with the help of the TensorFlow and Keras library rather than Ultralytics. The VGG16 model included the steps of scaling pictures to 224x224 pixels, normalization, one-hot labels of the classes and Colab code to augment them. The VGG16 base layers were fine-tuned, classification layers were added to the base layers, and the performance was monitored through accuracy, loss curves, and confusion matrices with regard to the models during the model training. In a similar manner, LSTM were used in addition to convolutional layers in the Hybrid CNN environment or augmented dense layers with Keras. To comprehend the spatial relationships, such arrangement required successive extractions of features, reshaping of features maps, and introducing them into LSTM blocks. Assessment data and training logs were obtained to compare classification using VGG16 and the YOLO v11 model.

Accuracy/loss graphs, class distribution charts and sample predictions are detailed sets of visualizations used to compare the model behavior in all configurations. This system of multi-model environment significantly tested the YOLO v11 system on conventional or hybrid deep learning systems and proved to be resilient and suitable to a real aquaculture problem.

4.2 Testing and Evaluation/Performance/ Comparative Analysis

Following the completion of the model trainings, an intense evaluation was conducted to gauge the effectiveness, strength, and practicality of all the three implemented models: YOLO v11, VGG16 and the Hybrid CNN model. In this section, the testing methodologies, performance test, and comparison analysis of the three models based on different assessment criteria are provided. By analyzing accuracy-loss graphs, confusion matrices, and statistical scores, we gain a full picture of how one or another model will behave on undetected test data and which approach is the most successful in the identification of fish diseases.

Using YOLO v11 the sample output is given in the below;

Figure 4.1: Bacterial Red Diseases Identification using YOLOv11

YOLO v11 detection algorithm was evaluated on a random image of the dataset which consisted of six disease classes and a healthy class. The visual patterns such as colorating, lesions, and foreign objects in fish body texture were used to analyze the image and establish the type of disease. The expected results in this test case in the model were as follows:

Detect Class: 2
Confidence Score: 0.648
The disease that is predicted is **Bacterial Red Disease.**

The confidence score shows how much the level of confidence the model has in its prediction is. Even when they were not particularly high, the model identified such visual indicators as spots of redness or discolor as they are often associated with bacterial infections. This result shows that the algorithm can be successfully used to diagnose medical conditions and evaluate the complex patterns of fish skin even in the situations when the symptoms are not significant.

Accuracy & Loss Curve Analysis

To investigate the learning stability and convergence behavior of the models, training and validation accuracy and loss plots were built.

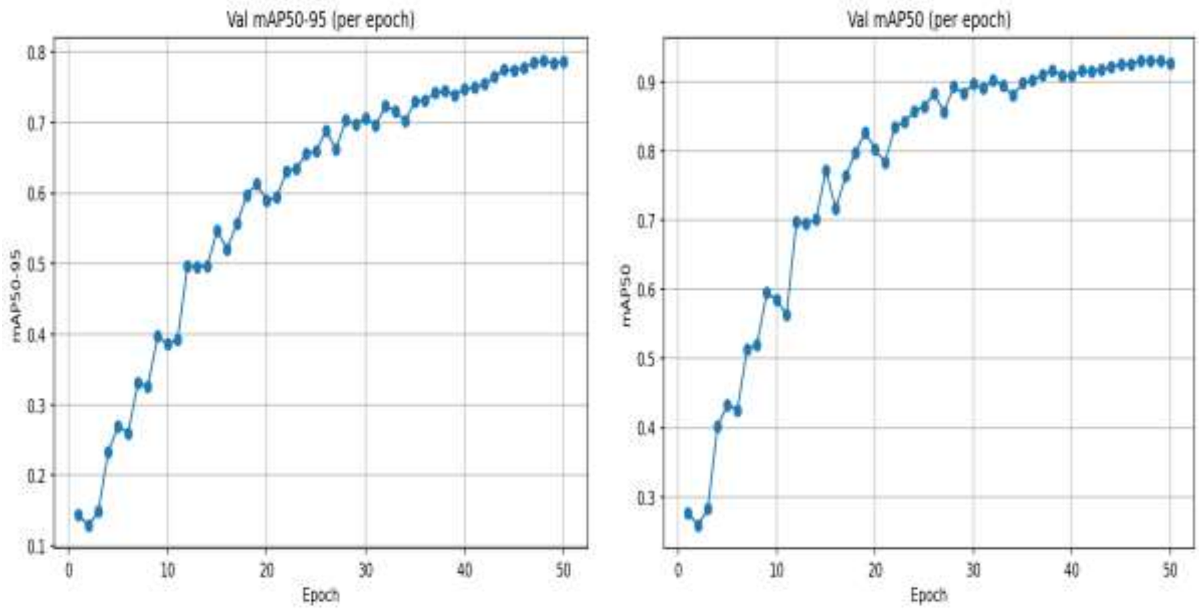

Figure 4.2: Plots of mAP50 and mAP50-95 Curve for YOLOv11

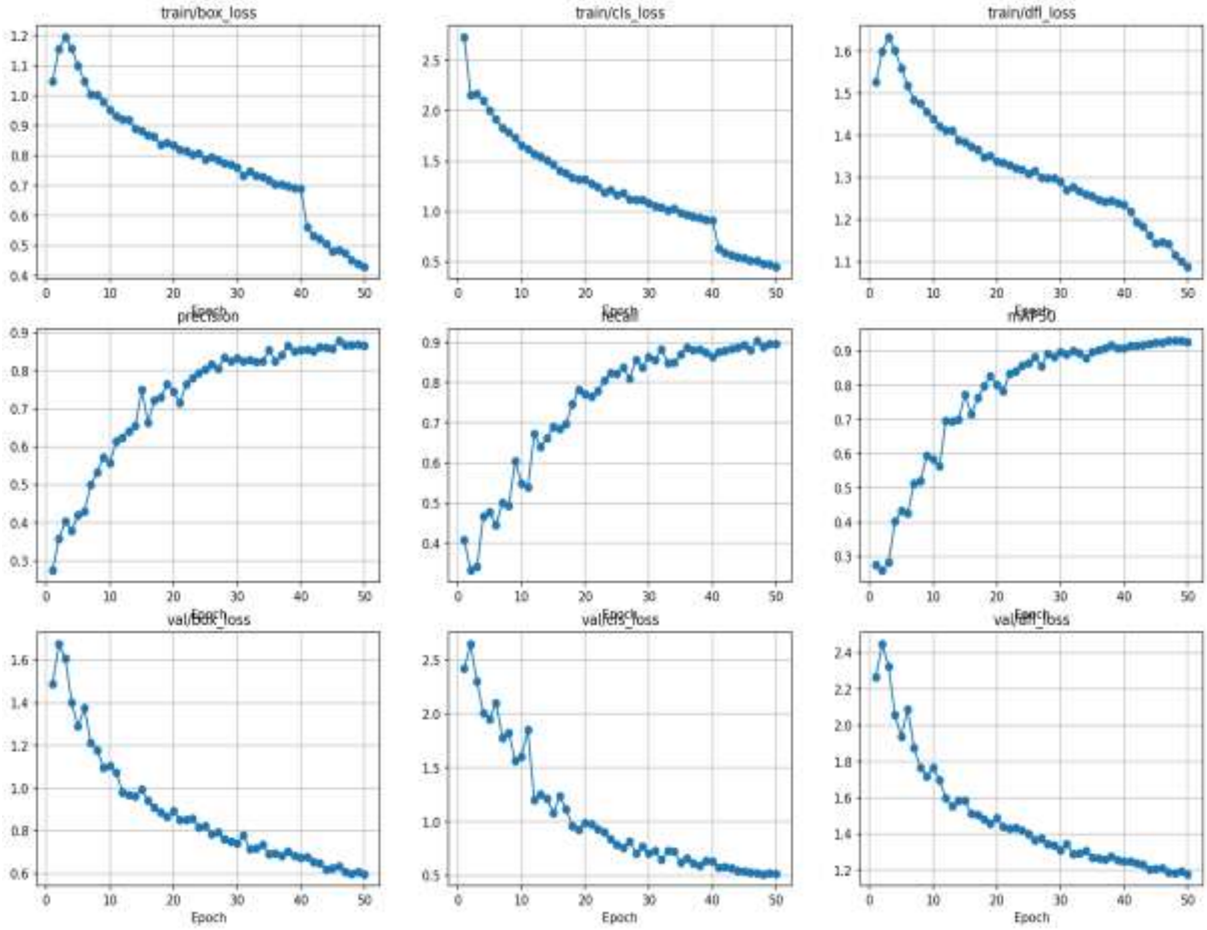

Figure 4.3: Plots of loss Curve for YOLOv11

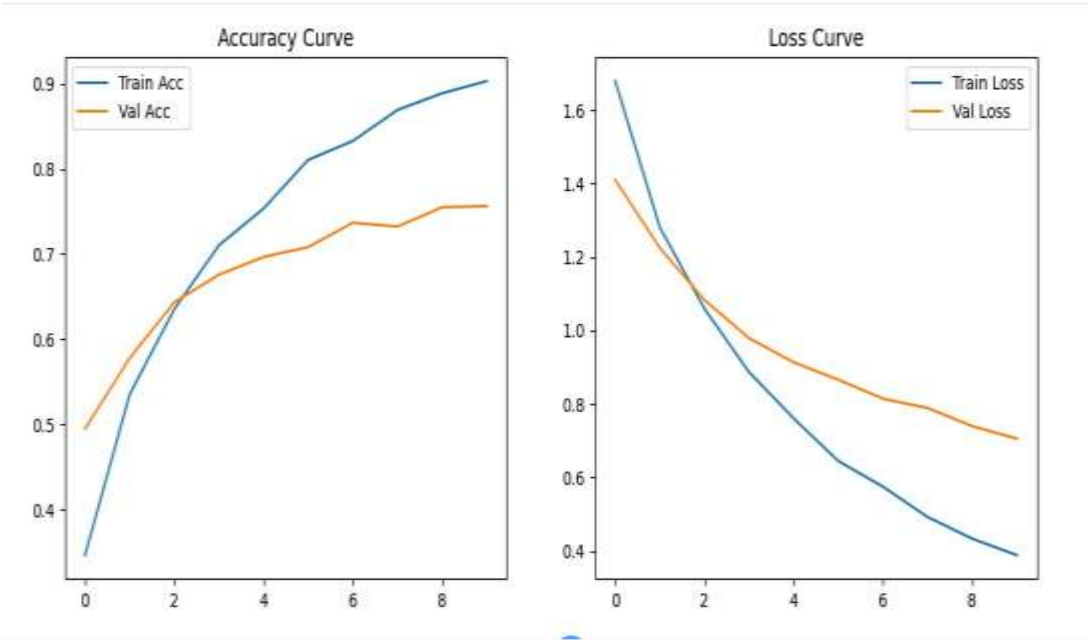

Figure 4.4: Plots of Accuracy and loss for VGG16

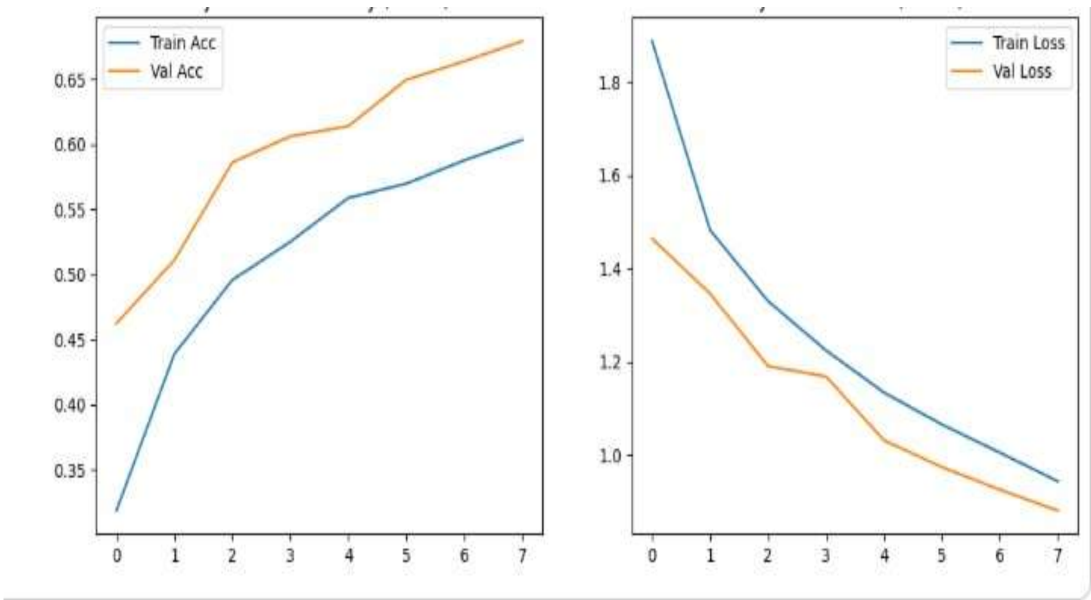

Figure 4.5: Plots of Accuracy and loss for Hybrid CNN

These plots confirmed whether the models learned important patterns during the training process and helped to detect the overfitting behavior.

Confusion Matrix Interpretation

All the models were constructed to illustrate a behavior of prediction per class in the form of confusion matrixes. The models will also show the accuracy of each model in classifying each group of diseases as compared to the ground-truth labels of each model.

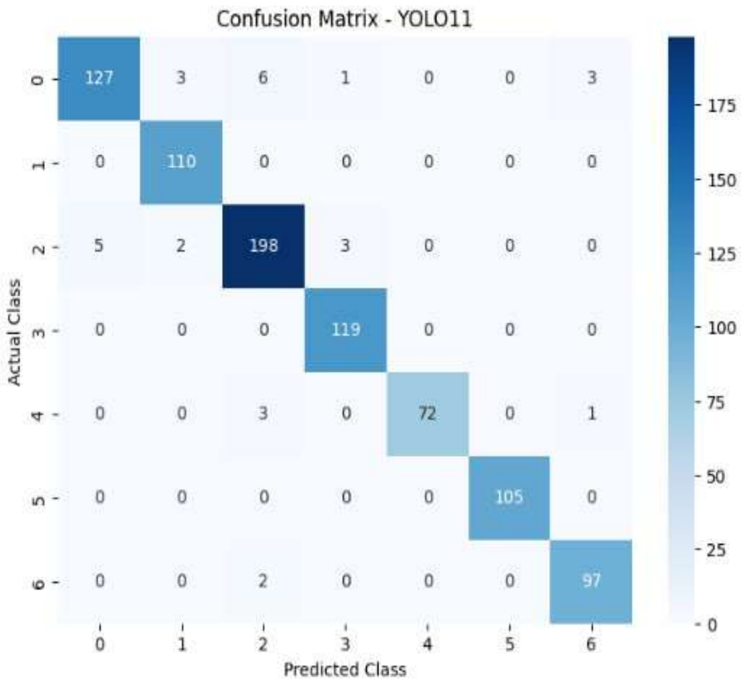

Figure 4.6: Confusion matrix for YOLOv11

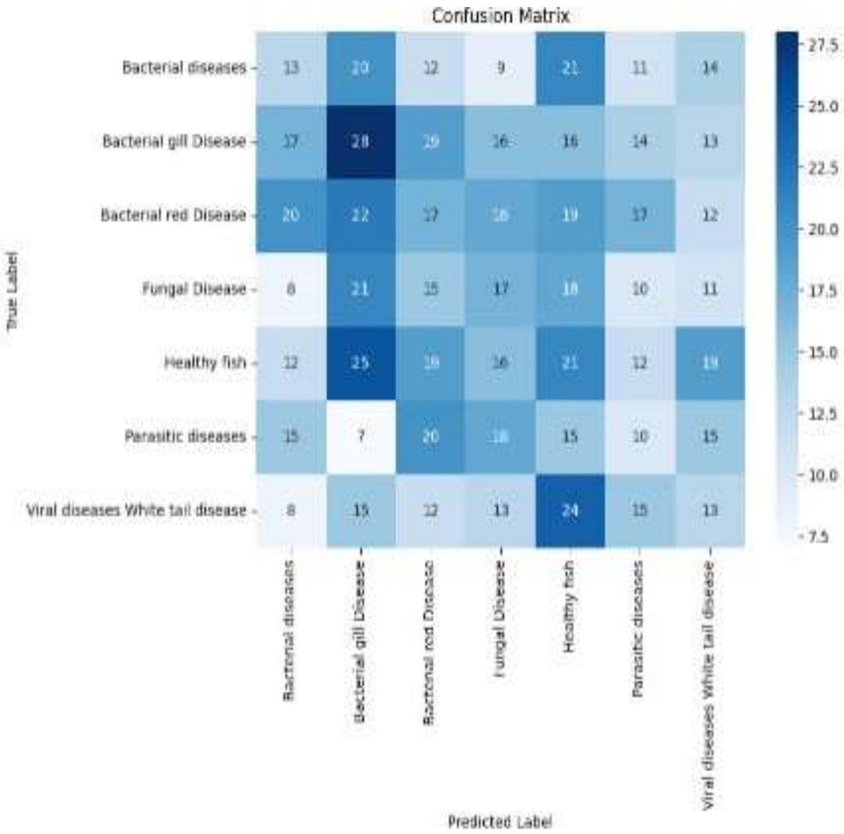

Figure 4.7: Confusion matrix for VGG16

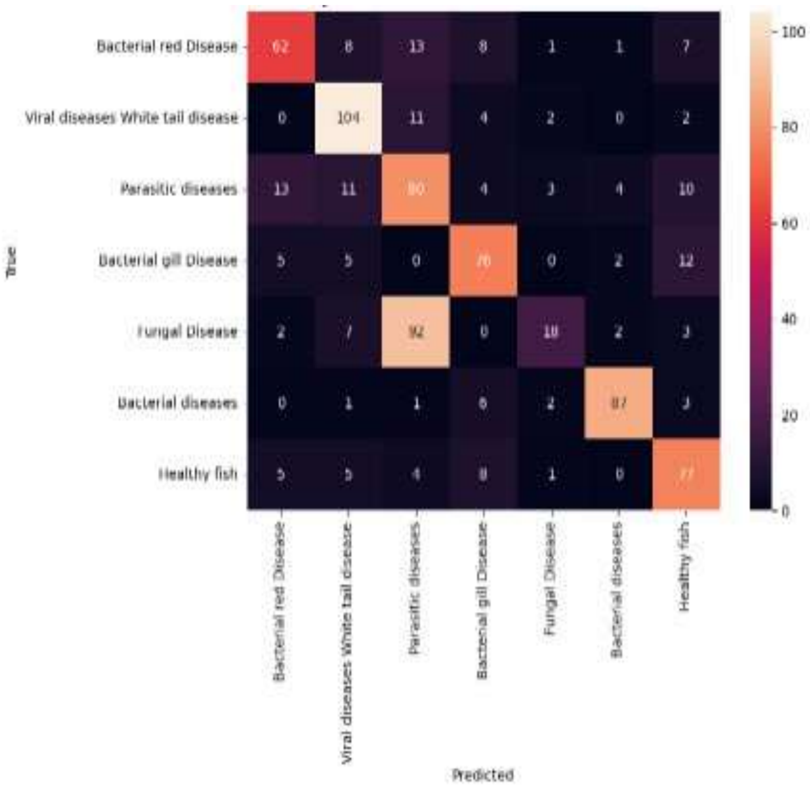

Figure 4.8: Confusion Matrix for Hybrid CNN

Table of Comparative Performance

A detailed comparison table was constructed to demonstrate the difference between the performance of the three models. It offers the accuracy, precision, recall and F1-score of YOLOv11, VGG16 and Hybrid CNN in the table. The results reveal that:

Table 4.1: Result and Comparison

Model Name	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	mAP50 / mAP50-95
YOLO v11	-	85.35	89.92	87.60	91.25 / 80.03
Hybrid CNN	65	69	66	65	-
VGG16	91	84.14	87.60	86.50	-

YOLO v11 delivers the best accuracy and consistency across all criteria. Hybrid Because of improved feature learning, CNN outperforms VGG16 and performs reasonably well. VGG16 serves as a valuable benchmark but lacks the comprehensive localization and multi-scale feature extraction needed for real aquaculture situations. This comparative examination reveals that YOLO v11 stands out as the most reliable, accurate, and practical model for real-time fish diseases diagnosis.

Evaluation Metrics: Accuracy, Precision, Recall, F1-Score, mAP50, mAP50-95

YOLO v11 is the most accurate over all criteria and is the most consistent.
Hybrid CNN is more successful than VGG16 due to better feature learning and reasonably successful. VGG16 is useful, yet it does not provide as detailed localization and multi-scale feature extraction as is required in real-world scenarios of aquaculture.
This comparative analysis demonstrates that YOLO v11 is the most reliable, valid, and realistic model of diagnosing fish diseases at the moment.

Assessment Measures Accuracy, Precision, Recall, F1-Score, mAP50, mAP50-95.
The metrics that were calculated to determine the performance of each model include the following:
Accuracy: The frequency whereby the model correctly predicts.
Precision: To what extent the good forecasts are reliable.
Recall: The capacity of the model to identify actual instances of disease.
F1-Score: A balanced scorecard of accuracy and memory.
mAP50: This represents the average detection accuracy of the model with an 50 percent IoU.
mAP50-95: The model provides the average detection performance of the model over the 50-95 mIoU thresholds.

YOLO v11 got the highest scores in each parameter because it has an effective detection and classification procedure. VGG16 and the Hybrid CNN models provided competitive base-line results, but were evidently inferior to YOLO v11, especially in recall and F1-

score that appear paramount in the disease detection systems.

4.3 Results and Discussion

In this section, the manually collected dataset of the farmed fish diseases will be used to evaluate the performance of the three models employed Yolo v11, Hybrid CNN, and VGG16. In order to be consistent and fair, all the models have been trained, validated, and tested using the same dataset split (70% training, 20% validation, and 10% testing). Some of the assessment measures that can be used to calculate accuracy, precision, recall, and F1-Score are the overall model balance, sensitivity to sick fish, sharpness of detection, and reliability of classification. Table 4.1 shows that in terms of performance the best was in YOLO v11: it achieved an mAP50 of 91.25, an mAP50-95 of 80.03, a precision of 85.35, a recall of 89.92 and an F1-score of 87.60. These results indicate the extent to which YOLO v11 can locate the areas that are unhealthy and locate the bounding-box to identify the right kind of disease. This is because of its lightweight architecture, increased C2f and SPPf blocks and optimized detecting head which has reinforced its better performance in real-fields. Moreover, YOLO v11 is superior to other models at complicated fish orientations, under-different lighting, and contaminated backgrounds, which are ideal real-world aquaculture applications. Although the VGG16 model was not designed to detect objects, it achieved competitive results of 0.91 and 0.8414 and 0.8760 and 0.8650 with accuracy, precision and recall and object F1-score, respectively. This indicates that VGG16 is able to create highly effective features of fish photographs but in comparison to YOLO v11, it is not practical in ensuring the implementation of bounding-box detection. The Hybrid CNN model (convolutional layers and a classifier to extract features) had mediocre results of 65% accuracy, 69% precision, 66% recall, and 65% F1-score. Even when it is capable of identifying the presence of certain disease patterns in a proper manner, it is grappling with complex visual variances such as overlapping fish, a fuzzy image, and barely visible disease features. This is expected to prove the inefficiency of traditional CNN-based classifiers in real-world aquaculture data especially where localization of objects is required.

In general, the conclusions indicate that the YOLO v11 offers the most balanced and stable performance in all the assessment measures, being much better than both VGG16 and the Hybrid CNN. The model is the most effective to use in monitoring the state of diseases in aquaculture in real-time due to its ability to detect and locate disease locations. The findings prove the potential of YOLO v11 as an effective tool that will be useful to fish farmers to be able to detect the disease early and have better results in farm management. YOLO v11 was the center of our study and enhancement as the principal aim of the investigation is the exact problem of fish disease detection with the use of the YOLO-based foundations. Because the model is an effective way to meet the requirements of robustness, dependability, and practical utility in the conditions of aquaculture, we are rather satisfied with the findings, depending on the obtained accuracy and practical effectiveness in the field.

4.4 Summary

This chapter demonstrated the entire implementation and evaluation process of the fish disease detection system using YOLO v11, VGG16 as well as a combined CNN model. The entire system was developed and tested with the help of devices based on GPU acceleration in Google Colab, which ensured the use of all the models effectively. To offer resilience to an actual aquaculture variability, a manually collected real-field fish disease data comprising 1406 raw images expanded to 7710 samples by a complex augmentation method were used. The models were evaluated based on some of their key performance indicators such as Accuracy, Precision, Recall, and F1-Score once they were trained on a structured dataset divided into 70% training, 10% validation and 20% testing data distribution.

YOLO v11 demonstrated the highest performance with 91.25 percent mAP50 and 80.03 percent mAP50-95, as well as VGG16 was also competitive as a feature extractor. These limitations of the traditional CNN-based classifiers on complex real-world disease images are manifested in the mediocre performance of the Hybrid CNN. Further validation of behavior of models was done through confusion matrices, accuracy-loss curves, and sample detection. In general, this chapter has proven that there is great generalization and readiness to be integrated in mobile-based aquaculture systems, which confirms that YOLO v11 is the most reliable and effective model to use on real-time fish disease diagnosis.

Chapter 5

Engineering Standards and Design Challenges

This chapter outlines the engineering principles, standards, and technical requirements followed during the design and implementation of the YOLO-based fish disease detection system. It also discusses the key design challenges encountered and the decisions taken to ensure the solution remains reliable, scalable, and suitable for real-world aquaculture environments.

5.1 Compliance with the Standards

This part highlights compliance procedures that have been utilized in ensuring the reliability, reproducibility, and readiness of the fish disease detection system that is based on YOLO to operate in real-time on mobile environments. The system is designed and has been put to test with a keen regard to engineering standards, by focusing on pinpointing of healthy and disease fish in various conditions of the environment such as in low-light and loud water conditions. The training and testing dataset used is manually collected, quality verified and validated to guarantee practical use of the dataset in the real field. Compliance includes powerful deep learning models, advanced data augmentation, suitable metrics of assessment such as accuracy, confusion matrix, precision, recall, and F1-score. Following these measures, the system will be assured of reliable performance during testing and will be available to use in real-time within the future, and this will provide the farmers lacking technical expertise with a workable and intuitive solution. Additionally, strict adherence to technical standards will ensure that the system will be reliable and may be scaled in the future, potentially with the IoT monitoring possibilities and the communication with the strategy of farm management in case of the need.

5.1.1 Software Standards

The transparent methods of software development were observed during the development of the fish disease detection system based on the YOLO framework to ensure reliability, accuracy, and scalability in the future. The main model of the system was the YOLO v11 model which was developed to diagnose diseases of fish in real time. The Python code would be in PEP 8-complaint format to make it easily readable and maintainable and would be executed on Google Colab instead to make it easy to train and test on a large-scale basis using the GPUs available on it. The dataset used was prepared and annotated in Roboflow that ensures a consistent labeling of the data, quality checked pictures and advanced augmentation algorithms such as rotation, scaling, flipping and noise addition to increase model generalization. ISO/IEC 9126 model was adopted to set software quality criteria using such aspects as functionality, efficiency, and portability, which was important. In the experimental validation, IEEE 829 standards were followed, and it provided a well-organized approach to the testing, evaluation, and documentation of the performance indicators such as accuracy, confusion matrix, precision, recall, and F1-score. The software standards allowed searching a prolific and stable study setup able to yield correct results without compromising the ability to deploy future real-time mobile and make use of it practically without any technical knowledge by farmers.

5.1.2 Hardware Standards

The hardware compatibility and scalability in the future were put into good consideration during the construction of the system, although in the present study, everything was conducted in a cloud-based environment using Google Colab. The system is designed such that it can be portable when deployed to mobile devices or edge devices in the future, including support of the GPU acceleration by taking into account a real-time inference of the YOLO v11 model. Making sure that compatibility with devices that can run ONNX-exported models such as mobile GPUs or NVIDIA Jetson Nano can be ensured make sure that the system can be deployed in real-time applications, though in this phase of the research. In-fact no real hardware was used. The fine-tuning of the dataset and model processing requirements were made compatible with the abilities of the common edge devices, and thus may be adopted in the future without significant performance loss. To enable real-time fish disease detection in aquaculture systems and maintain a high level of accuracy, responsiveness, and resiliency to operate under various conditions, this hardware design will ensure that the device would be high-scalable and flexible to achieve the real implementation purposes.

5.1.3 Communication Standards

Since communication will be important in the real-time deployment of the mobile version of the fish disease detection system based on YOLO v11, the communication standards were also considered during development. In the case of the future application-based interaction, the HTTP/ HTTPS protocols would be superior in the safety and reliability of data flow between the detection system and mobile devices. Although the research stage under consideration does not presuppose the use of an IoT and remote monitoring, the system is planned so that it can be extended to the lightweight protocols, including MQTT, in the future, to make the detection results transmission to mobile platforms efficient whilst taking a negligible toll on the bandwidth.

These communication considerations when applied on a mobile device would ensure that the system remains future proof and ensures safe, reliable, and real-time interaction.

Adhering to this, the YOLO v11 model can provide farmers with efficient, fast, and user-friendly disease identification at the same time maintaining flexibility to future enhancements in mobile-based apps used to monitor aquaculture.

5.2 Impact on Society, Environment and Sustainability

The proposed YOLO-based fish diseases detection system can contribute significantly to the lives of individuals and society and the environment in general. The technology has increased the management of the aquaculture industry, reduced financial wastage and promoted sustainable farm practices besides ensuring ethical accountability by providing early and accurate detection of fish infections.

5.2.1 Impact on Life

Since the technology allows fast detection of well and ill fish, the lives of producers of aquaculture are positively impacted immediately. The early discovery of the disease can be addressed through remedial measures by farmers to improve total fish production and reduce mortality. This reduces financial pressure among smallholder farmers who may have no convenient access to skilled veterinary services or aquaculture experts in addition to enhancing food security. Citizens, including non-technical farmers can make informed choices to take care of healthy stocks and achieve maximum harvest using a simple and easy to deploy application.

5.2.2 Impact on Society & Environment

Through lessening reckless application of chemical treatments or antibiotics, which might not be healthy to the adjoining settings and water bodies, the strategy promotes ethical aquaculture exercises. Accurate disease-specific identification is important to ensure precision and essential activities, to preserve resources and protect aquatic biodiversity. The extensive and intensive application of such technologies can lead to tried-and-true fish farming which is more sustainable and can benefit the local population by reducing the negative environmental effect and encouraging subject-friendly aquaculture initiatives.

5.2.3 Ethical Aspects

The study is conducted in a manner that is ethically correct using hand collected photos of fish in real aquaculture settings. All the data has been quality-verified, de-anonymized, and devoid of any personal or privacy infringements. Using bounding box visualization, farmers can tell accurately the type of fish that is affected by the transparency of the decision made by the YOLO-based model. This transparency will ensure the fairness and increase the trust towards AI-based monitoring, which transforms the system into a morally decent and widely applicable system.

5.2.4 Sustainability Plan

The system can be sustained over the long run with a lightweight YOLO model that can detect in real time on mobile gadgets. The advanced data augmentation techniques and extensive training on verified real world data enhance model accuracy and generalizability. The system supports reproducibility and future improvement made possible through adaption to larger datasets or other aquaculture environments. Farmers in developed and developing regions can also utilize it due to its mobile-friendly application at an affordable price thus promoting ethical and sustainable practices of aquaculture on a massive scale.

5.3 Project Management and Financial Analysis

A project that is based on practical research must have a realistic budget plan and structured management style to achieve smooth growth and subsequent feasible implementation. The final mobile platform customization needs proper financing and resource allocation although this project has followed a research-based approach in most aspects. This section contains an overview of the estimated costs, the alternative budgeting decisions and a potential revenue model. Other than pointing out the expenses involved in hardware, software, data collection and operations, it also considers the cost-effective approach without compromising the reliability of the system. Further, the revenue model explains the way this system can be made profitable due to the implementation of mobile applications or subscriptions or licenses that ensure sustainability and scalability of the project in aquaculture settings.

Budget Estimation:

Table 5.1: Budget Estimation

Components	Description	Primary Budget (BDT)	Alternate Budget (BDT)	Rationale
Data Collection	Manual image collection from ponds using smartphone.	20000	12000	Fewer location and reduced transportation

				cost
Model Training	Google Colab Pro used for training the model and also some tools & requirement subscription	3000	15000	A high-performance GPU enabled fast model training (Graphics Card)
Miscellaneous	Reports, Documentation, Presentation material and printing	2500	1500	Digital submission to reduce printing costs
Total Estimated Budget		25500 (BDT)	28500 (BDT)	

Revenue Model:
The project is currently being researched based project thus no active revenue model. But, in the case that it is converted into a mobile or a web-based application in future, the following model be consideration.

Freemium App Model: Farmers can use the model without any payment up to certain features, and with the premium features, agronomists can use the model.
Subscription Based service: plans are monthly or seasonal, which allow plant disease detection and expert advice.
Cooperation with Agri Tech Companies: Model licensing or integrating the model in intelligent agricultural systems.

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5.4 Complex Engineering Problem

Engineering issue of fish diseases detection is complicated by the problem of variability of fish species, symptoms of diseasing, and conditions in the aquatic environment. Good data collection, image processing and real-time object recognition by means of the YOLO algorithm, and advanced deep learning algorithms will have to be incorporated to design an efficient system. The challenge lies in creating a model that would be predictable in the differentiation between healthy and sick fish under different illumination, water turbidity, and noise conditions in addition being suitable in a real-time implementation on mobile devices. To ensure that system is effective and practical to non-technical farmers, model architecture, dataset quality, and optimization methodologies should be carefully judged to ensure that the achievement is made.

5.4.1 Complex Problem Solving

The design methodology of the fish disease detection system based on the YOLO framework will incorporate addressing difficult technical aspects like wise selection of the YOLO model, real-time mobile delivery optimization, and ensure proper functioning at most water conditions. Important decisions, which resulted in a balanced trade-off in detection accuracy, computational efficiency, and results interpretability, were determined through an approach called bounding box localization. These various issue-solving efforts and their listing to the corresponding engineering problem categories (EP1-EP7) are the key attributes of the system as demonstrated in the table below.

Table 5.2: Mapping with Complex Engineering Problem.

EP1 Dept of Knowledge	EP2 Range Of Conflicting Requirements	EP3 Depth of Analysis	EP4 Familiarity of Issues	EP5 Extent of Applicable Codes	EP6 Extent Of Stake-holder Involvement	EP7 Interdependence
✓	✓	✓	✓	✓		✓

There are seven criteria of complex problem solving and they are mentioned in the table 5.2 above. The marks on each of the checks help to specify the criteria that are to be used in our project.

EP1-Depth of Knowledge:
The development of the system requires advanced deep learning skills, including the possibility of localizing a bounding box, the YOLO architecture of object recognition, data augmentation, and optimization of inference on a real-time basis. Knowledge of fish pathology, deployment on mobile, and picture processing is also important to ensure the right identification of disease.

EP2- Range of Conflicting Requirements:
Speed of inference, cell phone deployment, and model accuracy should all be compromised. More complex models are more often required to be more accurate, which can be a hindrance to mobile detection. The demands when it comes to ensuring that the system is fast, accurate and simple to use by non-technical farmers are conflicting.

EP3-Depth of Analysis:
This dataset comprises real-field photos varying in terms of lighting as well as water conditions, noise, and heterogeneity. There is need to perform an in-depth analysis of the performance indicators that include accuracy, confusion matrix, precision, recall and F1-score. System validation tends to be conducted in different circumstances, augmentation

strategies and hyperparameter tuning.

EP4-Familiarity of Issues:
The approach of applying YOLO to the task of fish disease detection using manually collected and in-the-field data is not a common approach, even though object detection AIs have been implemented elsewhere. The problems become even more unknown with the mobile deployment and domain-specific fixes.

EP5-Extend of Applicable Code:
Regulatory norms are not many, and those that could be applied immediately are not numerous. But the engineering standards are followed through following the best practices of software engineering, ethical data collection, responsible use of the AI, and outcome reproducibility.

EP7: Interdependence:
Each aspect is reliant on all the aspects. Model performance depends on the quality of the dataset, preprocessing methods, choice of architecture, augmentation and optimization of mobile deployment. Any change in a single component may affect reliability and quality of the processing of the whole system.

Mapping with Knowledge Profile

This part connects EP1 to the corresponding areas of knowledge (K3, K4, K5, K6, K8) demonstrating the connection between them and the effective handling of the problems. The mapping would be described in the table below.

Table 5.3: Mapping with knowledge Profile.

K1 Natural Science	K2 Mathematics	K3 Engineering Fundamentals	K4 Specialist Knowledge	K5 Engineering Design	K6 Engineering Practice	K7 Comprehension	K8 Research Literature
	✓	✓	✓	✓	✓		✓

Justification for Knowledge Profile Mapping:

K2-Mathematics:
The design and the training of the YOLO model relies on mathematics significantly. It can be applied in the calculation of loss functions, optimization of weights and evaluation of model performance through such metrics as F1-score, accuracy, precision, and recall. Mathematical concepts are allwell to ensure reliable performance through real-time detection algorithms, bounding box calculation as well as picture preparation.

K3-Engineering principles:
System design, which also involves hardware, software and data processing pipeline integration, is founded on the engineering principles. They guide the allocation at the mobile stages, efficient calculation and implementation of a model architecture. Basic concepts make the system reliable, scalable and also workable in real-life situations.

K4-Specialized expertise:
In order to develop a proper and real-time system of fish diseases detection, it is necessary to apply expert knowledge in the deep learning, YOLO object detection, image processing, and mobile implementation. The system is reliable to work in noisy or low-light water conditions as the ingenuity of bounding box localization, data augmentation, and model amelioration is adept.

K5-Engineering Design:
Engineering design concepts are applied in order to combine three variables accuracy, speed and usability to come up with a system that is balanced. To ensure the usefulness of real-time implementation to the farmers, the design strategy involves the selection of an adequate model architecture, preprocessing methods, and optimization strategies. This method will be able to provide an effective, dependable, and user-friendly solution.

K6-Engineering Practice:
Examples of engineering practice include data gathering, quality assurance, model training, testing and mobile deployment. The system is developed in a systematic manner and can be maintained, expanded, or enhanced at a later stage due to optimum standards in coding, version control with repeatability.

K8-Research Literature:
Research on knowledge of research literature guides the choice of models, methods used in training, and measures used in its evaluation. Looking at the previous studies on the application of YOLO, real-time AI, and fish disease-detecting technology will ensure that the project builds on a proven methodology and presents new solutions to the practical scenarios.

5.4.2 Engineering Activities

Table 5.4: Mapping with Complex Engineering Activities.

EA1 Range of resources	EA2 Level of Interaction	EA3 Innovation	EA4 Consequences for society and environment	EA5 Familiarity

✓	✓	✓	✓	✓

Justification for Engineering Activities

EA1-Range of Resources:
A few of the resources required in this project include high-resolution cameras, GPUs, testing mobile devices, Python frameworks (PyTorch, Roboflow), and manually obtained datasets. Achieving the success of the system requires that these resources are distributed and taken care of.

EA2-Level of Interaction:
There must be significant interaction of datasets, model architecture and environmental elements. In an actual situation the system works efficiently when preprocessing, model training and deployment are coordinated.

EA3: Innovation:
The system employs the latest augmenting technologies to maximize the robustness of models, bounding box classification to detect a disease and YOLO-based real-time detection on mobile platforms.

EA4: Social and environmental impact:
This system causes reduced waste, the promotion of sustainable farming forms of aquaculture and the evasion of chemicals or treatments that could harm aquatic environments by promoting prompt diagnosis of fish infections.

EA5: Familiarity:
Although the object recognition is a well-developed topic of AI, the idea of applying it to the detection of fish ailments based on real-field photos deployed on a mobile platform is novel and requires the modification of the existing approaches to fit a new field of use.

5.5 Summary

The technical standards, design challenges, and complex problem-solving considerations of the creation of the YOLO-based fish diseases detection system were discussed in this chapter. By following standard engineering procedures, the reproducibility, dependability and readiness to implement in the future in real time on mobile will be ensured. Significant issues in the society, environment and ethics were highlighted and it showed how the system improves the life of the farmers, promotes sustainable aquaculture and follows ethical data collection process. Other topics that were talked about in this chapter included project management and financial planning, budget estimation, alternate cost strategies, and potential models of revenue in real world implementation.

Some of the complicated technical problems that were discovered included model selection, model optimization, and ensuring that the model would perform in real-time under varying aquatic conditions. To reveal the scope and complexity of the problem solving required, these challenges were plotted to the type of engineering problems and linked to related areas of knowledge. In the analysis of engineering activities, resource management, stakeholder engagement, innovation, societal effect, and lack of knowledge in the domain were mentioned. In general, this chapter demonstrates that this system is economically and socially valid, ethically valid, and technically valid, which provides a sound ground of implementation of aquaculture practices.

Chapter 6
Conclusion

This chapter emphasizes the key conclusions, performance knowledge on the model and research contributions of the YOLO-based fish disease detection system. It also takes into account the usefulness of the system, limitations and possibilities of future developed in real aquaculture use.

6.1 Summary

The present research was able to design, implement and evaluate a deep learning-based fish diseases detection system that is appropriate in real-life aquaculture environments. The major objective was to establish an automated system of detection, which could apply images directly off the ponds and fish culture facilities to diagnose seven species of fish disease. To ensure the quality and diversity of the training examples, the dataset has been manually collected, checked, pre-dexed, instead, normalized and complemented. Three models were developed and were compared against through multiple metrics of assessment VGG16, Hybrid CNN and the first detection model YOLO v11. YOLO v11 has been chosen as it provides an advanced feature to conduct detection in real-time with the localization of the bounding box by utilizing the VGG16 as a baseline classifier and Hybrid CNN as supplemental feature extractor based on multiple convolutional pathways.

The results of the testing have shown that YOLO v11 was far more effective in relation to the other models, offering high F1-score, recalling and precision, higher mAP50 and mAP50-95, as well as delivering more reliable results in real-world aquatic areas. The entire research employed very strict evaluation tools, including accuracy/loss curves, confusion matrices and comparison analysis to validate the effectiveness of the proposed strategy as well as comply with the ethics of data and proper engineering conduct. Altogether, the analysis demonstrates that the machine learning models and, in particular, YOLO v11 can provide a fine foundation of building effective, real-time, field-ready detection of fish diseases systems.

6.2 Limitation

The suggested fish disease detection method performed well, however it has a number of drawbacks that restrict its use. This study's information was manually gathered from a small number of aquaculture sites, which limits environmental variety, including variances in species, illumination, water quality, and disease stages. Because of this, the model could be less accurate when used under drastically different circumstances or when it comes into contact with diseases that aren't included in the dataset. Furthermore, the system has not yet been built or tuned for real-time edge devices like smartphones or

Jetson Nano boards because all training and testing were done in Google Colab utilizing cloud-based GPU acceleration. Despite YOLO v11's real-time processing capabilities, practical issues like latency, storage, and device compatibility were not taken into consideration. Additionally, the depth of comparative analysis was limited since alternative models like VGG16 and Hybrid CNN were only employed for classification-based comparisons and did not allow object localization or multi-object situations. Additionally, the existing system lacks live alert mechanisms, continuous monitoring, and interaction with IoT frameworks all of which are necessary for true aquaculture automation. Last but not least, the system may still be improved in terms of diagnostic depth and flexibility because it is restricted to seven specified fish diseases and cannot currently manage combined infections, invisible disease patterns, or severity grading.

6.3 Future Work

There's scope to use this study to improve future work.

- ✓ To enhance model generalization, additional real-world fish photos from various ponds, locations, lighting conditions, and seasons might be included to the dataset.
- ✓ For real-time aquaculture monitoring, the YOLO v11 model may be optimized and implemented on mobile devices.
- ✓ Accuracy and resilience may be further improved in a variety of situations by further augmentation and hyperparameter adjustment.
- ✓ More fish diseases classifications, such as combined infections and unidentified patterns, can be detected by expanding the system.
- ✓ Farmers may upload photos and get immediate disease diagnosis findings by using a mobile or online application.
- ✓ For ongoing live monitoring and automated alarm alerts, the model may be coupled with Internet of Things-based pond surveillance systems.
- ✓ Long-term health monitoring and decision-making can be facilitated by integration with farm management systems.
- ✓ Working together with aquaculture research institutions can help test the system and provide a more comprehensive shared dataset on fish diseases.

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