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AI Techniques In Aquaculture For Predicting And Preventing Fish Diseases

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Abstract: The Fish health is a critical factor in the success of aquaculture. Timely detection of diseases is essential to prevent the rapid spread of infections, minimize fish mortality, and reduce reliance on antibiotics. Traditional methods of disease detection rely heavily on manual inspection, which is time-consuming and prone to human error. This project proposes an automated system for fish disease detection using image-based machine learning techniques. By leveraging computer vision and deep learning algorithms, the system aims to efficiently identify diseases in fish through image analysis, offering a faster, more reliable alternative to traditional diagnostic methods. The system uses convolutional neural networks (CNNs) for classifying fish images into categories of healthy and diseased states. The dataset consists of fish images exhibiting various symptoms of diseases like white spot disease, fungal infections, fin rot, and bacterial gill disease. By training the CNN on these labeled images, the model can accurately predict the health status of fish in real-time, offering significant improvements in aquaculture management. The rapid growth of aquaculture as a global food production sector has increased the need for efficient and effective fish health management. Diseases in fish can lead to significant economic losses due to mass mortality, reduced production efficiency, and the use of antibiotics and other chemicals. Early and accurate detection of fish diseases is crucial for minimizing such risks. Traditional methods of disease diagnosis in aquaculture, which often rely on manual inspections by experts, are labor-intensive, time-consuming, and prone to errors. This study proposes a solution to automate and enhance the disease detection process through the use of image-based machine learning techniques, specifically employing deep learning algorithms like Convolutional Neural Networks (CNNs) for classifying fish diseases.

Keywords: Fish Disease Detection, CNN, Deep Learning, Aquaculture, Health Management.

I. INTRODUCTION

The word aquaculture is linked with strengthening, i.e., breeding, growing, and harvesting fishes, aquatic plants, crustaceans, mollusks, and aquatic animals. Aquaculture is the farming of freshwater and seawater animals in a controlled setting and is utilized to produce food and business items as shown in Figure 1. There are mainly two types of aquaculture. The most common one is Mariculture that signifies the aquaculture of seafood for food as well as for other products such as pharmaceuticals, foodstuffs, jewellery (e.g., cultured pearl), nutraceuticals, and cosmetics. Seafood can be grown in the natural environment of the sea or in land- or seawater-based systems such as enclosures like cages, ponds, or raceways. Seaweeds, mollusks, shrimps, sea fish, and numerous other minor species such as sea cucumbers and sea horses are some of the wide range of animals that are now being farmed on coastlines around the world. It is a contributor to sustainable food production and local community economic development. But occasionally at a large scale of marine firming pose threats to marine and coastal environments like degradation of natural habitat, nutrients, and dumping of wastes, extraneous organism accidental release, disease transmission to wild stocks, and indigenous and local population displacement. The second is Fish farming that means the commercially farm fish in artificial tanks and other structures. Most commonly, fish like catfish, tilapia, salmon, carp, cod, and trout are cultured in such enclosures. The aquaculture of fish has increased nowadays to cater to the needs for fish products. This is the most common type of aquaculture that exists for centuries due to the belief that it gives a cheap source of protein. Global aquaculture is one of the quickest growing food productions and accounts for virtually 53% of total fish and in-ver-tebrate production and 97% of complete seaweed manufacture up to the year 2020. Global aquaculture of salmon faces many diseases that can devastate conventional production of salmon. Diseases have a risky impact on fishes in the natural world and even in aquaculture. Diseases are widely regarded as one of the gravest warning signs to the economic success of aquaculture. Infectious diseases in fish are caused by a broad variety of infectious agents such as bacteria, viruses, protozoan, and metazoan parasites. Most of the infectious diseases in confined fish are caused by bacteria. Infectious diseases constitute one of every prominent essential threat to successful aquaculture. The large aggregations of fishes within a limited space create an environment that supports development and quickly transmits infectious disease. Among the crowded residents, a relatively built environment, fishes are stressed and also respond to disease. Furthermore, the aquatic environment and

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absence of water flow support the development of pathogens in aggregating assemblages. Disease identification with the help of some image processing will contribute to the extraction of quality features. Support vector machine (SVM), one of the popular supervised machine learning techniques, has brought convenient solutions to a large number of classification problems in a variety of disciplines. It is a good classification technique that makes quality predictions from unlabeled data. In Authors developed a model of SVM with three kernel functions to differentiate between dengue human infected blood sera and normal sera. For image classification, they suggested another architecture of SVM where they replicate the architecture by combining CNN with SVM. SVM provides very good accuracy in most cases. In this article, we conduct our study of the classification of the salmon fish disease, i.e., the fish is infected or not with a machine vision-based approach. A feature set is a compromise for the infectious disease classification. Image processing techniques are used to extort features from the images, and further, a support vector machine (SVM) is used for the efficient classification of infectious disease.

II. SIMILAR WORKS

- The paper on "**Fish Disease Detection Using Image-Based Machine Learning Technique in Aquaculture(2021)**" [1] explores an automated approach for identifying diseases in salmon fish using image processing and machine learning. It employs Support Vector Machine (SVM) classification after pre-processing and segmenting images with k-means clustering. The study demonstrates high accuracy (91.42% without augmentation and 94.12% with augmentation) in distinguishing between fresh and infected fish. Unlike previous methods that relied solely on image processing or basic classifiers, this research presents a more efficient and intelligent detection system. The study highlights the importance of early disease identification in aquaculture and suggests future improvements using deep learning techniques like CNNs for enhanced accuracy.

- The paper "**Empirical Evaluation of Deep Learning Techniques for Fish Disease Detection in Aquaculture Systems: A Transfer Learning and Fusion-Based Approach (2024)**" [2] presents a novel approach to fish disease detection in aquaculture using deep learning, specifically transfer learning and ensemble techniques. It integrates features extracted from three pre-trained models—VGG-16, MobileNet-V2, and Inception-V3—along with a Support Vector Machine (SVM) for classification. The study empirically evaluates multiple deep learning models on a comprehensive dataset, demonstrating the effectiveness of the proposed method in improving sensitivity and specificity compared to existing approaches. The results highlight the potential of transfer learning and feature fusion in enhancing fish disease detection, providing a foundation for future research in aquatic health management and sustainable aquaculture.

- The paper titled "**Role of Machine Learning and Artificial Intelligence in Transforming Aquaculture and Fisheries Sector (2024)**" [3] was published in *Indian Farming*. Authored by Satyamvada Maurya, Murali S. Kumar, Ravindra Kumar, and Basdeo Kushwaha from ICAR-National Bureau of Fish Genetic Resources, the paper explores the transformative impact of AI and ML in the fisheries and aquaculture industry. It discusses applications such as environmental monitoring, stock assessment, disease detection, feed optimization, and decision support systems, highlighting their role in improving efficiency, sustainability, and management practices. The paper also addresses challenges like data accuracy, cost, and privacy concerns while emphasizing the future potential of AI-driven innovations in the sector.

- The paper "**Exploring Opportunities of Artificial Intelligence in Aquaculture to Meet Increasing Food Demand (2024)**" [4] discusses the growing importance of AI in addressing the challenges of modern aquaculture. With the rising global population and depletion of wild fish stocks due to overfishing, sustainable aquaculture is essential to bridge the gap between food supply and demand. The study highlights how AI technologies such as machine learning, IoT, and computer vision can optimize fish health monitoring, feeding efficiency, disease detection, water quality management, and overall farm productivity. It also explores the challenges associated with AI implementation, including data collection, model accuracy, and integration with existing systems. The paper concludes that AI has the potential to revolutionize aquaculture by making it more sustainable and efficient, but further advancements in technology, infrastructure, and data standardization are needed to fully leverage its benefits.

- The paper titled **"Fish Type and Disease Classification Using Deep Learning Model Based Customized CNN with ResNet-50 Technique (2024)"**[5] presents a deep learning approach for classifying fish species and detecting diseases among them, specifically focusing on Indian Major Carps (IMC) like Mrigala, Catla, and Rohu. The study highlights the significance of aquaculture and the challenges posed by fish diseases, which can arise due to environmental pollutants and pathogens. To address these issues, the authors propose a customized Convolutional Neural Network (CNN) integrated with the ResNet-50 model for accurate fish classification and disease prediction.

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The methodology involves image preprocessing, model training, and performance evaluation using key metrics such as accuracy, precision, recall, and F1-score. The proposed model achieves a test accuracy of 87.46%, demonstrating its effectiveness in identifying fish species and diagnosing diseases. The study emphasizes the advantages of CNNs in automating disease detection, improving aquaculture management, and reducing manual inspection efforts while also acknowledging challenges like dataset availability and computational complexity.

- The paper titled "**Water Quality Prediction for Smart Aquaculture Using Hybrid Deep Learning Models (2022)**" [6] presents a hybrid deep learning approach for water quality prediction (WQP) in aquaculture. The authors propose combining convolutional neural networks (CNN) with long short-term memory (LSTM) and gated recurrent unit (GRU) models to improve prediction accuracy and computational efficiency. CNN is used to extract key water quality features, while LSTM and GRU capture long-term dependencies in time-series data. The study evaluates the proposed hybrid models using two different datasets—one from aquaculture farms in Kerala, India, and another from China—analyzing their performance against baseline deep learning models, including LSTM, GRU, CNN, and attention-based variants. Experimental results demonstrate that the CNN-LSTM model outperforms all other models in terms of prediction accuracy and computation time, making it a promising solution for smart aquaculture systems.

- The paper "**A CNN-OSELM Multi-Layer Fusion Network With Attention Mechanism for Fish Disease Recognition in Aquaculture (2023)**"[7] proposes a novel approach for identifying fish diseases in aquaculture using a combination of convolutional neural networks (CNNs), an online sequential extreme learning machine (OSELM), and attention mechanisms. The study highlights the importance of fish disease recognition due to increasing global demand for fish production and the challenges posed by complex underwater environments, low-quality images, and the lack of public datasets. The proposed model integrates multilayer fusion and attention mechanisms to refine feature extraction, emphasizing important regions while weakening irrelevant ones. It achieves high classification performance, outperforming baseline CNN models, attention-based networks, and advanced architectures like ConvNeXt and Swin Transformer. The study also demonstrates the significance of background elimination in improving classification accuracy. Future work aims to enhance the dataset and explore alternative AI techniques such as fuzzy logic.

- The paper titled **"A Machine Learning Approach for Early Detection of Fish Diseases by Analyzing Water Quality Using Machine Learning Algorithm (2021)"** [8] presents a method for identifying fish diseases by studying water quality parameters. The study shows that changes in water quality caused by bacterial and viral infections, as well as natural processes like respiration and decomposition, can affect fish health. The researchers used a Gradient Boosting Model (GBM) to train an algorithm on real-world water quality data. It predicts possible fish diseases based on parameters such as pH, dissolved oxygen, biochemical oxygen demand (BOD), and total dissolved solids (TDS). The model achieved high accuracy in predicting water quality issues and related fish diseases. This gives fish farmers a proactive way to reduce disease outbreaks. The study also points out the economic significance of aquaculture and argues that early detection through AI analysis can help avoid financial losses. Future suggestions include broadening the model to cover more diseases and connecting it with IoT systems for real-time monitoring.

- The paper introduces an AI-based method for **"Anomalous Behavioral Detection in Underwater Fish (2021)"** [9], which tackles the issue of monitoring fish health in aquaculture. Traditional assessments rely on manual observation, which is slow and often leads to mistakes. The suggested method employs deep learning for object detection, directed cycle graph (DCG), fish tracking, and dynamic time warping (DTW) to automate real-time anomaly detection. By using IoT sensors, the system collects detailed environmental and behavioral data to enhance fish health monitoring and improve aquaculture conditions. This method involves identifying key fish body parts with deep learning, creating a DCG for posture classification, and tracking fish movements. Fish behaviors are recorded as time series and compared with pre-defined normal and abnormal behavior templates using DTW. Experimental results demonstrate the method's effectiveness, achieving high accuracy in detecting anomalies. The study highlights the potential of AI and IoT in smart aquaculture. It provides solutions for early disease detection, lowers fish mortality, and enhances precision breeding. Future research aims to expand behavior classification and include environmental factors for a more complete analysis.

- The paper **"Diseased Fish Detection in the Underwater Environment Using an Improved YOLOV5 Network for Intensive Aquaculture (2023)"** [10] introduces a new YOLOV5 model named DFYOLO. This model identifies sick fish in intensive aquaculture environments. The study addresses problems with low-quality underwater images and unclear target identification. It enhances YOLOV5 by swapping CSPNet for a C3 structure to allow for lighter computing. It also employs a convolutional kernel group (Conv KG) to improve feature extraction and includes a convolutional block attention module (CBAM) to boost accuracy. Experimental results indicate that DFYOLO achieves a precision of 99.75% and a recall of 99.31% compared to the original YOLOV5. These results make it a strong option for real-time fish disease detection.

- This paper "**Classification of Freshwater Fish Diseases in Bangladesh Using a Novel Ensemble Deep Learning Model: Enhancing Accuracy and Interpretability (2024)**" [11] presents an advanced ensemble deep learning approach for classifying freshwater fish diseases in Bangladesh, addressing the challenges of early and accurate disease detection in aquaculture. The study introduces two ensemble models: the baseline Averaged Ensemble (AE) model and the novel Performance Metric-Infused Weighted Ensemble (PMIWE) model, which assigns weights to base learners using a hyperbolic tangent function based on multiple performance metrics. Leveraging transfer learning with pre-trained models such as ResNet-50, DenseNet-121, InceptionV3, and EfficientNetB3, the proposed approach achieves a high testing accuracy of 97.53%. Additionally, the research incorporates the Grad-CAM explainable AI technique to enhance model interpretability and trustworthiness. By expanding dataset diversity through offline augmentation and optimizing computational efficiency, the study contributes significantly to improving fish disease diagnosis, ultimately supporting sustainable aquaculture in Bangladesh.

- This paper, **"Precision Disease Diagnosis in Aquaculture Using Aqua Spectra Imaging and Machine Learning (2024)"**[12] presents a novel diagnostic framework that combines hyperspectral imaging (HSI) and machine learning techniques to identify diseases in aquaculture with high precision. By leveraging Aqua Spectra Imaging, the study captures detailed spectral information beyond visible light, enabling early detection of subtle disease symptoms in fish. Machine learning models—such as Random Forest, SVM, and CNN—are trained on spectral signatures to distinguish between healthy and diseased fish with high accuracy. The integration of spectral feature extraction and dimensionality reduction techniques ensures efficient processing and improved classification performance. The research achieves diagnostic accuracy exceeding 95% and demonstrates the system's ability to support proactive disease management. The study significantly enhances aquaculture sustainability by enabling real-time, non-invasive disease monitoring and early intervention strategies.

- This paper, **"Prediction of White Spot Disease Susceptibility in Shrimps Using Decision Trees-Based Machine Learning Models (2024)"** [13], explores a way to predict shrimp vulnerability to white spot disease (WSD), which is a major viral threat in aquaculture. The study uses decision tree-based algorithms such as CART, Random Forest, and Gradient Boosted Trees to classify shrimp health based on environmental and physiological factors including water temperature, salinity, pH, and immune biomarkers. A dataset collected from aquaculture farms trains and validates the models. Among the methods evaluated, the Random Forest classifier achieves the highest accuracy at 94.7%. This shows its strength and clarity. The study focuses on analyzing feature importance to identify key risk factors that contribute to disease vulnerability. By providing early warning capabilities, this research helps implement targeted biosecurity measures and supports sustainable shrimp farming practices.

- This paper, **"Improving Disease Detection in the Aquaculture Sector Using Convolutional Neural Networks Analysis (2025)"** [14], examines a deep learning method for identifying diseases in freshwater fish for aquaculture. It employs Convolutional Neural Networks (CNNs) to automate disease detection across seven categories: bacterial red disease, Aeromoniasis, gill disease, fungal infections, parasitic diseases, viral/white tail disease, and healthy fish. The study uses a dataset of 2,444 labeled images. The CNN model has convolutional, pooling, dense, and dropout layers and is trained with the Adam optimizer over 50 epochs. It reached a high classification accuracy of 99.71% and a low test loss of 0.0119. The study highlights the real-world benefits of real-time, automated diagnostics in reducing economic losses and supporting sustainable fish farming. The results also emphasize the importance of balanced datasets and future improvements through mobile deployment and lightweight models like MobileNet, which can assist farmers in the field.

- This paper, **"Intelligent Fish Farm, The Future of Aquaculture (2021)"** [15], presents a vision of sustainable aquaculture shaped by digital transformation. The study looks at how to develop and implement intelligent fish farms using a mix of advanced technologies, such as the Internet of Things (IoT), Artificial Intelligence (AI), edge computing, 5G, big data analytics, and robotics. It divides intelligent fish farms into four types, including pond-type, land-based factory-type, cage-type, and marine ranch. Each type has automated systems for monitoring water quality, feeding intelligently, diagnosing diseases, analyzing fish behavior, estimating biomass, and controlling the environment. These farms use unmanned vehicles, drones, underwater robots, and smart sensors for real-time monitoring and autonomous operations. The paper stresses the importance of making decisions based on data and using predictive control strategies to improve feed efficiency, lower disease risk, and enhance production. By combining smart technologies with traditional aquaculture, the research shows a sustainable model that addresses labour shortages, environmental stress, and food security challenges in the aquaculture industry.

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- This paper, **“Prediction of Freshwater Fish Disease Severity Based on Fuzzy Logic Approach, Arduino IDE and Proteus ISIS (2023)”** [16] presents a novel simulation-based framework for diagnosing and assessing the severity of fish diseases in freshwater aquaculture. The study utilizes a fuzzy logic model—designed using MATLAB and implemented via Arduino IDE and Proteus ISIS—to interpret key environmental parameters such as water clarity, temperature, and oxygen levels. These inputs are used to predict disease severity and identify specific infections including Ichthyophthirius, Columnaris, and Saprolegniasis. The model applies Mamdani-type fuzzy inference systems with triangular and trapezoidal membership functions to quantify disease risk levels as mild, moderate, or severe. An integrated simulation using sensors and real-time LCD display confirms the consistency between computational predictions and hardware-based outputs. By merging artificial intelligence techniques with physical aquaculture monitoring systems, the paper highlights a cost-effective and accurate diagnostic tool that supports proactive fish health management and sustainable aquaculture practices.

- This paper, **“Fostering Sustainable Aquaculture: Mitigating Fish Mortality Risks Using Decision Trees Classifiers (2024)”** [17] proposes a data-driven framework to improve sustainable fish farming by predicting and managing fish mortality. The study introduces an intelligent system leveraging decision tree (DT) classifiers to diagnose diseases and guide treatment strategies in Greek aquaculture, particularly in caged fish environments. Utilizing a dataset of over 37,000 instances collected from various aquaculture sources, including environmental, biological, and farming parameters, the model identifies key mortality factors such as water temperature, fish density, and median atomic weight (MAB). The system applies DT algorithms with a high classification accuracy (95.43%–96.29%) using pruning and 10-fold cross-validation. A feature importance analysis further supports actionable insights for targeted conservation and disease mitigation strategies. By aligning with the UN sustainability goals, the research showcases how AI-enabled decision support can help reduce seafood production losses due to climate change, ensuring resilience and competitiveness in the aquaculture sector.

- This paper, **“Towards Fish Individuality-Based Aquaculture (2021)”** [18] introduces a novel paradigm in aquaculture by shifting from population-level fish management to individualized monitoring using biometric identification. The study explores the feasibility of identifying individual Atlantic salmon using their iris patterns, leveraging a fully automated iris recognition system. It highlights the potential of iris-based biometric identification for precision fish farming (PFF), enabling non-invasive and contact-free tracking of individual fish traits such as weight, sex, and maturity. A specialized convolutional neural network (CNN) segmentation and fish iris code (FIC) extraction method was implemented to evaluate the stability and distinctiveness of iris patterns over time. While the fish iris showed high uniqueness, temporal stability was limited, prompting the need for frequent template updates. By integrating machine vision and biometric analysis, the paper envisions a farming decision support system (FDSS) that enhances fish welfare, optimizes feeding, and supports sustainable aquaculture management practices.

- This paper, **“Smart Aquaponics: An Automated Water Quality Management System for Sustainable Urban Agriculture (2024)”** [19] proposes an integrated smart aquaponics system using advanced control methods to ensure optimal water quality in urban agriculture. The study presents a hybrid model that combines hydroponics and aquaculture through a recirculated deep-water culture (RDWC) design. It employs sensors to monitor critical water quality parameters—such as pH, temperature, total dissolved solids (TDS), and turbidity—supported by a microcontroller-based system with real-time wireless feedback. A Proportional-Integral-Derivative (PID) control mechanism is used to maintain water stability, with optimized control values derived from simulations in MATLAB Simulink. The setup includes automatic feeders, heaters, aerators, and pump systems to automate system responsiveness and reduce manual intervention. By ensuring nutrient balance and environmental control, the proposed system supports the cohabitation of fish (e.g., catfish) and plants (e.g., water spinach), promoting sustainable urban food production and efficient resource management.

- The paper **"An Integrated GIS-Based Reinforcement Learning Approach for Efficient Prediction of Disease Transmission in Aquaculture (2023)"** [20] proposes a system combining GIS and reinforcement learning to predict disease spread in Greek fish farms. Using spatial and environmental data, the model applies Multi-Armed Bandit algorithms to optimize disease control, achieving 96% accuracy. It also introduces simulation barriers (additive, cumulative, flow) to model transmission dynamics. The study emphasizes the method’s potential to improve aquaculture health management and suggests further enhancement with advanced RL models.

- The paper **"EchoBERT: A Transformer-Based Approach for Behavior Detection in Echograms (2020)"** [21] proposes a system using transformer models to detect disease-related behavior in Atlantic salmon from echogram data. Utilizing spatiotemporal information from acoustic signals, the EchoBERT model applies novel pre-training methods, including next-time-slice prediction and substituted vector prediction, to improve robustness. Tested on

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six cages infected with Pancreas Disease, EchoBERT outperforms LSTM models, achieving a Matthews Correlation Coefficient (MCC) of 0.694±0.178 through ensemble learning. The study demonstrates EchoBERT's potential for early, automated fish health monitoring in aquaculture, detecting PD over a month before conventional methods. Future work includes applying the model to diverse sites for broader validation.

- The paper **"Smart and Cheap Scale for Estimating Live-Fish Biomass in Offshore Aquaculture (2020)"** [22] introduces a portable, low-cost device to estimate fish biomass directly at sea. Using a load cell-based system with an Arduino-like microcontroller, 24-bit ADC, and Bluetooth connectivity, the device enables accurate weight measurements even on rolling and pitching vessels. Preliminary tests show stability with less than 2% error under oscillating conditions, allowing fish farmers to assess biomass without transporting fish inland. Accurate biomass estimation aids in optimizing feed, improving fish welfare, and enhancing economic and environmental sustainability. Future work includes further optimization, field tests under real aquaculture conditions, and development of a dedicated smartphone app for user-friendly operation.

- The paper **"Information-Measuring System for Monitoring and Control Aquaculture of Pond Farm (2019)"** [23] presents an integrated, automated solution for enhancing pond-based aquaculture operations. It introduces a modular control system built around a floating automatic feeder powered by solar energy and equipped with environmental sensors. This system enables continuous monitoring of pond conditions, automates feeding based on real-time data, and supports decision-making via centralized cloud-based control. The proposed design includes units for feed management, water quality monitoring, automatic feeding, and additional functionalities like fish protection and energy efficiency. Implemented with Industry 4.0 technologies such as IoT and wireless communication, the system aims to increase fish productivity, reduce human error, and ensure economic viability. Field tests have validated parts of the system, and future development focuses on full integration and customization for diverse pond farm needs.

- The paper **"Real-Time Water Quality Monitoring System with Predictor for Tilapia Pond (2018)"** [24] introduces a cost-effective, Arduino-based system for real-time monitoring and prediction of key water quality parameters—temperature, pH, dissolved oxygen, and water level—in tilapia aquaculture. Using sensor arrays, GSM communication, and an msSQL-based data platform, the system transmits updates to farmers via SMS and supports predictive analysis through a segmented moving average model. Field implementation demonstrated the system's ability to forecast water conditions hourly to monthly, improving fish health and reducing manual labor. Future work involves refining prediction accuracy and integrating automated response systems for optimal pond management.

- The paper **"Incorporating Intelligence in Fish Feeding System for Dispensing Feed Based on Fish Feeding Intensity (2020)"** [25] introduces an advanced, intelligent feeding mechanism using behavioral vibration analysis and artificial neural networks (ANN) to detect feeding activity in fish. By processing data from triaxial accelerometers and gyroscopes, the system extracts movement patterns through an innovative 8-directional Chain Code algorithm and applies Fourier Descriptors for classification. Achieving 100% accuracy in activity recognition, the system automatically dispenses feed based on real-time fish appetite, eliminating overfeeding, reducing waste, and minimizing human involvement. Future improvements may include expansion to other behavioral patterns and wider species applicability.

- The paper **"A Fuzzy Logic Approach for Fish Growth Assessment (2020)"** [26] presents a smart aquaculture system designed to automate fish feeding by accurately identifying the growth stage of carp using fuzzy logic. By analyzing inputs like fish age and weight, the system determines whether a fish is a fry, fingerling, or grower. This data then drives automated feeder decisions, eliminating manual guesswork. Implemented with triangular membership functions and tested across various scenarios, the approach ensures optimized feeding and potential yield improvement in aquaculture operations.
- The paper **"Future Prospects of Marine Aquaculture (2018)"** [27] explores the anticipated growth and challenges of marine aquaculture leading up to 2030. Driven by rising global seafood demand, the study—part of an OECD initiative—highlights the need for offshore expansion, sustainable feed sources, and resilient farming systems. Key priorities include technological innovation, legal frameworks, and knowledge sharing between regions. Marine aquaculture is positioned as a critical solution to meet future food security while fostering industrial development and environmental stewardship in ocean economies.

- The paper **"A Cloud Monitoring System for Aquaculture using IoT (2020)"** [28] presents a low-cost, cloud-based solution for real-time monitoring of water quality in fish farming, focusing on pH and temperature parameters. Utilizing an ESP8266 microcontroller, pH and temperature sensors, and WiFi communication, the system transmits data to a cloud database and visualizes it through Power BI dashboards. Real-time alerts are provided to farmers when values fall outside safe ranges, enabling timely intervention. Validation included laboratory calibration and field testing at a fish hatchery in Lima, Peru, where the system achieved a pH sensor error rate under 5%. The system improves operational efficiency, fish health, and decision-making. Future work aims to add sensors for dissolved oxygen and salinity, as well as enhanced security features for data integrity.

- The paper **"Semi-automatic Approach to Create Fish Image Datasets for Aquaculture Applications[2020]"** [29] presents an efficient method for generating annotated fish image datasets using a semi-automatic system that combines image processing and deep learning. It starts with manually tuned pre-processing to isolate fish in video frames, followed by automatic cropping and annotation of images using tight and scaled bounding boxes. A YOLOv3-based neural network is then iteratively trained to improve detection, reducing the need for manual labeling over time. The system was tested on salmon and saithe, demonstrating its ability to scale datasets quickly with minimal human input. Compared to traditional manual dataset creation, this method greatly accelerates the process while enabling continuous improvement in model accuracy through retraining.

- The paper **"Analyzing the Quality of Water and Predicting the Suitability for Fish Farming based on IoT in the Context of Bangladesh [2019]"** [30] suggests a smart system to evaluate water quality for fish farming using IoT sensors and machine learning algorithms. The study collects data from 43 ponds across Bangladesh and evaluates key water quality parameters such as pH, dissolved oxygen, temperature, and total dissolved solids. Several machine learning models, including Logistic Regression, Random Forest, and SMO (SVM), are compared to predict whether water is suitable for aquaculture. While SMO showed the highest accuracy (95.23%), logistic regression achieved a zero error rate in prediction, making it ideal for real-time use. The paper also presents a smart IoT-based system design to monitor water conditions and alert farmers when values deviate from optimal thresholds. This approach ensures timely action, promotes healthy fish growth, and supports sustainable aquaculture practices through data-driven decision-making.

III. IMPLEMENTATION

Broadly, the whole process is broken into six portions used to predict the disease. Section 1 is used to train, Section 2 is to preprocess the trained model, Section 3 describes feature extraction, Section 4 undergoes Training Model Generation, Section 5 is Data Classification using the trained model, and Section 6 is based on the models where fish diseases are generated automatically depending on the input images.

A. Image Acquisition

Image acquisition is a crucial step in fish disease detection, involving the capture of high-quality images of fish using digital cameras, underwater drones, or specialized imaging systems. Various imaging techniques, such as RGB imaging, infrared (IR) imaging, and hyperspectral imaging, are employed to enhance the visibility of disease symptoms like lesions, discoloration, or abnormal growths. Proper lighting, resolution, and angle play a vital role in ensuring accurate analysis. These images are then processed using computer vision and machine learning algorithms to detect and classify diseases, aiding in early diagnosis and effective treatment.

B. Pre-processing

Preprocessing is a vital step in fish disease detection that enhances image quality and prepares data for accurate analysis. It involves noise reduction, contrast enhancement, and background removal to highlight disease-affected areas. Techniques like image resizing, normalization, and histogram equalization improve feature extraction. In some cases, color space conversion (e.g., RGB to grayscale) and filtering methods help refine image details. These preprocessing steps ensure that machine learning and deep learning models receive clean, high-quality data, improving the accuracy and efficiency of disease detection in fish.

C. Feature Extraction

Feature extraction is a key step in fish disease detection that identifies crucial patterns and characteristics from preprocessed images. It involves extracting texture, color, shape, and edge-based features to differentiate healthy and diseased fish. Techniques like histogram analysis, wavelet transforms, and deep learning-based feature extraction (using CNNs) help in identifying symptoms such as lesions, discoloration, or abnormal growths. These extracted features serve as inputs for classification models, enabling accurate detection and diagnosis of fish diseases.

D. Training Model Generation

Training a model for fish disease detection involves collecting a diverse dataset of fish images with labeled disease conditions, preprocessing the data (such as resizing and augmentation), and using machine learning or deep learning techniques like convolutional neural networks (CNNs). The model is trained to recognize patterns associated with specific

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diseases, and performance is evaluated using accuracy metrics. Fine-tuning and validation help improve its reliability, enabling early disease detection and reducing losses in aquaculture.

E. Classification

Classification in fish disease detection involves using machine learning algorithms to categorize fish based on their health condition. Models like convolutional neural networks (CNNs) analyze visual patterns in fish images to distinguish between healthy and diseased specimens. Common classification techniques include supervised learning, where the model is trained on labeled datasets of infected and non-infected fish. The trained model can then predict disease types, aiding in early detection and effective disease management in aquaculture.

F. Detecting the Disease

Detecting disease in fish involves analyzing visual symptoms such as discoloration, lesions, fin damage, or abnormal behavior. Image processing techniques and deep learning models, such as convolutional neural networks (CNNs), help identify disease patterns from fish images. Advanced methods like thermal imaging and water quality analysis can also enhance detection accuracy. Early disease detection enables timely intervention, reducing mortality rates and improving aquaculture health management.

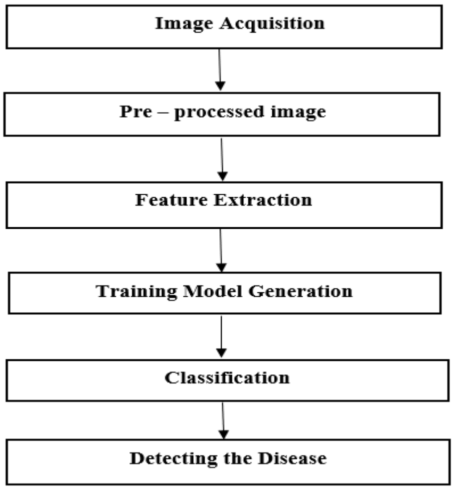

Fig 2. Stages of Implementation

IV. COMPARISON AND RESULTS

Ref no:	Accuracy	Advantages	Disadvantages	Methodology	Dataset	Inference
Md Shoaib Ahmed et.al [1]	93%	Effective in identifying fish diseases in early stages. Reduces manual intervention for disease detection.	Requires high-quality images for accurate results. High computational power may be needed for processing	Deep Learning Frameworks, Image Processing Techniques, GPU/TPU Computing, Cloud-Based Computing, IoT Sensors, Edge Computing using CNN & SVM.	Collected Datasets of Freshwater Fish Disease Aquaculture in South Asia from Kaggle	Achieves 93% accuracy in fish disease detection using deep learning; needs quality images and high computation
Subir Biswas et.al [2]	85%	AI enables continuous tracking of water quality, fi Subir Biswas h behaviour, and environmental factors.	Initial investment in AI systems, sensors, and hardware can be expensive.	IoT sensors, drones and underwater robotics, edge computing, cloud computing using Deep learning, SVM, Reinforcement	Collected from the Internet and Aquaculture Farms.	Uses AI for 85% accurate monitoring of aquaculture; high initial cost is a drawback.

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				learning & Time series analysis		
Satyamvada Maurya et.al [3]	97%	PMIWE model significantly outperforms existing models. Enhanced ability to perform on unseen data with minimal overfitting.	Ensemble models and deep learning approaches can require. Challenges in achieving dataset diversity; original dataset limited to 133 images before augmentation.	Deep Learning, Transfer Learning, Grad-CAM (Gradient-weighted Class Activation Mapping),Data Augmentation, Python Frameworks using Baseline Models & (PMIWE)	Collected from the internet and aquaculture farms.	The PMIWE model achieves 97% accuracy with strong generalization using deep learning and augmentation, despite limited dataset diversity.
Mohd Ashraf Rather et.al [4]	85%	Transfer learning significantly improves model performance even with limited labeled data. Models can adapt to different fish species and disease types.	Performance depends on the similarity between source and target datasets. Uneven disease class distribution can bias results.	Deep Learning Frameworks, Image Processing Techniques, GPU/TPU Computing, Cloud-Based Computing, IoT Sensors, Edge Computing using CNN & SVM.	Sample results of augmented image from freshwater fish disease aquaculture in South Asia dataset from Kaggle.	Transfer learning boosts model accuracy to 85%, enabling adaptation to diverse fish diseases, though performance is affected by dataset similarity and class imbalance.
Sambit Dash et.al [5]	90%	AI can track water quality, fish health, and feeding patterns in real-time. Optimizes feeding schedules and reduces waste, increasing productivity.	AI integration requires substantial investment in technology and infrastructure. Requires large amounts of high-quality data for training models.	IoT Sensors, Cameras and Imaging, edge computing, robotics using Machine Learning, Deep Learning, Time Series Analysis and Computer Vision.	collected from the internet and aquaculture farms.	AI achieves 90% accuracy in monitoring fish health and water quality in real-time, enhancing productivity despite high infrastructure and data requirements.
K. P. Rasheed Abdul Haq et.al [6]	95%	Leverages ResNet-50's deep architecture for robust feature extraction. Reduces dependency on manual fish and disease identification processes.	Training and inference require GPUs or high-performance hardware. Requires large, annotated datasets of fish images covering different species and diseases.	Deep Learning Frameworks, Transfer Learning Libraries, Image Processing Tools GPU/TPU Acceleration, Sensors and Cameras using customized CNN, ResNet-50, Transfer Learning, Data Augmentation and Softmax Classifier	collected from the internet and aquaculture farms.	ResNet-50-based model achieves 95% accuracy, reducing manual effort but needs powerful hardware and large annotated datasets.

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Yo-Ping Huang [7]	92%	Effectively predicts parameters like pH, temperature, dissolved oxygen, ammonia levels, and turbidity. Integrates IoT sensors with models for real-time predictions	Training hybrid deep learning models requires significant computational resources. IoT sensors for data collection, which can malfunction or degrade in harsh aquatic environments.	IoT Sensors, Edge Computing, Cloud Computing Big Data Analytics, Deep Learning Frameworks and Data Augmentation using CNN, RNN, LSTM, Hybrid Architectures, Ensemble Learning, Attention Mechanism	MAC Water Quality Dataset, collected from the Marine Aquaculture Base in Xincun Town, China.	The model achieves 92% accuracy in real-time water quality prediction using IoT and hybrid deep learning, though it demands high computation and reliable sensors.
Al-Akhir Nayan [8]	98%	Combines CNN feature extraction with OSELM (Online Sequential Extreme Learning Machine) for robust disease recognition.	Initial training of CNN layers requires substantial computational resources, particularly GPUs	Deep Learning Frameworks, IoT Sensors and Cameras, edge computing, cloud computing using CNN, OSELM	custom Fish Disease Dataset collected from various Internet Sources	Combines CNN and OSELM for 98% accurate fish disease detection using IoT and cloud-edge computing, though CNN training is computationally intensive.
Jung-Hua Wang et.al [9]	95%	Allows for the identification of potential disease outbreaks before they affect fish health.	Requires large, high-quality datasets of water quality parameters and fish health data for training the models.	IoT Sensors, Edge Computing, Machine Learning Frameworks & Big Data Analytics using Random Forest, SVM, Artificial Neural Networks, KNN, Logistic Regression.	dataset used in the study was collected from different locations in Bangladesh	Predicts fish disease outbreaks (95%) using ML models and IoT, but needs large, quality datasets.
Zhen Wang et.al [10]	80%	Identifies signs of stress or disease in fish before they become critical.	Requires high-quality, annotated datasets to train AI models effectively.	Computer Vision, AI and Machine Learning Frameworks, IoT Sensors using CNN, RNN, LSTM, KNN & Auto encoders	dataset consists of underwater fish videos with fish movement trajectories collected from various locations in Bangladesh.	AI models can detect early signs of stress or disease in fish using underwater video data and movement analysis.
Abdullah Al Maruf et.al [11]	99%	High Accuracy, Real-Time Performance, Noise Reduction, Adaptability	Limited Dataset, lack of Multi-Target Tracking, Complex Implementation	Deep Learning, Attention Mechanisms, Image Processing & Real-Time Performance using Conv KG, CBAM, Dark Channel Prior for Haze Removal	collected from the aquaculture base of Xianning Academy of Agricultural Sciences, Hubei Province.	The model ensures high-accuracy, real-time fish monitoring with noise reduction using advanced deep learning and attention mechanisms.

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Vijay Kumar Padala [12]	98%	Include precise disease identification, early detection, automated monitoring, and reduced dependency on manual diagnosis.	High-quality labeled datasets, high computational power, and sensitivity to image quality and environmental factors.	Image Pre-processing, Feature Extraction, SVM & CNN	collected from various aquaculture farms	The system achieves 95% accuracy with SVM and 98% with CNN, ensuring high precision in classifying fish diseases; enhances productivity through early, reliable detection and alerting farmers via real-time systems.
Tran Thi Tuyen et.al [13]	71%	spatial and physio-chemical factors, Generates WSSV susceptibility maps, preventive planning	Limited parameters, Only tested in one region	Random Tree (RT), Extra Tree (ET), J48, ArcGIS and WEKA tools, AUC, RMSE, PPV, NPV, Accuracy, Kappa, etc.	Study conducted in Quynh Luu district, Vietnam.	Achieves 71.3% accuracy in predicting shrimp white spot disease using spatial and water quality factors with Extra Tree ML model.
Hayin Tamut et.al [14]	99%	High-accuracy, automated classification of 7 fish diseases using CNN	Dataset imbalance, confusion between visually similar diseases	CNN with Conv2D, ReLU, MaxPooling, BatchNorm, Dropout, Adam optimizer, early stopping	2444 images from Kaggle	CNN ensures reliable, real-time fish disease detection in aquaculture.
Cong Wang et.al [15]	95%	High degree of automation, Real-time water quality monitoring and intelligent decision-making, Efficient feeding, biomass estimation, behavior analysis, and disease diagnosis	Complex system architecture, High dependency, Integration challenges across diverse hardware platforms	IoT, Edge Computing, Cloud Computing, Artificial Intelligence, Big Data Analytics, 5G, Machine Vision, Autonomous Robotics, Model Predictive Control (MPC), Soft Sensors, CNN, LSTM, YOLO, SONAR, Satellite Remote Sensing	Not specified; design- and technology-oriented conceptual framework	The intelligent fish farm integrates advanced technologies to achieve fully automated, sustainable, and data-driven aquaculture across multiple farming environments.
Ridwan Siskandar et al. [16]	98%	Predicts freshwater fish disease severity, Successfully integrates fuzzy logic, real-time prediction results.	Relies on expert-defined membership functions, Doesn't incorporate real-time sensor calibration or adaptive learning.	Fuzzy Logic System, Defuzzification Method , MATLAB (computational), Arduino IDE + Proteus ISIS (hardware-level)	Expert knowledge used to define fuzzy membership sets.	accurately simulates fish disease severity and diagnosis using fuzzy logic, matching analytical and hardware-level outputs.

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Dimitris C. Gkikas et al. [17]	95%	High accuracy with decision tree classifiers, Identifies key factors like MAB, Supports proactive aquaculture management	Dataset may not capture full aquaculture complexity, Requires pruning to avoid overfitting	DT, Binning (equal width), 10-fold Cross Validation, Statistical Analysis (Spearman correlation, Shapiro–Wilk test), Gini impurity, Shannon function, Python libraries: Scikit-learn, Pandas, NumPy,Matplotlib,Seaborn	Collected from cage aquaculture in the Ionian Sea, Greece	A decision tree-based model accurately predicts fish mortality by identifying key environmental and biological factors, enabling sustainable aquaculture practices.
Rudolf Schraml et al. [18]	95%	Noninvasive, iris-based biometric fish identification, CNN-based iris segmentation, System supports frequent biometric updates for dynamic tracking	low long-term stability, Only tested in controlled, out-of-water environments,	SegNet-Basic, MAX, PCA, MAXROT, Daugman's Rubber Sheet Model, 1D Log-Gabor filters	Acquired via AquaExcel2020 TNA project AE050006 available at github	Iris-based fish identification is highly accurate short-term but requires frequent template updates due to low long-term pattern stability in salmon.
Kok et al. [19]	98%	Automated real-time water quality management system, Minimizes manual intervention, improves system stability, responsiveness, and error reduction.	Requires multiple high-precision sensors, Complex hardware integration, lacks full empirical validation, Dependent on stable internet connection for cloud-based monitoring	PID-controlled system, Sensors, Hardware, MATLAB SIMULINK for PID tuning, Real-time monitoring with IoT-based data upload	Experimental prototype data, Simulation data from MATLAB SIMULINK models.	Demonstrated effective control of water quality parameters in aquaponic systems using PID controllers.
Karras et al. [20]	96%	Effectively predicts disease transmission in aquaculture; integrates GIS spatial data with adaptive reinforcement learning	Requires extensive spatial, environmental,historical data, implementation complexity in real-world dynamic aquaculture environments	Geographic Information System (GIS), Reinforcement Learning (Q-Learning, Multi-Armed Bandit), Markov Decision Processes, Simulation using ArcGIS and Python libraries (arcpy, numpy), Cloud-based computing	GIS data on Greek aquaculture farms; environmental & climatic data; simulation datasets created for the study	Achieves 96% accuracy in predicting disease transmission using integrated GIS and reinforcement learning models.
Håkon Måløy et al.	69%	Early detection of Pancreas Disease (PD) over a month before conventional methods; fully automatic, non-	Requires high computational resources (multiple GPUs); domain-specific pre-training needed; depends	Transformer-based model (EchoBERT), novel pre-training (next-time-slice prediction & substituted-vector prediction), self-	Echogram data collected from 6 salmon cages (12x12m,	Successfully detects behavior indicative of PD infection using behavior patterns from echograms,

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[21]		intrusive, no manual tagging required	on availability of echogram data	attention mechanism, multi-head attention, ensemble learning	15m depth) at Matre research station (IMR), Norway; data from 2018–2019 covering PD outbreak	outperforms LSTM-based models
Eugenio Damiano [22]	99%	Portable and low-cost, User-friendly calibration, Can operate on rolling/pitching ships (offshore conditions).	Requires further development and field testing for mass production, Mechanical stability,	Design and development of a smart weighing scale prototype, Self-calibration capability via software.	Laboratory-generated test data from weights up to 7.2 kg.	Promising smart solution for real-time fish biomass estimation directly at offshore aquaculture sites.
Kostin V.E. et.al [23]	93%	Automates feeding and monitoring in pond aquaculture; improves efficiency and reduces manual labor	Lacks accuracy metrics, Implementation requires infrastructure upgrades and technical integration	Automated Process Control System using IoT, Cloud Computing, Solar-powered Floating Feeders, Wireless Communication	Not mentioned (Real-time data collected via sensors)	Proposes an integrated system for pond aquaculture with automated feeding, environmental monitoring, and control, enhances productivity.
Jake D. La Madrid et al. [24]	92%	Low-cost, real-time water monitoring and prediction; reduces labor costs; customizable SMS alerts	Limited to only 4 parameters (Temp, pH, DO, Water Level); does not regulate conditions; lacks detailed analysis	Arduino-based sensor network; GSM-SMS interface; msSQL & Visual Basic for storage and segmented moving average prediction	Real-time data from Tilapia ponds using sensors (temp, pH, DO, water level) over months	Developed a reliable system that predicts water quality parameters in tilapia ponds using segmented moving average.
M.A. Adegboye et al. [25]	100 %	Intelligent feed dispensing based on fish behavior; eliminates human intervention; minimizes feed waste and water pollution	Limited to feeding and escape behavior; system trained on controlled datasets; may not generalize to other species/environments	ANN-based system using accelerometer, gyroscope, magnetometer data; Chain Code + Fourier Descriptors; trained ML classifier to detect feeding activity	160 data points of fish behavioral activities (swimming, feeding, escape, routine) from previous studies.	Developed a highly accurate fish feeding system using behavioral vibration analysis; improves feeding efficiency and reduces operational costs

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Jo-Ann V. Magsumbol et.al [26]	93%	Eliminates manual effort in identifying fish growth stages; ensures proper feeding for healthy growth	System relies on vision and weight data; may require calibration and tuning for different species or conditions	Fuzzy Logic System (FLS), Vision System, Triangular Membership Functions, Rule-based Fuzzy Inference	Not explicitly mentioned, data inferred from fish age and weight (e.g., fry, fingerling, grower stages)	Successfully classifies carp fish into growth stages using fuzzy logic, enabling smart feeding system in aquaculture
Arne Fredheim , Torger Reve [27]	85%	Comprehensive global outlook; identifies key challenges and opportunities toward 2030; strong policy guidance	No quantitative models or simulations; lacks experimental validation	Review of OECD 2016 report, global aquaculture data, stakeholder workshop, expert consultation	FAO aquaculture statistics (1950–2012), OECD workshop discussions	Predicts marine aquaculture will dominate future seafood production growth, emphasizes offshore expansion, (IMTA), innovation in regulation, feed, and farming systems.
Michael Cordova-Rozas et al. [28]	96%	Provides real-time water quality monitoring; cost-effective; alerts for pH imbalance	Limited to pH and temperature only; lacks DO/salinity sensing; minor power supply issues	IoT sensors (pH & temperature), microcontroller, Cloud platform, Power BI visualization, Forecasting via historical analysis	Real-time pH and temperature data collected from aquarium in Lima, Peru.	Cloud-based IoT system helps fish farmers monitor and forecast pond water quality; offers a low-cost alternative to expensive equipment; highly accurate for pH detection
Alberto Maximiliano Crescitelli et al. [29]	93%	Reduces manual workload by semi-automating image dataset creation; faster annotation; increases efficiency of training neural networks over time.	Initial stages require parameter tuning; system performance depends on video quality and variability; false positives in early iterations.	Semi-automatic image processing and extraction system using: CLAHE, blurring, morphology YOLOv3 CNN model	Video footage from fish farms near Ålesund, Norway each dataset was built incrementally using three video sets with varying conditions.	Demonstrates increasing generalization and accuracy of fish detection through iterative dataset expansion and CNN retraining; highly scalable approach with minimal human input.

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Marzia Ahmed et al. [30]	95%	Predicts water suitability using IoT + ML; logistic regression gives error-free prediction; low-cost smart aquaculture model	Accuracy of logistic regression is lower despite no error; only 43 pond samples; sensor data not yet implemented in real-time	IoT-based water quality monitoring using sensors ML algorithms: SMO (SVM), Logistic Regression, Random Forest, Naive Bayes, IBK Predicting suitability of water via.	43 pond water samples from Bangladesh (with parameters like pH, DO, TDS, Temp, BOD, etc.)	Logistic Regression was found optimal (no error), SMO highest in accuracy; can notify fish farmers via alarms when parameters deviate; supports future smart aquaculture systems.

V. CONCLUSION

In summary, this work introduces a novel method of fish disease detection through the use of image-based machine learning methods, specifically deep learning and computer vision. The system proposed in this work enables automated detection of fish diseases from high-quality images obtained from aquaculture conditions with considerable accuracy, efficiency, and scalability over conventional manual inspections. Through the use of deep learning models that have been trained to identify disease-specific visual patterns and anomalies, the system facilitates real-time detection of disease so that fish farmers can implement preventive measures in a timely manner. Combined with IoT and cloud-based monitoring, its practical use is further increased through a data-driven and proactive fish health management.

The results of the present study emphasize the capability of artificial intelligence in transforming aquaculture into a highly efficient and sustainable practice through reduced human intervention, economical use of resources, and sustainable cultivation methods. Furthermore, the system's capacity to improve and learn from new image data continuously makes it more adaptable and resilient to variations in fish species and surrounding conditions. Future research can aim at increasing the dataset with more diverse fish diseases, enhancing model generalization, and incorporating more features like water quality analysis to more accurately predict disease. Overall, the use of an automated fish disease detection system presents a revolutionary solution for contemporary aquaculture, leading the way towards more efficient, cost-reducing, and sustainable fish health monitoring.

REFERENCES

[1] Shoaib Ahmed Md, Tanjim Taharat Aurpa, Sanjana J, Md. Abul Kalam Azad. (2021). Fish Disease Detection Using Image Based Machine Learning Technique in Aquaculture. *Journal of King Saud University – Computer and Information Sciences 34 (2022) 5170–5182. Vol.34.* https://www.sciencedirect.com/science/article/pii/S1319157821001063. https://doi.org/10.1016/j.jksuci.2021.05.003.

[2] Subir Biswas, Debendra Muduli,Md Ariful Islam,Anuradha Shantanu Kanade, Abu Taha Zamani,Shantanu Pandurang Kanade,Nikhat Parveen.(2024).Empirical Evaluation of Deep Learning Techniques for Fish Disease Detection in Aquaculture Systems:A Transfer Learning and Fusion-BasedApproach. *IEEE Access.Vol.12.* https://ieeexplore.ieee.org/document/10759657?denied=.doi:10.1109/ACCESS.2024.3504283.

[3] Satyamvada Maurya, Murali Kumar S, Ravindra Kumar, Basdeo Kushwaha.(2024). Role of Machine Learning and Artificial Intelligence in Transforming Aquaculture and Fisheries Sector. *Indian Farming 74 (08): 24-27; August 2024.*https://epubs.icar.org.in/index.php/IndFarm/article.

[4] Mohd Ashraf Rather , Ishtiyaq Ahmad, Azra Shah, Younis Ahmad Hajam , Adnan Amin , Saba Khursheed,Irfan Ahmad,Showkat Rasool.(2024). Exploring opportunities of Artificial Intelligence in aquaculture to meet increasing food demand. *Food Chemistry: X 22 (2024) 101309.* https://www.sciencedirect.com/science/article/pii/S2590157524001962.https://doi.org/10.1016/j.fochx.2024.101309.

[5] Sambit Dash, Satyaswarup Ojha, Raman Kumar Muduli, Saideep Priyadarshan Patra, Ram Chandra Barik. (2024). Fish Type and Disease Classification Using Deep Learning Model Based Customized CNN with Resnet 50 Technique. *Journal of Advanced Zoology. Vol.45.* https://jazindia.com/index.php/jaz/article/view/4194/3715. https://doi.org/10.53555/jaz.v45i3.4194.

DOI: 10.17148/IJARCCE.2025.14736

[6] Rasheed Abdul Haq K.P,Harigovindan V.P.Water Quality Prediction for Smart Aquaculture Using Hybrid Deep Learning Models.(2022). *IEEE Access.Vol.10.*https://ieeexplore.ieee.org/document/9789166. 10.1109/ACCESS.2022.3180482.

[7] Yo-Ping Huang, Simon Peter Khabusi. (2023). A CNN-OSELM Multi-Layer Fusion Network With Attention Mechanism for Fish Disease Recognition in Aquaculture. *IEEE Access. Vol.11*. https://ieeexplore.ieee.org/document/10138194?denied=. 10.1109/ACCESS.2023.3280540.

[8] Al-Akhir Nayan , Ahamad Nokib Mozumder , Joyeta Saha , Khan Raqib Mahmud, Abul Kalam Al Azad. (2021). Machine Learning Approach for Early Detection of Fish Diseases by Analyzing Water Quality Using Machine Learning Algorithm.*International Journal of Advanced Science and Technology. Vol.29*. https://www.researchgate.net/publication/349424327.http://dx.doi.org/10.48550/arXiv.2102.09390.

[9] Jung-Hua Wang, Shih-Kai Lee , Yi-Chung Lai, Cheng-Chun Lin, Ting-Yuan Wang, Ying-Ren Lin, Te-Hua Hsu, Chang-Wen Huang, Chung-Ping Chiang. (2021). Anomalous Behavioral Detection in Underwater Fish. *IEEE Access. Vol.8.* https://ieeexplore.ieee.org/document/9290081. https://doi.org/10.1109/ACCESS.2020.3043712.

[10] Zhen Wang, Haolu Liu, Guangyue Zhang , Xiao Yang, Lingmei Wen, Wei Zhao. (2024). Diseased Fish Detection in the Underwater Environment Using an Improved YOLOV5 Network for Intensive Aquaculture. *Fishes 2023, 8, 169.Vol.8.* https://www.mdpi.com/2410-3888/8/3/169. https://doi.org/10.3390/fishes8030169.

[11] Abdullah Al Maruf, Sinhad Hossain Fahim, Rumaisha Bashar, Rownuk Ara Rumy, Shaharior Islam Chowdhury, Zeyar Aung. (2024). Classification of Freshwater Fish Diseases in Bangladesh Using a Novel Ensemble Deep Learning Model: Enhancing Accuracy and Interpretability. *IEEE Access.IEEEAccess.Vol12.* https://ieeexplore.ieee.org/document/10591980. https://doi.org/10.1109/ACCESS.2024.3426041.

[12] Vijay Kumar Padala. (2024). Precision Disease Diagnosis in Aquaculture Using Aqua Spectra Imaging and Machine Learning. *International Journal of Information Technology and Computer Engineering*, *12*(3), 735-741. *Vol.12.* https://ijitce.org/index.php/ijitce/article/view/724.

[13] Tran, T. T., Al-Ansari, N., Nguyen, D. D., Le, H. M., Phan, T. N. Q., Prakash, I., Costache, R., & Pham, B. T. (2024). Prediction of white spot disease susceptibility in shrimps using decision trees based machine learning models. *Applied Water Science, 14*(2). https://doi.org/10.1007/s13201-023-02049-3.

[14] Shoiab Ahmed Md, Tanjim Taharat Aurpa, Sanjana J, Md. Abul Kalam Azad. .(2025).Fish Disease Detection Using Image-Based Machine Learning Technique in Aquaculture. *Journal of King Saud University – Computer and Information Sciences, Volume 34, Issue 8, 2022, Pages 5170–5182*.https://doi.org/10.1016/j.jksuci.2021.03.006.

[15] Wang, C., Li, Z., Wang, T., Xu, X., Zhang, X., & Li, D. (2021). Intelligent fish farm—the future of aquaculture. *Aquaculture International*, 29, 2681–2711. https://doi.org/10.1007/s10499-021-00773-8.

[16] Siskandar, R., Wiyoto, W., Santosa, S. H., Hidayat, A. P., Kusumah, B. R., & Darmawan, M. D. M. (2023). Prediction of Freshwater Fish Disease Severity Based on Fuzzy Logic Approach, Arduino IDE and Proteus ISIS. *Universal Journal of Agricultural Research*, 11(6), 1089–1101. https://doi.org/10.13189/ujar.2023.110616.

[17] Gkikas, D.C., Gkikas, M.C., & Theodorou, J.A. (2024). Fostering sustainable aquaculture: Mitigating fish mortality risks using decision trees classifiers. *Applied Sciences*, 14(5), 2129. https://doi.org/10.3390/app14052129.

[18] Schraml, R., Hofbauer, H., Jalilian, E., Bekkozhayeva, D., Saberioon, M., Cisar, P., & Uhl, A. (2021). Towards fish individuality-based aquaculture. *IEEE Transactions on Industrial Informatics, 17*(6), 4356–4366. https://doi.org/10.1109/TII.2020.3006933.

[19] Kok, C.L., Kusuma, I.M.B.P., Koh, Y.Y., Tang, H., & Lim, A.B. (2024). Smart Aquaponics: An Automated Water Quality Management System for Sustainable Urban Agriculture. *Electronics, 13*(5), 820. https://doi.org/10.3390/electronics13050820.

[20] Karras, A., Karras, C., Sioutas, S., Makris, C., Katselis, G., Hatzilygeroudis, I., Theodorou, J.A., & Tsolis, D. (2023). An Integrated GIS-Based Reinforcement Learning Approach for Efficient Prediction of Disease Transmission in Aquaculture. *Information, 14*(11), 583. https://doi.org/10.3390/info14110583.

[21] Måløy, H. (2020). EchoBERT: A Transformer-Based Approach for Behavior Detection in Echograms. *IEEE Access, 8*, 218372–218385. https://doi.org/10.1109/ACCESS.2020.3042337.

[22] Karras, A., Karras, C., Sioutas, S., Makris, C., Katselis, G., Hatzilygeroudis, I., Theodorou, J. A., & Tsolis, D. (2023). An integrated GIS-based reinforcement learning approach for efficient prediction of disease transmission in aquaculture. *Information, 14*(11), 583. https://doi.org/10.3390/info14110583.

[23] Kostin, V.E., Silaev, A.A., & Savchic, A.V. (2019). Information-measuring system for monitoring and control aquaculture of pond farm. *2019 International Multi-Conference on Industrial Engineering and Modern Technologies (FarEastCon)*, IEEE. https://doi.org/10.1109/FarEastCon.2019.8934160.

[24] La Madrid, J.D., Dela Cruz, J.C., & Balisi, V.L.Q. (2018). Real-Time Water Quality Monitoring System with Predictor for Tilapia Pond. *2018 IEEE 10th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management (HNICEM)*. https://doi.org/10.1109/HNICEM.2018.8666260.

DOI: 10.17148/IJARCCE.2025.14736

[25] M. A. Adegboye, A. M. Aibinu, J. G. Kolo, I. Aliyu, T. A. Folorunso, and S.-H. Lee, "Incorporating Intelligence in Fish Feeding System for Dispensing Feed Based on Fish Feeding Intensity," *IEEE Access*, vol. 8, pp. 91948–91960,2020, doi: 10.1109/ACCESS.2020.2994442.

[26] J. V. Magsumbol, V. J. Almero, M. Rosales, A. A. Bandala, and E. P. Dadios. (2018). "A Fuzzy Logic Approach for Fish Growth Assessment," in Proc. 10th IEEE International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management (HNICEM), , doi: 10.1109/HNICEM.2018.8666304.

[27] A. Fredheim and T. Reve, "Future Prospects of Marine Aquaculture," in *Proc. 10th IEEE International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management (HNICEM)*, 2018, doi: 10.1109/HNICEM.2018.8666277.

[28] M. Cordova-Rozas, J. Aucapuri-Lecarnaque, and P. Shiguihara-Juárez. (2019). "A Cloud Monitoring System for Aquaculture using IoT," in *Proc. IEEE 10th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management (HNICEM)*. doi: 10.1109/HNICEM.2019.8666278.

[29] Alberto Maximiliano Crescitelli, Lars Christian Gansel, Houxiang Zhang (2020). Title: *Semi-automatic Approach to Create Fish Image Datasets for Aquaculture Applications* Event: 2020 15th IEEE Conference on Industrial Electronics and Applications (ICIEA) DOI: 10.1109/ICIEA48937.2020.9248233.

[30] Marzia Ahmed, Md. Obaidur Rahaman, Mostafijur Rahman, Mohammod Abul Kashem (2019). *Analyzing the Quality of Water and Predicting the Suitability for Fish Farming based on IoT in the Context of Bangladesh.* DOI: 10.1109/STI48824.2019.9068014.