A DEEP LEARNING APPROACH FOR PREDICTING FISH DISEASES IN FISHERIES

Balabadruni Koushik
School of computer science and engineering
Vellore Institute of Technology, Chennai
Tamil Nadu, India
venkata.nagakoushik2021@vitstudent.ac.in

Omtri Vijaya Krishna
School of Computer Science and Engineering
Vellore Institute of Technology, Chennai
Tamil Nadu, India
omtrivijaya.krishna2021@vitstudent.ac.in

Potturi Pujeth
School of Computer Science and Engineering
Vellore Institute of Technology, Chennai
Tamil Nadu, India
potturi.pujeth2021@vitstudent.ac.in

Vinothini A
School of Computer Science and Engineering
Vellore Institute of Technology, Chennai
Tamil Nadu, India
vinothini.a@vit.ac.in

Abstract— A major part of India's food production is its fisheries and aquaculture, which employ people in various capacities and contribute to the country's agricultural exports. On the other hand, fish disease has emerged as a major obstacle to the commerce and sustainable production of aquaculture products, which has an impact on the socioeconomic standing of fishermen in nations such as India. Fish diseases can cause serious issues, including widespread infections and monetary losses, which is why it is so difficult for aquaculture managers and fish farmers to identify diseases in fish at an early stage. In this paper, we propose a CNN-based fish disease prediction model to predict diseases like argulus, broken antennae and rostrum, EUS, redspot, bacterial gill rot, tail and fin rot. Various combinations of data augmentation, batch sizes, epochs, and the number of CNN layers are explored to achieve the best accuracy. The proposed model achieves an accuracy of 98.44%, a f1 score of 97.66%, a precision of 97.14%, and a recall of 98.57%. This model will help the farmers take timely actions to manage diseases effectively and maintain the health and sustainability of their fish populations.

Keywords: Deep learning, CNN, Fish, Image processing, Disease prediction, Fisheries.

I. INTRODUCTION

Image-based analysis can play a crucial role in early disease prediction and prevention in fish. By using high-resolution imaging techniques, such as microscopy or computer tomography, it is possible to identify the early signs of disease in fish, such as changes in skin colour, texture, and internal structure. This information can then be used to predict the onset of a disease and implement preventative measures, such as adjusting the water quality or changing the diet of the fish [23].

Deep learning algorithms can be trained on large datasets of fish images to accurately detect disease in real-time. By automating the analysis process, the risk of disease spread can be reduced, and the cost and time required for manual inspections can be reduced. Overall, image-based analysis has the potential to revolutionize the way diseases in fish are detected and prevented, leading to improved health and survival rates in aquaculture and fishing industries.

Artificial Intelligence supports more accurate, and cost-effective alternatives to traditional methods in fish disease prediction. The process involves collecting a large dataset of images of diseased and healthy fish, pre-processing the images, and training a deep-learning model on the images and their corresponding labels. The trained model can then be used to make predictions about the disease state of a fish based on its physical symptoms, as depicted in an image.

The deployment of image-based fish disease prediction systems has the potential to revolutionize the aquaculture industry by enabling early detection of diseases, reducing the spread of diseases, and improving the overall health and welfare of farmed fish. The use of this technology has the potential to increase efficiency, reduce costs, and improve the sustainability of fish farming operations.

II. RELATED WORK

There are various studies carried out on fish disease detection. The research on fish disease detection has been carried out by using image processing, machine learning, and deep learning techniques. Image processing involves converting a picture into a digital format and extracting valuable information through specific procedures. The image processing system typically applies preset signal processing techniques uniformly to all images treated as 2D signals. Within the realm of image processing, various neural network architectures have emerged, each offering unique capabilities. These architectures excel in tasks such as object recognition, image interpretation, and categorization [23][4][10].

Effective disease control strategies have been made possible by the capacity of image processing tools to identify diseases in aquaculture quickly and accurately, as demonstrated by a comprehensive review of these approaches [1]. Computer vision and Deep Convolutional Neural Network (DCNN) algorithms demonstrated the dependability of fish disease diagnosis. Expanding datasets for improved accuracy is the goal of future research [2]. Several machine learning techniques were used in the investigation into the early diagnosis of Epizootic Ulcerative Syndrome (EUS) in fish, highlighting the importance of dataset augmentation. 85.24% accuracy on the original dataset and 82.75% accuracy on the augmented dataset were attained using an SVM-based system [3]. A technique for accurately and quickly diagnosing fish diseases using CNN and YOLO algorithms was first presented in a study on home aquariums. With an astounding 91.4286% total accuracy, this approach supports early illness detection and prevention [4].

A thorough investigation of machine learning in intelligent fish farming covered issues, assessed outcomes, and talked about the field's future. The study provided insights into the quickly developing field of intelligent fish farming by focusing on fish biomass evaluation, behavior analysis, and water quality parameter prediction [5]. Introduces a hybrid metaheuristic algorithm combined with an improved machine learning technique to detect fish infections in aquaculture, which is crucial for disease prevention spread and ensuring industry income. It uses Artificial Neural Networks (ANN) and a hybrid algorithm (BWO-MA), which achieves earlier detection of fish diseases. A comparative analysis reveals that BWO-MA-based ANN outperforms other methods, reaching 96.439% accuracy, indicating a notable advancement in addressing aquaculture challenges [6]. Fish image classification with enhanced deep learning takes the role of conventional techniques for fish classification. The work uses state-of-the-art computer vision and CO-WOA. The identification of fish species in aquaculture is greatly advanced by this research [7].

To solve the difficulties in satisfying the rising demand for food, the concept of remote agriculture monitoring in aquaculture utilizes image processing and AI. With the help of the Canny-ROI-CNN algorithm, fish diseases may be identified and detected in real-time. Critical parameters can also be automatically controlled, allowing for rapid updates and interventions via the Internet of Things [8]. To identify chromosomal abnormalities in cancer and genetic illnesses, Multi-color fluorescence in situ hybridization (M-FISH) image segmentation and classification are improved by the adaptive fuzzy c-means (AFCM) algorithm. It performs better than traditional fuzzy c-means algorithms and region-based segmentation techniques by using a gain field to solve intensity inhomogeneities, which improves the accuracy of cancer and genetic disease diagnosis [9]. Studies on monitoring of fish morphological traits provide a unified strategy incorporating image processing and machine learning for non-invasive monitoring of fish morphological traits, including size and health indicators. Using unique methodologies, it calculates relative length, height, and occupied area in images with an estimation error ranging from 1.9% to 13.2%, comparable to systems trained on larger datasets. The technique offers complete functionality for fish dimension estimates and has been tested on four different fish species [10].

Few other researchers developed a smartphone-based detection approach employing image segmentation algorithms to identify unhealthy fish [11]. Due to increasing prevalence and climate change, it is imperative to comprehend the cause of diseases in aquatic creatures. Effective responses and sustainable resource management depend on the timely detection and confluence of microbiological advancements. Fostering healthier aquatic habitats and improving biosecurity are two benefits of bridging traditional and modern approaches [12]. The study bridges traditional and contemporary approaches to enhance biosecurity and foster healthier aquatic ecosystems. It is important to understand disease causation in aquatic organisms amid rising prevalence and climate change. Timely diagnosis and convergence of microbiological advancements are essential for effective responses and sustainable resource management [13].

An updated YOLO v5 model "FishDETECT" improves fish recognition and classification, overcoming difficulties in complicated backdrops and low light. The model achieves excellent accuracy rates and mAP50 metrics, [14]. In another work, researchers use machine learning and image processing to identify diseases in aquaculture that affect salmon fish. It achieves great accuracy in identifying diseased fish by applying segmentation, support vector machine (SVM) classification, and picture pre-processing. The method demonstrates the efficacy of the SVM algorithm with noteworthy accuracy of 91.42% and 94.12%, respectively, with and without image augmentation [15]. Object detection models like YOLOv5m is enhanced to identify the percentage of sick fish in a school, with an emphasis on red tilapia and Micropterus salmoides strains [16].

In this paper, we propose CNN based fish detection system that can detect the following diseases: argulus, broken antennae and rostrum, EUS, red spot, bacterial gill rot, and tail and fin rot.

A. Argulus

Freshwater fish are commonly parasitized by Argulus, which is present in UK fisheries. Adult lice are spherical, flat parasites that resemble jelly and feed on mucous and skin. Severe infections can swiftly result in discomfort, loss of condition, and even death[19].

B. Broken antennae and rostrum

Certain fish, like anglerfish, have sensory appendages on their heads called antennae that they utilize to attract or locate prey. Some fish, like billfish and paddlefish, have a projecting portion of their head or snout called a rostrum, which they utilize to cut, stun, or feel prey [19].

C. EUS

Epizootic ulcerative syndrome (EUS), which is a condition caused by the water Mold Aphanomyces invadans, is sometimes referred to as **red spot disease** (RSD) or mycotic granulomatosis (MG). Numerous freshwater and brackish fish species in Australia and the Asia-Pacific area are infected by it. In tropical and sub-tropical waters, the disease is most frequently observed during periods of low temperature and intense precipitation. Fish initially get red patches on their skin. These lesions grow into ulcers and large erosions that contain mycelium and necrotic tissue. Granulomas develop on the internal organs and death follows it [20].

D. Tail and fin rot

Although fin rot is one of the most prevalent illnesses in aquarium fish, it is also one of the easiest to avoid. The edges of the fins will turn discoloured and milky in the early stages of fin rot. This alteration is often so subtle that it is not detected until the fins or tail start to fray. A jagged edge is left when tiny bits of the fins start to break off and die as the infection spreads [21].

E. The bacterial gill disease

Several dangerous and deadly illnesses can harm a fish's gills, including the fungus known as branchiomycosis. The environmental factors of the water in which the fish are housed are typically the cause of this specific sickness. The decaying tissue in the fish's gills causes them to appear mottled or blotchy as a result of branchiomycosis. That's why it's also called "gill rot." Additionally, there might be hints of gray on the skin's surface. If left unchecked, the illness starts in the gills and progresses to the skin [22].

Figure 1. Classification of different diseases in fishes

III. PROPOSED WORK

Fish farmers and aquaculture managers often struggle to detect diseases in fish early enough, which can lead to significant problems like widespread infections and financial losses. The proposed CNN fish detection model shown in Figure 2 predicts six types of fish diseases: argulus, broken antennae and rostrum, EUS, red spot, bacterial gill rot, and tail and fin rot thereby classifying the fish as healthy or diseased.

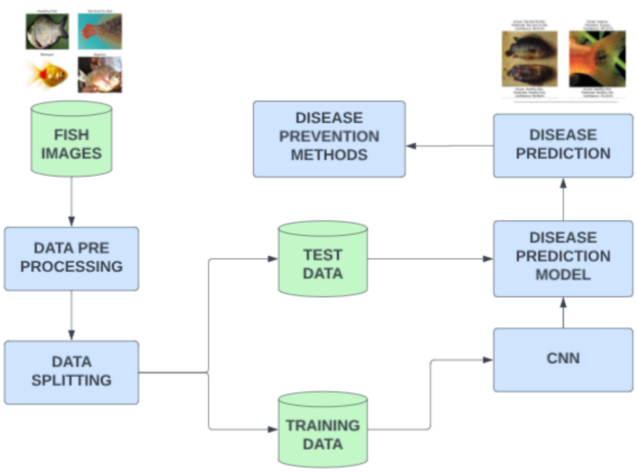

Figure 2: Architecture of proposed system

1. Data-Acquisition

Our team acquired a Kaggle dataset of fish images, encompassing both healthy and diseased fish, alongside essential metadata like species and disease labels. This dataset forms the cornerstone for training and assessing our model. The taget disease is shown in Figure 3.

```
class_names = dataset.class_names
class_names
```

```
['Argulus',
 'Broken antennae and rostrum',
 'EUS',
 'Healthy Fish',
 'Redspot',
 'THE BACTERIAL GILL ROT',
 'Tail And Fin Rot']
```

Figure 3: Target classes of diseased and healthy fish images

2. Data Preprocessing

In this phase, we preprocess the gathered images by standardizing them to a consistent dimension of 256x256, normalizing pixel values to a range between 0 and 1 (by dividing by 255), and applying data augmentation techniques like rotation and flipping. These steps enhance dataset quality, increase its size, and enhance the model's ability to generalize. After pre-processing, the data is split into 80% training data, 10% test data and 10% validation data.

3. Model Architecture

The proposed CNN model as shown in Figure 4 comprises 11 layers, combining Conv2D, MaxPooling, and Dense layers. We strategically utilized 32, 64 and 128 filters, each with a 3x3 kernel size, to capture intricate features effectively. In addition, we incorporated a MaxPooling layer with a 2x2 pooling size to reduce spatial dimensions. We trained the model with the training data, employing 70 epochs and verbose=1 to closely monitor the training progress. Lastly, we employed the softmax activation function to estimate probabilities, representing the likelihood of input images belonging to various classes, including healthy and diseased fish.

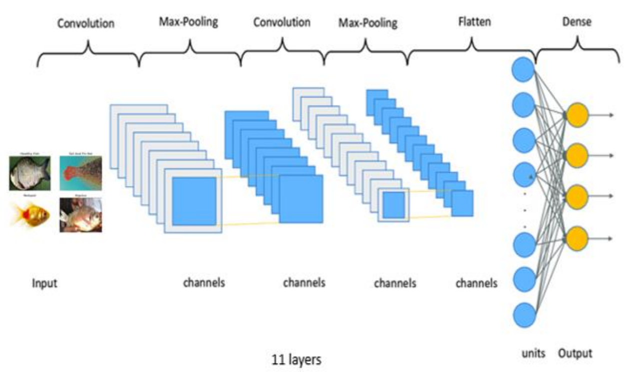

Figure 4: Architecture of the CNN model.

4. Model Evaluation

To comprehensively assess our model's performance, we conducted an extensive evaluation. We utilized the sparse categorical ross entropy loss function to calculate the validation loss and employed relevant metrics, including accuracy. Furthermore, we visualized the model's training and validation accuracy as well as the training and validation loss through graphical plots. These visualizations provided valuable insights into the model's learning process and its ability to generalize effectively.

IV. RESULT ANALYSIS

Our journey to optimize the model's performance involved a meticulous exploration of various hyperparameters, including optimizers, epoch counts, and the number of CNN layers. This exhaustive experimentation allowed us to fine-tune the model for maximum accuracy. The outcomes of these trials are summarized in Table 1, showcasing the interplay of different configurations on the model's accuracy.

Through meticulous experimentation and comparison, we achieved a remarkable accuracy of 98.43 % as the best-performing configuration for our model. In Figure 5, we present graphical representations of the model's training progress, illustrating the validation accuracy and validation loss. These visualizations provide invaluable insights into the model's learning dynamics and underscore the significance of the selected configuration in achieving an accuracy of 98.43%.

Table 1: Performance with different optimizers

Optimiser	Epoch	No of layers	accuracy
RMSprop	10	13	0.468
RMSprop	30	13	0.500
RMSprop	30	11	0.750
RMSprop	50	11	0.843
RMSprop	60	11	0.81
Adam	10	13	0.468
Adam	30	13	0.375
Adam	30	11	0.5625
Adam	50	11	0.9062
Adam	70	11	0.9844

Figure 5: Training validation loss, and accuracy

```
Accuracy: 0.984375
Precision: 0.9714285714285714
Recall: 0.9857142857142858
F1-score: 0.9766081871345029
```

Figure 6: Performance evaluation

Moreover, we diligently assessed our model for signs of overfitting and underfitting during the experimentation process. By closely monitoring validation performance and training dynamics, we ensured that our model achieved a delicate balance, striking the ideal equilibrium between accuracy and generalization.

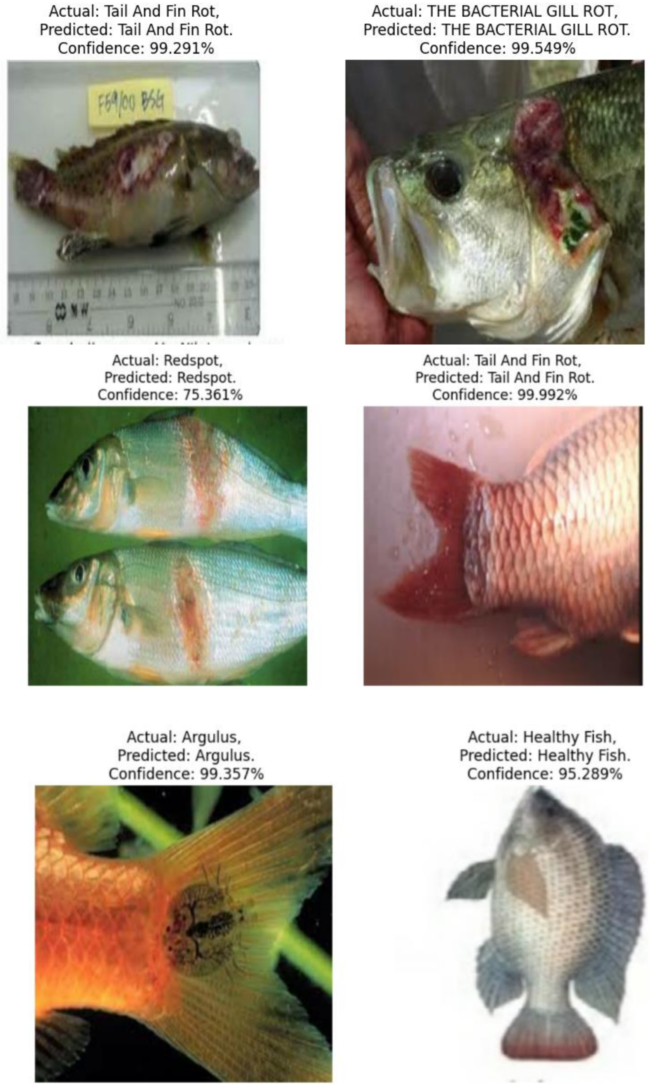

Figure 7: Predictions of 6 images along with actual, predicted class labels and the confidence of the prediction.

Once a fish disease is predicted, the system offers tailored recommendations on how to effectively address and manage the identified ailment, ensuring the health and well-being of the aquatic population.

The model is also evaluated with other performance metrics as illustrated in Figure 6. The predictions of the proposed model on test data set are illustrated in Figure 7 along with the confidence metric. This careful approach further solidified the reliability and robustness of our model for accurate fish disease prediction. The performance of the proposed system is compared with the state of art techniques as shown in Table 2.

Table 2: Comparison of the proposed model Vs existing

WORK	Techniques	Accuracy	F1-Score	Precision	Recall
Evaluation of ML Models for Detection and Prediction of Fish Diseases [3]	SVM, MLP	85.24%	85.10%	85.65%	84.96%
Disease Classification of Oranda Goldfish Using YOLO Object Detection Algorithm [4]	YOLO, CNN	91.4286%	-	-	-
Fish Disease Detection Using Image Based Machine Learning Technique in Aquaculture [15]	SVM, K-Means Clustering	92.0%	95.52%	92.75%	-
Our Work	CNN	98.43%	97.6%	97.14%	98.57%

V. CONCLUSION

In summary, our project pioneers the use of CNNs to predict fish diseases effectively. Through rigorous data preparation and model tuning, we have crafted a robust system for early fish disease detection. By considering various parameters and addressing overfitting risks, we have achieved impressive results 98.43% accuracy, 0.976 score, precision of 0.9714. This tool empowers fish industry professionals to proactively manage disease outbreaks. Looking ahead, further research can refine our approach, showcasing the impact of Artificial Intelligence on aquaculture sustainability and economic stability.

REFERENCES

[1] S. B. M. Azhar, N. H. B. Harun, N. B. Yusoff, M. G. B. Hassan and K. B. Chu, "Image Enhancement on Underwater Images for Protozoan White Spot Fish Disease Detection," *2022 International Conference on Intelligent Systems and Computer Vision (ISCV)*,

[2] M. L. Yasruddin, M. A. Hakim Ismail, Z. Husin and W. K. Tan, "Feasibility Study of Fish Disease Detection using Computer Vision and Deep Convolutional Neural Network (DCNN) Algorithm," *2022 IEEE 18th International Colloquium on Signal Processing & Applications (CSPA)*, Selangor, Malaysia, 2022,

[3] K. Sujatha and P. Mounika, "Evaluation of ML Models for Detection and Prediction of Fish Diseases: A Case Study on Epizootic Ulcerative Syndrome," 2023 Second International

Conference on Electrical, Electronics, Information and Communication Technologies (ICEEICT), Trichirappalli, India, 2023.

[4] J. K. Medina, P. Jasper P. Tribiana and J. F. Villaverde, "Disease Classification of Oranda Goldfish Using YOLO Object Detection Algorithm," 2023 15th International Conference on Computer and Automation Engineering (ICCAE), Sydney, Australia, 2023.

[5] S. Zhao, S. Zhang, J. Liu, H. Wang, J. Zhu, D. Li, and R. Zhao, "Application of machine learning in intelligent fish aquaculture: A review," Aquaculture, vol. 540, p. 736724, 2021.

[6] Jhansi and K. Sujatha, "An Enhanced Machine Learning Technique with a Hybrid Metaheuristic Algorithm to Identify the Fish Disease," Wireless Personal Communications, pp. 1-21, 2023.

[7] R. M. Aziz, R. Mahto, A. Das, S. U. Ahmed, P. Roy, S. Mallik, and A. Li, "CO-WOA: novel optimization approach for deep learning classification of fish image," Chemistry & Biodiversity, vol. 20, no. 8, p. e202201123, 2023.

[8] D. G. Harshith, S. Surve, S. N. Seeju Prasad, B. V. Ganesh and K. Anuros Thomas, "Remote Aquaculture Monitoring with Image Processing [ML] and AI," 2023 5th International Conference on Bio-engineering for Smart Technologies (BioSMART), Paris, France, 2023.

[9] G.Cao, H. -W. Deng and Y. -P. Wang, "Segmentation of M-FISH Images for Improved Classification of Chromosomes With an Adaptive Fuzzy C-means Clustering Algorithm," in IEEE Transactions on Fuzzy Systems.

[10] N. Petrellis, "Measurement of fish morphological features through image processing and deep learning techniques," Applied Sciences, vol. 11, no. 10, p. 4416, 2021.

[11] Md. Jueal Mia, Rafat Bin Mahmud, Md. Safein Sadad, Hafiz Al Asad, Rafat Hossain, "An in-depth automated approach for fish disease recognition," Journal of King Saud University - Computer and Information Sciences, vol. 34, no. 9, pp. 7174-7183, 2022..

[12] K. S. Hutson, I. C. Davidson, J. Bennett, R. Poulin, and P. L. Cahill,"Assigning cause for emerging diseases of aquatic organisms,"Trends in Microbiology, 2023.

[13] E. T. Yasin, I. A. Ozkan, and M. Koklu,"Detection of fish freshness using artificial intelligence methods,"European Food Research and Technology, pp. 1-12, 2023.

[14] Y. Wageeh et al., "YOLO fish detection with Euclidean tracking in fish farms," Journal of Ambient Intelligence and Humanized Computing, vol. 12, pp. 5-12, 2021.

[15] M. S. Ahmed, T. T. Aurpa, and M. A. K. Azad, "Fish disease detection using image-based machine learning technique in aquaculture," Journal of King Saud University-Computer and Information Sciences, vol. 34, no. 8, pp. 5170-5182, 2022.

[16] Z. Wang, H. Liu, G. Zhang, X. Yang, L. Wen, and W. Zhao, "Diseased Fish Detection in the Underwater Environment Using an Improved YOLOV5 Network for Intensive Aquaculture," Fishes, vol. 8, no. 3, pp. 169, 2023.

[17] https://www.researchgate.net/publication/322887538_Present_Status_of_Fish_Disease_Management_in_Freshwater Aquaculture_in_India_State-ofthe-_Art-Review

[18] https://www.kaggle.com/datasets/utpolkantidas/fresh-water-fish-disease-dataset

[19] https://canalrivertrust.org.uk/enjoy-the waterways/fishing/

[20] https://en.wikipedia.org/wiki/Epizootic_ulcerative_syndrome .

[21] https://www.thesprucepets.com/fin-rot-

[22] https://www.petmd.com/fish/conditions/infectious-parasitic/c_fi_branchiomycosis

[23] https://www.simplilearn.com/image-processing-article