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Intelligent Aquaculture System for Fish Disease Detection Using Machine Learning

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Abstract

Aquaculture is one of the key factors for global food security, but fish diseases bring about heavy economic losses and jeopardize sustainability. One of the most important aspects of global food security is aquaculture, but fish infections endanger sustainability and cause significant financial losses. Early diagnosis is not possible since traditional disease detection techniques are laborious and necessitate expert intervention. To effectively detect fish infections, this study suggests an Intelligent Aquaculture System that uses machine learning. The system encompasses water quality monitoring, image-based disease recognition, and predictive analytics to identify infections at an early stage. To detect illnesses early, the system uses predictive analytics, image-based disease detection, and water quality monitoring. To classify diseases with high accuracy, machine learning models are trained using a collection of photos of healthy and diseased fish as well as environmental characteristics. Proactive steps to stop outbreaks are made possible by real-time data from sensors and cameras, which improve detection accuracy. The suggested methodology promotes sustainable aquaculture methods, lowers losses, and enhances disease management. ML models are trained using a dataset of diseased and healthy fish images, along with environmental parameters to classify diseases with high accuracy. Real-time data from sensors and cameras enhance detection precision, allowing for proactive measures to prevent outbreaks. The proposed system improves disease management, reduces losses, and supports sustainable aquaculture practices.

Keywords: LoRa, WSN, IoT, low power consumption, open source

INTRODUCTION

Aquaculture is considered one of the leading food production industries in the world that highly contribute to seafood supply and economic development. The demand for fish and seafood continues to increase and, therefore, comes a need for sustainable and efficient aquaculture practices. Among other critical challenges fish farmers face is outbreaks of diseases, which cause the following: economic loss, low-quality fish, and degradation of environment. The traditional methods detect fish diseases by means of manual observation and laboratory testing, which consume much time and are relatively expensive processes. Indeed, if the infections are discovered late, they also spread fast [1]. Thus, the management of disease is essential in modern aquaculture.

Advances in technology will lead to intelligent aquaculture systems that may be used as a promising solution for automated fish health monitoring and disease detection. Machine learning is particularly promising because it can process

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complex biological and environmental data in order to diagnose fish diseases early. The integration of sensor-based water quality monitoring, computer vision-based fish health analysis, and predictive analytics in intelligent aquaculture systems can help in the improved diagnosis of disease, reduction in mortality rates, and increased farm productivity.

RELATED WORK

The integration of artificial intelligence (AI), machine learning (ML), and the Internet of Things (IoT) has significantly advanced the field of intelligent aquaculture. Much research work has been dedicated to the automation of fish disease detection and health monitoring, including image processing techniques, sensor-based data acquisition, and predictive modeling. This study reviews related work that formed part of the constituent pieces of machine learning-based fish disease detection and intelligent aquaculture systems.

1. *Conventional methods of fish disease detection:* Conventional methods of fish disease detection are based on manual observation, a microbiological test as well as histopathological examination. Veterinarians and other fish health specialists observe the fish for possible visible signs such as discoloration of skin, damage to fins, ulcers, and even erratic swimming habits. These methods are time-consuming, costly, and require specialized skills, which limit their use in large-scale fish farms [2].
2. *Machine learning for fish disease detection:* With the maximum of labeled fishes having been separated and supervised learning algorithms, in studies and research related to image classification and prediction based on environmental data, Convolutional Neural Networks (CNNs) have been extensively employed for fish disease detection in computer vision tasks. It has been proven through studies that CNN-based models can highly recognize common fish diseases such as bacterial infection, parasitic infestation, and fungal infection from images of affected fish.
3. *Image-based disease classification:* A lot of researchers have developed deep learning models that classify fish diseases directly from images. For instance a CNN model designed to automatically identify and classify fish diseases like Columnaris, White Spot Disease, and Fin Rot using a database of diseased fish images. The experiment shows that CNN outperforms conventional image processing methods with an accuracy of over 90%.

OBJECTIVES

The salmon fish project objectives and content structured around the key aspects of aquaculture. Aquaculture fish health monitoring includes detection of diseases in salmon fishes, the application of a number of techniques for improvement in efficiency of the disease management.

EXISTING SYSTEM

Image Preprocessing and Segmentation Process

All the raw fish images, despite their original dimensions, undergo preprocessing and resizing to a fixed size of 600×250 pixels. The resizing procedure ensures that all images meet our proposed framework and dimensions during model training and prediction. The image, after resizing, is then operated on by carrying out segmentation based on k-means clustering. This process divides the image into regions, depending on the pixel intensity and color similarity [3]. It is to divide the image into meaningful clusters where different regions represent different parts of the fish, such as the body, fins, and areas that may indicate disease. After the segmentation process, the image is analyzed to differentiate between infected and healthy areas. The infected regions stand out more against the background as the model for machine learning catches the patterns with ease and has ability to classify it.

- *Accuracy:* We compare accuracy scores for the regular and the augmented datasets and how data augmentation such as the addition of noisy or varied images may enhance generalization.
- *Precision, recall, and F1-score:* These metrics are calculated for each dataset to measure the balance between correctly identifying infected fish and avoiding misclassifications [4].
- *Training time and model efficiency:* A summary table of the training times and resource usage by the model aids in the determination of the system's efficiency.

Image-based disease classification is the technique of applying machine learning and deep learning algorithms to analyze medical images and classify diseases. The technique is commonly applied in areas such as radiology, dermatology, and pathology [5].

PROPOSED WORK

Proposed System

The proposed system integrates advanced image processing techniques with machine learning, specifically Support Vector Machine (SVM) classifiers, to effectively assess fish quality. The process begins with the user inputting an image of the fish through a user-friendly GUI application (Figure 1). This allows the system to capture images of the fish under various conditions and from different sources, such as cameras or stored files, providing flexibility for real-world usage in commercial fish processing and retail environments [6].

When a new image is processed, the SVM classifier analyzes the extracted features and outputs a classification result, indicating whether the fish is fresh or spoiled based on the learned patterns (Figure 2). This automated classification is based on the features derived from the fish image and serves as a reliable, objective means of determining the fish's quality. The system can thus categorize fish as either *fresh* or *spoiled*, providing an efficient, consistent, and accurate method of fish quality assessment.

Working Principle

SVM

Support Vector Machine (Finding the best hyperplane and the class separation for best hyperplane). SVM is one of the most common Supervised Learning algorithms, which has been used and logic function is employed for Classification as well as Regression and some other vector machine problems. However, majorly, it is used for Classification problems in Machine Learning [7].

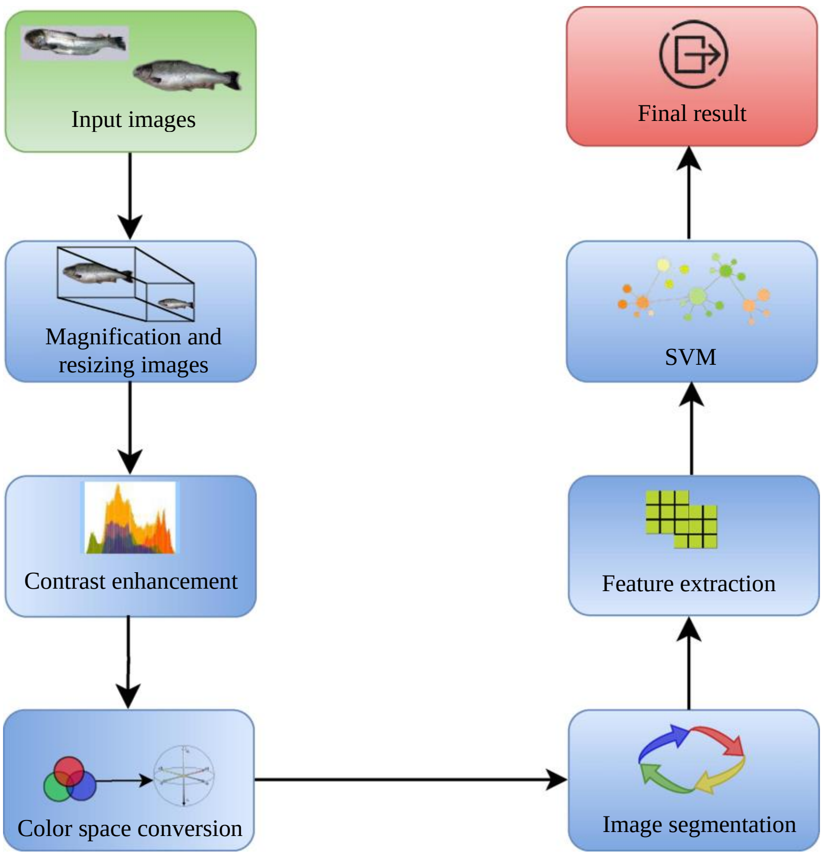

Figure 1. Flow Chart.

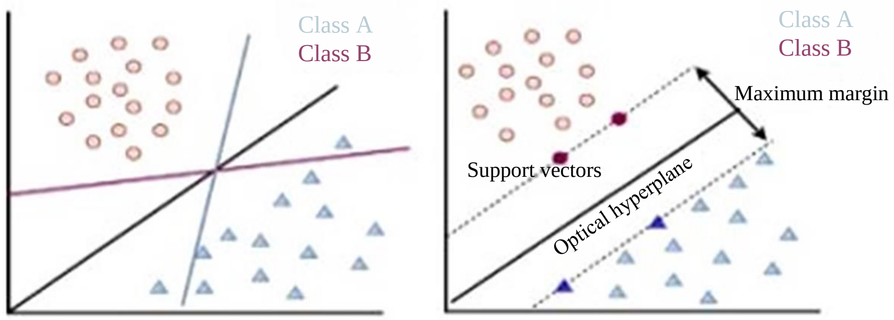

Figure 2. Support vector machine (optimal hyperplane and optimal hyperplane).

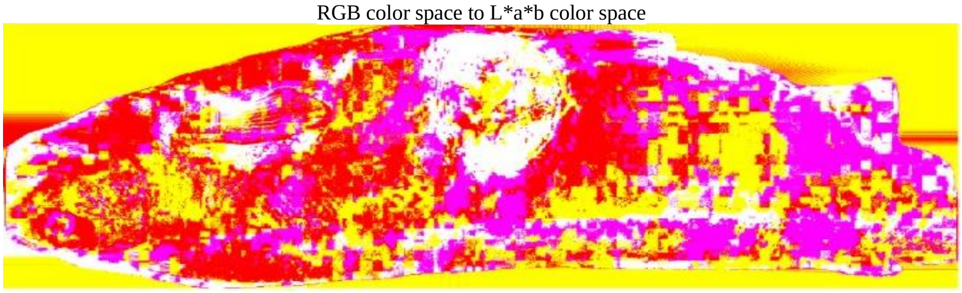

Figure 3. Color Classifications.

The goal of the SVM algorithm is to create the best line or decision boundary that can segregate n-dimensional space into classes so that we can easily place the new data point in the appropriate category in the future. This best decision boundary is called a hyperplane. SVM chooses the extreme points/vectors that help in creating the hyperplane. These extreme cases are called as support vectors, and hence algorithm is termed as Support Vector Machine.

GLCM

GLCM (Gray-Level Co-occurrence Matrix) is a statistical approach for image texture analysis. It has been significantly applied in numerous tasks of image processing and computer vision, mainly for feature extraction of machine learning models. For the machine learning task, GLCM is utilized to capture spatial patterns in an image, which is important for tasks such as object detection, classification, and quality analysis, such as detecting fish disease or quality.

Usually, the image is first converted to grayscale. In a grayscale image, each pixel represents an intensity value ranging from 0, which is black, to 255, which is white [8]. These values have different brightnesses or color intensities (Figure 3). To calculate GLCM, it considers a pair of pixels within a predefined window. An example would be to consider two neighboring pixels, one at some distance from each other, either horizontally or vertically (one to the right), or diagonally. For all such pairs, the matrix holds the frequency with which the intensities occur for each direction [9].

Raspberry Pi

It is a very cheap kit compared to others, highly portable, compact, all-in-one, single-board computer (Figure 4). This platform includes everything to create a full working computer. It is mainly used as an educational platform or prototyping system, often with hobbyist activities [10].

This is the core of the kit. The board contains a processor (CPU), memory (RAM), USB ports, GPIO (General Purpose Input/Output) pins for connecting peripherals, HDMI output for display, and Ethernet or Wi-Fi connectivity.

- *Power supply:* A power adapter with the appropriate voltage and current is used to power the Raspberry Pi. This ensures stable operation.

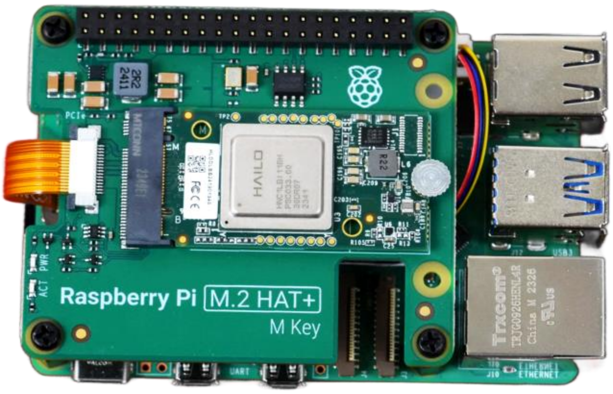

Figure 4. Raspberry pi board.

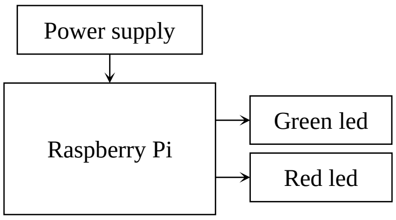

Figure 5. Block diagram

- *Micro SD card:* A micro SD card stores all information on this microcomputer. This micro SD card is the memory in which the OS and installed software are stored, along with data.
- *HDMI cable:* This cable is necessary to attach the Raspberry Pi to be able to work in a monitor or display. Generally, kits will include an HDMI cable that can support high definition resolutions.
- *Keyboard and mouse:* These are the most basic input devices used to interact with the system while setting it up and operating it. Some kits include wireless versions of these devices [11].
- *Case:* A protective case is used to house the Raspberry Pi kit board, which protects it from physical damage. It may also aid in heat dissipation, keeping the board cool during use.
- *Cables:* Several cables are used to connect peripherals such as monitors, audio devices, or external storage.
- *Learning programming:* This kit is comfortable with programming languages like python, java, scratch, etc., making it ideal for teaching and learning coding.
- *IoT projects:* Raspberry Pi can be used in Internet of Things (IoT) applications, integrating sensors and actuators for automation or monitoring.

Figure 5 shows the block diagram of the system.

Specifications

Equipped with a 1.2 GHz 64-bit quad-core ARMv8 CPU, Raspberry Pi is known for its excellent processing for the capabilities across all applications. The processor allows for a 64-bit architecture, which ensures that multi-threaded operations run efficiently and enables the running of modern software easily. Its design as a quad-core means that it can carry out multiple tasks at the same time, and it is suited for projects requiring moderate processing power, such as media centers, small servers, or home automation systems [12, 13].

In connectivity, it equips 802.11n Wireless LAN. This will let the Raspberry Pi connect to the wireless networks in order to obtain internet access and file transfer connections without any requirement for an external adapter. This also equips it with Bluetooth 4.0 for a wireless communication facility with different kinds of peripherals like keyboards, mice, speakers, or even wireless sensors. Its usability increases because of the convenience of a wireless setup and for mobile projects.

RESULTS AND DISCUSSION

Result

With an intelligent aquaculture system for fish disease detection using machine learning, Preciseness, Recall, Accuracy, and F1 Score are the various metrices which are calculated and finalized how well a classification algorithm used in the aquatic system will classify fish images or sensor data into categories, such as diseased (for example, {reject}) or healthy (for example, {accept}) (Figure 6).

Precision in the form of predictions is relative to the total of positive number of true predictions: true positive/all positive. Or, false precision measures the number of fish classified as diseased by the classifier that was actually diseased.

Precision =TP/TP+FP

Recall (also known as Sensitivity or True PositiveRate) is the fraction of true positive predictions (correctly identified diseased fish) out of all actual positive cases (both true positives and false negatives). It helps to evaluate how well the model identifies all actual diseased fish in the dataset.

Recall =TP/TP+FN

Accuracy is the overall measure of how well the model performs across both diseased and healthy. This can be identified and shown in the result table using the formula:

Accuracy =TP+TN/TP+TN+FP+FN

It can be more useful and practical in cases where there is most of an almost matched trade-off for precision and recall that, sometimes, which can sometimes be addressed by using the F1 score—especially when dealing with imbalanced classes.

F1 Score=2× Recall×Precision/Recall + Precision

HARDWARE

This image in Figure 7 displays a Raspberry Pi board connected through a USB interface to a camera module. It can detect the fish underwater for main processing unit of the Raspberry Pi; while the sensor for detecting the fish on the camera module includes a protective cover.

Camera feed output: If configured properly, the Raspberry Pi can capture and display images or live video streams from the attached camera.

Output

```
The Classified SVM Accuracy: 91.67%
Precision: 85.00%
Recall: 100.00%
Sensitivity: 100.00%
Specificity: 84.21%
False Positive Rate: 15.79%
False Negative Rate: 0.00%
F1 Score: 0.92
```

Class	SVM Accuracy	Precision	Recall	Sensitivity	Specificity	FPR(%)	FNR(%)	FN Score
Fresh Fish	92	92.75	98.46	100	50	50	1.54	5.52
Infected Fish	93	94.01	98.13	100	75	25	1.875	96.02
Fresh Fish	93.75	96.23	96.23	99.21	81.82	18.19	3.77	96.23
Infected Fish	94.9	98.52	98.68	99.99	88.89	11.11	4.31	97.08
Fresh Fish	91.67	85	100	100	84.23	15.87	0	0.92
Infected Fish	94.9	98.52	99	98.68	84.21	15.78	5.23	0.82
Fresh Fish	97.82	92	94.23	88.23	89.82	17.15	4	92.54
Infected Fish	93	94.23	98.19	99	87.65	18.16	5.24	5.43
Fresh Fish	91.13	82.22	98	95	85.25	15.87	0	0.92
Infected Fish	94.65	83.65	100	100	84.21	14.25	4.26	0.94

Figure 6. Result.

Figure 7. Raspberry pi connected with sensors.

CONCLUSION

Intelligent aquaculture system for the identification of fish disease using Machine Learning (ML), Support Vector Machine (SVM), Gray-Level Co-occurrence Matrix (GLCM) and Raspberry Pi with integrated camera and sensors shall be capable to change the aspect of monitoring health of the fishes. Conventional methods for identifying diseases take quite a long period, involvement of labor, and sometimes expert input to make them applicable for a vast aquaculture industry. The integration of ML, computer vision, and IoT-based water quality monitoring addresses this challenge by providing a real-time, automated, and cost-effective solution.

A Raspberry Pi-based system was developed with a camera module for image acquisition and sensors for water quality monitoring, such as temperature, pH, dissolved oxygen, and ammonia. The GLCM technique was used for feature extraction to capture texture-based patterns from fish images to distinguish between healthy and diseased fish. The extracted features were classified using an SVM model, which demonstrated high accuracy in detecting common fish diseases based on image and environmental data.

This study demonstrates that the integration of Support Vector Machine (SVM), Gray-Level Co-occurrence Matrix (GLCM), and a Raspberry Pi-based system provides an efficient and intelligent solution for fish disease detection and water quality monitoring in aquaculture. By leveraging machine learning (ML), image processing, and IoT technologies, the proposed system automates disease detection, enabling fish farmers to take timely preventive measures and improve overall aquaculture productivity. The SVM-based classification using GLCM features, combined with real-time monitoring via Raspberry Pi and environmental sensors, provides an automated, scalable, and cost-effective solution for fish disease detection.

REFERENCES

1. Fulu E, Kerr-Wilson A, Lang J. What works to prevent violence against women and girls: evidence review of interventions to prevent violence against women and girls. Pretoria (South Africa): South African Medical Research Council; 2014.
2. Garcia-Moreno C, Watts C. Violence against women: an urgent public health priority. Bull World Health Organ. 2011; 89(1): 2.
3. Gulati G, Anand TK, Anand TS, Singh S. Modern era and security of women: An intellectual device. Int Res J Eng Technol. 2020; 7(4): 212–218.
4. Opika KM, Rao CM. An Evolution of women safety system: A literature review. An International Bilingual Peer Reviewed Peered Research Journal. 2020; 10(40): 61–4.
5. Ahir S, Kapadia S, Chauhan J, Sanghavi N. The personal stun-a smart device for women's safety. In 2018 IEEE International Conference on Smart City and Emerging Technology (ICSCET). 2018 Jan 5; 1–3.

6. Akram W, Jain M, Hemalatha CS. Design of a smart safety device for women using IoT. Procedia Comput Sci. 2019 Jan 1; 165: 656–62.
7. Ometov A, Shubina V, Klus L, Skibińska J, Saafi S, Pascacio P, Flueratoru L, Gaibor DQ, Chukhno N, Chukhno O, Ali A. A survey on wearable technology: History, state-of-the-art and current challenges. Comput Netw. 2021 Jul 5; 193: 108074.
8. Nagamma H. IoT based smart security gadget for women’s safety. In 2019 IEEE 1st international conference on advances in information technology (ICAIT). 2019 Jul 25; 348–352.
9. Saranya N, Aakash R, Aakash K, Marimuthu K. A Smart friendly IoT device for women safety with GSM and GPS location tracking. In 2021 IEEE 5th International Conference on Electronics, Communication and Aerospace Technology (ICECA). 2021 Dec 2; 409–414.
10. Ruman MR, Badhon JK, Saha S. Safety assistant and harassment prevention for women. In 2019 IEEE 5th international conference on advances in electrical engineering (ICAEE). 2019 Sep 26; 346–350.
11. Bhate A, Sultana PH. Smart wrist band for women security using logistic regression technique. Int J Recent Technol Eng. 2019 May;8(1):2215–8.
12. Kanchana Devi V, Kavya A, Umamaheswari E, Karmel A, Kavitha D, Shruthi D. IoT-SDWD: Internet of Things-based security device for women in danger. In ICT with Intelligent Applications: Proceedings of ICTIS 2021, Volume 1. Singapore: Springer; 2022; 311–318.
13. Mishra AD. Women empowerment: issues and challenges. Indian Journal of Public Administration (IJPA). 2014 Jul; 60(3): 398–406.

