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# Fish Guard: A Holistic Approach to Automated Fish Farming with IoT and Image Processing

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**ABSTRACT**

**The ornamental fish industry, which is important to the global economy, faces challenges that hinder its productivity and sustainability, particularly feeding practices, water quality management and disease control. This research introduces an integrated system designed to automate and optimize these aspects using the ESP32 microcontroller. Offers a lower cost and more effective, low-power solution with real-time processing capabilities. The proposed system has developed along four main lines. An automated feeding system that adapts to the food needs of fish, a water quality management system that monitors and controls critical parameters through machine learning algorithms, and a disease management system that uses image processing techniques for early detection. The systems were tested in controlled environments, showing significant improvements in nutrient efficiency, water quality stability and disease prevention. Our findings suggest that the integration of these technologies can significantly enhance the operational efficiency and sustainability of ornamental fish farms.**

***Keywords--*** IoT, Ornamental Fisheries, Automated Feeding, Aqua Culture, Fish Disease Detection

## I. INTRODUCTION

"The ornamental fish industry in Sri Lanka was first an area of unidentified export potential when fish lovers used to import their favorite fish varieties back in the 1930s." [1]

Despite the ornamental fish industry's remarkable growth, it faces several challenges that threaten its sustainability and productivity, especially in the areas of feeding practices, water quality management and disease control [2][3]. Traditional methods in these areas often result in inefficiencies, such as overfeeding, inadequate nutrient supply, and inconsistent water quality monitoring, resulting in increased mortality and disease outbreaks, thus underscoring the urgent need for innovative solutions [4].

However, the specific application of IoT in the ornamental fish industry remains under-explored, with current research focusing primarily on large-scale aquaculture projects, without adequately addressing the unique needs of ornamental fish farming in diverse and confined ponds. The advent of IoT) technology offers a promising avenue to address these challenges [5]. Real-time monitoring and automated control the potential of the IoT to revolutionize aquaculture practices through improved operational efficiency, sustainability and fish health across systems is gaining recognition. Furthermore, the direct water connection of sensor probes introduces maintenance challenges, emphasizing the need for innovative designs that include self-cleaning mechanisms and industry addresses infrastructural, data-related, and cognitive-related challenges [6].

A significant contribution of this research is the novel application of ESP32 microcontrollers combined with advanced sensor technologies, predictive analytics, and machine learning algorithms to address critical challenges in ornamental fish industry [5]. Integrating these technologies into an integrated system demonstrates the feasibility of real-time data collection, analysis, and control in ornamental fish farming operations [6].

Finally, this research is water quality management, disease control, nutrition Addressing inefficiencies, improving operational efficiency, sustainability and fish health contributes to the field of precision aquaculture. The integration of IoT and AI technologies in aquaculture offers a transformative opportunity for the ornamental fish industry [2] [3].

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## II. LITERATURE REVIEW

Today, smart aquaculture represents a key trend towards sustainable development within the fish farming industry, leveraging intelligence and automation. The integration of advanced intelligent technologies has delivered substantial advantages across various sectors, including aquaculture. These technologies significantly decrease the need for manual labor, boost production efficiency, and promote environmental sustainability.

A thorough monitoring system for carp farming ponds was introduced by Ramadani et al. [7], with an emphasis on IoT-based water quality control. Their study emphasizes the value of wireless connection, accurate temperature measurement, and monitoring made possible by Internet of Things devices. This study emphasizes how important Internet of Things (IoT) technologies are to maintaining aquaculture's water quality, especially when it comes to integrating wireless sensor networks and temperature sensors.

Abinaya et al. [8] put up an innovative approach to use IoT for aquaculture water quality monitoring and control. Their method emphasizes how important sensor systems are effective monitoring parameters that are critical to fish health, such as temperature. With IoT technologies, this study advances sustainable practices by improving our knowledge of and ability to manage water quality in aquaculture settings.

In the case of Bangladesh, Ahmed et al. [9] carried out a thorough examination of the water quality and its appropriateness for IoT-based fish farming. This study highlights the use of IoT and machine learning algorithms in conjunction to evaluate water quality metrics and forecast how they would affect fish health. This research offers important insights into proactive management tactics for preserving ideal.

Water quality conditions in aquaculture by utilizing IoT sensors and machine learning techniques.

Researchers have investigated machine learning techniques for automated fish disease identification in addition to image processing. To identify fish infections, Malik et al. [10] looked at several image processing methods, such as features from the accelerated segment test (FAST) and histogram of gradient (HOG). Their research emphasizes how crucial feature extraction techniques are to improving the precision of illness identification. Additionally, Waleed et al. [11] created an automatic recognition system for fish disease detection in aquaculture settings using convolutional neural networks (CNNs). Their method shows promising results in accurately recognizing common fish diseases by using edge detection techniques and evaluating color data.

Complicated illness identification algorithms have also been developed because of recent developments in deep learning. To enhance classification performance, Al Noman et al. [12] developed a "HYBRID-CNN" architecture for the identification of Rohu fish infections. This design combines transfer learning and hybrid CNN approaches. In a similar vein, GR et al. [13] gave a summary of machine learning methods for aquaculture di To build comprehensive illness diagnosis systems, researchers have also investigated integrating hardware such as cameras and sensors with software algorithms. An IoT-based system and image processing were reported by Ranaweera et al. [14] for the identification of fish infections and tank monitoring. Their technology offers a comprehensive approach to disease control in aquaculture environments by integrating the detection of microorganisms with an examination of the water quality. Furthermore, Hameed et al. [15] created a real-time decision support system for classifying fish diseases and analyzing water quality using machine learning techniques. Their approach gives aquaculture professionals useful insights that allow for prompt responses to stop disease outbreaks. Sease detection, highlighting the significance of convolutional neural networks (CNNs) in attaining high scalability and accuracy.

The current status of automated feeding systems with real-time data acquisition [16] and [17] highlights existing automated feeding technologies, integrating IoT devices to acquire real-time data and using algorithms to find optimal feeding schedules. These systems emphasize efficiency and sustainability, marking a major shift from traditional methods. As described in [18], Recent advances in feeding algorithm innovation, focus on the refinement of feeding algorithms that consider various parameters such as species specificity and environmental conditions. Integrating IoT for Improved Monitoring and Control shows how the integration of automated feeding systems and collaboration between IoT technologies facilitates precise monitoring and control of feeding processes. The literature review identified these areas as ripe for further research, and a future where AI and machine learning further develop sophisticated feeding algorithms. suggests. Continual innovation is needed to strengthen the transformative impact of IoT and algorithm-based feeding systems on ornamental fish farming and to navigate the existing challenges to ensure adaptability and growth in the aquaculture industry. The proposed scheme overcomes the above weaknesses and challenges and gives a renaissance to ornamental fish farming.

In conclusion, current research emphasizes how crucial Internet of Things (IoT) technologies are becoming to aquaculture for controlling and monitoring water quality indicators in real time. These studies highlight how crucial sensor systems, wireless connectivity, and predictive analytics are to maintaining the best possible conditions for fish productivity and health. Aquaculture practitioners can

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improve operational efficiency, reduce hazards, and advance sustainable practices in fish farming environments by utilizing IoT-enabled technologies.

## III. METHODOLOGY

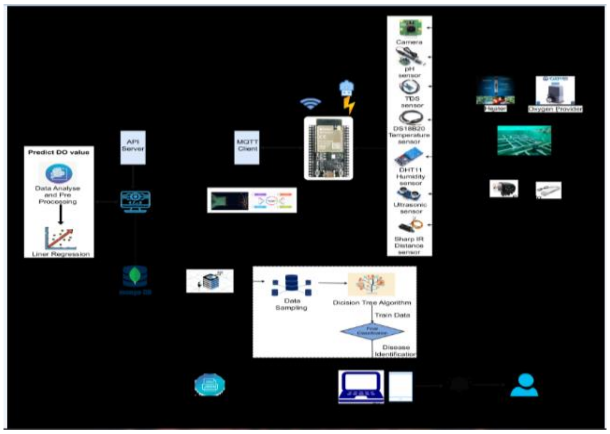


**Figure 1:** Overall system architecture diagram.

Figure 1 indicates the overall system architecture diagram of the proposed system. To implement the system data was collected from the online Kaggle site and real-time aquariums. For the implementation of web application used the MERN (MongoDB, Express.js, React.js, Node.js) stack, offering user friendly interfaces for accessing and managing system functionalities.

### *A. Real Time Water Quality Management*

In the hardware implementation phase of the automated real-time water quality monitoring system, more attention is given to the selecting and assembling of IoT hardware components.

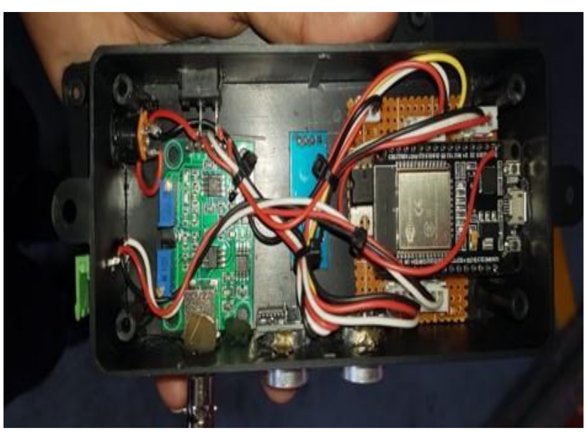


**Figure 2:** IoT Device for Detect Water Quality Parameters.

As Figure 2 the ESP32 microcontroller with integrated Wi-Fi capabilities acts as the cornerstone of the device network. It connects to an array of sensors, chosen for its precision and reliability in measuring specific water quality parameters that are crucial for aquaculture.

The Dallas DS18B20 water temperature sensor, designed for submersion, maintains the narrow temperature ranges required by various fish species by providing accurate temperature readings. The pH sensor, critical for detecting the acidity or alkalinity of the water, is calibrated to industry standards to ensure the health of the aquatic ecosystem. Humidity sensor monitors the water vapor present in the environment, and it will affect on overall health of the fish.

The Total Dissolved Solids (TDS) sensor measures the concentration of dissolved substances, which can affect tank cleanliness and the fish health. A machine-learning model has been developed to predict dissolved oxygen level utilizing the linear regression algorithm. This model gets sensor data from the pH sensor, water temperature sensor, humidity sensor and sharp sensor to estimate the dissolved oxygen value accurately.

The ammonia level is calculated using an Equation (1) derived from Millichip [19] that factors in the water temperature and pH value. The level of ammonia is managed indirectly through the regulation of pH level and temperature.

$$A = [10^{(0.0901821 + (\frac{2729.92}{273.15\text{-}T_c})\text{-}pH} + 1]^{-1} \tag{1}$$

Where:
A = Ammonia Factor
$T_c$ = Temperature in factor
pH = pH reading

Sharp sensor and ultrasonic sensors are used to measure the water level, to ensure the fish have sufficient space and water volume for their well-being.

Each sensor is connected to the ESP32 via a One Wire bus system, minimizing the complexity of wiring and enhancing the stability of the data transmission. The MQTT protocol transmits the data in a format conducive to real-time analysis and responsive actions. The power supply for the system is streamlined, through a 5V USB connection.

This hardware setup embodies modern aquaculture practices, utilizing IoT to build the gap between manual monitoring and the demands of a precise, data-driven approach to fish farming. With a focus on sustainability and efficiency, the system is designed to empower fish farmers, enabling proactive management of water quality with a level of precision that manual methods cannot achieve.

The front end is planned to supply clients with a user-friendly interface for observing genuine time water quality parameters. It shows sensor data graphs and alerts dynamically, leveraging the interface permits clients to connect with the system, configure settings, and get notifications for any inconsistencies identified by the backends' analysis.

The backend handles alarm logic, determining when the system's readings show a need for user notification. Integration with the frontend is encouraged through a REST API, empowering consistent data flow and real-time updates to the client interface.

***B. Give Predictions***

In here representing comprehensive methodology for the hardware and software implementation of an IoT-based fish farming automation system, focusing on the component that responsible for controlling water parameters, maintaining historical data, and providing predictive analytics of water parameters. In the hardware implementation cover the selection and integration of specific devices for water parameter control. By utilizing oxygen motors for pH regulation and heaters for temperature control within the fish tanks to maintain the water quality of the fish tank. The ESP32 microcontrollers are used to connect and control these controlling devices, facilitating seamless communication with the central control system. Wi-Fi connectivity is used to enable remote monitoring and control of water parameters, offering users both manual and automatic control options through a user-friendly web interface.

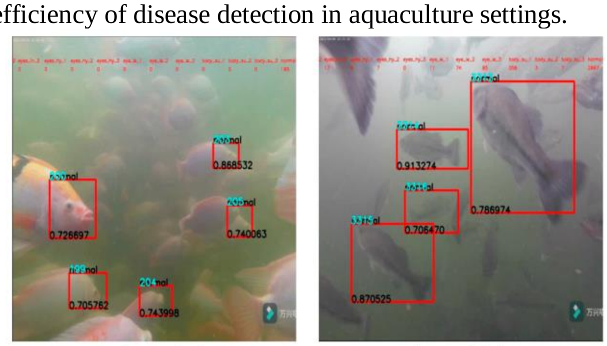
On the software implementation, to develop a robust system for data analysis, prediction, and user interaction utilize machine learning algorithms, specifically simple linear regression, and time series analysis, to analyze historical water parameter data and generate predictive models. In implementing the machine learning model used the Long Short Term Memory algorithm, Multi-Layer Perceptron, Convolution Nural Network and Linear regression for training the data set and Linear regression model get best performance here for the water parameters with 81.2 % accuracy. Because of this, choose the Linear Regression for the model training. Before model training, extensive data preprocessing steps are undertaken, including data cleaning, normalization, and feature engineering, to ensure the accuracy and reliability of predictions. Real-time updates are integrated into the prediction mechanism, allowing for timely adjustments based on changes of water parameter trends.

***C. Disease Detection***

During the hardware stage, the camera device's placement inside fish farms is crucial since it affects the quality of the images that are taken. Camera is placed in strategic locations across the farm to guarantee thorough coverage and precise fish population monitoring. During the setup procedure, variables like coverage and illumination are carefully considered to maximize image quality and reduce any possible sources of interference. The principal aim is to put the camera devices as optimally as possible while maintaining smooth connection with the ESP32 microcontroller. Camera collects high-definition photographs of every fish with meticulous setup and calibration, giving rise to an extensive dataset necessary for illness detection and control.

Pickle shows up as a vital tool for real-time data collection from camera device in the software phase. This makes it possible to continuously collect image data, which makes it easier to identify and treat diseases in a timely manner. Using convolutional neural networks (CNNs), a potent image processing technique, collected fish images are thoroughly analyzed to identify illnesses like Gill and Saprolegnia disorders. CNNs are excellent at spotting patterns and abnormalities in pictures, which makes them a good choice for spotting minute symptoms of disease in fish specimens. Software design places a high priority on real-time processing capabilities to enable quick analysis and reaction to new health issues. To maximize the system's responsiveness and efficiency, low latency performance and energy usage are also prioritized. Through the smooth integration of sophisticated image processing algorithms with camera-based data collection, the technology quickly identifies ill fish and sounds a warning for rapid assistance. This proactive strategy reduces the likelihood of disease outbreaks and maintains the general health of fish populations, which increases aquaculture productivity.

Figure 3 shows that different lighting conditions are a major factor to consider in the methodology's hardware and software phases. The positioning of the camera devices in the hardware configuration takes into consideration changes in lighting throughout the day to provide consistent image quality independent of external circumstances. Likewise, during the software stage, the image processing algorithms are trained to account for diverse lighting situations, enabling reliable disease identification in a range of circumstances. Through the resolution of issues brought about by varying illumination conditions, the methodology improves the accuracy and efficiency of disease detection in aquaculture settings.



(a) Strong light (b) Weak light

**Figure 3:** Different Light Conditions in the Underwater Environment.

Fish that are sickly provide vital information for developing and validating algorithms that detect diseases. The approach includes images of fish displaying symptoms of common diseases including Gill disease and Saprolegnia disease, so the algorithms can reliably identify and classify infected specimens. Targeted interventions and disease management tactics are made easier by the diverse dataset of images of unhealthy fish, which improves the algorithm's capacity to recognize subtle symptoms of illness and distinguish between different diseases.

***D. Feeding System***

The proposed system design and development of an automated fish-feeding system. Using real-time room temperature data analysis, this system aims to dynamically adjust feeding volumes and schedules in specific periods. The ESP32 microcontroller at the center of this system allows precise control of the food mechanism's processes to be combined with seamless collection of sensor data. One of the most critical variables in aquaculture in determining a fish's metabolic rate is water temperature. By using feeding algorithms to calculate feeding amounts based on real-time room temperature data, our approach directly addresses this need. This maintains optimal growth and health rates of the fish.

When the feeding scheduled time arrives, system check the tanks available for the feeding and feeding algorithm automatically call to get real time water temperature and after that calculate the mean value,

Given the minimum and maximum temperatures of the optimal range (Tmin and Tmax), the mean optimal temperature (Tmean) is calculated as equation 2:

$$T_{mean} = \frac{(T_{min} + T_{max})}{2} \tag{2}$$

Next calculate the Adjusted factor by Equation (3).

$$Adj\_factor = 1 + ((T_{current} - T_{mean}) \times Adj\_rate) \tag{3}$$

Adj_factor = Adjusted Factor
Adj_rate = Adjusted Rate

After calculating the Adjustment factor, finally Equation (4) is calculated the Adjusted feeding quantity.

$$\text{Adj\_quantity} = \text{base\_quantity} \times \text{Adj\_factor} \times \text{fish\_quantity} \tag{4}$$

Figure 4 feeding algorithm operates based on Real-time water temperature obtained by sensors and tank data stored in the database.

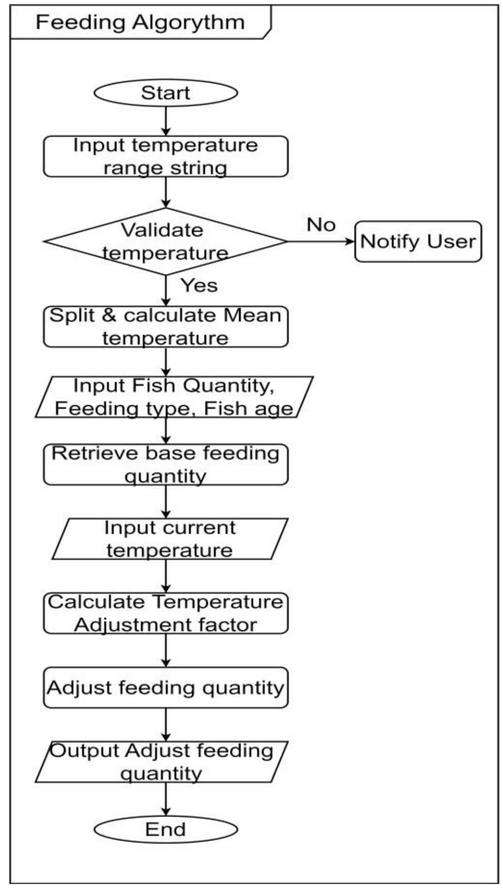



**Figure 2:** Feeding algorithm flow chart.

As a result of powerful processing capability, built-in wireless connectivity module, and flexibility to interface with a wide range of sensors and actuators, the ESP32 microcontroller serves as the foundation for our system's hardware architecture. The temperature sensor in the fish habitat is used to continuously monitor the room temperature, and the ESP32 is configured to gather data from it. The system has used a motor-driven feed dispenser as the feeding mechanism, that can release preset feed quantities. Signals received from the ESP32, which are determined by the feeding schedule computation, operate this dispenser. Real-time data transfer and system monitoring are made available by the ESP32's connection features, which are supported by a dependable power supply, guaranteeing continuous system functioning.

Using the Arduino IDE, we designed customized software for the ESP32 that allows it to read temperature data, detect when to feed it, and operate the feed dispenser. To communicate with our backend server, this firmware additionally incorporates wireless data communication modules.

The backend system is essential to analyze the water temperature that the ESP32 provided. It uses our unique feeding algorithm to calculate the optimum feeding

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amounts and schedule then stores the results in a MongoDB database for further study and optimization.

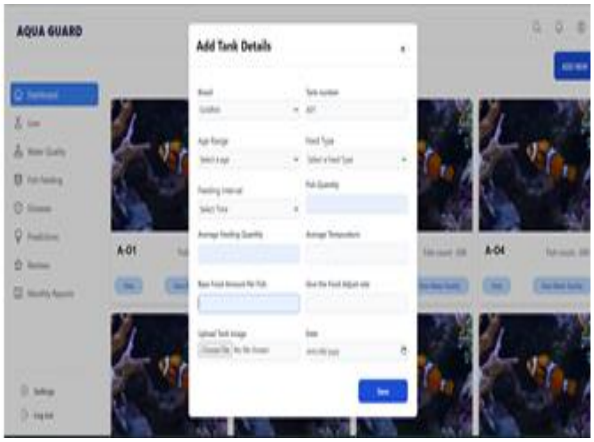


**Figure 5:** Tank Details User Interface.

Figure 5 shows the estimated feeding schedule, real-time temperature changes, and manual override choices to make user engagement easier. Users have flexibility and control over the aquaculture environment using this user interface, which enables them to remotely monitor and modify the feeding process.

## IV. TEST RESULTS

### *A. Real Time Water Quality Monitoring*

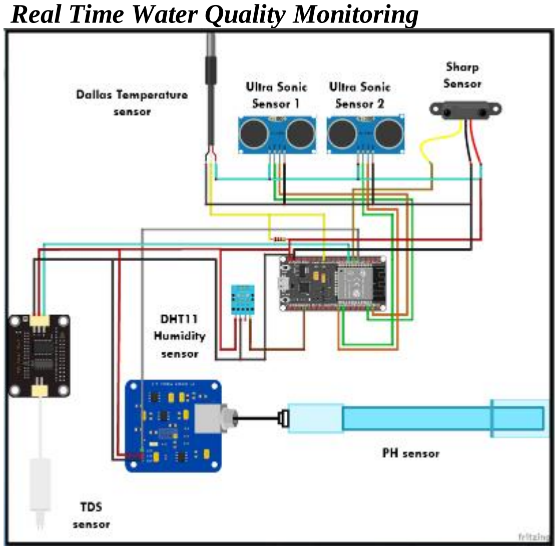


**Figure 6:** Interconnection of IoT Device

Figure 6 illustrates the operation and interconnection of the IoT device with sensors. The IoT device is responsible for gathering and transmitting data from the sensors to a central location, where the information can be analyzed and utilized to make informed decisions.

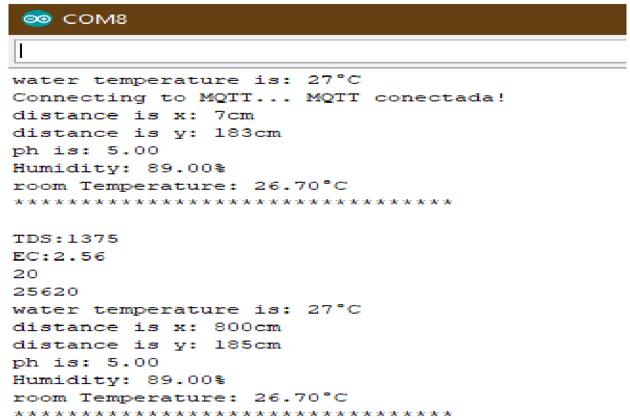


**Figure 7:** Sensor Readings of Water Quality Parameters.

Figure 7 is an example of the outputs generated by the IoT device, which can provide valuable insights into various aspects of the system being monitored. These outputs may include data on water level, TDS value, Ultrasonic results, pH values, Humidity value water temperature value and room temperature value readings.

Opting for Linear Regression in this analysis presents several advantages. It offers simplicity and clarity by providing an easily interpretable model demonstrating the relationships between pH, temperature, humidity, water level, and dissolved oxygen. Linear Regression is also computationally efficient and less susceptible to overfitting, making it appropriate for the dataset at hand. Its transparent nature facilitates model validation and results explanation, crucial for effectively communicating findings with web application. The dissolved oxygen prediction model developed using liner regression algorithm shows the accuracy as below in Figure 8.

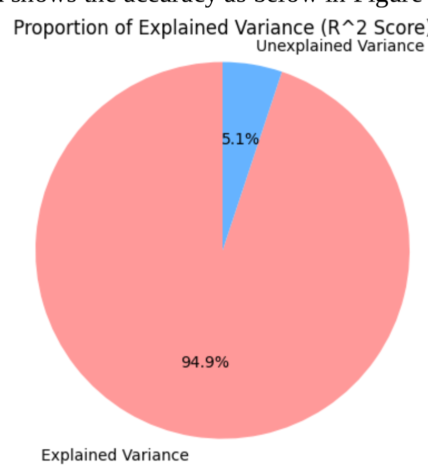


**Figure 8:** Accuracy of Predicted Dissolved Oxygen Value.

### *B. Give Predictions*

Table 1 provides a summary of the performance metrics for three different models used in the task. Model

1, utilizing the Adam optimizer, exhibited the highest MSE of 50, suggesting relatively poorer performance compared to the other models. Model 2, utilizing the Nadam optimizer, showcased the lowest Mean Squared Error (MSE) of 30, indicating its performance among the initial three models. Model 3 emerges as the most effective, achieving high accuracy (81.03%), testing precision (95.71%), and recall (92.59%). Interestingly, Model 3, which employed the Adam optimizer like Model 1 but was trained for a significantly higher number of epochs (300), demonstrated a competitive MSE of 36.68, suggesting potential for enhanced performance with prolonged training.

**Table 1:** Summary of the Performance Metrics.

| Evaluation Metrics | Model 1 | Model 2 | Model 3 (best) |
|---|---|---|---|
| Accuracy | 60.4% | 70.2% | 81.3% |
| MSE | 50 | 30 | 36.68 |
| MAE | 9 | 6 | 4.9 |
| Optimizer | Adam | Nadam | Adam |
| Precision | 80% | 87% | 95.71% |
| Recall | 23.7% | 46.15% | 92.53% |
| Epochs | 100 | 100 | 300 |

Figure 9 contains the line graphs, that represent the loss and accuracy of each predictive model.

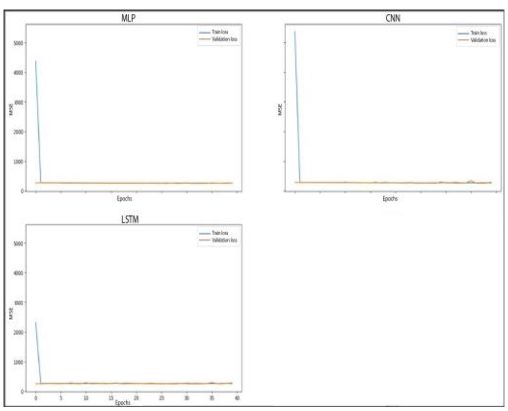

**Figure 9:** Line Graphs.

### *C. Disease Detection*

Promising outcomes were obtained when a Support Vector Machine (SVM) was used to identify fish diseases. Table 2 gives an overview of accuracy using the SVM model. The project's use of SVM yielded a noteworthy accuracy of 0.9675, with weighted average and macro average scores of 0.97 and 0.95, respectively. Based on the examination of a dataset with roughly 500 well curated and labeled fish photos for training, this accuracy was achieved. By using the annotated dataset to identify patterns and anomalies suggestive of different illnesses, the SVM model demonstrated its efficacy in the classification of fish diseases. The model's performance was notably enhanced by the integration of the camera for picture capture, which produced high-resolution images that are essential for precise illness detection. The system's successful deployment underscores its potential to completely transform aquaculture environments' approaches to disease management. By advancing technology-driven aquaculture solutions, this research opens the door to better farm productivity and more accurate fish health monitoring.

**Table 1:** Overall Performance of Svm Model.

| Evaluation Metrics | Accuracy Value |
|---|---|
| Precision | 0.98 |
| Recall | 0.97 |
| F1 score | 0.97 |
| Support | 833 |

### *D. Feeding System*

Calculate the feeding quantity based on the real time temperature experimented in several ways. Figure 10 proves that predicting feeding quantity using Neural Network model was not successful as the model given 50% accuracy.

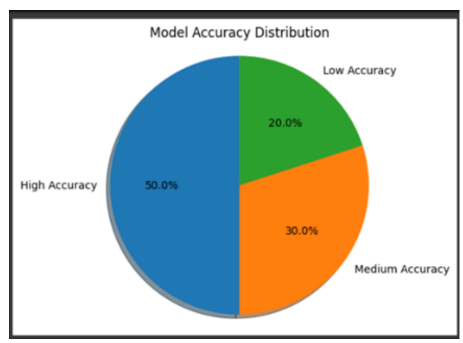

**Figure 10:** Model accuracy.

After analyzing the ornamental fish feeding timetable, the proposed system implements an algorithm based on the average feeding quantity per fish.

**Table 3:** Feeding Table Analyze.

| Name | Goldfish | Anjel Fish |
|---|---|---|
| Number of Fish | 6000 | 3000 |
| Feed Type | 01 | 03 |
| Feeding Qty | 200g | 200g |
| Feeding Interval | 3 | 3 |
| Average Temperature | 20°C to 23°C | 25°C to 28°C |
| Average food per Fish | 0.03 | 0.1 |

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User can create a fish tank in the system by giving the necessary information required as display in Table 3. As shown in Figure 11 while feeding interval triggers the system will receive the real-time room temperature through the Esp32. Finally, the feeding quantity will calculated and send it to the Esp32 board.

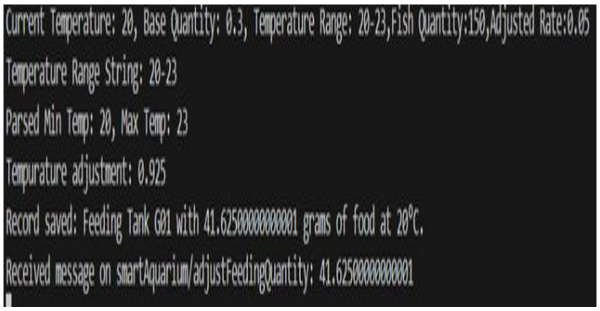


**Figure 11:** Backend Results.

Figure 12 device adjusts the waiting time for distribution food, based on the quantity measured in grams that distributed on five seconds. Assumed the 2 grams distributed in 1 second is display as 20 seconds for 40 grams in feeder waiting time.

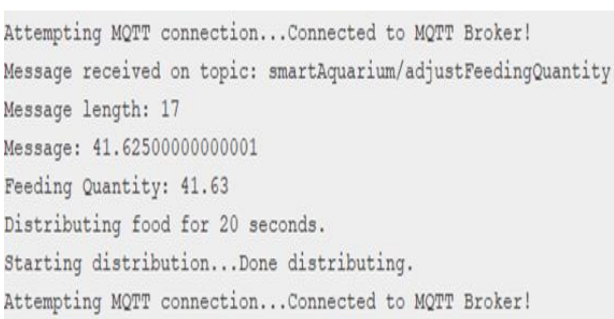


**Figure 12:** Result in Arduino ide.

Figure 13 user can review the summary of distributed feeding and the real time temperature based on the average temperature.

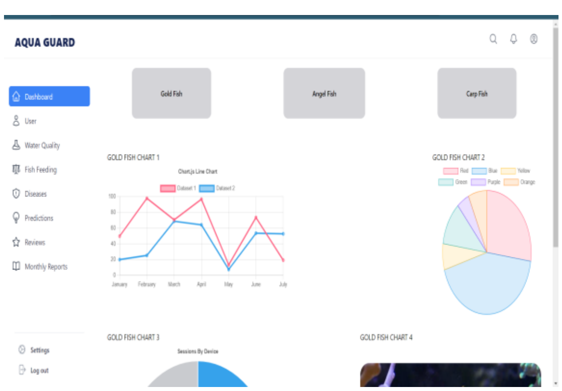


**Figure 13:** Summary View.

## V. CONCLUSION

This research indicates that the automated feeding system, when synchronized with real-time water quality monitoring, significantly improves nutrient efficiency, reducing waste and promoting optimal fish growth conditions. Moreover, the implementation of machine learning algorithms for water quality management has proven effective in maintaining stable conditions, crucial for the well-being of ornamental fish. The implications of this research extend beyond the operational efficiencies within individual farms, hinting at a broader impact on the ornamental fish industry. This study paves the way for a more sustainable, productive, and resilient industry by demonstrating the feasibility and benefits of integrating technology into aquaculture.

In conclusion, the Fish Guard system embodies a significant advancement in precision aquaculture, offering a blueprint for the future of ornamental fish farming. By harnessing the power of IoT and image-processing technologies, this research contributes to the body of knowledge in aquaculture, providing a solid foundation for future innovations to achieve the ultimate goal of sustainable fish farming.

## REFERENCES

[1] N. C. Thilakarathne. (2024). The ornamental fish industry in Sri Lanka. *High Rayz, Feb. 29.*

[2] S. Usha Kiruthika, Dr. S. Kanaga & R. Jaich. (2017). IOT based Automation of Fish Farming. *9*(1), 50–57.

[3] X. Yang, S. Zhang, J. Liu, Q. Gao, S. Dong & C. Zhou, (2020). Deep learning for smart fish farming: applications, opportunities and challenges. *Reviews in Aquaculture*, *13*(1), 66–90.

[4] J. -H. Chen, W. -T. Sung & G. -Y. Lin. (2015). Automated monitoring system for the fish farm aquaculture environment. *IEEE International Conference on Systems, Man, and Cybernetics, Hong Kong, China.*

[5] M.-C. Chiu, W.-M. Yan, S. A. Bhat, & N.-F. Huang, (2022). Development of smart aquaculture farm management system using iot and ai-based surrogate models. *Journal of Agriculture and Food Research*, *9,* 100357.

[6] Idachaba FE, Olowoleni JO, Ibhaze AE, & Oni OO(2017). IoT enabled real-time fishpond management system. In*: Proceedings of the world congress on engineering and computer science, 1*, 25-27.

[7] Ramadani, Mesita, Rizaldy, Hakim, Ash-Shiddieqy, Raafi, Brian , Zain, Alex , Mursid, Mahirul adziimaa & Ahmad. (2022). Design and

development of monitoring system on carp farming ponds as iot-based water quality control. DOI: 10.1109/ICRACOS53680.2021.9701980.

[8] T. Abinaya, J. Ishwarya, & M. Maheswari. (2019). A novel methodology for monitoring and controlling of water quality in aquaculture using internet of things (iot). *International Conference on Computer Communication and Informatics (ICCCI)*.

[9] M. Uddin et al. (2023). An overview on water quality, pollution sources, and associated ecological and human health concerns of the lake water of megacity: A case study on Dhaka city lakes in Bangladesh. *Urban Water Journal, 20*(3), 261–277.

[10] S. Malik, T. Kumar & A. K. Sahoo. (2017). Image processing techniques for identification of fish disease. *IEEE 2nd International Conference on Signal and Image Processing (ICSIP), Singapore*, pp. 55-59. DOI: 10.1109/SIPROCESS.2017.8124505.

[11] A. Waleed, H. Medhat, M. Esmail, K. Osama, R. Samy & T. M. Ghanim. (2019). Automatic recognition of fish diseases in fish farms. *14th International Conference on Computer Engineering and Systems (ICCES), Cairo, Egypt*, pp. 201-206. DOI: 10.1109/ ICCES48960.2019. 9068141.

[12] M. A. Al Noman, M. Shakil Hossen, M. Islam, J. F. Ani, N. Jahan Ria & A. Rakshit. (2022). HYBRID-CNN: For identification of rohu fish disease. *13th International Conference on Computing Communication and Networking Technologies (ICCCNT), Kharagpur, India*, pp. 1-6. DOI: 10.1109/ICCCNT54827.2022.9984516.

[13] R. GR, C. G. Raghavendra, S. Rohit, P. R. Shetty & S. H. M.P. (2023). An overview on machine learning techniques for identification of diseases in aquaculture. *4th International Conference for Emerging Technology (INCET), Belgaum, India*, pp.1-5. DOI: 10.1109/INCET57972.2023.10170241.

[14] I. U. Ranaweera, G. K. Weerakkody, B. M. E. K. Balasooriya, N. H. P. R. S. Swarnakantha & U. U. S. Rajapaksha. (2022). Image processing and iot-based fish diseases identification and fish tank monitoring system. *4th International Conference on Advancements in Computing (ICAC), Colombo, Sri Lanka,* pp. 144-149. DOI: 10.1109/ICAC57685.2022.10025327.

[15] N. Hameed, M. M. Hassan & A. Hossain. (2022). An explainable real-time decision support system for identifying fish diseases and Analysing Water quality. *14th International Conference on Software, Knowledge, Information Management and Applications (SKIMA), Phnom Penh, Cambodia*, pp.140-144. DOI: 10.1109/SKIMA57145.2022.10029415.

[16] U. W.G.A., J. R.T., N. N.G.K., S. L.S., L. P. Weerasinghe, & G. T. Dassanayake. (2023). Smart system for freshwater pisciculture(ornamental fish farming). *14th International Conference on Computing Communication and Networking Technologies (ICCCNT), Delhi, India*, pp. 1-8. DOI: 10.1109/ICCCNT56998.2023.10307267.

[17] K. Jadhav, G. Vaidya, A. Mali, V. Bankar, M. Mhetre & J. Gaikwad. (2020). IOT based automated fish feeder. *International Conference on Industry 4.0 Technology (I4Tech), Pune, India*, pp. 90-93. DOI: 10.1109/I4Tech48345.2020.9102682.

[18] S. Fernando, N. Jayaweera, S. Pitawala, R. Kaushalya, P. Ratnayake, & S. Siriwardana. (2022).Smart caring system for ornamental fish. *4th International Conference on Advancements in Computing (ICAC), Colombo, Sri Lanka*, pp. 192-197. DOI: 10.1109/ICAC57685.2022.10025039.

[19] A. D. M. Africa, J. C. C. A. Aguilar, C. M. S. Lim, P. A. A. Pacheco & S. E. C. Rodrin. (2017). Automated aquaculture system that regulates Ph, temperature and ammonia. *IEEE 9th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management (HNICEM)*.