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Applying IoT and Machine Learning for Enhanced Efficiency and Disease Management, Advancing Sustainability in Freshwater Prawn Farming

Aravindhaa V
School of Electronics Engineering
Vellore Institute of Technology
Vellore, India
aravindhaa483@gmail.com

K. Ved Karthik Manikanta
School of Electronics Engineering
Vellore Institute of Technology
Vellore, India
vedkarthik9999@gmail.com

Harshitha Mandula
School of Electronics Engineering
Vellore Institute of Technology
Vellore, India
harshithamandula7@gmail.com

Dharmik Allamaneni
School of Electronics Engineering
Vellore Institute of Technology
Vellore, India
dharmikallamaneni123@gmail.com

Sangeetha N
School of Electronics Engineering
Vellore Institute of Technology
Vellore, India
nsangeetha@vit.ac.in

***Abstract*— Freshwater prawn farming is a growing trend in aquaculture, offering a potential solution to meet the increasing global demand for prawns. Freshwater prawn farming requires careful consideration of several factors, including site selection, hatchery management, harvesting, and post-harvest handling. Southeast Asian countries, with their favorable tropical climates and diverse prawn species, play a significant role in this industry. The Giant Freshwater Prawn (*Macrobrachium rosenbergii*) is the most common freshwater prawn species found in India. The integrated IoT system proposed in this research has demonstrated superior efficiency as compared to conventional freshwater prawn farming methods, making it scalable for both small and large-scale prawn farming operations. It has been evidently found that the CNN algorithm employed to predict the disease outbreak in prawns has demonstrated an accuracy rate of 73.33% accuracy.**

Keywords—IoT, Sustainability, *Macrobrachium rosenbergii*, Freshwater prawn, Aquaculture, Machine Learning, CNN.

I. INTRODUCTION

Aquaculture, particularly prawn farming [1], plays a pivotal role in meeting the surging global demand for high-quality protein. Prawns cultivated through farming contribute to 55% of the global prawn production. In 2023, Ecuador, China, India, Vietnam, and Indonesia emerge as the top five prawn producers, collectively contributing to 74% of the global prawn production. Predominantly practiced in China, prawn aquaculture is also widespread in Thailand, Indonesia, India, Vietnam, Bangladesh and other southeast Asian countries. The revenue generated from prawn farming significantly impacts the economies of developing countries like India, Thailand, and Bangladesh, with most of the harvested prawns being exported to Western and Far Eastern countries. Notably, Pacific white-leg shrimp (*Litopenaeus vannamei*) and giant tiger prawns (*Penaeus monodon*) constitute approximately 80% of the total production. The Pacific white shrimp maintains a dominant position, while the black tiger shrimp's production steadily increases.

This research paper explores a unique approach to enhance sustainability and efficiency in prawn farming by integrating Internet of Things (IoT) [2], [3] and Machine Learning (ML) techniques. Leveraging real-time data acquisition through IoT sensors, our system optimizes environmental parameters such as water quality and temperature, promoting a healthier prawn habitat [4]. Additionally, ML algorithms analyse data through image processing to predict optimal health conditions of prawn and disease outbreaks, contributing to resource-efficient and health impact farming practices. A comprehensive analysis [5] validates the effectiveness of the proposed integrated system, demonstrating significant improvements in prawn growth rates, feed utilization, and disease prevention. This research balances technical innovation with ecological responsibility, a critical step towards creating a sustainable and profitable prawn farming sector.

II. STUDY AREA

The study area for this research document primary focus is on freshwater prawn (*Macrobrachium roserbergii)* farming practices, with a particular emphasis on the context of Southeast Asian countries, particularly India. Additionally, the research explores the global landscape of prawn production, highlighting key regions such as Ecuador, China, Vietnam, and Indonesia. The integration of IoT and Machine Learning techniques [6] in prawn farming is examined within the broader framework of aquaculture sustainability and efficiency enhancement.

The conceptual IoT [7] schematic design has been made using the licensed software of Fritzing. The Machine Learning algorithm has been developed using Convolution Neural Network (CNN) algorithm, using Google Collab. The Dataset used for this model is created in accordance with the requirements needed to predict the common diseases in the freshwater prawn, which includes White Spot disease, Black Spot disease and Soft-Shell disease.

III. METHODOLOGY

In this research paper, application of IoT with conceptual implementation of sensors [8] to monitor and regulate the fresh water prawn farming effectively and efficiently has been deployed. Along with, ML Algorithm has been implemented, which is used to predict the health nature of the prawn, such that whether it is diseased or healthy one[9]. The data collected by IoT sensors doesn't play any role with the dataset used for ML technique. The proposed methodology is provided with the help of flowchart as shown in Fig 1.

In the dataset used in this research, random prawn image is input, and the prawn image obtained after applying CNN [10], [11] technique of ML algorithm is the output. The output images tell us whether the prawn is diseased or healthy.

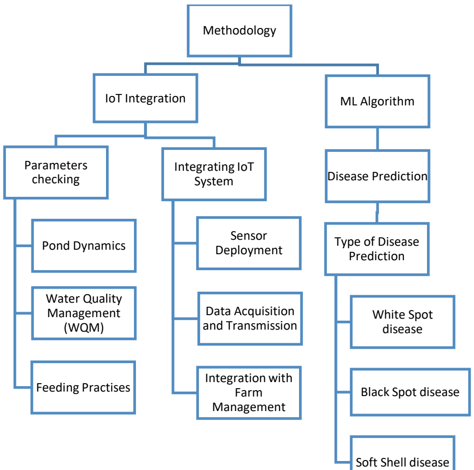

Fig. 1. Flowchart of the proposed methodology.

IV. IOT IMPLEMENTATION

1) Dissolved Oxygen (DO) –. The prawns are feeded with nutrients and also the excretion of prawns get dissolved and settled in water, which in turn leads to excessive growth of phytoplankton. This overgrowth of phytoplankton leads to the formation of dense layers, potentially covering the entire surface of the pond. Consequently, dissolved oxygen (DO) levels in the water are significantly depleted [12], particularly noticeable during night time. This can be predicted by integrating DO sensor [13] with Arduino as shown in Fig 2. To overcome this, the feeding level of prawn should be monitored and optimized and there by periodic exchange of water to mitigate nutrient buildup and control phytoplankton growth. Low DO can be predicted if prawns begin to crawl out of ponds or group at the edges of the pond in the daylight.

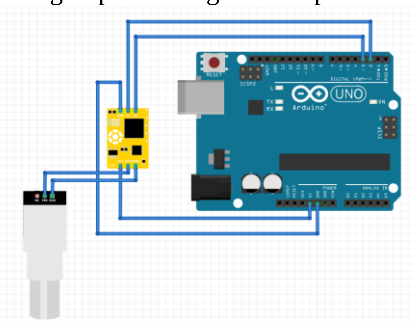

Fig. 2. Dissolved Oxygen (DO) sensor with probe connection.

2) pH – The pH refers to the acidity or alkalinity of the water, and it directly influences various biological and chemical processes within the aquatic environment. pH is a critical parameter [12], [13]that directly impacts the health, growth, reproduction, and overall productivity of freshwater prawn farming. To monitor pH levels effectively, IoT sensors can be integrated, as in Fig 3. allowing real-time data collection and analysis. These sensors enable farmers to maintain optimal pH conditions. Monitoring and maintaining stable pH levels within the optimal range, as shown in Table 2. are essential practices for maximizing productivity and successful prawn farming operations.

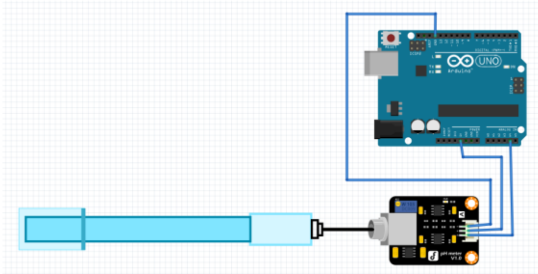

Fig. 3. pH circuit with probe connection.

3) Total Dissolved Solids (TDS) – Prawns are osmoregulators, meaning they actively regulate the balance of water and ions in their bodies to maintain proper internal conditions. High Total Dissolved Solids (TDS) and Electrical Conductivity (EC) levels in the water can disrupt this balance [13], leading to osmotic stress in prawns. Elevated levels of TDS and EC in water can affect the immune system of prawns, rendering them more vulnerable to diseases and infections. Some dissolved substances present in high TDS water, such as heavy metals, as shown in table 1. or certain chemicals from agricultural runoff, can be toxic to prawns at elevated concentrations. Increased dissolved solids and EC levels [8], [14] can be monitored effectively by integrating EC sensor with arduino, as shown in Fig 4. which also indicates the presence of pollutants or contaminants that can negatively impact prawn health, impairing growth, development, and reproductive success.

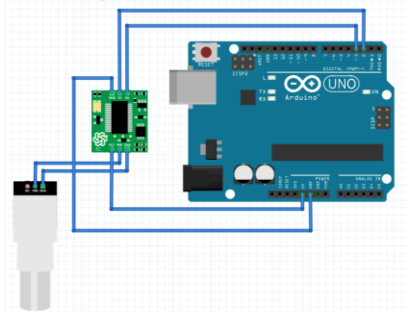

Fig. 4. Electrical Conductivity (EC) circuit with probe connection

TABLE 1. DISSOLVED SOLIDS - OPTIMAL RANGE CONDITIONS.

Parameters	Optimal Conditions
Ammonia – N(ppm)	<0.01
Nitrite – N(ppm)	<0.01
Nitrate – N(ppm)	<0.03
Zinc (ppm)	<0.0001
Copper (ppm)	<0.025
Chromium (ppm)	<0.1
Lead (ppm)	<0.1
Mercury (ppm)	<0.1
Cadmium (ppm)	<0.01

4) Turbidity - Phytoplankton serves as a primary food source for prawns in aquaculture ponds. However, excessive phytoplankton growth can deplete DO levels. High turbidity levels in water can reduce light penetration [13], affecting photosynthesis in phytoplankton, therby, reducing food availability for prawns. Integrating TS 300B sensor, as shown in Fig 5. for turbidity monitoring enables farmers to manage turbidity levels effectively, ensuring optimal conditions for phytoplankton growth and, subsequently, prawn productivity in freshwater prawn cultivation. Maintaining appropriate phytoplankton biomass is crucial for optimizing prawn growth.

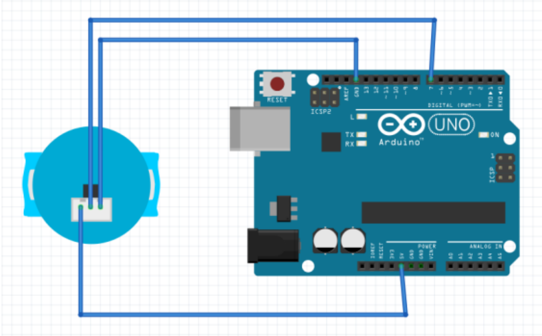

Fig. 5. TS 300B – Turbidity Sensor

5) Temperature – Freshwater prawn farming is significantly impacted by temperature [12], which influences prawn growth, reproduction, and overall health. Utilizing DS18B20 sensors, as shown in Fig. 6. enables precise temperature monitoring in prawn ponds. The optimal temperature range for freshwater prawn farming typically falls between 28°C to 33°C, as shown in Table 1. promoting optimal growth and reproductive success. Maintaining temperatures within this range ensures efficient feed conversion and minimizes stress, ultimately enhancing prawn yield and profitability [15].

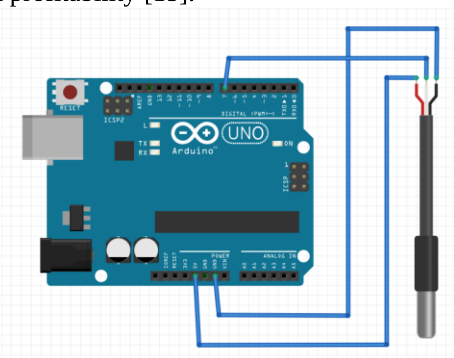

Fig. 6. DS18B20 Temperature Sensor.

6) Water Flow Senosr – Effective water flow helps in the removal of waste products [6] such as uneaten feed, feces, and metabolic by-products. Stagnant water can lead to the accumulation of waste, which can degrade water quality and promote the growth of pathogens. Water flow sensor, as shown in Fig 7. assist in maintaining continuous water circulation, thereby ensuring adequate oxygenation of the water, crucial for the respiration of prawns. Proper water flow ensures the uniform distribution of nutrients and feed particles throughout the pond. Water flow can help regulate water temperature by distributing thermal energy throughout the pond [16].

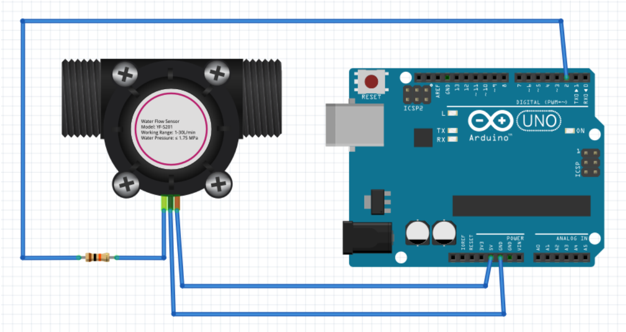

Fig. 7. YF – S201 Water Flow Sensor.

7) Water Level Sensor – Water level sensors are vital in freshwater prawn farming, helping in real-time monitoring and management of water levels. They ensure optimal water depth, preventing flooding or shortages that could stress prawns.[6] Additionally, these sensors, as shown in Fig. 8. help maintain habitat integrity, manage water quality, prevent escapes, and facilitate controlled water exchange. Overall, water level sensors play a crucial role in promoting prawn health, productivity, and sustainability in aquaculture operations [16].

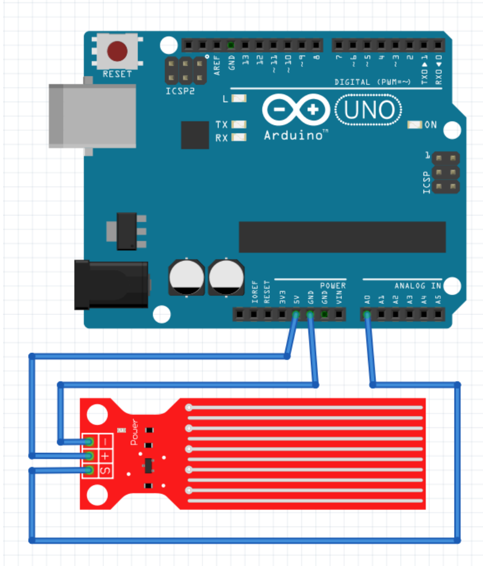

Fig. 8. Water Level Sensor.

TABLE 2. OPTIMAL RANGE CONDITIONS.

Parameter	**Sensor**	**Units**	**Optimal Range**
Dissolved Oxygen (DO)	Atlas Scientific EZO DO	ppm	5 – 7 (above 50% air saturation)
pH	SNU SEN0161	-	7.5 – 8.5
Total Dissolved Solids (TDS)	Atlas Scientific EZO Conductivity	ppm	250 – 500
Turbidity	TS 300B	NTU	5 – 25
Temperature	DS18B20	Celsius	28 – 33
Water Flow	YF – S201	-	Regulate water flow
Water Level	Water Level Sensor	-	Monitor water level

V. MACHINE LEARNING ALGORITHM

Convolutional Neural Networks (CNNs) are a specialized form of artificial neural networks (ANNs) tailored for analyzing structured grid-like data [17], such as images. Tasks like image classification, image recognition and object detection can be employed using CNN.

CNNs consist of various layers, such as convolutional, pooling, and fully connected layers [18]. These layers work together to process input images, like a random image of a prawn in this case, by applying filters (kernels) in the convolutional layers. This process enables the network to extract features from the image at different spatial scales, enhancing its ability to recognize patterns and objects. Pooling layers in CNNs perform down sampling on the feature maps produced by the convolutional layers. This down sampling reduces the computational complexity of the network while retaining crucial features. Finally, the fully connected layers aggregate the extracted features and perform classification or regression tasks. Table 3. Shows the number of images used in each class for creating the dataset.

In this research, the dataset has been created with three datasets, namely Test, Train, and Validation. [19] All the three datasets have been created by using multiple images, thereby to increase efficiency and accuracy in the output. The entire image dataset is split into a training dataset model, comprising 80% of the images, and a testing dataset model, which contains the remaining 20% of the images. The algorithm developed is capable to find whether a prawn is diseased or healthy, and is capable to predict the type of disease.

TABLE 3. NUMBER OF IMAGES IN EACH CLASS.

Class	Total Images
Healthy	485
White spot disease	365
Black spot disease	240
Soft shell disease	185

VI. RESULTS AND DISCUSSIONS

In this research paper, both Shrimp and Prawn holds same meaning and denoting the same thing throughout the paper. A random prawn image has been selected from the image dataset of prawn, to find whether the provided prawn is healthy or diseased. And the resultant output is obtained by using CNN technique [10], it has been evidently found that the proposed algorithm provides accuracy of 73.33%. This demonstrates the effectiveness of the proposed method in accurately identifying the health status of prawns based on visual features extracted from the image. Figure 9 (a) Shows the image of a prawn is classified as healthy shrimp. Figure 9 (b) shows the command prompt message for classifying the prawn as healthy, "The Shrimp is classified as: Healthy".

Fig. 9 (a) Healthy Prawn

```
Choose Files  undiseased.webp
• undiseased.webp(image/webp) - 10906 bytes, last modified: 11/2/2023 - 100% done
Saving undiseased.webp to undiseased.webp
1/1 [==============================] - 0s 91ms/step
The shrimp is classified as: Healthy
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Fig. 9 (b) Classified as Healthy Prawn using CNN.

Similarly, a diseased prawn images is subjected as input image to check the model efficiency, and it has been clearly found that the image of the prawn is classified as diseased as shown in Figure 9 (c). 73.3% accuracy has been made achieved in finding and classifying prawn image as diseased. Figure 9 (d) shows the command prompt message showcasing the classified image of prawn is diseased, "The Shrimp is classified as: Diseased".

Fig. 9 (c) Diseased Prawn.

```
Choose Files  diseased.jpg
• diseased.jpg(image/jpeg) - 6704 bytes, last modified: 11/2/2023 - 100% done
Saving diseased.jpg to diseased.jpg
1/1 [==============================] - 0s 250ms/step
The shrimp is classified as: Diseased
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Fig. 9 (d) Classified as Diseased Prawn using CNN.

Figure 10 (a) and Figure 10 (b) shows the graph of training model's Accuracy Chart and Loss Chart respectively, which indicates that after 30 epochs the accuracy is found to be 0.7333 which corresponds to 73.3% and the loss is found to be 0.385453 which corresponds to 38.5% loss after 30 epochs. Figure 10 (c) corresponds to the graph of validation accuracy, which is found to be 73.3%, and Figure 10 (d) corresponds to the graph of validation loss, which is found to be 43.2% after 30 epochs.

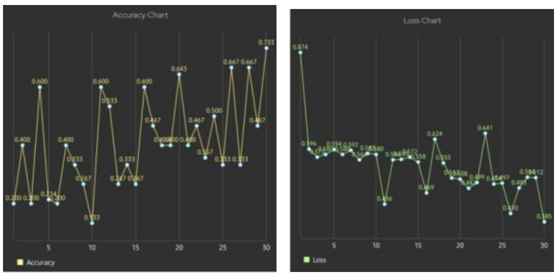

Fig. 10 (a) & Fig 10 (b) Accuracy of Training Model and Loss of Training Model

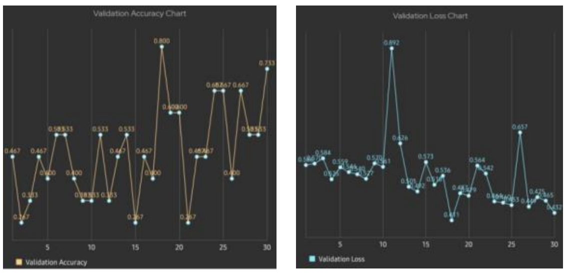

Fig 10 (c) & Fig 10 (d) Graph depicting validation accuracy and Graph depicting validation loss

Some of the common diseases affecting prawn includes, white spot disease, black spot disease, soft shell diseases. White spot disease, also known as White Spot Syndrome Virus (WSSV), is a highly contagious viral infection that affects prawns. WSSV can cause significant mortality rates [20], [21]. This can be controlled by integrating prawn farming with effective IoT management and by employing CNN technique to predict the disease. Figure 11 (a) displays the data pertaining to the image identified as a white spot diseased prawn by the CNN model.

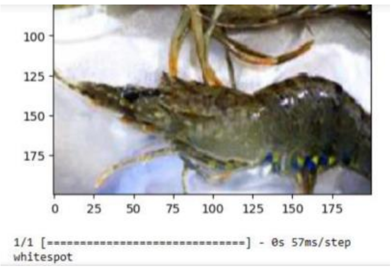

Fig. 11 (a) White Spot Disease.

Black spot disease, also known as black gill disease, arises from parasitic copepod infestations [22], causing dark lesions on prawn gills. These lesions hinder respiratory function, leading to oxygen uptake issues and potential mortality. The disease is commonly linked to poor water quality and overcrowded farming conditions. Figure 11 (b) depicts a prawn image identified with black spot disease by the CNN model. Integrating sensors for DO, pH, TDS, and turbidity enables efficient monitoring of water quality.

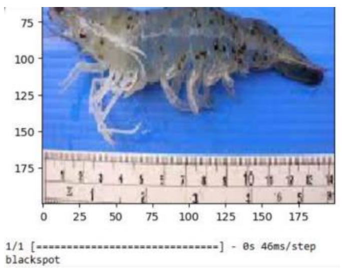

Fig. 11 (b) Black Spot Disease.

Soft shell disease, prevalent among prawns, arises from inadequate molting processes [23], [24]. Molting, a crucial phase where prawns shed their exoskeleton for growth, but sometimes the process is incomplete, resulting in a delicate, soft shell. This vulnerability makes them susceptible to infections and injuries, often resulting in fungal or bacterial infections. This leads to stunted growth [4], heightened mortality rates, and substantial economic losses within prawn farming industry. Figure 11 (c) depicts a prawn identified with soft shell disease.

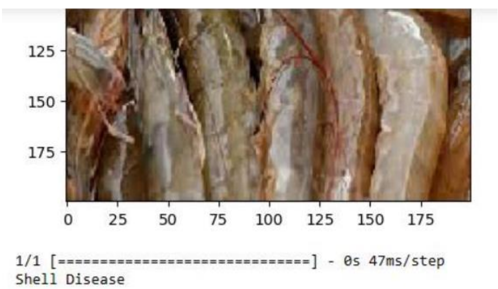

Fig. 11 (c) Soft Shell Disease.

The detailed Classification report for the disease identification of prawn is provided in Table 4. The report provides evaluation metrics for a classification model's performance across multiple classes. The report includes precision, recall, F1-score, and support for each class, as well as averages across all classes. For classes where there are no predicted instances, as indicated by 0 precision, recall, and F1-score, it suggests that the model did not predict any instances of those classes. The macro average provides the average precision, recall, and F1-score across all classes, giving equal weight to each class. The weighted average provides the average precision, recall, and F1-score across all classes, weighted by the support for each class.

TABLE 4. CLASSIFICATION REPORT

	precision	recall	f1-score	support
1	1	0.83	0.91	12
2	0	0	0	0
3	0	0	0	0
accuracy			0.73	12
macro avg	0.33	0.28	0.3	12
weighted avg	1	0.83	0.91	12

VII. CONCLUSION

In conclusion, the integration of IoT (Internet of Things) technology and machine learning algorithms presents a transformative approach to revolutionize freshwater prawn farming practices, enhancing efficiency, disease management, and advancing sustainability. By leveraging IoT devices such as DO sensors, water turbidity sensors, temperature sensors, and other sensors, prawn farmers can continuously monitor crucial environmental parameters in real-time. This real-time data facilitates proactive decision-making, enabling farmers to optimize feed management, water quality, and pond conditions to create an ideal habitat for prawn growth and development.

Moreover, the implementation of machine learning algorithms enables the analysis of large datasets allowing for predictive modelling of disease outbreaks and early detection of anomalies. By identifying patterns and trends in data, machine learning algorithms empower farmers to implement preventive measures and timely interventions, minimizing the impact of diseases and improving overall prawn health.

The convergence of IoT and machine learning technologies offers immense potential to drive innovation and sustainability in freshwater prawn farming. By embracing these advancements, prawn farmers can increase productivity, reduce resource consumption, increase profit, mitigate environmental risks, and contribute to the long-term viability of the aquaculture industry.

VIII. SCALABILITY

The focal point of this proposed research centers on the optimization of prawn cultivation practices within the Indian subcontinent. However, the devised principles, methodologies, and technological frameworks possess inherent scalability, allowing for their extrapolation to analogous regions worldwide where prawn cultivation is a prominent industry. While the primary focus remains on the prawn cultivation sector, the IoT-based system under consideration exhibits versatility, poised to cater to operations of varying scales, spanning from small-scale enterprises to large-scale commercial ventures. Moreover, the adaptable nature of the proposed system extends its applicability beyond the realms of prawn cultivation, potentially finding utility within broader domains such as aquaculture, agriculture, and allied sectors.

IX. ACKNOWLEDGEMENT

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