Real Time Cloud enabled Water Quality Supervising and Aerator Actuation in Shrimp Farming

Mocherla Chakradhar Abhinay *[1], Seetharam Reddy Ramireddy [2], Vamsiram Gandham [3], Vaegae Naveen Kumar [4]

School of Electronics Engineering, Vellore institute of Technology, Vellore, Tamilnadu, India
[1]chakradhar.abhinay@gmail.com, [2]seetharamreddy30@gmail.com,
[3]vamsiramg@gmail.com, [4]vegenaveen@vit.ac.in

Abstract. In general, the water sample from shrimp ponds is sent for testing once in 10 days, and there are cases where the water sample gets changed within these 10 days and it can sometimes adversely affect the growth of shrimps. This paper proposes and develops a real-time cloud based water quality monitoring and automated aerator actuation in shrimp farming system. The prototype mainly consists of sensor modules, relay modules, Long Range Radio (LoRa) transmitter, LoRa receiver, node microcontroller unit (NodeMCU) and other interfacing circuitry. This system uses the low power LoRa module as transceiver connected with an Arduino which interfaces various sensors and NodeMCU which sends the sensor data to the Google database. The parameters like dissolved oxygen, pH, turbidity, total dissolved solids (TDS), temperature and conductivity are measured to assess the water quality in shrimp pond. The dataset is formed based on the acquired values of the parameters and machine learning algorithms are used to predict water quality index. Water quality index is predicted by training the system using various machine learning models. The performance of various machine learning algorithms is compared. Problem of high electricity charges faced by aqua farmers is also addressed by turning on the aerators only when oxygen level in water is insufficient for the rearing of shrimps. The use of machine learning models to forecast water quality and the LoRa module for communication, effectively and remotely monitors the shrimp farming system, which saves time, money, and hazards.

Keywords: Shrimp farming, Arduino Uno, NodeMCU, LoRa module, Machine learning algorithms, Sensors.

1 INTRODUCTION

Shrimp farming is a significant economic activity in many nations since it increases employment prospects in the fields of production, processing, marketing, transportation, and other related services. Good quality of water is needed for shrimp growth which in return results in farm profit. The water parameters such as dissolved Oxygen, pH, turbidity, total dissolved solids (TDS), temperature and conductivity are few of the main conditions that are to be tested often in the pond [1]. Water quality monitoring is done manually in shrimp farms. The conventional way of water quality monitoring is to collect the water sample from the pond and send it to the test center. But, by the time the report is received from the test center, the characteristics of the aquaculture pond changes. This proves to be ineffective if the farmer wants to take any immediate action in order to control the damage to the shrimps.

Periodic sampling of shrimp pond is highly necessary to monitor, their growth performance. The Internet of Things (IOT) assists smart farming by connecting people and farm remotely through various gadgets. Based on shrimp parameters, IOT is used to estimate and forecast trends in the quality of water conditions utilizing water quality index (WQI) models. Different approaches came into existence for the determination of WQI in the aquatic environment. Rahman et al. [2] proposed a classification problem. A Multivariate time series data set obtained from time series data of aforementioned parameters, is applied as input to the machine learning model. There exist different approaches for the estimation of WQI in the aquatic environment such as particle swarm optimization [3], statistical and deterministic models [4-6].

Long et al. [7] developed a system with a sensor node that measures the water's pH, dissolved oxygen, and temperature. The results can be viewed on Android devices once the sensed data was relayed through Zigbee to a distant server. Aerators and pumps can both be controlled remotely by the server. The device was equipped with a camera module to transmit a real-time view of the producing pond. Rajesh et al. [8] proposed a system that enables users to check water temperature, turbidity, and pH on any internet-connected device without having to join the system's WiFi network. Cesar et al. [9] stored data with MYSQL server for further processing, communication between sensor block and the Arduino via UART, then transmission of data through Zigbee to the server and cloud service. Kuang et al. [10] proposed an extreme learning algorithm for the prediction of dissolved oxygen. The performance of the ANN-based estimation models was explained and compared with the multi linear regression (MLR) based model [11]. Carbajal et al. [12] used fuzzy inference system for assessment of WQI of shrimp pond.

Even though there are so many methods of automatic monitoring of shrimp framing are proposed, the following problems needs to addressed and solved. At present, the water sample from shrimp ponds is sent for testing once in 10 days, and there are cases where the water sample gets changed within these 10 days and it can sometimes adversely affect the growth of shrimps. The shrimp farmers also face problem of high electricity charges as most of them keep their aerators turned on even when oxygen level in water is sufficient for the rearing of shrimps. The other major problem that we tried to solve in this system is the lack of internet connection at the location of the shrimp farm. These issues motivated us to propose a system for real time cloud enabled water quality supervising and aerator actuation in shrimp farming. Various sensors such as analog turbidity sensor, analog pH sensor, TDS sensor, temperature sensor, dissolved Oxygen sensor are interfaced with Adrunio Uno, NodeMCU, LoRa transreceiver. The NodeMCU, ESP8266 is integrated with LoRa module to automate and remotely monitor the shrimp pond. The uniqueness of the system is the usage of two LoRa modules to transmit bi-directional information over a long range. In absence of internet connectivity, monitoring and controlling of the sensor values and the relay states can be done with the help of GSM module. In this paper we used both IBM cloud and Google database for storage of data and communication. Also, we used seven machine learning algorithms mainly, support vector machine, K-nearest neighbours, Gaussian Naïve-Bayes, decision Tree, multi-layer perceptron, logistic regression and random forest for accurate prediction of WQI to assess the survival of shrimp with a confidence score ‘1’ or ‘0’ along with percentage of survival.

2 Implementation Of Proposed Shrimp Farming System

The block diagram of proposed real-time cloud based water quality monitoring and automated aerator actuation in shrimp farming system is depicted in figure 2.1. In a typical shrimp pond, the parameters which are to be kept in optimal levels are dissolved oxygen, temperature, salinity, turbidity, pH level, alkalinity and hardness, ammonia and nutrient levels. Of these parameters the major ones which are required to supervise the water quality are found to be dissolved oxygen, pH, turbidity, temperature, and TDS. For real time monitoring and control of a shrimp farming system, the vital parameters required to supervise the water quality are dissolved oxygen (> 3 mg/l), pH (7.0 – 8.5), turbidity (< 1500 NTU), temperature (15 – 45 °C), and TDS (< 1100 ppm). Sensors required to obtain the values of the above-mentioned parameters are incorporated within a prototype so that all these values can be dynamically monitored. The prototype mainly consists of sensor modules, relay modules, LoRa transmitter, LoRa receiver, NodeMCU and other interfacing circuitry. A dataset is formed based on the acquired values of the parameters and machine learning algorithms are used to predict water quality index. These values are continuously monitored by the user in real time and necessary action can be taken whenever it is required to do so. The following sections describe various modules and procedures of the proposed system.

2.1 ***Hardware Design***

As shown in the Figure 2.1, sensors are calibrated and placed in the water and the sensor values are periodically monitored by Arduino UNO which reads sensor values from all sensors and serially transmits the sensor values to LoRa module. The LoRa module wirelessly transmits these sensor values up to a range of 15 KM. At the receiver LoRa which is placed within 15 KM range of the shrimp pond, the NodeMCU circuit serves the webpage and sends sensor data, relay state and water quality information to the Google sheets database and also IBM cloud. It even notifies users about abnormal sensor readings, changes in relay states and internet connectivity issues through text and email notifications. The machine algorithms will use the dataset available in the Google database to predict the water quality index.

The sensor values are periodically monitored by the NodeMCU and are serially transmitted to the LoRa Transmitter module. At the receiver, the LoRa module will wirelessly transmit these values to Blynk App and are updated in the IBM cloud. The NodeMCU will also send the data to Google database. In this paper we used both IBM cloud and Google database for storage of data and communication. If the measured values are not in optimal range, the user can supervise the sensor values anywhere in the world where there is internet connectivity. The predicted WQI of the machine learning model will assist the LoRA receiver to transmit back the control information to NodeMCU at the shrimp pond. This NodeMCU thereby control the aerator connected to Arduino Uno through Relay module. The Figure 2.2 depicts the flow chart of the two way communication between the NodeMCU and LoRa modules.

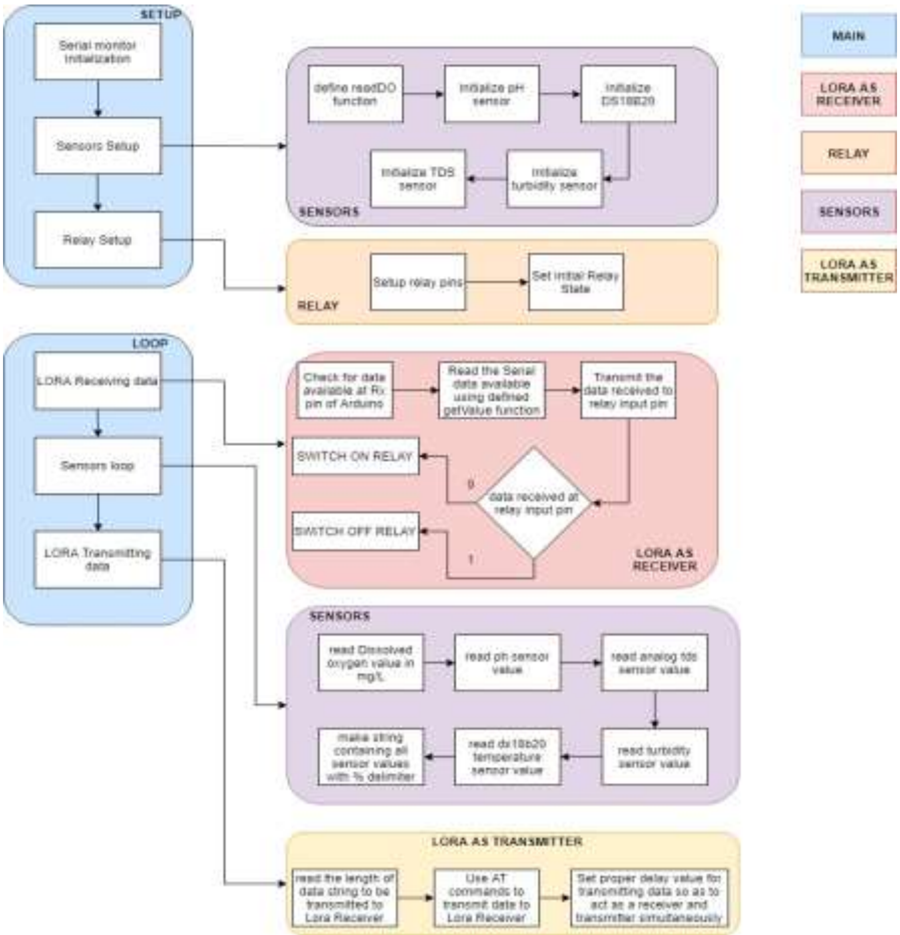

Figure 2.1. Block diagram of proposed real-time cloud based water quality monitoring and automated aerator actuation in shrimp farming system.

2.2 Acquisition of Dataset and Machine Learning Algorithms

Water Quality Index (WQI) can help the user to understand the condition of the shrimp pond and notify necessary steps to be taken to improve the water quality. To predict water quality, a binary value is assigned to WQI. A dataset is formed by collecting 6507 samples at different life cycles of the shrimp with each containing an array of sensor values as in the order of dissolved Oxygen, pH, turbidity, TDS, temperature and conductivity are collected. This dataset is used to train different machine learning models to predict the water quality. Given a random sample of water, the sensor modules sense the six parameters. These are applied as inputs to different machine learning algorithms. Support vector machine [13], K-Nearest neighbour [13], Naïve-Bayes [14], multilayer perceptron [15], logistic regression [16], decision tree [17] and random forest [18] are the different machine learning models used for prediction of WQI. These models predict the water quality whether it is good (with label 1) or bad (with label 0) and returns a Water Quality Index.

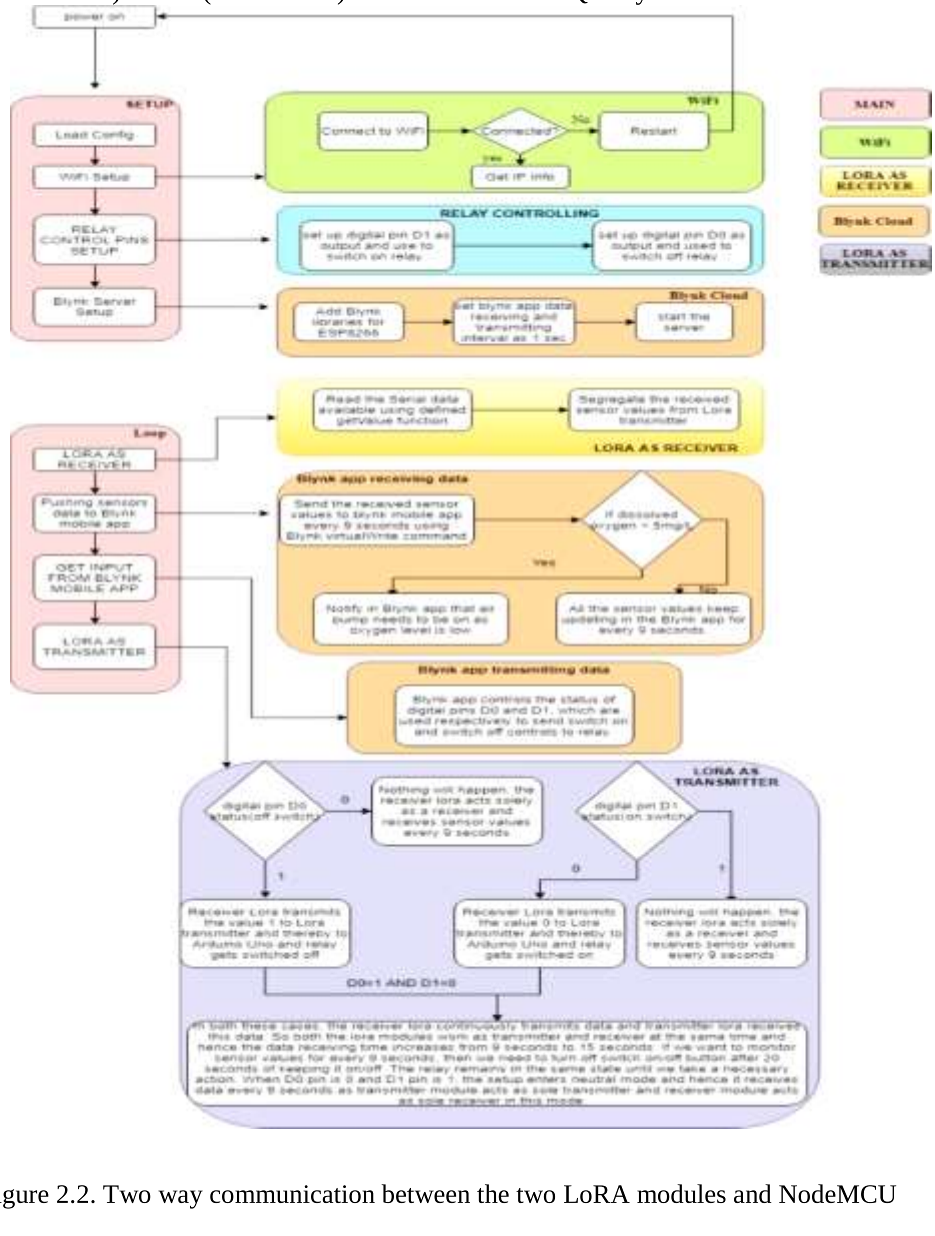

Figure 2.2. Two way communication between the two LoRA modules and NodeMCU

3 RESULTS AND DISCUSSIONS

The experimental set-up of sensor modules and related interfacing circuitry of the proposed system is shown in figure 3.1. The Arduino Uno reads sensor values from all sensors and serially transmits the sensor values to LoRa module. The LoRa module transmits these sensor values to LoRa receiver station which is up to a range of 15 KM. The sensor values are periodically monitored by the NodeMCU and are serially transmitted to the LoRa Transmitter module. At the receiver, the LoRa module will wirelessly transmit these values to Blynk App and are updated in the IBM cloud. The NodeMCU will also send the data to Google database. The LoRa module can even receive back the information about relay states from our receiver NodeMCU circuits and thereby control the aerator connected to Arduino UNO through Relay module. In this paper we used both IBM cloud and Google database for storage of data and communication. If the measured values are not in optimal range, the user can supervise the sensor values anywhere in the world where there is internet connectivity. The predicted WQI of the machine learning model will assist the LoRA receiver to transmit back the control information to NodeMCU at the shrimp pond.

In the training of the models, an acquired dataset of 6507 samples are used. The performance of machine learning algorithms mainly support vector machine, K-Nearest neighbour, Naïve Bayes, multilayer perceptron, logistic regression, decision tree and random forest are compared. The performance of these models is summarized in Table 1. The random forest model prediction has highest accuracy.

TABLE 1. ACCURACY COMPARISON

Algorithm used for model	Accuracy Score (in percent)
SVM	74.96
KNN	96.15
Naive Bayes	86.94
Decision Tree	99.94
MLP Neural Network	97.23
Random Forest	99.89
Logistic Regression	97.49

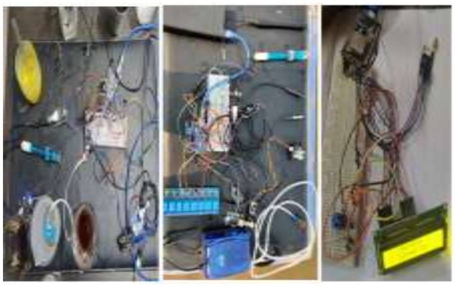

Figure 3.1. Hardware of proposed system

In this paper, real time cloud enabled water quality supervising and aerator actuation in shrimp farming project solves the problems that aquaculture farmers are facing right now. In this system, we are continuously monitoring the water quality every 10 seconds and the values are continuously stored in a database and are displayed in a website. Whenever the water quality degrades, we immediately notify the farmer through text messages, website notifications and even email notifications are sent regarding the same information. In order to cut down their electricity charges, we are using relay module to control aerators and we can now turn on the aerators only when the oxygen level goes below the fixed threshold value. The aerators can be controlled from our website when there is an internet connection and can be controlled through GSM module when there is no internet connection. The other major problem that we tried to solve in this system is the lack of internet connection at the location of the shrimp farm. We are using LoRa module, which wirelessly transmits sensor data up-to a range of 15 kilometers. Even in case if we still lose our internet connection after finding a perfect place within 15-kilometer range for our LoRa receiver modules, we interfaced SIM800A GSM module, so that we can still read sensor values and control our aerator in farm. We have also deployed a machine learning model using seven algorithms mainly, support vector machine, K-nearest neighbours, Gaussian Naïve-Bayes, decision Tree, multi-layer perceptron, logistic regression and random forest. These Algorithms are used to for accurate prediction of survival of shrimp with a confidence score ‘1’ or ‘0’ along with percentage of survival.

4 CONCLUSION

In this paper, a novel prototype is developed for effective monitoring and control of the shrimp farming system. The real time cloud enabled water quality supervising and aerator actuation in shrimp farming addresses the problems of aquaculture farmers. The proposed system continuously monitors the water quality every 10 seconds and the values are continuously stored in a database. Whenever the water quality degrades, the system immediately notifies the farmers through text messages, website notifications and even email notifications. The user may remotely monitor their farm from anywhere with the usage of NodeMCU and LoRa modules. It has achieved all of the necessary goals, thus the system now automatically monitors the shrimp farm, resulting in high accuracy and a decrease in the amount of manpower required. This system saves sensor data in the cloud over an internet connection. The integration of the LoRA transmitter and receiver for this prototype results in superior quality data for the owner of the shrimp farm. Finally this system offers efficiency and accuracy while being economical.

5 REFERENCES

[1] A, Davor, Viktor Pocajt, Aleksandra Perić-Grujić, and Mirjana Ristić. "Modelling of dissolved oxygen in the Danube River using artificial neural networks and Monte Carlo Simulation uncertainty analysis." Journal of Hydrology 519 (2014): 1895-1907.

[2] Rahman, Ashfaqur, Stuart Arnold, and Joel Janek Dabrowski. "Identification of variables affecting production outcome in prawn ponds: A machine learning approach." Computers and Electronics in Agriculture 156 (2019): 618-626.

[3] Deng, Changhui, XinJiang Wei, and LianXi Guo. "Application of neural network based on PSO algorithm in prediction model for dissolved oxygen in fishpond." In 2006 6th World Congress on Intelligent Control and Automation, vol. 2, pp. 9401-9405. IEEE, 2006.

[4] Miao, Xinying, Changhui Deng, Xiangjun Li, Yanping Gao, and Donggang He. "A hybrid neural network and genetic algorithm model for predicting dissolved oxygen in an aquaculture pond." In 2010 International Conference on Web Information Systems and Mining, vol. 1, pp. 415-419. IEEE, 2010.

[5] Ghosh, Lopa, and G. N. Tiwari. "Computer modeling of dissolved oxygen performance in greenhouse fishpond: an experimental validation." international journal of agricultural research 3, no. 2 (2008): 83-97.

[6] Hu, Xuemei, Yingzhan Hu, and Xingzhi Yu. "The soft measure model of dissolved oxygen based on RBF network in ponds." In 2011 Fourth International Conference on Information and Computing, pp. 38-41. IEEE, 2011.

[7] Guangli, L. O. N. G. "Design of an aquaculture detection system based on internet of things." Int J Simul Syst Sci Technol 17, no. 31 (2016): 28-1.

[8] Huy, Thong Nguyen, Khanh Nguyen Tuan, and Thanh Tran Trung. "An Application of WSN in Smart Aquaculture Farming." In Intelligent Computing in Engineering, pp. 975-984. Springer, Singapore, 2020.

[9] Encinas, Cesar, Erica Ruiz, Joaquin Cortez, and Adolfo Espinoza. "Design and implementation of a distributed IoT system for the monitoring of water quality in aquaculture." In 2017 Wireless Telecommunications Symposium (WTS), pp. 1-7. IEEE, 2017.

[10] Kuang, Liang, Pei Shi, Chi Hua, Beijing Chen, and Hui Zhu. "An Enhanced Extreme Learning Machine for Dissolved Oxygen Prediction in Wireless Sensor Networks." IEEE Access 8 (2020): 198730-198739.

[11] Folorunso, Taliha A., A. M. Aibinu, Jonathan Gana Kolo, Suleiman Omeiza Eku Sadiku, and Abdullahi Muhammad Orire. "Water Quality Index Estimation Model for Aquaculture System Using Artificial Neural Network." (2019).

[12] Carbajal-Hernández, José Juan, Luis P. Sánchez-Fernández, Jesús A. Carrasco-Ochoa, and José Fco Martínez-Trinidad. "Immediate water quality assessment in shrimp culture using fuzzy inference systems." Expert Systems with Applications 39, no. 12 (2012): 10571-10582.

[13] Pulluri, Kranthi Kumar, and Vaegae Naveen Kumar. "Qualitative and Quantitative Detection of Food Adulteration Using a Smart E-Nose." Sensors 22, no. 20 (2022): 7789.

[14] Grodniyomchai, Boonyawee, Khattiya Chalapat, Kulsawasd Jitkajornwanich, and Saichon Jaiyen. "A deep learning model for odor classification using deep neural network." In 2019 5th International Conference on Engineering, Applied Sciences and Technology (ICEAST), pp. 1-4. IEEE, 2019.

[15] Kumar, Vaegae Naveen, and Komanapalli Venkata Lakshmi Narayana. "Development of an intelligent pressure sensor with temperature compensation." Journal of Engineering Science and Technology 12.7 (2017): 1723-1739.

[16] Pulluri, Kranthi Kumar, and Vaegae Naveen Kumar. "Development of an Integrated Soft E-Nose for Food Quality Assessment." IEEE Sensors Journal 22, no. 15 (2022): 15111-15122.

[17] Tobing, Fenina Adline Twince, Muhammad Iqbal Dzulhaq, Marlinda Vasty Overbeek, and Eko Anto Setiawan. "Design of decision support system with C4. 5 algorithm methods in determining results vaname shrimp cultivation." In 2019 5th International Conference on New Media Studies (CONMEDIA), pp. 195-200. IEEE, 2019.

[18] Kaewchote, Jirabhorn, Sittichoke Janyong, and Wasit Limprasert. "Image recognition method using Local Binary Pattern and the Random forest classifier

to count post larvae shrimp." Agriculture and Natural Resources 52, no. 4 (2018): 371-376.