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AQUACULTURE MONITORING SYSTEM USING MACHINE LEARNING

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ABSTRACT

Aquaculture is the farming of aquatic creatures for food and other purposes. It is a growing industry that provides a significant amount of the world's seafood. Aquaculture management regulates and oversees these farms to ensure that they are operating effectively and sustainably. Machine learning and IoT can play a significant role in aquaculture management. Machine learning can be used to monitor and optimize farm conditions in real time, while IoT can be used to monitor and manage farms remotely. These technologies can help improve yields, reduce costs, and improve sustainability. In this paper, we propose an aquaculture management system using machine learning and IoT for fish and shrimp farms. The system monitors the environment and collects data from sensors placed on the farm. The data is processed using machine learning algorithms to identify patterns and predict problems. The system provides information on the optimum conditions for farming and the best time to harvest. Monitoring various things like temperature and pH and providing feed at the right time is important, which plays an important role in the output of the final crop.

Keywords: Internet of Things, machine learning, aquaculture farming, Arduino Uno, node MCU, ESP8266.

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INTRODUCTION

Aquaculture is a vital industry that plays a crucial role in meeting the growing demand for aquatic products as the world's population continues to increase. As the global population continues to grow, the demand for aquatic products is also increasing, making it essential to improve the efficiency and sustainability of aquaculture practices. In recent years, the emergence of cutting-edge technologies such as Machine Learning and the Internet of Things (IoT) has opened new possibilities for optimizing aquaculture operations. This research study aims to dive into these possibilities by exploring how these technologies can be used to improve the management of aquatic environments, promote the growth and health of aquatic creatures, and enhance the overall effectiveness of aquaculture operations. This study aims to dive into these possibilities by examining how these technologies can be applied to enhance the management of aquatic environments, improve the growth and health of aquatic organisms, and optimize aquaculture operations. This study will also examine the IoT and machine learning applications in aquaculture and pinpoint potential areas for future research.

LITERATURE REVIEW

Singh *et al.* [1] created a system to monitor and regulate various parameters of fresh water that are helpful in pearl farming. Maintaining the appropriate conditions would help in increasing the yield. The parameters in the freshwater are regulated by a microcontroller using actuators. They have used the data analytics approach in the proposed system. They used sensors and actuators for monitoring and maintaining a habitable underwater environment.

The [2] discusses the use of digital solutions such as agricultural management systems and robotics/AI to improve farm efficiency and decision-making. Studies have shown that these technologies can lead to improved crop yields and farm performance, but training and education for farmers are necessary for successful implementation. The paper also highlights the need for sustainable, data-driven agricultural practices to address 21st-century food production challenges and the shift towards "Agriculture 5.0," which is a key agenda item for major farm equipment manufacturers, with off-road equipment manufacturers playing a crucial role in this transition if agricultural robots are considered the next generation of farm machines.

A comprehensive IoT-based system for sustainable fish farming and traceability, consisting of an intelligent management module and an aquatic product tracking module is presented in [3]. It offers real-time monitoring, data storage, analysis, forecasting, and automation for fishpond management and traceability of the products.

Nagib *et al.* [4] developed an aquaculture monitoring system for catfish farming based on the Atmega328p and various sensors for measuring turbidity, pH, and water quality to check the sustainability of the water. This paper shows a system that was developed for Bangladesh.

Guangdong *et al.* developed this paper [5], which presents a promising IoT-based system for sustainable and efficient fish farming, with real-time monitoring and analysis of water quality and environmental parameters through integrated sensors. The system includes two modules: one for intelligent management and one for tracking aquatic products.

PROPOSED METHODOLOGY

In this paper, we develop a system for monitoring and controlling various parameters of water in an aquaculture system. Maintaining parameters like temperature, pH, and turbidity is important for the survival

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of aquatic creatures and for producing a good yield. Arduino Uno and ESP8266 are used to maintain and observe the optimal levels of water. The whole system is branched into parts. They are:

a) Monitoring
b) Controlling
c) Machine Learning

Monitoring

The monitoring part of the system takes care of observing and recording values. Various sensors are used to measure the parameters of water.

Temperature Sensor (DS18B20)

A DS18B20 sensor is used for monitoring the temperature of the water in aquaculture farms. This sensor is a waterproof sensor that contains a 12-bit ADC, which produces digital output and is suitable for this system. The DS18B20 can be operated in parasitic or normal mode; the parasitic mode uses the power from the signal, while the normal mode draws power normally [6].

Figure-1. DS18B20 (Temperature sensor).

DS18B20 is used in normal mode in this paper. This sensor can measure temperatures from -10 degrees Celsius to +85 degrees Celsius and contains an error margin of 0.5 degrees Celsius.

Turbidity Sensor

A turbidity sensor is a type of analogue optoelectronic sensor that measures the total dissolved solids and total suspended solids in water.

Figure-2. Turbidity sensor.

Turbidity is generally measured in nephelometric turbidity units (NTU), which is why it is also called a nephelometer. A higher nephelometric turbidity unit indicates more impurities in the water [7-10]. This sensor measures nephelometric turbidity units using light. The sensor measures the intensity of light scattered at 90 degrees, and the light scatters due to the presence of impurities in water.

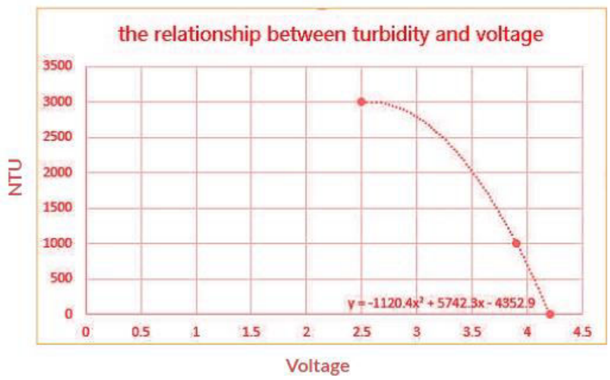

Figure-3. Graph for conversion of voltage to nephelometric turbidity units.

The sensor measures scattered light, which is then converted into a voltage and sent to the microcontroller. The voltage values are then converted into nephelometric turbidity units using the graph shown in Figure-3.

Gravity Analog pH Sensor

The acidity or basicity of water is measured using a pH sensor, which can be an analogue sensor such as the gravity analogue pH sensor. The pH value is then calculated using the Nernst Equation.

Figure-4. Gravity Analog pH sensor.

Maintaining the pH level of water is crucial for the survival of aquatic animals. The pH sensor used in this system can measure values between 0 and 14 pH, with an error margin of 0.15 pH. To prevent water damage to the system, the water is extracted from the body and collected in a container above the water level [11-13].

The temperature, turbidity, and pH of the water are measured by separate sensors and transmitted to an Arduino Uno. The Arduino Uno compares the recorded values to optimal ranges and indicates whether the parameters are within range using green and red LED

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lights. If the parameters are not optimal, corrective action can be taken before releasing the water back into the body [14].

In addition to the LED lights, the recorded values are also sent to the Thingspeak website every 15 seconds via an ESP8266 connected to the internet via WiFi. The Arduino code includes an API key that enables the data to be uploaded to Thingspeak for further analysis.

Controlling

The control part of the system plays a crucial role in maintaining the optimal values for temperature, pH, and turbidity. This control part consists of actuators, specifically motors that help to regulate and maintain the optimal values [15-17].

If the temperature of the water increases beyond the optimal range, the system can use nets to cover the pond and lower the temperature. Temperature changes can significantly impact the levels of dissolved oxygen in the water, which are critical to the survival of aquatic animals. The effect of temperature on dissolved oxygen levels is shown in the graph in Figure 5.

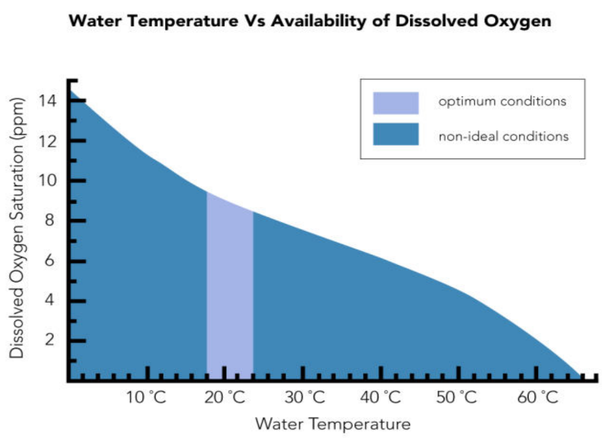

Figure-5. Dissolved oxygen saturation concerning water temperature.

Controlling the pH of water is possible by introducing fresh water into the pond. The addition of fresh water, which typically has a pH of around 7, can help to maintain the water's pH level. Similarly, running fresh water into the pond or lake can also reduce turbidity levels, which is essential for the survival of fish and other organisms in the body of water [18].

It is crucial to monitor and control these parameters to ensure the survival and growth of fish or other aquatic life in the water. To determine the optimal values for these parameters, data is collected from the farm over time. This collected data is then cleaned and pre-processed to eliminate any errors or outliers.

Finally, various machine learning models are tested, and the best model is selected to obtain optimal parameter values. This model is used to continuously monitor and control the system, ensuring that the water conditions remain optimal for aquatic life [19].

Machine Learning

The machine learning part of the system is done by applying time series analysis to aquaculture data, we can gain valuable insights that can inform our decision-making processes. These insights can help us optimize production and minimize environmental impacts, which ultimately leads to a more sustainable and profitable yield in the aquaculture industry.

With time series analysis, aquaculture managers can track trends and patterns in data over time, and use this information to make informed decisions about how to manage their operations [20]. By using historical data to predict future trends, managers can proactively address issues before they become major problems, which can save time, money, and resources [21].

Implementation of time series analysis in aquaculture management involves several crucial steps. The first step is to collect relevant data, including water quality parameters and environmental variables [22]. This data is then pre-processed and cleaned to ensure its quality and consistency.

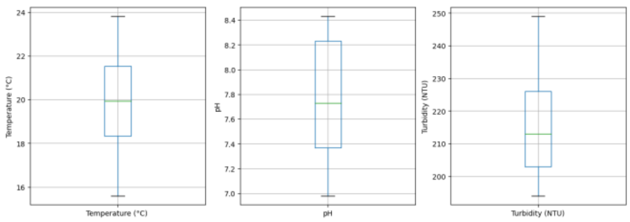

Figure-6. Finding and removing all the outliers.

Next, the data is split into a training set and a validation set, which is then used for model development and performance evaluation, respectively.

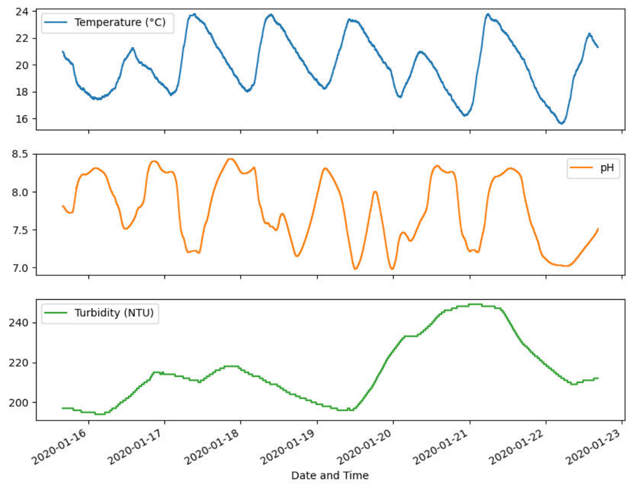

Figure-7. Resample the data to minute intervals and calculate the mean for each interval.

Several time series models can be applied, in this case, we used ARIMA (Autoregressive integrated moving average). These models are designed to analyze and forecast future trends in environmental parameters and fish

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production indicators. The forecasting results generated by these models can inform decision-making related to temperature, PH, feed management, and disease control, among others.

Applying time series analysis to aquaculture management can lead to more efficient and sustainable production practices [23-26]. By gaining insights into future trends and potential risks, managers can adjust their operations to optimize production and reduce environmental impacts. Moreover, the use of data-driven models can improve the accuracy of decision-making and reduce the uncertainty associated with traditional methods [27-31].

This paper aims to create a system that helps in monitoring and controlling an aquaculture farm remotely. This paper concentrates on creating a system that is efficient and affordable. To obtain efficiency, we used machine learning techniques, namely time series analysis, to predict the values five minutes earlier. To make the system affordable, Arduino Uno and ESP8266 microcontrollers are used for monitoring, and NodeMCU is used for controlling. As the monitoring and controlling part do not require huge processing power, this paper uses the Arduino Uno, ESP8266, and NodeMCU, which make the system affordable. A temperature sensor, pH sensor, and turbidity sensor are used for monitoring the major parameters of water, and with the help of an AC relay in the controlling part, the system will be able to switch aerator fans and motors to regulate the dissolved oxygen levels and temperature, respectively. The optimal ranges for temperature, pH, and turbidity are set using statistical analysis of the values taken from the farm. If the parameters of the water are not in an optimal range, then the controlling part acts accordingly. If the temperature in the water rises, then the motors activate automatically to reduce the temperature in the pond, as minute errors would harm the aquatic animals and eventually affect the yield.

RESULTS AND CONCLUSIONS

This paper takes shrimp farming as a case study. The optimal values are obtained from the data presented in [6]. The optimal values used in this paper are 25 to 32 degrees Celsius in temperature, less than 100 NTU turbidity, and a pH between 6.5 and 9.0. The sensors are kept in a bowl, as shown in Figure-8.

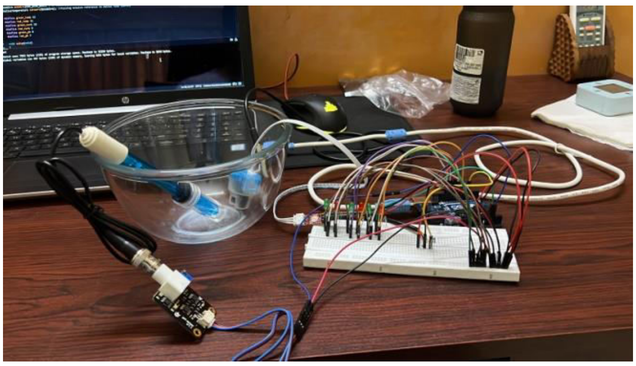

Figure-8. Monitoring the values.

The measured values are sent to Arduino Uno by the sensors and printed in the serial monitor of the Arduino IDE as shown in Figure-9.

```
Temperature: 27.56Celsius
voltage: 2.68
NTU: 2989.30
pH:9.67
Turbidity is high
Temperature is optimal
Ph is not in normal range
```

Figure-9. Output in the Arduino IDE.

The output also indicates whether the parameters are in optimal range or not and is also indicated using red and green leads.

We predicted values are 5 min ahead of the current values using the ARIMA (Autoregressive integrated moving average) model and got the following results,

```
Temperature MSE: 2.8961964941545424
Temperature MAE: 1.7011662063195927
pH MSE: 0.001999999999994131
pH MAE: 0.043999999999933335
Turbidity MSE: 1296.0
Turbidity MAE: 36.0
```

Figure-10. MSE and MAE values.

The MSE (Mean Squared Error) measures the average squared difference between the predicted values and the actual values of the environmental factor. In this case, the MSE for temperature is 2.8961, which indicates that the model has an average squared difference of 2.8961 between the predicted and actual values of Temperature. Similarly, the MSE for pH is 0.001999, which indicates that the model has an average squared difference of 0.001999 between the predicted and actual values of pH. The MSE for Turbidity is 1296.0, which indicates that the model has an average squared difference of 1296.0 between the predicted and actual values of turbidity.

The MAE (Mean Absolute Error) measures the average absolute difference between the predicted values and the actual values of the environmental factor. In this case, the MAE for Temperature is 1.7011, which indicates that the model has an average absolute difference of 1.7011 between the predicted and actual values of Temperature. Similarly, the MAE for pH is 0.0439, which indicates that the model has an average absolute difference of 0.0439 between the predicted and actual values of pH. The MAE for Turbidity is 36.0, which indicates that the model has an average absolute difference of 36.0 between the predicted and actual values of Turbidity.

Overall, the results suggest that the models used for predicting temperature and pH are more accurate than

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those used for predicting turbidity. The MSE and MAE values for Temperature and pH are relatively small, indicating that the models have a smaller average difference between the predicted and actual values. The MSE and MAE values for Turbidity, on the other hand, are relatively large, indicating that the model has a larger average difference between the predicted and actual values. These results can be used to improve the accuracy of the predictive models for environmental factors in aquaculture management, which can lead to more effective management practices and better growth and health of the fish.

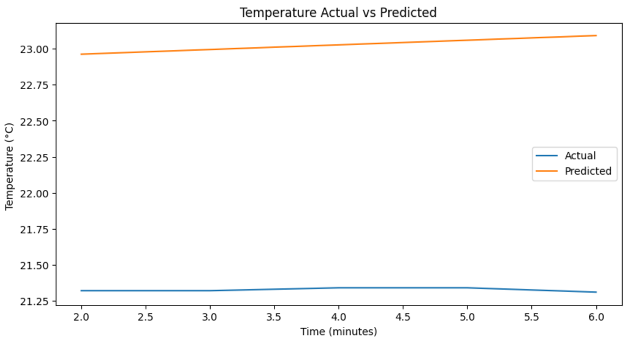

Figure-10. Temperature actual value vs predicted value.

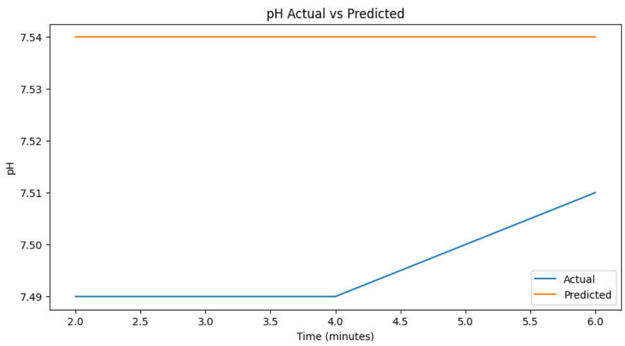

Figure-11. pH Actual value vs predicted value.

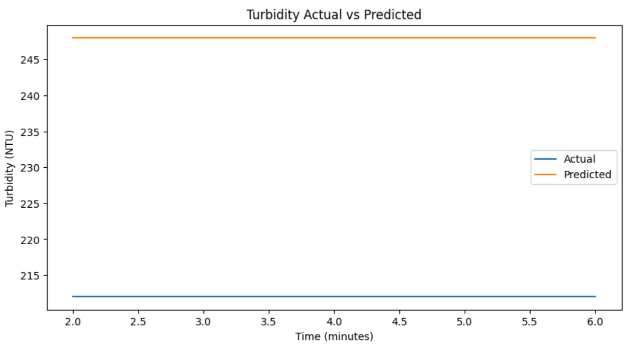

Figure-12. Turbidity actual value vs predicted value.

The observed data is sent to Thingspeak using the ESP8266. The below charts show the parameters in various fields.

Figure-13. pH.

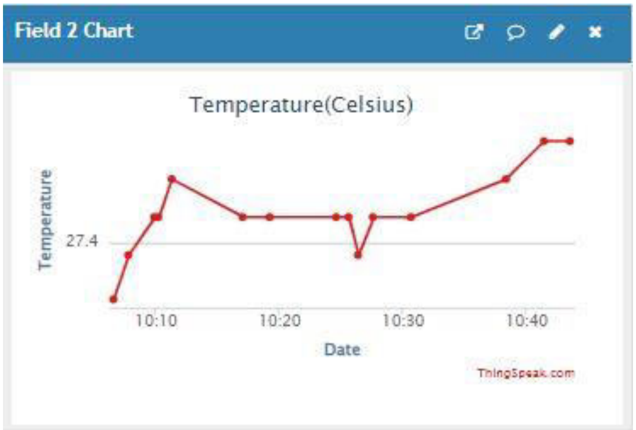

Figure-14. Temperature.

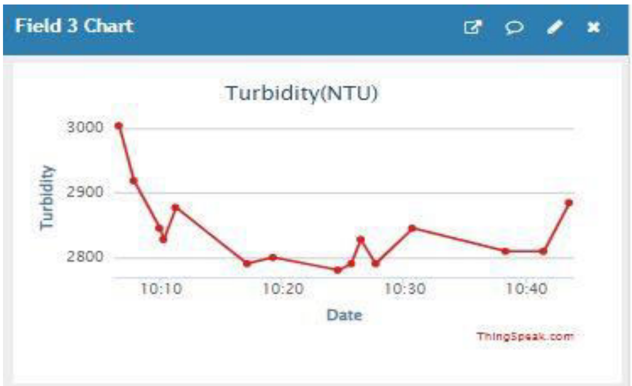

Figure-15. Turbidity values.

Figures 14, 15, and 16 represent the values of pH, temperature, and turbidity in fields 1, 2, and 3, respectively. The temperature is measured in degrees Celsius, and turbidity is measured in nephelometric turbidity units.

Since the pH is not in the normal range, flowing fresh water in the pond is required, and the motor switches on automatically.

The node MCU collects the predicted data from Thingspeak and acts accordingly to automate various other processes such as pumping of water (or) removing turbid water from the farm, controlling automatic feeders, and also controlling aerators according to the temperature of the water.

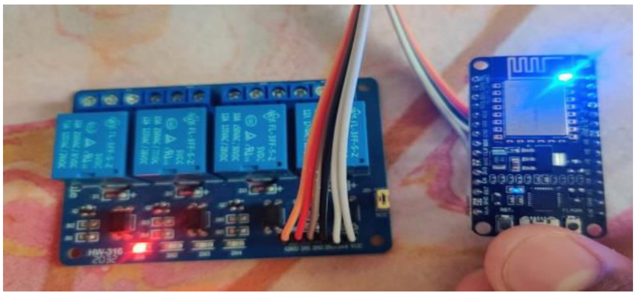

Figure-16. Control unit.

The control unit in Figure-16 acts according to the monitored values. According to the output from Fig. 9, we can see that turbidity and pH are not in the normal range. Thus, the third relay has been switched on, indicating motor switching on.

In conclusion, the aquaculture monitoring system proposed in this paper uses machine learning and IoT technologies to enhance the management and sustainability of fish and shrimp farms. The system monitors various parameters of the aquatic environment and collects data from sensors placed on the farm. The collected data is then analyzed using machine learning algorithms to identify patterns and predict potential problems. the farmers in case of any problems, thereby helping to reduce costs and improve yields. The system also provides information on the optimum conditions for farming and the best time to harvest. The proposed system has the potential to revolutionize the way aquaculture is managed and contribute to the sustainable production of aquatic products to meet the growing demand for food. Further research could explore the scalability of this system and its potential applications in other areas of aquaculture

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