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A Review on Shrimp Farming Using Iot Enabled Precision Farming

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Review Article

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ABSTRACT

The demand for prawns or shrimp is very high in the world as well as the local market. Countries having long coastal areas are suitable for shrimp farming. Kerala is such a state in India. Maintaining the good water quality is one important factor in successful shrimp farming. This paper mainly focuses on finding the best model that predicts the water quality accurately. After reviewing many papers, it has been seen that the LSTM method with sparse AutoEncoder predicts more accurately than other models.

INTRODUCTION

India has a coastline of 8,118 km and Kerala has 580 km. The country's as well as state's shrimp aquaculture industry is one of the growing, protein-producing sectors. This makes India's important foreign exchange. The success of shrimp farming mainly depends upon the quality of water along with the high quality seeds. The quality of water is determined by various parameters like turbidity, water temperature, dissolved oxygen, salinity, pH, soil characteristics, soil nutrients etc.

Through continuous monitoring of the pond we can achieve good yield. Majority of the shrimp farmers in Kerala are manually monitoring the water quality. They depend on laboratories for checking the pH, salinity, etc. This is very time consuming and usually they perform this checking weekly [1]. By this time there are chances that the environment may adversely affect the health and growth of shrimp. So the need for automated continuous real time monitoring is essential for getting a good yield.

This is a review paper, in which I reviewed some papers that propose methods for the continuous monitoring of the water and predicting the values of various water quality parameters. This predicted value will help the farmers to take necessary predictive measures. This paper is divided into four sections. First section gives an introduction to the paper. In the second section literature review is mentioned. Conclusion is given as Third Section. The last section lists out the references.

LITERATURE REVIEW

Live monitoring of the environment factors is very important in aquaculture and paddy farming. So they used an embedded system for monitoring and controlling the environment parameter situation. For this they used a microcontroller, Atmega328 IC in ArduinoUNO, a Raspberry Pi (third generation Model B was used in their project) and many sensors and actuators. They studied the situation of Pokkali field, popular in Alappuzha, Kerala, where rice and shrimp are cultivated alternatively. For shrimp farming management they monitored the amount of Dissolved Oxygen and PH. For paddy cultivation they monitored PH, soil moisture, and temperature, they accomplished this by using the following five different sensors, for measuring temperature, humidity pH, soil moisture and turbidity. They used Arduino software to program the microcontroller. They selected Python as their programming language.

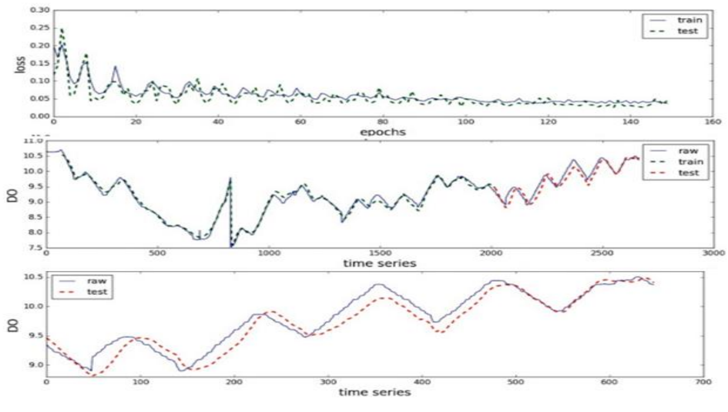
Shrimp farm's productivity can be increased by using an underwater surveillance system, which analyses the underwater situation in order to provide smart feeding and water quality control. They implemented the system in Taiwan. According to them using sensors, is not inadequate to check the growth and health conditions of shrimp. So they proposed a surveillance system with image defogging technology to get a clear image. Also they used AI Image Processing technology [2]. Object Detection Technology is used to identify objects. It also recognizes the remaining food at the bottom of the pond.

Steps: Collect the situation of the pond as image, through camera and water quality data from water quality sensor. Since the water is turbid in the pond the image obtained from camera may be foggy. So they performed Object Enhancement method for defogging to get clear images. For this they depend on wavelength compensation and dehazing. After that they performed AI Image recognition which includes the growth and quantity and quantity of remaining food recognition. For this they used Fast R-CNN method. The images and the sensor data are uploaded to an application and the processed data is made available in a Use Interface in real time. With this they can provide decisions on smart feeding, smart sewage, and also abnormal status decisions.

The sparse-Auto Encoder is used to extract features before giving the data to LSTM. Initially they fed the sensor data and the meteorological data to a preprocessor [3]. There they removed the missing values and perform normalization. Normalization makes the gradient descent faster which in turns gives a more prediction accuracy. As the next step they fed the normalized data to a sparse Auto Encoder. Multidimensional and sparse activation value learned from the hidden layers of SAE is given to LSTM. Train the data until the error has descended to a particular level or iteration count is reached. Use the trained sample to test the new values to predict the DO in the water.
They collected the data every 10 sec for 20 consecutive days. They measured DO, water temperature, Ammonia nitrogen content, and pH. They also measured atmospheric humidity, atmospheric pressure, atmospheric temperature and wind speed. They compare the results of DO prediction with Sparse Auto Encoder + Back Propagation Neural Network model, Single Long Short Term Memory model, Simple Back Propagation Neural Network model, Sparse Auto Encoder + Long Short Term Memory model.

They predicted the DO content in 3 hours, 6 hours and 12 hours. They found that as the time increases the prediction accuracy decreases (Figure 1). But the prediction accuracy of Sparse Auto Encoder + Long Short Term Memory model is better than other three models especially when considering the 12th hour prediction.

Figure 1. DO content in 3 hours, 6 hours and 12 hours. The time increases the prediction accuracy decreases.



To test the prediction accuracy they used Mean Absolute Error (MAE), Mean Square Error (MSE), Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE). They concluded that even though the combined usage of SAE and LSTM consume more time than using single LSTM, but when error is concerned combined

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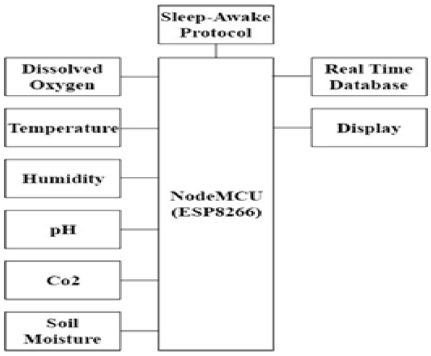
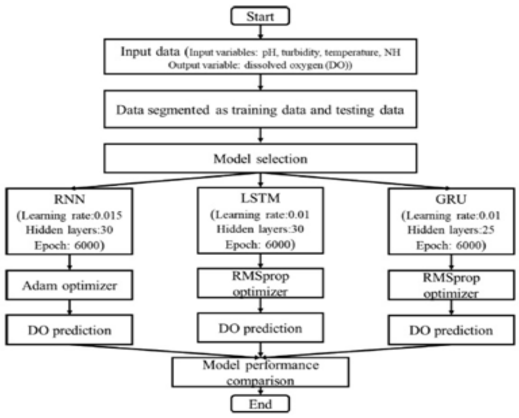
approach is better than singe LSTM. Similar result can also be found with SAE and BPNN. So they proved that using Sparse Auto Encoder will enhance the prediction accuracy. The authors researched on developing a live water quality analysis using IOT. They used a floating thermo coal made buoy with necessary boards and sensors to collect the data at real time (Figure 2).

Figure 2. A floating thermo coal made buoy with necessary boards and sensors to collect the data at real time.



They collect Dissolved Oxygen, Temperature, Humidity, pH, Co2, and Soil Moisture using sensors and are send to firebase cloud during each reading, with the help of ESP8266. The contamination of water is estimated using correlation values between multiple sensors using correlation coefficient. This paper compares the performance of RNN, LSTM and GRU in predicting DO in the pond. The evaluation is conducted based on the Mean Square Error, Mean Absolute Error, Mean Absolute Percentage Error, and the coefficient of determination. LSTM and GRU are variants of RNN. They collected DO, temperature, pH, NH and turbidity using an integrated PLC control box. The outliers were fixed by taking the median of six adjacent data.

Figure 3. The correlation coefficient between the data using correlation function.



The entire data has been divided into training set and test set. The training set contains 5040 data of 35 days. The test data contains 150 data of 1 day. Their model was designed to predict DO in one day advance. The authors used datasets which comprised the Dissolved Oxygen readings from two shrimp ponds. One pond is big and is in out-of-doors. Other one is small and is covered. Both are having same depth and are lined with plastic. They cultivated Tiger prawn in both the ponds. They used YSIEXO2 Multi parameter Sonde sensor for DO reading in 15 minutes interval. Data from the sensors are sampled automatically and send to CSIRO's Senaps data platform. They used 70% data as a training set and 30% data as test set. They investigated the performance of Support Vector Machine, Neural Networks and Linear Regression.

The authors concluded their paper by pointing out the following:

- The proposed system predicts Dissolved Oxygen using multiple timestamps ahead which shows better performance when compared with other methods.
- As the time stamps increases, the amount of previous data is huge.
- Here they predicted the DO without considering other parameters like temperature, saline content, speed of wind, pH etc.

DISCUSSION

The authors proposed a new method for predicting the water quality based on deep LSTM learning network. Here they predict pH and water temperature [4]. As the first step they removed the noisy and erroneous data from the sensors using linear interpolation, smoothing and average filtering methods. As a second step they find the correlation between various water quality parameters like pH, temperature, etc. As the last step they constructed a prediction model using LSTM. The results reflect the fact that short term prediction is more accurate than long term prediction.

The authors conducted experiment in a mariculture base at Hainan Province, China. Due to instability, aging or damage of sensor equipment and network problem data loss may happen. During preprocessing they recreate the missing value using linear interpolation method [5]. Denoising is achieved using moving average filter. With the help of Pearson Correlation coefficient they found the co relationship between the water quality parameters.

CONCLUSION

The quality of water is very important in shrimp farming. From the papers reviewed, it is understood that if a model that could predict the quality of water using different parameters, the farmers can take necessary actions to face the situation. Using Sensors we can collect real time data like dissolved oxygen, temperature, salinity, pH, turbidity etc. Then preprocess the data to remove missing data and outliers. The preprocessing has a great role in the performance of the prediction model. So from we came to see that using Sparse Auto Encoder gives more accurate results than implementing single LSTM and other models too. Using sensor data along with images were also proposed to monitor the growth of shrimps. For this they used R-CNN model. When comparing RNN, LSTM and GRU, it is found that LSTM and GRU perform almost similar. Ensemble prediction is another proposed method, which predicts the DO multiple steps ahead with minimum error, but as the steps increases, data size also increases. And also they considered only Dissolved Oxygen for prediction. Water quality is not only dependent on DO, and also DO is dependent on temperature, pH, salinity etc. From the papers reviewed it has been seen that LSTM with sparse Auto Encoder gives more accurate prediction with time series data.

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