Vietnam Journal of Catalysis and Adsorption
Tạp chí xúc tác và hấp phụ Việt Nam

https://jca.edu.vn

Monitoring Water Quality Parameters in Aquaculture Using Edge Computing

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ARTICLE INFO

Received: 27/3/2024
Accepted: 22/5/2024
Published: 30/6/2024

Keywords:
Edge AI, IoT, LSTM, Online Water Quality Monitoring and Warning

ABSTRACT

In this paper, we study an integration of temperature and pH sensors into the system to collect and monitor water quality parameters in aquaculture using a combination of edge computing (EC), Artificial Intelligence (AI) and Internet-of-Things (IoT). We develop and deploy a model using edge computing and a Long-Short Term Memory (LSTM) algorithm to forecast the aquaculture water quality at the network's edge. The system automatically operates and performs sampling, forecasting, and displaying predicting results on the user interface in real-time. The results of this paper demonstrate that the proposed solution with edge computing and LTSM can produce accurate forecasts with high reliability and prompt responses to water quality monitoring, thus reducing losses and harm due to water pollution in the aquaculture industry.

1. Introduction

Vietnam's socio-economic development strategy has played a particularly significant role in aquaculture. To be a leading sector in the national economy and to satisfy an increasing demand in quantity and quality from the global market, the aquaculture industry needs to strengthen research and apply and deploy scientific and technical advances, particularly in managing and monitoring aquaculture water environments. Therefore, deploying intelligent water environmental monitoring systems for Aquaculture 4.0 is crucial to Vietnam's economy and the aquaculture industry. In practice, water quality monitoring and management in the aquaculture sector in Vietnam follow traditional approaches in which water samples are manually collected and analysed at laboratories regularly. Even though they are simple, they have the following inherent difficulties: (i) The network of environmental management stations is small and unevenly distributed; (ii) Traditional analytical techniques are ineffective and produce inaccurate measurement results because the chemical, physical, and biological characteristics of water samples change rapidly with time (temperature, pH, etc.); (iii) High operational and equipment costs for technicians; (iv) Periodic monitoring is conducted infrequently (i.e., once a month or every two to three months during the growing seasons); (v) The environmental management system cannot remotely and automatically update data, thus making

https://doi.org/10.62239/jca.2024.047

measurement results inaccurate. Numerous solutions have been implemented in aquaculture water monitoring and environmental management systems [1-6] to resolve the above challenges. In the study [1], authors installed a system to monitor water parameters such as NH_4, NO_2, O_2, N_2, and salinity in shrimp ponds in Nam Dinh province. The system used Long-Range (LoRa) technology to transmit data on water parameters from the sensors to servers and clients' mobile phones. Another commercial water environmental monitoring system for shrimp and fish culturing was introduced by Vites Joint Stock Company [2]. The system allowed farmers to monitor the water temperature, pH, salinity, dissolved oxygen (DO), and Oxygen Reduction Potential (ORP) in ponds 24/24 via smartphones. The data is sent to a cloud server for storage using different communication technologies like WiFi, GPRS and 3G. In the research [3], the authors presented solutions for designing and developing an IoT system for monitoring and forecasting the lobster farming environment in Phu Yen.

The IoT system collects data from the environment and sends it to a server or cloud using GSM, 3G, or LoRa technologies. The data is then analysed using AI to provide the farmers with monitoring, forecasting environmental trends, and early warning of epidemics and risks. In the study [4], Pappu et al. created an intelligent IoT-based water quality monitoring system to measure pH and total dissolved solids (TDS) levels. In addition, the K-Means clustering machine learning algorithm was used to predict water quality. Preetham et al. developed a wastewater monitoring system in their study to measure and monitor parameters such as pH, DO, temperature, salinity, NH_3, H_2S, turbidity, and alkalinity [5]. Data on water quality and product quantity from each growing season will be sent to the company's server and analysed using AI algorithms to provide water quality prediction and suggestions for improving product quantity. Nguyen et al. introduced an IoT system for monitoring water quality in aquaculture and focused on the model for predicting quality parameters such as salinity, pH, temperature, and DO [6]. The authors suggested deep learning and a Long-Short Term Memory (LSTM) algorithm to estimate these indicators. Experimental results on the four indicator data sets under examination show that the proposed methodology is appropriate for use in real-world systems. By doing so, the system can help farmers manage the water quality and produce high-quality shrimp or fish in both quantity and quality.

In a couple of years, Edge AI, a combination of Edge Computing and AI, is emerging as a potential solution for prediction activities in a distribution fashion [7-9]. Practically, Edge AI can be installed on edge devices at the field (i.e., sensor node or gateway) to conduct analysis and prediction about the water quality of the aquaculture ponds. It is noteworthy that the implementation of Edge AI combined with IoT technology has provided some advantages: (i) Cutting down on the resources needed for traditional laboratory sampling and analysis, (ii) Ensuring continuous monitoring of any changes in water quality, and (iii) Identifying impending risks to help users take preventative measures to avoid harm.

Inheriting from the idea of Edge AI in IoT applications, the authors will study, propose, and deploy an online water quality monitoring and early warning system in aquaculture in this paper. The proposed system is expected to provide highly accurate predictions and decisions on water quality. Prediction results will be good references for farmers to propose suitable plans for their activities. The main contributions of this paper are two-fold:

- Integrate commercial temperature and pH sensors into the monitoring system and collect data on these parameters.
- Design and implement a model using Edge Computing and the LSTM algorithm to forecast aquaculture water quality and warn farmers early.

2. Experimental

Commercial IoT Sensors Integration

Sensors Preparation

In this work, the authors will integrate sensors, such as pH and temperature sensors, into the IoT system. The parameters of the sensors are shown below:

pH Analog Meter Pro Kit v2, an industry pH combination electrode, is made of a sensitive glass membrane with low impedance (Input voltage range: 3.3~5.5V; accuracy: ±0.1°C; Type of probe: Industrial Grade; pH measurement range: 0~14; Working temperature range: 0~60°C; Standard BNC probe connection);

High-resolution temperature sensor MAXIM DS18B20 (12bit) (Input voltage range: 3 ~ 5.5 VDC; consumption current: 1~1.5mA).

Sensor Integration

https://doi.org/10.62239/jca.2024.047

The proposed system consists of pH and temperature sensor probes with high stability, sensitivity, and low detection boundaries. These sensors are non-toxic, environmentally friendly, and highly accurate, making them suitable for use in a research environment.

Edge AI - based Water monitoring and management system

To effectively deploy Edge AI and IoT solutions in water quality monitoring in the aquaculture sector, the proposed system needs to satisfy the following requirements: The edge devices must have sufficient computing power to process data and make decisions in milliseconds; the edge devices must be able to protect data; and the database must be stored for backup purposes.

In this section, the authors will present a model for water quality prediction based on the integration of Edge Computing and AI. The AI model used in this study is LSTM, a variety of Recurrent Neural Networks (RNNs). The LSTM can learn long-term dependencies, especially in sequence prediction problems.

RNN is a contemporary algorithm for sequential data. It can remember the key characteristics of the input data it receives, providing a much deeper understanding of its sequence and context. This activity enables RNN to make reasonably accurate predictions about the location of the following data point. The RNN enables it to use the outputs of the previous states as inputs to process the following states.

Long Short-Term Memory (LSTM)

The LSTM is suitable for categorisation and forecasting problems based on time series data because it can recall past events (i.e., temperature or pH data). Thanks to the LSTM network, the RNN can keep the inputs in memory for a long time. This activity is due to the LSTM's ability to read, write, and erase data from its memory while storing it. A gate can be thought of as network memory. Depending on the significance of the information, the gate can determine whether to save it. The term "*weight*" can indicate how important information is.

The LSTM structure: The three gates in an LSTM are an input gate, a forget gate, and an output gate. These are analogue gates with sigmoid activation functions; their output ranges from 0 to 1. The input gate determines which value from the input is updated in memory. The forget gate determines what information to remove from the block conditionally and makes conditional output decisions based on the block's input and memory [10].

3. Results and discussion

Proposed Model of Water Quality Monitoring and Forecasting System

Temperature and pH are crucial parameters in aquaculture because they accurately reflect the water's physical, chemical, and biological characteristics. For example, for every 10-degree increase in temperature, a fish's metabolic rate doubles. In addition, the solubility of oxygen will decrease with increasing temperature, and the concentrations are usually lower, especially in the summertime. Thus, oxygen consumption, food conversion efficiency, food requirements, and growth are directly impacted by temperature [11].

In aquaculture, the suitable pH ranges from 6 to 9 (i.e., for shrimp, the pH is between 7.8 and 8.5). When the pH is too low (i.e., pH < 5.5), the ability to store minerals in the body of shrimp/fish is reduced, thus causing an increase in the concentration of H_2S. When the pH is too high (pH > 8.5), it is also the cause of increased NH_3 levels. In both cases, H_2S and NH_3 are highly toxic to aquatic organisms.

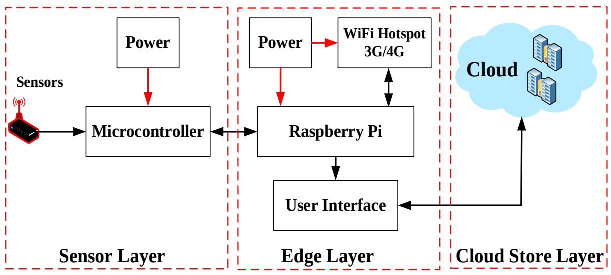


Fig. 1: Proposed System Model

As analysed, pH and temperature parameters directly affect the health of cultured aquatic products, including their growth, survival rate, and nutrition [11]. Therefore, we select pH and temperature as critical parameters that must be monitored and managed. Furthermore, we propose and implement a three-layer general system model shown in Fig. 1 to collect, process, and predict pH and temperature in the ponds.

Sensor Layer

The sensor class includes one (01) pH sensor (e.g., pH Analog Meter Pro Kit V2) and one (01) temperature sensor (e.g., DS18B20). These sensors measure the water's pH and temperature, respectively. Note that the pH sensor must be cleaned and calibrated monthly to ensure the accuracy of pH data collection. The ESP8266 NodeMCU microcontroller processes the data received by the sensors. This microcontroller will be programmed using open-source Arduino software.

Edge Layer

This layer collects data from the sensor layer, processes it, estimates the water's quality shortly, shows the user interface, and sends the output data to the storage and cloud computing system. Fig. 4 illustrates the device model and system for collecting and monitoring water quality parameters in aquaculture after integrating temperature and pH sensors. In this work, a Raspberry Pi 4B device (i.e., quad-core 1.5GHz CPU and 2GB RAM) operates as an edge device. The edge device is connected to the Internet via an Ethernet cable or WiFi Hotspot (which uses wireless data from 3G/4G mobile providers to give Internet access, thus enabling access to real-time data from sensors positioned at the ponds. Using the LSTM network, Raspberry analyses the data collected by the sensors and predicts any changes in the parameters of pH and temperature every 3, 6, 12, and 24 hours.

Cloud store layer

This layer monitors predictions' outcomes and displays results to remote users. In this work, we select a server storage service from an open-source platform, Thingspeak, to store and access data from the real-time edge processing layer. ThingSpeak enables the development of user applications like logging, location tracking, and monitoring. More importantly, ThingSpeak allows users to extract all data anytime and anywhere with Internet connections easily.

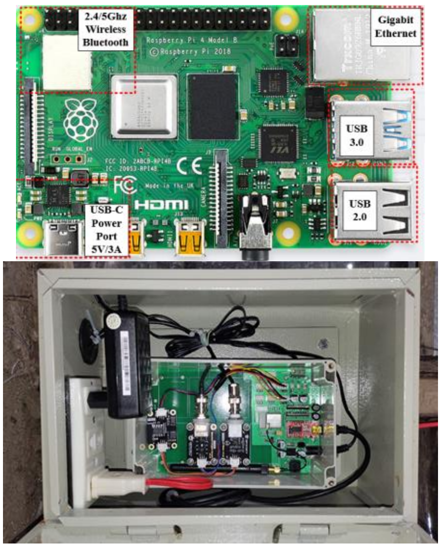


Fig. 2: Edge device – Raspberry Pi and system to collect and monitor water quality parameters after integrating temperature and pH sensors

Due to high humidity and temperature environments like ponds, all the devices shown in Figs. 3 and 4 will be packed in IP65 waterproof enclosure boxes with UV-resistant ABS material. By doing so, our devices can operate for a long time and be highly reliable.

LSTM predictive model

In this work, the authors develop an LSTM model with four hidden layers using Adam's optimisation approach with 71.051 model parameters to perform prediction models for the water quality parameters. The model predicts changes in temperature and pH using the historical data from the last 24 hours. A 24-hour period will require 48 data points at a sampling frequency of 30 minutes per data point. The model uses forecasting findings from the previous period as inputs to predict the change in temperature and pH in the next 24 hours.

Implementation

We deploy the proposed system model at a single shrimp pond in Tam Quan Bac, Hoai Nhon, Binh Dinh. The system collects data from the sensors with a frequency of 30 minutes per sample. Each data sample includes the two parameters of temperature and pH. We use a 4G connection to transmit data to Thingspeak's server. The overall duration for data collection is 90 days, 0 hours, and 51 minutes (i.e., from noon to 12:51), with 4.259 out of a total of 4.322 samples (approximately 98.5%). The training and testing datasets are 2,990 data points (i.e., about 70% of the total data set) and 1.281 data points (i.e., 30%), respectively.

LSTM model training results

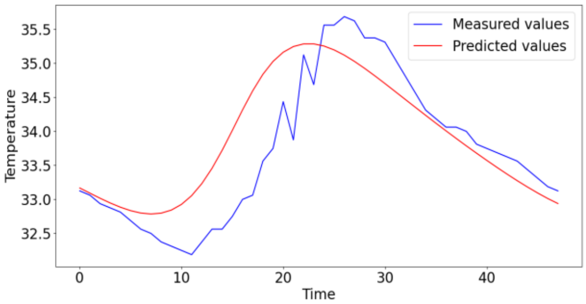
Model training outcomes using temperature and pH and results of model training for temperature and pH parameters showed, the model training process using the mean squared error (MSE) error function is asymptotic and stable at the minimal value for both temperature and pH prediction models.

The MSE losses in both cases are lower than 1% after roughly 60 epochs. As seen from Fig. 2(c) and 2(d), the predicted temperature and pH values are nearly identical to the actual values from the data set, respectively.

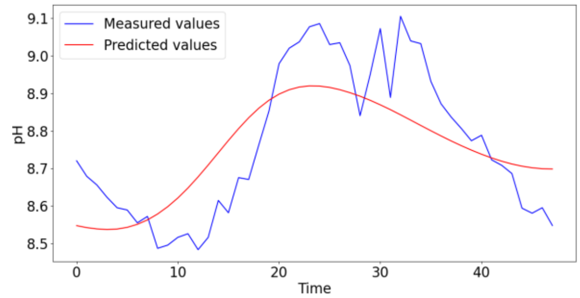
Estimated temperature and pH

Fig. 3 shows forecasted results for temperature and pH parameters over 24 hours. As depicted, the forecast pattern for the following 24 hours has a forecast time trend that matches the actual value change.

https://doi.org/10.62239/jca.2024.047



(a) Temperature



(b) pH

Fig. 3: Forecasted results of temperature and pH parameters in 24 hours

It illustrates that the model architecture with 48 historical data points as input gives the best prediction efficiency with the lowest error rate when comparing models with different input sizes using the mean squared error (MSE) and the mean average error (MAE).

Table 1: Temperature prediction error statistics with LSTM model for 20 consecutive days and Error statistics with LSTM model predicting pH for 20 straight days

LSTM model for 20 consecutive days					
LSTM input width = 24		LSTM input width = 48		LSTM input width = 96	
MSE	MAE	MSE	MAE	MSE	MAE
0.915	0.824	0.201	0.378	2.268	1.292
0.933	0.831	0.254	0.404	1.158	0.942
0.656	0.656	0.368	0.52	2.163	1.239
0.743	0.655	0.424	0.526	1.442	1.056
0.285	0.428	0.116	0.288	1.485	1.059
0.348	0.492	0.176	0.326	2.023	1.314
0.308	0.454	0.177	0.334	2.173	1.37
1.534	0.985	0.598	0.642	1.804	1.102
0.458	0.576	0.149	0.282	1.338	0.959
2.045	1.234	3.689	1.578	9.224	2.715
0.933	0.814	0.612	0.624	2.056	1.149
0.85	0.785	0.547	0.568	1.661	1.05
0.907	0.831	0.473	0.567	0.43	0.534
1.313	0.883	0.195	0.358	1.243	0.908
1.416	0.911	0.4	0.503	0.945	0.84
1.137	0.765	0.188	0.318	1.135	0.864
1.053	0.827	0.084	0.189	1.75	1.085
0.945	0.775	0.098	0.245	2.013	1.2
0.313	0.456	0.056	0.169	1.945	1.256
0.479	0.514	1.14	0.875	4.702	1.983
17.571	**14.696**	**9.945**	**9.694**	**42.958**	**23.917**

LSTM model predicting pH for 20 straight days					
LSTM input width = 24		LSTM input width = 48		LSTM input width = 96	
MSE	MAE	MSE	MAE	MSE	MAE
0.259	0.472	0.084	0.22	0.036	0.153
0.375	0.585	0.028	0.141	0.129	0.33
0.378	0.58	0.048	0.178	0.069	0.227
0.489	0.669	0.02	0.116	0.137	0.341
0.637	0.723	0.013	0.1	0.123	0.267
0.375	0.468	0.34	0.421	0.422	0.47
0.024	0.133	0.806	0.819	0.214	0.361
0.039	0.173	0.135	0.279	0.033	0.139
0.048	0.189	0.08	0.215	0.015	0.097
0.29	0.509	0.025	0.116	0.161	0.355
0.428	0.618	0.01	0.081	0.155	0.355
0.674	0.753	0.006	0.071	0.08	0.239
0.782	0.816	0.023	0.113	0.034	0.137
0.569	0.683	0.007	0.066	0.018	0.115
0.723	0.79	0.005	0.064	0.011	0.09
0.655	0.744	0.002	0.037	0.002	0.031
0.568	0.678	0.004	0.05	0.01	0.09
0.398	0.564	0.03	0.166	0.01	0.088
0.259	0.467	0.095	0.239	0.036	0.146
0.423	0.619	0.003	0.042	0.199	0.405
8.393	**11.233**	**1.764**	**3.534**	**1.894**	**4.436**

As analysed above, the dataset with high levels of stability is collected, and missing data is processed based on the analysis of the data sets' defining characteristics. The LSTM model enables parameter prediction with high accuracy and low error by analysing time series and examining outliers. The model provides accurate forecast results for the temperature parameter with a small margin of error. However, the pH value is affected by a variety of factors.

Consequently, more data parameters about the weather, light, when to use the product, and other factors are required to predict results accurately.

4. Conclusion

In this paper, the authors have successfully integrated commercial temperature and pH sensors into the proposed system to track, collect and monitor the water quality parameters in aquaculture. In addition, we developed and deployed a model using EC edge computing and the LSTM algorithm to forecast aquaculture water quality at the network's edge. The system runs entirely automatically and performs sampling, forecasting, and real-time display of forecast results on the user interface.

The achieved results in this paper demonstrate that the proposed solution of edge computing and AI can produce accurate forecasts with high reliability and prompt responses to water quality monitoring efforts, thus helping to reduce losses and harm brought on by water pollution to the aquaculture industry.

Acknowledgments

This research is funded by the Ministry of Science and Technology and Binh Dinh Province Department of Science and Technology under grant number ĐTĐLCN.44/22.

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