International Journal of Scientific Research in Science, Engineering and Technology
Print ISSN: 2395-1990 | Online ISSN : 2394-4099 (www.ijsrset.com)
doi : https://doi.org/10.32628/IJSRSET

A Network For Surveil and Weigh Up For the Quality of Water Using Machine Learning

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ARTICLEINFO

Article History:

Accepted: 10 April 2023
Published: 20 May2023

Publication Issue
Volume 10, Issue 3
May-June-2023

Page Number
180-185

ABSTRACT

Water is a valuable resource that is necessary for human survival as well as agricultural production. However, a variety of pollutants, including chemicals, pathogens, and other contaminants, can impair water quality. As a result, there is an increasing demand for dependable and efficient methods of monitoring and assessing water quality for both drinking and irrigation purposes. We propose in this paper a network for monitoring and assessing water quality that integrates multiple data sources, such as satellite imagery, in situ sensors, and water quality measurements. A smooth support vector machine (SSVM) can be used to monitor water quality parameters by classifying water quality samples into different categories based on the parameters measured. The smooth SVM can help improve the accuracy of classification, particularly in situations where the input data contains noise or errors. The network will analyse and interpret data using deep learning algorithms, providing insights into water quality parameters like temperature, pH, dissolved oxygen, turbidity, and nutrient levels. The proposed network will serve a variety of purposes, including providing real-time data for drinking water treatment plants, assisting in water resource management decision-making, and identifying potential sources of contamination in irrigation systems.

Keywords: Water monitoring network, machine learning, water quality index, and drinking and irrigation water, SSVM.

I. INTRODUCTION

Water is a vital resource for human survival, agriculture, and a variety of other applications. However, water quality is frequently harmed as a result of natural and human activities, with serious consequences for public health and the environment. As a result, monitoring and assessing water quality is critical to ensuring that it is safe for drinking and irrigation. With rising demand and climate change, ensuring the quality of drinking and irrigation water is becoming increasingly difficult. Traditional methods of water quality monitoring are frequently time-consuming, costly, and labor-intensive [1]. They may also not provide real-time data, resulting in delayed responses to potential water quality issues. To address this problem, this paper proposes a deep learning-based network for monitoring and assessing water quality for drinking and irrigation purposes [2]. The network is made up of sensors installed at various water sources, as well as a central database that collects data from these sensors. The data is then analyzed using deep learning algorithms to predict water quality levels [3]. Deep learning is a subset of machine learning in which algorithms are trained on large datasets to identify patterns and make accurate predictions. Deep learning can be used in water quality monitoring to analyze large amounts of data from multiple sources in order to identify patterns and predict water quality levels. The proposed network has a number of advantages over traditional methods of monitoring water quality [4]. The network can detect changes in water quality quickly by using sensors to collect data in real-time and alert authorities and farmers to take appropriate action. Furthermore, the application of deep learning algorithms can provide more accurate predictions of water quality levels, allowing for more effective decision-making. The network can be used for drinking as well as irrigation [5]. To ensure that drinking water is safe to consume, the network can monitor pH levels, dissolved oxygen, and total dissolved solids (TDS). To optimize crop growth and yield, the network can monitor factors such as salinity, temperature, and nutrient levels during irrigation. Using deep learning, the proposed network provides a cost-effective and dependable solution for monitoring and assessing water quality for drinking and irrigation purposes [6]. The network can assist authorities and farmers in making informed decisions about water usage and management by providing real-time data and accurate predictions.

II. RELATED WORKS

Due to increased traffic and service diversification, optical networks have become more complex in recent years, making it increasingly difficult for network operators to monitor large-scale networks and keep track of communication status at all times, as well as control and operate the various services running on the networks [7]. This issue is driving the need for autonomous optical network diagnosis, and expectations for the use of machine learning and deep learning are rising. Another trend is the active movement towards lowering the capital expenditure (CAPEX)/operational expenditure (OPEX) of optical transport equipment by utilising whitebox hardware, open source software, and open interfaces. In this paper [8], described in detail the concept of a series of workflows for the whitebox transponder, including obtaining optical performance data from the coherent optical transceiver, diagnosing optical transmission line conditions using deep neural networks (DNNs) on the collected data, and notifying the remote network management system (NMS) of the diagnosis results. Furthermore, as one of the use cases, we demonstrate fibre bending detection based on the diagnosis workflow. Offline and online demonstrations show that the deployed diagnosis system can identify the fibre bend with up to 99% accuracy in our evaluation environment [9].

The water-quality data utilized in this research was obtained through the Malaysian Department of Environment (DOE). Time-series data for selected parameter sets through four stations from 2006 until 2016 were utilized in this research. Six water-quality parameters were chosen for SVM modelling in this research, specifically pH, Suspended Solids (SS), Dissolved Oxygen (DO), Ammonia Nitrogen (AN), Chemical Oxygen Demand (COD), and Biochemical Oxygen Demand (BOD) [10].

III. PROPOSED SYSTEM

A smooth support vector machine (SSVM) is a type of SVM that introduces smoothness constraints into the optimization problem of a standard SVM. The aim is to provide better classification performance in situations where the input data contains noise or errors. In a standard SVM, the optimization problem is to find a hyperplane that separates the data points into different classes with the largest possible margin. However, in the presence of noise or errors, this margin can become too small or even zero, leading to poor classification performance. Smooth SVMs address this issue by introducing a smoothness constraint that encourages the hyperplane to have a smooth and continuous decision boundary.

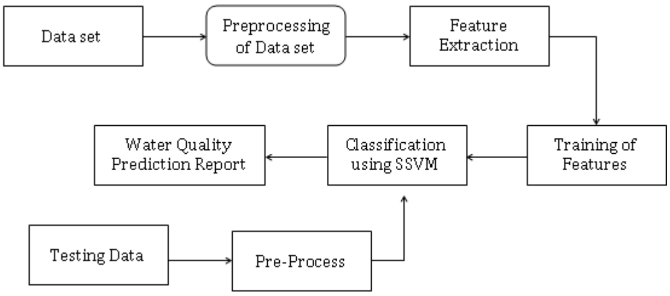


Figure 1: Overall Proposed Architecture

To monitor water quality parameters using a smooth SVM, you would first need to collect data on various parameters that affect water quality, such as temperature, pH, dissolved oxygen, turbidity, and more. You can collect the data using sensors and monitoring devices placed in the water or through water quality testing equipment. The data should be preprocessed to remove any noise or errors and feature engineered to select the most relevant features.

2 Smooth Support Vector Machine

We consider the problem of classifying m points in the n-th dimensional real space R^n, represented by m x m matrix A, according to membership represented by the m x n matrix A, according to membership of each point A_i in the classes 1 or -1 as specified by a given m x m diagonal matrix D with ones or minus ones along its diagonal. For this problem the standard support vector machine with a liner kernel AA' is given by the following for some v>0:

$$\min_{(\omega,\gamma,y)\epsilon R} ve'y + \frac{1}{2}w'w$$

$$\text{s.t.} D(Aq - e\gamma) + y \geq e \qquad (1)$$

$$y \geq 0$$

Here w is the normal to the bounding planes:

$$x'w - \gamma = +1$$

$$x'w - \gamma = -1 \qquad (2)$$

andγ determines their location relative to the origin. The first plane above bounds the class 1 points and the second plane bounds the class -1 point when the two classes are strictly linearly separable, that is when the slack variable y=0. The linear separating surface is the place

$$x'w = \gamma \qquad (3)$$

midway between the bounding planes (2). See figure 1. If the classes are linearly inseparable then the two planes bound the two classes with a "soft margin" determined by a non-negative slack variable y, that is:

$$x'w - \gamma + y_i \geq 1 \, for \, x' = A_i \, and \, D_{ii} = +1$$

$$x'w - \gamma + y_i \geq 1 \, for \, x' = A_i \, and \, D_{ii} = -1 \qquad (4)$$

Once the data has been preprocessed and feature engineered, a smooth SVM can be developed to classify water quality samples into different categories based on the measured parameters. The smooth SVM can be trained using a set of labeled data and validated using another set of labeled data to assess the accuracy of classification. The smoothness constraint in the SVM can help improve the classification performance by encouraging a smoother and more continuous decision boundary.

The smooth SVM can be deployed to monitor water quality parameters in real-time. The monitoring system can continuously gather data from sensors and monitoring devices placed in the water and classify the water quality samples based on the measured parameters. The system can be set up to alert authorities when the water quality falls below a certain threshold or when anomalies are detected in the water quality samples.

IV. MODULES DESCRIPTION

To design a network for surveilling and weighing up the quality of water using machine learning, you would need to consider several key components and factors. Here are some steps that could be followed:

Data Collection: To build a machine learning model to predict water quality, you will need to collect data on various factors that affect water quality, such as temperature, pH, dissolved oxygen, turbidity, and more. The data can be collected from various sources, including sensors placed in the water, water quality testing equipment, and other monitoring devices.

Data Preprocessing: Once you have collected the data, it needs to be preprocessed to remove any noise or errors. This can involve cleaning, formatting, and transforming the data to make it suitable for machine learning algorithms.

Feature Engineering: Feature engineering involves selecting the most relevant features from the data to use in the machine learning model. This step requires domain knowledge of water quality factors and their impact on water quality.

Machine Learning Model: Once the data has been preprocessed and feature engineered, a machine learning model can be developed to predict water quality. Various algorithms can be used, including decision trees, random forests, and neural networks.

Deployment: The machine learning model can be deployed to monitor and predict water quality in real-time. The model can be integrated with sensors and monitoring devices to continuously gather data and provide feedback on water quality.

4.1 Performance Metrics:

Three statistical parameters, including R Squared error (RSE), Root Mean Squared Error (RMSE) and mean absolute error (MAE), are used to test the PCR model efficiency. These criteria are expressed as follows:

$$RSE = 1 - \left(\frac{(explained\ variation)}{(Total\ Variation)}\right) \quad (5)$$

$$RMSE = \sqrt{\sum \frac{\left(y_{obs} - y_{pred}\right)^2}{n}} \quad (6)$$

$$MAE = \frac{\sum(\|y_{obs} - y_{pred}\|)}{n} \quad (7)$$

where, y_{obs} = actual value, y_{pred} = predicted value and n= total number of samples.

Four classification metrics, including accuracy, Recall, Precision, and F1-Score, are used to test the classification model performance. These metrics are expressed as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (8)$$

$$Recall = \frac{TP}{TP + FN} \quad (9)$$

$$Precision = \frac{TP}{TP + FP} \quad (10)$$

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (11)$$

Where, TP = True positive, TN = True Negative, FP = False Positive, FN = False Negative.

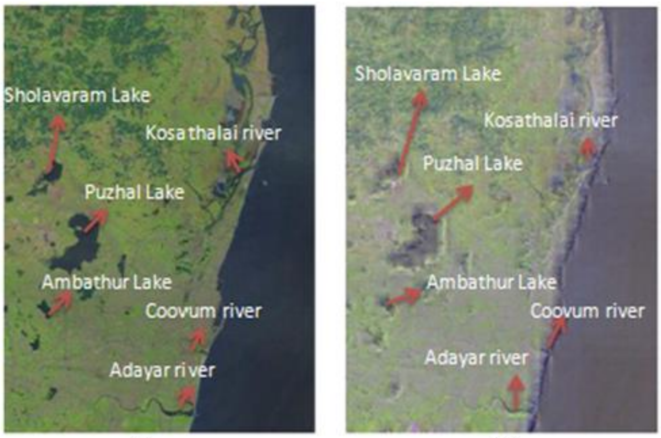
V. RESULTS AND DISCUSSIONS

The classification results by the different number ofconvolutional layers are shown in Table 1. The SSVM obtained the bestresults, and performances did not largely vary.

Table 1: Average Accuracy by the different number of convolutional layers in Erhai Lake

Iterations	2	3	4	5	6	7
Average Accuracy	88.90 %	92.26 %	92.49 %	92.40 %	92.10 %	92.08 %

To evaluate SSVM performance, we compared its classification performance with that of commonmachine-learning models SVM and RF. Visual features, such as texture and color features, were selectedfor classification.



(a) (b)

Figure 2:(a) LANDSAT image— Chennai city. (b)TDyWT applied LANDSAT image

Figure 3: Training Model

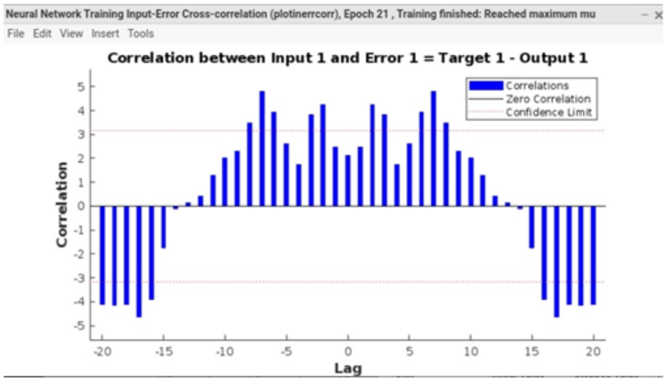


Figure 4:Cross-Correlation

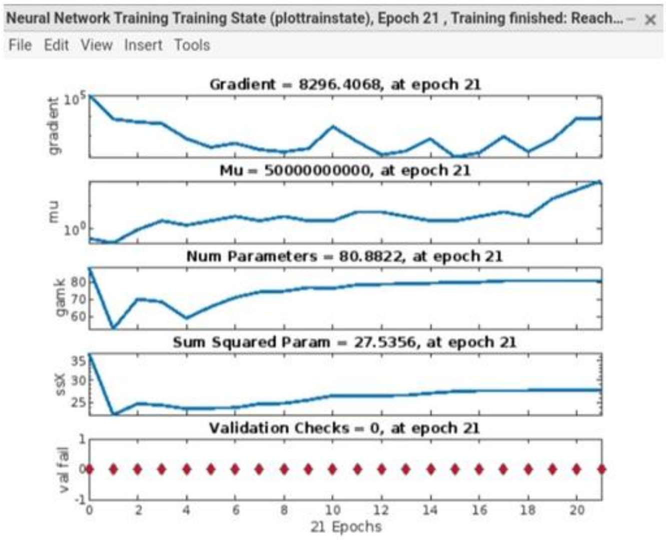


Figure 5: Validation State

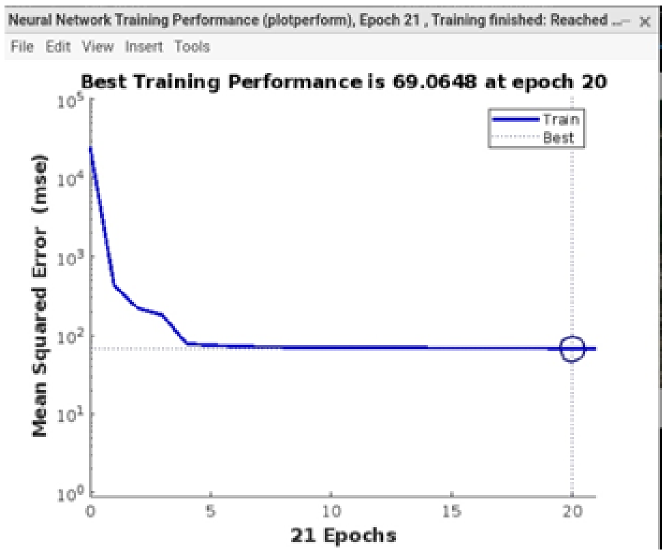


Figure 6: MSE analysis

Based on above experimental results, it shows that the proposed network will serve a variety of purposes, including providing real-time data for drinking water treatment plants, assisting in water resource management decision-making, and identifying potential sources of contamination in irrigation systems.

VI. CONCLUSION

In summary, a smooth SVM can be used to monitor water quality parameters by classifying water quality samples into different categories based on the measured parameters. The smooth SVM can help improve the accuracy of classification, particularly in situations where the input data contains noise or errors. Continuous improvement of the smooth SVM can be achieved by incorporating new data and feedback from the monitoring system. This can help ensure that the SVM remains accurate and relevant in monitoring water quality parameters.

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