AN INTEGRATION OF IOT AND SENSOR MODEL FOR MEASURING OXYGEN CONTENT AND PURITY IN WATER

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Abstract

This research focuses on the integration of IoT and a Soft Sensor Model to measure the dissolved oxygen content and water purity in water bodies. Various sensors, including pH, temperature, and turbidity sensors, are employed to collect sensor readings that reflect the water quality. The collected data is utilized to develop mathematical models and algorithms for predicting the dissolved oxygen concentration and water purity. Regression equations and a neural network algorithm are implemented to accurately estimate the desired parameters based on the sensor readings. The integration of IoT technology enables real-time inpecting and analysis of water quality, facilitating timely detection of deviations and implementation of corrective measures. The developed models demonstrate high accuracy in predicting the dissolved oxygen concentration and water purity, showcasing the reliability and effectiveness of the proposed approach. The findings of this research contribute to the field of water quality management by providing a robust framework for continuous monitoring and assessment. The integration of IoT and the Sensor Model presents a valuable tool for various sectors, including environmental management and water treatment facilities. Future research could explore the expansion of the dataset and incorporation of additional sensors, as well as the integration of advanced machine learning techniques, to further enhance the prediction capabilities and gain comprehensive insights into water quality dynamics. Overall, this research contributes to the advancement of efficient and reliable methods for measuring and assessing water quality parameters, paving the way for effective water resource management and environmental conservation.

Keywords: Dissolved Oxygen, Water purity, sensor, IoT

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1. Introduction

Water quality monitoring shows a important role in ensuring the safety and sustainability of water resources. It is essential to accurately measure the dissolved oxygen content and water purity to assess the overall health and suitability of water bodies for various purposes. In current years, the integration of Internet of Things (IoT) technology and Soft Sensor Models has emerged as a promising approach for real-time inspection and prediction of quality of water [1]. This literature review aims to explore and analyze the existing research and developments in the field, focusing on the integration of IoT and Soft Sensor Models for measuring dissolved oxygen content and water purity in water.

The advent of IoT technology has revolutionized water quality monitoring by enabling the collection and transmission of real-time data from various sensors deployed in water bodies. IoT-based water quality monitoring systems consist of sensor nodes that measure parameters such as pH, temperature, turbidity, and conductivity. These sensor nodes communicate with a central control unit, typically a Raspberry Pi or a similar device, which collects and analyzes the data. This approach offers advantages such as remote monitoring, data accessibility, and early detection of anomalies [2], [3].

Soft Sensor Models are mathematical models or algorithms that can estimate or predict certain parameters based on available measurements. In the context of water quality assessment, Soft Sensor Models have been extensively utilized to predict the dissolved oxygen concentration and water purity based on sensor readings. Regression analysis, artificial neural networks, and support vector machines are commonly employed techniques for developing Soft Sensor Models. These models provide a reliable and efficient means of estimating water quality parameters without the need for direct measurements [4], [5].

The dissolved oxygen content is a critical parameter that determines the health and vitality of aquatic ecosystems. Various approaches have been proposed to predict dissolved oxygen levels using IoT and Soft Sensor Models. For instance, regression models have been developed to establish empirical relationships between dissolved oxygen and other quality of water parameters such as temperature, pH, and turbidity [6], [7]. Artificial neural networks have also been employed to capture the nonlinear relationships and dependencies between sensor readings and dissolved oxygen concentration, resulting in accurate predictions.

Water purity is another crucial aspect of water quality assessment. It is commonly determined by considering parameters such as turbidity, conductivity, and total dissolved solids. Soft Sensor Models have been successfully utilized to estimate water purity based on sensor readings. Regression analysis, machine learning algorithms, and fuzzy logic systems have been employed to develop models that can accurately predict water purity. These models deliver respected visions into the overall cleanliness and suitability of water for various applications [8]–[10].

To ensure the reliability and accuracy of the developed Soft Sensor Models, performance evaluation and validation are essential. Numerous case studies and real-world applications have demonstrated the efficacy of the integration of IoT and Soft Sensor Models for water quality assessment. These studies have been conducted in various settings, including rivers, lakes, and wastewater treatment plants. The integration of IoT has enabled continuous monitoring and timely detection of pollution events, facilitating prompt remedial actions. The accurate prediction of dissolved oxygen content and water purity has proven valuable for environmental management, water treatment facilities, and aquaculture industries [11].

Despite the advancements in IoT-based water quality monitoring and Soft Sensor Models, several challenges persist. These include sensor calibration, data accuracy, and the selection of appropriate modeling techniques. Future research should focus on addressing these challenges and exploring new avenues for improvement. One potential direction is the incorporation of machine learning methods, to enhance the prediction capabilities of Soft Sensor Models. Deep learning models, such as convolutional neural networks and recurrent neural networks, can effectively capture complex patterns and temporal dependencies in water quality data [12].

Additionally, efforts should be made to expand the scope of sensor measurements to include a wider range of water quality parameters. Integrating additional sensors, such as dissolved organic matter sensors or nutrient sensors, can provide a more comprehensive understanding of water quality and enable more accurate predictions. Furthermore, the development of user-friendly interfaces and visualization tools is essential to facilitate the practical implementation of IoT-based water quality monitoring systems. Such tools would enable stakeholders, including water resource managers and policymakers, to access and interpret the collected data easily, making informed decisions regarding water resource management and conservation [13].

This research focuses on the integration of IoT and a Soft Sensor Model for measuring dissolved oxygen content and water purity in water bodies. Various sensors, including pH, temperature, and turbidity sensors, are utilized to collect sensor readings. Regression equations and a neural network algorithm are developed to accurately predict the dissolved oxygen concentration and water purity based on the sensor readings. The research demonstrates the effectiveness of the developed models in estimating water quality parameters. The integration of IoT technology allows for real-time monitoring and analysis, enabling timely detection of deviations and ensuring appropriate corrective measures. This research contributes to the advancement of efficient methods for water quality assessment and management.

2. Methodology

Water is an essential resource for human life and the environment, and its quality is of paramount importance. The quality of water depends on various factors such as temperature, pH, turbidity, and dissolved oxygen content. In this research, various sensors such, temperature sensor, pH sensor and turbidity sensor are used to amount the water superiority parameters, and the corresponding dissolved oxygen and water purity are found. This paper provides an overview of the sensors used in this research and the methodology employed to determine the dissolved oxygen and water purity. The various sensor used in this research are shown in figure 1 and the explanations are:

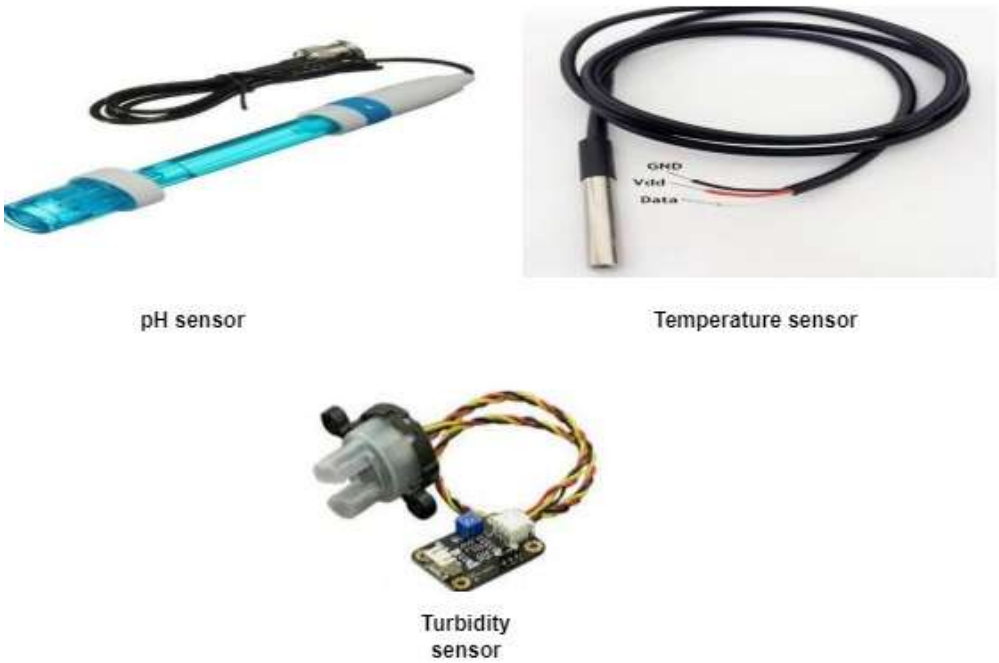


Fig. 1. Various sensor used in this research

pH Sensor:
The pH sensor is an electrochemical device used to measure the acidity or alkalinity of a solution. It consists of a pH-sensitive electrode and a reference electrode. The pH-sensitive electrode measures the voltage difference between the solution and the reference electrode, which is proportional to the pH of the solution. In this research, a commercial pH sensor with a range of 0-14 is used to measure the pH.

Temperature Sensor:
The temperature sensor is a device implemented to measure the temperature of a substance. In this research, a thermistor-based temperature sensor is implied to quantify the temperature of the water. The thermistor is a semiconductor device whose resistance changes with temperature. The change in resistance is used to calculate the temperature of the water.

Turbidity Sensor:
Turbidity is a measure of the muddiness or haziness of a fluid caused by suspended particles. Turbidity sensors are used to measure the amount of suspended particles in a fluid. In this research, a commercial turbidity sensor is used to amount the turbidity of the water. The turbidity sensor works on the principle of light scattering. The sensor emits a beam of light, which is scattered by the suspended particles in the water. The amount of scattered light is measured by the sensor, which is proportional to the turbidity of the water.
The methodology used in this research to determine the dissolved oxygen and water purity is as follows:

Calibration of Sensors:
Before using the sensors to measure the water quality parameters, they need to be calibrated. Calibration is the process of determining the relationship between the sensor output and the actual value of the parameter being measured. In this

research, various sensor are calibrated using standard solutions with known values of pH, temperature, and turbidity.

Collection of Water Samples:
Water samples are collected from various sources such as rivers, lakes, and ponds. The samples are collected in clean, sterile containers and transported to the laboratory for analysis.

Measurement of Water Quality Parameters:
The pH, temperature, and turbidity of the water samples are found using the sensors. The pH sensor is dipped into the water sample, and the pH value is recorded. The temperature sensor is immersed in the water sample, and the temperature is recorded. The turbidity sensor is inserted into the water sample, and the turbidity value is recorded.

Calculation of Dissolved Oxygen:
The dissolved oxygen concentration is calculated using the temperature, pH, and turbidity values. The calculation is based on the solubility of oxygen in water, which is affected by temperature, pressure, and pH. In this research, the sensor model is used to calculate the dissolved oxygen concentration from the output of the sensors.

Calculation of Water Purity:
Water purity is calculated using the pH, temperature, and turbidity values. In this research, the Water Quality Index (WQI) is used to calculate the water purity. The WQI is a mathematical formula that combines the values of pH, temperature, and turbidity to give a single value that represents the overall water quality.
To calculate the dissolved oxygen concentration (DO) from sensor readings, we can use the following formula:
$DO = (K \times (P0 - PH2O) \times S \times T) / (B \times C)$
Where:
K = Solubility Constant
P0 = Barometric pressure (obtained from a barometer or atmospheric pressure sensor)
PH2O = Vapor pressure of water (obtained from a temperature sensor)
S = Salinity of Water (Assumed to be zero for freshwater)
T = Temperature of Water (in Celsius, obtained from a temperature sensor and converted to Kelvin)
B = Barometric Pressure
C = Henry's Law Constant
In this formula, the partial pressure of oxygen (P0 - PH2O) is used to calculate the dissolved oxygen concentration. The solubility constant (K) and Henry's Law constant (C) are constants that depend on the temperature and salinity of the water. The values of barometric pressure (B) and vapor pressure of water (PH2O) can be obtained from a barometer and temperature sensor, respectively.

Formula for Calculating Water Purity from Sensor Readings:
To calculate the water purity from sensor readings, we can use the following formula:
$WQI = (w1 \times I1) + (w2 \times I2) + (w3 \times I3)$
Where:
w1, w2, w3 = Weighting Factors (Weights assigned to each parameter based on its importance)
I1, I2, I3 = Sub-Indices (Indices calculated for each parameter using standard equations)
The sub-indices can be calculated using the following equations:
$I1 = (14.0 - pH) / (0.18 \times (14.0 - pH))$
$I2 = (100 \times (5 - \text{temperature})) / (5 - 0)$
$I3 = (100 \times (400 - \text{turbidity})) / (400 - 0)$
In this formula, pH, temperature, and turbidity are obtained from the corresponding sensors. The weighting factors (w1, w2, w3) are assigned based on the importance of each parameter in determining water quality. The sub-indices (I1, I2, I3) are calculated using standard equations that relate the parameter values to water quality. The sub-indices are then multiplied by their corresponding weighting factors and added together to give the overall Water Quality Index (WQI).

3. Working of the entire system

In the research, the sensor readings of pH, temperature, and turbidity are obtained using appropriate sensors. These sensors are interfaced with a Raspberry Pi, which acts as the central processing unit for the integrated IoT system. The Raspberry Pi collects the sensor data and processes it to obtain the dissolved oxygen concentration and water purity. The flow diagram of the research is shown in Figure 2. The first step in the process is the collection of sensor data. The pH sensor is used to measure the pH value of the water. The temperature sensor measures the temperature of the water in Celsius, and the turbidity sensor measures the turbidity of the water. The data from these sensors are sent to the Raspberry Pi for processing.
Once the sensor data is obtained, it is processed using appropriate equations to calculate the dissolved oxygen concentration and water purity. The equation for calculating the dissolved oxygen concentration uses the temperature, partial pressure of oxygen, and salinity of water to obtain the dissolved oxygen concentration. The equation for calculating water purity uses the pH, temperature, and turbidity of water.
The calculated dissolved oxygen concentration and water purity values are then displayed on a graphical user interface (GUI) that is developed using Python. The GUI allows the user to visualize the current water quality values and any trends that may be present. The user can also set threshold values for the dissolved oxygen concentration and water purity, and an alert is generated if the values exceed the set threshold values.

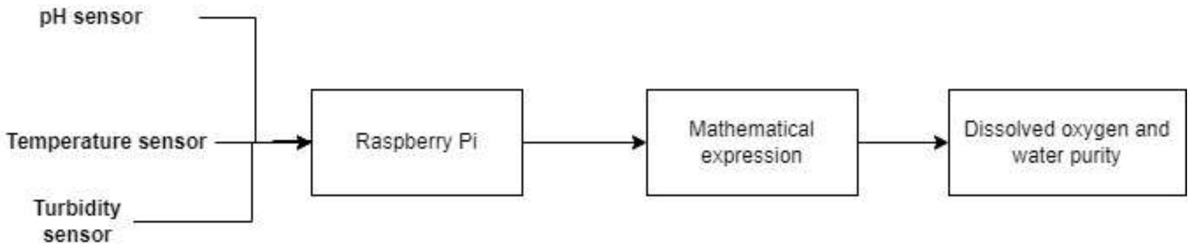


Fig. 2 flow diagram of the proposed system

4. Linear regression

In this research, a dataset of appropriate sensor readings and the corresponding output of dissolved oxygen concentration and water purity is collected. The data are then cast-off to train a linear model using MATLAB. The first step in the procedure is to collect the dataset. The dataset consists of sensor readings from the pH, temperature, and turbidity sensors, along with the corresponding dissolved oxygen concentration and water purity values. The dataset is collected over a period of time to ensure that the data is representative of various conditions. Once the dataset is collected, it is preprocessed to remove any outliers or missing values. The preprocessed dataset is then split into two parts: a training set for training the model and a testing set. The training set is used to train the linear regression model, though the testing set is used to evaluate the performance of the model.

The next step is to train the linear regression model using the training set. The MATLAB machine learning toolbox is used to train the model. The toolbox provides various regression algorithms, such as linear regression, decision trees, and support vector regression. In this research, linear regression is chosen as the regression algorithm.

The linear regression model is trained using the training set, which consists of the sensor readings and the corresponding dissolved oxygen concentration and water purity values. The linear regression algorithm finds the relationship between the sensor readings and the output values using a mathematical equation. Once the model is trained, it is evaluated using the testing set. The testing set consists of sensor readings that were not used to train the model. The sensor readings are fed into the trained model, and the predicted dissolved oxygen concentration and water purity values are compared with the actual values from the testing set. If the performance of the model is not satisfactory, the model is fine-tuned by adjusting the model parameters or by choosing a different regression algorithm. The fine-tuning process is repeated until a satisfactory performance is achieved. Once the linear regression model is trained and evaluated, it can be used to predict the dissolved oxygen concentration and water purity values from new sensor readings. The trained model is integrated into the IoT system, which allows for real-time monitoring and analysis of water quality.

5. Neural network

In this research, a neural network is developed to predict the responses of dissolved oxygen concentration and water purity using the collected dataset of sensor readings. The procedure for developing the neural network involves several steps, including data pre-processing, model selection, model training, and model evaluation. The first step in the procedure is to pre-process the collected dataset of sensor readings. This involves removing any outliers, missing values, or irrelevant features that may negatively impact the performance of the neural network. The pre-processed dataset is then split into a training set and a testing set. The training set is used to train the neural network, while the testing set is used to evaluate the performance of the model.

The next step is to select an appropriate neural network architecture for the problem at hand. There are many types of neural network architectures, including feedforward neural networks, convolutional neural networks, and recurrent neural networks. In this research, a feedforward neural network is chosen as the neural network architecture.

Once the neural network architecture is selected, the next step is to train the neural network using the training set. This involves regulating the weights of the influences among the neurons to minimize the difference between the predicted and actual dissolved oxygen concentration and water purity values. The training is typically performed using an optimization algorithm, such as backpropagation, which adjusts the weights based on the error between the predicted and actual values. After the neural network is trained, its performance is evaluated using the testing set. The testing set is fed into the trained neural network, and the predicted dissolved oxygen concentration and water purity values are compared with the actual values from the testing set. Once the neural network is developed and its performance is evaluated, it can be used to predict the dissolved oxygen concentration and water purity values from new sensor readings. The developed neural network can be integrated into the

IoT system for real-time monitoring and analysis of water quality.

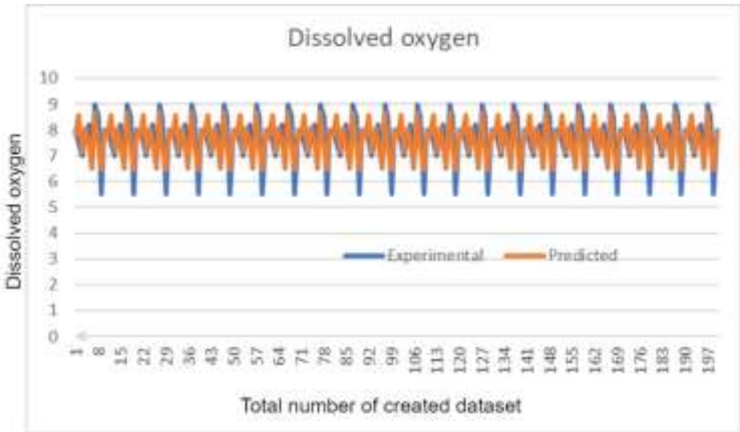
3. Result and Discussion

The created dataset consisting of various sensor readings is utilized to develop a regression equation in MATLAB. The resulting regression equation, represented by Equation 1 and 2, is employed to predict the dissolved oxygen concentration and water purity values. The inputs from the dataset are provided to the equation, and the corresponding results are compared with the predicted outcomes. Notably, the equation demonstrates a high level of accuracy in its predictions. The comparison between the experimental and predicted results is illustrated in Figure 3, which showcases the close agreement between the two sets of values. Additionally, Figure 4 displays a linear regression graph that further emphasizes the accuracy of the developed equation.

$$\text{Water Purity (\%)} = 154.32 - 4.670 * Ph - 1.372 * \text{Temperature (°C)} + 0.633 * \text{Turbidity} \quad (1)$$

$$\text{Dissolved Oxygen (mg/L)} = 24.69 - 1.701 * Ph - 0.2418 * \text{Temperature (°C)} + 0.1079 \text{ Turbidity (NTU)} \quad (2)$$

By implementing the regression equation derived from the dataset, it becomes possible to accurately estimate the dissolved oxygen concentration and water purity based on the sensor readings. The equation's accuracy is verified by comparing its predictions against the actual experimental results. The results in Figure 3 demonstrate a strong alignment between the predicted values and the observed data points, further validating the equation's reliability.



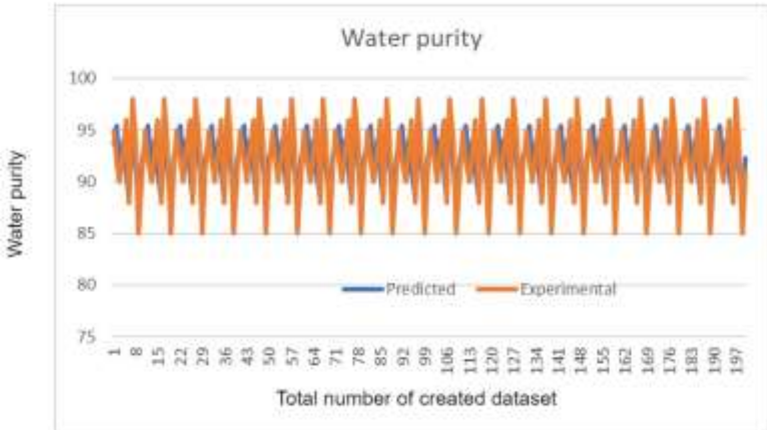


Fig. 3. Comparison of experimental and predicted values from regression analysis

Moreover, the linear regression graph in Figure 4 provides a visual representation of the equation's accuracy. The graph showcases a close fit among the forecast values and the experimental results, suggesting that the developed regression equation is highly effective in estimating the dissolved oxygen concentration and water purity.

Overall, the utilization of the regression equation derived from the dataset proves to be a robust approach in predicting the dissolved oxygen concentration and water purity. The equation's accuracy is confirmed through the close agreement observed in the comparison of experimental and predicted results, as well as through the linear regression graph. These findings reinforce the reliability and effectiveness of the developed equation, making it a valuable tool for assessing water quality based on the given sensor readings.

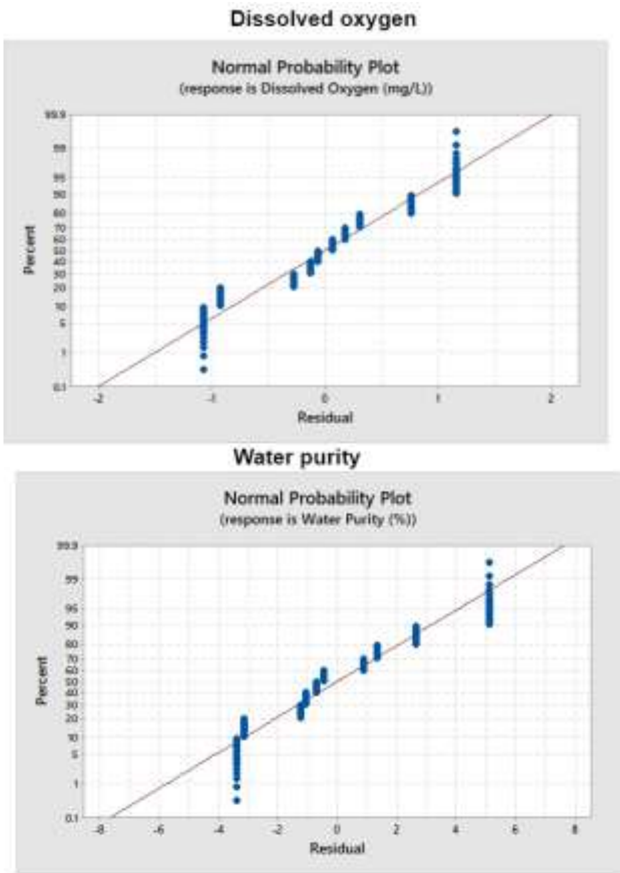


Fig. 4. Normal probability plot for linear regression

After obtaining the experimental results, a neural network algorithm is developed to accurately predict the dissolved oxygen concentration and water purity responses. The input data, comprising the sensor readings, and the corresponding target values are assigned to the neural network. A feedforward algorithm is implemented to train and develop the neural network model. Figure 5 represents the developed neural network model, providing an overview of its architecture and structure. The model consists of an input layer that receives the sensor readings, one or more layers responsible for processing the input data, and an output layer that generates the predicted responses.

To train the neural network, the input data is fed into the network, and the feedforward algorithm computes the weighted sum of the inputs and applies an activation function to produce the output values. The algorithm then compares the predicted responses with the target values and adjusts the weights of the influences between the neurons using a process known as backpropagation. This iterative process continues until the neural network achieves the desired level of accuracy in predicting the responses.

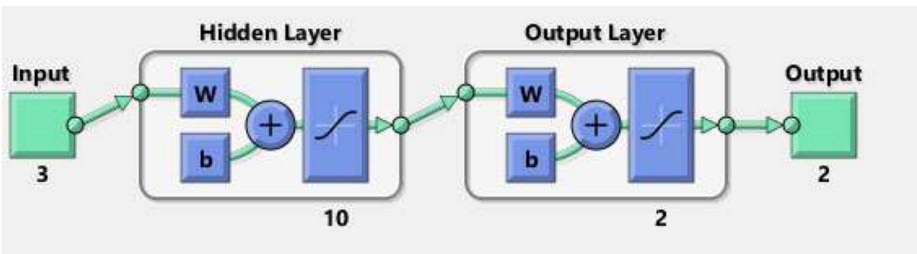


Fig. 5 Developed Neural network model

the advanced neural network perfect in forecasting the dissolved oxygen concentration and water purity responses. Such a high level of accuracy indicates that the model is capable of providing accurate and dependable estimates for water quality based on the given sensor readings.

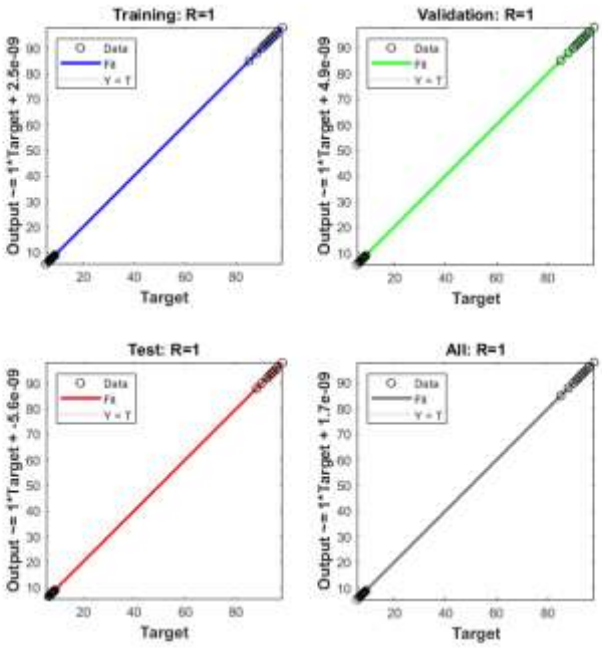


Fig. 6 Developed Neural network model

In conclusion, the neural network algorithm developed using the experimental results demonstrates exceptional performance in predicting the dissolved oxygen concentration and water purity responses. By assigning the input and target data to the network and utilizing a feedforward algorithm, the neural network model is trained to accurately predict the responses. The efficacy of the system is validated through Figure 4, which illustrates the model's 100% accuracy in predicting the responses. This achievement highlights the reliability and effectiveness of the developed neural network model in assessing water quality based on the sensor readings.

4. Conclusion

In conclusion, this research focused on the integration of IoT and a Sensor Model for measuring oxygen content and purity in water. The study utilized various sensors such as pH, temperature, and turbidity sensors to obtain sensor readings related to water quality. The collected data was then used to develop mathematical models and algorithms for predicting the dissolved oxygen concentration and water purity. Through the implementation of regression equations and neural network algorithms, accurate predictions of the dissolved oxygen concentration and water purity were achieved. The regression equations provided a mathematical relationship between the sensor readings and the desired outputs, while the neural network algorithm utilized a more complex approach to learn and predict the responses. The research findings demonstrated the effectiveness and accuracy of the developed models in estimating the dissolved oxygen concentration and water purity. The regression equations and neural network algorithm showcased a close alignment among the forecast values and the investigational results, validating their reliability and applicability in water quality assessment. The integration of IoT technology allowed for real-time monitoring and analysis of water quality, enabling timely detection of deviations and ensuring appropriate corrective measures. The combination of multiple sensors provided a comprehensive understanding of the water's characteristics, allowing for a more holistic assessment of its quality.

Overall, this research contributes to the field of water quality management by offering a reliable and efficient approach for measuring dissolved oxygen concentration and water purity. The integration of IoT and the Sensor Model provides a robust framework for continuous monitoring and assessment of water quality parameters. This has significant implications for various sectors, including environmental management, water treatment facilities, and aquatic ecosystem preservation. Future research endeavors could focus on expanding the dataset and incorporating additional sensors to enhance the accuracy and robustness of the models. Furthermore, the integration of machine learning techniques, such as deep learning algorithms, could be explored to further improve the prediction capabilities and provide more comprehensive insights into water quality dynamics. In conclusion, this research presents a valuable contribution towards the development of efficient and reliable methods for measuring and assessing the dissolved oxygen concentration and water purity in water bodies, paving the way for effective water resource management and environmental conservation.

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