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Rivers Monitoring System Using Deep Learning Technique

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Abstract

Purpose: The aquatic environment, including rivers and lakes, is crucial for the breeding and survival of fish and other animals.

Findings: However, these environments are vulnerable to both intentional and unintentional environmental pollution, which can have detrimental effects on the ecosystem and its inhabitants.

Methodology: Therefore, there is a pressing need for continuous monitoring of the aquatic environment to detect and address pollution in a timely manner. The challenge lies in establishing a monitoring system that can provide a continuous flow of information regarding the quality and health of the aquatic environment. Traditional monitoring methods often involve costly and time-consuming procedures, limiting their effectiveness in providing real-time data.

Recommendations: To address this, there is a demand for low-cost and timely sensor technologies that can be deployed extensively to monitor various parameters of the aquatic environment, such as water quality, pollution levels, and ecosystem health. The proposed system one step for developing and implementation a low-cost sensor technology that are capable of monitoring various parameters of the aquatic environment. To be established a robust and scalable monitoring system that can handle large-scale deployment of sensors in rivers and lakes.

Keywords: *Monitoring of The Water Environment, Wireless Sensors Networks, Data Nodes, Central Database Stations, Neural Networks*

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1.0 INTRODUCTION

The model's forecast implementation might be enhanced with the aid of water quality management, which includes monitoring data. A water quality prediction model might be employed in this study if modeling was practicable but a monitoring model wasn't or wasn't practical. The notion of merging monitoring and modeling models ahead of time might result in better data for about the same price [1-4]. If multiple management strategies are necessary, the construction of prediction models may also serve in analyzing and forecasting future water quality conditions. Wireless sensor networks (WSNs) have grown in popularity among researchers because they offer a promising architecture for a variety of control and monitoring applications [4-8].

These low-cost networks enable monitoring activities to be carried out remotely, in real time, and with little human participation. A typical WSN network is made up of two basic components: nodes and base stations [8-12]. "A node is a piece of equipment with sensing, processing, and communication capabilities that is in charge of measuring the variables associated with a specific application." The measurement data from the nodes must be gathered and made available by a base station, which may also provide gateway services to enable remote data administration. WSNs often use Wireless Personal Area Network (WPAN) or Low Power Wide Area Network (LPWAN). Area Network (LPWAN) standards, to relay measurement data to the base station.

IEEE 802.15.4, ZigBee, and GSM are among these standards. There is no one connection option that is regarded to be suitable for all WSNs, and the choice of a standard is completely based on the communication requirements and resource constraints of a specific application. These are common variables to consider when selecting a wireless connection solution. (WSN) technology can be used in many fields in Iraq [12-16], especially after the death of millions of fish in central and southern Iraq between December 31, 2018 and March 5, 2019, where these fish breeding projects exist in (Hilla, Al-Musayyab, Kufa, Diwaniyah, and the marshes), and cases of fish deaths can be avoided using (WSN) technology. Figure 1 depicts the fish farming initiatives in the aforementioned locations.

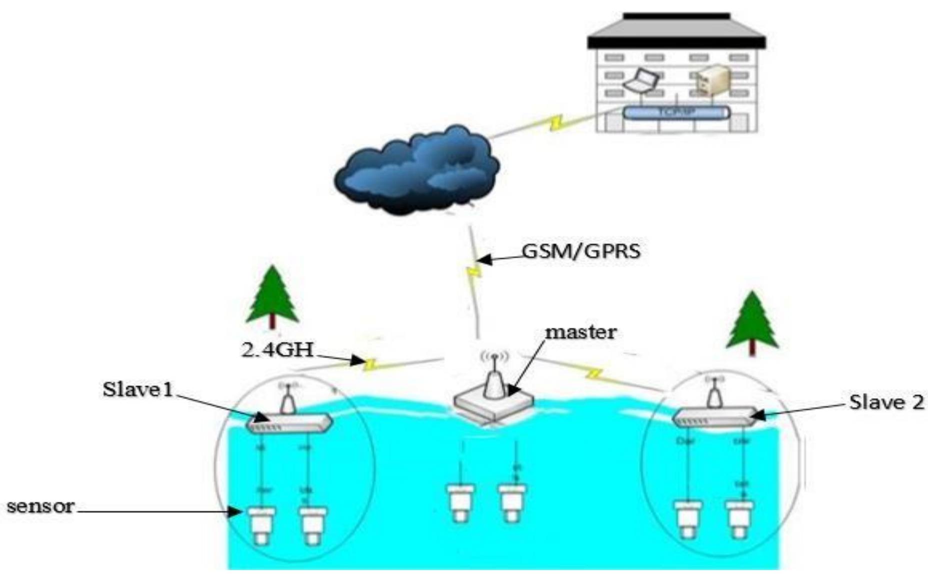

Figure 1: Wireless Sensors Networks

In this paper, the ecology of rivers and lakes has been studied through the use of wireless sensor networks (WSN). And with WSN technology, we were able to collect large amounts of data about the environmental conditions within these bodies of water in real time. In addition to studying the ecology of rivers and lakes through WSNs, an integrated system has been designed to collect and transmit this data in real time. This system consists of a network of spatially distributed sensors that are able to collect various physical and environmental conditions, such as temperature, turbidity, conductivity, and pH. The data collected by these sensors is then transmitted in real time through GPRS to a cloud-based platform for further processing and analysis.

Once the data is collected and transferred to the cloud, it is categorized using a multi-layered neural network (MLP). This network is trained to recognize patterns within the data and classify them according to various criteria, such as water quality, presence of certain types of plants and animals, and more. Overall, this research represents an important step forward in our understanding of the complex ecosystems found within rivers and lakes. Using WSN technology and a cloud-based MLP neural network, we have been able to collect and analyze large amounts of data about these ecosystems in real time, providing important insights into their health and performance.

Problem Formulation and Modeling Proposed System

The master node plays a crucial role as the central control unit in the proposed system for river monitoring. It encompasses the following hardware components, as depicted in Figure 2.

i. Mega 2650 PRO Microcontroller: This microcontroller acts as the central control unit for the river monitoring system.
ii. SIM800l GSM/GPRS Transceiver Unit: The SIM800l module enables communication through the cellular network, allowing the system to send and receive data.
iii. GPS NEO-M8N-0-10 Module: This module provides GPS functionality for location tracking.
iv. XL4015 Step-down DC-DC Converter: It converts the voltage from 12 volts to 5 volts, ensuring the stability of the system.
v. nRF24L01 Wireless Transceiver: The nRF24L01 module receives data from the slave nodes wirelessly.
vi. Channel 5V Optical Isolated Relay Module: This module is used for remote control of the master node's movement.
vii. pH Sensors: pH sensors measure the pH level of the river water, providing information about its acidity or alkalinity.
viii. TDU Sensors: TDU sensors measure the total dissolved units (TDU) or total dissolved solids (TDS) in the river water, indicating the amount of dissolved substances.
ix. Turbidity Sensor: The turbidity sensor measures the cloudiness of the water caused by suspended particles, offering insights into water clarity.
x. Temperature Sensors: Temperature sensors measure the temperature of the river water, providing information about its thermal characteristics.

2.0 FINDINGS

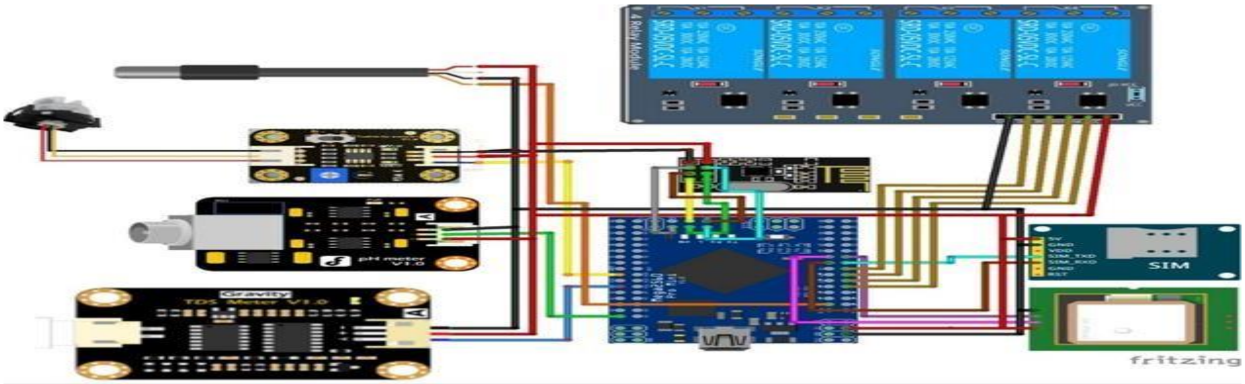

Figure 2: Shows the Basic Hardware Components in the Master

Data Transmission

The system collects data from the various sensors and sends it to the thinger.io platform. thinger.io is an IoT platform that facilitates cloud-based data storage, visualization, and analysis. It allows you to monitor and analyze the collected data remotely, the river monitoring system consists of a master unit with a Mega 2650 PRO microcontroller, various sensors (including pH, TDU, turbidity, and temperature sensors), Arduino Pro Mini processors for controlling the slave units, nRF24L01 wireless modules for communication between the master and slaves, and a SIM800l GSM/GPRS transceiver unit for data communication. The collected data is transmitted to the thinger.io platform for storage, analysis, and remote monitoring. As shown in the diagram, Figure 3.

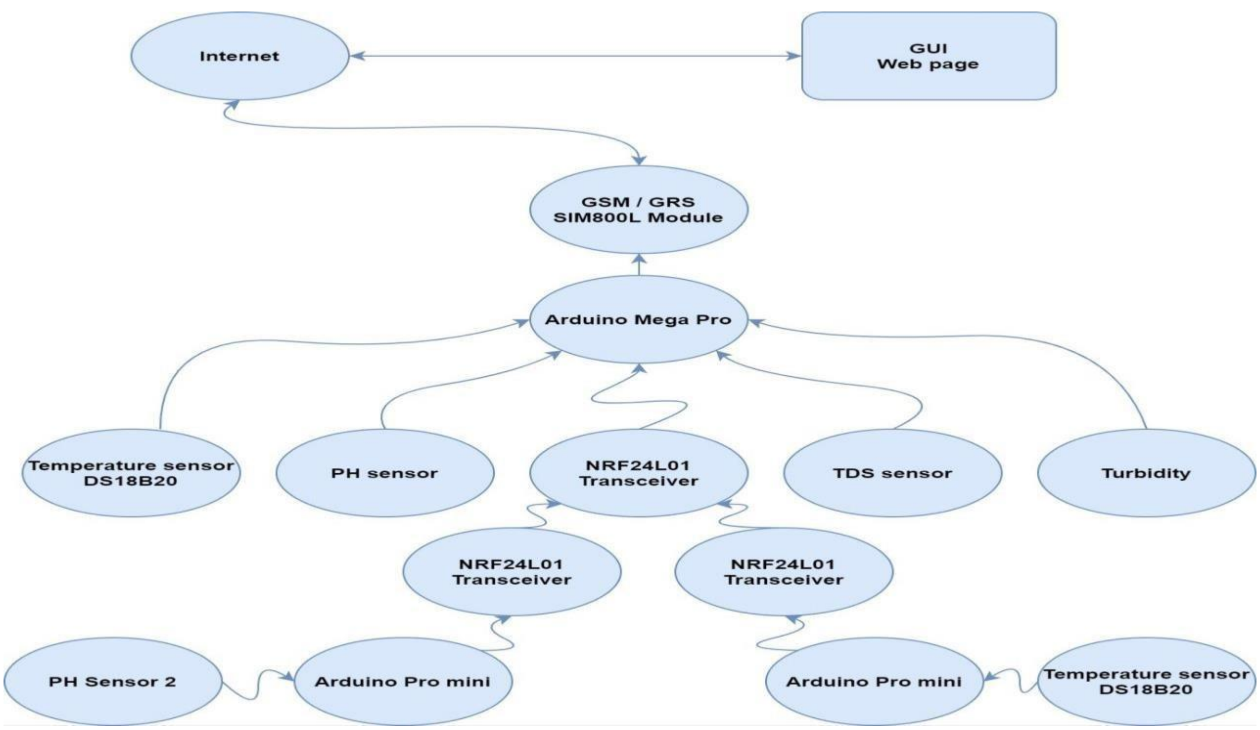

Figure 3: Schematic Diagram for the Proposed System

Simulation Setup and Simulation Results

A. Simulation Setup

The surge controller software is written in the Arduino programming language on the Arduino IDE. It is very similar to C/C++. The program code was written in the Arduino IDE, compiled on a local computer using the Arduino compiler, and the Arduino Due board was programmed using the Universal Serial Bus (USB). The priority of the river monitoring system is to collect and monitor data on river water quality parameters, such as pH, TDU (total dissolved units), turbidity, and temperature. It runs an IoT task and the system aims to provide accurate and real-time information about these parameters to assess the health and quality of river water.

By monitoring these key parameters, the system can help in early detection of any potential contamination or changes in water quality. This allows for immediate action to address any issues and ensure the protection of the river's ecosystem and the safety of surrounding communities that depend on the river as a source of water. In addition, the priority of the system is to transfer the collected data to the thinger.io platform, which enables remote monitoring, data storage, visualization, and analysis. This facilitates efficient data management and allows stakeholders to monitor river water quality trends, identify patterns, and make informed decisions based on the data collected to illustrate the data transmission process, refer to Figure 4, which presents the flowchart depicting the sequential steps involved in transferring the collected data.

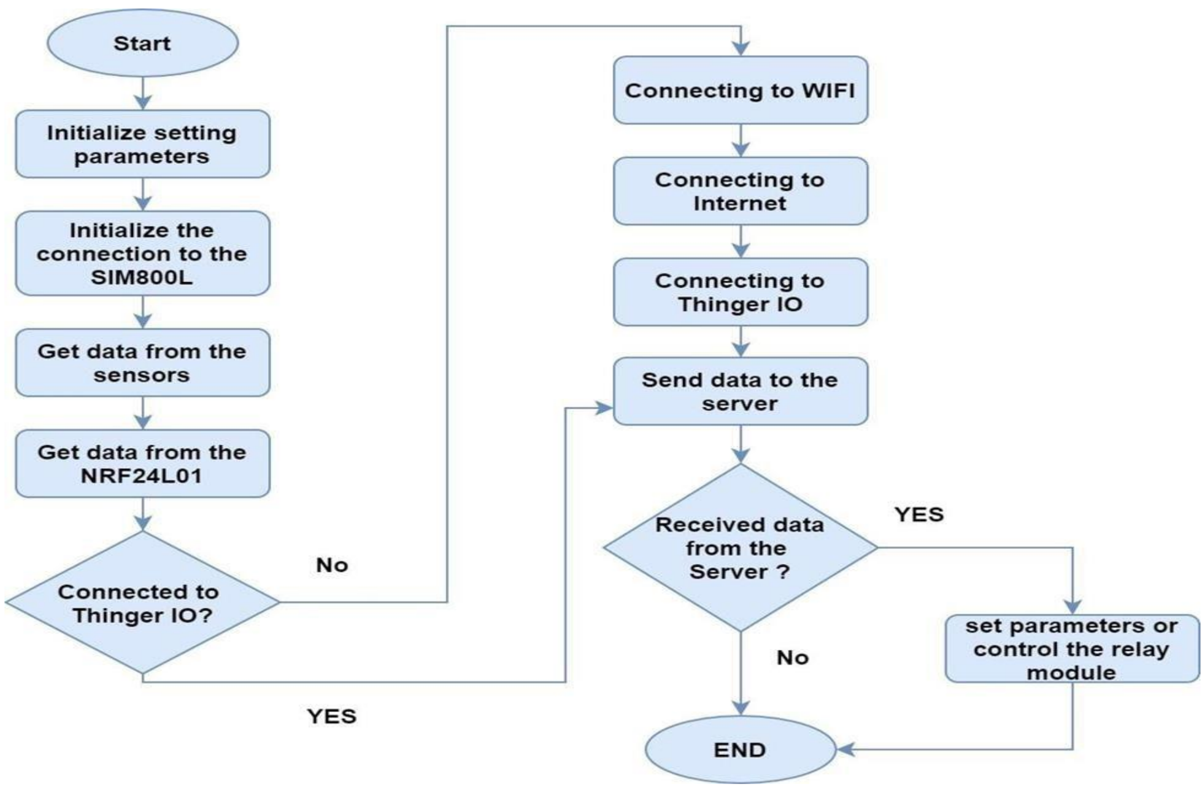

Figure 4: Flow Chart of the Wireless WSN System

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B. Simulation Results

The (pH, temperature, turbidity, and conductivity) for 60 samples are represented in MATLAB. The samples differed, as samples were taken from pure water, as shown in Figure 5, and samples were taken from the water of the Husseiniya River in Karbala, and as shown in Figure 6. These samples represent the sensor readings over time.

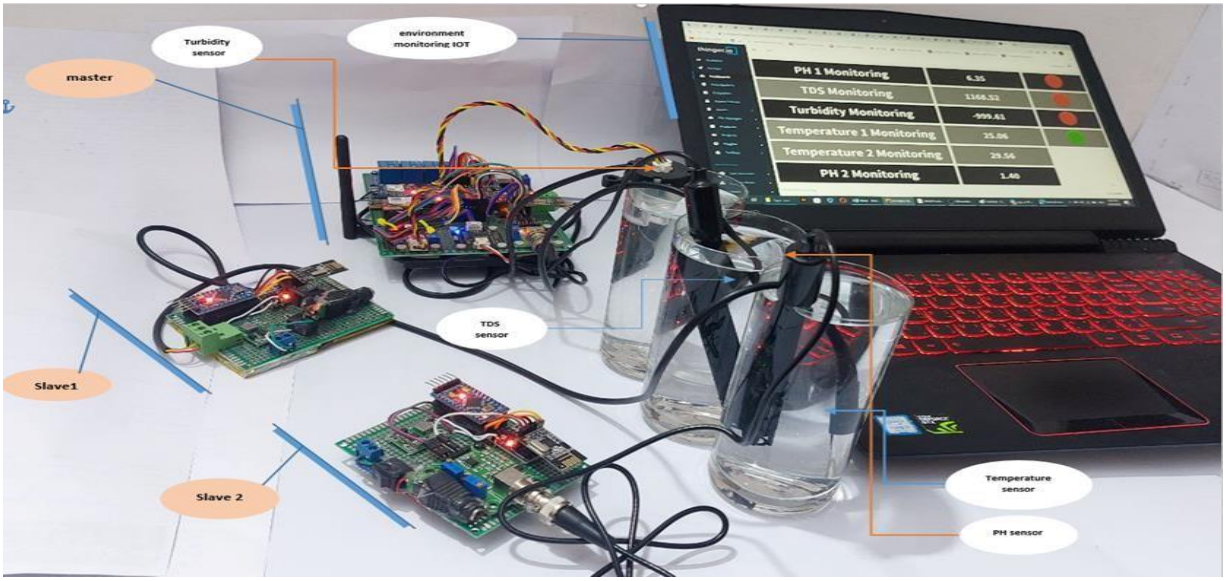

Figure 5: Shows How to Take Samples from Pure Water

Figure 6: Shows How to Take Samples from Husseiniya River in Karbala

Figure 7 shows the pure water pH sensor readings over time. The x-axis represents time in minutes (0 to 60 minutes), and the y-axis represents pH values (ranging from 1 to 14). The continuous blue line depicts the pH trend, while filled red circles indicate individual pH sensor readings at specific time points. Gridlines assist in aligning data points. Legend: 'curve' represents the blue line (pH sensor readings) and 'data points' represent the red circles (individual measurements).

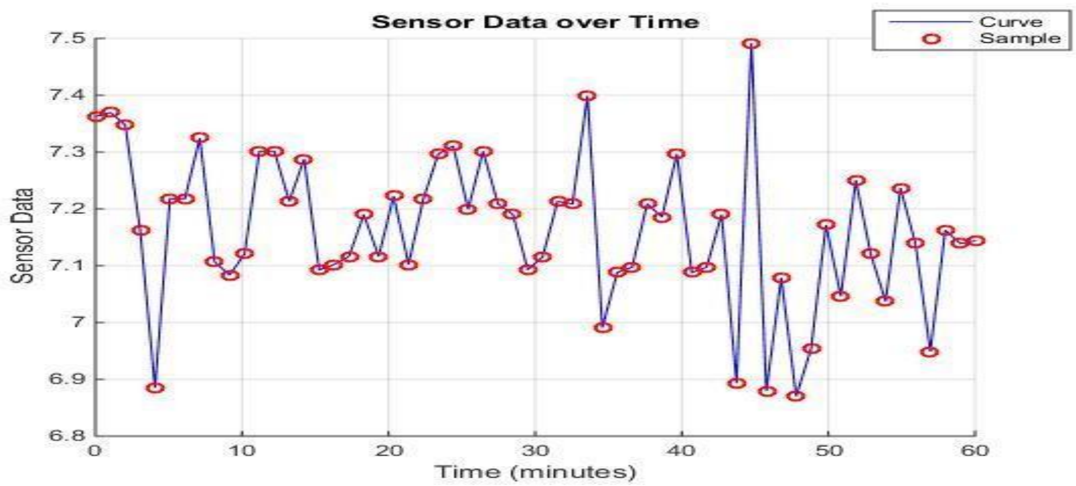

Figure 7: Pure Water Time Series Signal

The results are shown in Figure 7 for the case of the sensors. This data is used as input for a workbook file. When using this data, which are represented by four parameters where these samples are pure water (PH, T, D, NTU) with ANN, where the data of the four parameters is in the input layer, 30 nodes in the hidden layer and four exit as shown in Figure 8.

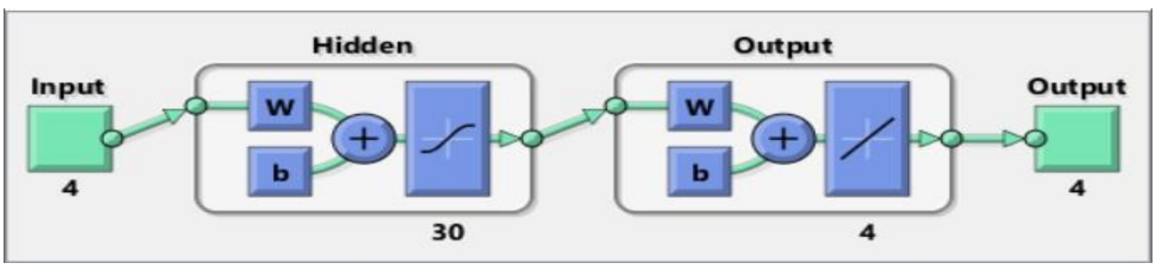

Figure 8: The ANN Structure Uses Four Inputs and Thirty Hidden Cells with Four Outputs

In the training phase, the train data is set by a very small percentage of the data set. The mean squared error characteristic of each period The training steps are shown in Figure 9.

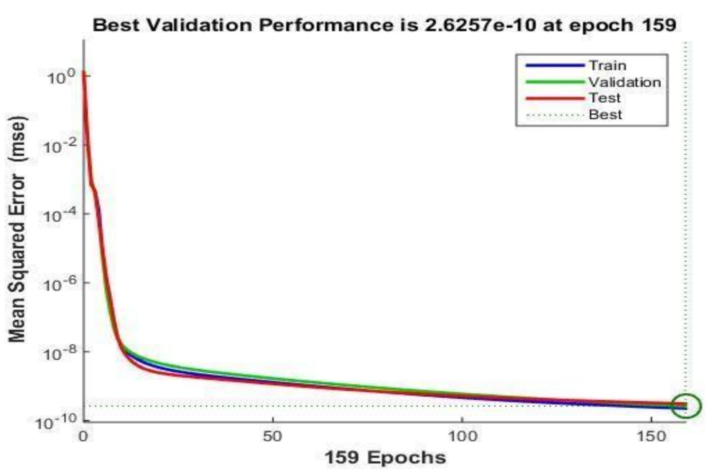

Figure 9: The Mean Squared Error for Each Period in the Training Stage

From Figure 9 it is clear that the mean squared error (MSE) reaches the point it did A value less than 0.0000001 means that the training process is going well and all signals are running It is saved in the neural network as a weight. The error graph is shown in the Figure 10.

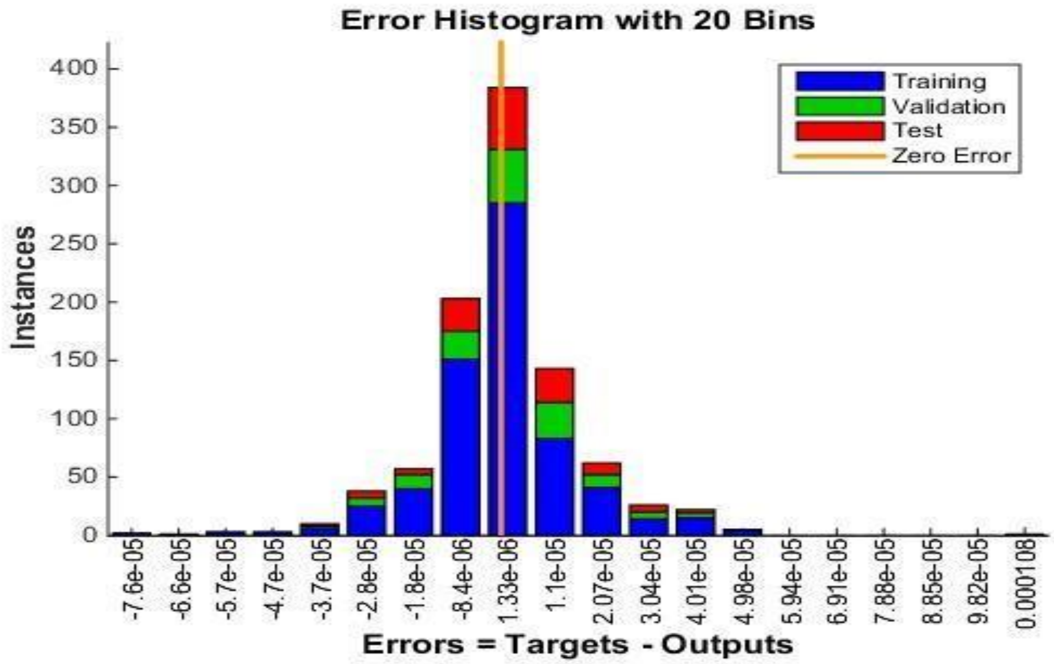

Figure 10: The Histogram of the Error

3.0 CONCLUSION AND RECOMMENDATION

A wireless sensor network (WSN) is a network of interconnected sensors that communicate wirelessly to collect and transmit data. In the context of water quality monitoring, a WSN can be deployed to monitor various parameters such as temperature, pH levels, turbidity, and conductivity. The sensors in the WSN are strategically placed in different locations, such as rivers, lakes, or water treatment facilities, to gather real-time data on water quality. These sensors can be equipped with IoT capabilities, allowing them to connect to the internet and transmit the collected data to a central server for analysis and interpretation. The use of a WSN for water quality monitoring offers several advantages. Firstly, it enables continuous and remote monitoring of water bodies, providing a more comprehensive understanding of water quality dynamics.

Secondly, it allows for timely detection of anomalies or changes in water quality, facilitating quick response and mitigation actions. Finally, the deployment of a WSN can lead to cost savings compared to traditional manual sampling and laboratory testing methods. The data collected by the WSN can be further analyzed using various techniques, including artificial intelligence (AI) approaches such as machine learning and deep learning. These techniques can help identify patterns, correlations, and trends in the data, enabling the development of predictive models for water quality assessment. For example, machine learning algorithms can be trained on historical data to predict the future behavior of water quality parameters based on current conditions. Overall, the combination of a wireless sensor network and AI technologies offers a powerful solution for monitoring and managing water quality. It allows for real-time data collection, analysis, and prediction, enabling timely decision-making and proactive measures to ensure the safety and sustainability of water resources.

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