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Developing Autonomous Sensor Networks forReal-Time Monitoring of Water Quality Parameters

B. Shivani [1], Ch. Shanjana [2], D. Venukumari [3], Dr.Mrs. N. Sowmya[4]
[1,2,3] UG Scholar, Dept. of ECE, St. Martin's Engineering College, Secunderabad, Telangana, India, 500100
[4]Assistant Professor, Dept. of ECE, St. Martin's Engineering College, Secunderabad, Telangana, India, 500100
shivanibaddam6@gmail.com

Abstract:

Water quality management is a critical concern in ensuring environmental sustainability, public health, and industrial processes. Historically, water quality monitoring has relied on manual sampling and laboratory analyses, that are time-consuming, labor-intensive, and incapable of providing real-time insights. Traditional systems for water monitoring typically involve basic sensor-based technologies with limited data processing capabilities, often failing to address dynamic environmental changes and detect anomalies promptly. However, these systems face significant limitations, including inadequate scalability, high maintenance costs, and an inability to process large, complex datasets efficiently. Additionally, the reliance on static thresholds for decision-making in traditional systems often results in delayed responses to water quality issues. With the growing concerns over industrial pollution, climate change, and population pressures, there is an urgent need for real-time, autonomous solutions that can deliver accurate, continuous monitoring and predictive analytics. This study focuses on developing autonomous sensor networks powered by deep learning for real-time monitoring of water quality parameters, including pH, turbidity, dissolved oxygen, and temperature. The proposed system employs advanced sensors, edge computing, and deep learning algorithms trained on extensive datasets to detect anomalies, predict trends, and enable automated decision-making. By addressing the limitations of traditional systems, this innovative framework enhances the accuracy, scalability, and cost-effectiveness of water quality monitoring. The significance of this research lies in its ability to provide timely interventions, promote sustainable water resource management, and mitigate risks to ecosystems and public health. The integration of deep learning with sensor networks represents a paradigm shift, enabling smarter, adaptive, and resilient water monitoring systems that align with the goals of environmental conservation and technological advancement.

1. INTRODUCTION

The traditional approach to water quality measurement (WQM) requires manual water sampling to determine the quality of water through analysis. This process involves the collection of water samples by humans for in situ testing by lab technicians in laboratories. While this process does not enable instantaneous WQM, it has been considered to be the most feasible solution. Research has generally been focused on improving laboratory techniques in analyzing water quality and the introduction of sampling-site laboratories near water bodies to make monitoring more efficient using existing techniques.

It is apparent that the existing WQM techniques have shortcomings. These flaws can be broadly classified as either human error in the collection of samples, during analysis, and during the recording of data or improper lab equipment and its handling in the same processes. Furthermore, there can be cross-contamination in water samples. These methods of WQM are neither instantaneous nor timely, leading to a delayed response in the case of an emergency. Recently, there has been an uptake on the application of wireless sensor networks (WSNs) in water quality monitoring. These methods are improving with time and keep advancing with improvements in technology and communication protocols. The WSN's ability to capture, analyze, transmit, and display water quality data has proven to be effective and instantaneous. The WSN nodes can obtain, process, and transmit water quality parameter data instantaneously using low-power communication techniques, low-cost sensors for obtaining data, and low-power circuitry.

Water quality is a critical global concern, directly influencing human health, aquatic ecosystems, and industrial processes. Conventional methods of water quality monitoring rely on manual sampling and laboratory analysis, which are time-consuming, labor-intensive, and provide delayed results. These traditional methods cannot offer real- time monitoring, making them inadequate for dynamic environments where water quality fluctuates rapidly. Autonomous sensor networks have emerged as an alternative for real-time monitoring. However, these systems face challenges like limited sensor battery life, data accuracy, and integration of large-scale data. Predicting and optimizing the battery life of these sensors is crucial to ensure uninterrupted monitoring and reduce maintenance costs. Furthermore, the high volume of data generated by these networks requires robust machine learning techniques to extract actionable insights. Addressing these challenges by combining sensor networks with advanced deep learning techniques is essential for developing an efficient, real-time water quality monitoring system.

2. LITERATURE SURVEY

Pasika and Gandla [1] proposed a monitoring system which consists of a number of sensors used to measure several quality parameters like turbidity, pH value, water level in the tank, dampness of the adjoining environment and temperature of the water. Mukta et al. [2] developed an IoT based Smart Water Quality Monitoring (SWQM) system which helps in incessant measurement of quality of water on the basis of four different parameters of water quality i.e., pH, temperature, turbidity and electric conductivity. On the basis of the collected data from sensors, the developed SWQM model will efficaciously examine the water quality parameters by employing fast forest binary classifier for classification of the sample of water under test is whether potable or not. Konde and Deosarkar [3] proposed a method for developing a Smart Water Quality Monitoring (SWQM) system with reconfigurable sensor interface device using IoT environment. Sensors. The SWQM system reduces the cost and time in determining the quality of water in water

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resources as part of managing environmental and ecological balance. In the suggested future work, WSN network will be developed involving of additional number of nodes to encompass the coverage area. Amruta and Satish [4] proposed a Solar Powered Water Quality Monitoring system by employing wireless Sensor Network. This developed novel water quality monitoring system has various advantages like consumption of less power, no carbon emission. Sughapriya et al. [5] developed a method for determining the quality of water using IoT and different sensor modules. This system uses different sensors for monitoring the water quality by determining pH, turbidity, conductivity and temperature. Unnikrishna Menon et al. [6] proposed a method for water quality monitoring in rivers which is developed based on wireless sensor networks that aids in incessant and remote monitoring of water quality parameters. In this system, wireless sensor node is designed to monitor the pH of water continuously, which is the key parameter that affects the water quality. Jerom B. et al. [7] proposed a Smart Water Quality Monitoring System based on IoT using Cloud and Deep Learning methods for monitoring the water quality of various water resources. In traditional methods, the procedure of monitoring implicates collecting the sample of water manually from different water resources, trailed by testing and analysis in the laboratory. Geetha et al [8] developed a low powered and naiver solution for monitoring quality of in-pipe water based on IoT. The developed model is used to test samples of water and the data collected from the sensors is uploaded over the internet is analyzed. This model is less complex and low cost smart water quality monitoring system with a core controller having built-in Wi-Fi module for monitoring quality parameters like turbidity, conductivity and pH. Sengupta et al. [9] proposed a cost effective technique for monitoring water quality and controlling in real-time using IoT. Kumar et al [10] proposed a cost effective system to monitor quality of water in real-time using IoT. The designed system used various sensors to measure the chemical and physical parameters of the water. This smart water quality system consists of a Raspberry pi controller interfaced with various sensors like pH sensor, turbidity sensors, temperature sensor and water level sensors. These sensors control the entire operation and monitoring is done by Cloud based wireless communication devices. Demetillo et al. [11] proposed a cost effective and water quality monitoring system in real-time that can be used in remote lakes, rivers and other water resources. The major hardware in the system comprises of a microcontroller, standard electrochemical sensors, a customized buoy and a wireless communication system. The developed system is capable of detecting pH, dissolved oxygen and water temperature at pre-programmed periodic intervals. The results of the experiment proved that the developed system has higher anticipation and could be employed for monitoring environment practically by giving end-users with pertinent and well-timed information for better action plan. Anuradha et al. [12] developed a cost effective system for monitoring the quality of water in real- time using IoT. The developed method is a sensor based Water Quality Monitoring System that is used to measure chemical and physical parameters of water.

3. PROPOSED METHODOLOGY

The project focuses on developing an autonomous sensor network for real-time monitoring of water quality parameters using deep learning. It bridges the limitations of traditional water quality monitoring systems by leveraging advanced data processing, predictive modeling, and energy optimization techniques.
Traditional methods for water quality monitoring are manual, slow, and resource-intensive. Automated systems often lack intelligence for real-time monitoring, dynamic adaptation, and predictive analytics. Battery life and energy efficiency of sensors remain a significant challenge in real-world deployments.
Real-Time Monitoring: Continuously monitor parameters like pH, turbidity, and dissolved oxygen using sensor networks.
Deep Learning Integration: Enhance predictive accuracy for key metrics like battery life and water quality trends.
Energy Optimization: Develop models to predict and extend the battery life of deployed sensors.
Feature Extraction: Use techniques like autoencoders and fuzzy clustering to reduce redundancy and improve decision-making.

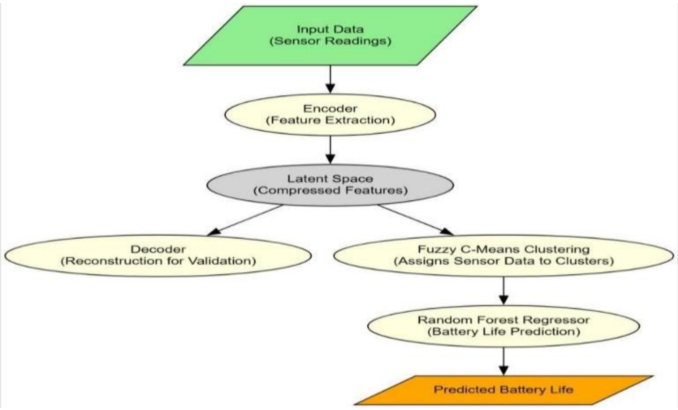

Fig 3.1: Proposed system

3.2 Workflow

1. Data Collection & Sensor Network Setup
Deploy sensors in water bodies (e.g., lakes, rivers, reservoirs) to collect real-time water quality data, including parameters like: pH, turbidity, temperature, dissolved oxygen, conductivity, pollutants (e.g., heavy metals, nitrates), and other relevant metrics. Sensors send data to a central system or server periodically.

2. Data Preprocessing & Cleaning
Data Loading: Import the dataset that contains the water quality data collected by the sensors (e.g., from a CSV file).

Data Cleaning**:** Remove duplicates and handle missing data (impute or drop rows/columns with NaN values).

Label Encoding: Convert categorical features (e.g., water quality types, location names) into numerical values using Label Encoder.

Scaling Features: Apply Standard Scaler to normalize the data and ensure all features are on the same scale.

3. Feature Engineering & Extraction
Autoencoders for Feature Extraction: Train an autoencoder model to extract meaningful and compact features from the raw sensor data.
Encoder part of the autoencoder is used to generate low-dimensional feature representations (latent space).

Fuzzy C-Means Clustering: Apply Fuzzy C-Means clustering to the encoded features from the autoencoder to group similar data points together. Assign each data point to a cluster based on the highest membership value.

4. Model Training
Define and Train Multiple Models**:**
Gradient Boosting Regressor (GBR)
XGBoost Regressor
MLP Regressor (Neural Network)
Random Forest Regressor with Fuzzy C-Means Autoencoder-based Feature Extraction

Split Data into Training and Testing: Use train_test_split to divide the dataset into training and test subsets.
Train Models: Train the models on the training dataset and evaluate them based on their ability to predict the water quality parameters or battery life.
Hyperparameter Tuning (Optional): Use Grid Search CV or Randomized Search CV to fine-tune model parameters and improve prediction accuracy.

5. Model Evaluation & Metrics Calculation
Evaluation Metrics: For each trained model, calculate the following performance metrics:
Mean Squared Error (MSE)
Mean Absolute Error (MAE)
R^2 Score (coefficient of determination)

Visualization: Plot Predicted vs Actual values using scatter plots for each model to visualize prediction performance.

6. Model Saving & Reusability
Save Models: Once the models are trained, save them using joblib so that they can be reused later without retraining.
Models are saved to specific paths for future deployment.

Load Models (for prediction): If the models already exist (pre-trained), load them directly for prediction without retraining.

7. Test Data Evaluation
Test Data Processing: Load the test dataset (separate data not used in training). Apply the same preprocessing steps (scaling, encoding) to the test data as was done with the training data
.
Feature Extraction**:** Extract features from the test data using the encoder model (autoencoder).

Fuzzy C-Means Clustering: Apply Fuzzy C-Means clustering to the encoded test features and assign cluster labels.

Model Prediction: Use the trained models (e.g., GBR, XGBoost, MLP, Random Forest) to predict water quality parameters on the test dataset. Append predicted values to the test data for comparison.

8. Performance Comparison & Selection
Compare Model Performance: Review the evaluation metrics (MSE, MAE, R^2) for each model. Select the best-performing model based on the lowest error (MSE, MAE) and highest R^2 score.

Visualize Results: Use scatter plots to compare predicted vs. actual values for the test data and model predictions.

9. Deployment for Real-Time Monitoring
Deploy the Model: Once the best model is selected, deploy it to the sensor network system. Sensor nodes continuously monitor water quality and send real-time data to a central system.

Make Real-Time Predictions: The deployed model uses the incoming sensor data to predict water quality parameters or detect anomalies in real-time.

4. EXPERIMENTAL ANALYSIS

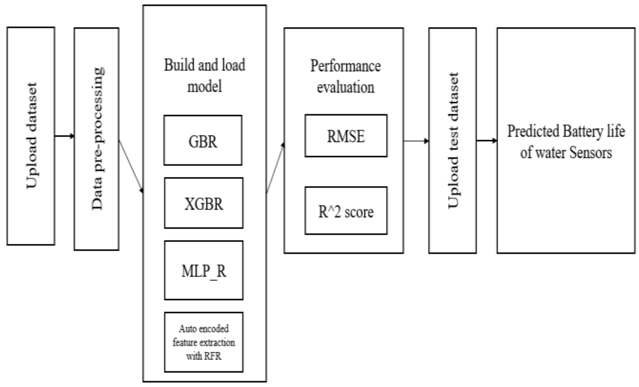

Fig- 4.1 Block Diagram

The project focuses on developing an autonomous sensor network for real-time monitoring of water quality parameters using deep learning. It bridges the limitations of traditional water quality monitoring systems by leveraging advanced data processing, predictive modeling, and energy optimization techniques.

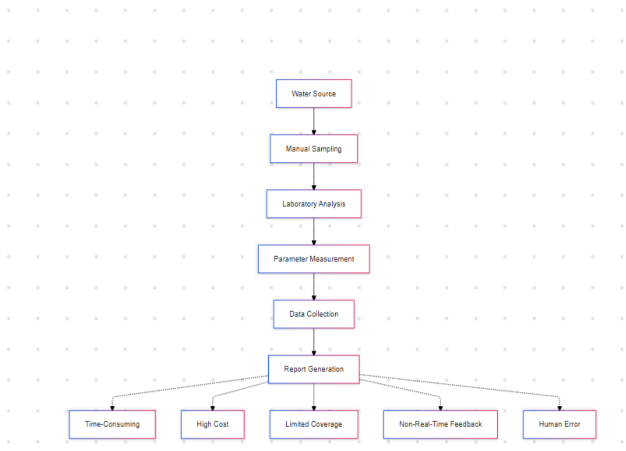

Fig- 4.2 Flow Diagram

Deploy sensors in water bodies (e.g., lakes, rivers, reservoirs) to collect real-time water quality data, including parameters like pH, turbidity, temperature, dissolved oxygen, conductivity, pollutants (e.g., heavy metals, nitrates), and other relevant metrics.

Sensors send data to a central system or server periodically.

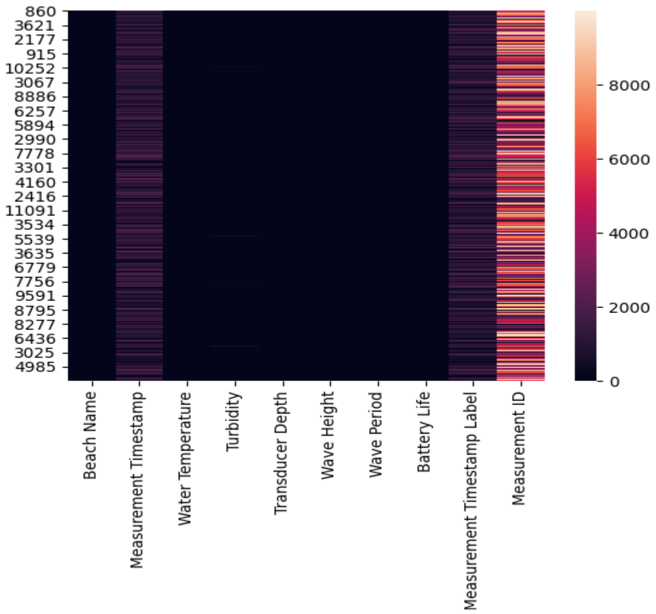

Fig 4.1: correlation heat map of the dataset

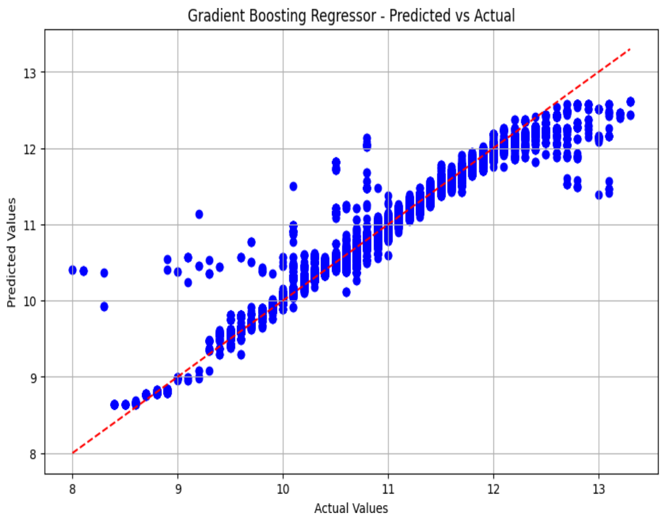

Fig 4.2: Scatter plot of true and predicted values obtained using GB regressor model

The above figure shows the whole dataset after uploading. This is the first step of the data preprocessing.

A correlation heatmap is a data visualization tool that displays the correlation coefficients between various features of the dataset. In the context of the project, the correlation heatmap is used to understand the relationships between different features (independent variables) in the dataset and the target variable as well as between each pair of features. The purpose of the correlation heatmap is to visually capture the degree to which these features are correlated with each other and with the motor speed. This helps identify which features might be most relevant for forecasting the motor speed. R^2-score (Coefficient of Determination): The R^2 score is a statistical measure that represents the proportion of the variance in the dependent variable that's explained by the independent variables in a regression model. It ranges from 0 to 1, where higher values indicate that the model's predictions closely match the actual data. An R^2 score of 1 indicates a perfect fit. scatter plot likely visualizes the performance of a GBR model. In this plot, each point represents a data instance. The x-axis represents the true values (actual observations) of the target variable, while the y-axis represents the predicted values of the target variable made by the Ridge model. Each point on the plot corresponds to a data instance, where its position relative to the diagonal line (which represents a perfect prediction) indicates how well the model's predictions align with the

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actual data. If the points are close to the diagonal line, it suggests thatthe model's predictions are accurate.

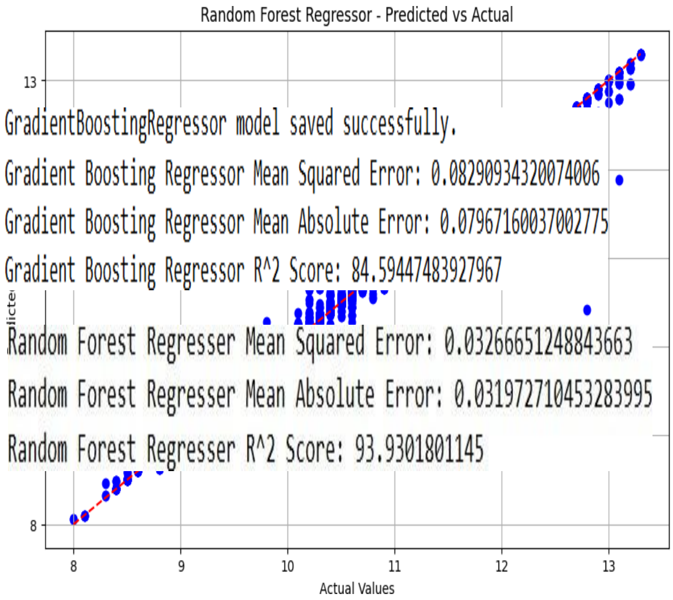

Fig 4.3: Scatter plot of true and predicted values obtained using Random Forest regressor model

Fig 4.4: R^2 of GB Regressor

The provided code is an end-to-end pipeline for developing and deploying a predictive model to monitor water quality parameters, specifically focused on predicting "Battery Life" based on various features.

Fig 4.5: R^2 of Random Forest Regressor

The design and development of water quality monitoring system demonstrates its capability to achieve more efficient and reliable outputs. The system is mainly focused on analyzing the water quality with 98% accuracy in real time. The observations of the indoor tests show that the output produced is almost precise and reliable. On the other hand, the outdoor test results shows the system efficiency for a broad spectrum of water bodies. The proposed system is portable and handy to use and does not require any higher level of expertise on the operation. The system is most suited for water bodies and places where humans cannot approach physically.FCM is a clustering algorithm where each data point can belong to multiple clusters with varying degrees of membership (fuzziness).It divides the data into CCC clusters, assigning each data point a membership value that sums to 1 across all clusters.Purpose in this pipeline: FCM is used to preprocess and transform the input space, enabling the system to capture the inherent structure and patterns in the data before autoencoder-based feature extraction.

	index	Beach Name	Measurement Timestamp	Water Temperature	Turbidity	Transducer Depth	Wave Height	Wave Period	Battery Life	Measurement Timestamp Label	Measurement ID
0	0	Montrose Beach	08/30/2013 08:00:00 AM	20.3	1.18	0.891	0.080	3.0	9.4	8/30/2013 8:00 AM	MontroseBeach201308300800
1	1	Ohio Street Beach	05/26/2016 01:00:00 PM	14.4	1.23	NaN	0.111	4.0	12.4	05/26/2016 1:00 PM	OhioStreetBeach201605261300
2	2	Calumet Beach	09/03/2013 04:00:00 PM	23.2	3.63	1.201	0.174	6.0	9.4	9/3/2013 4:00 PM	CalumetBeach201309031600
3	3	Calumet Beach	05/28/2014 12:00:00 PM	16.2	1.26	1.514	0.147	4.0	11.7	5/28/2014 12:00 PM	CalumetBeach201405281200
4	4	Montrose Beach	05/28/2014 12:00:00 PM	14.4	3.36	1.388	0.298	4.0	11.9	5/28/2014 12:00 PM	MontroseBeach201405281200

Fig:4.6 Result of dataset

5. CONCLUSION

The design and development of water quality monitoring system demonstrates its capability to achieve more efficient and reliable outputs. The system is mainly focused on analyzing the water quality with 98% accuracy in real time. The observations of the indoor tests show that the output produced is almost precise and reliable. On the other hand, the outdoor test results shows the system efficiency for a broad spectrum of water bodies. It is a versatile system, because of which simply by replacing the sensors and by making some changes with in the computer code, the system can be used to measure other parameters of water as well. The system is reliable and easy to maintain and it can be extended to measure water pollution as well. The model gave a fairly good idea of how the system can be implemented in several types of water bodies keeping the same design language and prospectus in mind. The proposed system is portable and handy to use and does not require any higher level of expertise on the operation. The system is most suited for water bodies and places where humans cannot approach physically.

In the future, parameters like conductivity, hardness, chloride, ammonia, iron, fluoride, etc. can also be considered for water quality measurement and these values are used to verify water purity for many reasons such as drinking water and daily requirements. The system can be improved more with further testing in different terrains and casing body made of material that is light strong and durable. For long range communication, the strategy is to implement a Php MySQL database and the data will be fed to the hosted website so any one from anywhere can have the real time data access.

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