Real-Time IoT-Enabled Water Quality Monitoring and Groundwater Availability Analysis Using Machine Learning

Project ID : W11

Capstone Project Phase 2

Capstone Project Phase ISA 1

Team Composition

Sl.No.	Name	SRN	Photo
1	Abhishek A Shetty	PES1UG21EC008	
2	Akash Chanabasu Katate	PES1UG21EC022	
3	Akash Ravi Bhat	PES1UG21EC025	
4	Tejas V P	PES1UG21EC910	

Guide : Prof. NAGARAJ L J

Outline of Presentation

- Introduction & Motivation
- Literature Survey
- Objectives
- Problem Statement
- Methodology
- Work Progress
- Required Hardware / Software details
- Results and Analysis
- Project Deliverables
- References
- Project timeline Gantt Chart

Introduction & Motivation

- Water pollution poses serious threats to ecosystems and public health
- Existing monitoring methods lack real-time data monitoring.
- Integrated approach using sensors to monitor water pollution, analysing the ground level water addressing these shortcomings effectively.
- The urgent need to enhance water quality monitoring drives this research.
- With pollution incidents on the rise, there's a huge demand for innovative solutions that offer real time data.
- Developing sensor networks, this study aims to bridge current monitoring gaps, empowering stakeholders with actionable data to reduce pollution risks.

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[1] K. Banerjee et al., "Assessing Water Quality Index Near Industrial Regions and Aiding in Effective Water Management and Controlling Water Pollution Level," 2022 5th International Conference on Contemporary Computing and Informatics (IC3I), Uttar Pradesh, India, 2022, pp. 1987-1991

Author's work	The author emphasizes the correlation between industrial waste discharge and changes in crucial water quality parameters, such pH level, and temperature, highlighting their collective influence on altering the Water Quality Index (WQI)
Inference	• This research presents an IoT-based solution for real-time water pollution monitoring. • The system aims to improve water quality management by providing timely alerts to authorities.
Limitations	• The study does not incorporate machine learning algorithms for advanced data analysis and predictive modeling. • The absence of machine learning techniques may limit the system's ability to provide deeper insights and predictive capabilities for water quality management.

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[2] Md. Jahirul Islam, Asaduzzaman, "Smart Water Quality Monitoring and Controlling System", 5th International Conference on Electrical Information and Communication Technology (EICT), 17-19 December 2021, Khulna, Bangladesh

Author's work	The paper introduces the problem of water contamination monitoring and the need for an IoT-based smart system to measure and alert the water quality parameters in real time.
Inference	The paper introduces an IoT-based water quality monitoring and control system, leveraging various sensors to monitor parameters like flow, pH, turbidity, and temperature in real-time. It highlights the system's ability to automate processes such as tank cleaning and send alerts for substandard water quality. Experimental results demonstrate a promising accuracy of 93% in detecting water quality issues. The system is cost-effective, utilizing low-cost components, with potential for further enhancement using industrial-grade sensors. Overall, the paper underscores the significance of IoT technologies in addressing global water quality challenges.
Limitations	One limitation is the potential accuracy compromise due to the use of low-cost components, while environmental factors like weather may affect sensor performance. Additionally, scalability and adaptation to diverse water quality standards and cybersecurity vulnerabilities are unaddressed.

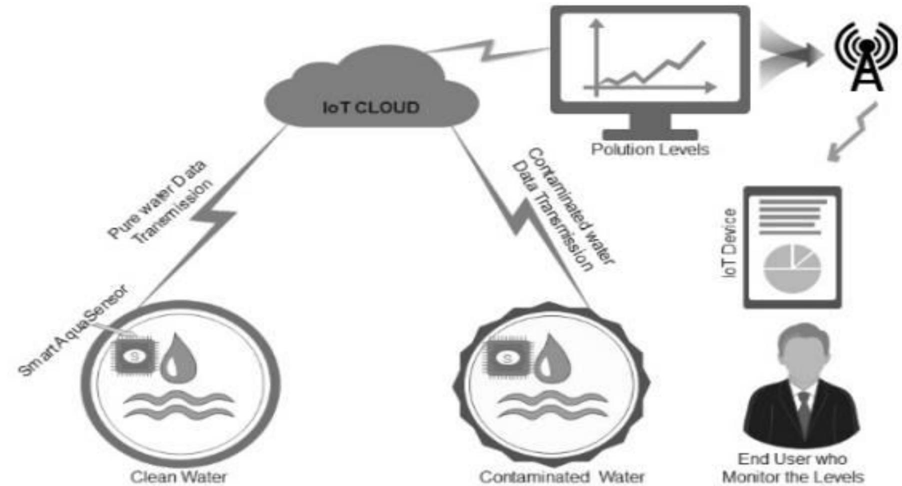

Fig. 1. Smart Water pollution Monitoring Systems with Smart Aqua sensors and IoT devices.

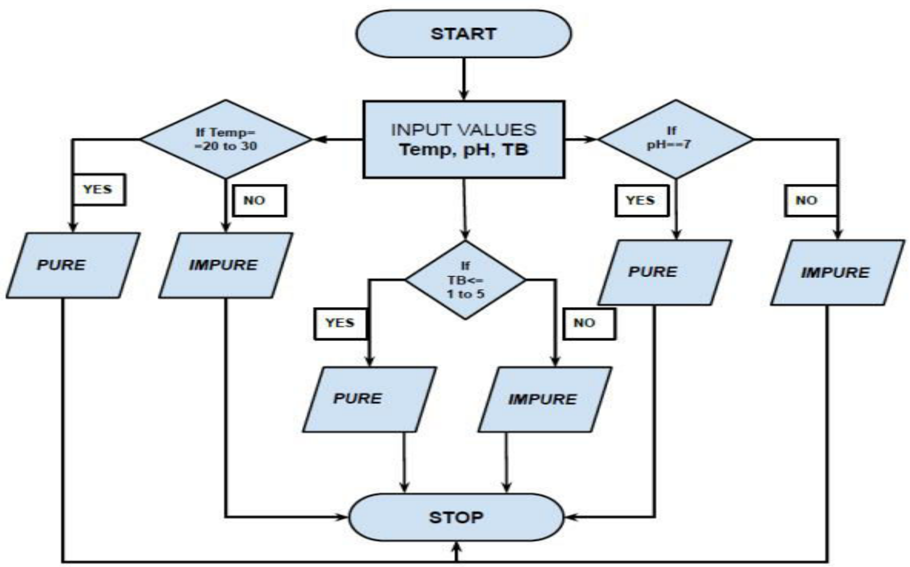

Fig. 2. System flow diagram

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[3] M. N. Vamsi Thalatam, P. Lanka and J. N. V. R. S. Kumar, "An IoT Based Smart Water Contamination Monitoring System," 2023 International Conference on Intelligent Systems for Communication, IoT and Security (ICISCoIS), Coimbatore, India, 2023, pp. 387-391

Author's work	The author proposes a system that leverages Internet of Things (IoT) technology to monitor water quality and quantity in real-time.
Inference	The paper presents a real-time water contamination monitoring system leveraging IoT and Embedded Systems to address challenges in urban water supply maintenance due to population growth and pollution. By measuring turbidity, pH, and temperature, the system aims to estimate water quality, offering efficiency and accuracy. Utilizing low-cost components and cloud-based analysis, it provides a cost-effective solution with potential scalability for widespread implementation. However, potential limitations include accuracy compromises with low-cost components and unaddressed cybersecurity vulnerabilities. Future enhancements could involve incorporating additional sensors for comprehensive water quality assessment, making it a promising solution for smart city applications.
Limitations	The main limitations of the proposed system include potential compromises in accuracy due to the use of low-cost components, particularly in comparison to industrial-grade sensors. Additionally, the system may be vulnerable to cybersecurity threats, especially when data is transmitted over the Internet. These limitations suggest the need for careful consideration of component quality and cybersecurity measures in future iterations to ensure reliable and secure operation.

[4] K. S., S. T.V., M. S. Kumaraswamy and V. Nair, "IoT based Water Parameter Monitoring System," 2020 5th International Conference on Communication and Electronics Systems (ICCES), Coimbatore, India, 2020, pp. 1299-1303

Author's work	The authors highlighted a three-layered approach for water monitoring, utilizing sensors for data acquisition, Gsm and Ethernet for transmission, and IoT platforms for processing.
Inference	-EXO Sonde will collect the data and monitoring will be done at server-side -Data from the primary controller is stored, then transmitted to the server via GSM, without real-time data due to occasional GSM connection issues.
Limitations	-The Exo Sonde is very expensive and lack of some other parameters which are affecting the quality of water -Once the data will be transmitted to the server. The timestamp will be removed. The transmission of data to the server is done through GSM. The GSM connection can't be achieved every time, hence the real time values are not always available.

Fig .2. EXO Module

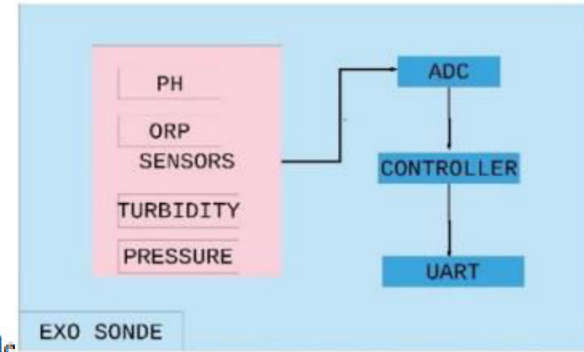


Fig .3. Architecture of EXO Sonde

III. SYSTEM OVERVIEW

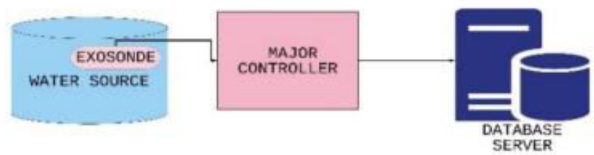


Fig .1. System Overview

The smart sensor options in the EXO are conductivity, dissolved oxygen content, pH, rhodamine, total algae, and turbidity

Result on server side

WATER PARAMETER MONITORING

STN_15_2020017000532_EXO

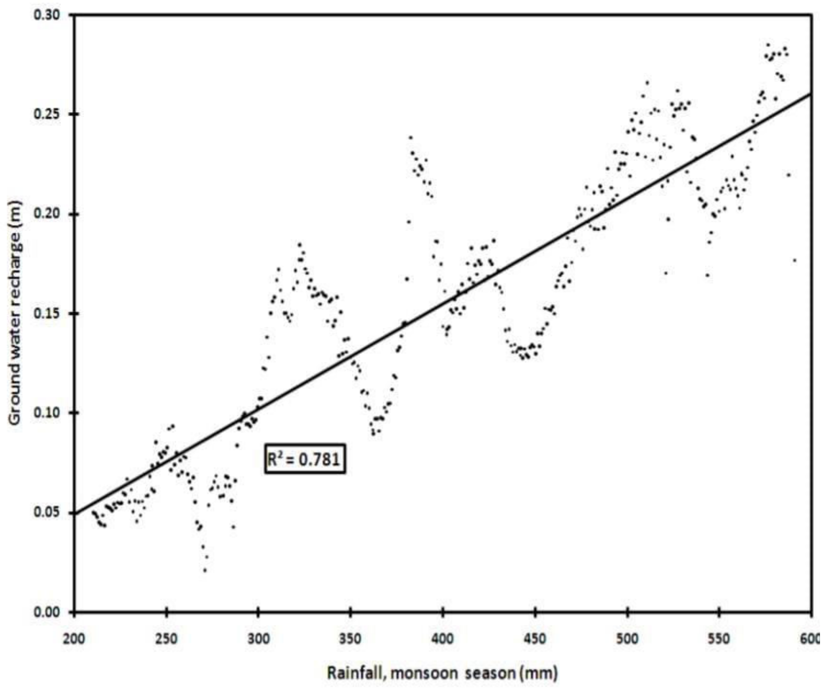
Node voltage = 1.5 volts

PRESSURE (Pascal)	TEMPERATURE (Degree celsius)	PH (no unit)	ORP (milli volt)	TURBIDITY (FTU)
-7841	28.807	9.47	410.05	0.31
-7464	28.812	9.47	410.02	0.30
-7932	28.806	9.47	410.00	0.30
-7971	28.818	9.47	409.97	0.31
-7427	28.815	9.47	409.95	0.27
-7806	28.813	9.47	409.99	0.30
-7865	28.818	9.47	409.86	0.30
-9124	28.817	9.47	409.80	0.28
-8708	28.823	9.47	409.75	0.29
-7683	28.536	9.31	422.29	0.29

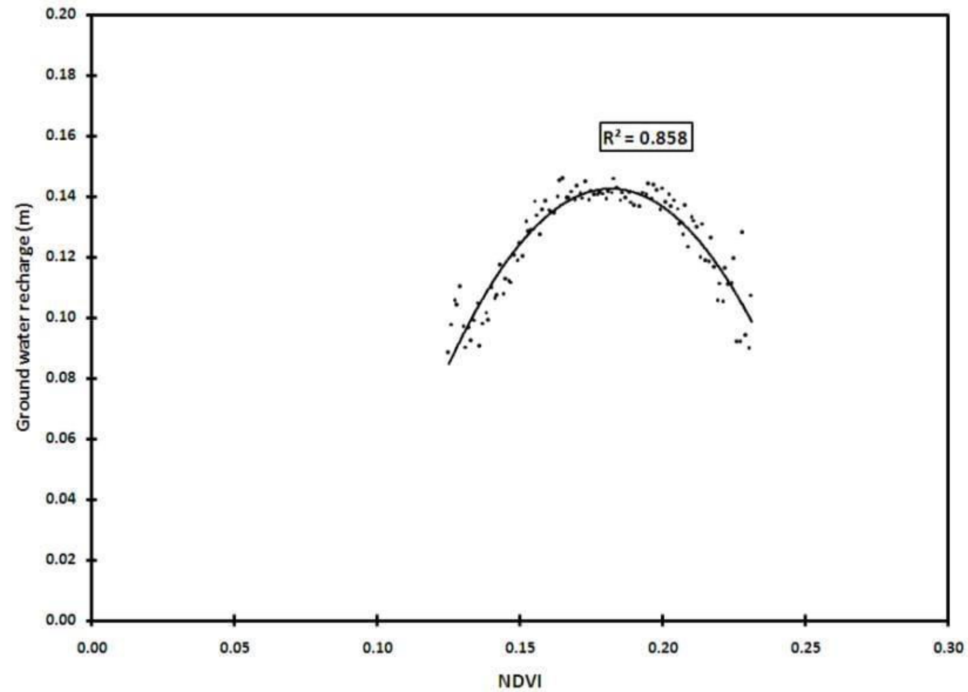
Fig .8. Monitoring server

[5] European Journal of Sustainable Development A methodology based on spatial distribution of parameters for understanding affect of rainfall and vegetation density on groundwater recharge Vijai Singhal and Rohit Goyal

Author’s work	The authors aim to understand the relationship between rainfall, vegetation density, and groundwater recharge.They utilize spatial distribution analysis to explore how these factors impact groundwater replenishment.
Inference	The study reveals that groundwater recharge increases with Normalized Difference Vegetation Index (NDVI) up to a certain point.Beyond that threshold, further vegetation density does not significantly enhance recharge.Additionally, the research identifies a linear correlation between groundwater recharge and rainfall
Limitations	Simplification. Data Availability Generalization Temporal Variability



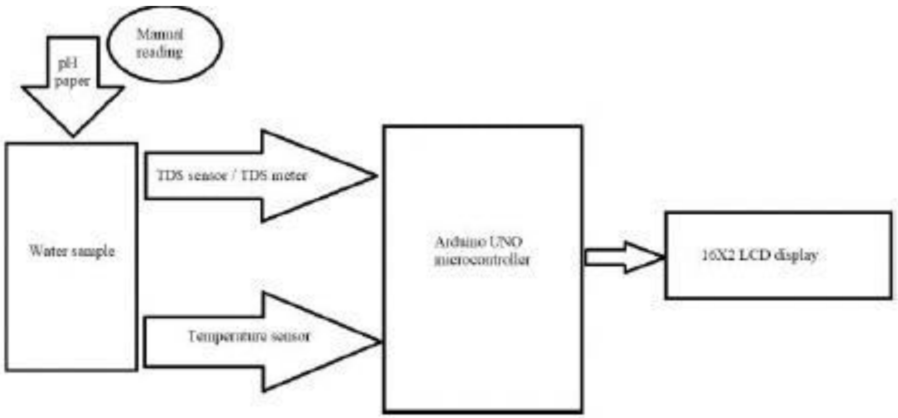
Ground water recharge (m)
Rainfall, monsoon season (mm)
$R^2 = 0.781$
0.00
0.05
0.10
0.15
0.20
0.25
0.30
200
250
300
350
400
450
500
550
600



Ground water recharge (m)
NDVI
$R^2 = 0.858$
0.00
0.02
0.04
0.06
0.08
0.10
0.12
0.14
0.16
0.18
0.20
0.00
0.05
0.10
0.15
0.20
0.25
0.30

[6] S. H. Priyadarshini, P. S., R. P. B., V. K. V. and A. D. V A, "AQUASENSE: Sensor Based Water Quality Monitoring Device," *2023 International Conference on Self Sustainable Artificial Intelligence Systems (ICSSAS)*, Erode, India, 2023, pp. 1786-1789

Author's work	Parameters Measured: The device collects water samples from different regions in Bangalore city and measures ph,turbidity
Inference	Temperature Influence: The temperature affects TDS measurements due to its impact on solubility. Affordability and Efficiency: AQUASENSE is an affordable and efficient alternative to existing water quality monitor
Limitations	Local Context: The device's effectiveness may vary based on the specific water sources and environmental conditions in Bangalore. Calibration: Regular calibration is essential to maintain accuracy.


Manual
reading
pH
paper
Water sample
TDS sensor / TDS meter
Temperature sensor
Arduino UNO
microcontroller
16X2 LCD display

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[7] "Study on reciprocal relationship among water amount-water quality-water efficiency based on the SWAT_WAQER model "2021 7th International Conference on Hydraulic and Civil Engineering & Smart Water Conservancy and Intelligent Disaster Reduction Forum (ICHCE & SWIDR)

Author's work	work involves developing and applying the SWAT_WAQER model to analyze the interplay between water consumption, efficiency, and river water quality in the Yulin Basin.
Inference	How changes in water consumption and pollution emissions impact river water quality.By using the SWAT_WAQER model. The authors simulate different water conservation scenarios in the Yulin catchment. The model predicts the effects of economic water consumption and pollutants on water quality.
Limitations	Model Assumptions Simplifications Local Context External Factors

[8] N. Iqbal et al., "Groundwater Level Prediction Model Using Correlation and Difference Mechanisms Based on Boreholes Data for Sustainable Hydraulic Resource Management," in IEEE Access, vol. 9, pp. 96092-96113, 2021, doi: 10.1109/ACCESS.2021.3094735.

Author’s work	The authors of the paper have collectively developed an ensemble machine learning model to predict groundwater levels, aiming to enhance the efficiency of borehole drilling and sustainable management of hydraulic resources.
Inference	The paper details a machine learning model for predicting groundwater levels, which could revolutionize groundwater management. It also shows that proper data handling improves prediction accuracy, influencing future groundwater studies.
Limitations	**Data Dependency**: The model’s accuracy is highly dependent on the quality and comprehensiveness of the input data. **Generalizability**: The model may not perform as well when applied to different geographical areas or datasets not represented in the training data.

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- [9] M. Jafril Alam, S. Kar, S. Zaman, S. Ahamed and K. Samiya, "Forecasting Underground Water Levels: LSTM Based Model Outperforms GRU and Decision Tree Based Models," 2022 IEEE International Women in Engineering (WIE) Conference on Electrical and Computer Engineering (WIECON-ECE), Naya Raipur, India, 2022, pp. 280-283, doi: 10.1109/WIECON-ECE57977.2022.10151230.

Author’s work	The authors of the study on forecasting underground water levels using machine learning and deep learning. However, the research highlights the significance of these models in addressing water depletion and emphasizes the superior performance of LSTM-based models for time series forecasting.
Inference	• The paper presents a study on forecasting underground water levels using machine learning and deep learning models, with the LSTM-based model outperforming others in accuracy.
Limitations	• The paper discusses the effectiveness of various machine learning models for forecasting underground water levels, highlighting that deep learning models, particularly LSTM, outperform traditional algorithms. However, it acknowledges limitations such as the need for more diverse data and the potential development of an attention mechanism-based system for improved forecasting.

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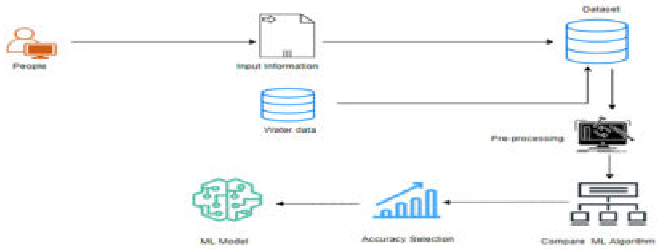
- [10] M, M. G. Dinesh, C. Lakshmipriya, V. Sharmila, A. Muthuram and S. S. R, "Water Quality Prediction using Machine Learning: A Comparative Study," 2023 Second International Conference on Augmented Intelligence and Sustainable Systems (ICAISS), Trichy, India, 2023, pp. 348-353

Author's work	The author investigates the suitability of machine learning methods such as SVM, XGBoost, Decision Trees, and K-NN for predicting water quality indicators, leveraging historical environmental data.
Inference	1. The study aims to propose a machine learning-based approach for forecasting the Water Quality Index (WQI) using supervised classification algorithms to achieve high accuracy. 2. The investigation seeks to evaluate and compare the performance of different machine learning methods using a provided dataset to enhance the ability to predict water quality.
Limitations	1. Quality and representativeness of the dataset used, potentially affecting the generalizability of the proposed machine learning models. 2. The effectiveness of the machine learning-based technique for seasonal variations, geographical factors, and changes in industrial activities.



METHODOLOGY

Results

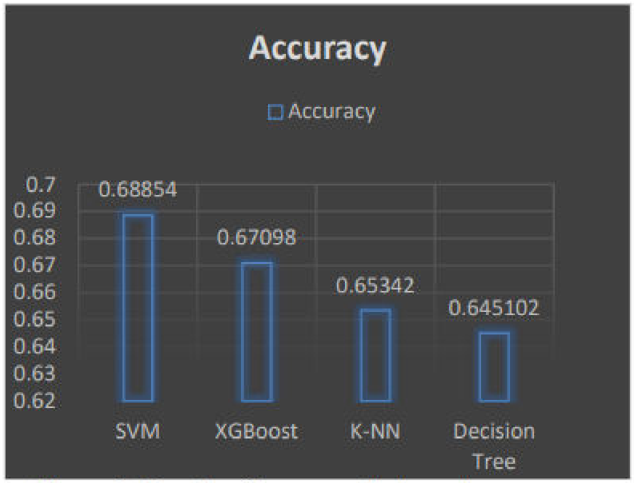


Figure 2: Results of water prediction using accuracy parameter:

[11] S. K. T. K, M. Hanumanthappa, S. K. P. S and H. B. V, "Data Driven Approach to Predict Ground Water Level using Support Vector Regression," 2022 International Conference on Applied Artificial Intelligence and Computing (ICAAIC), Salem, India, 2022, pp. 01-06

Author's work	VM-based model predicts groundwater levels and water consumption, aiding in sustainable resource management.
Inference	Geographical and climatic factors utilized to assess available water for diverse domestic needs.Data-driven approach offers insights for effective water allocation amidst growing scarcity and population demands.
Limitations	Reliance on historical data may limit predictive accuracy.Applicability may be restricted by geographical and climatic factors.

Objectives

- **Analyze Historical Groundwater Availability:** Evaluate groundwater availability using historical data and machine learning to understand resource trends and patterns.

- **Implement Real-Time Water Quality Monitoring:** Deploy IoT sensors to continuously monitor water quality parameters such as temperature, turbidity, TDS, and pH.

- **Calculate Water Quality Index (WQI):** Develop a WQI based on real-time sensor data to assess and visualize overall water quality.

- **Integrate Data for Insights:** Combine historical groundwater data with real-time water quality information to provide comprehensive insights into groundwater resource status and quality.

- **Visualize Results:** Present findings through graphical representations and reports to support decision-making and resource management.

Problem Statement

Monitoring Real-Time Reservoir Water Pollution Data and Analyzing Underground Water Levels for Sustainable Resource Management.

Sensor’s Information

Sensors	Significance	Range
LM35 Temparature sensor	Measures thermal energy by the movement of the molecules with kinetic energy.	It should not exceed 25° C
pH sensor	pH is a logarithmic scale that measures how acidic or basic a body of water is.	The pH of most suitable water lies within the range 6.5–8.5.
TDS sensor	Total dissolved solids (TDS) indicates harmful contaminants, like iron, manganese, sulfate, bromide, and arsenic	50–150 ppm: Excellent for drinking 150–250 ppm: Good 250–300 ppm: Fair
Turbidity Sensor	Turbidity sensors are used to reduce waste, improve yields, and analyze water quality in a wide range of industries.	0.5-1.0 NTU, but should never exceed 1.0 NTU

Temparature Sensor

The LM35 device is rated to operate over a −55°C to 150°C

The kinetic energy results in the movement of the molecules with internal thermal energy.

It affects the concentration of the dissolved gases and the saturation of the water.

Oxygen amount, rate of photosynthesis by plants inside the water, metabolic rates of aquatic animals are adversely impacted by the increased temperature.

Source: http://ln.run/urPeC

These sensors are accurate integrated circuit temperature sensors whose output voltage is linearly proportional to the temperature of the system.

The sensor is directly calibrated in Celsius the user does not need to manually calculate the result in centigrade scaling.

This sensor is recalibrated as it does not need any external calibration to provide accurate results.

Source:
http://www.state.ky.us/nrepc/water/ramp/rmtemp.htm#:~:text=Criteria:%20Water%20quality%20criteria%20for,22.2C%20(72%20F)

pH Sensor

A pH sensor helps to measure the acidity or alkalinity of the water with a value between 0-14

pH is a logarithmic scale that measures how acidic or basic a body of water is.

It's a crucial parameter for assessing water quality because it can affect the chemical and biological processes that occur in water bodies.

Source: https://shorturl.at/uALS3

TDS Sensor

The Gravity Analog TDS Sensor has a TDS measurement range of 0–1000 parts per million (ppm) and an accuracy of ±10% FS at 25°C

Total dissolved solids (TDS) in water can be important for water pollution

Because high levels can indicate harmful contaminants, like iron, manganese, sulfate, bromide, and arsenic. TDS can also impact the water's flavor, odor, and overall palatability.

Source: https://shorturl.at/epsJ0

Turbidity Sensor

The range of sensing capacity is 5 - 4000 NTU

Turbidity sensors are used to reduce waste, improve yields, and analyze water quality in a wide range of industries.

For samples with high amounts of TSS and TDS, the difference in the light intensity from the transmission beam is measured to obtain the turbidity result.

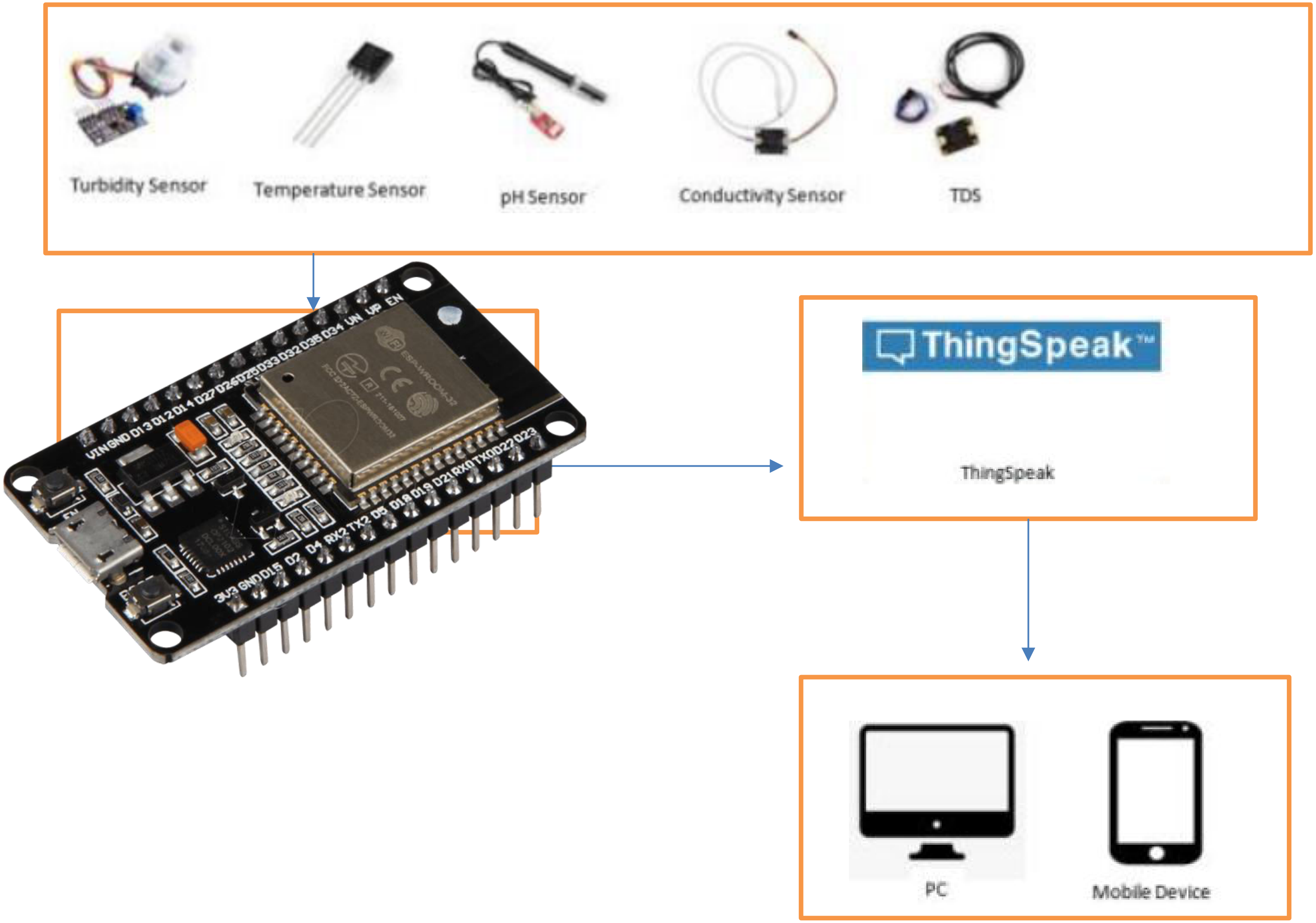
While light scattering is more suitable for samples with low amounts of TSS and TDS.

Turbidity sensors use light to detect a solution’s turbidity level, it is important to reduce the amount of external light when using the sensor.

Source: https://tinyurl.com/2ya3ryjk

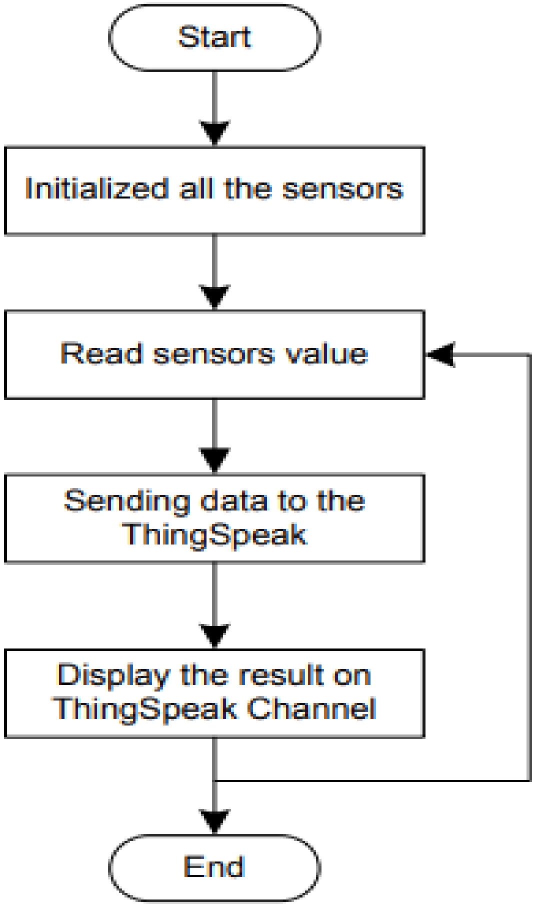
Methodology

System Architecture



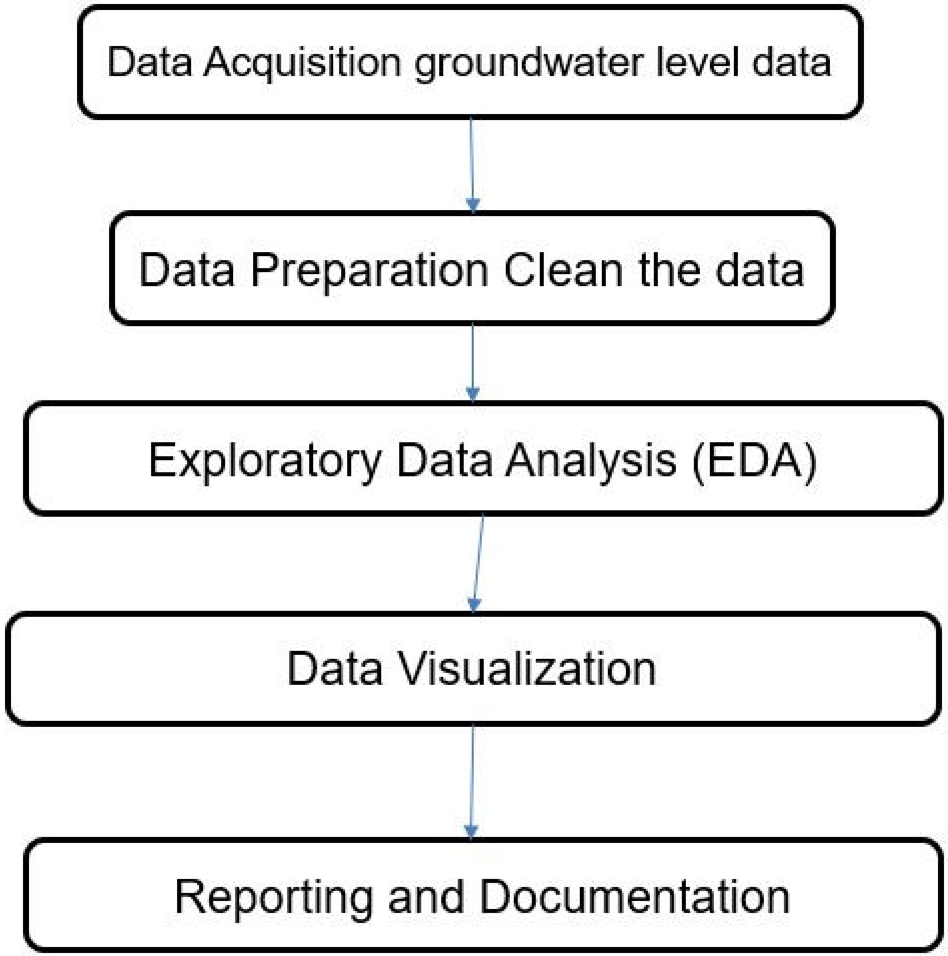
Methodology

Flow Chart of Real time Monitoring Water Pollution



Methodology

Analysis of Ground Water Level



Work Progress

- Ground water EDA and applied machine learning to the ground water dataset .
- We used 3 models namely : Linear regression , Random Forest , Gradient Boosting .
- Collecting sensor values in Real Time and plotting it in Think Speak cloud.
- We are working to plot the Water Quality index by combining all the data values from sensor in Real Time.

Hardware / Software Requirement

Hardware Components- Turbidity sensor, ESP 32, Temperature sensor, pH sensor, TDS sensor .

Software Components- ThingSpeak , Groundwater level dataset , Python.

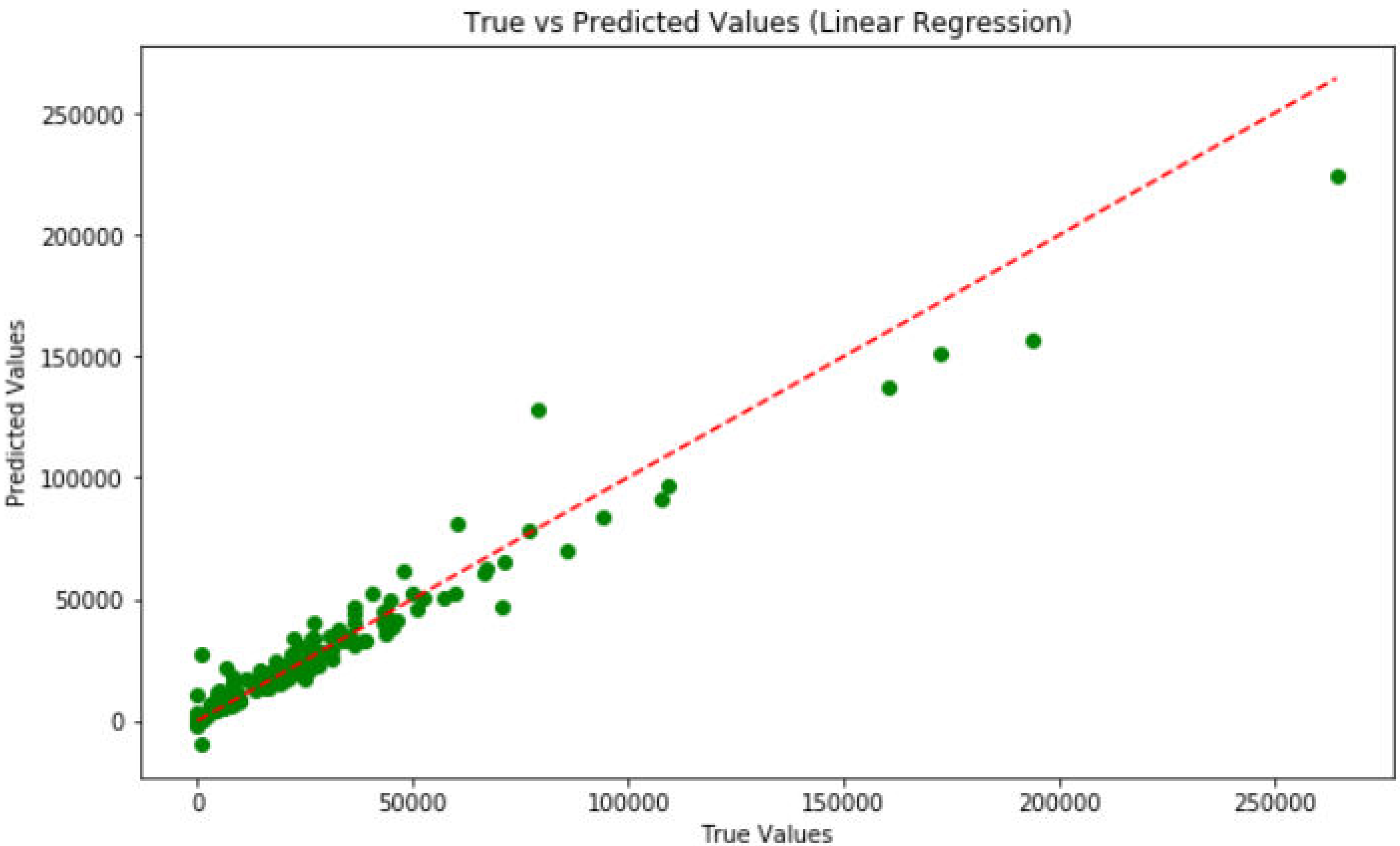
Dataset: https: https://www.kaggle.com/code/tuhinssam/india-ground-water-exploratory-data-analysis/input

The dataset is provided by https://data.gov.in/. The dataset is open for analysis and research.

Results and Analysis

Linear Regression model

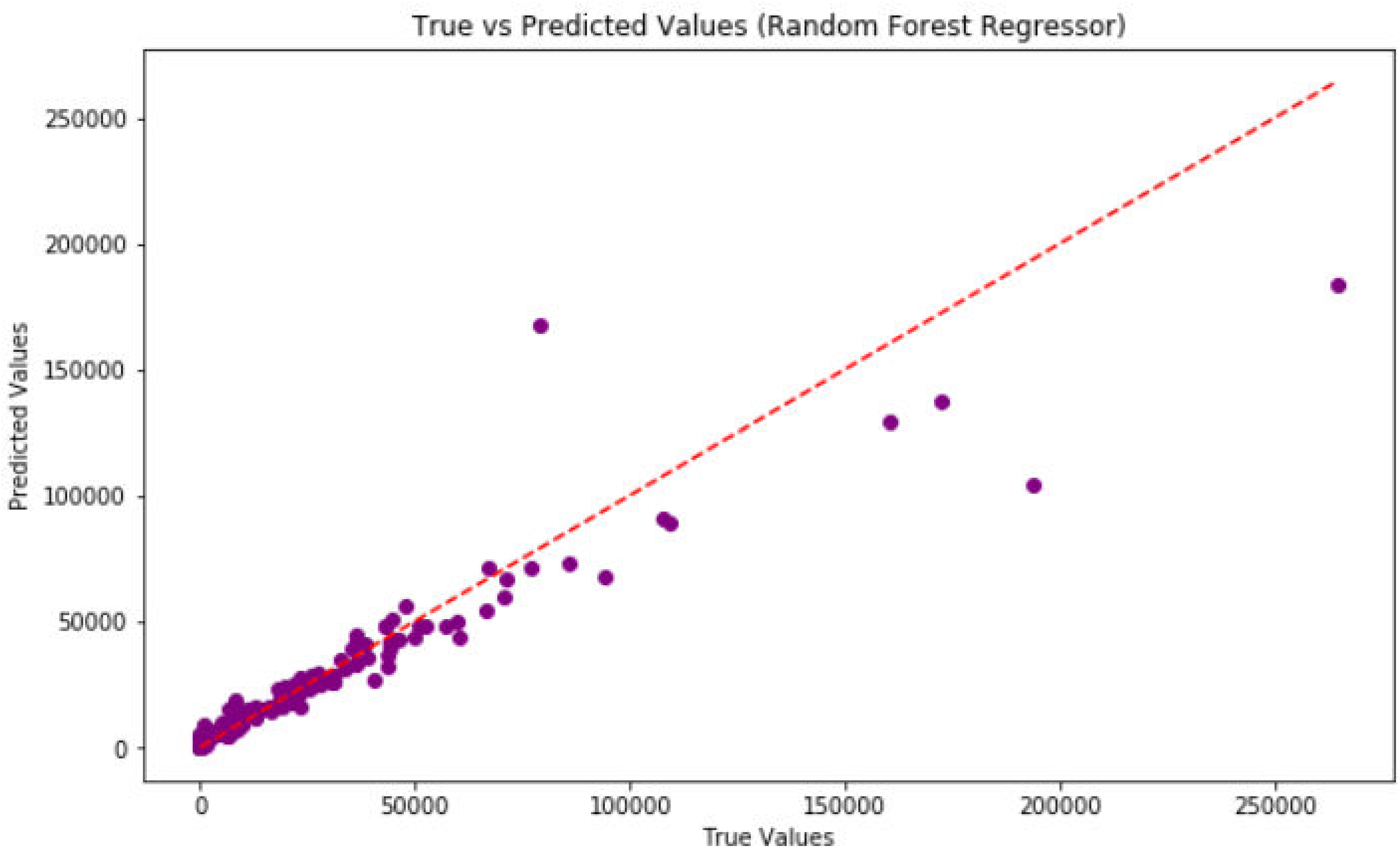
```
Linear Regression  R2 Score: 0.9380242645681784
```



Results and Analysis

Random Forest Regressor

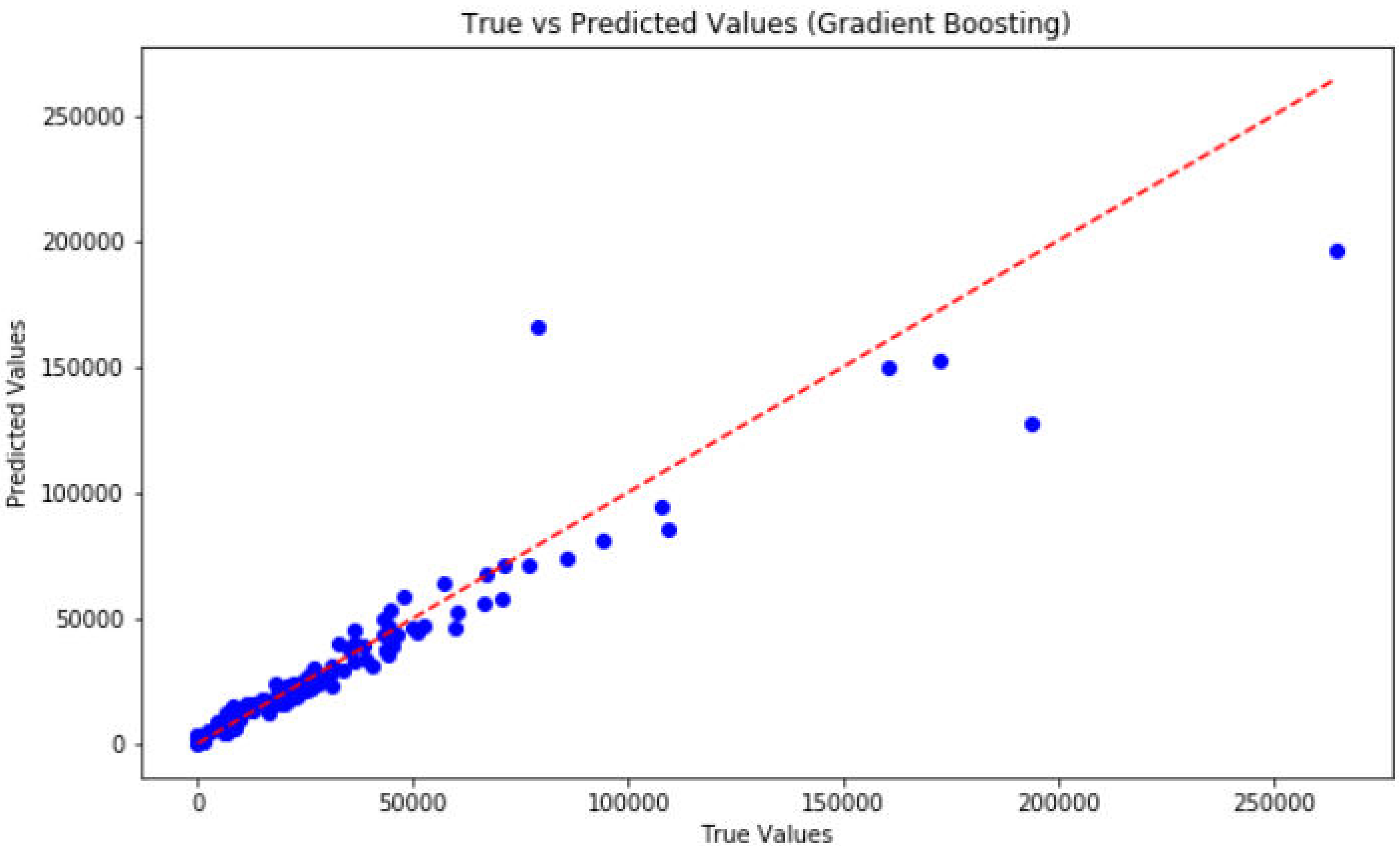
```
Random Forest Regressor  R2 Score: 0.8502557981172599
```



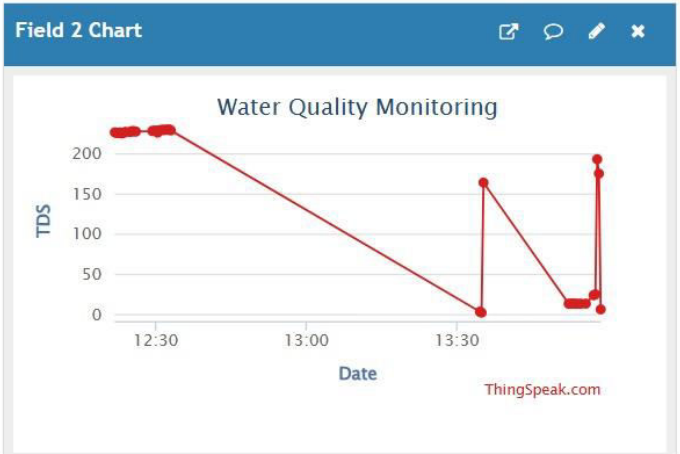
Results and Analysis

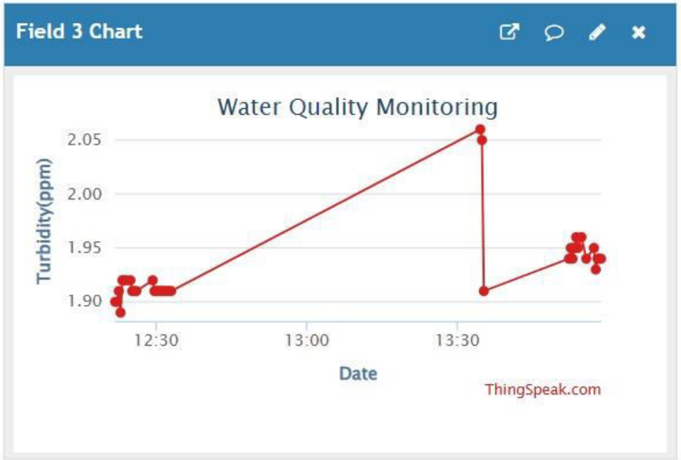
Gradient Boosting Regressor

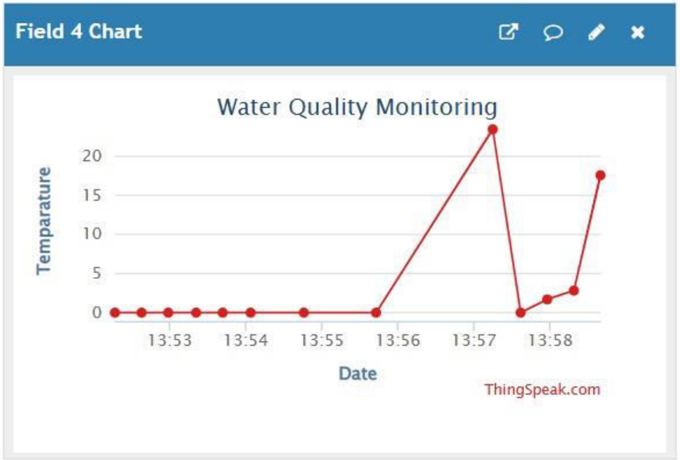
```
Gradient Boosting Regressor R2 Score: 0.8933798539388684
```



Results and Analysis







Results and Analysis

AFMotor_ConstantSpeed.ino

```
#include <WiFi.h>
#include <HTTPClient.h>

const char* ssid = "Esa";
const char* password = "tejas1@1";

const char* server = "http://api.thingspeak.com/update";
const char* apiKey = "IYLO08AJNP5RR3WL";

const int phPin = 35;
const int tdsPin = 33;
const int turbidityPin = 34;
const int lm35Pin = 32;


const float voltageReference = 3.3;
const float TDSFactor = 0.5;
const float NTUMultiplier = 1000;
const float phCalibrationFactor = 3.5;
const float phOffset = 0.0;
float phValue = 0;
float tdsValue = 0;
```

Output   Serial Monitor ×

Message (Enter to send message to 'ESP32 Dev Module' on 'COM3')

```
14:00:16.907 -> Error code: -1
14:00:36.907 -> pH Value: 0.00 | TDS (ppm): 7.81 | Turbidity (NTU): 1.94 | Temperature (C): 3.06
14:00:48.884 -> Error code: -1
14:01:08.924 -> pH Value: 0.00 | TDS (ppm): 7.81 | Turbidity (NTU): 1.93 | Temperature (C): 24.74
14:01:20.920 -> Error code: -1
```

Deliverables

- **Historical Groundwater Availability Analysis**: Insights into groundwater availability patterns based on historical data, using machine learning techniques.
- **Real-Time Water Quality Monitoring**: Implementation and evaluation of an IoT-based system for continuous monitoring of water quality parameters such as temperature, turbidity, pH, and TDS.
- **Water Quality Index Calculation**: Development of a water quality index from IoT data, with graphical representation in ThinkSpeak or similar platforms.
- **Predictive Insights**: Comprehensive analysis and predictive insights on groundwater resources based on historical trends.
- **Research Paper**: A detailed research paper documenting the methodology, results, and implications of integrating IoT for real-time monitoring with machine learning for groundwater analysis.

References

[1] K. Banerjee et al., "Assessing Water Quality Index Near Industrial Regions and Aiding in Effective Water Management and Controlling Water Pollution Level," 2022 5th International Conference on Contemporary Computing and Informatics (IC3I), Uttar Pradesh, India, 2022, pp. 1987-1991

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References

[5] European Journal of Sustainable Development A methodology based on spatial distribution of parameters for understanding affect of rainfall and vegetation density on groundwater recharge Vijai Singhal and Rohit Goyal

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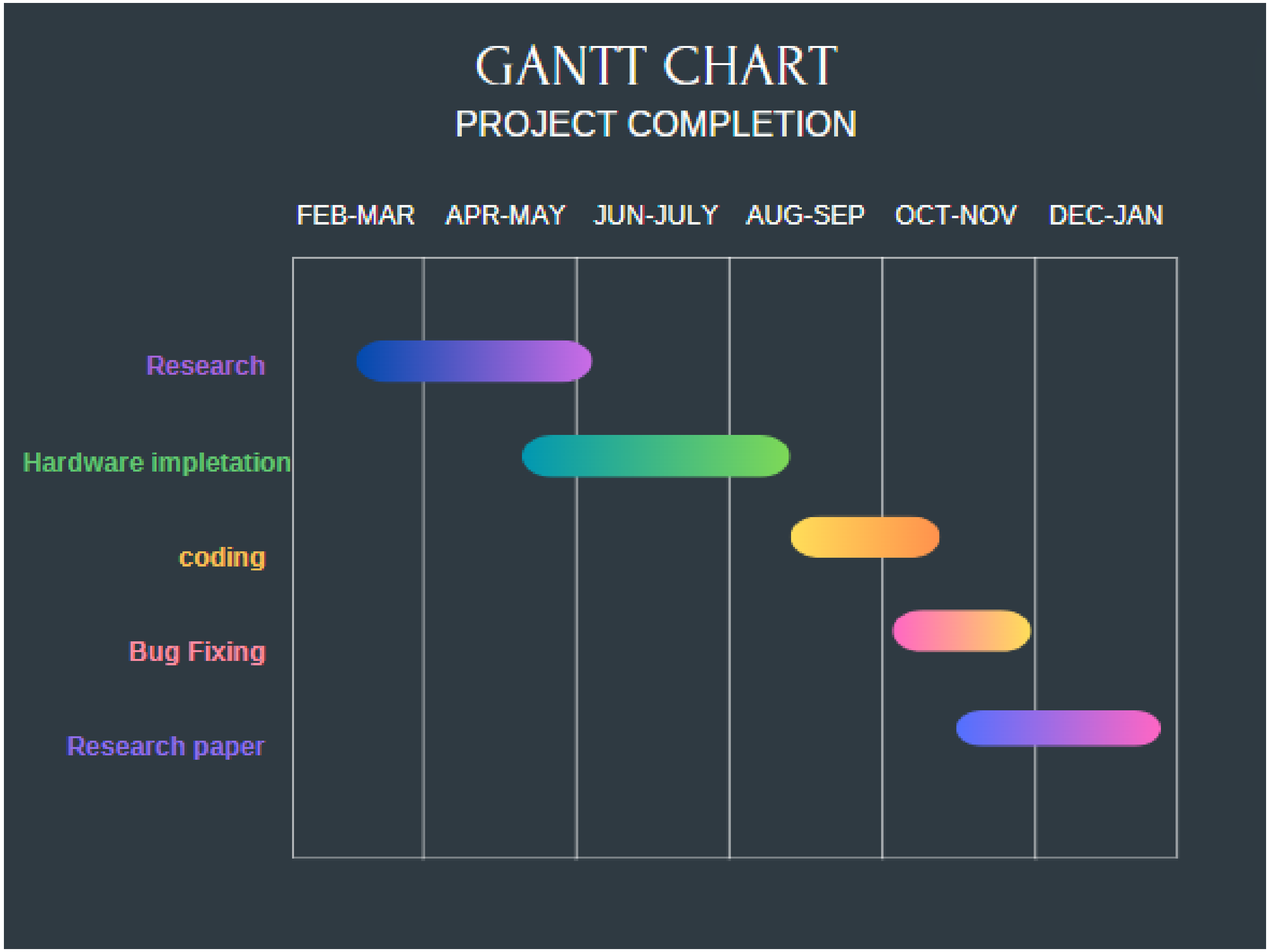
Summary

- Real-Time Monitoring: Live sensor data enables real-time monitoring of water quality, allowing immediate detection and response to pollution events.
- Precision and Efficiency: Utilizing live data ensures precise measurements, leading to accurate analysis of water quality and efficient water resource management.
- Pollution Control: Live sensor data helps identify pollution sources and levels, facilitating targeted interventions to mitigate environmental impacts.
- Groundwater Level Analysis: Understanding water resource dynamics, assessing impacts of climate change, and supporting sustainable water management.

Project timeline



Q & A

Thank You