PES UNIVERSITY

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Capstone Project Phase-1 Report

Water Quality Monitoring and Ground Level Water Analysis

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FACULTY OF ENGINEERING

DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING

PROGRAM B.TECH

DECLARATION

We, *Abhishek Shetty , Akash Katate ,Tejas V P, Akash Bhat,* , hereby declare that the report entitled " Water Quality Monitoring and Ground Level Water Analysis " is an original work done under the guidance of Dr. Purushotham U , Associate Professor in the Dept of ECE and is being submitted as a partial requirement for completion of Phase-1 of Project Work of the B.Tech ECE Program of study during Jan-May 2024.

Place : Bengaluru

Date : 08/05/2024

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Index

Introduction

Water pollution poses significant threats to ecosystems and public health, with adverse impacts ranging from biodiversity loss to the contamination of drinking water sources. Despite the recognition of these dangers, traditional monitoring methods often fall short in providing real-time data monitoring capabilities. This limitation hampers the ability to promptly identify and respond to pollution incidents, thereby exacerbating the risks posed to environmental and human health.

In light of these challenges, there is a pressing need for innovative approaches to water quality monitoring and management. Recognizing the urgency of the situation, this research endeavors to address these shortcomings through an integrated approach. At the core of this approach lies the utilization of sensors to monitor water pollution levels, offering a more comprehensive and timely understanding of environmental conditions.

By leveraging sensor technology, the study aims to analyze ground-level water quality parameters in real-time, enabling the detection of pollution sources and the issuance of alerts when contamination is detected. This proactive approach to monitoring holds promise in enhancing the capacity to safeguard water resources and mitigate pollution risks.

Moreover, the increasing frequency of pollution incidents underscores the critical importance of developing solutions that can provide real-time data. In response to this demand, the research focuses on developing sensor networks that can effectively bridge existing monitoring gaps. By establishing a network of interconnected sensors, stakeholders can access up-to-date information on water quality conditions, empowering them to make informed decisions and take timely actions to address pollution threats.

This project primarily aims to revolutionize water monitoring practices, with a particular focus on industrialized areas and domestic water bodies. While water pollution poses threats across various environments, industrialized regions often face heightened pollution risks due to the discharge of contaminants from industrial activities. By targeting these areas, the research seeks to develop tailored solutions that can effectively monitor and manage water quality in industrial settings.

Additionally, the project recognizes the importance of safeguarding domestic water bodies, such as rivers, lakes, and reservoirs, which serve as vital sources of drinking water and support diverse ecosystems. Through the implementation of sensor networks and real-time monitoring systems, the research aims to enhance the resilience of these water bodies against pollution threats, ensuring the provision of safe and clean water for both human consumption and environmental sustainability.

By addressing the specific needs of industrialized areas and domestic water bodies, the project aims to demonstrate the versatility and scalability of its monitoring solutions. By tailoring monitoring strategies to different contexts, the research endeavors to provide comprehensive and adaptable tools that can be deployed across diverse environments, ultimately contributing to the advancement of water quality management practices on both local and global scales.

Literature Survey

[1]

This research introduces an Internet of Things (IoT) solution designed to monitor water pollution in real-time, with the objective of enhancing water quality management through the prompt provision of alerts to relevant authorities. However, certain limitations exist within the study. Specifically, the absence of machine learning algorithms for advanced data analysis and predictive modeling is notable. This limitation may curtail the system's potential to offer deeper insights and predictive capabilities essential for effective water quality management. By not incorporating machine learning techniques, the system may overlook opportunities for more sophisticated analysis and forecasting, potentially hindering its overall effectiveness in addressing water pollution concerns.

[2]

The data collection process is facilitated by the EXO Sonde, with subsequent monitoring conducted on the server side. However, due to occasional GSM connection issues, real-time data transmission is not consistently achievable. The primary controller stores the collected data, which is then transmitted to the server via GSM. One notable limitation is the high cost of the EXO Sonde, coupled with its lack of certain parameters essential for comprehensive water quality assessment. Additionally, upon transmission to the server, timestamps are removed, further complicating the analysis process. The intermittent nature of GSM connectivity poses challenges, resulting in a lack of real-time data availability. These limitations underscore the need for alternative strategies to address the shortcomings and enhance the overall efficacy of the monitoring system.

Fig .2. EXO Module

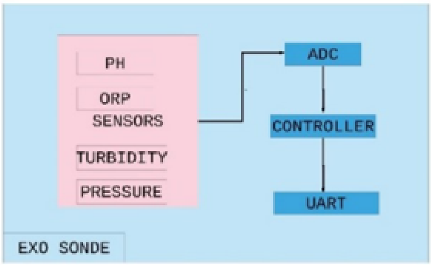


Fig .3. Architecture of EXO Sonde

III. System Overview

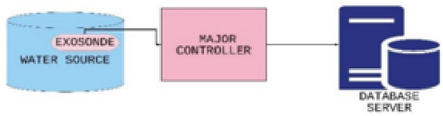


Fig .1. System Overview

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

[3]

The introduction of an IoT-based water quality monitoring and control system marks a significant advancement in the management of water resources. This system leverages a variety of sensors to enable real-time monitoring of crucial parameters such as flow, pH, turbidity, and temperature, thereby enhancing the ability to detect potential issues promptly. Moreover, the automation of processes such as tank cleaning further streamlines operational efficiency. An alert system is in place to notify stakeholders of any deviations from acceptable water quality standards. Experimental results showcase a promising accuracy rate of 93% in identifying water quality concerns, demonstrating the system's efficacy. Despite these achievements, certain limitations are acknowledged. The utilization of low-cost components may compromise the overall accuracy of the system. Additionally, environmental factors, including weather conditions, can impact sensor performance, potentially introducing inaccuracies. Furthermore, scalability and adaptation to diverse water quality standards remain unaddressed challenges, necessitating ongoing refinement to ensure the system's effectiveness across various contexts.

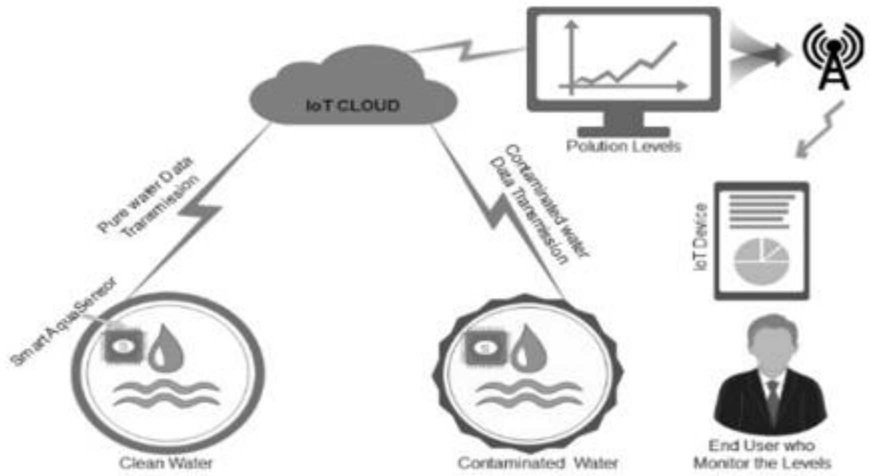


Fig. 1. Smart Water pollution Monitoring Systems with Smart Aqua sensors and IoT devices.

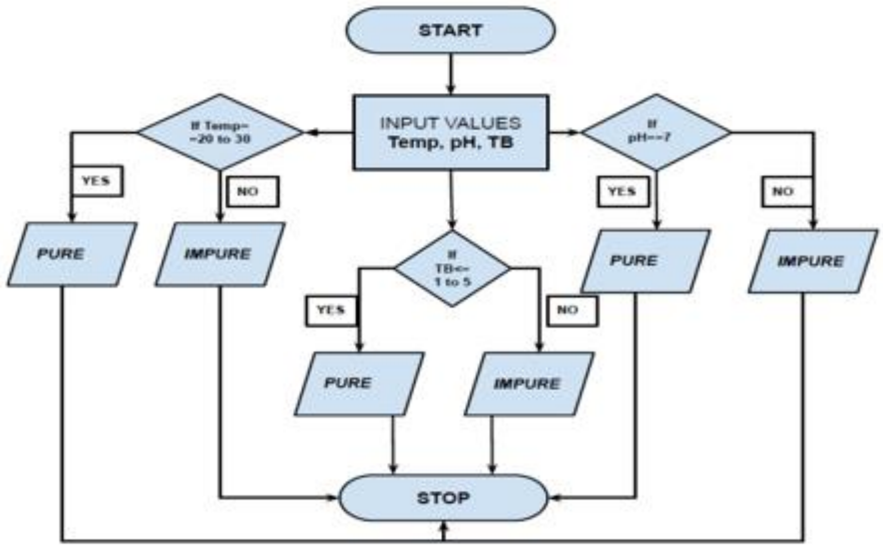


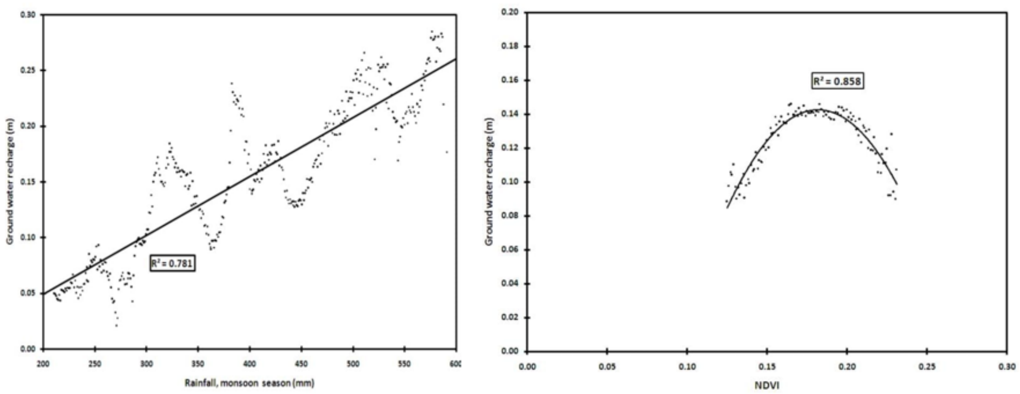
Fig. 2. System flow diagram

[4]

The introduction of a real-time water contamination monitoring system utilizing IoT and Embedded Systems represents a significant step towards addressing the challenges posed by population growth and pollution in urban water supply maintenance. By focusing on parameters such as turbidity, pH, and temperature, the system aims to estimate water quality with efficiency and accuracy. Leveraging low-cost components and cloud-based analysis enhances cost-effectiveness while recognizing its potential for smart city applications. However, certain limitations are inherent. The accuracy of the system may be compromised compared to industrial-grade sensors due to the utilization of low-cost components. Additionally, vulnerabilities to cybersecurity threats, particularly during Internet data transmission, pose risks to the system's integrity. Therefore, the importance of employing quality components and robust cybersecurity measures is emphasized to ensure reliable and secure operation, highlighting the need for continuous improvement in both hardware and software aspects of the system.

[5]

The study findings shed light on the relationship between groundwater recharge and the Normalized Difference Vegetation Index (NDVI), indicating that recharge increases with NDVI up to a specific threshold. Beyond this point, additional vegetation density does not notably enhance recharge. Moreover, the research highlights a linear correlation between groundwater recharge and rainfall. However, several limitations are acknowledged within the study. Simplification of the analysis process may have overlooked certain complexities inherent in groundwater recharge dynamics. Data availability issues could have impacted the comprehensiveness of the study, potentially influencing the accuracy of the findings. Generalization of results may not fully account for localized variations in environmental conditions, limiting the applicability of the findings across diverse contexts. Additionally, temporal variability in factors such as vegetation growth and rainfall patterns introduces uncertainty into the analysis, emphasizing the need for cautious interpretation of the results. These limitations underscore the importance of further research to refine understanding and improve the accuracy of groundwater recharge estimation methodologies.



[6]

The influence of temperature on Total Dissolved Solids (TDS) measurements is recognized, attributed to its effect on solubility. In addressing the need for affordable and efficient water quality monitoring, AQUASENSE emerges as a viable alternative to existing solutions. However, certain limitations warrant consideration. The effectiveness of the device may vary depending on the unique characteristics of water sources and environmental conditions specific to Bangalore or other locales. This underscores the importance of understanding the local context to optimize its utility. Additionally, regular calibration is imperative to uphold accuracy over time, highlighting the need for ongoing maintenance and quality assurance measures. These limitations underscore the importance of a nuanced approach to implementation and maintenance to ensure the reliability and effectiveness of AQUASENSE in diverse settings.

[7]

The study investigates the impact of variations in water consumption and pollution emissions on river water quality, employing the SWAT_WAQER model for analysis. By simulating various water conservation scenarios within the Yulin catchment, the authors aim to predict the consequences of economic water usage and pollutant discharges on water quality parameters. Despite the valuable insights provided by the study, several limitations are acknowledged. Model assumptions underpinning the simulation process may introduce inherent biases or inaccuracies into the results, warranting careful interpretation. Simplifications made within the modeling framework may overlook certain complexities inherent in real-world water systems, potentially influencing the robustness of the findings. Furthermore, the effectiveness of the model may be influenced by the specific local context of the Yulin catchment, limiting the generalizability of the results to other regions. Additionally, external factors not accounted for within the model, such as climate variability or land use changes, may introduce uncertainties into the analysis. These limitations underscore the need for cautious interpretation of the study findings and highlight opportunities for further refinement and validation of the modeling approach to enhance its utility in water resource management decision-making.

[8]

The paper presents a groundbreaking machine learning model designed to forecast groundwater levels, offering promising implications for the future of groundwater management. By leveraging advanced computational techniques, the model has the potential to revolutionize traditional approaches to groundwater monitoring and prediction. Moreover, the study highlights the significant impact of proper data handling techniques on prediction accuracy, underscoring the importance of data quality and preprocessing methods in influencing the outcomes of future groundwater studies. This insight emphasizes the critical role of robust data management practices in enhancing the effectiveness of predictive modeling efforts in groundwater research and management.

However, despite the potential benefits of the machine learning model, several limitations are acknowledged within the study. Firstly, the model's accuracy is highly dependent on the quality and comprehensiveness of the input data. Variations in data quality or availability may therefore impact the reliability and effectiveness of the predictions generated by the model. Additionally, while the model demonstrates promising performance on the dataset used in the study, its generalizability to different geographical areas or datasets not represented in the training data may be limited. This raises concerns regarding the model's applicability and reliability in diverse real-world contexts, highlighting the need for cautious interpretation and further validation of its performance across varying conditions.

[9]

The paper delves into a comprehensive study on forecasting underground water levels, employing both machine learning and deep learning models for analysis. Notably, the LSTM-based model emerges as the top performer in terms of accuracy, surpassing other methodologies. Despite the promising results, the paper acknowledges certain limitations inherent in the study. Specifically, it emphasizes the necessity for more diverse and comprehensive datasets to enhance the robustness and generalizability of the forecasting models. Additionally, while deep learning models, particularly LSTM, exhibit superior performance compared to traditional algorithms, the paper suggests the potential development of an attention mechanism-based system to further refine forecasting capabilities. By acknowledging these limitations, the paper underscores the ongoing need for innovation and refinement in groundwater level forecasting methodologies to address evolving challenges in water resource management effectively.

[10]

The study sets out to propose a novel approach utilizing supervised classification algorithms within machine learning to forecast the Water Quality Index (WQI) with heightened accuracy. Through an exhaustive investigation, various machine learning methods are scrutinized and compared using a designated dataset, aiming to bolster the capacity for predicting water quality. Despite its ambition, the study confronts several limitations. Firstly, the quality and representativeness of the dataset utilized pose concerns, potentially impinging upon the broader applicability of the proposed machine learning models. Secondly, the effectiveness of the machine learning-based technique may be compromised when confronted with seasonal variations, geographical factors, and fluctuations in industrial activities, suggesting potential challenges in real-world implementation. These limitations underscore the importance of exercising caution in interpreting the findings and highlight the imperative for further research to address these constraints and fortify the efficacy of machine learning approaches in water quality forecasting.

METHODOLOGY

Results

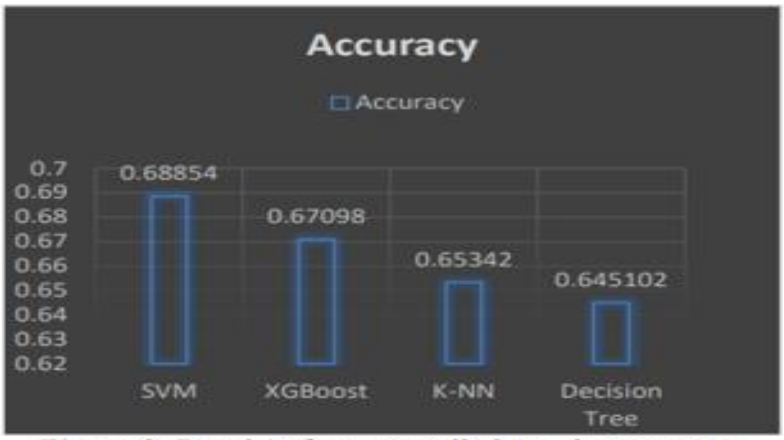
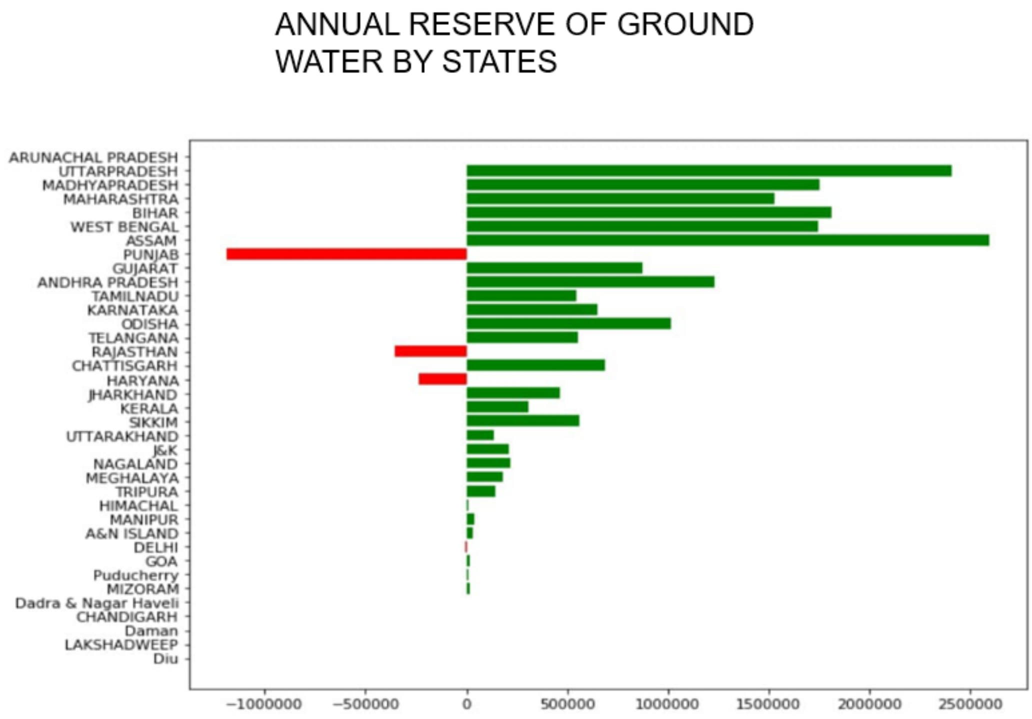


Figure 2: Results of water prediction using accuracy parameter:

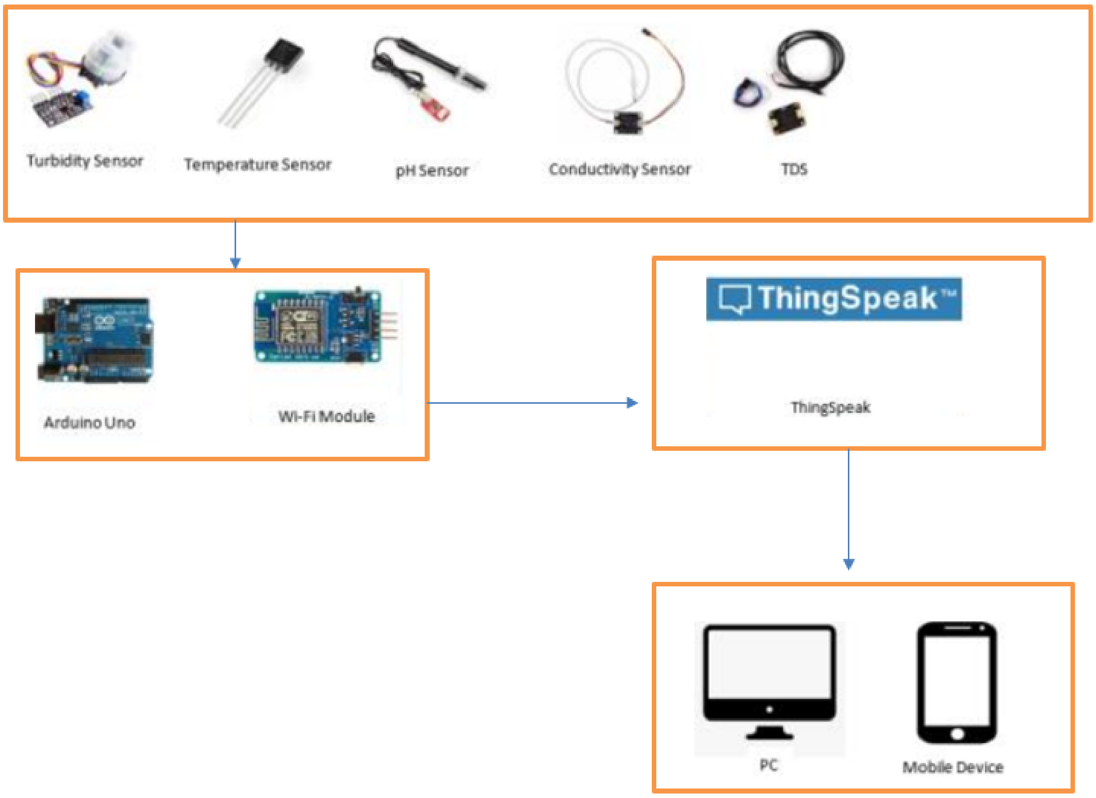
[11]

Geographical and climatic factors serve as crucial determinants in assessing the availability of water for diverse domestic needs. By employing a data-driven approach, this study aims to provide valuable insights for effectively allocating water resources amidst growing scarcity and increasing population demands. By analyzing historical data, the research endeavors to gain a comprehensive understanding of water availability trends and patterns, enabling stakeholders to make informed decisions regarding water allocation strategies.

However, the reliance on historical data may pose limitations to the predictive accuracy of the study findings. As environmental conditions continue to evolve, past trends may not fully capture future water availability scenarios, potentially affecting the efficacy of the proposed allocation strategies. Additionally, the applicability of the study's findings may be restricted by geographical and climatic factors unique to specific regions. Variations in terrain, climate, and hydrological characteristics can influence water availability dynamics, making it essential to consider the contextual relevance of the research outcomes when applying them to different locations. Despite these limitations, the data-driven approach remains a valuable tool for enhancing water management practices and addressing the complex challenges posed by water scarcity and increasing demand.

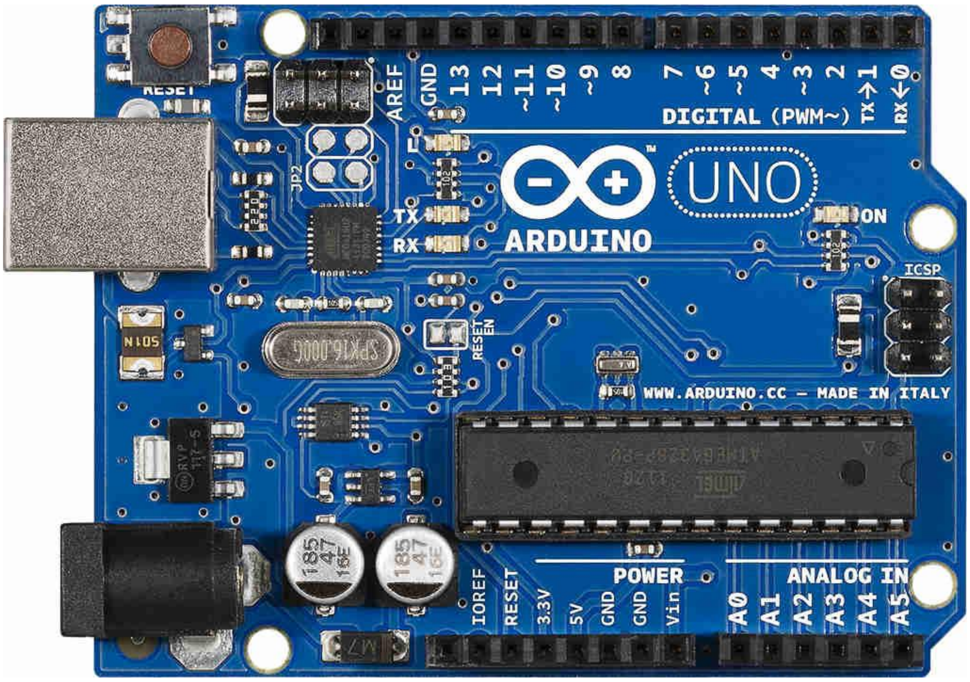


Methodology



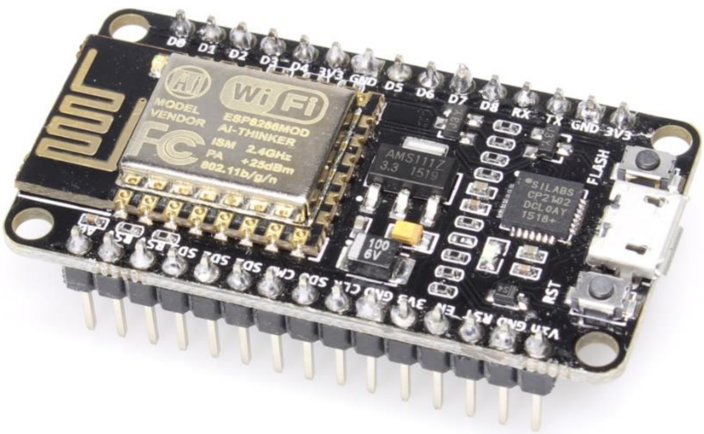
Arduino Uno

The Arduino Uno is a popular microcontroller board renowned for its versatility and ease of use in electronics projects. Powered by the ATmega328P microcontroller, it offers a wide array of digital and analog input/output pins, making it suitable for various applications ranging from simple LED blinking to more complex tasks like sensor interfacing and robotics. Its open-source nature allows for a vast community of enthusiasts and developers who contribute libraries, tutorials, and projects, fostering a collaborative environment for innovation. With its accessible programming language based on C/C++, the Arduino Uno empowers both beginners and experienced makers to bring their ideas to life through experimentation and creativity in the realm of embedded systems and physical computing.



ESP 8266

The ESP8266 is a highly versatile microcontroller chip renowned for its integrated Wi-Fi capabilities, ideal for IoT projects. With its 32-bit microcontroller, GPIO pins, and support for SPI and I2C communication, the ESP8266 facilitates seamless interfacing with external devices. Its ability to connect to Wi-Fi networks enables communication over the internet or local network, making it indispensable for IoT applications requiring internet connectivity. Programmed using languages like Arduino IDE and MicroPython, the ESP8266 enjoys extensive community support, offering a plethora of resources for developers. Despite its affordability, the ESP8266 offers powerful features, making it a popular choice for hobbyists and professionals alike in crafting innovative IoT solutions.



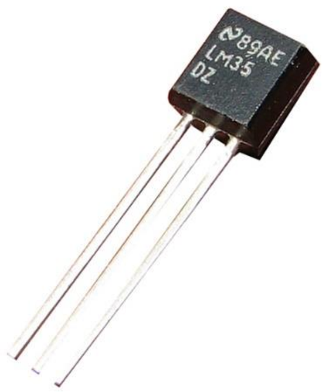
Temparature Sensor

The kinetic energy results in the movement of the molecules with internal thermal energy. Thus, it affects the concentration of the dissolved gases and the saturation of the water. To be precise, oxygen amount, rate of photosynthesis by plants inside the water, metabolic rates of aquatic animals are adversely impacted by the increased temperature.

Souce: http://ln.run/urPeC

LM35 series sensors are one of the choices in this sensor type. These sensors are accurate integrated circuit temperature sensors whose output voltage is linearly proportional to the temperature of the system. Since 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

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

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

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. Since 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

Conductivity Sensor

Water conductivity sensors are used in water-quality applications to measure how well a solution conducts an electrical current. This type of measurement assesses the concentration of ions in the solution. The more ions that are in the solution, the higher the conductivity.

Source: https://tinyurl.com/3nwepf22

Groundwater level analysis

Dataset : https://data.opencity.in/dataset/dynamic-ground-water-resources-of-karnataka-2020

Data Collection:

Obtaining the dataset containing parameters such as district, taluk, recharge from rainfall, recharge from other sources, natural discharges, extractable groundwater resource, extraction for irrigation, extraction for domestic use, and other relevant variables.

Data Preprocessing:

Cleaning the dataset by handling missing values, outliers, and data inconsistencies. Normalizing numerical features to ensure uniformity in their ranges. Encoding categorical variables using techniques such as one-hot encoding . Spliting the dataset into training and testing sets for model evaluation.

Exploratory Data Analysis (EDA):

Conducting exploratory data analysis to understand the distribution and relationships between different variables. Visualizing groundwater recharge, extraction, and other parameters across districts and taluks to identify patterns and trends. We Compute correlation coefficients to assess the relationships between groundwater levels and various factors.

Model Training and Evaluation:

We train the machine learning model on the training set using algorithms such as gradient descent, decision tree learning, or ensemble methods. We evaluate testing set using metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE) and Root Mean Squared Error (RMSE).

List of hardware/software needed

Hardware Components-

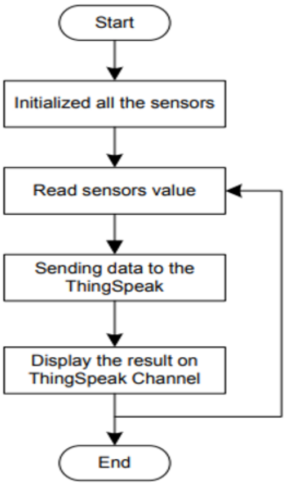
Turbidity sensor, Arduino Uno, ESP 8266, Temperature sensor, pH sensor, Conductivity sensor , TDS sensor .

Software Components

ThingSpeak , Groundwater level dataset , Python

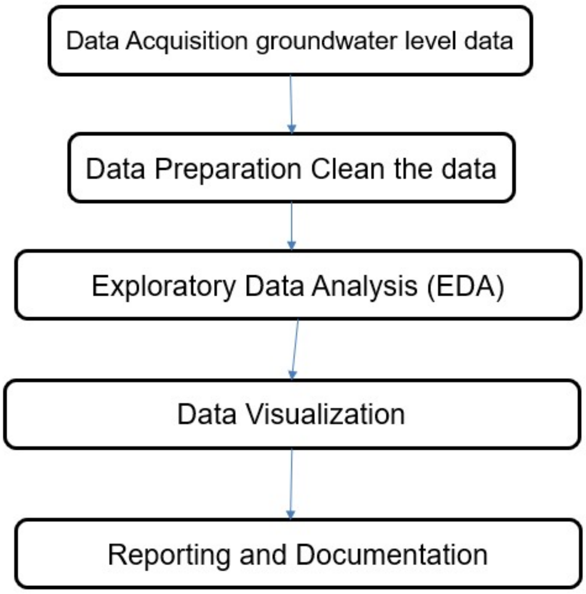
Flow Charts

Flow Chart of Real time Monitoring Water Pollution



The following flowchart is shows the system working of this study. The important part of the flowchart are the sensors initializing and setting up the ThingSpeak platform to be used to read and record all the data of this system.

Flow Chart of Analysis of Ground water level



The structured workflow for groundwater level data analysis begins with data acquisition, involving obtaining groundwater level data from reputable sources. Following this, the data undergoes preparation, where it is cleaned and preprocessed to ensure suitability for analysis. The next step involves exploratory data analysis (EDA), where the data is visualized to uncover trends and patterns. Subsequently, statistical analysis is performed to calculate descriptive statistics, summarizing the characteristics of the data.

The process continues with data visualization, utilizing plots and charts to illustrate groundwater dynamics effectively. Interpretation of the analysis results follows, aiming to derive insights and understand the behavior of groundwater based on the data. Finally, the findings are documented in a report, summarizing the analysis process and outcomes. This workflow emphasizes the importance of data exploration, analysis, visualization, and interpretation using Python to extract meaningful insights and support informed decision-making in groundwater resource management. Adjustments and expansions to each step can be made to suit specific project requirements and objectives effectively.

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