HYDRO WATCH: REAL-TIME WATER QUALITY ANALYTICS AND FILTRATION

A PROJECT REPORT

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In partial fulfilment for the award of the degree

of

BACHELOR OF ENGINEERING

IN

ELECTRONICS AND COMMUNICATION ENGINEERING



DEPARTMENT OF ELECTRONICS ENGINEERING
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ACKNOWLEDGEMENT

We consider it as our privilege and our primary duty to express our gratitude and respect to all those who guided, helped and inspired us in the successful completion of the project.

We owe solemn gratitude to **DR.K. RAVICHANDRAN**, Dean, Madras Institute of Technology, for having given consent to carry out the project work at MIT Campus, Anna University.

We wish to express our sincere gratitude to **Dr. P. INDUMATHI**, Professor and Head of the Department of Electronics Engineering, who has encouraged and motivated us in our endeavors.

We are extremely grateful to our project guide **Dr. K. MARIAMMAL**, Associate Professor, Department of Electronics Engineering, for her timely and thoughtful guidance and encouragement for the completion of the project.

We wish to extend our sincere thanks to the review panel faculty members **DR. S. VALLISREE, DR. O. VIGNESH and DR.T. SUBASHRI** for their valuable suggestions during all the reviews which took our project to greater heights. We would like to thank our project coordinator **MRS. M.P. KASTHURI,** all the teaching and non-teaching staff members of Department of Electronics Engineering, for their support in all the aspects.

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ABSTRACT

With the integration of cutting-edge sensor technology, cloud connection, and machine learning algorithms, "Hydro Watch" presents a novel approach to complete water quality management. The project uses a variety of sensors, such as temperature, turbidity, pH, and TDS sensors, to gather data in real time on important water parameters. By using The Things Network (TTN) for LoRa communication, the system sends this data to a user-made webpage for dynamic visualization and analysis, allowing users to track changes in water quality precisely. Users may obtain live data and gain insights into the dynamics of water quality thanks to MQTT integration. In order to enable prompt action in the event that non-potable water is discovered, Hydro Watch uses the XGBoost machine learning algorithm, which is most suited for this application, to forecast the potability of the water based on the collected characteristics. The user-friendly webpage's layout provides a central location for thorough data analysis, enabling users to make well-informed judgements on water treatment methods. Hydro Watch is a significant advancement in water quality monitoring that promises improved efficiency, reliability, and accessibility in ensuring safe and clean drinking water for communities worldwide. It does this by seamlessly combining state-of-the-art sensor capabilities, reliable communication protocols, and intelligent data analysis. The performance of the designed system is been compared with the existing system in terms of computational time and accuracy, the results are reported.

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LIST OF ABBREVIATIONS

TERM ABBREVIATION

LoRaWAN Long Range Wide Area Network

MQTT Message Queuing Telemetry Transport

LOS Line of Sight

TTN The Things Network

IOT Internet of Things

API Application Programming Interface

ML Machine Learning

NB-IOT Narrow Band Internet of Things

TDS Total Dissolved Solids

LPWAN Lower Power Wide Area Network

SWQMS Standardized Water Quality Monitoring System

CNN Convolutional Neural Network

RNN Recurrent Neural Network

CHAPTER 1

INTRODUCTION

1.1 OBJECTIVE

For there to be availability to drinkable water everywhere, real-time monitoring of water quality indicators including temperature, pH, and turbidity is essential. Modern sensors collect data and send it to a cloud platform via LoRa. This data is visualized via a user-friendly website that makes use of MQTT. Proactive decision-making is aided by machine learning, which forecasts trends in water quality. Real-time compliance is guaranteed by predictively guided automated filtration. This comprehensive strategy promises to reduce water hazards and promote universal access to clean drinking water by integrating sensor technology, cloud infrastructure, machine learning, and filtration.

1.2 MOTIVATION

The pressing problem of non-potable water, which is caused by pollution, insufficient filtration, and a lack of monitoring, affects communities all over the world. HydroWatch is one example of a solution that combines cloud analytics, machine learning, NB-IoT, and sensors for real-time monitoring. Its easily navigable website promotes informed decision-making by educating users and showcasing real-time metrics. Pre-emptive filtration becomes possible when machine learning forecasts changes in water quality. Using cutting-edge technology for proactive intervention, education, and real-time monitoring, HydroWatch provides a complete solution to non-potable water. Sustainable water management and enhanced public health are the goals of HydroWatch, which tackles the sources of contamination and provides communities with information. With the use of cutting-edge technology, the HydroWatch system offers a comprehensive response to the worldwide problem of non-potable water. It permits real-time monitoring, user education, and proactive action.

1.3 WORK FLOW

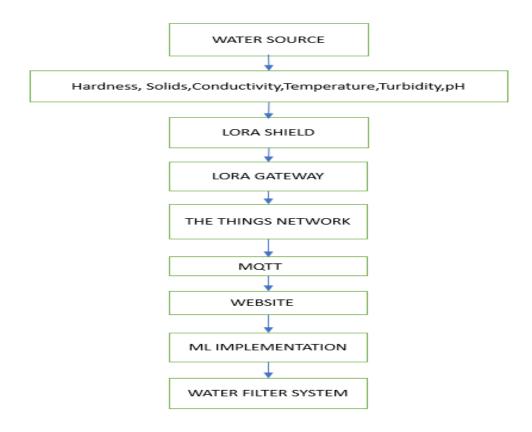


Figure 1.1 Proposed Work Flow of Hydro Watch

The work flow of the "Hydro Watch" system is been depicted in Figure 1.1. The water filter system is a complete solution that guarantees high-quality water and effective filtering by including a number of parameters, communication technologies, and data analytics. The system is linked to a water supply that has characteristics including pH, turbidity, temperature, conductivity, hardness, and solids. Long-range, low-power communication between the system and a LoRa Gateway is made possible by a LoRa Shield. The LoRa Gateway uses the MQTT protocol to send data to The Things Network. A webpage with analytics and visualizations of the data is hosted on the server. Additionally, the system implements machine learning for predictive maintenance and optimization. For effective and superior water filtration, the water filter system offers real-time monitoring, data analytics, and predictive maintenance.

1.4 SENSORS

A comprehensive water quality monitoring system necessitates the integration of multiple hardware components, each with a distinct role in the data collection and processing process. The popular microcontroller platform Arduino UNO from Arduino.cc acts as the system's central processing unit, coordinating all of the system's functions. It offers the interfaces and processing capacity required to link and manage the many modules and sensors.

1.4.1 pH SENSOR

Bytesware Electronics created an analog pH sensor electrode with amplifier circuit that is used to test pH levels. By transforming the analogue signal from the electrode into digital data that the Arduino UNO can process, this sensor guarantees reliable pH measurements.

1.4.2 TURBIDITY SENSOR

A sensor from BOQU Instrument Co., Ltd. is used to track turbidity levels. This sensor uses optical principles to find suspended particles in the water, giving important information on the quality and clarity of the water.

1.4.3 TOTAL DISSOLVED SOLIDS SENSOR

A Seeed Studio TDS sensor is integrated into the system to measure variables like conductivity, hardness, and total dissolved solids (TDS). With the help of this sensor, it is possible to measure the ions and dissolved materials in the water, providing vital details regarding its chemical makeup.

1.4.4 WATER TEMPERATURE SENSOR

A waterproof temperature probe (DS18B20) from Maxim Integrated is used to

detect the temperature. This sensor provides crucial information for evaluating water quality by guaranteeing precise temperature readings even in challenging aquatic conditions.

In order to facilitate wireless communication and control functions, the system incorporates an ESP32 DOIT module. This module makes it easier to communicate with the user-friendly website, enabling remote control and monitoring of the parameters related to water quality. Furthermore, it permits the water filtration system to be activated automatically in response to the website's potability status, which is retrieved via WebSocket connection. These hardware elements work together to enable the system to monitor important water quality parameters in real time, giving customers practical insights on how to keep water sources safe and drinkable.

1.5 LoRaWAN

LoRaWAN (Long Range Wide Area Network) is a wireless communication protocol designed for long-range, low-power IoT (Internet of Things) applications. Operating on unlicensed radio bands, LoRaWAN facilitates efficient communication between low-power devices and gateways. In this network, devices, such as sensors or actuators, can transmit small amounts of data over extensive distances to a gateway. The gateway then forwards the data to a network server, and the information is ultimately sent to the application server. What distinguishes LoRaWAN is its ability to enable battery-operated devices to communicate over several kilometers while conserving energy. The protocol employs a star-of-stars topology, ensuring scalability and flexibility. LoRaWAN supports various data rates, adapting to different use cases and environments. It finds applications in smart cities, agriculture, industrial IoT, and more, offering a cost-effective and accessible solution for connecting a network of devices and sensors, particularly in scenarios where long-range communication and extended battery life are paramount. The openness, combined with a robust security model,

contributes to its widespread adoption and its position as a prominent player in the evolving landscape of IoT connectivity.

1.6 MQTT

MQTT (Message Queuing Telemetry Transport) is a lightweight protocol designed for efficient communication in networks with low bandwidth, high latency, or unreliability. Employing a client-server architecture and a publishsubscribe model, MQTT enables devices to act as publishers, subscribers, or both. Topics, serving as communication channels, facilitate flexible communication in distributed systems. Devices publish messages to specific topics, with MQTT supporting various quality of service levels based on application reliability needs. Subscribers register with an MQTT broker, managing message distribution and enhancing scalability. Subscribers receive asynchronous messages based on topic subscriptions, enabling real-time communication crucial for applications like industrial automation and smart home systems. MQTT's lightweight nature is conducive to resource-constrained environments, minimizing overhead for devices with limited processing power. Operating on the principle of keeping connections open, MQTT reduces latency for message delivery, supporting lowpower states for devices until needed. In summary, MQTT's publish-subscribe model, coupled with topic-based communication, offers an effective and scalable solution for distributed communication in IoT and diverse networked applications, providing flexibility, reliability, and support for low-power devices across industries.

1.7 THE THINGS NETWORK

The Things Network (TTN) stands as a global, community-driven Internet of Things (IoT) network, embodying principles of openness, decentralization, and collaboration. Operating on the LoRaWAN protocol, TTN facilitates low-power, long-range communication, relying on a decentralized architecture with deployed

gateways acting as bridges between devices and the network server. TTN's ecosystem thrives on contributions from individuals and organizations deploying LoRaWAN gateways globally, creating an expansive network across urban and rural landscapes. Notably, TTN's commitment to openness allows free access to developers, fostering innovation in various IoT applications, from smart agriculture to industrial automation. The community-driven ethos extends to developer tools, including an API for seamless integration of IoT devices. TTN prioritizes security, implementing robust communication protocols and encryption mechanisms within its decentralized framework, mitigating risks associated with single points of failure. In essence, The Things Network emerges as a prominent, collaborative force in the global IoT landscape, championing accessibility, openness, and security to drive innovation and widespread adoption across diverse applications.

1.8 NARROWBAND-IOT

The low-power, wide-area network (LPWAN) technology known as narrowband internet of things (NB-IoT) is made to facilitate the effective transmission of little data packets over great distances. Because NB-IoT operates in licensed spectrum bands and provides improved coverage and penetration, it is a good choice for applications that need connectivity in difficult-to-reach places. NB-IoT devices are perfect for IoT deployments where frequent battery replacement is unfeasible due to their low power consumption. They can run on battery power for extended periods of time. Secure communication protocols, which are essential for sensitive applications like asset tracking, smart metering, and environmental monitoring, are supported by NB-IoT. These protocols ensure data integrity and privacy. Since NB-IoT is a standardised technology supported by international telecommunications standards groups, network operators and equipment manufacturers have embraced it, making it easier for it to be adopted and interoperable across various IoT ecosystems.

1.9 MACHINE LEARNING

The ML algorithm which has been implemented in this system is eXtreme Gradient Boosting(XGBoost). Strong and scalable, XGBoost is a machine learning method that excels at both regression and classification problems. It makes use of gradient boosting, an ensemble learning technique that creates a series of decision trees in order to repeatedly fix mistakes committed by earlier models. XGBoost uses parallelized tree construction and regularization approaches to maximize both computing efficiency and model accuracy. Large dataset handling, feature importance analysis, and reliable performance in a variety of fields have made it a popular choice for data science contests and real-world applications, which range from marketing and recommendation systems to finance and healthcare.

1.10 ARDUINO UNO

The Arduino Uno is a well-liked microcontroller board available from Arduino.cc that appeals to professionals, students, and hobbyists because of its cost, ease of use, and adaptability. It provides a strong platform for interactive electronic creations and is powered by the ATmega328 microprocessor. With support for an approachable version of C++, the Arduino IDE streamlines the development process. It interfaces with a range of parts, including sensors and displays, using different input/output pins and communication ports like UART and SPI. Prototyping is aided by integrated features such as a reset button and LED. The Uno's open-source design encourages developers and educators to work together and share materials and projects online. The learning curve and innovation in embedded systems and electronics are accelerated by this ecosystem.

1.11 FILTER SYSTEM

The filtering procedure is essential to the Hydro watch project's goal of guaranteeing potable water. A filtering system that is specifically made for the purpose is triggered when non-potable water is identified by analyzing water

quality criteria. The pH, TDS, turbidity, temperature, and other particular water quality concerns detected by sensors are all addressed by the careful engineering of this filtering system. The device purges impurities and enhances the quality of the water for a certain amount of time, usually two minutes. The device automatically turns off when the filtering cycle is finished, guaranteeing an effective and ongoing treatment procedure. By using an integrated approach to filtration, potability criteria are met, protecting public health and supplying clean, safe drinking water for a range of uses.

1.12 LITERATURE SURVEY

This study [1] offers a thorough analysis of communication technologies, both new and old, that might be used for Wireless Sensor Network (WSN) applications in Water Quality Monitoring (WQM). It draws attention to the shortcomings of current WSN systems as a result of constraints like low communication range and excessive power consumption connected to older communication networks. The study suggests incorporating low-power wide area network (LPWAN) solutions into WSN systems' communication architecture for WQM applications in order to alleviate these drawbacks. There are three types of LPWAN solutions that are recognized: low-power WiFi-based IEEE 802.11ah solutions, cellular-based LPWAN, and proprietary-based LPWAN. These long-range communication and low power consumption LPWAN variations make them attractive options for WQM data networking. The study also explores IEEE 802.11ah's potential as a better alternative to outdated Wi-Fi networks for data networking related to water quality. The purpose of this study is to improve the energy efficiency and reliability of WSN systems for WQM applications by suggesting novel architectural layouts and network configurations. It is anticipated that this fusion of IEEE 802.11ah and LPWAN networks will transform WQM applications by resolving long-standing energy problems and guaranteeing the consistent supply of water quality data to monitoring centers. In order to ensure the sustainability and safety of water resources, critical recommendations and future directions are offered to improve the performance of these communication networks for the next WSN systems in WQM applications.

This paper [2] deals with output units, sensor, microcontroller, and power supply are the four main parts that are the subject of this paper. The Power Supply Unit, which replaces conventional adapters with a battery and solar panel, improves environmental sustainability. The inexpensive Raspberry Pi 3 functions as the Micro-controller Unit, displaying sensor data thanks to its Linux operating system, integrated Wi-Fi, and Python programming. The pH, humidity, temperature, water level, turbidity, and water conductivity sensors on the Sensor Unit are all controlled via the Blynk app on an Android phone. A buzzer and LED are used to indicate threshold deviations. Through the use of Blynk app, Output Unit shows sensor readings, enabling real-time monitoring of water quality and prompt adjustment of parameters.

In this paper [3], in order to prevent water contamination, the literature emphasizes the significance of early warning systems, emergency water supplies, and water monitoring. With an emphasis on proactive pollution detection, the system makes use of equipment, data transfer, and remote diagnostics. For sustainable integration, local hydrogeological variables and water distribution system characteristics are taken into account while choosing an emergency water source. The goal of a multisource water supply network is to improve the security and dependability of urban water supplies. This research explores effective emergency response strategies and post-pollution disposal techniques, such as chemical deposition, adsorption, oxidation, and disinfection. The use of non-engineering solutions, such as emergency water sources and water supply shutdowns, is investigated. The literature concludes by highlighting the importance of surveys and post-emergency analysis and by offering a thorough framework for controlling and reducing water contamination.

This review study [4] emphasizes Ito achieve Quality of Service (QoS) criteria, a Standardized Water Quality Monitoring System (SWQMS) comprising data collection, transmission, and administration subsystems is proposed using Wireless Sensor Networks (WSN) in WQM. In addition to recommending low-power hardware and examining Low-Power Wide-Area Network (LPWAN) technologies like Ingenu RPMA and Wi-Fi HaLow for internet access, it emphasizes the significance of energy-efficient nodes. Case studies illustrate how LPWAN uses energy harvesting to prolong the life of SWQMS. With knowledge of electrical circuits, database administration, aquaculture, wireless networks, data management, and microcontroller programming, the paper emphasizes an interdisciplinary approach. To improve data interpretation and energy management in WSN for WQM, machine learning applications for route selection, node location, and water quality prediction are investigated.

This paper [5] is about installation of a cloud-based water management system driven by the Internet of Things, which combines several hardware and software elements to create a networked, intelligent framework. A cloud-based system is connected to a central hub, which communicates with several sensors measuring water level, conductivity, turbidity, velocity, and pressure. Wireless data transmission to the cloud is made possible with the Raspberry Pi, allowing for analysis and visualization. Real-time monitoring and SMS notifications are made possible by the internet connectivity and data transfer provided by WiFi and GSM modules. The study highlights the flexibility of Python programming on Raspberry Pi and highlights the role that cloud-based IoT devices play in improving water management by providing precise data and prompt decision-making.

This paper [6] focuses on forecast water quality, which integrates Internet of Things (IoT) technologies with LSTM Neural Networks (NN). The LSTM models are trained to forecast characteristics like pH, turbidity, and total dissolved solids using

data from Kerala Water Authority. The IoT module gathers data in real-time and transfers it to a database. It consists of pH, turbidity, and TDS sensors coupled to Arduino and NodeMCU. Water quality metrics are predicted by LSTM models that have been trained on historical data. The goal of this integrated system is to improve monitoring, guarantee prompt action for maintaining water purity, and provide early warnings of water contamination.

This paper [7], to overcome the drawbacks of current techniques, the research suggests a revolutionary approach to urban water quality monitoring. Through the use of NB-IoT technology, the system provides effective connectivity, making it possible to monitor in real time across various locations in Bolong Lake. Costs are reduced and deployment is made easier by utilising the current GSM and LTE infrastructure. The system architecture consists of a data display terminal (DDT), a water quality monitoring platform (WQMP), and a multi-parameter wireless communication network (MWQSWCN). Data is gathered and sent via the MWQSWCN to the WQMP, where it is processed, stored, and analysed. Users can get real-time data and pollution alerts using the web server interface, which makes interacting with the DDT easier. Effective water resource management and environmental preservation in metropolitan settings are guaranteed by this integrated strategy.

This paper [8] uses an Internet of Things (IoT)-based system for evaluating and monitoring the water quality of the Ganga River and the Sangam area in Prayagraj, India, is described in the article. The Libelium smart water kit and sensor probes allow the system to continuously gather data on variables such as temperature, conductivity, dissolved oxygen, pH, and oxidation-reduction potential. An algorithm is created to choose features and give weights for the assessment of water quality using principal component analysis and factor analysis. The Yamuna River's greater pollution levels are the reason behind the study's conclusion that the

Ganga River normally has superior water quality than the Sangam site. The average oxygen content of both rivers makes them unfit for drinking, even though they are ideal for irrigation and fishing. The Ganga River is emphasised for its importance as a resource for a number of events, including as religious and cultural gatherings like the Kumbh Mela, and for the environment and human health. Its water quality needs to be monitored.

This paper [9], to preserve freshwater biodiversity, the paper investigates how to use artificial intelligence (AI) and the Internet of Things (IoT) for real-time water quality monitoring. Important water quality indicators that affect biodiversity are identified, and the interrelationships between measurable and unmeasurable parameters are estimated using GRNN and MPR models. A promising applicability for contaminant monitoring and biodiversity protection is suggested by validation against lab data. Through a market survey, the research technique identifies critical water quality criteria and available sensors. A three-step framework that integrates preparing historical data, model building, and case study implementation is provided for estimating unmeasurable parameters. Five different sensor types are used in the Internet of Things water quality monitoring system, and data transmission and collection are handled by the Wemos D1 Mini chip with multiplexer, which ensures portability and Wi-Fi connectivity. The created Internet of Things system continuously gathers and sends five-parameter data via Wi-Fi to a web server, allowing for real-time monitoring. Statistical feature analysis looks at past data to find correlations between important parameters. For estimating unmeasurable water quality parameters, GRNN and MPR models are used because they provide good accuracy and effective training.IoT-connected sensors for realtime water quality monitoring hold promise for the preservation of freshwater biodiversity. In addition to developing IoT-based monitoring systems utilising GRNN and MPR models, this study presents a data-driven framework for estimating unmeasurable parameters and identifies critical parameters. Acceptable performance is shown by experimental validation, indicating the possibility for additional development and investigation of sophisticated machine learning methods, such as recurrent neural networks, for increased prediction accuracy.

This paper [10], through the use of hybrid deep learning (DL) models, CNN-LSTM and CNN-GRU, a novel method for aquaculture water quality prediction (WQP) is put forth in these research endeavours. In order to address problems in WQP, these models seek to combine the advantages of convolutional neural networks (CNN) with recurrent neural networks (RNN). CNN excels at feature extraction, whereas RNNs like LSTM and GRU are good at capturing long-term dependencies in timeseries data. The proposed hybrids provide a comprehensive solution for WQP by combining these models. The impact of changing hyperparameters on model performance was examined through experimentation using datasets from maritime aquaculture bases in China and aquaculture ponds in Kerala. The best hyperparameters were found for analysis and contrast. The CNN-LSTM hybrid model performs better in terms of prediction accuracy and computational efficiency than both attention-based DL models (attention-based GRU and attention-based LSTM) and baseline DL models (LSTM, GRU, and CNN). Interestingly, the hybrid models offer better computational efficiency and perform comparably to attentionbased models, which makes them useful for real-time WQP applications in intelligent aquaculture systems. This study highlights how hybrid DL models can improve WQP efficiency and accuracy, which is important for sustainable aquaculture methods.

Multiparameter water quality measurement instruments are being investigated for their potential applications in real-time data generation and forecasting algal blooms, including water pollution. Pontoon, a multiparameter water quality measurement system, was installed in Lake Dae-cheong to provide baseline data for algal monitoring and prediction. The system uses NB-IoT communication

network to transmit data from the device to a server. After laboratory pre-testing, the protocol was set up for two-way and polling communication. The system [11] was installed in October 2019 and has been functioning normally. However, the NB-IoT communication network experienced data collection issues during the initial trial phase due to time delays and issues with maintaining TCP socket connections.

This study [12] designs a narrowband Internet of things water quality monitoring system that combines an STM32F103 microcontroller with the Huawei Cloud IoT platform to address the issues of low efficiency and complexity associated with existing water quality monitoring methods. The targets automatically monitored waters' temperature, pH, TDS, and ORP data can all be continuously collected by this system. The Huawei CLOUD IoT platform allows users to query real-time monitoring information and automatically upload data in real-time. This overcomes the drawbacks of traditional water quality monitoring systems, such as protracted data collection cycles and subpar real-time performance, and has some innovative and useful applications.

This study [13] suggests an adaptable water quality monitoring system that may be set up to suit different aquatic species in pond aquaculture. The system connects wirelessly via Wi-Fi and NB-IoT and uses three different types of sensors: pH, temperature, and dissolved oxygen sensors. After processing these signals, a microcontroller transmits data to a cloud server. Farmers are notified by the system if the water quality falls outside of the predetermined range, which is regularly monitored. Additionally, a dashboard for real-time system monitoring is included. Three different species of aquatic creatures can be used with the system: tilapia, White sea bass and white shrimp. The user has the option to modify the controlled range. In comparison to typical tools, the prototype's accuracy for pH, temperature, and dissolved oxygen was 95.1%, 97.6%, and 98.5%, respectively. The system is

compatible with NB-IoT and Wi-Fi connections.

This study [14] proposes an Internet of Things (IoT)-based water consumption metering and quality monitoring system as a solution to the problems of water waste and low drinking water quality in Bangladesh. The system has a web/mobile application that allows users to monitor the quality of tap water in real-time. Water waste is decreased since billing records are kept of daily and monthly water consumption. The system uses quality monitoring to guarantee water purity and usage metering to cut down on needless water waste. Through the use of the Internet of Things, the metering, monitoring, and bill payment are completed remotely and online (IoT). By combining IoT, hardware, and software, the suggested solution reduces water waste, produces clean drinking water, and promotes environmental sustainability.

The goal of this [15] research is to use machine learning techniques at an edge device to automatically detect worrying occurrences in water quality. Creating an edge device to sense water quality parameters, identifying changes in water quality based on baseline measurements, sending out alarms when parameters go above threshold levels, and categorizing various forms of pollution are among the goals. The NSF Water Quality Index, user feedback, and the Weighted Arithmetic Index are the three water quality indicators that are used. Water quality indexes (WQI), which are based on six physico-chemical sensor characteristics, are used to determine the quality of water. The Support Vector Machine (SVM) algorithm is used to create a lightweight machine learning model, and alerting events are clustered to distinguish various categories. The goal of the project is to enhance safety and water quality monitoring.

1.13 ORGANIZATION OF THE REPORT

The organization of the thesis is as follows. Chapter 1 presents the introduction of

this thesis. Chapter 2 discusses the proposed mechanism of Hydro Watch system. It also deals with the design of individual blocks involved in this system. The results obtained from software and hardware implementation and analysis of the designed Hydro Watch system is presented in Chapter 3. Finally, Chapter 4 presents conclusion and future works to be carried out in this system.

CHAPTER 2

PROPOSED SYSTEM FOR MEASURING WATER QUALITY

2.1 POTABLE WATER ANALYSIS

Hydro watch is a water quality monitoring system that uses sensors to detect factors like temperature, turbidity, pH, and TDS. The data is sent to The Things Network via LORA connection for secure cloud storage. The user interface uses meter gauges and a specially designed webpage. Machine learning forecasts water potability based on these characteristics. Non-potable water is detected, and a filtration system is activated to address quality issues. This integration of sensor technology, cloud computing, and machine learning provides a robust solution for monitoring and maintaining water quality, with potential applications in household water management, environmental monitoring, and public health initiatives.

2.2 BLOCK DIAGRAM

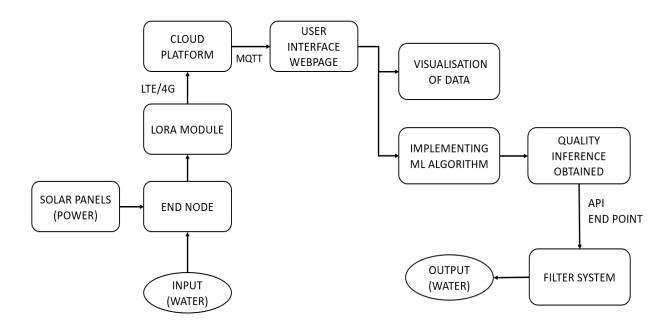


Figure 2.1: Block diagram of Hydro Watch

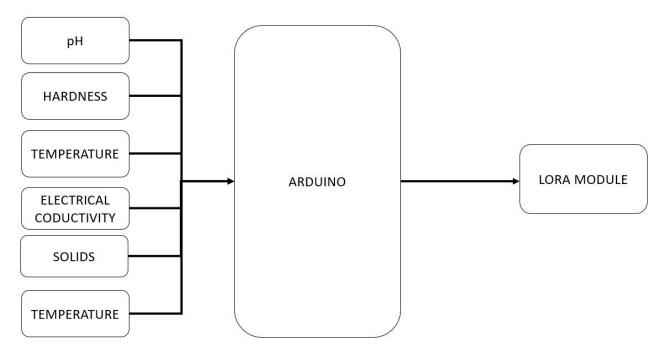


Figure 2.2: End Node of Hydro Watch

The Figure 2.1 shows the functional blockages of the entire Hydro Watch system. The Figure 2.2 depicts the End node the Hydro Watch system which consist of DS18B20 temperature sensor, analog pH sensor, TDS, turbidity sensor connected to Arduino uno.

2.2.1 SOLAR PANEL

Solar panels, also known as photovoltaic (PV) modules, employ the photovoltaic effect to convert sunlight into electrical power. Their many silicon-based solar cells generate direct current (DC) power when they are exposed to sunlight. This electricity can power whole power systems, businesses, and even buildings when condensed into solar arrays. Solar energy is sustainable as it doesn't rely on limited fossil fuels or release greenhouse gases into the environment. They are growing in popularity as a renewable energy source because of their long lifespan, low maintenance needs, and increased affordability. They are used to power the hydro

watch system naturally making it a energy-efficient system.

2.2.2 END NODE

The end node of this system consists of 4 sensors, pH, TDS, Turbidity and temperature, used for measuring water quality parameters. These sensors measure pH, Turbidity, Hardness, Solids, Electrical conductivity and temperature.

2.2.2.1 pH SENSOR

The pH sensor shown in Figure 2.3 measures the acidity or alkalinity of water on a scale of 0 to 14. It's vital for indicating water quality, as certain pH levels can indicate contamination or corrosion. In Hydro watch, the pH sensor helps identify potential issues such as acid rain runoff or alkaline contamination from industrial processes.



Figure 2.3: Analog pH sensor

2.2.2.2 TDS SENSOR

TDS sensors shown in Figure 2.4 measure the concentration of dissolved solids in water, including minerals, salts, and metals. This parameter is crucial for assessing water purity and suitability for consumption. In Hydro watch, the TDS sensor aids

in detecting elevated levels of dissolved substances, indicating potential contamination sources or water treatment needs.



Figure 2.4: TDS sensor

2.2.2.3 TURBIDITY SENSOR

Turbidity sensors shown in Figure 2.5 quantify the cloudiness or haziness of water caused by suspended particles. High turbidity levels can indicate sediment runoff, microbial growth, or industrial pollution. In Hydro watch, the turbidity sensor is instrumental in identifying water clarity issues and monitoring the effectiveness of filtration systems in removing suspended solids.



Figure 2.5: Turbidity sensor

2.2.2.4 DS18B20 TEMPERATURE SENSOR

Temperature sensor shown in Figure 2.6 measure the thermal energy of water,

providing insights into environmental conditions and potential contaminants' behavior. Temperature variations can impact water chemistry and microbial activity. In Hydro watch, the temperature sensor helps assess water quality fluctuations due to seasonal changes, industrial discharges, or climate-related factors, enhancing overall monitoring accuracy.



Figure 2.6: DS18B20 Temperature Sensor

2.2.3 ARDUINO UNO

Prominent among open-source microcontroller boards, the Arduino Uno is praised for having shaped an extensive array of electronic projects. Created by the Arduino Company, it makes use of the flexible ATmega328P microcontroller and is becoming quite popular among makers. It is suitable for both novice and seasoned developers. The Uno easily integrates with a wide range of sensors and actuators thanks to its many digital and analogue input/output pins, and its USB interface makes programming and power supply easier. nonprogrammers, accessibility for code development is ensured by the userfriendly Integrated Development Environment (IDE). Notably, users can personalize projects without getting bogged down in complex hardware details thanks to its compatibility with different shields. Supported by a vibrant

community, abundant tutorials, and a vast library repository, the Arduino Uno has become a valuable tool for education and prototyping, appealing to makers, students, and professionals alike. Its affordability, adaptability, and user-friendly design make it a preferred choice, influencing the development of innovative technologies in diverse industries, from simple LED projects to complex IoT and robotics applications.

2.2.4 LoRa SHIELD

The LoRa module is a pair consisting of shield and gateway where the shield is placed along with the system and the gateway is placed at the remote location where these data are going to be analyzed. The Figure 2.7 depicts the LoRa (Long Range) Shield, is a specialized hardware module tailored for long-range wireless communication using LoRa technology, typically compatible with platforms like Arduino.

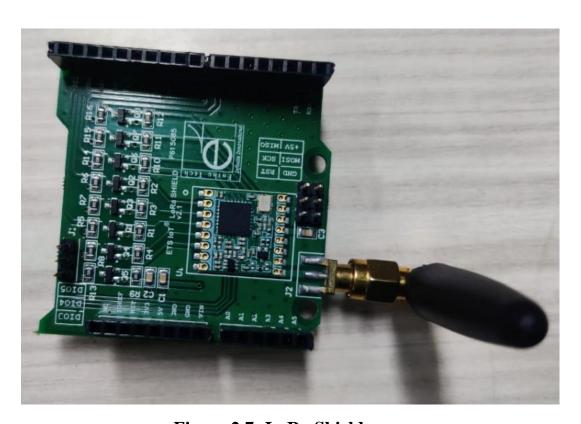


Figure 2.7: LoRa Shield

Serving as an extension to microcontrollers, LoRa Shields empower devices with the capability to communicate over extensive distances, making them ideal for low-power, long-range applications in the Internet of Things (IoT). The standout feature of LoRa technology lies in its remarkable communication range, spanning several kilometers in rural settings and maintaining significant distances in urban environments. This versatility positions LoRa Shields as indispensable for diverse IoT applications, including smart agriculture, smart cities, industrial IoT, and environmental monitoring, connecting sensors and devices dispersed over vast geographic areas. Apart from its impressive range, LoRa technology is acclaimed for its low power consumption, crucial for IoT devices operating on battery power. The technology's low data rate optimization further supports scenarios where small data packets need intermittent transmission, conserving energy and extending the operational life of connected devices.

Equipped with antennas, LoRa Shields ensure user-friendly integration into projects through common development platforms, providing developers with an accessible means to incorporate reliable and energy-efficient long-range wireless communication into IoT designs.

2.2.5 LoRa GATEWAY

A LoRa (Long Range) Gateway, figure 2.8, is a critical element in LoRaWAN (Long Range Wide Area Network) setups, acting as a crucial bridge between endnode devices and network servers. Operating as a conduit for long-range, lowpower communication in Internet of Things (IoT) applications, these gateways
receive data from LoRa-enabled devices and transmit it to a centralized network
server, facilitating bidirectional communication. Key to their functionality is
extending the communication range of LoRa-enabled devices, especially in subGHz frequency bands, making them ideal for expansive IoT applications like smart
agriculture and industrial monitoring. Equipped with multiple channels and
adaptable data rates, LoRa Gateways optimize network capacity and throughput,

efficiently managing communication parameters for reliable data transfer. Strategically placed for optimal coverage, these gateways connect to the internet, forming a vital link in the end-to-end communication chain. They play a pivotal role in aggregating data from diverse sources, enabling centralized management, analysis, and application of insights in the IoT ecosystem. Overall, LoRa Gateways are indispensable in building scalable and resilient IoT solutions across industries, forming the backbone of LoRaWAN networks. Because of its well-known small form, the LPS8 LoRa gateway may be deployed in a variety of spaces with limited space. Its tiny size and excellent range and connection capabilities enable it to function as a bridge between LoRa devices and the network server. Its performance and small design distinguish it from larger gateways while maintaining dependable connectivity. The range of LoRa communication is about 10km in urban areas and up to 15km in rural areas. This difference is mainly due to the lack of line of sight in the urban areas.



Figure 2.8: LoRa Gateway

2.2.6 THINGS NETWORK

The Internet of Things (IoT) can be made decentralised and community-driven with

the help of the Things Network (TTN), which runs on the LoRaWAN protocol. Strategically positioned throughout the world, LoRaWAN gateways serve as a link between IoT devices and the network server. Because of its decentralised architecture, TTN can operate in a variety of environments and guarantees longrange, low-power communication. Developers are empowered by TTN's openaccess model, which provides free platform access and a strong API for seamless device integration. Top priority is given to security, as evidenced by the use of strong encryption and communication protocols. TTN is a leading force in innovation and wide-spread adoption across a variety of IoT applications thanks to its collaborative ethos and dedication to accessibility. TTN places a high priority on security, and the platform is built with strict safeguards to protect communications and data. The decentralized framework incorporates robust protocols and encryption mechanisms to mitigate potential risks related to single points of failure. Because of its focus on security, TTN is able to continue serving as a reliable and strong solution for a wide variety of Internet of Things applications.

2.2.7 USER INTERFACE WEBPAGE

The user-created webpage employs MQTT protocol to visualize data fetched from the cloud, ensuring real-time insights. Accessible through password-protected authorization, the webpage prioritizes security. Utilizing MQTT integration from the cloud adds a layer of efficiency, enabling seamless, secure data transmission to the webpage. This setup not only enhances user privacy but also facilitates a dynamic and interactive experience for users, allowing them to access and interpret live data with confidence and ease.

2.2.8 ANALYZING AND VISUALIZING DATA

The user-created webpage for the Hydro watch project offers an intuitive interface designed for analyzing and visualizing live data, incorporating dynamic meter gauges alongside interactive line graphs. These meter gauges provide users with real-time insights into water quality parameters such as pH, TDS, turbidity, and temperature, enhancing understanding and decision-making. Integrated with machine learning algorithms, the webpage dynamically responds to incoming data, offering clear and concise presentations of information. Users can easily interpret fluctuations in water quality, observe trends, and make informed decisions regarding water potability. This seamless integration of meter gauges, dynamic line graphs, and machine learning fosters a user-friendly environment for comprehensive data analysis, empowering users to take proactive measures to maintain water quality standards.

2.2.9 WEB SOCKET

A communication protocol called WebSockets allows clients and servers to communicate in real time and both directions over a single, persistent connection. They perform exceptionally well in applications that demand real-time updates, like financial trading, gaming, and live chat. In contrast to conventional HTTP, WebSockets reduce overhead and latency by doing away with the requirement for repeated queries. The connection is upgraded to a WebSocket connection following an initial HTTP handshake, allowing for simultaneous data transmission between both ends. WebSockets are extensively supported by contemporary browsers, offer lightweight messages that conserve bandwidth, and can be implemented using a variety of programming languages and frameworks to create flexible real-time web applications.

2.2.10 MACHINE LEARNING ALGORITHMS

For predicting potability of water five machine learning algorithms have been trained and the best suited among them is been chosen based on their performance. Extreme Gradient Boosting (XGBoost) is a powerful machine learning algorithm that utilizes an ensemble of decision trees to make predictions. It trains trees sequentially, focusing on instances where previous trees underperform, thus boosting overall accuracy. XGBoost is known for its efficiency, scalability, and

effectiveness in various domains.

Long Short-Term Memory (LSTM) is a type of recurrent neural network (RNN) architecture designed for processing sequential data. It preserves information over long sequences, addressing vanishing gradient problems in traditional RNNs. LSTMs use gates to regulate information flow, enabling learning of dependencies and patterns in time-series data like speech and text.

Support Vector Machine (SVM) is a supervised learning algorithm used for classification and regression tasks. It finds the optimal hyperplane that best separates classes in a high-dimensional space, maximizing the margin between data points. SVM is effective for both linearly separable and non-linearly separable data with appropriate kernel functions.

Random forest is an ensemble learning technique in machine learning. It constructs multiple decision trees during training and outputs the mode of the classes for classification or the average prediction for regression. It improves accuracy and reduces overfitting by aggregating predictions from multiple trees.

A Gated Recurrent Unit (GRU) is a type of recurrent neural network (RNN) designed to capture long-term dependencies in sequential data. It uses gating mechanisms to regulate information flow, updating its internal state with each input. GRUs are effective for tasks like speech recognition, language modelling, and time series prediction.

Among the five trained ML models XGBoost is been preferred for its exceptional performance across various machine learning tasks. It offers high accuracy, scalability, and efficiency due to its optimized gradient boosting algorithm. XGBoost also provides feature importance evaluation, handling missing data, and regularization techniques, making it versatile and robust for real-world applications. The dataset used to train these models have been taken from reputed Kaggle site [16].

2.2.10.1 PERFORMANCE PARAMETERS

The figure 2.9 shows a four-quadrant chart, which is useful for assessing how well

a categorization model performs. Positive (1) and negative (0) numbers are separated into two categories on the chart. The true positive (TP) cases, in which both the predicted and actual values are positive, are shown by the top left quadrant. False positive (FP) cases, in which the expected value is positive but the actual value is negative, are represented by the upper right quadrant. True negative (TN) situations, in which both the actual and anticipated values are negative, are shown by the bottom left quadrant. False negative (FN) cases, in which the expected value is negative but the actual value is positive, are represented by the bottom right quadrant. By taking into account true positives, false positives, true negatives, and false negatives, this figure enables us to assess the model's performance. We may determine a number of performance indicators, including accuracy, precision, recall, and F1-score, by examining the values in these quadrants.

$$Precision = \frac{TP}{(TP+FP)} \tag{2.1}$$

$$Recall = \frac{TP}{(TP+FN)} \tag{2.2}$$

Actual Values

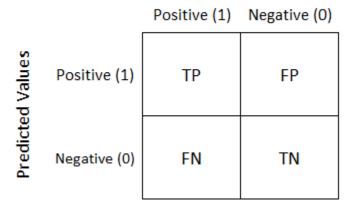


Figure 2.9: Confusion Matrix

$$Accuracy = \frac{(TP+TF)}{(TP+TF+FP+FN)}$$
 (2.3)

$$F1 Score = \frac{(2*Precision*Recall)}{(Precision+Recall)}$$
(2.4)

These are the equations 2.1, 2.2, 2.3, 2.4 for several assessment metrics used in binary classification issues. Precision, Recall, Accuracy, and F1 Score are among the measurements. Truth Positives (TP), False Positives (FP), and False Negatives (FN) are used to calculate these metrics. Precision and Recall are harmonic means that make up the F1 Score.

2.2.11 PARAMETERS AND SPECIFICATION

The expected range of potable water as shown in Table 2.1 refers to the acceptable levels of various physical and chemical parameters in drinking water to ensure it is safe for human consumption. These parameters include pH, turbidity, total dissolved solids (TDS), hardness, and the presence of certain minerals and contaminants such as fluoride, chloride, and nitrate. The Environmental Protection Agency (EPA) and the World Health Organization (WHO) have developed guidelines for these metrics based on in-depth research and investigations. Potable water specifications include, for example, a pH of 6.5 to 8.5, a maximum TDS of 500 mg/L, and a turbidity of less than 5 NTU. Going overboard might result in health problems such kidney damage, gastrointestinal troubles, and brain abnormalities.

Table 2.1: Expected range for potable water

PARAMETERS	RANGE	
рН	6.5-8.5	
Hardness	(0-400) mg/L	
Turbidity	(0-1) NTU	
Solids	(0-500) mg/L	
Temperature	(20-45) °C	
Conductivity	(0-800) μS/cm	

Thus, it is crucial to test and observe drinking water on a regular basis to make sure it is safe to consume and falls within the expected range of potable water.

2.2.12 FILTER DESIGN OF THIS SYSTEM

Figure 2.10 depicts the block diagram of the filter design used for filtration purpose in the hydro watch system. This depicts the work flow of the filter system when the water is found to be non-potable. After receiving the potability status of the water from the web page using web socket protocol in ESP32 DOIT module. The filter process will be initiated based upon the status of potability for two minutes automatically.

Acting as the initial layer in the filtration process as shown in Figure 2.11, gravel serves as a coarse filter, primarily tasked with removing large debris and sediments from the water. Its porous nature allows water to pass through while trapping larger particles, preventing them from clogging subsequent layers.

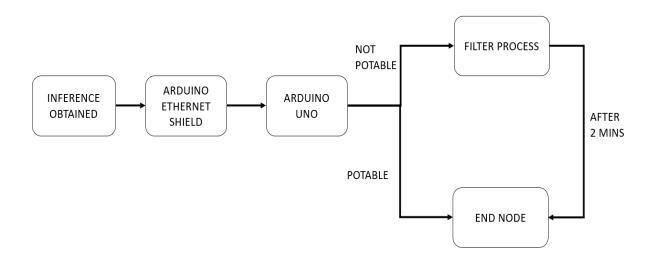


Figure 2.10: Filter process of the system

Fine sand serves as a secondary filtration medium, capturing smaller particles that may have bypassed the gravel layer. Its fine texture provides additional surface area for filtration, ensuring the removal of fine sediment, silt, and remaining debris. Fine sand aids in clarifying the water and enhances the efficiency of subsequent filtration stages.

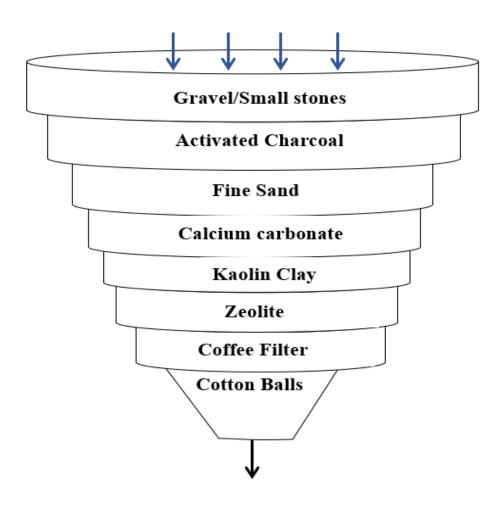


Figure 2.11: Filter Design of the system

Activated charcoal, also known as activated carbon, is widely used in filtration systems for its exceptional adsorption properties. It plays a crucial role in removing impurities and contaminants from water. Concerning the specified purposes, activated charcoal assists in temperature regulation by absorbing heat from the water, helping to stabilize temperature fluctuations. Its main function, however, lies in solids reduction, as it effectively traps organic compounds, chemicals, and other dissolved substances through adsorption. This layer also contributes to conductivity control by adsorbing ions and dissolved solids that may affect the

electrical conductivity of the water.

Calcium carbonate plays a vital role in pH control during water treatment. It helps stabilize the pH levels of water by neutralizing acidity or alkalinity, ensuring that the water remains within the desired pH range for safe consumption and effective filtration. Zeolite is commonly used for hardness reduction in water treatment processes. It works by exchanging ions with the water, effectively removing minerals that cause water hardness, such as calcium and magnesium. This helps prevent scaling and build-up in pipes and appliances while improving the taste and quality of the water.

Fine sand and kaolin clay are commonly utilized together as filtration media to remove suspended particles and turbidity from water. Turbidity refers to the cloudiness or haziness caused by the presence of finely divided particles in water. In the specified purposes, these layers play a crucial role in turbidity reduction by trapping and retaining suspended particles as water passes through. Fine sand acts as a physical filter, while kaolin clay, with its fine particle size and adsorptive properties, enhances the removal of colloidal particles and organic matter, resulting in clearer water. Cotton balls are often used as a post-filter in water treatment systems to provide a final stage of filtration and ensure the removal of any remaining impurities or particles. They serve as a physical barrier, capturing fine particles that may have bypassed earlier filtration stages, resulting in cleaner and safer water.

2.2.12 RESOURCE LIMITATION

Although the NB IoT module might potentially be used for our project, we are only able to complete our work via LoRa connectivity because there isn't an IoT sim card available that is used for commercial reasons and much needed for the functionality of NB-IOT communication.

Another drawback is that our project was completed using a prototype system, which is only appropriate for small-scale applications. Better sensors might potentially be used to do the task on a larger scale; however, this would raise the

project's expense.

The final issue was encountered upon receiving an automated alert from the Twilio user interface webpage; the subscription fees were too expensive.

2.3 SUMMARY

This Chapter explains each block involved in the Hydro Watch system in detail. Overall working of this system is such that using the turbidity, TDS, DS18B20, pH sensor it obtains the temperature, conductivity, hardness, solids, pH, turbidity values from the water, store those values in the things network cloud platform and from there the live data is been pushed to our customized webpage using MQTT protocol inbuilt in the TTN. Subsequently, the obtained live data is been visualized for better inference and monitoring. For predicting the potability of water suitable ml algorithms has been implemented.

Chapter 3

RESULTS AND DISCUSSION

3.1 IMPLEMENTATION

The proposed system is been programmed using Arduino IDE and VS CODE, in C++ and python languages respectively. Further the complex command centre monitoring is been carried out using DS18B20 Sensor, Analog pH Sensor, Turbidity Sensor, TDS Sensor, Arduino Uno, ESP32 DOKIT Module, LoRa shield and gateway.

3.2 RESULTS

The implementation results obtained for the proposed system is been discussed in this section.

3.2.1 VARIOUS LIQUIDS TESTED

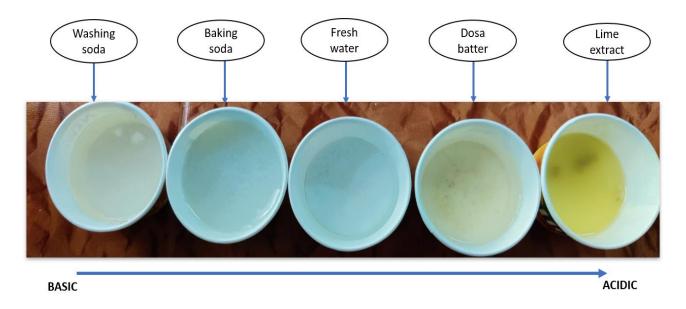


Figure 3.1: Different types of liquids tested

The Figure 3.1 shows the different liquids for which water parameters are obtained using sensors for further study the nature of those liquids. The liquids are selected based on their variability with respect to their pH values covering all sort of types of liquids from basic to acidic.

3.2.2 I2C SCANNER

```
Output Serial Monitor ×

Message (Enter to send message to 'Arduino Uno' on 'COM4')

I2C Scanner
Scanning...
I2C device found at address 0x57 !
done

Scanning...
I2C device found at address 0x57 !
done
```

Figure 3.2: I2C scanner to check the sensor connectivity

The Analog pH Sensor, Turbidity Sensor and TDS Sensor are all analog sensors, they communicate with the Arduino uno using the I2C protocol and hence for checking the connectivity of the sensor this scanner code is programmed to check whether we are able to print the sensor address as shown in Figure 3.2 to ensure its proper establishment communication between the sensor and Uno.

3.2.3 QUALITY PARAMETERS OF LIQUIDS

The water quality parameters of those liquids mentioned above are measured using the four sensors to indicate these six parameters, pH, Temperature, Hardness, Solids, Electrical conductivity and Turbidity. The Figures 3.3,3.4,3.5,3.6,3.7 shows these parameters of the selected 5 liquids.

```
Output Serial Monitor x

Message (Enter to send message to 'Arduino Mega or Mega 2560' on 'COM3')

—————

pH Value: 3.91

Temperature: 27.75 °C

TDS (ppm): 1289.06

Hardness (mg/L): 902.34

Solids (mg/L): 1031.25

Electrical Conductivity (µS/cm): 2578.12

Turbidity (NTU): 2.39
```

Figure 3.3: Quality parameters of lime extract

```
Output Serial Monitor ×

Message (Enter to send message to 'Arduino Mega or Mega 2560' on 'COM3')

-----
pH Value: 6.62
Temperature: 26.56 °C
TDS (ppm): 749.51
Hardness (mg/L): 524.66
Solids (mg/L): 599.61
Electrical Conductivity (µS/cm): 1499.02
Turbidity (NTU): 2.41
```

Figure 3.4: Quality parameters of Dosa batter mixture

```
Output Serial Monitor ×

Message (Enter to send message to 'Arduino Mega or Mega 2560' on 'COM3')

pH Value: 7.15

Temperature: 28.44 °C

TDS (ppm): 256.35

Hardness (mg/L): 179.44

Solids (mg/L): 205.08

Electrical Conductivity (µS/cm): 512.70

Turbidity (NTU): 0.61
```

Figure 3.5: Quality parameters of Fresh Water

Output Serial Monitor × Message (Enter to send message to 'Arduino Mega or Mega 2560' on 'COM3') pH Value: 10.33 Temperature: 29.31 °C TDS (ppm): 1264.65 Hardness (mg/L): 885.25 Solids (mg/L): 1011.72 Electrical Conductivity (µS/cm): 2529.30 Turbidity (NTU): 8.43

Figure 3.6: Quality parameters of Baking Soda

```
Output Serial Monitor ×

Message (Enter to send message to 'Arduino Mega or Mega 2560' on 'COM3')

pH Value: 11.07

Temperature: 39.00 °C

TDS (ppm): 1342.77

Hardness (mg/L): 939.94

Solids (mg/L): 1074.22

Electrical Conductivity (µS/cm): 2685.55

Turbidity (NTU): 5.25
```

Figure 3.7: Quality parameters of Washing soda

3.2.4 SENDING DATA TO TTN USING LORA SHIELD

```
Output Serial Monitor ×

Message (Enter to send message to 'Arduino Uno' on 'COM10')

Starting
-----
pH Value: 11.46
Temperature: 32 °C
TDS (ppm): 107.42
Hardness (mg/L): 75.20
Solids (mg/L): 85.94
Electrical Conductivity (µS/cm): 214.84
Turbidity (NTU): 10.14
```

Figure 3.8: Connecting to Cloud Console

```
Output Serial Monitor ×

Message (Enter to send message to 'Arduino Uno' on 'COM10')

Turbidity (NTU): 10.14

Packet queued
243774: EV_JOINING
303090: Unknown event
624410: EV_JOINED
625718: Unknown event
952493: EV_TXCOMPLETE (includes waiting for RX windows)
```

Figure 3.9: Completion of Serial monitor during LoRa Transmission

After collecting the data from the Analog pH Sensor, Turbidity Sensor, TDS Sensor and Temperature Sensor of a random water source, we transmit those values to the TTN using LoRa communication and Figures 3.8 and 3.9 shows the entire process seen at the transmitter side.

3.2.5 RECEIVING DATA AT THE TTN

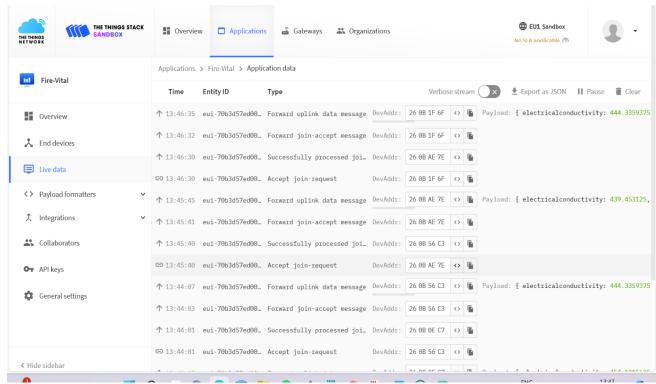


Figure 3.10: Data Receiving at the TTN Cloud

The live data transmitted by the shield is been received by the gateway and pushed to the cloud using the LAN OR 3G/4G. Figure 3.10 shows the data being received at the cloud side, the payload indicates the data transmitted.

3.2.6 MQTT SUBSCRIPTION IN THE TTN

After successful establishment of connection between the LoRa shield and gateway and proper arrival of live data we subscribe to the inbuilt mqtt integration present in the TTN as shown in Figure 3.11 to make it act as a broker to publish all the data to its subscribers.

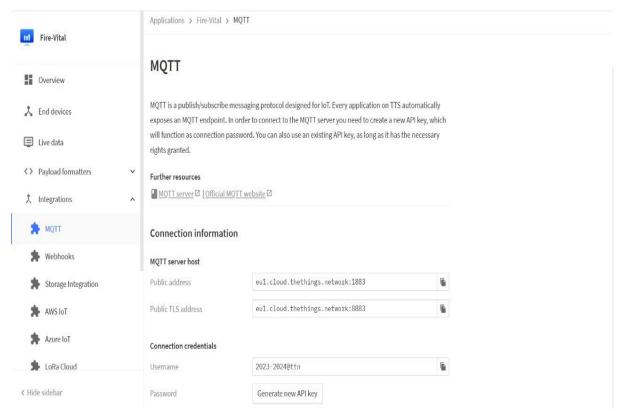


Figure 3.11: Configuring MQTT in the TTN Console

3.2.7 CONNECTION BETWEEN MQTT BROKER AND SUBSCRIBER

At the vs code, we have written program such that our local terminal is been subscribed to the mqtt broker available in the TTN as shown in Figure 3.12 and it starts receiving the live data with very little latency.

```
PROBLEMS OUTPUT DEBUG CONSOLE TERMINAL PORTS

PS C:\Users\heman\PHASE 2> python3 aqs.py
Connected To TTN MQTT Broker
Electrical Conductivity: 1450.1953125
Hardness: 507.568359375
pH: 9.493646621704102
Solids: 580.078125
Temperature: 27
Turbidity: 7.186274528503418
```

Figure 3.12: Subscribing to the MQTT broker and receiving data

3.2.8 CONNECTION OF LOCAL HOST WEBSITE

```
PS C:\Users\heman\FLASK> python app.py

* Serving Flask app 'app'

* Debug mode: on

WARNING: This is a development server. Do not use it in a production deploym

ent. Use a production WSGI server instead.

* Running on http://127.0.0.1:5000

Press CTRL+C to quit

* Restarting with stat

* Debugger is active!

* Debugger PIN: 465-539-729

Connected To TTN MQTT Broker

Connected To TTN MQTT Broker
```

Figure 3.13: Local Host Web Server is Hosted and Connected to MQTT Broker

We have created a website customized for easier analysis of the live data using graphs. Figure 3.13 shows the connection of our website with the subscriber in order to pull the live data to our website for analysis. The website is authorized with unique username and password for safer use of data.

3.2.9 WEBSITE HOME PAGE

The figure 3.14 depicts the website home page containing the welcome quotes and the navigation bar to the login page.

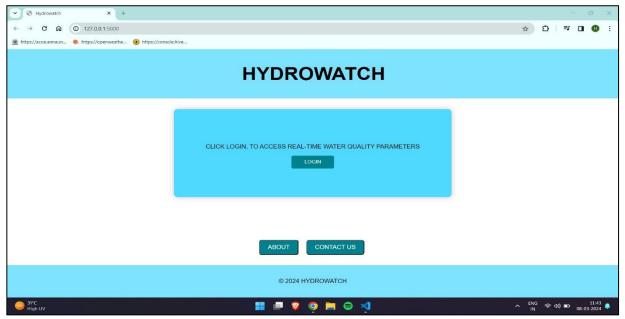


Figure 3.14: Website Main Page

3.2.10 OTHER PAGES IN THE WEBSITE

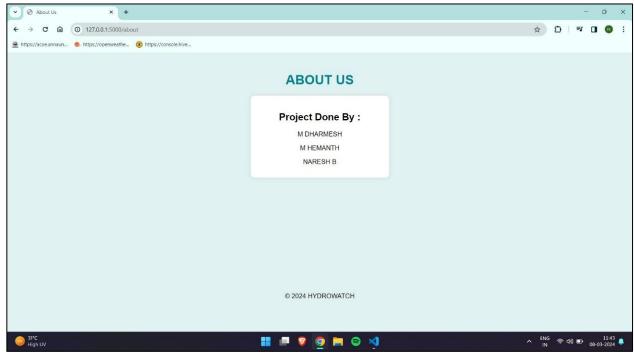


Figure 3.15: Website About Page

The Figure 3.15 shows the website about page where it presents the names of the team members who have created this Hydro Watch system.

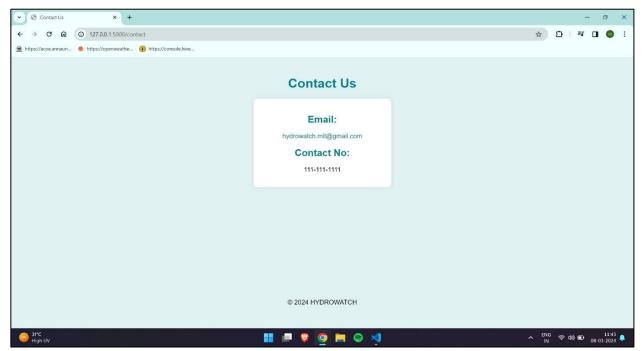


Figure 3.16: Website Contact Us

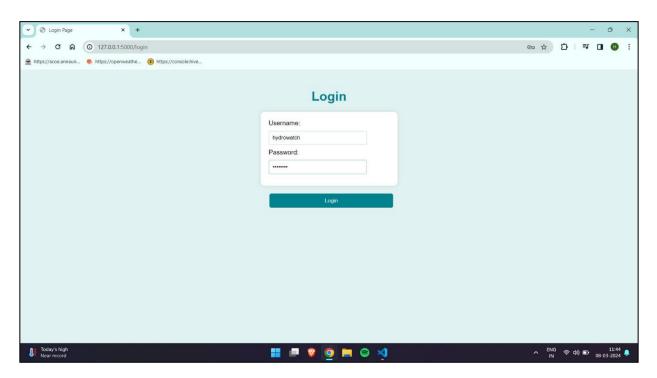


Figure 3.17: Website Login Page

The figure 3.16 depicts the about us page of our website. The Website Login page is been depicted in the Figure 3.17 containing the spaces to enter the username and password given to only the authorized users for better safety of the data.

3.2.11 VISUALIZATION OF DATA RECEIVED

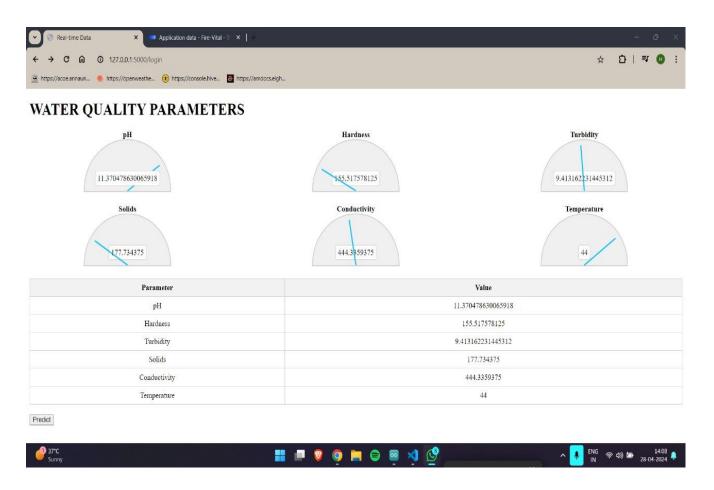


Figure 3.18: Visualization of Water quality parameters

The figure 3.18 shows the visualization of all water quality data in a meter gauges representation with a needle highlighting the values as in a speedometer. The meter gauges are been updated dynamically as the data is been received at the cloud with minimum latency. The values are printed in the same page as well for better understanding of the user.

3.2.12 ML MODEL PERFORMANCE

For predicting the potability of water with the obtained water quality parameters we have studied and trained 5 most suited ML models to our application and obtained their performances to find which better suites the system for better efficiency. The result is shown in Table 3.1.

Table 3.1: Performance of different ML models

ML MODEL	ACCURACY (%)	PRECISION	RECALL	F1 SCORE
XG BOOST	99.9	0.9843	0.9589	0.978
LSTM	99.6	0.9855	0.9539	0.9694
SVM	98.9	0.9477	0.96	0.9884
RANDOM FOREST	99.8	0.9769	0.9589	0.9989
GRU	99.4	0.9949	0.96	0.987

3.2.13 POTABILITY PREDICTION

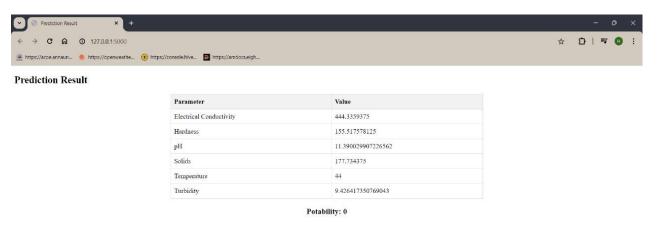




Figure 3.19: Potability Prediction in Webpage

From the table 3.1, we can infer that XGBoost ML model performs well in this application hence we have integrated this model with our website using Flask to find the potability of the water source for better understanding.

This is shown in the Figure 3.19, after visualization of these data in the meter gauges the site automatically refreshes and navigate to this potability page.

3.14 INITIALIZING ALERT MECHANISM



Figure 3.20: MQTT connection establishment

The Figure 3.20 depicts that Python script that connects to The Things Network (TTN) MQTT broker and subscribes to a specific topic to receive uplink messages from a LoRaWAN device. It also shows that after obtaining the potability condition if the potability is found 0 which is non-potable condition an alert mechanism is been initiated via the WhatsApp platform. The ideal preferred platform will be SMS but we lack the resource for its function hence chosen WhatsApp. The alert will be sent in about 15-20 seconds from the time of prediction due to the time taken to breach the policing of WhatsApp.

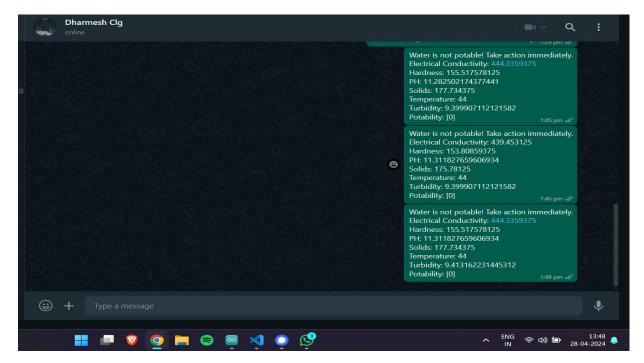


Figure 3.21: Output of alert mechanism

The alert message sent to the concerned person is sent through the whatsapp with the message 'WATER IS NOT POTABLE! PLS TAKE ACTION IMMEDIALTELY' and also the six water parameters as seen in Figure 3.21.

3.15 FILTER PROCESS



Figure 3.22: WebSocket Connected and Potability status

The Figure 3.22 depicts the potability value received from the webpage to ESP32 through websocket and turns the motor on for 2 minutes. The motor is actually

connected to a Turbine which sucks the water into our own designed filter to make the non-potable water into somewhat potable using suitable ingredients in appropriate quantity.



Figure 3.23: Water Filter Setup

The Figure 3.23 shows the layers of filter system which contains Gravel/Small stones, Activated Charcoal, Fine Sand, Calcium carbonate, Kaolin Clay, Zeolite, Coffee Filter and Cotton Balls.

3.2.16 SOLAR PANEL

The Figure 3.24 shows the prototype of solar panels fitted to our system where the panel are used to convert the natural sun light energy into usable energy for powering the Arduino uno. The number of solar panels needed for this depends on the amount of power each gives, in this prototype only two panels were needed for the functionality.

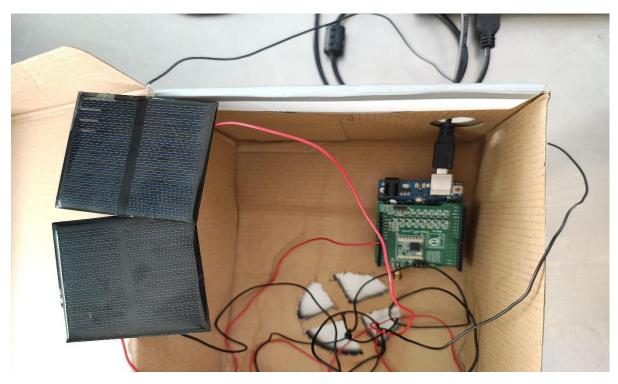


Figure 3.24: Solar Panel Powering sensors and Arduino Uno

3.2.17 HYDRO WATCH SYSTEM

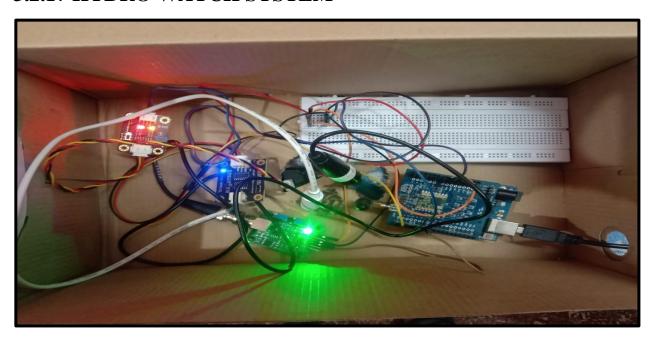


Figure 3.25 Top View of our System

Figure 3.25,3.26 depicts the complete Hydro Watch System comprising of 4 sensors, pH, TDS, Turbidity and temperature, used for measuring water quality parameters connected to LoRa shield mounted on Arduino uno for its

communication to cloud platform for further process.



Figure 3.26: Bottom View of our System

3.3 PERFORMANCE ANALYSIS

The Hydro Watch system is been analyzed in various section like range and compared with existing works related to it.

3.3.1 RANGE ANALYSIS

The proposed Hydro Watch system is been analyzed in real time by considering the reference point as the Anna Nagar Tower Park where the gateway is been stationed. Table 3.2 represents the operating range of the Hydro Watch System. It can be inferred that when receiver is placed in the outdoor environment, the operating range exceeds 2 kilometers whereas incase of indoor placement the range does not exceed 2 kilometers.

With the given Line of Sight (LOS) between the transmitter and the receiver the range can be maximized up to a distance of 10 kilometers in urban areas and up to 15kms in rural areas. This is because it will offer less multipath fading and the signal will undergo less attenuation and loss compared to the non-LOS condition.

Table 3.2: Analysis of working range of the system

DISTANCE	INDOOR	OUTDOOR
(LoRa Shield)		
Anna Nagar Tower	YES	YES
Metro station (300		
meters)		
Kora Food Street	YES	YES
(500 meters)		
Pizza Hut(1 Kilometer)	YES	YES
Thirumangalam Metro	NO	YES
station (2 Kilometers)		

3.3.2 COMPARING WITH EXISTING RESEARCH WORKS

Table 3.3: Comparison of our Hydro Watch with existing research

[5] V. Muthukumar	[12] Y. Wang	HydroWatch: Real-	
etal		Time Water Quality	
		Analytics and	
		Filtration	
• No Energy-	No energy-efficient	• Turbine blades	
efficient method	method was used.	convert	
was used.		mechanical	

• No ML model integrated just visualisation and storage of data is done.	• No ML model integrated just visualisation and storage of data is done.	rotations into electrical energy, making them ideal for low-power devices like wearables or sensors. • The system is integrated with XGBoost ML model for potability prediction hence, the system doesn't just store the data.
• They have implemented using Wi-Fi communication which is shot range.	 They have implemented using NB-IOT communication which is one of long range but requires a SIM card for its functionality. 	The system is implemented using LoRa communication which is very much suited for conditions where we can't network coverage.

Table 3.3 shows the comparative analysis of the existing researches in this line of research. It can be inferred from the table that Hydro Watch is much efficient compared to the existing works in terms of power efficiency and autonomous working of the system.

3.3.3 STATISTICAL ANALYSIS

The Figure 3.27 and Figure 3.28 shows the statistical comparison of Hydro Watch paper with [10] works on parameters like computation time and model accuracy of their ML models with Hydro Watch ML model. These parameters are compared based on the outputs taken from their system integrated with the respective ML models.

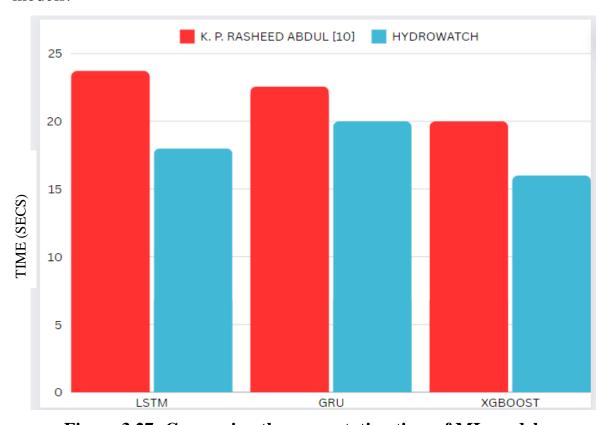


Figure 3.27: Comparing the computation time of ML models

Table 3.4 and 3.5 shows the computational time & accuracy analysis of the

designed system with the existing approach.

Table 3.4: Computational Time

J		
ML Models	K.P. RASHEED ABDUL et.al	HYDROWATCH
	'	
	[10]	
LSTM	24 secs	18 secs
GRU	23 secs	20 secs
XGBOOST	20 secs	16 secs

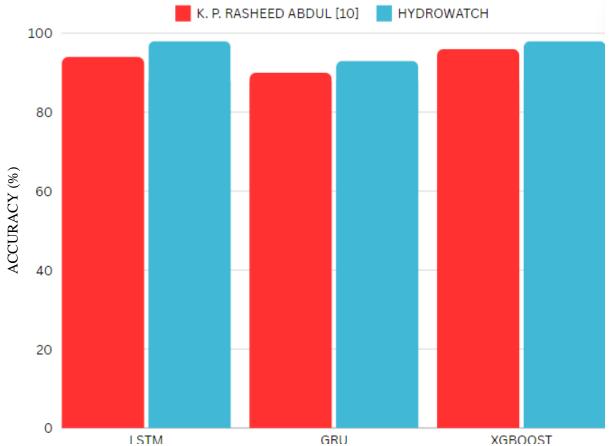


Figure 3.29: The accuracy (%) of ML models

Table 3.5: Accuracy (%)

ML Models	K.P. RASHEED ABDUL et.al [10]	HYDROWATCH
LSTM	94	98
GRU	90	93
XGBOOST	96	98

From both these graphs, its quite evident that Hydro Watch system performs well in terms of computational time and accuracy than the other models used in a similar research proving Hydro Watch system's efficiency.

3.4 SUMMARY

This Chapter discusses the results of each block involved in the Hydro Watch system in detail. It also discusses the various analysis conducted to test the performance of the Hydro Watch system.

CHAPTER 4

CONCLUSION AND FUTURE SCOPE

To sum up, the Hydro Watch project offers a thorough approach to water quality monitoring and potability assurance. The system gathers real-time data on water parameters by integrating sensors including temperature, turbidity, pH, and TDS with cloud-based data storage and transfer via LORA communication. Metre gauges and dynamic line graphs are used to provide insights from this data visualization on a user-created webpage.

If necessary, a specific filtration system is triggered by machine learning algorithms that forecast the potability of the water. System efficiency is further increased by features like WhatsApp notifications for non-potable water and energy-saving turbine mechanisms. All things considered, Hydro Watch is a shining example of ingenuity, providing a proactive and user-friendly method of preserving clean and safe drinking water. The results obtained from the comparative analysis with its existing works proves the hydro watch efficiency in terms of computational time and accuracy.

Hydro watch's future plans include incorporating state-of-the-art sensor technologies—like sensors based on nanotechnology—for improved monitoring of water quality. Drones with cutting-edge sensors might provide aerial coverage, enhancing ground-based technologies for an all-encompassing evaluation. Additionally, the combination of blockchain technology and artificial intelligence (AI) promises to enhance data administration and analysis, improve forecasts of water quality, and guarantee data integrity across the system. These developments might help Hydro Watch become more sustainable and effective, especially when combined with further materials science and renewable energy research. In the end, these developments hope to make a major contribution to international efforts to guarantee that everyone has access to clean, safe drinking water.

REFERENCES

- [1] G. A. López-Ramírez and A. Aragón-Zavala, "Wireless Sensor Networks for Water Quality Monitoring: A Comprehensive Review", in IEEE Access, vol. 11, pp. 95120-95142, 2023, doi: 10.1109/ACCESS.2023.3308905.
- [2] S. Mandal, S. Kumar and P. Ranjan, "Smart IoT-based Water Monitoring System using Redundancy Elimination Strategy", 2021 IEEE Bombay Section Signature Conference (IBSSC), Gwalior, India, 2021, pp. 1-4, doi: 10.1109/IBSSC53889.2021.9673314.
- [3] H. Zhang, X. Xie and Junsan Hou, "Water pollution accident control and urban safety water supply", 2011 2nd IEEE International Conference on Emergency Management and Management Sciences, Beijing, China, 2011, pp. 37-40, doi: 10.1109/ICEMMS.2011.6015613.
- [4] G. A. López-Ramírez and A. Aragón-Zavala, "Wireless Sensor Networks for Water Quality Monitoring: A Comprehensive Review", in IEEE Access, vol. 11, pp. 95120-95142, 2023, doi: 10.1109/ACCESS.2023.3308905.
- [5] V. Muthukumar, V. Selvakumar, M. Nalini and B. Chitradevi, "Cloud-based Smart Water Management System", 2023 International Conference on Sustainable Computing and Smart Systems (ICSCSS), Coimbatore, India, 2023, pp. 1633-1638, doi: 10.1109/ICSCSS57650.2023.10169753.
- [6] A. L. Lopez, N. A. Haripriya, K. Raveendran, S. Baby and C. V. Priya, "Water quality prediction system using LSTM NN and IoT", 2021 IEEE International Power and Renewable Energy Conference (IPRECON), Kollam, India, 2021, pp. 1-6, doi: 10.1109/IPRECON52453.2021.9640938.
- [7] H. Sui, G. Zheng, J. Zhou, H. Li and Z. Gu, "Application of NB-IoT Technology in City Open Water Monitoring", 2020 6th International Symposium on System and Software Reliability (ISSSR), Chengdu, China, 2020, pp. 95-98, doi: 10.1109/ISSSR51244.2020.00023.
- [8] M. Kumar, T. Singh, M. K. Maurya, A. Shivhare, A. Raut and P. K. Singh,

- "Quality Assessment and Monitoring of River Water Using IoT Infrastructure", in IEEE Internet of Things Journal, vol. 10, no. 12, pp. 10280-10290, 15 June15, 2023, doi: 10.1109/JIOT.2023.3238123.
- [9] Y. Wang, I. W. -H. Ho, Y. Chen, Y. Wang and Y. Lin, "Real-Time Water Quality Monitoring and Estimation in AIoT for Freshwater Biodiversity Conservation", in IEEE Internet of Things Journal, vol. 9, no. 16, pp. 14366-14374, 15 Aug.15, 2022, doi: 10.1109/JIOT.2021.3078166.
- [10] K. P. Rasheed Abdul Haq and V. P. Harigovindan, "Water Quality Prediction for Smart Aquaculture Using Hybrid Deep Learning Models", in IEEE Access, vol. 10, pp. 60078-60098, 2022, doi: 10.1109/ACCESS.2022.3180482.
- [11] C. -W. Lee, H. Jeong, J. -H. Ryu, J. Park and B. -C. Choi, "System for Multi Parameter Water Quality Monitoring Based on NB-IoT", 2021 International Conference on Information and Communication Technology Convergence (ICTC), Jeju Island, Korea, Republic of, 2021, pp. 759-761, doi: 10.1109/ICTC52510.2021.9620895.
- [12] Y. Wang and F. Lv, "Design of water quality monitoring system based on NB-IoT technolog", 2022 3rd International Conference on Computer Vision, Image and Deep Learning & International Conference on Computer Engineering and Applications (CVIDL & ICCEA), Changchun, China, 2022, pp. 825-828, doi: 10.1109/CVIDLICCEA56201.2022.9824243.
- [13] N. Wannee and T. Samanchuen, "A Flexible Water Monitoring System for Pond Aquaculture", 2022 International Conference on Digital Government Technology and Innovation (DGTi-CON), Bangkok, Thailand, 2022, pp. 91-95, doi: 10.1109/DGTi-CON53875.2022.9849186.
- [14] M. H. Jewel and A. Al Mamun, "Internet of Things (IoT) for Water Quality Monitoring and Consumption Management", 2022 4th International Conference on Sustainable Technologies for Industry 4.0 (STI), Dhaka, Bangladesh, 2022, pp. 1-5, doi: 10.1109/STI56238.2022.10103355.

- [15] Y. Kumar and S. K. Udgata, "Machine learning model for IoT-Edge device based Water Quality Monitoring", IEEE INFOCOM 2022 IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS), New York, NY, USA, 2022, pp. 1-6, doi: 10.1109/INFOCOMWKSHPS54753.2022.9798212.
- [16] https://www.kaggle.com/datasets/uom190346a/water-quality-and-potability