AI-Powered Water Quality Detection and Purification Recommendation System Using Refactor Index

A PROJECT REPORT

submitted by

ABIN SANTHOSH IES22CS006

to

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of

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in

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IES College of Engineering

Chittilappilly, Thrissur - 680 551

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DECLARATION

I undersigned hereby declare that the Project report (**”AI-Powered Water Quality Detection and Purification Recommendation System Using Refactor Index”**), submitted for partial fulfillment of the requirements for the award of degree of Bachelor of Technology of the APJ Abdul Kalam Technological University, Kerala is a bonafide work done by me under supervision of **Ms.Meethu M B**. This submission represents my ideas in my own words and where ideas or words of others have been included, I have adequately and accurately cited and referenced the original sources. I also declare that I have adhered to ethics of academic honesty and integrity and have not misrepresented or fabricated any data or idea or fact or source in my submission. I understand that any violation of the above will be a cause for disciplinary action by the institute and/or the University and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been obtained. This report has not been previously formed the basis for the award of any degree, diploma or similar title of any other University.

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CERTIFICATE

This is to certify that the report entitled **"AI-Powered Water Quality Detection and Purification Recommendation System Using Refactor Index"** submitted by **ABIN SANTHOSH (IES22CS006)** to the **APJ Abdul Kalam Technological University** in partial fulfilment of the requirements for the award of the Degree of **Bachelor of Technology in Computer Science and Engineering** is a bonafide record of the project work carried out under my guidance and supervision. This report in any form has not been submitted to any other University or Institute for any purpose.

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ABSTRACT

The proposed project introduces a smart water quality detection and purification recommendation system powered by artificial intelligence. The system uses sensors such as pH, turbidity, temperature, and dissolved oxygen to collect water data in real time. An ESP32 microcontroller with Wi-Fi and Bluetooth processes the readings and calculates a Refactor Index (RI), a single score that classifies water as Good, Moderate, Poor, or Unsafe. Results are displayed on an OLED screen and shared with users through a mobile application.Based on the RI score, the system also suggests suitable purification methods such as boiling, filtration, or UV treatment. This solution is low-cost, portable, and eco-friendly, making it useful for households, rural communities, aquaculture, and agricultural applications. By integrating AI and IoT technologies, the project ensures real-time monitoring, reduces health risks, and promotes sustainable water management.

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CHAPTER 1

INTRODUCTION

Water quality assessment has traditionally relied on laboratory-based chemical and biological tests, where samples are collected and analyzed to determine parameters such as pH, turbidity, and dissolved oxygen. While accurate, these methods are time-consuming, costly, and impractical for real-time monitoring, especially in rural or resource-constrained settings. Manual inspection or delayed testing often results in inconsistent evaluations and late detection of contamination, leading to health risks, waterborne diseases, and reduced trust in water sources. Such limitations also pose challenges for industries, agriculture, and aquaculture, where reliable water quality is critical for efficiency and safety. With the rising demand for clean water and growing environmental concerns, there is a pressing need for a low-cost, portable, and automated water quality monitoring system.

To address these challenges, the proposed project introduces an AI-powered water quality detection and purification recommendation system. The system integrates commonly available sensors, such as pH, turbidity, temperature, and dissolved oxygen, connected to an ESP32-WROOM-32 microcontroller. Data collected from the sensors is processed into a composite score known as the Refactor Index (RI), which simplifies water quality assessment by classifying results into categories: Good, Moderate, Poor, or Unsafe. The results are displayed on an OLED screen and shared via a mobile application, enabling users to easily monitor water quality in real time. Based on the RI score, the system also suggests appropriate purification techniques, including boiling, filtration, or UV treatment.

By leveraging artificial intelligence and Internet of Things (IoT) technologies, the system provides a reliable, efficient, and scalable solution for water quality management. It offers significant benefits for households, rural communities, and industries by enabling instant access to water safety information. Moreover, its solar-powered, eco-friendly design supports sustainable practices, reduces dependency on traditional testing methods, and minimizes health risks associated with contaminated water. In doing so, the proposed project demonstrates how smart technology can play a pivotal role in ensuring safe water access, environmental protection, and improved quality of life.

1.1 Overview

The proposed model introduces an AI-powered water quality detection and purification recommendation system that leverages the Refactor Index (RI) to provide real-time, accurate, and actionable insights for both communities and industries. The RI is a composite index (0–100) derived from parameters such as turbidity, pH, and dissolved oxygen, offering a simplified yet reliable measure of water quality. This model is powered by an ESP-32 SoC microprocessor, integrated with sensors (pH, temperature, turbidity, DO), and supported by a solar energy supply, making it a sustainable and low-maintenance solution.Once data is collected, the system calculates the RI, categorizing water into levels such as “Good,” “Moderate,” “Poor,” or “Unsafe.” Alongside detection, the AI-driven module suggests appropriate purification methods—for example, filtration, aeration, or chemical treatment based on the identified contamination profile. To ensure accessibility, results are displayed locally on an OLED screen and transmitted remotely via WiFi or Bluetooth to a user-friendly Android application, where individuals receive instant quality status updates and recommendations.For households and consumers, this system provides an easy, affordable tool to ensure safe drinking water and reduce health risks. For municipalities, aquaculture, and agricultural enterprises, it acts as a real-time monitoring and decision-support mechanism, improving efficiency, reducing testing delays, and enabling proactive water management. By combining IoT, AI, and renewable energy, the system represents a step toward sustainable and intelligent water governance, minimizing reliance on manual inspections and laboratory tests. With future expansions—such as integration of additional parameters (TDS, EC, heavy metals), cloud-based predictive analytics, and smart purification units—this approach showcases how artificial intelligence can transform environmental monitoring and contribute to global goals of health, sustainability, and resource conservation.

1.2 Significance of Study

The assessment of water quality has traditionally relied on manual sampling methods and laboratory-based chemical or physical analyses. While these approaches provide accurate results, they are often time-consuming, expensive, and location-dependent, making them unsuitable for continuous or large-scale monitoring. Such limitations can lead to delayed detection of contamination, inaccurate water classification, and ineffective management of water resources. In rural and remote regions, the unavailability of testing infrastructure further restricts timely assessment, posing risks to public health and environmental safety. With the rapid rise in industrialization, agricultural runoff, and urban wastewater discharge, water pollution has become a growing global concern. These challenges highlight the need for intelligent, real-time, and cost-effective monitoring systems capable of delivering reliable insights without requiring extensive human intervention. Moreover, traditional water testing methods often fail to integrate multiple parameters effectively, resulting in a fragmented understanding of overall water quality. To address these gaps, this study proposes an AI-powered water quality assessment system based on the Refactor Index (RI), which intelligently integrates various physical and chemical parameters—such as pH, turbidity, temperature, dissolved oxygen, and conductivity—to evaluate overall water quality in real time. The system leverages machine learning algorithms to analyze sensor data, classify water safety levels, and recommend suitable purification methods tailored to the detected level of contamination. The hardware architecture is built around IoT-enabled sensors connected to an ESP32 microcontroller, enabling wireless data transmission and real-time updates to a cloud-based or local database. Additionally, the system incorporates solar-powered operation, ensuring sustainability and functionality in energy-limited environments. The user interface, developed as a mobile application, allows users to monitor water conditions remotely, receive notifications, and view purification suggestions in an intuitive, user-friendly manner. This solution holds significant value across multiple sectors. For households, it ensures the availability of safe drinking water through instant detection and purification guidance. For farmers and agricultural managers, it supports the optimal use of irrigation water, reducing crop damage caused by salinity or contamination. In industrial and municipal contexts, it aids in regulatory compliance, process optimization, and sustainable water resource management. Therefore, the significance of this study lies in its comprehensive, practical, and scalable approach to water quality monitoring. By combining AI-driven analytics, IoT integration, and renewable energy, the system not only enhances the precision and accessibility of water assessment but also minimizes human error, reduces health risks, and contributes to environmental sustainability. Ultimately, this research demonstrates how advanced computational intelligence can transform traditional water testing into a smart, automated, and eco-friendly solution for modern society.

CHAPTER 2

RELATED WORKS

2.1 IoT-Based Smart Water Quality Monitoring System

Prasad, Gokhale, and Patil (2022) proposed an IoT-based water quality monitoring system designed to facilitate real-time analysis of essential water parameters. The system architecture employs an Arduino Uno microcontroller interfaced with multiple sensors, including a pH sensor, turbidity sensor, and temperature sensor. Data from these sensors are collected periodically and transmitted through an ESP8266 Wi-Fi module to a cloud-based platform such as ThingSpeak for remote visualization and analytics. This enables users to observe variations in water quality metrics over time through web and mobile interfaces. The authors highlight that such a setup can be effectively deployed in lakes, rivers, or domestic pipelines for continuous observation and contamination detection. The system exhibits significant advantages such as affordability, low power consumption, and simplicity in deployment. Moreover, the real-time feature provides users with timely notifications regarding parameter deviations. However, the study has some key limitations. It primarily focuses on the data acquisition and visualization aspects without incorporating advanced data analytics or intelligent decision-making models. No Water Quality Index (WQI) computation or predictive algorithm is integrated to interpret raw sensor readings into meaningful assessments. Additionally, the system lacks recommendations for corrective measures or purification strategies. Hence, although the proposed model is beneficial for basic monitoring, it is insufficient for advanced applications where decision support and adaptive intelligence are required. In comparison, the proposed AI-based system aims to bridge this gap by combining IoT-based data collection with intelligent processing. Through the use of machine learning algorithms, the proposed model not only monitors but also analyzes and interprets water quality dynamically, generating real-time purification suggestions to enhance water usability.

2.2 Water Quality Index (WQI) Calculation Using IoT Sensors

Kaur and Sharma (2023) advanced the research on IoT-integrated environmental monitoring by introducing a framework for automatic computation of the Water Quality Index (WQI). Their system utilizes IoT-enabled sensors to gather data on multiple parameters, including pH, turbidity, temperature, and dissolved oxygen (DO). These values are then transmitted wirelessly to a central server, where they are processed using the weighted arithmetic WQI method. The computed index provides a numerical representation of water quality, classified into categories such as "Excellent," "Good," "Moderate," "Poor," and "Unsuitable for Drinking." The system's major contribution lies in its ability to translate complex scientific measurements into a single comprehensible score that can be easily interpreted by non-technical users. It demonstrates how IoT can improve both the accessibility and interpretability of environmental data. However, the system's design is static, relying on fixed weightages that do not adjust to local environmental or seasonal variations. It also lacks self-learning capabilities and does not incorporate AI or machine learning algorithms for trend prediction or adaptive recalibration. Furthermore, the system does not provide feedback or purification recommendations based on computed results, limiting its utility in actionable decision-making. In the proposed AI-driven model, the static nature of WQI is addressed by implementing a dynamic learning mechanism that continuously refines its predictive accuracy. The integration of AI ensures that the WQI adapts to regional water characteristics and environmental fluctuations, thereby offering context-aware analysis and intelligent purification guidance.

2.3 AI-Based Water Quality Prediction Using Machine Learning

Singh et al. (2023) proposed a data-driven framework for predicting water quality using supervised machine learning algorithms. The authors employed large datasets comprising physicochemical parameters such as pH, turbidity, temperature, electrical conductivity (EC), total dissolved solids (TDS), and dissolved oxygen (DO). Several classifiers, including Support Vector Machine (SVM), Random Forest (RF), Decision Tree (DT), and Logistic Regression, were tested to categorize water samples based on quality classes defined by international standards such as WHO and BIS. Among these, Random Forest exhibited superior performance due to its robustness and ability to handle non-linear relationships among parameters. The system's predictive model achieved high accuracy, demonstrating the potential of AI and machine learning in automating water quality analysis. However, its implementation is limited by its reliance on offline datasets and laboratory-based samples. Real-time monitoring and dynamic adaptation to environmental changes are not supported due to the absence of IoT sensor connectivity. Furthermore, while the model provides predictive classifications (e.g., "safe" or "unsafe"), it lacks interpretability and fails to suggest remedial purification measures. The proposed system aims to enhance this framework by integrating live IoT sensor inputs with AI-based models to deliver real-time predictions and context-aware recommendations. The fusion of machine learning and IoT ensures continuous data collection, online learning, and intelligent water quality evaluation, making it more practical and user-centric.

2.4 Low-Cost Portable Water Quality Testing Device

Rajalakshmi and Kumar (2021) presented a low-cost and portable water testing device intended for resource-constrained environments. The proposed system employs basic sensors such as turbidity, total dissolved solids (TDS), and electrical conductivity sensors interfaced with a microcontroller for on-site water analysis. The data is displayed on an LCD screen, allowing instant readability without internet connectivity. The key objective of this design is affordability, ease of use, and portability, making it suitable for rural deployment or areas lacking laboratory infrastructure. Although the device successfully achieves low-cost testing, it is limited to providing raw measurements without performing any computational analysis or classification of water quality. The system neither integrates with cloud services for data storage nor includes an AI or WQI computation module for intelligent evaluation. Consequently, users must manually interpret the readings using standard reference tables. Additionally, the absence of remote monitoring or automated recommendations restricts its functionality in modern smart environments. The proposed AI-based solution extends this work by embedding machine learning capabilities and IoT connectivity into a similarly cost-effective portable device. This ensures both affordability and intelligence—enabling automatic classification, WQI computation, and purification recommendations without requiring technical expertise.

2.5 AI-Enabled Decision Support System for Water Treatment

Zhang, Li, and Huang (2024) designed an AI-enabled decision support system (DSS) to optimize water treatment processes. Their model integrates machine learning algorithms with domain-specific rule-based reasoning. It analyzes key input parameters—such as hardness, alkalinity, total dissolved solids, and chemical oxygen demand (COD)—to recommend appropriate treatment techniques including ion exchange, aeration, reverse osmosis (RO), or coagulation. The DSS leverages historical data and domain knowledge to identify the most efficient and cost-effective purification method. This system represents a significant advancement in intelligent decision-making for water purification. However, it is primarily developed for industrial and municipal-scale water treatment plants where computational resources and infrastructure are abundant. The model does not integrate IoT-based real-time sensor inputs and cannot function in decentralized, portable environments. Additionally, its implementation cost and energy requirements make it unsuitable for low-resource or household applications. The current research extends this concept by developing a compact, IoT-integrated version of such a decision-support framework. The proposed model operates efficiently on small devices, uses AI to determine contamination severity, and automatically recommends appropriate purification methods suitable for both domestic and field applications.

2.6 IoT-Based Real-Time Water Monitoring with Mobile Alerts

Reddy and Thomas (2022) developed a real-time IoT-based water monitoring system designed to provide instant alerts for water quality management. The system employs a network of sensors to continuously measure essential parameters such as *pH, turbidity, and temperature*, transmitting the collected data to a cloud server via a GSM module or other wireless communication protocols. Whenever these measurements exceed predefined thresholds, the system automatically generates SMS notifications or mobile app alerts, allowing users to take immediate corrective action and maintain safe water usage. While this approach ensures prompt awareness of unsafe water conditions, it primarily relies on fixed threshold-based logic, which limits its effectiveness under gradual environmental changes or seasonal variations, as small but cumulative deviations may go unnoticed. Furthermore, the system does not compute a composite water quality indicator, such as the Water Quality Index (WQI) or Refactor Index (RI), which could provide a holistic assessment by integrating multiple parameters into a single interpretable metric. It also lacks AI-based analysis, preventing the detection of complex contamination patterns or correlations among parameters, and offers no guidance for corrective actions, restricting its functionality to simple alerting. Additionally, the absence of predictive capabilities means the system cannot anticipate potential contamination events, leaving users in a reactive position rather than enabling proactive management. The proposed AI-based water quality monitoring system addresses these limitations by integrating advanced predictive modeling, adaptive learning, and intelligent decision-making. It computes a composite RI to provide a comprehensive assessment of overall water quality, applies machine learning models to detect subtle anomalies and complex contamination trends, and forecasts future water quality conditions, allowing early interventions.

2.7 Smart Water Quality Monitoring Using Cloud and Big Data Analytics

Ahmed, Bose, and Rani (2023) presented a cloud-based framework leveraging big data analytics for large-scale water quality monitoring. IoT sensors are deployed at multiple sites to capture parameters such as pH, turbidity, and dissolved oxygen. Data is transmitted to cloud infrastructure using MQTT and REST APIs for real-time aggregation. Big data tools such as Apache Spark and Hadoop are utilized for processing large volumes of time-series data, facilitating trend analysis and anomaly detection. The framework also provides data visualization dashboards for authorities and environmental agencies to make informed decisions. The system exhibits scalability and advanced analytical capabilities; however, it is heavily reliant on high-speed internet and expensive cloud infrastructure. The cost and computational demand make it impractical for rural or low-resource environments. Furthermore, the absence of embedded AI for on-device inference limits its real-time responsiveness. The model also lacks purification advisory modules, restricting its usability for end-users requiring immediate and practical actions. In the proposed research, an optimized version of such a system is developed where edge-level AI processing is integrated with IoT sensors. This eliminates the dependency on large-scale cloud infrastructure while maintaining analytical precision and providing real-time purification recommendations.

2.8 AI-Powered River Water Quality Assessment Using Deep Learning

Chen, Wang, and Zhou (2024) introduced a deep learning framework for large-scale river water quality assessment. The system combines satellite remote sensing data with IoT-based ground sensors to provide spatial and temporal water quality predictions. Convolutional Neural Networks (CNNs) are employed to analyze satellite imagery and identify pollutant dispersion patterns. The model can predict future contamination trends and assist government agencies in environmental planning and pollution control. While the model achieves high accuracy and automation in analyzing large water bodies, its implementation is limited to large-scale, government-level monitoring. The system does not interact directly with end-users and lacks the capability for local purification guidance or real-time household monitoring. Moreover, the high computational requirements and dependence on continuous satellite data restrict its use in portable or offline conditions. The proposed AI-based portable system draws inspiration from this large-scale approach but tailors it for small-scale applications. It focuses on real-time, on-device inference using machine learning models for instant contamination detection and purification recommendation without reliance on external data sources.

2.9 Comparative Analysis of Reviewed Systems

The literature reviewed reveals that while several IoT-based, WQI-based, and AI-driven systems exist, most solutions address isolated aspects of water quality assessment. IoT-based systems primarily emphasize real-time sensing and cloud connectivity but lack intelligent analysis. WQI-based models improve interpretability but remain static and rule-based. Machine learning approaches provide high prediction accuracy but are limited to offline datasets without IoT integration. Similarly, decision-support systems and deep learning models are typically designed for industrial or large-scale deployment rather than portable, user-friendly applications. Hence, there exists a technological gap for a hybrid, low-cost, AI-integrated IoT system that can perform real-time water quality assessment, compute adaptive indices, and offer purification recommendations. The proposed system in this research aims to fill this void by combining IoT sensing, AI-based prediction, and intelligent purification guidance within a compact, solar-powered device suitable for both household and community-level use.

2.10 Hybrid IoT–AI System for Smart Water Purification and Quality Control

Mehta, Joshi, and Banerjee (2024) proposed a hybrid Internet of Things (IoT) and Artificial Intelligence (AI)-based system for automated water purification and quality control. The system integrates multiple sensors—pH, turbidity, TDS, and temperature—with a NodeMCU microcontroller for real-time monitoring. Collected data is transmitted via Wi-Fi to a cloud platform, where an AI model processes the readings to determine the contamination level. Depending on the detected water quality status, the system automatically activates the appropriate purification mechanism, such as ultraviolet (UV) sterilization, activated carbon filtration, or reverse osmosis (RO). The authors implemented supervised machine learning models such as Decision Trees and Artificial Neural Networks (ANNs) to classify water into categories like “Drinkable,” “Contaminated,” and “Highly Polluted.” The ANN model achieved superior accuracy, enabling the system to respond autonomously by adjusting purification parameters. A mobile application interface was developed to notify users about system performance, water quality status, and purification progress in real time. The architecture demonstrates an efficient integration of sensing, analytics, and actuation for intelligent water treatment. Despite its innovative design, the system exhibits limitations in scalability and adaptability. The AI model operates on static training data and cannot adapt to changing water conditions without manual retraining. Furthermore, the reliance on continuous internet connectivity makes it less suitable for deployment in remote or off-grid regions. The purification module also lacks optimization for energy efficiency, which could affect long-term sustainability. The proposed research in this project addresses these shortcomings by developing a self-adaptive, AI-powered system that learns from continuous IoT sensor data and dynamically adjusts its prediction and purification recommendations. Unlike Mehta et al.'s system, the proposed model focuses on lightweight machine learning, solar-powered operation, and context-aware purification guidance, making it more cost-effective, portable, and suitable for rural and household applications.

CHAPTER 3

SYSTEM DEVELOPMENT

3.1 Proposed System

The proposed system is an AI-powered water quality monitoring and purification recommendation system that analyzes water parameters in real time. It uses sensors such as pH, turbidity, temperature, and dissolved oxygen to collect data, which is processed by an ESP32-WROOM-32 microcontroller. The system calculates a Refactor Index (RI) — a single, easy-to-understand score that classifies water as Good, Moderate, Poor, or Unsafe. Results are displayed instantly on an OLED screen and shared via a mobile application using Wi-Fi or Bluetooth connectivity. Based on the RI score, the system provides intelligent purification recommendations, such as boiling, filtration, or UV treatment. Designed to be low-cost, portable, and solar-powered, it ensures accessibility in both urban and rural areas. By integrating AI and IoT technologies, the system delivers accurate, automated, and eco-friendly water assessment—reducing dependence on manual testing. It promotes real-time monitoring, public health, and sustainable water management, offering a smarter approach to safe water access.

3.2 System Architecture and Methodology

Input: The system primarily takes real-time data from multiple water quality sensors, including pH, turbidity, temperature, and dissolved oxygen sensors. These sensors are connected to the ESP32-WROOM-32 microcontroller, which collects and transmits readings wirelessly. The data represents the physical and chemical characteristics of the water, forming the input base for analysis.

Output: The output of the system is a Refactor Index (RI) score that classifies the water quality into four categories—Good, Moderate, Poor, or Unsafe. In addition, the system provides purification recommendations such as boiling, filtration, or UV treatment, helping users take immediate corrective actions. The results are displayed on an OLED screen and shared with users through a mobile application for easy access.

Data Processing and AI Integration: At the core of the system lies an AI-based analytical module that processes sensor data to compute the Refactor Index (RI). The module normalizes readings, removes noise, and applies a trained model or threshold-based algorithm to generate reliable water quality predictions. By integrating artificial intelligence, the system ensures accurate and consistent assessment, even under varying environmental conditions.

Refactor Index Calculation: The RI is computed using a composite equation that combines sensor values such as turbidity, pH deviation, and dissolved oxygen ratio. Each parameter contributes to the overall water quality score, ensuring a multidimensional and precise representation. The RI ranges from 0–100, where higher values indicate better water quality. This numerical approach simplifies complex data into an easy-to-understand metric for users.

System Pipeline: The operational pipeline of the proposed system is designed to ensure seamless, real-time monitoring and intelligent decision-making for water quality management. The process starts at the sensor layer, where multiple water quality parameters such as turbidity, pH level, and dissolved oxygen are continuously measured from the water source. These sensors act as the foundation of the system, providing raw, real-time environmental data. Once the data is collected, it is transmitted to the ESP32 microcontroller, which serves as the processing unit. The ESP32 plays a crucial role in cleaning and organizing the sensor data by applying preprocessing techniques such as noise filtering, normalization, and feature extraction. After the data is refined, the microcontroller calculates the Refactor Index (RI), a numerical value that reflects the overall quality of the water. This RI score is then used to classify the water quality into categories like Good, Moderate, Poor, or Unsafe.Once the classification is complete, the system transitions to the output and communication layer. The processed data and the corresponding RI category are displayed on an OLED screen, allowing users to view results on-site instantly. Simultaneously, the same data is transmitted wirelessly through Wi-Fi or Bluetooth to a connected mobile application, making the results easily accessible even from remote locations.

User Interface (UI): A user-friendly mobile application serves as the front-end interface, allowing users to view real-time water quality results and suggested purification methods. The interface is designed for simplicity, ensuring that users with minimal technical knowledge can operate it effortlessly. Notifications and visual indicators (such as color codes) enhance clarity and usability.

Backend and Deployment: The backend consists of the ESP32-WROOM-32 microcontroller integrated with sensors and powered by a solar module for sustainable operation. The communication between hardware and software occurs via IoT protocols, ensuring seamless real-time data transfer. The system is scalable and adaptable for integration into community water systems, industrial monitoring, or smart home applications, making it versatile and cost-effective.

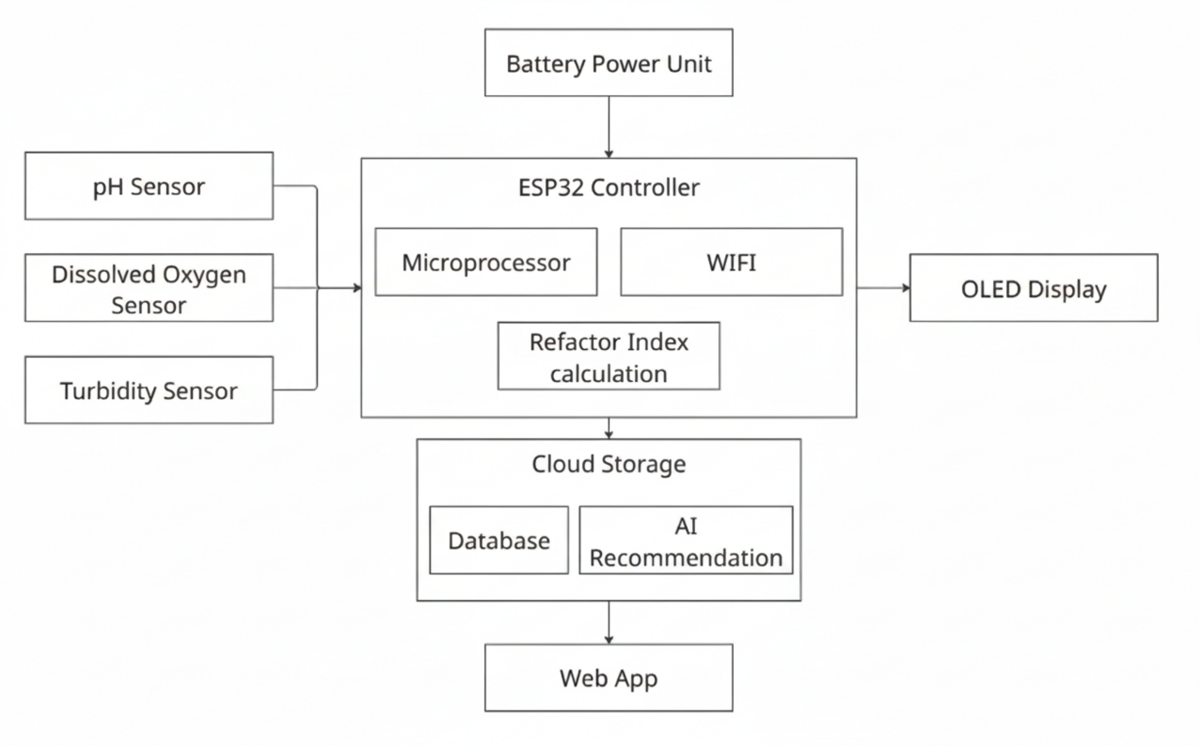

Figure 3.1: Proposed system methodology

3.3 Advantages

- **High Accuracy in Water Quality Detection:** The system employs an AI-powered model based on the Refactor Index (RI), which integrates multiple water quality parameters such as pH, turbidity, dissolved oxygen, and refractive index. By combining these measurements, the system delivers precise and reliable assessments, minimizing false alarms and ensuring accurate detection of even subtle contamination patterns.

- **Real-Time Monitoring:** Utilizing the ESP32 microcontroller and IoT-enabled sensors, the system continuously captures water quality readings and updates them instantly. This allows for immediate detection of contamination events, enabling users to respond proactively and prevent potential health hazards.

- **Smart Purification Recommendations:** The AI module analyzes water parameters and determines the most effective purification methods based on detected impurities.

Recommendations may include filtration, UV treatment, chemical disinfection, or boiling. This intelligent guidance ensures that users can take appropriate and efficient corrective measures for water safety.

- **User-Friendly and Accessible:** The system provides a mobile application and an OLED display interface, making it easy for users with minimal technical knowledge to monitor water quality in real time. Users can view current readings, historical trends, and purification recommendations without needing technical expertise.

- **Eco-Friendly and Sustainable:** The system can be powered by solar energy, promoting environmental sustainability and enabling operation in off-grid or remote locations. This reduces reliance on external electricity sources and lowers the overall carbon footprint of water monitoring operations.

- **Low-Cost and Portable:** Built using affordable components such as ESP32, laser diodes, photodetector modules, and standard sensors, the system offers a cost-effective solution suitable for households, small farms, schools, and small industries. Its compact and portable design allows for easy installation and mobility.

- **Cloud Connectivity and Data Logging:** By integrating with cloud platforms like Firebase, the system stores all sensor readings and computed RI values in real time. This allows users to remotely monitor water quality, track historical data, and analyze trends over long periods, supporting data-driven decision-making and water safety management.

- **Scalability and Flexibility:** The system can be easily expanded to include additional water quality parameters such as Total Dissolved Solids (TDS), conductivity, or additional chemical contaminants. It can also be scaled for applications ranging from individual households to community water networks, industrial plants, or smart city water monitoring projects.

- **Health and Safety Assurance:** By enabling early detection of poor-quality or unsafe water, the system helps prevent waterborne diseases and ensures safe water consumption. It supports public health initiatives, reduces the risk of contamination-related illnesses, and promotes overall community well-being.

3.4 Existing System

The current methods of water quality assessment are largely manual and laboratory-based, relying on chemical, biological, or physical analysis of collected samples. Although these methods provide accurate results, they are time-consuming, expensive, and unsuitable for real-time monitoring. In many regions, especially rural and developing areas, water testing is performed infrequently, which delays contamination detection and increases health risks. This dependency on manual testing and human interpretation often leads to inconsistent evaluations and limited access to safe water information.

3.4.1 Limitations of the Existing System:

Manual and Time-Consuming Process: Traditional water testing requires collecting samples and transporting them to laboratories for detailed analysis, which may take several hours or even days, delaying timely action.

High Cost and Resource Dependency: Laboratory testing involves specialized equipment, chemical reagents, and trained personnel, making frequent testing impractical and expensive for small communities or households.

Lack of Real-Time Monitoring: Conventional systems do not provide continuous tracking of water quality parameters, meaning sudden contamination events often go undetected until significant harm has occurred.

Limited Accessibility: In many rural or remote areas, access to testing facilities is minimal, forcing communities to rely on assumptions or outdated data regarding water safety.

No Automated Analysis or Recommendations: Current systems only generate numerical data without offering automatic evaluation or purification guidance. Users must interpret technical readings manually, which is challenging for non-specialists.

Error-Prone and Inconsistent: Manual sampling, handling, and record-keeping introduce human error, leading to inconsistent results or incorrect assessments of water safety levels.

Environmental Concerns: Frequent chemical-based testing produces waste materials and consumes significant resources, making it less sustainable for continuous monitoring.While some IoT-based and digital monitoring systems have been developed, most are limited to single-parameter detection or require complex configurations. None provide a comprehensive, AI-driven, and real-time solution that can both assess water quality accurately and recommend purification methods for immediate corrective action

3.5 Requirement Specification

3.5.1 Hardware Requirements

Processor: ESP32-WROOM-32 Microcontroller A dual-core processor with integrated Wi-Fi and Bluetooth is used for real-time data acquisition, computation of the Refactor Index (RI), and wireless communication with the mobile application.

Sensors: pH Sensor, Turbidity Sensor, Temperature Sensor, Dissolved Oxygen (DO) Sensor These sensors collect water parameters such as acidity, clarity, temperature, and oxygen concentration to evaluate overall water quality.

Display: 0.96-inch OLED Display Module Used for showing real-time Refactor Index values, water status (Good, Moderate, Poor, Unsafe), and purification suggestions.

Power Supply: Solar Panel with Rechargeable Battery A renewable power source ensures portability, sustainability, and continuous operation even in remote locations.

Connectivity: Built-in Wi-Fi / Bluetooth Module Enables wireless data transmission from the ESP32 microcontroller to the mobile application for remote monitoring and updates.

Additional Components: Breadboard, Jumper Wires, Voltage Regulator Used for prototyping, power stability, and interconnecting various hardware components.

3.5.2 Software Requirements

Front-end: Android Studio (Java/Kotlin) The mobile application is developed using Android Studio to provide users with real-time water quality results and purification recommendations through an intuitive interface.

Back-end / AI Integration: Python with TensorFlow / Scikit-learn AI algorithms are implemented to process sensor data and calculate the Refactor Index (RI). The backend logic interprets readings and triggers suitable purification suggestions.

Languages: Python, C/C++, Java, Kotlin Python is used for AI model development, C/C++ for programming the ESP32, and Java/Kotlin for mobile app development and integration.

Tools Frameworks: – Arduino IDE: For coding and flashing the ESP32 microcontroller. – Android Studio: For mobile app development and debugging. – TensorFlow / Scikit-learn: For machine learning model training and integration. – ThingSpeak or Firebase: For optional cloud data storage and visualization.

Operating Environment: Compatible with Android OS (version 8.0 and above) and supports IoT connectivity via Wi-Fi and Bluetooth.

3.5.3 Functional Requirements

- **Sensor Data Collection:** The system must accurately collect real-time readings from multiple sensors including pH, turbidity, temperature, and dissolved oxygen (DO). Each sensor should be calibrated to ensure high accuracy and stability over time. The collected data should represent the current state of water quality, and the sensors must continuously transmit data to the ESP32 microcontroller for further processing. The system should also handle noise and fluctuations in sensor signals through proper filtering and error correction techniques.

- **Refactor Index (RI) Calculation:** The ESP32 microcontroller is responsible for processing raw sensor data and calculating the Refactor Index (RI), an integrated parameter representing the overall water quality. The RI value is derived using a machine learning or rule-based algorithm that combines sensor readings according to predefined weights or thresholds. Based on the RI, the system must classify water into four categories Good, Moderate, Poor, or Unsafe. This classification helps users quickly understand water safety levels without requiring complex interpretation.

- **Purification Recommendation:** Once the water quality category is determined, the system should automatically suggest suitable purification methods corresponding to the contamination level. For example, if the RI indicates “Moderate,” basic filtration may be recommended, while “Poor” or “Unsafe” levels may trigger suggestions such as boiling, chlorination, or UV treatment. The system should ensure that the recommended methods are practical, cost-effective, and easily understandable by end users.

- **Data Transmission:** The computed RI values and related water quality information should be transmitted wirelessly to the user interface using communication modules such as Wi-Fi or Bluetooth. The data transfer process should be secure, fast, and reliable, minimizing any loss or corruption of information during transmission. In remote or offline conditions, the system may store data locally and synchronize it once a connection is re-established.

- **User Interface (UI):** The Android mobile application should present water quality results in a user-friendly format. It must display the Refactor Index value, corresponding water quality status, sensor readings, and recommended purification steps. The UI should employ visual indicators such as color codes (e.g., green for safe, red for unsafe) and icons for easy interpretation. Additionally, it should allow users to refresh readings, view previous logs, and receive notifications or alerts in case of unsafe water detection.
- **Real-Time Monitoring:** The system should support continuous and real-time monitoring of water quality. Sensor data must be updated automatically at regular intervals to ensure users receive the most current information. Any significant change in water quality parameters should immediately trigger alerts or notifications on the mobile application. This enables users to take prompt corrective action, ensuring safe water consumption and timely maintenance of purification systems.
- **Data Logging and Analytics:** The system should include a data logging feature to record historical readings and Refactor Index values over time. These stored records can be used for trend analysis, identifying seasonal variations, or detecting gradual deterioration in water quality. The logged data should be easily retrievable and exportable for research or policy-making purposes. Advanced versions may also include simple data visualization such as graphs or charts to support long-term analysis.

3.5.4 Non-Functional Requirements

Non-functional requirements define the qualitative attributes that ensure the system performs effectively, efficiently, and reliably in real-world conditions. These parameters determine how well the system operates rather than what it does. The non-functional requirements for the proposed AI-based water quality detection and purification recommendation system are explained below:

Performance: The system must process sensor inputs and display corresponding water quality results within 2–3 seconds after data acquisition. It should support continuous real-time monitoring without noticeable lag, even during simultaneous data collection from multiple sensors. High-performance data processing ensures immediate detection of anomalies and timely alert generation.

Scalability: The architecture should be flexible enough to accommodate additional sensing modules such as TDS (Total Dissolved Solids), DO (Dissolved Oxygen), or conductivity sensors. The system should also allow seamless integration with cloud platforms, enabling large-scale data storage, analytics, and future AI model upgrades. This ensures that the solution remains relevant and adaptable for expanded industrial or municipal applications.

Security: Secure communication protocols must be implemented between the ESP32 microcontroller and the mobile application or cloud server. All data transmissions—whether over Wi-Fi or Bluetooth—should be encrypted to prevent unauthorized access or manipulation. User credentials and sensitive sensor information must be securely stored to ensure data privacy and system integrity.

Usability: The mobile application interface must be user-friendly and suitable for both technical and non-technical users. Key results such as turbidity, pH, and overall quality status should be represented using clear visual indicators, including color-coded alerts (e.g., green for good, yellow for moderate, red for poor quality). The layout should be intuitive, minimizing user learning time and promoting accessibility.

Reliability: The system should maintain stable performance even under varying environmental conditions such as temperature fluctuations, sensor degradation, or minor power interruptions. Reliable hardware connections and software fault tolerance mechanisms (e.g., watchdog timers, auto-restart) must ensure uninterrupted monitoring. Consistent and accurate output under stress conditions strengthens trust and usability in critical field environments.

Maintainability: The system should allow easy maintenance for long-term operation, including sensor recalibration, firmware updates, and AI model retraining. Modular software architecture enables quick debugging, feature enhancements, or component replacements without full system reconfiguration. This reduces downtime and ensures continued system efficiency.

Portability: The overall design should be compact, lightweight, and power-efficient, enabling operation in both laboratory and field conditions. The device should support alternative power sources such as solar panels or rechargeable batteries, making it ideal for deployment in remote or rural areas. Portability enhances usability and ensures continuous monitoring even in resource-limited regions.

CHAPTER 4

SYSTEM LEVEL DESIGN

4.1 Level 0

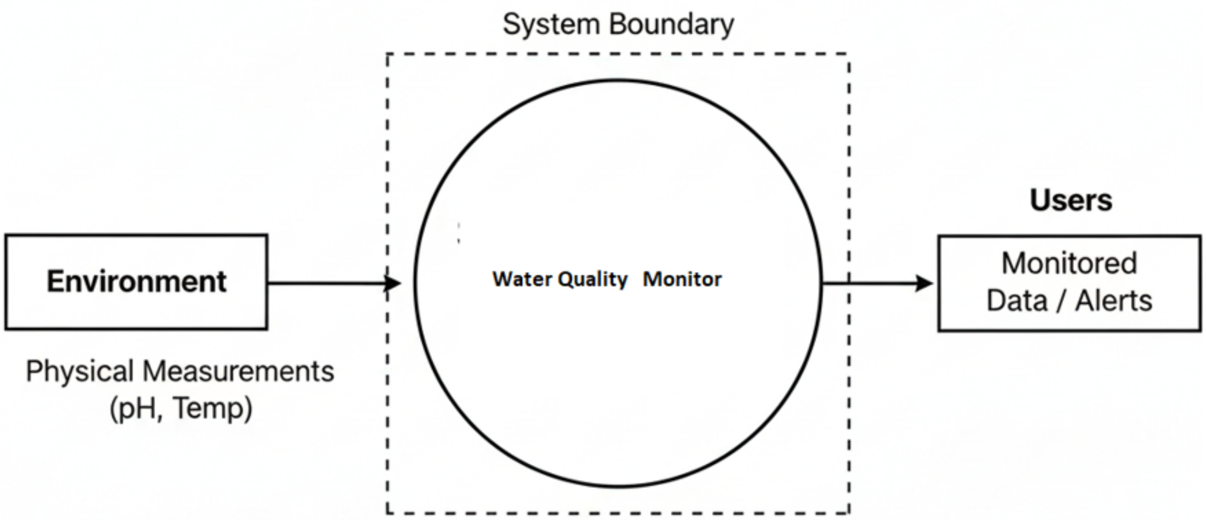

Figure 4.2: Level 0

- **Environmental Input:** This is the initial stage of the system where physical measurements such as *pH level* and *temperature* are collected directly from the surrounding water environment. These measurements serve as the primary input to the water quality monitoring system. The data may vary due to environmental factors such as time of day, location, and seasonal changes.

- **Water Quality Monitor:** This represents the core processing unit within the system boundary. The collected measurements are analyzed to determine water quality levels.

The system processes sensor data, filters noise, and applies predefined thresholds or AI-based algorithms to detect anomalies. It continuously monitors parameters and evaluates whether they fall within acceptable environmental standards. If any deviation or contamination is detected, the system generates alerts in real-time.

- **Output to Users:** The final output provides *monitored data* and *alert notifications* to the end users. These results are displayed through a user interface such as a mobile app or dashboard. Users can view current water conditions, track historical trends, and receive instant alerts about unsafe water quality levels, enabling timely actions for safety and maintenance.

4.2 Level 1

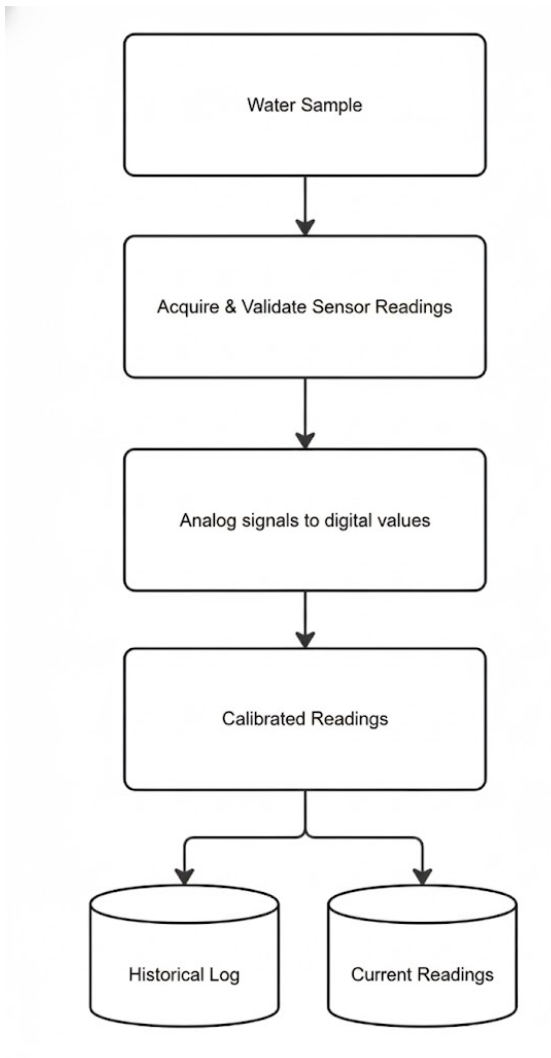

Figure 4.3: Level 1

- **Water Sample:**

- The process begins by collecting a water sample from a specific source such as a river, reservoir, borewell, or treatment facility. This sample serves as the system's input and represents the environmental conditions of the site. It contains several measurable physical and chemical characteristics that are essential for assessing water quality.
- **Acquire & Validate Sensor Readings:**
- Sensors such as pH, turbidity, temperature, and conductivity probes are deployed to measure the real-time quality parameters of the water sample. This module continuously acquires readings from multiple sensors and performs validation procedures to ensure data integrity. Validation includes filtering out noise, detecting outliers, handling missing data, and ensuring that all values fall within acceptable operational ranges. This step guarantees that only reliable data are passed on for analysis.
- **Analog Signals to Digital Values:**
- Since most sensors generate analog outputs that vary with the measured quantity, these signals are converted into digital form using Analog-to-Digital Converter (ADC) integrated within the ESP32 microcontroller. This conversion enables the microcontroller to interpret, process, and store data efficiently. The ADC acts as the link between the physical world (sensor signals) and the digital computation domain.
- **Calibrated Readings:**
- After digitization, the raw sensor values undergo calibration to correct deviations caused by sensor aging, temperature fluctuations, or environmental interference. Calibration uses predefined correction factors or mathematical models to enhance precision. The calibrated data reflect accurate and standardized readings, ensuring consistency across multiple sensing sessions.
- **Historical Log:**
- The system maintains a historical database that stores previously recorded sensor data. This database supports long-term trend analysis, anomaly detection, and statistical evaluation. By comparing new readings with historical data, the system can identify gradual contamination patterns, seasonal variations, and sensor performance trends. This module contributes significantly to predictive analysis and AI model training.
- **Current Readings:**
- The **c**urrent readings module holds the most recent calibrated measurements obtained from the sensors. These readings represent the live condition of the water sample and are used for real-time visualization on dashboards, OLED displays, or mobile applications. The system uses this data to issue alerts, generate quality classifications, and trigger

purification recommendations. The ability to instantly access current readings ensures timely responses to water contamination events.

4.3 Level 2

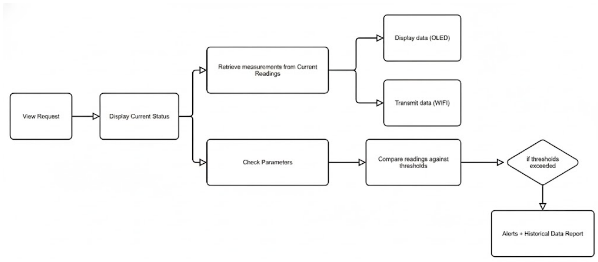

Figure 4.4: Level 2

- **View Request:**
- The workflow begins when a user initiates a request to check the current water quality status. This request activates the system to gather the latest sensor data and process it for analysis and visualization.
- **Display Current Status:**
- The system retrieves and displays the most recent measurements of key water parameters such as **pH, temperature, turbidity, and conductivity**. This gives users a snapshot of the present water condition.
- **Retrieve Measurements from Current Readings:**
- At this stage, real-time sensor data is collected and digitized by the microcontroller. The raw readings are prepared for both on-screen display and wireless transmission to the database.
- **Display Data (OLED):**
- The processed sensor readings are displayed on an **OLED module**, allowing immediate visual access for operators or field users. This feature supports on-site verification without the need for external devices.
- **Transmit Data (Wi-Fi):**
- Using the built-in Wi-Fi capability of the ESP32 microcontroller, the data is transmitted wirelessly to a **cloud server or central database**. This enables remote monitoring, analytics, and data logging for long-term use.

- **Check Parameters:**
- The system performs a validation check to ensure all sensor readings are received correctly and are within expected ranges. This step eliminates communication or sensor errors that could affect analysis accuracy.
- **Compare Readings Against Thresholds:**
- Each parameter value is compared against its corresponding **threshold limits**, which are predefined based on WHO and BIS water quality standards. This comparison identifies whether water is safe or requires purification.
- **If Thresholds Exceeded:**
- A decision node checks if any parameter has crossed its threshold value. If one or more limits are exceeded, the system proceeds to the alert stage; otherwise, it maintains normal monitoring.
- **Alerts + Historical Data Report:**
- When unsafe readings are detected, the system automatically generates **alerts** indicating contamination or poor water quality. These alerts are logged in the historical database for future trend analysis and are also displayed to the user in real time.
- The historical records enable performance tracking, comparison of water quality over time, and refinement of AI-based purification recommendations.

Overall, this workflow demonstrates an efficient integration of sensing, communication, and intelligent decision-making. By combining local display and cloud connectivity, the system provides both immediate feedback and long-term data insights, ensuring accessibility, reliability, and proactive response to changes in water quality.

4.4 Level 3

- **Physical Input:**
  - Represents the external water sample or environment being analyzed.
  - Parameters such as **pH, temperature, turbidity, and dissolved oxygen** are measured through physical sensors.
  - Sensor placement and sampling frequency are crucial for representative and accurate measurements.
  - Environmental conditions (e.g., sunlight, weather, seasonal changes) may affect readings, so robustness is essential.

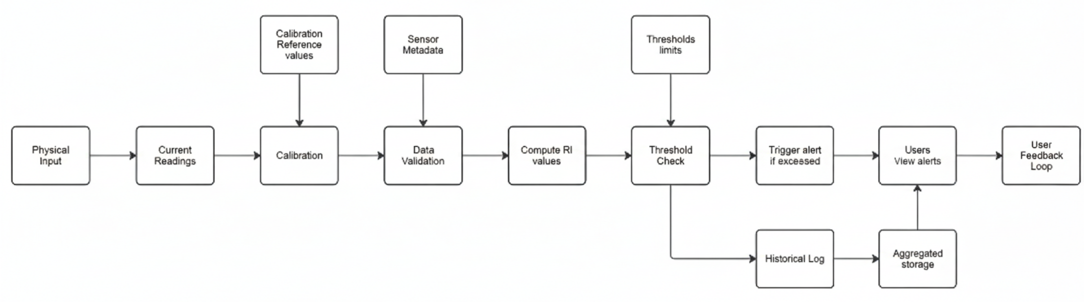

Figure 4.5: Level 3

- **Current Readings:**
  - Raw electrical signals from the sensors are converted into digital readings using ADC (Analog-to-Digital Conversion).
  - These readings are temporarily stored in buffer memory for calibration and validation.
  - Ensures that transient fluctuations or noise do not immediately affect system decisions.
- **Calibration:**
  - Calibration adjusts sensor readings based on **Calibration Reference Values**, which may come from laboratory standards or certified instruments.
  - Corrects systematic deviations caused by sensor aging, drift, or environmental interference.
  - Periodic recalibration is necessary to maintain long-term accuracy.
- **Data Validation:**
  - Validated readings are cross-checked against **Sensor Metadata**, including sensor type, tolerance, expected range, and historical performance.
  - Anomalous, incomplete, or out-of-range readings are discarded or flagged for review.
  - This ensures that only reliable data proceeds to further analysis.
- **Compute RI Values:**
  - The **Refractive Index (RI)** or a similar composite water quality index is computed using validated parameters such as pH, temperature, turbidity, and DO.
  - This RI acts as an aggregate measure of overall water quality, simplifying decision-making.
  - The calculation can be based on empirically derived formulas or trained AI/ML models for enhanced accuracy.
  - Allows a single index to represent complex multi-parameter water quality data.

- **Threshold Check:**
  - Computed RI and individual parameters are compared against predefined **Threshold Limits** to classify water quality as safe, moderate, or unsafe.
  - Thresholds may be derived from WHO/BIS standards, historical data, or adaptive machine learning models.
  - This step determines whether immediate action or alerting is required.
  - Supports dynamic adjustment if long-term trends indicate shifts in baseline water quality.
- **Trigger Alert if Exceeded:**
  - If thresholds are violated, the system triggers an alert event automatically.
  - Alerts may specify the type of contamination, severity, and recommended purification steps (filtration, boiling, UV treatment, etc.).
  - Ensures timely intervention to prevent consumption of unsafe water.
  - Alerting mechanisms can include push notifications, SMS, email, or app-based messages.
- **Users View Alerts:**
  - End users can view real-time alerts and water quality readings via a mobile app, web dashboard, or smart device.
  - Alerts include both numeric readings (e.g., RI score, pH, turbidity) and qualitative recommendations.
  - Provides actionable insights in an intuitive format, supporting informed decision-making.
- **User Feedback Loop:**
  - Users can submit feedback on the alert's accuracy or the effectiveness of recommended purification methods.
  - Feedback is stored and used to refine AI models, threshold settings, and alert accuracy.
  - Enables continuous learning and adaptation of the system to changing environmental conditions and real-world usage.
- **Historical Log:**
  - All validated readings, computed RI values, and alerts are stored in a historical database.
  - Supports trend analysis, anomaly detection, seasonal monitoring, and regulatory reporting.
  - Historical data can be used for predictive analytics and long-term water quality improvement planning.

- **Aggregated Storage:**
  - Centralizes historical and real-time data for efficient retrieval and analysis.
  - Enables integration with cloud-based analytics, reporting dashboards, and AI pipelines.
  - Facilitates data-driven decision-making for water management authorities, researchers, or industrial users.

Overall, this expanded data flow captures every stage of a robust water quality monitoring system—from physical sensing to user feedback and historical analysis. Each stage reinforces **accuracy, reliability, and adaptiveness**, ensuring that water quality assessments remain precise and actionable. The closed-loop architecture, incorporating calibration, validation, alerting, feedback, and historical storage, allows the system to **continuously learn and evolve**, adapting to environmental changes and user needs over time.

CHAPTER 5

CONCLUSION

The AI-Powered Water Quality Detection and Purification Recommendation System Using Refactor Index (RI) represents a significant advancement toward intelligent and sustainable water monitoring solutions. Traditional methods of water testing, such as laboratory-based chemical analysis and manual inspection, are often time-consuming, expensive, and require skilled personnel. These limitations make them unsuitable for continuous, real-time assessment—particularly in rural, remote, or resource-constrained areas where water contamination poses a serious public health risk. The proposed system addresses these challenges by integrating Artificial Intelligence (AI) ,Internet of Things (IoT) technology, and advanced sensor networks into a unified, user-centric framework. The system utilizes multiple sensors, including pH, turbidity, temperature, and dissolved oxygen, interfaced with an ESP32-WROOM-32 microcontroller to capture real-time water parameters. These readings are processed to compute a composite Refractive Index (RI), which serves as a key indicator of overall water quality. The AI model classifies the water into categories such as Good, Moderate, Poor, or Unsafe, providing both interpretability and actionable insights. Based on the computed RI, the system offers intelligent purification recommendations—such as boiling, filtration, aeration, or UV treatment—tailored to the detected contamination level. This dynamic guidance bridges the gap between raw sensor data and user decision-making, enabling immediate corrective action for safe water consumption. Beyond analytical accuracy, the proposed system emphasizes sustainability, affordability, and portability. The incorporation of solar-powered operation and low-cost sensor modules makes the solution viable for diverse environments, from domestic households and schools to industrial facilities and agricultural sites. Real-time data transmission through IoT connectivity ensures that users can monitor and manage water quality remotely via a mobile interface, enhancing accessibility and transparency. The integration of AI not only improves the precision of classification but also enables adaptive learning capabilities. Over time, the model can evolve by analyzing patterns from continuous data streams, improving its ability to detect emerging contaminants or unusual fluctuations. This adaptability marks a major step toward the development of a truly intelligent environmental monitoring system. In conclusion, the proposed system demonstrates how the convergence of AI, IoT, and sensor technology can revolutionize traditional water quality monitoring.

5.1 Future Scope

The proposed AI-Powered Water Quality Detection and Purification Recommendation System has demonstrated the feasibility of integrating IoT-based sensing, AI-driven analysis, and intelligent purification guidance into a single framework. However, water quality monitoring and management are dynamic domains, continually evolving with advances in sensor technology, machine learning, and data security. Future developments can focus on expanding the analytical capacity, automation, and scalability of the system to support broader applications in industrial, municipal, and environmental sectors. The following directions outline the key potential extensions for the project:

- **Integration of Advanced Sensor Types:**
    - Future versions of the system can incorporate a wider range of chemical and biological sensors to detect pollutants beyond physical parameters such as turbidity and pH. This may include sensors for heavy metals (like lead, arsenic, and mercury), microbial contaminants (E. coli, coliforms), and organic compounds (pesticides, nitrates, and dissolved organic carbon). By including these additional parameters, the system can provide a more holistic and accurate representation of water quality, aligning with standards set by the World Health Organization (WHO) and Bureau of Indian Standards (BIS).
- **Implementation of Predictive Maintenance:**
    - Machine learning models can be trained to monitor long-term trends in sensor data and operational patterns to implement predictive maintenance. Such models can forecast issues like sensor drift, calibration deviation, component wear, or power supply inefficiency, allowing the system to self-diagnose and alert users or technicians before a fault occurs. This approach ensures sustained accuracy, reduces downtime, and extends the lifespan of the hardware, thereby improving the reliability of large-scale water monitoring networks.
- **Real-Time Remediation and Control Automation:**
    - Integrating the proposed system with Automated Purification Units (APUs) can transform it from a diagnostic tool into a fully automated remediation platform. AI-generated recommendations could directly control purification processes such as filtration rate adjustments, UV sterilization duration, or chemical dosing levels. This would enable the system to respond autonomously to contamination events in real time, minimizing human intervention and ensuring immediate corrective action in both domestic and industrial environments.
- **Edge Computing and Low-Power AI Optimization:**

  - To improve responsiveness and operational independence, future versions can leverage edge computing technology. By deploying optimized AI models on local embedded devices, the system could perform complex water quality assessments without continuous cloud connectivity. This would enable ultra-low latency, enhanced data privacy, and energy-efficient operation—especially beneficial in remote or rural locations with limited internet access. Lightweight machine learning algorithms such as TinyML or TensorFlow Lite could be integrated for real-time edge inference.

- **Blockchain Integration for Secure Data Management:**
  - Incorporating Blockchain technology could ensure secure, transparent, and tamper-proof storage of sensor readings, analysis outcomes, and purification recommendations. Each transaction—representing a set of water quality measurements—would be encrypted and immutably stored on a distributed ledger. This guarantees data authenticity and builds public confidence, especially when water quality certification is required for regulatory bodies or inter-agency communication. Such integration could also facilitate a Decentralized Water Quality Audit System (DWQAS), improving governance and accountability in water resource management.

In essence, the future scope of the project lies in transforming the current prototype into a scalable, intelligent, and autonomous water management ecosystem. By integrating AI, IoT, edge computing, blockchain, and advanced sensors, the system can evolve into a comprehensive platform capable of not only monitoring but also predicting and actively improving water quality. Such innovations will play a crucial role in achieving sustainable water resource management, supporting environmental conservation, and safeguarding global public health.

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