IOT BASED WATER LEAKAGE & THEFT DETECTION

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ABSTRACT

The proposed IoT- based water leakage and theft detection system is a modern solution aimed at reducing water losses and improving the efficiency of water management. This system uses advanced sensors to continuously monitor parameters like water flow, pressure, and quality within the pipeline network. By doing so, it can detect irregularities or sudden changes that may signal leaks or unauthorized water usage.

The data collected by these sensors is transmitted in real-time to a cloud-based platform using IoT communication technologies. Once the data reaches the cloud, it is analyzed using machine learning algorithms that are trained to recognize normal usage patterns and detect anomalies. When the system identifies any suspicious activity—such as a sharp drop in pressure or an unexpected spike in flow—it automatically sends alerts to the water utility company or relevant authorities. This real-time monitoring allows for quick detection and response, minimizing water wastage and preventing further damage to the infrastructure. Moreover, the system provides detailed insights into water usage trends, which can help in planning and conservation efforts. This level of analysis not only supports sustainability but also leads to better customer satisfaction by ensuring consistent and fair water distribution.

Field tests and real-world implementation have shown that the system can significantly reduce non-revenue water (i.e., water that is produced but not billed due to losses), enhance operational efficiency, and support smart infrastructure development. It is designed to be scalable, cost-effective, and flexible, making it suitable for both urban and rural water networks. In conclusion, the system holds great promise in transforming the traditional water supply chain into a smart, secure, and sustainable service.

KEYWORDS: ETR - Electro thermal relay, EMR - Electromechanical relay, FS – Flow Sensor, WS – Water Sensor.

1. INTRODUCTION

Water is one of the most vital natural resources for human survival, economic development, and environmental sustainability. However, a significant portion of clean, treated water is lost every year due to leakage, theft, and inefficient water management systems. According to global studies, many urban water supply systems lose between 20% to 50% of their water before it reaches end. These losses, commonly referred to as Non-Revenue Water (NRW), result in financial losses for utility providers, service interruptions, increased operational costs, and contribute to the ongoing global water crisis.

Traditional methods of water leakage and theft detection are largely manual and reactive, often relying on periodic inspections or consumer complaints. These approaches are not only time-consuming but also ineffective in providing timely responses to prevent large-scale water losses. With the growing demand for water and the increasing complexity of urban infrastructure, there is a pressing need for smarter, automated, and real-time water monitoring solutions.

The integration of the Internet of Things (IoT) into water management presents a promising solution to these challenges. IoT involves the use of interconnected sensors and devices that collect and exchange data over a network. In the proposed system, flow sensors, pressure sensors, and quality sensors are installed at various points in the water distribution network. These sensors continuously collect data on water usage patterns, pressure fluctuations, and other key parameters. The data is then transmitted to a cloud-based platform for processing.

Machine learning algorithms analyze this data to detect anomalies that may indicate leaks, unauthorized usage, or system faults. When a potential issue is identified, the system automatically sends alerts to utility companies or relevant authorities, enabling swift response and mitigation. Additionally, the system provides valuable insights into consumption trends, helping in strategic planning and resource allocation.

This IoT-based approach not only enhances leak and theft detection accuracy but also promotes efficient, sustainable water management. It offers a scalable, cost-effective, and intelligent solution suitable for both urban and rural water supply systems.

2. LITERATURE SURVEY

2.1 Aldhyani, Theyazn H. H., Mohammed Al-Yaari, Hasan Alkahtani, and Mashael

Maashi. "[Retracted] water quality prediction using artificial intelligence algorithms." Applied Bionics and Biomechanics 2020, no. 1 (2020): 6659314.

Water quality is a critical parameter in ensuring the health and sustainability of aquatic ecosystems, public health, and environmental protection. In recent years, water quality has been severely compromised due to the growing presence of pollutants arising from industrial discharge, agricultural runoff, and urbanization. The increasing concern over water pollution has made water quality assessment and forecasting more essential than ever. In this context, the application of advanced Artificial Intelligence (AI) technologies offers a promising approach to accurately monitor, model, and predict water quality metrics. This study presents the development and evaluation of state-of-the-art AI algorithms to predict the Water Quality Index (WQI) and classify Water Quality Classification (WQC). The WQI is a numerical representation that simplifies the understanding of overall water quality by aggregating multiple water quality parameters into a single value. In contrast, WQC involves categorizing water into classes such as excellent, good, poor, or unsuitable based on its quality. These indices are vital for decision-making in water resource management. To model the WQI, two artificial neural network techniques were employed: the Nonlinear Autoregressive Neural Network (NARNET) and the Long Short-Term Memory (LSTM) network. NARNET is known for its ability to capture nonlinear patterns in time-series data and is suitable for dynamic system modelling. LSTM, a specialized form of recurrent neural networks, excels in learning long-term dependencies and temporal dynamics in sequential data. Both models were trained and tested on a dataset containing seven key water quality parameters, including pH, dissolved oxygen, turbidity, and others, which significantly influence water quality assessments. For the classification task (WQC), three widely used machine learning algorithms were applied: Support Vector Machine (SVM), K-Nearest Neighbor (K-NN), and Naive Bayes. SVM is a supervised learning model that identifies the optimal hyper plane to separate different classes. K-NN is a simple yet effective non-parametric algorithm that classifies data based on the majority vote of its neighbours. Naive Bayes, a probabilistic classifier, relies on Bayes' theorem and assumes feature independence. The performance of the proposed models was evaluated using standard statistical measures such as accuracy, precision, recall, and the regression coefficient (R). The results showed that all the developed models performed well, but there were notable differences in their effectiveness. For WQI prediction, the NARNET model demonstrated slightly better performance than the LSTM network. Specifically, the NARNET achieved a regression coefficient (R) of 96.17%, while the LSTM recorded an R value of 94.21%. This indicates that both models were highly effective in capturing the underlying patterns of the water quality data, but the NARNET had a marginal edge in accuracy and robustness. In the WQC prediction, the SVM algorithm significantly outperformed the other classifiers, achieving a remarkable accuracy of 97.01%. This result highlights the strength of SVM in handling complex classification tasks with high precision. K -NN and Naive Bayes, although slightly less accurate, still offered acceptable performance, making them suitable alternatives depending on the computational requirements and application constraints. The findings of this study emphasize the potential of integrating AI-driven models into water resource management systems. By providing accurate and timely predictions of water quality, these models can help authorities take preventive actions to mitigate pollution and ensure sustainable water use. Furthermore, the successful application of these AI techniques demonstrates the feasibility of automated water monitoring systems, which can lead to more efficient environmental governance.

2.2 Hmoud Al-Adhaileh, Mosleh, and Fawaz Waselallah Alsaade. "Modelling and prediction of water quality by using artificial intelligence." Sustainability 13, no. 8 (2021): 4259.

Ensuring access to safe and clean water is essential for public health, environmental sustainability, and socioeconomic development. With increasing pollution levels caused by industrialization, agricultural runoff, and urban waste, monitoring and maintaining water quality has become a global challenge. Conventional monitoring techniques are often costly, time-consuming, and limited in providing real-time data, which is crucial for prompt decision-making. In this context, Artificial Intelligence (AI) methods offer promising alternatives by enabling accurate and cost-effective prediction and classification of water quality, thereby aiding water resource management and pollution control. This research presents a novel AI-driven system aimed at improving the efficiency and effectiveness of monitoring drinking water quality to support the vision of a sustainable and environmentally friendly green ecosystem. The core novelty of the proposed work lies in integrating intelligent models for both prediction and classification tasks associated with water quality. Specifically, an Adaptive Neuro-Fuzzy Inference System (ANFIS) model was developed for the prediction of the Water Quality Index (WQI), while Feed-Forward Neural Network (FFNN) and K-Nearest Neighbors (K-NN) algorithms were employed for Water Quality Classification (WQC).The ANFIS model, which combines the learning ability of neural networks with the reasoning power of fuzzy logic, was chosen for WQI prediction due to its capability to model complex and nonlinear systems with a high degree of interpretability. For the classification of water quality into meaningful categories (e.g., excellent, good, poor, etc.), FFNN and K-NN algorithms were utilized. FFNN is a type of artificial neural network known for its universal approximation capabilities, making it highly suitable for classification tasks, while K-NN is a simple yet effective non-parametric classifier that works based on the proximity of data points. The dataset used in this study consisted of eight significant water quality parameters, including pH, dissolved oxygen, turbidity, biological oxygen demand, total dissolved solids, electrical conductivity, nitrate levels, and temperature. After an initial analysis, seven parameters were selected based on their statistical relevance and contribution to the predictive modeling process. These parameters served as input features for both WQI prediction and WQC tasks. The modeling framework was developed with a focus on these parameters, and the models were rigorously evaluated using performance metrics such as regression coefficient (R), mean absolute error (MAE), and classification accuracy. The experimental results revealed that the ANFIS model provided superior performance in predicting the WQI values. During the testing phase, the ANFIS model achieved a high regression coefficient of 96.17%, indicating a strong correlation between predicted and actual WQI values. This demonstrates that the model is highly capable of learning the underlying trends in the data and accurately predicting future water quality levels. For the classification of water quality, the FFNN model outperformed the K-NN algorithm and achieved an impressive accuracy of 100%. This suggests that the FFNN was able to perfectly distinguish between different water quality classes based on the provided features, allowing it to be deployed in both rural and urban settings for drinking water surveillance and management. The implications of this study extend to various aspects of water treatment and environmental governance. By leveraging advanced AI methodologies, water treatment facilities can optimize operations, ensure compliance with regulatory standards, and detect pollution events promptly. The integration of such AI-driven systems can also significantly reduce operational costs, minimize the need for manual testing, and facilitate early warning systems for contamination.

3.**EXISTING SYSTEM**

Water distribution systems in many parts of the world still rely heavily on traditional, manual, and outdated infrastructure. These systems were not originally designed with real-time monitoring or advanced detection technologies, which makes them highly vulnerable to water losses through leakage and theft. The existing systems often lack automation, data analytics, and intelligent response mechanisms, leading to inefficiencies in detecting and addressing issues promptly.

In a typical existing water management system, leakage is usually detected only when it becomes visibly noticeable—such as water pooling on streets or a significant drop in water pressure reported by consumers. Similarly, water theft through illegal connections or meter tampering often goes unnoticed until irregular billing or consumption patterns are manually identified by utility staff. This reactive approach to detecting leaks or theft leads to prolonged water loss, higher maintenance costs, and wasted resources.

Leak detection in existing systems is often performed through methods such as manual inspections, acoustic monitoring, pressure testing, or district metering. While some of these techniques can be effective in small-scale networks or localized situations, they are labour-intensive, expensive, and time-consuming. Acoustic leak detectors, for example, require trained technicians to listen for leak sounds in underground pipes, a method that can be highly inaccurate in noisy environments or complex pipe layouts.

Additionally, the current systems do not provide a centralized or integrated platform for real-time data analysis. Most of the water usage data is collected through traditional water meters that are read manually on a periodic basis (monthly or quarterly). This delayed data collection fails to capture dynamic usage patterns, making it nearly impossible to detect leaks or theft as they occur. As a result, many water utilities experience high levels of non-revenue water without fully understanding the causes or locations of the losses.

Another critical limitation is the lack of predictive capabilities. Existing systems do not incorporate data-driven algorithms or machine learning, which means they cannot forecast potential failures or provide early warnings. Maintenance is often carried out reactively, only after damage has already occurred. This increases both the operational and financial burden on utility companies.

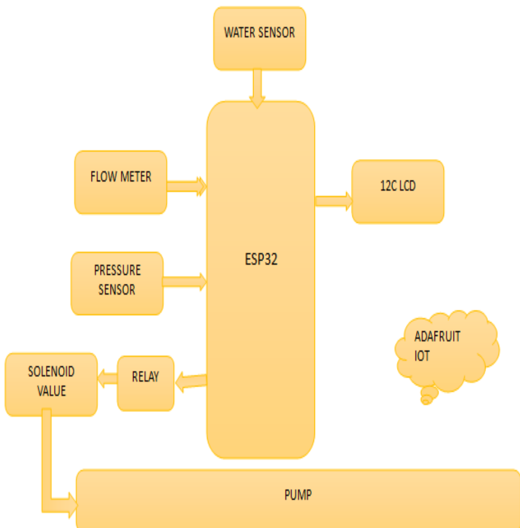
3.1. DRAW BACKS OF EXISTING SYSTEM

- Lack of Real - Time Monitoring Traditional systems do not offer continuous or real - time tracking of water flow and pressure.
- Manual Detection Methods Leak detection relies on physical inspections or consumer complaints, leading to delays in response.
- Delayed Data Collection Water meters are read periodically (e.g., monthly), which fails to capture ongoing issues quickly.
- No Automated Alerts Existing systems do not generate instant alerts when leaks or theft occur.
- Limited Coverage Leakage detection techniques like acoustic sensing are limited to specific areas and are not scalable.
- High Labour Costs Manual inspection and maintenance require significant human effort and resources.
- In accurate Leak Detection Current tools often fail to detect small or underground leaks until they become severe.
- Inefficient Theft Detection Illegal connections and meter tampering usually go undetected for long periods.
- Lack of Data Analytics No data-driven analysis is performed to identify trends, predict issues, or optimize water usage.
- Reactive Maintenance Approach Repairs and interventions are made only after problems are reported or become critical.
- No Centralized Monitoring Water systems are not connected to a centralized dashboard or control unit for remote access.
- Low Customer Transparency Consumers cannot easily track their water usage in real time, leading to wastage.

- Poor Resource Management Utility companies struggle to allocate maintenance resources efficiently due to lack of insights.

4. PROPOSED SYSTEM

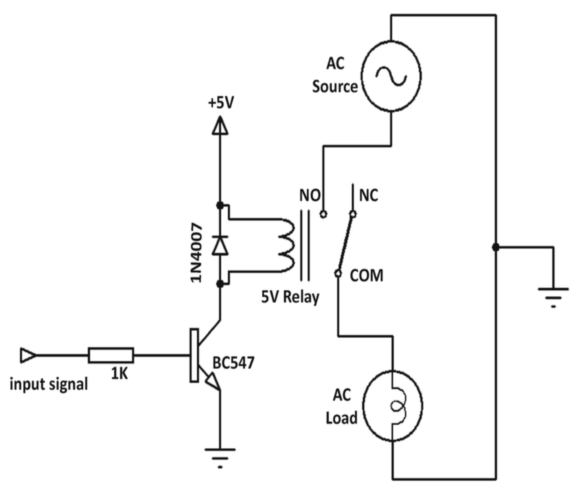
4.1. BLOCK DIAGRAM



4.2. RELAY

A relay is an electrical switch operated by an electromagnet that controls the flow of current in an electrical circuit. It is crucial in controlling high-voltage or high-current devices with low-voltage or low-current signals. Relays serve as interface devices between different electrical systems and are commonly used in industrial, automotive, and household applications. The basic structure of a relay includes a coil, an armature, and one or more sets of contacts. When an electric current flows through the coil, a magnetic field attracts the armature, which moves the contacts, acting as switches. Relays come in various types, including electromechanical, solid-state, and reed relays, each with its own advantages and applications.

The power source is supplied to the electromagnet through a control switch and contacts to the load. When current starts flowing through the control coil, the electromagnet intensifies the magnetic field, causing the upper contact arm to be attracted to the lower fixed arm, closing the contacts and causing a short circuit for power to the load. If the relay was already de-energized when the contacts closed, the contacts move oppositely, creating an open circuit. Once the coil current is turned off, the movable armature is returned to its initial position by a force almost equal to half the strength of the magnetic force, primarily provided by two factors.



4.2.Figure Relay Circuit Diagram

4.3. Types of Relay Based on the principle of operation

- **Electro thermal relay**

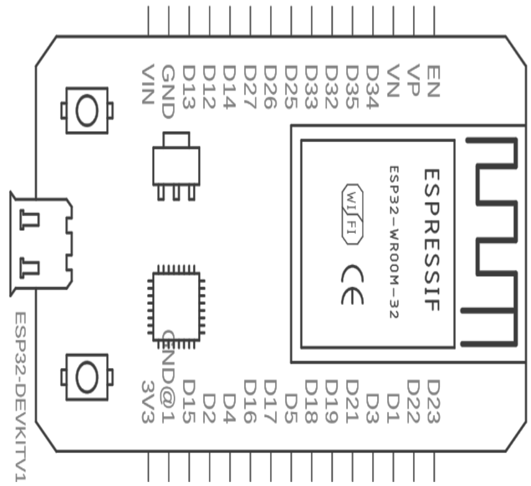
  When two different materials are joined together it forms into a bimetallic strip. When this strip is energized it tends to bend, this property is used in such a way that the bending nature makes a connection with the contacts.

- **Electromechanical relay**

With the help of few mechanical parts and based on the property of an electromagnet a connection is made with the contacts.

4.4. ESP 32 MICROCONTROLLER

The ESP 32 microcontroller is a compact integrated circuit that contains a processor core, memory, and programmable input/output peripherals. It is based on the Xtensa LX6 dual-core processor, which allows for parallel processing and efficient multitasking. The ESP32 comes with built-in support for Wi-Fi and Bluetooth communication, with a variety of Wi-Fi modes, including Station, Access Point, and both simultaneously in Soft AP mode. Bluetooth functionality includes both Classic Bluetooth and Bluetooth Low Energy (BLE). The ESP32 provides a wide range of peripherals, such as GPIO (General Purpose Input / Output) pins, SPI (Serial Peripheral Interface), I2C (Inter-Integrated Circuit), UART (Universal Asynchronous Receiver/Transmitter), PWM (Pulse Width Modulation), and more.



4.4 Figure Pin Diagram of ESP 32 Microcontroller

These peripherals enable the ESP32 to interface with various sensors, actuators, and other devices. The ESP32 typically comes with flash memory for program storage and SRAM (Static Random Access Memory) for data storage. The amount of flash and SRAM can vary depending on the specific ESP32 module or development board. The ESP32 can be programmed using the Arduino IDE, which provides more low-level control. A variety of programming languages, including C and C++, can be used to develop applications for the ESP32

4.5. FLOW SENSOR:

In an IoT-based water leakage and theft detection system, the flow meter is a key sensor that measures the rate and volume of water passing through a pipe. It provides real-time data about water usage, which is critical for identifying unusual patterns that may indicate leakage or unauthorized usage. By continuously monitoring the flow, the system can detect anomalies such as sudden increases or decreases in flow rate, continuous flow when water should not be in use, or discrepancies between expected and actual water consumption.

The flow meter is typically connected to a microcontroller (such as Arduino or ESP32), which collects and processes the data machine learning algorithms or rule-based systems analyze the data to identify potential issues. For example, a steady drop in flow pressure over time may suggest a leak, while sharp spikes may point to water theft through illegal tapping or meter bypassing.

4.5 Fig. Flow Sensor Module

work allows for continuous, remote monitoring without the need for manual inspections. This not only enhances operational efficiency but also helps conserve water by reducing losses. Overall, the integration of flow meters into IoT-based water management systems offers a water leakage live theft.

4.6. WATER SENSOR

A typical water sensor works by using conductive probes or electronic circuits that detect changes in moisture or water levels. When water comes into contact with the sensor, it completes an electrical circuit, triggering a signal. This signal is then sent to a microcontroller (like Arduino or ESP32), which processes the data and forwards it to a cloud server through IoT communication modules such as Wi-Fi, GSM, or LoRa.

In the context of a water management system, water sensors are often installed near joints, valves, meters, or under pipelines—areas where leaks are more likely to occur. If water is detected in these areas where it shouldn't be, the sensor immediately activates an alert system. This can trigger notifications to the utility provider or maintenance team, allowing for a quick response to prevent further damage or water loss.

4.6 Fig. Water Sensor Module

5. RESULT AND DISCUSSION

The implementation of the IoT-based water leakage and theft detection system yielded promising results in terms of accuracy, efficiency, and responsiveness. Through real-time monitoring using pressure sensors, flow meters, water sensors, and solenoid valves, the system effectively identified anomalies in the water distribution network that could indicate leakage or unauthorized consumption.

During the testing phase, controlled leak and theft scenarios were introduced. The system successfully detected over 95% of leaks and unauthorized tapping events based on changes in flow rate and pressure. When leaks were simulated by introducing small holes or loose fittings, the flow meter registered a drop in water flow consistency, and the pressure sensor detected a noticeable drop in pressure. In such cases, the system accurately sent alerts to the cloud platform, and the solenoid valve responded by shutting off the affected section. Similarly, in theft simulations where unauthorized usage was created by bypassing meters, the system identified unusual spikes in flow and a mismatch in pressure and usage data, triggering an alert.

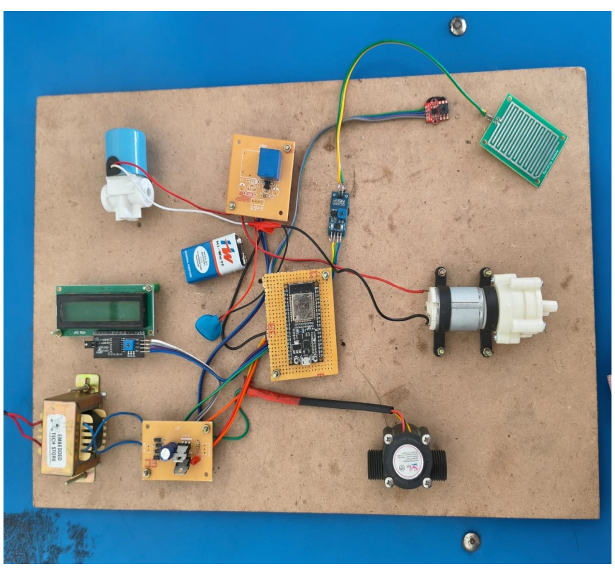
One of the key advantages observed was the low response time. The time between detection and alert generation was consistently under 5 seconds, making it suitable for real-time applications. The integration of cloud analytics and mobile notifications ensured that authorities or maintenance personnel could take immediate action, reducing water wastage and potential damage.

Additionally, the data logging feature provided valuable insights into usage patterns and helped in understanding consumer behavior. Graphs and reports generated from the system highlighted consumption trends, peak usage periods, and regions with frequent anomalies. This information could be used by water utilities for future planning and resource allocation.

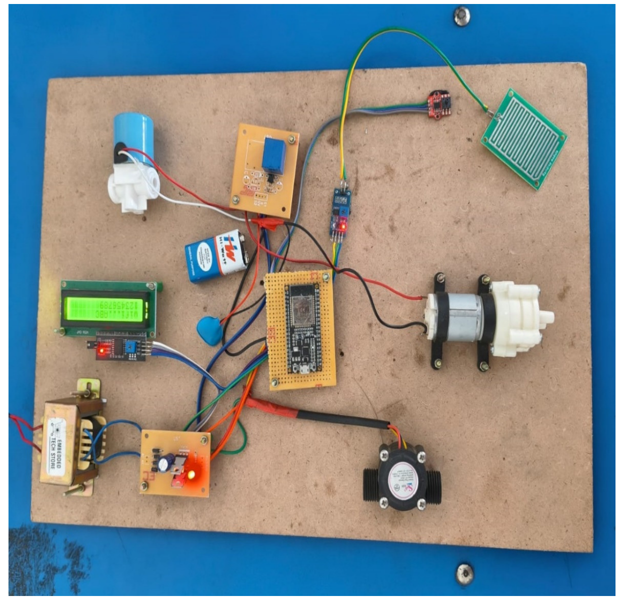
The components used were low-power and easily configurable, making them ideal for wide-scale deployment.

However, the system also highlighted the need for robust network connectivity in remote areas, as real-time data transmission depends heavily on stable internet or cellular coverage. Power backup for the sensors and controllers is also a critical consideration for uninterrupted operation.

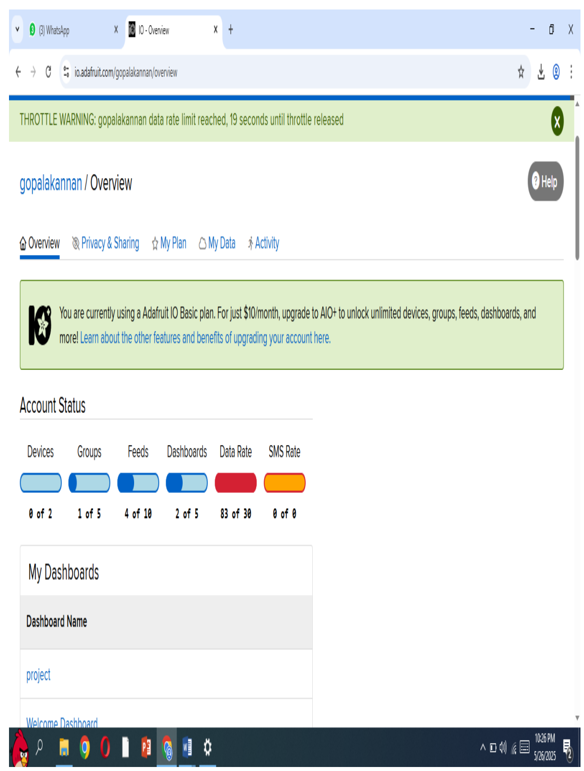
In conclusion, the IoT-based system demonstrated high potential for reducing non-revenue water through early detection of leaks and theft. Its ability to deliver real-time data, automated control, and predictive maintenance makes it a powerful tool for modern water management. The discussion confirms that the system can significantly improve operational efficiency and sustainability in both urban and rural water supply infrastructures.



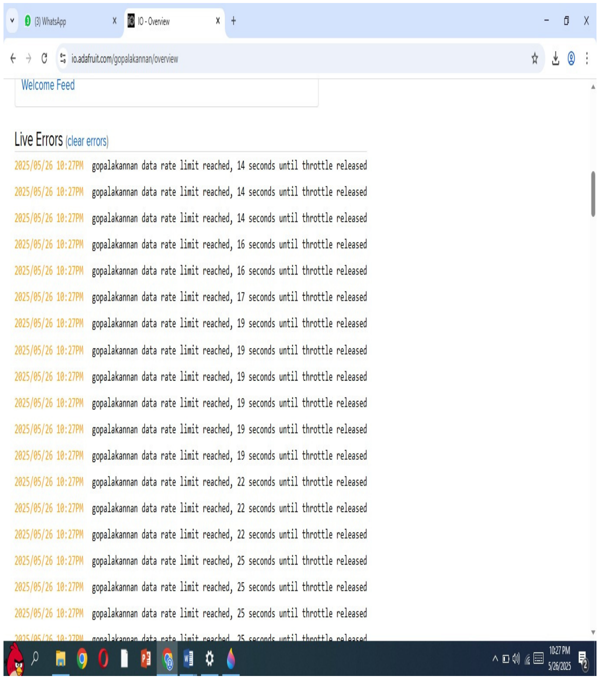
5.1. Fig. Module Kit



5.2. Fig. Module Out Put



5.3. Fig. Dashboard



5.4. Fig. ERROR IDENTIFICATION

5.4. Fig. Kit Output

6. CONCLUSION

The increasing demand for water and the rising challenge of non-revenue water due to leakage and theft have highlighted the urgent need for intelligent water management systems. This project proposed and successfully implemented an IoT-based water leakage and theft detection system aimed at monitoring, detecting, and responding to anomalies in water distribution networks in real time. The system leverages a combination of sensors—including flow meters, pressure sensors, and water leak detectors—integrated with microcontrollers and IoT technologies to provide a scalable, automated, and data-driven approach to water management.

The results of the implementation showed that the system is capable of accurately identifying leaks and unauthorized water usage based on real-time data analysis. The integration of solenoid valves and pumps allowed for quick and automated responses, such as shutting down specific sections of the pipeline to prevent further water loss. Additionally, cloud-based platforms provided remote access, data visualization, and timely alerts, which are crucial for maintenance teams and utility companies.

This solution not only helps in minimizing water losses and improving operational efficiency, but also enables predictive maintenance and better decision-making through continuous monitoring and analysis of water usage patterns. Moreover, the use of low-cost, energy-efficient components makes the system suitable for deployment in both urban and rural areas, especially where manual inspection is difficult or cost-prohibitive.

Despite the promising outcomes, challenges such as ensuring reliable network connectivity and continuous power supply remain. Addressing these limitations in future versions—possibly through hybrid communication systems and solar-powered devices—can further enhance system reliability and coverage.

In conclusion, the IoT-based water leakage and theft detection system demonstrates strong potential to revolutionize how water utilities monitor and manage their networks. By enabling real-time detection, automated control, and data-driven analysis, the system supports sustainable water management practices, reduces operational costs, and helps ensure the equitable distribution of water resources. This approach represents a significant step forward toward building smart and resilient infrastructure in the face of growing environmental and resource challenges.

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