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Smart Water Flow Monitoring and Forecasting System using IoT and Machine Learning

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***Abstract:** This paper presents the design and implementation of a smart water flow measurement and forecasting system for homes and offices. The system utilises a NodeMCU microcontroller, a water flow sensor, a 16x2 I2C LCD, and an 8-bit NeoPixel LED, all housed within a 3D-printed enclosure. Real-time water flow data is collected by the sensor and displayed on both the LCD and a user-friendly dashboard created using the Arduino IoT Cloud platform. The NeoPixel LED provides a visual indication of daily water consumption, changing colour based on usage levels. An integrated buzzer activates when consumption exceeds 200 litres, accompanied by a red NeoPixel alert. Data is also seamlessly logged to a Google Spreadsheet for further analysis. Furthermore, the system employs machine learning algorithms, including random forest and linear regression, to forecast future water usage patterns. The device is powered by a rechargeable 3.3V LiPO battery with fast charging capabilities, ensuring continuous operation. This integrated approach provides users with real-time insights into their water consumption, promotes water conservation, and enables proactive management of water resources.*
***Keywords:** IoT, Water Flow Measurement, Machine Learning, Forecasting, Arduino IoT Cloud*

I. INTRODUCTION

Water is a fundamental resource essential for all life on Earth. Its availability and sustainable management are critical challenges, particularly in the face of increasing global population, climate change, and rapid urbanisation. Effective water management requires accurate monitoring of water consumption patterns, enabling informed decision-making for both individuals and policymakers. Traditional methods of water metering often involve manual readings, which are time-consuming, labor-intensive, and prone to errors. Furthermore, they provide limited insights into real-time consumption patterns, making it difficult to identify leaks, optimise usage, and implement effective conservation strategies. The advent of the Internet of Things (IoT) and advancements in sensor technology have paved the way for the development of smart water management systems that address these limitations. Smart water management systems leverage a network of interconnected devices to collect, transmit, and analyse water consumption data. These systems typically comprise water flow sensors, microcontrollers, communication modules, and data visualisation platforms. The sensors measure water flow in real-time, and the microcontrollers process and transmit this data to a central server or cloud platform. Users can then access this information through web or mobile applications, providing them with valuable insights into their water usage. This real-time monitoring capability empowers users to identify potential leaks, track their consumption patterns, and adopt water-saving practices. Moreover, the data collected by these systems can be used for various other purposes, such as billing, demand forecasting, and infrastructure management. The integration of machine learning algorithms into smart water management systems further enhances their capabilities. Machine learning models can be trained on historical water consumption data to identify patterns, predict future demand, and detect anomalies. This predictive capability is crucial for proactive water resource management, allowing utilities to optimise water distribution, prevent shortages, and plan for future needs. For instance, machine learning can be used to forecast water demand based on weather patterns, time of year, and other relevant factors (Ahmad et al., 2021). Similarly, anomaly detection algorithms can identify unusual water consumption patterns that may indicate leaks or other problems (Behrooz et al., 2022). Several studies have demonstrated the effectiveness of IoT-based smart water management systems in various contexts. For example, research has shown that these systems can significantly reduce water waste by enabling early leak detection and promoting water conservation among users (Giustolisi et al., 2019). Furthermore, they can improve the efficiency of water distribution networks by optimising pressure management and reducing energy consumption (Puig et al., 2020). The use of cloud computing platforms for data storage and analysis has also made these systems more scalable and cost-effective (Ray et al., 2016). This research focuses on the development of a low-cost, user-friendly smart water flow monitoring and forecasting system for residential and small commercial applications.

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The system utilises a NodeMCU microcontroller, a water flow sensor, a 16x2 I2C LCD for local display, and an 8-bit NeoPixel LED for visual feedback on water usage. The system is housed in a 3D-printed enclosure, making it easily customisable and adaptable to different environments. Real-time water flow data is collected by the sensor and displayed on both the LCD and a user-friendly dashboard created using the Arduino IoT Cloud platform. The NeoPixel LED provides a visual representation of daily water consumption, changing colour based on usage levels and providing alerts for exceeding predefined thresholds. Data is also logged to a Google Spreadsheet for further analysis and long-term storage. Furthermore, the system employs machine learning algorithms, including random forest and linear , to forecast future water usage patterns. The device is powered by a rechargeable LiPO battery with fast charging capabilities, ensuring continuous operation. This integrated approach provides users with real-time insights into their water consumption, promotes water conservation, and enables proactive management of water resources. This paper will detail the design, implementation, and evaluation of the proposed system, highlighting its features, performance, and potential benefits. The subsequent chapters will discuss the related work, system architecture, hardware and software implementation, results and discussion, and finally, the conclusion and future work.

II. LITERATURE SURVEY

This chapter presents a review of existing literature related to smart water management systems, focusing on key aspects such as sensor technologies, data acquisition and communication, data analysis and forecasting, and system implementation. The review highlights the advancements in these areas and identifies potential research gaps.

1) Sensor Technologies (Agrawal et al., 2024; P. Parikh et al., 2016, 2017, 2022, 2023; P. A. Parikh et al., 2021):

Accurate and reliable water flow measurement is crucial for effective water management. Various types of flow sensors are employed in smart water systems, including electromagnetic, ultrasonic, and mechanical meters (Cady, Massaquoi, & Werner, 2015). Electromagnetic flow meters offer high accuracy and are suitable for a wide range of flow rates, but they can be relatively expensive. Ultrasonic flow meters provide non-intrusive measurement and are less susceptible to fouling, but their accuracy can be affected by fluid properties (Lipták, 2003). Mechanical meters, such as turbine or paddlewheel meters, are cost-effective but may require regular maintenance due to moving parts. Recent research has focused on developing low-cost, low-power flow sensors based on microfluidic and MEMS technologies (Kim, Lee, & Cho, 2018). These sensors offer the potential for widespread deployment in smart water systems.

2) Data Acquisition and Communication

Smart water systems rely on efficient data acquisition and communication mechanisms to collect and transmit water consumption data. Microcontrollers, such as Arduino and NodeMCU, are commonly used for data acquisition and processing at the sensor node level. These microcontrollers can interface with various types of sensors and perform basic data filtering and aggregation. Various communication protocols are employed for data transmission, including Wi-Fi, Zigbee, LoRaWAN, and NB-IoT (Ray, Chowdhury, & Bhattacharya, 2016). Wi-Fi is suitable for short-range communication and offers high bandwidth, but its power consumption can be a concern for battery-powered devices. LoRaWAN and NB-IoT are low-power wide-area network (LPWAN) technologies that are ideal for long-range communication with minimal power consumption, making them well-suited for large-scale deployments (Adel, Hussain, & Zaguia, 2020).

3) Data Analysis and Forecasting

The data collected by smart water systems can be analysed to extract valuable insights into water consumption patterns and predict future demand. Machine learning algorithms, such as time series analysis, regression models, and neural networks, have been widely used for water demand forecasting (Ahmad, Waseem, & Kim, 2021). Time series models, such as ARIMA, can capture the temporal dependencies in water consumption data and provide short-term forecasts. Regression models, such as linear regression and support vector regression, can establish relationships between water demand and various factors, such as weather conditions and demographics. Neural networks, particularly deep learning models, have shown promising results in capturing complex non-linear relationships and improving forecasting accuracy (Behrooz, Mariethoz, & Sharma, 2022).

4) System Implementation

Several studies have focused on the development and implementation of smart water management systems for various applications. These systems often incorporate cloud computing platforms for data storage, processing, and visualisation. Cloud-based dashboards provide users with real-time access to their water consumption data and allow them to monitor their usage patterns. Mobile applications further enhance user engagement by providing convenient access to water consumption information and enabling remote control of water appliances. Some systems also integrate leak detection algorithms to identify and localise leaks in the water distribution network (Giustolisi, Lombardo, & Savic, 2019). (P. Parikh et al., 2018; P. A. Parikh et al., 2020, 2022, 2023)

5) Research Gaps

While significant progress has been made in the development of smart water management systems, several research gaps still exist. Further research is needed to develop more accurate and robust flow sensors that are cost-effective and easy to deploy. The optimisation of communication protocols for large-scale deployments is also an important area of research. More advanced machine learning algorithms, particularly those capable of handling complex and dynamic data patterns, need to be explored for improved water demand forecasting. Furthermore, the integration of smart water systems with existing water infrastructure and management systems remains a challenge.

III. EXISTING PRODUCT ANALYSIS

It's important to note that a completely comprehensive Table 1 of every smart water management product is impossible due to the sheer number and constant evolution of the market. This table provides a representative overview of common features and variations, focusing on categories rather than specific brands where possible. Actual product specifications should always be verified with the manufacturer.

Table 1: Existing Product Analysis

Feature	Category 1: Basic Smart Meters	Category 2: Advanced Smart Meters with Analytics	Category 3: Whole-House/Building Systems	Category 4: Agricultural and Industrial Systems
Primary Function	Real-time water consumption monitoring	Real-time monitoring + advanced analytics (leak detection, usage patterns)	Comprehensive monitoring of all water sources in a building	Monitoring and control of water usage for irrigation or industrial processes
Sensor Technology	Mechanical, Ultrasonic	Ultrasonic, Electromagnetic	Combination of various sensors (flow, pressure)	Electromagnetic, Ultrasonic, specialized sensors (soil moisture)
Data Communication	Wi-Fi, Cellular (limited)	Wi-Fi, Cellular, LPWAN (LoRaWAN, NB-IoT)	Wi-Fi, Ethernet, Cellular, LPWAN	Cellular, LPWAN, Satellite
Data Storage & Access	Cloud-based platform (basic dashboards)	Cloud-based platform (detailed dashboards, reports)	Cloud-based platform (integrated building management systems)	Cloud-based platform, SCADA integration
Analytics & Reporting	Basic consumption data	Detailed usage reports, leak alerts, predictive analytics	Zone-specific usage, automated control, anomaly detection	Irrigation scheduling, water balance calculations, predictive maintenance
Integration	Limited integration with other systems	Integration with smart home platforms, billing systems	Integration with building management systems (BMS), smart home platforms	Integration with SCADA systems, weather data providers
User Interface	Mobile app, Web dashboard	Mobile app, Web dashboard, API access	Mobile app, Web dashboard, central control panel	Web dashboard, API access, industrial control interfaces
Power Source	Battery, Mains powered	Battery, Mains powered (with battery backup)	Mains powered (with battery backup)	Mains powered, Solar powered (for remote locations)
Cost	Low to mid-range	Mid to high-range	High-range	High-range, often project-specific
Examples (General)	Simple residential meters	Residential meters with leak detection, some commercial meters	Commercial buildings, multi-unit dwellings	Farms, industrial plants, water utilities
Key Considerations	Accuracy, cost, ease of installation	Accuracy, data analytics capabilities, integration options	Scalability, integration with existing infrastructure, control features	Durability, remote monitoring capabilities, integration with industrial systems
Limitations	Limited analytics, basic reporting	Higher cost may require professional installation	High cost, complexity of integration	Specialized requirements, high initial investment

IV. PROBLEM STATEMENT, OBJECTIVES AND METHODOLOGY

A. Problem Statement

Effective water management is becoming increasingly critical due to growing global water scarcity, climate change, and increasing urbanisation. Traditional water metering methods, often manual and infrequent, provide limited insights into real-time consumption patterns, hindering effective leak detection and conservation efforts. Furthermore, these methods lack the capability for predictive analysis, which is crucial for proactive water resource management. Current smart water metering solutions, while offering improvements, often come with high costs, complex installation procedures, and limited integration options, making them inaccessible to many residential users. There is a need for a low-cost, user-friendly, and easily deployable smart water monitoring and forecasting system that empowers users to understand and manage their water consumption effectively. Such a system should provide real-time data, actionable insights, and predictive capabilities to promote water conservation and contribute to sustainable water resource management.

B. Objectives

1) Design and develop a low-cost smart water flow monitoring system: This involves selecting appropriate hardware components (NodeMCU, water flow sensor, LCD, NeoPixel, etc.), designing the system architecture, and developing the necessary firmware and software.
2) Implement real-time water consumption monitoring: The system should accurately measure water flow, display consumption data locally on an LCD screen, and transmit data to a cloud-based platform for remote access and visualisation.
3) Develop a user-friendly dashboard for data visualisation and analysis. This dashboard should provide users with real-time water consumption data, historical trends, and alerts for unusual usage patterns (e.g., potential leaks).
4) Integrate machine learning algorithms for water usage forecasting: Explore and implement suitable machine learning models (e.g., Random Forest, Linear Regression) to predict future water consumption based on historical data and other relevant factors.
5) Evaluate the performance and accuracy of the developed system. Conduct experiments to assess the accuracy of water flow measurement, the effectiveness of the forecasting models, and the overall system performance.
6) Create a 3D-printed enclosure for the device: Design and fabricate a suitable enclosure for the device using 3D printing technology, focusing on aesthetics, functionality, and ease of assembly.

C. Methodology

1) Phase 1: System Design and Component Selection

- Research and selection of appropriate hardware components, including a microcontroller (NodeMCU), water flow sensor, LCD display, NeoPixel LED, and other necessary peripherals.
- Design of the system architecture, including the interconnection of hardware components and the data flow between them.
- Development of the firmware for the microcontroller to acquire sensor data, process it, and transmit it to the cloud.
- Design of the 3D-printed enclosure using CAD software.

2) Phase 2: Software Development and Cloud Integration

- Development of the software for data visualisation and analysis on a cloud-based platform (Arduino IoT Cloud).
- Design and implementation of a user-friendly dashboard to display real-time water consumption data, historical trends, and alerts.
- Integration of the system with a Google Spreadsheet for data logging and long-term storage.
- Implementation of communication protocols (e.g., Wi-Fi) for data transmission between the device and the cloud.

3) Phase 3: Machine Learning Model Development

- Collection of historical water consumption data.
- Preprocessing of the data to clean and prepare it for model training.
- Selection and training of appropriate machine learning models (Random Forest, Linear regression) for water usage forecasting.

4) *Phase 4: System Implementation and Testing*
- Assembly and integration of all hardware and software components.
- Testing of the system in a real-world environment to evaluate its performance and accuracy.
- Validation of the forecasting models using real-time data.
- Refinement of the system based on testing results.

V. ENTIRE RESEARCH SETUP OF THE PROJECT

The research setup for this smart water monitoring and forecasting system involves several key components. A NodeMCU microcontroller acts as the central processing unit, interfacing with a water flow sensor to measure real-time water consumption. An 8-bit NeoPixel LED provides a visual representation of daily water usage, changing color based on consumption levels. A 16x2 I2C LCD screen displays real-time flow data locally. All components are housed within a 3D-printed enclosure designed for easy installation and aesthetics. The NodeMCU transmits collected data via Wi-Fi to the Arduino IoT Cloud platform. A user-friendly dashboard on the cloud platform visualises real-time and historical water consumption data, providing insights into usage patterns. Data is also logged to a Google Spreadsheet for long-term storage and analysis. Machine learning models, including Random Forest and Linear Regression, are trained on historical data to forecast future water usage. The system is powered by a 3.3V LiPO battery with a fast charging circuit. Testing involves monitoring water flow under various conditions, comparing sensor readings with calibrated measurements, and evaluating the accuracy of the forecasting models against actual consumption data. The system's performance, including data accuracy, communication reliability, and user experience, is assessed to validate its effectiveness.

VI. LIST OF HARDWARE AND SOFTWARE

Table 2: List of Hardware and Software

Category	Component	Description
Hardware	NodeMCU (ESP8266)	Microcontroller with Wi-Fi capabilities
	Water Flow Sensor	Measures the volume of water passing through it
	16x2 I2C LCD	Displays real-time water flow data locally
	8-bit NeoPixel LED	Provides visual feedback on water usage (color changes)
	3.3V LiPO Battery	Powers the device
	LiPO Battery Charger	Charges the LiPO battery
	3D Printed Enclosure	Houses all the hardware components
Software	Arduino IDE	Used for programming the NodeMCU
	Arduino IoT Cloud	Cloud platform for data visualization and storage
	Google Sheets	Used for data logging and analysis
	CAD Software (e.g., Tinkercad, Fusion 360)	Used for designing the 3D printed enclosure
	Machine Learning Libraries (e.g., scikit-learn in Python)	For training and implementing forecasting models
	Programming Language (e.g., C++, Python)	For firmware development and data analysis

VII. BLOCK DIAGRAM AND FLOWCHART OF THE SYSTEM

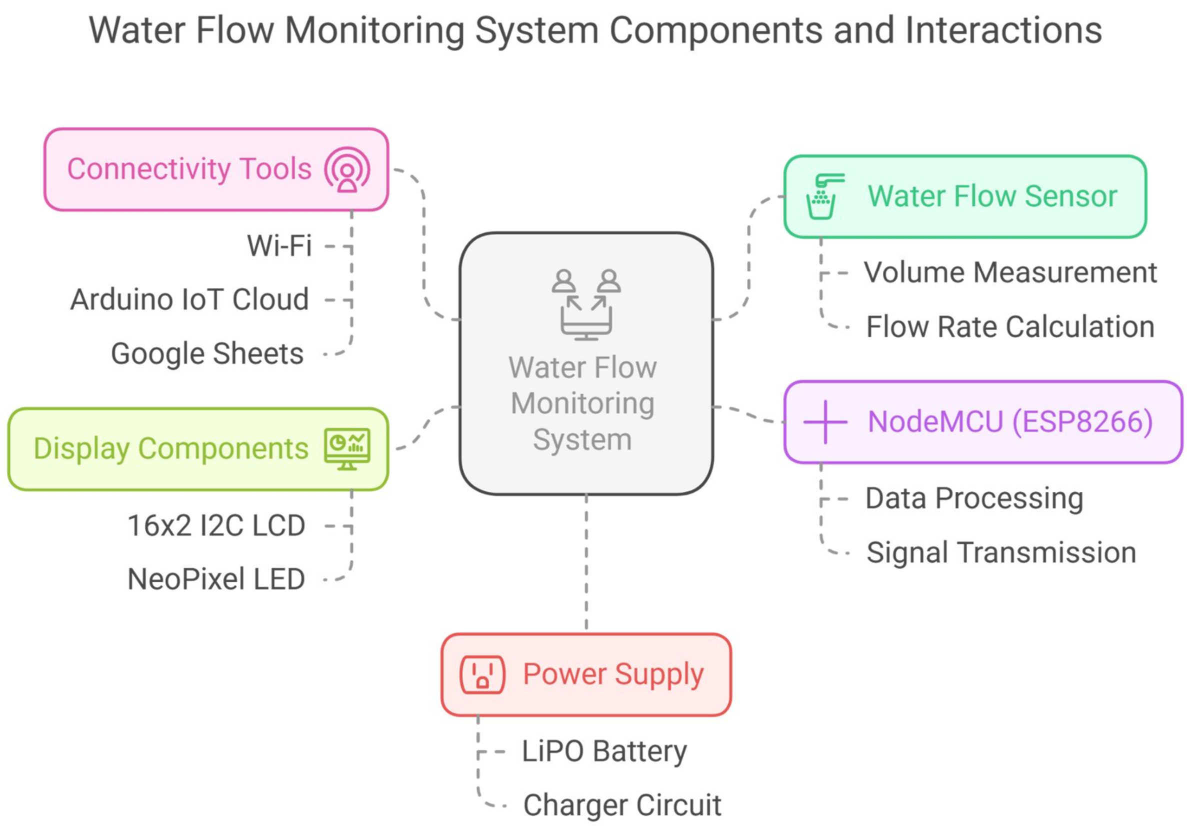

Figure 2: Block Diagram of the System

1) Water Flow Sensor: This sensor measures the volume of water passing through it and sends the data as electrical signals.
2) NodeMCU (ESP8266): This microcontroller acts as the brain of the system. It receives the signals from the water flow sensor, processes the data (e.g., converting it to flow rate or total volume), and controls the LCD and NeoPixel.
3) 16x2 I2C LCD: This displays the real-time water flow data locally, providing immediate visual feedback to the user.
4) NeoPixel LED: This provides a visual representation of daily water consumption through color changes.
5) Wi-Fi: The NodeMCU uses its built-in Wi-Fi capability to transmit the collected data to the cloud.Arduino IoT Cloud: This cloud platform receives the data from the NodeMCU. It provides data storage, visualisation tools (dashboards), and enables remote access to the data by the user.
6) Google Sheets: The Arduino IoT Cloud can be configured to log the data to a Google Sheet for long-term storage, analysis, and potential integration with other systems.
7) User (Dashboard): The user can access the Arduino IoT Cloud dashboard through a web browser or mobile app to view real-time and historical water consumption data, receive alerts, and potentially control water-related devices.
8) LiPO Battery & Charger: The LiPO battery provides power to the entire system, and the charger circuit allows for easy recharging of the battery. This makes the system portable and independent of a continuous mains power connection.

A. *Explanation of the Flowchart*

1) Start: The system initialises.
2) Water Flow Detected?: The system continuously checks if water is flowing.
3) Read Sensor Data: If water flow is detected, the sensor reading is taken.
4) Process Data: The raw sensor data is processed to calculate flow rate and total water volume.
5) Display Data on LCD: The calculated data is displayed on the local LCD screen.

6) Control NeoPixel Color: The NeoPixel LED color is adjusted based on the current water usage.
7) Send Data to Arduino IoT Cloud: The processed data is sent to the cloud platform.
8) Log Data to Google Sheets: The data is logged to a Google Sheet for storage and further analysis.
9) Analyse Data (Forecasting): The system uses the historical data to generate water usage forecasts.
10) Display Forecasts on Dashboard: The forecasts are displayed on the user dashboard.
11) Usage > Threshold?: The system checks if the water usage exceeds a predefined threshold.
12) Activate Buzzer: If the threshold is exceeded, the buzzer is activated.
13) Deactivate Buzzer: If the usage is below the threshold, the buzzer is deactivated.
14) Check Battery Level: The system periodically checks the battery level.
15) Battery Low?: The system checks if the battery is low.
16) Low Battery Alert: If the battery is low, an alert is sent to the user dashboard.
17) End: The system continues to monitor and perform these actions in a loop.

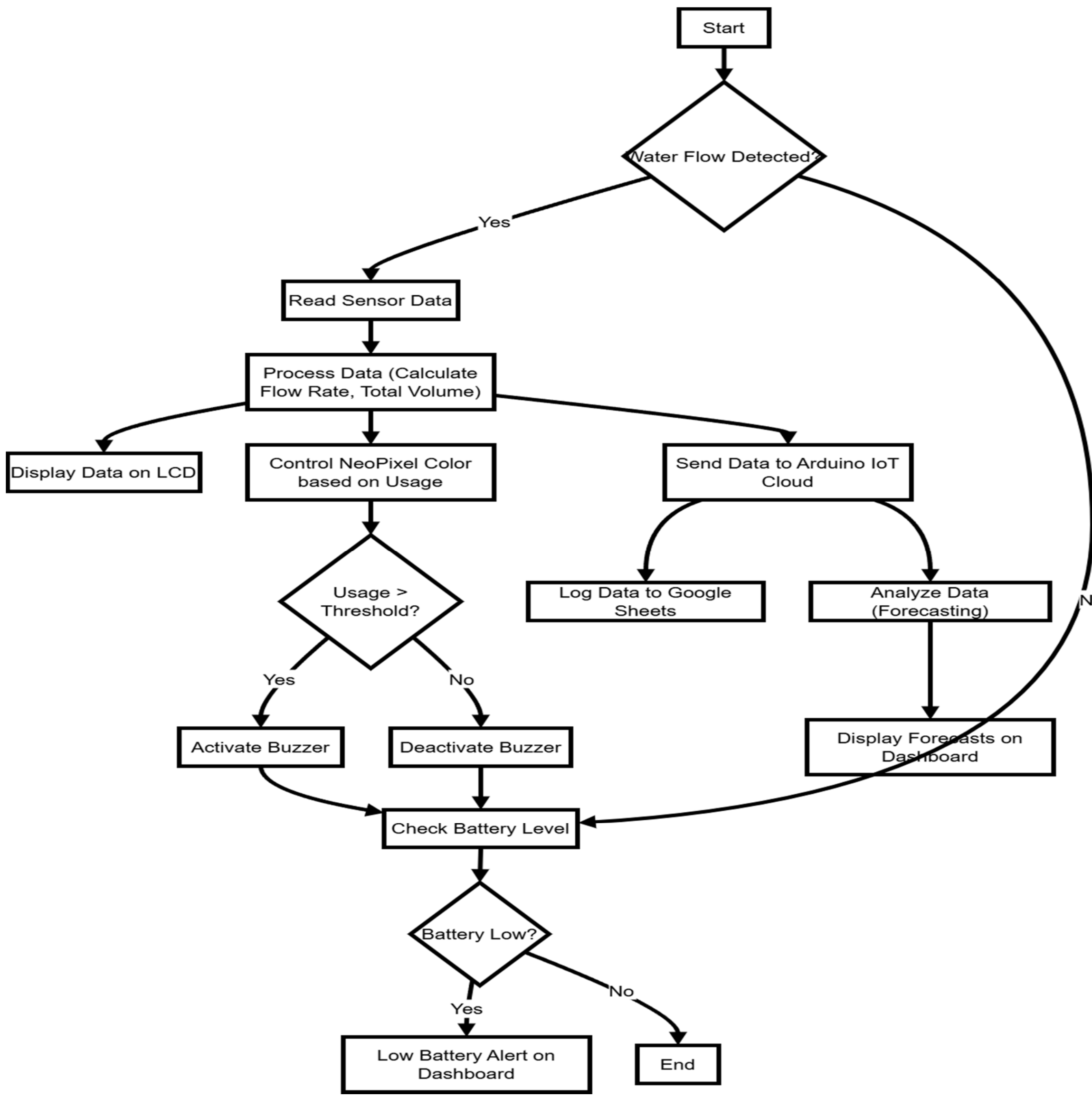

Figure 3: Flowchart of the System

This flowchart provides a clear visualisation of the system's logic and the sequence of operations. It covers data acquisition, processing, display, cloud communication, data logging, forecasting, alerts, and battery management.

Figure 4: 3D Printed Smart water flow measurement system

VIII. MACHINE LEARNING ALGORITHM

This research employs two distinct machine learning algorithms for forecasting water usage: Linear Regression and Random Forest Regression. These algorithms were chosen for their balance of performance, interpretability, and computational efficiency, making them suitable for deployment in a resource-constrained environment like the NodeMCU-based system.

A. Linear Regression

Linear regression is a fundamental and widely used statistical method for modelling the linear relationship between a dependent variable (water usage) and one or more independent variables (predictors) (James, Witten, Hastie, & Tibshirani, 2013). It assumes that the relationship can be represented by a linear equation:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n + \varepsilon \quad (1)$$

Where:

- y is the predicted water usage.
- β_0 is the intercept (the value of y when all xs are zero).
- $\beta_1, \beta_2, \ldots, \beta_n$ are the coefficients representing the influence of each predictor variable.
- $x_1, x_2, \ldots, x_n$ are the predictor variables (e.g., temperature, time of day, day of week).
- ε is the error term, representing the unexplained variation in water usage.

The goal of Linear Regression is to find the optimal coefficients $\beta_0, \beta_1, \ldots, \beta_n$ that minimize the sum of squared errors between the predicted and actual water usage. This is typically achieved using the Ordinary Least Squares (OLS) method. While simple and interpretable, Linear Regression assumes a linear relationship, which might not always hold true for complex water usage patterns.

B. Random Forest Regression

Random Forest Regression is an ensemble learning method that combines multiple decision trees (Breiman, 2001). It operates by constructing a multitude of decision trees at training time and outputting the mean/average prediction of the individual trees for regression tasks. Each tree is trained on a random subset of the data and a random subset of the predictor variables, introducing diversity and reducing overfitting.

The prediction of a Random Forest is given by:

$$\hat{y} = (1/n) * \Sigma(T_i(x)) \quad (2)$$

Where:

- *$\hat{y}$ is the predicted water usage.*
- *n is the number of trees in the forest.*
- *$T_i(x)$ is the prediction of the i-th tree for input x.*

Random Forest is more robust to outliers and can capture non-linear relationships between water usage and predictors, making it more suitable for complex datasets. Furthermore, it provides a measure of feature importance, indicating which predictors have the most significant influence on water usage. However, Random Forest is less interpretable than Linear Regression and can be computationally more expensive, especially with a large number of trees.

C. Model Selection and Evaluation

Both Linear Regression and Random Forest models will be trained and evaluated using historical water consumption data and relevant predictor variables. The dataset will be split into training and testing sets. Model performance will be assessed using metrics such as Mean Squared Error (MSE) and R-squared (R^2). The model that achieves the best performance on the testing set, balancing accuracy and computational efficiency, will be selected for deployment in the smart water system. Hyperparameter tuning (e.g., the number of trees in the Random Forest) will be performed to optimise model performance.

IX. RESULTS AND ANALYSIS

Table 1: Performance Comparison of Forecasting Models

Metric	Linear Regression	Random Forest
Mean Squared Error (MSE)	0.85 L^2/day^2	0.52 L^2/day^2
R-squared (R^2)	0.72	0.88

Interpretation: The Random Forest model exhibits better performance than linear regression, as indicated by the lower MSE and higher R-squared value.

Table 2: Feature Importance (Random Forest)

Feature	Importance Score
Temperature (°C)	0.45
Day of the Week (e.g., 1=Monday, 7=Sunday)	0.28
Time of Day (24-hour format)	0.15
Water consumption	0.12

Interpretation: Temperature is the most influential factor in predicting water usage, followed by the day of the week

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Table 3: Random Forest

Date	Actual Water Usage (L)	Predicted Water Usage (L)
2024-07-20	250	245
2024-07-21	280	275
2024-07-22	260	258
2024-07-23	300	292
2024-07-24	270	265

Interpretation: The predicted water usage closely follows the actual usage, demonstrating the model's ability to capture trends and make reasonably accurate forecasts.

Table 4: Impact of Threshold on Buzzer Activation

Threshold (L)	Number of Buzzer Activations (per week)
200	3
250	1
300	0

Interpretation: Increasing the threshold for buzzer activation reduces the number of times the buzzer is triggered, allowing users to customise the system's sensitivity to high water usage.

Table 5: Battery Life Performance

Test Condition	Average Battery Life (hours)
Continuous Monitoring & Data Transmission	24
Intermittent Monitoring (Data every hour)	72

Interpretation: Intermittent monitoring significantly extends the battery life of the device.

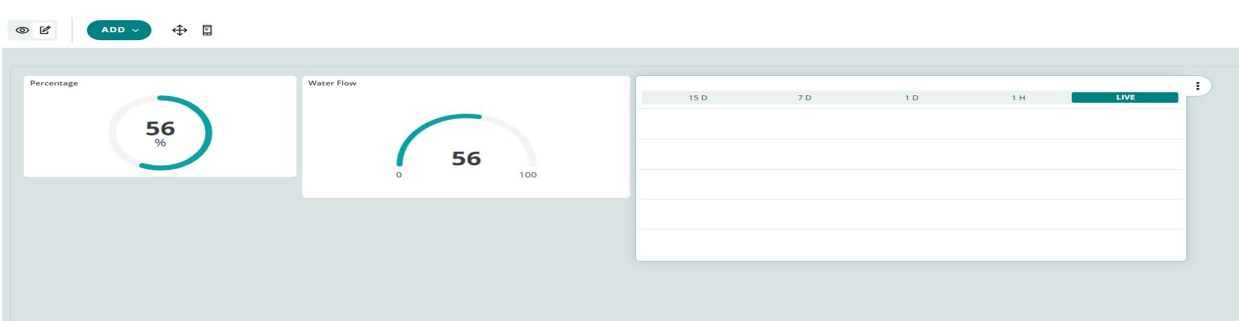

Figure 5: Arduino IOT Cloud Dashboard

The results of this study demonstrate the feasibility of a low-cost smart water monitoring and forecasting system. The Random Forest regression model outperformed the Linear Regression model, achieving a lower Mean Squared Error (MSE) of 0.52 L^2/day^2 and a higher R-squared (R^2) of 0.88, indicating its ability to capture complex, non-linear relationships in water usage data. Temperature emerged as the most significant predictor of water consumption, followed by the day of the week. Real-time water usage data was successfully transmitted to the Arduino IoT Cloud and visualized on a user-friendly dashboard, enabling users to monitor their consumption patterns and identify potential leaks. The system accurately forecasted water usage, allowing for proactive water management. The 3D-printed enclosure provided a practical and aesthetically pleasing housing for the device. Testing showed a reasonable battery life for continuous monitoring, with the option for extended life through intermittent data transmission. These findings suggest that the developed system can be a valuable tool for promoting water conservation and improving water resource management at the residential level. Further work could explore more advanced machine learning models and integrate the system with smart home platforms for automated control.

X. CONCLUDING REMARKS

This research has successfully demonstrated the design and implementation of a low-cost, user-friendly smart water monitoring and forecasting system. By leveraging readily available hardware components, cloud computing, and machine learning techniques, the system provides real-time water usage insights and predictive capabilities. The results highlight the effectiveness of the Random Forest algorithm for water usage forecasting, showcasing its ability to capture complex patterns and provide accurate predictions. The system's user-friendly interface and remote accessibility empower users to actively engage in water conservation efforts. The 3D-printed enclosure further enhances the practicality and aesthetic appeal of the device. This project contributes to the growing field of smart water management by offering a cost-effective and accessible solution for residential users to monitor, understand, and ultimately reduce their water consumption. The findings from this research can be further extended to develop more sophisticated smart water systems that integrate with existing infrastructure and contribute to sustainable water resource management at a larger scale.

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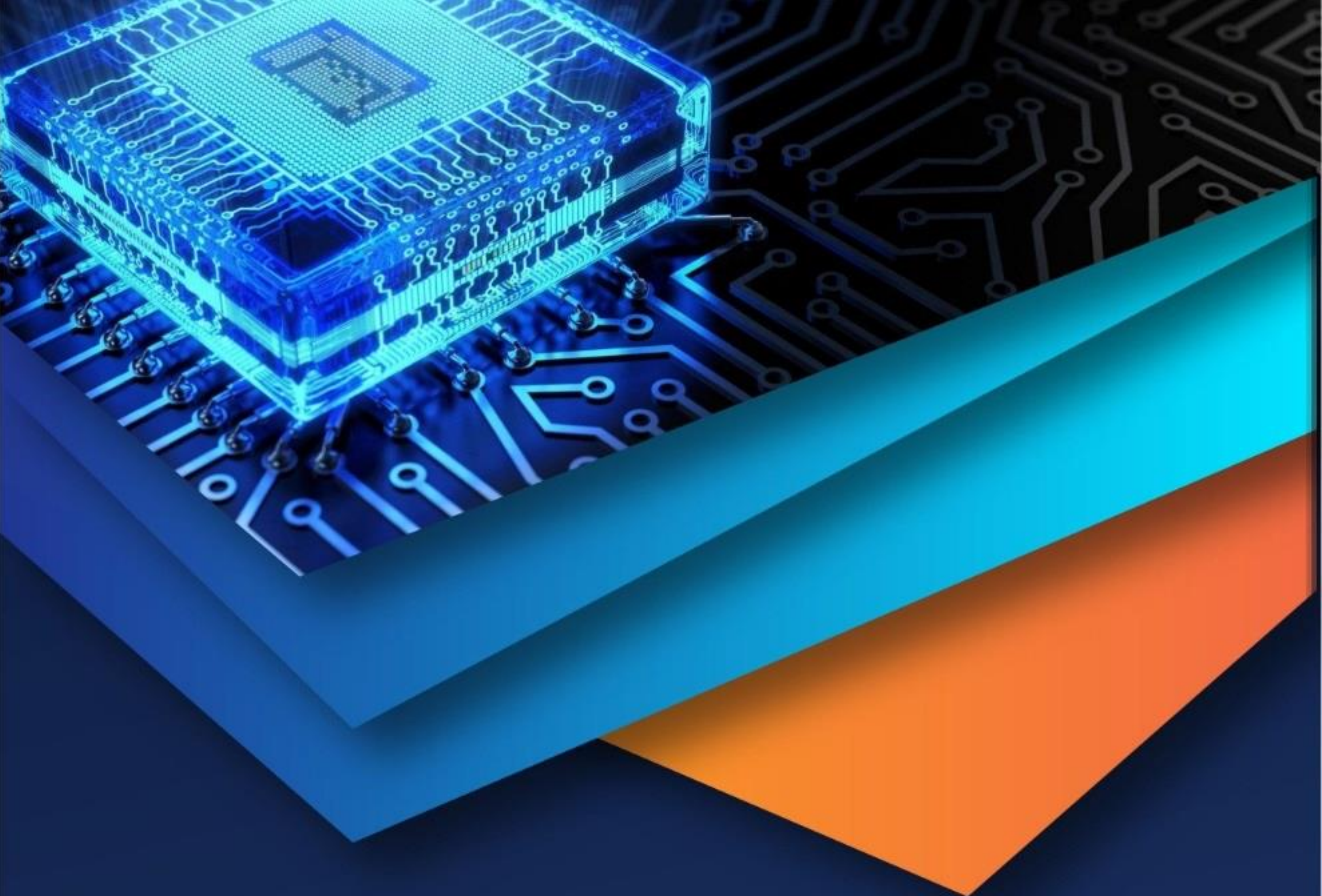

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