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Enhancing Water Management in Buildings Through IoT-Based Monitoring and Machine Learning Powered Analytics

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Abstract - **In both agricultural and residential buildings, effective water management is crucial. However, most of the existing literature has focused on Internet of Things (IoT)-based solutions for water management (e.g., turning water pumps on and off), but these approaches lack the ability to analyze water usage patterns or predict future consumption. This paper addresses this limitation by developing an automatic water level monitoring and control system using IoT and Machine Learning (ML) techniques. Specifically, an IoT circuit comprising various sensors, an ESP32 microcontroller, and related components was designed to collect real-time water usage data. The collected data was then preprocessed and analyzed using ML techniques such as Long Short-Term Memory (LSTM) networks for time-series prediction of water flow rates and Density-Based Spatial Clustering of Applications with Noise (DBSCAN) for anomaly detection in sensor data (including level, flow, pH, and turbidity). In summary, this work not only automates water level monitoring and control through IoT but also improves water management by applying ML techniques to predict future usage patterns and detect anomalies in real-time sensor data.**
Keywords: **Internet of Things (IoT), Water Management, Machine Learning (ML), Long Short-Term Memory (LSTM), Anomaly Detection**

I. INTRODUCTION

Water is one of the most essential natural resources for sustaining life, agriculture, and industrial development. Rapid urbanization, population growth, and climate change have placed significant stress on water resources, making effective water management a global priority. According to the United Nations, nearly two-thirds of the world's population may face water shortages by 2025 if current consumption patterns continue [1]. In both agricultural and residential sectors, improper utilization of water not only leads to wastage but also threatens long-term sustainability. Therefore, efficient monitoring, distribution, and prediction of water usage have become critical research areas in recent years.

Traditional water distribution systems in residential buildings and agricultural fields typically rely on manual monitoring and control mechanisms. This often results in delayed responses to water shortages, tank overflows, or pump failures, causing inefficiency and wastage [2]. To address these shortcomings, Internet of Things (IoT)-based solutions have gained popularity. By employing sensors and microcontrollers, IoT systems can automatically monitor water levels and control pump operations [3]. These systems enhance convenience and reduce dependence on human intervention. However, most existing IoT-based water management frameworks are designed primarily for binary control tasks (i.e., turning pumps on/off) without performing deeper analyses of water consumption patterns. As a result, they fall short in enabling proactive decision-making, predictive management, or anomaly detection in water usage [4].

The major contributions of this paper are summarized as follows:

1. Development of a robust IoT circuit for real-time water monitoring in residential contexts using ESP32 and multiple sensors.
2. Integration of IoT data with ML algorithms (LSTM and DBSCAN) for predictive analytics and anomaly detection.
3. Demonstration of an end-to-end system that not only automates pump control but also provides insights into water usage patterns, thereby helping prevent wastage and ensuring sustainability.

The remainder of this paper is organized as follows. Section II reviews related work on IoT-based water management systems and their limitations. Section III presents the architecture and implementation details of the proposed system. Section IV describes the dataset and preprocessing techniques. Section V discusses the experimental results. Section VI concludes the paper and outlines possible directions for future research.

II. REVIEW OF LITERATURE

Water management has been an active area of research in recent years, particularly with the growing adoption of Internet of Things (IoT) technologies. IoT-enabled systems have made it possible to remotely monitor water levels, control pump operations, and provide real-time alerts through low-cost sensors and wireless communication modules [5], [6]. Several researchers have implemented smart water management solutions for both residential and agricultural applications.

For instance, the authors in [7] developed a microcontroller-based automatic water pump controller using float sensors to monitor overhead tank and sump levels. This system significantly reduced manual intervention and prevented overflow, but it was limited to threshold-based control without predictive capabilities. Similarly, the work in [8] proposed an IoT-based water quality and quantity monitoring system employing pH, turbidity, and flow sensors to ensure the safety of drinking water. Although it successfully integrated multiple parameters, the focus remained on real-time monitoring and notifications, with no mechanism for analyzing long-term consumption patterns.

In the agricultural sector, IoT has been widely applied for irrigation management. In [9], an automatic irrigation controller was designed using soil moisture sensors, Arduino microcontrollers, and GSM modules to optimize water usage in farmlands. While this system improved efficiency, it still relied on fixed thresholds and could not adapt to changing water demand patterns. Another work, [10], explored cloud-based water management using ESP8266 microcontrollers, where sensor data was uploaded to a web platform for visualization. This system enhanced remote accessibility but again lacked predictive analytics.

Across these studies, a common limitation is that IoT solutions primarily function as reactive systems: they detect tank levels, water quality, or soil moisture and then trigger a control action (e.g., switching the pump on/off). Such systems operate on predefined rules and thresholds, making them unable to account for future water needs or unusual consumption events. This limitation reduces their effectiveness in preventing wastage caused by pipe leaks, pump malfunctions, or abnormal consumption spikes.

To address these challenges, researchers have begun integrating Machine Learning (ML) into water management. ML techniques can extract patterns from time-series data, enabling both prediction of future water usage and anomaly detection. For example, Long Short-Term Memory (LSTM) networks, a type of recurrent neural network, have shown promise in modeling temporal dependencies in water demand forecasting [11]. Similarly, clustering methods such as Density-Based Spatial Clustering of Applications with Noise (DBSCAN) have been successfully applied in sensor networks for detecting abnormal readings caused by noise, malfunction, or genuine anomalies [12].

Despite these advances, few works have combined IoT-based monitoring with ML-based prediction and anomaly detection in a unified framework. Most existing studies still treat IoT primarily as a data collection mechanism rather than as a foundation for intelligent analytics. This highlights a research gap in developing end-to-end systems capable of automatically monitoring, controlling, and learning from historical water usage data to improve long-term efficiency.

Therefore, this paper positions itself at the intersection of IoT and ML by proposing a system that not only performs automatic water level monitoring and pump control but also applies LSTM for time-series prediction of water flow rates and DBSCAN for anomaly detection in sensor data, including level, flow, pH, and turbidity. By bridging this gap, the proposed framework aims to deliver a more intelligent and sustainable solution for residential water management.

III. SYSTEM ARCHITECTURE AND IMPLEMENTATION

The proposed system combines traditional water level monitoring techniques with IoT connectivity and real-time control to optimize water usage, prevent overflow, and maintain water quality.

A. System Architecture

The overall architecture of the proposed system is illustrated in Fig. 1. In this design, the ESP32 microcontroller serves as the central hub, interfacing with multiple sensors and actuators.

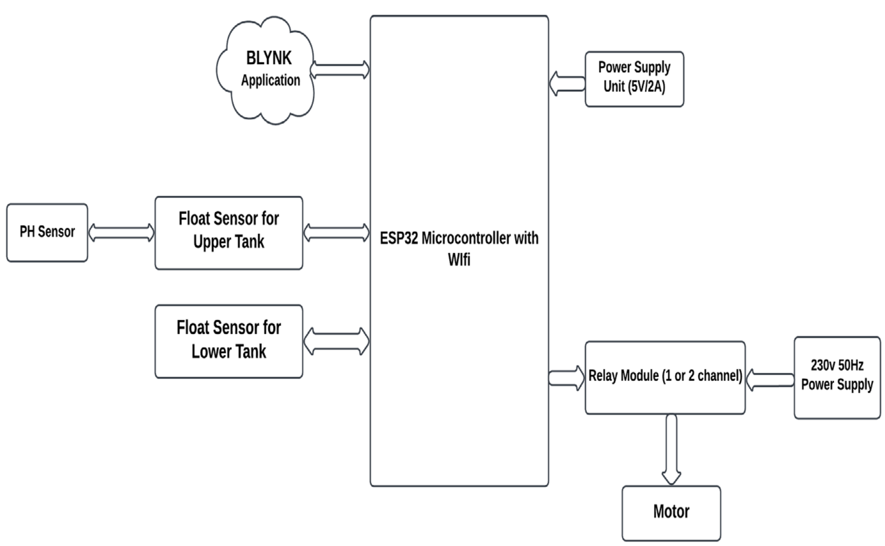

Fig. 1 Proposed System Block Diagram

The key components of the system are listed and described as follows:

1. *Water Level Sensors (Float and Ultrasonic):* Deployed in both the overhead and underground tanks to monitor water levels. The float sensor provides discrete threshold detection (high/low), whereas the ultrasonic sensor enables continuous water-level measurements.
2. *Relay Module:* Controls the water pump by receiving trigger signals from the ESP32.
3. *Motor (Submersible Pump):* Transfers water from the underground reservoir to the overhead tank.
4. *pH and Turbidity Sensors:* Monitor water quality. The pH sensor measures acidity/alkalinity, while the turbidity sensor assesses clarity to detect contamination.
5. *Power Supply Unit (5V/2A and 230V/50Hz AC):* Provides regulated power to the ESP32, sensors, and motor control unit.
6. *Enclosure and Miscellaneous Components:* Protect electronic circuits and support modular connections.

B. Implementation

The prototype implementation of the proposed system is shown in Fig. 2. The experimental setup consists of transparent water tanks for visibility, an ESP32 development board, sensors (float, pH, turbidity, and ultrasonic), a relay module, and a submersible pump. All components are mounted on a stable base with appropriate wiring to ensure reliable connectivity.

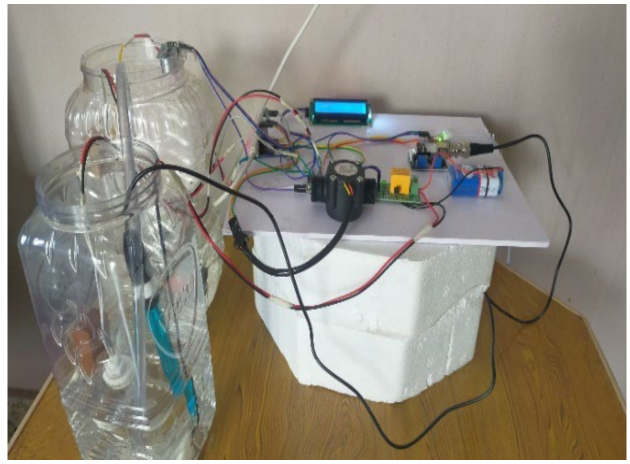

Fig. 2 Prototype implementation of the proposed system

The working of the proposed system is illustrated in Fig. 3. When the water level in the overhead tank is detected as low, the ESP32 checks the underground reservoir. If sufficient water is available, the ESP32 triggers the relay module to activate the motor.

The motor continues pumping until the overhead tank reaches its maximum level, at which point the ESP32 sends a signal to turn off the pump. During this process, the pH and turbidity sensors continuously monitor water quality.

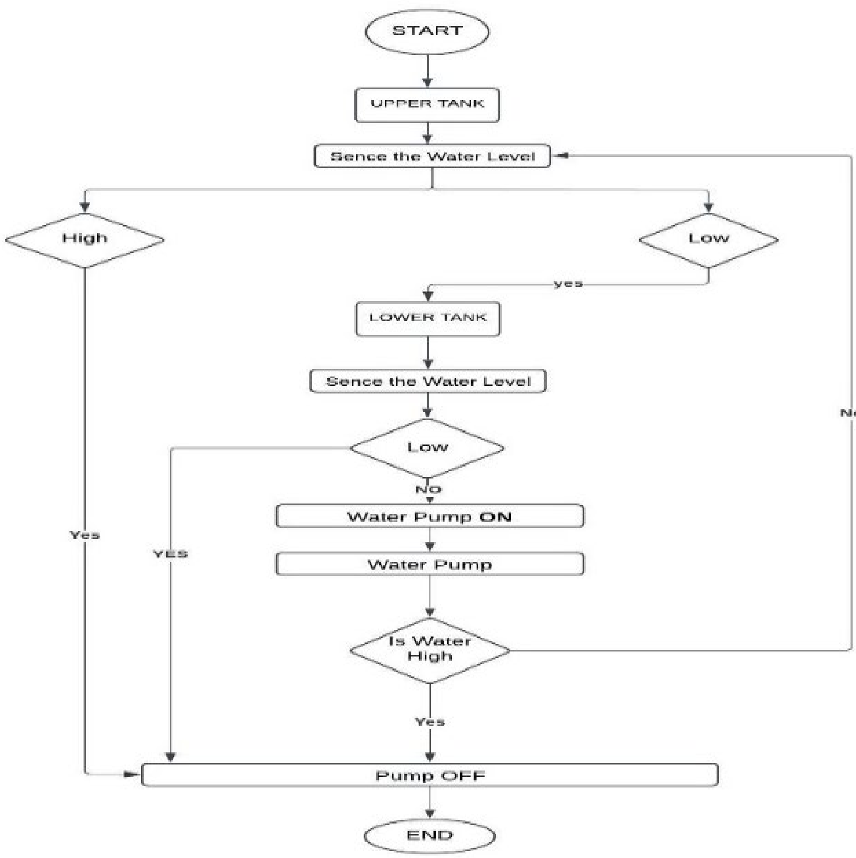

Fig. 3 Working of the Proposed System

Further, this modular and IoT-enabled implementation ensures that the system is scalable, user-friendly, and capable of deployment in real residential environments.

IV. DATASET AND PRE-PROCESSING

The dataset collected from the proposed system captures multiple attributes over the period from January 2025 to March 2025. Each record corresponds to a timestamp along with the operational states of the sump and overhead tanks, water quality indicators, and water flow readings. More specifically, the following attributes were recorded:

a. *timestamp:* Date and time of data collection (dd-mm-yyyy hh:mm format).
b. *sump_status*: Binary variable indicating the sump pump state (1 = active, 0 = inactive).
c. *tank_status:* Binary variable indicating the motor state of the overhead tank (1 = ON, 0 = OFF).
d. *sumpstatus:* Categorical label derived from sump state (e.g., tank full, half, empty).
e. *tank_message:* System-generated status messages about tank water levels.
f. *waterflow_rate (L/hr):* Flow sensor reading in liters per hour, representing consumption or filling rate.
g. *pH_value:* Real-time pH level of stored water, essential for monitoring water safety (WHO standard: 6.5-8.5).
h. *turbidity_NT:* Water clarity measured in Nephelometric Turbidity Units (NTU), indicating purity.
i. *tank_level:* Categorical representation of water level percentage (e.g., < 25%, 25-50%, 50-75%, > 75%).

Before applying machine learning models, the raw dataset was preprocessed. Missing values were filled with zero to avoid bias. Categorical data (e.g., *tank full, half, empty* and tank level ranges) were mapped into numerical values, such as tank full = 3, tank half = 2, tank empty = 1. In addition, correlation analysis was performed across different sensor variables, as shown in Fig. 4.

The correlation heat map demonstrates the relationships among features such as sump status, tank level, water flow rate, pH, and turbidity. For example, water flow rate exhibited weak correlations with chemical quality parameters (pH and turbidity), indicating that water quantity and quality are largely independent in the dataset. Such analysis is crucial for identifying redundant or weakly related variables prior to building predictive models.

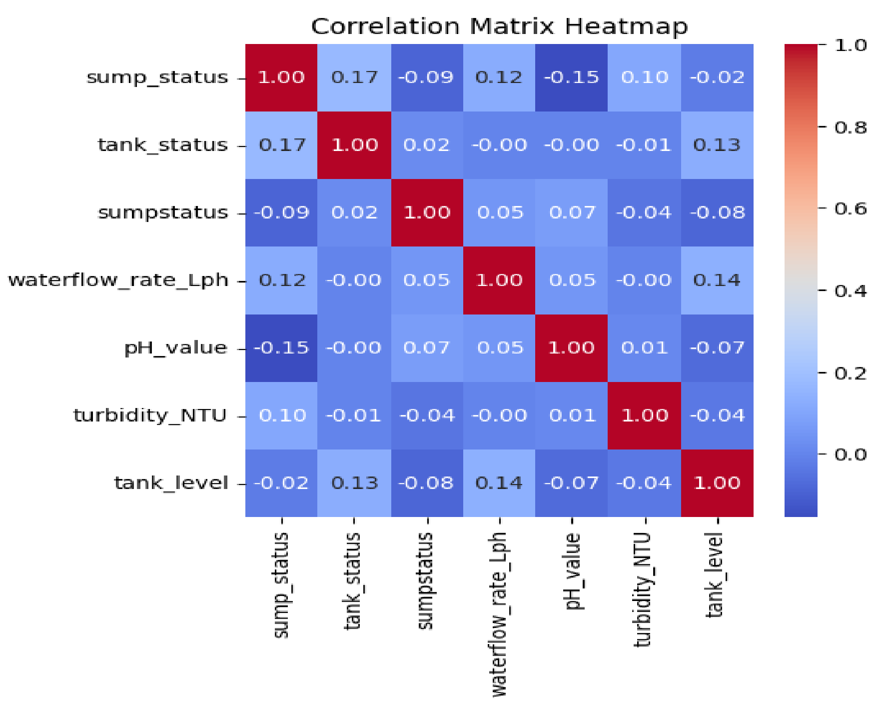

Fig. 4 Correlation analysis

V. RESULTS AND DISCUSSION

To forecast water usage patterns, an LSTM model was employed in this study. As illustrated in Fig. 5, the model was trained on historical water flow data and tested on unseen time steps. The blue line represents the actual water flow (liters per hour), while the orange dashed line denotes the predicted flow. The model successfully captured the overall trend of fluctuations, although some peaks and troughs were under- or over-estimated. This ability to forecast short-term water demand is particularly valuable in residential settings, where efficient pump scheduling can reduce both energy consumption and water wastage. The results confirm that LSTM, being a sequence-based model, is effective for modeling time-dependent water usage behavior-an outcome that traditional IoT-only control systems cannot achieve.

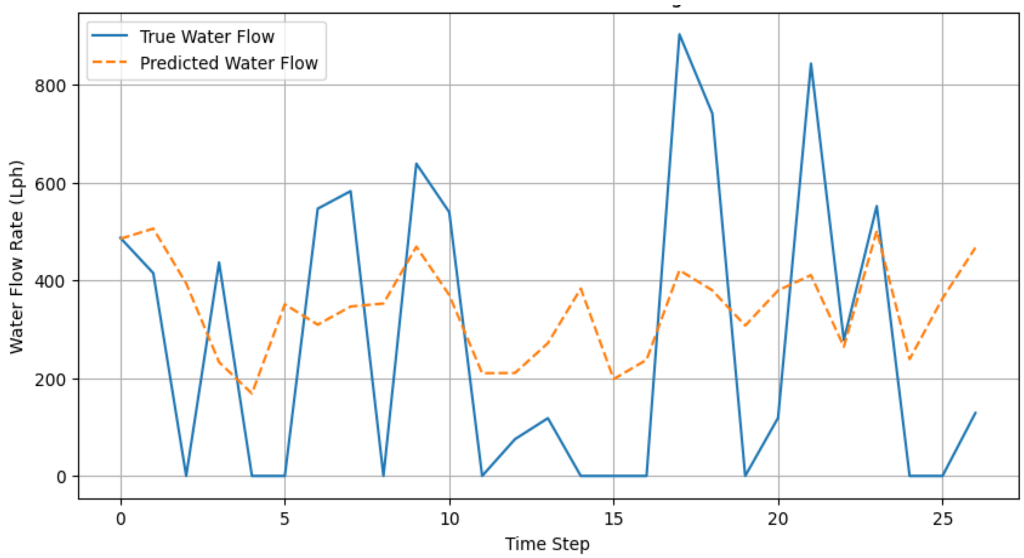

Fig. 5 Water Flow rate prediction using LSTM

For anomaly detection, DBSCAN was applied on multi-sensor data after dimensionality reduction using Principal Component Analysis (PCA). The clustering results are shown in Fig. 6. Different clusters (colored points) represent typical operating behaviors of the system, while points labeled as -1 indicate outliers or anomalies. These anomalies could correspond to sensor malfunctions (e.g., sudden drop in pH sensor readings) or unusual events (e.g., excessive water consumption or unexpected pump operation). By identifying these outliers in real-time, the system can issue alerts or trigger corrective actions, ensuring robust and reliable water management.

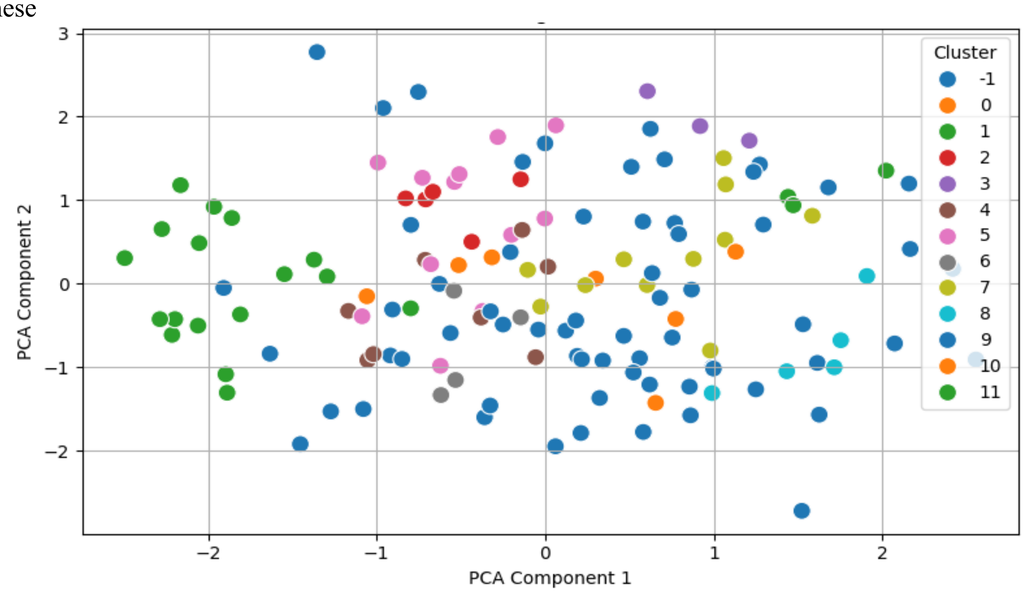

Fig. 6 Clustering of Sensor Behavior

In summary, LSTM contributes by predicting future water consumption, thereby enabling proactive pump control and reservoir scheduling. DBSCAN provides the capability to detect anomalies in real time, enhancing fault tolerance and system reliability. Together, these methods extend IoT-based automation into intelligent water management, addressing both efficiency and resilience.

VI. CONCLUSION

This work presented an intelligent water management framework that integrates IoT-based sensing with advanced machine learning techniques. Correlation analysis revealed the relationships among key water quality and quantity parameters, providing a foundation for further modeling. The LSTM model effectively captured temporal dependencies in water flow, enabling short-term demand forecasting and more efficient pump scheduling. DBSCAN clustering accurately identified abnormal sensor behaviors, ensuring reliability and real-time fault detection. Together, these approaches advance water management beyond traditional monitoring toward predictive and adaptive control. Future work will focus on large-scale deployment and optimization of these models for diverse water distribution environments.

Declaration of Conflicting Interests

The authors declare no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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Use of Artificial Intelligence (AI) - Assisted Technology for Manuscript Preparation

The authors confirm that no AI-assisted technologies were used in the preparation or writing of the manuscript, and no images were altered using AI.

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