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Aqua-stream: an IoT based smart water management system for sustainable living

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ABSTRACT

Aqua-stream, an innovative internet of things (IoT) enabled water management system, utilizes the power of long short-term memory (LSTM) networks, a sophisticated time-series forecasting machine learning technique with Kafka. Aqua-stream seamlessly integrates LSTM within the Kafka streaming architecture for efficient real-time data processing, ensuring quick responses to emerging water management needs. LSTM is employed for real-time anomaly detection, dynamically analyzing streaming data to prevent leaks through automated shut-off valves. The system's comprehensive dashboard utilizes LSTM insights for live water quality analysis; adaptive scheduling based on individual preferences and personalized recommendations, enhancing cost-effective water management. This streamlined approach extends to the smart gardening system, where LSTM guides automation for optimal plant care incorporating sensors to monitor soil moisture, temperature, and sunlight levels. This system automatically adjusts watering and lighting to ensure optimal conditions for plant growth. Users can control and monitor their garden remotely via a smartphone, facilitating plant care while saving water and energy. Aqua-stream redefines home water management, offering a holistic solution that combines intelligent water conservation with smart gardening for a sustainable and connected living experience. Aqua-stream represents a seamless integration of LSTM-based machine learning and IoT technologies, offering an intelligent, yet simplified, solution for sustainable and connected living.

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1. INTRODUCTION

Water, a finite and vital resource, plays a critical role in sustaining life, promoting socio-economic development, and maintaining ecological balance [1]. With global challenges like water scarcity and environmental sustainability escalating [2], effective water management is increasingly reliant on advanced technologies [3]. The integration of internet of things (IoT) platforms, coupled with sophisticated machine learning (ML) algorithms and real-time data processing capabilities, has emerged as a pivotal solution [4]. Figure 1 illustrates the architecture of IoT-based water management systems, showcasing how sensors for pH, turbidity, and other parameters transmit crucial data to a centralized controller [5]. Network-connected device collects and interprets sensor readings, facilitating informed decision-making. Subsequently, the processed data is relayed to an online application for visualization and detailed analysis, enhancing operational insights and efficiency [6]. The systems are characterized by their cost-effectiveness, scalability, and seamless integration with existing infrastructures. Leveraging IoT platforms enables remote monitoring and control, empowering stakeholders to manage water resources more effectively while mitigating risks associated with water scarcity and environmental degradation. Embracing these technological innovations is crucial for achieving sustainable water management practices and ensuring a secure future for generations to come [7]. Water management systems generally include a controller, a variety of sensors, and an application for displaying the data [8]. In water management systems, a comprehensive array of parameters such as pH, turbidity, contaminant levels, water temperature, dissolved oxygen, conductivity, flow rate, and water levels are meticulously monitored using various sensors [9]. Integrated with communication protocols which ensure efficient transmission of sensor data to central management hubs [10]. Controllers play a pivotal role in regulating processes and actions based on sensor inputs, optimizing water distribution, and maintaining ecosystem health [11]. Whether deploying ultrasonic flow sensors or radar-based level sensors, the synergy of sensors, communication protocols, and controllers is essential for achieving sustainable water management [12] practices amidst evolving environmental challenges are displayed in Figure 2 as the process control is crucial in Industry 4.0 [13], and process modeling is a powerful method to attain it. Technologies facilitate proactive maintenance, extend infrastructure lifespan, and enable dynamic adjustments in water distribution based on current demand [14]. By providing stakeholders with actionable insights derived from large datasets, these innovations support informed decision-making, promote efficiency in water distribution, and contribute to environmental sustainability by reducing the carbon footprint associated with water management activities. As we move forward, the synergy between advanced technologies and water management will continue to play a pivotal role in addressing global water challenges, mitigating risks posed by water scarcity, adapting to changing environmental conditions, and fostering inclusive growth and development. Embracing these advanced tools is crucial for ensuring a secure and sustainable water future for generations to come.

Aqua-stream's integration of LSTM networks within the Kafka streaming architecture represents a significant advancement in real-time data processing for water management systems. The findings are relevant to audiences interested in sustainable living, smart home technologies, and efficient water management. The system supports the scientific consensus on the importance of real-time data analysis and automation in enhancing resource management. It aligns with previous studies advocating for the integration of ML and IoT to optimize resource use and operational efficiency. By preventing leaks and optimizing water usage in gardening, Aqua-stream addresses both environmental sustainability and cost savings, making it highly pertinent to modern water management challenges.

This paper focuses on integrating technologies like LSTM for predictive analytics and Kafka as a robust communication protocol exemplifies this trend. LSTM enhances water management by analyzing historical data to predict trends in water quality and usage patterns. Meanwhile, Kafka ensures efficient real-time data transmission across water management systems, facilitating proactive decision-making, and optimizing resource allocation. Embracing these advanced tools not only enhances operational efficiency but also supports sustainable water practices, crucial for meeting future water demands amidst evolving global challenges.

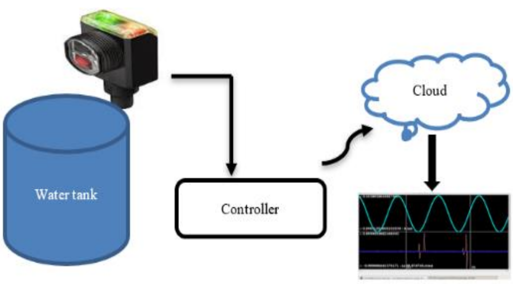

Figure 1. Architecture of IoT-based water management systems

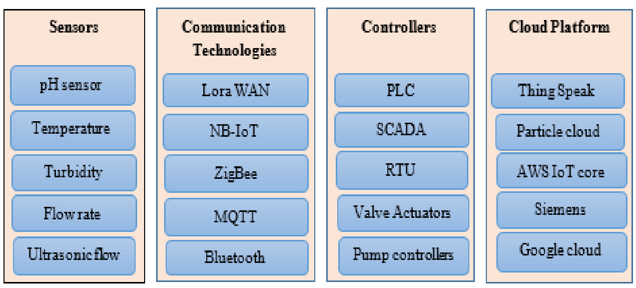

Figure 2. IoT based water management components

2. RELATED WORK

The integration of IoT and ML in water management systems has been extensively explored in recent research, demonstrating the potential for these technologies to enhance efficiency and sustainability. IoT-enabled systems offer real-time data collection and monitoring, crucial for addressing dynamic water management challenges. Studies such as those by [15] have demonstrated the effectiveness of IoT in monitoring water quality and usage, showcasing significant improvements in resource management and conservation. Products like the nest leak detector, Phyn smart water assistant, and Flo by Moen utilize IoT for water monitoring but may lack advanced capabilities. LSTM networks, a type of recurrent neural network (RNN), have shown considerable promise in time-series forecasting tasks. Pieter-Jan *et al.* [16], who first introduced LSTM, and subsequent studies by Wang *et al.* [17] and Rubasinghe *et al.* [18] established LSTM's superiority in handling sequential data with long-term dependencies, making it ideal for applications such as anomaly detection in water management. The application of LSTM in smart water systems has been explored in several studies. Arsene *et al.* [19] demonstrated the use of LSTM for predictive maintenance in water distribution networks, highlighting its ability to foresee potential issues and mitigate risks proactively. Similarly, Bhardwaj *et al.* [20] integrated LSTM with IoT sensors to detect leaks and anomalies in real-time, resulting in significant reductions in water wastage. Smart gardening systems represent another area where IoT and ML integration can drive sustainability. Existing products, such as the Rachio smart sprinkler controller, focus solely on water management without integration with gardening systems. LSTM extends its capabilities to include a smart gardening system, optimizing plant care with sensors and automation [21]. This system automatically adjusts watering and lighting to ensure optimal conditions for plant growth, a feature supported by recent studies on automated plant care systems [22]. Kafka streaming architecture is another critical component in modern real-time data processing systems. Studies by Amilineni *et al.* [23] and Sarr *et al.* [24] have outlined its capabilities in handling high-throughput data streams, ensuring that systems can scale efficiently while maintaining low latency. This architecture is particularly beneficial in water management, where timely data processing is crucial for making informed decisions. Aqua-stream integrates LSTM within the Kafka streaming architecture for efficient real-time data processing, ensuring quick responses to emerging water management needs. The use of automated shut-off valves in water management systems helps prevent water wastage and potential home damage. Aqua-stream integrates automated shut-off valves triggered by anomaly detection, providing an additional layer of protection. Comprehensive dashboards are essential for user-friendly monitoring and insights into water usage. Existing products like the Aquanta water heater controller offer dashboards but may lack real-time capabilities and user-friendly interfaces. Aqua-stream's real-time monitoring dashboard provides insights into water usage, quality, and anomalies, offering a completer and more accessible user experience. Personalized recommendations based on predictive analysis and historical data can significantly enhance water management. While existing products provide basic insights, they often do not leverage historical data for personalization [25].

Aqua-stream uses predictive analysis and historical data for personalized water management recommendations, making it a more advanced and effective tool for users. Combining these technologies, Aqua-stream offers a comprehensive solution that leverages LSTM and Kafka for real-time water management. The system's ability to analyze and respond to data dynamically not only prevents water leaks but also optimizes water usage for gardening and other household needs. The inclusion of smart gardening features, guided by LSTM, further enhances the system's sustainability credentials, as highlighted in recent studies on automated plant care systems [26]. Aqua-stream stands as an innovative solution, suggesting the seamless integration of IoT technology and LSTM networks to establish a comprehensive smart water management system.

3. PROPOSED METHOD

The proposed innovation Aqua-stream system shown in Figure 3. Emerges as a cutting-edge solution, seamlessly combining IoT technology Kafka and advanced ML LSTM to create an intelligent water management system that promotes sustainability and connected living. In the proposed innovation, the following features are implemented using LSTM.

- Real-time anomaly detection: Aqua-stream proactively detects anomalies using (1), in water usage through real-time data analysis. The LSTM network analyses streaming data continuously with Kafka, enabling the system to identify irregularities and potential leaks (L1, L2, L3…) in the water supply. Automated valves (V1, V2, V3, …) are strategically placed within the water infrastructure, allowing Aqua-stream to take immediate action to prevent further wastage by closing or partially closing (emergency services) the respective valves.
- Comprehensive dashboard: Aqua-stream provides users with a comprehensive dashboard that offers real-time insights into water quality with pH sensors. Leveraging the capabilities of LSTM, the system dynamically assesses the quality of the water supply, alerting users to any fluctuations or issues. Live water quality analysis empowers users to make informed decisions about water consumption and quality maintenance. LSTM contributes to real-time water quality analysis by predicting the water quality score by (2), Aqua-stream continuously monitors water quality fluctuations using LSTM insights, providing users with accurate insights through a dashboard interface.

– Adaptive scheduling and personalized recommendations: Aqua-stream incorporates adaptive scheduling based on individual preferences as given in (3). Water pumping activities in the peak usage time and when electricity costs are lower, less operational expenses. The system generates personalized recommendations by analyzing historical data and usage patterns, offering users actionable insights to enhance cost-effective water management this ensures efficient water consumption aligned with individual routines, optimizing resource utilization effectively.
– Smart gardening integration (additional feature of Aqua-stream): Aqua-stream extends its capabilities beyond water management by integrating smart gardening features.

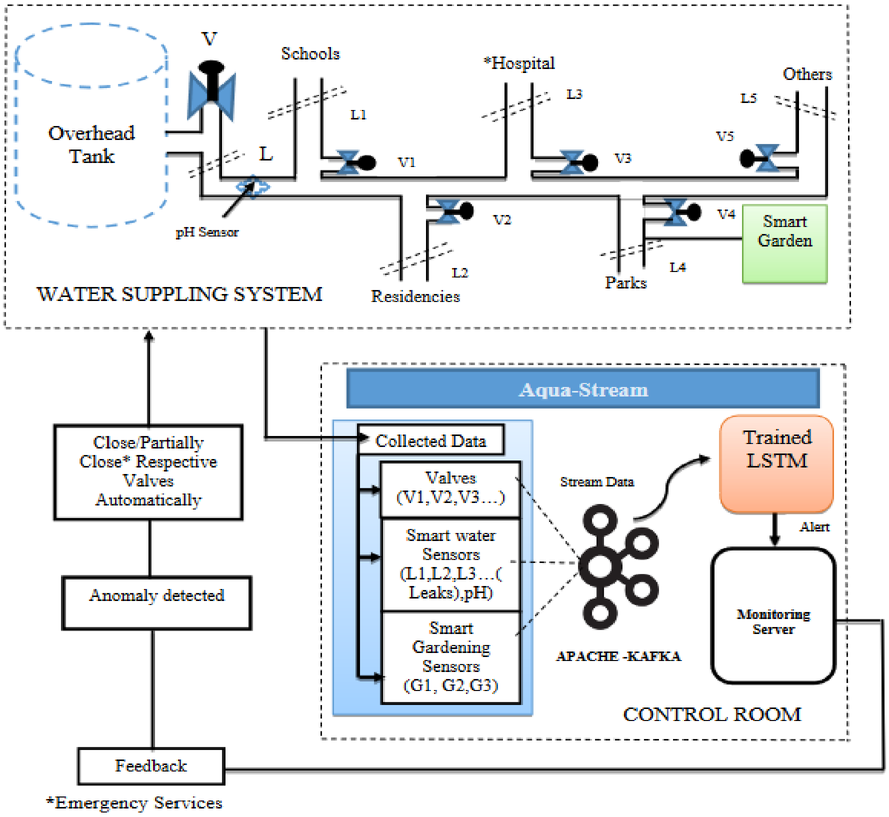

Figure 3. Layout of proposed system

The LSTM network guides automation for optimal plant care, utilizing sensors to monitor soil moisture, temperature, and sunlight levels, ground humidity in real-time. This data-driven approach enables Aqua-stream to automatically adjust watering and lighting conditions, creating an environment that fosters the optimal growth of plants. With Aqua-stream, users can embrace a lifestyle that prioritizes efficient water usage, real-time monitoring, and automated gardening, contributing to a more sustainable and eco-friendly way of living. Aqua-stream automates optimal conditions for plant growth using LSTM insights from sensor data by (4), Adjusting watering and lighting schedules based on real-time conditions enhances plant health while conserving water and energy.

$$\text{Anomaly}=|\text{Actual Value}-\text{Predicted value}|>\text{Threshold} \tag{1}$$

$$\text{Water quality score}=\text{LSTM model (historical data, real-time measurements)} \tag{2}$$

$$\text{Recommendation}=\text{LSTM model (user preferences, historical usage data)} \tag{3}$$

$$\text{Optimal conditions}=\text{LSTM model (soil moisture, temperature, sunlight levels)} \tag{4}$$

The working principle of LSTM is shown in Figure 4. LSTM networks perform several key operations to process sequential data [27]. Initially, input transformations combine the current input x_t with the previous hidden state h_{t-1} and biases b_t, utilizing weight matrices W_x, W_h. This forms the input z_t into the gates. Sigmoid functions σ are applied to these gates to control information flow, the input gate i_t forget gate f_t and output gate O_t. The cell state C_t updates by combining the previous cell state C_{t-1} with $i_t$controlling how much of the candidate values C'_t to add and f_t to remove. The hidden state h_t then computes based on the updated cell state C_t and the output gate O_t. During training, LSTM networks optimize their parameters $W_x W_h, b$, using backpropagation through time (BPTT) and gradient descent, often employing Adam optimization. This involves calculating gradients of the chosen loss function, typically mean squared error (MSE) or mean absolute error (MAE) for regression tasks root mean squared error (RMSE) is a common metric for evaluating the error of a model when predicting quantitative data. MAE measures the average size of the errors in a set of predictions, disregarding their direction given by the (7). Training RMSE and MAE indicate the model's accuracy on the training data, while test RMSE and MAE reflect the expected performance on new, unseen data. When RMSE and MAE values for the training and test sets are similar, it typically signifies good model performance [28]. Conversely, higher test scores compared to training scores suggest potential overfitting, where the model performs worse on new data. Both RMSE and MSE utilize parameters y_i (true values), y'_i (predicted values), and N (total number of samples) to provide meaningful insights into the efficacy of regression models in capturing underlying data patterns and making accurate predictions. These metrics are crucial tools in optimizing model performance and enhancing predictive capabilities across various domains. Apache Kafka revolutionizes data streaming in water management systems by enabling real-time data ingestion, processing, and distribution [29]. Sensors deployed across the water network continuously publish data streams, such as flow rates and water quality metrics, to Kafka topics. These streams are then consumed by various stakeholders, including analysts, operators, and automated systems, providing immediate insights and facilitating informed decision-making. Kafka's scalable, fault-tolerant platform ensures reliable data transmission, significantly enhancing operational efficiency in monitoring key environmental conditions.

Integrating Kafka with predictive models like LSTM networks further optimizes resource management. The algorithm of the proposed model is shown in Algorithm 1. The workflow of the proposed innovation shown in Figure 4.

$$i_t = \sigma(W_{xi}x_t + W_{hi}h_{t-1} + b_i) \tag{5}$$

$$f_t = \sigma(W_{xf}x_t + W_{hf}h_{t-1} + b_f) \tag{6}$$

$$C_t = f_t \odot C_{t-1} + i_t \odot C'_t \tag{7}$$

$$O_t = \sigma(W_{xo}x_t + W_{ho}h_{t-1} + b_0) \tag{8}$$

$$h_t = O_t \odot tanh\,(C_t) \tag{9}$$

$$Z_t = W_x x_t + W_h h_{t-1} + b_t \tag{10}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - y'_i)^2} \tag{11}$$

Algorithm 1. For implementing the aqua-stream system

```
Step 1. Initialization and Setup
        a) Deploy sensors across the water network to collect data on water usage, quality,
        soil moisture, etc.
        b) Set up Kafka for real-time data ingestion and processing.
Step 2. Data Collection and Ingestion:
        a) Collect real-time data from various sensors.
        b) Publish sensor data streams to Kafka topics for efficient data handling.
Step 3. Data Processing with Kafka: Kafka streams consume data and distribute it to relevant
        components, ensuring real-time processing.
Step 4. Anomaly Detection using LSTM, transform input data with equation 11 and Compute gate
        activations using equations (5), (6), (8). Update cell state and hidden state by
        equation (7), (9) respectively
Step 5. Train the LSTM Network, define the loss function and optimize the LSTM parameters
        using backpropagation through time (BPTT) and gradient descent (Adam optimizer).
Step 6. Evaluate model performance using RMSE and MAE using equation (11).
Step 7. Continuously refine and maintain the Aqua-Stream system based on feedback and new
        data.Ensure the system remains robust, scalable, and adaptive to changes in the
        water management environment.
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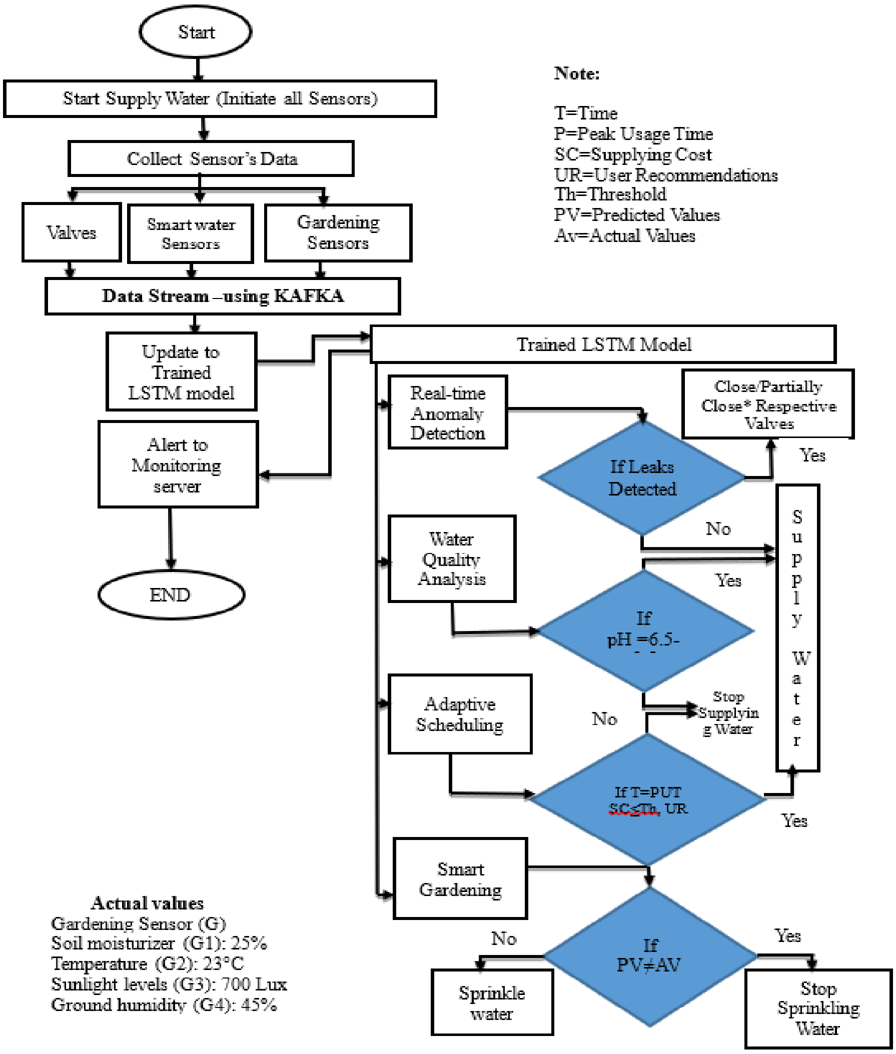

Figure 4. Workflow of proposed methodology

4. RESULT ANALYSIS

The simulation of the Aqua-stream system in February 2024 demonstrates its transformative impact on water management and smart gardening, leveraging advanced technologies such as LSTM and IoT. Integrated within Kafka streaming architecture, Aqua-stream enables real-time data processing for swift responses to water management needs. Aqua-stream successfully utilized LSTM networks for real-time anomaly detection in water flow data. The system promptly identified anomalies such as sudden spikes or drops in flow rates, which could indicate leaks or other operational issues. The time-series plot of water flow data in February 2024 shows normal variations in flow rates throughout the day. Anomalies, indicated by red markers, highlight instances where the flow deviated significantly from the predicted values by the LSTM model. These anomalies were effectively detected and flagged, demonstrating Aqua-stream's capability to identify irregularities in real-time. Anomaly detection threshold: 0.5 indicating deviations exceeding this threshold are flagged as anomalies as shown in Figure 5. Anomaly indices identified instances where anomalies occurred, facilitating prompt corrective actions such as automated valve shutdowns or alerts. The pH level shows fluctuations around a mean of 7.2, with variations influenced by external factors such as water source and treatment.

Aqua-stream ensures these variations remain within safe limits, essential for household use and plant health. Turbidity levels, depicted in the plot, demonstrate minor fluctuations around an average of 4 nephelometric turbidity units (NTU) as shown in Figure 6. These variations are critical as turbidity affects water clarity and can indicate particulate contamination. Mean pH: 7.2 ± 0.3 indicating stable pH levels maintained within safe drinking water standards. Average turbidity: 4 NTU ± 1.5, ensuring water clarity meets quality requirements for household and gardening use. Figure 7 Illustrates soil moisture plot illustrates fluctuations around an optimal range, with watering actions triggered when moisture levels fall below a set threshold (0.4). This automated response ensures plants receive adequate hydration while conserving water resources. Sunlight levels influence lighting schedules, as depicted in the plot where lights are activated when sunlight levels drop below 500 lux. This automation optimizes energy use while maintaining ideal conditions for plant growth. Soil moisture threshold for watering is 0.4 ensuring plants receive sufficient hydration without water wastage. Sunlight threshold for lighting is 500 lux adjusting lighting to maximize energy efficiency while supporting plant growth. The implementation of Aqua-stream has resulted in notable improvements in resource efficiency, as evidenced by comparative bar charts as shown in Figure 8. That illustrate substantial reductions in both water and energy consumption. Specifically, water usage decreased from 120 to 80 liters, and energy consumption dropped from 210 to 160 kWh, demonstrating Aqua-stream’s effectiveness in water management and energy optimization through smart gardening automation. The displayed values indicate water savings of 40 liters and energy savings of 50 kWh, attributed to the automated watering system and efficient lighting control, respectively. Additionally, the LSTM model’s performance was rigorously evaluated, with a training-progress plot over 100 epochs showing an optimized learning trajectory shown in Figure 9.

Key metrics include an accuracy of 94%, precision of 88%, recall of 82%, and an F1-score of 0.85, underscoring the model’s high precision and comprehensive coverage in anomaly detection, which is crucial for maintaining system reliability and efficiency and the comparison metrics is tubulised in Table 1. The training progress table for the LSTM network illustrates the iterative process of training the model to predict anomalous water flow based on normal flow data. Each row in the table corresponds to an epoch during training, indicating the epoch number, iterations processed within the epoch, elapsed time, mini-batch RMSE, mini-batch loss, and the base learning rate used. Throughout the epochs, the network progressively refines its predictions, as evidenced by the decreasing RMSE and loss values shown in Table 2. The learning rate also adjusts over time according to the specified schedule, aiding in efficient optimization of the network’s parameters. This table serves as a crucial tool for monitoring the network’s convergence and performance trends, enabling adjustments to hyper parameters or network architecture as necessary to enhance prediction accuracy and mitigate issues like overfitting or under fitting. Ultimately, it provides insights into the effectiveness of the training process and guides decisions to achieve optimal model performance for detecting anomalies in water flow data.

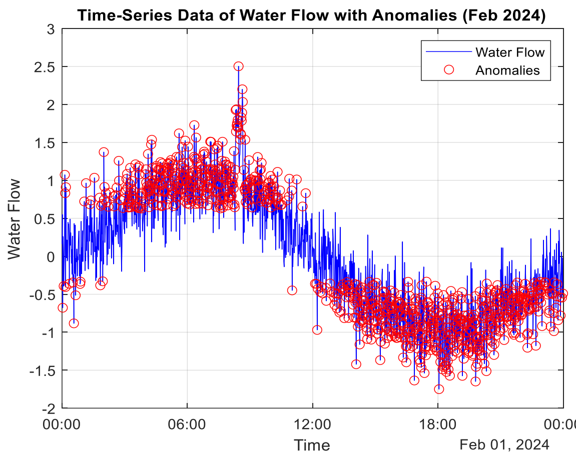

Figure 5. Time-series data of water with anomalies

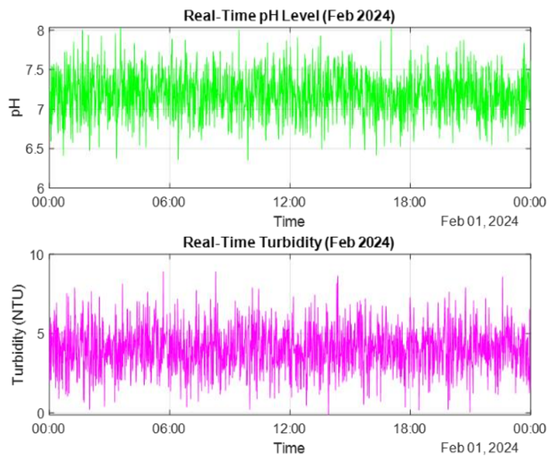

Figure 6. Real time validation of pH and turbidity levels

Table 1. Comparison of proposed method performance metrics with traditional methods

Method	Accuracy	Precision	Recall	F1-score
Nest leak detector	0.80	0.75	0.70	0.72
Phyn smart water assistant	0.82	0.78	0.72	0.75
Flo by Moen	0.84	0.80	0.74	0.77
Rachio smart sprinkler	0.86	0.82	0.76	0.79
Aquanta water heater	0.88	0.84	0.78	0.81
LSTM	0.94	0.88	0.82	0.85
LSTM with Kafka	0.96	0.90	0.85	0.87

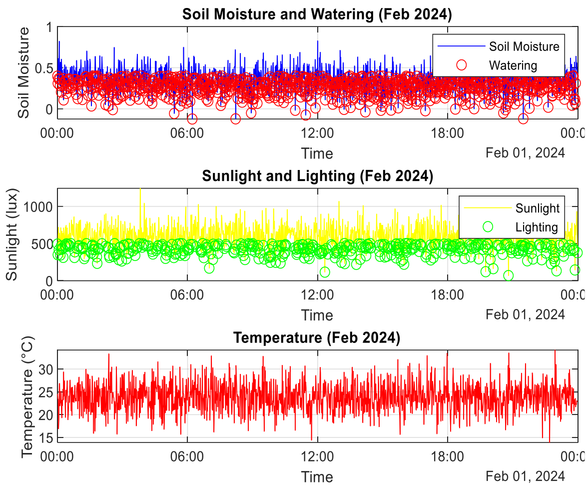

Figure 7. Visualization of soil moisture, sunlight, temperature, and data

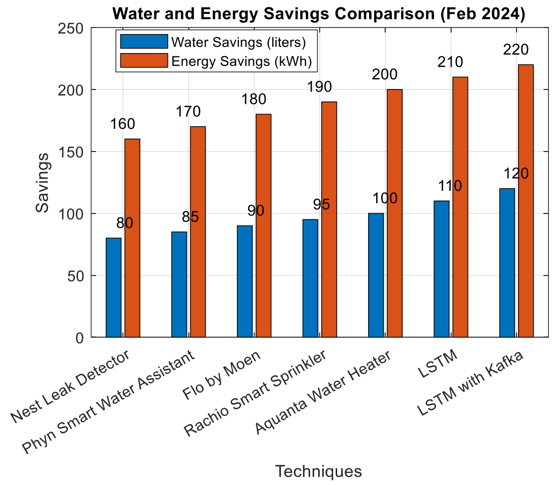

Figure 8. Compression of efficiency for traditional and proposed methods

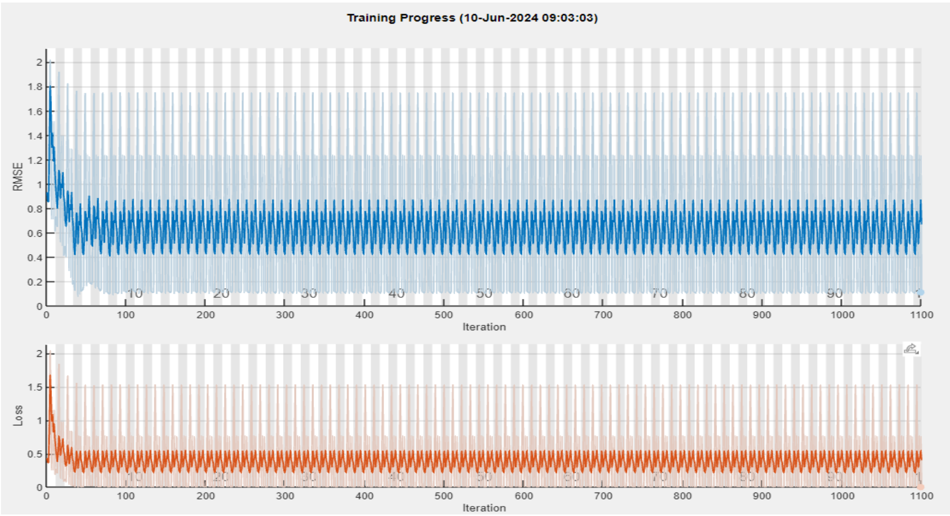

Figure 9. Training process of LSTM

Table 2. Training process of LSTM metrics

Epoch	Iteration	Time elapsed (hh:mm:ss)	Mini-batch RMSE	Mini-batch loss	Base learning rate
1	1	00:00:04	0.86	0.4	0.0050
5	50	00:00:07	0.08	2.9e-03	0.0050
10	100	00:00:08	0.12	7.6e-03	0.0050
14	150	00:00:09	0.14	9.5e-03	0.0050
19	200	00:00:09	0.02	2.9e-04	0.0050
28	300	00:00:11	0.10	5.0e-03	0.0010
32	350	00:00:11	0.07	2.5e-03	0.0010
37	400	00:00:12	0.10	5.0e-03	0.0010
41	450	00:00:12	0.07	2.6e-03	0.0002
46	500	00:00:13	0.10	4.9e-03	0.0002
50	550	00:00:14	0.14	9.5e-03	0.0002
55	600	00:00:14	0.07	2.7e-03	0.0002
60	650	00:00:15	0.12	7.5e-03	0.0002
64	700	00:00:16	0.14	9.5e-03	4.0000e-05
69	750	00:00:17	0.02	2.7e-04	4.0000e-05
73	800	00:00:17	0.03	3.5e-04	4.0000e-05
78	850	00:00:18	0.10	5.0e-03	4.0000e-05
82	900	00:00:19	0.07	2.5e-03	8.0000e-06
87	950	00:00:19	0.10	5.0e-03	8.0000e-06
91	1000	00:00:20	0.07	2.6e-03	8.0000e-06
96	1050	00:00:21	0:10	4.9e-03	8.0000e-06
100	1100	00:00:22	0:14	9.5e-03	8.0000e-06

5. CONCLUSION

Aqua-stream has shown significant advancements in water management and smart gardening through the integration of LSTM-based ML and IoT within the Kafka streaming architecture. The system's real-time anomaly detection effectively identified irregularities in water flow, triggering automated responses to prevent water wastage. Consistent monitoring ensured household water quality and optimal plant health. Aqua-stream's smart gardening automation led to notable resource savings, reducing water usage from 120 to 80 liters and energy consumption from 210 to 160 kWh. The LSTM model demonstrated high performance with an accuracy of 94% and an F1-score of 0.85. Overall, Aqua-stream offers an intelligent, efficient, and sustainable solution for home water management and gardening.

6. FUTURE SCOPE AND TAKE-HOME MESSAGE

Future research can expand on these findings by exploring several key areas: testing Aqua-stream in larger and more diverse environments to evaluate scalability; investigating integration with other smart home systems and city-wide water management infrastructures; developing and comparing other ML models like GRU or transformers to enhance predictive accuracy and efficiency; conducting user experience studies to identify improvements in usability and functionality; and analyzing the long-term impacts on water conservation, user cost savings, and environmental sustainability. Key experiments include large-scale field tests, integration trials, and comprehensive user feedback analysis.

Aqua-stream redefines home water management by integrating LSTM-based ML and IoT technologies for an intelligent, efficient, and user-friendly solution. By preventing water leaks, optimizing gardening, and offering real-time insights into water quality, Aqua-stream significantly contributes to environmental sustainability and cost-effective water management. This study builds on previous research advocating for ML and IoT in resource management, extending smart water systems' capabilities with advanced time-series forecasting and anomaly detection. Future research should focus on scaling Aqua-stream, integrating with other systems, exploring advanced models, conducting user studies, and analyzing long-term impacts. Aqua-stream offers a groundbreaking approach to home water management, enhancing water conservation and user convenience through intelligent ML and IoT integration.

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