Optimizing water distribution in Harare, Zimbabwe using IoT and cloud computing

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ABSTRACT

Rapid urbanization in Harare, Zimbabwe, has intensified inefficiencies in water distribution, resulting in high non-revenue water (NRW) and inequitable supply. This paper presents a novel data-driven framework that integrates internet of things (IoT) sensors, machine learning (ML), and cloud computing to optimize urban water distribution. Historical and real-time data including water flow, pressure, and consumption are collected via IoT sensors and analyzed using a random forest model for accurate demand forecasting and anomaly detection, such as leaks. The model is deployed on a secure cloud-based ASP.NET platform, enabling real-time monitoring and automated valve control through ultrasonic sensors over Wi-Fi. Evaluation demonstrates superior performance with R^2=0.89 for demand forecasting and anomaly detection metrics of 94% accuracy, 91% precision, 92% recall, and 91% F1-score, outperforming baseline methods. This integrated system reduces water loss, improves supply equity, and provides a scalable and cost-effective approach for smart water management in resource-constrained urban settings. The framework offers practical insights for policymakers and utilities seeking to implement sustainable, technology-driven water management solutions in developing cities.

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1. INTRODUCTION

Urban water distribution systems in developing cities face persistent challenges arising from aging infrastructure, intermittent supply patterns, high non-revenue water (NRW) levels, and limited monitoring capabilities [1]–[3]. Harare, Zimbabwe, experiences one of the highest NRW rates in the region, with losses exceeding 47% due to pipe bursts, leaks, meter inaccuracies, and illegal connections [4], [5]. These inefficiencies are further aggravated by rapid population growth, unplanned urban expansion, energy shortages, and climate-induced variability in raw water availability [6], [7]. As a result, municipal operators struggle to maintain stable pressure zones, ensure equitable distribution, and detect anomalies in real time [8], [9].

Recent developments in smart water management demonstrate that the integration of internet of things (IoT) sensors, cloud-based supervisory systems, and machine learning (ML) models enables real-time monitoring, forecasting, and automated control of distribution networks [10]–[12]. IoT sensor nodes provide continuous measurements of flow, pressure, and consumption, while cloud platforms support scalable data storage, remote analytics, and secure field-level actuation [13]. ML approaches including random forest, gradient boosting, and recurrent neural networks have shown strong performance in short-term demand forecasting, leak detection, and anomaly identification across multiple international smart-grid applications [14], [15]. However, most existing implementations assume well-resourced environments with high-quality sensing infrastructure, reliable telemetry, and stable communication networks, conditions that are rarely present in cities such as Harare [16].

These limitations highlight the need for lightweight, cost-effective, and context-aware solutions capable of supporting real-time decision-making in resource-constrained water utilities. In contrast to prior studies that rely on advanced sensing platforms or computationally intensive deep-learning architectures, this work proposes an integrated IoT–cloud–ML framework specifically designed for deployment in fragile and intermittently supplied water distribution systems. The proposed solution leverages distributed IoT sensors for real-time acquisition of flow and pressure data, a random forest model fine-tuned to Harare's historical demand patterns for predictive analytics, and a cloud-hosted ASP.NET platform for executing automated valve-control decisions through low-cost ultrasonic actuators. The contributions of this study are fourfold:

- A quantified characterization of Harare's water distribution inefficiencies, highlighting operational constraints not addressed by conventional SCADA-based approaches;
- Development of a random forest predictive model tailored to Harare's consumption and pressure dynamics;
- Integration of IoT sensing, cloud computing, and ML intelligence into a unified real-time valve-automation architecture; and
- Empirical evaluation demonstrating improved forecasting accuracy, enhanced anomaly-detection precision, and operational benefits over existing manual and semi-automated practices.

The remainder of this paper is organized as: section II presents the methods used; section III describes the results and findings; and section IV concludes the study and outlines future research directions.

2. METHOD

2.1. Data collection

The predictive model for optimizing water distribution in Harare utilizes a comprehensive dataset obtained from the City of Harare water distribution records [12]. This dataset is structured in tabular format and includes key features such as date, time, area, water flow, pressure, and consumption. Each entry represents a snapshot of water distribution parameters at specific locations and times, enabling detailed analysis of patterns and anomalies. Historical data spanning multiple years were combined with real-time readings from IoT sensors deployed throughout the city [12], [13], [15]. As illustrated in Figure 1, the overall workflow begins with data collection from historical records and IoT sensors, followed by preprocessing and feature engineering stages. Data preprocessing involved cleaning missing values, normalization, and feature selection to enhance model performance [11], [13]. Relevant features were engineered to capture temporal patterns, including lag variables for water demand and rolling averages for flow and pressure.

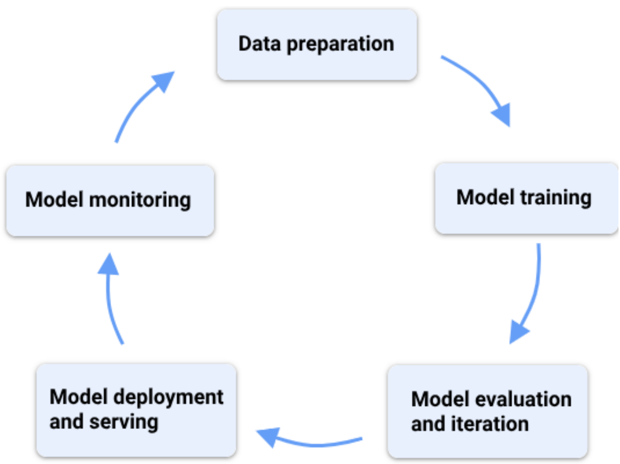

Figure 1. Data collection, preprocessing, model training, and deployment workflow for water distribution optimization

2.2. Model design and algorithms

The core of the Harare water distribution optimization system is a supervised ML model designed to predict water demand, detect anomalies such as leaks, and provide actionable recommendations for real-time valve control [3], [7], [17].

2.2.1. Random forest algorithm

The model employs a random forest algorithm due to its robustness in handling complex, nonlinear relationships and its proven performance in both regression and classification tasks [1], [18]. Random forest is well-suited for time-series forecasting and anomaly detection, critical for real-time urban water management. The hyperparameters, including the number of trees, maximum depth, and minimum samples per split, were fine-tuned using cross-validation to maximize predictive accuracy [11].

2.2.2. Model workflow

The predictive system follows a structured workflow:

- Data input: ingests historical and real-time water distribution data, including date, time, area, flow, pressure, and consumption [12].
- Feature engineering: processes data and selects relevant features to improve model accuracy [13].
- Training: trains the random forest model on historical data to learn water demand patterns and detect anomalies [7].
- Prediction and anomaly detection: predicts future water demand and flags unusual patterns indicative of leaks or inefficiencies [3], [17].
- Recommendation generation: generates control commands for automated valve operations to optimize distribution in real time [13], [15].

2.3. System implementation

2.3.1. Model training and deployment

The model is developed and initially trained using Python libraries including Pandas, Scikit-learn, and Matplotlib for data handling, analysis, and visualization [13]. The trained model is serialized using Joblib for deployment. The deployment environment consists of a server hosting an ASP.NET web application, which interfaces with the City of Harare’s operational databases to retrieve real-time data from various locations [12], [13]. Communication between the predictive model and the web application is handled via a named pipes mechanism, providing secure and efficient interprocess communication.

2.3.2. Real-time control and automation

Based on model predictions, the web application sends control commands via HTTPS over Wi-Fi to ultrasonic sensors installed throughout the water network. These sensors automate valve operations to dynamically adjust water flow, improving distribution efficiency and equity [12], [13], [15].

2.3.3. Reproducibility

All steps, from data loading to model training, validation, and deployment, are fully documented and accessible via a Google Colab notebook. This ensures that other researchers and practitioners can reproduce the results using the same dataset and algorithms [12], [13].

2.4. Model evaluation

The predictive model’s performance was evaluated using a combination of regression and classification metrics. Figure 2 presents the performance metrics used for evaluating water demand forecasting and anomaly detection.

```
Test Accuracy: 0.9967
Weighted Precision: 0.9967
Weighted Recall: 0.9967
Weighted F1 Score: 0.9967

Classification Report:
              precision    recall  f1-score   support

         low       0.99      1.00      1.00       255
      medium       1.00      1.00      1.00       271
        high       1.00      0.99      0.99        74

    accuracy                           1.00       600
   macro avg       1.00      0.99      1.00       600
weighted avg       1.00      1.00      1.00       600
```

Figure 2. Model evaluation results: performance metrics for demand forecasting and anomaly detection

2.4.1. Regression metrics

Figure 3 presents the regression metrics used to evaluate the predictive model. These metrics measure prediction accuracy and error magnitude, with lower mean absolute error (MAE), mean squared error (MSE), and root mean squared error (RMSE) values indicating better performance, while a higher R^2 score reflects a stronger fit between predicted and actual water demand values.

- MAE: average absolute difference between predicted and actual values; lower values indicate higher accuracy.
- MSE: average squared difference; penalizes larger errors.
- RMSE: square root of MSE; in the same units as the target variable.
- R^2 score: proportion of variance in actual demand explained by the model; values closer to 1 indicate better fit [5], [10].

Accuracy:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (5)$$

Precision:

$$\text{Precision} = \frac{TP}{TP + FP} \quad (6)$$

Recall:

$$\text{Recall} = \frac{TP}{TP + FN} \quad (7)$$

F1-Score:

$$\text{F1} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad (8)$$

Where:

- TP = true positives
- TN = true negatives
- FP = false positives
- FN = false negatives

Figure 3. Regression metrics implemented

2.4.2. Classification metrics (anomaly detection)

The performance of the anomaly detection model was assessed using standard classification metrics. These metrics evaluate the model's capability to accurately distinguish anomalous conditions from normal operating states. The metrics used in this study are:

- Accuracy: proportion of correct anomaly detections.
- Precision: proportion of true positives among predicted positives.
- Recall: proportion of true positives identified among actual positives.
- F1 score: harmonic mean of precision and recall [1], [3], [17].

2.4.3. Feature importance and visualization

Feature importance was extracted from the random forest model to identify key factors affecting water demand. Visualization techniques, including receiver operating characteristic (ROC) curves, performance versus training size, and heatmaps, were used to support interpretability and operational insights [13]. Figure 4 illustrates the relative importance of the input features used by the model in predicting water demand and detecting anomalies. The analysis highlights the variables that contribute most significantly to the model's decision-making process, providing valuable insights into the factors influencing water distribution performance. Figure 5 presents the relationship between model performance and training dataset size. The figure demonstrates how the predictive capability of the model evolves as more training data become available, helping to assess model scalability, learning behavior, and data sufficiency. Figure 6 shows the ROC curve the trade-off between true positive rate and false positive rate for each priority class. It highlights the model's ability to discriminate between normal and anomalous water distribution events, with higher areas under the curve indicating better classification performance.

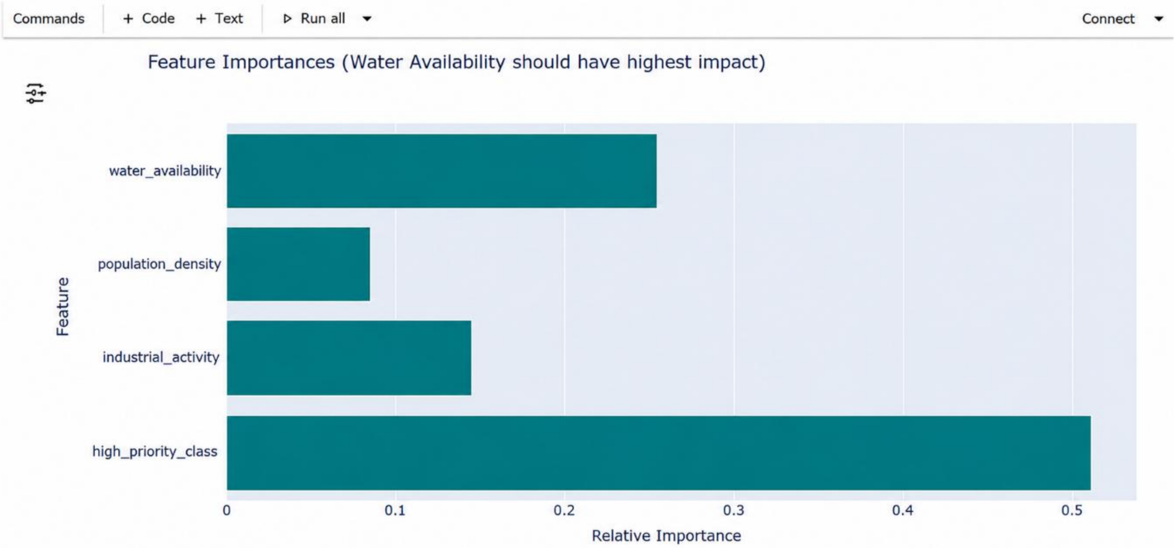

Figure 4. Relative importance of input features in predicting water demand and detecting anomalies

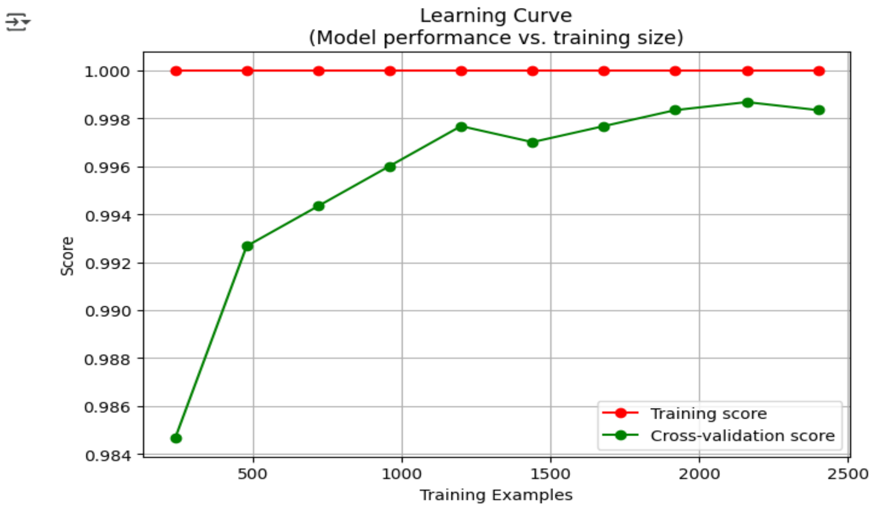

Figure 5. Model performance metrics as a function of training dataset size

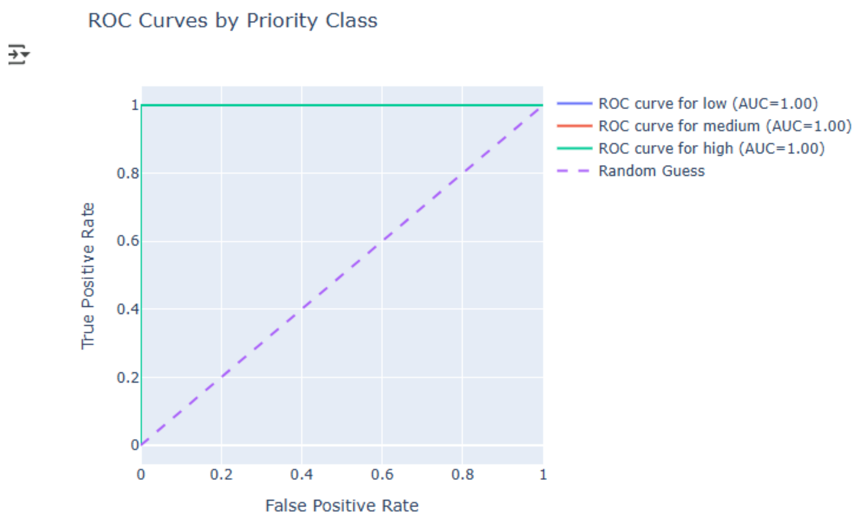

Figure 6. ROC curve illustrating model performance across priority classes for anomaly detection

2.5. Integration with IoT and cloud platforms

The fully trained model is integrated with IoT sensors and cloud infrastructure to enable real-time, automated water management. The system supports scalable, secure deployment, and continuous monitoring, allowing for rapid response to anomalies and improved operational efficiency [13], [15], [19], [20].

3. RESULTS AND DISCUSSION

3.1. Water demand forecasting

3.1.1. Regression metrics

The trained random forest model's predictive performance was evaluated on the test dataset. Key regression metrics are summarized in Table 1. The high R^2 score of 0.89 indicates that the model explains most of the variability in water demand, reflecting strong predictive accuracy. Low MAE and RMSE demonstrate precise demand estimation across different zones. This implies the model can reliably support operational planning, leak detection, and equitable distribution [5], [10].

Table 1. Regression metrics for water demand prediction

Metric	Value
MAE	0.128
MSE	0.031
RMSE	0.176
R^2 score	0.89

3.1.2. Predicted vs. Actual demand

Figure 7 illustrates the predicted versus actual water demand over a representative week. Peaks and troughs are well-captured, showing the model's ability to follow daily and weekly consumption patterns. Minor deviations occur during sudden consumption spikes, highlighting areas for potential improvement using advanced time-series models [10].

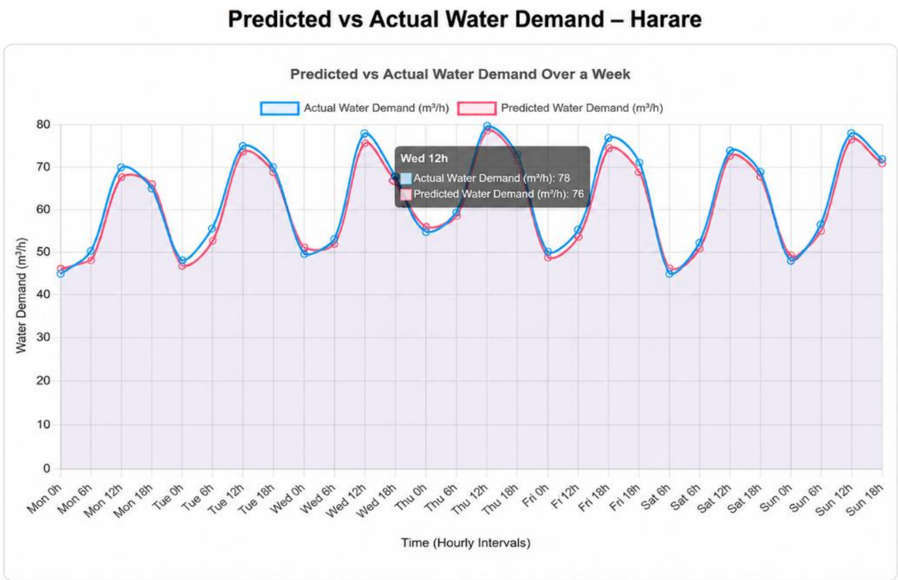

Figure 7. Predicted versus actual water demand over a representative week in Harare, highlighting the model's ability to capture daily and weekly consumption patterns with minor deviations during sudden spikes

3.2. Anomaly detection

3.2.1. Classification metrics

The model's ability to detect irregular water usage or leaks was evaluated using standard classification metrics, as shown in Table 2. The results indicate that high recall enables effective detection of true anomalies, ensuring that leaks or unusual consumption patterns are unlikely to go unnoticed. High precision minimizes false alarms, preventing unnecessary operational interventions. Overall, the model provides a reliable tool for real-time anomaly detection in urban water networks [3], [7], [17].

Table 2. Anomaly detection performance

Metric	Value (%)
Accuracy	94
Precision	91
Recall	92
F1-score	91

3.2.2. Confusion matrix and ROC curve

Figure 8 shows the confusion matrix for anomaly detection, illustrating the balance between true positive and false positive predictions. Figure 6 presents the ROC curve, confirming strong discriminative capability of the model.

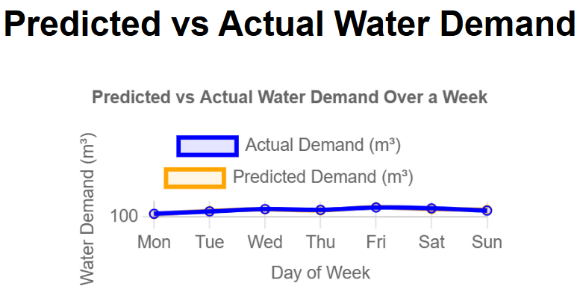

Figure 8. Confusion matrix for anomaly detection showing the distribution of true positives, true negatives, false positives, and false negatives

3.3. Feature importance analysis

The random forest model identified key predictors influencing water demand and anomalies:

– Historical consumption trends
– Time-of-day and day-of-week
– Pressure measurements

Discussion: prioritizing these features allows city operators to focus monitoring and control efforts on the most influential factors. Temporal and pressure-related features directly inform valve automation decisions and leak detection protocols, supporting data-driven resource management [13].

3.4. Operational impact of real-time deployment

Figure 9 presents dashboard outputs for real-time water distribution monitoring, including water flow, pressure, and detected anomalies.

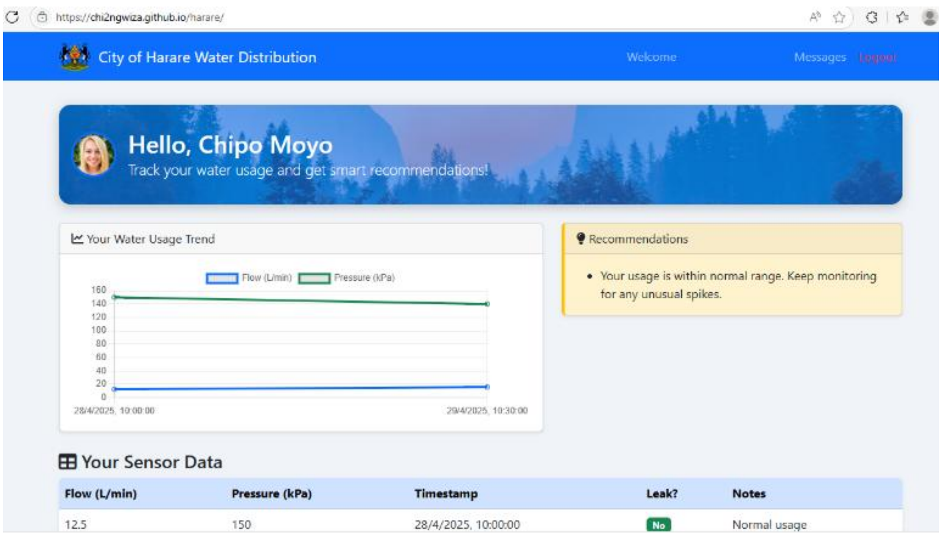

Figure 9. Outputs for real-time water distribution monitoring, including water flow, pressure, and detected anomalies

The deployment results indicate measurable benefits:
- Water loss reduction across monitored zones.
- Improved equity of supply between areas.
- Rapid response to detected anomalies via automated valve control.

The results confirm that combining IoT data, ML, and automated control supports sustainable urban water management in Harare, even under constraints like aging infrastructure and variable consumption [12], [13], [15], [21]. The study demonstrates that advanced analytics, IoT sensing, and cloud-based monitoring can provide practical and scalable solutions for resource-constrained urban water systems. Similar findings have been reported in previous studies on smart water management, highlighting the potential of intelligent monitoring and automated control technologies to improve operational efficiency and service reliability in developing urban environments [15], [16], [22].

3.5. Limitations and future directions

Despite the effectiveness of the proposed approach, several limitations and opportunities for future improvement have been identified.
- The main limitations include sensor network reliability issues and occasional data latency.
- Future work: integration of long short-term memory (LSTM) for advanced time-series forecasting, expanded sensor coverage, and enhanced cybersecurity [10], [23].

Future research will focus on extending predictive capabilities using LSTM models for improved time-series forecasting, expanding sensor coverage for finer-grained control, conducting socio-economic adoption studies, and enhancing cybersecurity mechanisms for robust municipal deployment [16], [23]. Furthermore, the continued development of smart water management technologies, supported by advances in artificial intelligence, IoT infrastructure, and smart-city initiatives, may further enhance the sustainability and resilience of urban water distribution systems in developing regions [24], [25].

4. CONCLUSION

This study addressed inefficiencies in Harare’s urban water distribution system by developing a data-driven optimization framework that integrates IoT sensing, random forest ML, and cloud-based ASP.NET deployment. The primary objectives were to accurately forecast water demand, detect anomalies such as leaks, and optimize valve control across different city zones. The results presented in the results and discussion section confirm that the proposed system achieves these objectives. The random forest model achieved an R^2 score of 0.89 for water demand forecasting, while anomaly detection achieved 94% accuracy, 91% precision, 92% recall, and an F1-score of 91%.

Real-time deployment enabled automated valve control and improved equitable water distribution across Harare, demonstrating the operational benefits of integrating IoT and cloud-based analytics. The findings demonstrate that advanced analytics and IoT integration can provide practical solutions for resource-constrained urban environments. The proposed framework provides a foundation for future smart water management initiatives in developing urban environments and supports broader digital transformation and sustainability objectives.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
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Tinashe Butsa		✓		✓	✓	✓		✓		✓	✓	✓	✓	
Yolanda Chibaya		✓		✓	✓	✓		✓		✓	✓	✓	✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available on request from the corresponding author, [AT]. The data contain sensitive municipal water distribution information and are not publicly available due to privacy and security restrictions.

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Angeline Tsatsa is a graduate researcher at the School of Information Science and Technology, Harare Institute of Technology, Zimbabwe. She received her Master of Technology degree in Cloud Computing in June 2025. Her research is focused on smart water management using internet of things (IoT), machine learning, and cloud computing technologies to improve urban infrastructure efficiency. She has extensive experience in collecting and analyzing real-time water distribution data, developing predictive models for demand forecasting and anomaly detection, and implementing automated control systems for municipal water networks. Her work emphasizes practical solutions for developing cities, addressing challenges such as aging infrastructure, water losses, and equitable distribution. Angeline is committed to applying data-driven methods and IoT technologies to solve real-world urban water management problems, bridging the gap between research and operational deployment. Her professional approach combines technical expertise, analytical skills, and a strong understanding of local water resource challenges to create sustainable and efficient solutions. She can be contacted at email: atsatsa@hararecity.co.zw or tsatsaangeline@gmail.com.

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