

Design and Optimization of Smart Pipe Network Systems for Urban Water Distribution Using IoT-Based Monitoring and Machine Learning Algorithms

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ABSTRACT

Increased urbanization and population growth are creating problems in urban water distribution systems, which include leakage, imbalance of pressure, energy loss, and poor utilization of resources. There is no monitoring and maintenance in traditional water systems, which has led to large-scale water losses. This research work demonstrates a design of an optimized smart pipe network system for urban water distribution by employing IoT technology and Machine Learning (ML). Sensors based on IoT technology were installed to monitor parameters such as water flow rate, pressure, and water levels in order to collect data for decision-making and analysis purposes. Hydraulic simulation was performed to evaluate the behavior of the network under different demand scenarios, while pre-processing techniques were employed for better data processing. These techniques included normalization, denoising, and filtering of outliers. SVM, LR, DT, and RF algorithms of ML were employed for prediction and optimization. Results showed that the SVM model achieved the best performance with MAE of 1.12 and RMSE of 1.68, demonstrating improved leakage control, pressure management, operational efficiency, and sustainable urban water distribution.

KEYWORDS: *IoT, Urban water distribution systems, ML Algorithm, Smart pipe network systems.*

1. INTRODUCTION

The urban water distribution systems are vital infrastructures that are responsible for providing a continuous supply of potable and safe water to urban residential, commercial, and industrial sectors [1]. As cities continue to develop, water-intensive growth, high population density, aging infrastructure, and a growing number of pipes are placing enormous operational stress on traditional water distribution systems. However, conventional pipe network systems have been plagued by problems of water leakage, pressure variation, pipe burst, non-revenue water, energy inefficiency and limited monitoring [2]. Such issues affect water supply systems' efficiency and raise the expenses involved in system operation and maintenance for towns and municipalities. Thus, the creation of intelligent and optimized water supply systems is an important need for sustainable urban management [3]. The recent developments in the Internet of Things (IoT) and

Machine Learning (ML) technologies have given novel solutions to enhance the performance, reliability and efficiency of urban water distribution networks [4].

Water supply systems can be equipped with IoT sensors for real-time monitoring, data collection, and remote control of the hydraulic parameters, including water pressure, flow rate, water quality, leak conditions, and water levels of the reservoir [5]. Operational data is continuously collected from the pipe network with the use of smart sensors and communication devices connected with the IoT technologies, and the data is wirelessly transferred to the centralized monitoring platforms [6]. This info is collected in real time, giving more visibility into the system, and it lets engineers and operators notice abnormal conditions right away, as soon as they show up. Smart monitoring solutions also help reduce the need for manual inspections, and they can improve the response speed during emergency

How to cite this paper: Satyawan Godara | Dr. Varinder Singh "Design and Optimization of Smart Pipe Network Systems for Urban Water Distribution Using IoT-Based Monitoring and Machine Learning Algorithms"

Published in International Journal of Trend in Scientific Research and Development (ijtsrd), ISSN: 2456-6470, Volume-10 | Issue-3, June 2026, pp.1212-1223, URL: www.ijtsrd.com/papers/ijtsrd133315.pdf

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scenarios like water leaks or water loss, [7]. On top of that, IoT driven frameworks support predictive

maintenance strategies, which should lower downtime and extend the useful life of pipeline assets.

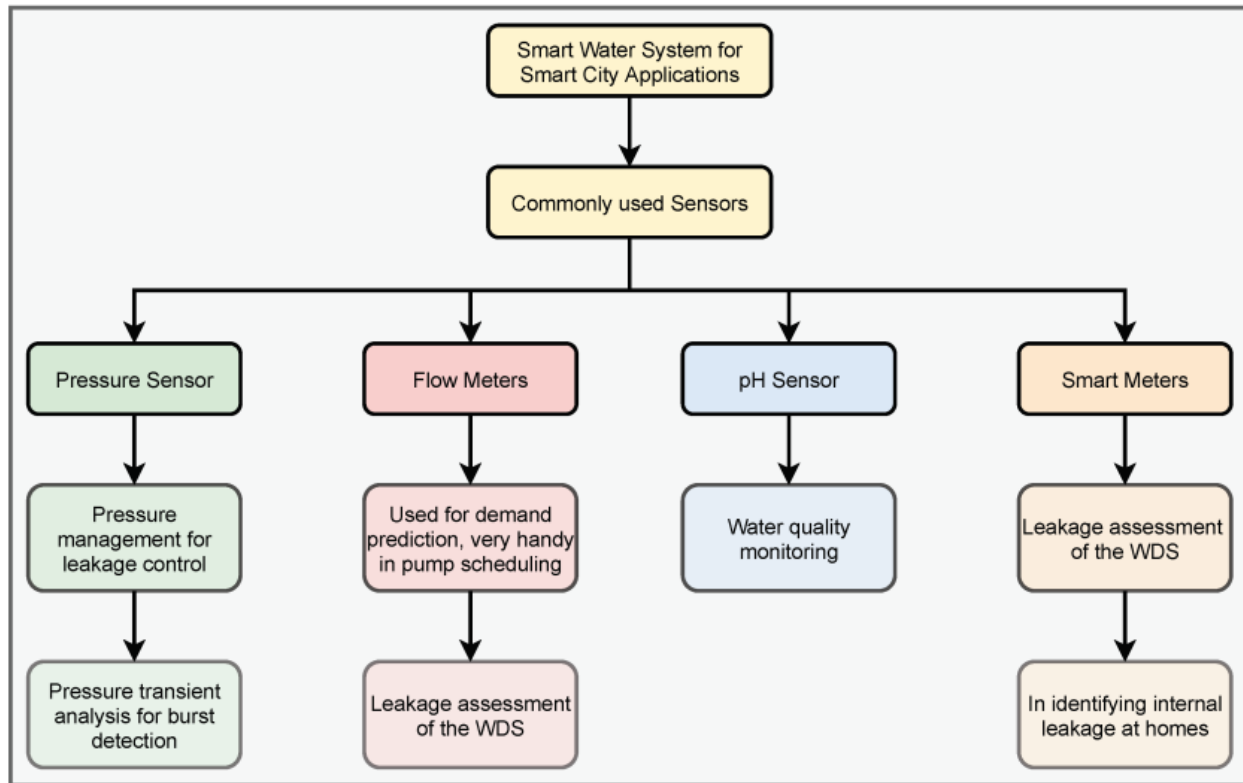


Figure 1: Sensors and their applications in smart cities [8].

The ML algorithms are very important in the processing and interpretation of the big amount of data collected through the IoT-enabled monitoring systems. The ML algorithm has the capability of pattern recognition, predicting system performance, identifying any anomalies, and improving network performance [9]. Some common examples where ML algorithms are used in water distribution management include “Support Vector Machine (SVM), Linear Regression (LR), Decision Tree (DT) and Random Forest (RF)” [10, 11]. These algorithms help in making decisions and automate the processes involved through their analysis. ML can be used by water authorities to reduce water losses, ensure reliable water supply, and maximize the efficiency of energy in the pumping process.

Smart pipe network systems are designed and optimized with hydraulic modelling, sensor placement optimization, pressure management, and intelligent control strategies as the main component features of the system. The hydraulic simulation tools simulate how water flows, pressure is distributed, and the efficiency of the network under different operational conditions. Hydraulic optimisation methods are used to determine the most efficient pipe diameters, pump scheduling, and sensor positioning for maximum hydraulic performance with minimal energy used. Integrating IoT and ML technologies into hydraulic modelling will provide a means to create a smart decision support system that will function autonomously and adaptively. These smart pipe network systems have the ability to adapt in real-time to fluctuations in water demand, environmental factors, and changes in infrastructure, thereby, increasing the resilience and sustainability of urban water supply systems.

The paper discusses the design and optimization of an intelligent system of pipes networks in urban water distribution by using IoT-based monitoring and ML techniques. The research employs IoT sensing technology to monitor critical factors like pressure, flow rate, water level, and leak condition in the network. The hydraulic model is simulated to assess the performance of the network. Sensor-based data from the simulation process is preprocessed and analyzed using various ML techniques such as “Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF), and Linear Regression (LR).” The application of this intelligent system enhances leak detection, pressure control, and efficient water distribution. The following are the research objectives of this study:

- To design an IoT-based smart water distribution monitoring framework for real-time collection of hydraulic parameters.

- To develop a hydraulic modeling and simulation system using EPANET and GIS tools for analyzing water flow behavior, pressure distribution, head loss, and leakage conditions in urban pipe networks.
- To apply ML algorithms including SVM, RF, DT, and LR for leakage detection, pressure prediction, water demand forecasting, and operational optimization of the water distribution network.
- To evaluate the performance of ML models using statistical performance metrics such as Accuracy, Precision, Recall, F1-Score, RMSE, and MAE for selecting the best-performing prediction model

2. Related Work

Current development of smart water distribution systems is geared toward leakage detection, pressure regulation, power efficiency and real-time monitoring via IoT and ML. Many intelligent frameworks have been developed that incorporate sensors, hydraulic models, cloud computing, and optimization algorithms to achieve high operational performance for urban water distribution networks. In these researches, intelligent monitoring systems were presented to support water loss reduction and efficient resource management as an important element for the sustainability in urbanizing developing countries. The Hybrid SVM-ANN-GT model introduced by Komba et al., (2026) [16] for the leak detection and location of water distribution systems achieved an accuracy of 96%, which is superior to the individual SVM and ANN models as the optimized sensor location used a graph theory approach. Additionally, the IoT-based framework developed by Kusuma et al. (2026) [17] utilized a pressure control using EPANET Digital Twin, PID controller and it was shown that the system provided stable pressure control with less than 2% overshoot and a tracking error under 0.5 m.

Velayudhan et al. (2024) [18] examined energy-efficient IoT communication architectures for smart water management applications, which resulted in nearly 40% energy efficiency improvements due to proper fog node placement. Effiom et al. (2024) [19] developed a pipeline leakage monitoring IoT-based system with an accuracy of 94% in detecting leaks by implementing pressure and temperature sensors along with cloud-based machine learning analysis techniques. Shao et al. (2023) [20] implemented IoT and ML algorithms that led to optimizing energy consumption while reducing water leakages to 1.17% and 6.98%, respectively. Rahu et al. (2023) [21] suggested an IoT-Machine Learning framework for predicting the water quality parameters, where MLP regression obtained an R^2 score of 0.93 and the Random Forest classifier was capable of obtaining 91% accuracy. Naqash et al. (2023) [22] presented an IoT framework based on blockchain technology to enhance the water management process by ensuring security and managing water leakages. Kumar et al. (2023) [23] created an IoT-based smart water management system incorporating multiple quality sensors along with LoRaWAN communication.

3. Research Methodology

3.1. Study Area

Figure 2 shows the location of an experimental prototype water delivery system in Pune, Mumbai. It was created in the training yard of a local water company. Figure 2 is a schematic depicting the experimental water system configuration in Pune. Hydraulic modelling software like EPANET and "Geographic Information System (GIS)" technologies are used to map the research region.

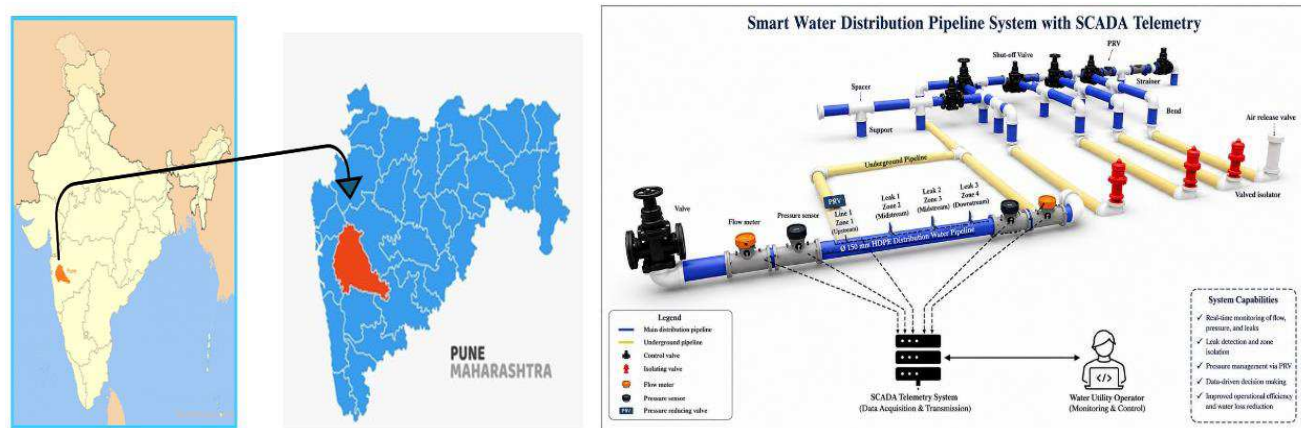


Figure 2: India map with zoomed in to the case study area location and diagram of the Pune experimental site, Pune region

Two flow meters and two pressure sensors were attached to a 110 mm inner diameter and 110 m length polyethylene pipe. A 100 mm water pipeline is attached to the pipe. A variety of 20 mm and 25 mm pipe outlets were used to imitate leaks in 110 mm pipe. The experimental data was monitored and recorded using a SCADA

wireless system that combined the flow meters and pressure sensors. Figure 3 shows the EPANET simulation scenario.

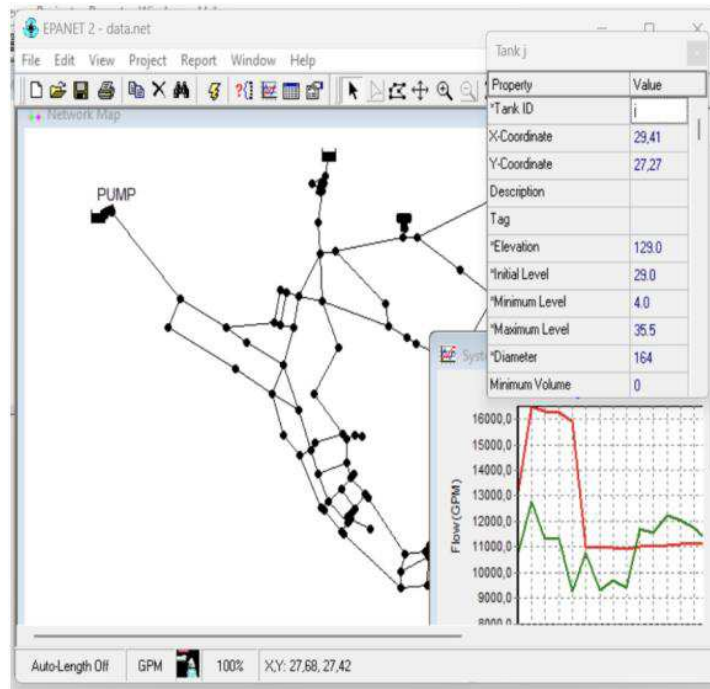


Figure 3: EPANET simulation scenario

Flow rate, pressure changes, addition of the change in pressure, and flow acceleration are some of the important characteristics that are included in the research. Including timestamp data helps build a thorough comprehension of the pipeline dynamics under various operating settings. Then, using the data collected, the best performance models are identified, and the water pipeline could be utilised to identify leaks and bursts.

3.2. IoT-Based Monitoring Framework

The design for the IoT-Based Monitoring Framework (illustrated in Figure 4) is the implementation of real-time monitoring, smart analytics and automation in urban water distribution systems. Smart sensors, wireless communication, cloud computation and ML algorithms were embedded in the framework in order to monitor the hydraulics like flow, pressure, leakage, tank levels, power consumption. The overall goal of this framework is to increase the water distribution efficiency and reduce water loss and improve pressure stability, and enhance the sustainability of urban water management systems.

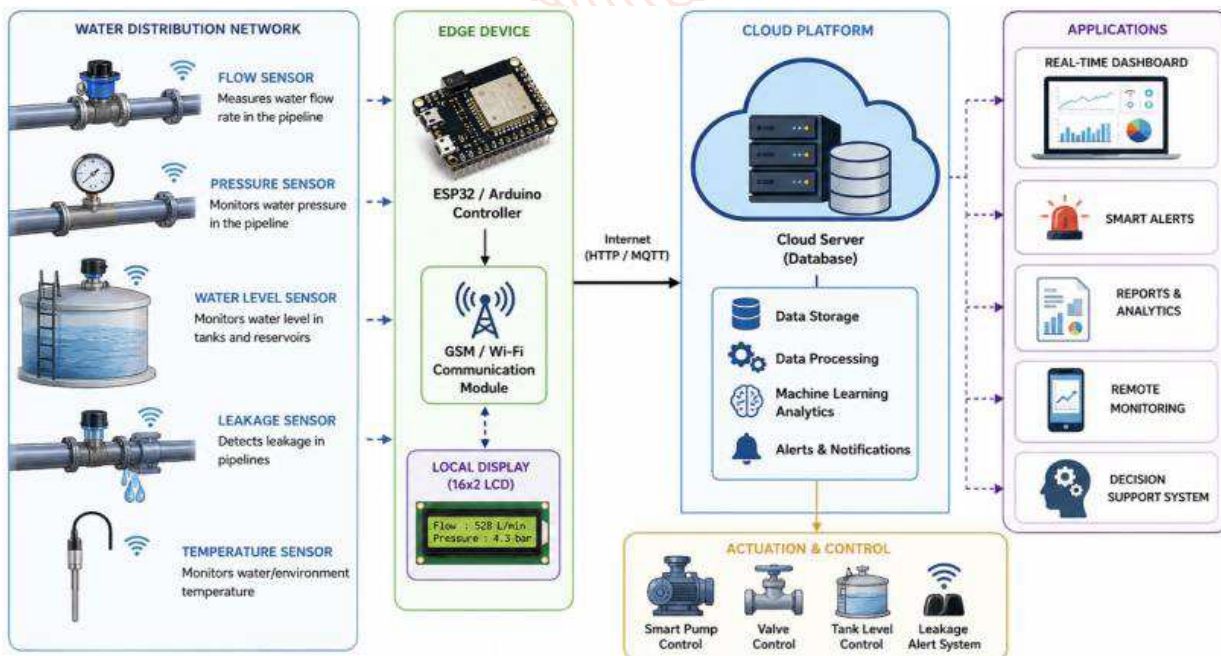


Figure 4: IoT-based Monitoring Framework

3.3. Hydraulic Modeling and Simulation

Hydraulic modeling and simulation are an important tool in smart pipe network system design for urban water distribution. In this study, hydraulic simulation is conducted to observe water flow characteristics, pressure distributions, head loss, and leaking phenomena and network performance under different working conditions. Real-time collected data from IoT sensors including flow sensors, pressure sensors, leak detection sensors is fed into the hydraulic model so that to get the best accurate analyzing for the system. EPANET was used to modeling the pipeline network and simulating the flow of water through pipes, junctions, pumps and storage tank. The result was useful to identify low pressure regions, large head loss area and leak possible area in the network.

The hydraulic simulation is carried out under peak demand, leakage, and pump failure conditions to evaluate system performance. The results obtained from simulation assist in

optimizing pressure regulation, reducing water losses, improving energy efficiency, and ensuring sustainable urban water distribution management.

3.4. Machine Learning Models

Figure 5 describes the flowchart of the IoT and ML-enabled optimization system of urban water distribution systems. The process starts with the acquisition of raw data from the sensors, and then preprocessing, sampling, and division of the datasets into the training and testing sets. Four ML techniques, such as SVM, Random Forest, Decision Tree, and Linear Regression, are utilized for the prediction and analysis tasks.

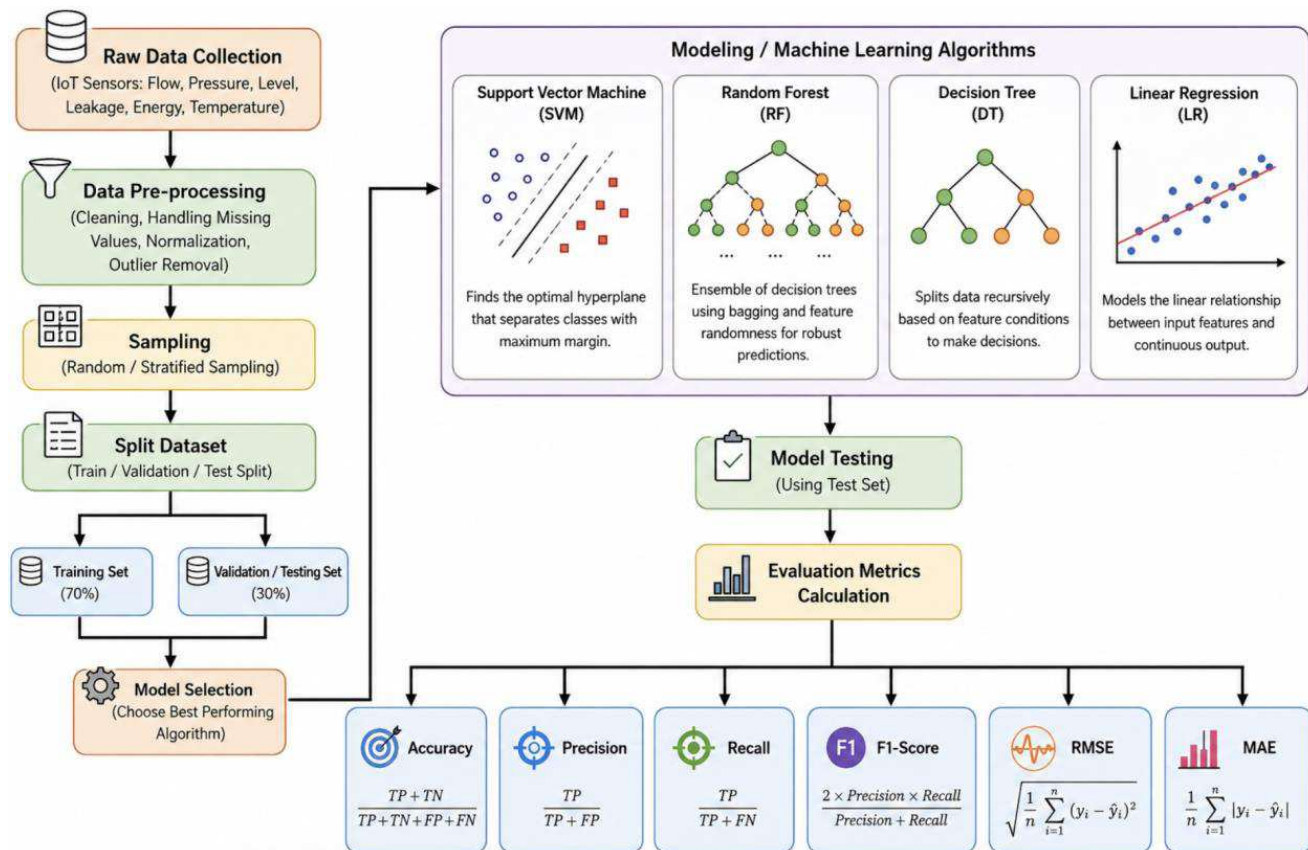


Figure 5: Urban water distribution workflow

➤ Data Preprocessing

The sensor data collected from the IoT platform is cleaned and pre-processed before applying ML algorithms. Data preprocessing includes missing value handling, Normalization, Noise filtering, and Dataset division. The processed data is divided into training and testing data for ML purposes. Training will use 70% of the total data, while testing uses 30%.

➤ Proposed Model

In this section, the authors proposed ML methods such as “Support Vector machine (SVM), Linear Regression (LR), and Random Forest (RF), and Decision Tree (DT)”.

A. Support Vector Machine (SVM)

Support vector machine (SVM) is a type of supervised ML approach used for classification and anomaly detection tasks. SVM makes use of an optimal hyperplane that creates a separation between various categories with maximum margin [26]. SVM is very efficient in managing complex, nonlinear, and high-dimensional data created by IoT sensors within urban water distribution systems. In this study, SVM is used for detecting leakage and abnormal pressure because it delivers accurate predictions and reliable fault diagnosis.

B. Linear Regression

It is a statistics and ML method used to estimate a continuous numeric value that has the dependence on an independent variable, and modeling the linear association between them. The approach is aimed to discover linear patterns on IoT sensor data, such as flow rate, pressure variation and water demand. In this study, LR is chosen as the method to be applied, since it is easy to compute, understand and to forecast the hydraulic variables of water distribution networks.

C. Random Forest (RF)

It is a popular ensemble ML algorithm that makes multiple decision trees to make prediction better and avoid the problem of over-fitting. It makes a multiple of trees through selecting random sub-sets of training data and outputs the result of prediction. RF is an ideal technique for large-scale and complicate IoT dataset for it efficiently solves the problem of non-linear relationship and messy sensor information. In this experiment, researchers employ RF to implement the tasks of pressure prediction, leakage identification and water demand forecast for it shows robust performance, higher accuracy and stability.

D. Decision Tree (DT)

It is an advanced ML model used for classification and regression analysis by making decisions in a hierarchy. This algorithm partitions data sets into branches depending on certain attribute criteria to create decisions. DTs are easy-to-understand, computationally fast algorithms, and can therefore be effectively applied to smart water monitoring systems that make use of IoT. In this study, DTs are employed for water consumption analysis, leakage classification, and performance evaluation. DTs play a crucial role in determining the significant hydraulic factors influencing the water delivery system performance.

3.5. Performance Evaluation

The four components that compose off the evaluation model are TP, TN, FP, and FN. Equations (3.1)–(3.6) were used to assess the model's performance, with $A_{accuracy}$, $F1_{score}$, $P_{precision}$, and R_{recall} being the relevant factors. This score is calculated by averaging the model's R_{recall} and $P_{precision}$.

$$Accuracy = \frac{TN+TP}{FP+TN+TP+FN} \quad (3.1)$$

$$Recall = Sensitivity = \frac{TP}{TP+FN} \quad (3.2)$$

$$Precision = \frac{TP}{FP+TP} \quad (3.3)$$

$$F1 - score = \frac{2 \cdot P \cdot R}{P+R} \quad (3.4)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (3.5)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (3.6)$$

4. Result and Discussion

In this section, they provide outcomes by using Python Language, 4GB Graphics processing unit, Intel Core i5 Gen7 processor, and 16GB RAM.

4.1. Water distribution evaluation index

Table 1 shows the ranges of classification of the monitoring parameters used for IoT in urban water distribution systems. It specifies the flow rate, pressure, water level, leak, energy consumption, and temperature conditions for the operation. These classifications are used to identify the performance of the system, detect abnormal conditions, increase the efficiency of water management, reduce leakage losses, and optimize the overall smart water distribution operations.

Table 1: Ranges for IoT-based monitoring parameters

Sensor Parameter	Range / Content	Remarks
Flow Rate	≥ 600 L/min	Excellent water distribution efficiency
	550– 600 L/min	High flow efficiency
	500– 550 L/min	Moderate flow condition
	≤ 500 L/min	Low water supply condition
Pressure	≥ 5.0 bar	Excellent pressure stability
	4.0– 5.0 bar	Stable operating pressure
	3.0– 4.0 bar	Moderate pressure condition
	≤ 3.0 bar	Low pressure in pipeline
Water Level	≥ 11 m	Sufficient storage level
	9 – 11 m	Normal operating range
	7 – 9 m	Low storage condition
	≤ 7 m	Critical water level
Leakage	$\geq 7\%$	High leakage condition
	4 – 7%	Moderate leakage
	2 – 4%	Low leakage
	$\leq 2\%$	Minimal leakage loss
Energy Consumption	≥ 140 kWh	Very high energy usage
	130– 140 kWh	Moderate energy consumption
	120– 130 kWh	Energy-efficient operation
	≤ 120 kWh	Highly optimized energy usage
Temperature	$\geq 32^\circ\text{C}$	High environmental temperature
	28– 32 $^\circ\text{C}$	Suitable operating temperature
	20– 28 $^\circ\text{C}$	Normal environmental condition
	$\leq 20^\circ\text{C}$	Low environmental temperature

4.2. IoT-Based Monitoring Sensor Data with Smart IoT System Performance

The system utilizes LabVIEW for the design of the man-machine interface, transmits data through serial connection, and simultaneously outputs both the current data and the parameter change waveform. Table 2 provides the IoT-based monitoring sensor data with smart IoT system performance. Figure 6-8 shows the graph of sensors.

Table 2: IoT-Based Monitoring Sensor Data with Smart IoT System Performance

Day	Flow Rate (L/min)	Pressure (bar)	Water Level (m)	Leakage (%)	Energy Consumption (kWh)	Temperature ($^\circ\text{C}$)	Smart IoT- Based System Performance
1	520	3.8	12.5	8.2	145	29	Moderate
2	534	4.0	13.2	7.6	143	30	Moderate
3	528	3.9	11.4	7.9	144	31	Moderate
4	545	4.6	14.5	6.8	141	30	Good
5	552	5.3	11.7	6.4	140	29	Good
6	548	4.1	10.5	6.7	142	30	Moderate
7	563	4.5	11.3	5.8	138	31	Good
8	571	3.7	12.6	5.2	136	32	Good
9	566	4.4	9.6	5.5	137	31	Good
10	579	4.8	10.8	4.9	134	30	Good
11	588	4.9	10.5	4.5	133	31	Very Good
12	581	4.7	10.7	4.8	135	32	Good
13	596	5.6	10.2	4.1	132	33	Very Good
14	603	5.2	9.9	3.7	130	32	Excellent
15	597	4.6	10.7	3.9	131	31	Excellent
16	610	5.3	9.6	3.4	128	30	Excellent
17	606	3.6	9.7	3.6	129	31	Excellent
18	618	5.5	11.4	3.0	127	32	Excellent
19	621	5.0	9.2	2.9	126	33	Excellent
20	615	5.4	9.4	3.1	128	32	Excellent

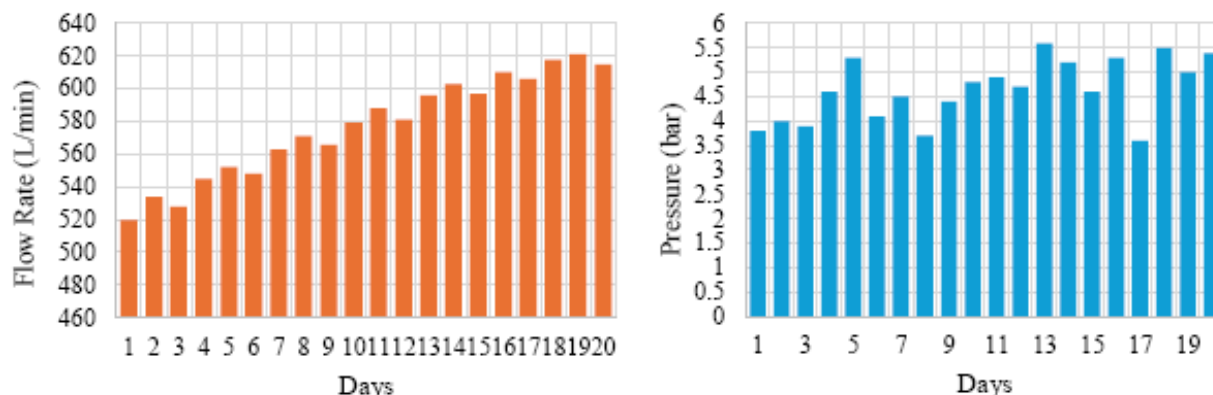


Figure 6: Flow rate and Pressure per days

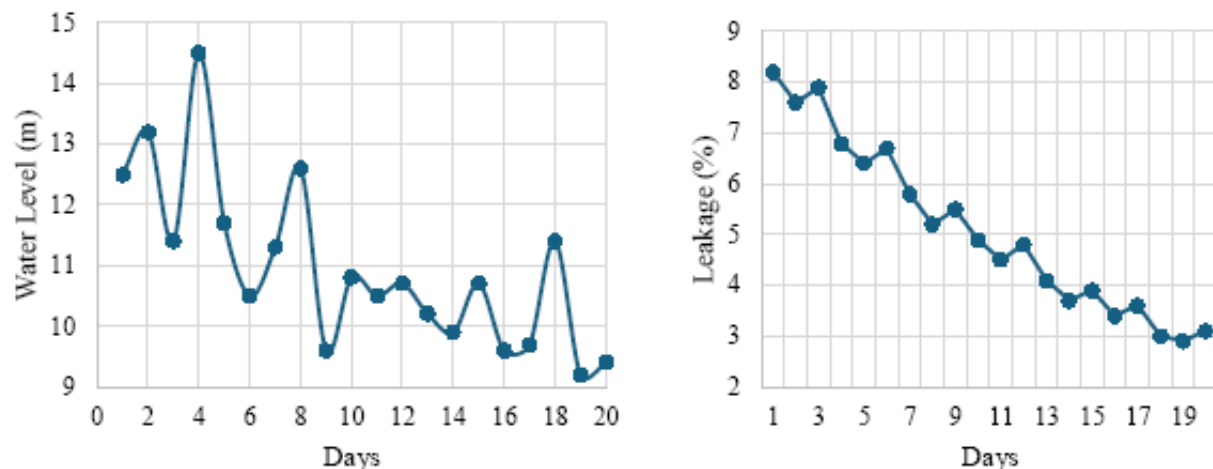


Figure 7: Water level and Leakage per days

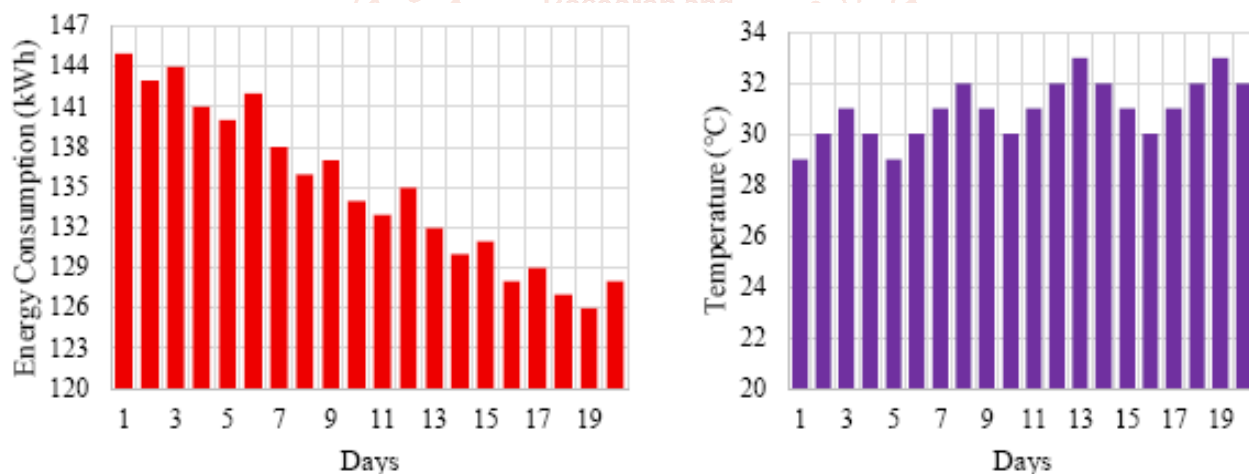


Figure 8: Energy Consumption and Temperature per days

4.3. Analysis of Machine Learning

KNN, LR, and BPNN were the three various ML algorithms that were used in an experimental investigation. On both the training dataset and the testing dataset, it computes the Accuracy, Precision, and Recall scores, as well as the F1 coefficient.

➤ SVM on Train dataset

A remarkable accuracy of 98% was demonstrated by the SVM model, which indicates that it performed very well in terms of making accurate predictions. The accuracy of its estimates was 98%, indicating that it had a high proportion of accurate positive predictions. The fact that the Recall came in at 99% demonstrates that the model has a great capacity to recognize genuine positives. Table 3 demonstrates that the F1-Score, which is likewise 99%, demonstrates that there is a strong balance between accuracy and recall. The SVM models are recognized for their correctness, but they are also noted for their power and computational complexity.

Table 3: Evaluation of the model using train dataset

Model	Training				Testing			
	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
LR	94.9	92	88	90	92.5	92.4	91	29
RF	85.71	93	50	65	73.5	64.2	71.3	72
DT	75.3	80.4	70.4	83	82.4	76.5	67.3	84
SVM	98	98	99	99	97.4	97	98.3	100

Similarly, on the testing dataset, the SVM version obtained the maximum evaluation, with an accuracy rate of 97.4%. With a recall rate of 91% and an accuracy rate of 92.5%, LR obtained an F1 score of 29%. In comparison to the other pre-trained models, RF had the weakest performance on the testing dataset, with an accuracy rate of 73.5% (Table 3). A graph depicting the calculation of the model on the training and testing dataset can be seen in Figure 9.

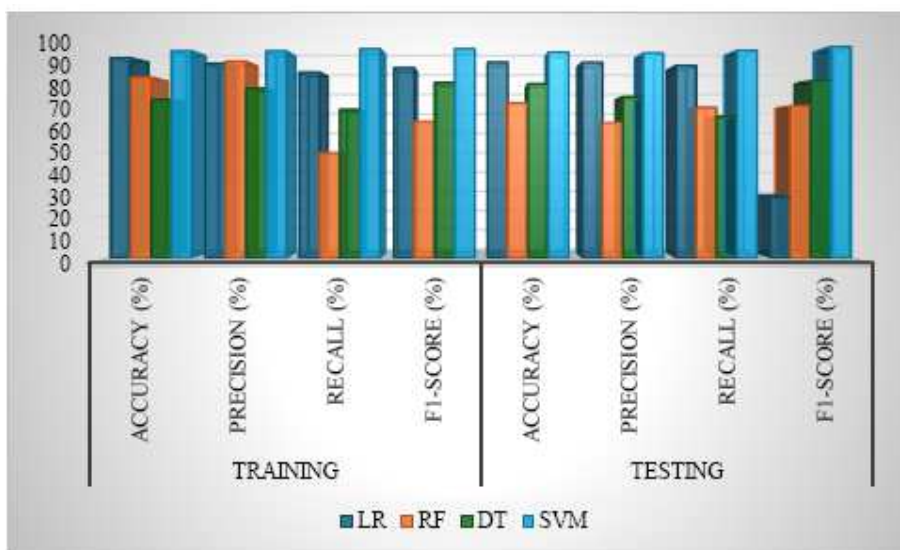


Figure 9: Graph of proposed models on train and test dataset

4.4. Error Metrics

Error evaluation results for the training and testing datasets used to evaluate the prediction capacity of the proposed ML models for the urban water distribution network based on the IoT technology are presented in Figure 10. In the case of the testing dataset, SVM has been found to predict with the lowest error (1.48 MAE and 2.06 RMSE), whereas LR was found to have made the highest prediction error (3.42 MAE and 4.18 RMSE). The prediction error of DT is 2.87 MAE and 3.51 RMSE, whereas that of RF was 2.15 MAE and 2.84 RMSE. In the case of the training dataset, excellent prediction performance has been observed for SVM (1.12 MAE and 1.68 RMSE). On the other hand, LR had higher prediction errors (2.96 MAE and 3.74 RMSE).

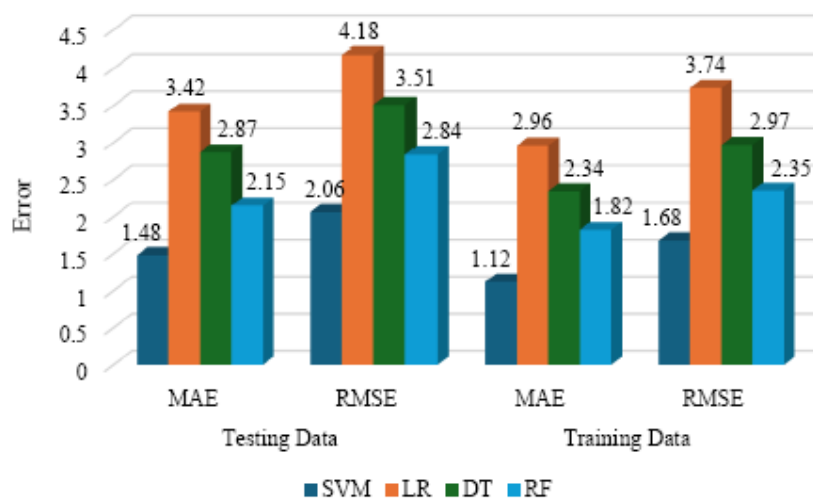


Figure 10: Comparison graph of Error metrics

4.5. Comparison Analysis

In this part, they estimate the proposed model in comparison to the existing models in ML. The following Table 4 presents a comparison of the accuracy values used by State-of-the-Art (SOTA) models. The proposed model (SVM) performs better than the previous work by achieving an accuracy of 98%. The graph of the comparison table is shown in the Figure 11.

Table 4: Evaluation of existing models compared to the proposed model

Author [Reference]	Methodology	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Mahmoud et al., (2025) [24]	XGBoost + Autoencoder	94.8	89.0	95.2	92
Kushwaha et al., (2025) [25]	ANN	91	85	84	90
Proposed Work	SVM	98	98	99	99

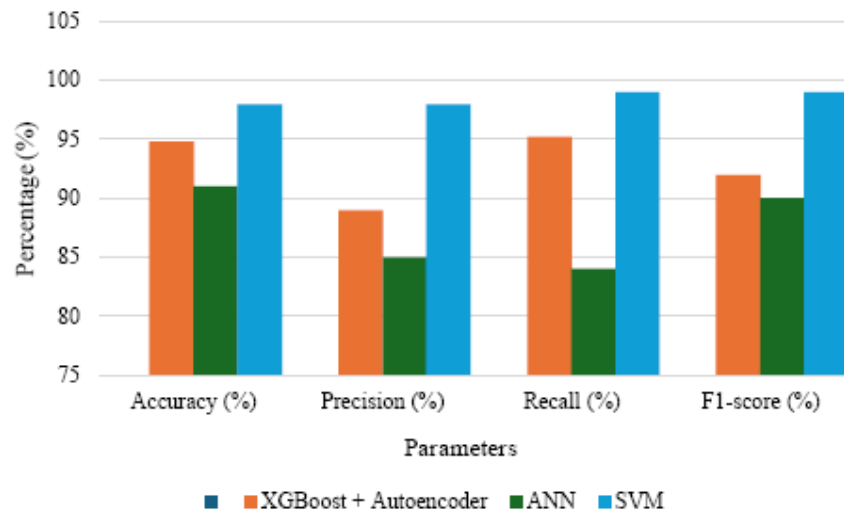


Figure 11: Comparison graph of SOTA methods.

5. Conclusion

The present research successfully developed and tested an IoT-based smart pipe network system for urban water distribution using ML algorithms and hydraulic modeling techniques. The study aimed to improve water distribution efficiency, reduce leakage losses, regulate pressure, and support sustainable urban water management. IoT sensors including flow, pressure, water level, leakage, and temperature sensors were integrated with ESP32/Arduino controllers and cloud communication platforms for real-time monitoring. Experimental implementation was carried out in Pune, where a smart pipeline prototype connected to a 100 mm water pipeline was developed and monitored using SCADA telemetry systems. Hydraulic simulation and network analysis were performed using EPANET and GIS tools. The collected sensor data was pre-processed and divided into 70% training and 30% testing datasets for ML analysis. SVM, RF, DT, and LR models were applied for leakage detection and pressure prediction. Among all models, SVM achieved the best performance with 97.4% testing accuracy, 97% precision, 98.3% recall, and lower error values of 1.48 MAE and 2.06 RMSE. During the 20-day monitoring period, leakage reduced from 8.2% to 2.9%, pressure

stability improved from 3.8 to 5.0 bar, and energy consumption decreased from 145 kWh to 126 kWh.

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