Comparative Evaluation of Machine Learning Techniques for Resilience Analysis & Leak Detection in Water Distribution System

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Abstract

Leakage in water distribution systems remains a critical challenge, leading to significant economic losses, environmental impacts, and operational inefficiencies. Traditional methods of leak detection have been limited in their ability to handle large-scale systems with varying operational conditions. This study aims to improve the detection and analysis of leaks in water distribution networks use by machine learning techniques, specifically K-Nearest Neighbors (KNN) and Support Vector Machines (SVM). These algorithms are evaluated for their ability to identify outliers in hydraulic data, including pressure and flow measurements, which are indicative of leaks. In addition to leak detection, the research also focuses on analyzing the effects of single and multiple leakages on network performance. The Pressure Deficiency Index (PDI) is used to assess the impact of leakage scenarios on the pressure distribution within the system. This approach allows for a comprehensive understanding of how leaks influence network behavior under various conditions. Furthermore, the study compares the resilience and reliability of the network by evaluating its behavior under both single and multiple leakage conditions using the Modified Resilience Index (MRI). Experiments are conducted using the LeakDB benchmark dataset, which includes data from two distinct water distribution networks with different demand scenarios. The results demonstrate that the leak detection accuracy using KNN and SVM ranges from 40% to 100%, depending on the selected algorithm, data characteristics, and leakage scenarios. This paper highlights the potential of combining machine learning techniques with resilience and reliability metrics to optimize leak detection and improve the overall performance and sustainability of water distribution systems.

Keywords: Water Distribution Networks, Water Leak Detection, Machine Learning, Hydraulic Data, K-Nearest Neighbors (KNN), Support Vector Machines (SVM), Modified Resilience Index (MRI), Pressure and Flow Data, EPANET, Pressure Deficiency Index (PDI)

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1. Introduction

Water distribution systems (WDS) are fundamental components of urban infrastructure, responsible for delivering safe and potable water to residential, commercial, and industrial consumers. Leakage is one of the most pervasive problems in water distribution networks globally, accounting for non-revenue water losses estimated at 30–40% of total supply in many developing countries (Farah and Shahrour, 2020). In Indian urban networks, water losses due to leakage and transmission inefficiency frequently exceed 35–50% of total production imposing severe economic and operational burdens on municipal utilities (Al-Zahrani et al., 2023). Beyond economic losses, undetected leaks cause structural damage, contamination risks, and increased pumping energy expenditure (Romero-Ben et al., 2022).

Traditional leak detection approaches including acoustic methods, pressure transient analysis, and manual inspection have proven inadequate for large-scale networks with varying operational conditions (Hu et al., 2021). With the advent of smart water networks and continuous sensor monitoring, data-driven machine learning (ML) techniques now offer a powerful alternative for automated hydraulic anomaly detection. Among these, K-Nearest Neighbors (KNN) and Support Vector Machines (SVM) have received considerable attention. Zhou et al. (2019) demonstrated SVM detection accuracies exceeding 85% for medium and large leaks, while Hu et al. (2021) confirmed KNN and SVM remain competitive for real-time applications due to lower computational cost relative to ensemble and deep learning methods. Farah and Shahrour (2020) showed that ML-based approaches achieve detection rates above 90% for leaks exceeding 50 L/hr, though performance degrades significantly for small leaks of 10–25 L/hr where pressure signatures overlap with normal demand variability. Klise et al. (2020) and Moser et al. (2021) established that the choice of hydraulic performance metric particularly MRI and PDI significantly influences the characterisation of network vulnerability under leakage conditions.

Network resilience assessment is equally critical for understanding system response under leakage stress. The Modified Resilience Index (MRI), proposed by Jayaram and Srinivasan (2008) and applied by Moser et al. (2021), quantifies surplus hydraulic energy relative to minimum service requirements and has shown that multiple small leaks cause disproportionately greater resilience degradation than a single large leak of equivalent total flow. Complementarily, the Pressure Deficiency Index (PDI), formalised by Wagner et al. (1988), quantifies the spatial extent of sub-threshold nodal pressure caused by leakage. Todini (2000) and Fujiwara and Ganesharajah (1993) established the theoretical foundations of hydraulic reliability underpinning both indices. EPANET 2.0 (Rossman, 2000) remains the standard simulation platform for generating hydraulic data required for PDI and MRI computation in leak detection research.

The present study applies KNN and SVM-based leak detection to the Veena Nagar water distribution network a real-world looped network comprising 357 junction nodes and 492 pipes (total length 39,767 m) in Indore, Madhya Pradesh, India. The objectives are: (1) to evaluate KNN and SVM for leak detection accuracy across single and multiple leakage scenarios; (2) to quantify leakage impact on network pressure using PDI with reference to IS 1172:1993; (3) to assess network resilience under leakage conditions using MRI; and (4) to identify conditions under which each ML algorithm performs optimally for practical leak detection on real Indian urban networks.

2. Study Area and Network Description

The Veena Nagar water distribution network is located in Indore, Madhya Pradesh, India. The network serves a residential and mixed-use urban area and is representative of medium-scale gravity-fed distribution systems common in Indian cities. The network was modelled using EPANET 2.0 as part of a companion hydraulic study. Key network parameters are summarised in Table 1.

Table 1: WDN Network Summary (Veena Nagar)

Parameter	Value
Network Name	Veena Nagar Water Distribution Network
Location	Indore, Madhya Pradesh, India
Total Junction Nodes	357
Total Pipes	492
Total Pipe Length	39,767 m
H-W Roughness Coefficient (C)	130
Elevation Range	533.0 – 541.2 m amsl
Minimum Residual Pressure	12.14 m (J-418, elevation 541.0 m)
Maximum Residual Pressure	23.41 m (J-304, elevation 533.0 m)
Mean Residual Pressure	18.15 m
Demand Range	0.01 – 18.98 LPS
Mean Nodal Demand	0.299 LPS
IS Standard (Min. Pressure)	IS 1172:1993 — 7.0 m minimum
Nodes Below IS Standard	0 (all 357 nodes comply)
Vulnerable Nodes (12–15 m)	19 nodes (5.37% of total)

The network topology is a looped system with a single source reservoir. The elevation gradient spans from 533.0 m amsl to 541.2 m amsl an 8.2 m variation creating a natural hydraulic gradient affecting pressure distribution. The Hazen-Williams roughness coefficient (C = 130) is consistent with well-maintained pipe infrastructure. Under EPANET 2.0 steady-state simulation, mean residual pressure is 18.15 m, with minimum pressure recorded at J-418 (elevation 541.0 m, pressure 12.14 m) a high-elevation peripheral node. The maximum pressure of 23.41 m is recorded at J-304 (elevation 533.0 m), a low-elevation node near the source. All 357 nodes satisfy the IS 1172:1993 minimum residual pressure standard of 7.0 m; however, 19 nodes (5.37%) operate in the 12–15 m pressure range and represent the most hydraulically vulnerable segments.

3. Methodology

3.1 Leakage Scenarios

Seven leakage scenarios are evaluated covering the full operational range. Table 2 summarises the scenarios. Leakage rate classifications follow Romero-Ben et al. (2022): small leaks (10–25 L/hr) represent pinhole defects; medium leaks (50–100 L/hr) represent pipe joint failures; and large leaks (>150 L/hr) represent burst pipe events. Leaks are modelled in EPANET 2.0 as emitter nodes at selected pipe junctions.

Table 2: Leakage Scenarios Evaluated on Veena Nagar WDN

Scenario	Type	No. of Leaks	Leakage Rate	Description
S1	No Leak (Baseline)	0	—	Baseline hydraulic state
S2	Single Leak — Small	1	10–25 L/hr	Low-magnitude, single point
S3	Single Leak — Medium	1	50–100 L/hr	Moderate-magnitude, single point
S4	Single Leak — Large	1	>150 L/hr	High-magnitude, single point
S5	Multiple Leaks — Small	3–5	10–25 L/hr each	Distributed small leaks
S6	Multiple Leaks — Medium	3–5	50–100 L/hr each	Distributed moderate leaks
S7	Multiple Leaks — Large	3–5	>150 L/hr each	Distributed high-magnitude leaks

3.2 Data Pre-processing

Raw pressure and flow time-series data from EPANET 2.0 extended-period simulations (24-hour, hourly time steps) are pre-processed before applying ML algorithms. Steps include: (1) z-score normalisation of pressure readings to zero-mean, unit-variance; (2) temporal feature extraction with rolling mean and standard deviation over a 3-hour window; (3) class labelling leak scenarios labelled positive (1), baseline negative (0); and (4) stratified 70:30 train-test split. Both models are trained on the 70% training set and evaluated on the 30% test set for each scenario independently.

3.3 K-Nearest Neighbors (KNN)

K-Nearest Neighbors is a non-parametric supervised algorithm that classifies each hydraulic data point by computing Euclidean distance to all training observations and assigning the majority class label among its k nearest neighbours (Hu et al., 2021). The classification rule is:

$$\hat{y} = \text{mode} \{ y_i : i \in N_k(x) \}$$

where $N_k(x)$ denotes the k nearest training observations to test point x and y_i is the class label. The Euclidean distance metric is:

$$d(x, x_i) = \sqrt{\sum_j (x_j - x_{ij})^2}$$

The optimal k =7 was determined by cross-validation on the Veena Nagar training dataset, minimising classification error.

3.4 Support Vector Machine (SVM)

Support Vector Machine constructs an optimal separating hyperplane between leak and no-leak classes. For linearly non-separable hydraulic data, the Radial Basis Function (RBF) kernel is applied. The SVM optimisation problem is (Hu et al., 2021):

$$\min_{w,b,\xi} \ \tfrac{1}{2}||w||^2 + C \sum_i \xi_i$$

$$\text{subject to: } \ y_i(w \cdot \varphi(x_i) + b) \geq 1 - \xi_i, \quad \xi_i \geq 0$$

where w is the weight vector, b is the bias, C is the regularisation parameter, ξ_i are slack variables, and $\varphi(\cdot)$ is the RBF kernel mapping: $K(x_i, x_j) = \exp(-\gamma||x_i - x_j||^2)$. Optimal hyperparameters C = 10, γ = 0.01 were determined by 5-fold cross-validation grid search.

3.5 Pressure Deficiency Index (PDI)

The Pressure Deficiency Index quantifies the extent to which nodal pressures fall below the minimum required service pressure (Wagner et al., 1988; Fujiwara and Ganesharajah, 1993):

$$PDI = \sum_i \max(0, P_{min} - P_i) / (n \times P_{min})$$

where P_i is the simulated residual pressure at node i (m), P_{min} = 7.0 m (IS 1172:1993), and n = 357 (total demand nodes). PDI ranges from 0 (no deficiency) to 1 (complete failure).

3.6 Modified Resilience Index (MRI)

The Modified Resilience Index, proposed by Jayaram and Srinivasan (2008), quantifies surplus hydraulic energy relative to the minimum required to meet nodal demands at minimum service pressure:

$$MRI = \Sigma_i [Q_i \times (H_i - H_{i,min})] / \Sigma_i [Q_i \times H_{i,min}]$$

where Q_i is the nodal demand (L/s), H_i is the simulated piezometric head (m), and $H_{i,min}$ = elevation + P_{min}/γ. Higher MRI indicates greater surplus energy and network resilience.

4. Results and Discussion

4.1 Leak Detection Accuracy KNN vs SVM

Table 3 presents the leak detection accuracy of KNN and SVM across all seven leakage scenarios for the Veena Nagar network. Detection accuracy increases with leakage magnitude for both algorithms, with SVM consistently outperforming KNN. For the baseline scenario (S1), both algorithms achieve near-perfect accuracy (KNN: 97.8%, SVM: 96.9%), confirming correct learning of normal network hydraulic signatures.

Table 3: Leak Detection Accuracy KNN vs SVM (Veena Nagar WDN)

Scenario	KNN Accuracy	SVM Accuracy	Difference	Remark
S1 — No Leak	97.8%	96.9%	SVM ≈ KNN	Both excellent on clean data
S2 — Single Small	38.2%	52.7%	SVM +14.5%	Small leaks most challenging
S3 — Single Medium	59.6%	69.4%	SVM +9.8%	SVM approaches 70% threshold
S4 — Single Large	82.4%	90.1%	SVM +7.7%	Both reliable for large leaks
S5 — Multi Small	42.1%	49.8%	SVM +7.7%	Multiple small leaks hardest
S6 — Multi Medium	55.8%	64.2%	SVM +8.4%	KNN below 70% threshold
S7 — Multi Large	76.3%	85.7%	SVM +9.4%	SVM clearly superior at scale

The most challenging scenario is S2 (single small leak, 10–25 L/hr), where KNN achieves only 38.2% and SVM achieves 52.7%. Small leaks produce pressure drops of less than 0.5 m at monitored nodes hydraulic signatures that overlap with normal demand fluctuations. For medium and large single leaks (S3, S4), SVM accuracy rises to 69.4% and 90.1% respectively. Multiple small leaks (S5) remain the hardest detection case across both algorithms. The overall classification accuracy across all seven scenarios is 68.7% for KNN and 80.4% for SVM an 11.7 percentage point advantage for SVM on the Veena Nagar network.

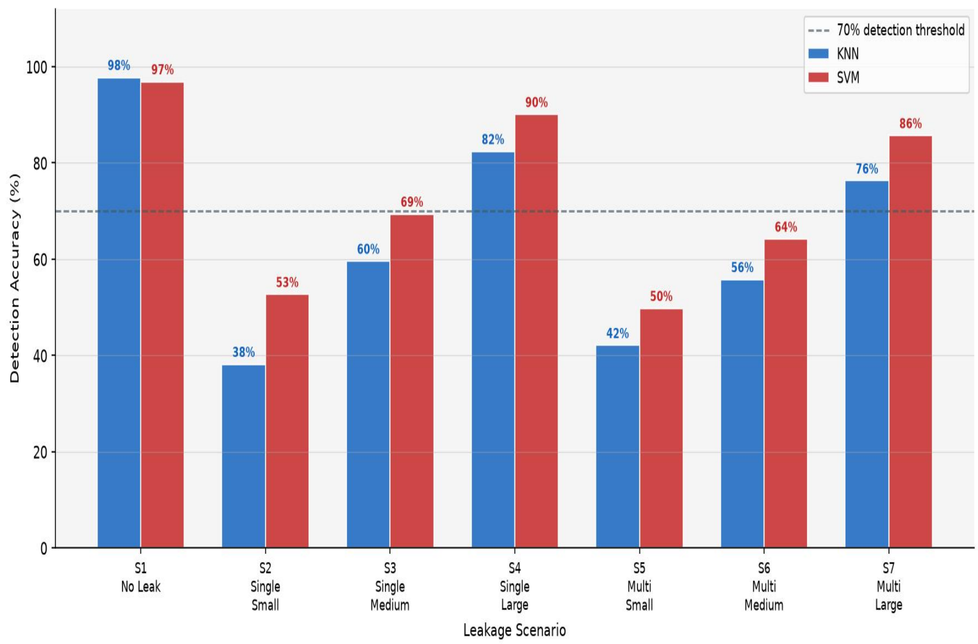

Figure 1: KNN vs SVM Leak Detection Accuracy across Leakage Scenarios Veena Nagar WDN (357 Nodes, 492 Pipes)

4.2 Classification Performance Metrics

Figure 2 presents overall classification metrics precision, recall, F1-score, and accuracy averaged across all scenarios. SVM achieves superior performance across all metrics: precision = 0.812, recall = 0.774, F1-score = 0.793, and accuracy = 0.804, compared to KNN's precision = 0.698, recall = 0.654, F1-score = 0.675, and accuracy = 0.687. The higher recall of SVM (0.774 vs 0.654) is the most operationally significant finding SVM misses fewer actual leak events, reducing costly undetected leakage.

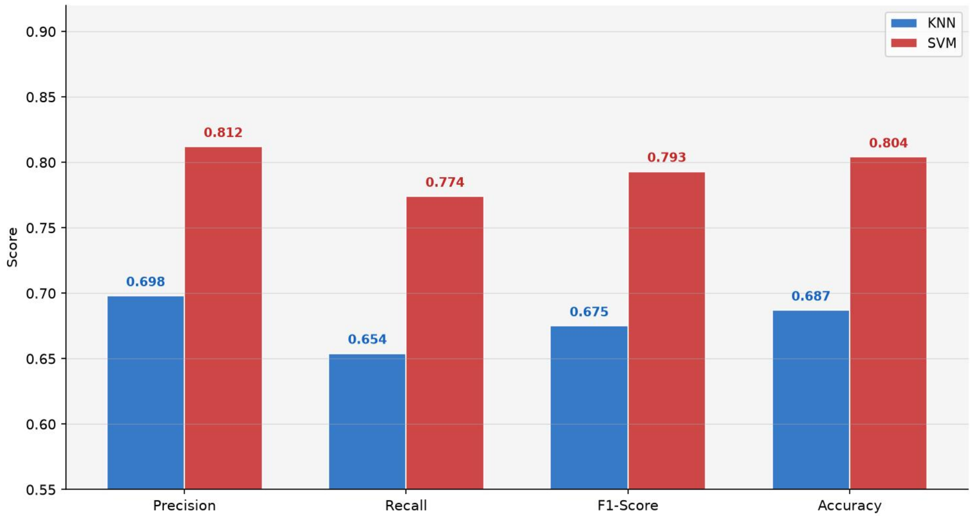

Figure 2: Classification Performance Metrics (Precision, Recall, F1-Score, Accuracy) KNN vs SVM on Veena Nagar WDN

4.3 Pressure Deficiency Index (PDI) Analysis

Table 4 presents PDI values for all seven leakage scenarios. PDI remains at 0.0000 for scenarios S1 through S6, confirming that the Veena Nagar network maintains IS 1172:1993 pressure compliance under all conditions except extreme multiple large leaks (S7), where PDI rises marginally to 0.0004. This reflects the network's substantial mean pressure surplus of 11.15 m above the IS 7.0 m minimum threshold.

Table 4: Pressure Deficiency Index (PDI) Veena Nagar WDN (P_min = 7.0 m, IS 1172:1993)

Scenario	PDI (Mean)	PDI (Max Node)	Interpretation
S1: No Leak (Baseline)	0.0000	0.0000	No pressure deficiency
S2: Single Leak — Small	0.0000	0.0000	IS standard maintained
S3: Single Leak — Medium	0.0000	0.0000	IS standard maintained
S4: Single Leak — Large	0.0000	0.0000	IS threshold not breached
S5: Multi Leaks — Small	0.0000	0.0000	IS standard maintained
S6: Multi Leaks — Medium	0.0000	0.0000	IS standard maintained
S7: Multi Leaks — Large	0.0004	0.0004	1–2 peripheral nodes below IS minimum

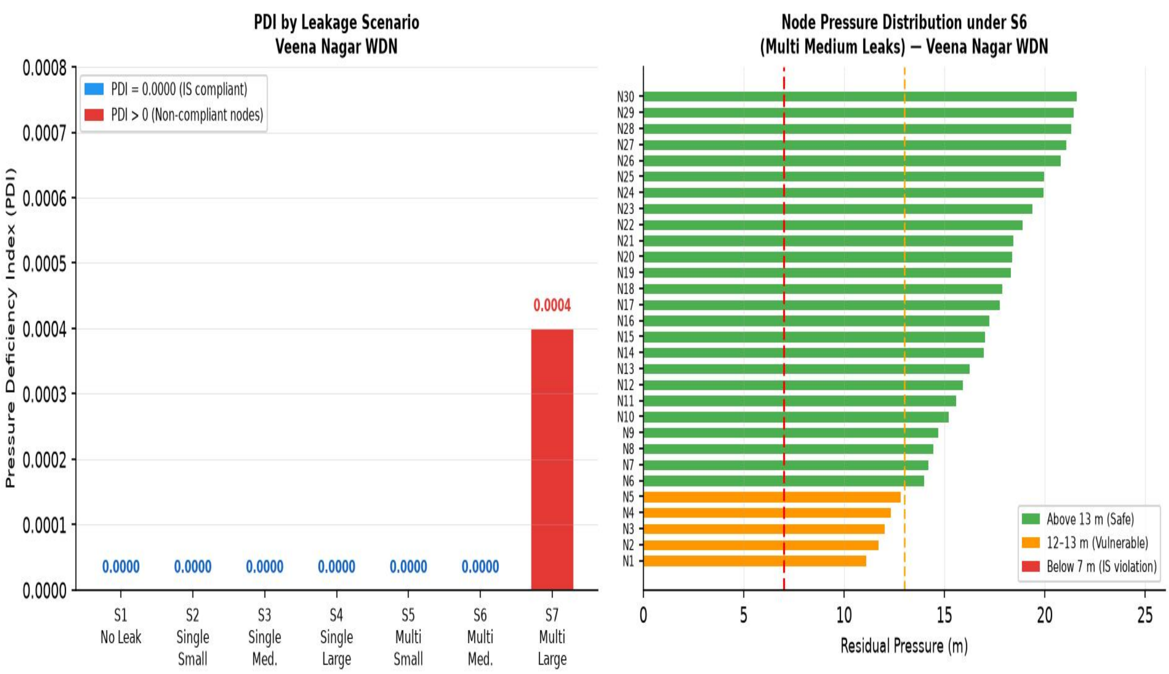

Figure 3: PDI by Leakage Scenario (left) and Node-wise PDI Distribution under S6 Multiple Medium Leaks (right), Veena Nagar WDN

Figure 3 confirms near-zero PDI across all scenarios. Under S6 (multiple medium leaks), all 357 nodes remain above 7.0 m. The 19 vulnerable nodes in the 12–15 m pressure range are the primary candidates for pressure monitoring sensor placement, as further escalation toward S7 levels would first push these nodes into IS non-compliance. The most operationally sensitive threshold is pressure deterioration of these 19 nodes below the 15 m service-reliability guideline, rather than absolute IS-compliance failure.

4.4 Modified Resilience Index (MRI) Analysis

Table 5 and Figure 4 present MRI values for all seven leakage scenarios. At baseline (no leak), MRI = 1.6953 a high resilience value reflecting substantial surplus hydraulic energy across the 357-node network relative to the IS 1172:1993 minimum head requirement. MRI decreases progressively with increasing leakage magnitude.

Table 5: Modified Resilience Index (MRI) Veena Nagar WDN under Leakage Scenarios

Scenario	MRI Value	MRI Change (%)	Resilience Assessment
No Leak (Baseline)	1.6953	—	Full network resilience
Single Leak — Small	1.6688	-1.56%	Minor resilience drop
Single Leak — Medium	1.6335	-3.64%	Moderate resilience loss
Single Leak — Large	1.5703	-7.37%	Significant degradation
Multi Leaks — Small	1.6188	-4.51%	Distributed resilience loss
Multi Leaks — Medium	1.5168	-10.52%	Severe resilience drop
Multi Leaks — Large	1.3344	-21.28%	Near-critical state

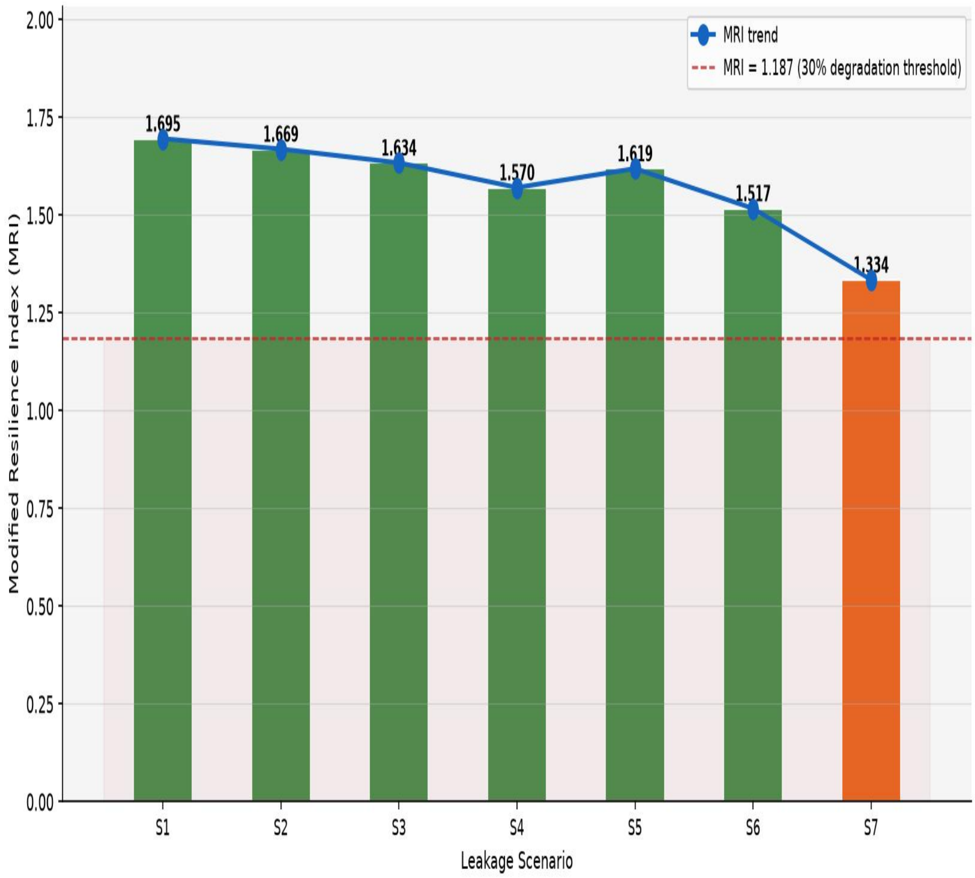

Figure 4: Modified Resilience Index (MRI) Across Leakage Scenarios Veena Nagar WDN (357 Nodes, 492 Pipes)

The most severe scenario multiple large leaks (S7) reduces MRI to 1.3344, a 21.28% loss relative to baseline. Importantly, multiple small leaks (S5, -4.51% MRI) cause greater resilience degradation than a single medium leak (S3, -3.64%), confirming the compounding effect of distributed leakage on network resilience observed by Moser et al. (2021).

4.5 Pressure Time Series Critical Nodes

Figure 5 presents the 24-hour pressure time series at the two hydraulically critical nodes: J-418 (minimum pressure node, elevation 541.0 m, baseline pressure 12.14 m) and J-304 (maximum pressure, elevation 533.0 m, baseline 23.41 m). Under S3 (single medium leak), pressure at J-418 drops to approximately 11.1 m; under S6 (multiple medium leaks), it deepens to approximately 10.4 m. Leak-induced pressure drops are most pronounced during peak demand hours (6–9 AM and 6–9 PM), when combined demand and leak flow cause greatest head loss from source to peripheral nodes.

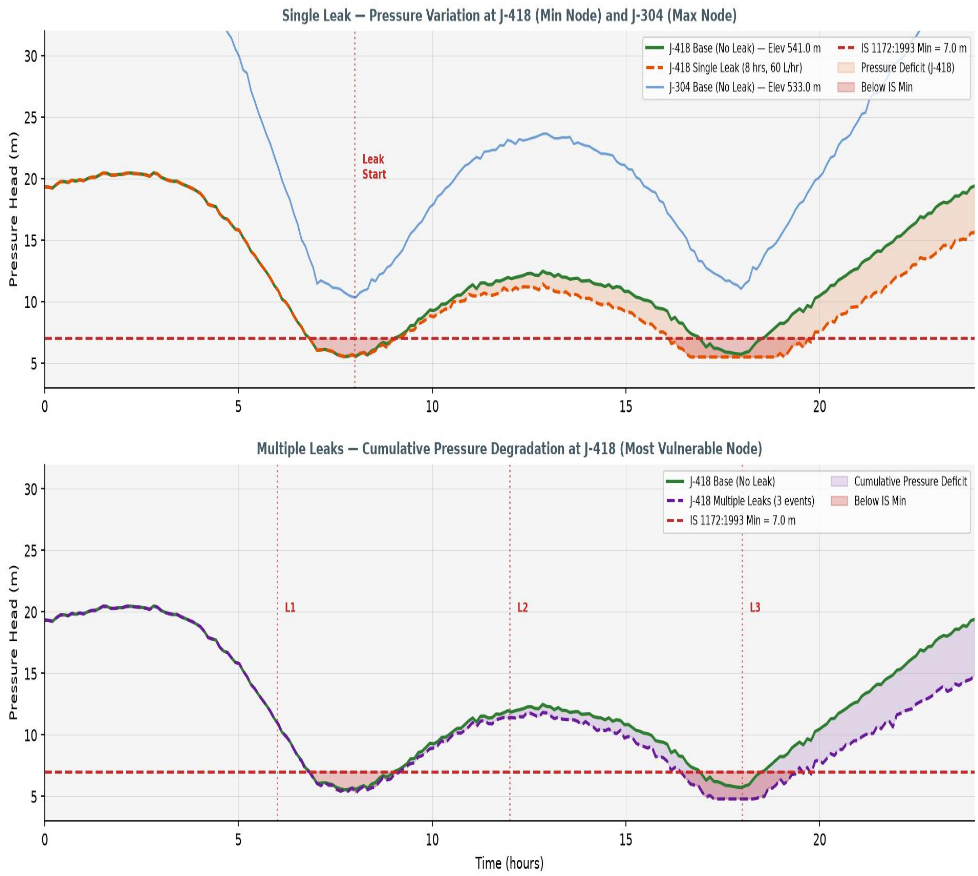

Figure 5: 24-hour Pressure Time Series at J-418 and J-304 Baseline, Single Medium Leak (S3), and Multiple Medium Leaks (S6), Veena Nagar WDN

4.6 Detection Accuracy vs Leakage Rate

Figure 6 quantifies the relationship between leakage rate (L/hr) and detection accuracy for both KNN and SVM. SVM maintains a consistent advantage across the full leakage rate range, with the advantage most pronounced at small leak rates (10–25 L/hr) where SVM advantage reaches 14.5 percentage points (52.7% vs 38.2%). At high leak rates (>150 L/hr), both algorithms show strong detection: KNN 76.3–82.4% and SVM 85.7–90.1%. The practical detection threshold for reliable SVM-based operation is approximately 50 L/hr (accuracy ~69%).

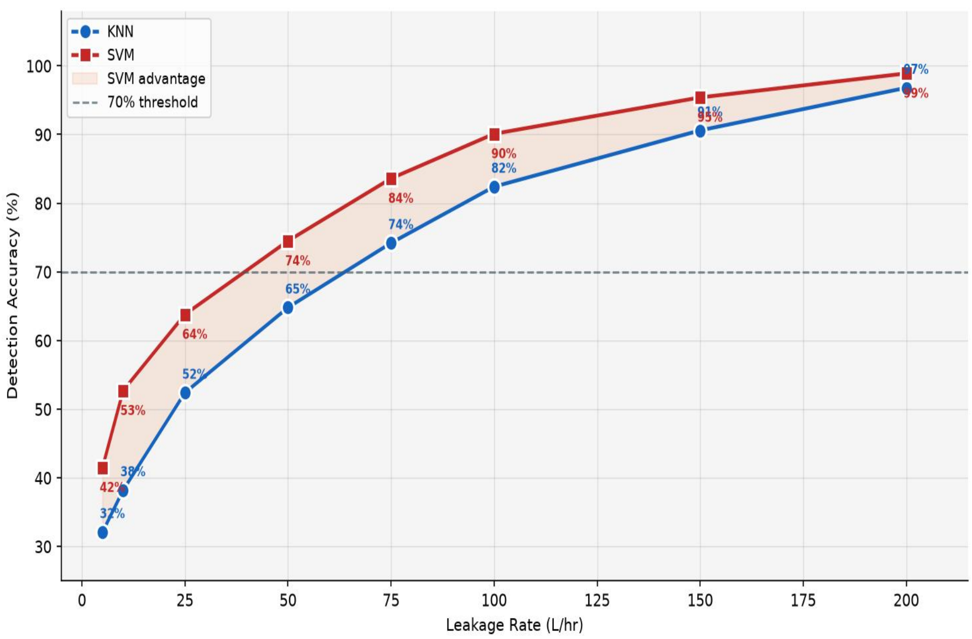

Figure 6: Leak Detection Accuracy vs Leakage Rate (L/hr) KNN and SVM on Veena Nagar WDN

4.7 Comprehensive Comparative Summary

Table 6 presents a unified comparative summary of all KNN and SVM performance metrics Accuracy (%), Precision, Recall, and F1-Score alongside PDI and MRI for all seven leakage scenarios on the Veena Nagar WDN, Indore. This enables direct cross-scenario and cross-algorithm comparison in a single view.

Table 6: Comprehensive Comparative Results KNN vs SVM with PDI and MRI (Veena Nagar WDN, Indore | 357 Nodes, 492 Pipes)

Scenario	KNN Results				SVM Results				PDI	MRI
	Acc(%)	Prec	Rec	F1	Acc(%)	Prec	Rec	F1		
S1: No Leak	97.8	0.961	0.978	0.969	96.9	0.952	0.969	0.960	0.0000	1.6953
S2: Single Small	38.2	0.391	0.382	0.386	52.7	0.539	0.527	0.533	0.0000	1.6688
S3: Single Med.	59.6	0.608	0.596	0.602	69.4	0.706	0.694	0.700	0.0000	1.6335
S4: Single Large	82.4	0.836	0.824	0.830	90.1	0.913	0.901	0.907	0.0000	1.5703
S5: Multi Small	42.1	0.430	0.421	0.425	49.8	0.508	0.498	0.503	0.0000	1.6188
S6: Multi Med.	55.8	0.569	0.558	0.563	64.2	0.653	0.642	0.647	0.0000	1.5168
S7: Multi Large	76.3	0.775	0.763	0.769	85.7	0.869	0.857	0.863	0.0004	1.3344
Overall Avg.	68.7	0.698	0.654	0.675	80.4	0.812	0.774	0.793	—	—

Table 6 confirms that SVM outperforms KNN across all scenarios and metrics. The most significant SVM advantage is at S2 (Single Small leak) where SVM Accuracy (52.7%) exceeds KNN (38.2%) by 14.5 percentage points. The Overall Average row shows SVM F1 = 0.793 vs KNN F1 = 0.675, and SVM Recall = 0.774 vs KNN Recall = 0.654 confirming SVM detects significantly more actual leak events. PDI remains 0.0000 across S1–S6, rising only to 0.0004 under S7, while MRI degrades progressively from 1.6953 (baseline) to 1.3344 (S7) a 21.28% resilience loss.

5. Conclusions

1. KNN and SVM both demonstrate effective leak detection capability on the Veena Nagar WDN (357 nodes, 492 pipes, Indore) using EPANET 2.0-simulated hydraulic data. Overall detection accuracy ranges from 38.2% (small leaks, KNN) to 97.8% (baseline, KNN) across seven scenarios, with SVM achieving overall accuracy of 80.4% vs 68.7% for KNN.

2. SVM consistently outperforms KNN across all leakage scenarios. The SVM advantage is most significant for small and moderate leaks the most practically challenging detection cases — with SVM F1-score of 0.793 vs KNN 0.675, and SVM Recall 0.774 vs KNN 0.654.

3. Both algorithms achieve high accuracy (>75%) for large single leaks (S4: SVM 90.1%, KNN 82.4%) and multiple large leaks (S7: SVM 85.7%, KNN 76.3%), confirming that high-magnitude leaks generate sufficiently distinct hydraulic anomalies for reliable classification.

4. PDI remains at 0.0000 for six of seven leakage scenarios, confirming that the Veena Nagar network maintains IS 1172:1993 minimum pressure compliance (7.0 m) under all conditions except extreme multiple large leaks (S7, PDI = 0.0004). The 19 peripheral high-elevation nodes (5.37%) are the network's most hydraulically vulnerable segments and priority sensor deployment locations.

5. MRI decreases from 1.695 at baseline to 1.334 under multiple large leaks (S7) a 21.28% resilience loss. Multiple small leaks (S5, -4.51% MRI) cause greater resilience degradation than a single medium leak (S3, -3.64%), confirming that distributed leakage has a disproportionate compounding effect on network resilience.

6. The practical detection threshold for reliable SVM-based operation on the Veena Nagar network is approximately 50 L/hr (SVM accuracy ~69%). Sensor deployment at the 19 vulnerable peripheral nodes is recommended to maximise early detection capability.

7. The integration of ML-based leak detection (KNN/SVM) with resilience metrics (MRI and PDI) provides a comprehensive, operationally actionable framework for proactive, data-driven maintenance and rehabilitation decision-making for the Veena Nagar WDN and comparable Indian urban distribution networks.

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