# Scalable Detection of Underground Water Leaks in Dense Urban Environments Using L-Band SAR and Machine Learning

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## ABSTRACT

Underground water leaks in urban networks result in significant resource loss, infrastructure degradation, and environmental damage—challenges that are particularly acute in high-density cities like Hong Kong, where aging and complex infrastructure complicates detection. Traditional methods such as acoustic sensing and manual inspections often fall short in efficiency and scalability. This study proposes the use of L-band SAR imagery from ALOS-2 combined with machine learning techniques to address these challenges. A robust leak detection framework was developed using six dual-polarized SAR images (HH and VV modes) alongside historical leak data from the Hong Kong Water Supplies Department (WSD). Features extracted via Gray-Level Co-occurrence Matrix (GLCM) metrics and backscattering coefficients were used to train various machine learning, deep learning, and ensemble learning models, with hyperparameter optimization performed using a grid search algorithm. Among these, the stacking algorithm delivered the best performance, achieving an accuracy of 80%. Despite these promising results, several critical issues remain unresolved—particularly data imbalance, the incorporation of physical leak characteristics, and the integration of additional environmental factors. Future research will focus on these challenges by exploring new data sources, such as four-polarization ALOS-2 images and Sentinel-1 C-band data, as well as advanced polarimetric and interferometric techniques, to further enhance the robustness and accuracy of leak detection models.

## 1. INTRODUCTION

### 1.1 Background

Water distribution networks (WDNs) are the lifelines of modern society, delivering safe and reliable water to homes, businesses, and critical services. Yet these systems face mounting pressures: aging infrastructure, extreme climatic events, and increasing urban demands all threaten their resilience. A single water main break can trigger service disruptions, flood streets, and result in costly repairs—a reality starkly illustrated by the 240,000 annual pipe failures in the United States or the 15% yearly water loss in Hong Kong’s underground pipelines (Alshami et al., 2024). Globally, utilities grapple with deteriorating infrastructure and escalating risks—from contamination to corrosion—that undermine public trust and strain budgets (Xing et al., 2024).

Water leakage alone is estimated to drain between 20% and 50% of treated water supplies worldwide, resulting in the loss of billions of dollars in revenue and significantly exacerbating water scarcity—especially in drought-prone regions (Arabi & Grau, 2024). Beyond these financial setbacks, persistent leaks accelerate infrastructure degradation by eroding roadways, destabilizing building foundations, and increasing the energy required for water treatment and pumping. As climate change intensifies droughts and population growth further strains water resources, the need for precise and scalable leak detection systems has never been more urgent (Alshami et al., 2023). Traditional leak detection methods, such as manual inspections, acoustic sensors, and ground surveys, are often too slow and labor-intensive to manage the scale of modern WDNs effectively. Consequently, there is a pressing need for a paradigm shift toward proactive, technology-driven solutions that can rapidly and accurately pinpoint leaks before they escalate into costly crises, thereby ensuring water conservation and maintaining infrastructure integrity. The following sections detail this vision. We begin by contextualizing the challenges facing WDNs and the limitations of current methods. Next, we outline our methodology, which integrates SAR data acquisition, machine learning, and geospatial analysis to identify leakage hotspots. We then present our findings, evaluating model accuracy and scalability in diverse urban settings. Finally, we discuss the implications for infrastructure resilience, address technical and operational challenges, and chart a path toward real-world implementation.

### 1.2 Literature Review

Ground Penetrating Radar (GPR) and manual inspections have long been the cornerstone for identifying anomalies in water distribution networks (WDNs) (Eyuboglu et al., 2003; El-Abbasy et al., 2016; El-Zahab et al., 2017; El-Zahab et al., 2018). For instance, GPR detects variations in soil dielectric properties caused by moisture infiltration (Hunaidi & Giamou, 1998); however, its application is often constrained by high operational costs and localized coverage, rendering it less effective for large-scale monitoring (Hunaidi, 2000). Moreover, these traditional methods are labor-intensive and require frequent manual inspections and extensive field surveys.

To overcome these limitations, remote sensing has emerged as a promising alternative that reduces labor intensity while expanding spatial coverage. In particular, optical remote sensing techniques—which utilize satellite or airborne imagery (Hadjimitsis et al., 2009)—have gained significant traction for leak detection in WDNs. These methods monitor vegetation indices such as the Normalized Difference Vegetation Index (NDVI) and Green NDVI (GNDVI), which can indirectly indicate moisture anomalies associated with leaks. For example, Chen et al. (2020) demonstrated that deep-learning models based on Landsat-8 imagery—which incorporate parameters such as land surface temperature (LST), fraction of vegetation cover (FVC), and the temperature vegetation dryness index (TVDI)—

can detect leak zones with an accuracy of approximately 85%. Similarly, Agapiou et al. (2013b) employed high-resolution QuickBird and SPOT imagery, using thresholds derived from ground spectroradiometry and NDVI to accurately pinpoint leak locations. In another study, Agapiou et al. (2013a) utilized medium-resolution data from Landsat 5 TM and Landsat 7 ETM+ (with a 30-meter pixel size) to examine areas with known leakage problems; however, despite the use of various post-processing techniques including vegetation indices, this approach detected only a single problematic leakage. In contrast, Hadjimitsis et al. (2013) showed that ground spectroradiometers and low-altitude hyperspectral systems—which capture spectral signatures in the visible (400–700 nm) and very near-infrared (750–900 nm) ranges—were significantly more effective. Their findings indicated that wet soils reflect 20–25% less light than dry soils, with the maximum difference observed in the very near-infrared. Additionally, vegetation's spectral response varies with moisture content—wet grass reflects around 12% in the green band and 35% in the near-infrared, compared to 5% and 25%, respectively, for dry grass—underscoring the importance of high spatial resolution in capturing subtle spectral differences critical for identifying water leakages.However, optical methods are not without limitations. They are sensitive to cloud cover, variations in illumination, and typically provide only shallow penetration, which restricts their ability to detect subsurface leaks (Ali et al., 2021). Airborne platforms, such as unmanned aerial vehicles (UAVs), offer higher spatial resolution due to their lower ground sampling distances. For example, Krapez et al. (2022) utilized near-infrared, short-wave near-infrared, and thermal spectral bands from aerial vehicles and achieved a model accuracy of 50%. Nevertheless, the scalability of these platforms is hindered by limitations in payload capacity and flight endurance, which necessitate trained remote pilots and incur additional labor, time, and financial costs. In contrast, satellite-based imagery that leverages optical sensors has been explored as a more autonomous, accessible, consistent, scalable, and cost-effective alternative for water leak monitoring. Despite these advances in optical remote sensing, UAV operations remain constrained by spatial coverage and flight endurance issues (Traoré et al., 2022). This has led to growing interest in Synthetic Aperture Radar (SAR) as a compelling alternative for leak detection. Unlike optical sensors, SAR can capture imagery under all weather conditions and at any time of day, while also providing the added benefit of subsurface penetration. SAR sensors emit microwave signals that partially penetrate the soil, making them sensitive to variations in soil moisture. Wet soils, with their higher dielectric constants, generate stronger backscatter signals than dry soils. Furthermore, SAR sensors operate in multiple polarizations—such as VV (vertical transmit/receive) and VH (vertical transmit, horizontal receive)—with VV being particularly sensitive to moisture in the top few centimeters of soil and VH providing valuable insights into surface roughness and deeper moisture layers (Ranjbar et al., 2021).Recently, Arabi & Grau (2024) demonstrated that texture analysis methods—most notably the Gray Level Co-occurrence Matrix (GLCM)—can be effectively employed to extract spatial patterns from SAR imagery, thereby enhancing the potential for leak detection. However, they also noted that the performance of these techniques in complex urban environments remains an area requiring further investigation. In summary, while optical, UAV, and SAR-based methods each offer unique advantages, significant challenges persist—especially in urban settings. Optical methods are vulnerable to environmental conditions such as cloud cover and variable illumination; UAVs are limited by operational complexity and flight endurance; and SAR, though promising, faces issues related to data interpretation in heterogeneous urban areas. Ongoing research into the integration of these remote sensing techniques with advanced deep learning approaches holds substantial potential for improving leak detection accuracy in these challenging contexts.

### 1.3 Research Rationale

Despite promising advancements in remote sensing for water leak detection, significant challenges persist. Optical sensors, while effective for detecting surface moisture and vegetation changes, are hampered by atmospheric conditions and lack the penetration necessary for subsurface anomalies. Although UAV-based systems provide high spatial resolution, they are limited by coverage and operational constraints. Conversely, SAR sensors—especially those operating in the L-band—offer the ability to penetrate surfaces and capture subsurface moisture variations. However, in urban environments, heterogeneous scattering from buildings and other structures can obscure the subtle signals generated by leaks.

Furthermore, while SAR platforms such as Sentinel-1 offer frequent revisit intervals (approximately every 6 days), other L-band sensors like ALOS-2—which provide superior subsurface sensitivity—often have lower temporal resolution. To address this limitation, our study assumes that leak-induced moisture anomalies persist for at least 30 days, thereby increasing the likelihood of detection within the available SAR data. We propose an integrated approach that combines L-band SAR data with advanced machine learning techniques. By fusing traditional backscatter metrics with texture features extracted via GLCM analysis, we aim to develop a robust classifier capable of distinguishing leak-induced moisture anomalies from background urban variability. This integrated methodology not only addresses the limitations of optical and UAV-based systems but also extends the spatial and temporal coverage essential for effective leak detection. Additionally, while GPR-based methods offer high-resolution local insights, their scalability is limited; thus, our approach leverages satellite-based SAR imagery to provide broad coverage and complement GPR data when available.

## 2. STUDY AREA AND DATASETS

The study area is Hong Kong, a densely populated metropolitan region with a highly complex underground water distribution network. The region's extensive pipeline system is prone to water leaks, exacerbated by aging infrastructure, increasing urban development, and frequent excavation activities. To enhance the ability to detect and monitor underground water leaks, this study integrates multi-temporal Synthetic Aperture Radar (SAR) imagery with historical leak reports and pipeline geospatial data. The dataset consists of six ALOS-2 SAR images acquired in dual-polarization (HH and VV modes) with a spatial resolution of approximately 6 meters. These SAR images were sourced from the Japan Aerospace Exploration Agency (JAXA) and procured specifically for this research. The available images cover two frames (Frame 3 and Frame 4) within the study area, ensuring comprehensive spatial coverage over key pipeline sections. Table 1 summarizes the SAR images and their corresponding availability in each frame. In addition to SAR imagery, the Water Supplies Department (WSD) of Hong Kong provided a dataset of historical leak points recorded between 2010 and 2021, which contains precise spatial and temporal information on past leak incidents. This dataset was critical for training and validating machine learning models. A visual representation of the study area, including the pipeline network, detected leak points, and SAR frame coverage, is provided in Figure 1. This figure illustrates the spatial distribution of key infrastructure elements and highlights the coverage of SAR imagery across the study area.


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Figure 1: a) study area. The green rectangles in panel c denotes the spatial coverage of ALOS-2 (6 m) frames.

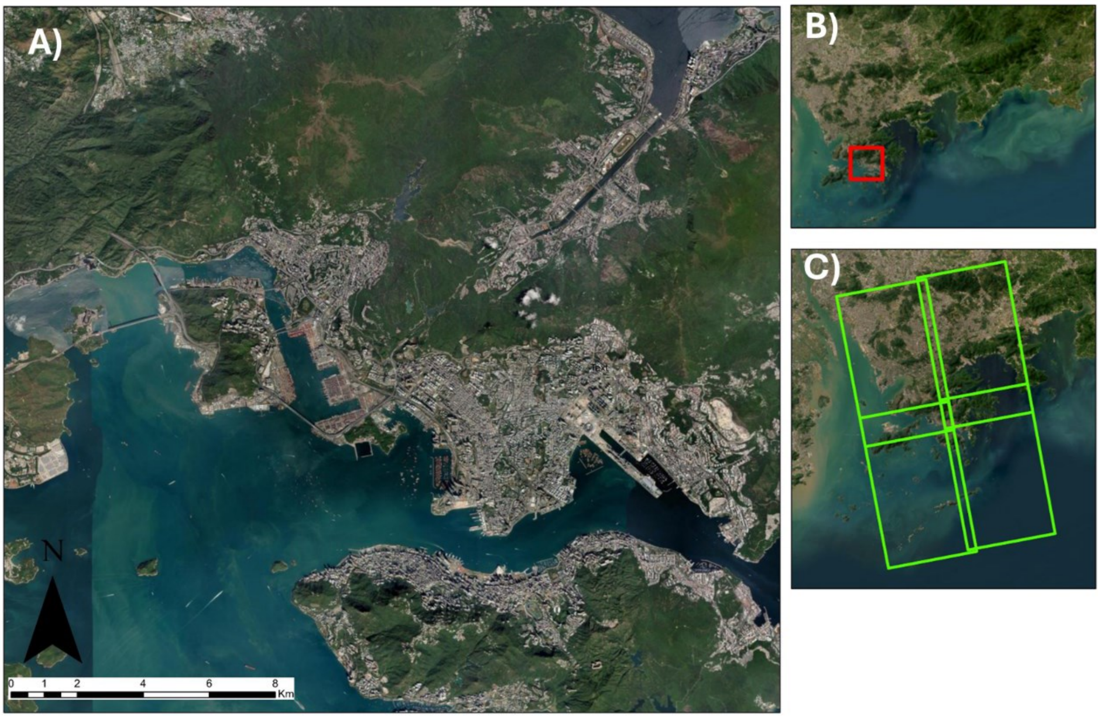


Table 1: Summary of Available ALOS-2 SAR Images and Frames

| Image ID | Frame 3 | Frame 4 |
|---|---|---|
| 14/12/2016 | ✓ | |
| 27/07/2016 | | ✓ |
| 26/07/2017 | ✓ | ✓ |
| 14/11/2018 | ✓ | ✓ |

## 3. METHODOLOGY

After the SAR images were preprocessed in the SNAP Toolbox (Braun & Veci, 2021)—including steps for radiometric calibration, thermal noise removal, speckle filtering, and terrain correction—the study proceeded with a detailed coregistration process using SNAP's "Coregistration" tool. In this stage, the images acquired at the middle temporal frames (Frames 3 and 4) were designated as the master images, while the remaining images were registered as slave images. The tool automatically aligned the slave images to the master by employing an image matching technique that analyzes overlapping regions based on pixel intensity values (Abdallah et al., 2024; Liu et al., 2023 **). Rigid body transformations—including translation, rotation, and scaling—were applied using advanced algorithms such as cross-correlation or normalized cross-correlation. Following the transformation, the slave images were resampled using nearest-neighbor or bilinear interpolation to ensure their pixel grids matched those of the master image, thereby preserving spatial resolution.

Once the coregistered dataset was established, the study extracted Gray-Level Co-occurrence Matrix (GLCM) texture features to capture the spatial relationships and textural characteristics inherent in the SAR data (Caballero et al., 2020). Specifically, the GLCM method computes the probability distribution of pixel pairs with specified gray-level values at a given offset, from which nine features—Mean, Variance, Correlation, Contrast, Dissimilarity, Homogeneity, Angular Second Moment (ASM), and Entropy—are derived for both VV and VH backscattering coefficients. This extraction was performed using a 3×3 window size, considering all angles, with a probabilistic quantizer set to 32 quantization levels, and a displacement of 4 (Ali et al., 2022).

Building upon these preprocessing and feature extraction steps, leak point selection was conducted using SAR images spanning a 30-day period, based on the assumption that leak effects persist throughout this timeframe. Leak points provided by the Hong Kong Water Supplies Department (WSD) were delineated using a 50-meter buffer, while non-leak points were selected from areas distant from the pipelines—also buffered at 50 meters—to ensure a clear distinction between the two classes. This process yielded a database of approximately 5,466 points, comprising 3,006 non-leak points and the remainder as leak points. For each point, a 32×32-pixel window was extracted from each of the 22 stacking bands for both polarization modes, and the mean values of the computed GLCM features within these windows were estimated and consolidated into a numerical table with a binary response variable (0 for non-leak and 1 for leak).

Subsequently, the study trained and evaluated 18 machine learning, deep learning, and ensemble models (detailed in the Results section, Figure 3b) using this database. Hyperparameter optimization was conducted via grid search—tuning parameters such as the number of estimators, learning rate, and maximum tree depth—to enhance model performance (Abdelkader et al., 2023; Ma et al., 2024), while 10-fold cross-validation was employed to ensure robustness and mitigate overfitting by reliably estimating performance across multiple data splits (Poulakis et al., 2003). Model evaluation was based on metrics derived from counts of True Positives (TP), True Negatives (TN),


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False Positives (FP), and False Negatives (FN), with precision quantifying the accuracy of predicted leak points and recall measuring the proportion of actual leak points correctly identified. The F1-score, representing the harmonic mean of precision and recall, alongside overall pixel accuracy, provided key insights into classification performance (Adham et al., 2024; Goutte & Gaussier, 2005; Zheng et al., 2024).

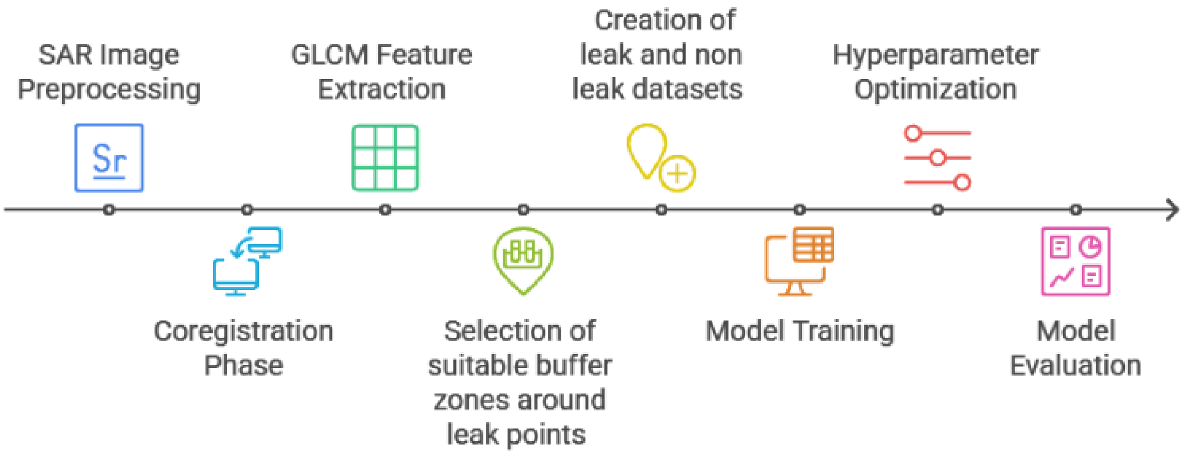


Figure 2: schematic flow chart of the proposed methodology

## 4. RESULTS AND DISCUSSION

The evaluation of multiple machine learning (ML) models for detecting underground water leaks reveals a nuanced spectrum of performance that highlights the distinct strengths and limitations of traditional ML methods, deep learning (DL) architectures, and ensemble-based approaches. Standalone classifiers such as Logistic Regression, Decision Tree, and Support Vector Machine (SVM) achieved moderate overall accuracies ranging from 73% to 77%. For example, Logistic Regression achieved an overall accuracy of 77% with a leak precision of 0.76, leak recall of 0.85, and an F1-score of 0.80. However, these models struggled with non-leak classification; the lower precision for non-leak predictions suggests that they have difficulty distinguishing overlapping features, which results in a higher rate of false positives. Similar trends were observed with the Decision Tree (73% accuracy) and SVM (75% accuracy), where the relatively weaker performance in non-leak detection underscores the inherent limitations of single-model approaches in complex urban environments.

In contrast, DL models demonstrated competitive, and in some cases superior, performance compared to traditional ML approaches. The Long Short-Term Memory (LSTM) network, for instance, achieved an overall accuracy of 78% with a robust leak recall of 85% and an F1-score of 0.81. This result indicates that the LSTM is particularly adept at capturing both temporal and spatial dependencies from the SAR-derived features, which is crucial for accurately detecting persistent leak effects over time. Similarly, the Deep Neural Network (DNN) model, with an overall accuracy of 77%, exhibited balanced precision and recall across both leak and non-leak classes, further supporting the viability of DL approaches for this application.

Ensemble-based methods, however, consistently outperformed both standalone ML and DL models. Gradient Boosting, CatBoost, and XGBoost each achieved an accuracy of 79%, with all three models reporting leak recall values of approximately 87% and balanced F1-scores near 0.82. These high recall rates are particularly critical, as they demonstrate the models’ strong ability to correctly identify the majority of leak events—an essential requirement for mitigating potential water loss and preventing infrastructural damage. Building upon these individual ensemble methods, the stacking algorithm—which integrates Logistic Regression, Random Forest, XGBoost, CatBoost, AdaBoost, and Gradient Boosting—emerged as the most effective approach, achieving an overall accuracy of 80%. The stacking algorithm leverages the complementary strengths of its constituent models to enhance predictive robustness. Its confusion matrix (as depicted in Figure 3a) indicates that it correctly identified 791 leak points and 534 non-leak points, while incurring 194 false positives and 121 false negatives. This balanced performance demonstrates the stacking algorithm’s enhanced capacity to minimize false negatives—an essential factor in ensuring that leak events are not overlooked—while maintaining high overall accuracy. The comparative performance, summarized in Figure 3b, clearly positions the stacking algorithm as a new benchmark for accuracy and class balance in leak detection applications.

Beyond overall accuracy, the evaluation framework incorporated detailed performance metrics derived from the standard confusion matrix components—True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). Precision, defined as the ratio of correctly predicted leak points to all points predicted as leaks, and recall, defined as the proportion of actual leak points correctly identified, were critical in assessing model reliability. The F1-score, which represents the harmonic mean of precision and recall, offered a balanced measure of model performance, particularly in the presence of class imbalances (Goutte & Gaussier, 2005; Hanley & McNeil, 1982).

In summary, while standalone ML and DL models provide valuable insights, the ensemble-based approaches—especially the stacking algorithm—demonstrate the highest efficacy for underground leak detection. The stacking approach not only achieves the highest overall accuracy (80%) but also exhibits balanced classification performance by effectively integrating the strengths of multiple models. This integrated strategy significantly enhances the reliability of leak detection in complex urban environments and establishes a robust framework for future monitoring and intervention efforts.

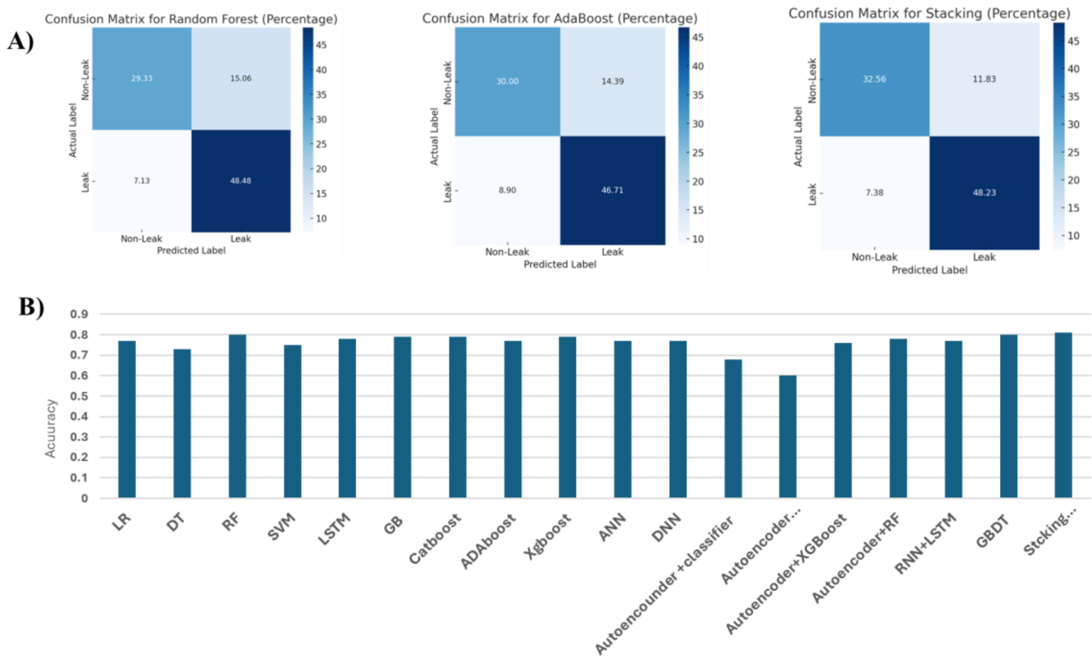


Figure 3: comparison of ML results. A) confusion matrix of three ML algorithms (i.e., Randon forest, Ada Boost, and Stacking). B) the accuracy comparison between all the models.

## 5. CONCLUSIONS

This study investigates the potential of utilizing high-resolution L-band SAR imagery from ALOS-2 (6 m spatial resolution) in combination with advanced machine learning, deep learning, and ensemble methods—optimized via grid search—for detecting underground water leaks in urban environments. By associating leak points with SAR acquisitions through a 30-day temporal window (assuming leak effects persist for roughly 30 days without repair), our methodology achieved an overall accuracy of 80% using a stacking algorithm. These promising results align with previous studies employing Sentinel-1 imagery and Random Forest models with GLCM feature extraction; however, significant differences exist between the platforms. While Sentinel-1 offers a high revisit frequency (approximately every 6 days), its spatial resolution is coarser (around 20 m) compared to ALOS-2. Additionally, the deeper penetration capability of ALOS-2 provides critical insights into subsurface anomalies in complex urban environments. Future comparative studies will be essential to understand the contributions of different SAR platforms and to refine the detection process.

Despite the promising performance of our SAR-based leak detection framework, several challenges persist that must be addressed to further improve detection accuracy and operational reliability. In light of these challenges, future research should focus on both refining current methodologies and exploring new, integrative approaches. Below, we outline several key research directions along with in-depth discussions on how they can contribute to advancing leak detection technologies.

- **Integration of Physical Leak Characteristics**

Future studies should investigate the impact of incorporating detailed physical properties—such as pipe pressure, diameter, material composition, and leak flow rate—into machine learning models. The integration of these parameters may provide additional context that enhances the predictive power of remote sensing data. For example, high-pressure leaks may create more pronounced moisture anomalies or distinct surface deformations compared to low-pressure events. Developing hybrid models that combine conventional backscatter metrics and texture features with physical leak parameters could yield a more comprehensive understanding of leak dynamics, thereby improving detection precision (El-Zahab et al., 2017; Xing et al., 2024a).

- **Combining Physics-Informed Neural Networks (PINNs) with GLCM Features**

The fusion of Physics-Informed Neural Networks (PINNs) with GLCM-based texture analysis represents a promising avenue for future research. PINNs are designed to incorporate known physical laws—such as fluid dynamics and stress equilibrium—directly into the learning process. By coupling PINNs with GLCM features extracted from SAR imagery, future models can benefit from both a physical understanding of leak propagation and the detailed surface pattern information captured by remote sensing. This integrated approach may enhance the robustness and interpretability of leak detection models, making them more adaptable to complex urban environments (Chen et al., 2020; Arabi & Grau, 2024).

- **Incorporating Environmental and Climatic Factors**

Environmental variables such as temperature, humidity, rainfall, traffic patterns, and pavement roughness can have a significant impact on SAR signal interpretation. Future research should explore the integration of these contextual data sources into the leak detection framework. By doing so, models could adjust for seasonal variations and urban infrastructure effects that currently contribute to classification uncertainty. A holistic model that fuses remote sensing data with real-time meteorological and urban context information could offer more reliable predictions, particularly in highly variable settings like Hong Kong (Ali et al., 2020).

- **Addressing Spatial and Temporal Uncertainties**

The precise localization of leak points remains challenging due to spatial heterogeneity and the limited temporal coverage of certain SAR platforms such as ALOS-2. Future studies should prioritize multi-temporal analysis techniques to monitor the evolution of leak-induced moisture anomalies over time. Additionally, integrating high-resolution topographic data and detailed urban infrastructure maps may help refine spatial models, reducing uncertainty in leak localization. These efforts will be particularly valuable in dense urban environments where small-scale variations can have a large impact on SAR backscatter (Hunaidi, 2000; Hunaidi & Giamou, 1998).

- **Optimizing SAR Signal Penetration and Data Fusion**

Although L-band SAR offers improved penetration capabilities compared to other bands, its performance under paved or densely built-up surfaces remains a concern. Future research should focus on optimizing SAR acquisition parameters and exploring the fusion of data from multiple wavelengths (e.g., combining L-band with C-band or X-band imagery). This multisensor approach may enhance the detection of subsurface anomalies by compensating for the limitations of any single sensor and providing a more comprehensive view of the subsurface environment (Traoré et al., 2022).

- **Leveraging Advanced SAR Processing Techniques**

To fully exploit the potential of SAR data for leak detection, advanced processing techniques such as polarimetric decomposition and interferometric SAR (InSAR) should be integrated into future frameworks. These methods can extract additional information regarding surface and subsurface conditions, such as fine-scale deformation and subtle moisture changes, thereby improving the discrimination between leak and non-leak areas. Enhanced processing techniques will likely reduce misclassification rates and improve the overall robustness of detection models (Caballero et al., 2020).

- **Validation with Larger and Multisensor Datasets**

The current study is based on a limited dataset of six dual-polarization SAR images, which may limit the generalizability of the findings. Future work should seek to expand the dataset by incorporating four-polarization images and data from multiple satellite systems (e.g., Sentinel-1) to improve both temporal resolution and spatial coverage. Employing cross-validation across larger, more diverse datasets will be critical for verifying model performance and ensuring scalability in different urban environments (Ali et al., 2021; Ma et al., 2024).

- **Comparative Analysis of SAR Platforms**

A thorough comparison between SAR platforms is essential to understand the trade-offs between high temporal frequency and spatial resolution. While Sentinel-1 offers frequent revisits (approximately every 6 days), its spatial resolution is coarser (around 20 m) compared to the 6 m resolution provided by ALOS-2. The deeper penetration capabilities of ALOS-2 may offer significant advantages in detecting subsurface leaks. Future comparative studies conducted within the same geographic area will be vital in determining which platform—or combination of platforms—yields the most reliable leak detection under varying environmental conditions (Arabi & Grau, 2024; Xing et al., 2024a).

By addressing these research directions, future studies can build on the foundation established in this work to develop more accurate, scalable, and resilient leak detection systems. Such advancements will not only contribute to the broader field of remote sensing-based infrastructure monitoring but also offer practical solutions for urban water management, reducing water loss and minimizing the socio-economic impact of leaks.

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