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Enhancing Leak Detection in WDNs with CWT and CNN Applied to Pressure Signals

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Abstract – Water distribution networks (WDNs) are critical infrastructure for supplying water to communities but are susceptible to leaks, leading to significant water losses, infrastructure damage, and increased operational costs. Effective monitoring and maintenance solutions are essential to address these challenges. This study presents an advanced leak detection system incorporating an artificial intelligence (AI)-based algorithm to enhance accuracy in identifying water leaks. Real-time pressure variations are sensed using pressure transducers, designed to resist environmental noise, thereby improving system reliability. To facilitate deep data learning (DL), a prototype PEHD hydraulic pipeline was built, measuring 100 m in length and 40 mm in diameter with a thickness of 2.4 mm, on which two pressure transmitters were installed at previously known positions linked to a dSPACE acquisition system. Pressure data, including leakage and no-leakage scenarios, is collected and transformed into 2D images using continuous wavelet transform (CWT). These 2D images are used to train convolutional neural networks (CNNs), optimized for extracting spatial and temporal features from image-based data. Transfer learning techniques, leveraging pretrained models like DenseNet, MobileNet, ResNet, and Xception, further enhance feature extraction. Additionally, machine learning (ML) classifiers such as SVM, KNN, and XGBoost are integrated with the CNN framework to improve classification accuracy under dataset splits (80%-20%). A hybrid approach, combining deep feature extraction with traditional classification methods, is proposed as an efficient and accurate solution for leak detection in WDNs.

I. INTRODUCTION

Water is a precious and fundamental resource essential for sustaining life, maintaining ecosystems, and fostering economic and social progress. Access to clean water is fundamental for human survival [1]. Access to clean, potable water is essential for public health, agriculture, and industrial operations, making its efficient management a global priority. Water distribution networks (WDNs), critical for supplying potable water to millions, pose significant challenges in management and monitoring due to their vast size and complexity [2]. These networks consist of extensive piping systems, which represent the most cost-effective, efficient, and secure method of delivering potable water to the population [3].

WDNs face a critical challenge in water resource management, with substantial volumes of treated water being lost primarily due to pipe leakage, significantly reducing the efficiency of water supply systems [4]. Water leakage in distribution networks can result in various adverse effects, including economic losses, environmental harm, and structural damage to roads, buildings, and nearby infrastructure. Additionally, leak sites may allow external pollutants and bacteria to infiltrate through leak holes[5]. Water leakage compromises water quality and poses significant risks to public health. Addressing this issue is essential for sustainable water management, cost reduction, and maintaining reliable supply systems. A breach in the pipe wall, such as an orifice, can cause physical changes in both the ground and the pipe, including variations in applied pressure and soil moisture levels. These phenomena serve as key indicators for monitoring water distribution networks. Consequently, operators have prioritized developing methods for early leak detection, enabling timely intervention and minimizing potential damage [6]. Leak detection in water distribution networks (WDNs) involves identifying and confirming the presence of leaks within the system. This process utilizes specialized monitoring equipment, including both modern and conventional leak detectors. These devices detect changes in parameters such as water pressure, vibrations, sound, or flow, which can indicate potential leaks. Network operators prioritize systems that are safe, efficient, and cost-effective, emphasizing the importance of prompt leak detection in evaluating water supply performance. Modern leak detection technologies employ a range of advanced devices and techniques to enhance accuracy and efficiency [7]. To achieve accurate detection and localization of leaks, numerous methods based on the analysis of measured signals have been proposed in the existing literature. These approaches leverage signal patterns to identify anomalies indicative of potential leaks [8, 9].

The new work proposed hybrid approach, this study advances the field of leak detection in WDNs by integrating advanced ML and DL techniques with real-time data collected from pressure transducers. The data, captured from both leakage and non-leakage scenarios, undergoes transformation into 2D images via CWT, enabling the extraction of intricate patterns related to water pressure variations. CNNs are employed to process these images, effectively capturing both spatial and temporal features essential for accurate leak identification.

By leveraging transfer learning with pretrained models such as DenseNet, MobileNet, ResNet, and Xception, the system is able to improve the efficiency of feature extraction, even with limited computational resources. Additionally, the integration of traditional machine learning classifiers like SVM, KNN, and XGBoost enhances the system's ability to classify leak events with high precision. The 80%-20% dataset split used for training and testing ensures robust model validation, confirming the effectiveness of the approach in various leak detection scenarios.

The proposed system significantly reduces the reliance on manual inspection and offers a scalable, real-time solution for water loss management in WDNs. Furthermore, this study addresses key challenges in water distribution management, including cost efficiency, low energy consumption, and real-time response, contributing to the broader goal of improving water sustainability and preserving valuable water resources.

II. Materials and Method

Leak detection in WDNs presents several significant challenges. A primary difficulty is the early identification of leaks, especially when they are small or concealed within underground pipes. These leaks are often subtle, remaining undetected for extended periods, resulting in substantial water loss and damage to infrastructure. In large and complex WDNs, traditional methods like acoustic monitoring or manual inspections may be inefficient due to the high labor and time requirements. Additionally, environmental factors and background noise can interfere with sensor readings, complicating detection efforts. These limitations underscore the need for more advanced detection techniques.

The proposed leak detection system utilizes pressure transducers to monitor pressure variations along the pipeline. The setup includes two transducers: one is fixed 1.5 m from the leak, while the other is positioned 14 m from the pump and can be moved in 1.5 m intervals along the pipeline up to 78 m. Leak detection is activated by a push-button, initiating a 20 s recording period to capture the transient pressure drop caused by the leak. The pressure wave resulting from the leak travels in both directions, reaching the transducers at different times, which enables the detection of leaks through the analysis of the pressure signal changes. As presented in Fig 1.

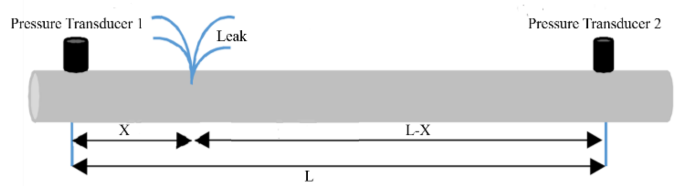

Fig. 1 The leak in a section of the pipe.

A. *Continuous wavelet transform (CWT)*

The CWT provides a detailed time-frequency analysis of seismic signals, efficiently detecting subtle changes linked to complex geological structures [18]. This technique converts 1D signals into 2D images, representing frequency on the y-axis and time on the x-axis, allowing visualization of time-series frequency data. These 2D wavelet-transformed images serve as input datasets for CNN models.

CWT is a key mathematical technique that provides a time-frequency representation of signals, enabling feature extraction across different scales and frequencies, is determined by Eq (1)

$$CWT_{(\sigma,\tau)} = \int_{-\infty}^{+\infty} w(t)\psi_{\sigma,\tau}(t)dt = \frac{1}{\sqrt{\sigma}}\int_{-\infty}^{+\infty} w(t)\psi\left(\frac{t-\tau}{\sigma}\right)dt \quad (1)$$

B. *Convolutional neural network (CNN)*

CNNs are a type of deep learning algorithm designed to analyze and learn visual features from large datasets. They are primarily used in image-related AI applications, such as object detection, image classification, and semantic segmentation, but their versatility extends to tasks like natural language processing and recommendation systems[20]. Advanced CNN architectures, including DenseNet, MobileNet, ResNet, and Xception, have been developed to enhance performance by addressing challenges like vanishing gradients, computational efficiency, and feature reuse.

III. Results and Discussions

This section presents the results of the proposed leak detection methodology, including the analysis of 1D pressure signals, their transformation into 2D images using CWT, First, pressure transducers are utilized to gather real-time pressure data, which is recorded using a dSPACE card. Second, the collected pressure signals are denoised using the Savitzky-Golay (SG) filter to eliminate noise and enhance data clarity. Next, the feature extraction step involves leveraging pre-trained CNNs, such as ResNet, DenseNet, MobileNet, and Xception, to extract meaningful features from the 2D pressure images. These models enhance the system's ability to distinguish between leak and no-leak scenarios. Finally, in the ML classification phase, extracted features are fed into machine learning classifiers, including Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and XGBoost, to categorize the data accurately as "leak" or "no leak." This comprehensive approach ensures precise, efficient, and reliable leak detection, as illustrated in Fig 2.

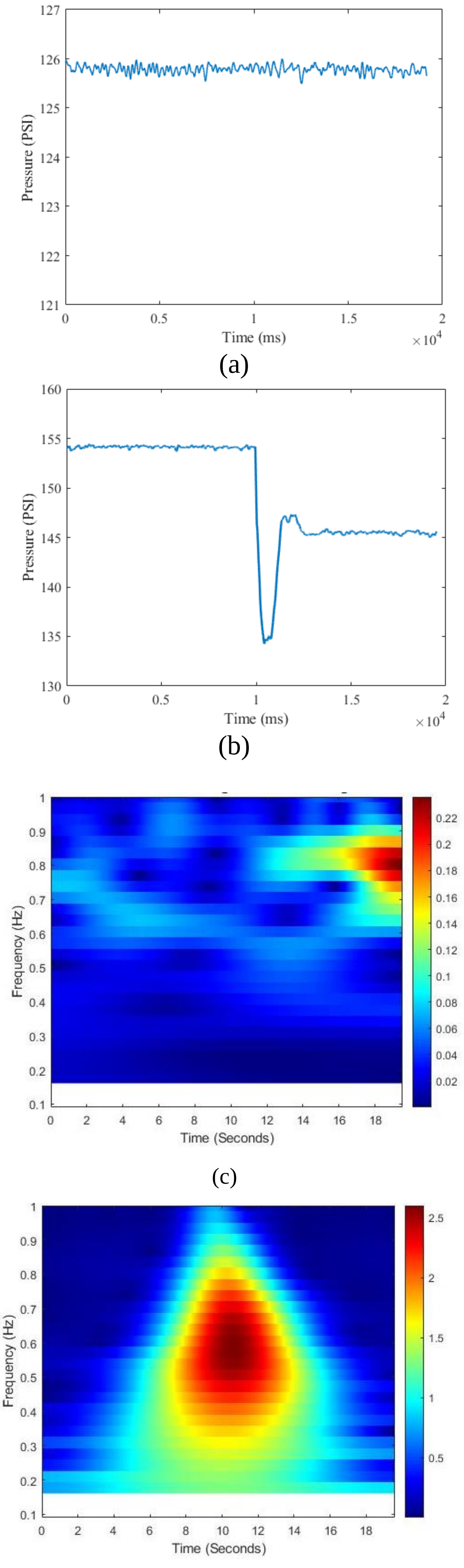

Fig. 2 1D pressure signals and 2D transformed images using CWT

The CWT using the Morlet wavelet function are presented in Fig 2. Specifically, Fig 2 (c) and (d) depict 2D pressure images generated from the 1D pressure signals shown in Fig 2 (a) and (b) for no-leakage and leakage scenarios, respectively. In Fig 2 (c), background noise dominates, with no indications of transient conditions. In contrast, Fig 2 (d) shows a significant signal at approximately 10 seconds, clearly indicating the presence of leakage.

This table presents the performance metrics of different AI-based models used for leak detection in water distribution networks (WDNs) under a 70%-30% train-test split. The models include four CNN architectures (DenseNet, MobileNet, ResNet, Xception) combined with three machine learning classifiers (SVM, KNN, XGBoost). The performance is evaluated based on five metrics: accuracy, sensitivity, specificity, precision, and F1-score.

Table 1. Performance of CNN and ML-Based Hybrid Models for Leak Detection in WDNs.

Leak_detetion_80%_20%						
CNNs	ML	Performance (%)				
		Acc	Sen	Spe	Pre	F1-score
DensNet	**SVM**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**
	KNN	95.83	100.0	87.50	94.11	96.96
	XGBoost	95.83	100.0	87.50	94.11	96.96
MobileNet	**SVM**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**
	KNN	70.83	69.56	100.0	12.50	82.05
	XGBoost	91.66	93.75	87.50	93.75	93.75
ResNet	**SVM**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**
	KNN	95.83	93.75	100.0	100.0	96.77
	XGBoost	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**
Xception	**SVM**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**
	KNN	95.83	93.75	100.0	100.0	96.77
	XGBoost	91.66	87.50	100.0	100.0	93.33

SVM consistently achieved 100% across all metrics for all CNN models, demonstrating its superior ability to classify leak scenarios accurately.

XGBoost consistently achieved 100% across all Performance for **ResNet** model, demonstrating its superior ability to classify leak scenarios accurately.

A. Good Performance with DenseNet and ResNet:

KNN and **XGBoost** showed good results with **DenseNet** and **ResNet**, achieving high sensitivity and **F1-scores**, though slightly lower in specificity and precision.

MobileNet Performance:

While **MobileNet** paired with **SVM** achieved perfect scores, **KNN** underperformed significantly, with lower specificity 12.5% and precision 69.56%.

Xception Model:

Xception paired with **SVM** also achieved perfect scores, while **KNN** and **XGBoost** showed slightly reduced sensitivity and **F1-scores**.

This highlights the importance of selecting the appropriate classifier to complement the CNN model for optimal leak detection performance.

B. Confusion Matrices

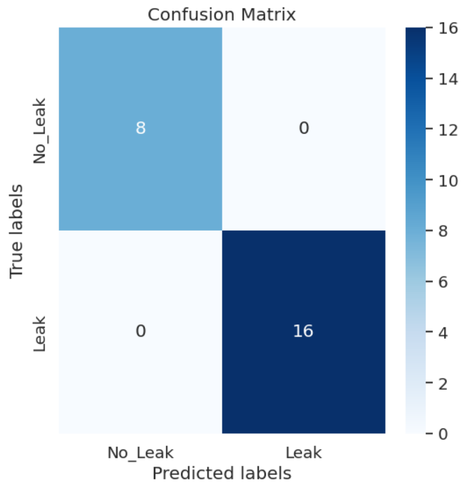

Fig. 3 Confusion Matrices SVM and XGBoost.

IV. CONCLUSION

Water distribution networks (WDNs) are vital for ensuring the consistent supply of water to communities, but they face significant challenges due to leaks, which lead to water loss, infrastructure damage, and increased costs. This study demonstrates an innovative approach to addressing these issues by integrating AI-based algorithms, DL, and ML techniques for accurate and reliable leak detection. Using a prototype PEHD pipeline, real-time pressure data was collected and transformed into 2D images, enabling advanced feature extraction through CNNs and transfer learning models. The hybrid approach, combining DL and traditional ML classifiers, provides a robust and efficient method for detecting leaks, showcasing its potential to enhance the reliability and sustainability of WDN management systems. This solution highlights the importance of advanced technologies in tackling real-world challenges in water resource management.

REFERENCES

[1] Miloud Bentoumi, Haddi Bakhti, Chaima Chabira, and Saber Mefteh, *DWT and STFT applied to Detect and locate leaks in WDNs.* Participant Statistics: p. 216.

[2] Haddi Bakhti, Miloud Bentoumi, Chaima Chabira, and Saber Mefteh, Design of leaks detection and localization in WDNs based on LabVIEW and pressure signals. Participant Statistics: p. 218.

[3] Chaima Chabira, Haddi Bakhti, Miloud Bentoumi, and Sabir Meftah. RNL used for the verification of the efficiency of a localization model in a real WDNs. in 2022 International Conference of Advanced Technology in Electronic and Electrical Engineering (ICATEEE). 2022. IEEE.

[4] Sabir Meftah, Miloud Bentoumi, Dirman Hanafi Burhanuddin, Haddi Bakhti, and Chaima Chabira, Novel Leak Detector Based on DWT an Experimental Study. International Journal of Robotics & Control Systems, 2024. 4(3).

[5] Zubaida Rehman, Noshina Tariq, Syed Atif Moqurrab, Joon Yoo, and Gautam Srivastava, Machine learning and internet of things applications in enterprise architectures: Solutions, challenges, and open issues. Expert Systems, 2024. 41(1): p. e13467.

[6] Kiran Joseph, Jyoti Shetty, Ashok K Sharma, Rudi Van Staden, Plp Wasantha, Sharna Small, and Nathan Bennett, Leak and Burst Detection in Water Distribution Network Using Logic-and Machine Learning-Based Approaches. Water, 2024. 16(14): p. 1935.

[7] Othmane Atanane, Asmaa Mourhir, Nabil Benamar, and Marco Zennaro, Smart Buildings: Water Leakage Detection Using TinyML. Sensors, 2023. 23(22): p. 9210.

[8] Dina Zaman, Manoj Kumar Tiwari, Ashok Kumar Gupta, and Dhrubjyoti Sen, A review of leakage detection strategies for pressurised pipeline in steady-state. Engineering Failure Analysis, 2020. 109: p. 104264.

[9] Nessrine Hartem, Etude des pertes d’eau dans les réseaux d’eau potable (cas réseau de la commune de Bendjerrah). 2020.