IoT-Based Intelligent Water Leak Detection System Using Transfer Learning: An Affordable Solution for Developing Countries

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Abstract

Water losses in distribution networks represent a major challenge for developing countries, particularly in Benin where they reach 30% of distributed volume. This research presents an intelligent and cost-effective leak detection system combining embedded systems, IoT (Internet of Things) and artificial intelligence. The methodology is based on a four-layer IoT architecture integrating the ADXL345 accelerometer, Arduino Uno and LoRaWAN (Long Range Wide Area Network) communication for vibro-acoustic signal acquisition. The innovation lies in applying transfer learning to adapt a CNN (Convolutional Neural Network) model trained on high-quality sensors (PCB33350) to consumer-grade MEMS (Micro-Electro-Mechanical Systems) sensors, addressing the scarcity of labeled data. The system integrates a React.js web platform with FastAPI backend. Results validate the approach's feasibility with a prototype operating continuously and has collected 19 hours of data for model training. The model achieves 96.2% sensitivity with a 66.7% F1-Score, prioritizing detection through a conservative strategy. The platform integrates real-time monitoring, geographic location, spectral visualization and history. This research demonstrates that a solution using consumer-grade components can effectively detect leaks with acceptable performance, paving the way for modernization of water infrastructure adapted to the Beninese context.

Keywords

IoT, leak detection, transfer learning, CNN, LoRaWAN

1. Introduction

Water is an essential resource for life, but it is increasingly threatened by the combined effects of population growth, rapid urbanization and climate change. In developing countries, ensuring equitable, continuous and quality access to drinking water represents a major technical and strategic challenge.

In drinking water distribution networks, leaks are one of the main factors of losses. According to the World Bank Water Supply and Sanitation Sector Board, water losses can represent up to 45% of distributed water in some sub-Saharan African countries [1]. Such a situation not only leads to waste of precious resources, but also to increased operating costs and reduced quality of service to populations.

At the same time, the rise of digital technologies, particularly those related to the Internet of Things (IoT), is profoundly transforming the way physical systems are monitored and controlled. IoT refers to a network of intelligent physical objects — sensors, actuators, embedded devices — capable of collecting, transmitting and processing data.

2. Problem Statement

In Benin, the Société Nationale des Eaux du Bénin (SONEB), responsible for providing drinking water in urban and peri-urban areas, faces similar difficulties. Aging infrastructure, pressure variations and urban growth increase the risk of leaks and complicate their rapid detection [2]. A report by the

CITA 2026 - Land, Smart Cities, and Sustainable Development, 25–26 June 2026, Cotonou, Benin

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African Development Bank (AfDB) published in 2014 estimated that total losses in the SONEB network amounted to approximately 26%, with a reduction target of 20% by 2023 [3].

Despite efforts to improve drinking water distribution in Benin, a significant portion of produced water does not reach users due to undetected leaks in underground pipes [4, 5]. One of the major problems lies in the absence of intelligent systems enabling real-time and automated leak detection.

This study aims to design and implement an intelligent water leak detection system based on connected sensors capable of identifying the acoustic and vibratory signatures characteristic of a leak in a pressurized pipe. The research hypothesis postulates that an embedded system based on vibro-acoustic signal analysis, integrated into a low-power IoT architecture and an intelligent detection algorithm, can enable automated and real-time monitoring of water distribution networks, even in resource-limited contexts.

3. Related Work

Leak detection methods in water distribution networks have undergone significant evolution over recent decades, transitioning from reactive manual techniques to automated and intelligent systems. This progression reflects a growing need for proactive monitoring to minimize physical and apparent losses, often grouped under the term *non-revenue water* (NRW). The state of the art in 2025 highlights a diversity of approaches, from direct physical principles to artificial intelligence algorithms, with a focus on acoustic and pressure signals as primary data sources.

3.1. Conventional Detection Methods

Conventional methods, standardized since the 1990s, rely on three main complementary approaches. The acoustic approach exploits vibrations generated by leaks in the 100 Hz to 5 kHz range, using geophones for localization with 1-5 m precision and acoustic correlators achieving 0.5-2 m on sections less than 500 m [6, 7]. Physical methods include tracer gas injection (helium, hydrogen at 5%) with over 90% success for leaks exceeding 1 L/h, and infrared thermographic imaging offering 80% sensitivity under favorable conditions [8, 9]. Finally, hydraulic analysis relies on minimum night flows (2h-4h) and pressure/flow monitoring, detecting with over 90% sensitivity leaks exceeding 10 L/h [1, 5]. While effective for point diagnostics, these approaches remain reactive and unsuitable for extended network monitoring.

3.2. Automatic Systems and Connected Sensors

The emergence of automatic systems in the 2010s marks a transition toward continuous water network monitoring. These systems combine permanent sensors installed on pipes with wireless communication technologies to transmit data in real-time to control centers.

Permanent sensors (pressure, flow, acoustic) continuously monitor network parameters, automatically detecting abnormal variations such as pressure drops exceeding 5-10% that signal potential leaks [5]. These devices, often battery-powered with several years of autonomy, capture vibro-acoustic signals in the 100 Hz to 5 kHz range characteristic of leaks.

Anomaly detection relies on statistical algorithms that compare current measurements to normal network profiles. Predefined thresholds (such as a night flow elevation exceeding 15%) trigger alerts, achieving over 85% detection for medium leaks [10]. More advanced techniques like autoencoders, which "learn" normal network behavior, offer performance exceeding 90% [11]. Specialized methods like FDM (Filter Diagonalization Method) finely analyze pressure signals [12], while adaptive LMS filters localize leaks with error less than 1.5 m [13].

IoT architectures use long-range communication protocols like LoRaWAN, which connect sensors to central servers over distances of 2 to 15 km with very low energy consumption (autonomy exceeding 5 years on battery) [14]. Systems like iPipe integrate acoustic sensors and geolocation for cloud monitoring [15], while mesh networks perform local pre-detection before transmission [16].

3.3. Intelligent Approaches Based on Artificial Intelligence

The most recent methods use artificial intelligence (AI) to automatically analyze sensor signals and detect leaks [17]. Unlike previous approaches requiring human intervention, these systems "learn" to recognize leak signatures from examples.

Classical Machine Learning Algorithms: These algorithms constitute a first step toward intelligent automation [18]. Support Vector Machines (SVM) create an optimal decision boundary between "with leak" and "without leak" signals, achieving detection rates of 85 to 90% on good quality signals [19]. Random Forests combine multiple decision trees to improve robustness, with performance around 88% even with little training data [10]. Clustering methods automatically identify patterns in data without needing labeled examples, particularly useful for exploring large amounts of data [20].

Deep Neural Networks: Deep neural networks represent the current state of the art [21]. Convolutional Neural Networks (CNN) excel in analyzing temporal signals and spectrograms, automatically learning relevant signal characteristics [22]. Specialized variants like TFCNN (Time-Frequency CNN) are particularly effective for vibro-acoustic signals, achieving detection rates exceeding 90% [23]. Hybrid CNN-LSTM architectures analyze both local patterns in signals and their temporal evolution, achieving 96% performance while significantly reducing false alerts [24].

Variational autoencoders (VAE) learn to "understand" normal network operation, then detect anomalies as deviations from this normal behavior [25]. Attention mechanisms allow the system to automatically focus on the most important parts of the signal. Techniques like joint time-frequency analysis (JTFA) simultaneously analyze temporal and frequency aspects of signals, achieving exceptional performance of 95.8% on standardized test networks [26].

Transfer Learning: Transfer learning refers to a set of techniques allowing reuse of knowledge acquired by a model on a source domain to improve performance on a different target domain [27, 28]. This approach is particularly relevant when labeled data from the target domain are rare or expensive to obtain, as is the case for leak detection in developing countries.

3.4. Comparative Synthesis and Identified Gaps

This literature review highlights a marked progression of leak detection methods over three decades. Manual approaches from the 1990-2000s (geophones, acoustic correlators, tracers) gradually gave way to automated systems integrating permanent sensors and wireless communication (2010s), then to artificial intelligence methods exploiting deep learning (2020s).

Performance has significantly improved: from 70% detection rate with conventional methods to over 95% with hybrid CNN architectures and time-frequency attention mechanisms [26]. In parallel, installation costs have increased (from a few hundred thousand FCFA per manual intervention to 45-120 million FCFA for an IoT system over 10-20 km), while requirements for labeled data and computational resources have grown for deep learning approaches.

Two types of signals dominate: vibro-acoustic signals (accelerometers, hydrophones) offer precise localization (error < 2 m) and low intrusiveness, but are sensitive to urban noise; hydraulic pressure signals allow global network monitoring but require precise modeling and high sensor density.

However, the majority of studies are conducted in developed country contexts with stable infrastructure. Their transposition to developing countries faces specific constraints: scarcity of labeled data, energy intermittency, unstable connectivity, network obsolescence and limited budgets. These constraints impose trade-offs between theoretical performance and operational viability, orienting research toward low-cost solutions based on consumer-grade MEMS sensors, low-consumption protocols (LoRa) and intelligent detection algorithms.

Table 1
Comparison of Microcontrollers for IoT Applications

Criterion	Arduino Uno	ESP32	STM32	Raspberry Pi
Processor	**ATmega328P**	Dual-core	ARM Cortex-M	ARM Cortex-A
Frequency	**16 MHz**	240 MHz	72 MHz	1.5 GHz
RAM	**2 KB**	520 KB	20 KB	1–8 GB
Flash	**32 KB**	4 MB	64 KB	SD Card
I2C/UART	**Yes**	Yes	Yes	Yes
Wi-Fi/BT integrated	**No**	Yes	No	Yes (Pi 3+)
Consumption	**50 mA**	160 mA	40 mA	500+ mA
Price (FCFA)	**13,000**	8,000	15,000	35,000+
Ease of use	**Very high**	Medium	Low	High

Sources: Datasheets from Atmel [29], Espressif Systems [30], STMicroelectronics [31] and Raspberry Pi Foundation [32]. Prices are indicative and based on local distributor rates converted to FCFA at February 2026 rate.

4. Methods and Data Source

4.1. Study Context and Hardware Selection

The developed leak detection system relies on a distributed IoT architecture, combining autonomous sensor nodes, long-range communication infrastructure and a software processing platform. Facing budgetary constraints of the Beninese context, each component was selected according to a cost/performance trade-off, prioritizing local availability and ease of operation.

4.2. Hardware Selection

Acquisition components form the heart of the detection system, integrating sensor, microcontroller and communication module for autonomous pipeline monitoring.

Vibro-Acoustic Sensor: The ADXL345 triaxial MEMS accelerometer was selected after comparison with other technologies (MPU6050, PVDF, PCB 3350) for its adequate spectral coverage (500-2000 Hz), precision comparable to piezoelectric sensors and cost/availability balance (3,700 FCFA vs 300,000+ FCFA for professional sensors).

Microcontroller: Arduino Uno was selected among several alternatives (ESP32, STM32, Raspberry Pi) for its immediate availability with compatible LoRa modules, programming simplicity and consumption/cost balance adapted to prototyping.

LoRaWAN Module: The Dragino LA66 module [33] (2-10 km range, low consumption) was chosen after evaluation of communication technologies (Wi-Fi, Zigbee, GSM/4G) for its range/autonomy balance and LoRaWAN compatibility allowing evolution toward public networks like TTN.

4.3. Reception and Processing Infrastructure

The reception infrastructure ensures collection, storage and processing of sensor data via free cloud solutions and a local processing server.

LoRaWAN Gateway: The 8-channel indoor gateway [37, 38] was preferred to outdoor solutions for its sufficient coverage in urban environment, simplified installation and reduced cost.

Network Server: The Things Network (TTN) is used as a free community LoRaWAN network server managing communication between gateways and IoT applications.

Cloud Platform: ThingSpeak ensures cloud storage of sensor data with REST (Representational State Transfer) API (Application Programming Interface), integrated visualization and processing capacity up to 3 million messages/year for free.

Table 2
Comparison of IoT Communication Technologies

Criterion	LoRaWAN	Wi-Fi	Zigbee	GSM/4G
Range	**2–10 km**	50–100 m	10–100 m	National
Consumption	**Very low**	High	Low	Very high
Data rate	**0.3–50 kbps**	150+ Mbps	250 kbps	1–100 Mbps
Module cost	**Medium**	Low	Medium	High
Subscription cost	**Free (TTN)**	Free	Free	Monthly
Wall penetration	**Excellent**	Medium	Medium	Excellent
Infrastructure	**Gateway**	Router	Coordinator	Operator antenna
Battery autonomy	**Years**	Days	Months	Days

Sources: Official specifications from LoRa Alliance [14], IEEE 802.11 [34], Zigbee Alliance [35] and 3GPP [36]. Characteristics are based on standards and manufacturer documentation.

Table 3
Comparison of Vibro-Acoustic Sensors

Criterion	ADXL345 (MEMS)	MPU6050 (MEMS)	PVDF LDT0-028K	PCB 33350 (Piezo)
Measurement range	**±16g**	±16g	High voltage	±500g
Resolution	**13 bits**	16 bits	High (piezo)	100 mV/g
Bandwidth	**1600 Hz**	260 Hz	40–180 Hz	0–10 kHz
Interface	**I^2C/SPI**	I^2C	Analog	IEPE
Consumption	**40 μA**	3.9 mA	$< 1\ \mu$A	2–10 mA
Price (FCFA)	**3,700**	2,500	10,000+	300,000+
Availability	**High**	High	Low	Low

Sources: Datasheets from Analog Devices [43], InvenSense [44], TE Connectivity [45] and PCB Piezotronics [46]. Prices are indicative and based on distributor rates (Mouser/DigiKey) converted to FCFA at February 2026 rate.

Processing Server: A local server (Intel Core i5/i7, 8-16 GB RAM, Kali Linux) hosts the entire software chain: data retrieval from ThingSpeak, signal preprocessing, CNN model inference, and database management.

4.4. Software Infrastructure and Development

The software infrastructure integrates analysis backend, user interface and AI development environment for a complete monitoring and alert solution.

Backend: FastAPI [39] ensures data retrieval from ThingSpeak, signal preprocessing, CNN model inference, and alert management.

Frontend: React.js [40] provides the interactive user interface for data visualization, alert management and backend API interaction.

Database: SQLite [41] locally stores CNN model analysis results, detected leak alerts and event history.

AI/ML Environment: CNN model development uses Python libraries TensorFlow/Keras, NumPy, SciPy, Librosa for vibro-acoustic analysis, and Scikit-learn for performance evaluation.

Reference Dataset: The model is trained on the dataset from Aghashahi et al. [42], comprising 280 recordings of 30 seconds with different leak types (orifice, cracks, joints) and no-leak conditions, enabling supervised training with real and diversified examples.

4.5. Study Data

Two data sources were used. The reference dataset from Aghashahi et al. [42] comprises 280 recordings of 30 seconds with different leak types (orifice, cracks, joints) and no-leak conditions, enabling supervised training with real and diversified examples.

For adaptation to the Beninese context, field data were collected in Saketé — a town located approximately 60 km north of Cotonou in the Plateau department of Benin, served by a SONEB water distribution network — using the ADXL345 accelerometer fixed on a mushroom farm pipeline. Over 19 hours of vibro-acoustic data were collected via the complete chain: ADXL345 → Arduino Uno → LoRa LA66 → Gateway → TTN → ThingSpeak.

4.6. Study Design

4.6.1. Four-Layer IoT Architecture

The developed leak detection system follows the four-layer IoT architectural paradigm, enabling a modular and scalable approach adapted to water distribution network constraints (Fig. 1).

Perception Layer: Integrates autonomous sensor nodes composed of an Arduino Uno microcontroller, an ADXL345 MEMS accelerometer, and a Dragino LA66 LoRa communication module. Deployed directly on pipelines, these nodes ensure continuous acquisition of vibro-acoustic signals characteristic of leaks.

Network Layer: Manages data transmission using the LoRaWAN protocol operating in the 868 MHz ISM (Industrial, Scientific and Medical) band for long-range (2-10 km) low-consumption communication. Data frames are routed via a LoRa gateway to The Things Network (TTN) server, then redirected to the ThingSpeak cloud platform.

Processing Layer: Centralizes system intelligence by hosting detection and classification algorithms. A server runs a FastAPI backend that periodically retrieves data from ThingSpeak, applies necessary preprocessing, and executes the trained CNN model for inference.

Application Layer: Provides the end-user interface as a web application developed in React.js enabling real-time sensor data visualization, leak detection alert display, event history consultation, and system parameter configuration.

4.7. Study Methods

4.7.1. CNN Model and Transfer Learning

The detection model implements a binary classification approach (LEAK / NO LEAK) based on a convolutional neural network with transfer learning for adaptation from high-quality sensors to ADXL345.

Preprocessing Pipeline: Temporal signals are segmented into 2-second windows with 50% overlap, then converted into 224×224 pixel mel-spectrograms via the Librosa library, capturing spectral signatures characteristic of leaks in the optimized 100-2000 Hz band.

Modular CNN Architecture: The architecture separates feature extraction from classification to facilitate transfer learning (Fig. 2). The Feature Extractor comprises four convolutional blocks (32 → 64 → 128 → 256 filters) extracting hierarchical features: basic contours and frequency transitions (block 1), spectral textures and repetitive patterns (block 2), complex structures and pattern combinations (block 3), high-level representations specific to leaks (block 4). Each block integrates 2D convolution, batch normalization, ReLU activation and max pooling. The binary classifier uses global average pooling followed by dense layers with dropout for regularization and final decision via sigmoid function.

Transfer Learning Strategy: Model adaptation from PCB33350 sensors to ADXL345 follows a three-phase approach illustrated in Fig. 3: (1) Source training of the complete model on high-quality PCB33350 data, (2) Freezing of convolutional layers to preserve learned features and initialization of a new ADXL345-specific classifier, (3) Targeted fine-tuning of the classifier only on ADXL345 data with reduced learning rate.

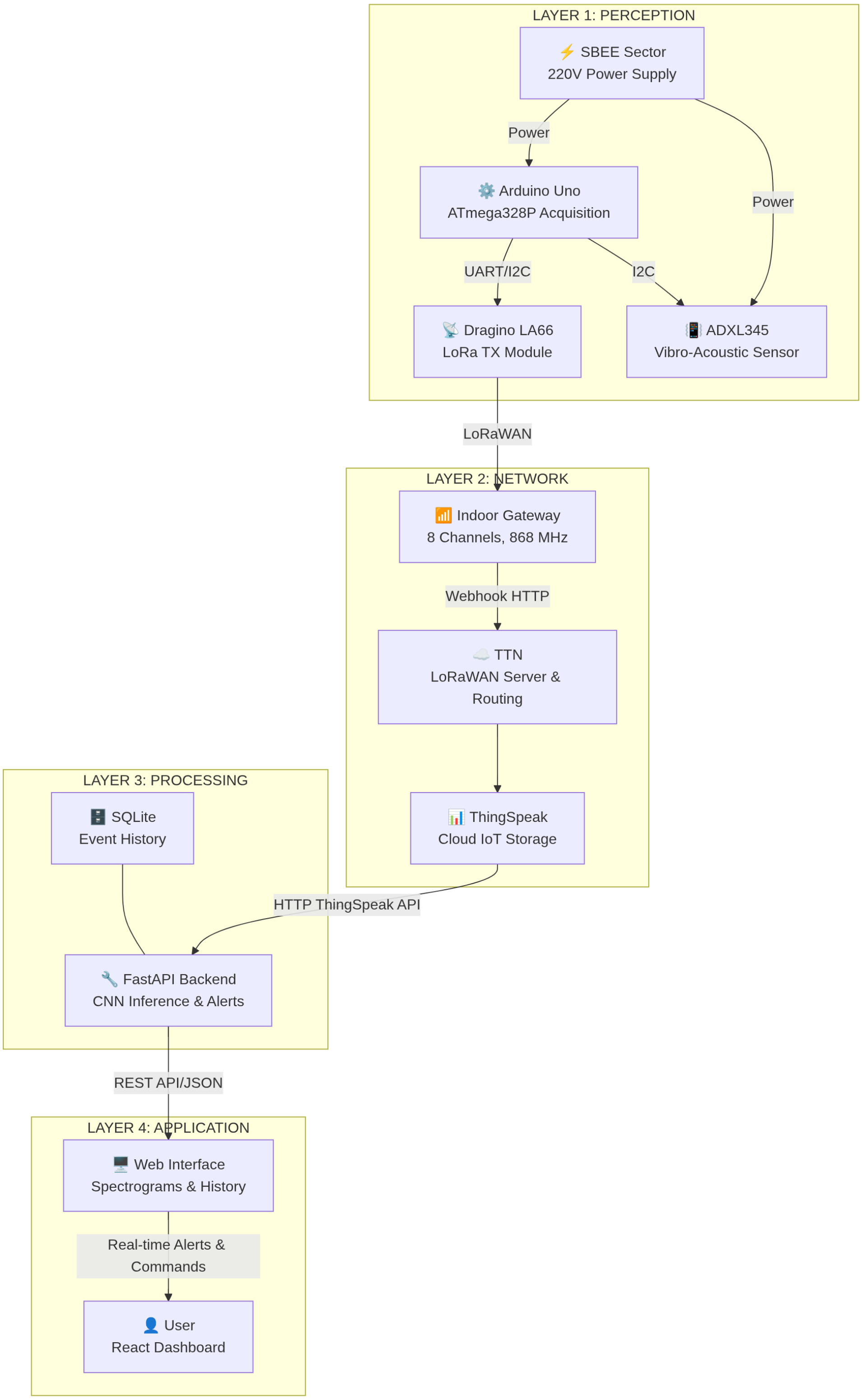

Figure 1: Complete system architecture with four IoT layers

4.7.2. Deployment and Data Collection

The prototype was deployed and tested on-site in Saketé, fixed directly on the mushroom farm pipeline. The system operates permanently on-site and continues to send data in real-time.

Training data were generated by controlled manipulation of the shut-off valve to simulate flow varia-

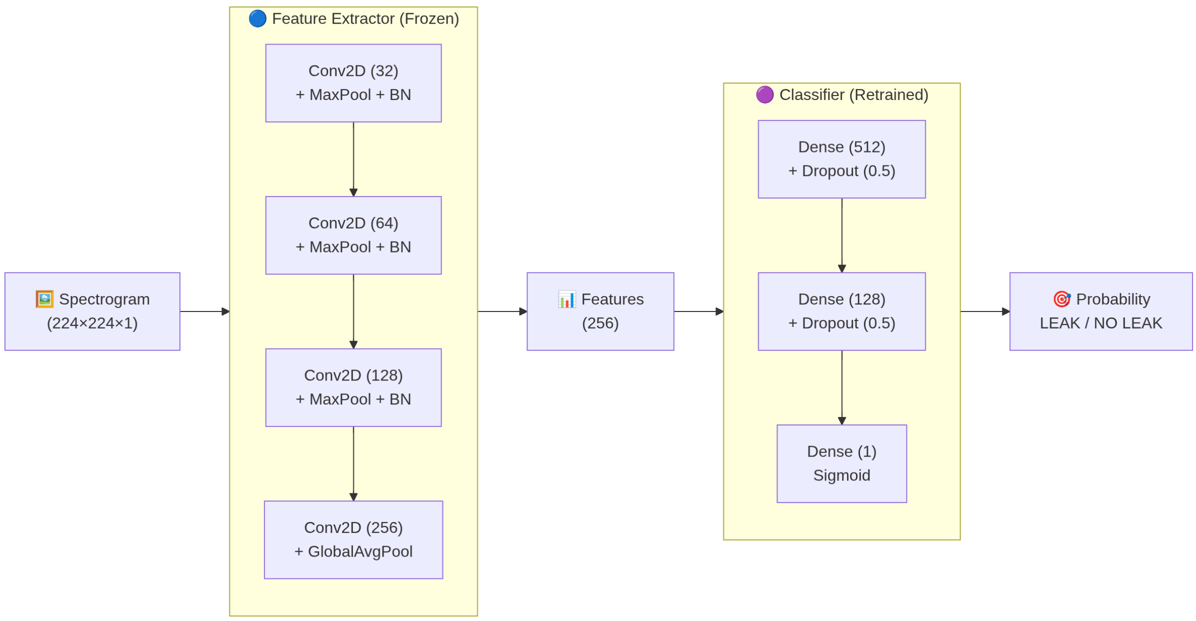

Figure 2: Compact modular CNN architecture for transfer learning

Figure 3: Transfer learning process PCB33350 → ADXL345

tions characteristic of leaks. Acceleration values from the three axes (X, Y, Z) are transmitted every 10 seconds via LoRaWAN. This choice respects the 1% duty cycle imposed by the ETSI (European Telecommunications Standards Institute) EN 300 220 standard [47] for the 868 MHz band. In Benin, ARCEP (Autorité de Régulation des Communications Électroniques et de la Poste) [48] adopts the EU868 frequency plan [49], aligned with these constraints to avoid network saturation.

5. Implementation

System implementation integrates selected hardware and software components into an operational architecture deployed in the field.

5.1. Acquisition Hardware

The prototype deployed in Saketé integrates the ADXL345 fixed directly on the pipeline. The system operates permanently and transmits acceleration values via LoRaWAN.

5.2. Communication and processing infrastructure

The 8-channel indoor gateway ensures reception of LoRa frames. The Things Network (TTN) is used as a free community LoRaWAN network server. ThingSpeak ensures cloud data storage. A local server hosts the entire software chain with FastAPI, React.js and SQLite.

Figure 4: Prototype deployed on-site in Saketé: ADXL345 sensor fixed on the pipeline

6. Results

6.1. Reference model performance

The CNN model trained on the PCB33350 reference dataset achieved exceptional performance: 99.8% Accuracy, 99.7% Precision, 100% Recall, and 99.9% F1-Score. The AUC-ROC (Area Under the Receiver Operating Characteristic Curve) of 1.000 indicates perfect class separation, establishing a solid foundation for transfer learning.

6.2. Transfer Learning Results

The ADXL345 dataset was constituted from field data collected in Saketé, segmented into 50-point windows with 50% overlap, then synthetically augmented to obtain 262 balanced segments. Transfer learning was performed by freezing feature layers and retraining only the classifier on ADXL345 data.

The model achieved the following performance on ADXL345 data:

- Accuracy: 52.8%
- Precision: 51.0%
- Recall (Sensitivity): 96.2%
- F1-Score: 66.7%
- AUC-ROC: 0.707

The confusion matrix reveals high sensitivity (96.2%) for leak detection at the cost of more moderate precision (51.0%) and low specificity (11.1%), indicating the model's tendency to favor detection over specificity. The AUC-ROC of 0.707 reflects this trade-off between sensitivity and specificity, characteristic of the conservative detection strategy adopted with a decision threshold of 0.3.

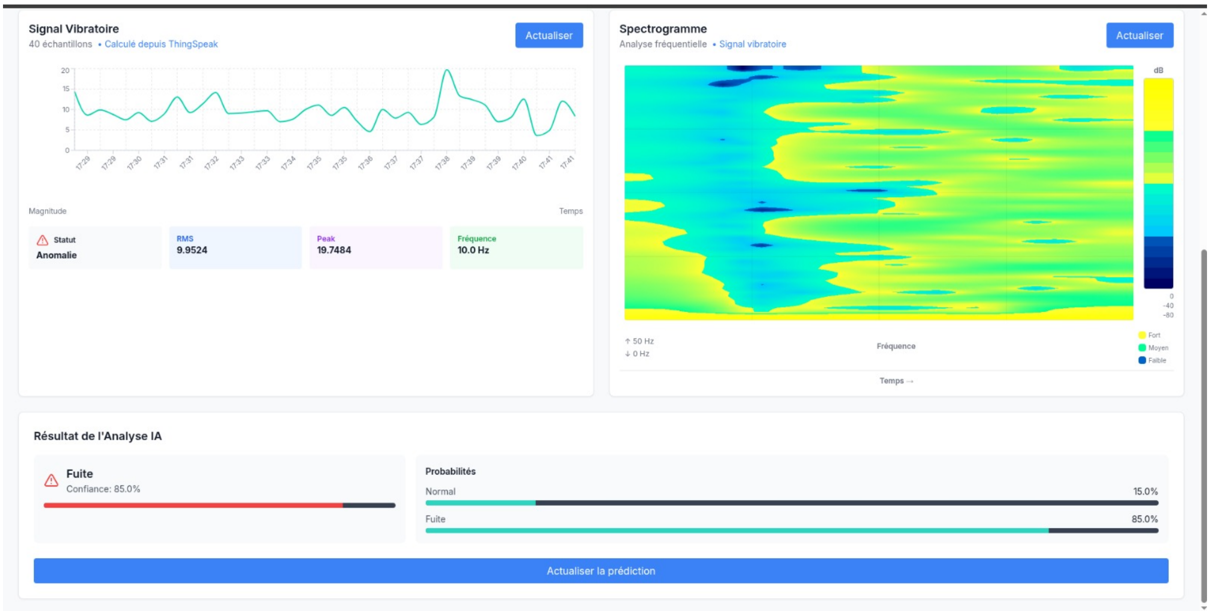

Figure 5: Monitoring interface: triaxial curves and real-time spectrogram

6.3. Monitoring Platform

The developed monitoring platform integrates a complete web interface enabling real-time sensor monitoring and automatic vibro-acoustic data analysis (Fig. 5). The interface presents an interactive network map for precise geographic sensor location, real-time monitoring displaying triaxial acceleration curves and corresponding spectrograms, and AI analysis results with leak detection probability and status.

6.4. Discussion

The 33-point performance difference between PCB33350 (F1-Score: 99.9%) and ADXL345 (F1-Score: 66.7%) models is expected, as PCB33350 sensors are high-precision professional sensors while ADXL345 is a cheaper and less precise MEMS sensor.

High sensitivity (96.2%) with moderate precision (51.0%) reflects a conservative strategy appropriate for critical infrastructure monitoring, where missing a real leak is more costly than false alarms. The decision threshold at 0.3 (instead of 0.5) confirms this safety choice.

Despite limitations of leak simulation by valve manipulation and limited sampling frequency (0.1 Hz due to LoRa transmission constraints), results prove that a low-cost detection system can operate in Benin and could be deployed on the SONEB network.

7. Conclusion and Future Work

This research demonstrates the technical and economic feasibility of an intelligent IoT leak detection system adapted to the Beninese context. The developed approach effectively combines embedded systems, IoT technologies and artificial intelligence to propose an innovative solution to water infrastructure monitoring challenges in developing countries.

Results validate the research hypothesis by confirming that an integrated solution using consumer-grade components can effectively detect leaks with acceptable performance and controlled cost. The main innovation lies in the successful application of transfer learning to adapt a model trained on professional sensors to consumer-grade MEMS sensors, addressing the scarcity of labeled data characteristic of field applications.

The prototype deployed in Saketé confirms the operational viability of the developed IoT architecture, successfully integrating ADXL345 acquisition, LoRaWAN transmission and web monitoring platform. This demonstration provides a solid foundation for larger-scale deployment on the SONEB network.

The implications of this research extend beyond the Beninese context and concern all African countries facing similar water infrastructure management challenges. The developed approach, prioritizing economic accessibility and local maintainability, paves the way for progressive technological modernization adapted to local constraints and resources.

Improvement perspectives include dataset enrichment with diversified real leaks, integration of complementary sensors to reduce false positives, and implementation of adaptive learning algorithms for continuous performance optimization. In the longer term, this research contributes to the emergence of an endogenous technological approach for water resource management in Africa.

Declaration on Generative AI

During the preparation of this work, the author(s) used ChatGPT in order to: translate part of the manuscript from French to English and perform grammar and spelling checks. After using this tool, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the publication's content.

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