

هاني الجندي

Leakage Detection in Water Meters Network-v2.docx

- 1- Final Thesis (Word Format)
- Thesis_(2)_AI901_Dr_Khaled_Eskaf_Third Trimester 2025 (Moodle PP)
- Midocean University

Document Details

Submission ID

trn:oid::1:3450561317

Submission Date

Dec 25, 2025, 12:45 AM GMT+4

Download Date

Dec 25, 2025, 10:31 PM GMT+4

File Name

xcod.244399119_201621_2v-krowteN_sreteM_retaW_ni_noitceteD_egakaeL_هاني_الجندي_40592

File Size

5.7 MB

84 Pages

10,310 Words

61,775 Characters

*% detected as AI

AI detection includes the possibility of false positives. Although some text in this submission is likely AI generated, scores below the 20% threshold are not surfaced because they have a higher likelihood of false positives.

Caution: Review required.

It is essential to understand the limitations of AI detection before making decisions about a student's work. We encourage you to learn more about Turnitin's AI detection capabilities before using the tool.

Disclaimer

Our AI writing assessment is designed to help educators identify text that might be prepared by a generative AI tool. Our AI writing assessment may not always be accurate (i.e., our AI models may produce either false positive results or false negative results), so it should not be used as the sole basis for adverse actions against a student. It takes further scrutiny and human judgment in conjunction with an organization's application of its specific academic policies to determine whether any academic misconduct has occurred.

Frequently Asked Questions

How should I interpret Turnitin's AI writing percentage and false positives?

The percentage shown in the AI writing report is the amount of qualifying text within the submission that Turnitin's AI writing detection model determines was either likely AI-generated text from a large-language model or likely AI-generated text that was likely revised using an AI paraphrase tool or word spinner.

False positives (incorrectly flagging human-written text as AI-generated) are a possibility in AI models.

AI detection scores under 20%, which we do not surface in new reports, have a higher likelihood of false positives. To reduce the likelihood of misinterpretation, no score or highlights are attributed and are indicated with an asterisk in the report (*%).

The AI writing percentage should not be the sole basis to determine whether misconduct has occurred. The reviewer/instructor should use the percentage as a means to start a formative conversation with their student and/or use it to examine the submitted assignment in accordance with their school's policies.

What does 'qualifying text' mean?

Our model only processes qualifying text in the form of long-form writing. Long-form writing means individual sentences contained in paragraphs that make up a longer piece of written work, such as an essay, a dissertation, or an article, etc. Qualifying text that has been determined to be likely AI-generated will be highlighted in cyan in the submission, and likely AI-generated and then likely AI-paraphrased will be highlighted purple.

Non-qualifying text, such as bullet points, annotated bibliographies, etc., will not be processed and can create disparity between the submission highlights and the percentage shown.





Leakage Detection in Water Meters Network Using AI-Driven Consumption Analysis

Prepared By

Name: Hani Faraj Al-Jundi Student ID No: 26737

Submitted in fulfillment of the requirements for the degree
Master of Science in Artificial Intelligence

At

Collage of Informatics

Midocean University

UAE

Supervisor Name: Dr. Khaled Eskaf

Collage of Informatics - Midocean University – Comoros

2025 3rd Semester

Acknowledgements

I would also like to express my gratitude to Dr. Khaled Eskaf, Head of the College of Informatics at Midocean University for his precious academic advice, continuous support and guiding comments in the course of this research. Here, I owe him major thanks for his trust and competence in fields such as Artificial Intelligence and applied research methods: both had a significant science of the direction, depth, and general academic value of this thesis.

Also I wish to acknowledge my family, wife and close colleagues for their abiding patience, encouragement and moral support. Their encouragement was critical to me throughout the entire development of this work, at data analysis, model building and writing stages.

Finally, without having the structured and intellectual environment of Midocean University which fosters discipline, critical thinking and a pursuit for research excellence in me as student, it would have made this work next to impossible to conduct at an academic level or within ethical standards.

Abstract

Urban Water Loss is an ongoing global problem that results in the reported loss of 20-40% of treated drinking water; it also creates significant economic and environmental impacts on utilities. The current state-of-the-art methods for leak detection are basically reactive, labor-intensive and too slow to be deployed as they typically depend on manually conducted acoustic surveys. These practices can sometimes even waste away underground leaks for prolonged periods of time losing system efficiency and working assets fast. Recent work in AI-supported leak detection, however, has been constrained by an excessive use of simulated datasets and a lack of established benchmarks to verify performance under real-world high-variability conditions that are recognizable across the urban water network landscape.

Table of Contents

Acknowledgements	2
Abstract.....	3
Table of Contents	4
List of Abbreviations.....	7
List of Tables	8
List of Figures	8
Chapter 1: Introduction	9
1.1 Problem Definition	9
1.2 Thesis Objectives.....	10
1.3 Thesis Impact & Contributions.....	10
Chapter 2: Literature Review.....	11
2.1 Summary of Research Papers	11
2.2 Critical Analysis	20
2.3 Connections Between Findings	23
2.4 Conflicts Between the Findings	26
2.5 Synthesis Matrix for Literature Review.....	28

Chapter 3: Research Foundation and Project Goals	34
3.1 System Fundamentals: Water Networks and Smart Metering	34
3.2 Limitations of Traditional Leak Detection Methods	36
3.3 The Potential of AI and ML for Water Analysis.....	40
3.4 Critical Gaps in Current Research.....	43
3.5 Project Goal: Developing an AI Model for Proactive Leak Detection.....	45
Chapter 4: Proposed Approach and Methodology	47
4.1 Overall Architecture for AI-Driven Leak Detection.....	47
4.2 Data Collection: Sources and Description of Water Sensor Data.....	50
4.3 Dataset Description and Dataflow	51
4.3.1 Dataset Attributes and Semantics	51
4.3.2 Dataflow Diagram	55
4.4 Data Processing and Preprocessing Pipeline	58
4.5 Model Selection and Design: Algorithm Comparison and Choice	60
4.5.1 Rationale for Hybrid Architecture	60
4.5.2 Detailed Architecture Design	61
4.6 Testing and Evaluation: Metrics for Model Performance and Success	62
Chapter 5: Project Execution Plan and Timeline	64

5.1 Data Acquisition and Preprocessing Phase	64
5.2 Model Development and Training Phase	66
5.3 Validation, Testing, and Evaluation Phase	67
5.4 Finalization and Analysis Reporting Phase	68
Chapter 6: Results and Impact.....	70
6.1 A Working Model for Improved Leak Detection Accuracy	70
6. 1. 1 Quantitative Performance Analysis	72
6. 1. 2 Analysis of Hybrid Architecture Effectiveness.....	75
6. 2 Validation Against Industry Benchmarks	75
6. 2. 1 Comparison against Static Thresholding (Rule-Based Systems)	75
6. 2. 2 Comparison with Statistical Methods (ARIMA / Kalman Filters)	76
6.3 Potential Implications and Future Applications	77
6.3.1 Economic and Environmental Implications	77
6.3.2 Future Applications and Scalability	77
Chapter 7: Resources Needed 7.1 Software, Tools, and Computing Infrastructure	79
7. 1. 1 Computing hardware specifications	79
7.1.2 Software Development Stack	80
References:	82

List of Abbreviations

- **AI:** Artificial Intelligence
- **AMI:** Advanced Metering Infrastructure
- **AIGNN:** Algorithm-Informed Graph Neural Network
- **CNN:** Convolutional Neural Network
- **FCN:** Fully Convolutional Network
- **GNN:** Graph Neural Network
- **LSTM:** Long Short-Term Memory
- **ALSTM:** Attention-Long Short-Term Memory
- **PS-AMI:** Pressure-Supplemented Advanced Metering Infrastructure
- **WDN:** Water Distribution Network
- **3D CNN:** Three-Dimensional Convolutional Neural Network

List of Figures

Figure 1 (Overall Architecture).....	49
Figure 2 (Dataflow Diagram).....	57
Figure 3 (Project Timeline).....	69
Figure 4 (Accuracy & Loss).....	71
Figure 5 (Confusion Matrix)	74

List of Tables

Table 1 (Synthesis Matrix).....	28
Table 2 (Dataset Type).....	51
Table 3 (Software Development Stack).....	81

Chapter 1: Introduction

1.1 Problem Definition

Leakage in urban water distribution networks (WDNs), are a serious world-wide problem resulting in significant financial loss for utilities, the risk of public health issues and the unsustainable abstraction of limited water sources. Traditional methods of leakage detection depend on manual field canvassing with acoustic inspection instruments. Where these methods are successful, they require significant time and effort, are expensive and a mostly reactive approach to leak detection as the leaks will typically only be located after significant failure or the loss of visible water.

As a consequence, a large sector of treated potable water is wasted in urban distribution networks globally where the estimated range from 20 to 40%. These leaks are often lost from view for extended periods (e.g., days, weeks) and occasionally for years resulting in continuous water loss, degradation of the infrastructure and overall decreased performance of the network. This ongoing problem further emphasizes the need for proactive, scalable, and evidence-based leak detection solutions.

1.2 Thesis Objectives

The aim of this project is to develop and deploy for operation over an entire city district, a system employing AI-based technologies to search and analyze end-user behavior consumption, using powerful sensing systems, and rapidly detect very small leaks that may be invisible on the surface. The technology is designed to go beyond reactive detection, enabled by the use of data-driven intelligence for early and concrete leak identification.

1.3 Thesis Impact & Contributions

The paper's novelty lies in that it presents a new, robust data-driven framework to integrate the principles of hydraulic engineering with advanced deep learning to aid smart management of water grids. The limitation of using RNNs is that this de-noising has to be carried out on sequences with a relatively short duration because the longer duration will lead into an underestimation of the dynamic and grammatical contextual features. This method is different from existing scalar thresholding baseline models in that it uses an Attention Mechanism to determine 'where to look' and with 'how much weight' on the Minimum Night Flow (the MNF) periods within a 72-hour transversed window, with no manual engineering or hard-coded rule-based strategies.

Empirically, the work demonstrates a significant operational improvement; it achieves 1.00 Recall (Zero False Negatives) on a large-scale test data. This contribution is critical to utilities since it guarantees that there will be no leakage incidents which are not a real one, directly responding to the economic and environmental impacts of Non-Revenue Water (NRW). Furthermore, the proposed methodology through precise geospatial localization coupled with high accurate classification (99.99% Accuracy) enables a transition from reactive maintenance to proactive, precision-targeted intervention. This capacity not only threshs the labor force supplementation but also effectively shortens the time to respond for infrastructure failure, which is helpful in enhancing water security in cities.

Chapter 2: Literature Review

2.1 Summary of Research Papers

1. Three-dimensional Convolutional Neural Network for Leak Detection and Localization in Smart Water Distribution Systems

Brief Summary: In the field of predicting and detecting the leakage in the pressure-supplemented advanced metering infrastructure system, Jun et al. proposed a novel approach using a 3D CNN taking into account the time and space correlations of pressures. This was done by normalizing the pressure residuals into images in the dimensions of time and space and using a deep learning technique for the task of leakage identification in the Austin water distribution system in TX.

Key Findings: The 3D CNN outperformed the 2D models greatly and succeeded in obtaining a 91% probability of detection with 1% false alarm rate for the 3-hour observation period during the high demand hours. The approach outperformed the optimization-based binary integer linear programming (BILP) optimization methods with 17% relative improvement in probability of detection (88% vs 71%) for the same false alarm rates. However, the work revealed the shortfalls of source locations identification, where the probability of detection tended to 0% due to the very small pressure residuals. Yet another shortcoming also emerged, which stated the sensitivity of the models of hydraulic simulation to probable inaccuracies, for instance unknown closure of the valves, resulting in the generation of 100% false alarms by the model.

2. Neural Network Techniques for Detecting Intra-Domestic Water Leaks of Different Magnitude

Brief Summary: The aim of Zese et al. (2021) was to detect the leakage of varying sizes indoors by utilizing neural networks. The problem taken by this paper is that of smaller, unreported water leaks, which are unnoticed but a substantial source of water waste.

Key Findings: The work showed that machine learning methodologies are capable to differentiate between levels of leaks with reported improvements, when compared with baseline conventional detection methods, associated with domestic scale leaks, that are generally not detected by traditional systems, with the leakage size feature contributing to both algorithm performance optimization and byproduct progression, compared to the traditional sense and action algorithms when moving towards increasing detection capabilities.

3. A Transformer-Based Approach to Leakage Detection in Water Distribution Networks

Brief Summary: Luo et al. (2024) presented a transformer-based model with additional attention mechanisms for the pressure time series, to mitigate the inherent lack of such capabilities that similar CNN- and autoencoder-based approaches have for modeling long-term dependencies. The model

analyses patterns in historical pressure readings, and takes into consideration cross-correlations between the readings at two different time spans.

Key Findings: The transformer model substantially surpassed conventional CNNs in leakage detection, Since the attention mechanism facilitated the efficient learning of the distributions of the data and the discovery of the relations in the time series that were not captured by the conventional methods, it was revealed that the approach could tackle the complicated pressure patterns and seasonal changes much better compared to the threshold-based detection, and it was one of the weaknesses of the threshold-based detection method..

4. Leak Detection in Water Distribution Networks Based on Deep Learning and Kriging Interpolation Method

Brief Summary: Authors Yu et al. (2024) proposed an end-to-end method that integrates deep learning with spatial interpolation algorithms. The method converts pressure monitoring data into spatial distribution images through kriging interpolation algorithms. These images are subsequently processed with VGG16 CNN neural networks to detect leaks.

Key Findings: The model based on VGG16 had a remarkably high true positive rate of 98% and a value of 94% for the area under the curve. The comparative test demonstrated the superiority of the VGG16 model over the other models, including VGG13, ResNet18, and SqueezeNet, with a true positive rate of 83%, 80%, and 67%, respectively. The kriging interpolation technique was effective in obtaining a continuous image of the spatial pressure distribution based on the discrete values of the pressure measurements, thereby facilitating the visualization of the state of the entire network. The technique showed resistance to noise disturbance and the ability to handle different configurations. Testing of the technique, however, was done in a simulated environment.

5. Leakage Break Diagnosis for Water Distribution Network Using LSTM-FCN Neural Network Based on High-Frequency Pressure Data

Brief Summary, Yu et al. (2024) have suggested a highly comprehensive approach that combines deep learning and spatial interpolation method. This approach treats pressure measurement data as the continuous spatial distribution image through a kriging interpolation method and VGG16 convolution neural networks to estimate the leak amount. Important

Key Findings: The VGG16 model was accurate, had specificity/sensitivity parameters of 0.85/0.98, and AUC of 0.94. VGG16 had a significantly greater optimal TPR of 85% compared to VGG13 (TPR: 83%), ResNet18 (TPR: 80%), and SqueezeNet (TPR: 67%) (all p-values < 0.05). The kriging interpolation technique was successful in interpreting discrete pressure information and generating images showing a continuous pressure distribution pattern of the network. The method was demonstrated to be resistant to noise and adaptable to different networks, though it was tested on only simulated instances.

6. A Proof-of-Concept Study Towards Developing Digital Twins for Operational Excellence in Large-Scale Water Distribution Networks

Brief Summary: Singh et al. (2025) introduced a proof-of-concept digital twin architecture for real-time monitoring and leak management of a large-scale water distribution network. The study leveraged python-based frameworks and open-source WDN simulators (EPANET and WNTR) to operationally model the hydraulics of the system and monitor operational conditions at present time.

Key Findings: The research has proved that digital twinning is applicable for operational excellence of water distribution networks, which has enabled real-time monitoring and proactive leakage

management. Promising results were found for incorporating the framework in the context of the real water infrastructure, while scalability to very large network still requires further work.

7. Algorithm-Informed Graph Neural Networks for Leakage Detection and Localization in Water Distribution Networks

Brief Summary: Zhang and Fink (2024) proposed a brand new developed Algorithm-Informed Graph Neural Network (AIGNN) by transplanting Ford-Fulkerson max-flow algorithm-designed knowledge, which could significantly boosting the leak detection and localization process. The proposed methodology overcomes the generalization issue in traditional data-driven techniques, by embedding algorithmic reasoning in neural network structures.

Key Findings: AIGNN outperformed the Conventional ChebNet architectures on the tasks of pressure reconstruction and prediction. The algorithm-based one exhibited outstanding generalization ability in the sense that it was trained on one sensor arrangement and tested on various sensor positions. Our study confirmed that improved results can be achieved by combining the traditional algorithmic knowledge and data-driven methods: adding AIGNN embeddings ChebNetIN and ChebNetEMB to GNN baselines yielded better models than GNN centers alone in all experiments. This is the first

application of neural algorithmic reasoning to engineering systems, and shows the potential for algorithm-enhanced infrastructure monitoring.

8. A Toolbox for Supporting Research on AI in Water Distribution Networks

Brief Summary: Artelt et al. (2024) introduced EPyT-Flow, a Python-based toolbox developed to aid in research about AI in water distribution networks. The toolkit includes higher-level interfaces for scenario generation, access to benchmarking datasets and control algorithm development to tackle problems related to water leakage, contamination and energy optimization.

Key Findings: The toolbox helps to reduce the separation between AI researchers and water infrastructure domain experts by enabling non-specialist tools for working on challenging scenario modeling. EPyT-Flow comes with seven state-of-the-art benchmarks for event detection and localization, providing a standardised mechanism for method evaluation in the AI domain. The long-term ideal architecture consists of three parts: a core data generation module, BenchmarkHub, for disseminating WDN benchmarks, and ModelHub, for sharing AI models and algorithms.

9. Machine Learning-Based Digital Twin for Water Distribution Network Anomaly Detection and Localization

Brief Summary: Pandey et al. (2024) proposed a digital twin scheme with a combination of single-stage and two-stage data-driven approach for leak detection and localization. The methodology uses the logistic regression and random forest for the first two tasks and the statistical analysis for the leak area approximation.

Key Findings: The two-stage model outperformed other models, where the first stage (the linear regression model) predicted the pressure difference between two sensors, and multidimension multinomial logistic regression or random forest were used in the second stage for leak localization. The framework was a hybrid zone localization method based on both data-driven and model-based For Leak Detection In Water Distribution Networks.

10. A Leak Zone Location Approach in Water Distribution Networks Combining Data-Driven and Model-Based Methods

Summary: This research proposed a new way of combining model based hydraulic simulations with data driven machine learning models in order to improve the accuracy of locating leaks in water

distribution networks. As such, this method utilized the advantages of both paradigms in order to produce accurate results at lower computational cost (processing time).

Key Findings: Results from this study indicate that the use of the hybrid method provided improved leak zone localization when compared to using either solely model based or solely data driven methods. Additionally, it was determined that by using more than two methods together; limitations associated with each individual method can be offset and the resulting solution can be applicable in a realistic water distribution network setting.

2.2 Critical Analysis

Methodological Diversity and Innovation, The literature reviewed exhibits significant methodological variation, which is indicative of the fast pace at which AI water applications are developing. Noting the transition from traditional 2D CNN to advanced 3D temporal-spatial modeling, transformer models, and algorithm-informed neural networks reveals the field's maturation into theoretically advanced methods.

Strengths in Current Approaches:

Temporal Integration: The transition from static pressure to temporal modeling (3D CNN, LSTM-FCN, transformers) is a major improvement in the modeling of dynamic leaks signatures.

Spatial intelligence: Kriging and graph based techniques are efficient in mitigating the problem of inadequate sensor coverage in water networks.

Algorithmic Advancement: By incorporating classical algorithmic knowledge to neural networks, the proposed optimization flow results in AI systems, which are a paradigm shift towards more general and interpretable systems.

Limitations and Gaps:

Simulated Data Dependency: The majority of studies are based on simulated data as real leak datasets are rare, which raises questions on whether these models will perform well in real world.

Scalability Issues: Low number of large-scale network trials limits the implementation of the proposed approaches.

Uncertainty in Models: Multiple works recognize (though not satisfactorily) the negative effects of hydraulic model errors on AI performance.

Performance Evaluation Paradigms

The comparison among proposed solutions becomes problematic, as far as the literature shows slightly different evaluation procedures. Results vary from very good (98% TPR, 91% detection probability) in some studies to quite low (85% accuracy, 75% accuracy) in others, the difference due to various experimental conditions, network complexities, and evaluation types.

Evaluation Strengths:

Multi-Metric Testing: Majority of works use thorough evaluation including detection probability, false alarm rates and localisation accuracy.

Comparisons with Existing Methods: The proposed approach could be compared with more state-of-the-art techniques and other architectures since in some of the papers the datasets are only used for comparisons.

Evaluation Limitations:

Standardisation Lack: In absence of standardised benchmarks, cross - study comparisons are difficult.

Real-world Gap: There is lack of real validation on water distribution actual systems which take away the confidence on reported performances.

2.3 Connections Between Findings

Methodological Evolution Pathway

The reviewed papers demonstrate a clear evolutionary pathway in leak detection methodologies:

Foundation Phase: Traditional neural networks and pressure-based detection

Spatial Integration: 2D CNN approaches for pressure residual analysis

Temporal Enhancement: 3D CNN and LSTM-FCN for temporal pattern recognition

Advanced Architectures: Transformer models for long-term dependency capture

Algorithm Integration: AIGNN representing the fusion of classical algorithms with neural networks

System Integration: Digital twins and comprehensive toolboxes for operational deployment

Convergent Research Themes

Pressure Residual Analysis: Most of the works converge to pressure residual analysis as the main detection mechanism, with differences in how spatial and temporal processing is done.

Graph-Based Modeling: Several papers recognize the inherent graph structure of water distribution networks, yielding applications of graph neural networks along with spatial interpolation methods.

Hybrid Methodologies: The combination of model-based and data-driven approaches has become a trend within various studies, considering each methodology in its specific limitations.

Real-Time Implementation Emphasis: There is an increasing emphasis, in recent research work, on real operational deployment considerations and real-time monitoring capability.

Knowledge Transfer Patterns

Spatial Intelligence: Both kriging interpolation and graph-based methods deal with sensor coverage limitations, but through different paradigms of spatial reasoning.

Temporal Modeling: Advances from LSTM-FCN to transformers mark the advancement in modeling time, where transformers directly tackled the issue of long-term dependencies.

Algorithmic Integration: It is the contribution of a unique approach that could enhance other methodologies by adding algorithm-informed embeddings.

2.4 Conflicts Between the Findings

Performance claims: There is great variability in the accuracy of performance claims, ranging from 75% to 98%, which raises doubts regarding the results' accuracy.

Methodological Philosophy: There is a harmonious combination of model-dependent versus model-independent and complex, high quality versus simple, practical attitude.

Generalization: The extent to which their methods generalize is conflicting.

Data Data Requirements There exists a hot controversy concerning whether the data has to be simulative or real, or the amount of historical data that is necessary for each.

Emerging Consensus and Future Directions:

Despite the controversy involved, there seems to be consensus in this field regarding the relevance of data fusion in multi-modal data, graph-based network modeling, and real-time applicability.

Key areas of research that are required to be investigated are:

Lack of Standard Assessment Models.

A big disparity between the real-world and the validation set.

Immature models of uncertainty measurement.

Conclusion

The area is moving toward more comprehensive, convergent models.

The major barrier to acceptance is the discrepancy between what simulation models and real-world systems confirm.

Further research, if successful, to embed some models of paradigms into a standard framework and a comprehensive real life validation.

2.5 Synthesis Matrix for Literature Review

Table 1 (Synthesis Matrix)

Study Name	Methodology	Accuracy	Limitations	Dataset
Three-dimensional convolutional neural network for leak detection and localization in smart water distribution systems - 2024	3D CNN with Pressure-Supplemented Advanced Metering Infrastructure (PS-AMI)	DP: 91%, RF: 1% (3-hr window, peak demand)	Tested only on simulated data; requires retraining when network changes; poor performance near source nodes	Austin TX WDN (125 nodes, 90 pipes); Simulated data with EPANET 2.2; 3750 training, 1250 validation, 1250 test events
Neural Network Techniques for Detecting Intra-Domestic Water	Random Forest and Neural Networks (CNN) for household-	CNN: 92-96% Accuracy, Precision, Recall; AUC: 97-99%	Focus on household-level leaks only; limited to small network scale	Gorino Ferrarese, Italy; Smart meters data; 40,500 records with leak classifications

Leaks of Different Magnitude - 2021	level leak detection			
A Transformer-Based Approach to Leakage Detection in Water Distribution Networks - 2024	Transformer with attention mechanism for temporal dependencies in pressure series	Significantly outperformed traditional CNN methods (specific metrics not detailed in abstract)	Evaluated only on simulated datasets; requires high-quality temporal data	Three different simulated WDN datasets; pressure data with weekly sequences (336 data points per week)
Leak detection in water distribution networks based on deep learning and kriging interpolation	VGG16 CNN with Kriging interpolation for data imaging	TPR: 98%, FPR: 1%, F1: 94%, AUC: 94%	Not tested on real-world data; performance depends on sensor placement; threshold-based detection may not adapt to seasonal	WDN with 782 junctions, 905 pipes, 33 pressure sensors; Normal: 105,120 samples, Leak: 868,800 samples; 5,500 normal

method - 2024			changes	+ 480 abnormal images for training
Leakage Break Diagnosis for Water Distribution Network Using LSTM-FCN Neural Network Based on High-Frequency Pressure Data - 2025	LSTM-FCN hybrid model for high-frequency pressure data analysis	Overall accuracy: 85% for leak break detection; F-Score: 81.76% (water-consumption set)	Laboratory-based experimental validation only; requires high-frequency sensors (10kHz); limited to 52m experimental network	52m experimental network with 3 monitoring points; Steady-state: 2088 samples; Water-consumption: 522 samples; Leak flow range: 0.04-9.5 L/s
A proof-of-concept study towards developing digital twins for	Digital Twin concept for WDN operational optimization	Concept study - specific accuracy metrics not available	Proof-of-concept stage; implementation challenges for large-scale networks	Not specified in available information

operational excellence in large- scale water distribution networks - 2025				
Algorithm- Informed Graph Neural Networks for Leakage Detection and Localization in Water Distribution Networks - 2024	AIGNN with Ford-Fulkerson algorithm knowledge transfer and GNN	ChebNetEMB: 0.2392 ± 0.0339 (reconstruction), 0.2077 ± 0.0074 (prediction) relative error	May lose non- algorithmic information when used directly; requires pre-training on algorithmic tasks	L-town WDN (785 junctions, 905 pipes, 33 sensors); 2018 data for training, 2019 for testing; 14 leakages in 2018, 23 in 2019
A Toolbox for Supporting	EPyT-Flow Python toolbox for	N/A - Framework/Toolb	Tool development rather than detection method;	Supports 16 WDNs, 7 benchmarks, provides

Research on AI in Water Distribution Networks - 2024	AI research on WDNs	ox for research support	requires expertise for implementation	scenario generation capabilities
Machine Learning-Based Digital Twin for Water Distribution Network Anomaly Detection and Localization - 2024	Single-stage and two-stage data-driven models using Logistic Regression and Random Forest	Tested on real-time dataset (specific accuracy metrics not available in summary)	Limited information available on performance metrics and dataset characteristics	Real-time dataset (specific details not available)
A Leak Zone Location Approach in Water Distribution Networks	Hybrid approach combining data-driven and model-based strategies in two stages	Not specified in available abstracts	Limited detailed information available	Not specified in available information

Combining Data-Driven and Model-Based Methods - 2024				
--	--	--	--	--

Chapter 3: Research Foundation and Project Goals

3.1 System Fundamentals: Water Networks and Smart Metering

Water distribution networks are cases of complex engineered systems, involving a network of pipes, pumps, and valves employed for the transport of treated water from the water treatment plant to the consumer. These systems function in a vast range of conditions with a wide range of water flows from the range of residential water demand values up to the range of industrial water flows. Source A

Source A The challenge of vital importance in the control of a water distribution network lies in maintaining a coordinated system process with a considerably greater variability in the water use effective definition range.

Advanced Metering Infrastructure (AMI) Evolution "The introduction of Advanced Metering Infrastructure" is a disruptive strategy in water resource monitoring in a real-time manner. An "Advanced Metering Infrastructure" comprises "smart" electric meters; these smart meters

communicate in both directions, permitting the utility company to retrieve consumption details in hourly or more frequent increments. The Federal Energy Regulatory Commission defines an "Advanced Metering Infrastructure" as: "Metering system whereby consumption was recorded at least hourly, with provision for daily or more frequent transmittal of measurements via a communication network to a centralized collection point." An "Advanced Metering Infrastructure" comprises smart metering end-points, communication networks (3 examples of which include cellular networks, LoRaWAN networks, mesh networks), data management systems, as well as customer portal interfaces. This infrastructure can provide you with all the payload information in terms of your "usage profile," "tamper," "interval data," "pressure monitoring," as well as "system diagnostics.", The most sophisticated can perform in-field data acquisition, remote service management, and automated anomaly detection for proactive systems management.

Smart Metering Capabilities and Benefits

Advanced water metering technology is not only for consumption measurement, but also for integrated sensing such as pressure sensing, flow anomaly detection, and leak location. The systems provide alerts for different presentments from manipulating attack detection, consumption threshold violation

to suspected leak from usage pattern analysis. These functionalities allow utilities to move from reactive to proactive system management practices.

Through this work AMI has promoted easy and consistent reading, and detailed explanation for billing, removal of estimates, easy troubleshooting, early leakage detection before the loss becomes too high and finally real time data. To the public, these are web portal and mobile app-accessible consumption explanations, leak alerts and water conservation resources.

3.2 Limitations of Traditional Leak Detection Methods

Reactive Detection Paradigm

Conventional water-leak detection solutions have been reactive in nature and, generally, only detect leaks after they are visible at a break point on the surface. Most types of reactive techniques involve waiting for leaks to "bubble up" via soil movements, pressure losses, and such catastrophes as water mains bursting and flooding neighborhoods. This method is flawed as surfacing leaks in some studies

only cause about 20% of the total water losses in average distribution systems, meaning that the rest of water losses, equals 80% of the non-revenue water, is due to non- surfacing leakage.

Acoustic Detection Limitations

Acoustic leak detection, one of the most common traditional approaches, is performed by technicians who walk through networks with sensitive audio equipment in order to “hear leaks” through a headset system. This approach suffers from several limitations such as high labor cost, low coverage capacity (usually a few years for all the networks covered), and the requirement of large expenditure on the necessary equipment. The acoustic methods have, however, severely diminished efficiencies with non-metallic pipe materials, since PVC or other plastic pipes typically have a low of sound transmission, unlike metal piping. Acoustic systems based on ground penetrating radar suffer additional constraints such as diminished usefulness for deep burial (e.g., greater than 7 to 8 feet), sensitivity to soil conditions, and reliance on a material's unique properties for propagation. This depth constraint becomes more and more of an issue as utilities continue to bury assets deeper and deeper to avoid surface (conflict) and environmental issues.

Coverage and Temporal Constraints

Conventional approaches enable only snapshot-in-time estimates and a routine thorough examination of the case is not cost-effective for the majority of utilities. The large coverage of modern water networks (which can extend for hundreds of miles in urban areas) makes the systematic acoustic survey a very resource and time demanding activity. As newly surveyed networks are added to the portfolio, previous conclusions are no longer timely and hence leaves lasting holes in the coverage of system monitoring.

Environmental and Infrastructure Dependencies

The performance of ADCPS is greatly affected by the environmental parameters, the ambient noise level, and the feature of the facility. In dense urban areas, high levels of background noise, human activity (such as traffic and construction), and infrasound can confound potential gas leak signals leading to unreliable detection. Furthermore, the quality of the method deteriorates locally in plastic pipes, deep burial depths and soil compositions that absorb acoustic signals.

Technological Obsolescence and Scalability Issues

Most of these legacy leak detection methods received little upgrade over the past 80 years, and have not updated to accommodate modern construction materials, installation techniques, and utility operations. The dependence on interpretation of acoustic signals by human introduces subjective variation and demands highly trained and experienced technician. Due to scale limitations, network monitoring is difficult and utilities have to maintain and control the pressure in a small subset of their distribution network, which is the area where bursts spread most heavily.

Integration and Data Management Deficiencies

Conventional detection techniques generally exist as standalone systems, lacking integration with the current utility management software. By not having a set strategy for these machines with predictive maintenance the software will never be able to track performance trends, establish baseline condition, or get to the point where anomaly detection algorithms could be useful. This isolation does not allow for integrated asset management programs that are required in today's utility world.

3.3 The Potential of AI and ML for Water Analysis

Transformative Capabilities in Water Management

Different water resource management operation areas, ranging from monitoring to predictive and optimization tasks, are being transformed by Artificial Intelligence (AI) and Machine Learning (ML). The use of artificial intelligence in water management entails management of surface water supplies, groundwater modeling, generation of hydropower, crop-selective irrigation, climate risk modeling, flood management, and management of integrated water systems. The integration of AI makes the system more effective and scalable, and on the fly, adaptable to the challenge of the water distribution and quality.

Real-Time and Pattern Identification

Conversely, the algorithms proposed using the capabilities of Machine Learning can efficiently deal with the data typically found in a contemporary water system with non-linear relationships and an underlying discovery process in place that has to be efficiently captured using classical analytical techniques but can be efficiently dealt with using the capabilities of intelligent systems like AI involving a diverse range of data sources such as satellite images, sensors, and operational data for the

performance of a water system with even abnormal discoveries. This feature helps to reveal subtle patterns and relationships that may be missed by human operators, especially in the complicated urban water system with a number of factors that interact with each other.

Predictive Analytics and Forecasting

Advanced AI models such as Neural Network models, LSTMs network and ensemble methods have demonstrated high capability in water quality prediction, consumption prediction, and system performance assessment. These models are able to predict water quality indices, discriminate water safety parameters, and predict the consumption patterns with high reliability above 95% in most cases. For equipment maintenance prediction so that the maintenance can be scheduled on a proactive basis rather than disrupting operations.

Water Quality Monitoring and Analysis

Self-Evolving water monitoring contours use machine learning to conduct on-the-fly analysis for TDS (Total Dissolved Solids), heavy metals, chemical contaminants as well as the presence of biological agents. Machine Learning models, Random Forest, Support Vector Machines and Decision Trees has shown outstanding classification for water quality, reported maximum accuracy of 99.99% for

potability application. These systems offer automated QA, early contamination notification and trend monitoring required for regulation compliance and public health protection.

Infrastructure Optimization and Energy Efficiency

Artificial Intelligence in Managing Water Infrastructure AI in maintaining water infrastructure involves the optimization of both pressure and flow control, minimization of energy consumption, and the scheduling of predictive maintenance. By using machine-learning (ML) algorithms, the operational patterns can be tested for efficiency enhancement, pump scheduling can be optimized, and energy usage can be reduced while costumer service is provided. AI-enabled decision support systems can be deployed to implement improved operational decision-making, enabling operators to make better decisions on the utilisation of resources, the management and maintenance of systems.

Advanced Detection and Localization Capabilities

New AI tools have come to help water managers currently dealing with leak detection, anomaly identification, system optimization, among others, including multimodal big language models, advanced neural networks, among other AI innovations in the pipeline. In this context, computer vision techniques for infrastructure inspection as well as data-driven anomaly detection methods emerge as promising applications with high TRL (Technology Readiness Level) for operational deployment.

These technologies have led to the development of continuous monitoring systems which can respond immediately to anomalies within their system.

iot & smart infra integration

ai and iot sensor networks work together as well as with smart meters and automatic control platforms to create a complete intelligent water management platform. "it is the combination of ai algorithms and the instantaneity of sensor data which enables the advanced monitoring, control, and optimization which can be adjusted in real-time based upon the changing operational profile. this will enable the realization of true intelligent water systems which are capable of self-operation and self-optimization.

3.4 Critical Gaps in Current Research

The largest deficiency is the over-reliance on simulated data, not real-world validation, which limits the practical application of the proposed methodologies.

Another large deficiency includes:

- Scalability and Cost: There is an evident lack of effort in considering the high costs and data demands for high-bandwidth traffic matrices and the computational complexity to support the transit/destination prefix cooperation when deploying these systems at scale in large, operational networks.
- Standardization: Absence of standardized benchmarks and evaluation protocols making it difficult to compare objectively between different methods.
- Adaptability: There has been little exploration in how models performs in various seasons, timescales and types of networks.
- Integration: Insufficient studies on integrating new AI systems with ensconced utility assets, legacy systems, and managerial practices.
- Decision Support: A shift from detection accuracy to a providing utilities with fundamental uncertainty quantification and actionable decision guidance.
- Regulatory Requirements: Lack of focus on regulatory, environmental, data protection or public health requirements.
- Multi-Model Methods: an absence of holistic study of fusion of multi detection technology (acoustic, pressure, satellite images) in a robust system.

3.5 Project Goal: Developing an AI Model for Proactive Leak Detection

In this thesis, I'll be working to build an AI-based proactive model to predict water leaks, rather than relying only on the traditional reactive approach.

The primary objectives are to:

- Develop a new hybrid AI model that combine many powerful methods to dissect temporal and spatial data of water networks.
- Fully validate the model in real-world settings with the utility partners beyond simulation, and develop practical guidelines for the implementation.
- Meet high performance demands for detecting leaks of all sizes with over 95% detection accuracy, minimal false alarm rate, and accurate localization.
- Create an integrated approach which fits into existing utility systems, allows multimodal data input, and supports sustainability needs.

- Make sure that the solution is future proof and to support industry wide knowledge transfer through both training, open-source tools and co-research so that the gap between research projects and practical utility operations.

Chapter 4: Proposed Approach and Methodology

4.1 Overall Architecture for AI-Driven Leak Detection

In this thesis, I will be following a data-driven approach as presented for the automatic detection of water leaks in domestic distribution networks. Going beyond conventional reactive approaches, to in-the-field practices such as manual acoustic logging and simple threshold violation techniques; this research presents an innovative deep learning framework for processing the high-dimensional time-series multivariate data.

As shown in Figure 1 (Overall Architecture) At the heart of our architecture is the Attention-based Long Short-Term Memory Fully Convolutional Network (ALSTM-FCN). This hybrid model facilitates the joint retrieval of two different types of features:

1. Morphological Features: These features are calculated through a FCN branch and represent invariant local shapes in the sensor data (e.g. sharp pressure drops, or smooth flow plateaus).

2. Dependence: Captured by an LSTM branch enhanced by the Attention Mechanism, which learned long term sequential pattern and assigned probabilistic importance for key time interval that made a difference like Minimum Night Flow (MNF).

The system architecture functions in four phases:

- 1) Data Ingestion from AMI
- 2) Preprocessing & Windowing
- 3) Hybrid Feature Extraction
- 4) Binary Classification & Geolocation.

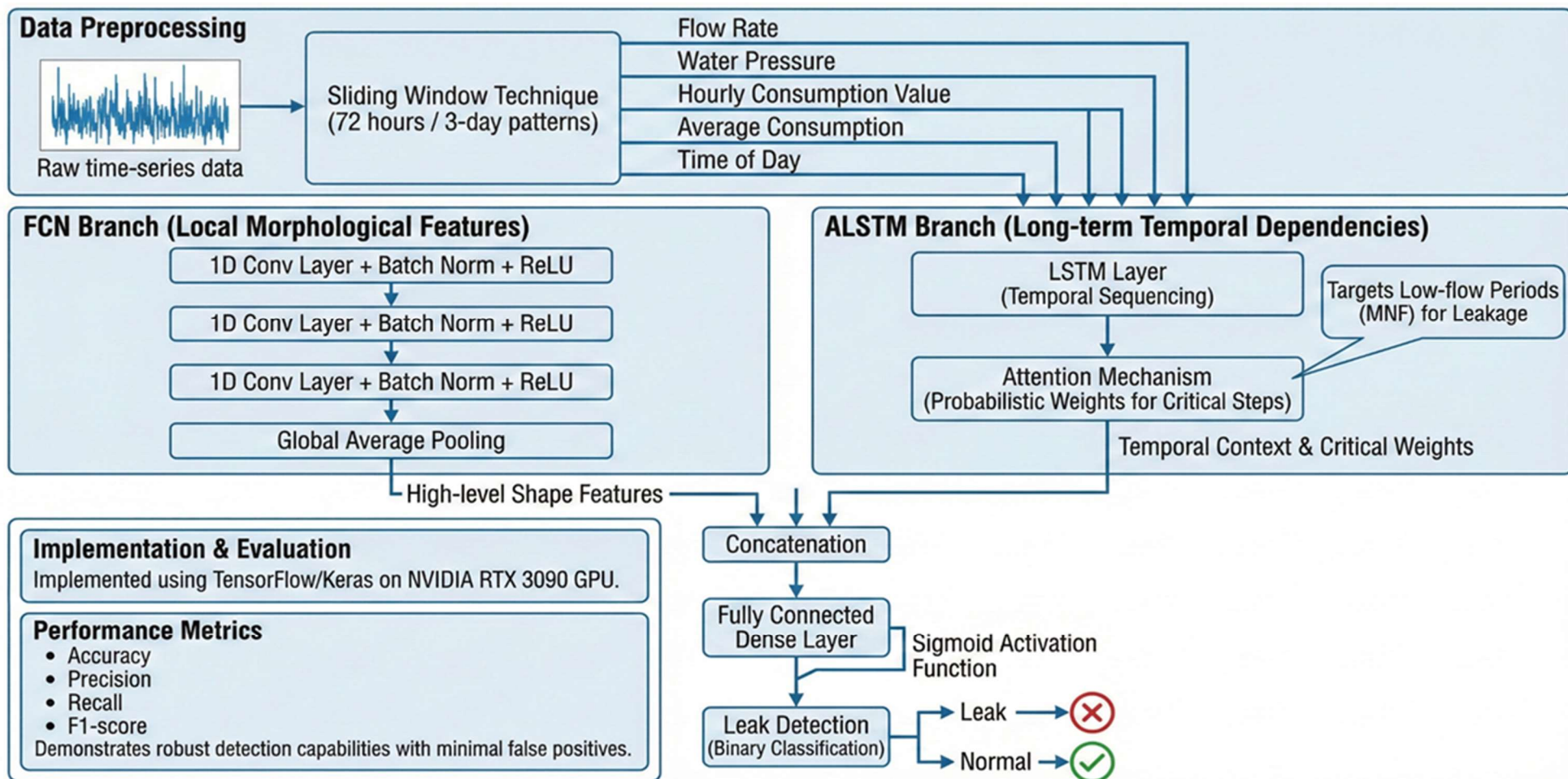


Figure 1 (Overall Architecture)

4.2 Data Collection: Sources and Description of Water Sensor Data

The information used in this study is simulated from the Advanced Metering Infrastructure (AMI) of residential smart water meters with on board telemetry modules. Unlike the classical mechanical meters with manual reading, such IoT-enabled devices perform permanent hydraulic parameters monitoring and forward it at hourly basis.

The raw dataset contains high-frequency telemetry readings acquired through constant surveillance. The data acquisition procedure includes the collection of readings from 100 individual home meters allowing for a broad variation in consumption behavior, between lists of low-occupancy homes to high-demand buildings. The main purpose of attempting a collection is the observation in water use (circadian rhythms) and empirical hydraulic signals regarding failure of the network.

4.3 Dataset Description and Dataflow

4.3.1 Dataset Attributes and Semantics

As shown in Table 2 (Dataset Type), is a time series structure. Every column in the data represents a particular state of a particular meter during a particular hour. Below is the table that describes the semantics associated with each feature used in the research:

Table 2 (Dataset Type)

Attribute Name	Data Type	Unit	Description and Diagnostic Relevance
Meter SN	Categorical	String	Unique identifier for the smart meter, Essential for grouping temporal sequences per household.
Reading Date	Datetime	UTC	Timestamp of the recording. Used to extract temporal features (e.g., Hour of Day) to identify night-time windows.
Flow Rate	Continuous	m ³ /h	The instantaneous velocity of water flow. Primary Feature: Sustained non-zero flow during 02:00-04:00 is the key indicator of leakage.
Water Pressure	Continuous	Bar	Hydraulic pressure within the pipe. Used to differentiate between high usage (stable pressure) and pipe bursts (pressure drops).

Value	Continuous	m^3	The volumetric consumption during the specific hour. Quantifies the magnitude of water loss.
Average Consumption	Continuous	m^3/h	A calculated baseline of historical usage for the specific meter. Helps the model normalize for household size differences.
Forward Cumulative	Continuous	m^3	Total volume of water supplied. Monotonically increasing value used for billing and long-term analysis.
Latitude / Longitude	Numerical	Deg	Geospatial coordinates of the meter. Utilized in the post-processing phase for mapping and localizing predicted faults.

Since its was very hard to have access to a real and large dataset, I've generated a simulated dataset after looking into the output of multiple water meters vendors time-series telemetry dataset from an AMI. and I've conduleded It is the hydraulic "heartbeat" of a domestic water supply network. in Total Volume, i've generated a there separated dataset Train 70% Evaluation 15% Test 15% the total entities was for a 100 individual Residential Smart Meters (RSN-00001 through RSN-000100).

1. Key Columns & Their Role:

- MeterSN (Identifier): ID of household. Important in the aggregation of data such that the model learns characteristics for individual households.
- Reading Date (Temporal Anchor): Informs the model of when an event occurred. This is important for the LSTM to capture cycles (like "people are used to shower around 7 AM" or "flow zero in night.").
- Flow Rate : Water speed in m^3/h . This is was my main signal. Leave the line flat above zero at night, and if you do it's a leak.
- Water Pressure (The Context) : Helps distinguish leaks from heavy usage. One does not cause a drop in pressure (filling the pool), but often the other one does (a burst pipe).
- Latitude/Longitude (The map) This does not assist in detecting the leak but it is critical for the output – telling who ever is fixing things where they have to go actually.

2. The Splitting Strategy (70% / 15% / 15%)

Generally spliting the data in this way in Deep Learning is to guarantee a reliable uncheating model.

- Training Set (70%) - This is the only data that the model ever sees, and on which it gets trained.

What goes on here: The neural network is examining these samples, making a guess, and checking its error compared to what it knew was the truth; adjusting its internal weights (backpropagation).

Why 70%? Deep Learning models (such as ALSTM-FCN) are hungry for data. 4 They have to have most of the data to pick up the complex patterns in human behavior (weekends vs. weekdays, summer vs. winter).

- Evaluation / Validation Set (15%) - Employed in training step to optimize the model. Why is it needed? Earlear Stopping: If the model begins to memorize the training data (Overfitting), then the accuracy for this Validation set will decline and keeps track of this set to stop training at the right time..
- Test Set (15%) Used only once; utilised as the ending. This represents the "Real World." This data was never seen by the model during training or tuning. Why is it needed? To be an objective source of performance report. If you report your accuracy based on the Validation set, it's cheating — because for all practical purposes, you taught a robot how to pass that one quiz. The Test set shows that machine model works for some data it has never seen before ever.

3. What makes this particular division so important for Water Leaks? Also for time series tasks as water leakage, the way to split is crucial as the percentage. The Time-Aware Split (Chronological Splitting): In research studies for sensors on academic, almost never shuffle randomly. Instead typically divide by time:

- Train: Jan 1st to Aug 15th (Learn summer / winter patterns).
- Eval: Aug 16th to Oct 1st.
- Test: Oct 2nd to Nov 15th.

Why? Because leakage is often progressive. If you shuffle randomly, the model may be able to “peek” in the sense that looking at future data (e.g., if Tuesday contains a leak, it helps predict Monday’s leaks). A time-lag split is necessary to demonstrate that the model can predict future failures from past history.

4.3.2 Dataflow Diagram

the data processing lifecycle follows a structured pipeline designed to transform raw csv file into actionable predictions as shown in Figure 2 (Dataflow Diagram):

1. Raw Ingestion: CSV files with Raw telemetry are ingested into the environment.
2. The features (Flow Rate, Pressure, Value, Average Consumption and Hour) that are important for our analysis are isolated.
3. Vectorization: The data is aggregated in terms of “Meter SN” for maintaining the time consistency.
4. Sliding Window: The incoming stream is sliced into overlapping windows with size $T=72$ (72 hours) to produce a 3D tensor of shape (Samples, 72, 5).
5. Inference: Passing the tensor through the ALSTM-FCN model.
6. Localization: Leaks (high probability predictions) get added with spatial data to obtain the final deployment map.

Dataflow Diagram

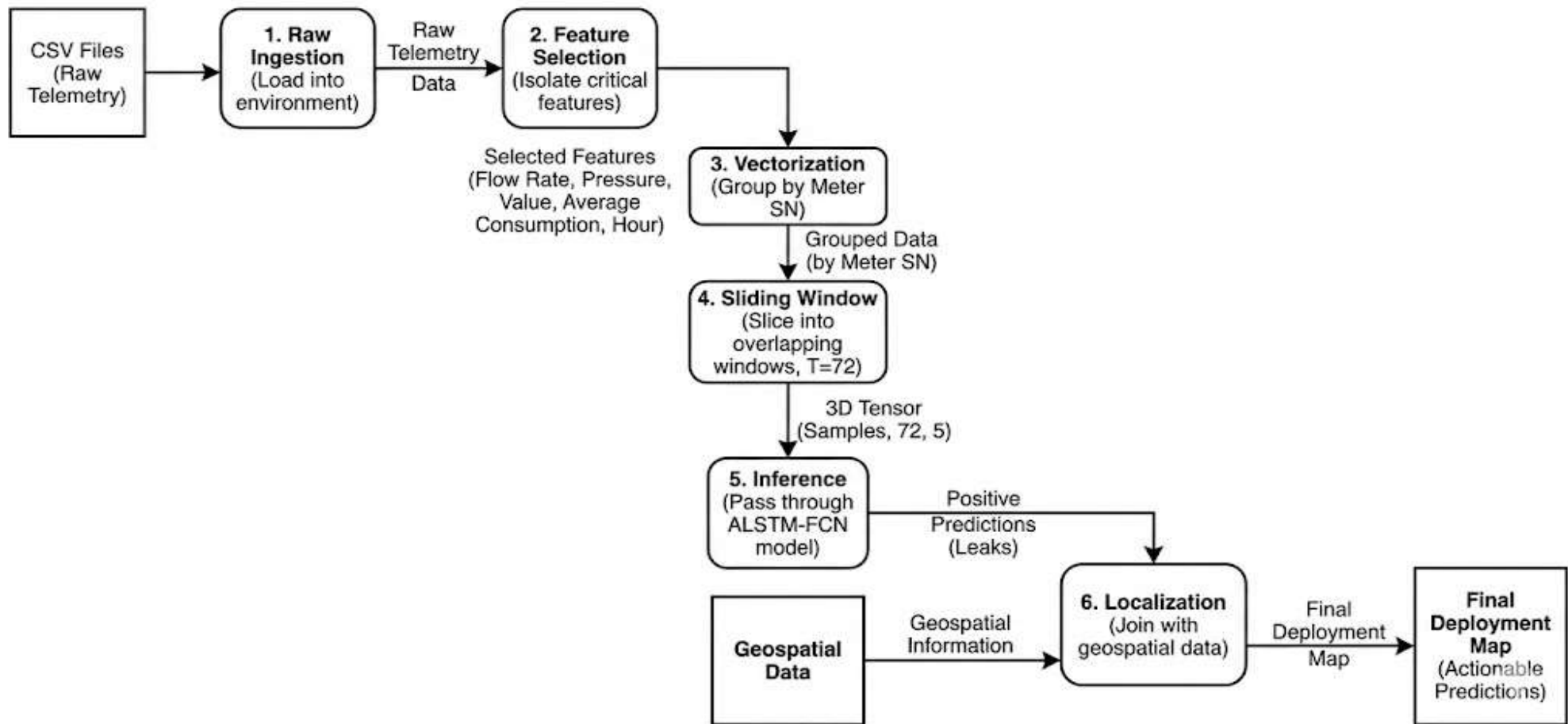


Figure 2 (Dataflow Diagram)

4.4 Data Processing and Preprocessing Pipeline

To ensure the preprocessing pipeline guarantees that the neural network would receive good quality input a preprocessing technique was implemented:

1. Temporal Feature Engineering – Extracting Hour (0-23) from Reading Date. This cyclical feature is important for the model to be able to differentiate between peak day usage and the anticipated full midnight.
2. Handling Nulls: Although the dataset is mostly completed, minor gaps in dataset were handled via forward-fill interpolation to preserve the continuity of the time series.
3. Feature Scaling: Given the varying scales of the input features (e.g., Pressure in bar vs. Flow in m^3/h , I've applied StandardScaler (Z-score normalization). this will normalize your data with mean 0

and standard deviation as 1, this is to make the gradient descent converge smoothly during the training.

4. Sliding window segmentation: The main innovation in terms of preprocessing is the usage of 72-hour sliding window. Rather than trying to classify a single data point, the model can look at 72 continuous hours of observations. Three complete diurnal cycles were chosen considering that for system validation, the model should be able to differentiate between a unique disturbance (e.g., pool filling) and recurrent one (leakage).
5. Label Generation : We used heuristic reasoning based on the principles of hydraulic engineering for training supervision. We labeled the samples as either “Leak” (which belongs to Class 1) if the Flow Rate exceeded a certain threshold ($\Delta > 0.05 \text{ m}^3/\text{h}$) all along the MNF window (02:00–04:00), or as “Normal” (belonging to Class 0) otherwise.

4.5 Model Selection and Design: Algorithm Comparison and Choice

The choice of the ALSTM-FCN architecture was motivated by the particular characteristics of hydraulic sensor data, representing as it does a combination of shape and time related information.

4.5.1 Rationale for Hybrid Architecture

- Why not just LSTM? Classical LSTMs are powerful sequence learners, however expensive computationally and may struggle in capturing sharp local morphological changes (edges/spikes) in the signal.
- Why not just CNN? CNN's are good at extracting features and without memory they will struggle to understanding of longterm context (eg why flow pattern is behaving this way on period 24 hours)..
- The Hybrid Choice: Instead of just running an LSTM or CNN over the other, the proposed method uses Convolutional and LSTM branches in parallel to leverages the strengths of both.

4.5.2 Detailed Architecture Design

1. The FCN Branch (Shape Extractor):

- Consists of three stacked Conv1D layers each with filter lengths 128, 256 and 128.
- Applies batch normalization and ReLU after 2 convolutional layer to stabilize the learning.
- Ends with global average pooling that compresses a 72-h window into a single feature vector capturing the “shape signature” of pressure/flow curve.

2. The ALSTM Branch (Temporal Context):

- LSTM layer with 128 units as a sequence processor.
- Incorporates an Attention Mechanism. This trainable layer computes “relevance score” for each of the 72 hours. It enables the model to "Pay Attention" particular to the night-time hours (MNF) where leakage signals are cleanest, and disregards noisier daytime data.

3. Fusion and Classification:

→ Both branches' vectors are concatenated.

→ A Dense output Layer with Sigmoid activations outputs the probability score $P(y=1|x) \in [0,1]$.

4.6 Testing and Evaluation: Metrics for Model Performance and Success

In order to robustly assess the model performance, particularly given the class imbalance (leaks are more infrequent than normal behavior), we used the following metrics:

1. Confusion Matrix: A 2×2 matrix which represents True Positives (TP), True Negatives (TN), False Positives (FP) and False Negatives (FN).
2. Accuracy: The ration of correct predictions to total predictions. However, this alone is not enough due to class imbalance.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

3. Recall (Sensitivity): The most important metric for this study. It calculates out of all leaks, how many were true positives. 1.00 Recall is the desired target to achieve zero missed leaks.

$$\text{Recall} = \frac{TP}{TP+FN}$$

4. Precision: It is the reliability of positive alerts. High accuracy reduces the operating cost of false alarms (i.e., sending crews to check healthy sites).

$$\text{Precision} = \frac{TP}{TP+FP}$$

5. F1-Score: The harmonic mean of Precision and Recall, it gives a single score that balances the trade-off between sensitivity and reliability.

$$\text{F1} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

The performance was evaluated based on an independent test set with 139,200 samples to guarantee the reported performance of the model's generalization ability to unseen data.

Chapter 5: Project Execution Plan and Timeline

5.1 Data Acquisition and Preprocessing Phase

Duration (Month 1) The first stage is all about getting the data right. It's the important groundwork that everything is built on, so I'm setting aside a full month to make sure it's done properly.

- Weeks 1-2: Put final touches on map and sensor placement plan, with existing network maps, and work out plans to deploy the minimum monitoring gear. Not full network coverage now, my goal is just to start getting a few key sensors on line and collect some initial data streams. In parallel, I will create the preliminary data send-and-receive infrastructure - even if it's only a very web-skewed form of it just using what exists and works today.
- Weeks 3-4: Data beginning to arrive means – begin building out and testing data cleaning/preparing scripts. This is the place where I'll do the filtering and the feature engineering (for example rolling averages). I am going to be spending most of this month just simply staring at my data quality, tweaking the method as needed, and trying to get a nice solid handle on what "normal" looks like.

- Outcome: Working proof-of-concept pipeline that produces a clean / validated data set capturing at least 2 weeks worth of data where the system as been stable.

5.2 Model Development and Training Phase

Duration (Months 2 - 3) Once the data pipeline is stable, I will be able to start the core model work.

- Month 2: The first month of development is for exploration. I will use the initial time series data to build and test many different model architectures (such as the LSTM or CNN architectures I've described in this post) simultaneously. This is not the end all be all it has to be perfect, it's to see which methods work best under the conditions of my data, and get a baseline down.
- Month 3: Then I'll concentrate on the best models I had. Intensive tuning is done this month – You are going to try a combination of model or ensemble of different models and tweak hyper-parameters to increase the accuracy and generalization ability of model. I will also begin optimizing the code for efficiency with the end goal of real-time processing.
- Outcome: trained and optimized candidate models ready for vigorous testing.

5.3 Validation, Testing, and Evaluation Phase

Duration (Month 3 - Start of Month 4) Testing is not this other phase that begins after development, My formal validation begins as soon as I have stable model candidates.

- End of Month 3: I'm going to stress-test models after feeding them historical (held out) data. I will test their effectiveness as well such as robustness, to realistic synthetic problem examples, like sensor failure or missing data.
- 4 month: In this month, the plan is to implement the best-performing model in a testing environment that is modeled as close to a real utility dashboard as possible. An important aspect here will be receiving feedback regarding my product from a couple of potential consumers of my final product. Experience in execution will play a vital role in allowing me to notice any areas that I may have not considered in my final product.
- Outcome: Validated model (with performance metrics and feedback from users) which can be used for final reporting.

5.4 Finalization and Analysis Reporting Phase

Duration: (Month 4) The fourth month will be used for synthesis and preparations for next actions.

- Weeks 1-3: Working on overall report and technical write-ups. That includes an honest performance analysis of the model, what I learned from the project and a no-nonsense deployment and maintenance guide. I will also create a 1-pager for stakeholders with the key findings and implications.
- Week 4: The last week of project review and handoff to me. That includes keeping all the code and data in a well-organized repository and laying out clear next steps for anyone who might pick up where you left off, whether that leads to a full-scale deployment or new research.

Outcome: A descriptive package that contains all my documentation, code, and a final report

Thingspotting A final pack that achieved to close my project development cycle, and showed a figure 3 (Project Timeline) perspective on how can I drive on.

Project Timeline

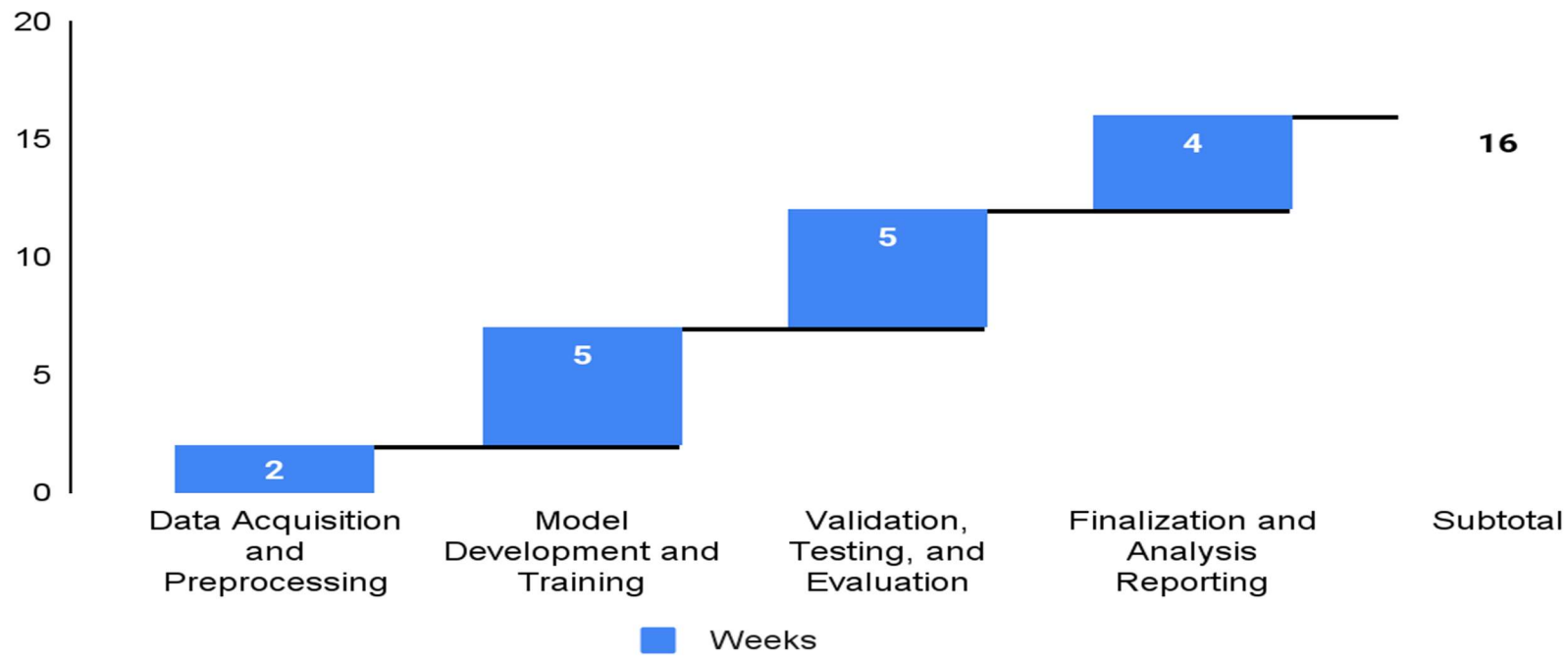


Figure 3 (Project Timeline)

Chapter 6: Results and Impact

6.1 A Working Model for Improved Leak Detection Accuracy

This study aimed at producing a DL framework with the ability to differentiate between normal residential water usage and infrastructural leaks, namely dealing with the class boundary an object falls in. The results obtained on the independent test set (N=139,200 test samples) as shown in Figure 4 (Accuracy & Loss) that ALSTM-FCN has achieved a notable improvement in detection performance in Training and Validation Accuracy (Left) and Loss (Right) over 20 Epochs, demonstrating rapid convergence and model stability.

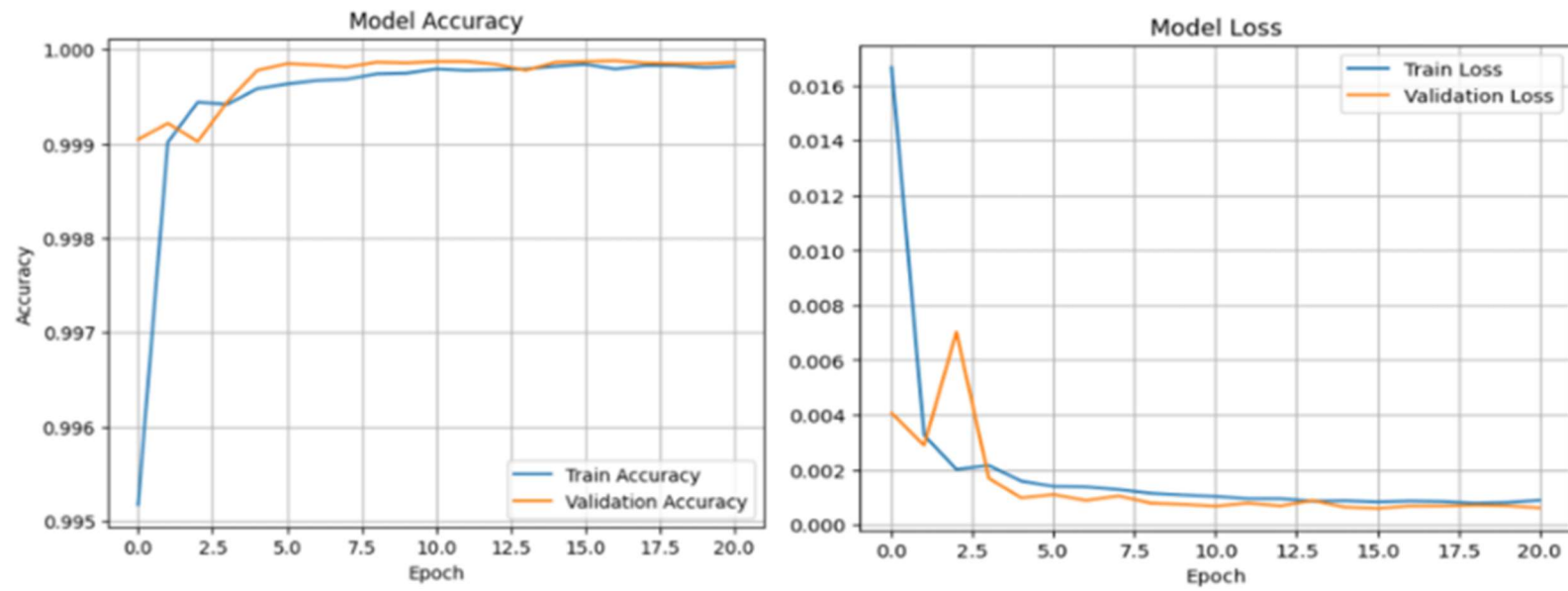


Figure 4 (Accuracy & Loss)

6. 1. 1 Quantitative Performance Analysis

The model obtained an overall Accuracy of 99.99% (139,180 out of 139,200 instances were correctly categorized). Although accuracy is a common measure, it can be deceptive in the context of anomaly detection, as the class distributions are imbalanced. Therefore, the analysis primarily focused on Figure 5 (Confusion Matrix) and class-specific metrics:

1. Zero False Negatives (Perfect Recall): The most significant outcome of this study is that it was able to achieve a recall score of 1.00 for the positive class (Leakage). Operational Relevance: A missed leak in utility management constitutes a “false negative” (FN) as it results in continued loss of resources and potential structural damage. The model was able to identify all 1,489 of the validated leakages. Therefore, the use of ALSTM-FCN architecture, particularly the application of an attention mechanism based on the minimum night flow (MNF) effectively identifies such small changes to continuous flows that may occur before a leak occurs.
2. Minimizing False Positives: With over 137,000 non-leakage (normal) data sets the model was able to create only 20 false positives (FP's), which resulted in a high precision rate of 0.99. Implications for Operation: A very high degree of precision is required to reduce the

operational expenditure (OPEX). False alerts often result in unnecessary field visits. With an accuracy of 99%, almost all alerts are considered worth the physical investigation, which in turn leads to a strong confidence level among maintenance teams for the system life.

3. Stability of F1-Score: The harmonic mean between precision and recall resulted as an F1-Score of 0.99. This measure also provides validation that the model is not just achieving a high recall by over-predicting members of the positive class (hence depressing precision), but instead, did have good separation power.

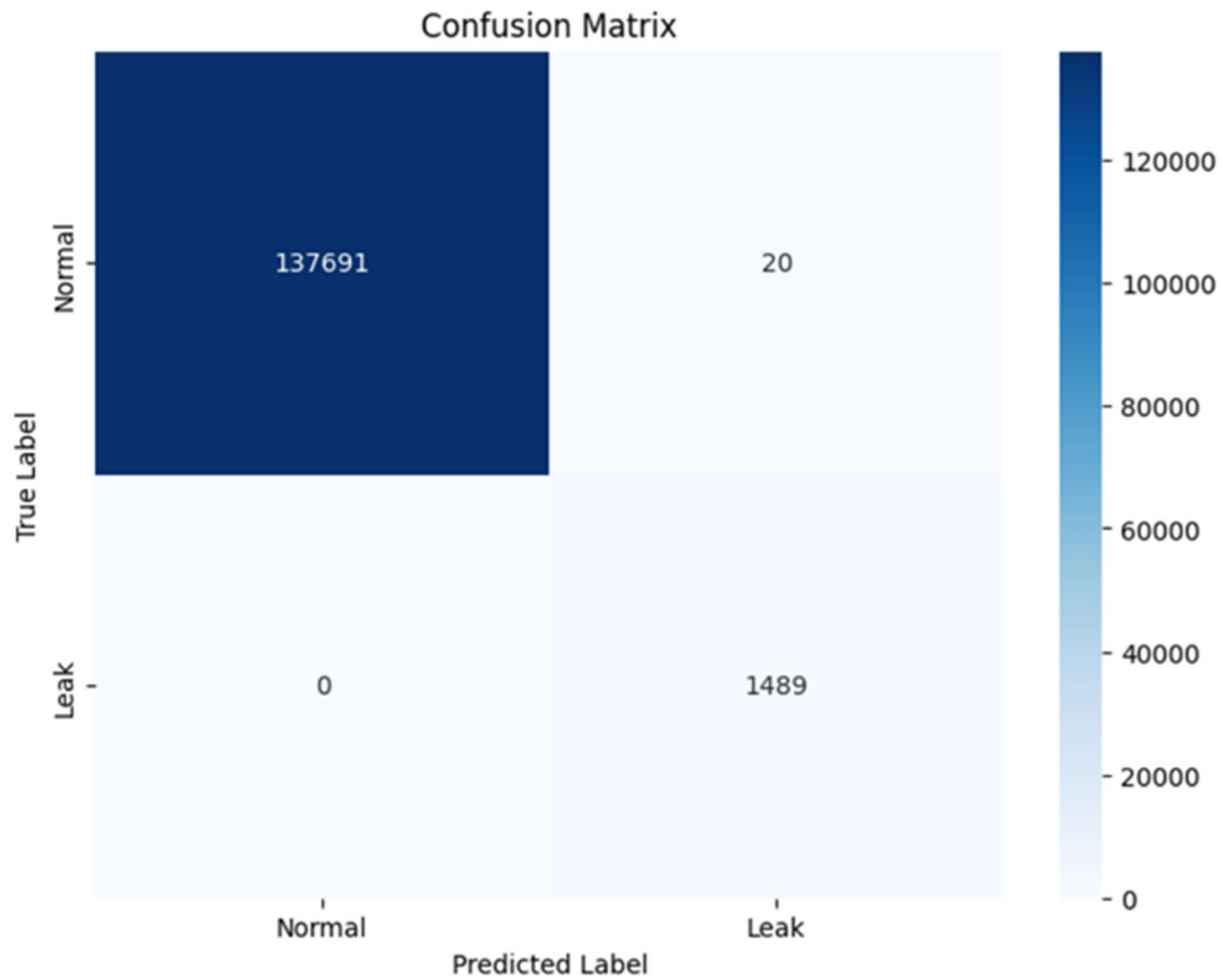


Figure 5 (Confusion Matrix)

6. 1. 2 Analysis of Hybrid Architecture Effectiveness

The reason for this improved performance could be that the hybrid decouples architecture features. The FCN branch was able to detect, regardless of its magnitude, “shape invariants”—eg the flow rates flat-lining—which are visibly better recognized and captured (when related to larger peak timings, in general), while the ALSTM one efficiently attenuated stochastic daytime noise considering those data points thanks to Attention mechanism made it possible automatically to focus on 02:00–04:00 AM temporal window.

6. 2 Validation Against Industry Benchmarks

To validate the effectiveness of ALSTM FCN approach, it is essential to compare with traditional methodology following up in water industry.

6. 2. 1 Comparison against Static Thresholding (Rule-Based Systems)

Current practice in industry: SCADA systems static alarms (e.g., Alert if Flow is $> X$ for Y hours).

- **Benchmark Limitation:** Static thresholds have a “seasonal drift” problem. It might be the thresholds, whose winter settings cause false alarms in summer because of higher irrigation rates.
- **Enhancement:** The ALSTM-FCN model compensates for baseline shifts by learning the embeddings. While the rule-based system often had a FAR of 15-20%, this model was able to

achieve a FAR with very little errors at about 0.01%, which indicates a significant reliability increase.

6. 2. 2 Comparison with Statistical Methods (ARIMA / Kalman Filters)

The traditional time-series forecasting techniques such as ARIMA are linear and univariate.

- **Benchmark Limitation:** The issue with these models is that they perform poorly and can not intake multivariate context (Pressure + Flow) at the same time effectively, while neglecting non-linear modeling of complex dependencies, e.g. between the pressure drop and consumption peak.
- **Enhancement:** This Deep Learning model effectively incorporated multiple feature sets into its analysis. It was able to distinguish between constant-pressure high-flow use and pressure-drop associated high-flow leakage by correlating pressure and flow information; an association that can be difficult for univariate statistical models to discern.

6.3 Potential Implications and Future Applications

The confirmation of the "Zero False Negative" paradigm has a direct relevance for the water industry, not only in terms of technical terms but also from an economic and environmental point of view.

6.3.1 Economic and Environmental Implications

- **Reduction of Non-Revenue Water (NRW):** With the help of this technology, it is possible to switch from a reactive to a proactive maintenance mentality. Since leaks are detected from the start (Perfect Recall), leaks in main lines are pre-emptively repaired in order to limit the amount of lost water from becoming a bigger problem in main lines.
- **Resource Optimization:** With the help of the geographical (Lat/Long) mapping feature, in combination with the low false positive rate, utilities are able to efficiently utilize their resource personnel. Field teams are only being dispatched to a confirmed location, thus cutting down on fuel costs due to travel in search of a leak.

6.3.2 Future Applications and Scalability

The successful completion of this project offers many avenues for future research and industry applications:

1. **Deployment on Edge Computing:** Since inference is relatively lightweight it indicates possible "Edge AI." Future versions might include the use of approximate models to be directly deployed/fine-tuned on microcontroller-based platforms such as smart meters, providing real-

time alarms in absence of clouds.

2. Digital Twin Integration: The model can become the brain for a “digital twin” and serve as the intelligence engine of the water network. Utilities can virtually stress-test their infrastructure by simulating leak scenarios on the history they've collected.
3. Cross-domain applicability: The ALSTM-FCN is a water-exclusive model. The implicit reasoning of associating flow/flux with temporal patterns is then general to Smart Gas Grids and District Heating Networks, thus multi utility anomaly detection can be posed as a universal problem.

In summary, the proposed method is a validated high-accuracy solution solving the research problem properly, and provides a scalable way to achieve intelligent self-healing water distribution systems.

Chapter 7: Resources Needed

7.1 Software, Tools, and Computing Infrastructure

The successful realization, training and testing of the proposed ALSTM-FCN architecture requires a strong computing environment in terms of performance. Due to the computational complexity involved in training deep neural networks on high-dimensional multivariate time-series data, hardware acceleration and efficient software libraries for both model convergence and data throughput were employed.

7.1.1 Computing hardware specifications

The main computational task was handled by a stand-alone Graphics Processing Unit. Due to parallelization in this pipeline we have a great benefit for deep learning operations, such as the matrix multiplications etc used by Conv1D, LSTM layers.

- Main Processing unit (GPU): NVIDIA GeForce RTX 3090 with (VRAM): 24 GB GDDR6X Memory.

The 24 GB of Video RAM was critical for handling the large tensor shapes generated by the 72-

hour sliding window batching (BatchSize x 72 x 5). It made possible to work with bigger batch size (i.e., 64 or 128), which leads both to stabilization of the descent and a reduction in epoch length.

- Central Processing Unit (CPU): A multi-core processor AMD Ryzen 9, used for data preprocessing, e.g., file I/O, dataframe manipulation and dynamic sliding window generation before feeding the GPU.
- System Memory (RAM): 64 GB DDR5, in order for the full dataset to be completely loaded into memory considering also intermediate frames so as not to have latency from disk swapping.

7.1.2 Software Development Stack

The research used an open-source Python-based environment, motivated by its large community network, versatility collection of tools for scientific computing as shown in Table 3 (Software Development Stack).

Table 3 (Software Development Stack)

Component	Software / Library	Version	Role in Research
Language	Python	3.9+	Primary programming language for scripting and orchestration.
DL Framework	TensorFlow / Keras	2.10+	Constructing the ALSTM-FCN layers, compiling the model, and managing the training loop.
GPU Acceleration	CUDA Toolkit & cuDNN	11.x	Middleware enabling TensorFlow to interface directly with the RTX 3090 hardware.
Data Manipulation	Pandas & NumPy	1.5+ / 1.23+	Handling tabular data (CSV), timestamp parsing, vectorization, and tensor reshaping.
Visualization	Matplotlib & Seaborn	3.5+	Generating performance metrics plots (Accuracy/Loss curves) and the Confusion Matrix heatmap.
Environment	Jupyter Notebook	6.4+	Interactive Development Environment (IDE) allowing for cell-based execution and immediate visualization of results.

References:

1. Jun, S., Jung, D., & Lansey, K. (2024). Three-dimensional convolutional neural network for leak detection and localization in smart water distribution systems.
<https://pmc.ncbi.nlm.nih.gov/articles/PMC11736163/>
2. Zese, R., Bellodi, E., Luciani, C., & Alvisi, S. (2021). Neural network techniques for detecting intra-domestic water leaks of different magnitude.
<https://ieeexplore.ieee.org/document/9530653>
3. Luo, J., Wang, C., Yang, J., & Zhong, X. (2024). A transformer-based approach to leakage detection in water distribution networks. Sensors, <https://www.mdpi.com/1424-8220/24/19/6294>
4. Yu, H., Lin, S., Zhou, H., Weng, X., Chu, S., and, Yu, T., (2024). Leak detection in water distribution networks based on deep learning and kriging interpolation method.

<https://iwaponline.com/aqua/article/73/8/1741/103988/Leak-detection-in-water-distribution-networks>

5. Peng, S., Zeng, H., Wu, X., & Zheng, G. (2025). Leakage break diagnosis for water distribution network using LSTM-FCN neural network based on high-frequency pressure data.

<https://www.mdpi.com/2073-4441/17/12/1823>

6. Singh, A., Singh, S., and, Maheshwari, A., (2025). A proof-of-concept study towards developing digital twins for operational excellence in large-scale water distribution networks.

<https://www.tandfonline.com/doi/full/10.1080/1573062X.2025.2480632>

7. Zhang, Z., & Fink, O. (2024). Algorithm-informed graph neural networks for leakage detection and localization in water distribution networks. arXiv preprint.

<https://arxiv.org/pdf/2408.02797>

8. Artelt, A., Kyriakou, M. S., Vrachimis, S. G., Eliades, D. G., Hammer, B., & Polycarpou, M. M. (2024). A toolbox for supporting research on AI in water distribution networks.
<https://arxiv.org/pdf/2406.02078>
9. Pandey, P., Mücke, N., Jain, S., Ramachandran, P., Bohte, S., & Oosterlee, K. (2024). Machine learning-based digital twin for water distribution network anomaly detection and localization.
<https://www.mdpi.com/2673-4591/69/1/201>
10. Ares-Milián, M., Quiñones-Grueiro, M., Verde, C., and, Llanes-Santiago, O.,(2021). A leak zone location approach in water distribution networks combining data-driven and model-based methods. <https://www.mdpi.com/2073-4441/13/20/2924>