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Detection of Leakages in a Pipeline Network based on Hydraulic Laboratory Modelling with Artificial Intelligence

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ABSTRACT: Pipeline transportation of resources is considered a vital method due to low operational cost, and simple design and implementation. However, the presence of leakages within pipeline networks gives rise to noteworthy jurisdiction regarding environmental impact, economic implications, and safety considerations. The prompt identification and precise localization of such leakages are of utmost importance in order to get rid of their potential consequences on human existence. This project aims to detect leakages in a pipeline network based on hydraulic laboratory modelling with artificial intelligence systems. The dataset from both the hydraulic laboratory network and EPANET simulation respectively were used to train and test a model, then validate using for leakage prediction and localization using artificial neural network. The results shows that pressure is a more valid parameter to detect leakages to flowrate in a pipeline network. Also, artificial neural network developed model performed very well in predicting leak sizes with an accuracy of 96.89% respectively. The model developed based achieved validation accuracies which vary broadly between about 85% and 90%. Also, the F-score ranged between 80% and 91% which makes the model is valid to be used to predict and localize the leaks in real time.

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Pipeline systems are used as the main transportation system for many applications, such as water distribution, oil and gas transportation, metropolitan heat systems, etc. Leakage in these pipeline systems can cause environmental and chemical damage. Leakage not only wastes resources but also creates environmental problems. Hence, monitoring systems for pipeline leakages are being increasingly demanded(Hieu *et al.*, 2014). A leak's frequency features, as well as its amplitude, depend on many factors, for instance, the size of leak, the type of transported fluid (i.e., water, oil), and pipeline pressure. If the pipe is large in diameter or less solid, then the leak sound contains lower frequency components. On the contrary, if pressure is higher, then higher-frequency components dominate. The amplitude of the leak sound is higher if the pressure or flow speed is higher or if the leak is large, but not very large (Billman & Isermann, 1984a; Hunaidi and Chu, 1999) as cited by (Hieu *et al.*, 2014) .If operational conditions of the pipeline, such as temperature, pressure, and flow do not change, then the leak sound is assumed to be a stationary signal, a signal whose frequency components do not change over time. The average economic loss due to incidents of pipeline leakages is enormous (Liu *et al.*, 2008). To size the 42 cost, in single incident of pipeline leakage at Sam Bruno community, USA on September 6, 2010. More 43 than 840,000 gallons of crude oil spilled into Kalamazzo River with estimated cost of $800 million. The cause of the pipeline damages varies. Figure 1 shows a pie chart that illustrates statistics of 45 the major causes of pipelines failure which include pipeline corrosion, human negligence, defects 46

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befalls during the process of installation and erection work, and flaws occurs during the process of 47 manufacturing and external factors (Bolotina *et al*., 2018).

Pipeline monitoring has become an important issue around the world for its high environmental and economic interest. In general, the main objective of a Leak Detection and Isolation (LDI) system is to detect and locate the smallest leaks as early as possible with minimal instrumentation. Usually, pressure and flow sensors are placed at pipeline ends, and are employed by the LDI system, that is used to locate them through mass balance and non-stationary calculations(Delgado-Aguiñaga *et al.*, 2018). The leak detection task in pipelines can be tackled by using Fault Detection and Isolation (FDI) tools based on a fluid model that represents the physical dynamics of a specific installation. These tools include, for instance, algorithms in frequency domain (Brunone & Ferrante, 2001) and time domain(Billman and Isermann, 1984b) ; (Bermúdez *et al.*, 2018; Kowalczuk and Gunawickrama, 2000) (Moustafa *et al*., 2012) based on the model described by (Chaudhry, 1979); (Wylie and Streeter, 1978). These algorithms were developed for a pipeline instrumented only with pressure and flow sensors at the ends and without branch junctions in between. Hence, the objective of this paper is to evaluate the detection of leakages in a pipeline network based on hydraulic laboratory modelling with artificial intelligence.

MATERIALS AND METHODS

Laboratory Setup: A laboratory-based test bench system was been designed to detect the leak, predict leak size and make the model effective and efficient. This system consists of U-shaped pipelines made of PVC pipes and is shown in Figure 1. Water was moved around in the system by a common water pump capable of providing up to 15 PSI of pressure. Three leaks were created in the pipe sections using hose bibb in three different locations. The first leak was created between sensor 1 and 2, the second leak was between sensor 3 and 4, and the third leak was between sensor 5 and 6. Sensor 1 and 2 are 25cm apart, sensor 3 and 4 are 25cm apart, sensor 5 and 6 are 25cm apart, sensor 2 and 5 are 125cm apart and Sensor 1 and 6 are 250cm apart. Leak-1 is located halfway between sensor 1 and 2, leak2 is located halfway between sensor 3 and 4, and leak-3 is located halfway between sensor 5 and 6. The flow and pressure sensors was installed to measure flow rate and pressure at different intervals.

.**Fig 1:** Laboratory Setup

A large number of datasets were been collected to verify the system. PVC pipes with three different diameters were used: 19mm, 25mm, and 38mm; three leak locations and five different leak sizes: 12.7mm, 10.2mm, 7.6mm, 5.1mm, and 2.5mm to collect data with different conditions. About 2000 data across the various nodes was transferred to the cloud network at appropriate intervals.

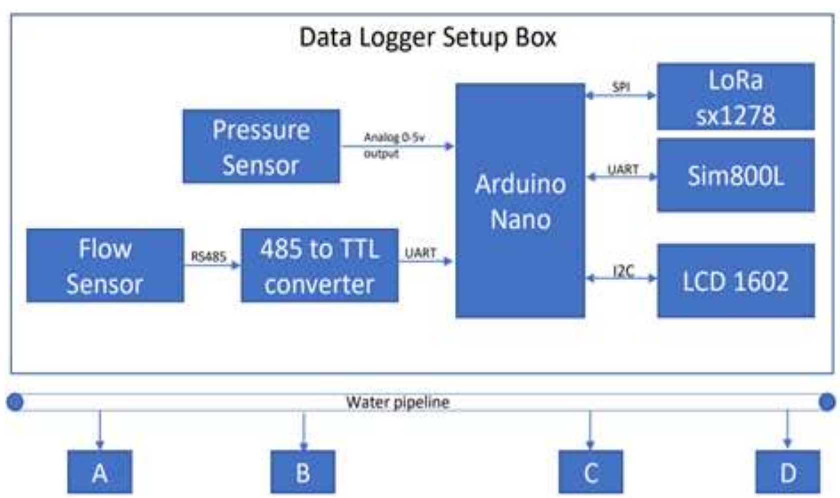

Fig 2: Data Logger Setup Box

Data Acquisition System: Data acquisition is the method of transforming data from one state to another state that is acceptable to the computing device for advance processing. The system consists of sensors, hardware, AT megs 328 (Arduino), GSM internet module and a computing device with programmable software.

Each of the data logger A, B, C and D box are all connected to the water pipeline and will be logging the values of the pressure and flow sensor to the server every 5 to10 seconds. The LoRa sx1278 will also be sending the same data through a LoRaWAN gateway to the server.

EPANET Simulation: The performance of the pipeline network in detecting leakages was evaluated through the utilization of the EPANET simulation. EPANET 2.2 software was employed. The simulation encompassed diverse scenarios, comprising distinct demand patterns, pipe diameters, and pressure conditions, with the aim of encompassing a broad spectrum of realistic operational circumstances. The results obtained from the EPANET simulation have provided significant revelations regarding the network's capacity to precisely identify leakages. The hydraulic network modelled in the laboratory was simulated on the EPANET software to compare the data from the simulation to a real life situation. The flow rate and pressure at across different nodes were gotten. The EPANET simulation gave allowances for parameters that could not be discovered through the laboratory experimental analysis like demand, water quality, temperature and volume. The data were analyzed at different nodes through the times series plot and frequency plot at different nodes.

Model Training through Artificial Neural Network: The training algorithm used for this model is scaled conjugate gradient. The dataset collected was 10000. 70% of this was used for testing, 15% was used for validation and 15% was used for training. Although the data division is random, the algorithm performance arrived at a cross-entropy error. The input layer represents the nodes which are 3 in number, while the output layer is 1. The output is a Boolean output in which it is either 0 or 1. If it is 0 for leak detection, it means no leakage. If it is 1, it means there is leakage. For localization, if the output is 0, It means leakage is at node 1. Also, if the output is 1, it means leakage is at node 2. The number of hidden layer used is 5 to prevent overfitting; so that the neural network can learn from the training and give good prediction. A scaled conjugate algorithm was used as well so the number of neurons was determined by the architecture. The epoch (the number of iteration) after which the neural network was able to converge is 19.

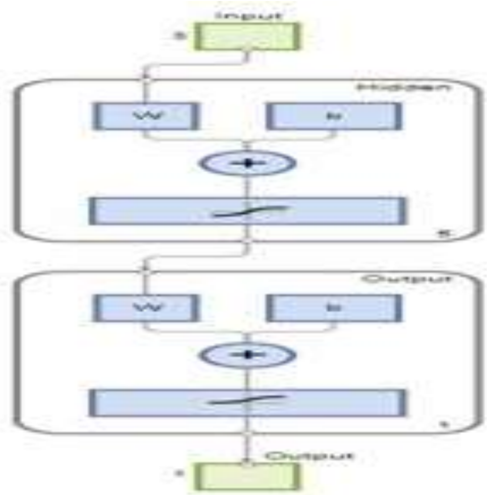

Fig 3: ANN Architecture

RESULTS AND DISCUSSIONS

Laboratory Hydraulic Modelling: In this study, data have been collected from the test-bench system with several conditions such as: (1) Three kinds of pipe diameters: 19mm, 25mm and 38mm; (2) 3 leak locations; and (3) Five leak sizes: 12.7mm, 10.2mm, 7.6mm, 5.1mm, and 2.5mm. A total of 2000 sets of data has been collected including datasets with and without leaks. Data were stored in the cloud and then analyzed to separate leak data sets from non-leak data sets. Next, a total of 900 sets of leak data were analyzed to localize leak and predict leak size. In this chapter, the result of the data analysis is discussed.

Separating Non-Leak and Leaks Dataset: The exponential curve fitting model was used to separate leak data sets from nonleak data sets. The accuracy of the separation of leak data sets from non-leak data sets is shown in Table 1. The above represent the mean pressure across different nodes after 11 iterations, for different pipe diameters both before and after leak, the graphs exhibit a stable pressure and consistent flow rate within the laboratory operating conditions. Upon analyzing the data for after leaks, it was observed that there was a consistent and significant reduction in pressure across the nodes during and after leaks. This observation justifies utilizing pressure as a key parameter for leak detection.

Table 1: Accuracy to separate non- leak from leaks dataset

Data sets	Test datasets	Correctly predicted	Accuracy
Leak data sets	100	98	98%
Non-leak data sets	100	100	100%

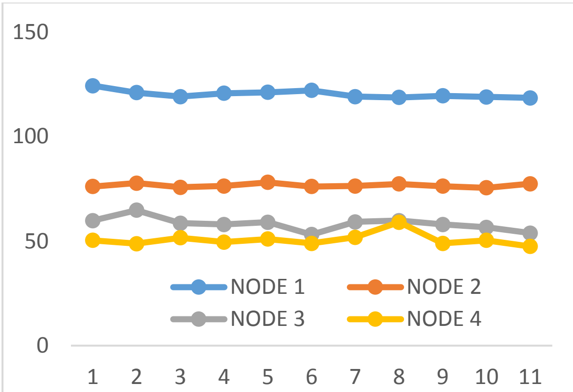

Fig 4: Mean Pressure Profile for 19mm (0.75 inches) pipe for different nodes at each iteration (Before Leak)

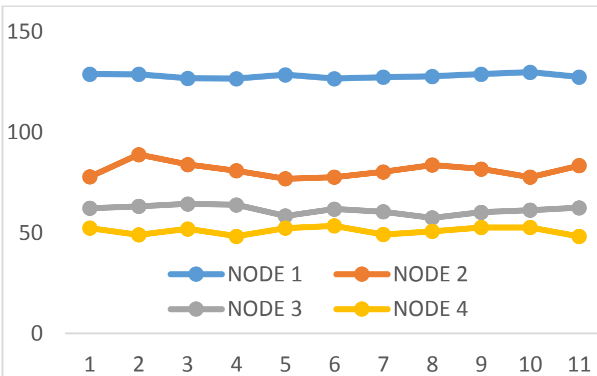

Fig 5: Mean Pressure Profile for 38mm (1.5 inches) pipe for different nodes at each iteration (Before Leak)

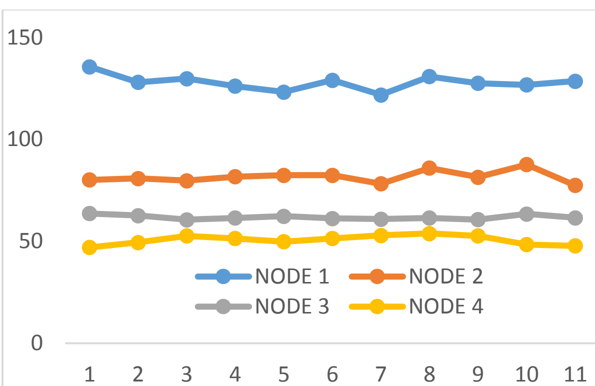

Fig 6: Mean Pressure Profile for 25.4mm (1.0 inches) pipe for different nodes at each iteration (Before Leak)

As data sets related to node-2 showed less efficiency because of the incorrect distance between sensors, so datasets associated with the node-1 and node-3 were considered only for accurate leak localization. The efficiency of leak location identification has been calculated. In this case, the accuracy of 85.6% is achieved. So, the distance between sensors plays a pivotal role in detecting leak location accurately. Thus, it can be concluded that distance between sensors should be 25cm or more to get an acceptable efficiency in identifying leak location.

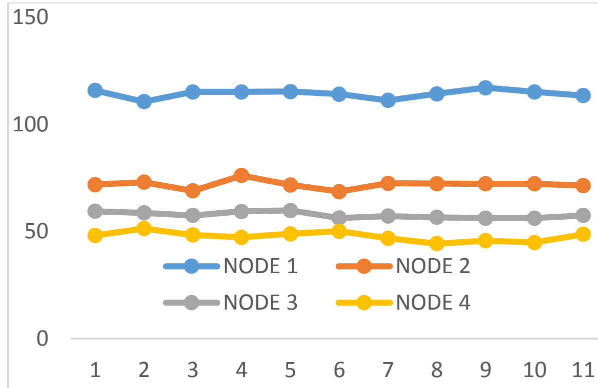

Fig 7: Mean Pressure Profile for 38mm (1.5 inches) pipe for different nodes at each iteration (After Leak)

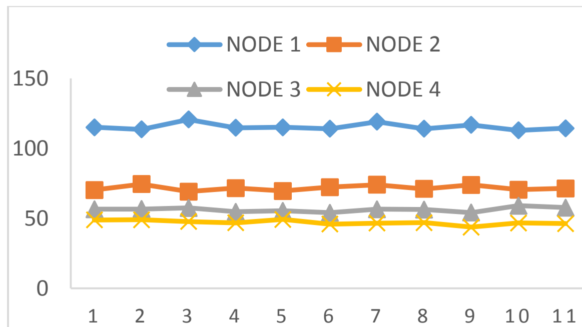

Fig 7: Mean Pressure Profile for 19mm (1.0 inches) pipe for different nodes at each iteration (After Leak)

EPANET Simulation at different intervals

Table 2: Node Results at 0.00 Hour

NODE ID	DEMAND (LPM)	HEAD (M)	PRESSURE (N/M^2)
1	0.00	213.36	0.00
2	0.00	251.93	$3.7 \times 10^5 N/M^2$
3	100.00	251.93	$3.4 \times 10^5 N/M^2$
4	100.00	251.72	$4.3 \times 10^5 N/M^2$
5	75.00	250.49	$4.8 \times 10^5 N/M^2$
6	75.00	252.07	$5.0 \times 10^5 N/M^2$
7	100.00	252.07	$3.7 \times 10^5 N/M^2$
8	-325.00	254.12	$9.1 \times 10^3 N/M^2$

Table 3: Node Results at 1.00 Hour

NODE ID	DEMAND (LPM)	HEAD (M)	PRESSURE(N/M^2)
1	0.00	213.36	0.00
2	0.00	251.93	$3.41 \times 10^5 N/M^2$
3	100.00	251.93	$4.29 \times 10^5 N/M^2$
4	100.00	251.72	$4.81 \times 10^5 N/M^2$
5	75.00	250.49	$4.87 \times 10^5 N/M^2$
6	75.00	252.07	$3.9 \times 10^5 N/M^2$
7	0.00	252.07	0.00
8	-325.00	254.12	$9.1 \times 10^3 N/M^2$

The above tables exhibit the hydraulic characteristics of the network at the different nodes, such as pipe diameters and pressure conditions, were identified as a contributing factor to the detection performance. The findings of the EPANET simulation indicate that leakages in larger diameter pipes or under higher pressure conditions were detected with higher precision in comparison to those in smaller diameter pipes or lower pressure zones. The aforementioned observation implies that the efficacy of the model could be impacted by the hydraulic behavior and attributes of the particular pipeline network under examination.

Table 4: Node Results at 2.00 Hour

NODE ID	DEMAND (LPM)	HEAD (M)	PRESSURE(N/M^2)
1	0.00	250.83	0.00
2	0.00	250.83	$3.67 \times 10^5 N/M^2$
3	75.00	250.72	$3.37 \times 10^5 N/M^2$
4	75.00	249.91	$3.65 \times 10^5 N/M^2$
5	100.00	250.93	$5.07 \times 10^5 N/M^2$
6	75.00	250.95	$3.68 \times 10^5 N/M^2$
7	0.00	213.36	$3.65 \times 10^5 N/M^2$
8	-325.00	253.64	$6.4 \times 10^3 N/M^2$

Table 5: Node Results at 3.00 Hour

NODE ID	DEMAND (LPM)	HEAD (M)	PRESSURE(N/M^2)
1	0.00	250.27	0.00
2	0.00	250.27	$3.62 \times 10^5 N/M^2$
3	75.00	250.05	$3.32 \times 10^5 N/M^2$
4	75.00	249.35	$3.60 \times 10^5 N/M^2$
5	100.00	249.35	$5.02 \times 10^5 N/M^2$
6	75.00	250.37	$3.62 \times 10^5 N/M^2$
7	0.00	250.42	$3.63 \times 10^5 N/M^2$
8	-325.00	253.01	$6.4 \times 10^3 N/M^2$

Table 6: Node Results at 3.00 Hour

NODE ID	DEMAND (LPM)	HEAD (M)	PRESSURE (N/M^2)
1	0.00	250.07	0.00
2	0.00	250.07	$3.24 \times 10^5 N/M^2$
3	75.00	249.85	$3.24 \times 10^5 N/M^2$
4	75.00	248.35	$3.17 \times 10^5 N/M^2$
5	100.00	248.35	$5.13 \times 10^5 N/M^2$
6	75.00	251.74	$3.42 \times 10^5 N/M^2$
7	0.00	251.45	$3.23 \times 10^5 N/M^2$
8	-325.00	252.88	$5.9 \times 10^3 N/M^2$

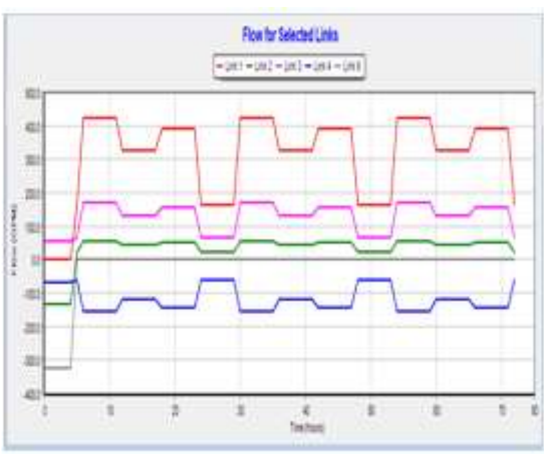

Fig 8: Times series plot showing the flow rate at different nodes.

The time series plot graph presented a clear visualization of the pressure dynamics within our hydraulic system and provided valuable insights into leak detection. The graph allowed us to identify the occurrence and duration of leaks and also facilitate a qualitative understanding of their severity. With the information gotten from this graph, we can calibrate our leak detection algorithms to improve our leak detection systems.

Model Training, Validation and Testing: The following table represent the no leak and leak dataset range used for training across the different nodes captured by the flow and pressure sensors.

Table 7: Dataset range for no leakage at 0

Node 1	Node 2	Node 3
39.00	35.90	29.66
38.00	35.85	29.55

Table 8: Dataset range for no leakage at 1

Node 1	Node 2	Node 3
34.00	31.77	29.66
33.00	35.85	29.53

Table 9: Dataset range for no leakage at 2

Node 1	Node 2	Node 3
35.10	32.08	26.36
35.00	31.93	25.94

Fig 9: The Confusion Matrix of the Model

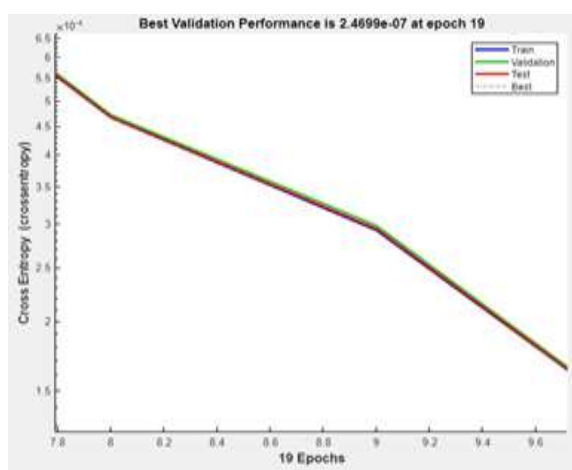

Figure 10: The Performance Plot of the Model

Table 10: The Training Plot of the Model

Unit			
Epoch	0	19	1000
Elapsed Time	-	00:00:00	-
Performance	0.33	2.45e-07	0
Gradient	0.689	5.8e-07	1e-06
Validation checks	0	0	0

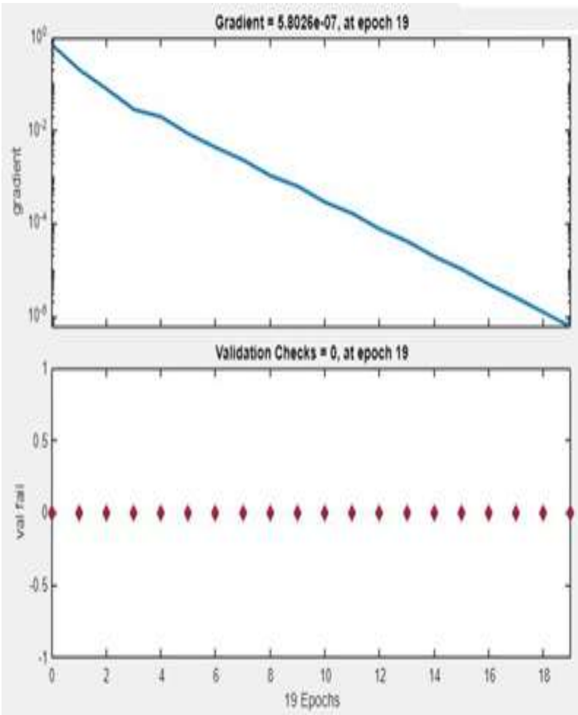

Fig 11: The Training State of the Model

The analysis of the constructed model's performance through ANN shows positive indicators in considering the research findings. High levels of accuracy and the ability to learn from training data are consistently displayed by the model, as evidenced by the ROC curves for the training, validation, and testing datasets. The ROC curves all pointing in the same way indicates that the model effectively generalizes to new data without being over- or under-fit. The performance plot has affirmed the validation of the model as the graph of the training, validation and testing datasets intertwined. These findings demonstrate that the trained neural network successfully extracted the necessary data patterns and features, resulting in accurate leak detection. The model's ability to classify leaks while reducing false alarms is supported by a number of additional performance indicators. These include confusion matrix, training plot, and training state. The results of this study show that the created model has potential for efficient leak detection, thereby advancing the state of the art in this vital area.

The model's performance and usefulness could be confirmed and improved by more extensive testing on larger datasets and real-world circumstances. As presented in Table 9, for the nonleaks, the performance of the detection models varies considerably when tested on the training and testing data sets. It was generally degraded when evaluated against the testing data set compared to the training data set. The measured accuracy ranged from about 87.7% to 90.2% and from about 85.3% to 88.7% when tested on the training and testing data sets, respectively. Also, the F-score of the model was around 88.7–91.3% and 80.7–86% when tested against the training and the testing data sets, respectively. However, the measured AUC was 0.97–1.00 and 0.87–0.95 when tested on the training and the testing data sets, respectively.

Table 11: Model Performance for Leak and Non Datasets

Datasets	Training			Testing		
	Accuracy	F-Score (%)	AUC	Accuracy	F-score (%)	AUC
Non Leak	90.2	91.3	1.00	87.7	88.7	0.97
Leak	88.7	85.6	0.95	85.3	80.7	0.87

Conclusions: This study has been able to present a clear and detailed procedure to set up the fluid network and leak simulation in EPANET, to generate the dataset, to apply artificial neural network to predict leakage and to apply the proposed system to a real-world leak detection system. The results of this study show that the created model has potential for efficient leak detection, thereby advancing the state of the art in this vital area. The model's performance and usefulness could be confirmed and improved by more extensive testing on larger datasets and real-world circumstances.

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