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AI-based acoustic leak detection in water distribution systems

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ABSTRACT

Water loss in distribution networks known as Non-Revenue Water (NRW) is one of the major challenges facing water utilities. In a densely populated city, the acoustic listening method manually conducted by waterworks operators during routine leak pinpointing tasks is vital for NRW reduction. However, this method is considered to be typically labor-intensive, skill-dependent, non-systematic, and sometimes imprecise due to fatigue and inexperience of newly trained staff. This paper presents the development of an AI-based water leak detection system with cloud information management. The system can systematically collect and manage leakage sounds and generate a model used by a mobile application to provide operators with guidance for pinpointing leaking pipes. A leakage sound collection and management system was designed and implemented. Leakage sound datasets were collected from some multiple areas of the Metropolitan Waterworks Authority. Machine learning algorithms including Deep Neural Network (DNN), Convolutional Neural Network (CNN), and Support Vector Machine (SVM), were developed and compared. The results show that the DNN performed better than SVM and as well as CNN, but with less complex structure. DNN was then selected to generate a model used in field trials for pinpointing leakage by novice operators. The field trial results show that the accuracy of the system is above 90% and the results were similar to those conducted by experts.

1. Introduction

One of the important issues that challenges water utilities is the management of water losses, so-called Non-Revenue Water (NRW). NRW is defined as the amount of water that cannot be billed, including unbilled authorized consumption, commercial losses, and physical losses. The majority of NRW results from water being physically lost through leaks in distribution pipes. This leads to unnecessarily increased operational costs. It was reported by Asian Development Bank that NRW was 35% on average in the Asian cities and can reach much higher levels. The estimated annual volume of NRW in urban water utilities in Asia was on the order of 29 billion m^3 or equivalent to nearly 9 billion US dollars per year [1].

The Metropolitan Waterworks Authority (MWA) of Thailand is responsible for the water supply of Bangkok, which is the capital of Thailand, and its vicinity. MWA has committed to NRW reduction by developing and employing advanced technologies and management strategies to cope with physical water losses during distribution systems. In Thailand, one major source of NRW is leakage from pipes with small diameters that connect household water meters and water distribution pipelines. The main causes of these leaks are aging pipelines and soil subsidence, which introduces stress and pressure on the pipelines. Since these small diameter pipes are used in most of the Bangkok metropolitan area and have a complex network topology, it is labor-intensive and resource-consuming to investigate and repair the leaks.

Leakage management strategies can be categorized into three groups, including passive control, regular survey, and leakage monitoring in zones or sectors [2]. Passive control is a reaction method where water supply staffs repair water pipes according to reports from customers, especially when leakage is visible or when the pressure drops. The regular survey is a method of inspection using acoustic devices to listen for leaks from one end of the distribution system to the other. Leakage monitoring is a method of monitoring the flows into zones or districts to measure leakage and prioritize the leak detection activities. An example of leakage monitoring is the background night flow analysis mentioned in the Bursts and Background Estimates concepts [2,3].

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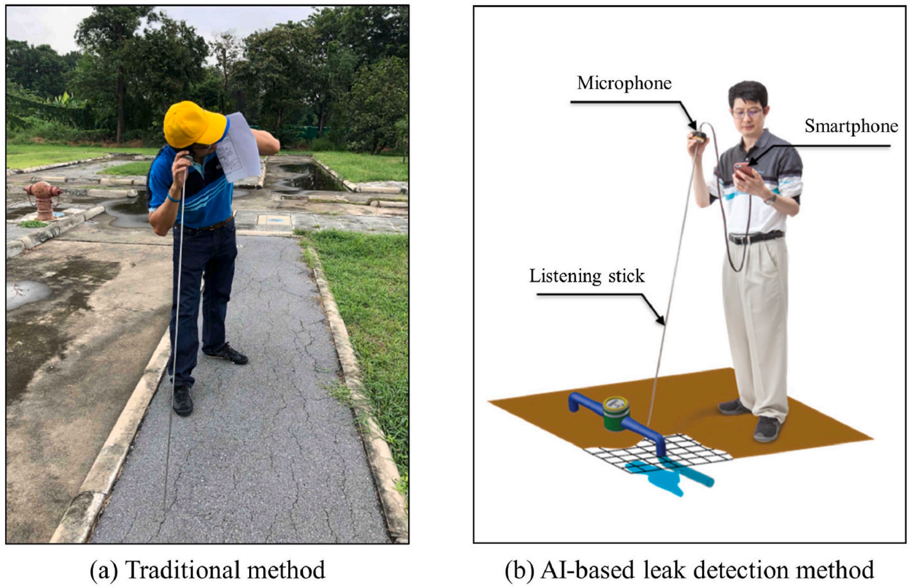


Fig. 1. Application of leak detection device in the field.

These concepts were first developed for the UK Water Industry in the early 1990s and have been accepted and adopted in many countries because they provide a simple and pragmatic approach to monitoring water leakage problems. In the background night flow analysis, the measurement of the minimum night flow into a district metered area is performed, which is an effective way to identify whether there is a serious leakage problem. On the other hand, leakage monitoring can be performed through water pressure monitoring and control in the water distribution systems simulation [4,5]. Hence, an optimized set of water distribution parameters, such as water pressures and pipe diameters, is determined to reduce water leakage.

Another aspect of leakage monitoring is leakage localization through an installation of acoustic or vibration sensors, permanently or temporarily, for each section of the water pipelines. Several techniques have been proposed for this kind of leakage localization such as flow-based analysis, noise correlator, and transient pressure wave techniques. Regarding flow-based analysis techniques, an ultrasonic flowmeter has been used to collect pipe flow data and the data is classified by One-Class-SVM, which is an unsupervised algorithm consisting of Support Vector Machine (SVM) to detect water leakages [6]. In a previous report, the measured data, such as pressure and flow rate of both inlet and outlet, are analyzed through rules generated using rough set theory and support-vector machines to detect leakages [7]. For noise correlator techniques, at least two sensors need to be installed along the water pipeline and the time shift between two signals with the highest correlation is determined to sequentially find the location of the leak. Previously, signals from pressure, velocity, and acceleration sensors are compared for cross-correlation leak detection performance [8]. It is found that pressure signals from a hydrophone provide the most effective results for leak localization, especially in the case of a small signal-to-noise ratio (SNR). Moreover, an extra step of leak detection has been considered using an ensemble of a 1D Convolutional Neural Network (CNN) and an SVM model to recognize the leakage first [9]. Then, an enhanced graph-based algorithm localizes the leakage using the signals from leakage nodes with cross-correlation computing and reduced time searching. On the other hand, another method used autocorrelation analysis where only one signal source can be used to locate the leakage [10]. Signals from a hydrophone, and radial and axial accelerometers are compared, and it was observed that longitudinal vibrations from axial accelerometers are the most effective signals for leak detection. For transient pressure wave techniques [11,12], a transient pressure wave is generated, e.g., from a side discharge valve, which propagates through the physical structure of the pipelines. The analyses of the transient wave that passes through special structures such as a junction, pressure reducing valve, or leak, can reveal those structures and locate them. For the techniques mentioned, the sensors and instruments are installed beforehand to automatically record signal data, detect, and localize the leaks. Therefore, these techniques can save the time and effort of the professional leak detection staff and water suppliers. However, the initial installation is costly and time-consuming. Furthermore, the applications of those techniques have only been studied in simple pipeline networks, and the results do not apply to the complexity of the consumer household water pipeline network.

Regarding regular surveys as a leak management strategy, it was reported that acoustic-based technologies have been widely applied to pipeline leak detection [13]. Geophones and acoustic rods are used to listen to buried pipelines from the surface. These devices are accurate and highly sensitive, such that they can detect the exact location of the leak. However, the accuracy depends highly on the proficiency and the experience of the operators. Typically, skilled professionals are required to listen and analyze the sound to determine if there is any leakage. After a long working period, these professionals may be exhausted, and their performance and accuracy for detecting the leakage sound can drop significantly. Moreover, the training process for an eligible person to perform this task requires on-the-job training that is time-consuming and costly. To expand the workforce and cover large residential areas in the cities, some other systematic approaches must be employed to minimize human error, and reduce costs and time. As previously reported [14], Adaptive Tabu Search (ATS) can be combined with an Artificial Neural Network (ANN) to improve the accuracy of leak detection using a ground microphone. The results showed an improvement compared with leak detection using ANN alone. In previous studies [15–17], CNNs have been applied for leak sound detection when time series data of the sound is transformed into images such as through recurrence plots, Mel-spectrograms, and Mel Frequency Cepstral Coefficients. These techniques show promising results. However, there have not been methods that use machine learning techniques along with an acoustic rod, which is the common tool widely used by waterworks staffs.

Therefore, MWA and the National Electronics and Computer Technology Center (NECTEC) collaborated on a project, developing an AI-based water leak detection system with cloud information

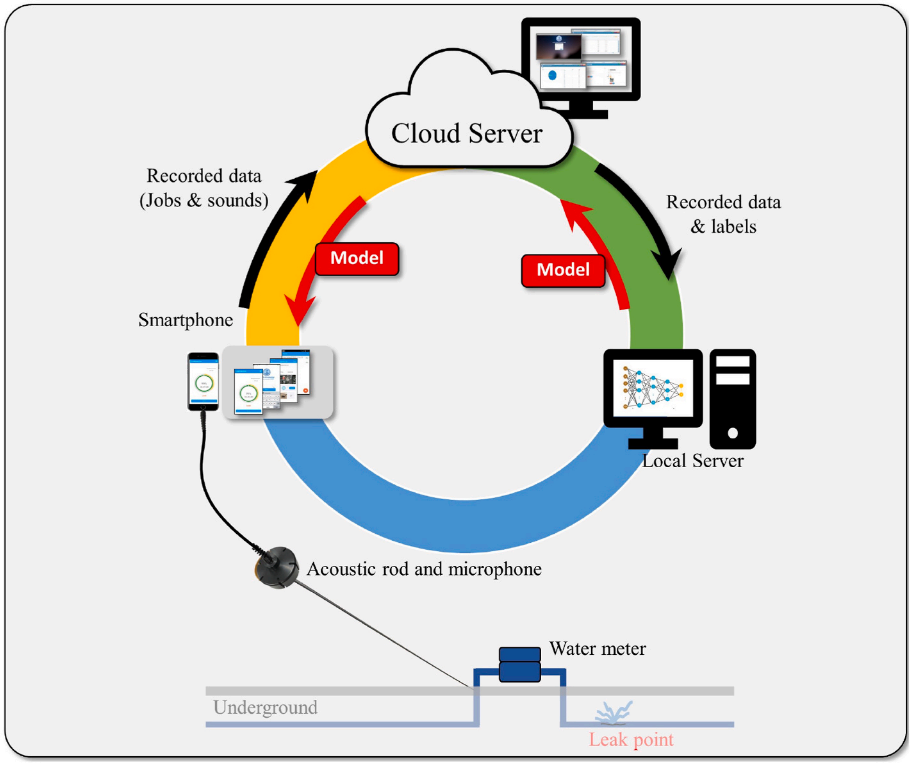


Fig. 2. AI-based water leak detection system with cloud information management.

management, in which is the focus of this paper. The main purpose of this project is to develop an AI-based water leak detection prototype that provides the operators with guidance to interpret the sound from the acoustic rod as either leakage or non-leakage and pinpoint the pipeline leak. This prototype allows novice operators to perform the leak pinpointing routine, thus MWA can reduce time and resources to train a new operator to perform the task. Moreover, human error in the sound interpretation due to fatigue can be minimized. Several machine learning methods, such as SVM, DNN, and CNN are compared based on the accuracy of leak detection of underground pipes. Training and testing datasets consist of both leakage and non-leakage sounds systematically collected through the cloud information management system from the confirmed underground leakages in urban areas. An evaluation regarding the accuracy and computation time is performed. Finally, the performance of the system in controlled environments and field tests conducted in Bangkok, Thailand, for several district areas is presented and discussed.

2. MWA leak detection system with cloud information management

MWA staff usually uses an acoustic rod to listen to the underground sounds for detecting leakage of the underground pipelines, as shown in Fig. 1 (a). The procedure generally requires skilled professionals to determine the accurate location of the leakage, but they become exhausted after continuously working for a long duration, which causes a decrease in the accuracy of detecting leakage. Moreover, novice staff require long on-the-job training to become eligible to perform this task.

To overcome these issues, the MWA and NECTEC developed an AI-based leak detection device and a classification model to distinguish leakage sound from the typical sound of water flow in the pipes, as shown in Fig. 1 (b). By leveraging machine learning techniques and selecting the technique that is most suitable for extracting the noticeable features of the leakage sound signals, an optimal classification model is derived using the sound data collected from leaking and non-leaking pipes in the field.

2.1. Overall system design

The overall platform of the leak detection system for the household water pipeline consists of 4 parts, including the smartphone, acoustic rod/microphone, cloud server, and local server, as illustrated in Fig. 2. The data is exchanged among the smartphone, cloud server, and local server using the internet as demonstrated in Fig. 3. The leakage data collection and classification model generation processes starts with using an acoustic rod to survey, identify, and locate the leakage sound. Then, the users login to the mobile application on the smart phone and fill in the details for the data collection. After that, the users can record acoustic signals through the smartphone and the microphone connected to the acoustic rod and upload the signals and job details to the cloud server. In this project, the acoustic rod is a stainless steel Fuji Listening Stick LSP 1.5 with 510 g weight, 1511 mm long, and a resonant chamber to amplify leak noise. The microphone connected to the acoustic rod through a custom made chamber cover is Rode SmartLav + omni-directional microphone with frequency range 20 Hz - 20 kHz and 67 dB signal-to-noise ratio.

After the pipeline repairing process is completed, the system administrator can label the sounds as “leak” or “no leak” through the web application. Then, the system administrator can download the acoustic signals, along with the ground-truth labels, on the local server and use them to train a new water leakage classification model. Finally, the result of the training process, which is an optimal model for the water leakage classification, is uploaded to the cloud server and transferred to the smartphone to be applied in the field.

The tasks of leakage sound classification and data collection are coordinated by using a mobile application and a web application as shown in Fig. 4 and Fig. 5, respectively. The mobile application, adopting a user-friendly design, is available on iOS and Android. It consists of 4 main parts, including login, leak detection, leakage job data collection, and leakage job data upload to the cloud. The web

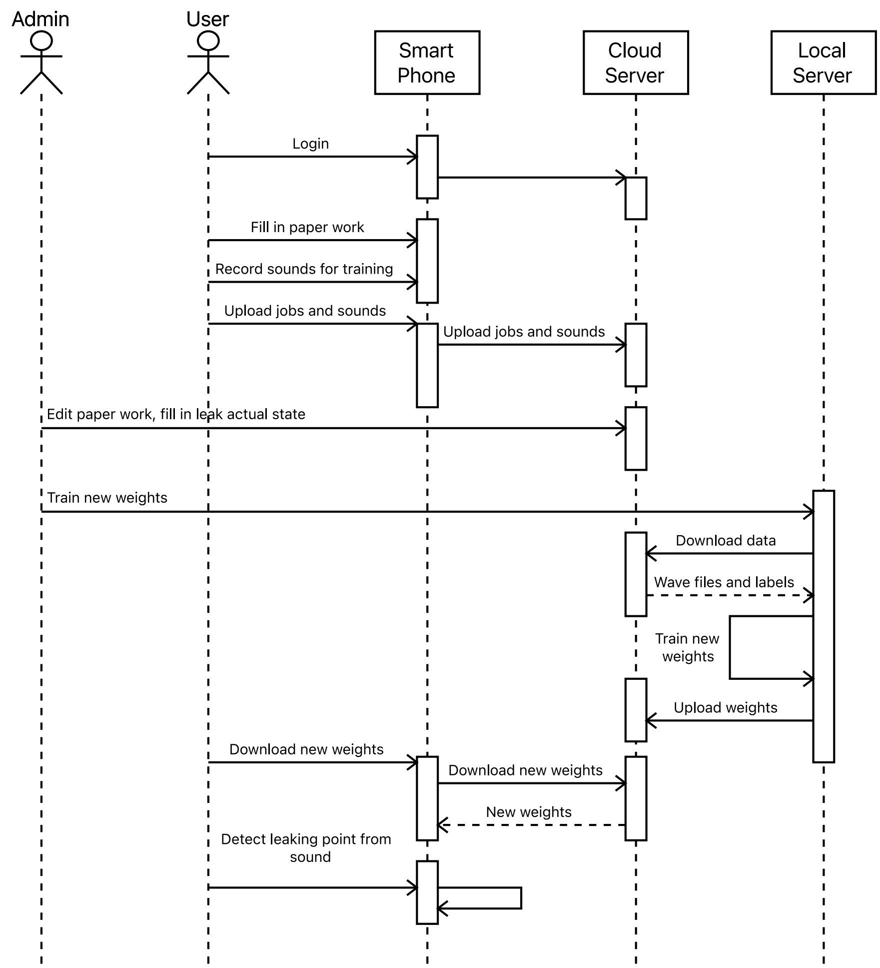
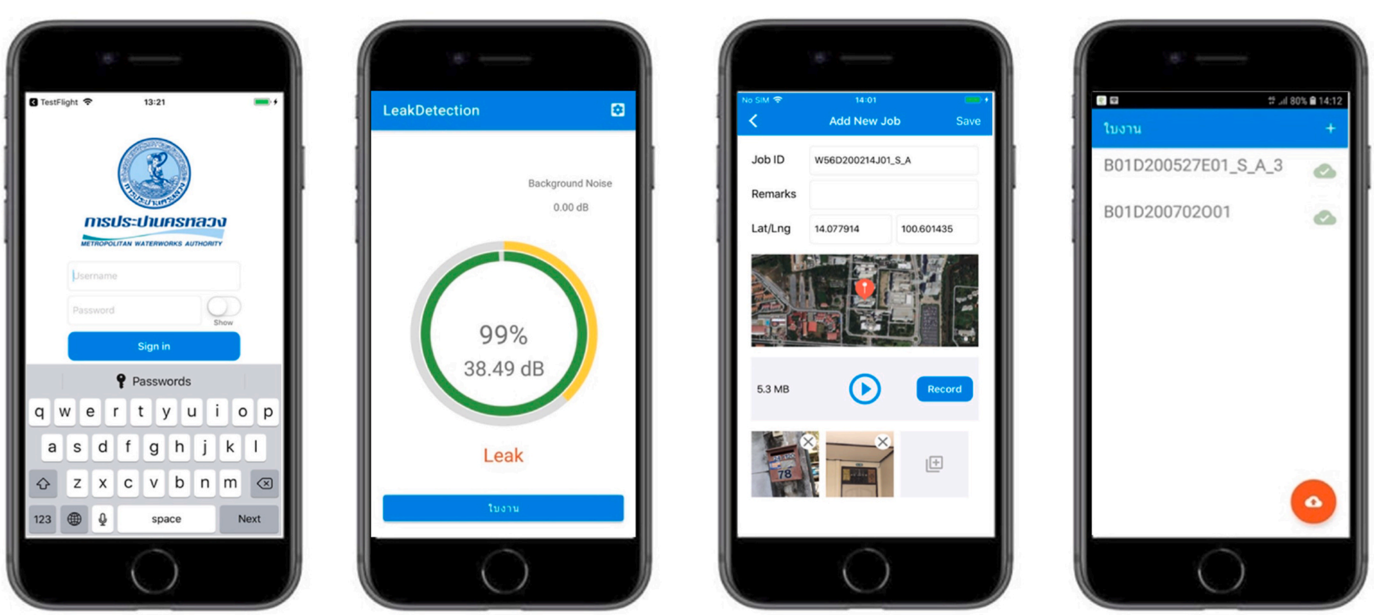


Fig. 3. Sequence diagram.



(a) Log in (b) Leak detection (c) Leakage data collection (d) Job upload

Fig. 4. Mobile application for the leak detection system.

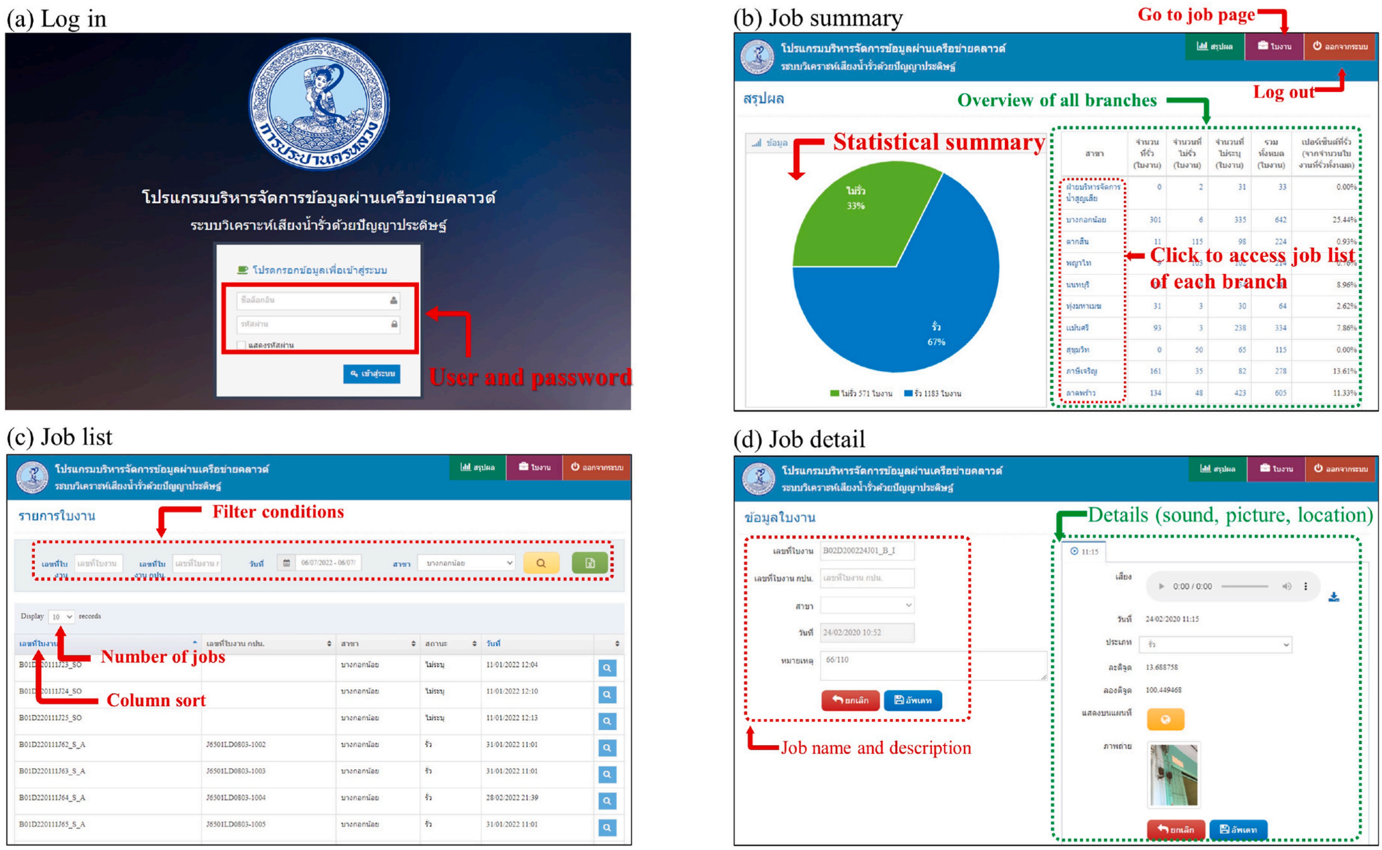


Fig. 5. Web application for leakage data management.

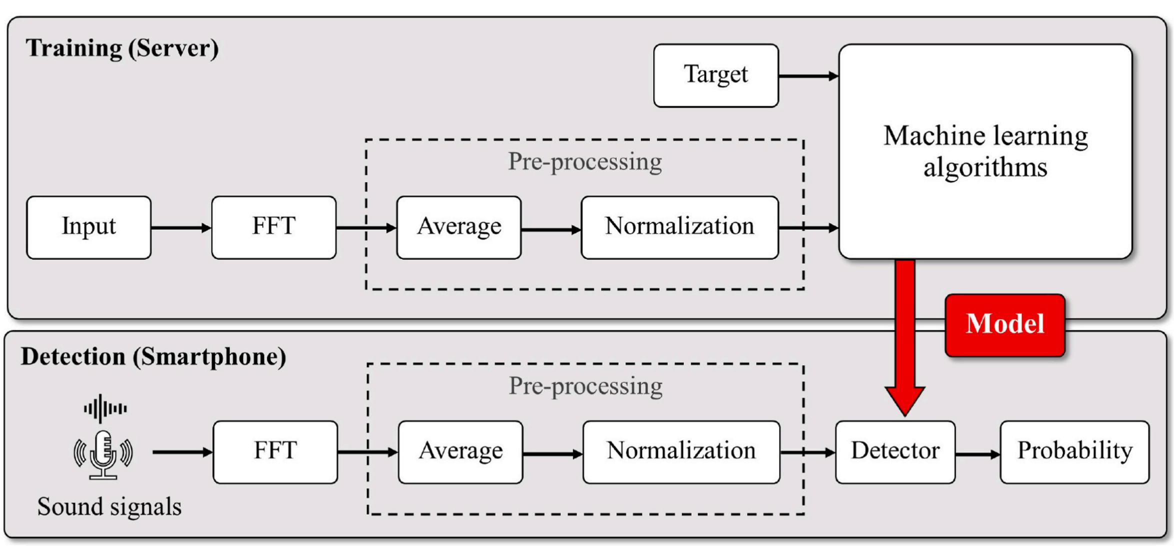


Fig. 6. The pathways of the data during training phase and leak detection phase.

application is responsible for the leakage data management and is accessible on a cloud server with user password authentication, as shown in Fig. 5 (a). Fig. 5 (b) shows a job summary, which is an overview of all the data. The leakage job list and job detail can be seen in Fig. 5 (c) and Fig. 5 (d), respectively. The screen in Fig. 5 (d) is designed for the administrator to label the sounds as “leak” or “no leak” as mentioned previously.

2.2. AI-based leak detection method

The leak detection method in the AI-based leak detection system is separated into two phases, including the training phase and detection phase, as illustrated in Fig. 6. In both phases, the sound data is collected from the field at the frequency of 44.1 kHz. Each frame composed of 2048 samples, or 46.44 ms, is transformed into the frequency domain using Fast Fourier Transform (FFT). Since the transform result is 2048 complex symmetrical data points, the frame is truncated to 1,024, and

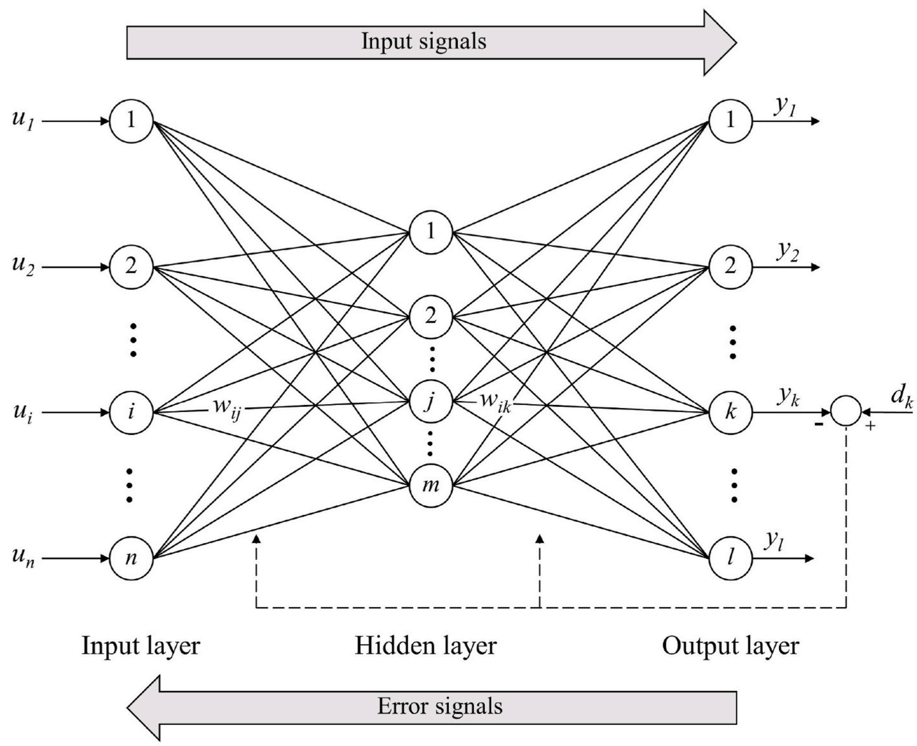


Fig. 7. The pathways of the data in an ANN.

the magnitude of those data is used in the next step. Then, the pre-processing step calculates the frame average for each spectrum from 14 frequency data frames representing 650.16 ms of sound. The frame average makes important features of the leakage sound and the non-leakage sound stand out and distinguishable for categorization. After that, the frame average is normalized to the magnitude between zero and one.

In the training phase, the pipeline repair team is sent to the locations where the sound inputs are collected and performs the repairing process. During the process, the actual results of the leakage are determined and used for labeling the target data that corresponds with "leak" or "no leak" sounds. The target data and sound input data are fed together to the machine learning algorithms for training and testing the leak detection models to find an optimal model that accurately distinguishes leakage sounds from non-leakage sounds. Finally, in the leak detection phase, the smartphone downloads the optimal leak detection model and uses it to guide novice operators by signaling whether the input sound is categorized as a "leak" or "no leak" sound.

3. Machine learning algorithms

In this paper, three well-known machine learning methods are compared, including SVM, DNN, and CNN.

3.1. Support Vector Machine

SVM is a well-known classification and regression method that is suitable for small and medium-sized datasets [18,19]. The basic idea of SVM classification is to use a hyperplane $\{x|a^T(x - x_0) = 0\}$, where x, a are vectors and x_0 is a constant vector, to separate the dataset into two groups. The parameters of the hyperplane can be identified by solving a quadratic programming problem shown in Eq. (1), where w, b are column vectors and constants defining a hyperplane, x^i is the data point i, and t^i is the corresponding target.

$$minimize_{w,b} \quad (1/2)w^T w \tag{1}$$

$$subject\ to\ t^{(i)}(w^T x^{(i)} + b) \geq 1\ for\ i = 1, 2, \ldots, m.$$

Since binary classification for the dataset in real-world problems might not be able to categorize data into two groups by a hard margin of a hyperplane, slack variables, ζ^i, are introduced into the problem formulation, as shown in Eq. (2), to allow the use of soft margins for the classification. Soft margin allows some data points to be on the wrong side of the hyperplane, with penalty costs to be minimized. Moreover, the mapping function or kernel function, $\varphi(\cdot)$, according to Mercer's conditions [19], can be applied to map the data into a higher dimension to linearly categorize non-linear datasets.

$$minimize_{w,b,\zeta} \quad (1/2)w^T w + C\sum_{i=1}^{m} \zeta^{(i)} \tag{2}$$

$$subject\ to\ t^{(i)}(w^T\varphi(x^{(i)}) + b) \geq 1 - \zeta^{(i)}\ and\ \zeta^{(i)} \geq 0\ for\ i = 1, 2, \ldots, m.$$

For multi-class classification, one can use n binary classification rules to separate the data of class k from the rest where $k = 1, 2, \ldots, n$. The highest value of the classification functions, $w_k^T\varphi(x^i) + b_k$, identifies the class where the data is categorized.

3.2. Artificial Neural Network

3.2.1. Basic principle of ANN

ANN has been a growing interesting approach to solving classification and data mining problems in various areas such as image processing, signal processing, pattern recognition, etc. [20–22]. The main advantage is that ANN does not require a user to specify any problem-solving algorithm and instead it learns from examples like human beings [23]. Moreover, ANN can identify and respond to patterns that are similar but not identical to the ones they have been trained on.

ANN can be defined as a model of reasoning based on the human brain, which is trained with historical data to perform a desired function by adjusting the weights (w) and bias (b) of the connections such that outputs match the outputs of the desired function [24]. A set of neurons are combined in a layer and a network can consist of a single layer or multiple layers. A very popular structure is based on the multi-layer organization, where the neurons of a layer connect to the neurons of a

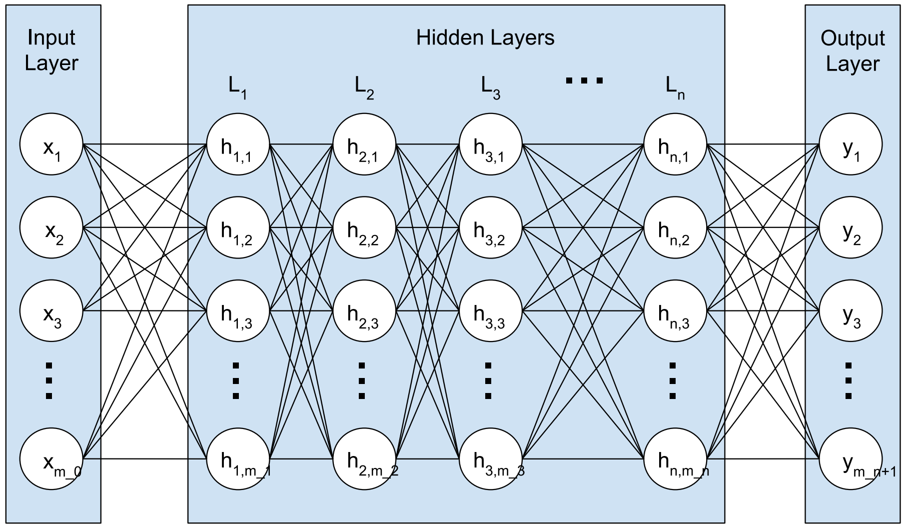


Fig. 8. Classical structure of a DNN.

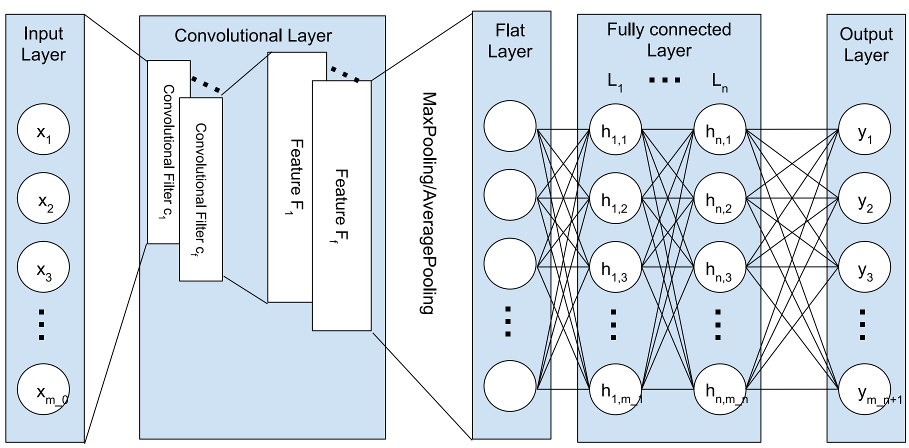


Fig. 9. General structure of a CNN.

subsequent layer. Typically, these layers are termed 'input', 'hidden', and 'output' depending on their positions in the ANN structure. The general structure for a three-layer back-propagation ANN is shown in Fig. 7.

The indexes i, j and k indicate neurons in the input, hidden and output layers respectively. The input signals $u_1, u_2, \ldots, u_n$ are propagated through the network from left to right. The weight w_{ij} connects the ith node in the input layer and the jth node in the hidden layer. In the same way, the weight w_{jk} connects the jth node in the hidden layer and the kth node in the output layer. The output of an ANN is defined as follows,

$$y_k = \theta_k + \sum\nolimits_{j=1}^{m} w_{jk} f(net_j) \tag{3}$$

where $f()$ is an activation function such as sigmoid, hyperbolic tangent, and ReLU. In the hidden layer, node j receives the signal net_j according to the following,

$$net_j = \theta_j + \sum\nolimits_{i=1}^{n} u_i w_{ij} \tag{4}$$

where θ_j and θ_k are bias terms of the hidden layer and the output layer, respectively.

3.2.2. Deep Neural Network

DNN is an ANN with multiple hidden layers as shown in Fig. 8. In the hidden layers, every unit in the previous layer fully connects to every unit in the next layer. Thus, this structure can be called "fully connected layers" [25–27]. These multiple hidden layers improve the performance in many research areas such as speech recognition, image recognition, and object detection.

Since this structure has so many neural units, it may cause a problem when training the model with a small training dataset. Consequently, the model is likely to perform poorly due to "overfitting". The "dropout" mechanism that temporarily removes the neural units randomly is proposed to prevent the deep model training from the overfitting problem [28,29].

3.3. Convolutional Neural Network

Unlike the classical ANN, the CNN has additional layers called "convolutional layers" that can generate representative features of the input data. In each convolutional layer, the inputs are convoluted by filters to generate the features. After that, CNN uses the fully connected network for learning the representative features, as shown in Fig. 9.

Since the features extracted by the convolutional layers are useful for recognizing patterns, CNN becomes an effective technique in several research topics such as image recognition [30,31], video recognition [32,33], and activity recognition [34,35].

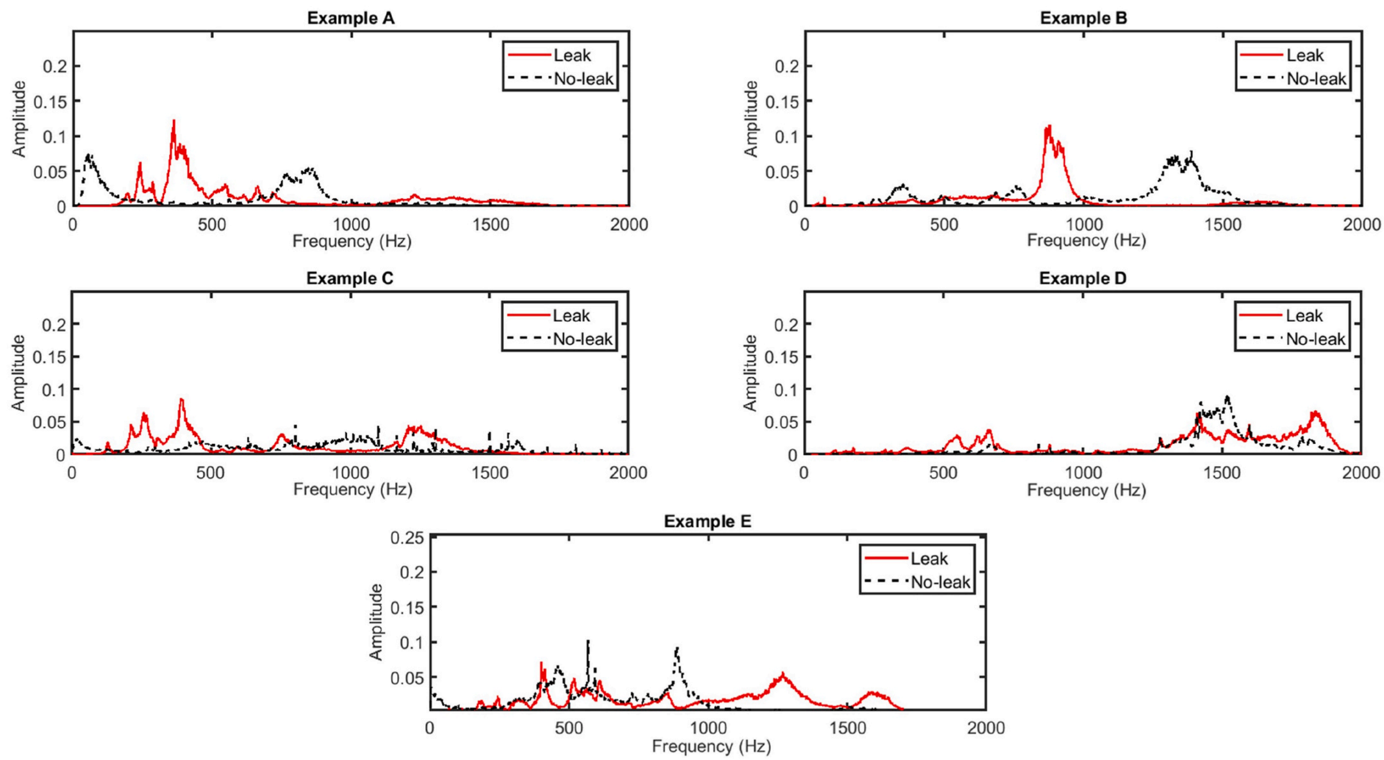


Fig. 10. Examples of frame average spectrum for leak and no-leak case.

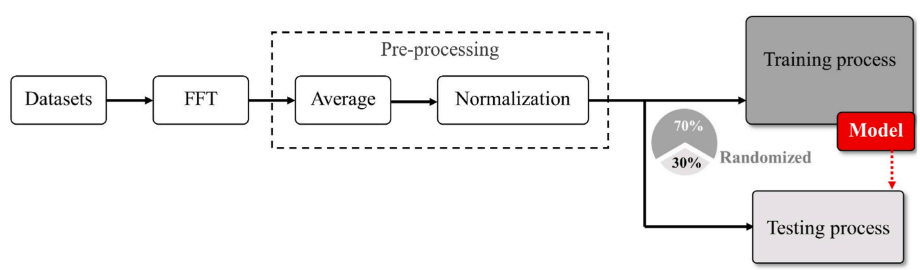


Fig. 11. Leak detection data processing method for comparing SVM, DNN, and CNN.

4. Experiments and discussions

4.1. Machine learning performance comparison

This section presents the comparison of leakage sound data classification performance among SVM, DNN, and CNN. The experiment was conducted by using real-world leakage and non-leakage sound data obtained from the MWA. The sound data were collected by the acoustic rod and microphone through the smartphone as shown previously in Fig. 1 (b) and analyzed by the machine learning algorithms. Examples of the frame average of the sound signals in the frequency domain are illustrated in Fig. 10. The results show that, in some cases, the signal characteristics of "leak" are specific to a certain band of frequencies, such as around 400–450 Hz, as shown in the Examples A, C, and E. However, in other cases, the signal characteristics of "leak" are different and it is more difficult to distinguish between "leak" and "no leak".

The leak detection data processing method is summarized in Fig. 11. The total amount of data collected from 688 leakage sites and 619 non-leakage sites is 108,481 samples, which are separated into 51,377 for "no leak" and 57,104 for "leak". The datasets are processed through FFT and the pre-processing, then randomized and divided into training and testing samples. Notably, the datasets from each site are grouped together during randomization to prevent data leakage problems. About 70% and 30% of the samples are used in the training and testing processes, respectively.

The SVM classification is computed by using a polynomial kernel, with the regularization parameter of 2 and polynomial degree of 3. The DNN and CNN models are trained by using an Adam optimizer and a

Table 1
Performance of SVM, DNN, and CNN (averaged over 10 trials with 300 training iterations).

Method	Training data			Testing data			Training
	Sensitivity	Specificity	Accuracy	Sensitivity	Specificity	Accuracy	time (mins)
SVM	0.7164	0.9070	0.8055	0.6885	0.8820	0.7829	1.29
DNN	0.9966	0.9974	0.9970	0.9374	0.9618	0.9489	14.01
CNN	0.9976	0.9961	0.9969	0.9317	0.99643	0.9471	15.44

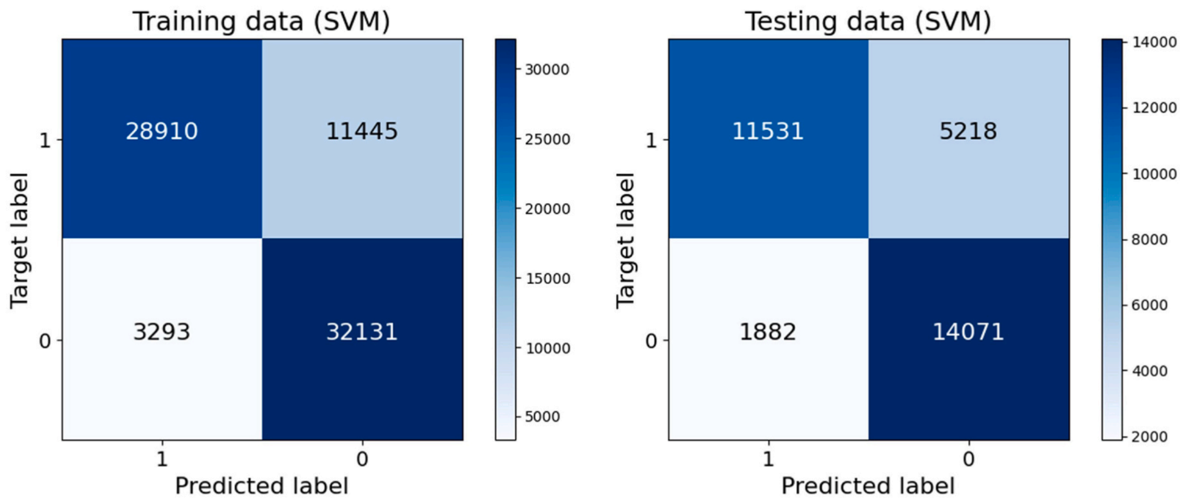


Fig. 12. Confusion matrix for SVM.

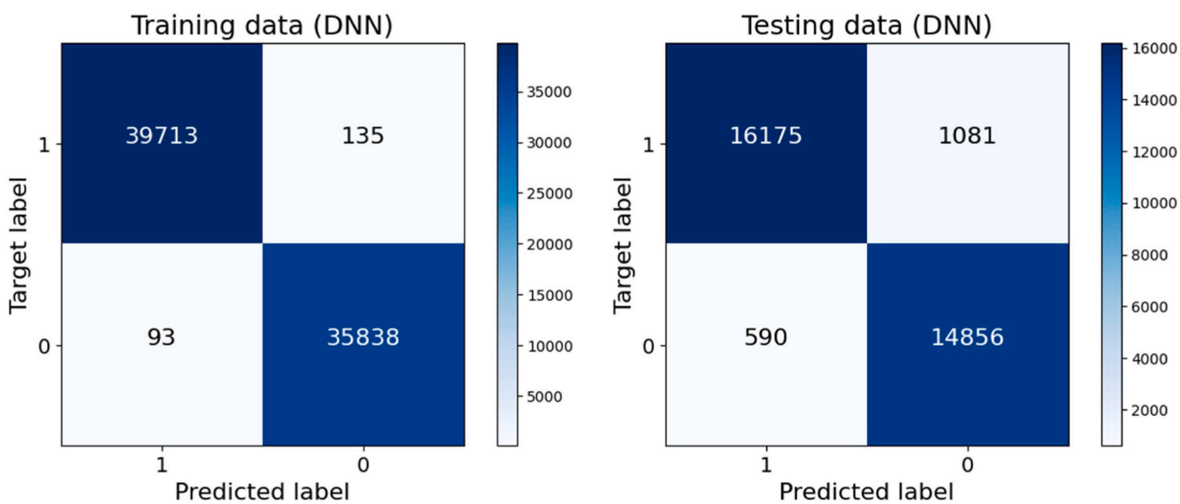


Fig. 13. Confusion matrix for DNN.

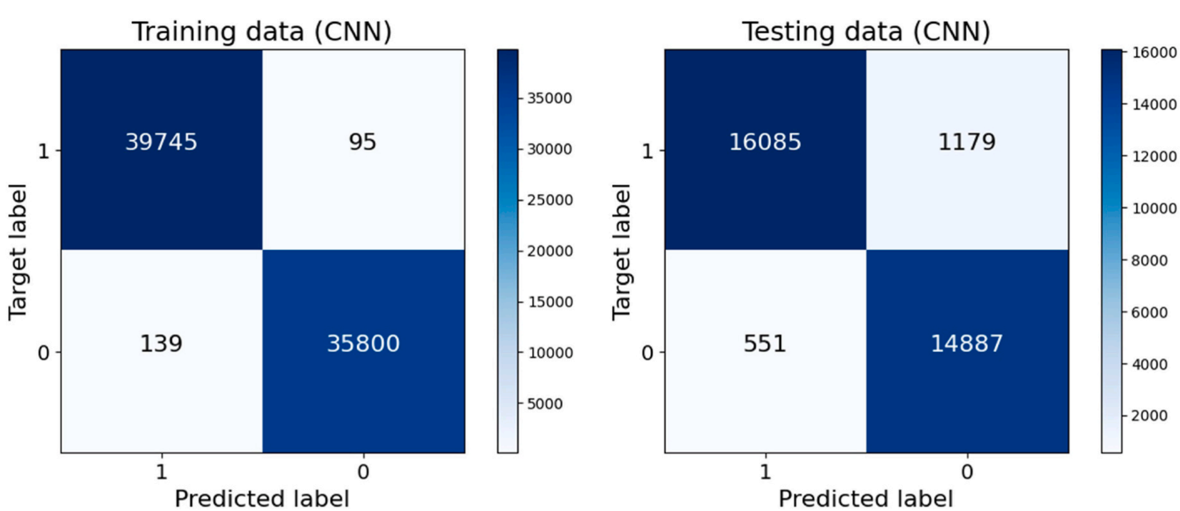
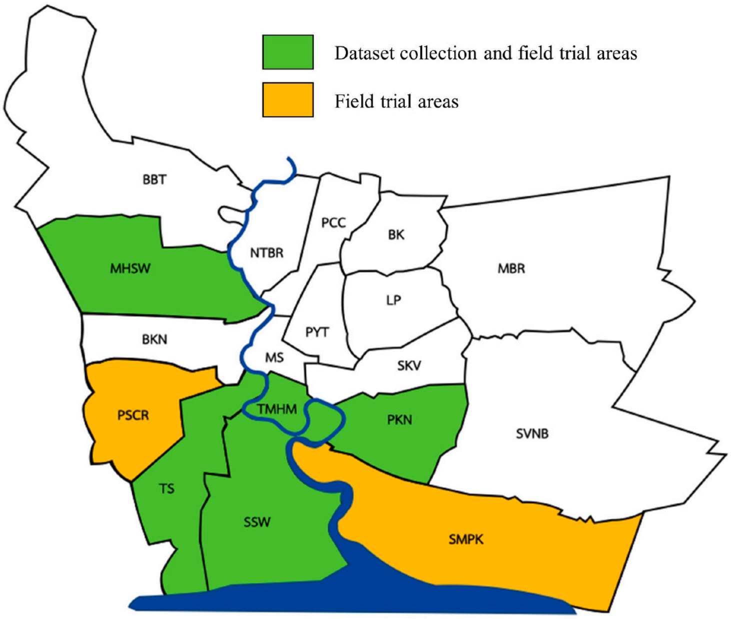


Fig. 14. Confusion matrix for CNN.



Name	MWA branch
BBT	Bangbuathong branch
BK	Bangkhen branch
BKN	Bangkoknoi branch
LP	Lad Phrao branch
MS	Mansri branch
MBR	Minburi branch
MHSW	Mahasawat branch
NTBR	Nonthaburi branch
PSCR	Phasicharoen branch
PYT	Phayathai branch
PKN	Phrakhanong branch
PCC	Prachachuen branch
TS	Taksin branch
TMHM	Thungmahamek branch
SMPK	Samut Prakan branch
SKV	Sukhumvit branch
SSW	Suksawat branch
SVNB	Suvarnabhumi brach

Fig. 15. MWA areas for the field trials and data collection.

sparse categorical cross-entropy loss function. The DNN network consists of an input layer (128 neurons), 3 hidden layers (64, 32, and 10 neurons), and 1 output layer (1 neuron). The activation functions are ReLU for the input layer and all of the hidden layers, and Softmax is used for the output layer. The CNN network includes a convolutional layer (1D CNN with 8 convolutional filters and the window size = 9), a pooling layer (max-pooling), and fully connected layers. The fully connected layers are used with an input layer (128 neurons), 3 hidden layers (64, 32, and 10 neurons), and 1 output layer (1 neuron) which are the same configurations as for the DNN.

The computer in this experiment is equipped with Xeon 3.6 GHz CPU, 160 GB RAM, 1 TB SSD M.2 PCIe 4.0, and NVIDIA Quadro RTX5000 16 GB graphic card. The classification performance of SVM, DNN, and CNN are summarized in Table 1, showing the average values of accuracy and training time over 10 trials. The accuracy, sensitivity, and specificity are calculated by using Eqs. (5)–(7), where TP is True Positive, TN is True Negative, FP is False Positive, and FN is False Negative. As observed, SVM takes less training time, about 1.25 min, compared with 14–16 min for DNN and CNN. However, SVM provides much lower accuracy than the other methods, with 78.29% for the testing datasets using SVM and 94.89% and 94.71% for DNN and CNN, respectively. The confusion matrix, shown in Figs. 12–14, illustrates the detail of the classification results, which show that the accuracy of SVM is degraded mainly due to false negatives in both the training and testing datasets. Hence, the sensitivity value of SVM in Table 1 is much lower than DNN and CNN. From the performance comparison, DNN provides a more accurate solution than SVM and has less complex structure than CNN. Therefore, DNN is the selected model for the AI-based leak detection since it provides the best accuracy with relatively less complex structure.

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ predictions} = \frac{TP + TN}{TP + FP + TN + FN} \tag{5}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{6}$$

$$Specificity = \frac{TN}{TN + FP} \tag{7}$$

4.2. Field trial

Bangkok is located in the central part of Thailand where the population is about 5.6 million people and the water consumption from MWA is about 1800 million m^3 per year. Apart from using sophisticated tools such as leak noise correlators, manually pinpointing leaks in pipelines by highly skilled operators using acoustic rods is still conducted during regular NRW reduction operations. However, the overall performance can be limited due to fatigue and inadequate numbers of highly skilled operators in some areas. Before using MWA AI-based leak detection devices to support newly trained operators, the DNN model was tested in the field to pinpoint leaking pipes in the water distribution system. The areas of the field tests are shown in Fig. 15 in the yellow and green areas. It is noted that the "leak" and "no leak" sound samples for model training and testing were collected from the green areas only. The DNN model was trained offline by the average frequency spectrum of the sound data to obtain an optimal classification model. The trained model was used for real-time leak detection in the field by analyzing the sound input from the leak detection device.

Table 2
Leak detection performance comparison for the field trials.

Device	Branch							Total
	SSW	TS	PKN	TMHM	MHSW	SMPK	PSCR	
Professional expert								
Detected point	6	3	9	3	14	9	2	45
Actual leakage	6	3	9	2	14	7	2	43
Leak detection device								
Detected point	6	2	9	3	15	8	3	46
Actual leakage	6	2	9	2	15	8	3	45

Fig. 16. An example of a repair report from MWA.

The performance of the leak detection device compared with MWA professional experts in the field trial is summarized in Table 2. The performance comparison was conducted in the 7 areas colored in green and yellow. The leakage results were confirmed by the actual drilling for repair as an example of repairing report shown in Fig. 16. The professional experts detected 45 leakage points, and 43 actual leakage points were confirmed. In parallel, by using the AI-based leak detection device in the same areas, novice operators detected 46 leakage points, and 45 actual leakage points were confirmed. The accuracy of the proposed device was 97.83%, while the accuracy of the professional experts was 95.56%. The results show that the accuracy of the proposed device is slightly higher than the professional experts. Notably, the results might be affected by the time sensitive nature of the professional experts during the leak detection which was not an issue for the novice operators using the leak detection device in the field trial.

5. Conclusion

The paper evaluates an AI-based water leak detection system with cloud information management. The main purpose of this work is to systematically collect and manage leakage sounds and generate a classification model. This system is designed to support the leakage pinpointing task by providing newly trained operators with guidance in making decision and to minimize the imprecision due to fatigue. Detailed description, platform system design, and experimental results of the AI-based leak detection device are presented in the paper. The paper has evaluated the performance and compared the accuracy of SVM, DNN, and CNN algorithms based on datasets from 5 of the MWA branch areas. The results show that the DNN performed better than SVM and performed as well as CNN, but with less complex structure. The DNN algorithm was used in training and applying the model in the field trials to detect water leakage along with the leak detection device. The field trials were conducted to compare the accuracy between professional experts and the developed device in 7 areas of the MWA branch areas. The results show that the AI-based water-leak detection system with cloud information management can classify leakage and no-leakage sounds for novice operators with similar accuracy compared with professional operators using conventional methods. For further advancement, additional data collection and field trials will be performed by MWA and NECTEC to improve the accuracy of the leak detection model and the usability of the device in the field. Other parameters, such as the time spent for leak pinpointing task and the sound level of ambient noise, will be introduced in the future study. The prototype system developed in this paper is a promising tool for reducing water loss, and it represents an innovative step towards the goal of sustainable water resource management for the improvement of environmental and human wellbeing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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