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INTELLIGENT IOT ENABLED PIPELINE LEAKAGE DETECTION AND MONITORING SYSTEM USING DEEP METAHEURISTIC LEARNING ALGORITHM

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Abstract

Pipeline networks are the safest transportation of oil and gas-related products that may be susceptible to failures. These kinds of failures are due to the reason of manufacturing defects, degradation of the material, environmental defects, and interference of the third party. These issues are addressed through the Internet of Things (IoT) based solutions and give promising outcomes in predicting the failures and monitoring. The IoT can combine the sensor technologies to monitor the gas flow, pressure, temperature, condition of the compressor, concentration, and other related features inside the pipeline. The leaks in the pipe are measured as a pin-sized hole that is detected by the IoT sensor with advanced technologies such as deep learning. This paper proposed deep learning with a meta-heuristic approach-based model to detect leaks in pipelines through IoT sensors. The Deep Learning model called Deep Auto Encoder Neural network (DAENN) is the unsupervised model that can accurately classify the leaking and non-leaking pipeline conditions. The detection accuracy is further enhanced with the Bat Optimization algorithm (BOA) which obtained improved accuracy while leaks occur in the pipeline inside the sensor monitoring area. This observation deploys the monitoring sensors to cover the mentioned monitoring area. The proposed model can increase the system's leak detection reliability and reduces the false alarm rate. The trained DAENN-BOA with its leak detection strategy is tested against a simulated dataset that secured promising results with an accuracy of 98.9% and a reduced error rate of 0.09.

Keywords: Internet of Things (IoT), Oil pipeline, Leakage detection, Deep learning, Auto Encoder, Bat Optimization algorithm.

1. Introduction

Pipelines are the major components of transporting and storing liquid and gaseous products. The recent decades have shown that pipeline systems are considered the safest and most economical approach for storing and transporting oil and gas products [1] and its infrastructure is considered critical to economic growth worldwide. Adegboye et al., [18] discussed the pipeline detection system with its used technologies. Ayeni et al., [11] reviewed the strategies that are implemented by oil saboteurs to steal crude oil from the oil and gas pipeline systems. The multiple investments for hydrocarbons and petrochemical are materialized to the reliable supply of stocks by the pipeline infrastructure [2]. Therefore, the piping installations around the world rapidly expand the energy needs of the population, indicating the complexity of the pipeline system, and its safety assessment [3]. Additionally, the usage of pipeline systems increases the structural defects because of erosion over time, human factors, fracture propagation, and environmental factors [4,5]. Leak detection is one of the major issues. Pipeline leaks are the sources of small cracks and pinholes that are not noticed for a long time that causes damage [6].

Various traditional approaches are used to recognize the pipeline's defects by analyzing the characteristics using digital signal processing approaches such as Fast Fourier Transform and Wavelet Transform. With the evolution of the fourth-generation industrial internet of things, machine learning approaches are popular due to their high accuracy compared to the traditional methods and their efficient implementation advances the multiplication of dedicated GPUs is the current research focus. With this, Deep Learning is employed to perform the pipeline leakage detection and leverage its efficacy to identify the small leakage diameters [7], processing the data in the time domain and frequency domain. The Auto Encoders are the neural networks that are trained on unlabeled data and distinguish the potential digression from the normal state which becomes very beneficial to detecting the fault pipeline conditions [8, 9]. Fan et al., [12] proposed a machine learning-based model to detect leaks in the water supply network.

Spandonidis et al., [10] developed a low-cost oil leakage detection system using smart wireless sensors. They implemented two detection methodologies. The 2Dimension convolutional neural network is used for supervised classification in spectrograms that are extracted by the acquired signals of accelerometers. Second, LSTM (Long Short-Term Memory) Auto Encoders are used to receive the signals from the accelerometers and provide leakage detection solutions. The processing of data in the cloud needs a high volume of storage which increases the execution time and is inefficient. To overcome these issues, this paper proposed deep learning with a meta-heuristic approach for the detection of leakage in pipelines. Aba et al., [13] developed a real-time pipeline monitoring system using an IoT platform and determine the damage location of the pipeline using pressure wave pulses. Cheddadi et al., [14] developed an IoT-enabled system that continuously monitors the environmental data of PV solar stations. Wang et al., [15] developed a novel PSO (Particle Swarm Optimization) method with Support Vector Machine (SVM) to analyze the data in the leak detection for oil pipeline systems. Coelho et al., [16] proposed a water leak detection system using a wireless sensor network that can monitor the water distribution such as irrigation systems. Lalitha et al., [17] developed an IoT-based oil and gas pipeline leak detection system. this model consists of the sensors such as a gas sensor, flow sensor, Solenoid valve, relay driver, and GSM module. Namuduri et al., [19] reviewed various Deep learning algorithms that are used to predict the maintenance of the engine failure. To precise the water leak location, they used autonomous algorithms. The major contribution of the work is as follows:

- An efficient, robust, and timely leakage detection system is proposed using a deep learning model for pipeline systems with the aim to detect the leakages in oil as well as gas pipelines has been proposed.
- The data are collected from the accelerometers placed beside the pipelines, and the data processor performs the early detection of leakages. Initially, the IoT sensors are used to collect the data at the physical layer, and data are processed in the data processing layer.
- The collected data are preprocessed and fed as input into the classifier called Deep Auto Encoder Neural Network in the data processing layer for detection. The classifier is further enhanced with an optimization technique called Bat optimization to choose the best value for weight and bias.
- Detection mechanism is formed and the requirement of detection mechanism is satisfied then the data are classified and leakages are notified to the user in the application layer.
- The proposed model is evaluated with the simulated environment which has various leakage diameters and node distances. It is evaluated based on the evaluation metrics and compared with the existing approach to show the efficiency of the proposed model.

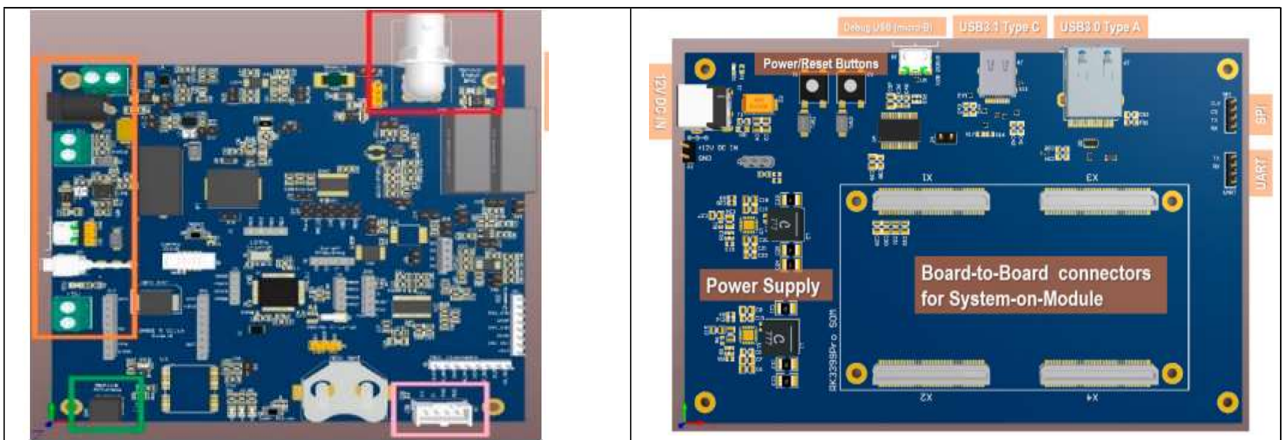
The remaining section of this paper is as follows: section 2 discusses the related works. Section 3 discussed the proposed system model, hardware and software requirements, and proposed materials and methods for the detection of leakage in pipeline systems. Section 4 evaluated the experimental results and discussed the result with the comparison between existing approaches. Section 5 concludes the proposed model merits with its future direction.

2. Materials and Methods

The existing pipeline monitoring systems are reactive rather than predictive and proactive which is not suitable to detect the leaks before damaging the pipeline. Internet of Things is an advanced technological innovation that moves the reactive approach to predictive and proactive. IoT is a network of physical devices comprised of sensors, actuators, software, identifier, and internet connectivity.

2.1.Hardware and Software components

The hardware components include sensor data receiving and data processing interfaces as shown in Fig 2. The sensor data receiving unit (Fig 2 (a) is responsible to receive the data till four accelerometers synchronize the data using pulse per second signal and transfer it into the data processing unit. The major components are analog to digital converter (ADS8688 [20]) which receives the analog data from the sensor and converts it into digital data. The GPS unit can produce the timestamp for each measurement of the data. Pulse per signal is used for synchronization with improved accuracy and the microcontroller sends the digitized information to the data processing unit. The GPS unit is responsible to synchronize the two nodes' data measurements. They used GPS unit is NEO-M8N [21]. The selected microcontroller is ESP32 Grover [22]. The data receiving unit is connected through Micro B USB with data processing interface unit ((Fig 2 (b)) for power supply by a +12VDC/2A jack. The major component is the RK3399Pro system module that consists of dual-core ARM cortectA72 microprocessors.



(a) Sensor Data Receiving Unit	(b) Data processing Interfaces unit

Figure 2: Hardware Component of the proposed leakage detection system

The software platform includes a series of embedded software responsible for data acquisition and feeding the input into the embedded AI approach via the LTE-M cellular network. In the central unit, the web application is hosted which displays the information about the leakage location with its sizes to the user as soon as possible. The web application also provides the operating condition monitoring and statistical data related to the operation with the system information.

2.2.Model training using proposed DAENN-BOA

Auto Encoder is a kind of unsupervised machine learning model based on a special kind of neural network which is trained to reconstruct its input so that the output consists of the information as same the input. In this paper, the Deep Auto Encoder neural network is implemented. The standard AE consists of one hidden layer, various Deep AENN consists of more than one hidden layer. The architecture of DAENN is shown in Fig 3.

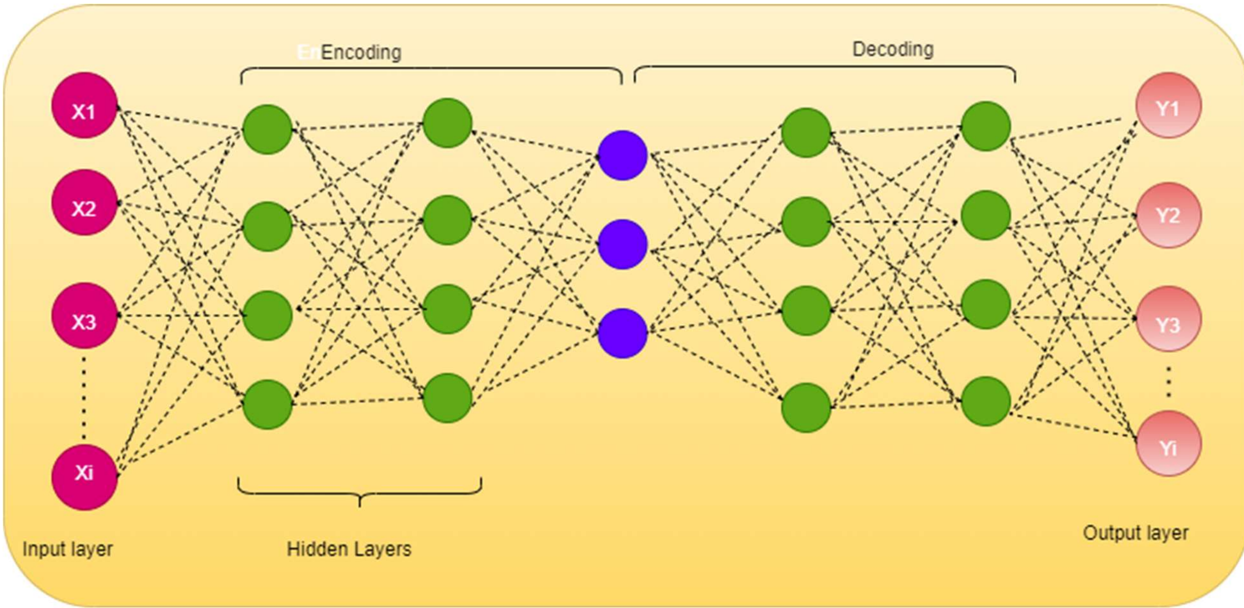


Figure 3: Deep AENN architecture

The DAE training process involves by compresses the input vector X into the small dimension called the encoding process. Then the compressed data is reconstructed to its original space in the decoding process. The input layer consists of ‘i’ neurons which is the number of input data. the hidden layers provide a nonlinear relationship to the training data. The output layer consists of one neuron to classify the output as a leaking or non-leaking state. The hidden layers are fully connected and each neuron output is denoted as in Eqn (1)

$$Y_k = f(\sum_{i=1}^{N} X_{i,k}.w_{i,k} + b) \qquad (1)$$

Where, $Y_k =$ the toutputof each hhidden layerneuron, $X_{i,k}$ – outlayer last la yer, $w_{i,k}$ – the weight of the neuron and b – bias of the neuron. The weight and bias are trained with a backpropagation algorithm. The variable f is the activation function which is used to increase the non-linear probability of the propagation. ReLU activation function is used for this study for the hidden layer which is denoted in Eqn (2)

$$f(X) = \max(0, X) \qquad (2)$$

The last hidden layer output is transformed to neurons in the output layer which is denoted in Eqn (3)

$$Y_z = g(Y_k.w + b) \qquad (3)$$

Where $Y_z =$ output of output layer, $Y_k =$ output of last hidden layer, w –weight, b – bias and g – tangent sigmoid activation function denoted in Eqn (4)

$$g(X) = \frac{2}{1+e^{-2x}} - 1 \qquad (4)$$

This model learns the relationship between input and output in the training process to classify the leaking and non-leaking state of the pipeline. The error between input and output is reduced by adjusting the weight and bias related to the input data. In order to reduce the reconstruction error, DAENN is forced to learn the hidden patterns of the input data. The leaking state is detected using the reconstruction error which is characterized as Root Mean Square Error as denoted in Eqn (5)

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(X_i - Y_i)^2} \tag{5}$$

Where RMSE- Root mean square error or reconstruction error, n – input vector dimension of X, Xi – sample actual data, and Yi –predicted data. To reduce the reconstruction error and overfitting issue, a meta-heuristic algorithm called the Bat Optimization algorithm is implemented to improve the detection accuracy with the best value of weight and bias. The overfitting issue is avoided by optimizing the weight using BOA which is a swarm intelligence algorithm based on microbats' echolocation behavior while all the bats make a short and loud pulse of sound. The Bat can sense the object the distance through returning echo. Likewise, it can also detect the distance between prey and obstacle which makes them hunt in dark too. A bat can fly randomly with the velocity called 'Vi' in the position 'Pi' with different frequencies 'F' and loudness 'L' to search for prey. The frequencies are adjusted automatically and pulse emission rate 'r' depends on target proximity. Each bat on prey can listen to other bat voices and fly towards to the prey direction.

2.3.Leakage detection mechanism

The leakage detection starts with the classification of leakage using proposed DAENN-BOA method. The decision for labeling the defective signals is as follows: among the collected 20000 measurements in 1s, the observed leakage threshold (Th) is more than 8000 then the system is labeled as defective. The threshold is selected arbitrarily and it avoids the false negative and reduces the occurrences of false positives. The Boolean variables true and false are denoted as 1 and 0, the decision process is denoted in Eqn (6)

$$Possiblity\_of\_leakage\ (PL) = \begin{cases} 1\ if\ Error\ E > Th \\ 0\ if\ Error\ E < Th \end{cases} \tag{6}$$

$$Leakage\ (L) = \begin{cases} 1\ if \sum_{i=t}^{t+200} \quad PL_i > 8000 \\ 0f \sum_{i=t}^{t+200} \quad PL_i < 8000 \end{cases} \tag{7}$$

While the above-mentioned requirement is satisfied, the leakage is detected and it is initiated by the DAENN classification. The pipeline signal is coverted to spectrogram with window of rolling 20s at each time point t and the last 20 seconds signals are transferred to time frequency area to generate spectrogram. The algorithm is defined as follows and the workflow of the proposed model is illustrated in Fig 4.

Algorithm: (DAENN-BOA)

Step 1: Initialize input data from sensor data, weight and bias, each bat position P_i, Velocity V_i, frequency F_i, loudness L, pulse rate R_i. r1 and r2 and r4 are the random values in the range [0,1] and r3 is in the range [-1,1], t- iteration number and Lavg is the average loudness of all the bats.

Step 2: trained the DAE neural network with input data for classification of leak

Step 3: weight and bias best value is found using BOA. Fitness value is evaluated

Step 4: for each bat do

Step 5: Based on frequency, velocity and locations, the new solutions is generated using the Eqn (8) to Eqn (10)

$$f_i = f_{min} + r1 \times (f_{max} - f_{min}) \quad (8)$$

$$V_i = V_i + (P_i - P_{best}).f_i \quad (9)$$

$$P_i = P_i + V_i \quad (10)$$

Step 5: if $r2 > r_i$ then

Step 6: Local solution is generated from the best possible solution as in Eqn (11)

$$P_i = P_i + L_{avg} \times r3 \quad (11)$$

End if

Step 7: if new solution is better than old solution and $r4 < L_i$ then new solution is accepted and update L and r_i as in Eqn (12) and Eqn (13)

$$L_i = L_i \times 0.8 \quad (12)$$

$$r_i = r_i.(1 - \exp(-0.04 \times t) \quad (13)$$

End if

Step 8: end for

Step 9: return best bat value for weight and bias.

Step 10: classify the data as leak or non-leak state using sec 3.4

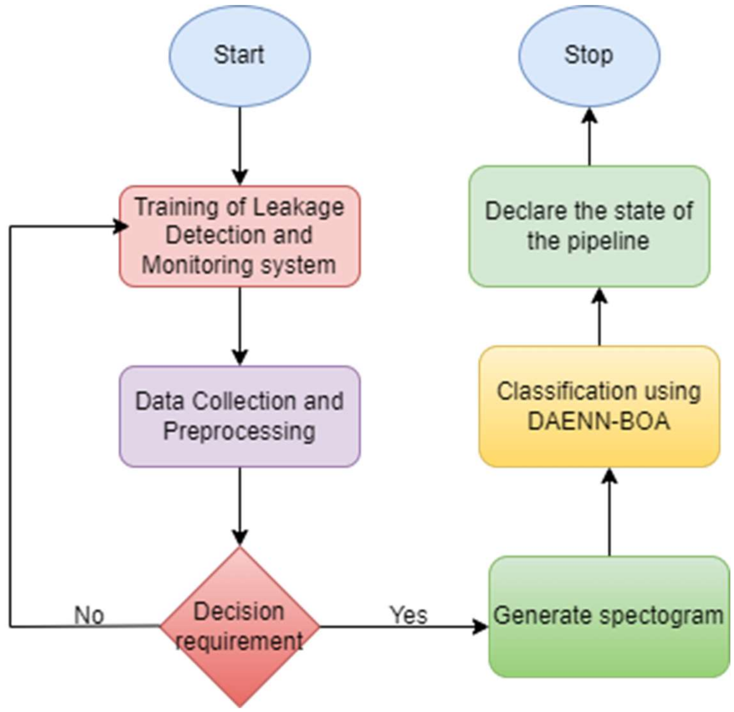


Figure 4: Workflow of the Proposed leakage detection model

3. Experimental Results and Discussions

At the initial setup of the simulation environment of the proposed model, the parameters such as distance between two sensors, and the procedure are as follows: Initially, the experiment is carried out by passing the water through the pipeline. The water pressure is set into the pre-defined value and throughout the experiment, it is not altered. In order to maintain the water pressure, the water is added inside the pipeline if needed. The source and destination nodes are fully aligned on the pipeline top to minimize the uncertainties and 90 degrees perpendicular to their plane is induced leakage because of mounting limitations. The same configuration is used for oil refinery use cases at verification section. Without leakage, an initial series of readings are taken which have a 10 min duration. During the trail, one faucet is turned to emulate the leakage at predefined diameter. The sampling rate is declared by the user and each node sampled the sensor analog data with the frequency of 25kHz. At each run, received a produced sample from the network which corresponds to 200,000-time steps and given 10second duration for each test with the sample rate of 25kHz. The other parameters included are distance between sensor and pipeline, distance between leakage place and sensor and the leakage range diameter from 1 mm to 6 mm. each testing is repeated for 15 times. Table 2 and 3 shows the dataset properties and hyper parameter settings of proposed model.

Table 2: Properties of simulated Dataset

Properties	Values
No leak signal (train set- validation and test set)	150 (90-30-30)
Leak signal (train set-validation and test set)	150 (90-30-30)
Inspection time for per signal	10seconds
Sampling frequency rate	25kHz

Signal length	200,000-time steps
Node distance	1800cm, 2250cm, 3550 cm
Leakage diameter	1-6 mm

Table 3: Selection of Hyper parameters of proposed DAENN

Parameters	**Value**
Number of hidden layers	3
Encoding-decoding unit	64
Learning rate	$2*10^{-3}$
Epoch	250
Batch size	8
Output layer	2 nodes
Weight and bias	From BOA algorithm

The proposed method is evaluated under various circumstances related to the distance of leakage from the nodes, the fluid circulation, leakage diameter and distance from the nodes on model efficacy. Based on various leakage diameters, the distance from the node is studied. The evaluation metrics such as Accuracy, Precision, Recall and Specificity stated in Eqn (15)-(18) are used.

$$Accuracy = \frac{TP+TN}{TP+FP+TN+F} \tag{15}$$

$$Precision = \frac{TP}{TP+F} \tag{16}$$

$$Recall = \frac{TP}{TP+FN} \tag{17}$$

$$Specificity = \frac{TN}{TN+FP} \tag{18}$$

Where, TP, TN, FP and FN denote True positive, True Negative, False positive and False negative respectively. Table 4 summarizes the evaluated results of the proposed model in terms of evaluation metrics and the results are compared with and without optimization.

Table 4: Leakage detection Performance Evaluation of Proposed DAENN-BOA and DAENN

Accuracy (%)			
Leakage Diameter (mm)	**Node distance (cm)**	**Accuracy (%) of DAENN-BOA**	**Accuracy (%) of DAENN**
6mm	750	98.9	96.8
12mm	750	98.9	96.4
6mm	1450	97.8	94.4

12mm	1450	97.9	94.8
6mm	1800	98.5	95.1
12mm	1800	98.7	95.8
6mm	2250	98.1	94.9
12mm	2250	98.5	95.4
6mm	3550	96.8	93.2
12mm	3550	97.6	93.7
Precision (%)			
Leakage Diameter (mm)	**Node distance (cm)**	**Precision (%) of DAENN-BOA**	**Precision (%) of DAENN**
6mm	750	98.6	95.7
12mm	750	98.6	95.1
6mm	1450	96.7	94.8
12mm	1450	97.8	94.5
6mm	1800	97.9	95.5
12mm	1800	98.1	95.4
6mm	2250	97.5	94.2
12mm	2250	97.6	94.6
6mm	3550	95.8	93.1
12mm	3550	96.2	92.9
Recall (%)			
Leakage Diameter (mm)	**Node distance (cm)**	**Recall (%) of DAENN-BOA**	**Recall (%) of DAENN**
6mm	750	98.6	96.8
12mm	750	98.3	96.4
6mm	1450	97.4	94.2
12mm	1450	96.7	94.4
6mm	1800	98.1	95.5
12mm	1800	97.9	95.7
6mm	2250	98.3	94.4
12mm	2250	97.9	95.9
6mm	3550	96.9	93.5
12mm	3550	97.5	93.9
Specificity (%)			
Leakage Diameter (mm)	**Node distance (cm)**	**Specificity (%) of DAENN-BOA**	**Specificity (%) of DAENN**
6mm	750	98.7	96.3
12mm	750	98.8	96.8
6mm	1450	97.9	94.7
12mm	1450	98.4	94.8

6mm	1800	98.4	95.3
12mm	1800	98.6	95.9
6mm	2250	98.1	94.3
12mm	2250	98.4	95.7
6mm	3550	96.3	93.1
12mm	3550	97.7	93.9

As stated in Table 4, the proposed methodology secured improved results with substantial external noise. The experiments were conducted with ten trails of various leakage diameter and node distance. While increasing the distance of the node, the metrics is decreased and among the various trails, the improved accuracy, precision, recall and specificity is secured by the proposed DAENN with BOA approach. The optimization approach efficiently increases the detection rate. With optimization, the model secured 98.9% of accuracy and without optimization; the detection accuracy is 96.8%. It has been evinced that the proposed NN with optimization approach considerably increases the accuracy of leakage detection in the pipeline signals. Additionally, the approach without optimization may susceptible to various types of errors.

In order to analyze the efficiency of the proposed model, it has been compared with the existing leakage detection approach using Long Short-Term Memory-Auto Encoder with Convolution neural network [10] in terms of the evaluation metrics. The comparison of accuracy for proposed and existing approach is shown in Fig 5. Compared to various leakage diameter and node distance, the proposed system secured improved accuracy compared to existing approach. The average performance of proposed and existing system in terms of the evaluation metrics is show in Fig 6. As an average, the proposed model secured 98.17% of accuracy which is higher than the existing approach which secured average accuracy of 95.05%. Likewise, the proposed model secured average precision, recall and specificity as 97.48%, 97.76% and 98.13% respectively. The secured results are superior than existing model which secured average precision, recall and specificity as 94.58%, 95.07% and 95.08% respectively.

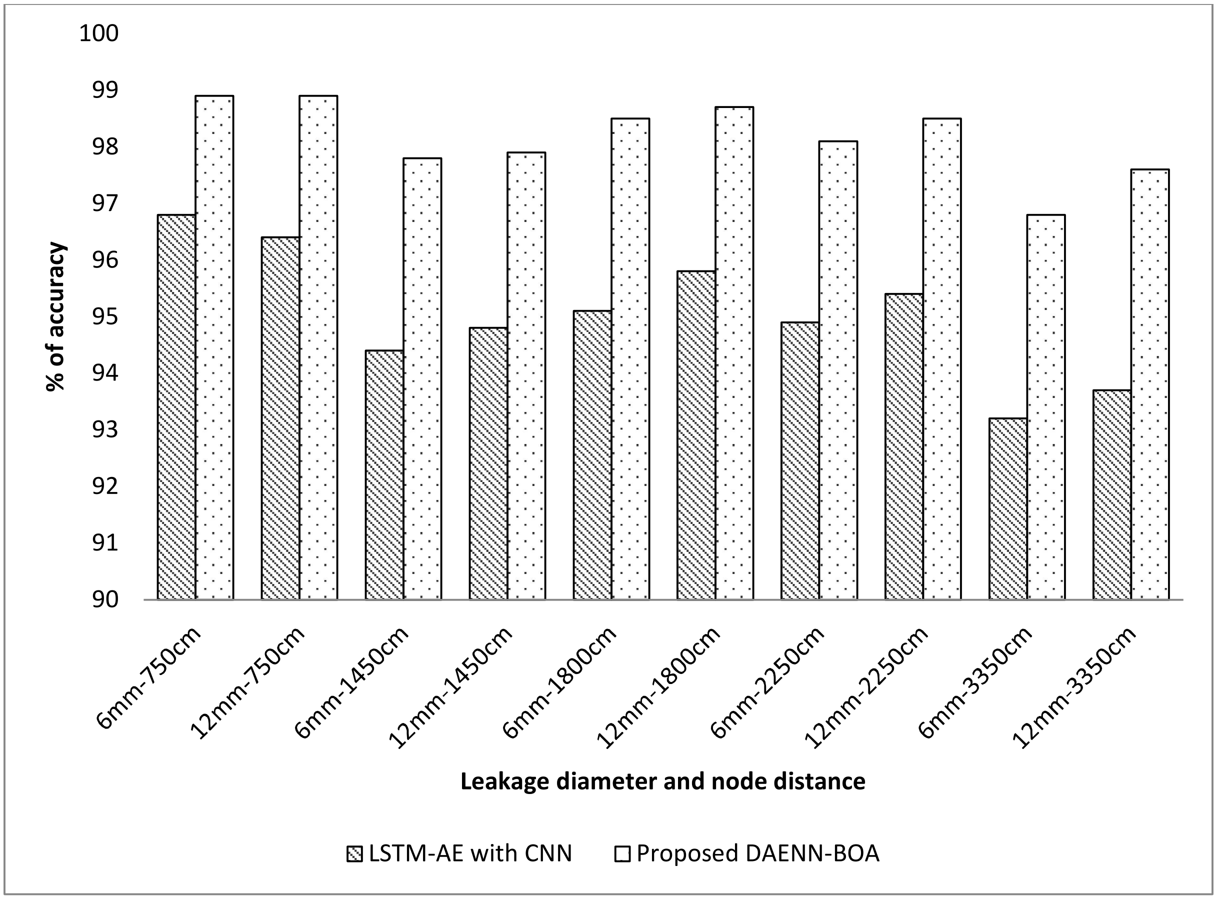


Figure 5: Accuracy Comparison of Proposed Vs Existing Leakage Detection System

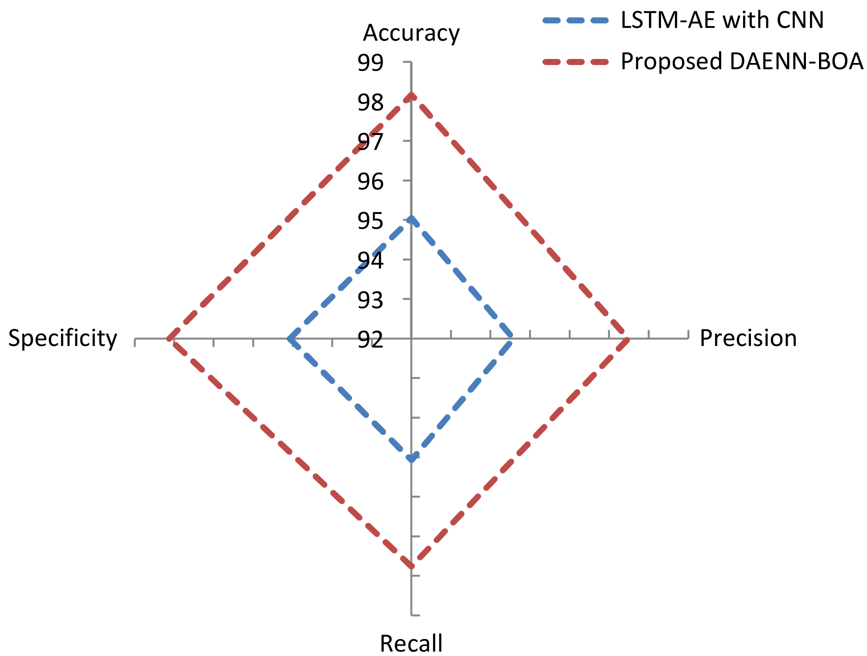


Figure 6: Performance comparison with DAENN BOA algorithm with LSTM-AE algorithms

The evaluation in terms of RMSE error is shown Fig 7 with various numbers of samples. As the number of samples increases, the error rate also increased gradually. For 3000 number of samples, the proposed model secured 0.09 as RMSE and the existing approach secured 0.18 of RMSE. Comparatively, proposed model secured minimum error than existing algorithm which proves the robustness of the proposed leakage detection system.

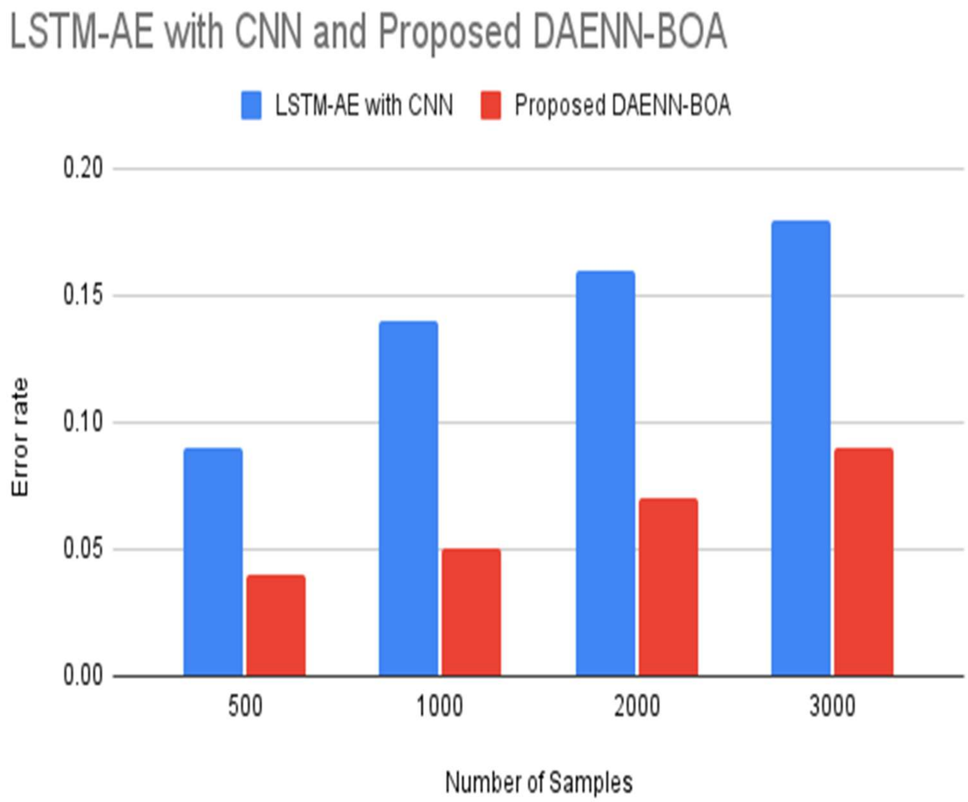


Figure 7. RMSE Error Comparison of CNN and DENN-BOA algorithms

Hence, from the experimental illustration, the proposed model secured improved accuracy with reduced error on the detection of leakage in pipeline and shows greater transferability with reduced error.

4. Conclusion

The proposed model is evaluated with the simulated environment which having various leakage diameters and node distances. It is evaluated based on the evaluation metrics and compared with existing approach to show the efficiency of the proposed model. The proposed model secured improved accuracy of 98.9% and RMSE of 0.09 which is minimum compared to traditional systems. Hence, the proposed model is efficient, accurate, robust and timely detection of leakages in the pipeline system. It can contribute to prevent the environmental disasters in the fuel industry and in future, the evolution of intelligent sensor-based solutions is implemented for liquid gas storing and transmitting procedures.