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Original Article

An IIOT Approach for Prediction of Gas Leakage in Pipeline Using Edge Software via k means

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Abstract *- In this rise in the technology era, many industrial revolutions have emerged in their routine functions. One such technology is the "Internet of Things". This is further named as "Industrial Internet of Things (IIOT) "when this technology is purely applied across any application in industries. Here in this paper, one of the real-time challenges prevailing in the oil and gas refinery industry is taken, which is "oil or gas leakage along the pipeline". The gas leakage is also meant as a loss of energy happening during transmission. As of now, such leakages are detected only by breakdown maintenance; the testing of the tube is done only after a huge loss has occurred. This traditional method can be replaced with a live detection mechanism employing the Internet of Things for monitoring the health condition of the pipe continuously. In other words, it means that the detection of leakage can be determined at the initial stage itself, rather than allowing it to result in a huge loss of energy. The audio signal of the gas flow in the healthy tube (without leakage) is trapped, and it is being considered as the train data. A similar audio signal of the gas flow in the leakage tube (i.e., the tube with leakage) is also captured and considered as test data. This test data and train data are fed to Edge Impulse Software for anomaly detection using the k-means algorithm. This method of predictive maintenance, using Edge Impulse, would convert the gas tube into a live detection mechanism throughout its length and alert with an early warning mechanism whenever gas leakage occurs.*

Keywords *- Industrial Internet of Things, Edge Impulse, k-means algorithm, Anomaly detection, Gas leakage detection.*

1. Introduction

The Gas leakage is usually detected a while after its occurrence, which may lead to huge loss of energy. Particularly when these gases are odorless, it is not so easy to detect the leakage. Recently, near Cuddalore, many people were affected by the chemical gas leakage from a chemical industry in SIPCOT, Cuddalore. Such gas leakage may lead to fatal consequences for the public in the nearby zone. To avoid such mishappenings, the earlier detection of gas leakage would be appreciable, or in other words, continuous monitoring of the strength of the wall of gas pipelines through IoT would be the remedial solution. The existing gas leakage detection system has certain limitations in its functionality, such as a limited detection range, slow response time, sensor degradation over time, false alarms, and a lack of real-time monitoring. Thus, these lacunas are considered constraints, and an innovative measure is introduced for the real-time continuous monitoring of gas leakage detection. This system will save the energy leakage, especially gas leakage in big oil refineries or gas processing industries. There is much research going on in this particular area of how to use technology to detect gas leakage. The accidents happened in the last three decades due to gas leakage and the need for an alarming system to detect the leakage of gas. He suggested a method having an LED and buzzer alarming system which turns ON when the gas leakage goes high [1]. The usage of GPS for detecting the location of the gas leakage, this system comprises a mobile phone as an alert mechanism where the type of gas, pressure rate, and leakage detection point will be notified as an sms in the mobile phone [2]. A method for unsupervised gas leakage detection by collecting the leakage data using SCADA was discussed in detail. The primary objective in this chosen method is to use a Deep Auto-Encoder (DAE) to understand typical aspects of flow in the leak-free operation state [3]. Infrared radiation can detect the tiny quantity of energy released by the gas.

Because thermal imaging improves exposure in low light conditions, through the detection of the objects' infrared radiation and producing a picture that depends upon those features, it is used as a way to detect gas leaks. The image is turned into a thermal image using image processing after being captured by a thermal camera. The thermal image is taken by the thermal camera. Only the gas leakage region can be seen in this thermal image. Distance computation can be used to determine the location of the leak [4]. A method to observe the natural gas leakage in offshore pipelines was discussed in detail. A love wave sensor or shear-horizontal wave sensor was suggested as the optimal technique for a real-time leak detection system in the gas pipeline network. A mix of Hilbert-Huang Transforms (HHT), important needs, standards, expressions, and threats resulting from the gas pipeline system failure is discussed in detail. Elastic waves propagate due to variations in wave energy, and sensors installed on the pipeline can detect these waves [5].

2. Literature Review

A method using a gas leakage alerting system consisting of a GSM modem is discussed in detail. The important feature of this work is to understand the presence of leakage, which is determined by the sensor measuring the gas concentration level. When the gas level is accurate, a signal is transmitted to the alarm system to initiate activation. This also powers the GSM modem and starts the exhaust fan, which is activated by the ATMEGA328p microcontroller via a relay circuit [6]. A method using an acoustic sensor, the operating principle of a system that correlates noise generated at points of leakage in a gas pipe network, is focused on. Sound wave noise captured by the energy converter device positioned on the ends of the regulated segment of the pipe network is enhanced, processed through a band-select filter, and encoded. The binary information is sent to a computer, and the reading outcomes are shown on a display as correlation curves indicating the coordinates of the gas leakage point in the pipeline [7]. The detection of a gas leakage system using force difference recognition by the unsymmetrical distinctive pressure method was discussed in detail. In this method, a differential pressure in an unsymmetrical distinctive force cylinder is suggested. It addresses the constraint in efficiency of leakage detection resulting from the unsynchronous heat reading from the two partitions in the unsymmetrical distinctive force method, and employs the distinctive force interchange calculation to replace the differential computation of the distinctive force. The enhanced distinctive force technique suggests a novel approach grounded in the detection principle and computation type.

Moreover, the impact of variables in the distinctive force interchange calculation on the leakage equation outcomes was virtually modeled, and the material meaning of the features in the distinctive force interchange calculation was clarified [8]. Artificial neural networks for leakage detection, a method utilizing Artificial Neural Networks (ANN), is suggested for identifying and diagnosing several leaks in a pipe network by detecting a flow method through just two readings. An irregular computational model of the pipeline is considered for the trialing, learning, and validation of the artificial neural network-based system. This machine learning model was taught using delays to capture the running state of the system. Initial findings show the approach's efficacy in identifying and diagnosing multiple concurrent faults [9]. The leakage detection in the water distribution network was discussed in detail. This article additionally introduces a new method to outline the detection stage of the leakage, namely the pick out confined spot strategy. In addition, two types of leakage identification models are recognized: the static leakage identification model and the dynamic leakage identification model. The two models are characterized along with their distinctive abilities. Ultimately, this article presents an overview of common leakage identification methodologies to offer a general comprehension of the leak detection research area [10].

A leakage identification in a gas pipeline and closing system, where it creates a circuit employing appropriate transducers, regulators, suppliers, and relay setups in identifying leaks and automatically halting the LPG emanates from a linear actuator and power source to the residence, equipped with a measurement and sending short messaging service notifications for all authorities. A primary focus in this work is to deliver a solution by shutting off the primary switch, and the warning indication is utilized as a yield. When implemented, the model can lower deadly incidents and minimize the issue of health hazards caused by low-quality cylinders [11]. A gas leakage detection model using a CNN model based on MFCC feature extraction. This method for detecting leaks in pipelines focuses on enhancing the safety of gas pipeline activities across different sectors and minimizing losses resulting from gas leaks.

This technique employs highly sensitive microphones to gather real-time audio signals in pipeline settings and applies the Mel-scale Frequency Cepstral Coefficients (MFCC) algorithm to derive features from the gathered audio signals. Subsequently, a convolutional neural network algorithm is employed to determine if a gas leak exists. This technique can precisely detect gas leaks in pipelines with an accuracy of up to 98.958% [12]. A combined approach suggested in this article achieved automatic identification of oil and gas leaks in pipelines along with an initial assessment of leakage severity.

The technique enhanced detection efficiency and precision, eliminates manual intervention, and does not depend on multiple sensors and intricate mathematical models. Simultaneously, the relevance of various feature extraction backbones in the segmentation of sonar images related to oil and gas leakage was examined. The method's feasibility was confirmed through experiments. This approach was evaluated against the impact of conventional manual detection in real-world engineering. Consequently, it served as a technical guideline for future engineering applications of oil and automatic detection of gas leakage [13]. A study that examines efficient and affordable leakage detection systems in oil pipes and air fuel pipelines, along with their advantages and disadvantages. The current methods are divided into three groups according to their technical features, termed as hardware-based (utilizing specific hardware for leakage monitoring), software-based (applying software for leakage monitoring), and intelligence-based (employing smart predictive algorithms for leakage identification) techniques. Every method was assessed based on the datasets utilized, pre-processing techniques (primarily applied in the intelligent techniques reliant on imagery, such as image pre-processing including image enhancement, denoising, and filtering), and examined classifiers' effectiveness, outcomes, and constraints. A comparative analysis was carried out to identify the most suitable technology for a specific operational environment, including software, hardware, intelligent, or hybrid.

Additionally, the study points out the deficiencies in existing research and outstanding issues related to the creation of reliable pipeline leak detection systems, recommending potential research avenues to address these issues [14]. A gas leakage monitoring system for large areas has been created, providing real-time alerts, utilizing Mobile Wireless Sensor Networks (MWSNs). The system is comprised of two components: the sensor terminal and the central server. A sensor terminal features a TDLAS gas sensor, known for its exceptional accuracy and compact size, a microcontroller, a satellite navigation receiver, a packet-switched mobile data service (GPRS) system, and a power source [15].

TinyML kit is a suggested solution that can be coded to detect anomalies and alert occupants through the use of BLE technology, along with a built-in LCD screen. Experiments have been used to demonstrate and evaluate two different testing scenarios. In the first instance, the smoke detection test resulted in an F1-Score of 0.77, while the ammonia test case achieved an F1-Score of 0.70 [16].

3. Fault Tree Diagnosis

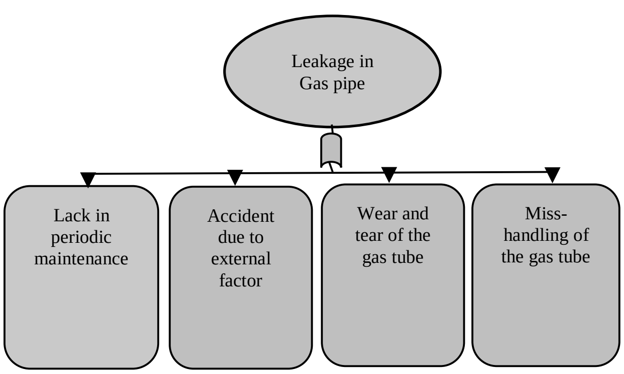

Fig. 1 Fault analysis tree

The fault tree diagnosis of this gas leakage in the pipe is pictured in Figure 1 above. The major factors for the leakage may include a lack of periodic maintenance of the pipe, accidents due to external factors, wear and tear of the gas tube material, and man-made mistakes (mishandling of the tube). The industrial internet of things in this gas leakage system offers real-time monitoring, automated alerts, and a safety ensuring response mechanism. The working principle of the entire mechanism encompasses detection, data processing, connectivity, alerting, and response, which may be considered as optional.

Usually, Gas sensors will be used for continuous monitoring of gas percentage in the environment. But the drawback in establishing the gas sensor throughout the length of the pipeline is that it is a highly impractical and costly method with less impact. Since more gas sensors are to be implemented, which means keeping it alive, more power consumption is required. An alternative method is proposed in this paper, i.e., instead of gas sensors, the flow of gas is trapped with an audio input signal, and if any leakage occurs, that affects the flow rate of the gas, which means the change in audio signal trapped implicates the occurrence of leakage in the tube.

The data obtained (audio test data and audio train data) are obtained and processed in Edge Impulse Software (a machine learning IoT-enabled Software). This mechanism is not only used for gas leakage but can also be used to cut off the gas flow in pipes when it reaches a certain threshold level. This variation can also be detected through the audio signal trapped by the real-time monitoring system, which is enabled in the pipe. Thus, this IoT mechanism enables early detection, remote monitoring, instant alerts, automation, and data logging, which can be used for any statistical-based decision-making process. In short, this IoT-based gas leakage detection mechanism has turned traditional breakdown maintenance into modern preventive maintenance applicable for such scenarios.

The hybrid combination by using Internet of Everything or ambient computing technology in industrial settings, including manufacturing, energy, transportation, and utilities, is known as Industrial IoT (IIoT). It entails tying sensors, machinery, and other gadgets to the internet in order to gather, process, and act upon data instantly, improving creative output, security, and efficiency. The internet of everything or ambient computing in industry consists of 1. sensors and devices which gathers information on humidity, vibration, temperature, pressure, etc. 2. Connectivity which enables to transfer data, use networks such as Ethernet, Wi-Fi, 5G, or LPWAN.3. Data analytics used to examine data for quality assurance, process optimization, and predictive maintenance.4. Automation enabling it possible for control and decision making.5.Continuous monitoring using Internet of Things.

Table 1. Comparison of Recent existing research with the proposed model for gas leakage detection in gas pipeline

Article/Report	Approach/Technology	Strength/Innovation	Limitations/Challenges
YO LO-based MWIRGas: Identifying Leakage of gas [17]	Usage of MWIR image + a YOLO-deep learning detector	Non-contact detection , Can visualize gas plumes that are invisible to human eye ,Good for industrial leak detection	Requires specialized IR camera (expensive) ,Computationally heavy, May struggle with very low-concentration leaks / very small plumes
Methane gas leakage detection with hybrid gas filters enhanced with infrared images [18]	Combines infrared imaging + R-CN Network (called “Gas-Faster R-CNN”	Specifically tailored for methane ,Good for automatic detection & localization ,Likely better accuracy for methane leaks compared to simple threshold sensors	Again, needs IR imaging hardware , Possibly slower inference time (R-CNNs are generally slower than YOLO) , May need training on large, labeled dataset of leaks
Infrared Imaging Detection for Hazardous Gas Leakage… (BBGFA-YOLO) [19]	IR imaging + improved YOLO network (with background estimation + attention modules)	Uses background information to better distinguish gas plume from scene , High accuracy (very good AP) ,Real-time detection	Needs a good dataset of gas plume images , IR cameras are expensive , Deployment complexity for real-world industrial setups
Detection of gas using RGBTCA Network [20]	Vision-based: fusing RGB + thermal (infrared) images using a CA network (RT-CAN)	Uses both color (RGB) and thermal — this helps because thermal alone is texture-poor ,Good detection performance (higher IoU, F2) , Introduces a new annotated dataset (Gas-DB)	Requires dual-modality camera setup (RGB + thermal) ,Potentially more expensive & complex hardware , May not detect very transparent or weak gas plumes well
Automated Detection of Methane Leaks by Combining Infrared Imaging & Gas-Faster R-CNN [18]	Combines infrared imaging + a Region-Based Convolutional Neural Network (R-CNN) called “Gas-Faster R-CNN”	Specifically tailored for methane ,Good for automatic detection & localization, Likely better accuracy for methane leaks compared to simple threshold sensors	Again, needs IR imaging hardware, Possibly slower inference time (R-CNNs are generally slower than YOLO), May need training on large, labeled dataset of leaks
Vision-Ultrasound Robotic System for Gas Leak Detection [21]	Multi-modal system: visual camera + 112-channel acoustic (ultrasound) camera on a robot + CNN	High accuracy (99%) for leak detection in noisy industrial environments , Robotic platform allows systematic inspection (hard-to-reach places) , Fusion of acoustic + visual data improves robustness	Very complex & expensive hardware (robot + acoustic camera) ,Requires power, mobility, and maintenance , May not be suitable for very small-scale domestic systems
LangGas: Zero-Shot Background removal for S-T Gas Leak Detection [22]	Computer vision + zero-shot learning + background subtraction, working on a synthetic dataset (SimGas)	Novel zero-shot method — doesn’t require heavy training on gas leak images ,Good for semi-transparent / weak leaks , Introduces a synthetic dataset — helps research where real leak data is scarce	Performance on real-world data may be lower (synthetic vs real) ,Zero-shot detection might have higher false positives / ambiguity ,Requires good background models; scene must be relatively static
Artificial Intelligence for Gas Leak Detection with Thermal Cameras + MOS Sensors [23]	Combines metal-oxide semiconductor (MOS) gas sensors with thermal cameras + AI for detection	Leverages both sensor data and vision, hence more reliable ,MOS sensors are relatively cheap, and thermal camera gives spatial context , AI helps reduce false positives	Integration complexity (synchronizing sensor + camera) , Thermal camera cost again is an issue , AI model needs good training data — may not generalize well to all leak types
Proposed machine learning model	Real time monitoring system using k means algorithm	Audio signal features extracted ,K means algorithm is used for anomaly detection	More audio sensor need to be embedded in system and it should be noise free environment.

This IIoT-based gas leakage detection is more apt as the continuous live monitoring system is enabled along with an early warning or alarming system, ensuring the safety and decision-making systems to operate monitoring, optimization, and management of energy. Hence, security, in order to safeguard vital infrastructure, has put strong security measures in place.

This IIOT technology has the benefits like using predictive maintenance, compared with traditional breakdown maintenance, which can help minimize downtime, monitoring and managing assets, defect identification and quality control, remote equipment, and minimizing the energy leakage in the production and processing sector that operates round the clock throughout 325 days in a year.

4. Input Signal – Train vs Test Audio Signal

Edge impulse software is used to upload the train data (audio signal trapped with leakage) and test data (audio signal trapped with leakage). Figure 2 shows how the train data is uploaded to the Edge Impulse software. Figures 4 to 6 show the three different train data sets. Figures 7 to 9 show the raw data of the input learning data 1, input learning data 2, and input learning data 3, respectively. Figures 10 to 12 represent the spectrogram (as a DSP result) of the train data 1, train data 2, and train 3, respectively. These training data are also known as reference data. Figure 13 shows the spectrum of test data. The audio data trapped in the pipe with leakage is considered to be the test data.

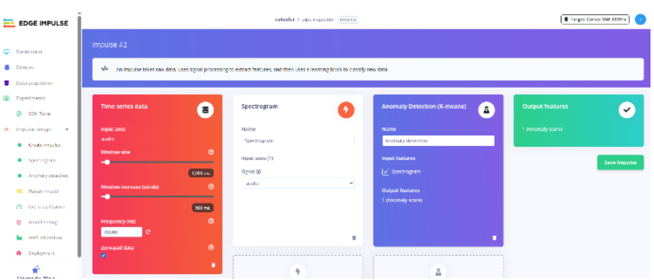

Fig. 2 Edge impulse platform

The sampling frequency of the audio signal for all three train data sets is considered to be the same, as shown in Figures 7 to 9. This reference data will be compared with test data, and the k-means anomaly detection is done to check if there is any deviation of the test audio signal from the reference train data signal. This deviation implies that leakage has occurred in the gas pipe.

5. Methodology

The step-by-step procedure of the overall methodology is portrayed in the flowchart as shown in Figure 3. Creating the project in Edge Impulse software would be the first step, followed by collecting the trained audio data and test audio data, further leading to adding the processing and learning blocks in Edge Impulse software, which can perform the anomaly detection between the reference (train data) and test data. The reference audio (train data) and test audio signal are captured through an audio sensor fixed at the edge of the gas pipe, which is continuously active and captures the audio signal, and this data is transferred to the Edge Impulse software through wireless mode.

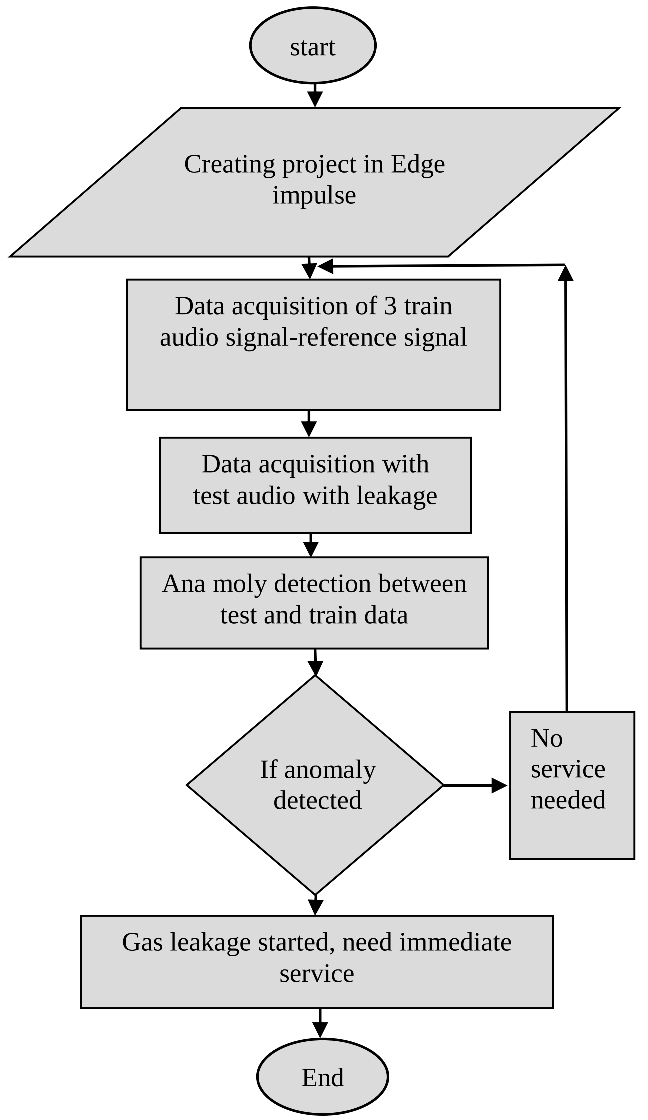

Fig. 3 Flowchart

In Edge Impulse which acts as both data acquisition and processing unit by creating a machine learning model which is been done by adding processing block and learning block (anomaly detection using k means algorithm), if there is any deviation of test data from the reference data then that is been identified conveying the message that some leakage has started occurring which has to be addressed immediately through predictive maintenance, thereby ensuring the safety and also minimizing the loss of energy.

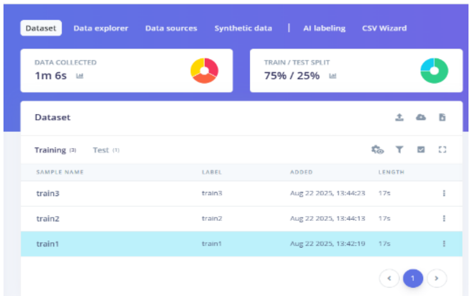

Fig. 4 Train data-1 in edge impulse s/w

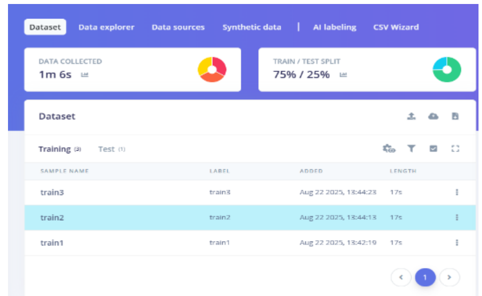

Fig. 5 Train data-2 in edge impulse s/w

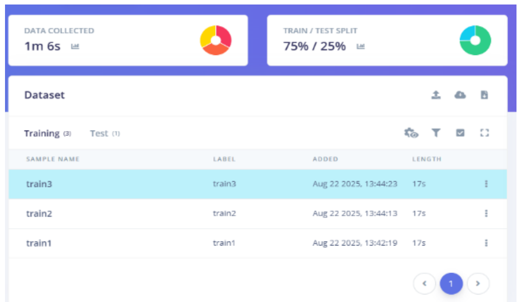

Fig. 6 Train data-3 in edge impulse s/w

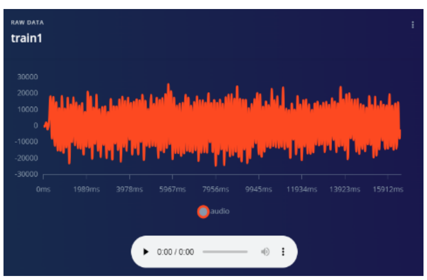

Fig. 7 Spectrum of train data-1

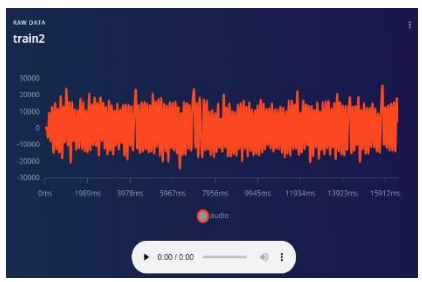

Fig. 8 Spectrum of train data-2

Fig. 9 Spectrum of train data-3

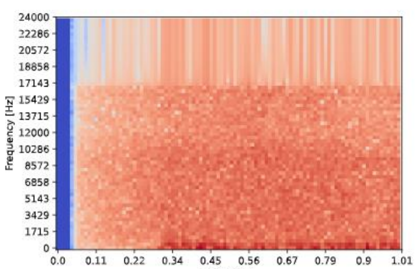

Fig. 10 Spectrogram of train data-1

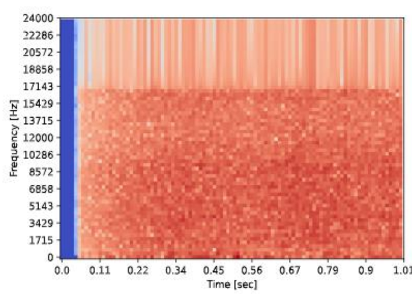

Fig. 11 Spectrogram of train data-2

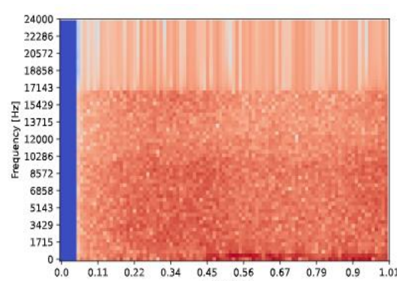

Fig. 12 Spectrogram of train data-3

Fig. 13 Test data-1 in edge impulse s/w with its spectrum and spectrogram

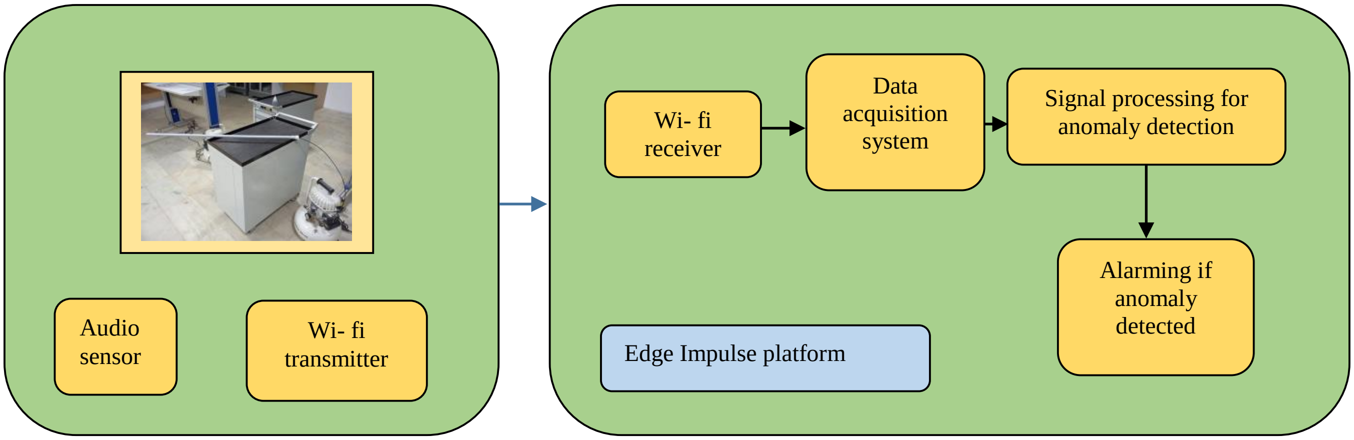

Fig. 14 Block diagram of lab test

Fig. 15 Gas pipe or channel

Fig. 16 Gas pipe indicating leakage point L_1

Fig. 17 Experimental setup

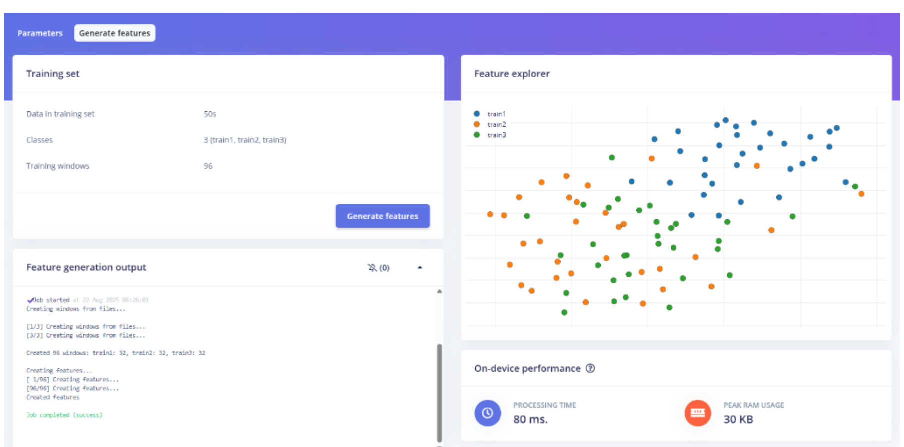

Fig. 18 Feature generated in edge impulse software for trained data

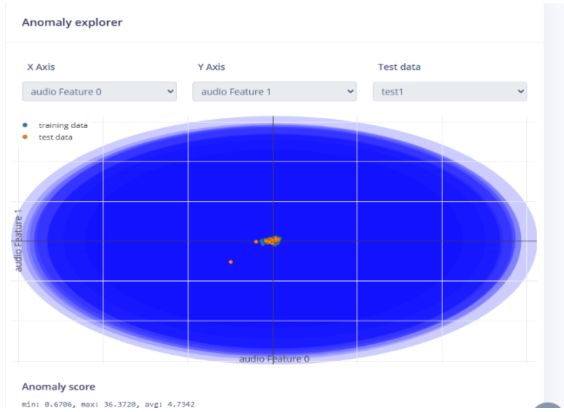

Fig. 19 Anomaly detected with test data ensuring the gas Leakage

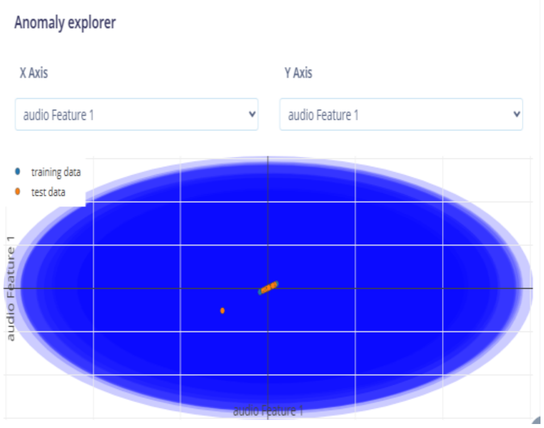

Fig. 20 Anomaly detected comparing feature 1

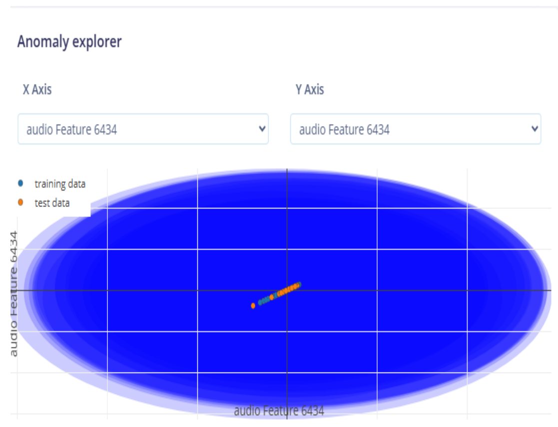

Fig. 21 Anomaly detected comparing feature 6434

Figure 14 shows the system model of the entire lab test module, which is done in real-time mode. The experimental setup of trapping the audio signal from the gas pipe is shown in Figures 15 to 17. Figure 15 shows the PVC pipe, which acts as the channel for conducting the gas. Figure 16 shows the marking of the leakage point L_1 on the PVC pipe. Adding a processing block in which it gets a spectrogram out of the sensor or audio data is done. It is excellent for continuous-frequency data or non-voice audio. The next process involves the learning block that deals with anomaly detection, in which it identifies outliers in fresh data, which is useful for identifying unknown states and assisting through the channel with leakage point L1, and now this trapped audio signal is considered to be test data. The entire process starts with how the impulse is created in Edge acts as a source for gas to pass through the channel (ie. pvc pipe), Initially the air is allowed to pass through the channel (without leakage) and that is considered as reference audio (train data) and then the air is allowed impulse platform and followed by the next step which is classifiers. It performs best when combined with dimension features, such as the spectral features block's output. Figure 18 shows the feature generated for the trained data set (reference data set). The term "Feature Generated for Trained Data" in Edge Impulse describes the intermediate numerical data that is taken from the raw sensor input (such as audio, pictures, or accelerometer data) by means of a feature extraction or signal processing block. It is not the raw data that is used to train the machine learning model, but rather these features. The features of the three trained data sets (trained data 1, trained data 2, trained data 3) overlap more or less as shown in Figure 18. Figure 19 clearly shows that the anomaly is detected when the test data is compared with the reference data (trained data). Table 2 shows the anomaly value with respect to each time stamp as the spectrum is considered for a continuous signal.

6. Discussion

The anomaly is detected between the reference audio signal (audio trapped from a gas pipe without leakage) and the test audio signal (audio trapped from a gas pipe with gas leakage). Both audio features 1 and 6434 confirm this anomaly detection twice, which aids in confirming the forecast that a gas leak will occur in the pipe, as seen in Figures 20 and 21, respectively. A lower anomaly indicates the beginning of the gas leak, whereas an average anomaly indicates the gas leak has begun and is halfway through. More anomalies indicate that the maximum amount of gas loss has occurred. This technology of implementing industrial internet of everything or ambient computation, where the convolution neural network models are created, can be further integrated with artificial intelligence potential in the near future which can send some sealing coat or paste over the leakage automatically, ensuring immediate remedial action over the gas leakage and thereby avoiding the loss of energy or accident due to leakage of poisonous gas. This implication of the artificial intelligence concept may help in employing an appropriate decision-making process at the time chaos happens due to accidental gas leakage. This study can be further expanded in the future to detect and analyze the area where the gas leakage has occurred, and also the reason for the gas leakage, since the appropriate time stamp is noted.

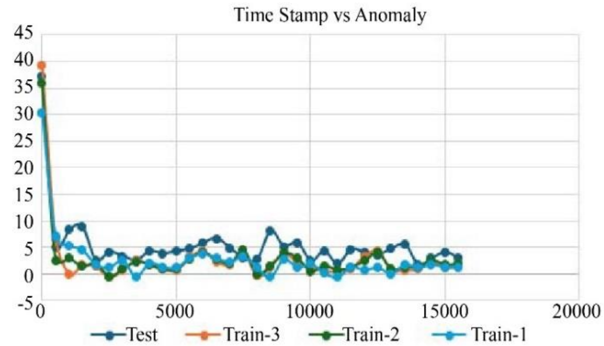

Fig. 22 Timestamp Vs Anomaly comparison

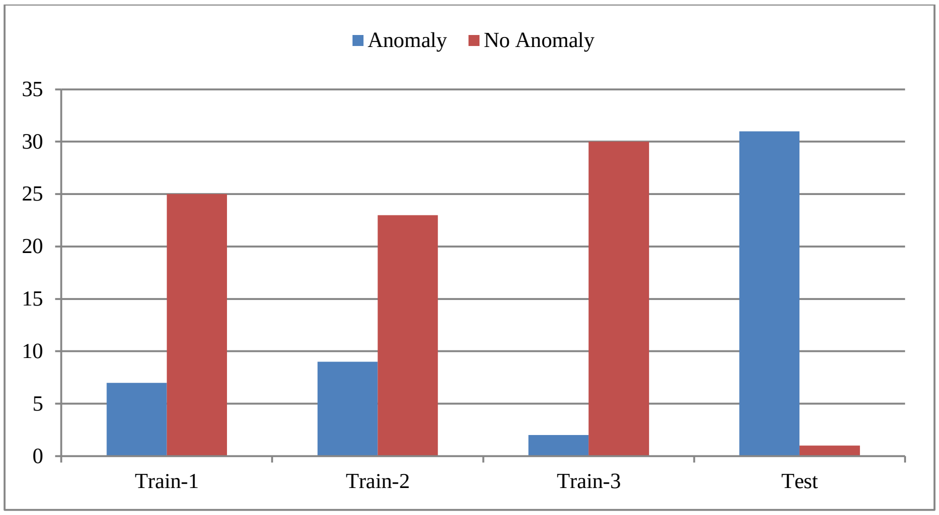

Fig. 23 Classification-count of anomalies

Table 2. Timestamp Vs Anomaly

Time stamp	Anamoly	Time stamp	Anamoly
0	37.20	8,000	2.71
500	4.94	8,500	8.09
1,000	8.27	9,000	5.16
1,500	8.84	9,500	5.93
2,000	2.57	10,000	2.41
2,500	4.13	10,500	4.24
3,000	3.35	11,000	1.87
3,500	2.54	11,500	4.62
4,000	4.23	12,000	3.99
4,500	3.84	12,500	3.62
5,000	4.27	13,000	4.70
5,500	4.69	13,500	5.55
6,000	5.84	14,000	1.75
6,500	6.68	14,500	2.89
7,000	4.84	15,000	4.10
7,500	2.97	15,500	2.95

Table 3. Crossvalidation of robustness

Fold	Train Data	Test Data	Result
1	Train1,Train2,Test	Train-3	Normal
2	Train1,Train3,Test	Train-2	Normal
3	Train2,Train3,Test	Train-1	Normal
4	Train1,Train2,Train3	Test	Anomalies detected

When the flow rate data, pressure difference data, and audio signal trapped data are all put together, they may give an effective online predictive monitoring system that is continuously active, detecting a leakage.

Figure 22 shows the comparison of anomaly value obtained while considering the live classification for each fold. The anomaly obtained for the test data case is more when compared to the other three train data sets. Figure 23 shows the count of anomalies obtained during classification.

7. Conclusion

Table 3 shows the robustness of cross-validation obtained while doing the anomaly detection for each fold. As there are 3 train datasets and 1 test dataset, the total number of folds used will be 4. And the table value says that in fold 4, the anomalies are clearly detected. Thus, the research study helps us to understand the role of IoT in predicting gas leakage in gas pipelines in industries. This would be an effective modern technological solution replacing the traditional statistical predictive maintenance. This article will pave the way for ensuring safety in the gas distribution network and provide a leakage-proof distribution network, thereby minimizing energy loss and gas leakage. Similarly, the same software is used here to identify the gas leakage in the distribution pipeline.

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