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Corrosion Detection and Prediction for Underwater pipelines using IoT and Machine Learning Techniques

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Abstract: Pipelines are commonly utilized to transmit chemical fluids over thousands of kilometres all over the globe. The pipes are designed to withstand a variety of environmental loading conditions, providing safe and durable delivery from the manufacturing location to the coast or distribution station. Leaks in piping systems, on the other side, are among the primary causes of numerous damages for pipeline operators and the surroundings. Pipeline failures may cause significant environmental catastrophes, human deaths, and financial losses. Significant research has been devoted to corrosion and localization using alternative strategies to avoid this threat and preserve an efficient and proper transmission infrastructure. This paper proposed a corrosion detection and prediction system using Internet of Things (IoT) and machine learning techniques. The system collaborates with two different methodologies, such as IoT utilized to collect data from underwater pipelines and various learning algorithms to identify corrosion possibilities. We have used analogue sensors such as thickness, GPS, pH, etc., to capture the current event. Based on pH value, impact of pipe thickness for a specific period has been analysed depending on learning algorithm. The standard defines policy rules and has used a semi-supervised learning algorithm for validation. The Q-learning based classification algorithm generates reward and penalty for each event and, based on that, defines the possibility of corrosion. A variety of extraction of features and selection methods were used during this research using the IoT model. An extensive experiment analysis of the proposed algorithm obtains higher classification and detection accuracy over the traditional machine learning classification algorithms.

Keywords: Underwater pipelines, semi-supervised machine learning, feature extraction and feature selection, internet of things, cloud database.

1. Introduction

The oil and gas business, commonly known as that of the world's greatest energy generator, is one of the world's major sources of income. Oil and gas are transported to various places through huge and sophisticated offshore pipeline networks. Natural gas pipes under the sea were built in the late 1900s and are still in operation today [1]. Corrosion and leaking are more likely to happen as the pipeline network grows and ages, and in recent decades, the numbers of leaks reported are more than double compared to past years [2]. Because of the potential for contaminating leaks into maritime environments from gas pipelines, continual pipeline inspection and the ability to pinpoint the specific gas leak are critical. The primary goal of undersea pipeline leakage detection is to limit pollution, save precious energy resources, avoid unpleasant catastrophes, and assure the pipeline's safe operation. The majority of undersea pipeline problems, according to significant study, are caused by equipment breakdown, construction faults, corrosion, temperature, external pressure, and harbour damage [3].

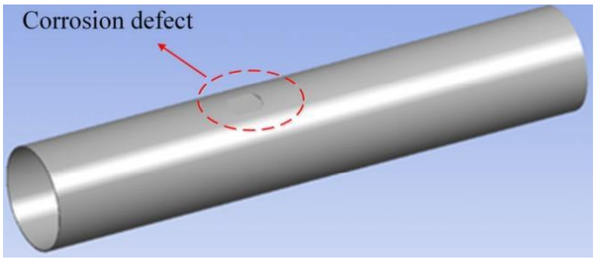

Fig. 1: Corroded pipe example in geometric modelling

In pipeline representations either with or without weathering defects are created throughout the modelling phase to investigate the impact of corrosion weaknesses on crack formation when they interact. The simulated pipeline is made of API 5L X70 metal. The pipeline's outer diameter is 914.4 millimetre, and the minimum wideness is 15.875 millimetre. The operating pressure is assumed to be 1 Mega Pascal for modelling purposes. A semi-elliptical structure with a diameter of 15.2 millimetres and a crack thickness of 2–12 millimetres represents the stress fracture. Structural analysis may be

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used to get the SIF values for the lowest part and edge point. The huge pressure in the pipe is 1 Mega Pascal. Cuboid corrosion faults emerge on the pipeline's outermost layer at the same time, increasing the radial gap in between fracture centre and the corrosion centre from 150 -500 millimetres. The thickness of the corrosion imperfection varies between 2 - 14 millimetres, with every increment of 1 millimetre. The geometrical modelling of a degraded pipeline is shown in Figure 1, while the finite element model generated in this study is shown in Figure 2.

Variables have varied effects in different sectors, and serious repercussions might be impacted by a variety of factors. Pipeline transportation inspection may be done in a variety of ways, and new ones are being created all the time. Internal (or software based) techniques, peripheral (or equipment) methodologies, and Temporary Test Based (TTB) methods are the three types of methods. In pipes, pressure ripples are formed, and the leaking is detected by monitoring fractional introspective of pressure waves in relation to the rupture [4, 5]. Depending on instantaneous pressure wave properties, transitory test based strategies are used to diagnose and evaluate leaks. Intrinsic leak detection methods are costly, and they frequently fail to detect leakage and processes on long tubes. Except for the acoustic approach, the effectiveness of external methods is dependent on water turbulence and flow, which are both costly and ineffective in most circumstances [6,7]. Because of the maximum adsorption of detectable light in sea water, optical cameras have found it tough. If not inconceivable, to investigate underwater pipelines; sound waves methods are usually considered being the most cost effective and having the widest coverage range for submerged quality inspection and backflow prevention. Gas bubbles are formed when a gas explosion develops underneath, generating auditory sounds. Underwater acoustic emissions are quickly propagated, and even a little breach may create a strong signal [6,8]. The sonar system's long-range capability and significant acoustic impedance difference among both gas bubbles and surrounding seawater makes it an effective instrument for inspecting seabed pipelines.

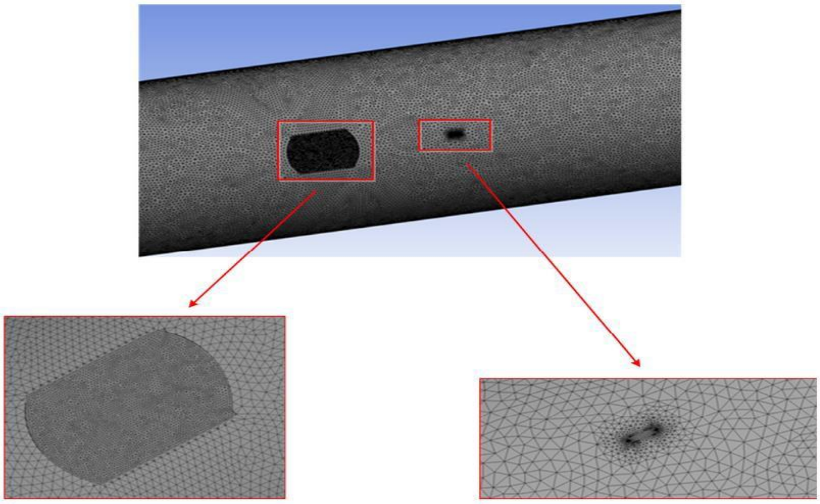

Fig. 2: The pipeline grid division. Refinement of the corrosion defect grid in part and Refinement of the grid at the crack

This paper's significant contribution is that a novel leak detection technique is proposed based on IoT model-based thickness of pipes. The thickness analogue sensor monitors the lines every six hours and saves the event information in the global dataset. According to semi-supervised classification algorithm, calculate the prediction weight is based on generated event. Finally, prediction of the corrosion possibility and creation of the alarm sensor with location details where corrosion is possible is done. The respective location has been traced based on a GPS sensor. To lessen economic and environmental repercussions, the developed technology can be utilized to optimize leakage detection systems and facilitate automated pipeline assessment. The paper's primary goals can be stated as follows:

- Effective early prediction of corrosion for underwater oil and gas pipelines using IoT and Semi-supervised machine learning methods.
- It gives correct prediction with location details and the current thickness of pipelines in the specific region.
- This system can predict the early corrosion prediction as well as runtime corrosion detection in real-time scenarios, respectively.

The remainder of the research paper is divided into the following units: unit II discusses different current strategies for detecting and predicting of corrosion using numerous learning algorithms which has been developed by earlier researchers. Unit III depicts the research technique employed in the proposed system's implementation, whereas the algorithm specification for the recommended implementation is depicted in unit IV. In unit V, we describe the experimental setup used to assess the developed work and the final outcomes achieved using our techniques, as well as a comparison with a number of state-of-the-art procedures is done. The result and its future perspectives are explained in unit VI.

2. Literature Survey

Visual techniques of leak detection include trained canines, experienced employees, clever pigging, and drones [10]. This approach involves skilled workers walking along pipes looking for abnormal circumstances. Trained observers may detect leaks visually or by smelling the stench originating from the fracture spot. Similarly, whenever oil seeps from a pipeline rupture site, the noises or vibrations produced can be utilized to locate pipeline defects. Both the dogs and the smart pigging work like experts. The pig may be embedded with sensors as well as data recording devices such as fluorescence, optical camera, as well as video sensors if sight is strong. Jia et al. used recorded acoustic waves to identify gas leaks along a 3.13 km gas pipeline [11]. Acoustic waves generated by leakage travelled up the pipeline at almost the same rate as gas during the investigation, however the high-frequency constituents diminished far faster than that of the low-frequency counterparts. As a result, it is observed that low-frequency signals are sufficient for detecting pipeline leaks.

Infrared thermography (IRT)-based pipeline leakage detection devices might even detect pipeline defects. IRT monitors temperature variations in the pipeline surroundings with infrared cameras [12]. To identify hydrocarbon leaks, the dielectric constant of the medium all around sensor is modified. [12]. Capacitive sensors are used in subsea pipes as a local coverage point sensors. The sensors detect hydrocarbons by measuring the difference in capacitance between seawater and hydrocarbons. The sensor's sensitivity to leak size depends on the distance between the leak location and the drift of the leaked medium. In order to detect high-pressure leakage of the steam, Oh et al. [14] presented an acoustic data condensation technique. The suggested technique effectively characterised the acoustic signature by using reduced data sets. The main advantages of adopting acoustic emission for pipeline network monitoring are the ease of questioning and installation, which does not need system downtime. However, background noise may readily hide the sound of major spillage at high flow rates.

In [15], damaged acoustic signals were examined using LPCC and HMM. To analyze corrupted signals, the HMM was used, and LPCC was selected as the usual signal feature. The rate of acoustic signal detection improved to 97 percent, according to the studies. Bradford et al. [16] used aircraft GPR to detect spillage in and under snow. Oil under the snow diminishes the impedance contrast with inner ice, resulting in abnormally low amplitude radar reflections, according to the researchers. A 2 cm thick oil accumulation stuck beneath sea ice and snow can be discovered with a 51 percent decline in reflected force using a 1Gega Hertz GPR device. Even though the signal to noise ratio is minimal, the researchers assume that their technique excels others (SNR). Furthermore, because GPR-based pipeline leakage detection equipment is consistent and exact, they are excellent for subterranean pipelines, but not for extended pipeline networks. The efficiency of IRT for underground pipes varies depending on pipe depth and covering medium such as concrete. Similarly, in clay soils, iron pipe corrosive agents may hide cast iron pipelines from GPR. A sufficient bandwidth is necessary for the GPR to work properly at the specified resolution and noise levels. It is critical that electromagnetic radiation is effectively coupled into the earth and penetrates sufficiently deep.

The utilization of suitable wavelength light sources to stimulate molecules to higher energies is used in fluorescence techniques for hydrocarbon spillage investigation [13]. To detect hydrocarbon spillage, the ratio between the proportion of hydrocarbon fluid leaked and the intensity of light released at a specific wavelength can be detected. Leak detection employing fluorescent dyes (unfiltered UV) has proven effective [17]. Mounting fluorescence detectors on a ROV manipulator allows for rapid scanning and identification of leaks independent of tidal flow direction. If indeed the fluorescent dye concentration is high, however, the monitoring surroundings must be viewable in order for the process to work optimally. The effects of unamplified black light can easily deceive bystanders, causing them to stop monitoring the leakage site [18]. Despite the fact that recent submersible (tuned) fluorimeters can send information to a companion vessel for real-time viewing, this barrier still persists in hazy seas.

EMI-based approaches measure changes in structural physical impedance produced by pipeline deterioration causes, which can be utilized to detect pipeline failure. The dynamic impedance of EMI transducers is monitored to identify leaks [19]. The EMI employs a surface-bounded piezoelectric sensor for detecting pipeline abnormalities using high-frequency structural excitation (usually greater than 30 kiloHertz). The EMI approach has been used to monitor many constructions, including pipelines. The advent of autonomous submerged vehicles (AUVs) in subsea pipeline assessment and observing has decreased the need for human operators and hence there is a risk of human fatalities. Although AUV supervisory control is comparable to ROV teleoperation, only limited experienced operators are needed [20].

AUVs and ROVs are widely used to monitor oil and gas infrastructure. Commercial ROVs and AUVs are used in the sectors like gas and oil. Unmanned pipeline inspection vehicles have the benefit of being a remote operating system, making them suited for distant and dangerous environments. Unmanned vehicles also have lower maintenance costs and improved operational safety. Sadly, these systems have flaws. For example, buying or renting an AUV/ROV is quite expensive. Clouds, winds, and other climatological elements may also limit vehicle performance. Unmanned systems are also subject to regulatory restrictions in specific locations owing to safety concerns, since they lack the ability to detect and avoid other AUVs [21].

Since, bolted flange connections are commonly used in the building of petroleum pipeline systems, reliable monitoring techniques are required. It is possible to detect real-time bolt looseness using vision-based approaches. The vision-based method is presented by Nguyen et al. Park et al. [23] It is possible to adapt pipeline surveillance by applying the vision-based monitoring method for assessing bolted joint looseness in wind turbine tower structures. Wang et al. [24] suggested a novel vision-based bolt looseness method of detection to overcome the challenges of recognising the state of bolt images taken from unpredictable perspectives. The implemented algorithm can recognise the mark on the bolt and the location of the bolt on the flange connection offline. More online training is necessary to make this system more robust. In a pool of massive flag bolts, the method should really be possible to perceive loose bolts.

Saikat Bose et. al. [25] advocates for the use of a novel data security protocol to verify the appointment of candidates for service. The process began with the private information being obfuscated in the e-initial mail's section for each area on the server run by the commission. Circular orientation of private share pieces and their hosted matrix intervals are determined by hash operations. The same hash operations and public sharing are used to verify any digitally signed letters that are downloaded from the designated location. On-the-spot fingerprints are hidden using identical concealment techniques in two sections for each section of the electronic letter. Each region's fourth segment is encrypted using a hash function to protect the copyright signature of the posting location. The commission's server verifies the legitimacy of the appointment and the validity of the candidate's signatures to ensure that the certified electronic letter is sent in its whole to the designated location. The effectiveness of the suggested procedure is established above the previous ways by the improved test findings from broader angles.

3. Proposed System Design

This system collects data from the IoT module that evaluates various sensors and it is connected to the microcontroller. Our fundamental aim is the detection of low thickness on underwater pipelines. As previously indicated, the 2000-event sample has been partitioned into different subsets. The training and testing subsets take up 70% and 30% of the total dataset, respectively. The first selection is used for training the model. The second subset is used for assessing the ability of model's prediction when it comes to predicting the corrosion state of new data samples that haven't been seen in the learning algorithm. Furthermore, this study effort did a random subsampling of the original dataset consisting of 20 runs to properly measure model efficiency and to reduce the unpredictability produced by the data sampling method. In each run, 30% of the data is randomly collected to form the testing subset; the remaining data is utilized for training the model. As a consequence, by averaging forecast results derived from repeated collecting data, the entire performance of the model is accurately assessed.

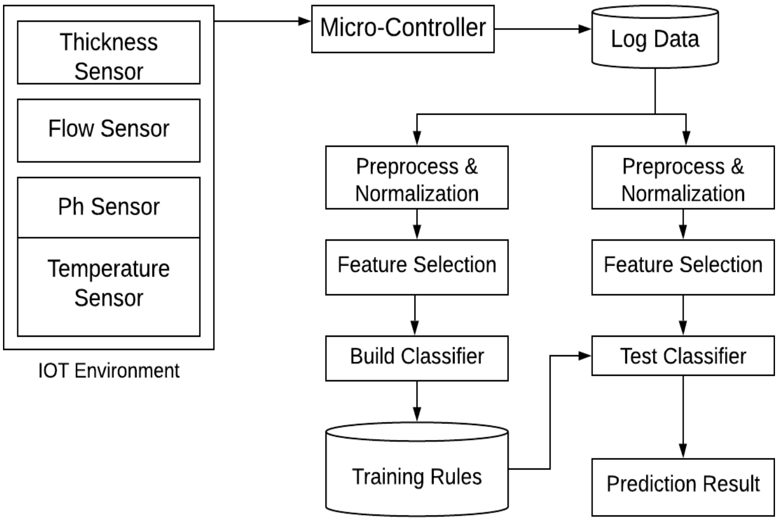

Fig. 3: Proposed system architecture

The background knowledge is training rules generated by train classifies, which basically validate the test input data generated from real time IoT dataset. According to the proposed algorithm, each event describes as reward or penalty, and each event's weighted state changes as a result. The initial training rules plays the important roles for predict the events celled as Background Knowledge (BK), and those BK utilized in throughout execution.

Algorithm Design

In the proposed system as illustrated below, the classification algorithm is used for evaluating whether the event is normal or dangerous. In step 1, we have designed all training rules and in step 2 testing data is described. Step 3 and 4 describes assignment of reward or penalty and returning a class label as the final outcome.

Input : Traindata[], Testdata[], weighted threshold, distance function DF[]

Output : Generated class label for test instance

1. Read Test data from test matrix
$$Test\_Instance[] = \sum_{n=1}^{Testdata.len} (Att\ [n] \ldots \ldots Att[n])$$
2. Read train data from train matrix
$$Train\_Instance[] = \sum_{m=1}^{traindata.len} (Att\ [m] \ldots \ldots Att[m])$$
3. Calculate distance from both instance vector
$$Weight_{Corr(n,m)} = \sum_{n=1}^{Test\_Instance.len} (Att\ [n] \ldots Att[n]) \sum_{m=1}^{Train\_Instance.len} (Att\ [m] \ldots \ldots Att[m])$$
4. If($Weight_{Corr(n,m)} > Th$)
   Reward ++;
   Else
   Penalty ++;
5. Calculate Final distance from both reward and penalty
$$F = \sum_{event=1}^{event\_count} \left(\frac{penalty}{event\_count} \right) * 100$$
6. Return F as final class.

4. Results and Discussions

In the result section, we compared our system's result using various machine learning and semi supervised machine learning classification algorithms. The IoT environment has been generated for the Collection of data from underwater oil and gas pipelines. Each event has been generated in every 6 hours, and we have monitored almost 30 days of real-time data. Different analogue sensors are used for generating the event, and a Microcontroller has been deployed to collect data from all analogue sensors.

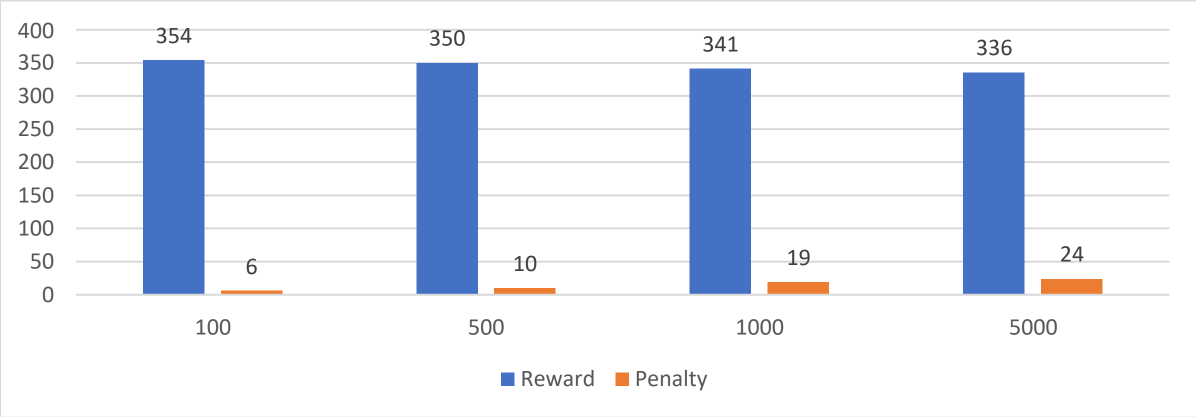

Fig. 4: No. of events with achieved reward penalties according to policies

The above Figure 4 describes the number of events generated in the last 30 days and, according to design policy, how many events got rewarded as well as penalties. The penalty is nothing but the value which violates the generalized values by sensor

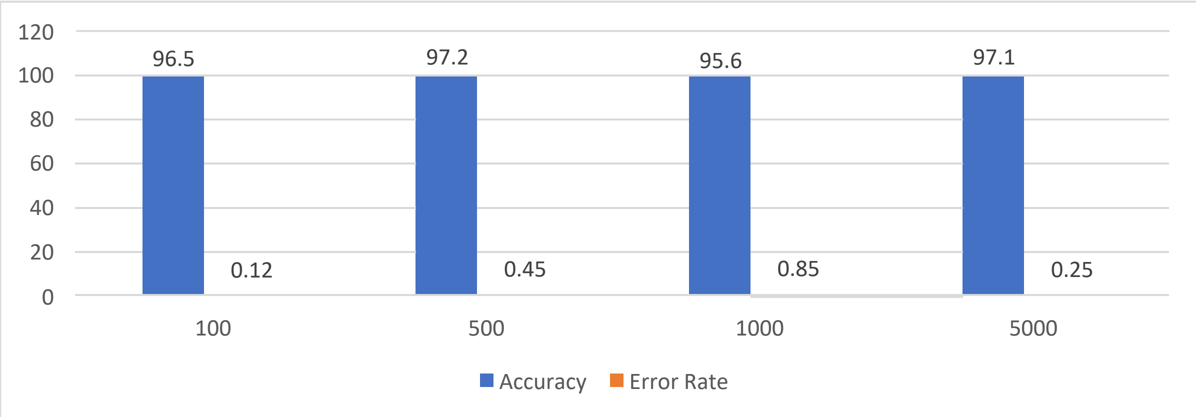

Fig. 5: Detection accuracy vs no. of events generation by IoT model

In another experiment, we collected a number of events by using our IoT module and evaluated them with our classification algorithm. The four experiments have been done using values like 100, 500, 1000 and 5000. The average accuracy we have achieved was around 97.5%.

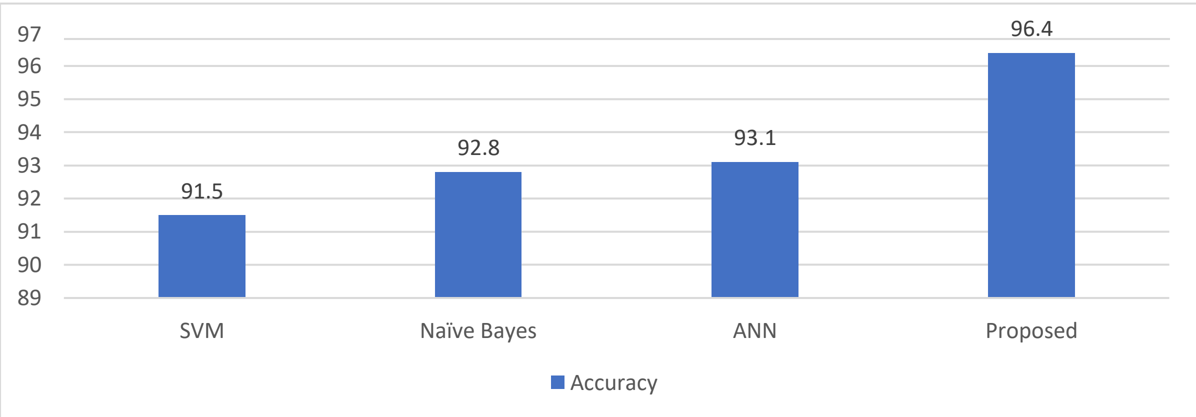

Fig. 6: Event detection classification accuracy with proposed vs existing classification

The SVM, NB, and ANN free machine learning classification algorithms has been evaluated in a similar environment. Parallelly our proposed Q-learning classification algorithm has been evaluated by using same data. As a result, q learning provides around 97% detection accuracy, which is 4-5% higher than conventional machine learning algorithms.

5. Conclusion

The detection and prevention of corrosion is an important task for prevention disaster in underwater oil and gas pipelines. The main concern with underwater gas pipes is the likelihood of leakage due to corrosion. Any leak detection error may have serious environmental and economic consequences. These systems proposed an effective leak detecting technique with IoT and ML. Leak gas bubble signals must be distinguished from background signals for these systems to work. Currently, inspection requires a system, professional operator, a combination of sensors, making it a time-consuming, difficult, and expensive process. This research proposes an effective approach for detecting corrosion of pipeline natural gas, utilising coherent combination gas bubble acoustic dispersion fields. The proposed technique uses the IoT-ML system as a strong instrument for gathering reliable information over a vast region, independent of frequency and range for inspection of pipeline as well as leakage detection. The developed method gives better detection accuracy over the traditional machine learning algorithms. Validation of the proposed system with deep learning classification algorithms will be the research's future work.

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