iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 **Issue:** V **Month of publication:** May 2025

DOI: https://doi.org/10.22214/ijraset.2025.71874

www.ijraset.com

Call: 08813907089 | E-mail ID: ijraset@gmail.com

Surface Pipeline Leak Detection Using Machine Learning

Farisa Jabin T[1], Shyma Muhammed[2]
[1]PG Scholar, [2]Assosiate Professor, Dept of Electrical and electronics Engineering MES College of Engineering Kuttippuram, Kerala, India

Abstract: Petroleum, also known as "rock oil," is a material that has developed over many years beneath the earth's surface. The sea (both onshore and offshore) is one of the main suppliers of petroleum products. Transporting oil or petroleum products from the Middle Sea region to the shore region involves a number of steps that are successfully completed via pipeline transportation. One of the biggest problems with oil and gas production is pipeline leakage. Every time there is a leak, they pose a very serious harm to the environment. This study focusses on inspecting pipelines for leaks by looking for cracks or holes in them. This study offers a revolutionary machine learning-based method for pipeline leak detection. This study offers a unique method for detecting pipeline leaks that makes use of machine learning (ML) techniques. The goal of the suggested method is to improve leak detection procedures' accuracy and efficiency. A large dataset of sensor data gathered from a moving object, calling it as Rover, is used to train the machine learning model. By looking at these data, the model can learn to identify patterns and anomalies that point to leakage. In order to increase the reliability of leak detection, developing a verification framework and an in-pipe inspection robot, mentioned earlier as Rover, that allows the operator to validate their discovery of a leak by passing it via a neural network-based system. The proposed method has several advantages over traditional leak detection methods. This work can be used to compare the leak detection system with sensors on the rover and in the pipeline. These two approaches' accuracy can be compared to determine which is best.
Keywords: Surface leak detection, Machine learning, Rover

I. INTRODUCTION

As the world's main fuel sources, oil and natural gas are significant sectors of the energy market and have a significant impact on the global economy. The processes and procedures needed to produce and distribute gas and oil are extremely intricate, expensive, and dependent on cutting-edge technology. Because of the upstream side of the industry or the production process, natural gas and oil have historically been associated. Natural gas has been regarded a nuisance for a significant portion of the industry's history and continues to be flared in significant quantities in various countries, particularly the US. Natural gas has become increasingly important in the global energy supply due to shale gas development in the United States and its reduced greenhouse gas emissions compared to other fossil fuels coal.The two most significant elements of the oil transport network are transferring pump units and pipelines.

Concrete pipes are available in a variety of sizes and shapes depending on specifications, while simultaneously maintaining a uniform thickness within the globe. When petroleum products enter circular pipelines at uniform velocity because of the no-slip condition, the carried fluid particles come into contact with the pipe's surface at certain intervals, causing the system to completely stop. Higher pressure decreases brought on by this total stop reduce the fluids' flow rates. Higher pressure decreases cause pipeline cracks and breaks, which may negatively impact production performance by lowering the flow rate at the destination during transit.

When pipelines leak, they might pollute the air, water, soil, and climate. When there is a lot of rain or flooding, pipelines that cross rivers and streams are more likely to burst. Recent high-profile pipeline accidents in the Kalamazoo, Susquehanna, and Yellowstone rivers have harmed drinking water and river ecosystems. Although the majority of pipelines are underground, maintaining them requires a large buffer of land, which disrupts the soil and obliterates wildlife habitat, trees, and plants. By 2030, 60,000–150,000 acres of forest could be removed for the construction of pipelines in the Marcellus Shale region. To maintain safe production, effective transportation, and a clean environment, it is crucial to monitor and control the integrity of oil pipelines before they break.

Previous studies on pipeline inspection are discussed. Pipeline inspection techniques can be divided into two categories, according to [4], [5], depending on whether the inspection is conducted within or outside the pipe or on the type of equipment or sensors used. Here are a few ways to locate leaks without going inside a pipe. Leaks can be discovered, for example, by auditing the resource in question [4].

Water providers, for instance, can identify leaks by comparing the amount of water supplied to a region with the actual amount of water used there. This cannot find a leak; it can only indicate that there is a source of water or fluid loss. A common acoustic method for locating leaks in subterranean pipes is to deploy listening rods, sometimes known as ground microphones, above or beneath the ground to listen for leakage [5]. Placing acoustic sensors at different points along the pipe itself is another comparable technique. The idea behind the aforementioned methods is to continuously check the acoustic sensors' output and search for any anomalies in the pipe vibration noise that is being recorded [6]. Long, above-ground pipes can have flaws discovered by inspectors physically inspecting the pipeline or by visual examination using helicopters. In addition to visual inspection, fibre optic cables have been found to be useful for leak detection using temperature measuring devices; however, both the cable and these devices need to be installed along the pipeline [6].Time-domain reflectometry (TDR) is another method for monitoring the state of underground pipes [9]. The concept is based on detecting leaks in metallic pipes by delivering signals on a metallic rod that is above ground and parallel to the underground metallic pipeline.

The TDR device measures the signal strength reflected back by the metallic pipeline. Reading disparities lead to the discovery of a copper pipeline leak. The work in [10] proposes a method to continuously monitor acoustic sensors installed on a pipeline and uses statistical analysis to the data collected in order to ascertain whether a leak exits. This method applies a quasi Gaussian approach to a leak-free data set from a known acoustic sensor.Sometimes in-pipe inspection techniques are more accurate than out-of-pipe techniques. mainly because the instruments used for in-pipe inspection usually come into close contact with the leak, allowing for a more accurate location determination. In writing, a Pipeline Inspection Gadget, or PIG, is the technique most commonly used for inner pipe inspection [17].

PIGs carry out a variety of tasks associated with in-pipe inspections. Among these are the following assignments: Initially metal loss identification; secondly, pipeline geometry inspection; thirdly, crack identification; fourthly, leak detection; and fifth on the list product sampling. Further details on each of the tasks stated above are available in [17]. Onboard sensors are frequently used by PIGs to perform the aforementioned tasks.A more recent trend is the use of machine learning and neural networks in addition to traditional sensor-based techniques to detect leaks [6], [18].

These approaches make an effort to tackle the problems of recognising and detecting pipeline breaks as well as figuring out whether a pipeline leak exists. One such technique that was covered in [19] is the use of acoustic sensors to gather data from a pipeline and Artificial Neural Networks (ANNs) to interpret the data. Another technique [20] uses an ANN in conjunction with ultrasonic sensors to identify pipeline leaks. Robots for in-pipe inspection have also been researched. A robot for in-pipe navigation is described in detail in [20]. The robot's goal is to use a 2-D laser scanner to map the pipe in front of it.

Monitoring and locating leaks in pipelines that transport liquids like water, gas, or oil is known as pipeline leak detection. This is essential to avoid economic loss, safety risks, and environmental harm.

Among the methods are inline inspection instruments, acoustic detection, flow measurement, and pressure monitoring. Early indicators include changes in flow rate, pressure decreases, and audible leaks. High-frequency noises connected to leaks can be picked up by acoustic sensors. Pigs or other inline inspection instruments go through the pipeline to look for corrosion, cracks, or additional imperfections that can cause leaks. Pipeline operators can ensure safe and effective operations by proactively identifying and addressing possible leaks by combining these techniques. To find leak locations, operators have employed a range of strategies, each with special characteristics.

Morgan and associates (2016) One of the simplest methods was to use line trackers and monitors to keep an eye on the pipeline's Right of Way (RoW) and notify the operators of any leaks.The signal processing techniques depend on the interpretation of measurements made by the different sensors placed on the pipeline, whereas the state estimation methodology computes and tracks the different line states using dynamic pipeline models to detect the presence of a leak.

The knowledge-based methods distinguish between various defective (leak) scenarios and conditions and normal (no-leak) ones using a multitude of data collected from several sensors. Visual inspection using equipment such as acoustic LDSs, infrared thermography, ultrasonic processes, or electromagnetic techniques is the most widely utilised methodology for leak identification.

ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue V May 2025- Available at www.ijraset.com

II. OBJECTIVE

The project aims to design Pipeline leak detection system using machine learning and implementation through inspection Robot, calling it as a Rover.

BLOCK DIAGRAM

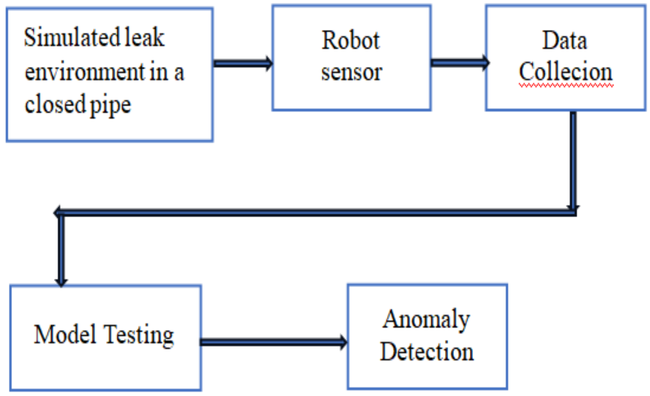


Fig. 1. Block Diagram of Surface leak detection using Machine Learning

III. DISCUSSION ON THE BLOCK DIAGRAM

A. Pipelne :

Choosing the appropriate pipeline is crucial since it affects cost, efficiency, and safety. Here pipe with closed end is selected. Because This kind of configuration mimics a segment of an extended pipeline transporting a fluid at a specific pressure. In order for the pressure of a leak-free pipe to remain reasonably constant in a segment distant enough from the pipe's ends, and for a leak to cause a change in pressure, close to where the spill occurred. Here PVC pipe is selected for this labscale setup. PVC pipe's cheaper cost when compared to metal alternatives (steel, aluminium) can be a big plus for early research, educational, or small-scale proof-of-concept projects, particularly if money is the main limitation.Closed PVC pipe with two meter length and 160mm diameter is selected for this work. Created a leak simulation point using a hole. An air pump is used to pressurize a sealed section of the PVC pipeline with air.

Fig. 2. PVC pipe with leak point

B. Rover Design:

A movable robotic unit intended to move through the pipeline (internally or externally) and check it for leaks and other irregularities could be referred to as a "rover" in the context of pipeline leak detection. Internal rovers can carry various sensors to detect leaks.

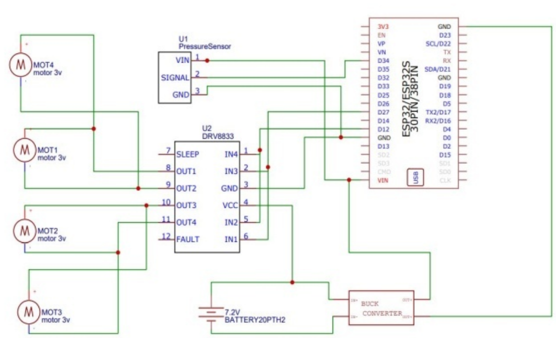


Fig. 3. Schematic diagram for Rover design

The core components of rover systems are :
1) A microcontroller (ESP32) for control and processing.
2) A pressure sensor for environmental or system monitoring.
3) A motor driver (DRV8833) to control the rover's movement and potentially other actions via four DC motors.
4) A battery and buck converter for providing the necessary power.

ESP32 is the rover's main "brain" that controls all of its functions. Through its GPIO pins, the ESP32 will be set up to read the data from the pressure sensor (U1).ESP32 will transmit digital signals to the motor driver. The ESP32 has integrated Wi-Fi and Bluetooth modules. Receiving commands from a human operator to direct the rover's movement and actions.Measuring the pressure at its sensing point and producing a signal proportionate to the observed pressure is the main purpose of the pressure sensor (U1). This signal will then be read by the ESP32 microcontroller (U3) to determine the pressure value.Since the motors run at 3V and the ESP32 normally uses 3.3V or 5V, the voltage level needed by the sensor is probably 3V or 5V, even though it isn't stated here. The sensor would probably have access to a regulated 3V or 5V line because the buck converter is stepping down the 7.2V battery voltage.Here pressure sensor used is the absolute pressure sensor. An absolute pressure sensor measures the pressure relative to a perfect vacuum (zero pressure). Its output indicates the total pressure exerted on the sensor, including the atmospheric pressure.The DRV8833 can independently operate two DC motors because it is a dual H-bridge driver. Nonetheless, it seems to be managing four motors (MOT1, MOT2, MOT3, and MOT4) in this design.

C. Simulation of Rover Design:

The main purpose of the Proteus Design set, a proprietary software tool set, is electrical design automation. Electronic design experts and technicians mostly utilise the software to generate electronic prints and schematics for printed circuit board manufacture. Applying a hex file or a debug file to the microcontroller portion of the design is how Proteus' microcontroller simulation operates. After that, it and any attached analogue and digital components are co-simulated. This makes it possible to utilise it for a wide range of project prototyping in fields including user interface design, temperature control, motor control, and It is also useful for the general hobbyist community and is easy to use as a teaching or training tool because it doesn't require any hardware.

Proteus simulation is shown in figure.4. this diagram shows a circuit likely designed to control four DC motors using an Arduino microcontroller and an L293D motor driver IC. This diagram depicts a rover's fundamental motor control mechanism. The Arduino would be configured to manage navigation, maybe read information from other and regulate the rover's motion in response to autonomous algorithms or user input The selection of four motors points to a rover design that would be easier to manoeuvre. To fully comprehend the odd L293D setup controlling four motors and the missing motor power supply details, more information is required. Here included the commands like forward, reverse, stop and buzzer . By giving the commands through virtual command window motors will work accordingly.

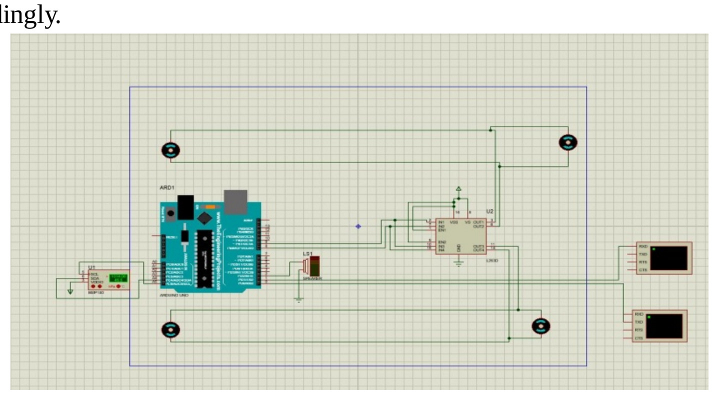


Fig. 4. Proteus simulation for rover design

D. Rover Hardware

Figure 5 and figure 6 showing the front and back side of the rover. The schematic diagram is established in the PCB well packed. A perforated circuit board, often known as a protoboard or perfboard, serves as the foundation for the rover. This board enables point-to point wiring and offers a framework for mounting the electronic components.It has the potential to be used for various tasks, including pipeline inspection and leak detection, by incorporating appropriate sensors and programming the ESP32 to navigate and analyze sensor data.

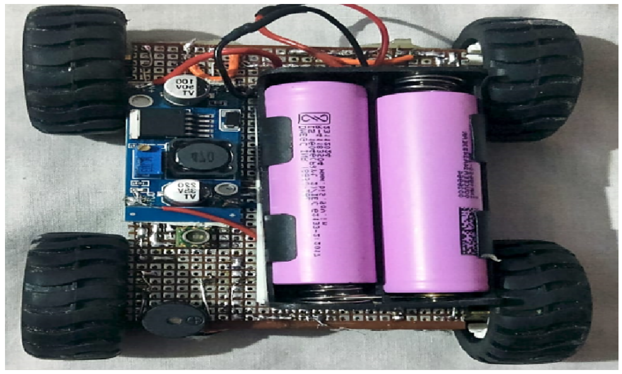


Fig. 5.RoverBackside

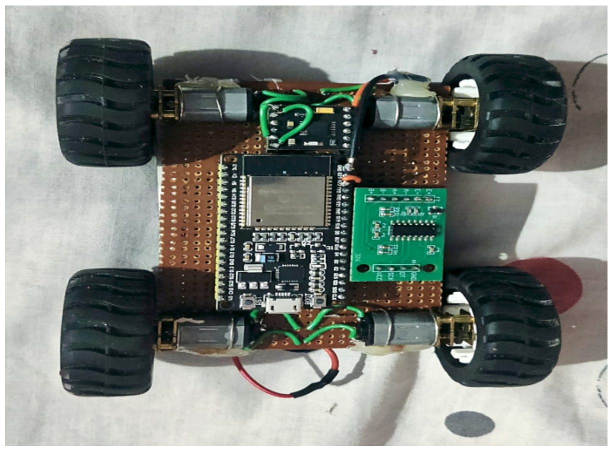


Fig. 6.RoverFrontside

E. Google Firebase:

Google Firebase is a comprehensive platform of cloud-based toolsthat simplifies app development by providing a secure and efficient backend, enabling developers to build, deploy, and scale applications across various platforms. Arduino can communicate with the ESP module, and the ESP module handles the connection to Wi-Fi network and the communication with Firebase. Firebase's real-time database allows Arduino to send and receive data instantly, enabling applications like remote monitoring, control systems, and IoT projects with live updates. In this work Google fire baseplatform is used to communicate with rover. The programm is already saved in firebase about the commands like "FORWARD", "REVERSE" "STOP", and "BUZZER". By giving the commands the rover will start to move through the pipeline. During this time we can simply save the datas from the pressure sensor in to a excel file by using Autofront data option from the gogle firebase. Figure 6.8 shows the google firebase command windoe for rover.

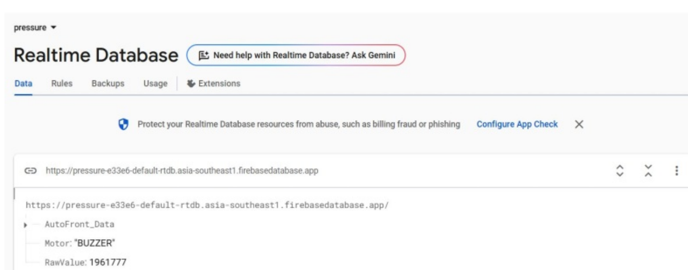


Fig. 7.Firebase command window for rover

IV. WORKING

Machine learning model is used to train the data we get from the pipeline implementation. Data collection is the first step. The steps are listed below.

- An air pump works by adding energy to the air, increasing its pressure above the surrounding atmospheric pressure.

- To create a difference in pressure, there usually needs to be some form of restriction or resistance to the airflow within the pipeline.
- An air pump can be used to maintain a desired pressure in a pipeline with a leak. The pump needs to supply enough air to compensate for the leakage and keep the pressure at the target level.
- Open one end of pipeline and insert the rover in to it.. And close and seal the pipeline.
- Move the Rover in forward direction, apply the pressure using air pump. Take readings of no leak case
- Release the air and create the leak using release of pressure. • Taking the readings using autofront option.
- Repeat the steps along 40 cm, 95 cm and 180 cm of pipeline length.

Evaluation using machine learning
Random forest model and LSTM model is used to Evaluation process.Anensemble learning technique forclassification, regression, and other problems, random forests, also known as random decision forests, generates a large number of decision trees during training. The class chosen by the majority of trees is the random forest's output for classification problems. The average of the trees' predictions is the result for regression tasks.The tendency of decision trees to overfit to their training set is compensated for by random forests. Building a large number of decision trees during the training phase is how a Random Forest model, a strong and adaptable machine learning technique, works.
An LSTM cell, in contrast to the basic nodes in conventional RNNs, consists of a number of interdependent parts that enable it to selectively recall, forget, and update data while processing a sequence. These parts are frequently called gates. In an LSTM cell, the main gates are:Forget gate, input gate, cell state and output gate.What data from the prior cell state should be erased is decided by the forget gate. It returns a vector of values between 0 and 1 for each number in the cell state after examining the current input and the previous concealed state. Long-term dependencies can be learnt by LSTMs with the usage of these gates. The input gate aids in adding fresh, pertinent information, the output gate regulates the information flow to the following time step, and the forget gate allows the cell to eliminate unnecessary previous information.

V. EVALUATION RESULTS AND DISCUSSION

A. Random Forest model

Evaluation results for implemented pipeline with sensors placed on rover not in the pipeline. Evaluation results for random forest model are given below in the table 1.

Table 1: Evaluation results for random forest model

	Precision	Recall	F1 score	Support
0	0.97	0.99	0.98	572
1	0.89	0.89	0.89	570
2	0.91	0.88	0.89	550

Here we got the accuracy as 92%.
Confusion matrix is give in figure 8.

B. LSTM Model

Evaluation results for LSTM model are given below in the table 2. Here we got the accuracy as 98%. Confusion matrix is shown in figure 9.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue V May 2025- Available at www.ijraset.com

Table 2: Evaluation results for LSTM model

	Precision	Recall	F1 score	Support
0	1.00	0.99	0.99	540
1	1.00	0.94	0.97	573
2	0.94	1.00	0.97	578

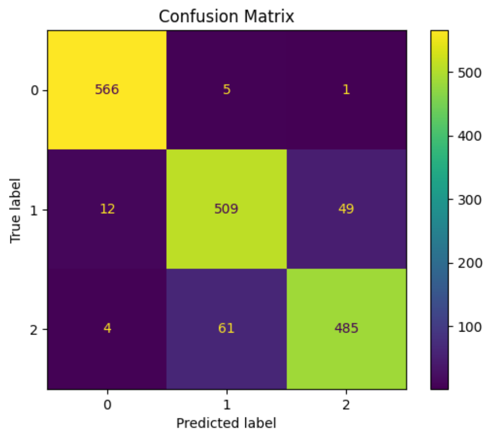


Fig. 8.Confusion matrix for Random forest model

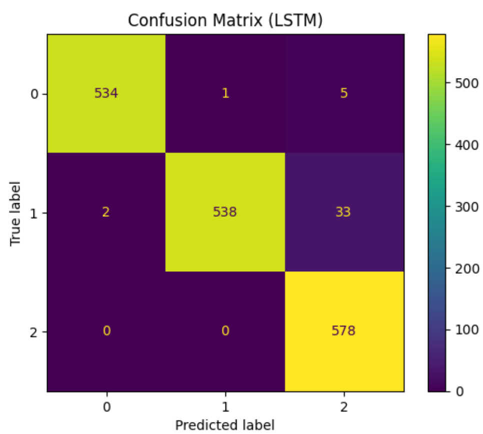


Fig. 9.Confusion matrix for LSTM model

VI. CONCLUSION

The research has produced a low-cost leak detection system that can detect low pressure leaks that are located distant from the inlet and outlet pressure sensors and that the conventional system would overlook due to the deterioration of the leak-induced pressure variation. Installing a pressure sensor with remote gearbox capabilities at the pipeline's 10 kilometer midpoint completes the system. This sensor reacts more effectively to changes in pressure brought on by leaks close to the inlet. According to experiments, leaks at the intake had the best probability of being discovered because of the high pressure there, but leaks halfway to the outlet have the best chance of going unnoticed because of the low pressure there. Here, the accuracy is low because the simulation only obtains a small number of datasets. with a gradual decline in sensor activity.suggesting a sensor-equipped pipeline robot.Phase 2 of this work will be carried out in order to improve the accuracy. Equipped the pipeline and setup a Rover with pressure sensors that can move through the pipeline. Rovers may move straight through the pipeline, making it possible to locate leaks with extreme precision. This allows for the integration of data from sensors and the analysis of spatial patterns. A fixed sensor on a pipe only provides localized information. Pipeline leak detection accuracy using sensors placed on pipeline 72% and Pipeline leak detection accuracy using sensors placed on rover 98%.

VII.FUTURE SCOPE

We can develop a real time in pipe leak detector using the neural network tools, the advantages are which is far economical and budget friendly than PLC or Scada based real time leak detection system.

REFERENCES

[1] Danial Waleed, Syed Hamdan Mustafa, Shayok Mukhopadhyay, Mamoun Abdel Hafez, Mohammad A. Jaradat, Kevin Rose Dias, Fahad Arif, Jawwad Imtiaz Ahmed, An in-pipe leak detection robot with a neural-network based leak verification system, : DOI 10.1109/JSEN.2018.2879248, IEEE Sensors

[2] Adegboye, M.A., Fung, W.K., Karnik, A., 2019. Recent advances in pipeline monitoring and oil leakage detection technologies: principles and approaches. J. Sens. 19 (11), 2548. doi:10.3390/s19112548.

[3] Idachaba, F., Rabiei, M., 2021. Current technologies and the applications of data analytics for crude oil leak detection in surface pipelines. J. Pipeline Sci. Eng. 1 (4), 436–451. doi:10.1016/j.jpse.2021.10.001, ISSN 2667-1433.

[4] F. Batzias, C. Siontorou, and P.-M. Spanidis, “Designing a reliable leak bio-detection system for natural gas pipelines,” Journal of Hazardous Materials, vol. 186, no. 1, pp. 35–58, Feb 2011.

[5] D. Chatzigeorgiou, K. Youcef-Toumi, and R. Ben-Mansour, “Design of a Novel In Pipe Reliable Leak Detector,” IEEE/ASME Transactions on Mechatronics, vol. 20, no. 2, pp. 824–833, Apr 2015.

[6] L. Boaz, S. Kaijage, and R. Sinde, “An overview of pipeline leak detection and location systems,” in 2014 Pan African Conference on Science, Computing and Telecommunications (PACT). IEEE, 2014, pp. 133–137.

[7] T. Takayama, H. Takeshima, T. Hori, and T. Omata, “A twisted bundled tube locomotive device proposed for in-pipe mobile robot,” IEEE/ASME Transactions on Mechatronics, vol. 20, no. 6, pp. 2915–2923, 2015.

[8] Z. Liu and Y. Kleiner, “State-of-the-art review of technologies for pipe structural health monitoring,” IEEE Sensors Journal, vol. 12, no. 6, pp. 1987–1992, 2012.

[9] A. Cataldo, G. Cannazza, E. De Benedetto, and N. Giaquinto, “A new method for detecting leaks in underground water pipelines,” IEEE Sensors Journal, vol. 12, no. 6, pp. 1660–1667, 2012.

[10] F. Wang, W. Lin, Z. Liu, S. Wu, and X. Qiu, “Pipeline leak detection by using time-domain statistical features,” IEEE Sensors Journal, vol. 17, no. 19, pp. 6431–6442, 2017.

[11] W. Mpesha, M. H. Chaudhry, and S. L. Gassman, “Leak detection in pipes by frequency response method using a step excitation,” Journal of Hydraulic Research, vol. 40, no. 1, pp. 55–62, 2002.

[12] A. Lay-Ekuakille, A. Trotta, and G. Vendramin, “FFT-based spectral response for smaller pipeline leak detection,” in Instrumentation and Measurement Technology Conference, 2009. I2MTC’09. IEEE, 2009, pp. 328–331.

[13] A. Lay-Ekuakille, G. Vendramin, A. Trotta, and P. Vanderbemdem, “STFT based spectral analysis of urban waterworks leakage detection,” in XIX IMEKO World Congress, Fundamental and Applied Metrology, Lisbon, Portugal, 2009.

[14] A. Lay-Ekuakille, G. Vendramin, and A. Trotta, “Spectral analysis of leak detection in a zigzag pipeline: A filter diagonalization method-based algorithm application,” Measurement, vol. 42, no. 3, pp. 358–367, 2009.

[15] A. Lay-Ekuakille, C. Pariset, and A. Trotta, “Leak detection of complex pipelines based on the filter diagonalization method: robust technique for eigenvalue assessment,” Measurement Science and Technology, vol. 21, no. 11, p. 115403, 2010.

[16] A. Lay-Ekuakille and P. Vergallo, “Decimated signal diagonalization method for improved spectral leak detection in pipelines,” IEEE Sensors Journal, vol. 14, no. 6, pp. 1741–1748, 2014

[17] G. Desjardins and R. Sahney, Pipeline Pigging and Integrity Technology, J. Tiratsoo, Ed. Scientific Surveys Limited/Clarion Technical Publishers, 2003.

[18] P.-S. Murvay and I. Silea, “A survey on gas leak detection and localization techniques,” Journal of Loss Prevention in the Process Industries, vol. 25, no. 6, pp. 966–973, 2012.

[19] R. Santos, E. De Sousa, F. Da Silva, S. Da Cruz, and A. Fileti, “Detection and on-line prediction of leak magnitude in a gas pipeline using an acoustic method and neural network data processing,” Brazilian Journal of Chemical Engineering, vol. 31, no. 1, pp. 145–153, 2014.

[20] S. H. Kim, S. J. Lee, and S. W. Kim, “Weaving laser vision system for navigation of mobile robots in pipeline structures,” IEEE Sensors Journal, vol. 18, no. 6, pp. 2585–2591, 2018.

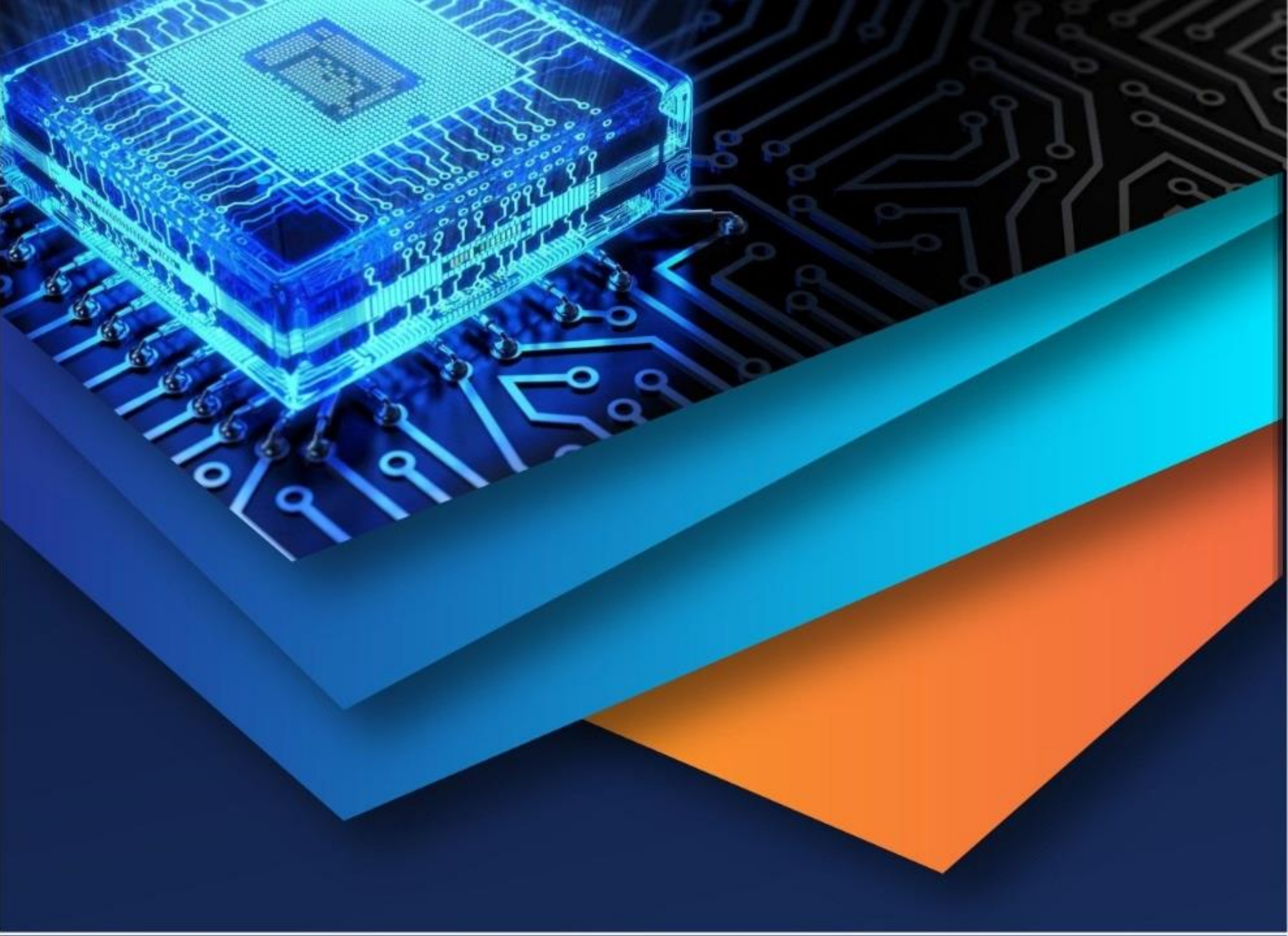
[21] Darkhan Zholtayev, Daniyar Dauletiya, Aisulu Tileukulova Manat Nursultan ,DiasAkimbay,YersaiynBushanov ,AskatKuzdeuov , And Azamat Yeshmukhametov, “Smart Pipe Inspection Robot With In-Chassis Motor Actuation Design and IntegratedAI-Powered Defect Detection 10.1109/ACCESS.2024.3450502,2024

[22] System” E Fajardo, D Moctezuma, “Water leak detection through satellite imagery and deep learning”, Sustainable Water Resources Management, springer 2025

[23] H Yuan, Y Liu, L Huang, G Liu, T Chen, G Su, J Dai, “Real-time detection of urban gas pipeline leakage based on machine learning of IoT time-series data”, Measurement, 2025 - Elsevier

[24] F Saleem, Z Ahmad, JM Kim, “Real-Time Pipeline Leak Detection: A Hybrid Deep Learning Approach Using Acoustic Emission Signals”, Applied Sciences (2076 3417 …, 2025 - search.ebscohost.com

[25] R Wang, F Cui, G Dong, X Zhao, Q Cheng, “A Pipeline Leakage Detection Technique Using Ground Penetrating Radar Polarization Method” Water Resources …, 2025 – Springer



doi crossref

10.22214/IJRASET

INDEX COPERNICUS

45.98

ISRA JIF

IMPACT FACTOR: 7.129

TOGETHER WE REACH THE GOAL

IMPACT FACTOR: 7.429

ISI

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY