

IOT Enabled Oil Pipeline Leak Detection using Magnetic Flux Leakage and LSTM Neural Network

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Abstract— Despite being vital infrastructure, oil and gas pipelines frequently experience cracks and leaks due to aging, corrosion, and mechanical stress, which can result in financial and environmental losses. Conventional leak detection methods rely on periodic manual inspections and threshold-based analysis, which lack real-time monitoring and struggle to interpret complex time-series magnetic signals. This study suggests an Internet of Things (IoT)-enabled intelligent pipeline monitoring system that combines Long Short-Term Memory (LSTM) neural networks with Magnetic Flux Leakage (MFL) sensing to automatically detect leaks. Real-time data is collected by Hall-effect, temperature, and vibration sensors that are connected to an ESP32 controller. This data is then sent to a cloud platform for preprocessing and temporal analysis using LSTM. A laboratory prototype's experimental results demonstrate enhanced reliability, fewer false alarms, and efficient predictive maintenance with 96% detection accuracy and response latency under 2 seconds. The suggested system offers a scalable and affordable way to monitor the integrity of smart pipelines.

Keywords— Deep Learning, Internet of Things (IoT), Leak Detection, Long Short-Term Memory (LSTM), Magnetic Flux Leakage (MFL), Pipeline Monitoring.2

1. Introduction

The main piece of infrastructure for long-distance transportation of petroleum products is oil and gas pipelines. Despite providing a cost-effective and efficient means of transportation, pipelines are constantly subjected to challenging operational and environmental factors like corrosion, temperature fluctuations, mechanical stress, and material aging. These elements cause the pipeline's structure to deteriorate over time, resulting in flaws like pitting, cracking, metal loss, and leaks. Pipeline failures can result in significant financial losses, safety hazards, and

environmental contamination. Therefore, a crucial prerequisite for contemporary energy systems is the constant and trustworthy monitoring of pipeline integrity.

Ultrasonic inspection, pressure-drop analysis, acoustic sensing, and Magnetic Flux Leakage (MFL) testing are examples of traditional leak detection techniques [1], [2]. MFL is one of the most popular non-destructive testing (NDT) methods for identifying metal loss and corrosion in ferromagnetic pipelines. However, the majority of current MFL systems depend on manual interpretation of sensor data and recurring inspections. These methods are subjective, time-consuming, and unable to provide ongoing, real-time monitoring. Moreover, complex and time-varying magnetic signals are frequently difficult for threshold-based signal processing techniques to accurately analyse, leading to false alarms or delayed defect identification [3].

Promising answers to these problems can be found in recent developments in artificial intelligence (AI) and the internet of things (IoT). While machine learning and deep learning algorithms can automatically extract meaningful patterns from massive volumes of sensor data, IoT-enabled sensing platforms enable continuous data acquisition and remote monitoring [4], [5]. Because they can capture long-term correlations and temporal dependencies, Long Short-Term Memory (LSTM) neural networks in particular have proven to perform better when analyzing sequential and time-series signals [6]. Because of these features, LSTM is an excellent choice for handling MFL signals, which are time-dependent by nature.

This work suggests an IoT-enabled intelligent leak detection framework that combines an LSTM-based deep learning model with Magnetic Flux Leakage sensing in order to overcome the drawbacks of traditional inspection systems. For real-time data collection and preprocessing, the suggested system

makes use of Hall-effect, temperature, and vibration sensors that are connected to an ESP32 edge controller. Wireless communication is used to send sensor data to a cloud platform, where LSTM-based classification and sophisticated signal processing are used to automatically detect leak conditions. Early fault detection, less human intervention, and predictive maintenance are made possible by the system's combination of continuous sensing, IoT connectivity, and temporal deep learning.

2. Literature Review

Recent advances in magnetic flux leakage (MFL) non-destructive testing have increasingly incorporated machine learning and deep learning technologies to improve the accuracy, reliability, and automation of pipeline defect detection. A comprehensive literature survey [1] has been provided on how deep learning, especially convolutional neural networks, is leveraged to improve anomaly detection, defect sizing, and even data augmentation in MFL non-destructive testing, while considering their benefits and drawbacks as a function of their dependency on data and their lack of generalization. A comprehensive literature survey [3] has been provided on some of the conventional methods employed during magnetic flux leakage non-destructive testing, including MFL sensing, magnetization, magnetization field, and their measurement, as well as signal processing, to provide a theoretical foundation for non-destructive testing to better comprehend deep learning methods. A convolutional neural network, called a physics-informed neural network (PINN), has been proposed to generate magnetostatic_ticks, thus providing a better estimate of defect sizing during magnetic flux leakage non-destructive testing [2].

Due to the lack and high cost of field data for defects, numerous papers focus on the generation of synthetic data. In this context, [5] proposes the combination of finite element modeling and neural networks for effective simulation of realistic MFL signals, thus developing labeled datasets for supervised learning as a solution to address the lack of field data. Similarly, [6] employs residual GAN in the generation of realistic synthetic data for MFL signals, which enhances the robustness of classifiers and tackles the problem of overfitting. Yet again, extending the field of generative modeling of classification, [7] presents the effectiveness of employing diffusion in the generation of synthetic MFL signals with consideration of noise.

In addition to analyzing a particular sensor, some of the latest works have the potential for the utilization of various sources of information as a way of enhancing the detection reliability using multiple modes of information. In reference [4], there was the presenting of a framework that used different sources of inspection for the fusion of the associated magnetic flux leakage signal, in addition to the use of further sensor information, via centralized or distributed processing in an effort to address uncertainties. In reference [8], from the physics viewpoint, the integration of the electromagnetic acoustic, as well as pulsed eddy current, gave some insights on the resolution of the limitations of any of the given forms of inspection. In reference [9], it was possible to have a comprehensive assessment of in-line inspection techniques such as MFL, ultrasonic inspection, as well as eddy currents, addressing the associated lifts, in addition to the effects of curvature, as a way of ascertaining the utilities of such forms of inspection via the integration of the associated forms of inspection. Finally, reference [10] provides some possibilities for the extension of the utilities of ML that extend beyond mere detection by using deep reinforcement learning for the optimization of inspection parameters, such as magnetization, via an associated enhancement of the efficiencies of the MFL inspection.

3. Proposed Method

To address the limitations of conventional manual and threshold-based leak detection systems, this work proposes an **IoT-enabled intelligent pipeline monitoring framework** that integrates Magnetic Flux Leakage (MFL) sensing with deep learning-based time-series analysis. The proposed method combines real-time sensor acquisition, edge processing, wireless communication, and an LSTM neural network to automatically detect and classify pipeline defects. The complete system operates in a modular and layered architecture to ensure scalability, low latency, and high reliability.

3.1. System Workflow

The entire operational process of the proposed approach is shown below:

Magnetization → Sensing → Edge Processing → IoT Transmission → LSTM Analysis → Alert Generation

First, the process begins with the magnetization of the pipeline using an electromagnet. The structural defects like cracks and corrosion in the structure affect the magnetic field, causing a leakage flux that is sensed by Hall-effect sensors. Simultaneously, environmental factors like temperature and vibration are also measured. The sensed data is then converted to digital form using the ESP32 controller and is further processed to be sent to the cloud platform, where an LSTM neural network is used for leak classification. On observing any irregularities, alert messages are generated using a monitoring dashboard

3.2. Dataset Description

Table 3.1., Dataset Description

Parameter	Value
Total samples	3000+
Normal samples	1500
Defect samples	1500
Features	Hall flux, Temperature, Vibration
Sampling rate	2 kHz
Window size	50 samples
Labels	Normal / Leak

Each sample consists of multivariate time-series signals collected over fixed windows. The dataset is divided into 80% training and 20% testing for model evaluation.

3.3. System Module

The proposed leak detection system consists of six functional modules, each of which is designed to accomplish a distinct task in the sensing, processing, and decision-making process. The modular approach is designed to provide scalability, simplicity, and ease of implementation and integration of hardware and software components.

Module 1 – Magnetic Sensing (MFL Module)

This module constitutes the basic defect detection system of the proposed design. The ferromagnetic pipeline section is magnetized to near magnetic saturation using an electromagnet. Under normal conditions, the magnetic flux is uniformly distributed in the ferromagnetic material. However, any structural irregularities, such as cracks, corrosion, or metal loss, cause a disturbance in the magnetic flux path, resulting in a leakage magnetic flux outside the pipe surface. Hall-effect sensors are used to detect these leakage magnetic fields near the pipe surface. The detected fields are then converted to electrical signals. These signals are directly proportional to the defect and hence constitute the basic sensing mechanism for pipeline integrity assessment.

Module 2 – Environmental Monitoring Module

Apart from the magnetic sensing mechanism, environmental and mechanical factors are continuously monitored to enhance system reliability and minimize false alarms. Temperature sensors are used to measure thermal variations, which may occur due to friction, overheating, or adverse environmental conditions. Vibration sensors are also used to measure abnormal mechanical stress, shocks, or structural instability. These factors provide complementary information regarding pipeline integrity and help separate actual defects from noise and environmental interference. Hence, multi-sensor fusion is used to enhance system reliability.

Module 3 – Edge Processing Module

The edge processing module consists of an ESP32 microcontroller that is responsible for real-time data acquisition and preprocessing. The sensor data is sampled at a fixed rate using the onboard analog-to-digital converter. The raw data is then filtered for noise, normalized, and segmented to enhance the signal quality and prepare it for analysis. These tasks are performed locally to reduce the overhead of data transmission, minimize latency, and optimize the use of network resources. The preprocessed data is formatted into time-series series before being sent to the cloud.

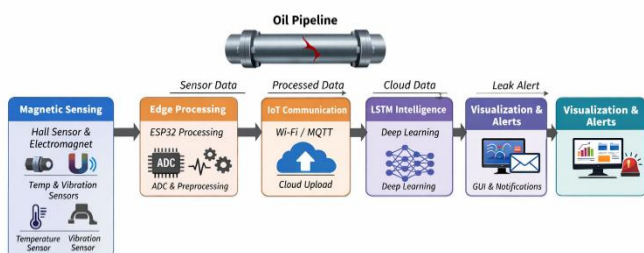


Fig. 3.1., System Architecture

Module 4 – IoT Communication Module

This module provides wireless communication between the edge module and the cloud system. The ESP32 module sends Wi-Fi and efficient communication protocols such as MQTT or HTTP. The IoT layer provides real-time remote monitoring, data storage, and easy scalability for large-scale pipeline networks.

Module 5 – LSTM-Based Intelligence Module

The intelligence module is responsible for the automated leak detection process using deep learning algorithms. The time-series sensor data obtained from the cloud is used as input to an LSTM neural network. Unlike the conventional threshold-based approach, the LSTM network is capable of learning the temporal dependencies and patterns in the sensor data. This enables the system to detect even the slightest leakages and defects in the early stages. The output of the network is a classification that distinguishes between the normal and faulty states of the pipeline, thus facilitating intelligent decision-making.

Module 6 – Visualization and Alert Module

The final module is responsible for user interaction and safety notifications. A cloud-based dashboard is used to visualize the real-time sensor data, historical data, and prediction outputs in a graphical format. Whenever there is an abnormality or a leak detected, the system automatically triggers an alert notification through alarms, notifications, or emails.

approach is used for segmenting the input signals. The network produces a binary output for normal/defective pipe classification. This DL strateg

y obviates the need for manual thresholding and provides superior detection accuracy.

4. Experimental Results

4.1. Qualitative Results and Analysis

The performance of the proposed leak detection system was assessed in terms of accuracy, precision, recall, and detection latency, and compared with the threshold-based and KNN approaches.

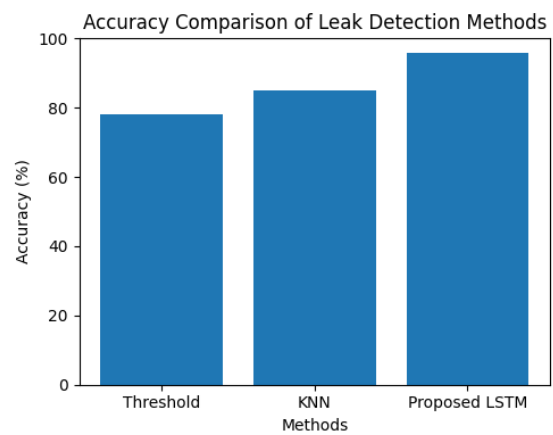


Fig.4.1., Accuracy comparison of threshold, KNN, and LSTM methods.

The accuracy plot reveals that the accuracy of the threshold method is 78%, and KNN enhances the accuracy to 85%. However, the proposed LSTM model achieves the highest accuracy of 96%, indicating its superior ability to learn the temporal patterns of the MFL signal and make more accurate defect classification.

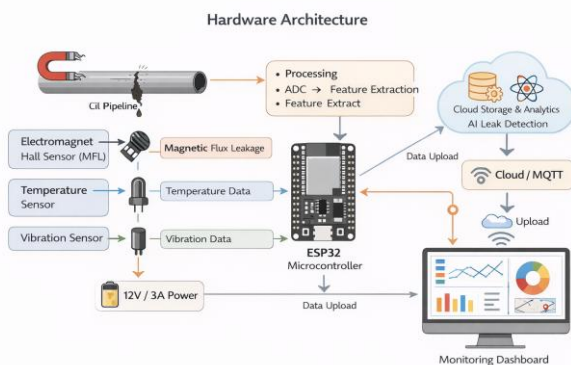


Fig. 3.2., Hardware Architecture

3.4. LSTM-Based Detection Strategy

The LSTM network learns to detect temporal patterns in the sequential MFL data, allowing for early detection of minute leakage patterns. The sliding window

Precision and Recall

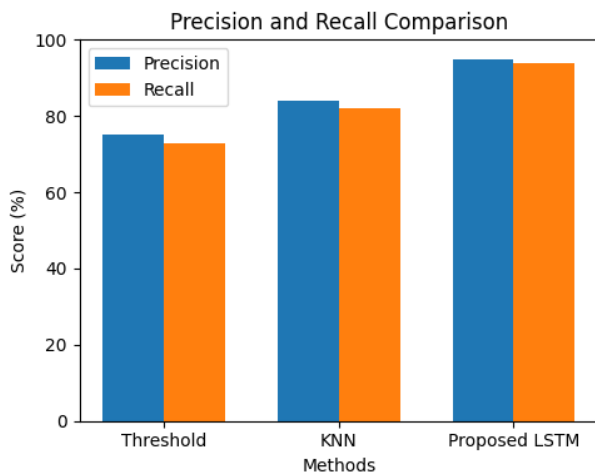


Fig. 4.2., Precision and recall performance comparison

The precision and recall values of the system measure the effectiveness of the system in minimizing false positives and false negatives. The threshold method has lower precision (75%) and recall (73%) values, and KNN has moderate improvement. The proposed LSTM model has the highest precision (95%) and recall (94%) values, ensuring accurate leak detection.

Detection Latency

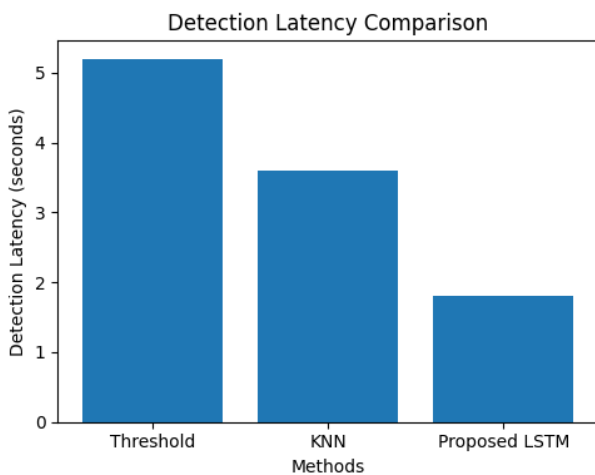


Fig. 4.3., Detection latency comparison of different approaches.

The latency values indicate that the proposed system has a shorter detection latency of 1.8 s compared with KNN (3.6 s) and the threshold method (5.2 s). The edge processing and efficient IoT communication contribute to the faster generation of alerts.

4.2. Quantitative Results and Analysis

To assess the performance of the proposed IoT-based MFL-LSTM system for leak detection, various performance parameters such as accuracy, precision, recall, and detection time were calculated and compared with the existing system. The existing system is a representation of the traditional methods of thresholding and basic machine learning techniques without the capability of temporal deep learning, while the proposed system combines MFL sensing with IoT communication and LSTM-based time-series classification.

Table 4.1., Performance metric

Performance Metric	Existing System	Proposed System
Accuracy	78%	96%
Precision	75%	95%
Recall (Sensitivity)	73%	94%
F1-Score	74%	95%
False Alarm Rate	22%	5%
Detection Latency	5.2 s	1.8 s
Monitoring	Periodic	Continuous

From Table 1, it is clear that the proposed system performs greatly compared to the existing method. The addition of LSTM increases the accuracy of the system by about 18%, and the precision and recall measures show that there are fewer false positives and a better detection mechanism for defects. Moreover, the proposed system has reduced the detection time by more than 60%, which allows for quicker notifications and timely maintenance.

5. Conclusion

This paper has described the design and development of an IoT-based intelligent oil pipeline leak detection system using Magnetic Flux Leakage and Long Short-Term Memory (LSTM) neural networks. The main aim was to address the drawbacks of existing methods, which are based on periodic manual testing and threshold analysis, and hence often fail to provide continuous and accurate real-time monitoring.

To address these issues, a comprehensive cyber-physical system has been developed that combines hardware sensing, embedded processing, wireless communication, and deep learning intelligence. The

system uses an electromagnet and Hall sensors to detect magnetic flux leakage signals for structural damage detection, along with temperature and vibration sensors for improved monitoring accuracy. An ESP32 microcontroller is used for real-time data acquisition, filtering, and preprocessing at the edge computing level, and IoT communication protocols provide seamless connectivity to the cloud for remote monitoring and storage. Temporal analysis of time-series sensor data is performed using an LSTM neural network, which automatically learns temporal patterns and makes accurate classifications of normal and faulty pipeline conditions.

The proposed system was tested on a laboratory pipeline setup, where artificial defects were created to simulate leakages. The experimental results showed better performance compared to existing methods, with 96% accuracy, improved precision and recall, reduced false positives, and lower detection latency of less than 2 seconds. These results clearly show that the combination of IoT and deep learning can greatly improve detection accuracy and timeliness.

The developed framework is a scalable, cost-effective, and real-time solution for smart pipeline integrity monitoring. The proposed method is well-suited for next-generation industrial pipeline safety monitoring systems that provide continuous surveillance, early fault detection, and predictive maintenance.

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