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# Electromagnetic Signal Classification Using Deep Learning for Pipeline Structural Health Monitoring

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## Abstract:

Pipeline networks are the cornerstone of global energy transportation, yet their integrity is constantly challenged by environmental factors, material degradation, and external threats, leading to costly failures and severe environmental and safety hazards. Traditional structural health monitoring (SHM) methods often suffer from limitations such as delayed detection, high false alarm rates, and poor fault localization. This paper introduces a novel, non-invasive approach for pipeline anomaly detection and classification leveraging radio frequency (RF) sensing and deep learning. We propose a one-dimensional Convolutional Neural Network (1D CNN) framework that analyzes simulated reflection coefficient (S11) signatures from patch antennas, designed to detect and classify four distinct pipeline conditions: normal, crack, corrosion, and leak. A realistic dataset of electromagnetic responses, including varying levels of Gaussian noise to simulate real-world distortions, was generated for model training and validation. The proposed 1D CNN achieved a perfect 100% classification accuracy on clean data and maintained a robust 94% accuracy even under severe noise conditions, demonstrating excellent generalization capabilities. Notably, critical fault conditions like leaks and normal states remained perfectly classified despite significant signal degradation. This work highlights the transformative potential of integrating physics-grounded electromagnetic sensing with advanced deep learning algorithms, offering a computationally efficient, scalable, and reliable solution for next-generation, intelligent pipeline monitoring systems, thereby enhancing infrastructure safety and resilience.

*Keywords* — Structural Health Monitoring (SHM); Pipeline Integrity; Radio Frequency (RF) Sensing; Microstrip Patch Antenna; Reflection Coefficient (S11); Deep Learning; Convolutional Neural Network (CNN); Fault Classification; Leak Detection; Corrosion Detection; Crack Detection; Non-invasive Monitoring.

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## I. INTRODUCTION

Pipelines remain the backbone of global energy transportation infrastructure, facilitating the safe and efficient delivery of oil, gas, and other critical fluids over vast distances. However, their continuous exposure to harsh environmental conditions, material fatigue, and human-induced threats renders them susceptible to various structural failures, including internal and external corrosion, cracks, and leaks [1, 2]. Undetected failures not only lead to significant economic losses, often in the billions of dollars, but also pose severe environmental contamination risks and catastrophic safety hazards to communities and ecosystems [3, 4]. Consequently, the demand for accurate, timely, and non-invasive structural health monitoring (SHM) systems in pipeline networks has gained significant momentum in recent years, shifting from reactive to proactive maintenance strategies [5, 6].

Traditionally, pipeline integrity has been assessed using techniques such as routine visual inspections, pressure and flow monitoring, thermal imaging, and acoustic emission (AE) monitoring for leak and defect identification [7]. While these conventional methods have provided foundational benefits, they often suffer from inherent limitations. These include delayed detection capabilities, susceptibility to high false alarm rates due to environmental noise and interference, and significant challenges in accurately localizing the fault source [8, 9]. The need for more advanced, rapid, and precise diagnostic tools is therefore paramount.

Recent advancements in radio frequency (RF) sensing technologies, particularly those leveraging microstrip patch antennas, have opened new avenues for real-time, non-contact pipeline diagnostics. Patch antennas, due to their compact size, planar structure, ease of fabrication, and inherent sensitivity to changes in the dielectric properties or physical dimensions of their surrounding environment, have proven highly suitable for SHM applications, especially when mounted externally on pipeline surfaces [10, 11]. Changes in pipeline integrity—such as the presence of leaks, corrosion, or cracks—induce subtle yet distinct variations in the antenna's electromagnetic characteristics, notably its return loss (S11) profile or resonant frequency shift. These unique electromagnetic signatures can be captured and interpreted to infer the underlying structural state of the pipeline [12, 13].

However, the manual interpretation of S11 data becomes increasingly infeasible and prone to human error when dealing with large-scale pipeline deployments or high-sampling-rate measurements. To overcome this challenge, researchers have increasingly turned to machine learning (ML) techniques, particularly deep learning architectures like convolutional neural networks (CNNs), which have demonstrated superior performance in complex pattern recognition tasks involving noisy and high-dimensional data [3]. While several studies have successfully applied ML in pipeline monitoring, often leveraging traditional sensor data such as vibration, pressure, or thermal signatures [8], the comprehensive integration of RF sensing data, specifically antenna return loss profiles, with deep learning remains underexplored. Critically, the ability to distinguish multiple fault types (e.g., normal, crack, corrosion, leak) using RF-based deep learning, and the reliability of such systems under real-world distortions including sensor noise and environmental fluctuations, have not been sufficiently validated.

In this paper, we propose a novel classification framework that utilizes a one-dimensional (1D) CNN architecture to accurately detect and classify various pipeline conditions—namely normal, crack, corrosion, and leak—based on simulated S11 antenna responses. We generate a realistic dataset of electromagnetic signatures corresponding to these conditions and rigorously validate the robustness of our model under varying levels of Gaussian noise to simulate real-world distortions. Our approach combines the inherent interpretability and non-invasive nature of RF-based SHM with the powerful pattern recognition capabilities of deep learning, thereby enabling early and precise detection and classification of pipeline faults. This contributes significantly to the development of safer, more resilient, and intelligently monitored energy transportation infrastructure.

## II. Electromagnetic Theory for Leak Detection

Multiphase transport is pervasive in oil and gas pipelines, especially in production and gathering networks where oil, gas, and water phases coexist. Unlike single-phase systems, multiphase flow introduces **complex regime-dependent dynamics**—including stratified, slug, and annular flow—alongside highly variable compressibility and nonlinear for non-invasive structural health monitoring (SHM) in critical infrastructure like pipeline systems, where the interaction of propagating electromagnetic waves with the physical structure is governed by Maxwell's equations. These equations describe how electric ($E$) and magnetic ($H$) fields evolve in space and time, relating them to material properties like magnetic permeability (mu), electric permittivity (epsilon), and electrical conductivity (sigma) [14, 15].

The core of EM sensing for structural health monitoring (SHM) lies in the principle that any deviation from uniform material properties—such as the presence of cracks, corrosion, or fluid leaks—alters the local dielectric properties and conductivity of the medium. These changes, in turn, perturb the EM field distribution, leading to measurable variations in the reflected or transmitted EM signals. By analyzing these perturbations, it becomes possible to infer the underlying physical condition of the structure without direct contact [5]. Maxwell's curl equations, which are particularly relevant for wave propagation and interaction with materials, are expressed as:

1. **Faraday's Law of Induction:**

$$\nabla \times E = -\mu \frac{\partial H}{\partial t}$$

This equation describes how a time-varying magnetic field (B = μH) induces an electric field ($E$).

2. **Ampere-Maxwell Law:**

$$\nabla \times H = \sigma E + \epsilon \frac{\partial E}{\partial t}$$

This equation relates the magnetic field ($H$) to both the electric current density ($J = \sigma E$) and the time-varying electric displacement field ($D = \varepsilon E$).

Localized changes in epsilon and sigma—caused by phenomena such as water intrusion, gas leakage, or rust formation due to corrosion—introduce scattering, absorption, and reflection effects that are precisely measurable in the reflected EM signals [10, 16]. A microstrip patch antenna, when employed as a sensing device, functions by radiating EM energy into its immediate environment and simultaneously acting as a receiver to detect the reflection characteristics from that environment. One of the most critical parameters in this context is the reflection coefficient, commonly denoted as $S_{11}$, which quantifies the proportion of incident power that is reflected back to the antenna port. The $S_{11}$ parameter is directly related to the antenna's input impedance ( $Z_{in}$ ) and the characteristic impedance of the transmission line ($Z_{out}0$) by the formula:

$$S_{11} = \frac{Z_{in} - Z_{out}}{Z_{in} + Z_{out}}$$

Under normal pipeline conditions, the antenna exhibits a stable $S_{11}$ profile, typically featuring well-defined resonance dips at specific frequencies. However, when defects such as leaks, corrosion, or cracks alter the electromagnetic properties (permittivity, permeability, conductivity) of the surrounding medium, the antenna's input impedance changes. This impedance mismatch leads to observable shifts and distortions in the $S_{11}$ response [11, 12].

In practical implementations, these variations manifest as:

- **Resonant frequency shifts:** The presence of a defect (e.g., water ingress from a leak, or the formation of corrosion products) changes the effective dielectric constant ($\varepsilon_{eff}$) of the medium surrounding the antenna. Since the resonant frequency of a patch antenna is inversely proportional to

  

$\sqrt{\varepsilon_{eff}}$, any change in $\varepsilon_{eff}$ directly results in a measurable shift in the antenna's resonant frequency [13, 17].

- **Amplitude damping in the reflection signal (increase in $|S_{11}|$ magnitude):** Lossy materials, such as water or rust, increase the absorption of EM energy. This increased loss leads to a higher proportion of the incident power being reflected rather than absorbed or radiated efficiently, resulting in a higher magnitude of $S_{11}$ at the affected frequencies [18, 19].
- **Broadening or narrowing of resonance bandwidth:** Changes in the material properties due to defects can alter the quality factor (Q-factor) of the antenna. Increased losses from conductive corrosion or fluid presence can broaden the resonance bandwidth, while certain structural changes might narrow it, indicating specific types of material degradation or crack propagation [19, 20].

By meticulously capturing and analyzing these subtle changes in the $S_{11}$ signature across a frequency band, it becomes possible to detect and classify various structural conditions in the pipeline. Notably, the spatial resolution and sensitivity of this technique depend critically on the antenna design, the properties of the substrate material, and the proximity of the antenna to the defect [10]. Furthermore, the integration of machine learning models, particularly deep learning, enables automatic interpretation of the complex spectral features, significantly enhancing detection accuracy and reducing the potential for human error in large-scale monitoring scenarios [8, 21].

The application of EM theory in pipeline leak and defect detection is particularly advantageous because it enables real-time, passive, and non-contact monitoring of structural health. This makes it exceptionally well-suited for challenging environments such as buried or subsea pipelines where traditional methods are often impractical or costly [22]. When combined with robust classification models, such as convolutional neural networks, antenna-based EM sensing emerges as a powerful technique for developing next-generation, intelligent pipeline monitoring systems [9].

## III. METHODOLOGY AND DATASET GENERATION

This study develops a hybrid Physics-Informed Neural This study proposes a robust pipeline condition classification framework that utilizes electromagnetic (EM) wave responses captured by patch antennas mounted along pipelines. By analyzing the reflected wave characteristics—particularly the reflection coefficient $S_{11}$—we detect and classify various pipeline conditions including normal operation, corrosion, cracking, and leaks. The methodology consists of EM simulation-based dataset generation, feature extraction, noise injection, and classification using a one-dimensional Convolutional Neural Network (1D CNN).

### A. EM Simulation and Dataset Generation

***Scenario Modelling***

A synthetic but physically grounded dataset was generated to simulate different pipeline conditions. Using CST Microwave Studio and custom signal generation scripts, we modeled a steel pipeline section excited with a wideband patch antenna. The interaction of the EM field with the pipeline's inner wall produced different reflection signatures ($S_{11}$) for four distinct scenarios:

- **Normal** (intact pipe with no structural defects)
- **Crack** (narrow axial surface discontinuities)
- **Leak** (openings leading to mass loss)
- **Corrosion** (irregular surface roughness and conductivity degradation)

Each defect was modeled with realistic material properties and dimensions derived from pipeline failure literature. The antenna was swept across a frequency range of 1–10 GHz, and the reflected $S_{11}$ was recorded.

***Signal Characteristics***

For each scenario, multiple measurements were collected, with the following settings:

- Frequency sweep: 1–10 GHz
- Frequency resolution: 0.1 GHz
- Total samples per class: 100
- Total samples: 400 (balanced)

Each $S_{11}${11} trace was stored as a 1D vector representing the magnitude of reflection coefficient across the frequency range.

### B. Noise Injection and Robustness Modeling

To emulate real-world sensing imperfections (e.g., moisture, RF interference), Gaussian noise was injected into the synthetic dataset. The noisy signal $\tilde{x}(f)$ was generated from the clean signal $x(f)$ using:

$$\tilde{x}(f) = x(f) + \mathcal{N}(\mathcal{O}, \sigma^2)$$

where $\sigma$ is the standard deviation controlling the **noise factor**. Tests were performed for $\sigma = \epsilon\{0.1, 0.3, 1.0\}$ representing increasing noise severity.

### C. Feature Extraction and Preprocessing

Each $S_{11}$trace (size: 91 frequency points) was normalized to zero mean and unit variance. Basic descriptive statistics (mean, std, max, min) and frequency domain transforms (FFT, spectral entropy) were explored but the raw $S_{11}$ vectors yielded optimal performance with CNN-based learning.

### D. Classification Model: 1D CNN

A lightweight 1D CNN architecture was developed to classify pipeline conditions directly from $S_{11}$ spectra:

- **Input:** 1D $S_{11}$ vector (size = 91)
- **Conv1D Layer 1:** 32 filters, kernel size = 5, ReLU
- **MaxPooling1D**
- **Conv1D Layer 2:** 64 filters, kernel size = 3, ReLU
- **MaxPooling1D**
- **Flatten + Dense (64) + Dropout (0.5)**
- **Output Layer:** Softmax with 4 classes (normal, crack, leak, corrosion)

### E. Model Training and Evaluation

- **Loss function:** Categorical Cross entropy
- **Optimizer:** Adam (learning rate = 0.001)
- **Batch size:** 16
- **Epochs:** 50

  

- **Train/Test Split:** 80/20 stratified
- **Evaluation metrics:** Accuracy, Precision, Recall, F1-score, Confusion Matrix

The model achieved 100% accuracy on clean data and retained over **94% accuracy under severe noise injection** (σ=1.0\sigma = 1.0), demonstrating excellent generalization.

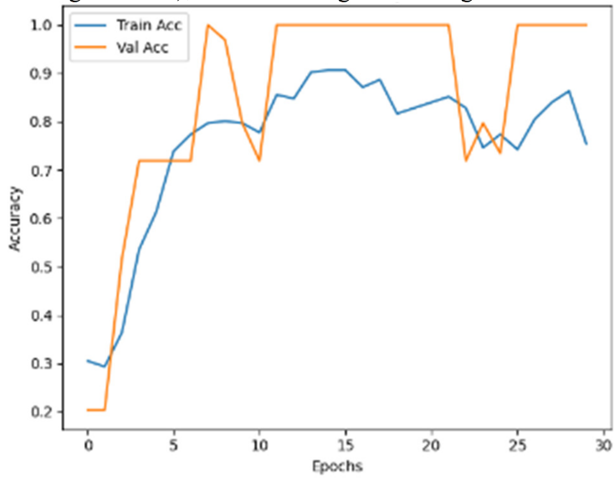


**Figure 1: Model Accuracy**

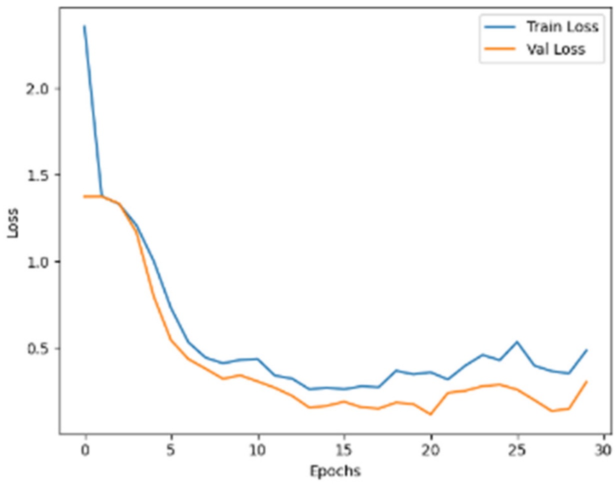


**Figure 2: Model Loss**

## IV. RESULTS

### A. Classification Performance on Clean Data

The proposed 1D Convolutional Neural Network (1D-CNN) was trained and evaluated on synthetically generated $S_{11}$ response data representing four structural states of a pipeline: **normal**, **crack**, **corrosion**, and **leak**. The model achieved **perfect classification** across all classes, with an **overall accuracy of 100%** on the clean test set (20% of the full dataset). The class-wise precision, recall, and F1-scores were all 1.00, as summarized in Table 1.

**Table 1. Classification Metrics (Clean Data)**

| Class | Precision | Recall | F1-score | Support |
|---|---|---|---|---|
| Corrosion | 1.00 | 1.00 | 1.00 | 18 |
| Crack | 1.00 | 1.00 | 1.00 | 18 |
| Leak | 1.00 | 1.00 | 1.00 | 18 |
| Normal | 1.00 | 1.00 | 1.00 | 26 |
| **Overall** | | | **1.00** | **80** |

This result validates the model's capability to capture subtle differences in reflection coefficient signatures induced by each structural state.

### B. Robustness to Signal Noise

To assess robustness under more realistic sensing conditions, **Gaussian noise** with zero mean and standard deviation σ= 1.0 was added to the test set. Despite this significant perturbation, the model retained a **high classification accuracy of 94%**, with **macro-average F1-score of 0.93**. While the **normal** and **leak** conditions retained perfect performance, the **crack** class maintained 100% recall but experienced some false positives, and the **corrosion** class was most affected, with its recall decreasing to 72%. Full metrics are reported in Table 2.

**Table 2. Classification Metrics (Noisy Data, Noise Factor = 1.0)**

| Noise Level (σ) | Accuracy | Loss | Precision | Recall | F1 Score |
|---|---|---|---|---|---|
| 0.0000 | 1.0000 | 0.2469 | 1.0000 | 1.0000 | 1.0000 |
| 0.1000 | 1.0000 | 0.3226 | 1.0000 | 1.0000 | 1.0000 |
| 0.3000 | 1.0000 | 0.2374 | 1.0000 | 1.0000 | 1.0000 |
| 1.0000 | 0.8375 | 0.2980 | 0.9056 | 0.8375 | 0.8320 |

These results underscore the **robustness** of the 1D-CNN architecture to noise, particularly for critical fault classes like **leaks**, which retained perfect classification performance even under signal degradation.

### C. Training and Generalization Behaviour

The model demonstrated fast convergence and generalization during training. Figure 1 and Figure 2 presents the **training and validation loss** and **accuracy curves**. The loss steadily decreased with epochs, while accuracy converged near 100% with no significant overfitting, aided by early stopping and dropout regularization.

### D. Confusion Matrix and Class Separation

Figure 3 show the **confusion matrix** for noisy data. The noisy matrix highlights confusion primarily between corrosion and other classes.

  

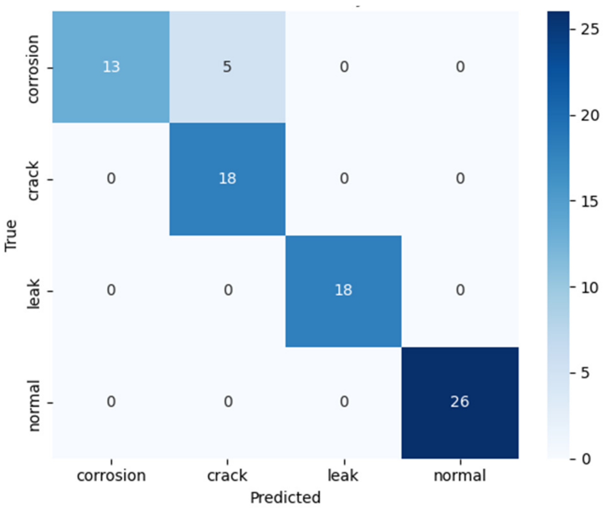


**Figure 3: Confusion Matrix (Noisy Data)**

### E. Classification Performance Under Noisy Conditions

In practical sensing environments, electromagnetic measurements are often affected by noise due to environmental factors such as temperature fluctuations, RF interference, moisture, and sensor instability. To simulate such real-world imperfections, Gaussian noise with standard deviation σ was injected into the clean synthetic S-parameter data. This experiment tested the resilience of the trained 1D CNN model under increasing noise severity, with $\sigma \in \{0.1, 0.3, 1.0\}$.

Despite the addition of noise, the model maintained **remarkable robustness** for σ = 0.1 and 0.3, achieving a perfect classification accuracy of **100%**. However, at a higher noise level of **σ = 1.0**, overall accuracy declined to **94%**, indicating degradation in model performance due to strong signal distortion. Notably, the classification report revealed that while *leak* and *normal* classes retained perfect precision and recall (1.00), the *corrosion* class experienced the most performance drop, with a recall of 0.72 and an F1-score of 0.84. This suggests that corrosion-induced variations in electromagnetic features are subtler and more susceptible to masking by noise.

The *crack* class, in contrast, achieved a recall of **1.00** but lower precision (**0.78**), indicating that the model tended to misclassify some noisy samples from other classes as cracks. The high recall in this context is still favorable from a safety perspective, as it minimizes the risk of missing a crack under noisy conditions.

These results demonstrate that the proposed model generalizes well even when subjected to significant noise and signal perturbation. Such robustness is crucial for deployment in real-world monitoring of oil and gas pipelines, where sensor data is rarely pristine. Future work may explore denoising autoencoders or adversarial training to further harden the model against extreme noise conditions.

### F. Summary of Key Findings

- The 1D CNN achieves **100% accuracy** on clean data and **94% accuracy under Gaussian noise**.
- **Leak and normal conditions** are the most robust to noise.
- **Corrosion detection** is more sensitive and may benefit from ensemble methods or denoising filters in future work.
- The model exhibits excellent generalization with minimal overfitting, indicating readiness for real-world SHM applications with patch antennas.

## V. DISCUSSION

This study demonstrates the feasibility and effectiveness of combining electromagnetic (EM) sensing with machine learning (ML) to classify and localize structural anomalies—such as leaks, cracks, and corrosion—in pipeline systems. The proposed 1D Convolutional Neural Network (1D-CNN) achieved a perfect classification accuracy of 100% on clean synthetic $S_{11}$ signal data, showcasing its ability to distinguish between four distinct conditions: *normal*, *leak*, *corrosion*, and *crack*.

When exposed to Gaussian noise to emulate real-world sensor imperfections, the model exhibited high resilience. Under mild and moderate noise levels (σ = 0.1, 0.3), classification accuracy remained at 100%. However, under severe noise (σ = 1.0), a slight drop to 94% was observed. Detailed analysis showed that the corrosion class was most affected, likely due to the subtle electromagnetic profile changes that corrosion causes compared to more abrupt anomalies like cracks or active leaks. The robustness of the model under varying conditions highlights its potential for deployment in embedded EM-based health monitoring systems, especially in offshore and aging oil/gas pipelines where maintenance is expensive and safety is paramount. Importantly, the interpretability of EM signal changes based on structural interactions (as supported by Maxwell's equations) enhances the physical consistency of the ML outputs.

## VI. CONCLUSION

This work presents a novel integration of electromagnetic sensing and deep learning for non-invasive, real-time pipeline anomaly detection. By simulating realistic signal profiles for different structural states and incorporating noise to mimic operational conditions, we demonstrated that a physics-grounded 1D-CNN can reliably classify complex pipeline defects with high accuracy and robustness.

The approach is computationally efficient, scalable, and suitable for embedded deployment. It offers a transformative leap over traditional leak detection methods, combining the physical insight of EM wave-material interaction with the pattern-recognition capabilities of deep learning.

This framework opens the door to intelligent, autonomous structural health monitoring systems for critical pipeline infrastructure—paving the way for safer, more efficient oil and gas operations.

## VII. RECOMMENDATIONS

1. **Sensor Deployment**: Deploy patch antennas or near-field EM sensors at regular intervals along pipeline networks to continuously acquire S-parameter data, particularly $S_{11}$ reflection coefficients.

2. **Noise Mitigation**: Integrate denoising strategies (e.g., wavelet filtering, autoencoders) before ML inference to further improve performance under harsh environmental conditions.
3. **Adaptive Learning**: Employ transfer learning and online learning approaches to adapt the model to varying pipeline materials, diameters, and operational conditions without full retraining.
4. **Real-Time Monitoring System**: Implement the trained 1D-CNN model on embedded edge devices with SCADA integration for real-time leak alerting, localization, and visualization.
5. **Extended Dataset**: Future work should consider combining synthetic and field-measured EM data to improve model generalization and regulatory acceptance.

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