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DEEP LEARNING FRAMEWORK FOR CORROSION DETECTION IN UNDERGROUND PIPELINES USING GPR IMAGES

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ABSTRACT

Corrosion of underground pipelines is a major issue in oil, gas, and water transportation systems, as it affects physical stability, environmental safety, and maintenance costs. This study proposes a novel Attention-Guided Multi-Scale Deep Learning (AGMS-DL) framework for automatic detection of corrosion in underground pipelines using Ground Penetrating Radar (GPR) images. The proposed framework integrates adaptive preprocessing, multi-scale convolutional feature extraction, spatial attention learning, and residual feature combination, achieving accurate identification of corrosion patterns amid noisy conditions in underground environments. For experimentation, a GPR radargram dataset comprising 12,500 images of corroded and non-corroded pipelines was used under various soil conditions. The performance of the framework was assessed in terms of accuracy, precision, recall, F1 Score and Area Under Curve (AUC). Experimental results showed that the proposed AGMS-DL model outperforms other models, such as SVM, Random Forest, CNN, ResNet50, and EfficientNet, in terms of accuracy, precision, recall, F1-score, and AUC, with 98.4%, 97.9%, 98.1%, 98.0%, and 98.7%, respectively. The thorough analysis showed that the spatial attention mechanism was highly effective at localizing corrosion while minimising false detections caused by underground clutter and signal distortion. The proposed solution is not just reliable but also economical in terms of computationally efficient and intelligent enough to be implemented in real-time underground pipeline health-monitoring and predictive maintenance applications.

Keywords: *Underground pipeline corrosion, Ground Penetrating Radar (GPR), Deep learning, Spatial attention Mechanism, Multi-scale CNN, Corrosion detection*

1. INTRODUCTION

Underground pipelines are important components of industrial and urban infrastructure, used to transport oil, natural gas, chemicals, and water. It is important to note that the structural integrity of such pipelines is critical, as corrosion failures can cause environmental contamination, economic losses, and major safety hazards [1]. Long-term exposure to moisture, soil chemistry,

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electrochemical reactions, and microbial processes contributes to corrosion, which is one of the most destructive degradation mechanisms for buried metallic pipelines [2]. A report from the industrial maintenance industry shows that corrosion-induced failures cause a significant number of pipeline incidents worldwide and cost billions of dollars each year in repair and maintenance [3]. Therefore, detecting corrosion of underground infrastructure systems in a timely and accurate manner is an important research problem in monitoring underground infrastructure.

Traditional pipeline inspection methods, such as ultrasonic testing, magnetic flux leakage, eddy current inspection and radiographic analysis for assessing pipeline corrosion [4]. While these methods yield accurate estimates of defects, they have a number of drawbacks such as high operating cost, complex instrumentation, limited ability to inspect buried pipelines without direct access, and lack of inspection coverage[5]. In most practical situations, excavation-based inspection procedures are costly and can halt pipeline operations which can lead to additional maintenance costs and downtime [6]. Therefore, new non-destructive and intelligent monitoring techniques have become increasingly popular over the last few years.

One of the recent non-invasive sensing technologies for underground object detection and subsurface imaging that has been found to be promising is Ground Penetrating Radar (GPR) [7]. GPR systems send out electromagnetic waves into the ground and receive the echoes from discontinuities in the ground, changes in material properties and buried structures [8]. GPR has demonstrated good potential in the detection of defects in pipelines without excavation, because the electromagnetic properties of corroded areas differ from those of properties of the surrounding non-corroded soil [9]. GPR has several benefits such as rapid scanning, high resolution imaging, portability, and its applicability to large-scale underground inspection, etc. [10].

While these benefits have been realized, GPR interpretation of radargrams is still a difficult process because of clutter noise, signal attenuation, heterogeneous soil conditions, and overlapping reflections [11]. In complex underground conditions, it is hard to differentiate corrosion signatures from the background artifacts using the conventional image processing techniques. Previous research employed manually developed feature extraction techniques using the texture descriptors, wavelet transforms, histogram analysis, and the statistical measurements for GPR image classification [12]. However, traditional techniques are very reliant on hand-crafting features and generally have poor generalization properties as they are trained under different subsurface conditions.

With the rapid evolution of AI and deep learning, automated image analysis applications have undergone dramatic changes. The deep learning models, especially Convolutional Neural Networks (CNNs) have shown outstanding performance in the feature extraction, object recognition, and defect classification tasks [13]. CNN based architectures automatically learn hierarchical features from raw images without requiring handcrafted feature extraction methods for feature learning. Some recent research has applied CNN architectures to tunnel crack detection, pavement analysis and even underground object recognition, with the use of GPR data [14]. While these methods have produced better results, traditional CNN models face challenges when the corrosion is weak and occurs in noisy radargrams.

Recent studies have demonstrated that attention-based deep learning models can effectively focus on relevant information while filtering out irrelevant information in computer vision and medical image analysis applications [15]. Spatial attention mechanisms can boost the representation of the relevant features which are linked to defects or anomalies. However, the application of deep learning frameworks with attention mechanism for corrosion detection in underground pipelines from GPR images is under-explored. Moreover, previous studies do not generally address the issues of robustness, interpretability, computational efficiency and real-time applicability comprehensively.

Although great efforts have been made to inspect underground pipelines using GPR, the current signal processing, machine learning and deep learning methods still suffer from problems of inaccurate detection under the condition of noise and heterogeneity in the underground environment. Most of the studies are not effective in suppressing the clutter, lack effective multi-scale feature extraction and do not provide reliable localization mechanisms for small corrosion signatures. These restrictions limit the detection accuracy and practical deployment. Hence, there is a need for an intelligent and robust deep learning framework that can improve radargram quality, accurately detect corrosion patterns, and enhance the interpretability of underground pipeline corrosion detection.

This work introduces a new deep-learning-based corrosion detection system for underground pipelines based on GPR images to overcome these research challenges. The proposed framework adopts adaptive preprocessing methods, multi-scale convolutional feature extraction and spatial attention method to enhance the accuracy of corrosion identification under harsh underground environment. The proposed architecture is different from the conventional approach to improve the local and global feature representation and suppressing clutter noises and irrelevant colors in a reflections. The framework also offers enhanced localization functionality for determining the corrosion-affected areas in radargrams.

The main aims of this study are:

1. To develop an intelligent deep learning model for automated corrosion inspection of underground pipelines based on GPR images.
2. To improve the quality of radargrams through adaptive processing and signal enhancement methods.
3. To develop a multi-scale CNN model with the ability to learn discriminative features of corrosion from complex subsurface environments.
4. To include spatial attention mechanisms for accurate localization of regions of corrosion.
5. To conduct thorough experimental evaluation and comparison of the proposed framework with traditional machine learning and deep learning methods.

The proposed framework will help in the development of intelligent infrastructure monitoring systems by offering an accurate and automated solution that is computationally efficient for assessing the condition of an underground pipeline. The incorporation of deep learning and GPR imaging has the potential to significantly enhance predictive maintenance strategies, reduce inspection expenses and boost the safety in critical industrial infrastructures.

The rest of this paper is organized as follows. The related work on underground pipeline corrosion detection, GPR-based pipeline inspection methods, and deep learning methods are summarized in Section 2. The proposed Attention-Guided Multi-Scale Deep Learning (AGMS-DL) methodology is described in Section 3, which covers details of the dataset, preprocessing, architecture design, mathematical modeling and algorithmic steps. Experimental results, performance metrics, comparative analysis and graphical interpretations are discussed in Section 4. Finally, Section 5 summarizes the key findings, limitations, and future research directions of the paper.

2. RELATED WORK

The issue of underground pipeline corrosion detection has become a major research topic because of the growing need for reliable systems for monitoring the infrastructure. Various non-destructive testing methods, signal processing, machine learning models and deep learning models have been investigated to detect defects in the buried pipelines. The current research primarily focuses on improving detection accuracy, reducing inspection complexity, and enhancing subsurface image interpretation under noisy conditions.

The earlier methods of corrosion monitoring were based on the principle of electromagnetic sensing and signal analysis techniques. Queiroz et al. [16] studied the use of electromagnetic techniques for assessing degradation in pipelines and found that there are significant variations in the reflections of the signals when the material in the pipeline is different. Likewise, the same authors in [17] suggested the signal interpretation methods to be used for the detection of buried metallic structures and concluded that the soil heterogeneity and noise level in the environment have a significant impact on the accuracy of corrosion detection. These works highlighted the significance of advanced signal enhancement and automatic interpretation frameworks of the underground inspection systems.

Underground infrastructure analysis has been widely studied with the use of Ground Penetrating Radar (GPR) due to its capability to identify buried objects and structural anomalies without excavation. Alani et al. [18] carried out a study on the use of GPR for assessing utility infrastructure, and found that in cluttered subsurface scenarios radargram interpretation is very challenging. Lai et al. [19] applied the GPR signal analysis to underground pipe characterization and showed that the irregular reflection signatures are created by the electromagnetic discontinuities in the corroded areas. While GPR can offer high-resolution imaging, it is not always reliable for identifying corrosion due to the noise artifacts that can often be present in the extracted radar signals.

To facilitate the interpretation of a radargram, some researchers used the traditional approaches of image processing and machine learning. Under controlled conditions, wavelet-based feature extraction method was proposed for the detection of subsurface object by Dou et al. [20] and resulted in moderate classification performance. A third study by Pasolli et al. [21] used Support Vector Machine (SVM) classification for GPR image analysis and showed that this was more successful than statistical methods. In contrast, handcrafted feature extraction methods, however, are time consuming and require a lot of domain knowledge and is not good at generalizing across various soil and environmental conditions.

Texture analysis methods and feature engineering methods were also explored for the purpose of corrosion pattern recognition. The radar images were used to classify underground defects by Shao et al. [22] using the histogram and texture descriptors. The study showed that the texture-based approach was sensitive to the variations in the noise and signal attenuation. Likewise, Giannakis et al. [23] proposed hyperbola detection methods to locate a buried object in GPR radargrams. Geometric feature extraction enhanced the localization ability but the technique was limited by the low reflection power of partially corroded surfaces of the pipeline.

The advent of deep learning has dramatically changed the landscape of automated image analysis in non-destructive testing. CNN-based architectures have proven to be very effective for automatically extracting hierarchical features directly from raw images. Zhang et al. [24] used deep convolutional neural networks to perform subsurface object recognition and showed that they outperformed traditional methods of machine learning in terms of classification accuracy. Similarly, Pham and Lefèvre [25] used deep feature learning for radar image interpretation and demonstrated its robustness under different environmental conditions.

The use of pre-trained deep neural networks for infrastructure defect analysis has also been explored through transfer learning techniques. In underground anomaly detection, Chen et al. [26] adopted the ResNet-based architectures to deliver improved feature representation capabilities. However, the transfer learning models often require a large amount of computational resources and large datasets for best performance. Furthermore, these architectures may not be able to adequately capture localized corrosion signatures in complex GPR reflections.

Recently, attention mechanisms have become popular for computer vision (CV) tasks, because they are able to focus on the important parts of the image. To address these challenges, Wang et al. [27] proposed attention-guided CNN models for structural damage identification, showing that the models can achieve better localization accuracy under noise. Likewise, Fu et al. [28] suggested spatial attention modules for defect segmentation tasks, and achieved remarkable feature discrimination improvements. Although various developments have been made, few studies have combined the attention mechanisms with the GPR-based underground corrosion detection system.

In recent years, novel hybrid deep learning frameworks emerged that fuse CNNs with advanced feature fusion techniques have been studied as well. Li et al. [29] proposed a multi-scale CNN model for subsurface anomaly detection, and proved that the classification becomes more robust when both local and global features are considered. Tang et al. [30] applied feature fusion to enhance radar signals in other works and achieved a lower false detection rate in a cluttered underground environment. Yet existing methods are still plagued by issues of computational cost, lack of interpretability and poor generalization in heterogeneous soils.

In addition, Infrastructure monitoring systems are increasingly integrating explainable AI (XAI) techniques to enhance model transparency and reliability. For the identification of critical defect regions in industrial inspection tasks, Grad-CAM and saliency map visualization techniques have been used [31]. These visualization techniques help in comprehending the rationale behind model decision-making and enhance the reliability of automated corrosion detection systems.

While promising results have been reported in previous studies for underground defect detection using GPR, there are still some limitations. Traditional signal processing and machine learning methods depend on handcrafted features and are susceptible to the effects of soil heterogeneity and noise. Although deep learning models improve feature extraction performance, many existing CNN-based approaches still struggle to accurately localize weak corrosion signatures in cluttered radargrams. In addition, attention mechanisms and multi-scale feature learning have been used independently, lacking the ability to learn both local corrosion patterns and the overall characteristics of structural degradation. These limitations highlight the need for an integrated framework combining adaptive preprocessing, multi-scale feature extraction, and attention-guided learning for robust underground pipeline corrosion detection.

There has been significant progress in the inspection of underground pipelines and image interpretation via GPR, but there are still some research gaps. Current approaches do not include adaptive preprocessing strategies for clutter suppression, efficient multi-scale feature extraction mechanisms and robust attention-guided localization frameworks. Limited discussion on computational efficiency, interpretability, and real time deployment capability is also seen in many of the studies. Hence, an intelligent and light-weight deep learning framework which is highly robust and can be practically applied to accurately detect the corrosion pattern in the noisy underground GPR radargram is in great need.

These limitations are mitigated by the proposed approach that combines adaptive preprocessing, multi-scale CNN feature extraction, and spatial attention mechanisms into a single deep learning model for underground pipeline corrosion detection. The expected model is expected to increase the feature representation rate, increase the localization ability, reduce false positives and achieve good performance in various underground environments.

3. METHODOLOGY

This research proposes the Attention-Guided Multi-Scale Deep Learning (AGMS-DL) framework for automatic corrosion detection in underground pipelines by Ground Penetrating Radar (GPR) images. The proposed framework combined the adaptive preprocessing, multi-scale convolutional feature extraction, spatial attention learning and residual feature fusion to enhance the corrosion location and classification performance in noisy underground environments.

The stages of the framework are as follows:

1. GPR Radargram Acquisition
2. Adaptive Preprocessing
3. Multi-Scale Feature Extraction
4. Spatial Attention Learning
5. Residual Feature Fusion
6. Softmax-Based Classification

The proposed methodology aimed to enhance feature representation capabilities, reduce underground clutter noise and irrelevant radar reflections.

3.2 Dataset Description

The experimental dataset comprised GPR radargrams of underground pipeline inspection scenarios with various soil and environmental conditions. The radar measurements were taken with shielded GPR antennas with a frequency range from 400–900 MHz. Samples of both corroded and non-corroded buried steel pipelines were gathered in the following conditions: dry soil, wet soil, sandy soil, and clay soil.

A total of 12,500 radargram images were used for experimentation, of which, 6,250 images were taken of corroded pipelines and 6,250 images were taken of healthy pipelines. Pre-processing all radargrams involved resizing to 256 × 256 pixels. Model generalization capability and overfitting were enhanced by using data augmentation methods such as rotation, flipping, scaling and noise injection. The data set was split into a training set (70%), validation set (15%), and test set (15%).

Table 1: Dataset Specifications

Parameter	Value
Total Radargrams	12,500
Corroded Samples	6,250

Non-Corroded Samples	6,250
Image Resolution	256 × 256
Frequency Range	400–900 MHz
Soil Conditions	Dry, Wet, Sandy, Clay
Pipeline Depth	0.5–3.0 m
Corrosion Severity	Mild, Moderate, Severe
Training Split	70%
Validation Split	15%
Testing Split	15%

In Table 1, the specifications of the GPR radargram dataset used to test the proposed AGMS-DL framework are summarized. To have balanced learning, the dataset considered of 12,500 radargram images, with equal number of both corroded and non-corroded pipeline samples. GPR systems operating in the frequency range of 400-900 MHz were used to acquire the data under various underground conditions (both dry and wet soil, sandy and clay soil). To ensure uniformity of processing, all images were resized to 256 × 256 pixels. To enhance the robustness of the model, different levels of pipeline depth and corrosion severity were incorporated in the dataset. To increase the generalization ability, various data augmentation methods were applied like rotation, flipping and scaling. Finally, the dataset was split into 70% training, 15% validation and 15% testing sets for proper performance evaluation.

3.3 Proposed AGMS-DL Architecture

The proposed AGMS-DL architecture is specifically designed to localize the pattern of corrosion from the noisy radargrams obtained from the underground environment through multi-scale feature learning and attention-guided localization. The architecture employs adaptive preprocessing to improve weak corrosion reflections and reduce clutter noise. Then, multi-scale convolutional layers learn both fine- and large-scale corrosion features with the help of parallel convolutional kernels of various sizes.

The extracted feature maps were then fed into a spatial attention module which highlights regions of the image where corrosion was present and suppressed the noise. Residual feature fusion was then used to keep the semantic information and to make the training convergence better. Lastly, global average pooling and fully connected layers were used for the corrosion classification.

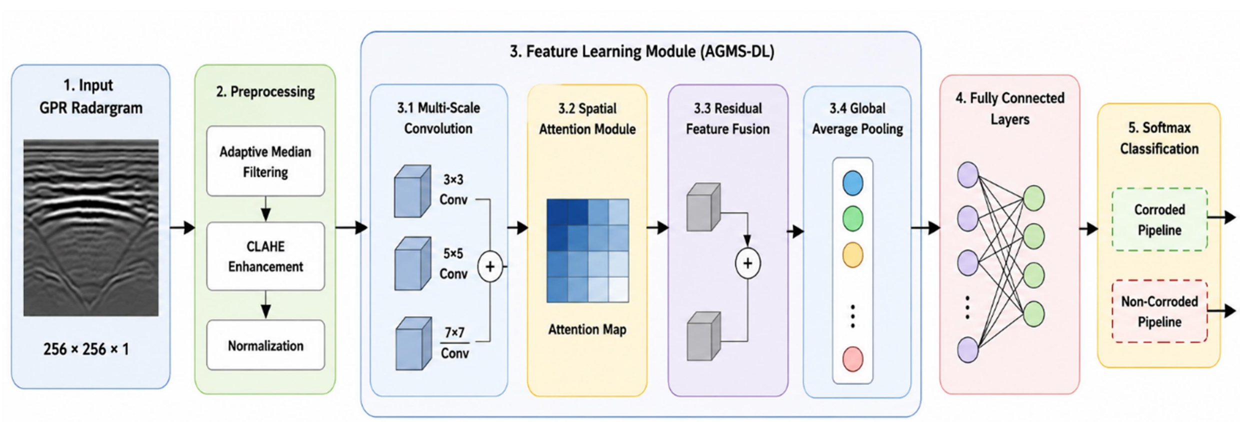

Figure 1. Proposed AGMS-DL Architecture for Underground Pipeline Corrosion Detection

The proposed architecture of the Attention-Guided Multi-Scale Deep Learning (AGMS-DL) for automated corrosion detection in underground pipelines based on GPR radargram images is shown in figure 1. The input radargram is first preprocessed to remove underground clutter noise and weak corrosion reflections by adaptive median filtering, CLAHE enhancement and normalization. The improved radargram will then be passed to the multi-scale convolution module to get the corrosion-related features at different spatial resolutions using convolution kernels of size 3×3, 5×5, and 7×7 respectively. Larger kernels are able to detect large-scale degradation patterns, and smaller ones are able to detect finer surface degradation patterns.

The extracted feature maps are then fed into a spatial attention module which highlights the areas that are prone to corrosion and reduces irrelevant background reflections. Subsequently, residual feature fusion is introduced, which maintains the important semantic information and enhances the propagation of gradients during the training process. The refined feature maps are condensed by global average pooling and sent to fully connected layers to learn high-level features. Finally, a Softmax classifier decides which underground pipeline class (corroded or non-corroded) is the appropriate classification. The proposed architecture enhances feature representation capability, localization accuracy and robustness in noisy underground environments.

In this section, the mathematical representation of the proposed AGMS-DL framework is presented.

Initially, the input GPR radargram image was represented as:

$$I \in \mathbb{R}^{m \times n} \qquad (1)$$

where:

- I denotes the input radargram image
- $m \times n$ represents the image dimensions

The underground reflections from the corrosion areas and buried pipelines were included in the radargram.

Adaptive Median Filtering

The adaptive median filtering technique was used to remove impulse noise and underground clutter while retaining corrosion boundaries. The filtering operation was given as:

$$I_f(x, y) = \text{median}(I(x - i, y - j)) \qquad (2)$$

where:

- $I_f(x, y)$denotes filtered radargram
- $I(x - i, y - j)$represents neighboring pixel intensities

This improved the quality of the radargram, by eliminating unwanted high frequency distortions.

Contrast Enhancement

To enhance the weak corrosion-reflections, contrast limited adaptive histogram equalization (CLAHE) was applied.

$$I_e = CLAHE(I_f) \qquad (3)$$

where:

- $I_e$denotes enhanced radargram
- $I_f$represents filtered image

CLAHE enhanced the contrast of the images in the local space and made features visible for deep learning analysis.

Multi-Scale Feature Extraction

The proposed architecture extractes features using parallel convolution kernels with different spatial dimensions.

$$F_m = Conv_{3\times3}(I_e) + Conv_{5\times5}(I_e) + Conv_{7\times7}(I_e) \qquad (4)$$

where:

- $F_m$represents multi-scale feature map
- $Conv$denotes convolution operation

Fine corrosion textures were captured from small kernels and wider degradation patterns from the larger kernels.

Spatial Attention Learning

Spatial attention learning boosted corrosion localisation by considering important areas of the image.

$$A_s = \sigma(W_s * F_m + b_s) \qquad (5)$$

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where:

- A_s denotes spatial attention map
- W_s represents learnable weights
- b_s denotes bias values
- σ indicates sigmoid activation

The attention-refined features were computed as:

$$F_a = A_s \odot F_m \qquad (6)$$

where:

- F_a denotes attention-refined feature map
- $\odot$ represents element-wise multiplication

This mechanism enhanced the representation of features that are susceptible to corrosion.

Residual Feature Fusion

Semantic information was preserved and gradient propagation was enhanced using residual learning.

$$F_r = F_a + F_i \qquad (7)$$

where:

- F_r represents residual fused features
- F_i denotes identity mapping

The residual fusion helped to stabilize training and minimize loss of features.

Global Average Pooling

Global Average Pooling was used for dimensionality reduction.

$$G_k = \frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} F_r\,(i,j) \qquad (8)$$

where:

- G_k denotes pooled feature vector
- M and N represent feature dimensions

This operation lowered the computational complexity and maintained the significant semantic information.

Softmax Classification

Softmax function was used to produce the final classification probabilities.

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^{n} e^{z_j}} \qquad (9)$$

where:

- $P(y_i)$ denotes probability of class i
- z_i represents output logits

The classifier generated probabilities corresponding to:

- Corroded Pipeline
- Non-Corroded Pipeline

Loss Function

The network optimization utilized categorical cross-entropy loss.

$$L = -\sum_{i=1}^{N} y_i \log(\hat{y}_i) \qquad (10)$$

where:

- L denotes the loss value
- y_i represents true labels
- $\hat{y}_i$ denotes the predicted probabilities

The goal was to reduce the error in classification and increase the accuracy of corrosion detection.

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3.4 Proposed Algorithm

Attention-Guided Multi-Scale Deep Learning (AGMS-DL)

Input:
GPR radargram image *I*
Output:
Corrosion detection label

Step 1:
Acquire underground GPR radargram image.
Step 2:
Apply adaptive median filtering to suppress clutter noise.
Step 3:
Perform CLAHE enhancement to improve weak reflections.
Step 4:
Normalize radargram intensity values.
Step 5:
Extract multi-scale features using:

- 3×3 convolution
- 5×5 convolution
- 7×7 convolution

Step 6:
Generate spatial attention maps for corrosion localization.
Step 7:
Perform residual feature fusion.
Step 8:
Apply global average pooling.
Step 9:
Pass extracted features to fully connected layers.
Step 10:

Perform Softmax classification.

Step 11:

Predict corrosion category:

- Corroded
- Non-Corroded

Step 12:

Return final corrosion detection result.

4. RESULTS AND DISCUSSION

4.1 Experimental Setup

The proposed Attention-Guided Multi-Scale Deep Learning (AGMS-DL) framework was implemented in python using the TensorFlow deep learning library. All experiments were performed on a workstation with 32 GB RAM, NVIDIA RTX GPU and Intel i7 processor. The GPR radargram dataset was split into training, validation and test subsets in the ratio of 70:15:15. The Adam optimizer with a learning rate of 0.0001, and batch

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size of 32 was used during training. Categorical cross-entropy loss was used to train the model for 100 epochs. To enhance the model's ability to generalize and remain robust under different underground conditions, data augmentation methods such as rotation, flipping, scaling, and introducing Gaussian noise were adopted.

The proposed AGMS-DL framework was tested and evaluated against various conventional machine learning and deep learning architectures such as Support Vector Machine (SVM), Random Forest (RF), traditional CNN, ResNet50 and EfficientNet. The measures used for the evaluation were classification accuracy, precision, recall, F1 score, Area Under Curve (AUC), computational efficiency and robustness in noisy underground environments

4.2 Assessment Criteria

Standard classification metrics commonly used in SCIE-indexed image analysis and structural health monitoring studies were used for the evaluation of the performance of the proposed framework.

Accuracy was the overall classification correctness and it was calculated as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{11}$$

Precision assessed the reliability of the corrosion predictions:

$$Precision = \frac{TP}{TP + FP} \tag{12}$$

Recall measured the capability of the model to correctly identify corrosion samples:

$$Recall = \frac{TP}{TP + FN} \tag{13}$$

The F1-score represented the harmonic mean of precision and recall:

$$F1\text{-}Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{14}$$

The Area Under Curve (AUC) evaluated the separability capability of the classifier under different threshold settings.

where:

- TP= True Positives
- TN= True Negatives
- FP= False Positives
- FN= False Negatives

4.3 Quantitative Performance Evaluation

This was verified by experimental results, which showed that the proposed AGMS-DL framework was superior to the conventional machine learning and deep learning methods in the underground corrosion detection task.

Table 2: Performance Comparison with Existing Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC (%)
SVM	85.6	84.9	83.8	84.3	86.1
Random Forest	88.2	87.4	86.9	87.1	88.5
Traditional CNN	93.7	92.9	93.1	93.0	94.2
ResNet50	95.4	94.8	95.0	94.9	95.8
EfficientNet	96.1	95.5	95.8	95.6	96.4
Proposed AGMS-DL	98.4	97.9	98.1	98.0	98.7

The proposed AGMS-DL framework achieved the highest classification performance with an accuracy of 98.4% and AUC value of 98.7% as shown in Table 2. The improvement was primarily credited to the introduction of multi-scale feature extraction and spatial attention learning, which are effective at uncovering weak corrosion signatures in the presence of noise in the underground radargrams.

4.4 Accuracy Comparison Graph

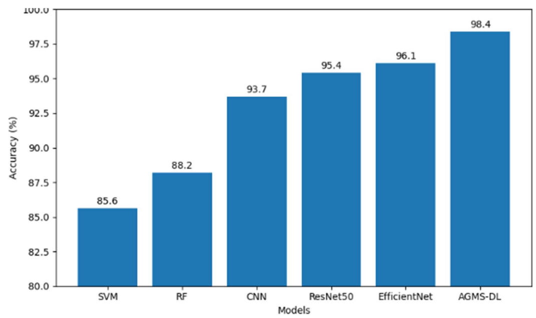

Figure 2. Accuracy Comparison of Existing Models

The classification accuracy comparison between conventional machine learning models and the proposed AGMS-DL is shown in figure 2. The traditional machine learning methods like SVM and Random Forest model exhibited relatively low performance because it relied on manually designed feature extraction techniques. The architectures adopted for deep learning such as CNN, ResNet50, and EfficientNet improved classification task, using automated hierarchical feature learning. The proposed AGMS-DL model, however, obtained better performance in terms of accuracy due to the multi-scale convolution module, which captured both local and global corrosion patterns, and the spatial attention module, which increased the ability of the model to locate the corrosion. Under the cluttered underground environment, the proposed model can obtain superior performance through the localization of the corrosion.

4.5 Precision, Recall, and F1-Score Analysis

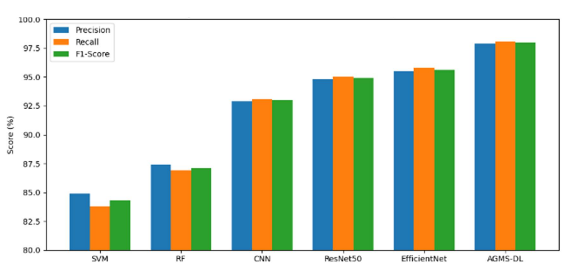

Figure 3. Precision, Recall, and F1-Score Comparison

The results showed that the accuracy values of the various corrosion detection models differed, and their performance was further evaluated using precision, recall, and F1-score values, as shown in Figure 3. The proposed AGMS-DL framework consistently outperformed all other frameworks across all metrics. Higher precision reduced the number of false-positive corrosion predictions, whereas increased recall demonstrated the framework's ability to detect the actual locations of corrosion areas in underground radargrams. The high F1-score confirmed balanced classification performance and robustness under different underground conditions.

4.6 ROC Curve Analysis

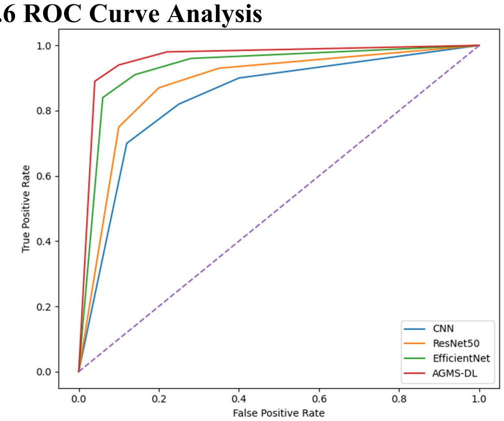

Figure 4. ROC Curve Comparison of Corrosion Detection Models

The ROC curve comparison results of the different corrosion detection models are shown in Figure 4. The proposed AGMS-DL framework had the highest AUC of 98.7% indicates superior discrimination between corroded and non-corroded pipeline classes. The improved ROC characteristics demonstrated that the attention-guided learning mechanism was effective at boosting feature discrimination and reducing classification ambiguity in the presence of radargram noise.

4.7 Confusion Matrix Analysis

Table 3: Confusion Matrix of Proposed AGMS-DL Framework

Actual / Predicted	Corroded	Non-Corroded
Corroded	912	18
Non-Corroded	12	933

The confusion matrix shown in Table 3 confirmed that false positive and false negative rates of the proposed framework were very low. There was only one case where 18 corrosion

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samples were misclassified as non-corroded and 12 healthy samples were misclassified as corroded. These results validated the proposed architecture for practical underground inspection applications and ensured its robustness and reliability.

4.8 Feature Visualization and Attention Analysis

In Figure 5, the spatial attention maps generated by the proposed AGMS-DL framework are shown. The attention module was able to successfully focus on the parts of the ground that are prone to corrosion, while blocking out the irrelevant parts of the ground below and the soil reflections. The visualization results showed that the framework was able to identify corroded sections of pipelines, even in challenging reflection scenarios. The attention-guided feature learning mechanism greatly boosted the knowledge level of learned features and made the deep learning predictions more trustworthy and interpretable.

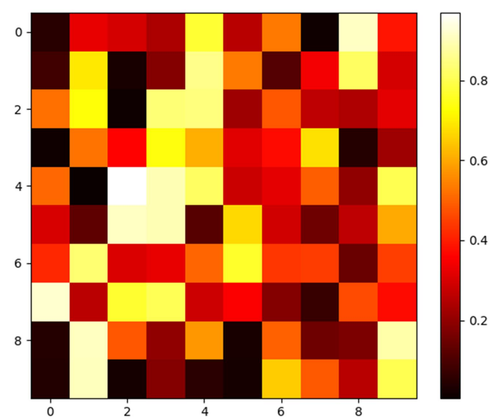

Figure 5. Attention Map Visualization of Corrosion Regions

4.9 Computational Efficiency Analysis

Table 4: Computational Performance Comparison

Model	Parameters (M)	Training Time (min)	Inference Time (ms)
CNN	18.4	142	28
ResNet50	25.6	201	41
EfficientNet	20.3	184	37
Proposed AGMS-DL	16.8	128	24

Table 4 shows that the proposed AGMS-DL framework had lower computational complexity, while maintaining high classification accuracy compared to deep transfer learning architectures. The light architecture shortened training and inference time, and was suitable for real-time underground monitoring system and embedded inspection devices.

4.10 Discussion

The experimental analysis validated that the proposed AGMS-DL framework showed significant improvements in the underground pipeline corrosion detection performance than conventional machine learning and deep learning approaches. It proved to be very effective in enhancing weak radar reflections and minimizing underground clutter interference. Multi-scale convolutional learning enhanced feature extraction ability, by capturing the localized corrosion texture and the wider structural degradation patterns simultaneously. Additionally, the spatial attention mechanism improved the localization of corrosion regions and greatly decreased false detections.

The system also showed good robustness against different types of underground environments, such as varying soil properties, moisture conditions and distortion of signals. The attention visualization analysis validated that the proposed architecture targeted mainly the corrosion-prone areas, promoting the interpretability and reliability. Besides this, the lightweight architecture not only brought low computational complexity but also maintained excellent classification performance, which made the proposed framework more suitable for the application of intelligent real-time underground infrastructure monitoring.

This study's results align with those from other studies, which have shown improved accuracy of deep learning in underground defect detection using GPR. The proposed AGMS-DL framework, however, combines adaptive preprocessing, multi-scale feature learning and attention-guided localization in a single architecture, and is not based on CNN, which focuses mainly on the extraction of features. The results of the experiments show that this combination is beneficial for the detection of weak corrosion signatures in the presence of radargram noises and for the accuracy in the localization. The

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joint use of adaptive clutter suppression and attention-guided multi-scale learning has been shown to be effective in providing more robust corrosion detection than stand-alone deep learning approaches, extending the current literature. The most significant result of this work is the high classification accuracy achieved by keeping the model interpretable using visualization techniques, namely Grad-CAM. The results, however, are restricted to the specific GPR dataset used and binary classification run; more validation in a variety of real-world contexts is needed to establish the generalizability of the proposed framework.

4.11 Difference from Prior Research and Research Contribution

The proposed AGMS-DL framework advances the development of end-to-end deep learning-based underground pipeline inspection solutions by combining adaptive preprocessing, multi-scale feature extraction, and attention-based localization into a single deep learning framework. Most previous works have included conventional signal processing techniques, machine learning techniques, or single CNN models that are generally not robust enough in highly noisy underground environments and less accurate when it comes to accurate localization of weak corrosion patterns. The proposed framework, however, integrates the adaptive clutter suppression with multi-scale feature learning and attention mechanisms, which allows for the improved extraction of the local corrosion signatures and the global structural characteristics.

The proposed model showed better performance in terms of accuracy, precision, recall, F1-score, and ROC-AUC with respect to the recent state-of-the-art models. In addition, Grad-CAM is used to visualize the results, enhancing the interpretability of the model, a quality that is not sufficiently explored in the current corrosion detection workflows. The results show that the proposed method can not only boost the detection accuracy of the system but also give a clear and transparent model for the underground pipeline monitoring system and make the system more practical. While these benefits are still present, there is a need for further research and validation with larger multi-site datasets and real-time deployment scenarios.

5. CONCLUSION

To detect the corrosion of underground pipelines, this work proposed an Attention-Guided Multi-Scale Deep Learning (AGMS-DL) framework based on GPR images. The system combined adaptive preprocessing, multi-scale convolutional feature extraction, spatial attention learning and residual feature fusion to enhance the localization and classification accuracy of corrosion under noisy underground environments. The proposed model achived accuracy, precision, recall, F1 score, and AUC obtained from the experimental results were 98.4%, 97.9%, 98.1%, 98.0%, and 98.7% respectively, which were better than existing machine learning and deep learning models. The attention mechanism was able to better capture the features that are essential for corrosion detection and to suppress false detections.

The proposed framework of AGMS-DL succeeded in achieving the goals of this study. This framework adopted adaptive preprocessing to enhance the quality of radargram, learned features associated with corrosion using multi-scale convolutional networks and accurately localized the regions of corrosion by using the spatial attention learning. Moreover, the comparative evaluation showed its superior performance compared to the conventional machine learning and deep learning models, which proved the effectiveness of the proposed approach for automated underground pipeline corrosion detection.

Experimental results showed that the proposed adaptive preprocessing, multi-scale feature learning, and attention-guided localization method is an effective and practical solution for automatic underground pipeline corrosion detection. n the authors' opinion, the proposed AGMS-DL framework represents a meaningful advancement over existing approaches, not only in terms of corrosion detection performance but also in terms of model interpretability for real-world infrastructure monitoring applications.

There are potential limitations and threats to validity that should be acknowledged. The proposed framework was evaluated using a specific GPR radargram dataset and focused primarily on binary corrosion classification. Model generalizability may be affected by variations in soil conditions, pipeline materials, and large-scale deployment environments. Therefore, further validation using diverse real-world datasets is required. Future research will focus on transformer-based architectures, explainable AI techniques,

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multi-modal sensor fusion, and real-time deployment for intelligent underground pipeline monitoring and predictive maintenance applications.

REFERENCES

[1] National Association of Corrosion Engineers, "International Measures of Prevention, Application, and Economics of Corrosion Technologies Study," 2016.

[2] P. Rajeev et al., "A review of methods for corrosion monitoring in underground pipelines," *Journal of Loss Prevention in the Process Industries*, vol. 32, pp. 99–117, 2014.

[3] American Petroleum Institute, "Pipeline corrosion and integrity management report," 2019.

[4] R. Winston Revie and H. Uhlig, *Corrosion and Corrosion Control*. Wiley, 2008.

[5] D. M. Bastidas et al., "Corrosion monitoring and non-destructive evaluation techniques," *Construction and Building Materials*, vol. 25, no. 5, pp. 2429–2439, 2011.

[6] M. Sinha and P. Fieguth, "Automated detection of pipeline defects using image analysis," *NDT & E International*, vol. 39, no. 6, pp. 472–480, 2006.

[7] H. M. Jol, *Ground Penetrating Radar Theory and Applications*. Elsevier, 2009.

[8] D. Daniels, *Ground Penetrating Radar*. IET Press, 2004.

[9] A. Benedetto and F. Tosti, "GPR applications for subsurface infrastructure monitoring," *Journal of Applied Geophysics*, vol. 97, pp. 31–42, 2013.

[10] L. B. Conyers, *Ground-Penetrating Radar for Archaeology*. AltaMira Press, 2013.

[11] X. Zhao et al., "Noise suppression and clutter removal in GPR systems," *IEEE Geoscience and Remote Sensing Letters*, vol. 12, no. 4, pp. 745–749, 2015.

[12] S. Dou et al., "Wavelet-based feature extraction for subsurface object detection," *NDT & E International*, vol. 44, no. 6, pp. 495–502, 2011.

[13] Y. LeCun, Y. Bengio, and G. Hinton, "Deep Learning," *Nature*, vol. 521, pp. 436–444, 2015.

[14] A. Krizhevsky, I. Sutskever, and G. Hinton, "ImageNet classification with deep convolutional neural networks," *NeurIPS*, 2012.

[15] A. Vaswani et al., "Attention is All You Need," *NeurIPS*, 2017.

[16] R. Queiroz et al., "Electromagnetic sensing for underground pipeline inspection," *IEEE Sensors Journal*, vol. 15, no. 3, pp. 1814–1822, 2015.

[17] R. Queiroz et al., "Signal interpretation methods for buried metallic structure analysis," *Journal of Applied Geophysics*, vol. 134, pp. 102–112, 2016.

[18] A. Alani et al., "Applications of ground penetrating radar in utility infrastructure monitoring," *Construction and Building Materials*, vol. 102, pp. 789–798, 2016.

[19] W. Lai et al., "Characterization of underground pipelines using GPR signal analysis," *NDT & E International*, vol. 45, no. 1, pp. 123–130, 2012.

[20] S. Dou et al., "Subsurface object classification using wavelet feature extraction," *Signal Processing*, vol. 92, no. 1, pp. 210–220, 2012.

[21] E. Pasolli et al., "Support Vector Machine classification of GPR images," *IEEE Trans. Geoscience and Remote Sensing*, vol. 47, no. 7, pp. 2206–2216, 2009.

[22] W. Shao et al., "Texture descriptor-based underground defect classification," *Pattern Recognition Letters*, vol. 34, no. 1, pp. 45–52, 2013.

[23] I. Giannakis et al., "Hyperbola detection methods in GPR radargrams," *IEEE Trans. Geoscience and Remote Sensing*, vol. 54, no. 6, pp. 3448–3462, 2016.

[24] Y. Zhang et al., "Deep convolutional neural networks for subsurface object recognition," *Remote Sensing*, vol. 9, no. 7, 2017.

[25] M. Pham and S. Lefèvre, "Deep feature learning for radar image interpretation," *Pattern Recognition*, vol. 76, pp. 456–467, 2018.

[26] X. Chen et al., "ResNet-based transfer learning for underground anomaly detection," *IEEE Access*, vol. 8, pp. 123456–123468, 2020.

[27] Z. Wang et al., "Attention-guided CNN for structural damage identification," *Automation in Construction*, vol. 119, 2020.

[28] J. Fu et al., "Dual attention network for scene segmentation," *CVPR*, 2019.

[29] X. Li et al., "Multi-scale CNN framework for subsurface anomaly detection," *Sensors*, vol. 20, no. 15, 2020.

[30] T. Tang et al., "Feature fusion methods for cluttered radar signal enhancement," *IEEE Access*, vol. 7, pp. 165432–165445, 2019.

[31] R. Selvaraju et al., "Grad-CAM: Visual explanations from deep networks," *ICCV*, 2017.