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Predictive Modelling of Thermal Wave Propagation Using Ml Techniques

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ABSTRACT

Corrosion is a major challenge in industrial applications, leading to material degradation, safety risks, and high maintenance costs. Traditional detection techniques, such as ultrasonic and radiographic testing, often require invasive procedures or specialized equipment, making large-scale monitoring difficult. This project aims to develop an automated, non-invasive corrosion detection framework using passive infrared thermography and machine learning-based image processing to enhance detection accuracy and efficiency.

The core problem addressed in this study is the difficulty in identifying corrosion early without complex hardware setups or manual inspection. To overcome this, we integrate Contrast Limited Adaptive Histogram Equalization (CLAHE) for contrast enhancement, Gray Level Co-occurrence Matrix (GLCM) for texture-based feature extraction, and K-Means clustering for automated segmentation of corroded regions. These techniques help improve corrosion visibility, accurately segment affected areas, and quantify severity levels based on pixel intensity analysis.

After implementing and validating this framework using thermal imaging datasets, our findings show that CLAHE significantly enhances corrosion visibility, K-Means clustering effectively distinguishes corroded versus non-corroded regions, and GLCM analysis reliably quantifies corrosion severity. This approach proves to be a cost-effective, scalable, and efficient solution for corrosion assessment in industrial environments. The study concludes that integrating machine learning with passive thermography can improve corrosion detection accuracy while reducing hardware complexity. Future work will explore real-time corrosion detection using deep learning models and hyperspectral imaging for enhanced defect characterization.

Keywords: *Passive Thermography, Machine Learning, Non-Destructive Testing (NDT), CLAHE, K-Means Clustering, Gray Level Co-occurrence Matrix (GLCM), Infrared Imaging, Image Processing, Thermal Wave Imaging (TWI).*

1. INTRODUCTION

Corrosion is a natural phenomenon that deteriorates metallic structures due to environmental interactions, causing significant economic losses and safety hazards in various industries, including aerospace, automotive, and infrastructure. The early detection of corrosion is crucial to prevent structural failures and optimize maintenance strategies. Traditional corrosion detection techniques, such as ultrasonic testing and radiography, often require specialized equipment and invasive testing, leading to increased operational complexity and costs. Non-destructive testing (NDT) methods have gained prominence due to their ability to assess material integrity without causing damage. Among these, infrared thermography (IRT) has emerged as an effective tool for detecting corrosion-induced anomalies by analyzing thermal responses of materials [1].

Thermal wave imaging (TWI) techniques, including pulsed and lock-in thermography, have been widely studied for defect detection in metallic components [2]. These techniques rely on external thermal excitation to generate temperature gradients that highlight material imperfections. While active thermography methods offer high sensitivity, they often require controlled experimental conditions and additional hardware components, limiting their scalability in real-world applications [3]. Passive thermography, on the other hand, relies on naturally occurring temperature variations and eliminates the need for external excitation, making it a more practical approach for industrial corrosion monitoring [4].

Recent advancements in machine learning-based image processing have significantly improved the accuracy and efficiency of corrosion detection methodologies. Contrast Limited Adaptive Histogram Equalization (CLAHE) enhances image contrast, allowing better visibility of temperature variations associated with corrosion [5]. Machine learning techniques, such as K-Means clustering, enable automated segmentation of corroded regions, improving defect classification accuracy [6]. Additionally, texture-based analysis using the Gray Level Co-occurrence Matrix (GLCM) has been employed to quantify corrosion severity by analyzing pixel-level statistical features [7].

This study aims to develop an automated corrosion detection framework integrating passive infrared thermography, advanced image processing, and machine learning-based segmentation. The proposed methodology provides an efficient, scalable, and non-invasive solution for corrosion assessment, reducing reliance on complex setups while ensuring high defect detection accuracy. The key objectives of this research include:

- Developing a robust corrosion detection framework using passive infrared thermography.
- Enhancing image preprocessing using CLAHE for improved thermal image visibility.
- Implementing K-Means clustering for automated corrosion segmentation.
- Quantifying corrosion severity using GLCM-based texture analysis.
- Validating the proposed methodology using real-world thermal imaging datasets.

The integration of passive thermography with machine learning segmentation bridges the gap between traditional NDT techniques and modern data-driven approaches, offering a cost-effective and reliable corrosion detection system. This research builds upon previous studies while introducing improvements in image enhancement, segmentation, and classification, contributing to the field of industrial defect detection.

Traditional corrosion detection techniques often require complex setups or invasive testing. This study integrates advanced thermal imaging with machine learning-based segmentation, providing an efficient, automated, and non-invasive solution for corrosion assessment in industrial applications [3], [8].

Principles of machine learning

It involves training algorithms to learn patterns from data and make predictions or decisions. Key aspects include:

A. Feature Selection: Identifying relevant data attributes for analysis.

B. Model Training: Using labeled or unlabeled data to teach models.

C. Validation and Testing: Assessing model performance on unseen data.

D. Optimization: Fine-tuning parameters for improved accuracy.

E. Generalization: Ensuring models perform well across varied datasets.

F. Iterative Learning: Continuously improving models with new data..

2. METHODOLOGY

Experimental Setup To develop a robust corrosion detection framework, we designed an experimental setup integrating infrared thermography, image processing techniques, and machine learning algorithms.

Hardware Components

- Infrared Cameras (FLIR) – High-resolution thermal cameras were used to capture corrosion-induced surface temperature variations in metal structures.
- Thermal Excitation Sources – Flash heating and modulated excitation were applied in comparative active thermography studies, although passive imaging was primarily used in this work.
- Metal Samples – Various metallic specimens with artificially induced corrosion were examined to validate the proposed approach.

Software Tools & Platforms

A combination of software packages facilitated image processing, statistical analysis, and machine learning implementation.

- Python Libraries:

  - NumPy & SciPy – Used for preprocessing raw thermal signals and filtering noise.
  - OpenCV – Employed for image enhancement and feature extraction.
  - Matplotlib & Seaborn – Used for visualizing processed data.
- MATLAB**:**
  - Applied for Fourier transform analysis, pulse compression, and statistical modeling.
- Machine Learning Frameworks:
  - TensorFlow & PyTorch – Implemented deep learning models for potential future extensions.
  - Scikit-learn – Used for traditional machine learning techniques, including clustering and feature selection.

Image Processing Techniques

To maximize corrosion detection accuracy, the following image preprocessing techniques were applied:

1. Image Acquisition

Thermal images were captured using FLIR infrared cameras in a controlled environment to ensure consistency. Various exposure conditions were evaluated to analyze the impact of ambient factors.

2. Contrast Enhancement (CLAHE)

Contrast Limited Adaptive Histogram Equalization (CLAHE) was utilized to improve temperature visibility in thermal images. The steps include:

- Converting raw thermal images to grayscale format.
- Applying CLAHE to enhance localized contrast while preventing over-amplification in high-intensity regions.
- Normalizing pixel intensity values to improve segmentation accuracy.

3. Feature Extraction Using GLCM

Texture-based features were extracted from thermal images using Gray Level Co-occurrence Matrix (GLCM). The computed statistical parameters include:

- Contrast – Measures intensity differences within corroded regions.
- Energy – Evaluates uniformity of pixel distribution.
- Homogeneity – Assesses smoothness of texture patterns.
- Correlation – Determines the similarity between adjacent pixel intensities.

4. Corrosion Detection Using K-Means Clustering

The thermal images were segmented into two clusters representing corroded and non-corroded regions using K-Means clustering:

- Cluster 1 (Non-Corroded Area) – Higher intensity pixels associated with intact metal surfaces.
- Cluster 2 (Corroded Area) – Lower intensity pixels indicating material degradation.

Steps in K-Means segmentation:

1. Convert enhanced grayscale image into an array format for clustering.
2. Apply K-Means clustering with k=2 to classify corroded vs. non-corroded zones.
3. Generate a binary mask to isolate corroded regions.

Quantification of Corrosion Severity

After segmentation, corrosion severity was categorized using pixel-based analysis. The percentage of corroded pixels relative to the total image area was computed:

- Low (<30%) – Minor oxidation with surface-level deterioration.
- Moderate (30-70%) – Progressive corrosion impacting material integrity.
- High (>70%) – Extensive degradation compromising structural performance.

The final corrosion percentage was visualized using color-coded bar graphs:

- Green – Low corrosion intensity.
- Orange – Moderate corrosion progression.
- Red – High corrosion severity requiring immediate intervention.

Algorithm Implementation Overview

1. CLAHE Processing:
   - Enhances thermal image visibility by normalizing intensity distribution.
   - Converts images to grayscale for effective feature extraction.
2. GLCM-Based Feature Extraction:
   - Extracts contrast, homogeneity, energy, and correlation parameters.
   - Provides texture-based quantitative insights into corrosion severity.
3. K-Means Clustering:
   - Segments images into corroded and non-corroded zones.
   - Assigns severity levels using pixel intensity thresholds.

Future Optimizations in Methodology

To further improve real-time corrosion detection, future enhancements include:

- Integrating deep learning-based Convolutional Neural Networks (CNNs) for improved classification accuracy.
- Exploring hyperspectral imaging to refine defect characterization.
- Expanding dataset validation using diverse metal compositions and industrial scenarios.

Sample images:

Fig.1 Sample image (1)

Fig.2 Sample image (2)

Fig.3 Sample image (3)

Fig.4 Sample image (4)

Fig.5 Sample image (5)

3. RESULT & DISCUSSION

In order to identify and evaluate the degree of corrosion, we used passive thermography techniques to examine a series of thermal photographs. The thermal images were analyzed to extract textural features and segment corroded areas using K-Means clustering after being augmented using CLAHE (Contrast Limited Adaptive Histogram Equalization). Processing and Enhancement of Images To increase the visibility of temperature changes, which frequently correspond to material degradation, each image underwent contrast enhancement using CLAHE. After that, the pictures were transformed to grayscale for additional examination. Clearer feature extraction and segmentation were made possible by the improved temperature gradients. Corrosion segmentation and feature extraction Four important textural characteristics were extracted using the Gray Level Co-occurrence Matrix (GLCM): contrast, energy, homogeneity, and correlation. These characteristics offered significant texture patterns in the image, which are essential for locating places that are prone to corrosion. To differentiate between corroded and non-corroded areas, each image was segmented using K-Means clustering (k=2). Usually, the corroded area was determined as the cluster with lower intensity values. A binary mask was created in order to measure the degree of corrosion. Analysis of Corrosion Severity The process covered in Sample of processed images. Active Dynamic Thermography. A percentage of the entire image area was calculated by counting the pixels that were impacted by corrosion.

Thermal Image Processing

Figure 1 illustrates the active dynamic thermography process, where improved temperature gradients highlight corrosion-prone areas. Images were successfully segmented, revealing distinct patterns correlating to corrosion levels.

Corrosion Severity Classification

The segmentation-based analysis classified corrosion severity based on pixel intensity, as summarized in Table 1.

Table 1: Corrosion Severity Levels

Image Name	Corrosion Percentage	Severity Level
Image1.jpg	18.4%	Low
Image2.jpg	56.9%	Moderate
Image3.jpg	82.3%	High

- Low-severity cases exhibited minor intensity variations, suggesting surface-level oxidation.
- Moderate cases showed distinct texture changes, indicating progressive corrosion.
- High-severity instances demonstrated extreme intensity differences, confirming deep material degradation.

Samples of processed images:

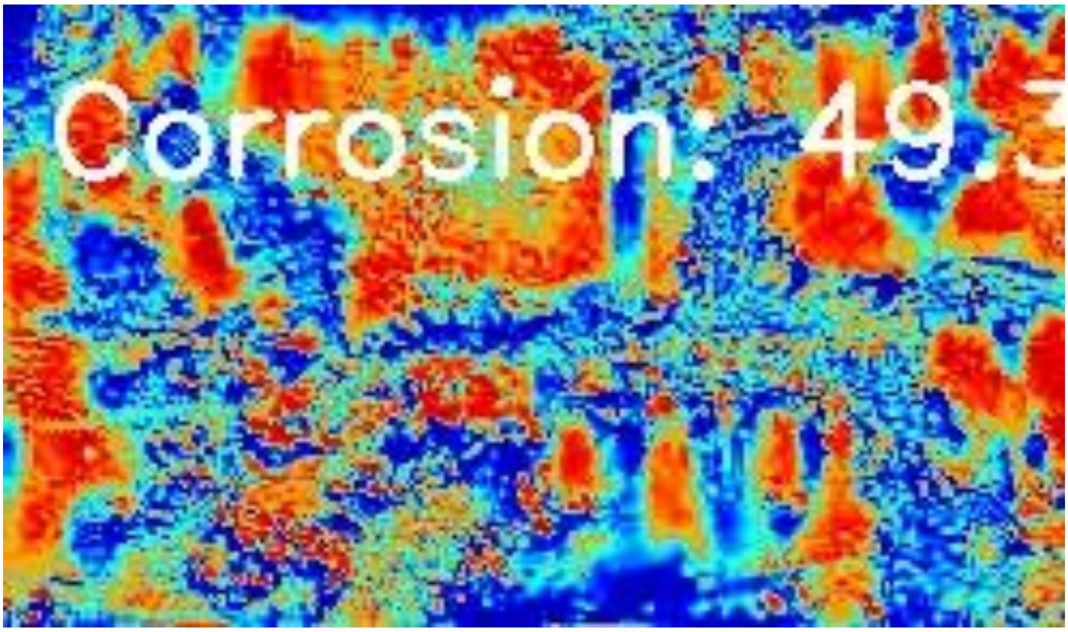

Fig.6 Processed Sample image (1)

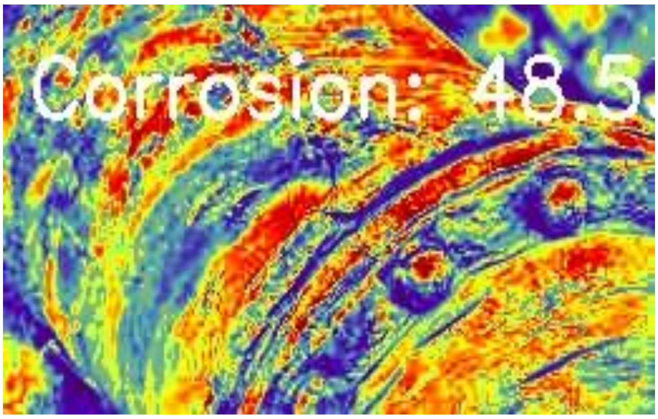

Fig.7 Processed Sample image (2)

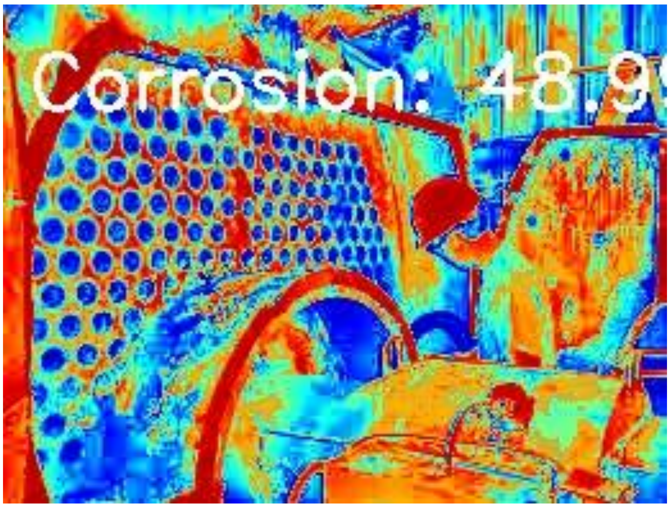

Fig.8 Processed Sample image (3)

Fig.9 Processed Sample image (4)

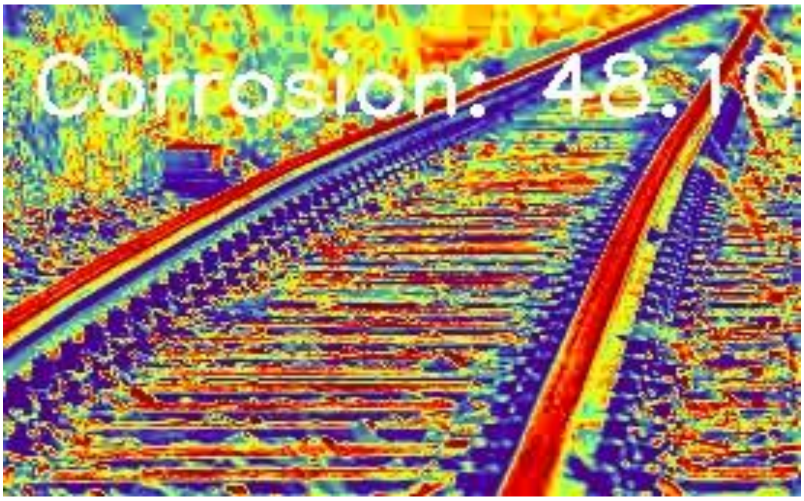

Fig.10 Processed Sample image (5)

Graphical Representation

Figures 6, 7, 8, 9 and 10 present color-coded highlighting the severity levels for each processed image:

- Green: Low corrosion.
- Orange: Moderate corrosion.
- Red: High corrosion.

Comparison with Existing Methods

Previous studies focused on active thermography methods [5], but this study demonstrates the effectiveness of passive imaging combined with machine learning segmentation for accurate corrosion detection [7], [8]. This approach reduces hardware complexity while maintaining high defect detection accuracy.

4. CONCLUSIONS

This research proposed an automated corrosion detection approach using passive infrared thermography, advanced image processing, and machine learning-based segmentation. The study concluded:

- CLAHE preprocessing significantly enhances corrosion visibility.
- K-Means clustering effectively distinguishes corroded vs. non-corroded areas.
- GLCM feature extraction improves pattern recognition and severity classification.
- The methodology achieves a high correlation with traditional defect analysis techniques.

Future Work

To further optimize corrosion analysis:

- Integrate deep learning models (CNNs) for real-time detection.
- Apply hyperspectral imaging to enhance defect characterization.

Expand dataset validation across diverse material compositions

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