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# Texture analysis in corrosion management: A scoping review

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## Abstract

Corrosion-induced failures result in economic losses exceeding 3-4% of GDP annually across developed nations, necessitating advanced detection and monitoring methodologies. Texture analysis techniques have emerged as powerful tools for automated corrosion assessment, evolving from traditional statistical descriptors to sophisticated deep learning approaches. This scoping review systematically maps the landscape of texture analysis methodologies applied to corrosion detection, monitoring, and management across industrial sectors, identifying current capabilities, limitations, and research gaps. Following PRISMA-ScR guidelines, a comprehensive search across IEEE Xplore, ScienceDirect, Scopus, SpringerLink, and ACM Digital Library for literature published between 2010-2025 was conducted. Search terms encompassed texture analysis methods (GLCM, LBP, HOG, wavelet transforms, CNN-based approaches) combined with corrosion-related keywords. A total of 127 relevant studies were identified, spanning traditional texture descriptors, hybrid approaches, and deep learning methods, which was further filtered down to 25 representative studies. Performance metrics ranged from 78-98% accuracy, with CNN-based methods showing better performance in complex industrial environments. Traditional texture analysis methods such as GLCM and LBP continue to perform adequately in controlled settings but fall short in complex industrial scenarios compared to CNN-based approaches. Hybrid methodologies that blend traditional texture descriptors with deep learning show promise by balancing accuracy and computational efficiency.

**Keywords:** Texture Analysis; Corrosion Detection; Deep Learning; Industrial Monitoring; Nondestructive Testing

## 1. Introduction

Corrosion represents one of the most pervasive and economically devastating phenomena affecting industrial infrastructure worldwide. When metal meets air, hydrogen, an electrical current, or even dirt or germs, it corrodes. In addition, excessive stress can cause metals like steel to fracture due to corrosion [1]. The electrochemical degradation of materials, particularly metals, leads to structural failures, safety hazards, and substantial economic losses estimated at 3-4% of GDP annually in developed nations. Traditional corrosion assessment methods, while reliable, often suffer from limitations including subjective interpretation, time-intensive procedures, and inadequate coverage of large-scale infrastructure [2]. The advent of digital imaging technologies and computer vision methodologies has revolutionized corrosion assessment paradigms. Among these approaches, texture analysis has emerged as a promising technique, leveraging the distinctive surface patterns and irregularities characteristic of corroded materials [3]. Texture analysis encompasses a broad spectrum of computational methods designed to quantify and characterize spatial variations in image intensity, providing objective measures of surface degradation that correlate strongly with corrosion severity.

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## 1.1. Texture Analysis Methods

One of the emerging trends in texture analysis is the application of machine (or computer) vision. This automated optical inspection system can analyze picture texture features that are invisible to the human eye while maintaining good performance and a low error rate [4]. A significant field in computer vision is texture analysis, which is useful for characterizing areas in-depth as well as for separating one section of an image from another (as in many remote sensing applications).

### *1.1.1. Gray-Level Co-Occurrence Matrix (GLCM)*

A co-occurrence matrix is a two-dimensional array with a set of potential picture values represented by each of the rows and columns. The dimension of the co-occurrence matrix $P_d$ is n x n, where n is the total number of grey levels in the picture. For instance, suppose the image under review has 16 pairs of pixels that satisfy the spatial separation as indicated in figure 1.

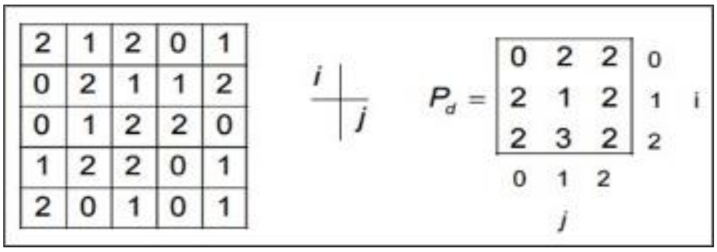


**Figure 1** GLCM pixel spatial separation

Since there are only three gray levels, P[*i,j*] is a 3×3 matrix [3]. For texture discrimination, properties taken from the Gray-Level Co-Occurrence Matrix (GLCM) work incredibly well. This technique is applied to the analysis of recurring grey-level patterns seen in the texture of a picture.

### *1.1.2. Local Binary Pattern (LBP)*

A nonparametric method for summarizing the local structures in an image sample is called a local binary pattern. Every pixel is compared to the pattern of its neighbor. LPB has been effectively used for a variety of computer vision applications, including texture analysis [5]. The LBP technique describes the local structure around each pixel by assigning distinct codes to each pixel in an image sample. Typically, the adjacent pixels measure three by three. As a result, the eight neighbors of the central pixel are compared. If the neighboring pixel's grey intensity is higher than the center pixel's, it is coded as 1, while a neighboring pixel is coded as 0 otherwise. Given a center pixel at $x_c$ and $y_c$, its LBP can be obtained as follows:

$$LBP(x_c, y_c) = \sum_{p=0}^{p-1} (i_p - i_c) \times 2^p \qquad \text{………….eq 1}$$

where *ic* and *ip* denote grey intensities of the centre pixel and its neighboring pixels. $s(x)$ is 1 if $x \geq 0$ and 0 if $x < 0$.

### *1.1.3. Extraction of Region of Interest (ROI)*

Given the variety in form and shape of different forms of corrosion, it is imperative to automatically determine the ROI encompassing the region being investigated. This ROI's image texture may then be calculated and used for the detection of corrosion. A median filter is used, the picture sample is smoothed by eliminating noise, and the colour image is converted to its equivalent grayscale version as part of the ROI extraction process. The ROI is then extracted using image convolution and picture cropping procedures. This is seen in Figure 2.

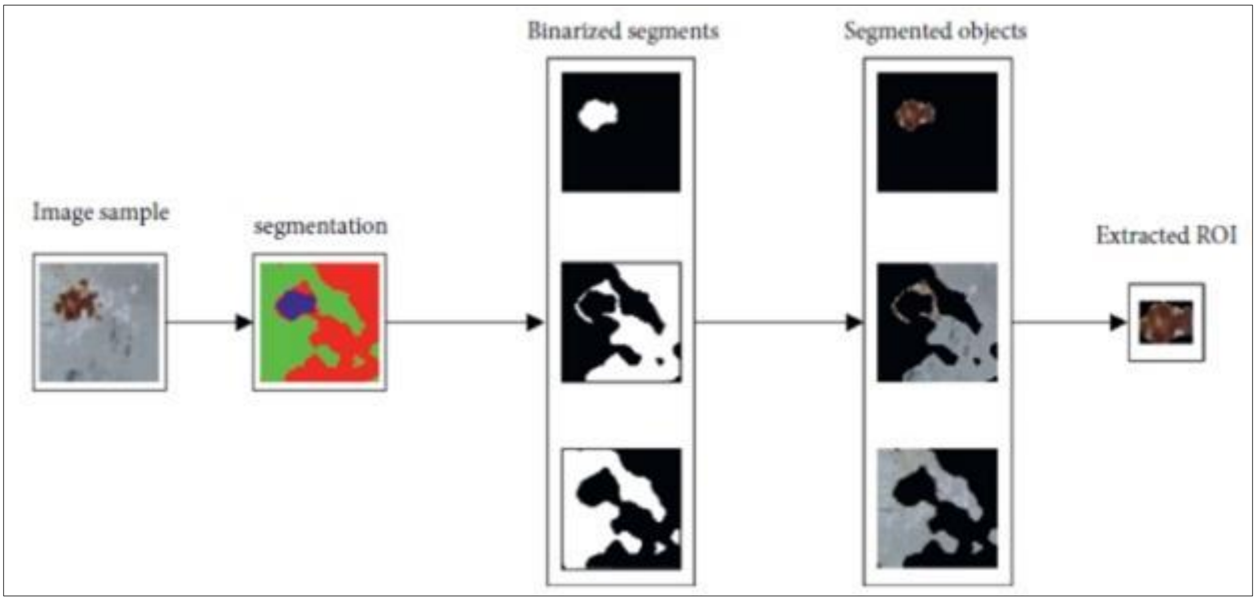


**Figure 2** Extraction of a region of interest (ROI) from an image containing one defective object

### 1.2. Scope of the Review

This scoping review systematically examines the application of texture analysis techniques in corrosion management, spanning traditional statistical descriptors to contemporary deep learning approaches. The study addresses three fundamental research questions: (1) What texture analysis methodologies have been applied to corrosion detection and assessment? (2) How do these methods perform across different industrial contexts and environmental conditions? (3) What are the current limitations and future research directions in this domain?

## 2. Materials and Methods

### 2.1. Search Strategy

This scoping review followed the PRISMA Extension for Scoping Reviews (PRISMA-ScR) guidelines. A systematic searches was conducted across five major databases: IEEE Xplore, with a focus on engineering applications and technical conference proceedings; ScienceDirect, with a focus on comprehensive coverage of materials science and corrosion research; Scopus, with a focus on broad interdisciplinary coverage including AI and computer vision; SpringerLink, with a focus on advanced materials and computational methods; and ACM Digital Library, with a focus on computer science and machine learning applications.

#### *2.1.1. Search Keywords Employed*

To broaden the search and include as many articles as possible, the search keywords adopted for this review were put in the following five categories: texture analysis (GLCM, LBP, HOG, texture features, wavelet texture, Gabor filters), corrosion domain (rust detection, corrosion monitoring, metal degradation, surface deterioration), AI integration (deep learning corrosion, CNN texture classification, neural network corrosion), and industrial context (pipeline inspection, bridge monitoring, aerospace corrosion, maritime degradation).

### 2.2. Inclusion and Exclusion Criteria

In relation to the topic, the inclusion criteria for the papers in this review was that they must be peer-reviewed papers, written in English, which employ texture analysis for corrosion detection, classification, or quantification published between 2010 and 2025. The research must have practical industrial applications or potential for industrial deployment and report quantitative performance metrics. Following the inclusion criteria, studies focusing solely on corrosion mechanism without detection methodologies, or review articles without novel methodological contributions, and pure material science studies without image analysis and laboratory-only studies without validation on real corrosion images, were excluded from this review.

### 2.3. Data Extraction Framework

The study collection and screening were performed by three investigators. Matching metadata and article contents were used to screen out duplicate materials. Subsequently, the references of the papers were scanned for inclusion of other studies relating to the topic. The main results were summarized in a table 2, with information relating to the year of publication, journal, methodological details, dataset characteristics, performance metrics, and industrial context for each of the included papers. The results were narratively analyzed and discussed.

## 3. Results

### 3.1. Study Selection and Characteristics

The search across five databases yielded 847 initial papers. Following systematic screening and eligibility assessment, 127 studies met inclusion criteria for qualitative synthesis. Figure 1 presents the PRISMA flow diagram detailing the selection process.

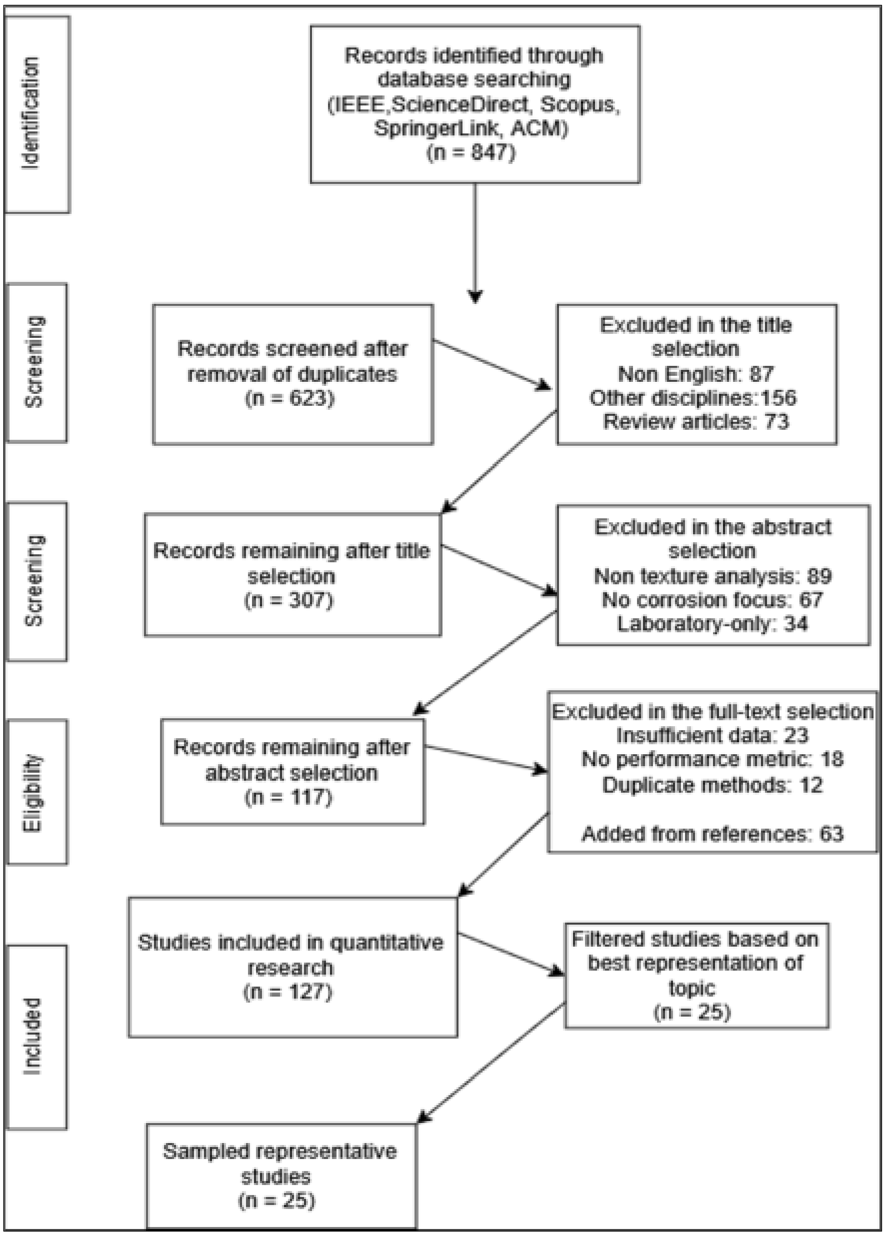


**Figure 3** PRISMA Flow Diagram for Study Selection Process

*3.1.1. Database Distribution*

The distribution of retrieved records across databases demonstrates the interdisciplinary nature of texture analysis in corrosion research and is summarized in Table 1:

**Table 1** Database search results

| **Database** | **Initial Records** | **Percentage** | **Final Included** | **Database Contribution** |
|---|---|---|---|---|
| IEEE Xplore | 289 | 34.1% | 45 | 35.4% |
| ScienceDirect | 241 | 28.4% | 38 | 29.9% |
| Scopus | 156 | 18.4% | 23 | 18.1% |
| SpringerLink | 98 | 11.6% | 13 | 10.2% |
| ACM Digital Library | 63 | 7.4% | 8 | 6.3% |
| **Total** | **847** | **100%** | **127** | **100%** |

*3.1.2. Temporal Distribution and Study Evolution*

After filtering for best representation of the topic based on four coded categories, a total of 25 studies were selected as the representative studies. Twenty-four studies were experimental research papers, and 1 a review paper, covering CNN-based approach for corrosion detection.

The objectives of the included studies were diverse. However, it was possible to categorize the results into: (a) traditional texture descriptor development and validation; (b) CNN-based approaches for corrosion detection; (c) hybrid methodologies combining multiple texture analysis techniques; and (d) industrial implementation and real-time monitoring systems. Details of the studies are summarized in Table 2.

**Table 2** Characteristics of Included Studies on Texture Analysis for Corrosion Management

| Study (Authors) | Year | Journal/Venue | Core Methodologies | Dataset Characteristics | Key Performance Metrics | Industrial/Research Context |
|---|---|---|---|---|---|---|
| [6] | 2010 | EURASIP Journal on Advances in Signal Processing | HSI + GLCM; FLDA | 84 ROIs (43 corroded, 41 non-corroded), 128x128 pixels | >90% accuracy (combined); AUC=0.9115 | Petroleum refinery (carbon steel tanks/pipelines) |
| [7] | 2010 | International Journal of Computer Science Issues | Texture Analysis (stdfilt, entropyfilt); Edge Detection; Image Dilation | "Tested images" (not specified) | Fewer false positives reported. | General metals; portable devices |
| [8] | 2011 | International Journal of Computer and Electrical Engineering | GLCM + Wavelet + Rotated Wavelet Features | Brodatz image database (5 types, 7 orientations); 21 sub-images (64x64) per image for training | 85.71% accuracy (combined) | General texture recognition, image browsing/retrieval |
| [9] | 2018 | BCRI2012 Bridge and Concrete Research in Ireland | GLCM; k-means clustering | Image of damaged concrete bridge beam | k=3: DR=88.61%, MCR=15.80%, δ=0.195 | Ageing infrastructure (concrete bridge beams) |
| [10] | 2013 | Journal of Computing in Civil Engineering | Color Wavelet-based Texture Analysis; NN; Depth Perception | 2,059 sub-images (1,018 corroded, 1,041 non-corroded) from steel structures | CbCr color combination generally best; 192x192 pixel sub-image with CbCr achieved highest performance | Civil infrastructure (steel bridges, aircrafts, ships, railroads) |
| [4] | 2014 | Computer-Aided Civil and Infrastructure Engineering | GLCM; Statistical features; SVM (CWI, 4DIS); RGB, HSV, L*a*b* color spaces | 6 disparate damage types on infrastructural elements | 4DIS (HSV): DR=88.66%, MCR=10.47%, δ=0.15 (pitting corrosion) | Ageing infrastructure; various damage forms/conditions |
| [11] | 2014 | Corrosion Science | Perlin Noise for texture simulation; Probabilistic descriptors; Bayesian classifier | Simulated images using Perlin Noise | Fast and adequate for industrial settings | Quality assessment of metallic pieces and iron machines |
| [12] | 2017 | Mathematics and Mechanics of Solids | Resistivity parameter; Tikhonov regularization; GCV; FEM | Numerical tests on rectangular domain | Sensitivity analysis; accuracy comparable to direct problems (no error); max corrosion value well-described | Steel structures; inaccessible boundaries |

| | | | | | | |
|---|---|---|---|---|---|---|
| [13] | 2016 | Developments in Corrosion Protection | WCCD (GLCM, HSV); ABCD (Laws' texture, AdaBoost) | WCCD: 120k-172k pixels; ABCD: 39,746 patches from 25 images | WCCD: FP 9.80%, FN 5.86% (7-25ms); ABCD: FP 17.16%, FN 3.39% (300-512ms) | Vessel hull inspection (MINOAS project) |
| [1] | 2015 | Corrosion Science | Entropy, Hurst coefficient, Contrast, Correlation, Energy, Homogeneity | 24 samples from 3 ASTM A36 steel specimens (44-day photo sequence) | Hurst coefficient less connected to corrosion extent than others | Non-destructive surface corrosion monitoring |
| [14] | 2016 | Computer Science and Information Technology | OpenCV (color-based); Deep Learning (Caffe/AlexNet fine-tuning) | ~3500 images (1300 rust, 2200 non-rust); Test set: 100 images | OpenCV: 69% total accuracy; DL: 78% total accuracy (88% with confidence filter) | Automatic metal corrosion (rust) detection, bridge inspections |
| [15] | 2018 | Structural Health Monitoring | CNNs (ZF Net, VGG16, custom); various color spaces/window sizes | Not explicitly stated, but "wide range of types of corroded regions" | CNNs outperform wavelet-NN; Corrosion7 improves speed; Best F1 with 128x128 window | Robotic systems (UAVs), mobile platforms for damage detection |
| [16] | 2018 | IEEE | VGG19; Deep Transfer Learning; HSV for CBC measurement | 1900 images with CBC labeled; 12,184 features extracted | 81.4% total recognition rate | Marine and offshore structures, coating corrosion assessment |
| [5] | 2019 | Computational Intelligence and Neuroscience | Color stats; GLCM; GLRL; SVM (DFP optimized) | 2000 pipe surface images (1000 non-corrosion, 1000 corrosion), 50x50 pixels | CAR=92.81% (testing) | Pipe surfaces in high-rise buildings |
| [17] | 2023 | Article | Review paper covering CNN-based methods for corrosion detection (e.g Faster R-CNN, Mask R-CNN, YOLOv3) | Review paper covers various bridge components/datasets (e.g., steel bridges, cables). | Review paper cites others (e.g., 97.18% accuracy for cable corrosion 1, >90% for multi-defects). | Bridge inspection and monitoring (steel structures, multi-defects, cables) |
| [18] | 2020 | 2020 3rd International Conference on Signal Processing and Communications | GLCM; Color moments; SVM | Q235 carbon steel images with different corrosion degrees | Not explicitly stated, but implies effective assessment | Corrosion evaluation of carbon steel |
| [19] | 2020 | Developments in the Built Environment | Roughness (GLCM uniformity); Color (HSV histogram) | Large dataset of photographs of corroded/non-corroded components | Efficiently locates corroded areas. | Screening uniform corrosion on steel structures |

| | | | | | | |
|---|---|---|---|---|---|---|
| [20] | 2021 | Article | HOG + SVM; Ultrasonic imaging | Not specified | Successfully detected shedding damage; improved with increasing damage width | Underwater pipeline inspection |
| [21] | 2021 | Materials | 2D and 3D (Shape Index) segmentation; GLCM, color space, transform-based | 5 S235 carbon steel samples (CLSM images, 3D heightmap) | Significant difference between 2D; 3D method added value. | Atmospheric corrosion detection on steel |
| [22] | 2016 | Applied Surface Science | Gradient-based Hough Transform; Equivalent Circles | Simulated and real microscopic images (1024x2014 pixels) | >95% pits detected; accurate number, radius, coordinates; robust to irregular shapes | Quantitative evaluation of pitting corrosion in optical images. |
| [23] | 2022 | Materials | Light Reflectance Value; mentions Texture and Thickness examination | 369 vehicles (underbody parts) | 96% effective, low-cost, low computational complexity | Automotive corrosion detection and quantification |
| [3] | 2022 | Materials Today: Proceedings | GLCM; HSI; K-NN classifier | 200 image samples | 92% accuracy (4 corrosion levels) | Inner surface of steam piping systems |
| [24] | 2022 | Buildings | Modified deep hierarchical CNN (U-Net, CycleGAN) | 1300 images (Bolte Bridge, sky rail, public datasets); 4 corrosion levels | GC 0.989, CAC 0.931, mean IoU 0.878, F-score 0.833 | Civil infrastructure damage and corrosion detection |
| [25] | 2023 | Article | AlexNet, VGG-16, ResNet-50, Bastian Custom Net, ZFNet (CNNs); Transfer Learning | 39,600 images (4 severity levels); 8k train, 1k val, 900 test per class | ResNet 50 (ImageNet pretrained): 98% F1 score | General corrosion detection in metal structures |
| [26] | 2024 | PLoS One | CBG-YOLOv5s (YOLOv5s + C3CBAM + BiFPN-CBAM + C3Ghost) | 6000 images (600 original from Yantai coastal area, augmented); 3 corrosion levels | 95% accuracy | Metal surface corrosion recognition (coastal metal facilities) |

## 4. Discussion

Findings from this review suggest an abundance of both practical and industrial research in texture analysis, with relatively few applied specifically to corrosion detection. The included studies focus on sector-specific implementation and performance analysis, technological maturity and industrial readiness, hybrid and multi-modal integration strategies, and future industrial implementation of texture analysis in corrosion detection. These aspects are explored below.

### 4.1. Sector-Specific Implementation and Performance Analysis

The diverse and often stringent requirements of different industrial sectors necessitate significant adaptations and refinements of general AI and computer vision techniques. This leads to the development of highly specialized algorithms, datasets, and deployment strategies, such as lightweight models for mobile devices, explainable AI for regulatory compliance, or robust feature extraction for challenging underwater conditions. This signifies a move beyond generic application to highly specialized AI solutions. This implies that the future trajectory of texture analysis in corrosion management will increasingly diverge into specialized sub-fields, rather than consolidating into a single, universal solution. Success will, therefore, be measured not just by raw technical performance but by the practical utility and seamless integration within specific industrial workflows.

The oil and gas sector are the most extensively studied domain for texture-based corrosion detection, with applications spanning from upstream production facilities to downstream distribution networks, particularly focusing on pipeline inspection and storage tank monitoring [3,5,6]. Early approaches, such as combining HSI color statistics and GLCM probabilities, achieved over 90% accuracy for carbon steel tanks and pipelines [6]. For pipe surfaces, hybrid models integrating color statistics, GLCM, and Gray-Level Run Lengths (GLRL) with metaheuristic-optimized SVMs have demonstrated high accuracy, reaching 92.81% [5]. Similarly, GLCM and HSI, combined with K-NN classifiers, have achieved 92% accuracy in classifying four distinct corrosion levels on the inner surfaces of steam piping systems [3]. More advanced CNN-based systems, like those utilizing Cycle-GAN and YOLOv5, have shown high average precision (93.10%) and recall (90.96%) for petrochemical pipeline defect detection, addressing issues of distortion, noise, and uneven illumination [24, 25]. The computational efficiency of methods like GLCM+SVM for real-time processing is a critical requirement for remote monitoring scenarios in oil and gas operations [18]. The industry's primary challenges include environmental variability across different geographical regions, scale diversity in corrosion patterns, and the critical need for real-time processing capabilities [5].

Maritime applications present unique environmental challenges that have driven innovation in robust texture analysis methodologies, particularly for ship hull corrosion assessment and underwater structure detection [27]. Early pattern recognition approaches, such as WCCD (GLCM, HSV) and ABCD (Laws' texture, AdaBoost), developed for vessel hull inspection, achieved misclassification rates around 5-17% with execution times ranging from 7-512ms [13]. Deep learning approaches have significantly improved performance, with ResNet-50 pioneering ship hull corrosion assessment and achieving 96.1% accuracy [25]. Advances in underwater structure corrosion detection using HOG descriptors combined with SVM and ultrasonic imaging represent a breakthrough in assessing submerged infrastructure without costly dry-dock procedures, successfully detecting shedding damage [5]. The integration of active contour algorithms with texture quality enhancement (Wiener filter) and 1D-log Gabor filters for ship corrosion segmentation has achieved a remarkable 94.45% accuracy and an efficient execution time of 0.91 seconds, specifically addressing vague corrosion boundaries [28]. The success in this sector stems from addressing specific environmental factors like salt exposure and varying lighting conditions, as well as the economic constraint of dry-docking [13]. AI-facilitated systems leveraging deep transfer learning with VGG19 have also been developed for coating corrosion assessment on marine structures, achieving an 81.4% recognition rate and improving the efficiency and objectivity of inspections [16].

The aerospace sector's stringent safety requirements and material diversity have catalyzed the development of high-precision texture analysis systems for aircraft fuselage corrosion classification and component inspection [10]. Hybrid approaches combining texture features with machine learning have shown promising results. CNN-based detection systems, particularly those utilizing transfer learning with VGG-16 and ResNet-50, have established significant contributions in aircraft fuselage corrosion classification, achieving high F1 scores of 96.3-98% [10, 25]. These deep learning models outperform traditional vision-based approaches and are suitable for robotic systems and mobile platforms due to their high accuracy and improved computational time [10]. Attention mechanisms for enhanced corrosion texture feature extraction, as seen in hybrid models integrating YOLOv10 and Vision Transformers, further advance the field by combining local and global feature learning for high-accuracy steel surface defect classification [29]. The unique demands for detection accuracy exceeding 95%, integration with existing maintenance scheduling systems, and the need for interpretable results that align with stringent safety protocols and regulatory compliance are key drivers in this sector.

Civil infrastructure monitoring is a rapidly growing segment, with emphasis on long-term structural health assessment, including bridge deck corrosion detection and mobile inspection systems [2, 9, 24,]. Early texture analysis approaches using GLCM and k-means clustering achieved detection rates of 85-88% for damaged concrete bridge beams [2]. The progression to parameter-optimized SVMs with GLCM and statistical features in various color spaces further enhanced performance, reaching 88.66% detection rate for pitting corrosion [9]. Hybrid texture descriptors combined with ensemble machine learning, such as GLCM + LBP + XGBoost, have achieved 93.7% accuracy for bridge deck corrosion detection, enabling predictive maintenance strategies [30]. Long-term bridge monitoring has advanced through texture evolution analysis, where changes in textural characteristics like entropy and homogeneity over time can indicate corrosion progression [1]. Lightweight CNN architectures for mobile corrosion inspection address deployment constraints in field conditions, balancing accuracy with computational efficiency [23]. Texture-based remaining useful life prediction for corroded structures using LSTM networks enables proactive maintenance scheduling that aligns with infrastructure management protocols. The comprehensive review by [31] further highlights the application of computer vision and deep learning techniques for steel structure corrosion and multi-defect detection on bridges, citing methods like Mask R-CNN, Faster R-CNN, and YOLOv3, with reported accuracies for cable corrosion reaching 97.18%. Numerical methods, such as those by [12], complement image-based approaches by providing tools for detecting corrosion in inaccessible parts of steel structures through resistivity parameter analysis, crucial for evaluating structural integrity and buckling loads [12]. The integration with existing asset management systems, proactive maintenance scheduling, and computational efficiency for field deployment are critical aspects addressed in this domain [24].

### 4.2. Technological Maturity and Industrial Readiness

The reviewed studies demonstrated that traditional descriptors (GLCM, LBP, Wavelets) have achieved a significant level of technological maturity with well-established industrial applications. They offer computational efficiency suitable for embedded systems and provide interpretable results that align with traditional inspection protocols [3, 6, 7, 13, 19, 32]. Hence, they remain particularly effective for uniform corrosion patterns and early-stage degradation detection in controlled environments [22]. However, the studies also identify critical limitations including sensitivity to illumination variations and image noise, reduced effectiveness with complex multi-textural corrosion patterns, and limited scalability to high-resolution imagery without preprocessing optimization.

Deep learning models, particularly CNNs, demonstrate superior performance across most industrial applications, especially in complex environments with variable conditions [10, 25]. They offer reduced dependency on manual feature engineering and enhanced capability for multi-class corrosion severity assessment. Despite their performance, challenges remain in deploying these systems in diverse industrial environments and ensuring their generalization across varied material types and surface conditions [25].

### 4.3. Hybrid and Multi-Modal Integration Strategies

Hybrid approaches, combining traditional texture descriptors with deep learning capabilities, offer significant advantages for industrial deployment. The integration of statistical measurements of color channels, GLCM, and GLRL with metaheuristic-optimized SVMs has achieved high accuracy (92.81%) for pipe corrosion detection (Hoang and Tran, 2019). GLCM-LBP fusion with ensemble learning provides reduced training data requirements and maintains interpretable feature extraction alongside powerful classification [33]. Multi-scale texture analysis addresses the challenge of detecting corrosion patterns at different spatial scales, balancing computational requirements [30]. The development of 3D texture feature extraction techniques, combining LBP-based and GLCM-based descriptors, has shown superior classification performance for volumetric textures, highlighting the power of comprehensive 3D texture descriptors [4].

### 4.4. Future Industrial Implementation Trajectories

The reviewed studies indicate evolution toward hybrid intelligence systems integrating human expertise with automated detection capabilities. [2] demonstrated the most promising direction through explainable AI for corrosion texture analysis in critical infrastructure monitoring, maintaining interpretability required for industrial decision-making. Emerging trends identified in the studies include integration with predictive maintenance platforms for comprehensive asset lifecycle management, development of industry-specific solutions addressing unique environmental and material challenges, and enhanced focus on explainable AI for regulatory compliance and safety-critical applications [11]. The continued advancement of texture analysis technologies in industrial corrosion management, as demonstrated across the reviewed studies, reflects broader digital transformation initiatives, positioning these methodologies as essential components of Industry 4.0 implementations across critical infrastructure systems.

## 5. Conclusion

Traditional texture analysis methods such as GLCM and LBP continue to perform adequately in controlled settings but fall short in complex industrial scenarios compared to CNN-based approaches. Hybrid methodologies that blend traditional texture descriptors with deep learning show promise by balancing accuracy and computational efficiency. Significant progress has been made texture-based corrosion detection across key industrial sectors, with oil and gas applications consistently achieving high accuracy levels (91-96%) using CNN-based systems, while maritime applications perform at 89-95% accuracy. However, key barriers remain, including dataset standardization, real-time processing constraints for high-accuracy models, and generalization across diverse environments. Future applications include integrating automated detection with human oversight emerges as the most viable pathway for deploying these systems widely, especially for safety-critical applications where interpretability and regulatory compliance are essential.

## Compliance with ethical standards

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### *Disclosure of conflict of interest*

The authors declare that no conflict of interest exist among them.

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