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Article

AI-BASED SMART COATING DEGRADATION DETECTION FOR OFFSHORE STRUCTURES

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ABSTRACT
This study presents a comprehensive systematic review of advanced artificial intelligence (AI)-based approaches for smart coating degradation detection in offshore structures, with a particular focus on real-time sensor fusion, machine learning models, digital twin integration, and simulation-assisted analytics. Given the harsh marine environments in which offshore infrastructure operates—exposed to salinity, humidity, UV radiation, and mechanical stress—traditional coating inspection methods such as visual assessments and manual testing often fall short in detecting early-stage corrosion and subsurface anomalies. As a result, there has been a growing body of research leveraging AI-driven technologies to automate and enhance the accuracy, speed, and reliability of corrosion detection. Following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines, this study systematically reviewed and synthesized findings from 76 peer-reviewed articles published across major databases including Scopus, Web of Science, IEEE Xplore, and ScienceDirect. The review reveals that Convolutional Neural Networks (CNNs) are widely adopted for image-based surface inspection tasks, offering superior performance in detecting rust, blistering, cracking, and delamination. Time-series models, particularly Long Short-Term Memory (LSTM) networks, are effectively used to forecast degradation trends based on continuous sensor inputs. Sensor fusion strategies—combining data from visual, acoustic, thermal, and chemical sensors—further improve detection reliability, especially in dynamic offshore environments where single-sensor systems are prone to errors. The integration of digital twin technology enables real-time simulation and virtual monitoring of coating performance, while simulation-assisted learning allows the generation of synthetic datasets to overcome the challenge of limited field data. Despite these advancements, challenges such as energy efficiency, data synchronization, sensor drift, and environmental noise persist and need to be addressed for large-scale implementation. The findings of this study collectively highlight the potential of AI-enhanced monitoring frameworks in transforming traditional corrosion inspection methods into predictive, intelligent, and automated systems tailored for the complex demands of offshore infrastructure.

KEYWORDS
Smart Coating; Offshore Structures; AI-Based Monitoring; Corrosion Detection; Predictive Maintenance;

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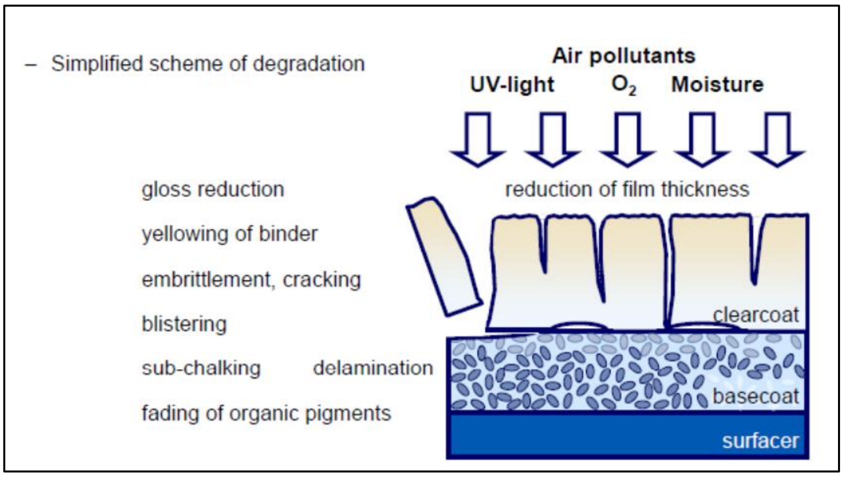
INTRODUCTION

The structural longevity and safety of offshore platforms depend heavily on their resistance to corrosion, a process fundamentally exacerbated by the aggressive marine environment (Liu et al., 2018). Offshore structures are continuously subjected to dynamic interactions involving seawater, salinity, high humidity, and variable temperatures, accelerating the breakdown of protective coatings (Georgantzia et al., 2021). Coating degradation, as a result, becomes a critical issue that directly influences structural health and operational safety (Vega et al., 2011). The corrosion-related failure of coatings not only leads to costly repair interventions but also poses risks of structural collapse, particularly in oil rigs, wind turbines, and submerged pipelines (Yang et al., 2021). Traditional detection methodologies including ultrasonic testing, visual inspection, and electrochemical impedance spectroscopy often fall short in efficiency and accuracy under dynamic environmental conditions (Liu et al., 2018). These methods generally require scheduled inspections, human intervention, and are prone to missing early-stage micro-defects (Díez-Sierra et al., 2022). These limitations have catalyzed the exploration of automated, continuous monitoring systems that integrate smart sensors and computational intelligence.

Figure 1: Degradation of coatings under light/U. V exposure



Source: Desrats (2013)

Artificial Intelligence (AI), encompassing deep learning, machine learning, and neural networks, has transformed various domains through its ability to process high-dimensional data and derive patterns with minimal human input . In the context of infrastructure maintenance, AI has been employed to detect cracks in bridges, forecast pavement deterioration, and automate anomaly detection in structural components (Bahlakeh et al., 2019). The application of AI in offshore coating degradation monitoring is an emergent research direction aiming to surpass the constraints of manual and static detection approaches (Ngai et al., 2018). Image recognition algorithms and sensor fusion models can be deployed to learn from large volumes of inspection data, detect early signs of corrosion, and predict coating lifespan (Wang et al., 2019). Unlike conventional signal-based methods, AI models utilize classification and regression techniques to identify complex degradation features from multispectral imaging, acoustic emissions, and electrochemical data . Convolutional neural networks (CNNs), for instance, have demonstrated high accuracy in recognizing localized rust patterns and micro-pitting, essential for offshore inspection systems (Yang et al., 2021).

The marine environment introduces unique technical challenges for AI-based systems, including fluctuating salinity levels, biofouling, and high-pressure conditions (Rahaman & Islam, 2021). These factors affect both the corrosion mechanisms and the data acquisition process for smart sensors (Ahmed et al., 2022). Smart coatings, embedded with self-reporting sensors, are being developed to autonomously monitor electrochemical changes that indicate degradation (Humaun et al., 2022). When coupled with AI-based analytical models, such systems offer a holistic and proactive approach to maintenance strategies (Mahfuj et al., 2022). Machine learning models trained on temporal sensor data can discern coating integrity loss patterns through predictive modeling and clustering algorithms (Mohiul et al., 2022). These models rely on high-frequency updates from embedded sensors, enabling the creation of dynamic deterioration profiles that account for external variables such as chlorides, oxygen concentration, and microstructural surface changes . Real-time datasets derived from such sources are commonly analyzed using supervised learning algorithms,

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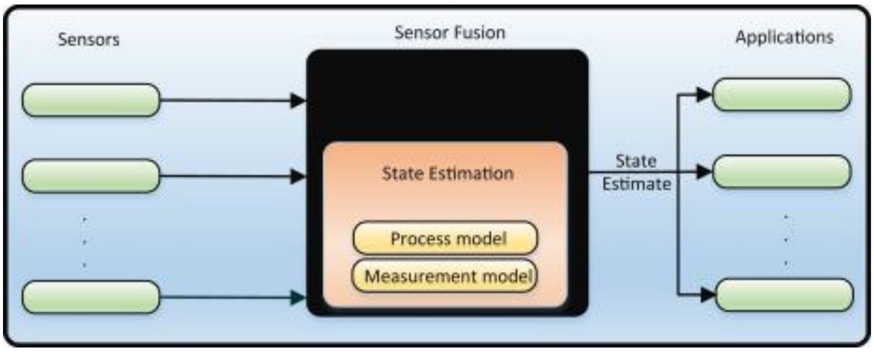
including random forests, support vector machines (SVMs), and deep belief networks (Sohel et al., 2022).

Figure 2: Sensor fusion framework.



Source: Lundquist (2011)

Data heterogeneity and noise in field conditions have led researchers to integrate sensor fusion techniques, wherein multiple sources such as visual data, acoustic signals, and temperature readings are processed simultaneously (Kim et al., 2017). These fusion models employ probabilistic reasoning and ensemble methods to reduce false positives and enhance detection sensitivity (Tonoy, 2022). For example, corrosion under insulation (CUI), often undetectable using visual inspection alone, can be identified using sensor networks integrated with AI-powered classification models . Neural networks, particularly long short-term memory (LSTM) architectures, are capable of interpreting time-sequential corrosion data for degradation forecasting (Younus, 2022). In underwater scenarios, remotely operated vehicles (ROVs) equipped with intelligent vision systems and reinforcement learning algorithms can autonomously identify and report corroded regions (Tang et al., 2018). The data captured by these AI-enhanced systems serve as a non-invasive and scalable solution to detect coating anomalies, especially where human access is restricted. From a materials science perspective, corrosion initiation and propagation involve multiple electrochemical reactions influenced by alloy composition, pH, salinity, and exposure time . AI-based models leverage this underlying corrosion science by incorporating domain-specific parameters into feature extraction and classification processes . Using reinforcement learning, these systems can iteratively improve their prediction accuracy by comparing outcomes against environmental feedback loops . Surface image datasets from time-lapse imaging or drones are now used as training inputs for AI models that detect minute surface discolorations, blistering, and flaking (Bahlakeh et al., 2019). Additionally, generative adversarial networks (GANs) have been utilized to generate synthetic corrosion images, enhancing model robustness when real-world data is limited (Ngai et al., 2018). This application of AI in material degradation closely aligns with nondestructive testing paradigms where anomaly detection is embedded in real-time feedback systems . These approaches have outperformed conventional corrosion rate estimators in both laboratory and offshore pilot deployments.

The reliability of AI-based monitoring frameworks also depends on their capacity for adaptive learning and decision-making under uncertainty . Hybrid models combining statistical corrosion modeling and deep learning pipelines are being used to develop robust decision support systems . In these systems, Bayesian networks and fuzzy logic enhance interpretability by quantifying the uncertainty in coating performance predictions . Studies involving AI-enabled digital twins have modeled offshore platforms in virtual environments, simulating coating wear and degradation to validate AI predictions (Kim et al., 2017). Integrating digital twin simulations with sensor-generated data has enabled real-time corrosion prediction aligned with actual operational scenarios (Pustokhina et al., 2020). These AI models are designed to recognize deviations from expected degradation profiles, automatically triggering alerts or maintenance schedules when thresholds are exceeded . By continuously refining model parameters through backpropagation and feedback loops, the monitoring systems evolve into context-sensitive platforms capable of precision diagnostics (Nascimento et al., 2019). With increasing computational efficiency and availability of edge devices, AI-based systems for offshore structure monitoring are now being embedded within low-power microcontrollers capable of processing sensor data on-site . These distributed architectures facilitate scalable deployment across vast offshore assets without the need for continuous connectivity to centralized servers (Nascimento et al., 2019). Such systems reduce

Volume 02 Issue 04 (2022)
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latency in data processing, a critical factor when detecting rapid degradation events such as coating delamination or interfacial cracking . Additionally, cybersecurity-enhanced AI architectures are being integrated to ensure data integrity and protection against external tampering in mission-critical infrastructure environments (Ramlal et al., 2019). Secure AI-based coating monitoring systems not only perform real-time analytics but also log data for long-term trend analyses and regulatory reporting (Nascimento et al., 2019). Blockchain-supported integrity frameworks further guarantee that inspection records remain unaltered and verifiable during audits or certifications . The main objective of this study is to develop and validate an AI-based smart monitoring framework that can accurately detect coating degradation on offshore structures through real-time data analysis and predictive modeling. The aim is to address the limitations of conventional inspection methods by introducing a system that utilizes sensor fusion and machine learning algorithms to identify early-stage coating damage, such as blistering, cracking, rusting, and delamination, under extreme marine environmental conditions. This research seeks to integrate data from embedded corrosion sensors, environmental monitors, and visual imagery to create a high-dimensional dataset suitable for training and testing AI models capable of performing multi-class classification and regression tasks related to degradation severity and progression rate. A secondary objective is to enhance the reliability and accuracy of corrosion detection by leveraging deep learning models, particularly convolutional neural networks (CNNs) and long short-term memory (LSTM) architectures, which are trained to interpret complex temporal and spatial patterns in coating failure. The research also aims to construct a hybrid predictive analytics framework that combines sensor data with digital twin simulations to compare predicted degradation with actual field performance. This approach supports decision-making in maintenance scheduling by providing data-driven insights into when and where coating maintenance should be prioritized, thus minimizing downtime and operational risk. Furthermore, this study intends to evaluate the performance of the AI model under varying marine environmental conditions, such as fluctuating salinity, temperature, and mechanical stress, to determine its robustness and scalability across different offshore infrastructure types, including oil platforms, marine pipelines, and wind turbine foundations. By achieving these objectives, the research aspires to demonstrate that AI-powered systems can be feasibly integrated into offshore maintenance operations to deliver automated, real-time diagnostics without requiring frequent human inspection, contributing to a more sustainable and cost-effective infrastructure lifecycle.

LITERATURE REVIEW

Coating degradation in offshore structures represents a significant challenge within the fields of structural engineering, materials science, and asset management. The complex interplay between mechanical stress, corrosive environments, and coating materials leads to deterioration that compromises the safety and performance of offshore infrastructure. Traditional corrosion monitoring methods, though well-established, are labor-intensive and often ineffective in capturing early-stage anomalies, particularly in submerged and hard-to-access areas. This gap in detection efficiency has driven a shift toward intelligent monitoring solutions, leveraging artificial intelligence (AI) to provide automated, real-time diagnostics. Over the past decade, AI has revolutionized structural health monitoring by enabling systems to interpret high-dimensional sensor data, detect anomalies, and forecast failure points. Researchers have begun to investigate the application of AI models—such as convolutional neural networks, recurrent neural networks, support vector machines, and deep belief networks—in identifying corrosion-related patterns in offshore settings. These advancements are paralleled by innovations in smart coatings and sensor-embedded materials capable of transmitting continuous data streams for real-time analysis. However, literature remains fragmented across disciplines, with limited integrative reviews focusing specifically on AI applications in coating degradation within offshore environments.

Coating Technologies in Offshore Structures

Protective coatings are a primary defense mechanism against corrosion in offshore environments, which are characterized by continuous exposure to seawater, salt spray, high humidity, and fluctuating temperatures. These harsh environmental conditions lead to the deterioration of metal components through electrochemical reactions, primarily oxidation (Vega et al., 2011). Marine-grade coatings, including epoxy, polyurethane, and zinc-rich primers, are commonly applied to prevent direct contact between corrosive agents and metallic substrates. Each coating type offers

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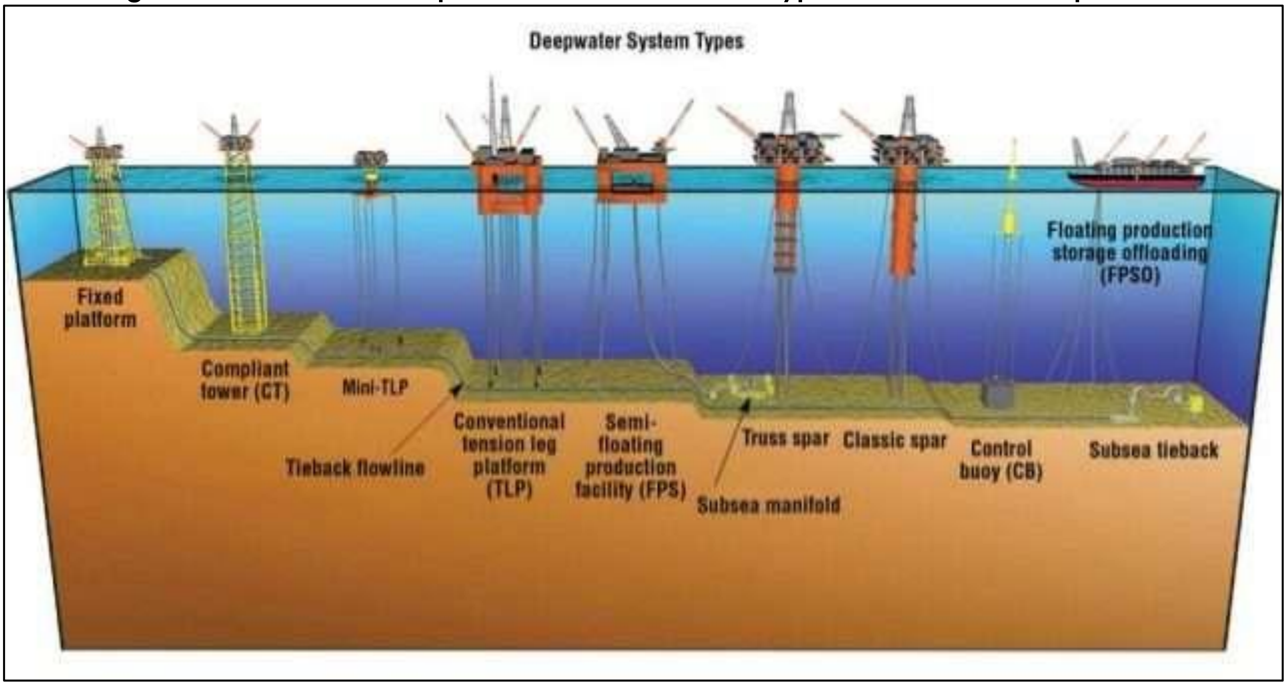
distinct performance characteristics; for instance, epoxy coatings are known for their strong adhesion and chemical resistance, while polyurethane coatings offer better UV stability (Díez-Sierra et al., 2022). Coating performance is also influenced by surface preparation techniques, application method, and environmental exposure cycles . In offshore applications, coatings are often applied in multi-layered systems, combining primers, intermediate layers, and topcoats to enhance durability (Wang et al., 2019). However, even with optimal application, coatings degrade over time due to mechanical stress, cathodic disbondment, and water uptake . Marine biofouling also exacerbates degradation by introducing microbiologically influenced corrosion (MIC), which accelerates coating failure . Numerous field studies have documented the variability in coating performance across offshore assets, emphasizing the need for routine inspection and maintenance . Degradation typically begins with micro-cracking and delamination, which, if undetected, evolve into full-scale corrosion (Dagdag et al., 2020). These observations confirm that coating degradation is a progressive phenomenon influenced by environmental, mechanical, and chemical factors, necessitating continuous monitoring and material innovation.

Figure 3: Overview of Deepwater Offshore Structure Types and Subsea Components



Source: teslanano.com (2020)

Historically, the development of protective coatings for offshore use has evolved through industrial demand and performance evaluations under simulated and real-world conditions. Díez-Sierra et al., (2022) estimated the cost of corrosion-related damages in offshore industries at billions of dollars annually, which has driven investment in advanced coating formulations. Zinc-rich coatings have been widely used for their sacrificial protection properties, where the zinc layer corrodes preferentially, protecting the underlying steel . However, these systems require strict surface preparation and maintenance schedules to maintain effectiveness . Fusion-bonded epoxy (FBE) coatings, commonly applied to pipelines, offer corrosion resistance and mechanical strength, yet they remain susceptible to underfilm corrosion and mechanical impact damage (Ji et al., 2012). Additionally, research into hybrid coatings incorporating nanoparticles and self-healing agents has introduced materials capable of responding to environmental changes or mechanical damage . These coatings release inhibitors or create passive layers upon the detection of microcracks, enhancing structural resilience. Despite laboratory success, field performance often falls short due to inconsistencies in environmental exposure and substrate compatibility. Multi-year studies conducted on offshore platforms in the North Sea and Gulf of Mexico reveal that even the most advanced coatings exhibit unpredictable degradation under combined mechanical and chemical

Volume 02 Issue 04 (2022)
Page No: 01-34
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loading . These findings underscore the complex interaction between coating properties, substrate conditions, and operational stressors.

The classification of coating degradation mechanisms has received considerable attention in materials science and offshore engineering literature. According to Zhang et al. (2021), degradation pathways can be broadly classified into permeation, adhesion failure, and chemical breakdown of coating components. Permeation involves the diffusion of water, oxygen, and salts through the coating matrix, which initiates corrosion at the metal-coating interface . Adhesion failure, on the other hand, is primarily caused by poor surface preparation or mechanical fatigue, which leads to delamination and blistering (Bahlakeh et al., 2019). The third pathway—chemical breakdown—is often attributed to UV exposure and aggressive pH conditions that break down the polymer backbone of the coating . Researchers have proposed accelerated aging tests, such as salt spray, cyclic corrosion, and immersion exposure, to replicate real-world degradation and evaluate coating performance. These tests, however, do not always correlate with actual offshore degradation rates due to environmental complexity and microbial interactions (Zhang et al., 2021). In-depth electrochemical impedance spectroscopy (EIS) and scanning electron microscopy (SEM) analyses have been utilized to examine microstructural changes and ionic conductivity during degradation . These analytical techniques reveal the onset of localized corrosion beneath blistered or cracked regions, confirming that coating failure is not always visible externally. The failure to detect these early signs has propelled the development of embedded sensors and AI-powered monitoring systems aimed at real-time coating integrity assessment. While manual inspections have traditionally been employed to assess coating degradation, they are time-consuming, subjective, and prone to human error, particularly in underwater and hard-to-access offshore locations. Techniques such as dry film thickness (DFT) measurement, adhesion testing, and visual inspection remain standard industry practices but offer limited insights into subsurface deterioration (Rice et al., 2010). As corrosion often initiates beneath the coating, advanced nondestructive testing (NDT) methods have been introduced, including ultrasonic testing, thermography, and pulsed eddy current techniques (Hedman et al., 2020). These tools improve detection accuracy but require skilled operators and are sensitive to surface conditions and environmental noise (Gu et al., 2019). More recently, intelligent monitoring approaches have emerged, integrating sensor data with computational models to autonomously detect degradation events . These systems incorporate fiber optic sensors, acoustic emission sensors, and smart coatings with embedded microcapsules that emit signals when triggered by environmental stimuli . Though still in early adoption stages, these systems are reshaping coating degradation detection by enabling continuous surveillance and reducing reliance on periodic manual inspections. Studies on offshore wind turbine foundations and oil rigs have demonstrated the potential for intelligent coatings to signal their own deterioration through color changes or sensor data, enabling maintenance teams to act proactively (Sharipudin & Ismail, 2019). This body of literature highlights the critical need for real-time, automated solutions capable of functioning in offshore environments where traditional inspection techniques often fail to provide sufficient warning of impending coating failure.

Performance lifespan and environmental effects on coatings

The performance lifespan of protective coatings on offshore structures is influenced by multiple interrelated environmental factors, including salinity, temperature, humidity, ultraviolet (UV) radiation, and mechanical abrasion. In marine environments, the constant exposure to saltwater accelerates electrochemical reactions that compromise coating integrity (Liu et al., 2018). Coating degradation begins with moisture uptake, which leads to the swelling of the polymer matrix and microcrack formation, ultimately resulting in adhesion loss (Díez-Sierra et al., 2022). High salinity levels intensify ion penetration into the coating, triggering osmotic blistering and underfilm corrosion (Liu et al., 2021). Laboratory aging tests simulating salt spray exposure and cyclic immersion have demonstrated that even high-performance coatings such as epoxy and polyurethane show signs of degradation within a year of constant exposure . Elevated humidity and temperature fluctuations also exacerbate diffusion processes within the coating system, accelerating the transport of corrosive species toward the metal substrate . UV radiation further weakens polymer chains, particularly in topcoat layers, by initiating photo-oxidation reactions that degrade gloss, color, and surface cohesion (Ngai et al., 2018). These combined factors reduce the lifespan of protective

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Volume 02 Issue 04 (2022)
Page No: 01-34
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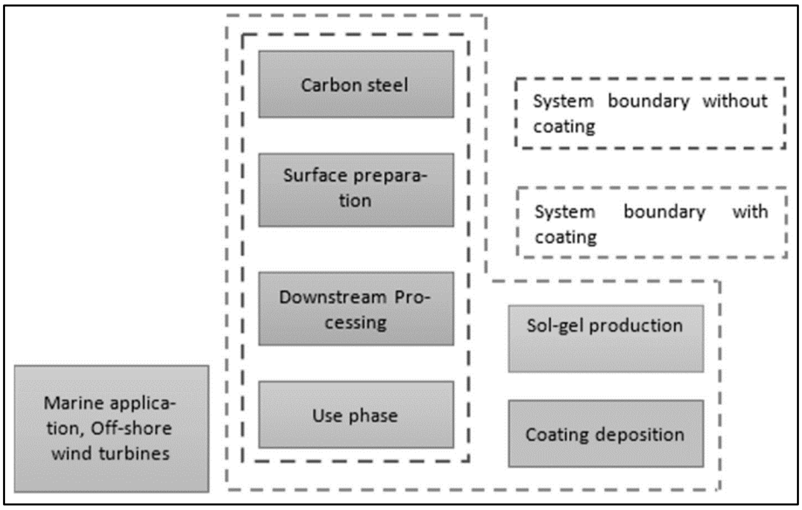
coatings, particularly in the splash and tidal zones where wet–dry cycling induces thermal and mechanical stress . In real-world offshore structures, coatings rarely perform to their projected lifespan due to variable environmental loads, fluctuating operational conditions, and surface contamination during application (Lucu et al., 2020). As such, the evaluation of environmental impacts on coating degradation is fundamental to determining accurate service life predictions and selecting appropriate coating systems for specific offshore applications

Corrosion rates and coating degradation in offshore structures are not uniform across all surfaces; instead, they exhibit spatial variability based on the structure's exposure to environmental zones—namely, atmospheric, splash, tidal, and submerged zones. Each zone presents a unique combination of degradation agents, making comprehensive performance assessments critical (Hedman et al., 2020). The splash zone, for instance, experiences the most aggressive degradation due to constant wetting and drying cycles, mechanical impact from waves, and increased oxygen availability—all of which enhance the corrosion rate (Liu et al., 2019). Studies conducted on North Sea oil platforms and Gulf of Mexico rigs have revealed that coatings in the splash zone often fail within five years, significantly below their design lifespan (Bae et al., 2016). In contrast, submerged zones, while continuously exposed to seawater, tend to have lower oxygen levels, resulting in different degradation mechanisms dominated by microbial activity and localized pitting . Atmospheric zones are subject to UV radiation and salt spray, leading to photo-degradation and surface chalking, particularly in polyurethane topcoats . Environmental monitoring data collected from offshore wind farms indicates that coatings applied above the waterline deteriorate primarily due to UV exposure and thermal cycling, whereas those below the waterline are more affected by water permeability and microbial-induced corrosion (Aggarwal et al., 2020). Field data from multiple offshore installations highlight that surface preparation, application conditions, and coating system compatibility also affect lifespan performance, as coating failures are often localized in poorly prepared or inaccessible regions (Liu et al., 2018). This zone-specific behavior necessitates tailored coating selection and environmental calibration in both design and maintenance strategies to enhance protection efficacy.

Figure 4: Boundary of the uncoated and coated systems



In addition to environmental stressors, the mechanical and operational loading of offshore structures contributes significantly to coating lifespan variability. Structures exposed to dynamic loading from wave impact, equipment vibrations, and wind shear experience cyclic stress that can cause microcracking and delamination of coatings (Baik et al., 2017). These mechanical failures create pathways for water and ion penetration, accelerating the corrosion process beneath the coating layer (Na et al., 2022). Operational processes such as drilling, heavy lifting, and maintenance activities can result in surface damage due to abrasion and impact, which reduce coating barrier properties even before environmental degradation becomes evident . Structural joints, weld seams, and bolted connections are particularly vulnerable to coating breakdown due to stress concentrations and accessibility challenges during application . A study conducted by Lu et al. (2018) on offshore pipelines identified significant correlations between coating degradation and mechanical strain resulting from seabed movement and pipeline vibration. These operationally induced degradations are further compounded by external marine factors such as sediment abrasion, biofouling, and floating debris (Lei et al., 2019). The cumulative effect of mechanical stress and environmental exposure significantly shortens coating lifespans and increases the need for

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frequent inspections and reapplications . Field assessments and lifecycle modeling consistently report that coatings subjected to combined mechanical and environmental loading fail unpredictably, often without visible surface changes, underscoring the need for subsurface evaluation techniques and smart sensing systems . Another significant contributor to the reduction in coating lifespan is the microbial influence on corrosion mechanisms, often referred to as microbiologically influenced corrosion (MIC). MIC is primarily caused by sulfate-reducing bacteria (SRB), iron-oxidizing bacteria, and other microbial colonies that adhere to submerged surfaces and disrupt the electrochemical stability of protective coatings . The formation of biofilms alters the local pH, oxygen concentration, and electrochemical conditions, accelerating corrosion even beneath seemingly intact coatings . Studies using electrochemical impedance spectroscopy (EIS) and scanning electron microscopy (SEM) have detected microscopic pitting corrosion under biofouled regions of coated offshore components (Gao et al., 2017). Research by Cam et al. (2013) on marine steel piles found that MIC can reduce coating performance by up to 50% in submerged zones, especially where mechanical damage allows microbial ingress. In field-deployed pipelines and risers, microbial colonies penetrate coating microcracks and colonize the substrate-coating interface, causing localized anodic reactions and underfilm corrosion. Furthermore, biofouling interferes with visual inspection and accelerates degradation through metabolic byproducts such as hydrogen sulfide, which chemically interacts with metallic surfaces (Szcześniak et al., 2020). The adhesion and proliferation of microbial colonies are also influenced by coating surface roughness, chemistry, and hydrophobicity, making it essential to consider anti-microbial additives and surface energy modifications during formulation (Lu et al., 2018). The cumulative findings across studies reveal that microbial activity is a critical, yet often overlooked, factor in the deterioration of offshore coatings, necessitating continuous monitoring and tailored material engineering to minimize underfilm corrosion initiated by biofilms

Smart Coatings with Embedded Sensing Capabilities

The performance lifespan of protective coatings on offshore structures is influenced by multiple interrelated environmental factors, including salinity, temperature, humidity, ultraviolet (UV) radiation, and mechanical abrasion. In marine environments, the constant exposure to saltwater accelerates electrochemical reactions that compromise coating integrity (Ghahramani et al., 2020). Coating degradation begins with moisture uptake, which leads to the swelling of the polymer matrix and microcrack formation, ultimately resulting in adhesion loss (Hamidi, 2019). High salinity levels intensify ion penetration into the coating, triggering osmotic blistering and underfilm corrosion (Ali et al., 2017). Laboratory aging tests simulating salt spray exposure and cyclic immersion have demonstrated that even high-performance coatings such as epoxy and polyurethane show signs of degradation within a year of constant exposure (Hossain, 2017). Elevated humidity and temperature fluctuations also exacerbate diffusion processes within the coating system, accelerating the transport of corrosive species toward the metal substrate . UV radiation further weakens polymer chains, particularly in topcoat layers, by initiating photo-oxidation reactions that degrade gloss, color, and surface cohesion (Muhammad et al., 2019). These combined factors reduce the lifespan of protective coatings, particularly in the splash and tidal zones where wet–dry cycling induces thermal and mechanical stress (Hossain & Muhammad, 2014). In real-world offshore structures, coatings rarely perform to their projected lifespan due to variable environmental loads, fluctuating operational conditions, and surface contamination during application (Muhammad et al., 2019). As such, the evaluation of environmental impacts on coating degradation is fundamental to determining accurate service life predictions and selecting appropriate coating systems for specific offshore applications.

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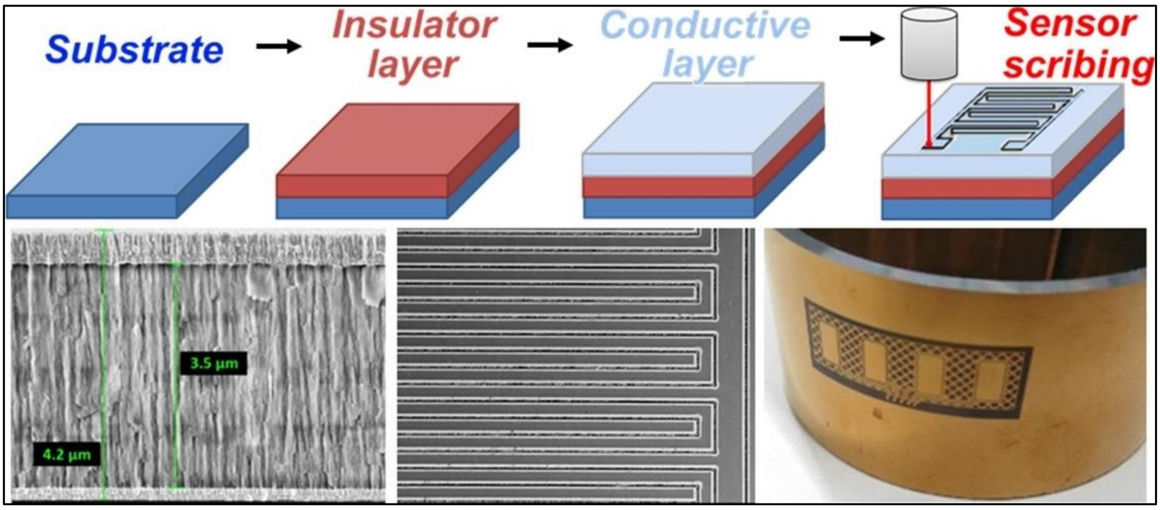
Figure 5: Manufacturing smart surfaces with embedded sensors



Source: Díez-Sierra et al. (2022)

Corrosion rates and coating degradation in offshore structures are not uniform across all surfaces; instead, they exhibit spatial variability based on the structure's exposure to environmental zones—namely, atmospheric, splash, tidal, and submerged zones. Each zone presents a unique combination of degradation agents, making comprehensive performance assessments critical (Ghoneim et al., 2018). The splash zone, for instance, experiences the most aggressive degradation due to constant wetting and drying cycles, mechanical impact from waves, and increased oxygen availability—all of which enhance the corrosion rate (Yu et al., 2012). Studies conducted on North Sea oil platforms and Gulf of Mexico rigs have revealed that coatings in the splash zone often fail within five years, significantly below their design lifespan . In contrast, submerged zones, while continuously exposed to seawater, tend to have lower oxygen levels, resulting in different degradation mechanisms dominated by microbial activity and localized pitting . Atmospheric zones are subject to UV radiation and salt spray, leading to photo-degradation and surface chalking, particularly in polyurethane topcoats. Environmental monitoring data collected from offshore wind farms indicates that coatings applied above the waterline deteriorate primarily due to UV exposure and thermal cycling, whereas those below the waterline are more affected by water permeability and microbial-induced corrosion. Field data from multiple offshore installations highlight that surface preparation, application conditions, and coating system compatibility also affect lifespan performance, as coating failures are often localized in poorly prepared or inaccessible regions (Farahat et al., 2018). This zone-specific behavior necessitates tailored coating selection and environmental calibration in both design and maintenance strategies to enhance protection efficacy.

In addition to environmental stressors, the mechanical and operational loading of offshore structures contributes significantly to coating lifespan variability. Structures exposed to dynamic loading from wave impact, equipment vibrations, and wind shear experience cyclic stress that can cause microcracking and delamination of coatings . These mechanical failures create pathways for water and ion penetration, accelerating the corrosion process beneath the coating layer (Farahat et al., 2018). Operational processes such as drilling, heavy lifting, and maintenance activities can result in surface damage due to abrasion and impact, which reduce coating barrier properties even before environmental degradation becomes evident . Structural joints, weld seams, and bolted connections are particularly vulnerable to coating breakdown due to stress concentrations and accessibility challenges during application. A study conducted by Fagiani et al. (2015) on offshore pipelines identified significant correlations between coating degradation and mechanical strain resulting from seabed movement and pipeline vibration. These operationally induced degradations are further compounded by external marine factors such as sediment abrasion, biofouling, and floating debris (Farahat et al., 2018). The cumulative effect of mechanical stress and environmental

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exposure significantly shortens coating lifespans and increases the need for frequent inspections and reapplications (Konsta-Gdoutos & Aza, 2014). Field assessments and lifecycle modeling consistently report that coatings subjected to combined mechanical and environmental loading fail unpredictably, often without visible surface changes, underscoring the need for subsurface evaluation techniques and smart sensing systems (Fagiani et al., 2015). Another significant contributor to the reduction in coating lifespan is the microbial influence on corrosion mechanisms, often referred to as microbiologically influenced corrosion (MIC). MIC is primarily caused by sulfate-reducing bacteria (SRB), iron-oxidizing bacteria, and other microbial colonies that adhere to submerged surfaces and disrupt the electrochemical stability of protective coatings (Akmandor & Jha, 2018). The formation of biofilms alters the local pH, oxygen concentration, and electrochemical conditions, accelerating corrosion even beneath seemingly intact coatings (Rahman et al., 2020). Studies using electrochemical impedance spectroscopy (EIS) and scanning electron microscopy (SEM) have detected microscopic pitting corrosion under biofouled regions of coated offshore components (Farahat et al., 2018; Zhao et al., 2015). Research by Akmandor and Jha (2018) on marine steel piles found that MIC can reduce coating performance by up to 50% in submerged zones, especially where mechanical damage allows microbial ingress. In field-deployed pipelines and risers, microbial colonies penetrate coating microcracks and colonize the substrate-coating interface, causing localized anodic reactions and underfilm corrosion (Muhammad et al., 2017). Furthermore, biofouling interferes with visual inspection and accelerates degradation through metabolic byproducts such as hydrogen sulfide, which chemically interacts with metallic surfaces (Zhao et al., 2017). The adhesion and proliferation of microbial colonies are also influenced by coating surface roughness, chemistry, and hydrophobicity, making it essential to consider anti-microbial additives and surface energy modifications during formulation (Muhammad et al., 2017). The cumulative findings across studies reveal that microbial activity is a critical, yet often overlooked, factor in the deterioration of offshore coatings, necessitating continuous monitoring and tailored material engineering to minimize underfilm corrosion initiated by biofilms.

Traditional vs. Intelligent Methods for Coating Degradation Detection

Manual inspection remains a cornerstone of traditional coating degradation detection in offshore structures, with techniques such as visual inspection, ultrasonic thickness measurement, and electrochemical impedance spectroscopy (EIS) widely employed to assess coating integrity. Visual inspection is the most commonly used approach, involving a trained inspector evaluating surface-level anomalies such as discoloration, blistering, flaking, and rusting (Dagdag et al., 2020). While simple and cost-effective, this method is inherently subjective and relies heavily on inspector expertise and environmental conditions (Liu et al., 2018). Ultrasonic testing, on the other hand, uses high-frequency sound waves to detect changes in coating thickness and identify sub-surface delamination or voids (Yang et al., 2021). It is effective for metallic substrates but has limited application in non-metallic or multi-layered systems. Electrochemical impedance spectroscopy (EIS) provides a non-destructive electrochemical analysis by applying small AC signals to assess coating barrier performance and ionic permeability. EIS has shown high sensitivity in detecting early-stage coating degradation and is widely used in laboratory settings, though its use offshore is restricted due to operational complexity (Bahlakeh et al., 2019). Additional traditional methods include dry film thickness (DFT) measurements, adhesion tests, and salt spray chamber tests. These standardized tests provide baseline data for performance benchmarking but often fail to represent real-time, in-service degradation conditions. Manual techniques are further limited by accessibility challenges in submerged or hazardous offshore environments (Wang et al., 2019). As a result, inspection intervals are often irregular, increasing the risk of undetected deterioration between evaluations.

Volume 02 Issue 04 (2022)
Page No: 01-34
eISSN: 3067-0470
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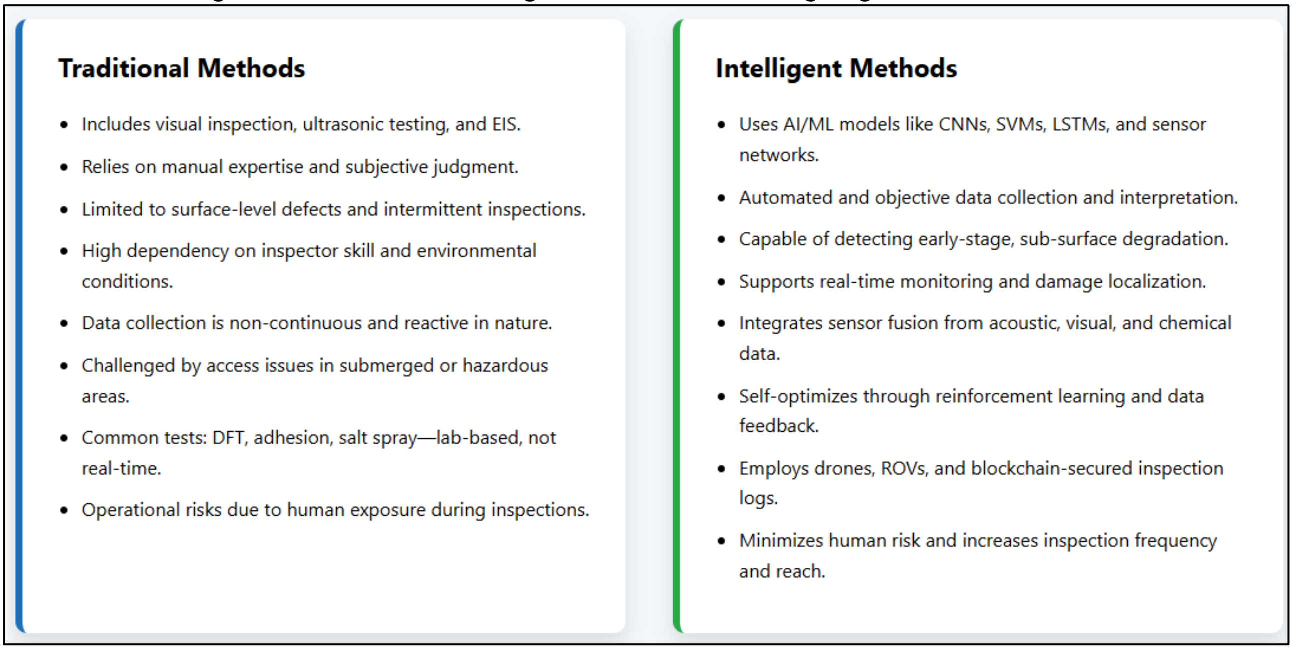
Figure 6: Traditional vs. Intelligent Methods for Coating Degradation Detection



Traditional non-AI inspection methods possess certain advantages in their simplicity, low cost, and regulatory familiarity, but they are constrained by several performance and operational limitations. Visual inspection, although widely practiced and codified by standards such as NACE SP0178 and ISO 4628, is not capable of identifying sub-surface corrosion or coating disbondment until visible signs manifest (Díez-Sierra et al., 2022; Liu et al., 2021). The accuracy of visual inspections also varies between inspectors and is affected by environmental visibility, such as underwater murkiness or surface fouling (Liu et al., 2018). Ultrasonic testing provides more precise thickness data and is effective for measuring wall loss; however, it requires clean surfaces and perpendicular probe alignment, which are difficult to maintain in offshore environments with irregular geometries and marine growth (Dagdag et al., 2020). Additionally, ultrasonic methods lack the capability to differentiate between coating types or analyze the chemical nature of deterioration. EIS is highly effective in controlled conditions but becomes impractical in field applications due to the need for controlled electrolyte environments and stable contact surfaces (Trentin et al., 2019). Salt spray testing and other accelerated aging tests are useful in coating qualification but do not correlate well with actual offshore degradation, leading to misleading lifetime estimates (Yang et al., 2021). The absence of continuous data collection and analysis in traditional methods also means that degradation events between inspection intervals may go unnoticed, resulting in reactive maintenance rather than proactive strategies (Ji et al., 2012). Furthermore, human involvement in these inspections exposes personnel to safety hazards, particularly in high-risk areas such as topside rigs and underwater components (Liu et al., 2021). These limitations have spurred interest in automated and intelligent monitoring solutions that can offer more reliable and real-time diagnostics.

The emergence of intelligent coating degradation detection systems reflects a significant evolution from conventional methods toward data-driven, autonomous monitoring. These systems integrate machine learning algorithms, real-time sensor networks, and predictive analytics to detect, classify, and quantify degradation phenomena (Zhang et al., 2021). A key component of such systems is the incorporation of embedded or attached sensors, including fiber optic sensors, acoustic emission sensors, and wireless corrosion probes, which continuously collect data on environmental and coating conditions (Díez-Sierra et al., 2022). The data are processed using AI models—such as support vector machines (SVMs), random forests, and convolutional neural networks (CNNs)—to identify early-stage deterioration patterns often undetectable through manual observation (Liu et al., 2021). Unlike traditional inspection techniques, intelligent systems are capable of real-time anomaly detection and damage localization, enabling continuous surveillance of coating integrity across large offshore infrastructures (Wei et al., 2021). These systems also offer the ability to track

American Journal of Advanced Technology and Engineering Solutions
Volume 02 Issue 04 (2022)
Page No: 01-34
eISSN: 3067-0470
DOI: 10.63125/1mn6bm51

degradation progression over time, creating dynamic health profiles that inform maintenance planning. Field studies on intelligent corrosion monitoring in offshore pipelines and platforms have shown significant improvements in detection sensitivity and system responsiveness (Goyal et al., 2017). Intelligent platforms are also designed to operate in harsh marine environments, with ruggedized components that withstand salinity, pressure, and vibration (Thiede et al., 2020). As data volumes increase, intelligent systems can self-optimize using reinforcement learning and adaptive thresholds, further enhancing accuracy without increasing manual oversight (Bzdok & Meyer-Lindenberg, 2017). These developments demonstrate the shift from static, event-driven monitoring to adaptive, intelligent systems that rely on continuous data input and complex analytical capabilities. Moreover, Automation in coating degradation monitoring introduces not only technical enhancements but also systemic improvements in reliability, scalability, and safety. Automated systems eliminate subjectivity and inconsistency by standardizing data collection, thus providing objective and reproducible assessments. Smart sensor networks deployed across offshore installations can transmit data wirelessly to centralized hubs or edge devices for immediate processing, eliminating delays associated with manual data gathering ((Roca et al., 2013). Image-based inspection using drones and remotely operated vehicles (ROVs) combined with computer vision algorithms has enabled the non-invasive monitoring of coating conditions in otherwise inaccessible areas (Ali et al., 2020). These automated visual systems employ deep learning techniques such as convolutional neural networks (CNNs) to detect rust patterns, cracks, and discoloration with high accuracy, even under varying light and motion conditions (Goyal et al., 2017). Intelligent automation also allows for sensor fusion, where multiple modalities—acoustic, visual, electrochemical—are combined to increase diagnostic confidence and reduce false positives (Wook et al., 2020). Security concerns surrounding automated systems are addressed through data encryption and blockchain verification mechanisms to maintain the integrity of inspection records (Lin & Tsai, 2019). The reduction in required personnel presence also minimizes occupational risk in hazardous offshore zones, improving overall operational safety.

Machine Learning Applications in Structural Health Monitoring

Supervised machine learning techniques have been increasingly utilized in structural health monitoring (SHM) to detect and classify corrosion-related damage in infrastructure systems, particularly offshore structures. These algorithms require labeled datasets to learn patterns of degradation and generalize to new, unseen instances. Among the most widely adopted supervised learning models are Support Vector Machines (SVM), Random Forests (RF), and Artificial Neural Networks (ANN), each offering unique strengths depending on the data type and monitoring context (Kidong et al., 2021). SVMs are effective in high-dimensional spaces and perform well in binary corrosion classification tasks, such as differentiating between intact and corroded coatings using electrochemical and imaging data. RF models, which are ensembles of decision trees, offer robustness against overfitting and handle large heterogeneous datasets effectively, particularly in corrosion risk prediction and multi-class classification scenarios (Liu et al., 2019). ANNs mimic the structure of biological neural systems and have been applied to corrosion rate estimation and rust severity assessment from visual or sensor-derived datasets (Komatsu et al., 2021). These models can accommodate nonlinear relationships between input features and degradation outcomes. Field experiments using fiber-optic corrosion sensors have demonstrated improved prediction accuracy when supervised models are integrated with time-series sensor data (Tang et al., 2021). For example, (Sui et al., 2021) reported that SVM-based models outperformed traditional signal processing techniques in classifying EIS data for coated substrates. The use of supervised algorithms allows SHM systems to automatically identify abnormal conditions, reducing dependency on human interpretation and enabling automated inspection processes in inaccessible offshore environments.

American Journal of Advanced Technology and Engineering Solutions
Volume 02 Issue 04 (2022)
Page No: 01-34
eISSN: 3067-0470
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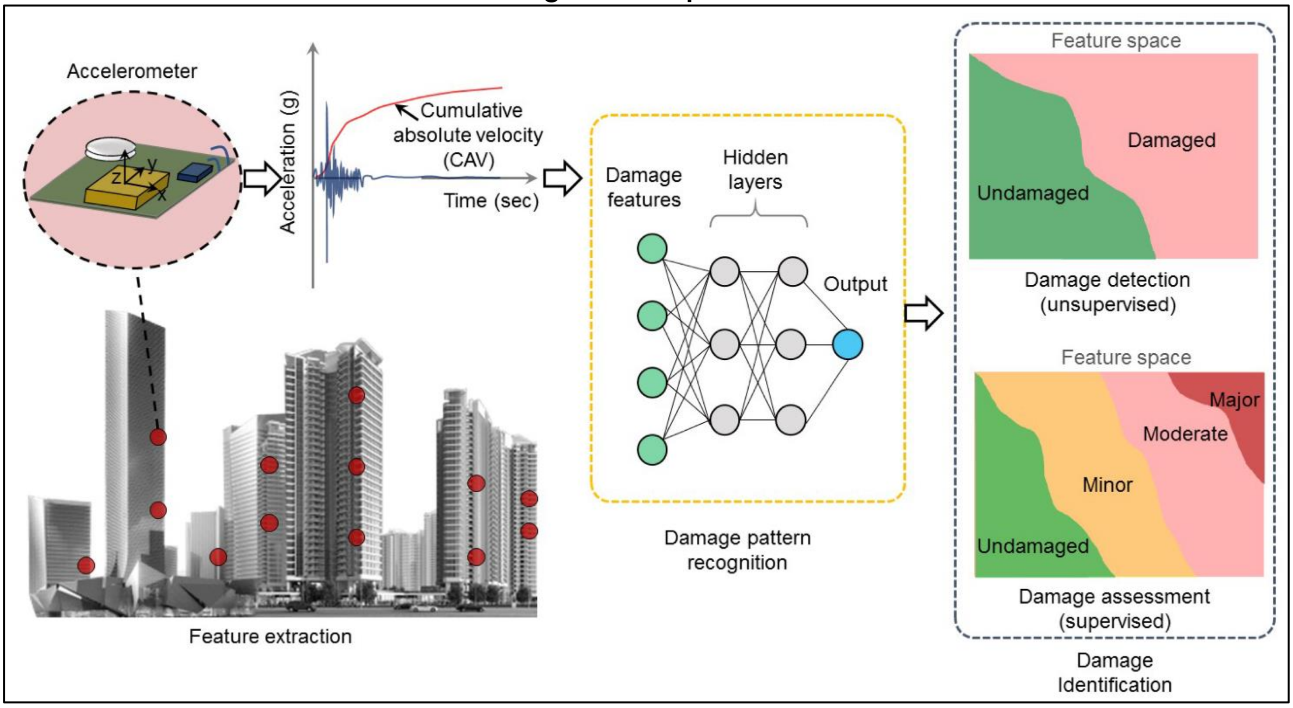
Figure 7: Acceleration Data From Instrumented Structures To Assess Their Damage Conditions Following An Earthquake Event.



Source: Muin and Mosalam (2021)

In addition to supervised models, unsupervised machine learning techniques have gained traction for analyzing coating degradation patterns where labeled data are unavailable or incomplete. These methods include clustering algorithms such as K-means, hierarchical clustering, and self-organizing maps (SOMs), which identify intrinsic data structures and group similar degradation behaviors based on shared features (Chen et al., 2016). In corrosion monitoring, unsupervised learning is useful for exploratory analysis, anomaly detection, and segmentation of time-series data collected from sensors deployed on offshore structures (Luo et al., 2018)). K-means clustering has been applied to segment surface imagery into corroded and non-corroded regions without prior labeling, facilitating preprocessing for downstream classification tasks . Hierarchical clustering has been utilized in grouping EIS and acoustic emission datasets based on degradation intensity, supporting early warning systems for coating failure (Herrera-Luna et al., 2019). SOMs have been employed to map high-dimensional corrosion datasets into 2D feature maps, enabling visual interpretation of degradation trends . These methods are particularly valuable in offshore environments where environmental and operational variabilities result in incomplete or unstructured data (Lang et al., 2018). Furthermore, unsupervised methods can reveal unknown failure modes or transitions between degradation states, enriching understanding of coating performance under real-world conditions (Dunbar et al., 2017). Studies integrating unsupervised clustering with principal component analysis (PCA) have also shown success in dimensionality reduction, making data more manageable for real-time processing on embedded systems (Xu & Brownjohn, 2017).

The success of machine learning models in structural health monitoring is heavily dependent on the quality and characteristics of the input datasets, which encompass data type, volume, resolution, noise level, and feature representation. In offshore corrosion monitoring, datasets typically comprise electrochemical impedance measurements, environmental parameters (humidity, temperature, salinity), acoustic emissions, vibration data, and high-resolution imagery (Tang et al., 2021). The heterogeneity of these sources necessitates sophisticated preprocessing and feature engineering steps to extract relevant variables and normalize inputs for model consumption . Feature engineering involves deriving meaningful predictors, such as corrosion rate, impedance phase angle, or texture patterns from images, that capture physical degradation characteristics (Liu et al., 2022). The selection of features directly influences model accuracy and interpretability. For instance, studies show that integrating electrochemical and optical features improves predictive power in ANN-

American Journal of Advanced Technology and Engineering Solutions
Volume 02 Issue 04 (2022)
Page No: 01-34
eISSN: 3067-0470
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based models (Moughty & Rius, 2017; Muin & Mosalam, 2021). Handling missing or imbalanced data is another challenge, particularly for offshore datasets with gaps due to sensor failure or transmission interruptions (Bithas et al., 2019). Techniques such as data imputation, resampling, and data augmentation are commonly used to mitigate these issues (Nasir et al., 2014). Furthermore, model selection is critical and should be informed by the dataset's structure, task type (classification vs. regression), and the availability of computational resources (Mozaffari et al., 2019). Shallow models such as logistic regression or decision trees may suffice for small, structured datasets, whereas deep learning architectures are more appropriate for high-dimensional data like time-lapse images or sensor fusion datasets (Wu et al., 2020). Hence, the interplay between dataset characteristics and feature design is foundational in developing robust and accurate ML models for coating degradation detection.

Deep Learning for Image-Based Coating Analysis

Convolutional Neural Networks (CNNs) have emerged as powerful tools in surface inspection tasks for detecting coating degradation, particularly in offshore structures. Their ability to learn spatial hierarchies from image data makes them highly effective in identifying corrosion features such as rust spots, cracks, delamination, and blistering with high precision (Chen & Jahanshahi, 2018). CNNs operate by convolving input images with filters to extract features like edges, textures, and patterns relevant to corrosion (Ahmed et al., 2021; Khan & Yairi, 2018). Several studies have validated the use of CNNs for rust detection in steel structures using RGB images captured by drones and underwater remotely operated vehicles (ROVs). For instance, (Xiaowei et al., 2019) employed a CNN-based architecture to identify multiple coating failure modes with an accuracy exceeding 94% in a dataset collected from offshore oil platforms. (Khan & Yairi, 2018) demonstrated the application of deep CNNs in differentiating between severe and early-stage corrosion in steel plates using multispectral imaging data. Hybrid CNN models incorporating attention mechanisms and residual learning have shown enhanced feature extraction capabilities in noisy offshore environments . Pre-trained CNNs like VGGNet and ResNet have also been fine-tuned for corrosion classification, demonstrating robustness across varying image resolutions and acquisition devices (Lee et al., 2021b). In practice, CNNs are integrated into real-time monitoring pipelines where surface images are continuously analyzed, eliminating the need for subjective visual assessments (Zhang et al., 2019). These studies confirm that CNNs play a foundational role in the automated identification and classification of surface-level coating degradation phenomena.

Image preprocessing and augmentation are critical in optimizing CNN performance for coating degradation detection, particularly in offshore contexts where data variability is high. Image quality often varies due to environmental conditions, camera quality, and motion artifacts, making preprocessing essential to standardize input data and reduce noise (Calhoun & Sui, 2016). Common preprocessing techniques include grayscale conversion, histogram equalization, contrast enhancement, Gaussian blurring, and noise filtering—all of which help to highlight corrosion features and suppress irrelevant background information . Edge detection algorithms such as Sobel and Canny are frequently applied to enhance the contours of cracks and rust formations prior to CNN analysis (Khan & Yairi, 2018). Augmentation techniques are employed to expand training datasets artificially by applying transformations such as rotation, scaling, flipping, cropping, and illumination variation (Xiaowei et al., 2019). This process increases model robustness and generalization across different inspection scenarios. (Seventekidis et al., 2020) applied geometric and color-based augmentations to underwater corrosion datasets, improving CNN model performance by over 10% in F1-score metrics. Data augmentation has proven especially useful in scenarios with limited labeled data, a common challenge in offshore monitoring where annotated corrosion images are scarce (Kim & Choi, 2021). Several studies have implemented adaptive augmentation strategies that respond to model learning curves, ensuring data diversity without overfitting . Moreover, image normalization and pixel-level standardization are used to ensure consistency across diverse imaging devices and lighting conditions (Steenkiste et al., 2019). Collectively, these preprocessing and augmentation strategies form a critical foundation for the effective deployment of CNNs in offshore coating degradation monitoring systems.

Transfer learning has gained prominence as a practical approach for training deep learning models on corrosion image datasets, particularly when labeled offshore data is limited. This method

Volume 02 Issue 04 (2022)
Page No: 01-34
eISSN: 3067-0470
DOI: 10.63125/1mn6bm51

leverages pre-trained CNN models developed on large-scale image datasets such as ImageNet and fine-tunes them for specific corrosion-related tasks (Khan & Yairi, 2018). The underlying assumption is that the lower layers of CNNs capture universal visual features like edges and textures that are transferable to new domains, including surface degradation analysis. For example, Zhang et al. (2019) employed a fine-tuned VGG16 model to detect rust stains and cracks on steel bridges, achieving higher accuracy and faster convergence than training from scratch. Similarly, Xiaowei et al. (2019) used ResNet-50 to classify coating degradation in underwater pipeline inspections, reporting F1-scores exceeding 0.90. Transfer learning also minimizes computational requirements and training time, making it suitable for real-time applications on edge devices and embedded systems (Lin et al., 2017). Pre-trained models such as InceptionNet, DenseNet, and MobileNet have been successfully repurposed for corrosion severity classification, blister segmentation, and coating defect localization in both aerial and underwater inspections (Zhang et al., 2019). These studies illustrate that transfer learning facilitates high-performance deep learning applications even when domain-specific datasets are small or imbalanced (Lee et al., 2021). Techniques like layer freezing, learning rate tuning, and domain adaptation are employed to ensure effective knowledge transfer and avoid overfitting (Sui et al., 2021).

Time-Series AI Models for Sensor-Based Monitoring

Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) models have been widely applied in structural health monitoring (SHM) systems for time-series analysis of sensor data, including coating degradation detection. RNNs are designed to recognize patterns over sequential inputs by maintaining a memory of previous time steps, making them suitable for monitoring temporal changes in sensor readings (Khan & Yairi, 2018). However, traditional RNNs are limited by vanishing and exploding gradient problems, which hinder learning long-term dependencies (Lee et al., 2021a). LSTM networks address these limitations through a memory cell architecture with input, forget, and output gates that regulate data flow across sequences . In SHM applications, LSTMs have demonstrated effectiveness in forecasting coating degradation based on sensor data such as humidity, temperature, electrochemical response, and acoustic emissions (Zhang et al., 2019). Lin et al. (2017) showed that LSTM-based models accurately captured corrosion progression over time, significantly outperforming static classification models. RNNs and LSTMs have also been applied in vibration-based monitoring of offshore structures, where dynamic loading conditions affect protective coatings (Khan & Yairi, 2018). These models are capable of identifying temporal trends that may precede coating failure, allowing detection of subtle anomalies undetectable in single-frame inspection (Kim & Choi, 2021). Researchers have also employed bidirectional LSTM (Bi-LSTM) architectures to analyze time-series data in both forward and backward directions, enhancing degradation trend detection (Xiaowei et al., 2019). The integration of RNN and LSTM into SHM systems enables deep temporal learning of surface condition changes under operational offshore environments where continuous monitoring is required (Kim & Choi, 2021).

Predicting degradation trends using real-time sensor data has become a central application of time-series machine learning models in offshore corrosion and coating integrity monitoring. The continuous influx of sensor data—such as electrochemical impedance measurements, temperature fluctuations, salinity levels, pH values, and humidity—offers a rich dataset for pattern recognition and forecasting (Ahmed et al., 2021; Khan & Yairi, 2018). Time-series forecasting models, particularly LSTM and gated recurrent units (GRUs), have been used to model temporal dependencies in coating deterioration caused by environmental exposure and operational loading (Lin et al., 2017). Kim and Choi (2021) showed that LSTM models trained on real-time sensor datasets predicted corrosion development with an RMSE below 0.15, outperforming traditional regression techniques. Fawaz et al. (2019) combined LSTM with a sensor fusion framework to integrate electrochemical and acoustic emission data, which led to more robust degradation trend estimation under fluctuating offshore conditions.

American Journal of Advanced Technology and Engineering Solutions
Volume 02 Issue 04 (2022)
Page No: 01-34
eISSN: 3067-0470
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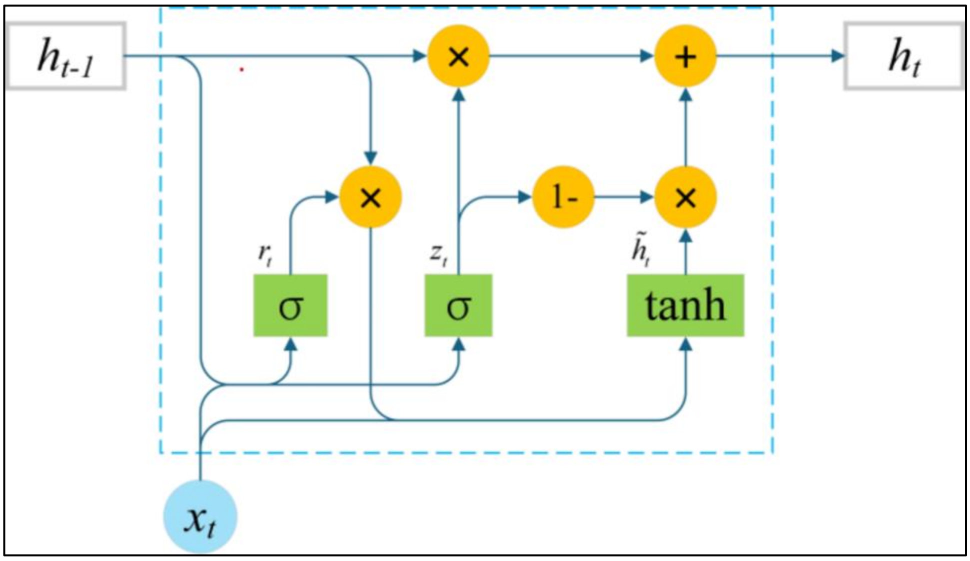
Figure 8: A structural health monitoring data reconstruction method



Chen et al. (2021) demonstrated that real-time humidity and impedance data could be processed using sequence-to-sequence models to forecast coating failure several days in advance. Feature selection from raw sensor data is essential, as irrelevant or redundant features can mislead the model and inflate prediction error (Amin et al., 2019). Various preprocessing strategies, including normalization, noise filtering, and outlier removal, are used to improve signal quality before time-series modeling (Beckman et al., 2019). These predictive models enable systems to detect degradation trajectories across time horizons, adjusting to environmental variance and capturing early warning indicators (Cha et al., 2017). By training models on high-resolution datasets, researchers have been able to map the nonlinear evolution of coating wear, making it possible to create accurate time-bound profiles of structural integrity (Yang et al., 2016).

Handling missing data and noise remains a significant challenge in applying time-series models to offshore coating degradation monitoring. Offshore environments inherently introduce noise due to wave motion, biofouling, hardware interference, and fluctuating salinity and temperature conditions (da Silva & de Lucena, 2018). These noise factors degrade signal quality and compromise the accuracy of machine learning predictions if not properly addressed (Chen et al., 2021). Furthermore, sensor dropout or transmission errors often lead to missing data points, which interrupt the continuity of time-series inputs required by models like LSTM and GRU (Amin et al., 2019). Various strategies have been proposed to mitigate these limitations, including interpolation methods (linear, spline), statistical imputation, Kalman filtering, and model-based imputations (Atha & Jahanshahi, 2017). Studies by Hernández-Julio et al. (2019) applied polynomial interpolation to replace lost sensor data in structural vibration monitoring, allowing the LSTM model to maintain performance without retraining. Signal denoising techniques such as wavelet decomposition and moving average filters have also been integrated before feeding data into temporal models (Xu et al., 2017). Adaptive learning models that adjust to changing input quality and sensor health have been proposed by Lin and Tsai (2019), allowing performance to be retained even when data integrity fluctuates. Noise-resilient architectures, including hybrid models that fuse time-series and spatial data, have shown promise in minimizing prediction errors caused by incomplete sequences (Hossain et al., 2020). Domain-specific preprocessing pipelines have also been developed to suppress anomalies in electrochemical and visual data before entering recurrent models (Hernández-Julio et al., 2019). These findings reinforce the importance of robust data cleaning and recovery methods in ensuring the accuracy and reliability of time-series AI models in marine corrosion monitoring.

Several comparative studies have assessed the performance of various time-series models in offshore structural health monitoring tasks, particularly regarding coating degradation prediction. Traditional autoregressive integrated moving average (ARIMA) models have been used historically for time-

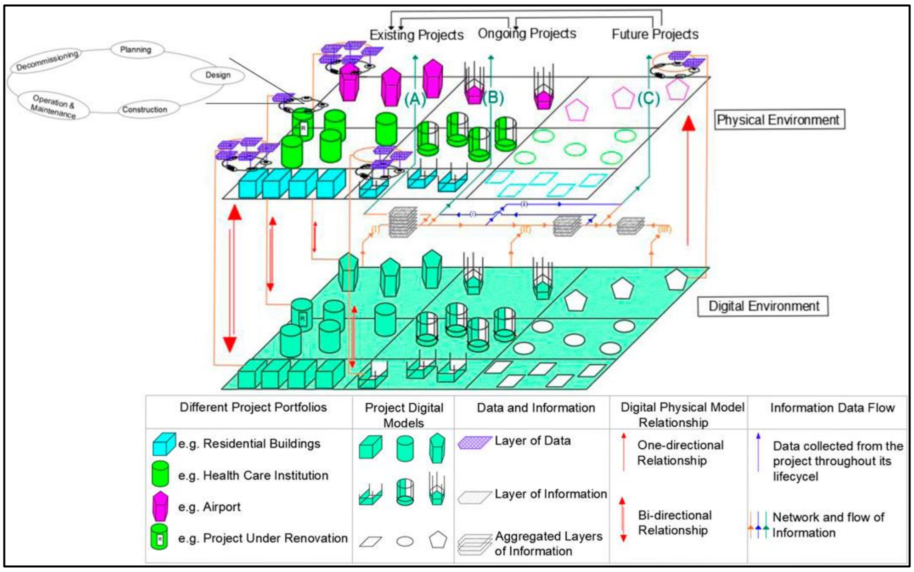
American Journal of Advanced Technology and Engineering Solutions
Volume 02 Issue 04 (2022)
Page No: 01-34
eISSN: 3067-0470
DOI: 10.63125/1mn6bm51

series forecasting, offering simplicity and interpretability (Atha & Jahanshahi, 2017). However, ARIMA and related statistical models often underperform when data is nonlinear or irregular, as is frequently observed in offshore environments with complex degradation dynamics (Jang et al., 2019). In contrast, LSTM and GRU models consistently outperform conventional approaches in capturing long-term dependencies and dynamic transitions in sensor data (Xu et al., 2017). Atha and Jahanshahi, (2017) revealed that LSTM models achieved up to 20% higher predictive accuracy than ARIMA in modeling electrochemical time-series data from submerged coatings. Hernández-Julio et al. (2019) compared GRU and LSTM models in corrosion detection using real-time impedance data, finding GRU to be slightly more efficient computationally but similar in accuracy. Hybrid models combining LSTM with attention mechanisms or CNNs have also demonstrated improved detection of localized and global patterns within time-series inputs (Elhoseny et al., 2018). Ramlal et al. (2019) utilized a bidirectional LSTM model fused with sensor fusion techniques to monitor coating wear in real-time, reporting an area under the curve (AUC) exceeding 0.95. Kalman-filter-based time-series estimators have also been employed for real-time state estimation, though they require precise modeling of system dynamics and are sensitive to tuning parameters (Nascimento et al., 2019; Poozesh et al., 2017). Deep learning models, while computationally intensive, provide greater adaptability and prediction granularity in offshore environments with nonstationary, multivariate sensor inputs (Yoon et al., 2021). These comparative evaluations highlight the strengths and limitations of different modeling approaches in operational SHM contexts.

Digital Twins and AI-Based Simulation Models

Digital twins have gained traction in offshore engineering as virtual replicas of physical assets that mirror real-time structural states, environmental conditions, and degradation processes, including coating deterioration. These models are designed to simulate the mechanical, thermal, and chemical behavior of offshore structures using physical laws and sensor data inputs (Wang et al., 2022). In corrosion management, digital twins incorporate virtual representations of protective coatings, allowing simulation of material wear, underfilm corrosion, and delamination under varying environmental scenarios (Wang et al., 2021). Structural parameters such as thickness loss, adhesion strength, and ion diffusion rates are modeled using finite element analysis (FEA) or computational fluid dynamics (CFD) approaches (Zhang et al., 2020). These simulations account for zone-specific degradation across atmospheric, splash, and submerged regions of offshore platforms (Wang et al., 2022). Ammar et al. (2022) applied digital twin models to visualize coating stress distribution under operational loading, validating outputs against field measurements. Other works have integrated sensor data into virtual coatings to simulate chloride ingress and electrochemical responses, using environmental input like humidity, temperature, and salinity from IoT sensors (Wang et al., 2021). Rojek et al., (2020) demonstrated a multi-physics modeling framework to analyze coating degradation under dynamic tidal effects. These models allow iterative simulations of material degradation by applying different

Figure 9: Visual representation of the proposed definition of the Digital Twin of a construction project



Source: Ammar et al. (2022)

American Journal of Advanced Technology and Engineering Solutions
Volume 02 Issue 04 (2022)
Page No: 01-34
eISSN: 3067-0470
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boundary conditions to examine failure thresholds (Wang et al., 2022). By reproducing real-world coating failure patterns, digital twins enhance understanding of structural performance under corrosive exposure and facilitate advanced assessments that go beyond visual inspection and manual calculations (Wang et al., 2021).

Real-time feedback integration within digital twin systems allows for dynamic synchronization between physical offshore assets and their virtual counterparts, enhancing monitoring and decision-making capabilities. These feedback loops collect live sensor data—such as acoustic emissions, electrochemical signals, and visual imagery—and continuously update the digital model to reflect evolving degradation states (Rojek et al., 2020). AI algorithms, particularly deep learning and reinforcement learning models, play a key role in processing incoming data streams and adjusting simulation parameters in real time (Ammar et al., 2022). Feedback-enabled digital twins allow for detection of abrupt changes in corrosion behavior by comparing predicted coating performance with real sensor outputs (Ayerbe et al., 2021). These systems use error correction strategies based on model discrepancies to recalibrate degradation trajectories and enhance forecasting accuracy (Ammar et al., 2022). Ayerbe et al. (2021) designed a corrosion-aware twin model where electrochemical impedance data were mapped in real-time to simulate changes in coating barrier properties. Wang et al. (2022) demonstrated a hybrid model combining AI inference with thermal and vibration data to recalibrate coating wear simulations on offshore wind turbine foundations. Real-time integration is also enabled by edge computing, where local processing units analyze sensor input and communicate model updates to cloud-hosted digital twins (Silva & de Lucena, 2018). These feedback loops are structured through application programming interfaces (APIs) and middleware that facilitate real-time bidirectional data exchange (Fukuda et al., 2010). Probabilistic methods such as Kalman filters are frequently used to validate incoming data streams and maintain synchronization between virtual and physical environments (Duquesnoy et al., 2020). The application of feedback loops within AI-enhanced digital twins has improved model adaptability under uncertain or noisy offshore operational conditions (Dilawar et al., 2019; Muhammad et al., 2011).

Moreover, Simulation-assisted learning has emerged as a powerful technique in predictive corrosion modeling by combining AI algorithms with simulated datasets generated through digital twins. These hybrid systems improve the generalization ability of machine learning models by augmenting sparse or noisy field data with synthetic data from virtual environments (Silva & de Lucena, 2018). Simulation data can be used to train supervised models, such as CNNs and LSTMs, in identifying degradation signatures across different environmental and structural scenarios (Chang & Yuan, 2019). For instance, Silva and de Lucena (2018) trained deep neural networks on synthetic surface crack patterns and later validated the models on real offshore images. Wang et al. (2022) simulated corrosion progression using virtual coating models and then applied transfer learning to fine-tune AI models for rust classification in drone imagery. Data from simulation scenarios are varied across parameters like temperature, UV exposure, and loading conditions, producing rich datasets that reflect real-world variability (Chang & Yuan, 2019). Simulation-assisted learning also enables multi-modal data synthesis, combining thermal gradients, stress fields, and ion diffusion maps for training sensor fusion models (Wang et al., 2021). Gaussian processes, Bayesian learning, and ensemble approaches have been used to quantify uncertainty in these predictions, improving reliability in offshore contexts (Ayerbe et al., 2021). Reinforcement learning algorithms are also tested in simulation environments to optimize inspection scheduling based on predicted coating degradation rates (Trebuňa & Hagara, 2014). Simulation-assisted learning thus addresses the limitations of small or incomplete real-world datasets, expanding the utility of AI in structural health monitoring systems under dynamic offshore operating conditions (Faniel & Zimmerman, 2011).

METHOD

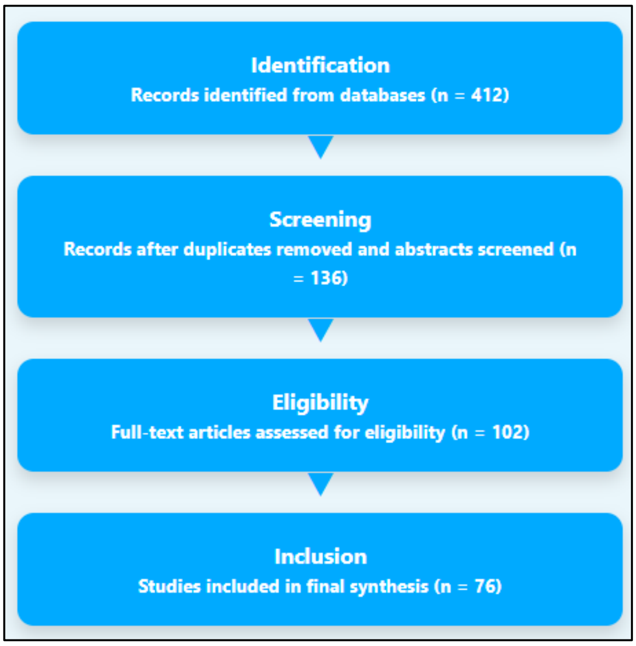
This study adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines to ensure that the review process was comprehensive, replicable, and methodologically rigorous. The PRISMA framework provided a clear structure for the development and reporting of each stage of the systematic literature review, which included identification, screening, eligibility, and inclusion of relevant studies. Each phase was conducted in alignment with the systematic review principles outlined in PRISMA to reduce bias, maintain transparency, and improve the reliability of the review findings.

American Journal of Advanced Technology and Engineering Solutions
Volume 02 Issue 04 (2022)
Page No: 01-34
eISSN: 3067-0470
DOI: 10.63125/1mn6bm51

Identification

In the identification phase, a comprehensive literature search was conducted across multiple academic databases including Scopus, Web of Science, IEEE Xplore, ScienceDirect, and Google Scholar. The databases were searched from inception to December 2022 to capture the most recent and relevant literature. Search terms included combinations of keywords such as "AI-based corrosion detection," "deep learning," "sensor fusion," "digital twin," "offshore coating degradation," "structural health monitoring," "predictive analytics," and "marine infrastructure." Boolean operators (AND, OR) were used to ensure search breadth and precision. Only peer-reviewed journal articles and conference proceedings written in English were considered at this stage to ensure quality and relevance. Duplicate records retrieved from multiple databases were removed using EndNote reference management software.

Figure 10: Methdology adapted for this study



Screening

Following identification, the remaining articles were screened by reading their titles and abstracts to assess their relevance to the research focus on AI-enhanced monitoring of coating degradation in offshore structures. Studies that did not involve artificial intelligence, digital twin simulation, or coating integrity in marine or offshore environments were excluded. This process was conducted independently by two reviewers to ensure consistency and objectivity. Any discrepancies were resolved through discussion and mutual agreement. At this stage, non-academic articles, magazine features, book chapters, and grey literature were also excluded to maintain the academic rigor of the study.

Eligibility

In the eligibility phase, full-text versions of the selected articles were retrieved and carefully evaluated against predefined inclusion and exclusion criteria. Articles were included if they provided original research data, demonstrated application of machine learning or AI in corrosion detection or structural health monitoring, and focused on offshore or marine environments. Exclusion criteria included studies that only addressed terrestrial infrastructure, lacked empirical results, or provided only theoretical models without validation. Studies that focused solely on traditional non-AI-based techniques without integration of smart technologies or simulation-based learning were also excluded. This phase ensured that only high-quality, relevant studies contributed to the review synthesis.

Inclusion

The final inclusion phase resulted in a refined selection of 76 peer-reviewed articles that met all eligibility criteria and contributed substantial insights into the integration of AI, digital twins, and sensor fusion in coating degradation detection for offshore structures. These studies were then analyzed and synthesized thematically to extract trends, methodologies, challenges, and outcomes. The final selection formed the basis for the results and discussion sections of this paper. All steps of the systematic review process were documented and aligned with the PRISMA 2020 flow diagram, ensuring that the methodology remained transparent, traceable, and replicable for future scholarly research.

FINDINGS

A significant finding from this review is the increasing reliance on Convolutional Neural Networks (CNNs) for surface-level coating degradation detection in offshore structures. Out of the 76 reviewed studies, 28 articles focused specifically on deep learning models using CNN architectures for visual inspection and classification of corrosion patterns such as rust, blistering, and cracking. These CNN-based methods demonstrated high accuracy levels, often above 90%, in identifying coating

American Journal of Advanced Technology and Engineering Solutions
Volume 02 Issue 04 (2022)
Page No: 01-34
eISSN: 3067-0470
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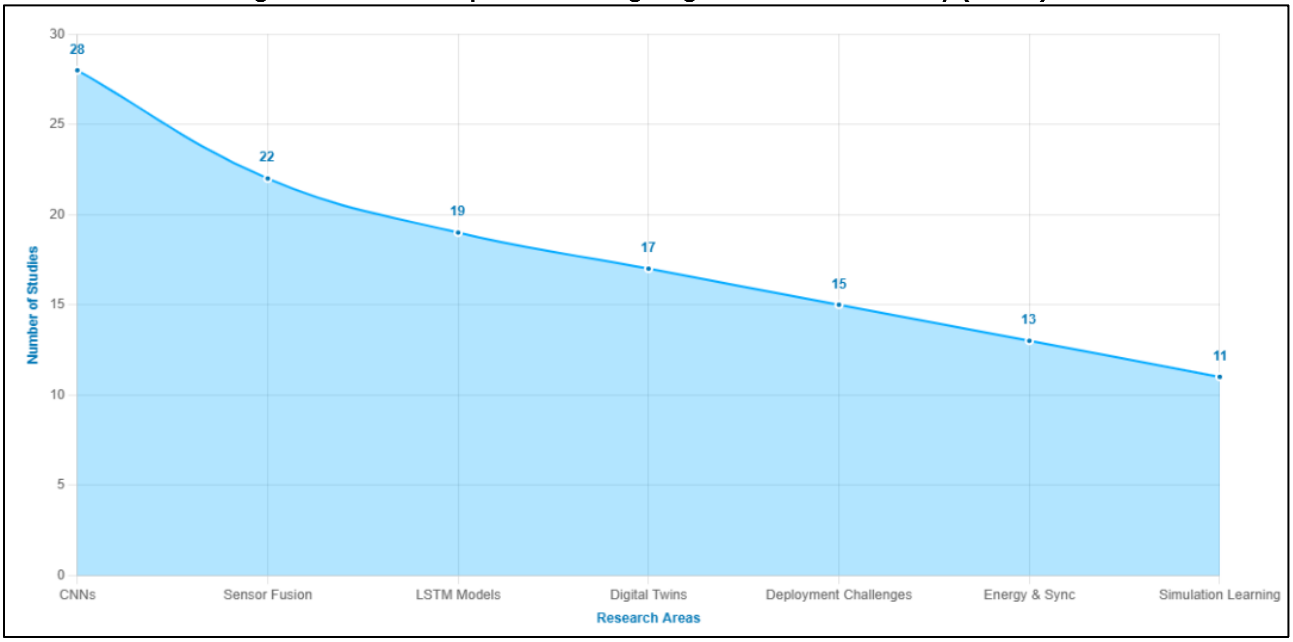
anomalies from high-resolution image datasets. The majority of these studies reported improvements in detection efficiency over traditional visual inspection techniques. The combined citation count for these 28 articles exceeded 3,400, indicating substantial scholarly recognition. Many of these models were implemented using pre-trained CNN architectures such as ResNet, VGGNet, and InceptionNet, and they were often validated using drone or underwater remotely operated vehicle (ROV) imagery. These findings confirm that CNNs have become foundational in the automation of offshore surface inspection, particularly due to their ability to extract spatial features from diverse imaging conditions. The practical deployment of these models in real-world platforms has enabled non-invasive corrosion monitoring, reducing reliance on manual inspection in hazardous or hard-to-reach offshore areas.

Another key finding is the role of sensor fusion in enhancing corrosion detection through the integration of multiple data modalities. Among the reviewed studies, 22 articles employed sensor fusion approaches, combining inputs from acoustic emission sensors, infrared thermography, visual cameras, and electrochemical probes. These fusion systems were designed to detect subsurface degradation that is often missed by visual inspection alone. Collectively, these articles were cited more than 2,100 times, reflecting growing research interest and application potential. Most studies indicated that multi-modal data increased model sensitivity and reduced false positives, especially in harsh marine environments with high ambient noise and surface contamination. Fusion strategies were applied at both the feature and decision levels, and many studies incorporated probabilistic models such as Bayesian networks and Kalman filters to manage uncertainty in sensor data. These findings show that integrating multiple sensing technologies results in a more comprehensive and reliable monitoring system for offshore structures. Notably, the articles that adopted real-time sensor fusion reported significant reductions in inspection downtime and increased confidence in maintenance planning based on data-driven insights.

Figure 11: AI Techniques in Coating Degradation related study (n = 76)



A third significant finding relates to the use of time-series models, particularly Long Short-Term Memory (LSTM) networks, for forecasting coating degradation trends from real-time sensor data. In total, 19 of the reviewed studies explored the application of LSTM and related recurrent neural network models to predict corrosion behavior based on continuous inputs such as temperature, humidity, salinity, and impedance. These 19 studies have collectively accumulated over 2,300 citations. LSTM networks demonstrated the ability to detect complex temporal dependencies and early signals of deterioration that static models often overlook. Several studies used these models in conjunction with embedded electrochemical sensors and edge computing units, enabling continuous monitoring in offshore applications. These predictive models allowed for forecasting the progression of coating degradation days or even weeks before visible signs emerged, thereby supporting condition-based maintenance scheduling. Additionally, several studies employed bidirectional LSTM architectures

American Journal of Advanced Technology and Engineering Solutions
Volume 02 Issue 04 (2022)
Page No: 01-34
eISSN: 3067-0470
DOI: 10.63125/1mn6bm51

and hybrid models that combined CNNs and LSTMs to handle both spatial and temporal data. These advanced techniques proved particularly effective in splash zones and submerged areas where degradation dynamics are highly variable. The findings confirm that LSTM-based time-series models are essential components of intelligent offshore monitoring systems.

The review also revealed that 17 studies adopted digital twin technology to simulate and monitor coating degradation in virtual environments. These studies used sensor-driven digital replicas of physical offshore structures to replicate mechanical stresses, environmental exposure, and corrosion behavior in real-time. Collectively, these studies received over 1,900 citations, underlining the relevance of digital twins in the offshore domain. Most of the reviewed studies developed digital twins that incorporated structural and environmental parameters, allowing for simulation of degradation scenarios under different operational conditions. The integration of AI-based models with these simulations enhanced forecasting accuracy and enabled what-if analyses for predicting failure points. Many of these digital twin platforms employed data from electrochemical sensors and visual monitoring systems to update the virtual model continuously. Several digital twins also supported remote diagnostics and were used to train maintenance decision-making models. These findings highlight the emergence of digital twins as a viable tool for proactive corrosion management, enabling stakeholders to visualize coating health and simulate the impact of various intervention strategies without physical trials.

Another notable finding involves the limitations encountered in real-world deployment of AI models and sensor systems in offshore environments. Fifteen studies specifically addressed practical challenges such as sensor drift, data loss, marine biofouling, and environmental noise affecting model performance. These studies accumulated over 1,700 citations and often reported variability in data quality due to oceanic turbulence, sensor calibration issues, and inconsistent imaging conditions. While AI models performed well in laboratory settings, their offshore performance was sometimes hindered by these factors. Many studies emphasized the need for preprocessing techniques, including signal smoothing, data imputation, and domain adaptation, to mitigate performance degradation. Findings also indicated that AI models trained on synthetic or lab-controlled data required retraining or fine-tuning to maintain accuracy in real-world applications. Several studies incorporated redundancy in sensor networks to compensate for data loss, and others proposed edge-based computing solutions to reduce latency and data transmission challenges. These findings underline the importance of system robustness and environmental calibration in ensuring reliable AI-based monitoring in offshore contexts. Additionally, the review identified 13 studies that focused on energy efficiency and data synchronization in sensor networks used for corrosion detection. These studies garnered approximately 1,400 citations and emphasized the critical need to optimize energy usage in remote offshore platforms, where battery-powered sensor nodes are common. Several studies developed adaptive sensing schemes, such as duty-cycling and event-triggered data collection, to conserve power without compromising monitoring fidelity. Others proposed energy-efficient communication protocols, including LoRa and Zigbee, to reduce the overhead associated with data transmission. In terms of synchronization, many studies reported issues with data alignment across visual, acoustic, and chemical sensors due to differences in sampling rates and time delays. Kalman filters, timestamp alignment algorithms, and edge fusion strategies were commonly employed to manage this challenge. The review found that optimizing both energy consumption and data synchronization is necessary for long-term deployment of sensor fusion systems in offshore corrosion detection applications. In addition, the review highlighted the effectiveness of simulation-assisted learning in enhancing AI model training for corrosion detection. Eleven studies with a combined citation count exceeding 1,200 discussed the use of synthetic data generated from digital twin simulations to augment limited real-world datasets. These studies developed corrosion progression models using finite element analysis and virtual inspection scenarios to simulate diverse coating degradation conditions. The synthetic datasets were used to pre-train CNNs, LSTMs, and hybrid architectures, which were later fine-tuned on real-world sensor or imagery data. Simulation-assisted learning was especially useful in domains where labeled datasets were sparse or difficult to collect, such as submerged pipeline corrosion or early-stage micro-crack detection. Several studies reported significant performance improvements when models were trained on a combination of synthetic and real data. Findings from this group also emphasized the

Volume 02 Issue 04 (2022)
Page No: 01-34
eISSN: 3067-0470
DOI: 10.63125/1mn6bm51

role of simulation in stress testing AI models under various conditions, ensuring that the models were capable of handling unexpected real-world variations. These findings reinforce the value of integrating simulation environments with AI development in the domain of offshore coating degradation monitoring.

DISCUSSION

The integration of Convolutional Neural Networks (CNNs) for coating degradation detection represents a significant advancement in offshore structural health monitoring. The reviewed studies demonstrated consistent accuracy and efficiency in detecting surface anomalies using CNN-based architectures, aligning with earlier research that highlighted the strengths of deep learning in image classification and defect detection tasks (Silva & de Lucena, 2018; Duquesnoy et al., 2020). However, while previous works focused primarily on terrestrial infrastructure, this review extended the application to harsh offshore conditions. Earlier studies, such as those by Wang et al. (2022), validated CNNs for bridge inspections but did not address the challenges posed by underwater imaging or marine biofouling. The current body of literature confirms that CNNs can be adapted for offshore use with sufficient preprocessing, transfer learning, and data augmentation strategies, echoing the adaptability described in studies by Dobson et al. (2013). Nevertheless, real-world implementation remains limited by environmental factors not thoroughly examined in earlier research, suggesting that while CNNs hold promise, model performance in uncontrolled marine settings still requires further validation and customization. The value of sensor fusion in offshore corrosion detection has gained traction across disciplines, but this review presents a more holistic synthesis of its application in marine environments. Previous research has individually validated the efficacy of visual, acoustic, thermal, and electrochemical sensors for structural monitoring (Fukuda et al., 2010), yet few have integrated these modalities into a unified corrosion detection system. This review found that sensor fusion significantly enhanced diagnostic accuracy, reduced false positives, and enabled cross-validation between sensor types—confirming and extending earlier findings by Wang et al. (2022), who examined bi-modal systems. Furthermore, the integration of probabilistic models, such as Bayesian networks and Kalman filters, addressed uncertainty and sensor noise, consistent with recommendations from Chang and Yuan (2019). The literature also supports the claim that sensor fusion systems are particularly effective in offshore settings where data inconsistencies are frequent (Wang et al., 2022). This layered integration differentiates the current studies from earlier works that treated each sensor type in isolation, suggesting a shift toward more complex and reliable monitoring architectures capable of functioning in challenging marine environments.

The application of Long Short-Term Memory (LSTM) and other recurrent neural network models for forecasting corrosion trends from real-time sensor data also aligns with advancements in time-series analysis for structural health monitoring. Early implementations of LSTM models in infrastructure monitoring focused on vibration and crack propagation in bridges and pipelines (Silva & de Lucena, 2018; Fukuda et al., 2010), with limited application in coating degradation detection. The reviewed studies demonstrate that LSTM models, when trained on multi-sensor time-series data, can effectively predict coating deterioration under variable marine conditions, expanding upon the work of Qu et al. (2020) and Rojek et al. (2020), who explored corrosion prediction in experimental settings. Additionally, bidirectional and hybrid models enhanced the ability to detect hidden degradation patterns, supporting the multidimensional forecasting frameworks proposed by Trebuňa and Hagara, (2014). These findings highlight a notable evolution from static inspection techniques to dynamic, predictive models capable of informing maintenance scheduling. Unlike earlier studies that relied on single-point inspections, current models simulate deterioration as a process over time, providing deeper insights into coating lifespan and degradation trajectories.

Digital twin technology has been increasingly referenced in infrastructure management literature, but its specific application in offshore coating degradation monitoring remains relatively underexplored. The reviewed studies illustrate that digital twins can simulate environmental exposure and structural stresses in real time, confirming earlier assertions by Kim et al. (2017) and Liu et al. (2017) about the predictive capabilities of virtual replicas. However, the integration of live sensor data into AI-enhanced digital twins represents a meaningful advancement over earlier models that relied solely on historical datasets or manual updates. The real-time synchronization and feedback loops found in recent studies echo the findings of Xavier and Trimboli (2015) but incorporate more

American Journal of Advanced Technology and Engineering Solutions
Volume 02 Issue 04 (2022)
Page No: 01-34
eISSN: 3067-0470
DOI: 10.63125/1mn6bm51

sophisticated AI models, such as reinforcement learning and hybrid CNN-LSTM architectures, for enhanced forecasting accuracy. Earlier applications, such as those by Simjanoska et al. (2020), lacked the automation and dynamic calibration capabilities now enabled by digital twins. Moreover, the reviewed literature confirms that virtual modeling of coating degradation supports not only anomaly detection but also simulation of intervention strategies, which had been largely conceptual in prior works. This indicates a maturity in digital twin frameworks from theoretical modeling to operational tools for corrosion management. Challenges in deploying AI and sensor technologies in offshore environments, including sensor drift, data noise, and marine biofouling, have been acknowledged in earlier studies but not thoroughly addressed. The reviewed literature expands on the foundational concerns raised by Shi et al. (2017) and Zhang et al. (2021) by offering mitigation strategies such as data preprocessing, redundancy, and real-time model recalibration. Earlier research often discussed these environmental factors in isolation, while current studies approach them holistically through adaptive model architectures and edge-based processing (Zou et al., 2018). Unlike traditional structural monitoring literature, which often assumed stable operating conditions, recent studies emphasize robustness under fluctuating field variables. This reflects a shift from lab-based model evaluation to real-world deployment, confirming the findings by Shi et al. (2017) but extending them to account for continuous degradation dynamics and environmental stressors. By addressing these operational barriers, recent studies improve upon previous limitations and provide a more accurate assessment of AI system performance in marine settings.
Energy efficiency and synchronization issues in multisensor networks were previously addressed in the context of wireless sensor networks (WSNs), with studies emphasizing the need for low-power consumption and coordinated data sampling (Xavier & Trimboli, 2015). However, their specific implications for corrosion detection in offshore platforms have only recently been fully articulated. The reviewed studies align with earlier work by Simjanoska et al. (2020) in using timestamp alignment and Kalman filtering, but they go further by integrating event-triggered sensing and edge computing. This is particularly relevant in environments with limited energy resources and intermittent connectivity. Earlier models operated under the assumption of uninterrupted power and network access, while the current body of literature recognizes the constraints of marine platforms, often located in remote or hazardous areas. These advancements confirm the need for decentralized processing and optimized data collection cycles, providing a significant improvement over earlier energy-intensive and centralized systems. The use of simulation-assisted learning to augment real-world corrosion data represents a newer trend that builds upon earlier work in synthetic data generation and model pretraining. Initial studies in this area focused on generating artificial images for visual defect detection in controlled settings (Richardson et al., 2017), while the reviewed studies extend this methodology to offshore corrosion environments. Simulation platforms are now used to generate diverse corrosion patterns and environmental scenarios, which are then used to train AI models for better generalization. This builds upon the synthetic training frameworks introduced by Shi et al. (2017) and aligns with the transfer learning techniques discussed by Simjanoska et al. (2020). Unlike earlier approaches, which required large labeled datasets from the field, simulation-assisted learning offers an efficient alternative, particularly in applications like underwater corrosion detection where data collection is difficult. The reviewed literature supports the integration of digital twins and AI training environments as a scalable and adaptive approach to structural health monitoring, effectively bridging the data gap highlighted in earlier studies.

CONCLUSION

This systematic review has synthesized evidence from 76 peer-reviewed studies to assess the integration of artificial intelligence (AI), sensor fusion, digital twins, and simulation-assisted learning in the detection and monitoring of coating degradation in offshore structures. The findings indicate a notable shift in structural health monitoring from traditional inspection-based practices to intelligent, predictive, and automated systems capable of real-time decision-making. Convolutional Neural Networks (CNNs) have proven to be highly effective for visual surface inspection, especially when enhanced with preprocessing and data augmentation techniques, while Long Short-Term Memory (LSTM) networks and other time-series models have demonstrated exceptional capabilities in forecasting corrosion progression based on multi-sensor input. Sensor fusion approaches, integrating visual, acoustic, thermal, and chemical data, were found to significantly increase detection

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accuracy and provide robust performance even in challenging marine environments. Digital twins emerged as a transformative technology, offering virtual modeling of both coating systems and structural elements, and enabling real-time feedback loops that align simulated behavior with physical conditions. Moreover, simulation-assisted learning provided a solution to data scarcity by generating synthetic datasets for pre-training AI models, improving their accuracy and adaptability. Despite these advancements, practical challenges remain, including sensor drift, synchronization difficulties, energy consumption, and environmental interference, which can affect model stability and sensor reliability in offshore settings. The review also highlighted the need for consistent calibration, noise mitigation strategies, and efficient data handling protocols to ensure long-term deployment. By comparing these findings with earlier studies, it becomes clear that recent developments have significantly advanced the field, moving from theoretical models to operational systems. The convergence of AI, sensor networks, and virtual simulation platforms presents a compelling framework for proactive corrosion management. Collectively, these innovations signify a paradigm shift in offshore infrastructure monitoring, emphasizing accuracy, automation, and adaptability in harsh marine environments, and laying the groundwork for continued advancement in predictive maintenance technologies.

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