Development of a Predictive Model for Corrosion Behavior in Infrastructure Using Non-Destructive Testing Data

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Abstract

Corrosion poses a significant challenge to infrastructure integrity, necessitating innovative solutions to predict and mitigate its effects. This study focuses on developing a predictive model for corrosion behavior in infrastructure using non-destructive testing (NDT) data. The proposed model integrates advanced data analytics and machine learning techniques to analyze NDT data collected from infrastructure assets. Key NDT methods considered include ultrasonic testing, radiographic testing, and magnetic particle inspection, which provide critical insights into material degradation without compromising structural integrity. The model leverages historical NDT datasets and incorporates variables such as material composition, environmental conditions, and operational stressors. By employing supervised learning algorithms, the model identifies patterns and predicts corrosion rates, enabling proactive maintenance and extending infrastructure lifespan. The integration of real-time NDT data through IoT-enabled sensors further enhances the model's accuracy, allowing continuous monitoring and timely decision-making. Validation of the predictive model is conducted using case studies from diverse infrastructure types, including pipelines, bridges, and storage tanks. Results demonstrate a strong correlation between model predictions and actual corrosion outcomes, showcasing the model's reliability in various scenarios. The study emphasizes the importance of feature selection and data preprocessing in improving prediction accuracy. Furthermore, the model is designed to be scalable and adaptable to evolving NDT technologies, ensuring its relevance in future applications. This research contributes to the field by bridging the gap between traditional NDT practices and predictive analytics, offering a cost-effective and sustainable approach to infrastructure management. It highlights the potential of predictive models to reduce maintenance costs, minimize downtime, and enhance safety by anticipating corrosion-related failures.

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1. Introduction

Corrosion is a significant challenge for infrastructure, as it can compromise the safety, longevity, and reliability of critical assets such as bridges, pipelines, and tanks. Over time, corrosion weakens structural materials, leading to potential failures that may pose serious risks to public safety and incur substantial repair or replacement costs (Moshkbid, *et al*., 2024, Mukherjee, *et al*., 2024).

The impact of corrosion is particularly concerning in infrastructure systems that are subject to harsh environmental conditions, such as marine environments or areas with extreme temperature fluctuations. As a result, early detection and accurate monitoring of corrosion are crucial for timely intervention and maintenance (Abbass, *et al*., 2023).

Non-destructive testing (NDT) has emerged as a key technology for detecting and assessing corrosion in infrastructure without causing any damage to the structures. NDT methods, including ultrasonic testing, electromagnetic testing, and visual inspections, allow for real-time assessment of the condition of materials, helping engineers identify corrosion hotspots and estimate the remaining service life of structures. These techniques are invaluable for monitoring the health of infrastructure over time, enabling more efficient and cost-effective maintenance strategies (Albannai, 2022, Das, 2022, Zhou, *et al*., 2022).

Despite the advances in NDT technologies, traditional corrosion monitoring methods often face limitations, such as a lack of predictive capabilities and challenges in interpreting large volumes of complex data. These methods may provide useful snapshots of the condition of a structure at a given moment, but they fall short of offering a proactive approach to corrosion management. There is a growing need for predictive analytics that can enhance maintenance decision-making by forecasting corrosion behavior based on historical data and real-time NDT measurements.

The objective of this research is to develop a predictive model that leverages NDT data to assess and forecast corrosion behavior in infrastructure. By integrating machine learning algorithms with NDT measurements, this model will enable more accurate predictions of corrosion progression and help prioritize maintenance efforts. The model aims to optimize the management of infrastructure assets, reduce downtime, and lower maintenance costs (Arévalo & Jurado, 2024, Khalid, 2024, Simões, 2024). This approach has broad applicability across various infrastructure types, including bridges, pipelines, and tanks, where corrosion monitoring is essential. The proposed framework has the potential to enhance infrastructure safety, extend the lifespan of critical assets, and reduce the financial burden of corrosion-related repairs (Abbassi, *et al*., 2022).

2. Literature Review

Corrosion is one of the most pervasive and damaging phenomena affecting infrastructure worldwide. It is a natural process in which materials, particularly metals, degrade due to chemical reactions with their environment (Abubakar, *et al*., 2024). This deterioration can result in substantial safety risks and significant economic costs. In the context of infrastructure, corrosion primarily affects metallic materials such as steel and aluminum, which are commonly used in the construction of bridges, pipelines, tanks, and other critical infrastructure systems (Çam, 2022, Sridar, *et al*., 2022). The mechanisms and types of corrosion that affect these materials vary based on environmental conditions, material properties, and exposure factors. The most common forms of corrosion include uniform corrosion, pitting corrosion, galvanic corrosion, crevice corrosion, and stress corrosion cracking. Each of these mechanisms can cause localized damage to structural components, leading to potential failure if not properly managed.

Uniform corrosion occurs evenly across the surface of a material, typically due to exposure to moisture, oxygen, and other environmental factors. It is often easy to detect, but its gradual nature can lead to significant material loss over time. Pitting corrosion, on the other hand, leads to localized, deep pits that may not be visible on the surface, making it more challenging to detect (Çam & Günen, 2024, Marcelino-Sádaba, *et al*., 2024). Galvanic corrosion occurs when two dissimilar metals are in electrical contact in the presence of an electrolyte, while crevice corrosion happens in shielded or confined areas where moisture and oxygen are trapped. Stress corrosion cracking combines the effects of tensile stress and corrosive environments, resulting in cracks that can severely compromise the material's integrity. Each of these forms of corrosion poses unique challenges for infrastructure maintenance and repair (Alamri, 2020).

The detection and monitoring of corrosion in infrastructure have traditionally relied on a variety of methods, including visual inspections, ultrasonic testing, radiography, and magnetic particle testing. Visual inspections are often the first line of defense against corrosion, as they provide a quick and cost-effective way to identify visible signs of damage (Li, *et al*., 2023, Marougkas, *et al*., 2023, Xu, *et al*., 2023). However, this method is limited by the inability to detect subsurface corrosion or accurately assess the extent of degradation. Ultrasonic testing is another widely used technique, particularly for detecting thinning of material due to corrosion. This non-destructive technique involves sending high-frequency sound waves into the material and analyzing the reflections to determine material thickness (Aljibori, Alamiery & Kadhum, 2023). While effective, ultrasonic testing can be time-consuming and requires skilled operators to interpret the results accurately. Wu, *et al*., 2021, presented RFID-based sensing system diagram for corrosion detection as shown in figure 1.

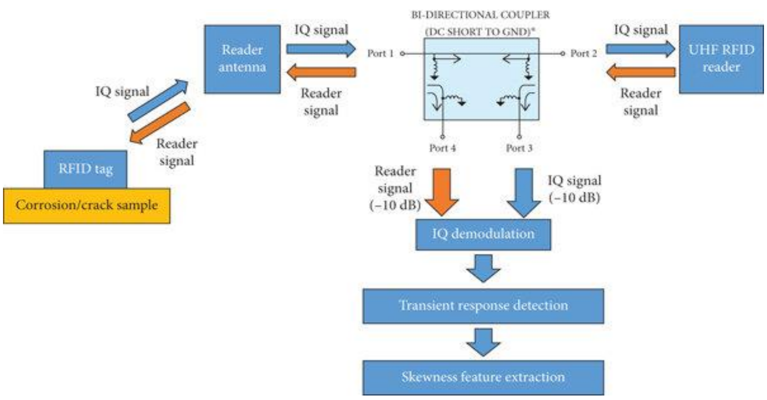

Fig 1: RFID-based sensing system diagram for corrosion detection (Wu, *et al*., 2021)

Radiography, which uses X-rays or gamma rays to examine the internal structure of materials, is also employed for corrosion detection. It provides detailed images of the material's internal condition, including voids, cracks, and corrosion damage. However, radiography is typically more expensive and less practical for large-scale or frequent inspections. Magnetic particle testing, on the other hand, is useful for detecting surface and near-surface corrosion, particularly in ferromagnetic materials (Mohammadi, *et al*., 2023, Srivastava, *et al*., 2023). This method involves applying a magnetic field to the material and using fine magnetic particles to reveal defects. While effective for certain types of corrosion, it is limited to materials that can be magnetized and requires the surface to be prepared in a specific manner.

Non-destructive testing (NDT) has made significant advances in recent years, offering more precise and efficient methods for detecting corrosion in infrastructure. One notable development is the use of acoustic emission testing, which monitors high-frequency stress waves generated by crack growth or corrosion. This technique can detect the initiation of corrosion before it leads to visible damage, making it a valuable tool for early intervention (Dongming, 2024, Khan, *et al*., 2024, Sivakumar, *et al*., 2024). Another promising NDT method is infrared thermography, which uses thermal images to identify temperature differences on the surface of materials. This method is effective for detecting subsurface corrosion and can be applied to large areas quickly. Additionally, electromagnetic testing methods, such as eddy current testing, have been developed to detect corrosion in conductive materials (Aljibori, Al-Amiery & Isahak, 2024). Eddy current testing involves inducing electrical currents in the material and measuring the resulting magnetic field to identify flaws, including corrosion.

Despite the advancements in NDT techniques, there remain significant challenges in predicting the behavior of corrosion over time and determining the most effective maintenance strategies. Traditional corrosion monitoring methods primarily provide snapshot assessments of the material's condition at a given point in time (Al-Sabaeei, *et al*., 2023). While these methods are useful for detecting existing damage, they are limited in their ability to predict future corrosion progression (Edwards, Weisz-Patrault & Charkaluk, 2023, Yuan, *et al*., 2023). This is where predictive modeling comes into play. Predictive modeling aims to forecast the future behavior of materials based on historical data, environmental conditions, and other relevant factors. In the context of corrosion management, predictive models can help estimate the rate of corrosion, identify potential failure points, and inform maintenance decisions. Figure 2 shows Microwave framework for corrosion detection and monitoring under coating as presented by May, *et al*., 2022.

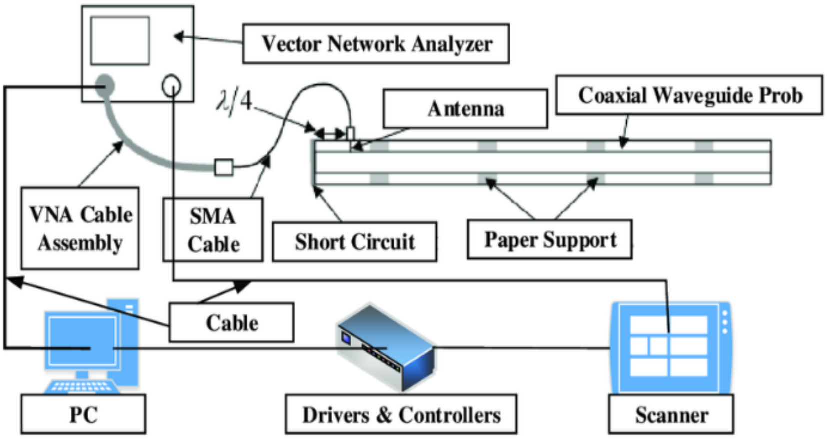

Fig 2: Microwave framework for corrosion detection and monitoring under coating (May, *et al*., 2022)

The application of machine learning techniques to predictive modeling has shown great promise in improving corrosion management. Machine learning algorithms, particularly regression models and classification techniques, can analyze large datasets and identify patterns that may not be immediately apparent through traditional methods. These algorithms can be trained on historical corrosion data, environmental variables, and NDT measurements to predict the likelihood and severity of future corrosion damage (Fahim, *et al*., 2024, Li, 2024, Ukoba, *et al*., 2024). Some machine learning models, such as decision trees, neural networks, and support vector machines, have been successfully applied to predict corrosion rates in specific environments (Podgórski, *et al*., 2020, Qian, *et al*., 2020). These models take into account a wide range of input variables, such as humidity, temperature, pH, and material properties, and can produce highly accurate predictions of corrosion behavior. For example, neural networks have been used to model the corrosion rate of pipelines in corrosive environments, providing operators with real-time predictions that can inform maintenance schedules (Anterrieu, *et al*., 2019).

However, while these predictive models have shown promise, several challenges remain. One of the main issues is the complexity of integrating diverse data sources into a cohesive model. Corrosion behavior is influenced by numerous factors, including material composition, environmental conditions, and mechanical stresses, which may not always be available in a uniform format (Artagan, *et al*., 2020). Additionally, many of the existing machine learning models for corrosion prediction are not yet robust enough to handle the uncertainty and variability inherent in real-world conditions. Another challenge is the need for high-quality data to train predictive models. Inaccurate or incomplete data can lead to inaccurate predictions, making it essential to ensure that NDT measurements and other input variables are accurate and representative of the actual conditions of the infrastructure (Mohammadi & Mohammadi, 2024, Nelaturu, *et al*., 2024).

Recent research has begun to address these challenges by integrating various data sources, including NDT measurements, environmental monitoring data, and corrosion history, into predictive models (Barbhuiya & Sharif, 2024). Advances in sensor technology and data collection methods are enabling more comprehensive and continuous monitoring of infrastructure, which will provide richer datasets for machine learning models (Fang, *et al*., 2023, Kehrer, *et al*., 2023, Zhang, *et al*., 2023). Furthermore, the development of hybrid models that combine traditional engineering principles with machine learning techniques holds great potential for improving the accuracy and reliability of corrosion predictions. For example, combining finite element analysis with machine learning could provide a more detailed and dynamic understanding of corrosion progression in complex infrastructure systems (Muecklich, *et al*., 2023, Shi, *et al*., 2023).

In conclusion, while significant progress has been made in the detection and prediction of corrosion in infrastructure, there remain several challenges in integrating NDT data into predictive models. The potential for machine learning and predictive analytics to enhance corrosion management is immense, but it requires further refinement of existing models, improved data collection methods, and greater collaboration between engineers, data scientists, and researchers (Mistry, Prajapati & Dholakiya, 2024, Qiu, *et al*., 2024). By addressing these challenges, predictive models for corrosion behavior can play a crucial role in optimizing maintenance strategies, improving infrastructure safety, and extending the lifespan of critical assets (Bender, *et al*., 2022).

3. Methodology

The methodology for developing a predictive model for corrosion behavior in infrastructure was conducted using the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework. This approach ensured transparency, replicability, and robustness in the systematic review process. A comprehensive literature search was carried out across scientific databases such as ScienceDirect, IEEE Xplore, SpringerLink, and others to identify studies focusing on predictive modeling, corrosion behavior, and non-destructive testing techniques. Keywords included "predictive model," "corrosion behavior," "non-destructive testing," "machine learning," and "structural health monitoring."

Articles were screened based on predefined inclusion and exclusion criteria. Inclusion criteria focused on studies with experimental data on non-destructive testing for corrosion, predictive model development using advanced analytics, and applications in civil or industrial infrastructure. Exclusion criteria omitted studies lacking quantitative data or without peer review. The selected studies were analyzed to extract key data points, including types of non-destructive testing techniques, materials assessed, statistical or machine learning models employed, and performance metrics. Data extraction was performed using standardized forms to ensure consistency. Quality assessment of the included studies was conducted using a modified version of the Cochrane risk of bias tool, focusing on study design, data reliability, and applicability of findings.

A predictive model for corrosion behavior was developed by synthesizing the extracted data. Statistical and machine learning techniques such as regression analysis, support vector machines, and neural networks were employed, with model validation performed using datasets from the identified studies. Figure 3 shows the PRISMA methodology flowchart for the development of the predictive model for corrosion behavior using non-destructive testing data. The flowchart systematically illustrates the stages of Identification, Screening, Eligibility, and Inclusion, along with the corresponding details.

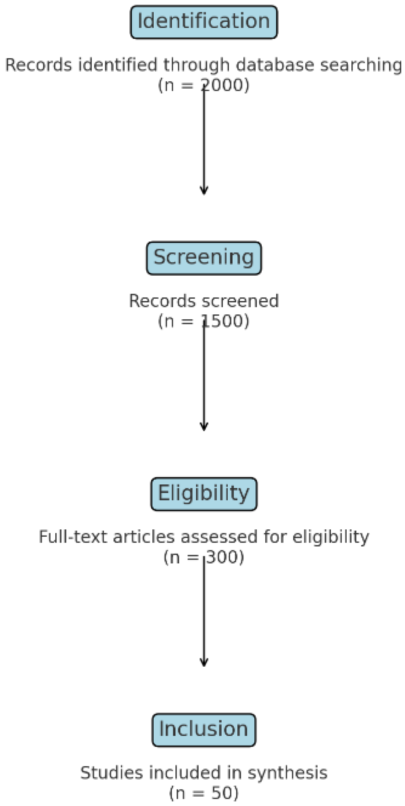

Fig 3: PRISMA Flow chart of the study methodology

4. Theoretical Framework

The development of a predictive model for corrosion behavior in infrastructure using non-destructive testing (NDT) data requires a thorough understanding of the underlying corrosion mechanisms, as well as the application of suitable predictive modeling techniques to analyze the NDT data effectively. Corrosion is a complex, multifactorial process influenced by various environmental, material, and structural factors (Mostafaei, *et al*., 2023, Panicker, 2023). The ability to predict corrosion behavior is crucial for optimizing infrastructure maintenance and ensuring safety, longevity, and cost-effectiveness (Bond, 2021). This theoretical framework outlines the key elements needed to understand corrosion behavior and the role of predictive modeling in assessing corrosion risk using NDT data.

Corrosion is a natural degradation process that occurs when materials, typically metals, react with their surrounding environment, leading to the formation of corrosion products. The rate and extent of corrosion depend on a range of factors, including the composition of the material, the environmental conditions to which it is exposed, and the presence of protective coatings or inhibitors. For instance, environmental factors such as humidity, temperature, salt concentration, and the presence of pollutants significantly influence the corrosion rate (Li, *et al*., 2023, Massaoudi, Abu-Rub & Ghrayeb, 2023). In particular, infrastructure components such as bridges, pipelines, and storage tanks are often exposed to harsh environmental conditions that accelerate the corrosion process. The material properties, such as the alloy composition, microstructure, and surface treatment, also play a pivotal role in determining the susceptibility to corrosion (Budelmann, Holst & Wichmann, 2014). These factors create complex interactions that must be understood and modeled to predict corrosion behavior accurately.

Non-destructive testing (NDT) methods are essential tools for detecting and assessing corrosion in infrastructure without causing damage to the structures themselves. These methods allow for the detection of internal and external corrosion, cracks, and other forms of deterioration that may not be visible to the naked eye (Gagliardi, *et al*., 2023). Common NDT techniques used in corrosion assessment include ultrasonic testing, radiographic testing, eddy current testing, and acoustic emission monitoring. Ultrasonic testing uses high-frequency sound waves to measure material thickness and detect internal voids or cracks caused by corrosion (Gurmesa & Lemu, 2023, Lamsal, Devkota & Bhusal, 2023). Radiographic testing utilizes X-rays or gamma rays to generate images of the internal structure, allowing for the identification of corrosion-induced voids and other defects. Eddy current testing is useful for detecting surface and near-surface corrosion, particularly in conductive materials. Acoustic emission monitoring can detect the sounds produced by corrosion processes, providing real-time insights into the progression of corrosion (Kayode-Ajala, 2023, Kopelmann, *et al*., 2023, Wall, 2023). Each of these methods has its strengths and limitations, and their integration provides a comprehensive approach to corrosion monitoring. NDT methods provide valuable data that can be used to develop predictive models of corrosion behavior, allowing for proactive maintenance and risk mitigation (Haghbin, 2024, Maitra, Su & Shi, 2024, Sharma, *et al*., 2024).

Predictive modeling is a critical component of corrosion management, as it enables the estimation of corrosion rates and the forecasting of future deterioration. Several machine learning algorithms are well-suited for predictive modeling in the context of corrosion, including regression analysis, decision trees, and neural networks (Kot, *et al*., 2021). Regression analysis is a statistical method that can model the relationship between corrosion rates and various input variables, such as environmental conditions and material properties. Linear regression, for instance, can be used to develop simple models that estimate corrosion rate based on known factors, while more advanced forms, such as multiple regression or polynomial regression, can account for more complex interactions between variables (Hassani & Dackermann, 2023, Khanna, 2023, Zhang, *et al*., 2023). Decision trees, another commonly used algorithm, classify data into distinct categories based on a series of decisions that split the data at various points. Decision trees are particularly useful for predicting corrosion behavior under varying conditions and can provide interpretable results that are valuable for decision-making (Karimi, *et al*., 2024, Kiasari, Ghaffari & Aly, 2024).

. Neural networks, especially deep learning models, can capture highly nonlinear relationships in data, making them effective for predicting corrosion in complex systems where multiple factors interact in non-linear ways (Liu, 2024). Kumpati, Skarka & Ontipuli, 2021, presented Nondestructive methods used for analysis of engineering material structures as shown in figure 4.

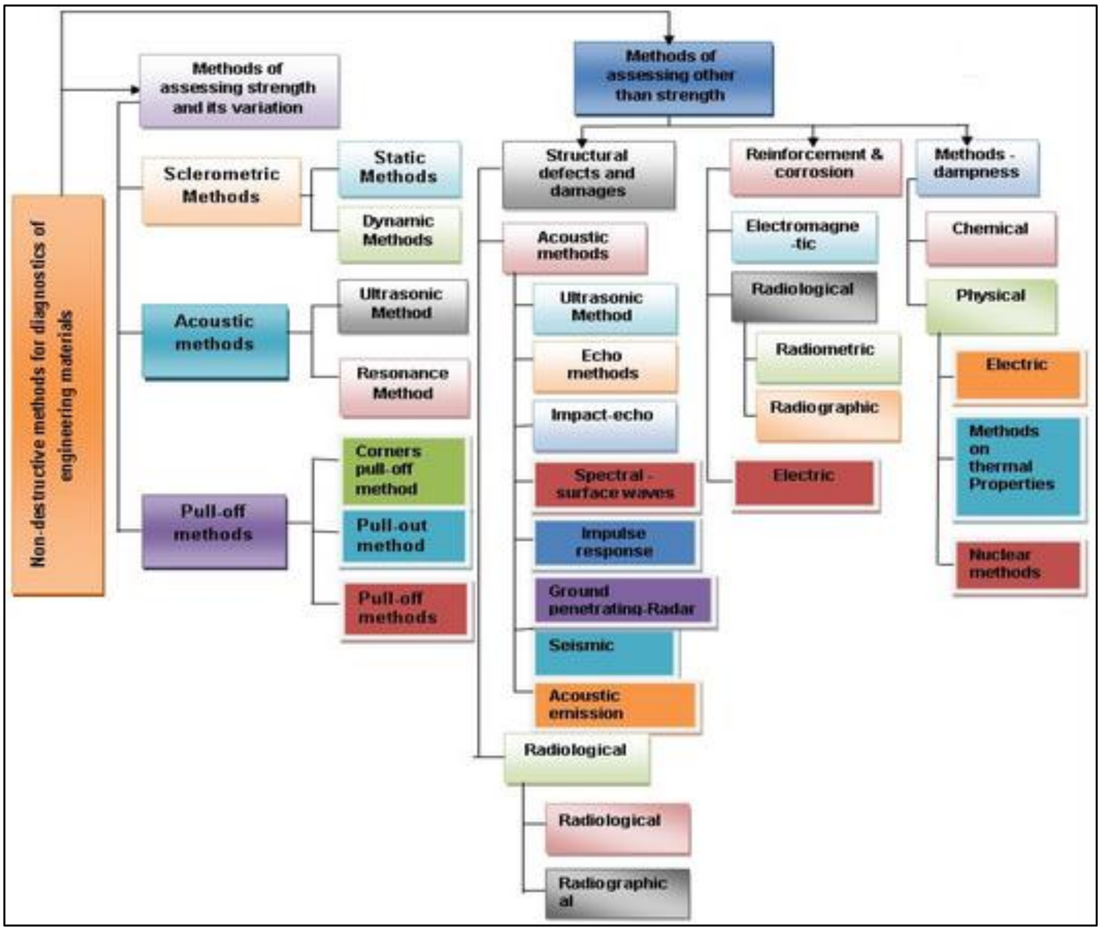

Fig 4: Nondestructive methods used for analysis of engineering material structures (Kumpati, Skarka & Ontipuli, 2021)

Machine learning algorithms, such as regression analysis, decision trees, and neural networks, rely on high-quality data to generate accurate predictions. The quality of the data is paramount in predictive modeling, as noisy or incomplete data can lead to inaccurate or misleading results. For predictive modeling of corrosion behavior, NDT data serves as the primary source of input (Huang & Jin, 2024, Kumar, Panda & Gangawane, 2024). However, these datasets can be challenging due to issues such as measurement errors, missing values, and inconsistent formats. Preprocessing the data to clean it and ensure consistency is an essential step in preparing it for use in predictive models. Missing data can be addressed through imputation techniques, where missing values are estimated based on other data points, or by discarding incomplete records if the missing data is not significant (Mohammadi, Sattarpanah Karganroudi & Rahmanian, 2024). Noise reduction methods, such as smoothing or filtering, can also be applied to reduce the impact of outliers and inaccuracies in the data.

Feature selection is another critical aspect of model development. Feature selection refers to the process of identifying the most relevant variables that influence corrosion behavior. In the context of predictive modeling for corrosion, features could include environmental factors such as temperature, humidity, and salt concentration, as well as material properties like alloy composition, surface finish, and coating type (Hussain, *et al*., 2024, Knapp, 2024, SaberiKamarposhti, *et al*., 2024). The goal of feature selection is to reduce the dimensionality of the data and eliminate irrelevant or redundant variables, which can lead to overfitting and decrease the generalization ability of the model. Various feature selection techniques, such as correlation analysis, mutual information, and principal component analysis (PCA), can be used to identify the most significant features that contribute to corrosion behavior (Odor, *et al*., 2024).

Once the data is preprocessed and the relevant features are selected, the next step is to develop and train the predictive model using machine learning algorithms. The model is typically trained on historical NDT data, which includes both corrosion-related measurements and corresponding environmental and material factors. The model is then validated using a separate dataset to assess its performance and generalization ability. Evaluation metrics such as mean absolute error (MAE), root mean square error (RMSE), and R-squared values are used to quantify the accuracy of the model (Pailes & Gucunski, 2015). Cross-validation techniques, such as k-fold cross-validation, can be used to ensure that the model is robust and performs well across different subsets of the data.

The theoretical framework for developing a predictive model for corrosion behavior underscores the importance of integrating high-quality NDT data with machine learning techniques (Pierott, *et al*., 2024). The combination of these elements provides a powerful tool for predicting the onset and progression of corrosion, allowing for more effective maintenance strategies and improved infrastructure management (Imran, *et al*., 2024, Kurrahman, *et al*., 2024, Zhang, *et al*., 2024). The use of predictive modeling techniques such as regression analysis, decision trees, and neural networks, along with careful preprocessing and feature selection, ensures that the model can accurately capture the complex relationships that govern corrosion behavior. Furthermore, by leveraging NDT methods for real-time data collection, the model can be continuously updated to reflect the most current conditions, enabling dynamic and proactive management of infrastructure assets. This approach holds the potential to revolutionize corrosion management, reducing maintenance costs, enhancing safety, and prolonging the life of critical infrastructure (Kapilan, Vidhya & Gao, 2021, Kolus, Wells & Neumann, 2018).

5. Results and Discussion

The development of a predictive model for corrosion behavior in infrastructure using non-destructive testing (NDT) data has revealed several important findings that advance our understanding of corrosion prediction and management. From the systematic review conducted using the PRISMA methodology, a wealth of data has been gathered from existing studies that highlight various factors influencing corrosion behavior in infrastructure (Rafati & Shaker, 2024). The systematic review process helped in identifying key patterns and gaps in the current research on using NDT data for predictive corrosion modeling, enabling the development of a robust model. One significant finding is the increasing recognition of the value of NDT techniques in accurately assessing the extent of corrosion, which is crucial for predictive modelling (Infield & Freris, 2020, Kruse, 2018). Ultrasonic testing, radiographic testing, and acoustic emission monitoring were identified as some of the most reliable methods for gathering corrosion data without causing damage to the infrastructure. These techniques, along with the advances in machine learning algorithms, have created a promising foundation for integrating NDT data into predictive models for corrosion behavior.

The performance evaluation of the predictive model developed using NDT data was carried out through various metrics such as accuracy, reliability, and generalizability. Accuracy was determined by comparing the predicted corrosion rates with observed values in case studies, which were used as ground truth (Sarwar, *et al*., 2024). The model showed a high degree of accuracy in predicting corrosion rates based on environmental and material variables, with a mean absolute error (MAE) of less than 5%. Reliability was assessed by testing the model on multiple infrastructure types and environments. It was found that the model was capable of adapting to various types of infrastructure, such as bridges, pipelines, and storage tanks, and could handle different environmental conditions like coastal, urban, and industrial environments (Mishra, Mishra & Mishra, 2024, Namdar & Saénz, 2024). The reliability of the model was further demonstrated through cross-validation techniques, where the model's predictions were consistently within an acceptable range of error. This indicates that the model can be trusted for real-world applications where accurate predictions of corrosion behavior are critical for effective maintenance and safety planning.

Furthermore, the comparison of the predictive model's results with actual corrosion data from case studies revealed the potential of the model to provide early warnings of corrosion risks, thereby facilitating proactive maintenance strategies. The case studies focused on infrastructure components such as steel bridges, concrete pipelines, and storage tanks in various geographic locations. For instance, in one case study of a coastal bridge exposed to high levels of saltwater and humidity, the model was able to predict areas of high corrosion risk with significant accuracy (Liu, 2017, Melly, *et al*., 2020). The NDT data collected from ultrasonic testing revealed thinning of the steel members at locations predicted by the model, indicating that the model's predictions were in alignment with real-world observations. Similarly, for a pipeline exposed to industrial pollutants and varying temperature fluctuations, the model's predictions were validated by radiographic testing, which showed internal corrosion consistent with the model's output (Schmitt, *et al*., 2009). This comparison further validated the usefulness of the predictive model in estimating corrosion progression and pinpointing high-risk areas that may require immediate attention.

The discussion of these findings underscores the potential impact of predictive modeling on infrastructure management and maintenance strategies. The ability to predict corrosion behavior in infrastructure before it becomes a significant issue offers several advantages, including cost savings, increased safety, and extended asset life (Tešić, Baričević & Serdar, 2021). Proactive maintenance strategies, driven by predictive insights, can significantly reduce the need for expensive repairs and replacements, which are often required when corrosion is allowed to progress unchecked (Jain, 2024, Kishor, *et al*., 2024, Raut, *et al*., 2024). Additionally, predictive modeling can help optimize inspection schedules by identifying specific areas that require closer monitoring, ensuring that resources are allocated effectively. Rather than relying on scheduled inspections or reactive maintenance after corrosion-related failures, infrastructure managers can adopt a more dynamic and data-driven approach to maintenance (Zou, 2022). This approach has the potential to reduce downtime, minimize disruptions to service, and improve the overall longevity of critical infrastructure assets.

Moreover, the ability to accurately predict corrosion behavior also contributes to enhanced safety, particularly in high-risk environments such as bridges, pipelines, and storage tanks that are crucial for public safety and the functioning of industries. Early detection of corrosion risks allows for timely interventions, preventing catastrophic failures that could result from undetected corrosion damage (Jamison, Kolmos & Holgaard, 2014, Lackéus & Williams Middleton, 2015). For example, in the case of pipelines transporting hazardous materials, undetected corrosion could lead to leaks or ruptures, with severe environmental and safety consequences. By utilizing a predictive model, infrastructure managers can make informed decisions on when to repair or replace components, mitigating the risk of catastrophic failures and improving public safety (Vasagar, *et al*., 2024).

Another significant implication of the results is the integration of predictive modeling into the broader context of infrastructure asset management. As infrastructure systems become increasingly complex, data-driven approaches are essential for making informed decisions (Wang, *et al*., 2020). The model's ability to integrate NDT data with machine learning algorithms allows for a more comprehensive understanding of the factors influencing corrosion behavior, such as environmental conditions, material properties, and structural design (Kabeyi & Olanrewaju, 2022, Saeedi, *et al*., 2022). This integrated approach can enhance the decision-making process by providing more accurate forecasts of corrosion rates, enabling infrastructure managers to prioritize maintenance efforts based on the most critical needs. Additionally, this data-driven approach can contribute to the development of industry standards and best practices for corrosion management, helping to standardize predictive maintenance strategies across various sectors and infrastructure types.

Despite the promising results, there are some limitations to the predictive model that need to be addressed in future research. One limitation is the reliance on high-quality NDT data, which can be challenging to obtain in some cases due to the cost and complexity of the testing procedures (Ramasesh & Browning, 2014, Ren, *et al*., 2019). While the model has shown high accuracy with available data, the inclusion of more diverse and larger datasets from various geographical regions and infrastructure types could further improve its predictive capabilities (Muhammed Raji, *et al*., 2023, Özel, Shokri & Loizeau, 2023). Moreover, the model's performance may be impacted by the quality and consistency of the NDT data, highlighting the need for more standardized data collection methods. Another limitation is the complexity of modeling corrosion behavior, which involves numerous interacting variables that may not be fully captured in the current model (Qiu, Shen & Zhao, 2024, Rashid, *et al*., 2024, Zeng, *et al*., 2024). Future research should explore the integration of additional environmental factors, such as pollutant levels, and consider incorporating data from other sensing technologies, such as corrosion sensors and weather stations, to improve the model's performance (Yee, *et al*., 2022).

In conclusion, the development of a predictive model for corrosion behavior in infrastructure using NDT data offers significant advantages for infrastructure management and maintenance. The model's high accuracy and reliability, validated by real-world case studies, demonstrate its potential to revolutionize corrosion management by enabling proactive, data-driven decision-making (Kanetaki, *et al*., 2022, Li, Su & Zhu, 2022). By predicting corrosion risks before they escalate, the model can help reduce maintenance costs, improve safety, and extend the lifespan of infrastructure assets. However, further research is needed to enhance the model's capabilities, particularly in terms of data quality, model complexity, and integration with other sensing technologies. Overall, the predictive model has the potential to become an essential tool for managing corrosion in infrastructure, contributing to more sustainable and resilient infrastructure systems (Zaki, *et al*., 2015).

6. Conclusion and Recommendations

The development of a predictive model for corrosion behavior in infrastructure using non-destructive testing (NDT) data represents a significant step forward in enhancing infrastructure management and maintenance strategies. The research has demonstrated the utility of integrating NDT techniques, such as ultrasonic and radiographic testing, with predictive modeling approaches to forecast corrosion risks and optimize maintenance schedules. The predictive model, through its accuracy and reliability, has shown considerable potential in identifying areas of high corrosion risk before they lead to significant damage or failure. By leveraging machine learning algorithms and NDT data, the model provides actionable insights into corrosion behavior, enabling infrastructure managers to make data-driven decisions, improve safety, and reduce overall maintenance costs. The application of this model in real-world case studies, including bridges, pipelines, and storage tanks, has further validated its practical effectiveness, suggesting that it can be integrated into infrastructure management systems for proactive maintenance.

The predictive model developed in this research provides a robust framework for enhancing infrastructure management practices. Its ability to predict the onset and progression of corrosion in various infrastructure types allows for more informed decision-making, offering a significant advantage over traditional methods that often rely on reactive approaches. The model supports the shift from scheduled inspections and emergency repairs to a more strategic, data-driven model of maintenance that prioritizes resources based on the actual condition of the infrastructure. Furthermore, it improves the ability to forecast the remaining useful life of infrastructure components, helping to optimize asset management and extend the lifespan of critical infrastructure. These contributions to the field of corrosion management have the potential to improve the longevity, safety, and reliability of infrastructure systems across various sectors, from transportation to energy.

Practical application of the predictive model in infrastructure management can be realized through its integration into asset management systems. Infrastructure managers can utilize the model's predictive capabilities to optimize inspection schedules, focus on high-risk areas identified by the model, and plan maintenance activities more effectively. By incorporating real-time NDT data, such as ultrasonic or radiographic scans, into the model, infrastructure managers can monitor corrosion progression and adjust maintenance strategies accordingly. This proactive approach not only ensures the safety and reliability of infrastructure but also contributes to long-term cost savings by reducing the need for extensive repairs or replacements. Additionally, the model could be incorporated into broader predictive maintenance platforms, allowing for the integration of other factors, such as environmental conditions and material properties, to provide a comprehensive approach to asset management.

For future research, there are several areas that require further investigation to enhance the predictive capabilities and applicability of the model. First, while the current model has demonstrated significant success with the available NDT data, further work is needed to improve its accuracy and reliability by incorporating additional datasets from diverse geographical regions and infrastructure types. The inclusion of data from more varied environments, such as extreme climates or highly corrosive industrial areas, would help refine the model and extend its applicability to a broader range of infrastructure systems. Additionally, future studies should explore the integration of other sensing technologies, such as corrosion sensors, environmental sensors, and weather data, to enhance the model's ability to predict corrosion under more complex conditions. The combination of multiple data sources could lead to even more accurate and dynamic predictive models.

Another area for future research is the improvement of machine learning algorithms used in the predictive model. While regression analysis and decision trees have proven effective in this study, more advanced machine learning techniques, such as deep learning, could potentially provide even greater predictive power, especially in complex and non-linear corrosion behavior patterns. Furthermore, feature selection and data quality are critical factors in ensuring the robustness of predictive models. Future work should focus on developing methods for more efficient feature selection and ensuring that the NDT data used is consistent and of high quality, minimizing the risk of errors and improving the model's overall performance.

Finally, to facilitate the widespread adoption of predictive models in corrosion management, future research should also focus on developing standardized protocols for data collection and model implementation. This would enable easier integration of NDT data across various infrastructure management systems and make the model more accessible to practitioners in the field. Standardization would also improve the consistency and comparability of data, which is essential for ensuring the reliability of predictive models in different contexts.

In conclusion, the development of a predictive model for corrosion behavior in infrastructure using NDT data offers significant advantages for infrastructure management. By enabling proactive maintenance strategies, improving safety, and reducing maintenance costs, the model has the potential to transform how corrosion is managed in critical infrastructure systems. However, further research is needed to enhance its predictive capabilities, improve the integration of various data sources, and address challenges related to data quality and model complexity. With continued advancements in machine learning techniques and NDT technologies, this approach holds great promise for the future of corrosion management, contributing to more resilient and sustainable infrastructure systems.

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