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The application of artificial intellegence in corrosion monitoring

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Abstract: Corrosion is a natural undesirable occurrence due to chemical and electrochemical reaction of metals with encompassing environment, as a result it deteriorates and damages the surface of the metallic material. It has a significant short and long-time economic impact because it creates failure, leakage and damages of metal. Every year it causes billions of dollar damages. Because of diverse boundary of corrosion surface and different level of texture it is very difficult to detect corrosion using current technologies. Hence, there is a need to investigate the robust corrosion detection algorithms that are suitable for all degrees of corrosion level. In this paper firstly, we have illustrated different class of Artificial Intelligence and secondly AI application approached in corrosion monitoring is explained. The outcomes of this review paper will bring forward the new and additional knowledge to develop the different AI methods which can avoid unexpected failure and damages due to corrosion

Keywords: *Artificial intelligence, corrosion, monitoring, marine, metal.*

1. Introduction

When a metal experiences corrosion, it degrades chemically into its oxides and sulfides as a consequence of chemical or electrochemical reactions [1]. Because of its multidisciplinary nature it has become one of the most challenging aspects in the field of science and engineering [2]. Moreover, corrosion poses significant short-term and long-term threats that costs billions of dollars [3]. The National Association of Corrosion Engineers (NACE) estimates that the yearly cost of corrosion is approximately 2.5 trillion US dollars, or 3.4% of the world's Gross Domestic Product (GDP) in 2013 [4]. Direct costs have included the expense of equipment, labor, maintenance, and the expense of replacement deteriorated equipment. The indirect costs of corrosion include production losses, environmental impacts, transportation disruptions, accidents, and fatalities. [5].

In shipping industry marine structures are significantly damaged by the corrosion, it will not only reduce the efficiency of mechanical property but also the different structural parts [6] such as hull structural failure [7]. According to statistical data [8] corrosion is responsible for 90% of the structural failure cost of a ship. Therefore, long term corrosion detection is the great realistic significant method to the prevent the occurrences of catastrophic accidents of marine structures. In addition to financial gains, early detection of structural deterioration prior to failure can also avoid dangerous circumstances for both people and the environment and prevent catastrophic failures of structures indirectly it reduces the cost [9,10]. According to researchers the approximate cost can be reduce 18-35% by utilizing proper strategy [4]. Another study indicates that using the current artificial technologies can minimize the yearly expense of corrosion by 20–25% [11,12].

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Sharon and Itzhak [13] used image processing to study the corrosion in stainless steel in the year of 1997. The most significant advantage of that method is, it is capable to identify almost all superficial defects such as cracks and corrosion however feature extraction operations are essential. Requires of large manpower, huge workload, financial resource, feature extraction methods often effected to apply in corrosion detection [14]. Therefore, it was essential to develop other methods to corrosion prediction and detection. Consequently, new methods of artificial intelligence have able to attract researcher because of enormous advantages over human intelligence [15,16] advanced technology to solve complex problems [17-19], faster decision making [20]. Big data, machine learning, neural networks, deep learning, image classification and recognition, face recognition, character recognition, Pattern recognition [21-25].

The objective of this paper is to provide a state art of review on artificial intelligence method in corrosion prediction and detection within the period of 2017-2022. Table 1 is represented the review corresponding to the review protocol. A number of 153 notable works on this issue have already been found after a search of the selected databases and the compilation of a list of literatures. These papers were evaluated within the parameters of the research, wherein 48 studies were chosen for further analysis in this work.

The discussion in this paper is divided into two divisions. First division, a description on artificial intelligence and their branches such as; pattern recognition, machine learning and deep learning is elaborated. Second division of this paper, Artificial intelligence approaches in corrosion detection and prediction is elaborated.

Table 1 description scope of bodies within the body of literature

Subject	Description
Database	The Web of Science (WoS), Scopus, ScienceDirect, IEEE
Keywords	‘’artificial Intelligence + corrosion+ detection’’, “artificial + intelligence” and “current + trends”.
Type of publications	Journal & conference paper
Publication language	English
Time interval	2017-2022

2. Artificial Intelligence

Artificial intelligence (AI) is the capability of a machine to mimic human behavior, respond perceptively, solve problem and make decision automatically without human interference or with less human interference. The main objective if AI research involve automated planning, natural language processing, perception, general intelligence, knowledge representation and robotic [26-30]. Numerous AI branches, such as Machine learning (ML), deep learning, pattern recognition (PR), evolutionary computation, neural networks, expert system, discriminant analysis, metaheuristic optimization, swarm optimization, image processing, computer vision have been used in marine research. Among those technologies pattern recognition, deep learning and machine learning are the most reliable and efficient method in the field of corrosion engineering [31]. In this section we have illustrate the technical background of main AI braches such as, pattern recognition (PR), Machine learning (ML) and Deep learning. Figure 1 presents the different intelligent technique and their correlation.

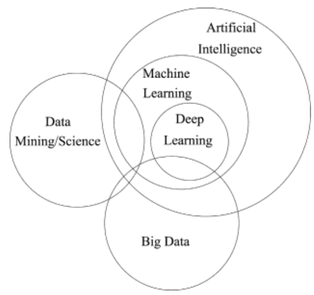

Figure 1: AI techniques interrelation [20]

2.1. Pattern Recognition

The main objectives of pattern recognition are to classify object into a category or a number of classes. The objects could be signals, speech, images, handwriting; it depends on the application. A pattern is represented by a number of features. To create decision boundaries between pattern classes statistical theory are applied. The recognition system in pattern recognition consists of two modes such as, learning (training) and classification (testing) as illustrated in fig 2. In the training mode, the appropriate features for representing the input patterns are exposed by means of the selection module/ feature extraction, and the classifier is trained to partition the feature space. Using the trained classifier, input patterns are assigned to one of the classes, while the designed classifier's performance, such as, system evaluation module evaluates the classification error rate. Generally, Pattern Recognition can be classified into two categories, Supervised pattern recognition and unsupervised pattern recognition. In Supervised pattern recognition a set of labelled training samples are available but in unsupervised pattern recognition the training data are not levelled additionally there is no preceding information concerning on class level. Unsupervised PR also called clustering.

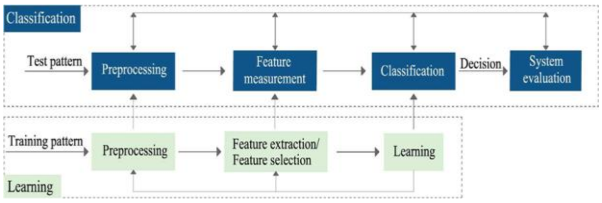

Figure 2: Schematic of pattern recognition [20]

2.2. Machine Learning

Machine learning is a subdivision of Artificial Intelligence. The objective of machine learning is to construct and develop of mathematical models which can be trained deprived of comprehensive knowledge [32]. The main objectives to enable intelligent decision-making, ML is used to create and evolve mathematical models that can be taught without having complete knowledge of all the influencing external factors. [33-36]. Additionally, these methods trained by given data and capable to solve problems without or with minimum human intervention and predict the future actions utilizing complex learning and predicting algorithm [37-41]. These models can be predictive to make decisions, learn from data, or do both. [42,43]. ML models are successfully utilized in numerous fields of research such as, Computational finance [44,45], image and speech processing [46-48], energy production [49,50], hydrology [51,52], computational biology [53,54], over few decades and bring significant advancement in science and engineering along with developments in quality of our daily life.

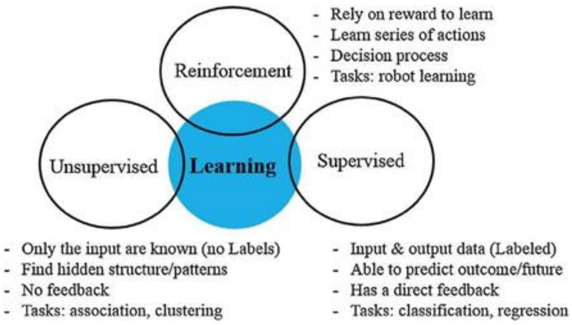

Figure 3: machine learning categories [55]

2.3. Deep Learning

Deep learning is one of the subdivision of machine learning. Fundamentally a neural network that has three or more than three layers. A single layer can make predictions but additional hidden layer assists to enhance and improve the correctness. These neural networks capable to learn from big data and act as human brain. Deep learning technology are applied in many areas such as; law enforcement, finance, customer service, engineering technology application.

3. AI METHODS IN CORROSION MONITORING

In this chapter we have illustrated a basic introduction about corrosion and the brief explanation of corrosion monitoring methods.

3.1. Corrosion:

Corrosion is a natural phenomenon [56]. happens when metallic materials gradually convert into undesirable substances such as hydrogen, oxygen, bacteria and electrical current, due to the chemical and electrochemical response to the encompassing environment Moreover, corrosion is inevitable and susceptible to the degradation of metallic materials [57]. The anodic and cathodic of electrochemical reactions are involved to create corrosion process [58]. Corrosion is categorized according to the environment exposure and attack morphology. General or uniform attack, galvanic or two-metal corrosion, pitting, intergranular corrosion, selective leaching, erosion corrosion, and stress-corrosion cracking are the eight types of corrosion [59].

3.2. The infrared thermography:

Infrared thermography is common computer vision and image processing approaches for corrosion detection [60-62]. These methods produce better accurate and resolution corrosion detection because of recently developed infrared detector. The developing and monitoring cost is deducted but thermal image can be interrupted due to low signal strength and noise. This technique records the electromagnetic energy emits by metallic materials. Then, corrosion patterns can be located from the thermal images. Application of thermography-based techniques applied in optical [63], laser [64], induction [65] and microwave [66], photovoltaic (PV) electroluminescence module [67] for crack and corrosion detections on pipelines energy, surface inspection, practically, source, etc. however, each of these methods have limitation regarding their energy, surface inspection, practically, source, etc.

3.3. Rules of hull girder:

Used by applied by [68] to detect the corrosion effect in bulk carrier. That method was able to detect the corrosion as a predictive maintenance method which significantly reduce the corrosion effect on the ship hull. The limitation of this method are, insufficient historical data can be effect the sensitivity of the model maintenance planning. Even the prediction model is accurate unplanned and unexpected behavior can be occurred.

3.4. Texture Analysis:

Texture analysis has been used in [69-72] This a one kind of image processing techniques and to object classification computer vision is used. Texture analysis improves classification results by reducing errors for isolated data detection.it can accomplish an accurate detection, recognition and classification of corroded regions in the images. Additionally, texture analysis is capable to identify the corrosion and non-corrosion regions [73,74]. Application of SVM; water pipelines [75], underwater pipelines [76], steel bars [77], bridge cables [78], equipment [79], aircraft structures [80], wind turbine blades [81] and many more.

3.5. Extreme Value Analysis (EVA):

The real-time data of degradation process from the inspection reports were used to develop a prediction model by considering the peaks over threshold (POT) [82]. The main purpose of this model is to make prediction of the depth of pits that required immediate maintenance. Achieved a high performance in detecting and assessing corrosion failures. However, might require fine-tuning and parameterization for assessing multiple sections of corrosion failure.

3.6. Expected Behavior (EB):

This model can be used as indirect method of any corrosion model [83]. It is able to detect specific fault parameters such as air pressure and gas temperature. However, the well-maintained ship was inevitable due to the occurrence failures which can exhibit energy efficiency, safety and reliability. Such condition can contribute to corrosion and fouling in the turbocharger and nozzle ring of the vessel.

3.7. Non-destructive methods:

The purpose of non-destructive testing to corrosion detection is to inspect and evaluate the materials without affecting its serviceability. The common method of non-destructive approaches such as [84,85]; Acoustic emission used to real large-scale structure [86], fracture propagation [87,88], carbon steel welding join [89], monitored pitting corrosion of stainless steel [90,91], accelerated corrosion testing [92]. magnetic flux leakage [93] and magnetic perturbation techniques [94] for detecting the corrosion in pipelines, guided waves [95] to detection of corrosion under insulation where reflections of guided waves and their arrival time reveals the presence of defects and their axial location. Long Range Ultrasonic Testing (LRUT) for long distance pipeline inspection [96], eddy current to detect stress corrosion in gas transmission pipes [97]. A comparison of different non-destructive testing techniques for corrosion monitoring is given below (see Table 2). Others corrosion detection methods illustrated in table 3.

Table 2: Non-destructive testing techniques comparison for corrosion monitoring [1]

Corrosion monitoring technique	**Advantages**	**Limitations**
Vision Based Inspection	Reliable Monitoring Inexpensive.	Off-line Processing. Computationally Expensive. Limited Access Issues.
Magnetic Flux Leakage	Active type NDT, Fast surface and sub- surface inspection, Relatively Inexpensive.	Limited to ferromagnetic materials. Alignment between magnetic. flux and defects are necessary.
Guided waves Based Inspection	Active type, NDT On-line Monitoring.	High frequency Ultrasonic. waves are required. Cross-talk issues Expensive.
Radiographic Inspection	Active type NDT, Not limited by Material type, Accurate and Reliable.	Safety Hazards Expensive. Required Interpretation for Results.
Acoustic Emission	Passive type NDT, On-line Monitoring, Relatively Inexpensive.	Interpretation of AE is important.

3.8. Framework of Impressed Current Cathodic Protection (ICCP):

ICCP is a kind of knowledge-based model to predict corrosion behavior. In order to established this model machine learning and historical data are utilized [98] evaluate it with survival, regression and classification analysis. This model applied to estimate and detect the corrosion progress and maintenance time in a result it was able to create an external corrosion prevention mechanism for an effective corrosion control. In order to develop this model many AI approached are used which can create complexity for this model.

3.9. UHF RFID (Ultra High Frequency Radio Frequency Identification:

This model used in marine environment to detect corrosion on steel [99]. The UHF RFID sensor detected the corrosion area by calculating the difference between the steel layer and the concrete moisture degree. Proposed method was capable to monitor and control the mass loss of steel by detecting corrosion status. To develop accurate model a sensor network development is essential.

Ref	Method	Description
[100]	Artificial Neural Network	Concrete corrosion monitoring in swage system. To predict the metal loss BP-NN (Back Propagation Neural Network) with sigmoidal activation function was trained. To detect pitting corrosion in steel reinforced concrete.
[101]	Hybrid Machine Learning Algorithms	To find corrosion rate in gas pipeline.
[102]	Electrochemical Noise (EN)	To find pitting, uniform and passivation Corrosion rate.
[103-105]	Magnetic Resonance Imaging (MRI)	For corrosion analysis.
[106]	Fitting Neural Network (FNN)	Investigate of corrosion rate in subsea pipeline.
[107]	Thermal Spraying Method	To assess the corrosion mechanism and coatings.
[108]	A Wasserstein distance-based analogous method	To predict distribution of non-uniform corrosion on reinforcements in concrete.
[109]	Fourier transform and Gaussian filter	Monitor and predict the corrosion degree
[110]	Python-based Deep Learning Approach	Automatic metal corrosion (rust) detection.
[111,112]	Two Weak Classifiers	Automatically detect corrosion in storage tanks, vessels and on pipelines.
[113]	HSI (Hue, Saturation and Intensity)	Applied for corrosion detection.
[114]	The hybrid wavelet packet transforms	For carbon-steel pipeline corrosion detection.
[115]	Wavelet image coefficient	To determine the atmospheric corrosion characteristics.
[116]	SOM (Self-Organizing Map)	To investigate the deteriorations of corrosion-induced crack and rebar corrosion.
[117]	SOM-based neural network	Corrosion evolution analysis and identification mechanism of restressed steel.
[118]	Hybrid Intelligent Algorithm Method	Predicts the corrosion rate of the multiphase flow pipeline.
[119]	Convolutional Neural Network	Hull structural plate corrosion damage detection.
[120]	Tree-based Ensemble, Kernel-based Technique	Predicted the corrosion and stress corrosion cracking 81 % accuracy using ensemble techniques and 87 % accuracy using the kernel-based technique.
[121]	Feed-Forward Artificial Neural Network (FFANN), Principal Component Analysis-Gradient Boosting Machine (PCA-GBM)	Predict corrosion in offshore pipeline.
[122]	CorrDetector	Structural corrosion detection from drone images
[123]	Wavelet Analysis	To determine the effect of nitrogen for pitting corrosion.
[124]	The Hybrid Metaheuristic Regression Model	For real-time tracking of corrosion in steel rebar.
[125]	Automated Method	To identify corrosion mechanism by obtaining a set of historical data.
[126, 127]	Single Support Vectors Regression (SVR)	Predicting the corrosion rate of 3C steel in five different seawater environments.
[128]	Phenomenological Model	Pitting corrosion of steel in concrete.

4. Advantages and Challenges

In this chapter the advantages and challenges of corrosion monitoring method is discussed.

Sometimes detection of corrosion is very dangerous and harmful for the people such as sewage pipes. In terms of sewage pipes, it is critical to address the challenges of assessing and maintaining corrosion in situ. The sewage pipes contain many bacteria and other microorganisms that are settling inside which can pose health threats to the corrosion inspectors because of the practical approaches. applying AI can be reducing with minimal exposure and physical contact to the health threats. In terms of ship structures, the most affected area is engine room, ship hull which is very difficult to reach because of small are [129]. Meanwhile, the oil and gas pipelines are isolated and located underwater. The wastewater pipelines also very small for human to reach. Because of that, the robotic vehicles and drones can be used to reach those places. Also, the LiDAR with point cloud can be used for corrosion detection on the ship hull. This imaging method can estimate the corroded areas by using an integrated 2D camera and RGB values on the ship structures

However, the challenges of implementation AI applications in corrosion monitoring such as, high upskilling cost, reliability issues, lack of skilled workers, industry adaptability, higher maintenance and higher installation cost. The high upskilling cost is also a challenge in implementation of AI approaches. The highly trained skilled workers are often task specialized and must get experience from the prolonged training. The worker needs to have the fundamental knowledge in artificial intelligence which is a quite difficult to find. On the other hand, the system itself might face the regular reliability issues. This can happen if the model contains many errors and bugs. Due to that, the algorithm must be developed and tested by the experts. the industry adaptability is still low especially in the underdeveloped countries. The industries there are heavily relied on the low-cost unskilled labour. The production output could be affected because of the labour shortage. The high maintenance cost and installation cost can contribute to the adaptability.

5. Conclusion

Corrosion continues to become the largest concern faced by researchers, academia and industries ranging from ship builders, wastewater pipelines to oil and gas pipelines. In this paper, the state-of-the-art artificial intelligence approaches have been assessed and summarized in relation to corrosion monitoring. Fundamentals, limitations and advantages of these approaches has been illustrated. Most of the reviewed methods have provided the significant quantitative and qualitative information in terms of corrosion.

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