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Review

Application of Artificial Intelligence in Marine Corrosion Prediction and Detection

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Abstract: One of the biggest problems the maritime industry is currently experiencing is corrosion, resulting in short and long-term damages. Early prediction and proper corrosion monitoring can reduce economic losses. Traditional approaches used in corrosion prediction and detection are time-consuming and challenging to execute in inaccessible areas. Due to these reasons, artificial intelligence-based algorithms have become the most popular tools for researchers. This study discusses state-of-the-art artificial intelligence (AI) methods for marine-related corrosion prediction and detection: (1) predictive maintenance approaches and (2) computer vision and image processing approaches. Furthermore, a brief description of AI is described. The outcomes of this review will bring forward new knowledge about AI and the development of prediction models which can avoid unexpected failures during corrosion detection and maintenance. Moreover, it will expand the understanding of computer vision and image processing approaches for accurately detecting corrosion in images and videos.

Keywords: corrosion prediction; corrosion detection; predictive maintenance; computer vision; image processing

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1. Introduction

Corrosion is the chemical decomposition of the metal into its components by interacting chemically or electrochemically; corrosion degrades metals into their oxides and sulfides [1]. Because of its interdisciplinary approach, corrosion has become one of the most challenging parts of science and engineering [2]. Moreover, corrosion poses significant short-term and long-term threats that cost billions of dollars [3]. According to the NACE, corrosion cost approximately 2.5 trillion US dollars, or 3.4% of the global GDP in 2013 [4]: (1) the direct costs include the price of supplies, labor, upkeep, and the expense of replacing corroded equipment, (2) the indirect costs of corrosion include production losses, environmental effects, transportation delays, injuries, and fatalities [5,6]. Of the 3–4% of GDP [7], 15–35% of this sum is believed to be preventable, with a significant portion linked to inspection costs [8].

In the shipping industry, marine structures are significantly damaged by corrosion, which will reduce the efficiency of mechanical properties and the different structural parts [9], such as hull structural failure [10]. Statistical data [11] shows that corrosion is responsible for approximately 90% of ship structural failure costs. Therefore, long-term corrosion detection is an excellent method to prevent catastrophic marine structure accidents. In addition to financial advantages, early detection of structural deterioration before failure can also minimize hazardous situations for both people and the environment and prevent catastrophic failures of structures [12,13]. The approximate cost can be reduced by 18–35% using proper strategy [4]. Furthermore, using the current artificial technologies, 20–25% of the yearly direct cost could be reduced [14,15].

In 1997, Sharon and Itzhak [16] employed image processing to explore how corrosion affected stainless steel. The most significant advantage of that method is that it can identify nearly entirely superficial defects (cracks and corrosion). However, it requires substantial human resources, workload, and financial resources. Feature extraction methods are often used in corrosion detection [17]. Therefore, developing other methods for corrosion prediction and detection is essential. Consequently, new ways of artificial intelligence have been able to attract researchers because of enormous advantages over human intelligence [18,19], advanced technology to solve complex problems [20–22], faster decision making [23] such as big data, machine learning (ML), deep learning (DL), neural networks (NN), face recognition, pattern recognition, image classification, and recognition, character recognition [24–28]. Cost reductions and risk reductions have been the driving forces for research into automated corrosion detection over the past ten years [29–34].

This paper aims to deliver a state-of-the-art review of artificial intelligence methods in corrosion prediction and detection from 2017 to 2022. Table 1 represents the review corresponding to the review protocol. A search of the chosen databases followed by curating a list of literature has resulted in 379 notable works on this topic. These studies were analyzed within the research scopes, where 151 studies were chosen to be explored in this work.

Table 1. Description of scope of bodies within the body of literature.

Subject	Description
Database	Web of Science, Scopus, Science Direct, IEEE
Keywords	''Artificial intelligence + corrosion+ detection," "Predictive + maintenance + corrosion," "Artificial + intelligence" and "current + trends," "Computer vision + corrosion + monitoring," "Image processing + corrosion + monitoring."
Publication type	Journal and conference paper
Language	English
Time interval	2017–2022

The discussion in this paper is divided into two sections. First, a description of artificial intelligence and its branches, such as; pattern recognition, machine learning, and deep learning, is elaborated. Additionally, three subdivision of machine learning (reinforcement learning, supervised education, and unsupervised learning) is discussed. Second, the artificial intelligence approaches in corrosion detection and prediction are elaborated. Two primary corrosion detection and monitoring methods are discussed: (1) predictive maintenance approaches and (2) computer vision and image processing approaches.

2. Artificial Intelligence

Artificial intelligence (AI) is a machine's capability to impersonate human behavior, respond perceptively, solve problems and make decisions automatically without human interference or with less human interference. The main objective of AI research involves general intelligence, automated planning, perception, natural language processing, knowledge representation, and robotics [35–39]. AI applications, for example, machine learning (ML), deep learning (DL), pattern recognition (PR), evolutionary computation, neural networks, expert systems, discriminant analysis, metaheuristic optimization, swarm optimization, image processing, and computer vision, have been used in marine research. Among those technologies, pattern recognition, deep learning, and machine learning are the most consistent and effective methods in corrosion engineering [23]. In this section, we have illustrated the technical background of the main artificial intelligence branches (machine learning, pattern recognition, and deep learning). The artificial intelligence techniques are shown in Figure 1, along with their correlation.

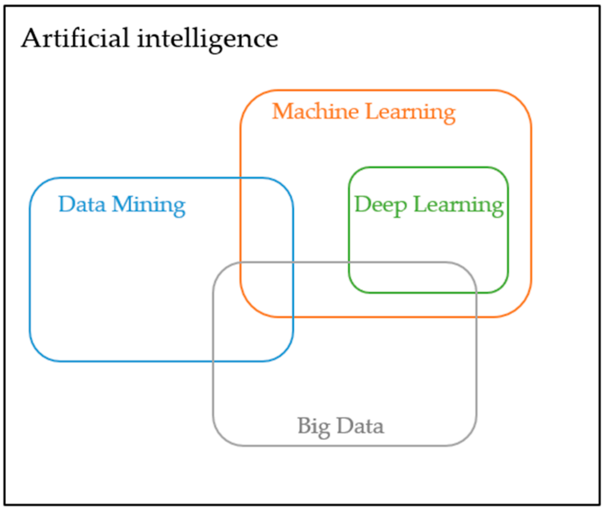

Figure 1. AI techniques interrelation.

2.1. Pattern Recognition

The main objective of pattern recognition is to classify objects into several classes. The objects could be signals, speech, images, or handwriting, depending on the application [40,41]. Several elements collectively serve to represent a pattern; the statistical theory is used to define decision boundaries across pattern classes. The pattern recognition system is divided into two modes: learning and classification (Figure 2). Learning and classification are called training and testing; in the learning mode, the selection module and feature extraction disclose the relevant features for describing the input patterns, and the classifier is taught to partition the feature space. The input patterns are assigned to a particular class by using the trained classifier, whereas the performance of the designed classifier, such as the system evaluation module, evaluates the classification error rate. Generally, pattern recognition can be categorized into two groups: supervised PR and unsupervised PR. Unsupervised pattern recognition uses training data that are not leveled, whereas supervised pattern recognition uses a collection of labeled training samples. Additionally, there is no preceding information concerning class level. Unsupervised PR is also called clustering. The generative and discriminative pattern recognition models and their algorithms are shown in Figure 3.

As there are few applications of pattern recognition in corrosion, researchers [42] used a PRS (pattern recognition system) based on electrochemical noise (EN) to detect the uniform and pitting corrosion and passivation of 304 steel (EN). They discovered that the PRS-EN parameters' accuracy of 99.7% was higher than those created using only statistical parameters (92.4%) and principal component analysis-selected parameters (97.8%). The same approach was used by [43,44] to identify the type and rate of corrosion in metal coatings and onshore pipelines using inline inspection (ILI) [45].

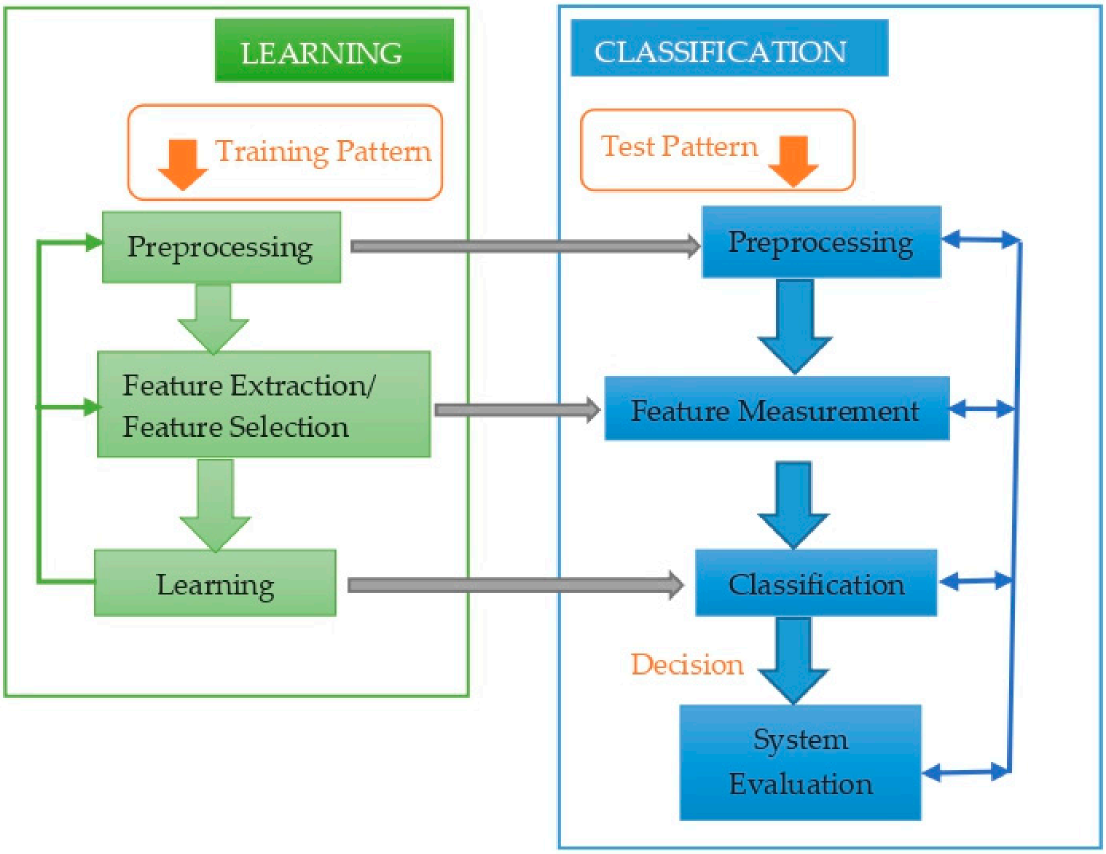

Figure 2. Schematic of pattern recognition.

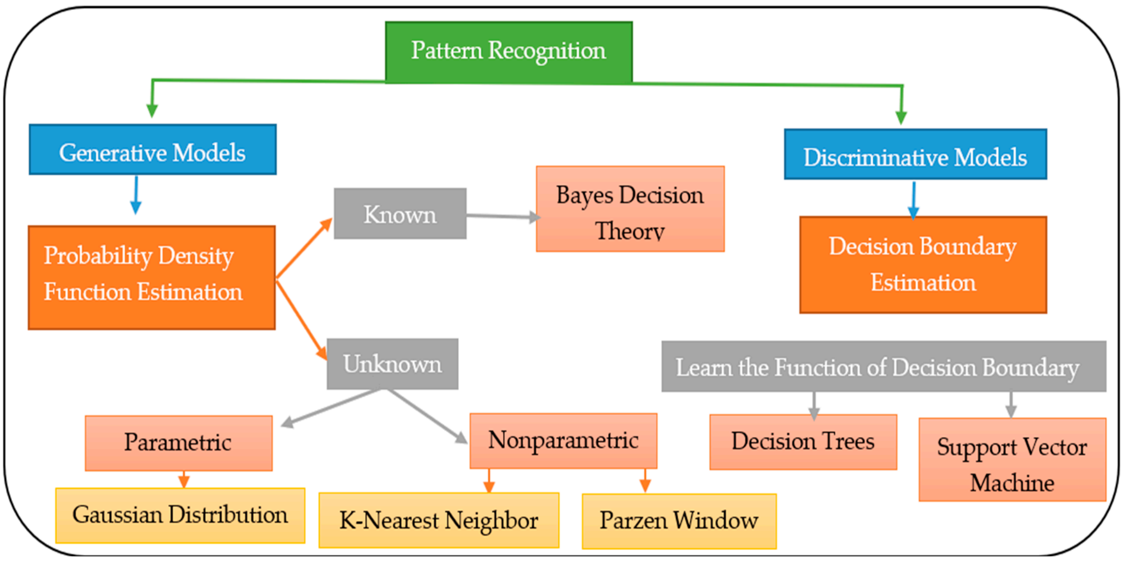

Figure 3. Pattern recognition model and algorithm structures (generative and discriminative pattern).

2.2. Machine Learning (ML)

ML is a subdivision of artificial intelligence. Building and developing mathematical models that can be trained to process extensive information is the goal of machine learning [46]. The primary objective of ML is to create and improve mathematical models that can be taught without having complete knowledge of all the external factors that influence decisions [47–50]. Additionally, these methods are trained by given data and capable of solving problems without or with minimum human intervention. Furthermore, it can predict future actions utilizing complex learning and indicating algorithms [46,51–55]. These models can either be predictive to perform decisions, acquire knowledge from data or both [56,57]. ML models have been successfully utilized in numerous fields of research, such as computational finance [58,59], image and speech processing [60,61], energy production [62,63], hydrology [64,65], and computational biology [66,67]. Over a few decades, it has brought substantial advancement in science and engineering along with developments in the eminence of our daily life.

Pattern recognition (PR) and deep learning (DL) are AI subsets that generally differ. Since PR and ML are thoroughly linked fields, their application areas primarily overlap [23]. However, ML focuses on learning algorithms, while PR concentrates on approaches for classification tasks [68]. The primary responsibility of pattern recognition is to identify patterns in data. Besides, learning is not required to categorize them. However, ML systems are built with the ability to learn on their own. Alternatively, Machine learning systems are created to learn independently [23].

A subset of machine learning is called deep learning. In reality, data representation can be learned using DL, and ML problems can be solved once the representation is created. Without a doubt, a high-dimensional challenge has its dimensions reduced via deep learning. The three primary subcategories of ML algorithms are reinforcement learning, supervised learning, and unsupervised learning. Figure 4 shows different machine learning categories. An overview of these groups is provided in the following chapters.

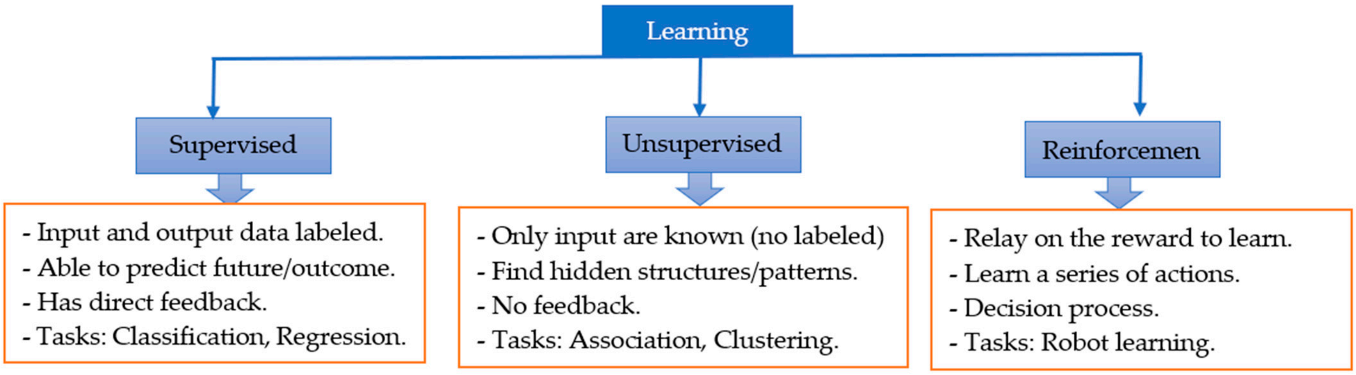

Figure 4. Machine learning categories.

2.2.1. Supervised Learning

In supervised learning, one or more output variables are predicted based on the input variables' values. The training data set with n samples and accompanying output values might serve as an example of an input variable (labels). The output variable could be a continuous variable (regression problem) or a discrete variable (classification problem) [68]. In contrast to classification, regression is used whenever an ML model aims to predict continuous target variables [23]. Applications for supervised learning include software engineering [69–72], natural language processing [73], computer architecture [74], and seafaring. The two main supervised learning techniques categories are parametric and non-parametric models. The parameters are fixed in parametric and non-parametric models, and the number of parameters depends on the training set [68]. Figure 5 depicts a common generic model of supervised learning.

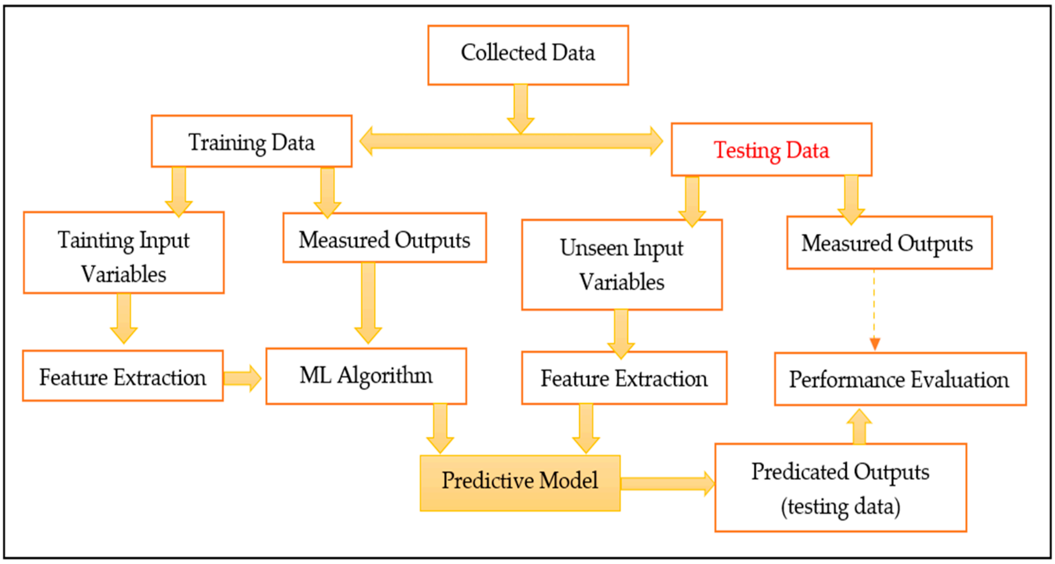

Figure 5. General supervised learning model.

2.2.2. Unsupervised Learning

Unsupervised learning uses a machine learning algorithm to cluster and analyze unlabeled datasets [75]. These algorithms can group data and discover hidden patterns without human intervention. Algorithms used in ML approaches are accustomed to concluding datasets with input data but no labeled responses. To develop the prediction model, the data is explored to detect hidden patterns or structures. Beforehand the algorithm is not instructed on what to do; henceforth, the algorithm must discover what is in the data. Clustering is the most common unsupervised learning used to find the possible grouping or inherent pattern in the given data. The Gaussian mixture model and k-means are types of clustering approaches [76]. A typical general unsupervised learning model is shown in Figure 6 and Table 2.

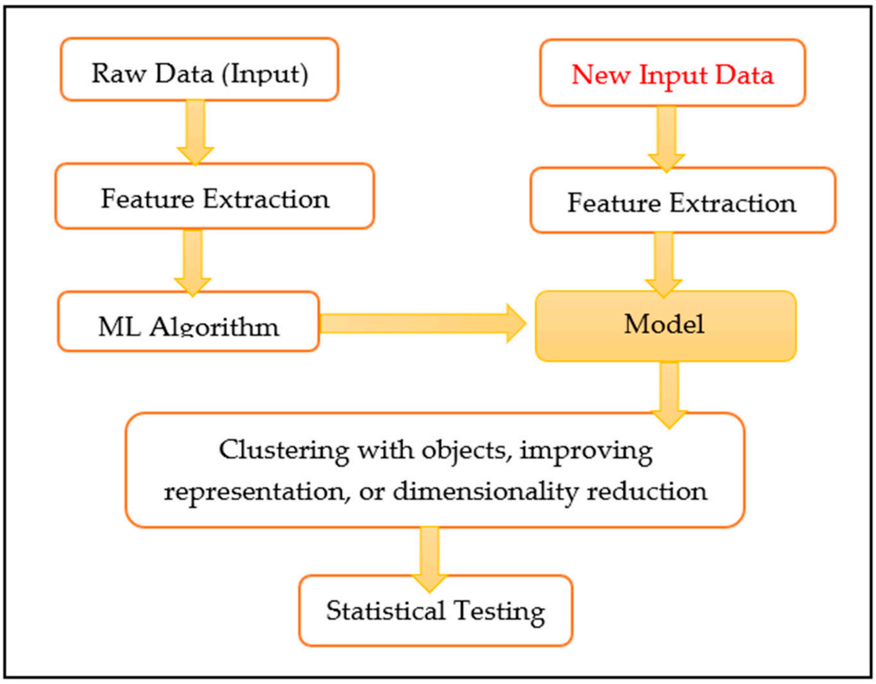

Figure 6. General unsupervised learning model.

Table 2. Basic differentiation between supervised and unsupervised learning.

Element	Supervised Learning	Unsupervised Learning
Input data	Labeled	Unlabeled
Feedback mechanism	Have	Don't have
Data classified	Based on the training dataset	Assigns properties of given data to classify it.
Division	Regression and classification	Clustering and association
Application	For prediction	For analysis
Algorithm	Logistic regressions, decision trees, support vector machine	Hierarchical clustering, K-means clustering, apriori algorithm.
Class number	Known	Unknown

2.2.3. Reinforcement Learning

Reinforcement Learning is a machine learning algorithm that allows the machine or software agents to intelligently regulate the best behavior within a definite context and exploit the performance. RL models are enforced to learn optimum objectives through the trial-and-error method [77]. As shown in Figure 7, the RL paradigm enables an agent to remember by investigating the potential actions and modifying its behaviors in response to the reward. Exploiting the long-term performance is the main focus of the agent. Therefore, the agent can consider future outcomes and the present reward for individual activities. RL is predominantly more efficient in dynamic and not completely deterministic environment RL [68]. Recent research discloses that RL has been applied in many different fields, such as speech recognition [60,61,78–81], computational biology [82–84], computational finance [85–87], computer vision, and image processing [88–93], energy production [94,95]. Various field methods have been adopted for this purpose [96,97]. Figure 8 displays some of the most popular algorithms used in machine learning.

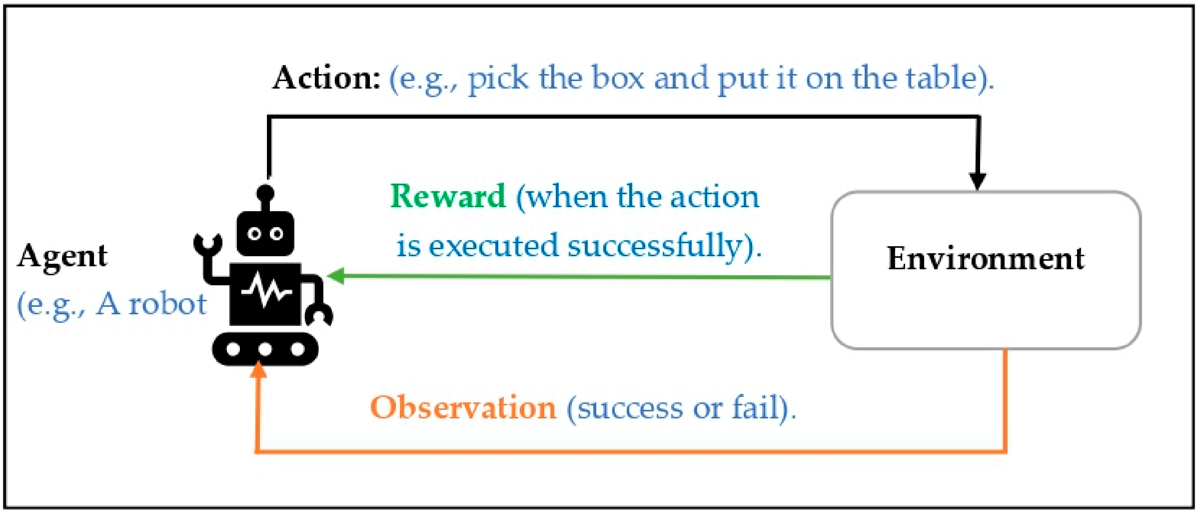

Figure 7. Reinforcement learning model.

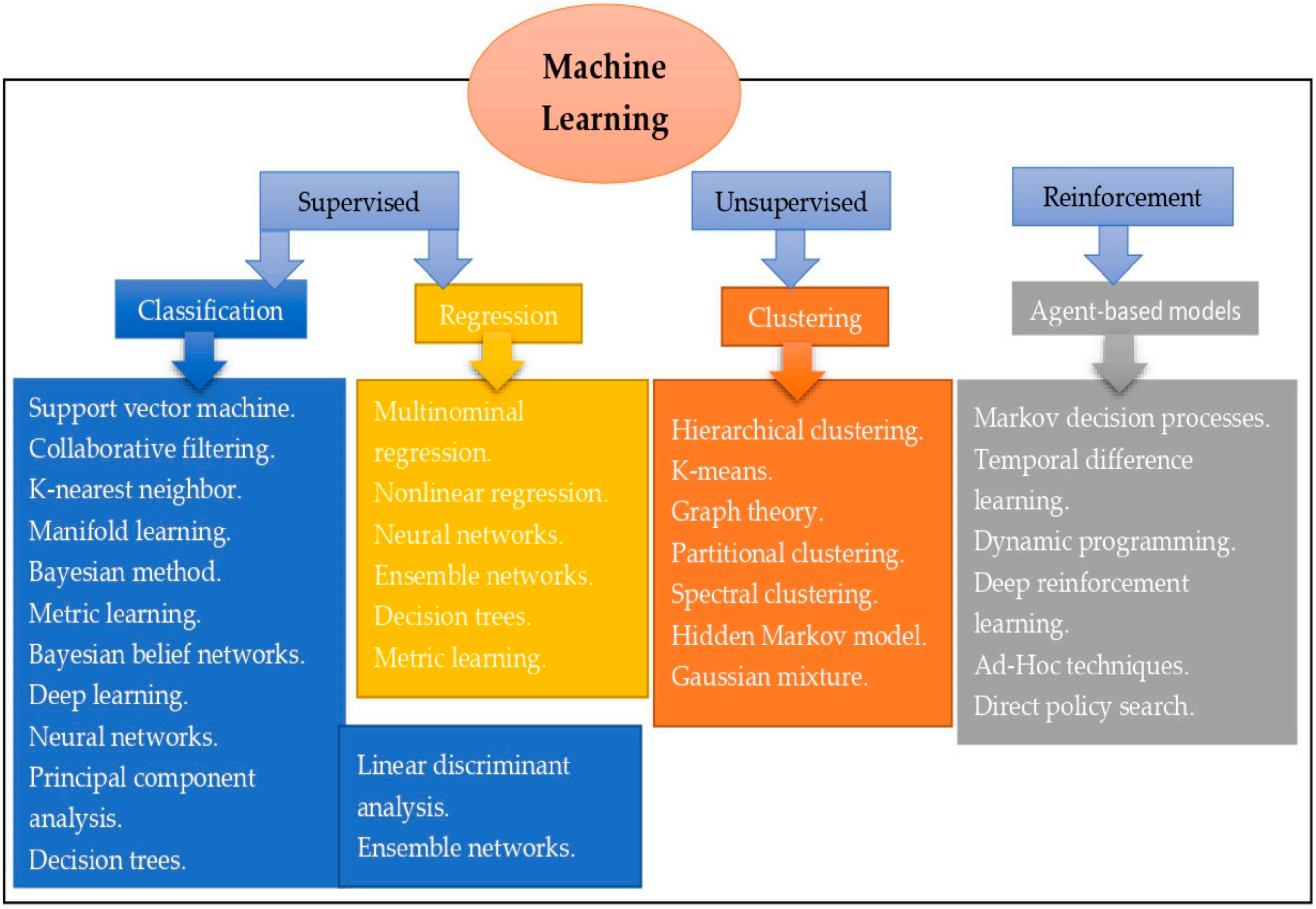

Figure 8. Machine learning categories and algorithms.

2.3. Deep Learning (DL)

Deep learning is a subset of machine learning and is essentially a three-or-more-layer neural network. A single layer can make predictions, but an additional hidden layer enhances and improves the correctness. These neural networks can learn from big data and act as the human brain [23]. Deep learning techniques are applied in many areas: law enforcement, finance, customer service, engineering technology application [98], turbines [99], aero engines [100], bearings [101], etc. Although deep learning models can significantly improve integrity estimation, a recent assessment found that they have not been used in corrosion [102]. Deep learning models can be crucial in corrosion prediction integrity estimates [103]. A notable result was obtained by [104] utilizing a deep learning method to measure the corrosion rate in a natural gas pipeline using a back-propagation artificial neural network (BP ANN). Artificial neural networks operated by [105] predicted the CO_2 corrosion rate. The same method was used by [106] to indicate the internal corrosion rate. In the following chapter, corrosion detection approaches are discussed.

3. Corrosion Detection Approaches

This section is divided into two subsections: (1) predictive maintenance approaches for corrosion detection and (2) computed vision and image processing techniques. A short introduction about corrosion is present at the beginning of this section.

Corrosion is a natural phenomenon [107] that 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 [108]. The anodic and cathodic electrochemical reactions are involved in the corrosion process [109]. Corrosion is categorized according to environmental 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 [110]. A general attack is a uniform electrochemical reaction that happens on the entire surface of a material. This kind of corrosion is predictable and can be contained. Galvanic or two-metal corrosion occurs between two metals due to the potential difference when both metals are submerged in a corrosive solution [111]. The resistant metal becomes a cathode, while the less resistant metal becomes the anode. The cathode metal will corrode less than the anode metal. Localized corrosion, called crevice corrosion, occurs when there are limited volumes of stagnant solution. It always attacks the lap joints, gaskets, and holes; pitting is the most intense corrosion form. It is a localized attack and can create holes in the metal.

Moreover, it is hard to locate them as they are covered with corrosion products. Intergranular corrosion is a localized attack on the grain boundaries. This type of corrosion creates a small, corroded area. Selective leaching happens when one element of an alloy is removed from it [112]. This phenomenon occurs in chromium, cobalt, iron, aluminum, and zinc. Erosion corrosion happens because of the rapid movement between a metal surface and a corrosive fluid, which accelerates the corrosion process. Abrasion and mechanical wear are also involved. Tensile stress and the corrosive media contribute to stress-corrosion crack propagation. A crack is produced from the steel caustic embrittlement and brass season cracking. These eight forms of corrosion can occur in the pipeline, ship hulls, bronze statues, copper roofs, steel bridges, metallic equipment, and many more. In terms of ship structures, fatigue and corrosion can reduce the strength of ships and vessels, which can cause structural failures [113]. The primary corrosion elements of the ship structures are the single metal element (ship hull).

Meanwhile, ship structures are categorized into the atmospheric and immersed zones of stiffeners and plates. The factors influencing corrosion in the atmospheric zone are temperature, humidity, steel type, ventilation, pressure, carbon dioxide, sulphuric acid, oxygen, sulfur dioxide, and chloride concentrations. Meanwhile, the immersed zone's main influencing factors are the seawater pressure, pH value, seawater velocity, temperature, salinity, carbon dioxide, sulphuric acid, and hydrogen sulfide concentrations. Because of that, a good maintenance strategy must be adopted for corrosion detection and maintenance activities. The cost of corrosion is high and estimated to be billions of dollars, which burdens the related industry if it is not detected in the early stage [20]. Due to that, numerous approaches have been established to reduce and minimize the impact of corrosion on the industry [114]. In the following subsection, we present predictive maintenance approaches for corrosion detection.

3.1. Predictive Maintenance Approaches for Corrosion Detection

Predictive maintenance (PdM) is a strategy involving detecting the early signs and acts of breakdown by doing proactive maintenance work [115]. A smooth operation can be ensured by attending to and acting on any failure, even if there is no major breakdown of the materials. PdM contains a set of mathematical models that will detect when the error happens and when to do maintenance [1]. The main objectives of PdM are to reduce maintenance time, production downtime, and the cost of component supplies. Due to that, PdM has been used in various industries to ensure the quality, efficiency, reliability, and safety of equipment and materials. Recently, PdM has been gaining attention in corrosion detection and maintenance due to its efficiency in predicting and determining an affected material's corrosion level. It can be categorized into knowledge-based, physic-based, data-based, and hybrid models [116]. In the following subsection, a brief description of those approaches is provided.

3.1.1. PdM with Knowledge-Based Model

The PdM knowledge-based model is a model that uses cases, facts, rules and experiences in developing its prediction model [117]. The data on maintenance and operation are gathered over many years. Recently, IR4.0 allowed this model to be integrated and automated with machine learning, statistical and artificial intelligence.

A framework of impressed current cathodic protection (ICCP) system was introduced in [118], where the machine learning and historical data were used to predict the downstream test post. This knowledge-based model was evaluated with survival, regression and classification analysis. The knowledge in the test post potential was used to estimate and detect the corrosion progress and maintenance time. According to the results, the proposed method managed to create an external corrosion prevention mechanism for effective corrosion control. Despite that, this model used many AI approaches, which can increase the complexity of the developed prediction model.

The vast knowledge of sulfur was used by [119] to investigate the existing maintenance strategy in the maritime industry. The new marine fuel caused a big challenge due to the consistent changes in physical and chemical properties, which can contribute to the corrosion progression. Thus, the planned maintenance work will be inadequate, which can endanger ships' operations. The very low sulfur fuel oil (VLSFO) characteristic was monitored with PdM to reduce the critical risk potential. Based on the results, the proposed method managed to provide corrective action and detection for corrosion from sulfur emissions. Nevertheless, this prediction model was determined to evaluate the Sulphur 2020 amendment.

The rules of hull girder [120] were used to assess the corrosion effect on the bulk carrier. The web section and flange section on the cross-section property and vertical bending moment were investigated to determine the residual strength of the ship hull. Then, a prediction model was developed from the incremental-iterative method and probabilistic corrosion rate estimation model. The parameters of cross-section property, neutral axis position and vertical bending moment were measured to determine the accurate maintenance activities. The results showed that the proposed method could detect and reduce the corrosion effect on the ship hull. However, the lack of historical data can affect the sensitivity of the prediction model for maintenance planning. The unplanned and unexpected corrosion behavior can still occur even with an accurate prediction model.

The reliability, availability and maintainability (RAM) analysis [121] was developed to predict the future trends of maintenance planning. The real-time data from the fuel injection valve case were measured from the container ship. The valve itself can be affected by corrosion which can reduce the efficiency of ship engines. According to the result, the developed prediction model can enhance the routine and non-routine maintenance activities on the ship engine. Nevertheless, the optimization of the prediction model can be done to further increase the reliability of maintenance planning.

The other PdM knowledge-based corrosion prediction models include the marine steel structures based on the climatic condition cases [122], the facts of ferrography lubricants [123], the rules of double hull girder tanker [124] and the experiences of random field approach [125].

3.1.2. PdM with Physic-Based Model

The PdM physic-based model is a prediction model that uses physics laws, real conditions, original equipment and the behavior of the tool or material. Recently, a digital twin was developed from the subject itself and then compared with the behavior of the physical tool or material. Due to that, the digital twin can be fine-tuned to operate and match the function of the actual subject.

The under-deposit corrosion (UDC) on the firetube boiler [126] was investigated to improve the predictive maintenance of the system. The three-pass seawater steam boiler was monitored for six years to obtain the necessary data. According to the result, the corrosion on the firetube boiler was formed from the hematite minerals and carbonates.

Nevertheless, the usage of UDC propagation and phosphate congruent control (PCC) managed to improve the prediction model of predictive maintenance. Despite that, the prediction model itself might not be suitable for the other boilers because of the different parameters and external environment in the workplace.

Wear debris analysis (WDA) [127] was proposed to analyze the wear conditions of the industrial gearbox with the different types of wear failure and gear pitting modes. The moisture corrosion-attacked wear, contaminant-induced abrasive wear and acid attack were simulated on the industrial gearbox in order to monitor and create a prediction model for predictive maintenance. Based on the results, the wear debris morphological analysis managed to detect and anticipate wear and its mechanism. The studied parameters were typical for the industrial gearbox. However, the size, brand and configuration might reduce the accuracy of the developed prediction model since most of the industrial gearboxes were custom-made.

Furthermore, the UHF RFID (Ultra High-Frequency Radio Frequency Identification) sensor [128] was developed to detect corrosion steel in the marine environment. The steel deterioration happened due to the broken thin oxide film layer because of the presence of chloride. Hence, the UHF RFID sensor detected the corrosion area by calculating the difference between the steel layer and the concrete moisture degree. It can measure up to a few micrometers thickness of the metallic film. According to the result, the proposed method managed to monitor and control the mass loss of steel. However, this method did not use PdM in its process. The developed sensor network could be suitable and accurate for developing a PdM physic-based prediction model.

The study on the effect of long-term corrosion in physical infrastructure [129] was proposed to determine the most suitable mathematical model, especially for the marine corrosion of ships. The effect of marine corrosion, such as crevice severity and pit depth, was investigated to create efficient maintenance decision-making. The empiricism degree of corrosion was compared with the available prediction model. However, the historical data on corrosion progression under oxygenated conditions might require several decades to collect. This can increase the complexity of the prediction model.

The Weibull distribution [130] was introduced as the prediction model for the aging ship structural corrosion. The prediction models were developed from the degradation process of stiffener and plate. The ship structures were grouped into the zone, compartment, and structural types, such as longitudinal deck girder, stringer deck, top wing plating, inner side wall, inner bottom, side shell, bilge keel, deck, hopper plating, hatch coaming, bottom plating, machinery space, void space, ballast water tank, fuel oil tank, freshwater tank, cargo hold, atmospheric zone, splash zone and immersed zone. The developed prediction models can be individually adjusted for each ship's structural elements from the real-time data and historical data. This prediction model can also be fine-tuned by calculating the means of influencing factors. Based on the result, the proposed method can predict corrosion at the aging ship structures. Despite that, this model required large data for each fine-tuning of the ship's structural elements. The data can be analyzed at the edges or sensor nodes and stored in the cloud in order to reduce transmission costs and data transmission errors.

The other PdM physic-based corrosion prediction models include the prognostic of physics-of-failure [131,132], RUL of ship hull structure profile [133] and ship hull tanker profile [134]. These physics models were validated and compared with the respective simulations.

3.1.3. PdM with Data-Based Model

The PdM data-based model is a prediction model that uses a data-driven approach in its implementation, such as stochastic, statistical, and machine learning. This prediction model is heavily dependent on real-time and historical data. Due to that, the presence of noise and uncertainty in data could affect its behavior. Validation with the knowledge-based and physic-based models is required to verify its result. Despite that, not all prediction models with machine learning, statistical and artificial intelligence are considered data-based models. The core or fundamental of the developed prediction model will determine its own category.

The data-based model was proposed for corrosion failure prediction with extreme value analysis (EVA) [135]. EVA was used to make predictions of the depth of pits that required immediate maintenance. The real-time data of the degradation process from the inspection reports were used to develop a prediction model by considering the peaks over threshold (POT). The developed prediction model was validated with the block maxima (BM) approach to assess corrosion failure. This prediction model achieved high performance in detecting and assessing corrosion failures. However, this prediction model was not implemented in the multiple sections in the same workflow. The prediction model might require fine-tuning and parameterization for assessing multiple sections of corrosion failure.

The framework of Bayesian inference [136] was constructed to predict corrosion defects. The prediction model used both real-time data and historical data for the employment of generalized extreme value distribution (GEVD). The real-time data were frequently updating the model, while the historical data were indirectly assisting the corrosion defect distribution. This prediction model achieved the highest reliability and can adapt to the defect depth distribution. Nevertheless, the real-time data were quite sensitive for parameter estimation, even with guidance from historical data. This could reduce the accuracy of the developed prediction model if the historical data were unavailable.

The combination of the expected behavior (EB) model and the exponentially weighted moving average (EWMA) was introduced in [137] for the shipboard corrosion system. The learning potential was explored from the recorded voyage data. This prediction model can detect certain fault parameters, such as air pressure and gas temperature, that could be useful for developing a corrosion model. Despite that, the well-maintained ship was inevitable due to the occurrence of failures which can exhibit energy efficiency, safety and reliability. Such conditions can contribute to corrosion and fouling in the turbocharger and nozzle ring of the vessel.

The new innovative prediction model [138] was developed with time-series anomaly detection and machine learning. The maintenance decision-making was provided by the board sensors on the engine and ship hull. The lifetime of the hull managed to be extended with reduced maintenance costs. A huge amount of data was available through the data sources' exploitation and deployment. The results showed that the proposed method could predict corrosion on specific parts of the ship's engine. Nevertheless, the sensors' placement was on the specific parts of the vessel, which can reduce the accuracy of the prediction model. The model itself might need fine-tuning and parameterization for the different parts of the vessel.

The mathematical model was adopted from the real-time data of the ship's ballast tank [139] to predict corrosion damages on the ship structure. The nonlinear time-dependent formulation was derived from the probability density function (PDF) method by selecting the best fit of the real-time corrosion data. Then, the curve fitting method was selected for sub-parameters. According to the results, the adopted prediction model was accurate for determining RUL and corrosion damage over time. Despite that, the prediction model might require fine-tuning for each nearshore, offshore, onshore, and ship structures.

The other PdM data-based corrosion prediction models include the 25 years of monitoring of historical data of ship hulls [140], the condition-based predictive maintenance of customized self-healing systems [141], the spatial dependence of material, geometric and corrosion growth properties [142], and the synthesized life-cycle risk analysis framework [143].

3.1.4. PdM with Hybrid Model

The PdM hybrid model is a combination of at least two PdM prediction models from the knowledge-based, physic-based or data-based models. This prediction model has different configurations than the multi-model PdM. Due to that, not all multi-model PdM can be considered as a hybrid model.

Big data and machine learning were used in [144] to initiate solutions for the shipping industry, such as for hull corrosion. This hybrid method used the sensor network to collect both real-time data and historical data to reduce disruption during operations. The results showed that the number of breakdowns and failures could be reduced with PdM. The key parameters demonstrated the strong correlation and influence between equipment. The maintenance decision-making was improved in terms of accuracy and speed. Even though this method can create an efficient prediction model, it probably can create disruption within the shipping industry due to its implementation complexity. Furthermore, the potential failure mode and failure identification mode must be defined prior to developing the prediction model.

The strain sensing method [145] was developed for the detection of thickness loss in the ship hull. The hybrid model of structural health monitoring and classical detection tool was investigated for hull structure maintenance and corrosion detection. The real-time data and historical data were collected from the in-situ sensors. The damaged ship hull conditions were estimated with a Monte Carlo simulation. Then, the Gaussian and mean-shifted methods were considered to measure the deterministic signals from the static strain. The results showed that the strain measurement could be used for the detection of thickness loss in the ship hull. Nevertheless, this method did not consider the effect of noise in the historical data, which can challenge the dynamic of the signal.

The risk-based maintenance scheduling [146] was reviewed and applied for ships and vessels. Previously, this method was implemented in other industries. The decision analysis and probabilistic modeling were suggested for the decision-making of the prediction model. The fatigue crack propagation and corrosion scenario were used for the optimization of the prediction model. The reliability-centered maintenance (RCM) was also combined with the current framework for the evaluation of the prediction model in terms of maintenance cost and availability. The proposed prediction model achieved a reduced maintenance cost. It also managed to detect corrosion from risk-based scheduling. However, the prediction model was still in development and not integrated with the sensor network.

The computerized maintenance management system (CMMS) [147] was used as a framework for the prediction model of all maintenance activities on board the ship. This prediction model covered all related activities for the maintenance of equipment and ship structure corrosion. The constructive features, mission, equipment, and ship structure corrosion were integrated as a parameter to determine the decision-making for maintenance activities. The CMMS managed to create the planning for all equipment and ship structure, resulting in better maintenance resources, recording data of maintenance activities, and optimizing maintenance planning. Nevertheless, this prediction model was implemented for a special or custom-made ship. Fine-tuning and parameterization could be a challenge to implementing a similar prediction model on other ships.

The digital twin and artificial intelligence were proposed in [148] for the ship hull structures. The optimization method of finite element (FE) was implemented to create a prediction model. After that, the artificial neural network (ANN) was used for fitting and classification. The results showed that the specific location could be determined with this prediction model; thus, the sensitive area on the ship's hull can be monitored closely for any damage or corrosion. The physic-based model of the digital twin and the data-based models of FE and ANN have been proven for the ship hull structure analysis.

3.2. Computer Vision and Image Processing Approaches for Corrosion Detection

Computer vision is an artificial intelligence field where the computer or machine is required to imitate or emulate the human visual system via machine learning. The computer or device can see and interpret patterns from optical inputs. Computer vision and image processing are promising approaches because of their nondestructive testing, high accuracy, and fast detection of corrosion boundaries. It replicates the human visual system complexity and interprets inputs from their color, size, texture, etc. Meanwhile, image processing is a method to enhance, improve and transform images by tuning the features and parameters of the given images. The images can be changed with many techniques. These digital images have particular values and location elements such as pixels, picture elements, and visual elements. Therefore, image processing is used for corrosion detection since its techniques can enhance, sharpen, filter, and segment the corroded area in images. Many computer vision and image processing algorithms have recently been established for corrosion detection, assessment, and prediction. These approaches are based on color, texture, filtering, pixilation, clustering, classification, segmentation, wavelet transformation, and image enhancement. The computer vision and image processing processes for corrosion detection can be divided into five main processes or elements: image acquisition, image pre-processing, image segmentation, feature extraction, and image classification shown in Figure 9. Additionally, the researcher introduced corrosion detection methods and their application, shown in Table 3.

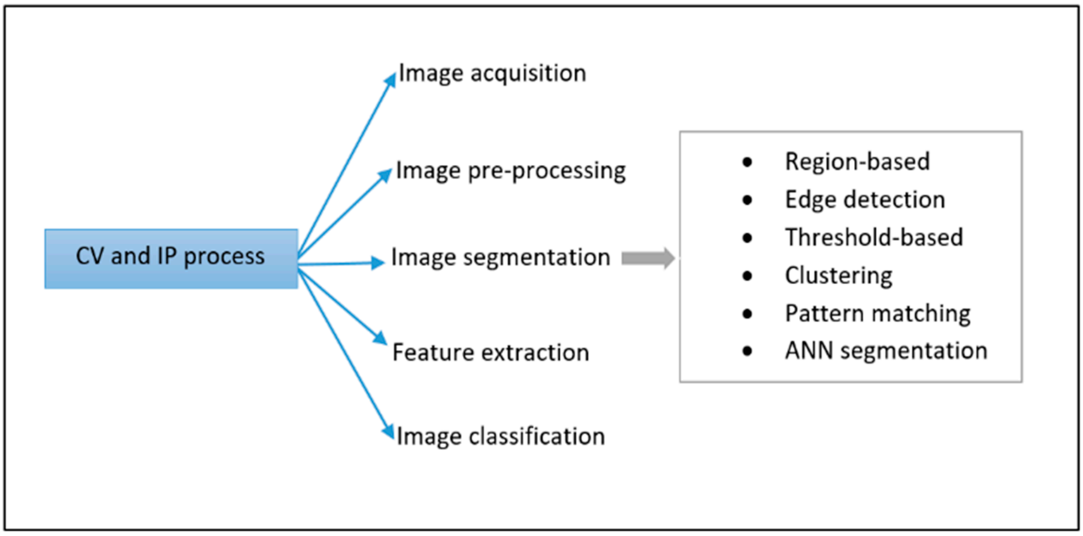

Figure 9. Computer vision and image processing elements.

Table 3. Short description of different corrosion detection approaches and their applications.

Models	Descriptions	Applications
Knowledge-Based Model	Used artificial intelligence to predict the progress of corrosion from images and videos.	-Automated sewer inspection [149,150]. -Combination of CCTV and machine learning [151–153].
Probabilistic Model	Used for corrosion detection when the real-time data and historical data are insufficient. Require in-depth knowledge and expertise in physic and mathematics to develop a sophisticated mathematical model. Quite difficult to develop.	-Gamma distribution [154]. -Gamma process and copulas of Spatio-temporal [155]. -Probabilistic model and finite element [156]. -Monte Carlo finite element [157,158].
Statistical Model	Used statistical analysis to predict and detect the corrosion progress based on historical data. The historical data can be collected from the installed CCTV in the gas pipeline, sewer, and many more.	-Markov chain with gray level co-occurrence method [159,160]. -Polynomial regression [161] and linear regression [162,163].
Deterministic Model	The relationships between variables or parameters of corroded material are studied from the field experiments via images and videos. Easier to develop and could be inaccurate in terms of extrapolation results [164].	-Structural health monitoring (SHM) and digital twin [165]]. -Texture descriptors with cellular automata [166]. -Others [167,168].

3.2.1. Infrared Thermography

For the purpose of detecting corrosion, infrared thermography is frequently used in computer vision and image processing methods [129,169–171]. Due to the recently created infrared detector, these methods produce better corrosion detection accuracy and resolution. The cost of monitoring and development is reduced, but noise and weak signal strength can cause thermal images to be interrupted. The electromagnetic energy that metallic materials emit is captured using this method. Then, using the thermal images, corrosion patterns can be found. Application of thermography-based techniques applied to optical [172], laser [173], induction [174], microwave [175], photovoltaic (PV) electroluminescence module [176] and other systems for crack and corrosion detections on pipelines energy, surface inspection, practically, source, etc. However, each of these methods has limitations regarding their energy, surface inspection, practically, source, etc.

3.2.2. Texture Analysis

Texture analysis has been used in [177–180]; image processing techniques and object classification computer vision are used. Texture analysis improves classification results by reducing errors for isolated data detection. It can accurately detect, recognize and classify corroded regions in the images. Additionally, texture analysis can identify the corrosion and non-corrosion regions [181,182]. Application of SVM; water pipelines [183], underwater pipelines [184], steel bars [185], bridge cables [186], equipment [187], aircraft structures [188], wind turbine blades [189], and many more.

3.2.3. Non-Destructive Methods

Nondestructive testing for corrosion detection (Table 4) is used to check and assess materials without compromising their usability. Standard nondestructive techniques include acoustic emission utilized for real large-scale structures [190–192], fracture propagation [193–195], monitored pitting corrosion of stainless steel [196,197] and accelerated corrosion testing [198–201]. Under insulation, guided waves were employed to detect corrosion. The presence of flaws and their axial location is revealed by guided wave reflections and their arrival time. Magnetic flux leakage and magnetic perturbation techniques are used to detect corrosion in pipes. Eddy currents are used to find stress corrosion in gas transmission pipes, whereas long-distance pipeline inspection uses long-range ultrasonic testing (LRUT) [202]. Meanwhile, Table 5 shows the other corrosion detection methods in the literature.

Table 4. Non-destructive testing techniques comparison for corrosion monitoring.

Methods	Advantages	Limitations
Vision-Based Inspection (VSI)	Inexpensive and consistent monitoring.	Off-line processing. Costly in terms of computation. Concerns with minimal access.
Magnetic Flux Leakage (MFK)	Inexpensive, rapid inspection of the surface and subsurface. Active type.	Restricted to ferromagnetic substances. It is required to align the magnetic flux and flaws.
Guided waves-based inspection	On-line monitoring and active type.	Ultrasonics with a high frequency. Waves are necessary. Crosstalk problems. Expensive.
Radiographic inspection	Not constrained by material kind, precise, trustworthy, active type.	Safety risks are pricey. Required results interpretation.
Acoustic emission	Inexpensive. On-line monitoring, passive type.	It's crucial to interpret AE.

Table 5. Other corrosion detection methods.

References	Methods	Descriptions
[203–206]	Artificial neural network	Concrete corrosion monitoring in the sewage system. Investigate pitting corrosion in steel-reinforced concrete.
[207]	Hybrid machine learning Algorithms	Find the corrosion rate in a gas pipeline.
[92]	ANN and image processing	Detect the corrosion level of the concrete structure of reinforced steel.
[95]	Tomographic acoustic micro imaging (TAMI)	Evaluate the pitted region and corrosion depth in the scanning acoustic microscopy (SAM) images.
[208]	Electrochemical noise (EN)	Find pitting, uniform, and passivation corrosion rates.
[97,209]	Magnetic resonance imaging (MRI)	For corrosion analysis.
[210]	Fitting neural network (FNN)	Investigate the corrosion rate in the pipelines.
[94]	Thermal spraying method	Assess the corrosion mechanism and coatings.
[211]	A Wasserstein distance-based analogous method	Predict the non-uniform deterioration of reinforcing materials.
[93]	Fourier transform and Gaussian filter	Monitor and predict the corrosion degree.
[83]	Synchrotron radiation computed tomography (SRCT)	Tested for corrosion rate measurement, composite failure analysis, and electrochemical reaction visualization.
[33]	A python-based deep learning approach	Automatic metal corrosion (rust) detection.
[30,212]	Two weak classifiers	Automatically detecting corrosion on pipelines, storage tanks, and other containers.
[46]	HSI (Hue, Saturation, and Intensity)	Applied for corrosion detection.
[45]	The hybrid wavelet packet transforms	Carbon-steel pipeline corrosion detection.
[213]	Wavelet image coefficient	Determine the atmospheric corrosion characteristics.
[66]	HSV color space	Locate the corroded and non-corroded regions.
[214]	2D-wavelet filtering	Identify structural damage.
[47]	Backpropagation method, radial basis function, and extreme learning machine	Predict stress corrosion cracking.
[215]	SOM (Self Organizing Map)	Investigate the deterioration of corrosion-induced crack and rebar corrosion.
[216]	SOM-based neural network	Analysis of the progression of corrosion in prestressed steel and identification of the process.
[217]	The hybrid intelligent algorithm method	Predicts the corrosion rate of the multiphase flow pipeline.
[218]	CNN	Hull structural plate corrosion damage detection.
[219]	Tree-based ensemble, kernel-based technique	85% accuracy with the kernel-based technique and 81% accuracy using ensemble techniques for predicting corrosion and stress corrosion cracking.
[220]	Principal component analysis-gradient boosting machine, feed-forward ANN	Predict corrosion in offshore pipelines.
[221]	CorrDetector	Structural corrosion detection from drone images.
[1]	Machine learning algorithm	Prevent pipeline corrosion.
[222]	Wavelet analysis	Determine the effect of nitrogen on pitting corrosion.
[223]	Hybrid metaheuristic regression model	Monitoring corrosion in steel rebar in real-time.
[224]	Automated method	Determine the cause of corrosion by collecting a set of historical data.
[225]	Single support vectors regression (SVR)	Estimate the 3C steel corrosion rate in five distinct marine conditions.
[30]	Phenomenological model	Determine pitting corrosion of steel in concrete.

4. Conclusions

Corrosion endures become one of the biggest concerns in the maritime industry. In our paper, we have summarized the state-of-the-art artificial intelligence approach in marine-related corrosion monitoring. These methods' working fundamentals, advantages, and limitations have also been discussed. Most of the reviewed methods have provided significant quantitative and qualitative information regarding corrosion detection. Due to that, the present corrosion condition can be assessed, and the future corrosion condition can be predicted accordingly. The outcomes of this review can bring forward new, and additional knowledge of AI approaches for corrosion detection, assessment, and prediction. However, more study is needed to take advantage and fully exploit the recent advancements of IR4.0 technology in terms of advanced sensors and artificial intelligence to achieve impressive and better future performances for corrosion detection, assessment, and prediction.

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