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Advancements and Challenges in Convolutional Neural Networks for Marine Corrosion Detection and Classification

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ABSTRACT

Marine corrosion significantly undermines the structural integrity of maritime infrastructure, necessitating the development of sophisticated techniques for its early detection and classification. This paper offers an exhaustive critical review of Convolutional Neural Networks (CNNs) applied in marine corrosion detection and classification, covering research from 2018 to 2023. It compiles insights from various scholarly articles, elucidating the progression of CNN methodologies in tackling the intricate challenges associated with corrosion in marine, offshore and oil & gas sectors. This review meticulously examines the deployment of CNN technologies in evaluating corrosion across a myriad of maritime assets, including ships, marine structures, offshore platforms and oil & gas pipelines, also construction materials. It explores a broad spectrum of methodologies, underscoring the advancements in CNN-based strategies for corrosion monitoring. Importantly, the review pinpoints key obstacles, innovative strategies and forthcoming trends in the field, offering a comprehensive summary of current research on marine corrosion detection and classification through CNNs. The insights gained from this thorough analysis are instrumental in deepening the understanding of technological and methodological progress, serving as a guide for future research endeavours in the crucial field of maritime asset integrity management.

1. Introduction

Corrosion, a fascinating chemical dance between metals and their environment, unfolds as these sturdy materials transform stable compounds like oxides, hydroxides and sulphides. Picture this: metals exposed to the whims of humidity and pollution, engaging in a silent but impactful tango. In the vast realm of the maritime industry, corrosion emerges as a silent foe capable of wreaking havoc

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on metals [1-3]. The secret ingredients of this metal metamorphosis include the tag team of water and electrochemistry, the creation of protective scales, the gentle caress of low velocity, the unique composition of steel and the unexpected attacks by localized bacteria. It's like a symphony of elements conspiring to gradually age the materials designed to withstand the test of time [4-6]. The consequences of corrosion are evident in various sectors, such as ship structures and offshore and oil and gas pipelines, resulting in substantial financial losses, environmental pollution and, unfortunately, significant casualties. The impact of corrosion goes beyond material damage, encompassing broader implications for the economy and the environment [7-9].

The global economy has experienced a substantial estimated loss of around 2.5 trillion US dollars, equivalent to 3.4% of the world's GDP, attributed to corrosion [10]. In Figure 1(a) and 1(b), the direct cost of corrosion across various sectors in China is depicted, providing valuable insights [11]. Notably, a report singles out the Arab world as the region most severely impacted by corrosion, accounting for 16% of their total GDP, as indicated in Figure 1(c) [9]. Significantly, a considerable portion of these expenditures, ranging from 15% to 35% of the GDP share, can be mitigated, with inspection costs pivotal in these efforts [12-16]. This underscores the potential for proactive measures, including effective inspection strategies, to reduce the economic impact of corrosion.

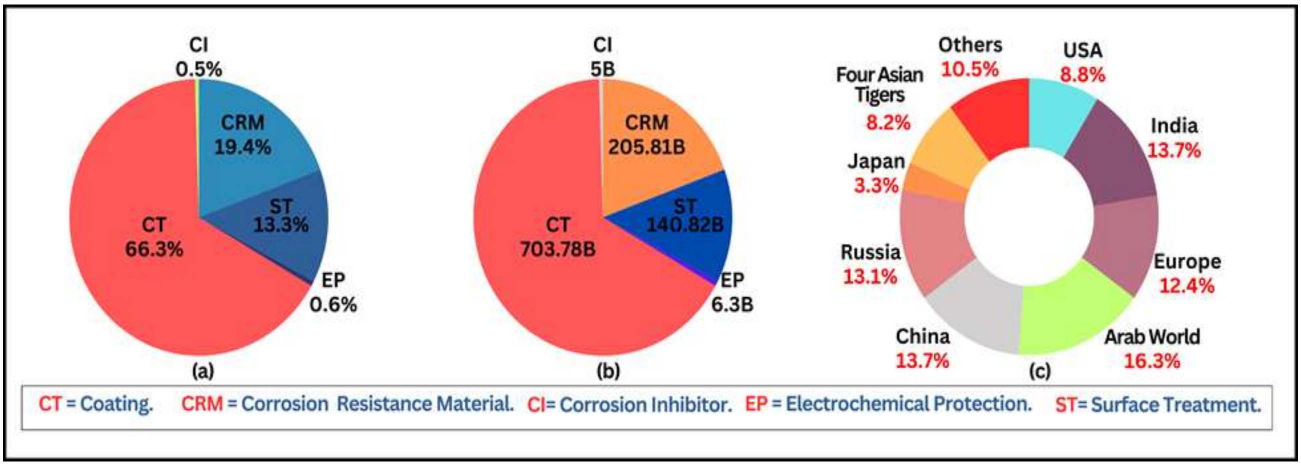


Fig. 1. Corrosion cost statistics (a) Corrosion cost percentage across different domains (b) Direct corrosion cost amount (in RMB) (c) Corrosion cost as a percentage of countries' GDP [9,11]

Furthermore, corrosion poses a significant threat to marine structures, reducing mechanical efficiency and compromising structural integrity. This, in turn, can result in critical issues such as hull failure, breakdown of docks or offshore structures, pipeline leaks and, most importantly, potential threats to human lives [17-20]. Corrosion accounts for approximately 90% of the expenses associated with failures in maritime structures [21-23]. An alarming statistic underscores the pervasive impact of corrosion, revealing that roughly 25-30% of the steel produced annually succumbs to corrosion, incurring substantial direct costs of a staggering $276 billion. This amount corresponds to an estimated 3.1% of the Gross Domestic Product (GDP) of the United States [24,25]. These costs encompass repairing and inspecting corroded surfaces and structures and disposing hazardous corrosion waste materials. Additionally, they include expenses related to applying protective coatings like paintings and surface treatments [26].

Another report by the British Hoar Committee emphasizes that corrosion costs account for 3% of the British Gross National Product (GNP), with the potential to reduce these costs by 23%. In industrialized nations, an estimated 3.5-5% of their income or GNP is allocated to corrosion-related expenses, covering losses, replacements, maintenance and prevention measures. Beyond direct financial impacts, corrosion also incurs various other costs, such as production losses due to shutdowns and leakages, product contamination and maintenance expenditures [27-29]. To overcome these limitations, long-term corrosion monitoring strategies are essential. Long-term corrosion detection and prevention are crucial for avoiding catastrophic marine structural incidents [30-32]. Beyond the financial advantages, early identification of structural deterioration significantly reduces risks to human safety and environmental harm while preventing potential structural breakdowns [33-36].

The objectives of this review paper are multifaceted, aiming to provide a critical review of the application of Convolutional Neural Networks (CNN) in the context of corrosion detection and classification related to marine, offshore and oil and gas infrastructure. Additionally, we aspire to pinpoint potential areas for future research and advancements by understanding the strengths and limitations inherent in existing methods. Through this comprehensive review, we aim to contribute to the ongoing discourse in corrosion studies and foster a deeper exploration of CNN's potential in addressing challenges within marine and offshore environments. The overall research design is shown in Figure 2.

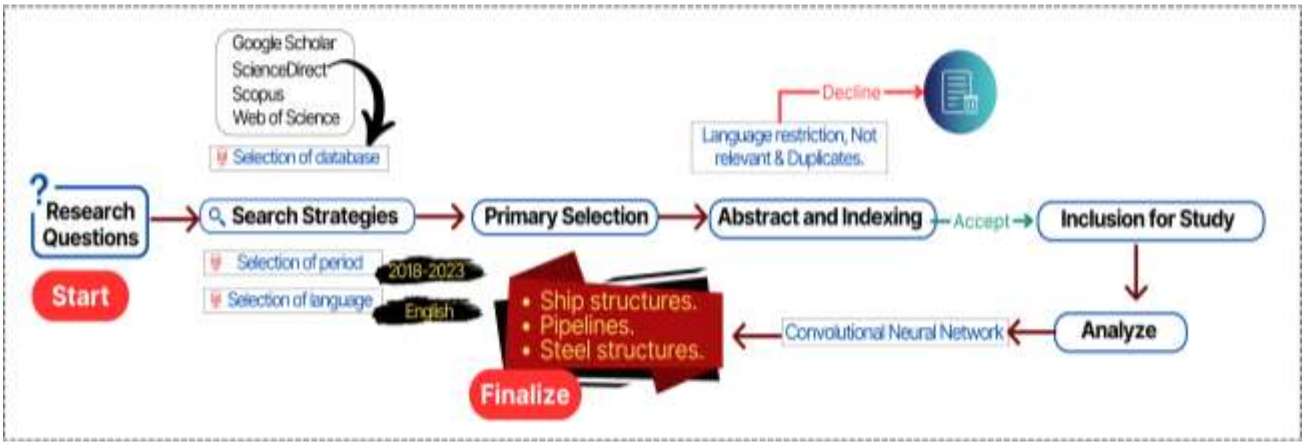


Fig. 2. Overall research methodology flowchart

This review paper comprises five chapters; Chapter One serves as the introduction, laying the foundation for the review. Chapter Two, titled 'Findings,' encompasses an in-depth exploration of CNN fundamentals and their applications in marine corrosion detection, encompassing ship structures, offshore environments, oil and gas pipelines and ship construction materials, focusing on steel. Chapter Three, 'Discussion,' synthesizes the key insights and trends identified in chapter two while addressing potential limitations and biases in the literature. Chapter Four, 'Recommendations,' offers practical recommendations to enhance CNN-based corrosion detection in marine settings alongside considerations for policy and industry. The final chapter, 'Conclusion and Future Research,' provides a conclusive summary of the paper's contributions and outlines promising avenues for future research in this vital field.

2. Findings

2.1 Fundamentals of Convolutional Neural Network

In the late 1980s, the inception of CNNs marked a promising development in visual tasks. However, their full potential remained largely untapped, lying dormant in the realm of possibilities until the mid-2000s [37]. During this period, advancements in computing power, the availability of large labelled datasets and improved algorithms collectively contributed to their resurgence [38,39]. A turning point was reached in 2009 with the establishment of ImageNet, an extensive database consisting of many object categories and more than ten million images. To evaluate and contrast classification and detection techniques, the ImageNet Challenge was created with a dataset including one thousand classes extracted from the ImageNet database [40,41]. The advent of potent graphical processing units (GPUs), alongside the establishment of ImageNet and the triumph of CNNs in the ImageNet Challenge, sparked a notable surge of research interest in CNNs. This period marked the beginning of a neural network renaissance and CNNs emerged at the forefront of this resurgence, experiencing rapid progression since 2012. Subsequently, CNNs have been extensively employed for a range of applications, including object classification [42], object detection [43,44], object segmentation [45,46], action recognition [47-49], medical applications [50,51] and more. Across various domains, CNNs have consistently demonstrated superior performance compared to prevailing classification algorithms. Typical CNN algorithm structures are shown in Figure 3.

In corrosion research, CNN is used to identify and classify corrosion patterns on metal surfaces [52]. High-resolution photos of metal surfaces are transmitted into the network *via* this application. Using filters, the convolutional layers retrieve pertinent information, such as textures and edges linked with corrosion. Activation layers introduce non-linearities, whereas pooling layers reduce the spatial dimensions of the sample. Once global patterns have been captured, the data is flattened and processed using fully connected layers, following the application of many convolutional and pooling layers. In addition to classifying corrosion levels and recognizing specific types of corrosion, the output layer generates forecasts. To decrease prediction errors, the network is trained on labelled datasets while its parameters are adjusted. Furthermore, CNNs are valuable instruments for automated corrosion analysis in various metal structures, as their capacity to generalize to novel, unforeseen corrosion patterns is confirmed through subsequent evaluation on a test dataset [42,47,53].

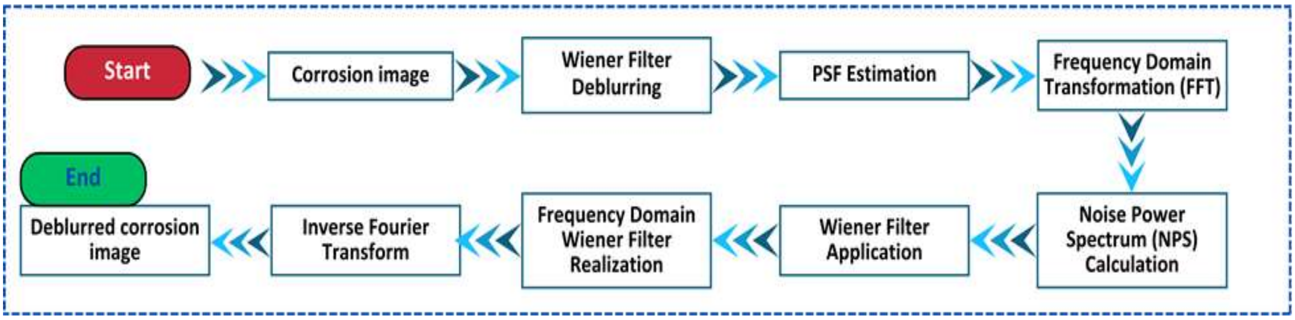


Fig. 3. CNN model structure

2.2 CNN Application in Ship Structures

Corrosion is a pervasive and persistent challenge that the maritime industry faces, particularly concerning ship structures [3]. Ships, whether cargo vessels, naval warships or offshore platforms, operate in harsh and corrosive environments, such as saltwater and humid atmospheres. These conditions subject ship structures, including the hull, superstructure and various components, to the relentless threat of corrosion. Corrosion in ship structures primarily occurs due to electrochemical reactions between the metal surfaces and the corrosive agents in their environment [54]. Figure 4 illustrates some ship structures affected by corrosion.

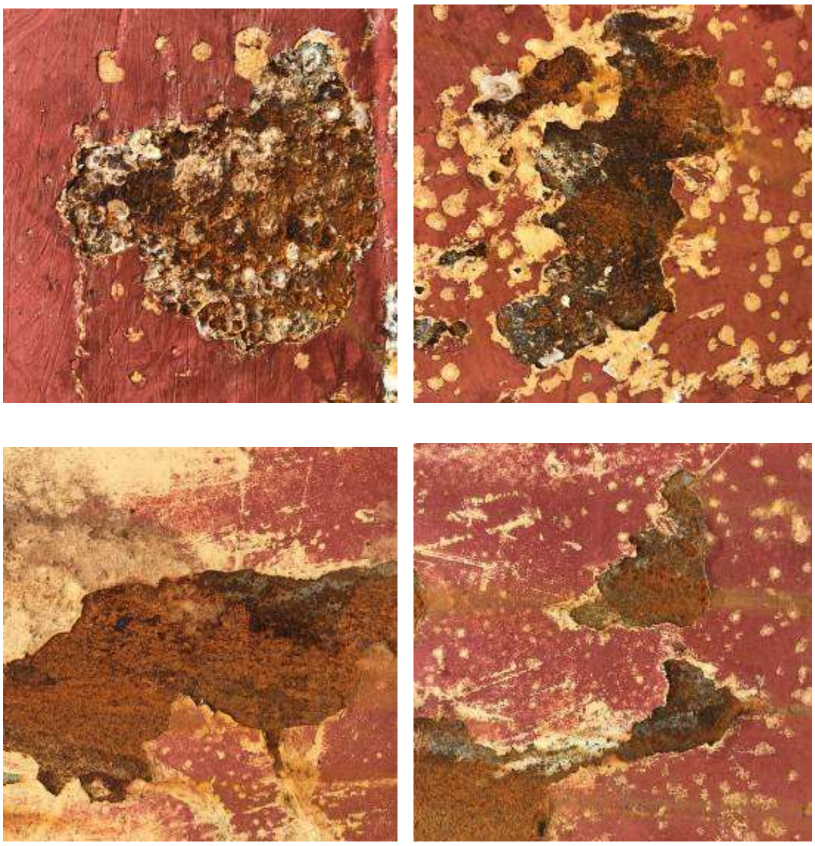
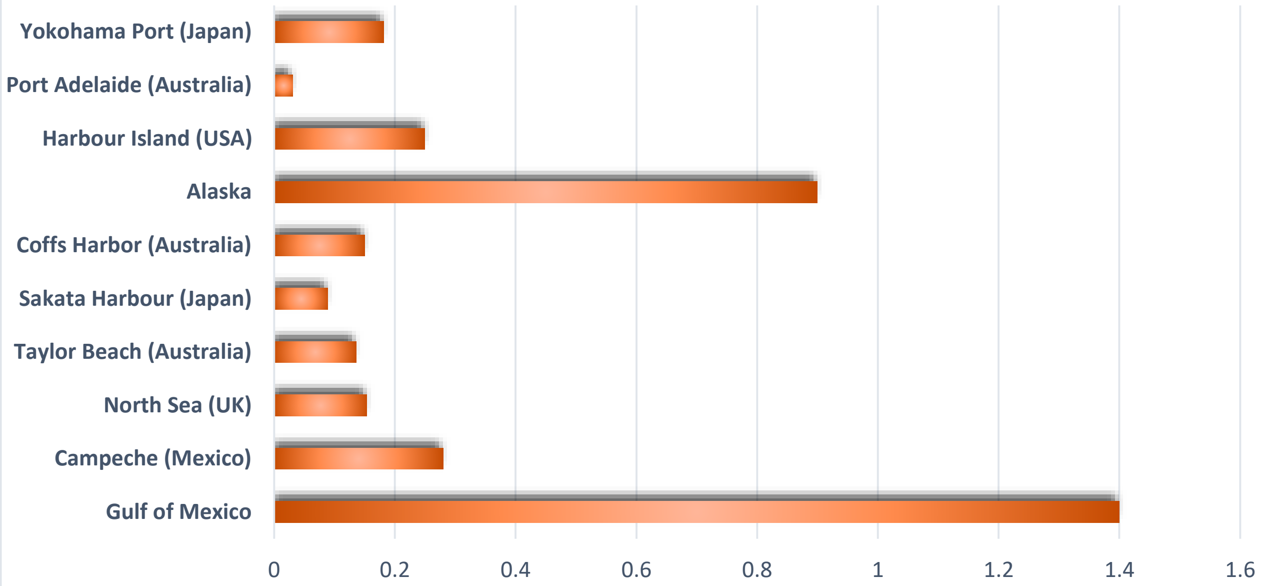


Fig. 4. Ship structures affected by corrosion

Furthermore, as shown in Figure 5, the corrosion rate can vary significantly in different regions, highlighting the diverse characteristics of corrosion challenges faced by ships operating in distinct geographical areas. These variations in corrosion rates necessitate tailored corrosion mitigation strategies and maintenance practices to ensure the longevity and safety of maritime assets.

The application of CNNs in combating corrosion in ship structures is a promising and innovative approach applied to corrosion detection and prediction that can significantly enhance maintenance and safety measures in the maritime industry. Yao *et al.,* [54] applied CNN to detect and identify corrosion damage to ship hull structural plates. The CNN model was constructed using the AlexNet model as its foundation. In the results, CNN can effectively detect a range of superficial structural damages, encompassing delamination, voids, spalling and corrosion damage. Simultaneously, establishing a detection pattern for corrosion damage significantly enhances the efficiency of the corrosion detection classifier. Training a CNN typically necessitates a vast dataset encompassing various categories and conditions. However, in this research, the dataset was limited, especially regarding images captured under conditions of weak light intensity, blurriness and shade. As a result, it was determined that the generalization ability of the AlexNet for the HCDR network model (HCDR refers to the English initials of the four words “hull structural plate”, “corrosion”, “damage” and “recognition”) fell short when applied to such images.

Shirsath *et al.,* [55] applied a hybrid automated corrosion detection of different compartments of vessels. The investigation delves into exploring and experimenting with automated corrosion detection methods focusing on the visual features of corrosion. The author employed artificial intelligence techniques to extract relevant information from images, particularly emphasizing colour and texture as critical attributes for identifying corrosion on surfaces. A specialized colour-tracking algorithm was developed and evaluated utilizing images acquired from different compartments of vessels to identify corrosion based on colour.



	Gulf of Mexico	Campeche (Mexico)	North Sea (UK)	Taylor Beach (Australia)	Sakata Harbour (Japan)	Coffs Harbor (Australia)	Alaska	Harbour Island (USA)	Port Adelaide (Australia)	Yokohama Port (Japan)
Series1	1.4	0.28	0.154	0.136	0.089	0.15	0.9	0.25	0.031	0.182

Fig. 5. Corrosion rate (mm/year) in different regions

Deep learning algorithms were employed for texture-based corrosion detection and this study investigated two unique methodologies. The initial methodology entails employing transfer learning to train a binary classification model within a CNN framework. In addition, a sliding algorithm was applied to this model to enable the detection and localization of corrosion on plates that have been severely damaged. Corrosion detection is conceptualized as an object detection problem in the second approach. Transfer learning was utilized to train a Single Shot Detector (SSD) to identify rust in images of the actual environment. Two datasets were produced to streamline the training process and evaluate all models. The first dataset consists of photos depicting corroded metals in a controlled laboratory setting. On the other hand, the second dataset comprises real-world images of corroded compartments obtained during bulk carrier inspections. The study's findings indicate that the proposed approaches exhibit efficacy in detecting corrosion (94% on test data). Moreover, Matthaiou *et al.,* [56] applied a hybrid model including CNN-Transfer learning for corrosion detection in different vessel compartments from digital images. The methodology considered the visual attributes of corrosion, explicitly focusing on colour and texture. Texture-based approaches outperformed colour-based ones. However, this method encountered challenges when applied to real-world vessel images due to a noisy background in the corrosion images.

Liu *et al.,* [57] pioneered the development of a faster region-based CNN (faster R-CNN) specifically tailored for the analysis of coating breakdown and corrosion (CBC) in ship structures. For feature learning, the methodology employed a collection of 1,900 photos capturing marine and offshore structures with CBC. 12,184 features were collected from these photos and classified into the following five categories: surface-based CBC, CBC on edges, CBC on welding joints and non-coating failure (including hard rust and pitting). For the purpose of validation, a subset of 2,437 features (20 percent of the total 12,184 features) was selected at random. The observed overall rate of recognition was 81.4%. Another application of faster region-based CNN was applied by Xu *et al.,* [58] to detect corrosion in coated metal plates. The dataset employed in this study comprised images of metal plates with coatings exposed to corrosive environments and systematically monitored and photographed. The experimental results showcased an impressive Average Precision (AP) value exceeding 94 on the testing set. Moreover, the prediction error for the proportion of the corrosion area was meticulously maintained within a commendable 10%. Capitalizing on these promising detection outcomes for the corrosion area, the study further facilitated maintenance decision-making by assigning a standardized protection rating to the metal surface. Nevertheless, the detection results need further categorization and refinement for more direct guidance during manual maintenance processes to optimize worker operations.

Furthermore Andersen *et al.,* [59] applied Faster-RCNN and YOLO to detect corrosion in marine vessels. They developed and assessed a pipeline that employs a compact deep-learning model to activate a larger one upon detecting corrosion. The resulting segmentation is subsequently utilized to assess the vessel conditions. A total of ten architectures and combinations were experimented with, ranging from traditional classification to object detection and instance segmentation. Each of these architectures underwent rigorous training on a diverse dataset featuring images from ballast tanks that showcased varying degrees of corrosion. The outcomes reveal that standard object localization architectures like YOLO and Faster-RCNN tend to overestimate the extent of the corroded area. Bahrami *et al.,* [60] implemented Faster R-CNN to detect corrosion in ship containers, initially exploring models like SSD Mobile Net and SSD Inception V2. They utilized fixed-size anchor boxes, which proved limiting due to corrosion defects' diverse sizes and shapes. An enhanced architecture was introduced to address this, integrating cutting-edge models with anchor box optimization. This improvement allows the models, especially Faster R-CNN, to excel in detecting corrosion across various defect sizes. Faster R-CNN operates in two stages: feature extraction using techniques like VGG or ResNet and a Region Proposal Network (RPN) for bounding box proposals. In the subsequent stage, these proposals guide feature extraction, optimizing class label prediction and bounding box refinement. Notably, Faster R-CNN's approach minimizes redundant computations, enhancing performance efficiency compared to direct cropping methods [53].

An additional study on corrosion detection in containers was conducted by Bahrami *et al.*, [61]. High-resolution and temporal context region-based CNN (HRTC R-CNN) was utilized. To extract semantic information across a variety of fault scales, HRTC R-CNN employs a multi-depth, multi-stream backbone and multiscale super-resolved feature creation. For the purpose of semantic extraction, the deep network processed low-resolution images, whereas the shallow network received high-resolution images to preserve positional information. To bolster the framework's performance, an attention mechanism and two memory banks were integrated to harness context information from unlabelled images. Within the corrosion defect detection (CDC) process, a novel optical flow-based image stitching method was introduced to compute the percentage of corrosion across the entire container surface. Through extensive experiments conducted on the corrosion defect dataset, the proposed approach exhibited exceptional accuracy and robustness.

CNN architecture was used by Soares *et al.,* [62] for corrosion detection in marine vessel structures and the research demonstrated satisfactory results, achieving an accuracy of 92% for synthetic underwater images within the test dataset. Recently, Siswantoro *et al.,* [63] applied CNN for corrosion detection in ship structures; the results demonstrate that, among 127 images, the predominant labels were pitting corrosion, followed by general corrosion, with edge corrosion being the least prevalent. Despite the program's capacity to identify corrosion across three distinct categories during the preliminary study, it exhibited suboptimal accuracy. The test evaluation yielded mean recall and accuracy values of 0.5 and 0.3, respectively. The reduced efficiency might be due to the inadequate amount of data utilized during the training and testing phases.

2.3 CNN Application in Offshore and Oil & Gas Pipelines

In the context of offshore and oil and gas pipelines, corrosion stands as a pervasive and formidable challenge. Corrosion, the gradual degradation of pipeline materials due to environmental factors, has been a persistent concern for these industries. Its effects extend beyond mere material deterioration, often leading to catastrophic consequences such as accidents and structural failures. Corroded pipelines can develop weaknesses and vulnerabilities, increasing the risk of leaks, spills and environmental damage. Moreover, the financial toll of pipeline failures, coupled with the potential for reputational damage, underscores the critical need for effective corrosion management strategies. Figure 6 provides a visual representation of the percentage of pipeline failures attributed to corrosion. It highlights the significant role that corrosion plays in pipeline integrity and emphasizes the need for effective corrosion management strategies within the industry.

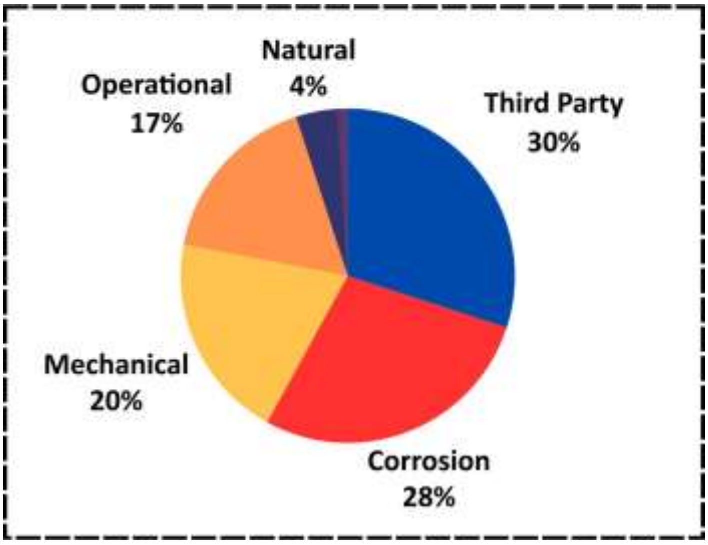


Fig. 6. Ratio of pipeline failure causes

Furthermore, Figure 7 shows the cause of corrosion in pipelines. In this subsection of our review paper, we delve into the pivotal role that CNNs play in addressing the complex issue of corrosion in offshore and oil and gas pipelines.

In 2019, Bastian *et al.,* [64] employed a custom-designed CNN to detect corrosion in water, oil and gas pipelines effectively. The author utilized an extensive dataset comprising over one million images, each categorized into four corrosion levels. A custom CNN architecture was developed, carefully designed to have fewer trainable parameters compared to the fine-tuned CNN architecture used in previous studies [65-67], which often involves managing a substantial number of trainable parameters. Notably, the proposed method showcased its ability to examine corrosion from standard RGB images, unlike the utilization of MFL images [68]. In terms of classification, the classifier was trained to assess the corrosion level within an image in a single pass, eliminating the need for sliding window approaches applied in prior works [65,67]. Furthermore, an unsupervised recursive region-based approach was employed for corrosion localization, deviating from supervised methods such as the FasterRCNN detection and segmentation approach found in previous research [69,70].

The proposed network in this research [64] excels at classifying images into four categories based on the level of corrosion: no corrosion, low, medium and high levels of corrosion. A comprehensive database comprising over 100 thousand images depicting pipelines with varying levels of corrosion was meticulously curated and categorized into these classes. Comparative evaluations demonstrated the superior performance of the proposed model over ZFNet [71] and VGGNet [72] across various evaluation metrics. Notably, CNN surpassed these models and their fine-tuned versions regarding trainable parameters and evaluation metrics. In addition to classification, the proposed method incorporates the localization of corroded regions within the image, achieved through a recursive region-based method. This integrated approach enables the efficient identification of corroded regions. One noteworthy advantage of this approach is its ability to seamlessly integrate with aerial robots, enabling accurate detection of exterior corrosion in pipelines in various environments and real-time non-destructive inspection.

In their study, Vriesman *et al.,* [73] proposed representation learning via deep neural networks as a substitute for manually constructed features in the automated visual assessment of corroded metallic pipes. A texture CNN (TCNN) was utilized instead of manually constructed features such as Haralick descriptors (HD) and Local Phase Quantization (LPQ). One notable benefit of TCNN is its capacity to acquire a suitable textural representation and establish decision bounds using a solitary optimization procedure. The experimental results demonstrated that it is possible to achieve a 99.20 percent accuracy rate when discerning various levels of corrosion on the inner surface of pipe walls.

Bastian *et al.,* [74] assembled a dataset of more than 140,000 pipeline images showcasing diverse degrees of corrosion. They employed a CNN that was explicitly created to classify these pipeline images according to the level of corrosion. Notably, their in-house CNN design featured a minimal number of parameters compared to existing CNN classifiers. Despite its simplicity, this custom CNN achieved a remarkable classification accuracy of 98.8%. The system exhibited a remarkable capacity to distinguish between images depicting corroded pipelines and those featuring patterns mimicking corroded pipelines but lacking corrosion. The proposed network exhibited superior performance when compared to other state-of-the-art classifiers.

In 2021, Bhowmik [75] presented a CNN integrated with a computer vision-based digital twin concept for Offshore Pipeline Corrosion Monitoring. The CNN algorithm was employed to automate the identification and classification of corrosion from Remote Operated Vehicle (ROV) images and In-Line Inspection data. The Deep Learning algorithm, specifically CNN, exhibited an accuracy of approximately 81% in correctly identifying and classifying corrosion. Significantly, the deep-learning approach showed a considerably reduced processing time, while utilizing the digital twin facilitated the instantaneous formulation of prescriptive or predictive tactics predicated on inspection outcomes. Parjane *et al.,* [76] applied Deep CNN (DCNN) for corrosion detection in underwater pipeline structures. The Deep CNN demonstrated superior detection accuracy (0.997) compared to the Naïve Bayes machine learning algorithm. The CNN utilized multiple convolutional layers and collaborated with activation functions to achieve its detection performance.

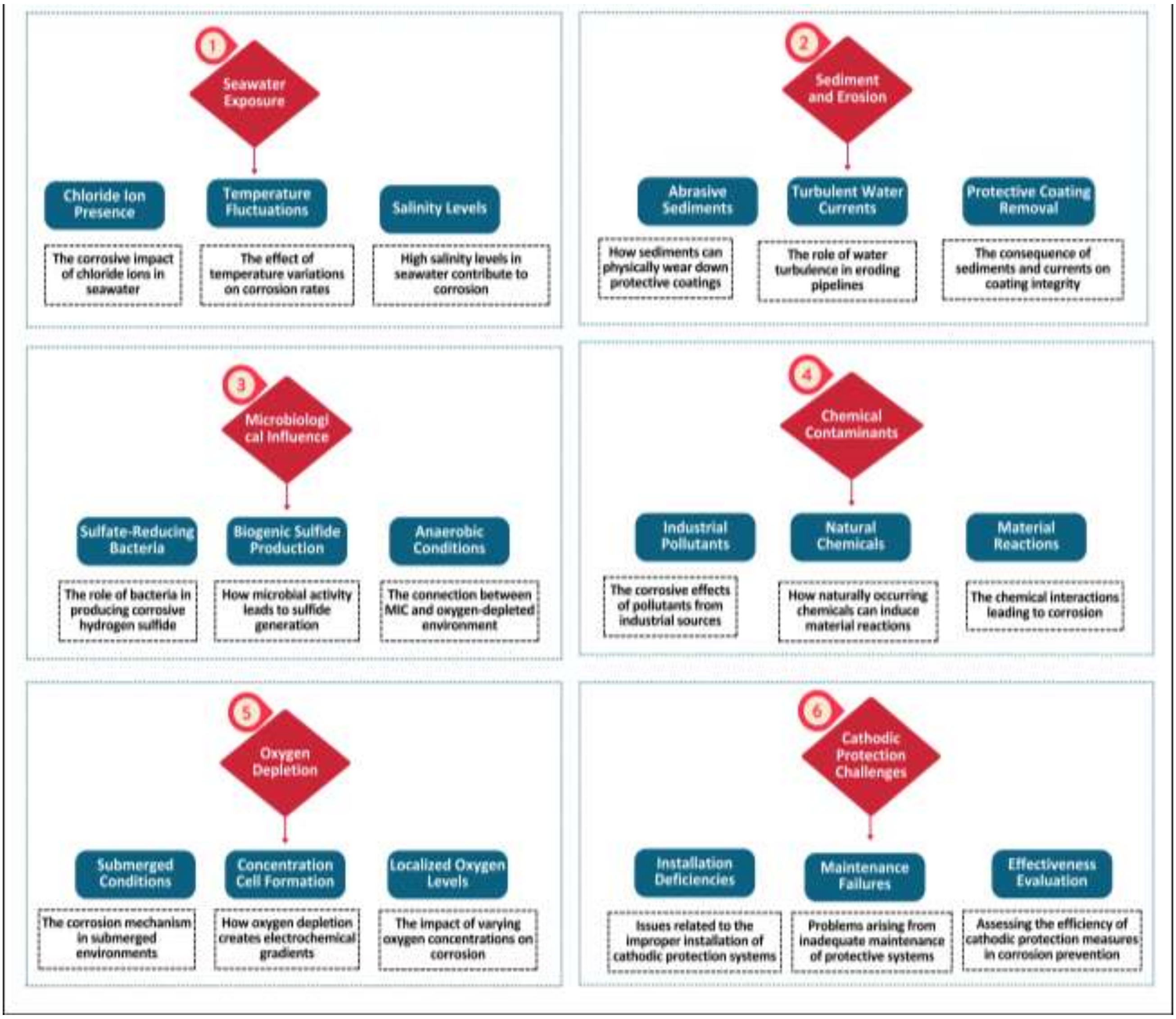


Fig. 7. Pipeline corrosion causes

Sasilatha *et al.,* [77] applied for autonomous corrosion maintenance in underwater structures. The CNN is employed to classify images, facilitating the detection of objects within submerged corroded structures. His proposed model attained an impressive classification accuracy of 98.83%. However, it's noteworthy that this method's effectiveness is particularly suitable for our underwater robot to detect objects, yet it may not outperform typical methods when applied to other datasets. Additionally, including dropout layers and other technologies did not significantly impact this model. It is suggested that reconstructing the network using a more intricate algorithm could potentially enhance its effectiveness. Yu *et al.,* [78] used CNN to classify corrosion in oil and gas pipelines. Their proposed approach can provide essential information, including the corrosion area's location, type, boundary and extent. This comprehensive information facilitates intelligent decision-making in pipeline maintenance. Furthermore, the method is versatile and can be extended to evaluate corrosion cracks in other metal components with complex geometries.

Ferreira *et al.,* [79] introduced a CNN architecture inspired by LeNet-5 for estimating the harshness of corrosion defects in pipelines. The architecture underwent training and testing through a Monte Carlo Cross-Validation procedure, repeated 100 times. The results indicate that the proposed architecture demonstrated strong performance, with a mean Root Mean Square Error

(RMSE) of 0.4448 and a mean R-squared (R^2) value of 0.9637. Huang *et al.,* [80] utilized a CNN-LSTM approach for corrosion detection in pipelines. The experimental findings revealed impressive detection accuracy, with rates of 99.9% for 0.5 mm deep crack damage, penetrating crack damage and corrosion damage and 99.8% for inside crack damage. The proposed method demonstrated the ability to accurately detect the location and size of the damage in the pipelines.

Recently, Yang *et al.,* [81] applied a combination of CNN and wavelet packet energy (WPE) for monitoring internal corrosion in pipelines. The accuracy of classification achieved surpassed 99.01 percent. Consequently, this methodology presents a quantitative strategy for overseeing the corrosion condition of pipelines, enabling timely and precise evaluation of the extent of internal corrosion. The WPE-CNN model exhibits considerable promise in efficiently overseeing pipe interior corrosion when coupled with the proposed time reversal strategy. Furthermore, Saragih *et al.,* [82] utilized YOLO, an image-processing algorithm based on CNN, to automate corrosion inspection in pipelines. The results suggest that the proposed method is capable of achieving detection with an accuracy rate of 64%.

2.4 CNN Application in Ship Construction Material (Steel)

In 2018, Ma *et al.,* [65] utilized CNN for corrosion segmentation in ship steel structures. They developed a segmentation model by fine-tuning an existing CNN architecture and training it on datasets created from numerous images. By integrating the trained CNN classifier with a sliding window technique, they were able to recognize the corrosion zone within an image. One year later, Ahuja *et al.,* [83] implemented CNN to classify steel surface corrosion grade. The results showcased that the proposed approach achieved an impressive accuracy exceeding 93.4% for identifying corrosion grades. Notably, the actual corrosion results and those predicted by the model exceeded expectations, especially considering the constraints of a limited training dataset. The author suggests that an even more robust model could be developed through training on a larger dataset, incorporating varying Intersection over Union (IoU) thresholds. This approach has the potential to enhance the model's accuracy and performance significantly.

In 2021, Barile *et al.,* [84] conducted an analysis of corrosion behaviour in steel plates using Acousto-Ultrasonics with the assistance of a D-CNN. The CNN exhibited more than 99% efficiency, demonstrating its effectiveness in classifying signals. Furthermore, Pirie *et al.,* [85] used CNN to recognize corrosion grades in steel structures. Using salt spray tests, they initially established an image dataset of corroded steel plates. Subsequently, they developed a CNN model named VGG-Corrosion that was explicitly designed to assess the corrosion grade of the affected steel plates. Their study further investigated the impact of transfer learning, learning rate and batch size, aiming to pinpoint the optimal hyperparameter formations for training an effective corrosion classification model. In the best combination of these hyperparameters, the mean average accuracy for assessing corrosion grades in the test results reached an impressive 90.96%.

In another study by Idusuyi *et al.,* [86], two CNN models were developed and trained utilizing images captured with a mobile phone camera and a digital microscope. These CNN models were designed to categorize corroded images into three distinct classes, depending on the surface area of the sample covered by corrosion products. The study's results demonstrate that CNN corrosion classifiers for steel exhibit strong performance, achieving accuracy above 80% for both models. The effectiveness of CNNs was particularly notable in handling multiclass corrosion scenarios. Recently, Jiang *et al.,* [87] applied CNN to investigate random pitting corrosion damage in marine steel columns. This network was designed to assess damage by taking the vibration mode of the steel column as input. The results demonstrated a notably high detection accuracy of the network, meeting the practical engineering standards. This outcome underscores the substantial theoretical significance and practical applicability of using this approach to assess damage in steel components.

3. Discussion

Within the CNN domain utilized for corrosion detection and classification, numerous scholarly investigations have yielded significant findings, each showcasing unique efficacy and constraints. The Faster R-CNN [57] for Coating Breakdown and Corrosion (CBC) assessment achieved a notable identification rate of 81.4 percent and effectively classified the data into five unique groups. Nevertheless, utilizing a sizable dataset consisting of 1,900 images to train features presents pragmatic obstacles for hull structural plate corrosion damage detection by Yao *et al.,* [54], who successfully identified a variety of superficial structural damages. However, the researchers encountered difficulties generalizing their findings due to a restricted dataset and suboptimal performance under specific environmental conditions. Corrosion detection in marine vessel structures by Soares *et al.,* [62] achieved a notable level of precision (92 %) when applied to synthetic underwater photos. However, the study's emphasis on synthetic images has prompted apprehensions regarding its practicality.

Bahrami *et al.,* [60] used Faster R-CNN to detect ship container corrosion. Although the initial performance of the model was subpar in terms of accuracy and recall, it surpassed alternative approaches once the anchor box was optimized. In their recent publication [61], HRTC R-CNN utilizes temporal context and high resolution to identify corrosion defects in ship containers. However, this approach provides computational intensity issues. Another Faster R-CNN by Xu *et al.,* [58] encountered difficulties in forecasting the proportion of corrosion area and recommended additional categorization. Andersen *et al.,* [59] utilized Faster-RCNN and YOLO to detect corrosion in marine vessels. While the authors demonstrated competence in detecting the presence of corrosion, they encountered issues related to the specificity of the dataset and an overestimation of the corroded region.

CNN for Automated Corrosion Detection was shown to have a high capability by Shirsath *et al.,* [55], who utilized colour and texture information; nonetheless, the authors stated that performance depends on a solid dataset. Siswantoro *et al.,* [63] successfully diagnosed corrosion in multiple categories; nevertheless, the inadequate amount of data analysed was cited as the reason for unsatisfactory accuracy and recall. In their study, Matthaiou *et al.,* [56] proposed a Hybrid CNN-Transfer Learning Model that prioritized texture and colour. The authors found that texture-based techniques exhibited superior performance despite the difficulties posed by noisy backgrounds in real-world photos. Although CNN-based approaches demonstrate encouraging outcomes in the realm of corrosion detection and classification, their efficacy is frequently tested on vast and varied training datasets. Furthermore, they confront difficulties when confronted with real-world circumstances, such as inadequate performance in demanding environments and computational intricacies for real-time implementations.

When considering the detection of corrosion in offshore, oil and gas pipelines, examining different CNN applications in this field unveils their respective merits and weaknesses. The bespoke CNN developed by Bastian *et al.,* [64] demonstrates commendable accuracy while requiring fewer trainable parameters. However, its vulnerability to various situations is attributed to its unique architecture. The classification accuracy of the method proposed by Rajendran *et al.,* [77] is an impressive 98.83 percent, making it applicable to autonomous underwater robots; however, its effectiveness influenced by the particular training dataset utilized. Yu *et al.,* [78] exhibit adaptability by furnishing comprehensive corrosion data to aid maintenance decision-making; however, the efficacy of the approach in practical situations is not explicitly mentioned.

The CNN developed by Ferreira *et al.,* [79] with LeNet-5 has robust performance, as evidenced by its low RMSE and high R^2 values. However, the paper does not explicitly address scalability or practical applicability. CNN with a digital twin for monitoring, developed by Bhowmik in [75], incorporates real-time capabilities but has comparatively diminished accuracy (81%). The second custom CNN developed by Bastian *et al.,* [74] achieves good accuracy in picture classification, but its simplicity present difficulties in complex circumstances. The DCNN proposed by Parjane *et al.,* [76] exhibits exceptional accuracy in detecting underwater pipeline structures; nevertheless, its applicability to different settings is restricted.

CNN with wavelet packet energy developed by Yang *et al.,* [81] provides good classification accuracy; however, optimal performance contingent on particular situations. The YOLO program developed by Saragih *et al.,* [82] automates the corrosion inspection procedure; nonetheless, it demonstrates a reduced accuracy rate (64 %). TCNN for automatic visual inspection by Vriesman *et al.,* [73] excels at recognizing corrosion levels; nevertheless, additional validation is required to ensure real-time viability. The CNN-LSTM method proposed by Huang *et al.,* [80] exhibits exceptionally high rates of accurate detection, albeit potentially requiring significant processing resources. Although these CNN applications demonstrate exceptional performance in pipeline corrosion detection (frequently attaining accuracy rates exceeding 98 %), they encounter obstacles regarding the specificity of the dataset, adaptability to diverse environments, computational complexity and practical applicability. Specific monitoring requirements should inform the technique selection, considering the compromises between precision and practical implementation.

The application of CNNs for the identification and examination of steel corrosion has been the subject of investigation in several studies, each of which utilized unique approaches with varying degrees of success. In their study, Ma *et al.,* [65] optimized a pre-existing CNN architecture and applied a sliding window method to segment corrosion in ship steel structures. While the results were favourable, the authors acknowledged the computational burdens associated with the method. Idusuyi *et al.,* [86] effectively handled multiclass corrosion scenarios utilizing mobile and microscope pictures with two CNN models that achieved an accuracy of over 80%. However, the performance of these models influenced by factors such as image quality and variety.

Barile *et al.,* [84] utilized acoustic ultrasonic analysis with CNN to classify corrosion-related signals with an efficiency greater than 99%. This accomplishment demonstrates the researchers' high capability; however, it raises concerns regarding the method's effectiveness under varying environmental conditions and with steel compositions that differ from the one described. Ahuja *et al.*, [83] successfully categorized corrosion grades with an accuracy surpassing 93.4%, suggesting that a more extensive dataset might enhance the model's robustness. Jiang *et al.,* [87] utilized numerical simulation and CNN to analyse pitting corrosion in maritime steel columns with excellent detection accuracy; however, the complexity of the methodology, including numerical simulations and finite element software, is acknowledged [88-90]. Furthermore, Pirie *et al.,* [85] developed the VGG-Corrosion CNN architecture, which demonstrated dataset-specific efficacy by attaining an accuracy of 90.96 percent via salt spray test dataset construction.

Therefore, CNNs demonstrate considerable efficacy in detecting steel corrosion, achieving encouraging levels of accuracy. However, these networks are constrained in terms of dataset diversity and size, computational efficiency and the possibility of improved performance with larger training datasets. The investigations demonstrate the multifunctionality of CNNs in detecting corrosion through various methodologies, including signal analysis, picture classification and numerical simulations. As methodologies progress and more extensive datasets become accessible, the dynamic environment suggests that CNNs possess considerable promise for applied corrosion detection and classification.

4. Recommendations

In the domain of CNN-based corrosion detection and classification for synchronized marine structures, pipelines and steel applications, recommendations and future research Centre on fundamental concepts. Primarily, it is critical to confront the obstacle posed by the diversity and magnitude of the dataset. Researchers must prioritize the development of all-encompassing datasets that include a wide range of environmental variables and corrosion scenarios. The expansion and variety of datasets are of the utmost importance in improving the resilience and precision of CNN models in these many contexts. Additionally, it is crucial to prioritize the enhancement of computing efficiency. Ongoing research endeavours ought to investigate techniques for optimizing algorithms, integrating hardware developments and parallel processing to enhance the practicality and scalability of corrosion detection approaches based on CNN. Incorporating CNNs with advanced imaging techniques and supplementary sensing technologies, such as acousto-ultrasonics, can further enhance the understanding of corrosion conditions. Moreover, in order to guarantee the feasibility of CNN-based approaches in practical settings, forthcoming investigations ought to prioritize thorough validation and testing under real-world conditions. This should involve evaluating the models' ability to adjust to the intricate circumstances of marine structures, pipelines and steel corrosion. The combined objective of these suggestions is to enhance the efficiency and versatility of CNNs in detecting and classifying corrosion in various environments.

5. Conclusion

In conclusion, regarding CNNs applied to corrosion detection and classification, our extensive discussion has unveiled a landscape of diverse methodologies with distinctive strengths and limitations. Each scholarly investigation, from Faster R-CNN applications to specialized CNNs for offshore structures, oil and gas pipelines and steel corrosion, has contributed valuable insights into the efficacy and challenges of these techniques. Our comprehensive analysis underscores the need for future research to address critical challenges. Priority should be given to developing comprehensive datasets encompassing diverse environmental variables and corrosion scenarios. Enhancing computing efficiency is crucial and ongoing efforts should explore algorithm optimization, hardware integration and parallel processing.

Thorough validation under real-world conditions is paramount to ensuring the practicality of CNN-based approaches. This involves evaluating the adaptability of models to the intricate circumstances of marine structures, pipelines and steel corrosion. In light of these considerations, our recommendations emphasize the importance of advancing fundamental concepts, encompassing dataset expansion, computing efficiency optimization and comprehensive validation, to enhance the efficiency and versatility of CNNs in corrosion detection across diverse environments. As methodologies evolve and datasets become more extensive, the dynamic environment suggests that CNNs indeed hold considerable promise for applied corrosion detection and classification. Future research efforts, guided by these recommendations, can contribute to the continuous advancement of CNN-based techniques in safeguarding the structural integrity of underwater assets.

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