Heliyon 10 (2024) e24142

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Research article

# Intelligent analysis of corrosion characteristics of steel pipe piles of offshore construction wharfs based on computer vision

Shuxia Han [a], Bingde Li [b,*], Wei Li [c], Yi Zhang [d], Puyuan Liu [b]

[a] *College of Science, Northeast Forestry University, China*
[b] *Department of Engineering Management, School of Civil Engineering, Harbin Institute of Technology, China*
[c] *China Communications First Highway Engineering Bureau Third Engineering Co., Ltd, China*
[d] *China Communications Second Harbor Engineering Bureau Third Engineering Co., Ltd, China*

ARTICLE INFO

*Keywords:*
Offshore construction wharfs
Steel pipe pile
Corrosion characteristics
Computer vision

ABSTRACT

The lower part of offshore construction wharfs is mostly a steel structure system composed of steel pipe piles, whose corrosion level directly affects the structural safety performance of steel wharfs in service. The currently common corrosion detection methods can only sample and inspect steel pile after it has been dismantled, making it impractical for in-service monitoring during the operational period of the steel pile. In this paper, a deep learning-based image classification model is first established to recognize the type of corroded area on steel pipe piles. The model achieves a recognition accuracy of 99.14 % in automatically identifying different types of corroded areas, including full immersion zone, tidal range zone, and splash zone. Subsequently, digital image processing technology is utilized to automatically calculate the corroded area of steel pipe piles. The method proposed in this paper can obtain the key information, such as type of corrosion area and area of the steel pipe pile corrosion area, without damaging their structural performance during the service. With this data, the mechanical performance of steel pipe piles can be analyzed, and the structural safety of the in-service steel pipe piles can be determined, thereby ensuring the safety of the construction wharf.

## 1. Introduction

Wharfs for offshore construction play a crucial role as transportation facilities for vehicles, personnel, equipment and materials during the bridge construction process, and is also the first construction platform to overcome the complex marine environment during the construction of the cross-sea bridge [1], as shown in Fig. 1. As a temporary structure, the service life of offshore construction wharfs is generally 5–10 years, which is lower than the main structure in terms of component and node safety reserves, and the structure is more prone to safety hazards. The steel piles of the substructure of offshore construction wharfs are generally made of carbon steel, which has a large corrosion rate in the marine environment, and due to cost considerations, more effective anti-corrosion measures are rarely adopted [2]. At present, offshore construction wharfs only rely on anti-corrosion coatings and the inherent corrosion resistance of steel to resist marine corrosion. With in-creasing service age, corrosion intensifies, which can easily lead to structural damage [3]. Scholars have found that spun high-strength concrete pipe piles are more durable than steel pipe piles [4,5]. However, in practical applications, they are relatively less commonly used. Therefore, this paper focuses on researching the corrosion of steel pipe piles.

* Corresponding author.
*E-mail address:* 13224569678@163.com (B. Li).

https://doi.org/10.1016/j.heliyon.2024.e24142
Received 12 August 2023; Received in revised form 3 January 2024; Accepted 4 January 2024
Available online 6 January 2024

Taking the offshore construction wharf used during the construction of the Pingtan Strait Public-Rail Cross-Sea Bridge of Fuping Railway, the first public-rail cross-sea bridge in China, as an example, the marine environment of the region is extremely harsh, with strong winds and high waves, with maximum level 14 wind on the Beaufort scale and maximum wave heights reaching 9 m [6]. Additionally, the region is located in one of the most corrosive seawater environments in the world, with a maximum corrosion rate of up to 1 mm per year, the offshore construction wharf suffered serious corrosion damage as shown in Fig. 2.

For the offshore construction wharf, the main cause of structural damage due to corrosion in steel structures is the lack of timely protection for local corrosion within the structure. As corrosion progresses and the cross-sectional area of the corroded parts gradually decreases, stress concentration occurs at the corroded area, which accelerates the structural damage [7]. In addition, there are significant differences in the degree of corrosion depending on the location. According to different corrosion mechanisms, the corrosion areas of steel piles under the construction wharf in marine environments are usually divided into five parts: marine atmospheric zone, splash zone, tidal range zone, full immersion zone and the sea mud area [8]. For example, in general, the corrosion rate of steel pipes in the splash zone is 3–10 times higher than in other areas, which corresponds to an increase in structural defects in the middle of the steel member, weakening the stable load-bearing capacity of the structure [9].

To prevent the impact of localized corrosion on structural safety, it is necessary to constantly prevent the occurrence of corrosion. Professional experts or relevant authorities should scientifically evaluate the remaining load-bearing capacity and deformation performance of steel components and structures after corrosion. In the early stages of mild corrosion, timely repair measures should be taken. However, in practice, the shape, location, size, degree and quantity of damage to the corrosion layer of steel components are random, and the local corrosion caused by the damage to the corrosion layer is also random [10]. Therefore, in some actual engineering structures, only by manual visual inspection method is difficult to accurately measure the geometric information of local corrosion damage. In order to achieve timely detection and treatment of local coating damage or local corrosion, it is necessary to take a more effective means of corrosion detection.

Currently, research on corrosion of offshore steel structures generally involves obtaining relevant data through in-situ sampling methods on steel structures. As in-situ sampling of offshore steel construction wharfs essentially involves damaging the structure, it will affect the structural performance of the steel wharf during its subsequent service period. Direct sampling during the service period is also very difficult, while sampling after the removal of the steel piles not only loses the natural reference of the sea level but also fails to meet the requirements for corrosion detection during the use of the steel piles. Therefore, it is necessary to adopt a non-destructive method to measure the degree of corrosion in each corroded area of the steel pipe pile during its service life, without damaging its structural properties.

In addition to the destructive in-situ sampling method for corrosion detection of steel piles under offshore steel construction wharfs, there are other means of testing the structural properties of steel piles without damaging them.For example, acoustic wave detection method, the method uses ultrasonic equipment to emit ultrasonic waves with a frequency of 20 kHz or above to the steel pipe piles being detected, the use of sound waves in the object propagation characteristics, through the reflection of sound waves, scattering, transmission and other analysis, to detect internal defects, foreign bodies and corrosion of the object [11]; The method uses electrochemical principles to test the degree of corrosion of metal materials. It utilizes chemical reactions occurring on the surface of metal materials to measure changes in potential or current density of the metal, in order to determine whether corrosion has occurred and the extent of the corrosion [12]; Magnetic memory method is a non-destructive testing method that uses the magnetic memory characteristics of ferromagnetic materials to detect internal defects in the material. This method generates a magnetic field inside the tested steel pipe pile through equipment to magnetize it. If the steel pipe pile is corroded, the magnetic field at the corrosion site will be disturbed, thereby affecting the magnetic field distribution inside the steel pipe pile, resulting in a change in the magnetic memory effect. Using this principle, the degree of corrosion of the steel pipe pile can be determined by a magnetic sensor. [13]; X-ray inspection method, this method is based on X-ray penetration of steel piles and detection of the degree of absorption or scattering to determine the degree of corrosion of steel piles, because the corroded areas and non-corroded areas will have different degrees of influence on the penetration of X-rays, so through the signal received by the detector to measure the intensity of X-rays, you can determine the degree of corrosion in different areas of steel piles [14]. Although all of the above methods can achieve non-destructive testing of the corrosion degree of steel pipe piles, but the operation steps are cumbersome or expensive equipment, it is difficult to use on a large scale. After conducting online price research, we found that the Portable X-ray inspection machine and Fast electrochemical corrosion measurement instrument are approximately ten times more expensive than the method proposed in this paper. The Ultrasonic flaw detector

**Fig. 1.** Example of offshore construction wharf.

**Fig. 2.** Corrosion status of the steel construction wharf after 4 years of operation.

is also about twice the price of the method presented in this paper.

With the development of computer technology and deep learning theory [15], computer vision has shown more powerful ability than human in image classification work. Thus, it can automatically extract image features and achieve high-precision image classification and detection tasks. Computer vision technology has been mainly studied and applied in the field of structural health inspection in civil engineering, with deeper research in structural crack detection [16–20], pavement damage detection [21,22], and structural damage detection [23], while shallow and little research has been conducted for the identification and feature extraction of corrosion in steel structures.

In order to judge the corrosion area of steel pipe pile, this paper proposes a method for judging the corrosion area of steel pipe pile in marine environment based on statistical method, deep learning and digital image processing technology. That is, a digital camera is used to photograph the steel surface, manually distinguish the corrosion area types, and construct a macro corrosion area dataset, and use convolutional neural network and transfer learning methods to construct a high-accuracy automatic classification model for macro corrosion area types. In addition, digital image processing was used to obtain the outline of its macroscopic corrosion area and calculate the corrosion area.

The method can use UAVs to capture and sample in-service steel pipe piles, then judge the type of corrosion area and extract the corrosion area, thereby compensating for the deficiency of in-situ sampling. This method obtains data such as corrosion area and type of corrosion area without damaging the in-service steel pipe piles, providing data support for subsequent mechanical modeling and calculation of steel pipe pile bearing capacity.

## 2. Materials and methods

The method proposed in this paper mainly consists of two parts. The first part involves the recognition of the type of corrosion areas on the lower steel pipe piles of offshore steel construction wharfs, achieved through computer vision technology and image classification techniques based on deep learning. Firstly, the existing Q235B corrosion image data from the China National Materials Corrosion and Protection Scientific Data Center and the newly collected and labeled steel pipe pile corrosion image data from the construction site of the Pingtan Strait Public-Rail Bridge were integrated into the dataset for this paper. Based on this dataset, which included images of steel pipe piles on the wharf, the amount of data was increased using data augmentation techniques. The dataset was then divided into training, validation, and test sets, completing the data preparation process. Afterwards, the method of comparative study is used to select whether to use the transfer learning method for the training of the image classification neural model. In addition, the performance of several neural networks in this classification task was also compared, i.e., the best performing network model was selected from GoogleNet, ResNet101 and DenseNet, and finally it was used for the recognition of corrosion area types on the lower steel pipe piles of steel wharfs in a marine environment. After the recognition of corrosion area type is completed, the second part of the method will implement the extraction and calculation of corrosion area of steel pipe pile using computer vision techniques. Firstly, the image is converted to grayscale, and then the morphological filtering method with open and closed operations is used to reduce the background noise and complete hole processing respectively. After that, based on the pixel value of the processed image, the global threshold segmentation method is used to divide each pixel point in the steel pipe pile image into corrosion area and non-corrosion area. Then, contour detection is performed on the threshold segmented image, and false pixel points are filtered out, finally the corrosion area of steel pipe pile can be calculated. The research methodology in this paper is shown in Fig. 3.

### 2.1. Type of corrosion area recognition based on image classification technology

#### 2.1.1. Data source

The sources of the image dataset constructed in this paper include two parts: the China National Materials Corrosion and Protection Science Data Center and the construction site collection of the Pingtan Strait Public-Rail Bridge.

(1) Q235B corrosion image data from the China National Materials Corrosion and Protection Science Data Center

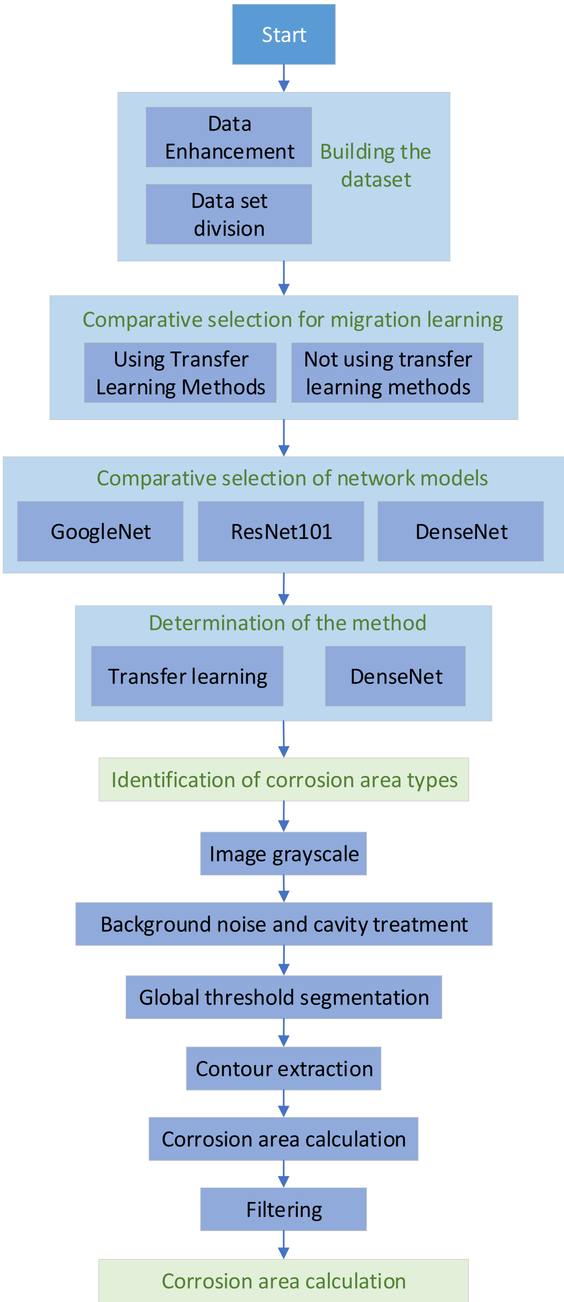
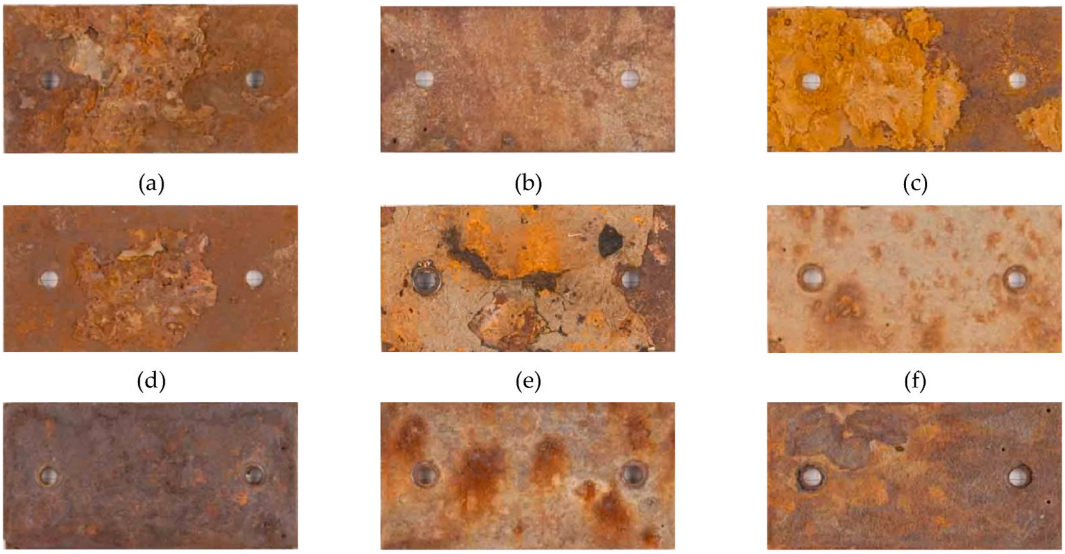



**Fig. 3.** Research methodology of this paper.

China National Materials Corrosion and Protection Science Data Center provides images of corrosion of standard specimens of various common metallic materials in atmospheric, soil and water environments (as shown in Fig. 4), and because the steel pipe piles studied in this paper are corroded in the marine environment and the material of the steel pipe piles is Q235B. In order to maintain the similarity of the data, the image samples provided by China National Materials Corrosion and Protection Science Data Center are selected from Q235B which is consistent with the corrosive environment and material of the target of this paper's research. A total of 9 test image data from 3 seawater stations in Xia Men, San Ya and Zhou Shan were used to ensure the applicability of the resulting model.

Corroded areas of steel pipe piles at construction sites can be distinguished by the natural reference of sea level, and data sets can be constructed by taking and cropping photographs. In this paper, a total of 103 high-resolution images of corrosion of some steel pipe piles were collected at the construction site of the Pingtan Strait Road-Rail Bridge using a Sony A6400 micro-single camera with a 24–105 mm zoom lens before the steel pipe pile removal work (as shown in Fig. 5). The sea level is used as a reference to distinguish the position of splash zone, tidal range zone and full immersion zone in the image, which is cropped out as the image data sample of steel



(a) (b) (c)

(d) (e) (f)

(g) (h) (i)

**Fig. 4.** The China National Materials Corrosion and Protection Science Data Center Q235B marine corrosion image: **(a)** full immersion zone (Xia Men); **(b)** full immersion zone (San Ya); **(c)** full immersion zone (Zhou Shan); **(d)** tidal range zone (Xia Men); **(e)** tidal range zone (San Ya); **(f)** tidal range zone (Zhou Shan); **(g)** splash zone (Xia Men); **(h)** splash zone (San Ya); **(i)** splash zone (Zhou Shan).

(2) Acquisition of steel pipe pile corrosion image data at the construction site of Pingtan Strait Road-Rail Bridge.

pipe pile corrosion zone classification in this paper. Corrosion zone image sampling method is shown in Fig. 6.

### 2.1.2. Construction of the dataset

(1) Data Augmentation

In the field of deep learning, the larger the number of samples in the dataset, the better the trained model and the better the generalization ability of the model. Due to the limited source of Q235B steel corrosion image data and the small amount of data in this study, data augmentation [24] is used to enhance the sample quality without substantially increasing the data, so that the limited data can produce values equivalent to more data, and thus improve the generalization ability and robustness of the model. In this paper, we use geometric transformations including flip, rotate, shift, crop, deform and scale, as well as color transformations such as noise addition and image blurring to expand the dataset in order to enhance the generalization ability and robustness of the model. Fig. 7 shows the image data augmentation method and the resulting augmented images, used to establish a dataset for classifying the type of corrosion areas in steel pipe piles.

After the initial data undergoes data augmentation, a total of 561 full immersion zone images, 693 splash zone images, and 561

(a) (b)

**Fig. 5.** Example of image data acquisition at construction site: **(a)** Site image sample 1; **(b)** Site image sample 2.

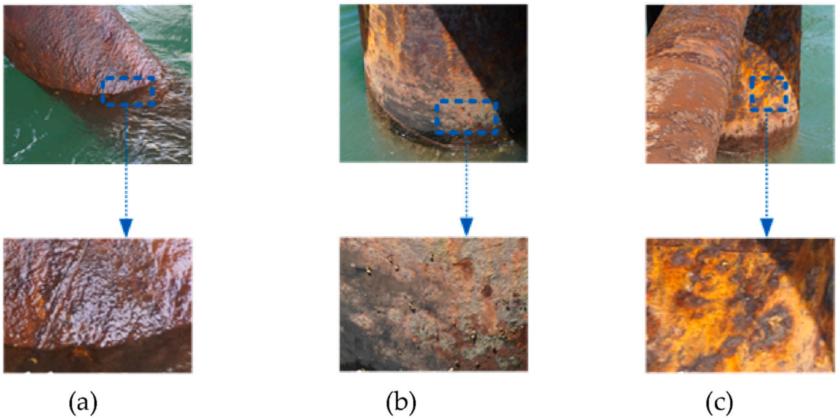


**Fig. 6.** Sampling method of corrosion zone images: **(a)** Full immersion; **(b)** Tidal range zone; **(c)** Splash Zone.

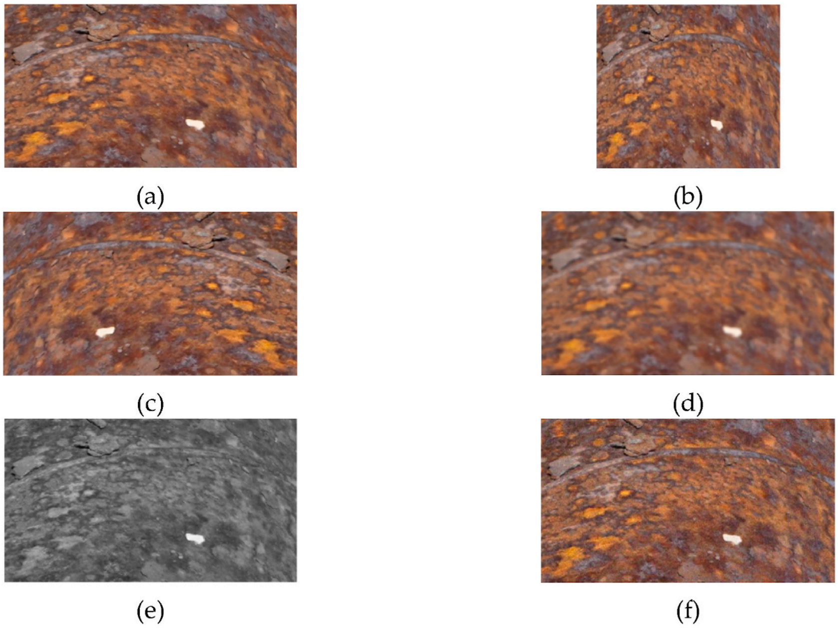


**Fig. 7.** Image data augmentation methods and augmentation results: (**a**) Original image; (**b**) Change the aspect ratio; **(c)** Horizontal Flip; **(d)** Gaussian blur; **(e)** Grayscale; **(f)** Random Noise.

(2) Dataset division

**Table 1**
Corrosion area classification dataset Partitioning.

| Division of the dataset | Corrosion zone | Number of images (unit: sheets) |
|---|---|---|
| training dataset | tidal range zone | 392 |
| | splash zone | 485 |
| | full immersion zone | 392 |
| validation dataset | tidal range zone | 112 |
| | splash zone | 138 |
| | full immersion zone | 112 |
| test dataset | tidal range zone | 57 |
| | splash zone | 70 |
| | full immersion zone | 57 |

tidal range zone images were obtained. It is divided randomly into training set, validation set, test set in a 7:2:1 radio based on their quantity, and used to train the parameters of the neural network model, as shown in Table 1.

#### 2.1.3. Test plan

In order to achieve precise classification of the type of corrosion areas, this paper uses the above dataset to compare the performance differences between the same model with different initialization parameters and pre-trained weights, and the performance differences between various convolutional neural network models when using pre-trained weights. The final model that satisfies the research accuracy requirements is selected. The specific experimental protocol design is shown in Table 2, and the specific protocol is as follows.

(1) Test Group I

In this set of tests, the GoogleNet network model is selected to investigate the effect of using pre-training weights (i.e., transfer learning method) on the performance of the model on corrupted region classification data, i.e., to compare the effect of using the official pre-training weights in model training with and without the official pre-training weights on the model training results.

(2) Test Group II

Three groups of models, GoogleNet, ResNet101, and DenseNet, were selected for this set of tests, all using pre-trained models obtained through ImageNet training, to compare the performance of different common convolutional neural network models on the corrupted area classification dataset, and finally select the model that meets this study and engineering applications.

Some scholars have pointed out that applying excessive data augmentation can distort the contents of images and, as a result, produce poor training examples [25]. Therefore, here we compare the training effects of the one-stage scheme and the two-stage scheme [26]. The one-stage scheme involves using original data and data augmented during the entire training process. The two-stage scheme, on the other hand, consists of initially training with heavy data augmentation, followed by fine-tuning using little or no data augmentation (e.g., flipping).

#### 2.1.4. Analysis of test results

The hardware and software environment for this experiment is shown in Table 3, and the model training parameters were set as: The model was trained for 500 epochs, with a learning rate of 0.001, using the CrossEntropyLoss function and the Adam optimizer. The model weights for each 50 epochs are tested on the test set not involved in training to check the accuracy, and the model weights are saved for each iteration.

This set of experiments uses GoogleNet as an example to compare the performance of the model in conducting corrosive areas types classification work with and without the transfer learning method in both cases. Fig. 8 shows the classification accuracy of the training model on the validation and test sets. It is clear that the model converges faster and with significantly higher recognition accuracy when using the transfer learning method than when not using the transfer learning method.

This set of experiments compares the performance of three convolutional neural network models, including GoogleNet, ResNet101, and DenseNet, in automatic classification work of corroded areas types when all using transfer learning methods. Fig. 9 shows the accuracy of the three models for classification work on the validation and test sets, indicating the accuracy of the three models on the test set every 100 epochs. It is clear that the DenseNet model performs relatively best on the validation and test sets, and the accuracy of the DenseNet model on the test set is 98.83 % at an epoch of 500.In this set of experiments, taking DenseNet as an example, with the precondition of utilizing pre-training weights, we adopted the two-stage scheme for training. The initial 420 epochs involved training with all data, including both original data and data augmented during the process. Subsequently, the following 80 epochs exclusively utilized the original data for training. The training and testing results are shown in Fig. 10. In comparison to Test Group II, which used the one-stage scheme, there is a certain improvement in accuracy, reaching 99.14 %. The results demonstrate that employing the two-stage scheme can mitigate the adverse effects caused by data augmentation to some extent.

### 2.2. Corrosion area extraction based on digital image processing

The percentage of corroded area on steel pipe pile is an important indicator to measure the degree of corrosion on steel pipe pile,

**Table 2**
Program design for corrosion zone classification tests.
(3)Test Group III

| Group | Number | Model Selection | Using pre-trained weights |
|---|---|---|---|
| Group I | A1 | GoogleNet | × |
| | A2 | GoogleNet | ✓ |
| Group II | B1 | GoogleNet | ✓ |
| | B2 | ResNet101 | ✓ |
| | B3 | DenseNet | ✓ |

**Table 3**
Corrosion zone classification test software and hardware environment.
(1)Test Group I

| | | |
|---|---|---|
| Hardware Environment | CPU | Intel i7-11800H |
| | GPU | Nvidia RTX3070 Laptop 8G |
| | Memory | 16G |
| **Software Environment** | Operating System | Windows 11 |
| | Programming Languages | Python 3.8 |
| | Main Library | Pytorch 1.10.0、OpenCV4.5.5、Numpy1.22.3 |
| | Compiler | Pycharm Community |

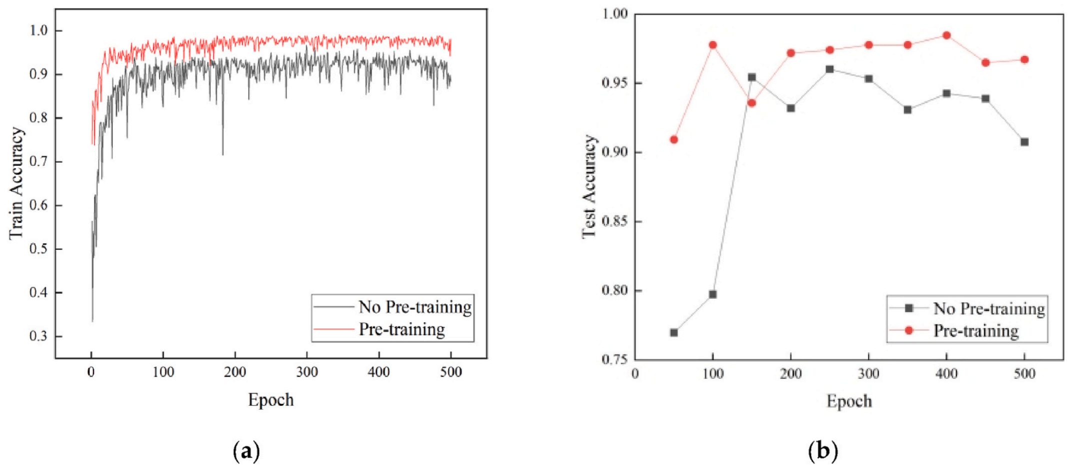



**Fig. 8.** Comparison of model training results for Test Group I: (**a**) Validation Accuracy; (**b**) Test accuracy of experimental group I.

(2) Test Group II

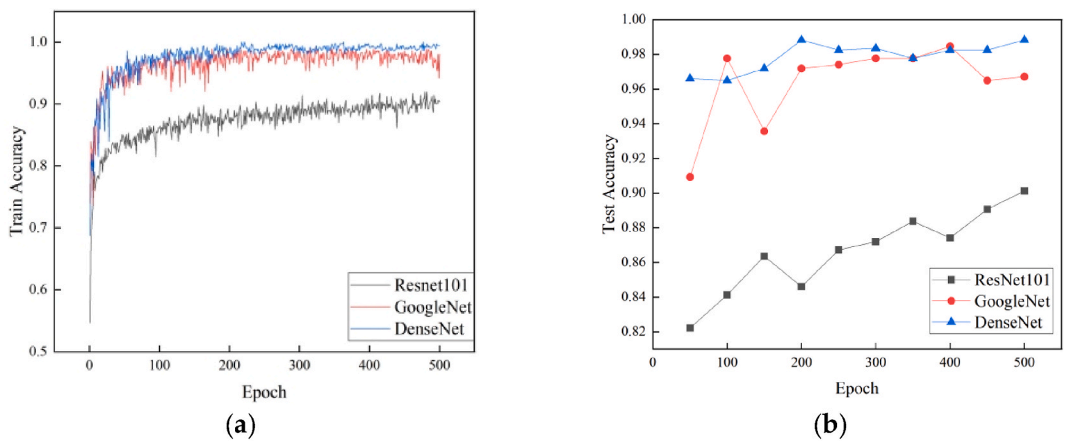



**Fig. 9.** Comparison of training results of Test group II: (**a**) val_accuracy; (**b**) test_accuracy.

(3) Test Group III

and is also an important indicator to evaluate the safety performance of steel pipe pile. In this paper, a corrosion area extraction method based on digital image processing using the grayscale thresholding method was developed. Using this method, the corrosion on the surface of steel pipe piles can be accurately measured and extracted quickly. The main processing includes, Image grayscale conversion, background noise and hole processing, global threshold segmentation, contour extraction, area calculation and filtering 6 steps, the technical process is shown in Fig. 11. The local presence of residual liquid in the sampled region, as illustrated in Fig. 6, led to the application of background noise and hole processing to eliminate noise and reduce the impact of liquid reflections. Finally, the use

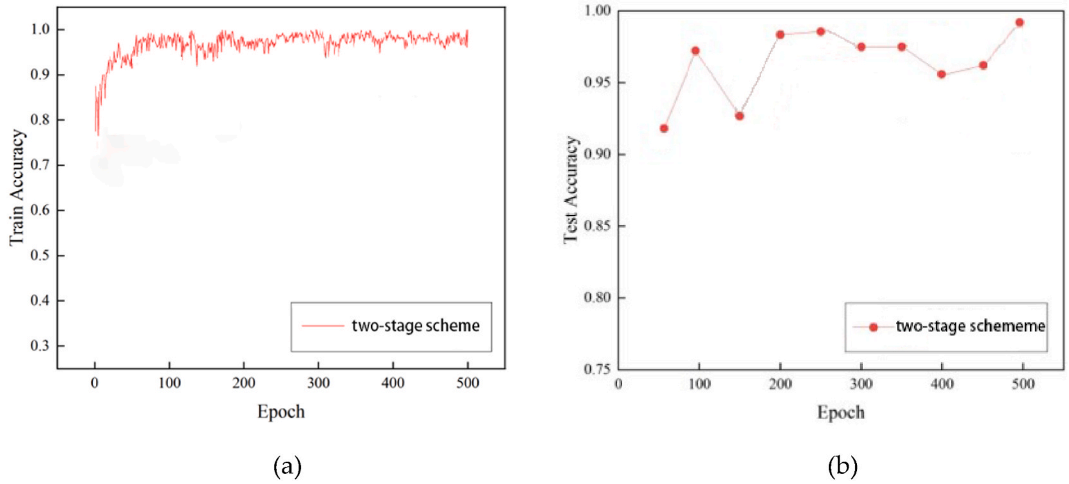



**Fig. 10.** Training results of Test group III(a) val_accuracy; (b) test_accuracy.

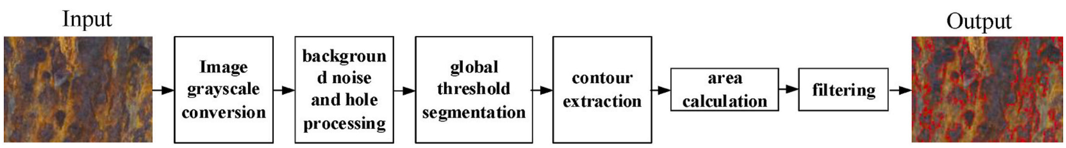



**Fig. 11.** Corrosion area extraction.

of global threshold segmentation to categorize pixels into two classes further diminished the influence of liquid reflections. This article verifies the effectiveness of the method by implementing it in the software and hardware environment shown in Table 3.

### 2.2.1. *Image grayscale conversation*

In the macroscopic corrosion image of steel, areas with different degrees of corrosion exhibit varying levels of brightness and darkness. Specifically, the more severe the corrosion, the darker the overall color of the pixels in that area. And in the feature extraction work for corroded images, only two types of pixel points are of interest: corroded regions and non-corroded regions. Therefore, a color RGB three-channel image is converted to a grayscale image of a single color channel. The grayscale value range from 0 to 255, with brighter pixel points, have higher grayscale values. The pixels with a gray value of 255 are white, and the pixels with a gray value of 0 are black. Corrosion corresponds to areas with deeper colors and smaller gray values, while non-corroded areas correspond to areas with lighter colors and larger gray values.

The image of the corroded area of the steel pipe pile (Fig. 12) is grayed out after the image grayscale conversion (Fig. 13). After applying grayscale processing to the image of the corroded area of the steel pipe pile (Fig. 12), a grayscale image was obtained (Fig. 13). By comparing Figs. 11 and 13, it can be seen that the light-colored points in the grayscale image correspond to the non-corroded areas in the original steel pipe pile image, while the dark-colored points correspond to the corroded areas.

**Fig. 12.** Input images.

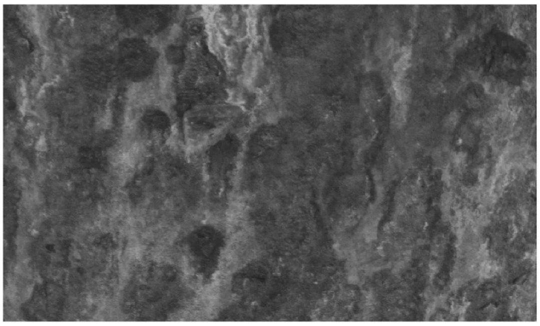


**Fig. 13.** Grayscale conversion.

### 2.2.2. Background noise and hole processing

Image noise [27] is a random variation in brightness or color information generated during image capture, bringing errors and additional information to the image. Therefore, it is necessary to filter the image to ensure the accuracy of the subsequent image processing work. The quality of the image filtering effect will directly affect the effectiveness and reliability of the subsequent image processing and analysis.

During the noise reduction process, the morphology open operation filtering method is used to remove isolated noise points in the image while essentially maintaining the shape and contour of objects in the image. Then, the morphology close operation filtering method is used to fill small cracks, gaps, and holes within the foreground objects in the image. The processed image is shown in Fig. 14.

### 2.2.3. Global threshold segmentation

This study only focuses on two types of points of interest in the image, namely corroded and non-corroded. In a grayscale image, the grayscale value of each pixel is any integer between 0 and 255.In the global threshold segmentation operation, the gray value of pixels with gray value greater than the threshold will be set to 255 (white), and the gray value of pixels that are less than or equal to the threshold will be set to 0 (black). The grayscale image is transformed into a more understandable binary image after the threshold segmentation operation. Therefore, the pixel points on the steel plate image are divided using the threshold segmentation method, so that the grayscale value of the pixel point representing the corrosion is 0 and the grayscale value of the non-corrupted pixel point is 255.

When segmenting images of corroded regions using the threshold segmentation method, determining the threshold value is the most critical aspect. This paper provides a simple algorithm to determine the threshold value. An image containing an estimable percentage of corrupted areas is selected and the grayscale values of all pixels are sorted. If the image size is h*w, and the area of the corrupted area is a%, that is, there are num pixels belong to the corrupted area, num is calculated as in Equation (1), then the grayscale value k corresponding to the num pixel points of the sorted list is the threshold value.

$$num = [h * w * a\%], \tag{1}$$

Where y = [x] denotes the integer function, i.e., y = [x] = a, a<x < b (a, b are integers and b-a = 1).

According to this method, a picture in the dataset with a corrosion area that occupies about 80 % of the entire surface of a steel pipe pile was selected in this paper, as shown in Fig. 15. Fig. 14 has a height of 163 and a width of 131, containing a total of 163*161 = 26,243 pixels. Transforming Fig. 15 into a grayscale image and sorting the 26,243 grayscale values, the number of pixels in each gray level was statistically obtained, and its grayscale distribution was obtained as shown in Fig. 16. According to equation (1), the value of num is 21,028, and the value of threshold k is finally calculated to be 82.

The global image thresholding segmentation method is adopted, and the value of threshold k is 82. After performing the segmentation operation on Fig. 14, a binarized image containing only black pixels with a gray value of 0 and white pixels with a gray value of 255 is obtained, as shown in Fig. 17. To facilitate the subsequent contour extraction operation, the binary image needs to be processed by inverse operation, as shown in Fig. 18. In the processed image, white pixels represent corroded areas and black pixels represent non-corroded areas.

### 2.2.4. Contour extraction

Contours can be simply understood as curves connecting all consecutive points. After obtaining the binary image through the threshold segmentation method, it is necessary to extract the contours in the image. After the binary image obtained by the threshold segmentation method, the contours in the image need to be extracted. The principle of contour extraction uses the method of hollowing out internal points, assuming that the gray value of the background pixel is 0 and the gray value of the target pixel is 255. If the gray value of a pixel and its 8 neighboring pixels are all 255, the point is considered as an internal point rather than a point on the contour.

Fig. 19 shows the results of Fig. 19 after the preliminary contour extraction. Due to the presence of small contours in the image obtained by mis-checking, the contours obtained by mis-checking mostly originate from the noise in the image and are irrelevant contour information. Therefore, a filtering operation is performed on the results in Fig. 19 to sieve out the irrelevant small contours and finally obtain the main contours of the corroded area. The final corrosion zone contour extraction results are shown in Fig. 20.

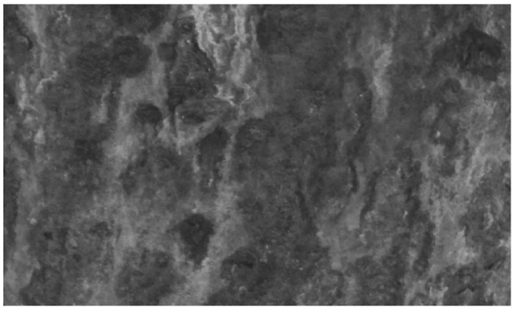


**Fig. 14.** Background noise and hole processing results.

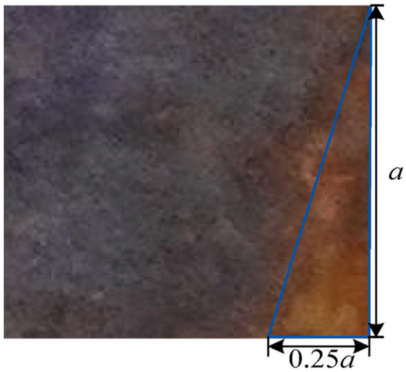



**Fig. 15.** Pictures of steel pipe piles.

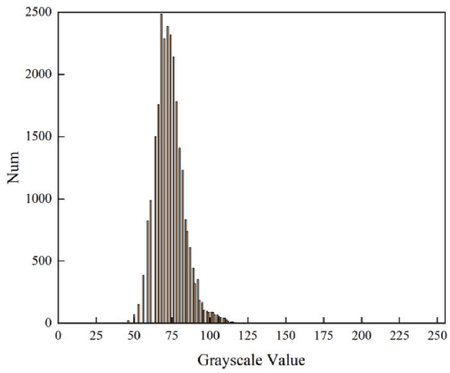



**Fig. 16.** Grayscale distribution.

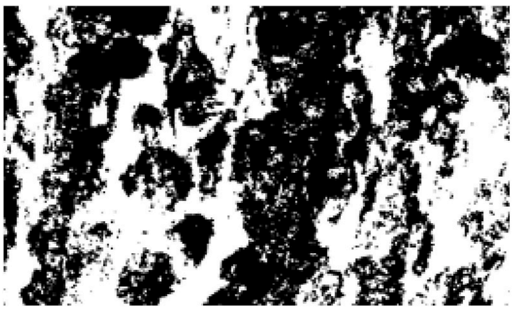


**Fig. 17.** Threshold segmentation.

**Fig. 18.** Reverse color processing.

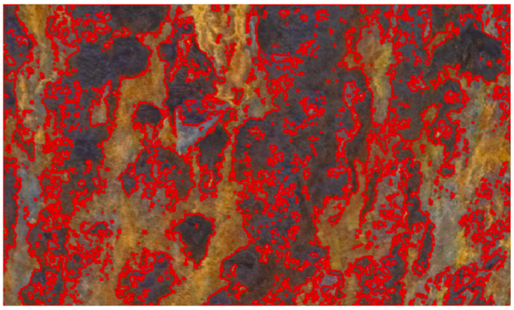


**Fig. 19.** Preliminary extraction.

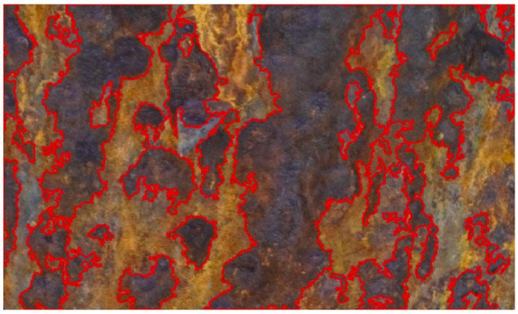


**Fig. 20.** Contour of the corrosion zone.

### *2.2.5. Area calculation*

The size of the steel plate is w0*h0, place the steel plate horizontally and take a photo and crop the photo to a size that only retains the appearance of the steel plate without scaling to get an image size of w1*h1. If the total number of pixel points within the corrosion contour is N, the area S of the corrosion zone is calculated as shown in Equation (2).

$$S = \frac{w_0 h_0}{w_1 h_1} * n, \tag{2}$$

The size of the steel plate detected in this section is w0*h0 = 3.0 cm*3.0 cm, the size of the image taken is w1*h1 = 162*272, and the final automatic calculation gets the corrosion areas of the steel plate as S = 6.887 $cm^2$.

## 3. Discussion

The study on an automatic classification model for corrosion areas in steel pipe piles, which is based on image classification techniques, conducted two sets of experiments. The results of Test groupI show that using transfer learning methods in the process of model training can significantly improve the accuracy of image classification work. The results of the Test Group II show that DenseNet has the highest accuracy among the three mod-els, and DenseNet is also the fastest converging in training, and the cost of training DenseNet model is lower. In summary, the DenseNet model using transfer learning method achieves high accuracy and low training cost in automatic classification of images showing corrosion on the surface of steel pipe piles. This model is well-suited for practical applications in steel pipe pile sampling.

In the research of corrosion feature extraction method based on digital image processing technology, this paper validates the method with a specific steel pipe pile image. The experimental results demonstrate that the method effectively and quickly extracts the contour of the corrosion area and the number of pixels within the contour, which corresponds to the area of the corrosion area of the steel pipe pile. The extraction results in Fig. 17 demonstrate the effectiveness of the method.

In practical construction, the method proposed in this paper can be used to obtain the type of corrosion area and corresponding data of steel pipe piles located beneath a steel construction wharf in marine environments. The specific approach is as follows: Use an unmanned aircraft or underwater drone with tracing capability, and pre-define the travel route based on the layout of the steel pipe piles under the steel construction wharf. Then, capture images and mark the position of each part of the steel pipe piles during the travel process. After the data collection is completed, the collected images are individually recognized for areas of corrosion on the steel pipe piles and the area of corrosion is calculated. Finally, use these data as a basis to judge the structural safety performance of steel pipe piles.

## 4. Conclusion

This paper proposes a method for recognizing the type of corrosion areas and calculating the corrosion areas of steel pipe piles in marine environment based on computer vision technology and deep learning theory. This method enables nondestructive detection of the corrosion degree of steel pipe piles, and makes up for the limitations of the traditional in-situ sampling method which destroys the original structural properties of steel pipe piles when determining the corrosion degree. In addition, this method also addresses the problems of complicated and expensive equipment in various nondestructive testing methods, such as acoustic detection, electrochemical detection, magnetic memory, and X-ray detection. This method makes up for the limitations of these existing methods. Because the method proposed in this paper is cost-effective and offers a rapid detection advantage, it can be used for quick assessments. However, it cannot detect the internal corrosion of steel pipe piles. Therefore, in practical applications, this paper's method can be initially employed for a swift evaluation to identify potentially severely corroded areas. Subsequently, a combination of methods such as acoustic wave detection, magnetic memory, or X-ray inspection can be applied to conduct a more comprehensive internal inspection of the steel pipe piles. This approach allows for a quick and efficient corrosion detection process.

This paper conducted a multi-scale corrosion characterization study on the construction wharf of the first cross-strait public-rail bridge in the sea area of East China Sea. Firstly, an automatic classification model of steel plate corrosion area type is established based on image classification technology, and the method can realize efficient and accurate automatic classification of corrosion areas of steel structures in service at sea. Then, a corrosion area extraction method for images of steel pipes piles is established based on digital image processing methods, which can effectively and quickly extract the corroded area of the steel pipe pile with the area size being quantified. The method can easily and effectively identify and calculate the corrosion area of the steel piles under the steel construction wharf, and does not damage the original structural properties of the steel piles in service. Finally, the structural safety of steel pipe piles can be evaluated based on the corrosion area type and size data obtained using this method. This provides effective support for the safety assessment of steel pipe piles in service.

However, the method proposed in this paper also has certain limitations, for example, it is difficult to ensure the safety of unmanned aircraft or underwater drones when the sea where the steel construction wharf is located has high winds and waves, so the use of this method to detect the corrosion degree of steel pipe piles needs to be carried out under good sea conditions. However, the method proposed in this paper also has certain limitations. For example, it may be difficult to ensure the safety of unmanned aerial vehicles or underwater drones when the sea where the steel construction wharf is located has high winds and waves. Therefore, it is recommended that this method be used to detect the corrosion degree of steel pipe piles under good sea conditions. In future research, it is possible to develop more stable unmanned equipment and improve the recognition accuracy of algorithm models in order to increase the applicability of this method.

## Additional information

No additional information is available for this paper.

## Disclaimer/publisher's note

The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.

## CRediT authorship contribution statement

**Shuxia Han:** Writing – review & editing, Writing – original draft, Conceptualization. **Bingde Li:** Visualization, Validation, Supervision, Software, Investigation, Formal analysis. **Wei Li:** Visualization, Validation, Supervision, Software, Project administration, Conceptualization. **Yi Zhang:** Formal analysis, Data curation. **Puyuan Liu:** Writing – review & editing, Writing – original draft.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## References


[1] Yusak Oktavianus, et al., Long-term performance of trestle bridges: Case study of an Indonesian marine port structure, J. Mar. Sci. Eng. 8 (5) (2020) 358.
[2] Ruilin Xia, et al., Non-uniform corrosion characteristics of the steel pipe pile exposed to marine environments, Ocean Eng. 272 (2023) 113873.
[3] Naftary Gathimba, et al., Surface roughness characteristics of corroded steel pipe piles exposed to marine environment, Construct. Build. Mater. 203 (2019) 267–281.
[4] Jingran He, et al., Experimental study on permeability of spun high strength concrete material during mechanical loading, Construct. Build. Mater. 403 (2023) 133034.
[5] Jingran He, et al., Damage–Permeability analysis of pretensioned spun high strength concrete pipe piles based on stochastic damage model, Eng. Fail. Anal. 140 (2022) 106578.
[6] Liangjiang Chen, et al., " Overall design and technical characteristics of the bridge of Fuping Railway.", Railroad Standard Design 64 (S1) (2020) 1–6, https://doi.org/10.13238/j.issn.1004-2954.202008310004 (in Chinese).
[7] J.L. Alamilla, M.A. Espinosa-Medina, E. Sosa, Modelling steel corrosion damage in soil environment, Corrosion Sci. 51 (11) (2009) 2628–2638.
[8] Kazuaki Zen, Corrosion and life cycle management of port structures, Corrosion Sci. 47 (10) (2005) 2353–2360.
[9] Wei-min Zhao, et al., Erosion–corrosion of thermally sprayed coatings in simulated splash zone, Surf. Coating. Technol. 205 (7) (2010) 2267–2272.
[10] Luciano Procópio, The role of biofilms in the corrosion of steel in marine environments, World J. Microbiol. Biotechnol. 35 (5) (2019) 1–8.
[11] U.C. Thibbotuwa, A. Cortés, A. Irizar, Ultrasound-based smart corrosion monitoring system for offshore wind turbines, Appl. Sci. 12 (2) (2022) 808.
[12] Da-Hai Xia, et al., Electrochemical measurements used for assessment of corrosion and protection of metallic materials in the field: a critical review, J. Mater. Sci. Technol. 112 (2022) 151–183.
[13] Bingxun Zhao, et al., Application of metal magnetic memory testing technology to the detection of stress corrosion defect, Appl. Sci. 10 (20) (2020) 7083.
[14] Vahid Jamshidi, Reza Davarnejad, Simulation of corrosion detection inside wellbore by X-ray backscatter radiography, Appl. Radiat. Isot. 145 (2019) 116–119.
[15] Kazuaki Zen, Corrosion and life cycle management of port structures, Corrosion Sci. 47 (10) (2005) 2353–2360.
[16] Allen Zhang, et al., Automated pixel-level pavement crack detection on 3D asphalt surfaces using a deep-learning network, Comput. Aided Civ. Infrastruct. Eng. 32 (10) (2017) 805–819.
[17] Chul Min Yeum, Shirley J. Dyke, Vision-based automated crack detection for bridge inspection, Comput. Aided Civ. Infrastruct. Eng. 30 (10) (2015) 759–770.
[18] Prateek Prasanna, et al., Automated crack detection on concrete bridges, IEEE Trans. Autom. Sci. Eng. 13 (2) (2014) 591–599.
[19] Young-Jin Cha, et al., Autonomous structural visual inspection using region-based deep learning for detecting multiple damage types, Comput. Aided Civ. Infrastruct. Eng. 33 (9) (2018) 731–747.
[20] Young-Jin Cha, Wooram Choi, Oral Büyüköztürk, Deep learning-based crack damage detection using convolutional neural networks, Comput. Aided Civ. Infrastruct. Eng. 32 (5) (2017) 361–378.
[21] Christian Koch, Ioannis Brilakis, Pothole detection in asphalt pavement images, Adv. Eng. Inf. 25 (3) (2011) 507–515.
[22] Hiroya Maeda, et al., Road damage detection and classification using deep neural networks with smartphone images, Comput. Aided Civ. Infrastruct. Eng. 33 (12) (2018) 1127–1141.
[23] Yuqing Gao, Khalid M. Mosalam, Deep transfer learning for image-based structural damage recognition, Comput. Aided Civ. Infrastruct. Eng. 33 (9) (2018) 748–768.
[24] Connor Shorten, Taghi M. Khoshgoftaar, A survey on image data augmentation for deep learning, Journal of big data 6 (1) (2019) 1–48.
[25] Munawar, Hafiz Suliman, et al., Civil infrastructure damage and corrosion detection: an application of machine learning, Buildings 12 (2) (2022) 156.
[26] Fondevik, Simen Keiland, et al., Image segmentation of corrosion damages in industrial inspections, in: 2020 IEEE 32nd International Conference on Tools with Artificial Intelligence (ICTAI), IEEE, 2020.
[27] Charles Boncelet, Image noise models, in: The Essential Guide to Image Processing, Academic Press, 2009, pp. 143–167.