

# Surface Corrosion Detection and Classification for Steel Alloy using Image Processing and Machine Learning

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## Abstract

Usually Stainless steel is notable for corrosion resistance; however, corrosion can happen in the environment with low oxygen and high salinity environment. The visual approach for corrosion detection is completely dependent on the quality of images and specialist's knowledge and experience. Corrosion detection and analysis can be done either through chemical based approach or image processing based approach. Digital Image Processing is widely used non-destructive approach for detecting corrosion on the metal surface. It provides cost-effective, fast and reasonably accurate results provided appropriate algorithms have been used depending on the environmental conditions, corrosion type, lighting conditions etc. Several algorithms related to colour, texture, noise, clustering, segmentation, image enhancement, wavelet transformation etc. have been used in different combinations have been developed by different research groups for detecting corrosion using digital image processing techniques. This paper presents an adaptive self-learning approach for image processing based classification techniques for detecting different types of corrosion in steel. Corrosion has different colour and texture properties that can be analysed using image processing techniques. In the present paper, the research done in this field has been extensively reviewed to identify the challenges and the achievements in this area. For the present work, a combination of image segmentation approach along with machine learning approach has been used for classification of corrosion at the different concentration level of HCl and significantly reasonable results were obtained.

**Keywords:** Computer Vision, Image Processing, Corrosion, Segmentation, Wavelet, GLCM, SVM, Machine Learning

## Introduction

Steel is an Iron alloy with other elements like Carbon, Chromium etc. in different percentage. The properties of steel e.g. hardness, ductility, and tensile strength varies with different percentage of element

mass. It is widely used in construction and various other applications because of its high tensile strength, better corrosion resistance and low maintenance cost. Different types of corrosion are visually different and require different image processing algorithms. Below are the images of above mentioned corrosion types:



**Fig. 1 Types of Corrosion: (a) General Corrosion; (b) Pitting Corrosion; (c) Crevice Corrosion; (d) Intergranular Corrosion; (e) Galvanic Corrosion; (f) Erosion Corrosion and (g) Stress Corrosion.**

The introduction of digital image processing opens expanded real life opportunities to sense in a variety of environments. While physical & chemical tests are highly effective for corrosion detection, however are difficult to perform on large surface area. Digital Image processing based approaches are non-destructive and are economical to perform on large areas like ships, metal bridges, electric pole etc.

These provide fast, reasonably accurate and objective results. Various image processing techniques like image enhancement, noise removal, line detection, edge detection, registration, wavelet transformation, texture detection, morphological functions, colour analysis, segmentation, clustering and pattern recognition etc. are base functions that could be combined to detect corrosion on metal articles.

## Corrosion Detection Using Image Processing: Architecture

This section provides the basic architecture for the corrosion detection using the image processing techniques.

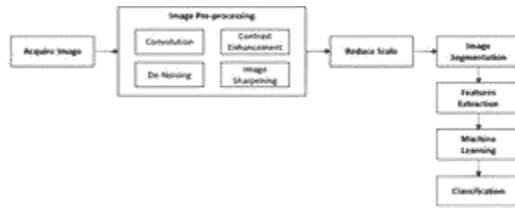


Fig. 2 Typical Flow for Corrosion Detection

The typical steps involved in the process are:

1. **Acquire Image:** The very first step of image processing is essentially capturing of the images with the help of suitable camera with good resolution. The acquired images can be microscopic images or regular images from drone or CCTV.
2. **Image Pre-Processing:** The images acquired by microscope can be maintained to have better resolution and lightning conditions. However there may be images obtained through drone or CCTV in outdoor environment which may have high background noise and unwanted reflections. To use these images for computer vision, the noise need to be reduced using pre-processed by different filtering techniques. The various Image processing filters can be simple Median Filter OR complex filters like histogram equalization, Morphologic operations, Image stitching, Shadow removal etc.
3. **Image Segmentation:** Once the image is pre-processed, the next step is to identify the corrosion area in the image using Image Segmentation techniques such as Edge Detection, Region Growing, Thresholding and Clustering.
4. **Feature Extraction:** For image processing, the features need to be extracted from the image. The features may be related to colour, texture, shape etc. using Haar wavelets, Hough transform, Laplacian of Gaussian (LoG), Histogram of Oriented Gradients (HoG), Garbor filtering, Canny edge detection, Background subtraction and Wavelet transform etc. filters.
5. **Machine Learning:** Once the image attributes are collected, a suitable supervised machine learning algorithm can be implemented for classification and analysis. Alternatively, unsupervised machine learning or neural network based models. Both supervised and unsupervised approaches have their advantages and disadvantages. Depending on image dataset, a suitable approach can be used for creating a model that can be used for classification and analysis
6. **Image Classification & Analysis:** In this step, classification is based on certain known features such as size, position, contour measurement, texture measurements etc. The image classifiers can be categorized based on Feature, Model and Pattern of

the corroded area in the image. This step helps in detecting the corrosion in the images. Once corrosion is detected, the total corrosion area is calculated, to estimate whether the image is partially corroded or fully corroded to take appropriate action.

## Related Work

Researchers have used different image processing techniques for the detection of the corrosion in the steel structures. The existing corrosion detection and analysis techniques can be categorized into different categories as:

### 1. General Image Processing:

Primarily the image processing techniques are based Filtering, Morphology and Edge based thresholding.

Widely used techniques are:

- **Colour based:** Corroded images have high presence of red colour as compared to green and blue. Analysing the red colour in the image can be used for detecting the presence of corrosion in the images. As colour is dependent on lightning conditions, the other parameters e.g. Hue, Saturation and Value are widely used parameters for corrosion detection.
- **Texture Analysis:** The metal surface shows different roughness at different stages of corrosion growth. The texture or pattern of corroded area may be different at different region of images. The texture analysis can be used for segmentation of corroded and non-corroded parts.
- **Wavelets:** The Wavelet approach is based on Fourier Transform (FT) and overcome the shortcomings in FT. There are many different types of WTs, among those types Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT) are widely used transforms.

**2. Learning Based:** Learning base approaches are based on supervised and unsupervised machine learning. Researchers have mainly used Support Vector Machine (SVM), AdaBoost, Artificial Neural Networks (ANN), Decision Tree and Deep Learning approaches.

– **Classification using Support Vector Machine (SVM):** In this technique, classification is based on the colour of the corroded area. The degree of the corrosion and the colour of corroded area enables to detect the corrosion area.

– **Artificial Neural Network (ANN):** ANN is identical to neurons in human brain. The neural network is formed by a set of neurons interconnected with each other through the synaptic weights. Knowledge is acquired by Neurons during the learning phase, which is utilized during the

verification phase. The number of neurons and synaptic weights can be changed according to needs.

### Experiment

Surface corrosion has been studied on Mild steel at different concentration of HCl. The corrosion growth varies with the concentration of HCl. A combination of different image segmentation algorithms has been used along with machine learning based approach for classification. The lab setup consists of Mild steel samples of 4cm x 4cm placed under controlled environment for one month under different concentration of HCl as 1MHCl, 2MHCl, 200 ppm, 300 ppm, 400 ppm and 500 ppm.

Concentration	Temperature	Humidity	No. of Days
200ppm	35 <sup>0</sup> c	90	15
300ppm	35 <sup>0</sup> c	90	15
400ppm	35 <sup>0</sup> c	90	15
500ppm	35 <sup>0</sup> c	90	15
1 M	35 <sup>0</sup> c	90	15
2 M	35 <sup>0</sup> c	90	15

**Table 1 Detection Method and References**

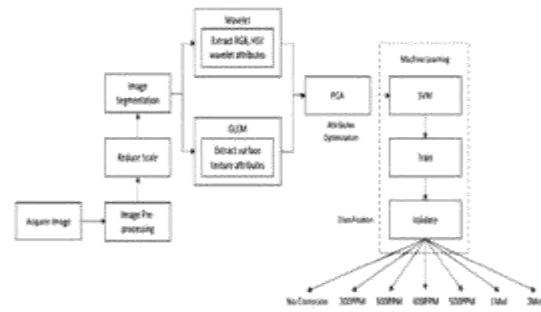
It was observed that the corrosion growth was different at different concentration levels. Corrosion images had strong presence of red colour and texture was also different. Images were taken using electronic microscope and more than 1400 samples were prepared of the size of 256x256 pixels. Below are the sample images at different concentration level:



**Fig. 3 Corrosion in Mild Steel: (a) Without Corrosion; (b) 100ppm HCl; (c) 200ppm HCl; (d) 300ppm HCl; (e) 400ppm HCl;**

An Image processing and machine learning based approach has been proposed to classify the samples into aforesaid categories. The flow diagram for the proposed approach is as shown in Fig-4

The proposed work consists of a combination of colour and texture attributes as histogram and GLCM. The texture features are deployed using GLCM algorithm for 19 properties and 9 properties from histogram of Red, Green, Blue, Hue, Saturation and Value attributes.

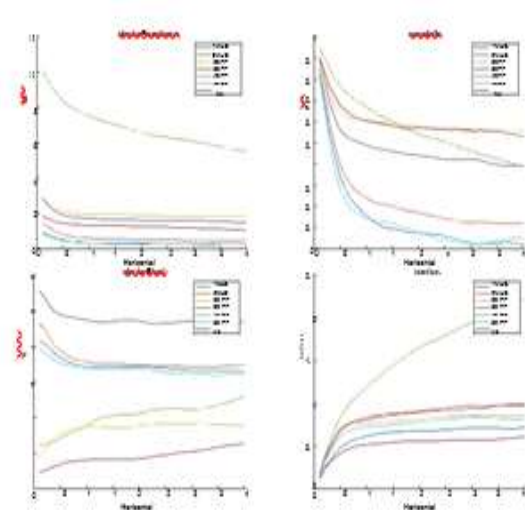


**Fig. 4 Process Flow for Samples Classification Machine Learning**

In this research, we proposed to use SVM for machine learning. SVM is a supervised machine learning based on statistical attributes of objects. SVM classifiers are used to classify pixels based on the texture feature vector assigned to each pixel. SVMs are generally two-class classifiers, however multiclass classification can also be achieved by one-versus-one and one-versus-all relationship. The most common technique is one -versus-rest classifiers, which has been used in this experiment to achieve classification among seven different categories.

These categories of images contain objects of a variety of texture that are arranged in horizontal and vertical directions. A set of 40 offsets that vary in distance have been taken to cover whole image. The plot for GLCM parameters with horizontal offset shows that there is correlation between GLCM parameters and pixel directions for different classes of images.

The GLCM parameters for different concentration of HCl is as shown in figure 5:



**Fig. 5 (a)Cluster Prominence; (b) Correlation; (c) Cluster Shade; (d) Contrast**

## Results

Overall 48 attributes per image were provided to machine learning algorithms for training and classification over a sample of more than 1400 images. The images were classified into No Corrosion, 200 ppm, 300 ppm, 400 ppm, 500 ppm, 1M HCl, 2M HCl, based on the lab environment for different concentration of HCl solution for corrosion growth. The proposed approach has provided significantly acceptable results with 92.4% accuracy over classifying samples into these 7 classes.

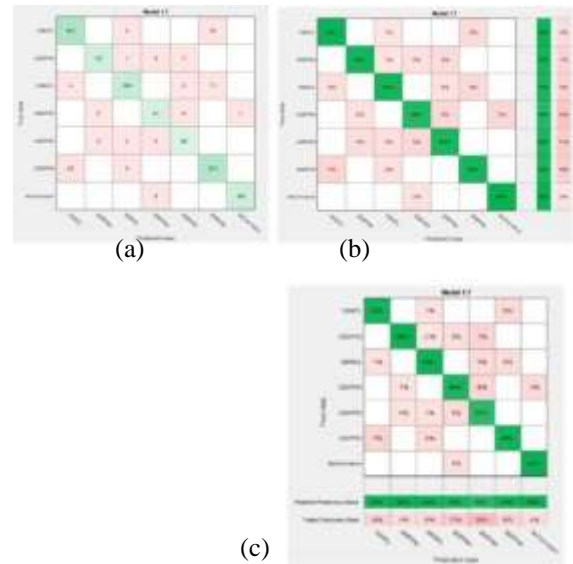
Type	Model	Accuracy	Prediction Speed (obs/sec)	Trainin g Time (sec)
Tree	Complex Tree	77.20%	6900	7.3351
Tree	Medium Tree	69.60%	15000	1.1009
Tree	Simple Tree	58.10%	14000	0.9514
SVM	Linear SVM	86.60%	3700	7.2516
SVM	Quadratic SVM	93.00%	3400	5.6185
SVM	Cubic SVM	90.70%	2900	5.7702
SVM	Fine Gaussian	78.00%	1900	8.4624
SVM	Medium Gaussian	89.10%	2200	6.1713
SVM	Coarse Gaussian	80.00%	2500	5.202
KNN	Fine KNN	84.10%	7000	1.3544
KNN	Medium Knn	83.20%	7700	0.83548
KNN	Coarse KNN	66.40%	7000	0.87792
KNN	Cosine KNN	82.80%	7700	0.92997
KNN	Cubic KNN	83.00%	780	6.2359
KNN	Weighted KNN	85.80%	7300	0.8539
KNN	Boosted KNN	75.20%	1600	21.29
Ensemble	Bagged Trees	86.90%	1600	10.062
Ensemble	Subspace Discriminant	83.90%	1200	0.8233
Ensemble	Subspace KNN	67.50%	570	10.122
Ensemble	RUSBoosted Trees	75.00%	1700	14.667

**Table 2 Machine Learning Performance Results**

The proposed approach has provided significantly acceptable results with 92.4% accuracy over classifying samples into these 7 classes. The confusion matrix is as shown in **figure 6**

As the corrosion growth is not uniform across the samples, the experimental results indicated that 7.2% of the regions were wrongly classified with next class of the corrosion. The number of samples for 200 ppm, 300 ppm and 400 ppm were comparatively less, which resulted in false results, the machine learning algorithm could be better trained by providing more samples. The false results can be further optimized further by removing the outliers from the samples. The microscopic images were fine images with defined region of interest, which helped in achieving the model with high accuracy. Though SVM as supervised

machine learning algorithm are known for less accuracy, however with the help of refined images and more than 40 attributes per image, it could classify the images with reasonably good results.



**Fig. 6 (a) Confusion Matrix; (b) False Negative (c) True Positive**

## Summary & Conclusion

The work has reported an average accuracy of 92.4% with field images of surface corrosion at 6 different level of HCl concentration. The texture features are deployed using GLCM algorithm for 19 properties. As an enhancement of the present work texture features were combined with other features like RGB colour and HSV properties of image to improve the accuracy.

## Future Work

Currently the images taken for this research were fine images from microscope, however practically for outdoor scenario e.g. gas/oil pipelines it may not be feasible to have microscopic images. The outdoor images can be taken from drone or pig or even CCTV camera may be of low resolution. For future work, we suggest developing a representative data set for regular images instead of microscopic images, where image processing techniques can be applied for segmentation and clustering.

Also neural network based algorithms can be applied for automated solution for corrosion detection and analysis on metal articles. The metal articles can be small objects inside the museum or even large pipeline in the outdoor environment.

Also a mathematical model can be built for corrosion analysis at various stages and metal decay using

supervised machine learning and analyse the validity and performance using time series analysis. Computer vision based corrosion detection methods may also be used for the trend analysis and extrapolating the trends. This will help in taking timely preventive actions to stop the further deterioration of the metallic surfaces

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