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Surface Corrosion Grade Classification using Convolution Neural Network

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Abstract: ***Corrosion is a prevalent issue in the oil and gas industry. Usually, pipelines made of Iron are used for oil and gas transportation. The pipelines are large and distributed over big fields above the ground, underground and even underwater. Corrosion gets developed because of environmental variables such as temperature, humidity and acidic nature of the liquids. There are different techniques for detecting and monitoring corrosion development, both destructive and non-destructive. Visual inspection is a common technique of surface corrosion analysis, but manual inspection is extremely dependent on the inspecting person's abilities and expertise. The findings of the manual inspection are qualitative and may be biased, may result into the accidents because of incorrect analysis. Corrosion must be accurately detected in early phases to prevent unwanted accidents. This paper will present a computer vision-based approach in combination with deep learning for corrosion classification as perISO-8501 standard. The findings of the assessment are unbiased and in a fair acceptable range similar to the outcomes of the visual inspection.***

Keywords: Corrosion Detection, Image Processing, Convolution Neural Network, Mask RCNN

I. INTRODUCTION

Steel is a ferrous alloy with distinct percentages of other components such as carbon, chromium, etc. Steel's characteristics such as hardness, flexibility, and tensile strength vary with varying element mass proportion. Because of its high tensile strength and low maintenance, it is commonly used in building and other applications.

The visual inspection approach for surface corrosion detection is highly subjective and qualitative. Classification results may differ from inspector to inspector as it is a manual technique. BS EN ISO 8501 is an industry standard that is widely recognized for surface corrosion classification. ISO 8501 is a visual standard for the cleanliness of the metal surface and defines a different level of corrosion. The surface corrosion condition on the steel surface before blasting is depicted in four different stages as shown in Figure 1.

ISO 8501 also describes the classification of surfaces following blast cleaning. The various classifications are as follows:

Light Blast Cleaning: As per definition, light blast cleaning should result in the surface free of dirt, visible oil and/or grease and rust, and foreign matter etc., when viewed without magnification.

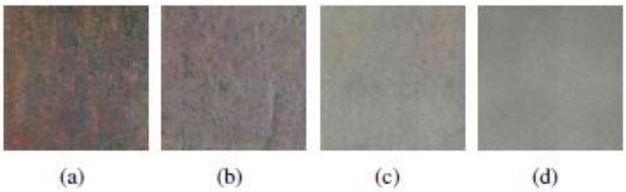

Fig. 1. Grades of Corrosion: (a) Grade 1; (b) Grade 2; (c) Grade 3; and, (d) Grade 4

Thorough Blast Cleaning: As per definition Thorough Blast Cleaning should have properties of Light Blast Cleaning and also any residual contamination must adhere strongly.

Very Thorough Blast Cleaning: As per definition Very Thorough Blast Cleaning should have properties of Thorough Blast Cleaning and also any residual traces of spots or stripes of contamination shall appear only as slight stains.

Blast Cleaning to Visually Clean Steel: As per definition Blast Cleaning to Visually Clean Steel should have properties of Thorough Blast Cleaning and also paint coatings and foreign material.

In this study, we propose a deep learning-based framework that can not only detect corrosion from images accurately and efficiently but can also be easily extended to other similar problems in detecting damage. Our framework gains the ability to classify different grades of corrosion from images by applying the state of the art deep learning algorithms. In addition, the transfer learning technique is implemented to reduce the amount of data needed and yield high precision.

In order to make the inspection process unbiased and quantitative, a computer vision and machine learning based method can be used to classify the surface corrosion condition. The analysis results are comparable with the visual inspection results in acceptable range.

II. RELATED WORK

In recent years, the image processing based corrosion detection and analysis approaches have been carried out for inspections in various fields, particularly where access is not viable owing to environmental and other variables engaged [1]. According to the survey [2] on solutions to corrosion based on computer vision, most of the methods are based on image characteristics.

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The current methods for detecting and analyzing corrosion can be classified into various classifications such as:

General Image Processing: The image processing techniques are based primarily on image threshold based on Filtering, Morphology, and Edge. Corroded images have a relatively high red color presence as compared to green and blue, which can be used to identify ROI for corrosion. The texture of the metal surface is another significant property for the image-based algorithm. Increased corrosion also increases the roughness of the metal surface. Researchers [3], suggested using entropy and wavelet energy values to classify and quantify corrosion pictures for metal surfaces. They used the least mean square algorithm (LMS) for classification and also used template matching to calculate the proportion of rust in the images. Researchers [4] have proposed corrosion detection in the ship based on two-stage color based weak classifier. The algorithm relates the calculated energy with the rough texture of the corroded area, using a symmetric gray level co-occurrence matrix (GLCM). The patches of pixels passed the first stage are filtered in the second stage based on their roughness. In HSV color space, the color information of ROI is then observed to distinguish corroded pixels with non-corroded pixels.

Learning Based: Learning based approaches are based on supervised and unsupervised machine learning. Researchers have mainly used AdaBoost, Support Vector Machine (SVM) [5], Decision Tree, Neural Network and Deep Learning approach. ANN is identical to human brain cells. A set of neurons are interconnected with each other through the synaptic weights to form a neural network. Neurons acquire knowledge during the learning phase, which is utilized during the verification phase. It is possible to change the number of neurons and synaptic weights depending on requirements.

Figure 2 shows a generic ANN architecture. It has an input layer from where the input data x enters the model and pass through one or more hidden layers. Finally, in the end, an output layer y that predicts ^y the original output. The input propagates forward, layer by layer through all the hidden layers that contain artificial neurons until the output layer is reached.

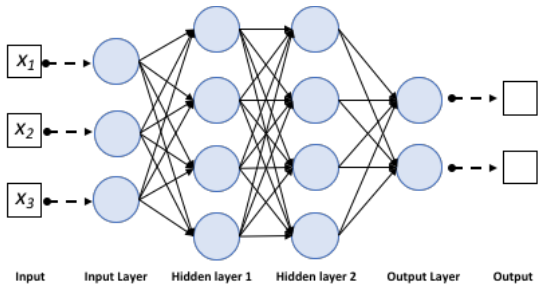

Fig. 2. General ANN architecture

Here in the fig. 3, two neurons are shown in the output layer, i.e. two labels are to be predicted, e.g. whether the image has corrosion or not.

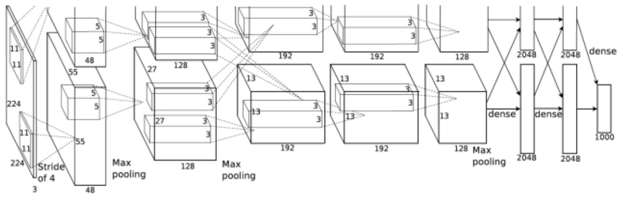

Fig. 3. AlexNet Architecture [10]

The adoption of deep learning based on recognition of damage has increased recently. As seen from the 2012 ImageNet Large Scale Visual Recognition Challenges (ILSVRCs) awards, the CNNs have become more common in recent years for solving the complicated Computer Vision related problems. This challenge encourages users for object detection and image classification algorithms / architectures involving even up to 1000 class recognition. The first CNN winning the ILSVRCs challenge was AlexNet architecture 4. It consists of 5 convolution layers, max pooling layers, dropout layers, 3 fully connected layers and uses ReLU as an activation function [6]. In 2014, another CNN architecture VGGNet [7] showed that it is possible to reduce the number of parameters and increase the depth of the network, achieving better performance than the AlexNet architecture. AlexNet has an error rate as 11.24%; however, VGGNet has achieved an error rate of 7.3%. Figure 4 shows, there are more convolutional layers in this architecture than AlexNet, which are lower in terms of filter sizes, leading towards a reduction in parameters but can learn more high-level characteristics than earlier CNNs.

Convolutional Neural Networks (CNN), has accomplished excellent improvements in object classification [8] [9] [7] [10] [11] [12], image segmentation [13], and object detection [14] [15]. CNN's performance was very high-level features compared to well-known hand-designed characteristics such as HoG, SIFT, LBP [16] etc.

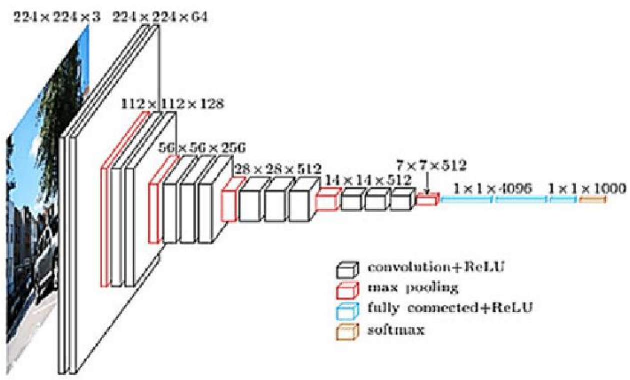

Fig. 4. VGGNet Architecture [45]

Researchers are designing the custom models for CNN to have better and faster results. [17] proposed a 5 layer CNN to detect the cracks in metals images while [18] evaluated 5 CNN architectures for corrosion detection from images.

Their techniques function similarly first, large input images are cropped to smaller images of fix size, and then CNNs are implemented to identify, classify whether smaller images have a presence of cracks or corrosion. A summary of approaches used by researchers is as below:

Approach	Particular technique	References
General image processing	Color, Texture and shape	[19] [20] [21] [22] [23] [24] [25]
	Luminosity, contrast and noise	[4] [20] [22] [26]
	Fourier Transform	[27] [25] [28]
	Wavelets	[3] [28] [29] [30]
	GLCM	[19] [4] [26]
	Morphology	[31] [32]
	Edge-based (thresholding + thinning)	[33] [34]
Learning-based	Neural Network (NN)	[35]
	Backward propagation Neural Network (BPNN)	[36]
	Convolutional Neural Network (CNN)	[37] [38]
	Support Vector Machine (SVM)	[5] [36] [39] [40] [21]
	K-Nearest-Neighbors (KNN)	[36]
	AdaBoost	[4]
	Deep Learning	[18] [41] [42] [43]
	Decision Tree	[36]

TABLE I summary - corrosion detection techniques

III. METHODOLOGY

The basic building block of our models is the Convolution Neural Network. Three stages are included in our framework to effectively apply the deep learning model are data acquisition, training of the model, and model assessment.

A. Data Collection and Pre-processing

In this section, we explain briefly how to label and prepare the information for training the model. We also include some significant statistics and additional reference data on the dataset.

Image Capture and Labelling: The dataset of corrosion images for training the proposed deep learning model is obtained from microscopic images of corrosion developed in the lab with different concentration of HCL. The samples were processed through Light Blast cleaning to remove the oil, grease, and dirt. A set of 862 images in total has been collected with four different corrosion grades. These images we cropped to 512x512 pixels for the deep learning dataset To train the model, the images were labeled using VIA tool, which is open source labeling tool. VIA provides the options to label in different shapes as a rectangle, a circle, a polygon etc., we have used rectangle as well as polygon to label the corroded area in the images with a separate label for grades of corrosion. Once the dataset is labeled, we divided it into the training set and testing set for training and validation in the ratio of 80:20.

Image Pre-Processing: Pre-processing and augmentation techniques are implemented before the information training for better speed and performance. As proposed [7], the image pixel value is subtracted by the mean RGB pixel value. In addition, the pixel values are standardized for better convergence, resulting in zero mean and unit variance of the input of the pixels. Next, Data Augmentation [10] methods are typical for both improving efficiency and adding model robustness. The techniques used for augmentation include horizontal flip, vertical flip, horizontal and vertical flip combined. It produced three times more information than the original dataset.

B. Hardware Setup:

There are various online infrastructure providers for running the Deep Learning models; however, we have used Google Colab. It has NVIDIA K80 graphics card to provide GPU support and ran software on Ubuntu 16.04 OS, python3.6, and tensorflow1.8, etc. Faster R-CNN deep learning network is used in this research along with VGG16 as the CNN framework.

C. Model Setup and Construction - Transfer Learning:

One significant barrier to training deep learning models is the big dataset needed; however, the amount of data required for training the model can be significantly reduced with the transfer learning [44] and fine-tuning methods. For the current study, we have used state of the art Mask R-CNN model with the custom dataset and transfer learning. The Mask R-CNN framework is based on Faster R-CNN architecture with enhancements to the layers. For a given image, Mask R-CNN returns the mask & bounding box coordinates of each object in addition to the class label. We successfully trained our model on the custom dataset by initializing the weights of convolutional operations in the block with the weights pre-trained on MS COCO dataset. By leveraging transfer learning, we took advantage of MobileNets and Resnet´s pre-trained model architecture. We inherited the model architecture with transfer learning, the image data attributes, and classes on which the model was trained, and most importantly, the final model´s weights and biases. The deep convolution model is implemented using Tensorflow library with updated the neural network weights from pre-trained models. Some other model hyper parameters are adapted and selected based on both practice and test information results of the model.

IV. RESULTS & DISCUSSIONS

To show our framework's efficiency and precision, we first compare our model with another supervised model [5] with the same image dataset. Next, it validates the suggested structure with test information that is not used during model training. The Quadratic SVM model was able to detect corrosion with 82.4% accuracy.

We have set training parameters for all tests with the following values: epoch-20, batch size-100, learning rate-0.001, momentum-0.9. With total loss got stable after 20 epoc, so we stopped further training.

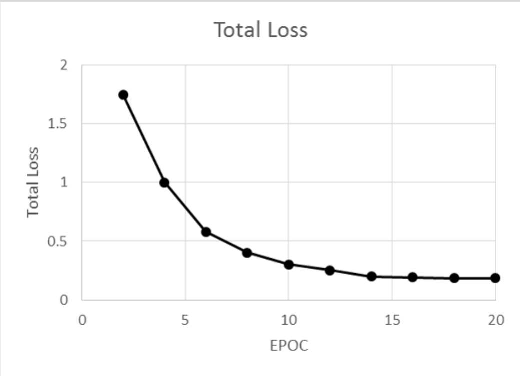

Fig. 6. Total Loss

We evaluated the accuracy of our model with a Jaccard index at (Intersection over Union) of 0.5 and using the mean Average Precision metric. With 93.4% accuracy, the suggested deep learning model has given significant improvements in outcomes. Another benefit of the suggested model is to highlight the region of corrosion.

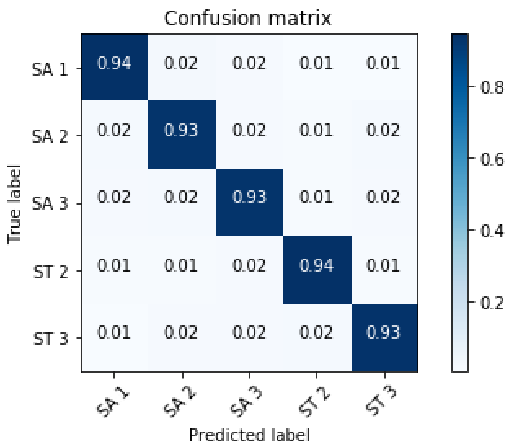

Fig. 7. Confusion Matrix

V. CONCLUSION

CNN is a very powerful method to detect and classify different types of image objects. This paper presented image processing based methodology for the segmentation of corrosion in different grades using unsupervised learning. It was demonstrated that the use of a CNN outperformed the prior approach of corrosion detection where wavelet characteristics were implemented. The proposed approach has resulted in a higher accuracy of more than 93.4% for corrosion grade identification in four defined categories. The results of actual corrosion and predicted by the model were beyond expectations considering the limited amount of dataset available for training. A more robust model can be created by training on a large dataset with varying our IoU threshold, leading towards better accuracy of the model.

VI. FUTURE WORK

For the future, CNNs may be expanded further to classify different types of corrosion with a greater number of neurons. The fully connected layers may also be updated to have better results. An interesting evaluation would be further evaluating the actual number of neurons required for the same or even number of corrosion grades. The parameters for any selected clustering algorithm can be calculated automatically by means of cluster stability assessment and cluster validation techniques to automate detection and quantification in real-life applications. In addition, CNNs can be used by using the sliding window strategy to analyse the corrosion growth on the full-scale image with quantifying the corroded region in the image. Having the ability to automatically detect corrosion, analyse the growth of corrosion through drones will help an inspector and significantly reduce the time and cost of inspecting oil & Gas pipelines or any other civil structure.

VII. ABBREVIATIONS AND ACRONYMS

ANN	Artificial neural network
CNN	Convolutional Neural Network
GLCM	Gray Level Co-occurrence Matrix
HoG	Histogram of Oriented Gradients
HSV	Hue saturation Value
LBP	Local Binary Pattern
LMS	Least Mean Square Algorithm
SVM	Support vector machine
SIFT	Scale-invariant Feature Transform
R-CNN	Region-proposed Convolutional Neural Network

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