Corrosion Classification Study of Mild Steel in 3.5% NaCl using Convolutional Neural Networks

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Abstract- Corrosion detection using advanced equipment could be sometimes unavailable in resource-limited settings. To make up for the corrosion testing gap, image capturing and processing with Convolutional Neural Networks (CNN) have gained prominence in corrosion studies. In this study, two CNN models were built and trained using images taken with a mobile phone camera and a digital microscope. The CNN models were built to categorize corroded images into three different classes based on the surface area of the sample that were covered by the corrosion products. The study shows that CNN corrosion classifiers perform very well with accuracy above 80% for both models. The use of CNN was found to be effective for multiclass corrosion.

Keywords- Convolutional neural network, Corrosion, Corrosion detection, Image processing.

1 Introduction

Corrosion is an irreversible, spontaneous process that could cause deterioration in metals resulting in damage and potential threats to the environment and life. Due to the losses associated with corrosion, significant research efforts have been made on various methods of corrosion detection. Corrosion detection and inspection methods could be performed directly using instrumentation in the process stream or non-contact techniques like digital image processing techniques (De Kerf *et al.*, 2021). Images obtained from corroded parts using cameras and microscopes can be further processed and examined to ascertain the extent of corrosion on the component under investigation (Ejimuda & Ejimuda, 2018; Igoe & Parisi, 2016; Liu *et al.*, 2019).

In recent years, Convolutional Neural Networks (CNN) have gained prominence as a post image analysis tool for corrosion and other studies (Chun *et al.*, 2019; Petricca *et al.*, 2016; Zuchniak *et al.*, 2021). In a separate study, data from acoustic emission waveforms were trained using CNN to investigate corrosion behaviour of CORTEN steel (Barile *et al.*, 2022). The results showed that the CNN had more than 99% accuracy. CNN has also been used to detect corrosion damage on hulls (Yao *et al.*, 2019), perform quality checks on bolts (Rajan *et al.*, 2021), inspect and characterize corrosion on external pipelines (Bastian, Ranjith, & Jiji, 2019), metallic corrosion on civil infrastructures (Zhang *et al.*, 2021) and more. In brief, a Convolutional Neural Network (CNN) is a type of artificial neural network that can extract features directly from images and provide valuable information on the process.

The CNN architecture consists of the convolutional base (consists of layers that performs feature extraction) and the dense head (for processing, classification and segmentation) (Atha & Jahanshahi, 2017; Sony, Dunphy, Sadhu, & Capretz, 2021). Therefore, this study was designed to build a CNN capable of identifying and classifying the type of corrosion in mild steel using image data alone.

2 Materials and Methodology

In this study, two Convolutional Neural Networks were built to classify corrosion images based on the levels of corrosion. Images from a digital microscope and mobile phone camera were used in the model

2.1 Sample Preparation

Mild steel was cut into five (20 mm x 20 mm) samples. The samples were covered with bakelite and the surfaces were ground using three grades of emery paper (600, 800, and 1200). This was followed by polishing using emery paper and alumina powder (0.3 um). The samples were then immersed in a 3.5 wt% of NaCl for 14 days.

2.2 Image Dataset

Images of the samples were taken on 8-hour intervals daily for 14 days. The mobile phone images were taken using a 64 MP Infinix Note 8 camera, while the microscopic images were taken using a hand-held microscope at a magnification between 500x and 1000x. A total of 220 microscopic images and 215 mobile phone images were obtained. Samples of the images are shown in Figs. 1 and 2.

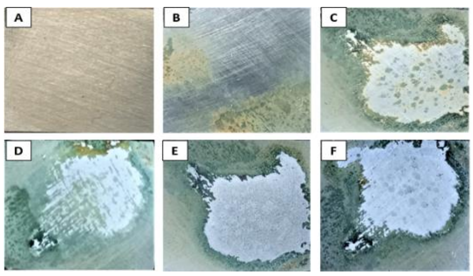

Fig. 1: Images from Mobile Camera taken at 0, 3, 6, 10, 12 and 14 days

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Section C- MECHANICAL/MECHATRONICS ENGINEERING & RELATED SCIENCES
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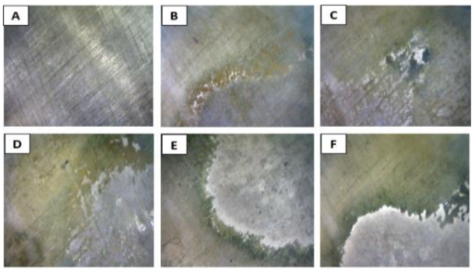


Fig. 2: Images from Hand held Microscope taken at 0, 3, 6, 10, 12 and 14 days

2.3 Image Annotation

In this study, three corrosion classes were created based on the surface area of the sample covered by the corrosion residue as shown in table 1. The images were annotated and grouped into their specific classes using the VoTT image annotation tool (an open-source application). After annotation there were 81 images in class 1, 147 in class 2 and 207 in class 3.

2.4 The Convolutional Classifier

The first classification CNN model (Model 1) was trained using mobile phone images, while the second model (Model 2) was trained using microscopic images. The architectures for both models were similar and were built on the ResNet 50v2 model. To optimize the models built, Adam optimizer was used as the loss monitor, categorical cross-entropy as loss function and sparse categorical accuracy as optimization metric. The ResNet Architecture (Ji *et al.*, 2019) is shown in Fig. 3.

3 Results and Discussion

In this section, the performances of the CNN models built were evaluated and the outcomes from Model 1 and Model 2 are presented. The models were evaluated using 63 evenly distributed (21 from each corrosion class) images from their corresponding dataset.

3.1 Evaluation Metrics

The evaluation metrics used in this study were precision, recall, accuracy and F1_Score. In addition, a confusion matrix was used to further explore the results of the models. Equations 1 to 4 were used to compute the selected metrics.

$$Accuracy = \frac{TP+TN}{Total\ Prediction} \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

$$F1\_score = \frac{2 \times Precision \times Recall}{Precision+Recall} \quad (4)$$

where FP = False Positive, FN = False Negative, TP = True Positive and TN = True Negative.

3.2 Classifier Training

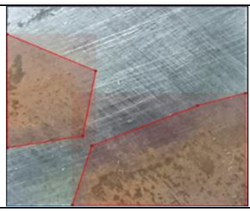
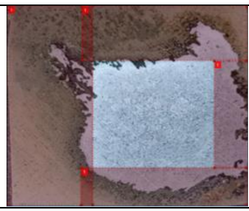
In this study, two corrosion classifiers were trained, using a 12GB RAM GPU on Google Colab which was a free cloud environment for building machine learning models with minimal setup. The learning rate was set at 1e-5 and a large epoch value was used with early stopping to ensure the model converged at best possible value for accuracy. The optimization metric was sparse categorical accuracy and each model took about 6 hours to run and converge.

3.3 Results from Models

3.3.1 Model 1

The model built using mobile phone images (Model 1) had an accuracy of 84%. The model performances on the evaluation metrics are shown in Table 2. The accuracy value for model 1 appeared to be high, but this value did not fully describe the performance of the model. Careful examination of the recall score of model 1 on images from class 2 showed that the model had some difficulty in classifying images with class 2 corrosion. From the confusion matrix shown in Fig. 4. Six out of the twenty-one images in class 2 were wrongly classified as class 1 by the model. The poor performance of the model on class 2 images can be attributed to the fact that elements in class 2 do not have very distinct features, which made it difficult for the model to predict with confidence. The receiver Operation Characteristics Curve (ROC) alongside the Area under the Curve (AUC) for model 1 is shown in Fig. 5. The ROC curve is a plot of true positive rate against false positive rate and shows the performance of a classification model at all thresholds. Looking at the ROC curves and the AUC values, it is clear that the model had challenges classifying images in class 1, but in general the model performance was above average.

Table 1. Corrosion Classes Used and their Corresponding Images

Class	0	1	2
Details	No corrosion to low level corrosion	Medium Level Corrosion	High Level Corrosion
Surface area covered by corrosion products	< 10%	10% < X < 50%	> 50%
Image			

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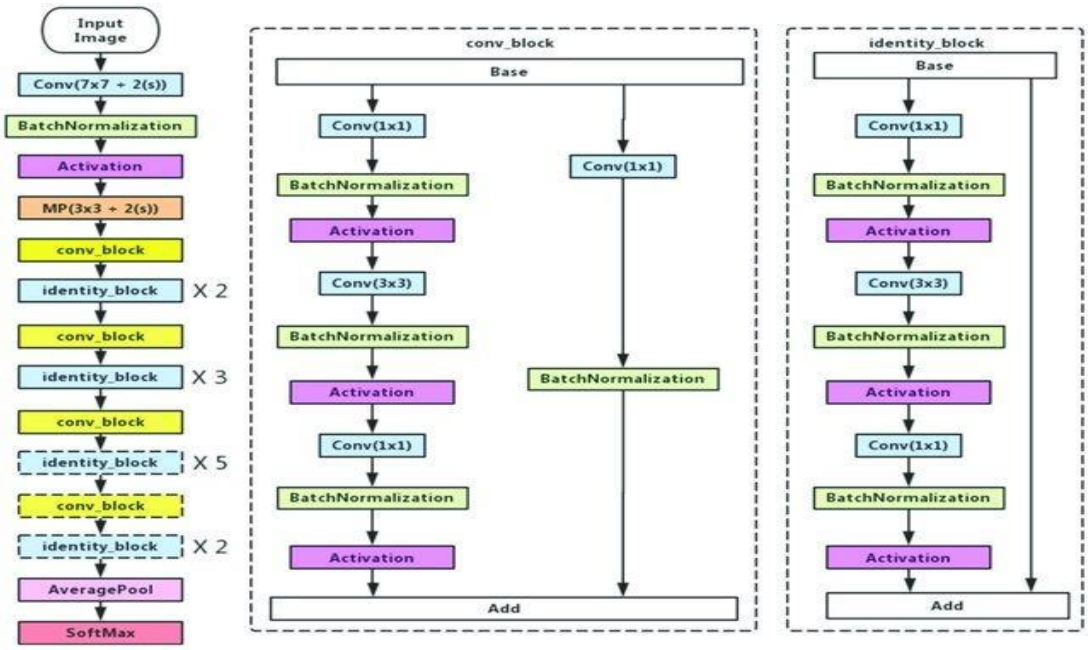

Fig. 3: ResNet 50 Architecture (Ji *et al*., 2019)

Table 2. Performance of Model 1 Using Standard Metrics

	Precision	Recall	F1_Score
Class 0	0.76	0.90	0.83
Class 1	0.82	0.67	0.74
Class 2	0.95	0.95	0.95

3.3.2 Model 2

The model built using microscopic images (Model 2) had an accuracy of 92%. The model performance using the standard evaluation metrics are shown in Table 3. The performance of model 2 was evaluated using the standard metrics and it is clear that model 2 performs very well on all the classes, with all values going above 85%. The confusion matrix (Fig. 6) for model 2 also shows that the model performed at a very high level, with only 3 out of the 21 images in class 1 getting misclassified. The ROC curve for model 2 (Fig. 7) shows that the AUC values for all the classes were above 0.9; this shows that the model performed very well in classifying images from all the classes, but there was a slight dip in the performance when classifying images in Class 2.

Both models built in this study had accuracies going above 80%. A bar chart showing the average precision, recall, f1_score and accuracy of the models is shown in Fig. 8. From the results presented, it was observed that both models had the most difficulty when predicting images from class 1, with model 2 performing slightly better. The improved performance of model 2 to model 1 can be attributed to the fact that the microscopic data provides more information about each class of corrosion; hence the CNN model can extract more features and make predictions more reliable. Salt deposits were visible on the microscopic images. Both models performed well on class 2 corrosion images with only one misclassified image.

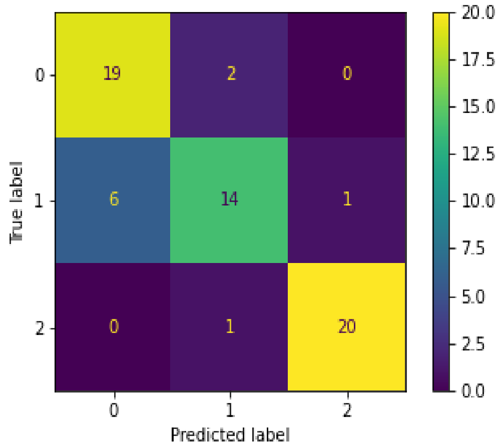

Fig. 4: Confusion Matrix for Model 1

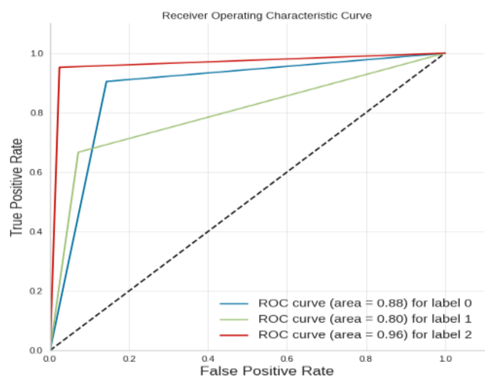

Fig. 5: ROC Curve for Model 1

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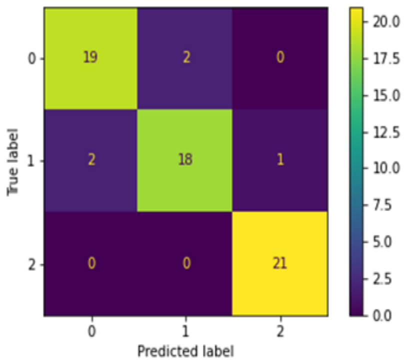

Fig 6: Confusion Matrix for Model 2

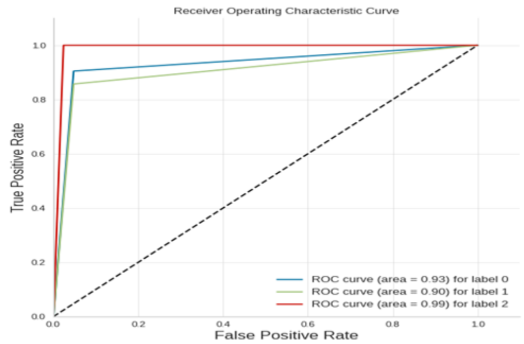

Fig 7: ROC Curve for Model 2

Table 3. Performance of Model 2 Using Standard Metrics

	Precision	Recall	F1_Score
Class 0	0.90	0.90	0.90
Class 1	0.90	0.86	0.88
Class 2	0.95	1.00	0.98

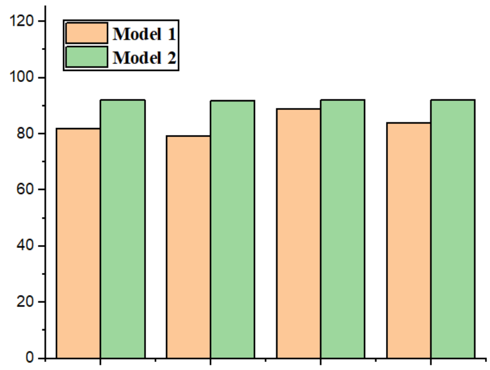

Fig. 8: Comparison between the performance of Model 1 and Model 2

4 Conclusions and Recommendations

In this study, two convolutional neural networks were built to classify corrosion based on the surface area of the mild steel sample covered by corrosion products. The first model was built using images taken with a mobile phone camera, and the second model was built using images taken with a microscope. The results of the study showed that Convolutional neural networks perform extremely well in multiclass corrosion classification tasks, with the accuracies of both models above 80%. The model built with microscopic image data had 92% accuracy and the model built with images taken with a digital camera had 84% accuracy. The models can be made industry-grade by training the models using real-life images of underwater pipe systems, oil rigs etc.

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