DETECTION CORROSION BY USING CONVOLUTIONAL NEURAL NETWORKS TECHNIQUE

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***ABSTRACT**: There are traditional methods for detecting corrosion, such as using cameras and physical examinations, but they are not useful for many types of corrosion. Artificial intelligence AI predict corrosion into metals these are smart technologies will contribute to enhancing efficiency, productivity and sustainability across the various stages of the metals process. Knowing the initial corrosion helps to identifying corrosion area of the surface and taking the necessary measures to prevent it. In this research, we propose an automatic method for examining images of metal surfaces and classifying the pitting corrosion strength through Convolutional Neural Networks (CNNs). It use open source dataset of steel bridge corrosion was created along with the annotations that matched them. This database contains 2530 images are separated into two sections: 980 with no corrosion and 1550 with corrosion. Initially, image processing is done to make the image specifications suitable for the CNN model. After that, a number of CNN models are compared, with pre-trained models being used with transfer learning technology. The best evaluation accuracy results are 98% in the training set. As a result, the outcomes show how well the suggested algorithm works as an assistance model for corrosion detection.*

***KEYWORDS**: Convolutional Neural Networks (CNN), Corrosion, Deep Learning, Image Processing*

1 INTRODUCTION

Artificial Intelligence is a one of fastest inventions in the recent years. The idea of AI is a machine that learns and makes decisions independently. Artificial intelligence and manufacturing will go hand in hand as humans and machines must partially cooperate in environments (Aldriasawi et al. 2024). One of the algorithms of AI that can be used in recognition is the Artificial Neural Networks (ANN), which are models that mimic the functioning of the human brain in machine. An imagination of the biological neural network but from a different perspective, meaning similarity in the method of performance but in a different way. Neural networks are constantly learning and thus can evolve and make intelligent decisions based on deep analysis of data. Among their most important applications of ANNs are prediction, such as medical diagnosis and economic forecasting (Fnides et al. 2024). Researchers faced some problems in traditional ANN where accuracy is limited and cannot be improved even with increasing the size of training datasets or the number of hidden layers. Therefore, researchers developed these networks and the new networks were named Deep Neural Networks (DNN), and the word deep refers to the number of hidden layers. It became possible to increase accuracy by increasing the number of hidden layers or increasing the size of the training database. In recent years, Deep Learning (DL) especially Convolutional Neural Networks (CNNs) have shown excellent accuracy in many pattern of classification problems (Słapczyński, T. 2022). It was first introduced by Hinton et al 2006, which led to a major shift in computer vision systems. This method relies on the multi-layer (deep) (Kim, Y. 2014). Paral et al. (2021) propose an AI-based approach for detecting damage in structural steel connections, which are vulnerable to issues like bolt loosening, corrosion, and fatigue. Traditional methods require expensive sensors and localized instrumentation, which the authors aim to overcome using Convolutional Neural Networks (CNNs) and Continuous Wavelet Transform (CWT) on global vibration signals. Their model, which incorporates an updated finite element (FE) model of the steel structure, provides an efficient alternative for health monitoring. The methodology is validated through experiments on a two-story steel frame, successfully identifying damage in beam-column connections. Automated corrosion detection is an important and active research area where many researchers have studied different fields. A study by Krizhevsky et al. 2017 estimated automated corrosion detection by using Machine Learning ML with CNN. The model detection base on features extraction texture and color, it obtained a 95.75% training accuracy with a 0.1193% loss. Khalaf et al. (2024) address the significant challenge of corrosion in the oil and gas industry, which leads to high maintenance costs and productivity losses. Traditional corrosion monitoring methods often fail to provide effective solutions. The research reviews the emerging role of artificial intelligence (AI) in revolutionizing corrosion monitoring. It discusses the detrimental impact of corrosion, factors influencing it, and how AI-driven corrosion prediction models can proactively identify and mitigate issues. The paper also explores AI applications in data analysis, predictive modeling, and real-time monitoring strategies. Finally, the study highlights challenges in implementing AI, including data acquisition, quality, algorithm selection, and the need for human expertise in decision-making. Yao et al. (2019) propose a new method for detecting and recognizing hull structural plate corrosion damage in ships, leveraging artificial intelligence, particularly deep learning. Traditional image-based corrosion detection methods require extensive feature extraction, which is resource-intensive. To overcome this, the authors use a Convolutional Neural Network (CNN) model trained on a large dataset of classified corrosion images. The trained model, combined with an overlap-scanning sliding window algorithm, helps accurately identify and locate corrosion damage. The proposed method accelerates the adoption of AI technologies in naval architecture and ocean engineering, offering a more efficient approach for corrosion detection and damage recognition. The proposed approach of this study is to detect pitting corrosion on surface of metal by using Convolutional Neural Networks. CNN is based on classification corrosion object from many types of objects in the images. Early identification and detection of corrosion is an ideal method and solutions in the metals problems. They will be help visual inspection from damage that it will happen later and take decision early. This study focused on giving an overview of pre-processing and augmentation data. It showed the importance step of pre-processing step in increase efficiency and accuracy of CNN in detection pitting corrosion.

2 DEEP LEARNING (DL)

Processing vast volumes of data and intricate patterns in voice, images, and languages is essential to deep learning by passing them through deep neural networks and training to glean valuable insights from this data. Deep learning is currently the most effective AI technique for multiple applications. Deep learning is used for hundreds of studies, ranging from natural language processing to computer vision. Frequently, deep learning has been better than ever. Deep learning is widely used in universities to study intelligence and in industry to build intelligent systems to help humans with a variety of tasks. The roll of DL in image processing relay in the manipulation with pixel value in a building system has ability thresholding image processing. DL is often used to process computer vision tasks with the great progress in Deep learning applications. Some of application deep learning in corrosion detecting in (Khalaf et al. 2024, Yang et al. 2022, Petricca et al. 2016).

2.1 Convolutional Neural Network

One particular kind of deep neural network is called a Convolutional Neural Network (CNN) that derives its mechanism of action from biological processes specifically seen in the visual lobe of the human brain in particular. Convolutional networks are called by this name because they contain convolutional layers that extract features and place them within feature maps. The convolution process helps diminish the number of parameters, enabling a deeper network with fewer parameters and also solves the problem of exploding gradients that occur in training traditional networks. It is usually followed by a pooling layer that collects the features and cuts down the size of the feature matrices while maintaining the characteristics for each matrix (Mzili et al. 2024, Akpanyung & Loto 2019, Hoang 2020, Nosonovsky & Aglikov 2024). Then the flatten layer converts all feature matrices into a single vector in order to link it to the final output layer, which is the full connection layers that perform the classification process. All layers as shown in Figure1.

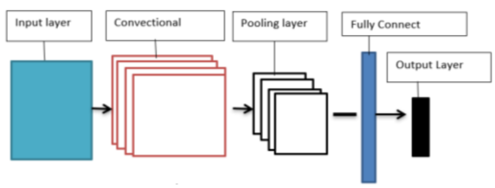

Fig.1 CNN structure

The Structure above is consisting of four basic layers, which are:

a) Input Layer: The convolution layer: Layer Convolute, which is the first and main layer in the CNN. This layer uses what is called a kernel or filter through which the image is scanned, then the pixels are collected. Pixel and the final values are extracted as features called a features map.
b) Layer Pooling: This layer often comes after the convolution layer, and this layer reduces the dimensions of the image, and this layer consists of several types,
c) Fully Connected Layer: This is the last layer, in which neurons are connected to each other, in order to produce the final result. Activation layer type is often used with the convolution layer, and is abbreviated as Relu, (It converts the filtered inputs to a specific value, and then sends it to the next layer).
d) Output Layer: Training the learning model CNN requires a large and appropriate amount of images and for classification. This can be a challenging and labor-intensive task.

3 CORROSION

The use of metals is widespread in various sectors including the industrial sector, railways, and corrosion applications. Metal corrosion has an impact on the effectiveness of the metal, which leads to a functional malfunction in the system's equivalence. Corrosion is one of the most serious problems that metal structures suffer from as a result of the damage it causes to these structures. Corrosion takes different forms and each form occurs due to conditions imposed by the type of metal, the nature of its surface, the type of medium and its condition, and each form of corrosion has a specific preventive method and in general we can distinguish between the following forms of corrosion:

- General electrochemical corrosion (regular).
- Localized electrochemical corrosion (focused).
- Galvanic corrosion.
- Hydrogen cracking corrosion.
- Ion current corrosion.
- Biological corrosion.
- Erosion and erosion corrosion.
- Stress corrosion.
- Combustion corrosion (direct oxidation).
- Localized corrosion: Localized corrosion
- Localized corrosion attacks a limited area of the metal structure, and is classified as one of the following three types:

a) Pitting corrosion:

The metal surface has minute flaws due to localized corrosion. (b) Pitting corrosion is located under the surface deposits formed by the accumulation of corrosion products. Pitting occurs when a small gap or pitting forms in the metal resulting from the removal of negativity in a small area, so this area becomes an anode, while part of the remaining metal becomes a cathode, and a local galvanic reaction occurs, and the deterioration penetrates this small area of the metal and can lead to its collapse. This type of corrosion is often difficult to detect because it is relatively small and sometimes hidden and covered with corrosion product compounds. Engineers face great difficulty in identifying corrosion areas, which is very important for engineers in analyzing the condition of elements to reach the infrastructure, such as the case of pitting corrosion. The need has emerged to use computer hardware and software that provide more information and thus achieve integration with the rest of the maintenance operations and improve performance using digital images in pitting corrosion.

4 METHODOLOGY

An open source pitting corrosion dataset and the corresponding annotations were produced for this project. Database contains 2530 samples of corrosion image from are available in www.shutterstock are departed into 1550 training and 980 testing 980 for detection corrosion. Corrosion is the breakdown of metal, and humans use the shape of an object to recognize it. Deep learning is used to extract corrosion-containing portions of images. In an image with a lot of other items and backgrounds, it considers corrosion as an object. A outline of work in the Figure 2.

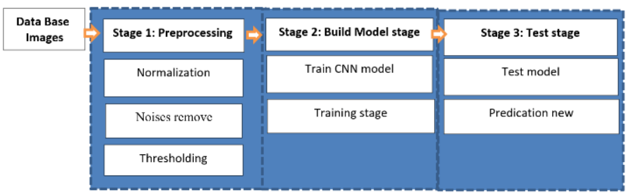

Fig. 2 Outline of Proposal work

This technique is combined in order to achieve the final result and not through a single process and within stages are:

4.1 Preprocessing

Set operations are performed on the image to achievement aim of improvement images, Preprocessing used different techniques were combined in order to getting final result. The output of the computer vision process is signals that are understood by the computer model and extracted features, characteristics of images. The output of acceptable images that satisfy computer vision process and assist in the preparing perfect samples for implementation by CNN. Successful improvement is achieved when a set of techniques are combined in order to achieve the final result and not through a single process and within the steps of the research processing are :-

4.1.1 Normalization

All input images are reshaped into same size and scale.

4.1.2 Noise processing

Determine the important part of the image from another the unimportant by eliminating noise in the image. Many improvements and filters were available to improve the quality of image. In this model utilized a median filter in noise reduction.

4.1.3 Thresholding

Database images are Color Images. The component within image based on into three red, green and blue as shown in figure 3. Other step in the preprocessing for Image Thresholding which are provide contrast between the desired object (foreground) and the background. also eliminated the small blobs effected in vision pitting corrosion. The results are shown in figures 4.

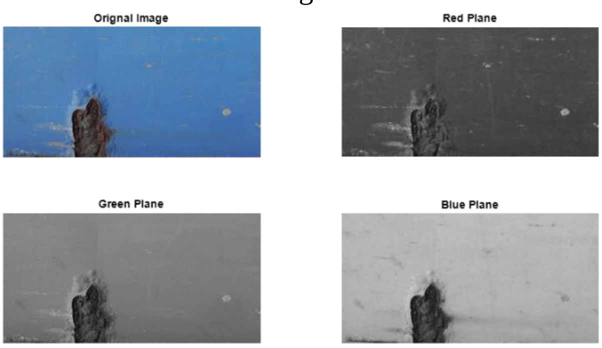

Fig. 3 Description of original image with component image (r,g,b)

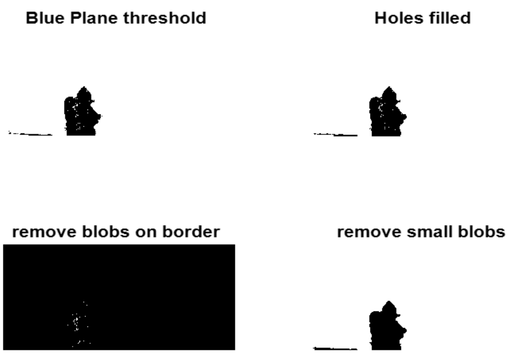

Fig. 4 Image after Thresholding

4.2 Build Model

Building and training a convolutional neural network: This stage includes two parts: building the neural network, then training it and obtaining the final classification model. Before going into the details of our neural network, some basic concepts must be clarified. The classification process performed by convolutional neural networks is done in several steps:

a) Feature extraction process which includes convolutional layers and pooling layers.
b) Convert features to one-dimensional vector using flattening layer
c) Processing features with fully dense layers.
d) Give the output on the output layer.

The convolutional neural network consists of 4 basic layers: the input layer, the flat layer, the fully connected layer, and the output layer.

- Input Layer: The input layer contains 3 a one-dimensional convolution layer which is used ReLU and each layer is followed by a Max Pooling 1D. The convolutional layers each contain 64 filters which are size of kernel 5x5
- Flattening layer: This layer transforms the features extracted from the previous layers into a one-dimensional flat layer.
- The layers process the extracted features and use the ReLU function.
- Output layer: It is a fully connected layer that contains 5 neurons and uses the activation function Soft Max

After implementation of CNN and completing the training and testing process, we start to review and evaluate the results we obtained from our proposed model. We obtained an accuracy of 98.75% for training and 96.64% for testing (Figure 5). While the error rate is 0.050 for training and 0.1425 for testing as in Figure 6.

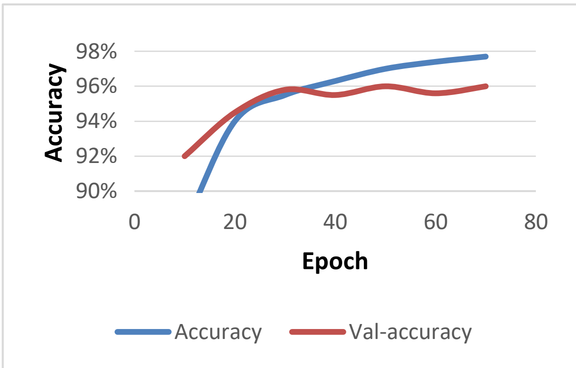

Fig. 5 Training accuracy and test accuracy achieved by the proposed model.

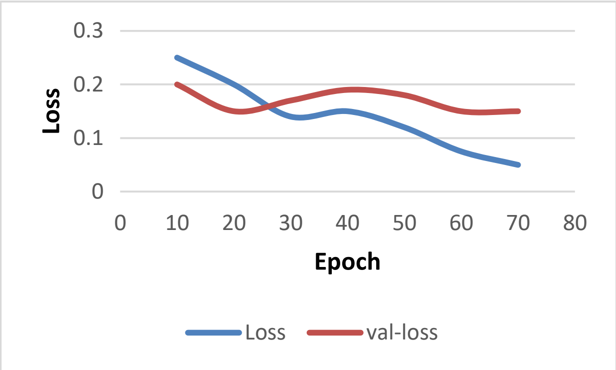

Fig. 6 Error value for training data and test data

5 CONCLUSION

The great interest in CNN has been in identifying structural damages, including corrosion detection classification. The eye sees the image, then the brain analyzes it, and extracts features from it. Just as humans organize their ideas and concepts in a hierarchical manner, starting from simple concepts to more complex concepts, convolutional networks extract features starting from general features to complex features. The image features are an area of sudden change in value, such as edge areas, that cannot be observed. The current research involve corrosion detection within computer vision**.** This study attempts to create a model for detection pitting corrosion in the shortest possible time and cost, as it helps in classifying a large number of corrosions in high accuracy compared to others techniques. The results showed that CNNs give high accuracy 98% in pitting corrosions with low-complexity algorithm according to reasons:

a) Preprocessing steps are improve and minimized features of image. In addition efficiency of CNN in the mining by reducing amount of input data which increases the productivity. Preprocessing of proposal algorithm and features extracted by CNN layer. They worked together efficiently in terms of accuracy and time, which increased the quality of the proposed research in machine learning. CNN based automatically on a features extraction, classification and outputs.

b) A big problem point in the object (corrosion), most of pitting corrosions aren't uniform in the shape but the model chosen matches the nature of the pitting corrosion being studied. it can be noted model achieved a best result.

c) Designing structures suggested of right number of convolutional networks layers overlapped the difficulties of huge database.

d) This research treats corrosion pitting as an item in a image where pay attention to the shape and size corrosion early by algorithm while human can be identify pitting corrosion by vision.

e) AI systems are used to monitor working conditions and detect corrosion automatically.

f) Finally, we conclude this application helps in the post-mining phase to reduce the environmental impact by improving mining operations**.**

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