# CNN-Based Detection Of Welding Crack Defects In Radiographic Non-Destructive Testing

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**Abstract –** *In the industrial sector, the focus in recent years has been on enhancing production and minimizing human error. Therefore, engineers have used Non-Destructive Testing to evaluate material by combining artificial intelligence technologies with NDT. One of the field applications of NDT is the detection of welding defects.*
*The use of neural networks can greatly enhance the accuracy of detecting defects in industrial welding. A convolutional neural network with triple classification for welding defects has been suggested. In the first step, the original images are cut down to 150 x 150 pixels. Subsequently, the images are categorized into three groups: Training, Testing, and Validation.*
*In the triple classification experiment (Crack, other types of Defects, No Defects), the CNN model had 6 layers and 9,667 parameters. The model accuracy approached 92% after 800 epochs. The F1 factors of crack, other types of defects, and no defects were 100%, 91%, and 90%, respectively.*
*The article provides methods used by CNN in detecting welding defects and highlights the potential to improve defect detection accuracy.*

**Keywords:** Non-Destructive Testing, CNN, Welding Defects, Artificial Intelligence

## I. Introduction

### I.A. Overview:

Artificial intelligence (AI) has been widely used to improve efficiency and accuracy while reducing human errors in various fields. In the case of power plants, for example, AI algorithms can assist in classifying power system conditions, detecting faults, forecasting electric loads, reducing emergency problems and breakdowns caused by surge loads. [1] [2] [3]
The application of AI in various fields has yielded promising results and is expected to progress further. However, maintaining public trust and acceptance requires ensuring that AI algorithms are transparent, explainable, and ethical.
AI has been used in Non-Destructive Testing (NDT), particularly for the detection and characterization of weld defects. The integrity of the materials is examined using NDT techniques without causing any damage or compromising their usability. The use of numerous NDT techniques is widespread and effective for monitoring engineering components and architecture.
Radiographic testing (RT) is crucial NDT technique that is frequently used in weld inspection, especially in new construction. However, interpreting the results of RT can be challenging as it is affected by various external factors, and image quality. The integration of AI, specifically computer vision, can significantly enhance the detection of welding defects by reducing the impact of external factors and minimizing human errors in result interpretation.

### I.B. Welding and welding defects:

Welding is the process of joining two or more pieces to form a larger piece through the use of heat and/or pressure. Welding is an important part of the manufacturing process, and its condition must be checked because the weld area affects the strength and durability of structures. [4]
Welding defects are caused by stresses, poor welding processes, and environmental changes. Their severity varies according to the type, position, and size of the weld. A crack, undercut, porosity, overlap, slag inclusion, incomplete fusion, and incomplete penetration are examples of welding defects. [5]

### I.C. Radiographic Non-Destructive Testing:

Internal welding defects are imaged using X-ray or gamma ray technology. The transmission or absorption of radiation in a material is determined by the photon's energy, material type, and thickness.
Radiation penetrates the material under test in RT, and the intensity of the radiation received on the other side informs about the material density, which could be related to inhomogeneities in material thickness or internal defects. If the object is dense, most of the radiation is absorbed, and the image produced is brighter, and vice versa.
Welding defects cause differences in the density of the material and, as a result, in the amount of energy absorbed or transmitted [6] Figure 1 shows the appearance of some welding defects in radiographs; for example, the longitudinal dark line in the upper image is a weld centerline crack.

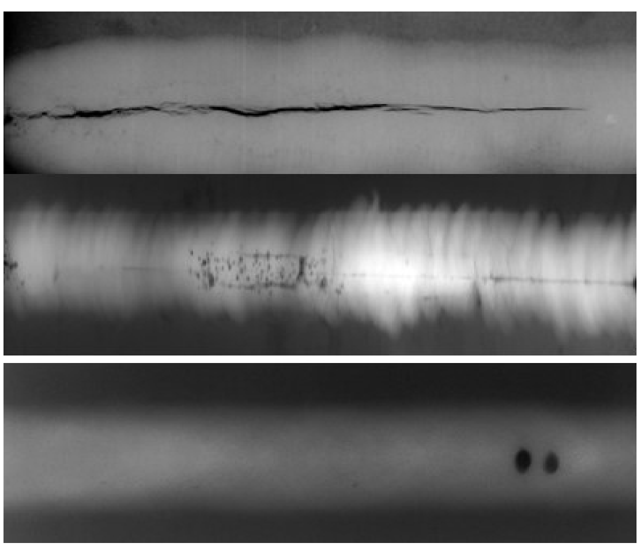

*Figure 1 Radiography test samples of welding defects*

## II. Neural Networks:

### II.A. Deep Neural Networks (DNN):

Deep Neural Networks (DNNs) have more than three hidden layers; in recent years, DNNS have had hundreds of layers added. [7] Because of the powerful computers and access to large amounts of data, it was possible to address issues that were previously too complex for ANN, such as image recognition, as shown in figure 2. [8]
Due to the limited capabilities of devices and technologies, neural network applications grew slowly at first. The first applications that used neural network techniques to recognize the defect's edge in the weldment were pattern recognition, image segmentation, and feature extraction. [9]
The era of deep neural networks in applications began to emerge shortly after. Many industrial applications now use deep neural networks, such as image recognition of welding defects, monitoring of operating conditions in power plants, and fault detection and monitoring of electric flow, which has greatly reduced errors and maintenance time. [10]

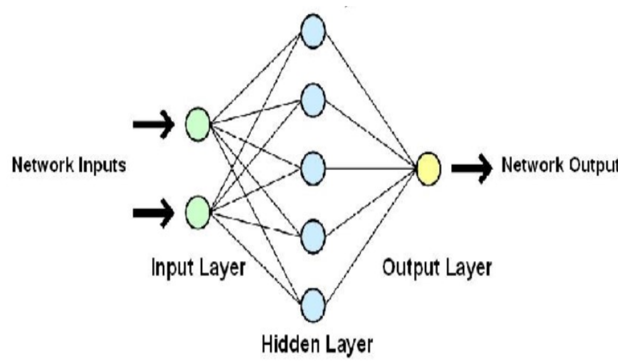


*Figure 2 Basic structure of the neural network*

### II.B. Convolutional Neural Networks:

The convolutional neural networks are one of the most commonly used models in image recognition using supervised learning techniques. The CNN is made up of multilayers, such as convolutional and pool sampling layers, which serve as the network's core in order to extract features. The network model operates on the principle of increasing accuracy through frequent training by using gradient descent to reduce the loss function and adjust the weight parameters. [11]

### II.C. Filters, stride and Padding:

A convolutional filter is a small array of numbers; images are also arrays containing numbers. These images in a binary system will be two-dimensional arrays. If the RGB system is used, the filters will be arranged in a three-dimensional array. The filters in the figure below pass over a patch of the image, followed by the dot product filter on an equal-sized piece of the image. Therefore, the output will be one number per operation; a new matrix is produced at the end of the process, as shown in figure3. [12]

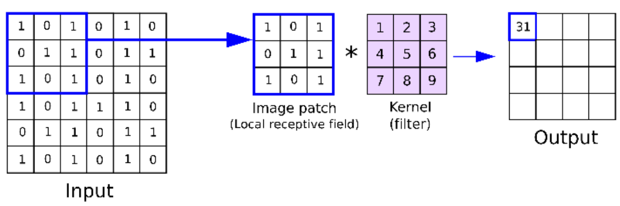


*Figure 3 An illustration of filter usage in the neural network.*

The depth of the image output is determined by the number of filters used in the convolution layers. Each filter used in a network is learning something from images, such as edges, color, and points.
The stride is the number of steps that the filter slides in the input, when the value of the stride is 1, that means it moves by one pixel at a time.
Padding is zero numbers are added within the border of the image but this does not affect the output volume. The filling is used to increase the cover area of filters. This helps the kernel process the image and gives CNN a more accurate analysis of the images.
The output size is calculated in the following way:

$$output\ size = \frac{(n + 2p - f)}{s + 1} \qquad (1)$$

Where n is the number of filters, p is padding, f is size of filter and s is stride. [13]

### II.D. Max poling:

Deep learning has two methods for pooling, average pooling, and max pooling. In the first method, the average per value is calculated under the filter used in the image, and with each movement, the average value of pixels in the image is taken and the average of these numbers is obtained. The equation for average pooling is:

$$fave(X) = \frac{1}{N}\sum\nolimits_{i}^{N} = 1Xi \qquad (2)$$

Where X is a vector representing activations from a rectangular box of N permutations in an image or a channel. In the other method, the maximum value is taken from pixels. [14] [15] Pooling layer gradually reduces input dimensions, reducing memory consumption to maintain variables and improve statistical performance. Reducing the number of variables in value sequencing reduces the dimensions of the feature map. Converts general feature descriptions into actionable information by retaining relevant information and removing unnecessary details, as shown in figure4. [16] [17]

$$f_{max}(X) = max_i x_i \qquad (3)$$

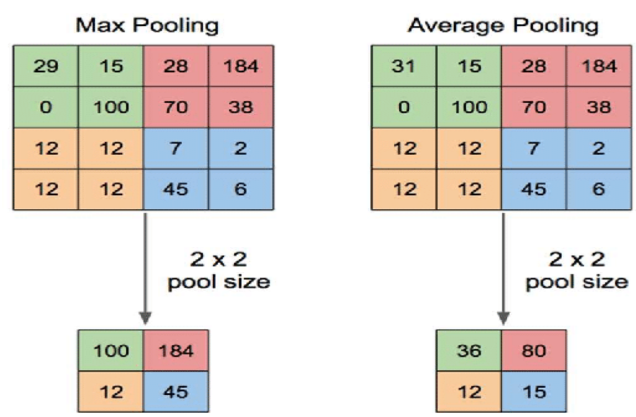


*Figure 4 An illustration of the use of Max and average polling in the neural network.*

### III. Related Work:

In the beginning, computer vision was modest, and the development in the field of AI was in its infancy, and results were simple, as reported by Frangi. [18] Frangi using the filter to extract features such as a crack in images and Matrix-based edge detection. Therefore, subsequent studies were concerned with the development of the results and focused on using modern techniques to improve the detection of defects. contributed to developing the results by using Total Variation Denoising, a technique used to

reduce the noise and enhance the possibility of edge detection of images. [19]
In an experiment conducted by Xavier Maldague used encoder-decoder architecture in two neural networks. The encoder-decoder gets features extracted from images and helps the neural networks find defects more accurately.
Deep convolutional network was based on the architecture of SegNet model to detect the porosity type of welding defects. Furthermore, the sliding window technique was used to make predictions for each pixel in the images taken. The model obtained 80% for the F1 coefficient, which shows the network's ability to predict the pixels belonging to the defects in the correct regions. The results showed that using DNNs to detect the defects in welds can be predicted, and the results are promising. [20]
Therefore, Chiraz Ajmi developed a MATLAB code to crop the original image and used Wiener and Gaussian filters to enhance images. Then, resize the images to 227 × 227 pixels. To prevent overfitting in the model, Chiraz Ajmi used three methods of data augmentation, image translations, horizontal reflections, and changing the intensity of RGB channels.
242 images of lack of penetration and 453 images of porosity are in the dataset. The images split into training and testing with 80% and 20% respectively. Chiraz Ajmi used the AlexNet network, which got the accuracy in this experiment to reach 100% for training, testing, and prediction. That means that the network has correctly predicted all images with an error rate of zero percent. [21]
Complementing the development taking place in the field of Deep Learning. Bharath Chandra used VGG-19, 19 convolution layers, one flattens layer, and Dropout, with over 144 million parameters. Filters keep increasing with the progress of the network. Then, used Transfer learning to weights or parameters of a pre-trained the model; this technique uses when the dataset is small and to prevent overfitting.
A model of VGG-19 was used to classify four categories, porosity and solid inclusions, cracks, and good weld or no defects. The images were cropped to 128×128 pixels and split into four categories manually, each class containing 1000 images.
Within 70 epochs, the model converged with training and validation accuracy of 93.17% and 91.14%, respectively, and the average precision and average recall are 91%. [22]
Lu Yang worked on a model that can detect several types of defects in welding by using the model DNN. This model helped Lu Yang to classify various kinds of defects such as porosity (PO), slag inclusion (SL), leak of penetration (LP), hypo-fusion (OF), and crack (CR). Therefore, 220 samples have been used with five types of welding defects and a 5-folds cross-validation technique to avoid model overfitting. The average training accuracy was 97.95%, and the average test accuracy was 91.36%. These results give the impression that the model will work well and deliver optimal results. [23]
In the field of flight engines, engineers' experiments contributed to detecting welding defects by using X-ray images to detect eight different types of defects. Cracks, incomplete fusion, incomplete penetration, porosity, slag inclusion, undercut, spatter, and blowholes are the eight most common defects. The images are divided into 66% for training and 33% for testing. In the beginning, the images will be entered with the Fast R-CNN to feature a defect object detection map. Then, the data will be used as input for AE-RTISNet. The results for the model met the technical requirements of a qualified human inspector. The average efficiency (mAP) obtained in the test was 0.82 with no defects and 0.8 with certain defects. The results of the experiment also contributed to shortening the duration of the maintenance cycle by making the work of quality inspectors easier. The preliminary estimate for working hour reduction per engine is more than 60 hours. [24]
Xinghui Dong has made significant advances in defect detection techniques by using unsupervised learning to separate the common variable regions in an image; it depends on taking values that remain the same over a wide range of different thresholds within the image, this technique is called Maximally Stable Extremal Regions (MSERs). The experiment used 43 x-ray images, with at least one defect in each image, and used the 10-fold cross-validation technique in the training process to increase the number of images in training. The images were cropped to 64×64 pixels to fit the model used in the experiment. Receiver Operating Characteristic (ROC) curve and plotted the true positive and the false positive to measure the model performance.
The model was trained for three stages, where the impact of the number of filters 32, 64, and 128 was clear, and the highest Area Under the Curve (AUC) value was 0.9825. The effect of the Z-Normalization technique is obvious. The value of AUC increased from 0.88 to 0.98. Softmax showed a slightly higher AUC than the random forest technique, the latter producing higher true positive rates when false positive rates were less than 11%. [25]
In unsupervised techniques, Shuo Feng used the Principal Component Analysis method to make two types of datasets, 15 datasets with variance >99% and ten datasets with variance >95%. These two sets were used as inputs in the model training and testing of Support Vector Machine (SVM), Spiking Neural Networks (SNN), and Deep Neural Network (DNN). The accuracy of SVM was

between 96% and 91% for training and for tests was from 89% to 85%. The accuracy of SNN was from 99% to 0.959 for training and 89% to 87% for the test. DNN accuracy was from 98% to 96% for training, and 93% to 90% for the test. [26]

Another experiment by Li Yaping used a new method to identify defects in welds by using the Suspected Defect Region (SDR), a small image segmented as a SDR. The model categorizes images into linear defects, circular defects, and noise based on the characteristics of the image. In SDR images, a model with 3 × 3 and 5 × 5 convolution kernels is used, which gave better and higher resolution compared to a larger number of convolution kernels. The CNN composed of four convolution layers, four pooling layers, and two fully connected layers. [27]

Also, wenhui Hou developing unsupervised methods to classify welding defects using two models based on a stacked sparse auto-encoder (SSAE), a model usually used for dimensionality reduction or feature learning. Moreover, Otsu's method was used to determine the optimal threshold by reducing the contrast within the layer to the black and white threshold pixels. The K-fold cross-validation technique was used to split the dataset. The first model reached precision and F1 equal to 88% and 88%, respectively, while the second model reached precision and F1 equal to 89%, and 89%, respectively [28]

## IV. Materials and Methods:

### IV.A. Dataset:

The dataset was collected from the public available GDXray. 88 X-ray images with different kinds of defects have been divided into three series and are part of the group "Welds" as shown in figure 5. The images were taken by Berlin, Germany's BAM Federal Institute for Materials Research and Testing. Some instances are shown in the image below.

The images are classified as training, validation, and testing. The training sample is utilized to train and teach the neural network model, resulting in the best weights and biases values. The validation data set is a data sample used for providing an unbiased evaluation of a model while the model's hyperparameters are tuned for the training data set. A validation set is used to evaluate a specific model.

The test data set is the sample data used to determine whether the model is best suited for the training data set. This set of data contains the criteria for evaluating the model.

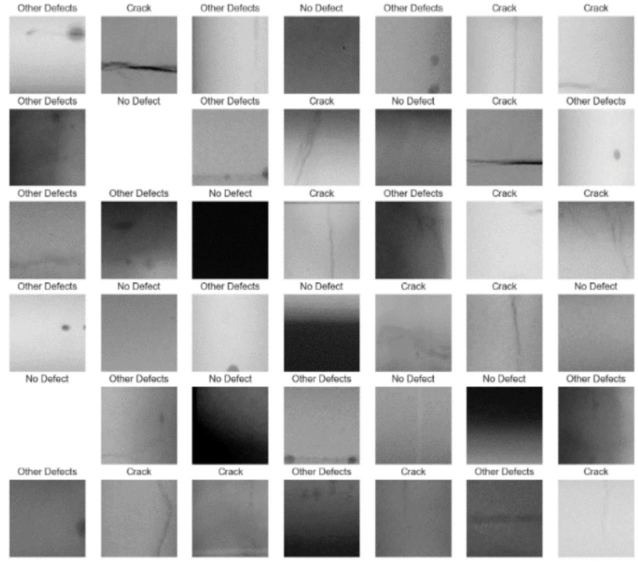


*Figure 5 Samples for the data used in the model.*

### IV.B. Data Preparation:

Although the convolutional neural network is frequently used to recognize images, data increase techniques must be used because data appears to be scarce for model training. The most common method is to divide images into small sections known as patches. This patch was used as a defect. Furthermore, as shown in the figures below, a single image will generate multiple defects.

The images were divided into 150X150 pixels using Matlab code, resulting in approximately 300 times the number of images in the database.

The model was used in this experiment to categorize the X-ray images based on the type of defect. Preparing the dataset is one of the most important steps before building the CNN model. This step is almost as important as creating the neural network model because it is the foundation of the model. As a result, artificially intelligent engineers take care of the data preparation step.

The purpose of data preparation is to make the images (in the research) more appropriate and clearer. Furthermore, all of the data must be the same size because if some images are different sizes, the model will be more difficult to learn and will not achieve high accuracy.

### IV.C. Data Augmentation:

Data augmentation is a traditional technique used in deep learning to augment the data by obtaining more data for the training process and improving the model's accuracy. These data are obtained by combining modified copies of data extracted from a single image. As a result, when the dataset is large, accuracy suffers and overfitting is avoided.

It is possible to obtain approximately fifty times the amount of data currently available through this technician. In this study, a Python code was used to augment the data, with the clarification that one image has generated approximately 30 images, as shown in figure6.

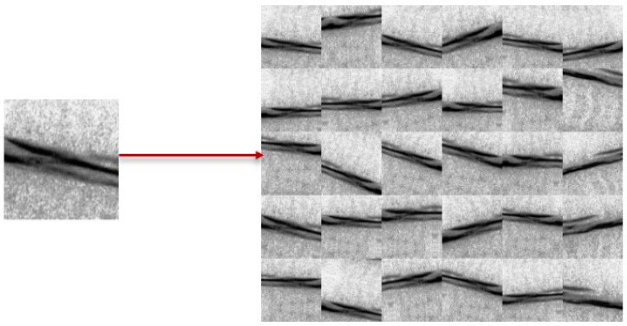

*Figure 6 Data Augmentation used in the experiment.*

## V. Results and Discussion:

This section will present the results of the experiment along with observations and a comparison of the findings for various classes. First, the tripartite classification findings for Crack, other types of Defects, No Defects will be displayed. Python has been used to implement each of our algorithms. Used the OpenCV code from the free, open-source computer vision library in our suggested data augmentation strategies. TensorFlow served as our deep learning framework, allowing us to build, training, and make predictions using our models. The dataset is split into three categories, training, validation, and test with 1746 images for each category, as shown in figure below.

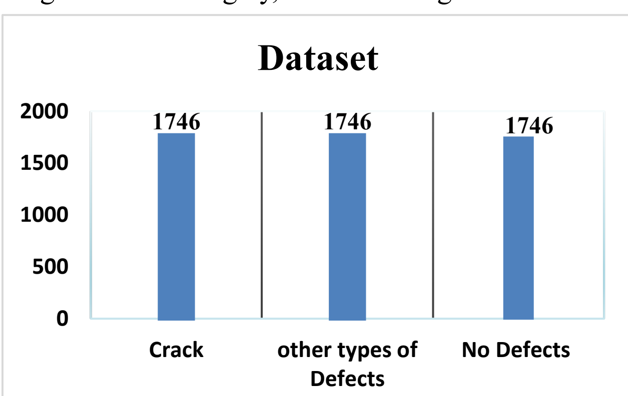


*Figure 7 Sorting data by welding defect type.*

The model for our experiment is a CNN. The reason to use this type of model is that CNN can handle images with various aspects and be able to differentiate one from the other. In comparison to different classification algorithms, ConvNet requires less pre-processing. Also, can learn about feature extraction.

Our model used Conv2D with 32 filters and a size of 3X3. Then, one layer of MaxPooling by 4X4. The second layer is Conv2D, which has 16 filters and a 3X3 window size. as well as one layer of MaxPooling2D by 4X4. Then, one Dropout layer was added to reduce our model's overfitting by 30%. Two fully connected layers with activation functions Sigmoid 32 and 16 Finally, the output layer with 3 classes. Therefore, used the Adam optimizer with learning rate=0.0001.

It is noticeable that when using the sigmoid function in the last layers of the experiment network, it gives better results and less loss value than when using the RELU. The reason for the difference between these two functions is that in the layers, there is a picture of the existence of several defects. For example, the network checks for defects such as cracks, pores, and other different defects in one image. In other words, the output is not a possible distribution.

This experiment gets three categories No Defect will represent as 0, Crack as 1, and Other Defects will be as 2. Have some equations ready to determine the parameter for our model. Because only images will enter the neuron, the input layer has no parameters; only the shape of the input image will be determined. As a result, the number of parameters is 0.

Weight matrices are provided for the CONV layer. To compute the parameters, multiply the width m, height n, and filters d from previous layers by the filters k from the current layer.

*Table 1 The number of parameters used in the neural network.*

| Layer (Type) | Output Shape | Parameters |
|---|---|---|
| Conv2D_4 | (None,148,148,32) | 896 |
| MaxPooling | (None,37,37,32) | 0 |
| Conv2D_4 | (None,35,35,16) | 4624 |
| MaxPooling | (None,8,8,16) | 0 |
| Dropout | (None,8,8,16) | 0 |
| Dense 1 | (None,8,8,32) | 544 |
| Dense 2 | (None,8,8,16) | 528 |
| Flatten | (None,1024) | 0 |
| Dense 3 (Softmax) | (None,3) | 3075 |
| Total parameters | 9667 parameters | |

In the triple classification experiment (Crack, other types of Defects, No Defects), the CNN model had 9,667 parameters with 800 epochs. The curve of accuracy and loss to number of iterations is shown in fig.8. The recognition accuracy increases and tends to be stable, with the number of iterations increasing more for training than validation. Also, found that the loss decreases with iteration progress, as shown in figures8 &9.

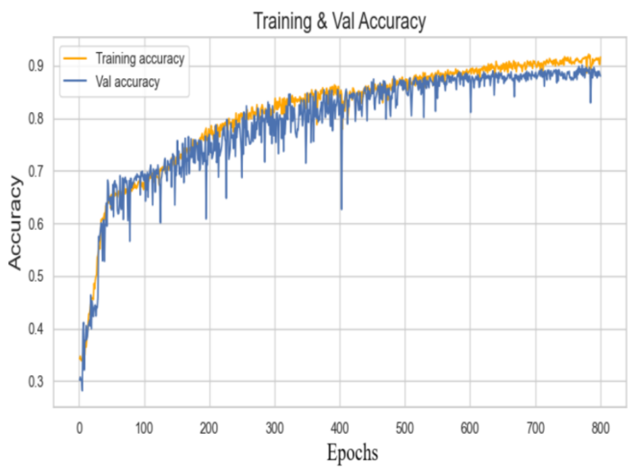


*Figure 8 Comparison of the model's accuracy between training and validation*

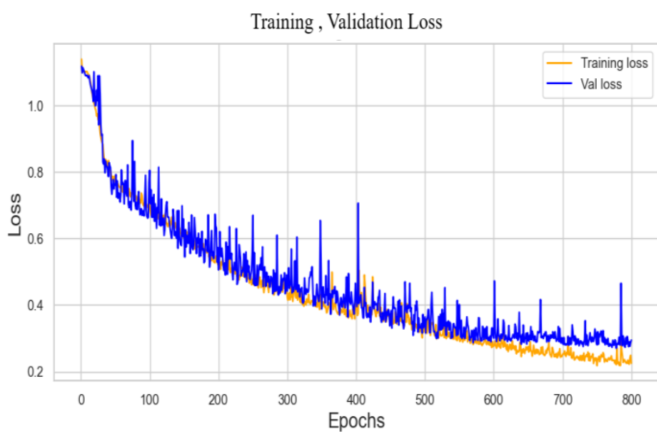


*Figure 9 Comparison of the model's loss between training and validation.*

The deep learning model achieved a high accuracy of 90% on the test set during 20 epochs, indicating that it can generalize well to new data and avoid overfitting (See Fig10).

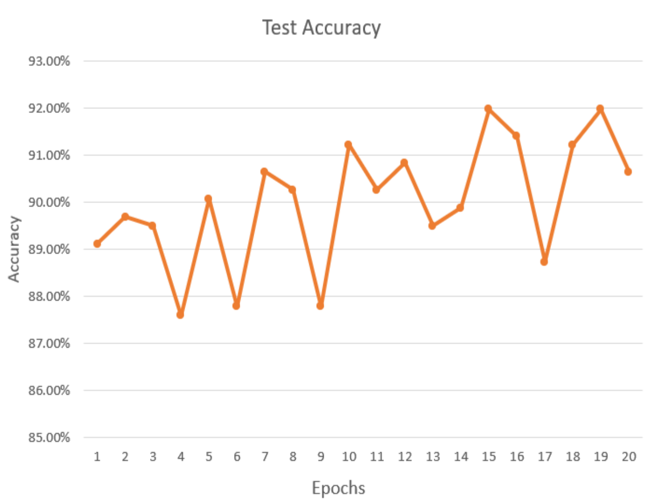


*Figure 10 The testing process evolved during 20 epochs for the model.*

**TN / True Negative:** When the predicted and actual both are negative.
**TP / True Positive:** When the predicted and actual both are positive.
**FN / False Negative:** When the predicted negative and actual positive.
**FP / False Positive:** When the predicted positive and actual negative.

$$Precision = \frac{Ture\ Positive}{Ture\ Positive + False\ Positive} \quad (4)$$

$$\text{Recall} = \frac{\text{Ture Positive}}{\text{Ture Positive} + \text{False Negitive}} \quad (5)$$

$$\text{F1} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (6)$$

```
Outcome values :
 44 0 0 48
Classification report :
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        44
           1       0.86      0.96      0.91        50
           2       0.96      0.85      0.90        54

    accuracy                           0.93       148
   macro avg       0.94      0.94      0.94       148
weighted avg       0.94      0.93      0.93       148
```

*Figure 11 The deep learning model report outlines several parameters.*

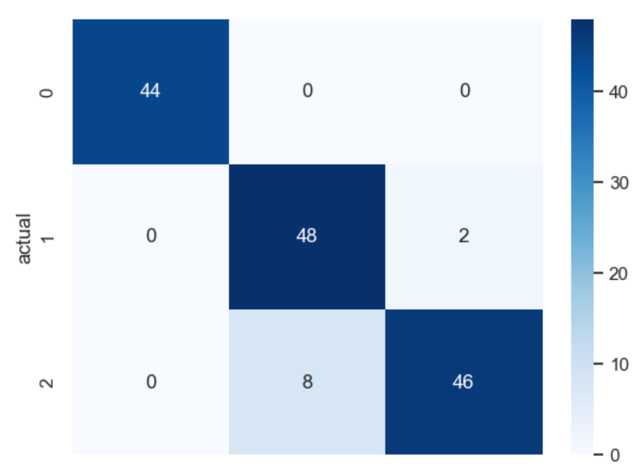


*Figure 12 Illustrate the confusion matrix for the model prediction.*

Noted that the recall of No defects class is 100%, this means our model predicted all images correctly. The Crack class is 96%, that means from 50 images, 48 images predicated correctly. And other types of defects is 86% Just 8 images predicted incorrectly.

## VI. Conclusions

Neural network technologies are witnessing significant development that has inspired engineers to use them in several applications, including automating the evaluation of the results of welding inspection using radiography. Neural networks helped mitigate human factors, saving time and improving the reliability of results interpretation. This article highlighted the concept of neural networks in industrial radiography, highlighting image processing methods using codes to help the model improve results.

The convolutional neural network has been proposed with a triple classification for welding defects (crack, other types of defects, and No defects). The CNN model had six layers and 9667 parameters. Model accuracy approached 0.92% after 800 epochs. The accuracy of the class "No Defects" is 100%, which means that our model correctly predicted all the images. The crack class accuracy is 96%, meaning that of 50 images, 48 are correctly expected. The other defect types are 85% image, with only 8 incorrectly predicted.

With further research and development, neural networks can significantly improve the accuracy and efficiency of the inspection process.

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