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WELDING CRACKS DETECTION USING DEEP CONVOLUTION NEURAL NETWORK- A Systematic Review

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ABSTRACT: Establishing a solid theoretical foundation for structured deep neural networks is greatly desired due to the successful applications of deep learning in various practical domains. This paper aims at an approximation theory of deep convolutional neural networks whose structures are induced by convolutions.The difficulty in theoretical analysis of the networks with linearly increasing widths arising from convolutions can be overcome by introducing a downsampling operator to reduce the widths. As we prove that the downsampled deep convolutional neural networks can be used to approximate ridge functions nicely, which also hints some advantages of these structured networks in terms of approximation or modeling. We also prove that the output of any multi-layer fully-connected neural network can acquire by that of a downsampled deep convolutional neural network with free parameters of the same order, which in general, the approximation ability of deep convolutional neural networks is at least as good as that of fully-connected neural networks. Finally, a theorem for approximating functions on Riemannian manifolds is unveiled, which reveals that deep convolutional neural networks can be used to learn manifold features of data.

Keywords

INDEX TERMS: Classifier, convolutional neural networks (CNN), radiographic images, transfer learning, weld defect detection

1 INRTODUCTION

The term Deep Learning or Deep Neural Network mentions to Artificial Neural Networks (ANN) with multi layers. Over the last few decades, its been considered to be one amongst the foremost powerful tools, and has become very popular within the literature because it's in an exceedingly position to handle a large amount of information. The interest in having deeper hidden layers has recently take up to exceed classical methods performance in several fields; especially in pattern recognition. one amongst the foremost popular deep neural networks is that the Convolutional Neural Network (CNN).

Analysis of the standard of welded joints may be a mandatory procedure before commissioning of such facilities as heating pipelines , gas pipelines and other forms of metal formation. This analysis is critical for the detection and localization of assorted sorts of defects on the weld. Defects of welded joints majorly reduces the general durability of the whole structure, ignoring which might subsequently cause significant human-made consequences. There are two leading varieties of analysis of the standard of welded joints: destructive and non-destructive. Currently, non-destructive testing methods are accustomed a greater extent. At the instant, there are a a lot of non-destructive testing methods aimed toward detecting defects in welded joints.The most revealing and virtual are considered to be radiographic methods of non-destructive testing. At preliminary stage, sites with suspected defects are analyzed using x-rays. On the selection side of the place with the alleged defects, a special film or plate is installed, which fixes the amount of energy saw the fabric under study. Consequently, the film is scanned and transform into digital form. At the last word stage, the digitized image is recognized by a flaw detection engineer. This process can take an unlimited amount of some time. as an example, it's visiting take a specialist 10 to twenty minutes to acknowledge and archive one ring weld. within the case of, as an example, a multi-kilometer section of the pipeline, this process can take over one hour. Also, it should be noted that because of fatigue, negligence, lack of coaching or a mixture of other human factors, the flaw detector engineer can make involuntary mistakes which can end in various production consequences. Significantly simplify, and in some cases completely solve the matter of visual analysis of the digitized images, can use the most recent achievements within the sphere of digital signal processing and computer vision. Modern studies show that computer vision systems are able to do finally ends up within the analysis and classification of images near the results obtained within the visual analysis of those images by an individual's. This statement is confirmed by research within the arena of computing supported the employment of neural network.

2.LITERATURE REVIEW

a) CRACK DETECTION IN HISTORICAL STRUCTURES BASED ON CONVOLUTIONAL NEURAL NETWORK

*Krisada Chaiyasarn1, Mayank Sharma2, Luqman Ali 2, Wasif Khan2 and Nakhon Poovarodom1

ABSTRACT: Regular inspection and maintenance work is required to ensure the structural integrity of historic structures, especially the masonry structures which are deteriorating due to ageing and man-made activities. The structures are typically examined by visual inspection, which is a costly and laborious procedure, and often, the inspection results are subjective. In this study, an automatic image-based crack detection system using Convolutional Neural Network (CNN) for masonry structures is proposed to aid the inspection procedure.

b) Road crack detection using deep convolutional neural network

Lei Zhang; Fan Yang; Yimin Daniel Zhang

Abstract: Automatic detection of pavement cracks is an important task in transportation maintenance for driving safety assurance. However, it remains a challenging task due to the intensity inhomogeneity of cracks and complexity of the background, e.g., the low contrast with surrounding pavement and possible shadows with similar intensity. Inspired by recent success on applying deep learning to computer vision and medical problems, a deep-learning based method for crack detection is proposed in this paper. A supervised deep convolutional neural network is trained to classify each image patch in the collected images. Quantitative evaluation conducted on a data set of 500 images of size 3264 χ 2448, collected by a low-cost smart phone, demonstrates that the learned deep features with the proposed deep learning framework provide superior crack detection performance when compared with features extracted with existing hand-craft methods.

c) Detection of sealed and unsealed cracks with complex backgrounds using deep convolutional neural network

Panel JuHuyan aWeiLib SusanTighea JunzhiZhaib ZhengchaoXub YaoChenb

Abstract: Crack Deep Network (CrackDN) is proposed in this research with the purpose of detecting sealed and unsealed cracks with complex road backgrounds. CrackDN is based on Faster Region Convolutional Neural Network (Fast-RCNN) architecture by embedding a sensitivity detection network parallel to the feature extraction Convolutional Neural Network (CNN), both of which are then connected to the Region Proposal Refinement Network (RPRN) for classification and regression. The state-of-the-art aspect of this research lies in the fusion of sensitivity detection network, which facilitated the CrackDN of being able to detect sealed and unsealed cracks with sever complex background.

d). Automatic detection of welding defects using the convolutional neural network

Roman Sizyakina, Viacheslav Voronina, b, Nikolay Gapona, Aleksandr Zelensky, and

Aleksandra Piˇzuricac

Abstract: Quality control of welded joints is an important step before commissioning of various types of metal structures. The main obstacles to the commissioning of such facilities are the areas where the welded joint deviates from acceptable defective standards. The defects of welded joints include non-welded, foreign inclusions, cracks, pores, etc. The article describes an approach to the detection of the main types of defects of welded joints using a combination of convolutional neural networks and support vector machine methods. Convolutional neural networks are used for primary classification. The support vector machine is used to accurately define defect boundaries. As a preprocessing in our work, we use the methods of morphological filtration. A series of experiments confirms the high efficiency of the proposed method in comparison with pure CNN method for detecting defects

e) Weld Defect Detection and Image Defect Recognition Using Deep Learning Technology

Yu Cheng, HongGui Deng, YuXin Feng, JunJiang Xiang

Abstract—Welding defects not only bring several economic losses to enterprises and individuals but also threatens people's lives. We propose a deep learning model, where the data-trained deep learning algorithm is employed to detect the weld defects, and the Convolutional Neural Networks (CNNs) are utilized to recognize the image features. The Transfer Learning (TL) is adopted to reduce the training time via simple adjustments and hyperparameter regulations. The designed deep learning-based model is compared with other classic models to prove its effectiveness in weld defect detection and image recognition further. The results show this model can accurately identify weld defects and eliminates the complexity of manually extracting features, reaching a recognition accuracy of 92.54%. Hence, the reliability and auto902mation of detection and recognition is improved significantly. Actual application also verifies the effectiveness of TL in weld defect detection and image defect recognition. Therefore, our research results can provide theoretical and practical references for efficient automatic detection of steel plates, cost reduction, and the high-quality development of iron and steel enterprises.

f) CLASSIFICATION OF WELD DEFECTS BASED ON CONVOLUTION NEURAL NETWORK

A.I. Gavrilov, Bauman Moscow State Technical University, Moscow, Russian Federation

Abstract-Automatic welding technology has been widely applied in many industrial fields. It is a complex process with many nonlinear parameters and noise factors affecting weld quality. Therefore, it is necessary to inspect and evaluate the quality of the weld seam during welding process. However, in practice there are many types of welding seam defects, causes and the method of corrections are also different. Therefore, welding seam defects need to be classified to determine the optimal solution for the control process with the best quality. Previously, the welder used his experience to classify visually, or some studies proposed visual classification with image processing algorithms and machine learning. However, it requires a lot of time and accuracy is not high. The paper proposes a convolutional neural network structure to classify images of welding seam defects from automatic welding machines on pipes. Based on comparison with the classification results of some deep machine learning networks such as VGG16, Alexnet, Resnet-50, it shows that the classification accuracy is 99.46 %. Experimental results show that the structure of convolutional neural network is proposed to classify images of weld seam defects have availability and applicability.

i) Transfer Learning With CNN for Classification of Weld Defect SAMUEL KUMARESAN 1 , K. S. JAI AULTRIN2 , S. S. KUMAR3 , AND M. DEV ANAND2

ABSTRACT-Traditional Image Processing Techniques (IPT), used for automating the detection and classification of weld defects from radiography images, have their own limitations, which can be overcome by Deep Neural Networks (DNN). DNN produces considerably good results in fields which offer big dataset for it to train. DNN trained with small datasets by conventional methods produces less accurate results. This limits the use of DNN in many fields. This study focuses to overcome this limitation, by adopting transfer learning using pre-trained deep convolutional neural networks. By this method, a weld defect radiographic image classifier, which can classify 14 types of weld defects, was constructed. 940 Image patches of weld defects were manually collected and labelled from GDXray database. Subsequently the features of this weld defect dataset were extracted using VGG16 and ResNet50 CNNs, both pre-trained on the ImageNet database. Then machine learning models such as Logistic Regression, Support Vector Machine (SVM) and Random Forest were trained on these extracted features. The Classifier based on SVM trained on features extracted by ResNet50 outperforms the other counter parts with an accuracy of 98%. In all these cases, transfer learning improves performance and reduces the training time and computational system requirements.

g)“Welding and Bonding Technologies” F. Yusof, M.F. Jamaluddin, in Comprehensive Materials Processing, 2014

Abstract-Welding defects can be defined as weld surface irregularities, discontinuities, imperfections, or inconsistencies that occur in welded parts. Defects in weld joints could result in the rejection of parts and assemblies, costly repairs, significant reduction of performance under working conditions and, in extreme cases, catastrophic failures with loss of property and life.

These defects originate from various sources. In most cases, the defects occur as a result of improper weld design and unsuitable welding processes and choice of incompatible materials. In addition, a lack of knowledge of the process, poor workmanship, and inadequate training of the welder can also contribute to these defects. Furthermore, there are always certain flaws in the welding due to the inherent weakness in welding technology and the characteristics of metals (1).

3. OBJECTIVE OF CNN

The personnel burden is a difficulty with the visual inspection of welding defects that occur in bend test fragments. This study focuses on to construct an automatic evaluation system for welding defects that occur in bend test fragments. This paper describes the automated detection of defective areas from bend test fragments using R-CNN. First, we've described the structure of the proposed R-CNN, followed by the experiments for evaluating R-CNN and their results. Finally, we've got provided a conclusion and discussed future issues.

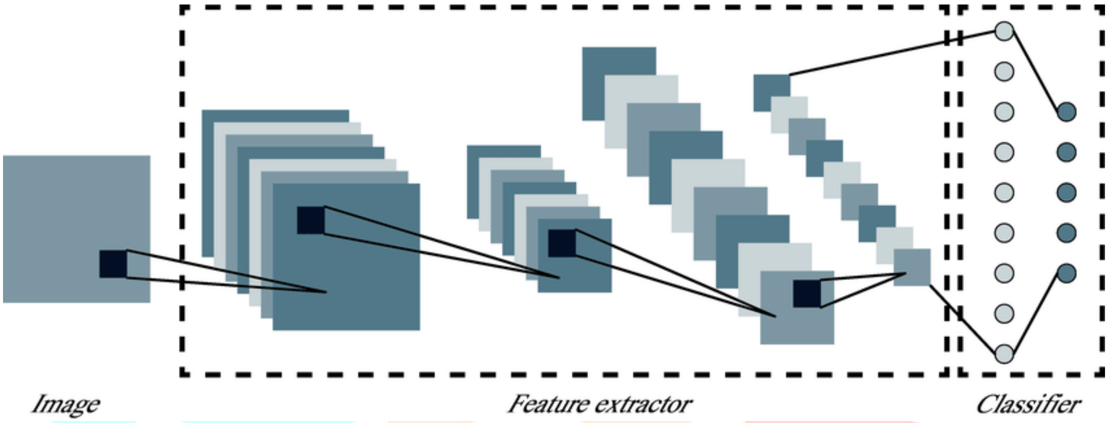

Fig.3.1 welding crack detection layers

3.1 Advantages of CNN models

- Decreasing the needs of human effort developing its functionalities.
- It is easy to understand
- It has the highest accuracy among all algorithms that predicts images
- Little dependence on pre processing
- Fast to implement.

3.2 Disadvantages of CNN models :

- Classification of Images with different Positions
- Coordinate Frame
- Adversarial examples

3.3 MATERIALS AND METHODS

a) Analysis of steel plates surface defects

The hot-rolled steel plates will have some surface defects thanks to the assembly process and also the steel billets; such defects are divided into steel defects and process defects per the causes . The structure of surface defects is shown in Figure. Scars are metal flakes with irregular shapes that attach to the surface of the steel strip .This defect can cause problems like metal peeling or holes during subsequent processing and utilization. Bubbles are irregularly distributed round or elliptical convex hull defects on the surface of the steel strip, which might cause problems like delamination or low welding during subsequent processing and utilization. Inclusions are lumpy or elongated inclusive defects within the slab exposed on the surface of the steel strip after the inclusions or slag inclusions are rolled. Mentioned defects will cause holes, cracks, and delamination during subsequent processing. Iron oxide scale may be a quite surface defect formed by pressing an iron oxide scale into the surface of the steel strip during the new rolling process. This defect will directly affect the surface quality and coating effect of the steel strip. Roll marks are irregularly distributed convex and concave defects on the surface of the steel strip, which may cause folding defects within the rolling process. Edge cracking could be a phenomenon within which one or either side of the steel strip edges are cracked along the length direction, which can cause problems like interruption of the strip during the following processing and utilization .Scratches are linear mechanical damages on the surface of the steel strip not up to the rolled surface. The scratched iron sheet is difficult to eliminate by pickling after oxidation, which is straightforward to cause breakage or cracking .Scrapes are mechanical damages on the surface of the steel strip within the kind of points, strips, or blocks. The iron oxide scale at the scrapes is challenging to get rid of by pickling. Problems like bending and cracking is also caused.

B. Detection technologies for steel plates surface defects

Traditional detection technology:

Traditionally, technologies of detecting steel surface defects are divided into manual detection methods and non-destructive detection methods.The manual inspection is based on the visual inspection and manual experience,

Fig.3.3.1. Types of defects

which requires on-site observations in harsh environments, causing considerable damages to the health of the staff member; besides, solely wishing on workers experience often causes problems, like missed inspections,making it tough to ensure the standard of the steel plates .As we all know about traditional non-destructive detection is split into eddy current detection,infrared detection, and magnetic leakage detection. Eddy current detection is suitable for detecting defects on the surface and lower layer of the plate,which requires a more extensive current guarantee. Hence, it consumes much energy, and therefore the surface of the plate must be at a continuing temperature, making it unsuitable for industry requirements . Infrared detection adds induction coils within the production process of commercial steel plates. If the steel billets move, the induced current are going to be generated on the surface; if a defect is found, the present will increase, which is a superb thanks to detect the defects. However, infrared detection can only be used in products with lower detection standards, and fewer sorts of defects may be detected .Magnetic leakage detection is predicated on a proportional relationship between the amount of steel defects and also the magnetic concentration. Subsequently calculating the density of magnetic leakage, the defect location and area of the steel will be calculated; however, this detection method is disadvantageous for surface detection . While science and technology advances, a machine vision detection technology is proposed, which utilizes lasers and charge-coupled components to detect the surface of steel plates after digitization effectively.

Deep learning detection technology:

As deep learning technology proceeds continuously, it moderately presents assumed advantages in image recognition and classification. CNNs can extract image features. The detection capability of neural networks is upgraded by continuously increasing the number of layers and network widths of CNNs .

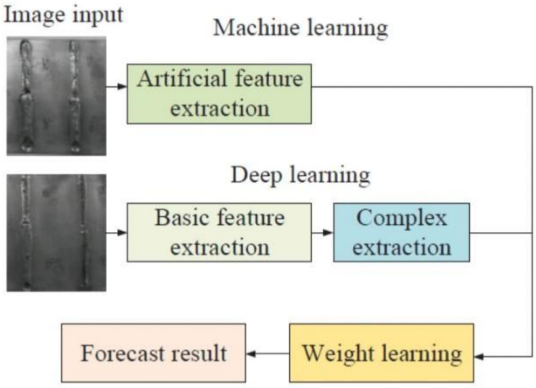

Fig.3.3.2. Types of detection techniques

Such an improvement can effectively avoid the subjectivity and inefficiency within the manual extraction process. Research on recognizing the weld defect images is various; especially, deep learning technology processes and organizes one feature to quantify the abstract features in line with the extraction principle, in this way using these features to classify and recognize images . Above Figure 3.3.2. exhibits the difference between deep learning processes and traditional machine learning. Deep learning can obtain high-dimensional image features from the pc file, fit the features, and eventually, utilize the training method of weights to increase the accuracy of classification prediction. However, while analyzing welds of business steel plates, deep learning cannot learn due to the dearth of complete datasets; additionally, current research mostly focuses on improving the weld recognition ability; however, a whole automatic detection system isn't built, increasing the problem in actual industrial applications.

C. Image pre-processing
C.

Image pre-processing is the input image data to convert it in the direction of consequential floating-point tensors for feeding into Convolutional Neural Networks. Just for the understanding tensors are used to accumulate data, they can be presumed as multidimensional arrays. A tensor constitute a 64 X 64 image having 3 channels will have its proportions (64, 64, 3). Actually, the data is stored on a drive as JPEG files, so let's see the steps taken to achieve it.

Algorithm:

- Transform these into floating-point tensors for input to neural nets.
- Measuring the pixel values (between 0 and 255) to the [0, 1] interval (as training neural networks with this range gets efficient).
- Decrypt the JPEG content to RGB grids of pixels including channels.

The focus of pre-processing is to enhances the quality of the image so that we can analyze it in a better way. Before pre-processing we can repress undesired deformation and enhance a few features which are necessary for the particular application we are working for.

- Read the picture files (stored in data folder).

The steps to be taken are: Read image. Resize image. Remove noise (Denoise) Segmentation

C.Deep learning neural networks

Convolution Neural Networks: CNN is a useful superintended deep learning model. It is a feed-forward neural network
whose artificial neurons can acknowledge to some surrounding units within the analysis. CNNs are extensively applied to image recognition, including AlexNet, Visual Geometry Group Nets (VGGNets), and further models that reduce the recognition error rate of CNNs on a typical ImageNet dataset. Generally, deep learning models have minimum three hidden layers. While the number of hidden layers increases, the models parameters will further increase, thereby increasing the complexity of the model, if the possibility to complete more complicated tasks. Whether a shallow model in which every layer of the network is fully connected and adopted for image classification and recognition, another model will contain many parameters. In the instance of multiple hidden layers, the parameters contained in the model will exhibit explosive growth, creating adverse impacts on space occupation, iterative calculation, and convergence speed

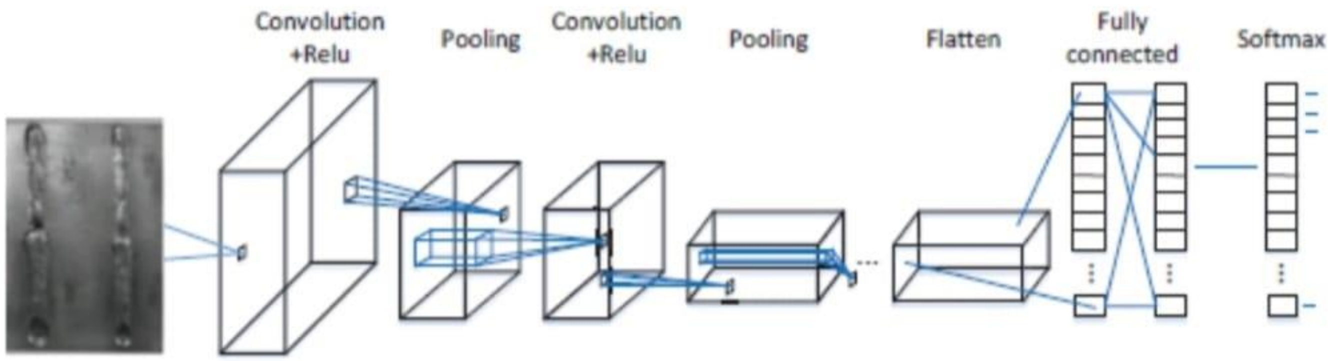

Fig.3.3.3.The structure of CNN.

of the model. The hidden layers in CNNs can significantly decreases the number of parameters in the model via weight sharing and sparse connections, so that increasing the training speed of the model . Figure 3.3.3 shows the structure of CNN.

4.METHODOLOGY

Weld defect recognition plays a key role in the manufacturing process of large-scale equipment. Traditional methods generally incorporate several serial steps, like image pre-processing, region segmentation, feature extraction, and type recognition. The outcome of each step have significant impact on the accuracy of the final defect identification. The convolutional neural network (CNN) has powerful pattern recognition ability, which can control the above problem. Though, there are two problems: first one is that the pooling strategy has defective dynamic adaptability and the other is the insufficient feature selection ability. To overcome these issues, we propose a CNN-based weld defect recognition method, which involves an improved pooling strategy and an enhanced feature selection method. According to the features of the weld defect image, an improved pooling strategy that examines the distribution of the pooling region and feature map is introduced. Moreover, in order to enhance the feature selection ability of the CNN, an enhanced quality selection method integrating the Relief algorithm with the CNN is proposed. A case study is introduced for demonstrating the proposed techniques. The results reveal that the proposed method has higher accuracy than the traditional CNN method, and establish that the proposed CNN-based method is well applied for weld defect recognition.

Prototypical tasks in image processing involves displaying images, basic manipulations like cropping, flipping, rotating, etc., image segmentation, classification and feature extractions, image restoration, and image recognition. Because Python's growing popularity as a scientific programming language and the free availability of many state-of-art image processing tools in its ecosystem, it's an suitable choice for these image processing tasks.

Python has been used to design the model in CNN. U-net is the type of CNN which is used to get the higher accuracy image. Convolutional Neural Network is a Deep Learning algorithm specially planed for working with Images and videos. It extracts images as inputs, extracts and learns the features of the image, and categorize them based on the learned features.

1.Importing the libraries

2.Reshaping the size and shape

3.Import Tensorflow.

4.Create the model

5.To import model into drive from google.Collab

6.Download and prepare the CIFAR10 dataset.

7.Verify the data.

8.Create the convolutional base.

9.Add Dense layers on top.

10.Compile and train the model.

11.Evaluate the model.

Process of crack detection

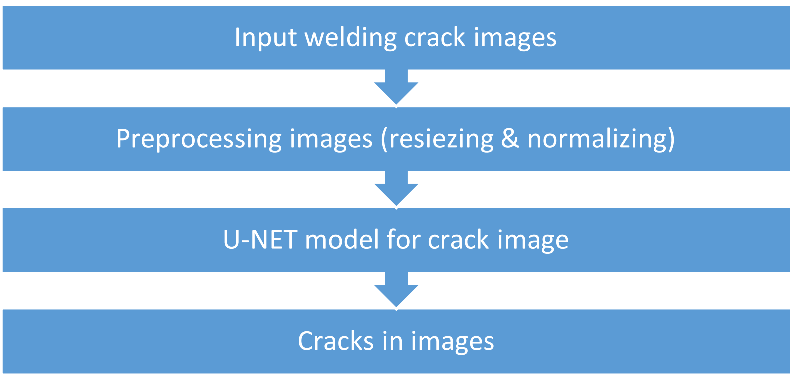

Fig.4.1 Process of crack detection

The above figure shows how the welding cracks can be detected by deep CNN. Initially we have to train the model by giving it images of welding cracks. which then preprocess the images by normalizing it and reseizing it. The type of CNN is used here is U-NET in which 16 convolution layers has been applied to get accurate crack detection. After feeding all the information to the model it is ready to detect the crack which comes in output result.

4.1 TRAINING MODEL

It involves the sample output data and the corresponding sets of input data that have an impact on the output. The training model is used to run the input data by the algorithm to correlate the processed output against the sample output. Models can be trained to profit businesses in numerous ways, by quickly processing huge volumes of data, identifying patterns, finding anomalies or testing correlations that would be hard for a human to do unaided. Training a model only means learning (determining) virtuous for all the weights and the bias from labeled examples. In supervised learning, a machine learning algorithm builds a model by inspecting many examples and attempting to find a model that minimizes loss; this process is called empirical risk minimization.

Three steps to training a machine learning model

Step 1: Start with existing data. Machine learning needs us to have existing data—not the data our application will use when we run it, but data to learn from. ...

Step 2: Examine data to identify patterns. ...

Step 3: Make predictions

4.2TESTING MODEL

Train/Test is a method to compute the accuracy of your model. It is called Train/Test since you split the data set into two sets: a training set and a testing set. 80% for training, and 20% for testing. You instruct the model using the training set. You trial the model using the testing set.

Unit testing is a technique in which particular module is tested to inspect by developer himself whether there are any errors. The main focus of unit testing is test an individual unit of system to analyze, detect, and fix the errors. Python allows the unit test module to test the unit of source code.

Conclusion

We will use U-NET CNN to detect welding cracks. It will take 100 iterations to get accurate higher accuracy . In this project we will use convolution neural network to detect welding cracks and the type of CNN is U-NET will be using python software which is easy to code and gives accurate image of cracks in welding.

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I. *Krisada Chaiyasarn1, Mayank Sharma2, Luqman Ali 2, Wasif Khan2 and Nakhon Poovarodom1 CRACK DETECTION IN HISTORICAL STRUCTURES BASED ON CONVOLUTIONAL NEURAL NETWORK

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III. Panel JuHuyan aWeiLib SusanTighea JunzhiZhaib ZhengchaoXub YaoChenb “Detection of sealed and unsealed cracks with complex backgrounds using deep convolutional neural network”

IV. Roman Sizyakina, Viacheslav Voronina, b, Nikolay Gapona, Aleksandr Zelensky, and Aleksandra Piˇzuricac “Automatic detection of welding defects using the convolutional neural network”

V. Yu Cheng, HongGui Deng, YuXin Feng, JunJiang Xiang “Weld Defect Detection and Image Defect Recognition Using Deep Learning Technology”

VI. A.I. Gavrilov, Bauman Moscow State Technical University, Moscow, Russian Federation “CLASSIFICATION OF WELD DEFECTS BASED ON CONVOLUTION NEURAL NETWORK”

VII. SAMUEL KUMARESAN 1, K. S. JAI AULTRIN2, S. S. KUMAR3, AND M. DEV ANAND2” Transfer Learning with CNN for Classification of Weld Defect”

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