Advances and Applications of Deep Learning in NDT of Welding

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Abstract. With the advancement of the industrial intelligence process, as the core link to ensure the structural safety of major projects, the demand for precision and efficiency of weld quality inspection is increasing. Recently, the breakthrough progress of deep learning technology has promoted the strategic transformation of weld quality assessment from traditional manual interpretation to the direction of intelligence and automation. This paper systematically sorts out the status of the integration and application of deep learning technology with mainstream weld non-destructive testing (NDT) methods. First, this paper classifies weld defects. Secondly, this paper constructs a technology matrix of NDT welding methods, explaining the advantages, disadvantages, and application occasions of various methods. Finally, using a literature review and case study approach, the paper summarises the practical applications of deep learning in these methods, providing insights into current application practices and suggestions for future developments. By systematically combining interdisciplinary research results, this study integrates the key technology mapping in the field of deep learning and weld NDT, which has an important guiding value for grasping the research hotspots and breaking through technical bottlenecks in the field.

Keywords: Weld Defects, Deep Learning, Nondestructive Testing

1 Introduction

Intelligent Manufacturing is profoundly changing the pattern of the manufacturing industry, empowering the national strategy - Made in China 2025 [1-2]. As the core process of modern manufacturing, the welding procedure is a key area that needs to be tackled in China's manufacturing industry [3]. It directly affects safety in production and product reliability in various fields from shipbuilding to electronic assembly. Welding uses heat, pressure, etc., through the form of thermal, electric, or mechanical energy output, prompting multiple workpieces to form a close connection at the atomic or molecular level. After the workpieces have cooled and solidified, a strong weld is formed.

Due to the influence of the welding procedure, welding material, welding environment, operators' technical level, and other factors, the formation of defect-free

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welds is not a simple matter. Although researchers have done a great deal of research in reducing the possibility of defect formation and reducing the impact of defects on the strength of the workpiece, welding always inevitably forms defective welds, affecting the strength of the workpiece, and then becoming a potential safety hazard to the extent of endangering people's physical and mental health, resulting in property losses. The types of welding defects mainly include cracks, porosity, incomplete fusion, incomplete penetration, and so on. Inspection of weld quality mainly includes Destructive Testing and NDT. Although destructive testing gives more accurate results, it can only be performed on the sampling survey and is inapplicable to parts that are on a large-scale assembly line or have already been assembled. Therefore, to show the inside of the weld seam by other means without damaging the weld, the NDT of the weld is often used by industry to inspect parts non-destructively.

Radiographic testing (RT), ultrasonic testing (UT), magnetic particle testing (MT), automated optical inspection (AOI), and machine vision inspection (MVI) are commonly used NDT methods. Each inspection method has a distinctive feature: no damage to the workpiece. This is an element that traditional destructive testing does not have. But some shortcomings are difficult to improve upon. One of the most significant and pressing drawbacks is that these inspections still require a fully trained operator to inspect each part individually. Traditional manual inspection suffers from low inspection efficiency, high human resource requirements, and poor consistency, which can lead to errors and omissions. NDT methods not only require specific equipment to detect signals, but also suffer from problems such as high noise, slow detection speed, and low detection accuracy.

To save human resources in weld NDT, improve inspection efficiency and enhance industrial productivity, deep learning is used in the identification or classification of weld defect types in the weld NDT segment. Currently, the mainstream deep learning algorithms are convolutional neural network (CNN), recurrent neural network (RNN), long short-term memory (LSTM), generative adversarial network (GAN), etc. Some of these algorithms perform differently in weld NDT.

This study addresses the three core challenges in traditional weld NDT - the detection bottleneck caused by the inefficiency of manual interpretation, the difficulty of identifying defects in automated methods limited by noise interference and low contrast, and the problem of adapting small sample data to complex industrial scenarios faced by the deep learning model and systematically researches the integration mechanism between deep learning and NDT technology. By constructing a matrix of weld defect detection technologies and analysing interdisciplinary literature, this study focuses on clarifying the effect of the feature extraction function of CNNs and the data enhancement effect of GANs in improving the robustness of detection.

2 Background on weld defects

2.1 Categories of Weld Defects

As shown in Fig. 1, general categories of weld defects mainly include cracks, porosity, incomplete fusion, Incomplete penetration, and so on.

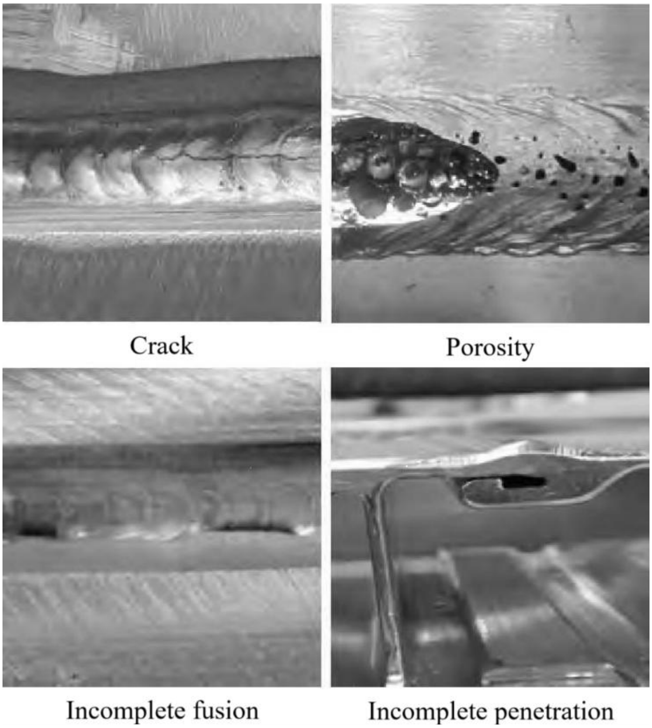

Fig. 1. Common defects in MIG welding of aluminium alloys [4]

2.1.1 Cracks.

A crack is a gap in a weld resulting from the formation of a new interface after the atomic bonding in the weld has been disrupted [3]. Cracks are defects, which form in the weld in a solid state due to factors such as stress, material properties or external environment. Cracks can be classified as macro-cracks, micro-cracks and ultramicro-cracks according to the size of cracks.

2.1.2 Porosity.

Porosity forms during the welding procedure [3]. If the gas in the molten pool does not escape completely before the metal solidifies, the gas will remain in the weld and eventually form porosity. The sources of gases mainly include gases absorbed from the external environment (e.g. air) or gases generated during the welding procedure (e.g. hydrogen, carbon monoxide, etc.). The presence of porosity reduces the strength, plasticity, and sealing of the weld. In addition, it is one of the most important types of welding defects.

2.1.3 Incomplete fusion.

Incomplete fusion is a welding defect in which the weld metal and the base or weld metal are not fully fused [4]. Incomplete fusion is an area-type defect that significantly reduces the load-bearing cross-sectional area and causes severe stress concentrations and is second only to cracks in terms of its hazardous effects.

2.1.4 Incomplete penetration.

Incomplete penetration is defined as the portion of the weld metal that is not completely melted and bonded between the weld metal and the base metal or between the weld channel metals [4]. Incomplete penetration leads to degradation of the mechanical properties of the material, stress concentration, and ultimately crack generation in the material.

2.2 Weld NDT methods

The weld NDT methods include radiographic testing, ultrasonic inspection, magnetic particle inspection, automatic optical inspection, and machine vision inspection.

2.2.1 Radiographic testing.

Radiographic testing is a method of using ionizing radiation, such as X-rays and γ-rays, to penetrate an object and obtain details of the internal structure of the object by detecting the attenuation and transmission characteristics of the rays inside the object [5-6]. It is widely used in industrial NDT, medical imaging, security inspection, and other fields, with the merits of high sensitivity and extensive application. The process of RT is shown in Fig. 2.

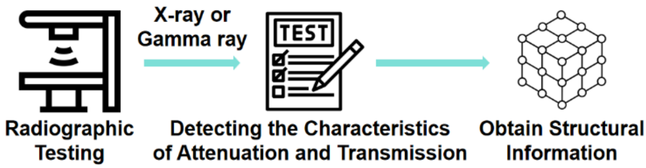

Fig. 2. Basic principle of ray detection (Picture credit: Original)

2.2.2 Ultrasonic testing.

Ultrasonic testing is a technique of detecting and evaluating defects within a material by using ultrasonic technology to emit sound waves (typically more than 20 kHz and have good directionality) into the material, which is under test, and by collecting the reflected signals from the ultrasonic waves at the defects to form different waveforms [7-8]. It is widely used in industrial NDT, medical diagnosis, construction, civil engineering, etc., and has advantages of high sensitivity and extensive application. The process of UT is shown in Fig. 3.

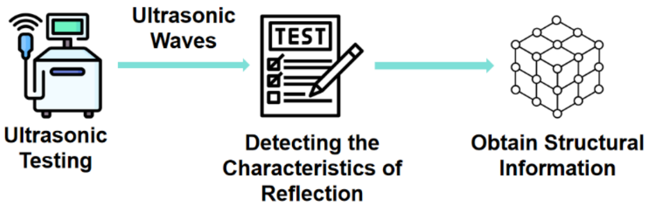

Fig. 3. Basic principle of ultrasonic detection (Picture credit: Original)

2.2.3 Magnetic particle testing.

Magnetic particle inspection is a method based on the principle of magnetic field. When a ferromagnetic material is magnetised, if there are defects on or near the surface of the material (e.g. cracks, air holes, etc.), the magnetic permeability at the defects will change, resulting in magnetic field distortion and the formation of a leakage field. The magnetic powder will gather at the defects under the effect of the leakage field, forming visible magnetic traces, thus showing the location and shape of the defects.

2.2.4 Automated optical inspection.

Automated optical inspection is an automated inspection method based on optical imaging principles and computer vision technology [9-10]. It uses an optical imaging system (e.g., a high-resolution camera, etc.) to acquire images of products and uses algorithms to locate the location of defects and identify the type of defects. It is extensively applied to defect detection in electronic manufacturing processes such as printed circuit board (PCB) assembly, surface mount technology (SMT), and so on. The process of MVI is shown in Fig. 4.

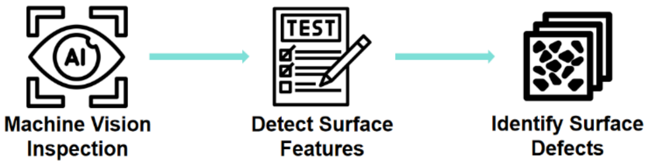

Fig. 4. Basic principle of machine vision inspection (Picture credit: Original)

3 Deep learning in weld NDT

3.1 Application of CNNs in weld NDT

The CNN is a deep learning model specially designed to process data with grid structure. It has achieved significant results in fields such as bioinformatics, image categorisation, image retrieval, targeting and natural language processing. A CNN is comprised of five layers: input, convolutional, pooling, fully connected layer, and activation function. The input layer receives data, the convolutional layer uses specific activation functions and filters to perform calculations to extract data features, and the pooling layer is responsible for the dimensionality reduction of the data features to reduce the amount of data computation to the level where the computational cost is low. The fully connected layer is responsible for the final output of the result. CNNs use local receptive fields for forward propagation, i.e., convolution is performed only for a certain local data window to extract local features, and then data dimensionality reduction is performed by pooling, which extracts the mean or maximum value of the region. During training, the loss function is calculated, and the backpropagation algorithm updates the model. After training, the computer can recognise the image features.

3.1.1 CNN-based weld NDT applications.

To address the issue of automatic inspection of laser welding defects in the battery manufacturing industry, Yang et al. proposed an optimised Visual Geometry Group (VGG) model to increase the efficiency of defect classification using Transfer Learning theory and training method of VGG model [11]. After inputting images gotten from the production line of battery, the model identifies and classifies the defects of welds in these images. Ultimately, the improved VGG-16 model achieved 99.87% of the tested accuracy and outperforms five other CNN models.

To improve the detection accuracy of typical defects in lap welds in galvanised steel sheet, Ma et al. tested and compared four training methods: 1) AlexNet built from scratch, 2) VGG16 built from scratch, 3) the output features of a pretrained VGG16 in ImageNet, 4) the convolutional block attention mechanism introduced in the VGG16 structure to achieve model fine-tuning [12]. Ultimately, without data enhancement, the average accuracy of VGG16 and Alexnet on the test set is 89.17% and 95.83%, respectively. Data augmentation improves the accuracy of the model. Meanwhile, the study demonstrates that transfer learning can achieve accurate classification while reducing training time in case of sample shortage.

To improve the efficiency and accuracy of NDT of pipeline weld defects, Ji et al. developed a framework integrated feature pyramid network (FPN) based on Faster-RCNN and designed Squeeze and Position Attention Mechanism (SPAM). A data augmentation method based on geometric transformations (e.g., flip, rotation, translation, cropping, etc., rotating 180 degrees and mirroring up and down are used in this experiment) is employed to simulate defects of different shapes at different locations [13]. Ultimately, the improved model fusing FPN and SPAM solved the detection challenge of small target size and weak image contrast, and the mean average precision of the model was improved by 4%.

To improve the manufacturing quality and automation level of Keyhole Tungsten Inert Gas in the welding area, an online monitoring system was created by Xia et al. [14]. The system uses the XVC-1000e HDR welding camera to acquire images, and a cutting-edge ResNet was designed to recognise various states of welding. Retinex algorithm for image augmentation promoted the diversity of the training dataset. To optimise the training process, Resnet was paired with a metric learning strategy of center loss. In addition, to comprehend and elucidate the efficiency of the deep learning process, visualisation techniques such as feature maps, guided Grad-CAM, and t-SNE were used in this research. The overall accuracy of the classification of different welding states reached more than 98%, which is more than enough to satisfy actual production needs.

3.1.2 CNNs combined with other methods for weld NDT applications.

Liu et al. proposed an expert knowledge-empowered CNN for welding radiographic image recognition (WRIR). This study designed two self-supervised learning (SSL) tasks: brightness adjustment and deblurring of radiographic images to simulate expert experience [15]. The expertise acquired from the SSL methodology was applied to direct the CNN in identifying weld defects, which inductive bias of the rationalized model. With faster convergence speed and no overfitting, both the Rec and F1-score of the network reach 97.65 % In addition, this study showed that it performed well with small sample sizes. The model was suitable for domains like aerospace structural components where the sample size is small.

To identify cracks, corrosion, and other defects in metal pipelines, Shang et al. utilised a CNN-LSTM hybrid model to decode ultrasonic guided waves to detect damage in metal pipelines and extracted 29 features as inputs to categorise different types of defects in oil/gas pipelines [16]. Finally, this advanced model achieved a superior result, whose accuracy stands at 94.8% and is better than the models using only CNN or LSTM. At lower noise levels, the hybrid model exhibited better performance, however, as the noise intensity increases, its prediction accuracy showed a systematic decay and eventually broke the threshold of acceptable threshold. The results also demonstrated that pre-extracted features, such as mean value in the dimensional time domain, waveform index in the dimensionless time domain and root-mean-square value in frequency domain, improved data classification and significantly increased the robustness of deep learning methods.

In order to interpret the Electromagnetic Acoustic Transducer (EMAT) signals measured from gas pipelines circumferential welds and use them to detect the cracks in pipeline girth weld, Yan et al. introduced a method combining a deep CNN and a Support Vector Machine (SVM) classifier to capture and identify the high-level cracking-related features of A-scan signals under actual working condition, which were classified into defective and non-defective groups [17]. The result showed that the framework of CNN-SVM prominently improved classification accuracy when compared with other frameworks.

By introducing advanced model architecture, migration learning, algorithmic fusion, hybrid model synergy framework, expert knowledge fusion, data augmentation, optimisation of CNN variants, and improvement of attention mechanism in CNNs and making visual interpretation and robustness optimisation of the study, deep learning can better identify defects in welds through weld NDT, which in turn can make an outstanding contribution to improving industrial productivity.

3.2 Application of GANs in weld NDT

The GAN is a deep learning model based on adversarial learning, first advanced by Goodfellow et al. in 2014, which means it is a relatively novel neural network. It has achieved significant results in areas such as image generation, image segmentation, and video prediction. A GAN is mainly comprised of a generator and a discriminator. The generator model is an arbitrarily structured neural network whose input is random noise and whose output is generated samples. The Generator will generate samples that need to be as close as possible to the distribution of the real samples to conceal and deceive the Discriminator. The discriminator can likewise be an arbitrarily structured neural network whose inputs are real samples or samples generated by the generator, and whose output is a probability value indicating the probability that the input sample is a real sample. The goal of the discriminator is to determine as accurately as possible whether the input sample is a real sample or a generated sample. Both are optimised according to their respective loss functions through an adversarial process. After training, the generator produces high-quality data, thus reducing the impact of the low size of real sample of labelled data on model training.

Guo et al. proposed a GAN combined with Xception transfer learning for x-ray testing of weld NDT to alleviate the problem of imbalanced data and improve defect detection accuracy [18]. In this study, an innovative model called "Contrast Enhancement Conditional GAN" (CECGAN) was proposed, which integrated contrast enhancement and a categorical variable into the framework of the GAN model to remove the influence of low contrast industrial photographs during feature extraction and prevent mode mixing during training process. The CECGAN worked well in balancing the data distribution by resampling and generating realistic training data with a small sample size.

Dai et al. put forward a method called BAGAN-GP to generate defective spot images and constructed a classifier based on the ResNet-50 model pre-trained on ImageNet [19]. BAGAN-GP generated high-quality images. Six types of defects, such as "edge welds", "distortion", "burn through", etc., were included in these minority-class images. The addition of these images to the training set resulted in better classification performance. The result is applicable for the analysis of industrial welding defect images in low-quality datasets.

With the help of GANs, the problem of data imbalance can be alleviated or even solved, and the trained models are far better than the traditional models in terms of recognition accuracy. GANs have not emerged for a long time, but they are developing rapidly, and there are already many variants, such as Deep Convolutional GAN (DCGAN), Conditional GAN (CGAN), and CycleGAN, etc..GANs represent a potential and novel direction. Future research can achieve better results by adopting its variants and incorporating innovative algorithms.

3.3 Application of other networks in weld NDT

Singh et al. constructed a framework using a Deep Neural Network (DNN) for establishing microstructural properties of locally anisotropic weldments in real time from ultrasonic array data [20]. If this neural network is deployed on a standard desktop computer, the trained DNN can predict grain orientation to within 3°. The prediction occurred within 0.04s, which is almost real-time. Ultimately, the resulting weld structure characterisation will be used for weld defect detection with an improved signal-to-noise ratio of 5.3 dB.

3.4 Discussion

Deep learning techniques, especially CNN and GAN, have shown extraordinary application potential in the field of weld NDT, which provides important technological support for automation and intelligence in this field. This section reveals the unique advantages of different deep learning models and methods in defect classification, feature extraction and data enhancement through several typical cases, and maps out the limitations of current research and future directions for improvement.

3.4.1 Core advantages and innovative directions of CNNs.

Due to the local receptive fields and hierarchical feature extraction capability, CNN has become a mainstream method for weld defect detection. Studies have shown that the introduction of strategies such as data augmentation, attention mechanism (e.g., SPAM module), and feature pyramid network (FPN) can significantly enhance the detection accuracy of models for small targets and low-contrast defects [13]. In addition, combining Self-Supervised Learning (SSL) to simulate expert experience or fusing traditional methods such as LSTM and SVM can enhance the model's generalisation ability and robustness in small-sample scenarios [15-17]. However, the performance of CNNs is still limited by the quality of training data and annotation cost, and complex models (e.g., ResNet) may increase the computational burden, which is not conducive to real-time detection in industrial applications [14]. Further optimisation can be achieved in the future through lightweight design (e.g. MobileNet), adaptive feature fusion, and multi-task learning.

3.4.2 Breakthroughs and challenges of GANs.

By synthesise high-quality data, GANs effectively alleviate the challenges of data imbalance and sample scarcity in weld inspection. For example, CECGAN generates realistic defect images through contrast enhancement, and BAGAN-GP combines a gradient penalty strategy to improve the diversity of minority class samples [18-19]. These methods significantly assure the accuracy of the classifiers while lowering the cost of data acquisition. However, GAN-generated samples may suffer from distributional bias and insufficient model training stability (e.g., gradient vanishing and mode collapse problems). The combination of variant models (e.g., DCGAN, CGAN, CycleGAN, etc.) and innovative algorithms can be explored in the future to generate defect data that better match industrial scenarios.

3.4.3 Multi-modal fusion and interpretability of model.

Current research is gradually focusing on multi-modal data fusion and model transparency. For example, literature [14] enhances welding images by the Retinex algorithm and combines visualisation methods (Guided Grad-CAM, t-SNE) to explain the basis of decision-making of models; Singh et al. use DNN to process ultrasonic array data to realise the linkage between microstructural properties and defect detection [20]. These methods provide examples of collaborative analysis of multi-source data in complex scenarios. However, the fusion of multiple physical field signals (e.g., acoustic and optical) in existing studies is still insufficient, and the interpretability of the models needs to be further combined with domain knowledge (e.g., welding procedure parameters) to enhance credibility.

3.4.4 Real-world challenges for industrial deployment.

Despite the excellent performance of deep learning models in laboratory environments, their industrial deployment still faces the following challenges: (1) factors such as light, noise, and material differences in real working conditions may reduce the model generalisation ability, (2) the balance between real-time requirements and model complexity, (3) the strong dependence on annotated data, which urgently requires breakthroughs in semi-supervised or unsupervised learning techniques. Future research needs to strengthen interdisciplinary cooperation, design dedicated network architectures in combination with welding procedure mechanisms and promote the optimisation of the adaptation of edge computing and embedded devices.

The applicability of different test methods is shown in Table 1.

Table 1. Applications of different test methods

Methods of testing	Object or field of testing	Literatures
AOI	Battery	[11]
Active vision	Galvanized steel sheet	[12]
X-ray testing	Pipeline	[13]
MVI	Keyhole TIG	[14]
RT	aerospace structural component	[15]
UT	metallic pipelines	[16]
UT	Gas pipelines	[17]
X-ray testing	pipeline	[18]
MVI	Automotive industries	[19]
UT	Austenitic stainless steel	[20]

4 Conclusion

Deep learning technology has demonstrated a strong potential for application in weld NDT. This paper adopts the literature induction method, focusing on the application of CNN and GAN in weld NDT. The research results show that the application value of deep learning NDT technology lies in: high-precision defect classification, small sample adaptability, data augmentation and balancing, and real-time performance. However, the application of deep learning still has the following problems in terms of industrial weld defect detection, such as the sample data volume is too small, the sample data is imbalanced or of poor quality, the generalisation ability is poor, the over-fitting, the model training time is long, high requirements of computational resource, the timeliness is weak, and the interpretability is poor. To solve these problems, relevant research should be carried out in the future in the direction of data enhancement, transfer learning, model optimisation, and domain knowledge fusion.

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