



Advancing Technology: An Approach to Convolutional Neural Network in Automatic Welding Systems

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Abstract. The application of Convolutional Neural Networks (CNN) in welding systems has played a key role in promoting automation improvements and technological implementation. The traditional welding process largely relies on manual operation and the experience of professionals, especially in defect detection, process control, and quality assessment. This study focuses on analyzing how CNN technology can improve the automation level in welding systems. By providing a detailed introduction to the basic working principle of CNN, several applications of optimization based on CNN in welding processes were classified, summarized, and analyzed, including image classification and analysis of welding defects, precise control in infrared cutting processes, data preprocessing for noise suppression and feature enhancement, and feature analysis of welds. After introducing CNN technology into these key links, welding automation has achieved higher detection accuracy, faster defect identification, and more reliable quality control, significantly improving manufacturing efficiency and product consistency. This article further explores the potential of intelligent solutions based on CNN in complex welding environments, providing reference for the development of future intelligent automated welding systems.

Keywords: Convolutional Neural Network, Welding Automation, Precise Detection

1 Introduction

Welding is a joining process that involves heating, melting, and mixing metals, sometimes plastics, to produce joints [1] with similar properties to the joining material. Welding is a key process in metal manufacturing, which greatly affects the load-bearing capacity, strength, and stiffness of equipment, posing a huge threat to system safety and equipment reliability [2, 3]. The quality and safety of such equipment are largely dependent on the identification and assessment of welding defects [4]. In order to improve the welding quality and detection accuracy, it is crucial to conduct research and apply intelligent welding quality detection, monitoring, and control in the welding production process [3, 4]. Various welding defects are unavoidably present during the welding process because of variation in the

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environment, or procedures and parameters [2, 3, 5]. With the advancement of deep learning algorithms, it can compensate for the lack of adaptability and penetrability in models that recognize physical laws through understanding the manual welding process. And it can automatically learn and extract complex latent features. The application of deep learning algorithms in automatic welding is gradually being widely used in machining systems to avoid the impact of errors on actual production [6].

Among them, CNN is the main model algorithm in automatic welding, which has great advantages [2, 4, 7]. Nowadays, on many automated production lines, CNN has proven to be an efficient model structure for comprehending picture and data materials [8], delivered cutting-edge outcomes in image recognition with feature analysis [4, 9, 10]. The technology that can grow the network to millions of parameters and a huge number of label datasets that can aid in the learning process is the key to attaining these achievements. In this case, CNN stands out particularly in learning and analyzing powerful image features [4]. CNN has powerful feature extraction ability and robustness to noise make it perform well in welding image detection, defect classification, weld seam tracking, and other applications [6, 8]. Compared with traditional image processing algorithms, CNN has stronger adaptability, higher detection accuracy, and feasibility in complex scenes [3, 10-14].

In summary, with the rapid development of computer vision and deep learning technologies, CNNs are becoming increasingly widely used in the field of automated welding, playing an important role in improving welding quality, increasing production efficiency, and reducing manual intervention [6, 9]. The application of CNN in automation not only improves the intelligence level of welding systems, but also provides strong support for the development of intelligent manufacturing and industrial automation [6, 7]. The purpose of this paper is to examine the state of research and application for these important techniques. Conduct a thorough analysis of CNN's usefulness in welding industry and offer theoretical justification and suggestions for the advancement of automated welding in the future.

2 Convolutional Neural Network(CNN)

The convolutional layer is the core layer of CNN, used to extract local features from the input image. Generate feature maps by performing point-wise multiplication and addition operations on local regions of the image using filters [7][9], as shown in fig 1. Edges, texture, forms, and other aspects of images can be captured at several levels using different convolution kernels. Without altering the convolution layers itself, CNN employs rectified linear unit (ReLU) as the non-linear activation function to improve the network's capacity for representation. This improves the non-linear characteristics of decision functions and the neural network as a whole. Subsequently, pooling is a non-linear form of down sampling that divides the input image into several rectangular regions and outputs specified values for each sub region. Usually, the max pool is used to output the maximum value. The pooling layer reduces the dimensions of feature maps, lowers computational complexity, and enhances the

translation invariance of features [9]. After feature extraction is completed, several fully connected layers are usually connected to map the extracted high-dimensional features to specific classification labels or regression outputs. The last layer is usually the Soft-max layer, which is used to convert the classification results into probability distributions, making it easier to directly output category labels. After being processed by multiple convolutional layers and max pooling layers, the advanced inference of the neural network is completed by fully connected layers. Similar to traditional non-convolutional artificial neural networks, each neuron in the fully connected layer is connected to all activation values of the previous layer. Therefore, these activation values can be calculated through affine transformation, that is, matrix multiplication is first performed, and then a bias term is added, which can be fixed or obtained through learning [7, 9].

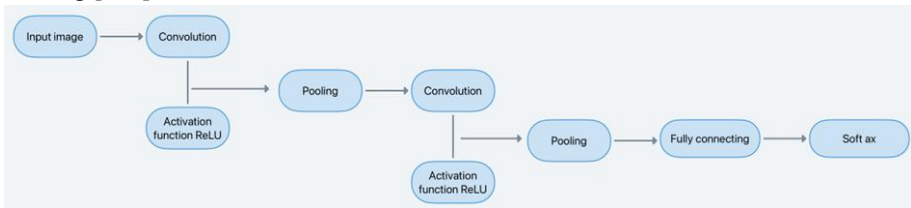


Fig. 1. Examination of CNN procedures [7]

3 Data Preprocessing

Overall, CNN performs excellent data processing in image processing, which is also the main approach in automatic welding systems, like rotating machinery fault diagnosis. Shengnan et al.'s research improves the accuracy of diagnosis and the generalization ability of the model, optimizing the data processing of welding systems through CNN. By utilizing analysis of many traditional data preprocessing techniques, train CNN models to enhance their learning ability in fault diagnosis and achieve precise control of intelligent automated fault diagnosis. Combining the advantages of Fourier transform and wavelet transform, S-transform (ST) further optimizes the time-frequency distribution image, improving stability and performance under noise interference [14]. In addition, cyclic spectral coherence has been used for bearing fault diagnosis due to its advantages in cyclostationary signal processing, achieving excellent feature extraction results [15]. In terms of data augmentation, various methods are used to expand the datasets to improve the generalization performance of the model [14]. For example, data augmentation strategies such as Gaussian white noise, signal translation, rotation, and mirroring were used in the study to increase data diversity. The performance and applicability of CNN in fault diagnosis under appropriate data preprocessing methods can be obtained through experimental data [15]. Especially as Shengnan et al. mentioned, the importance of convolutional layers in the preprocessing of CNN model principles. By stacking multiple convolutions, more complex feature patterns can be learned, improving overall diagnostic accuracy [14]. CNN automatically extracts key patterns from time-

frequency images without the need for complex operations such as image filtering and enhancement. In multi-channel data or multi-source fusion data scenarios (such as temperature, vibration and current analysis), CNN can efficiently process and extract the correlation between the features of each channel. Compared with traditional methods, CNN extracts key content from different physical signals through different convolution kernels, which can achieve more comprehensive data fusion preprocessing.

4 Detection of Weld Seam

Due to numerous unpredictable factors during the welding process, defects such as porosity, cracks, undercutting, incomplete penetration, and weld offset are prone to occur [2]. A study proposes an improved Faster Regions with Convolutional Neural Networks (Faster R-CNN) network model based on CNN, aiming to enhance the detection performance of weld defects. This model adopts a two-stage object detection method, combining Region Proposal Network (RPN) and Fast R-CNN, effectively improving the efficiency of feature extraction and candidate box generation [12]. On this basis, researchers further introduced the Feature Pyramid Network (FPN) to enhance the ability to extract multi-scale features. FPN significantly improves the detection performance of small targets, such as tiny weld defects, by fusing high-level and low-level features. In addition, the study also employed Deformable Convolutional Networks (DCN) to enhance the model's ability to capture complex deformation features. DCN improves the recognition performance of irregular weld defects by adjusting the sampling point position by calculating the offset [13]. In addition, researchers introduced background suppression mechanisms to further optimize the robustness of the model. This mechanism obtains background approximations through global average pooling and combines them with the original feature map to enhance the contour and texture features of weld defects, effectively reducing background noise interference [13]. The improved model exhibits significant advantages in both detection accuracy and speed, especially in detecting weld defects in complex background environments, demonstrating stronger stability and better performance.

In another study, TAL Brabo robotic arm was used for weld seam tracking verification. To accomplish real-time welding categorization and path tracking, the robotic arm is managed by MATLAB and linked to a CNN model via ActiveX COM [8]. The experimental results demonstrates that this technique has a wide range of possible applications and can effectively increase the accuracy of welding seam detection. The experimental results show that the CNN based weld seam classification method can achieve high-precision weld seam recognition, with training and validation accuracy reaching over 98% [8].

5 Classification and Analysis of Weld Defects

In order to address the dependence of traditional Convolutional Neural Networks (CNNs) on large-scale annotated data and their lack of interoperability, particularly in fields such as aerospace and oil pipeline detection proposed a series of improvement methods by researchers [8, 14].

Regarding improving the accuracy of welding radio-graphic inspection (WRIR), Liu et al. pointed out that due to the complex imaging features of welding defects in radio-graphic images [16], different types of defects require a large amount of contrast adjustment, and it is difficult to achieve effective generalization with low efficiency. Therefore, they introduced two self supervised learning tasks to simulate the observation patterns of experts in practical operations, enabling CNN to converge faster under small sample conditions while improving the interoperability of the model. Through comparative experiments, this method achieved very high values (97.65%) on F1 score, and compared to traditional CNN models, its performance is more stable on small sample datasets [16].

On the other hand, Tang et al. suggested Multi Level Cascaded Network (MCFNet) [5], a hybrid technique that combines CNN and Transformer, for the categorization of weld defects in Time-of-Flight Diffraction (TOFD) ultrasonic testing[5]. Due to the large amount of noise and interference fringes in TOFD images, CNN is prone to information loss when extracting key defect features, while Transformer, although possessing global feature modeling capabilities, has high computational complexity. In order to achieve this, the study developed a fast and effective Transformer module, EFTM, that substitutes the cascaded group attention (CGA) mechanism for the conventional multi-head self-attention, known as MHSA mechanism, lowering computational costs of increasing classification accuracy. It also introduced a multi-scale feature fusion (MSFF) model to extract defect features at several scales [5]. According to the testing finding, MCFNet's accuracy in identifying TOFD weld defects is roughly 98%, making the probability of errors extremely low. Compared to models such as ResNet and YOLOv5, it achieves a better balance between computational complexity and accuracy.

Overall, the above two methods theoretically adopt different optimization strategies to apply CNN intelligence in welding systems. Liu et al. [16] focus on enhancing the performance of CNN on small sample datasets and improving its interchangeability by combining self-supervised learning with expert knowledge. This method is suitable for industrial testing scenarios with high data acquisition costs and difficult labeling, such as aerospace manufacturing. Tang et al. [5] integrated the Transformer structure to optimize the attention mechanism and multi-scale feature fusion, making it suitable for large-scale detection tasks with high real-time requirements.

6 Power Management of Remote Control

Božič et al. proposed a laser power control strategy based on CNN aimed at optimizing the welding quality during remote laser welding processes [17]. This strategy utilizes optical triangulation feedback, uses CNN to classify the welding process in real time, and combines proportional integral derivative (PID) controller to dynamically adjust the laser power to ensure that the weld seam reaches the ideal penetration depth. In the experiment, the research team selected AISI 304 stainless steel plates with a thickness of 1.5 millimeters for welding testing and divided the welding process into three states: partial penetration, complete penetration, and excessive penetration. CNN identifies the current state by analyzing welding images and adjusts the laser power accordingly to maintain it within the optimal welding parameter range. According to experimental finding, this method classified accuracy on the datasets can reach 94%, and the control system can achieve complete penetration within 1.0 seconds [17]. Furthermore, CNN primarily concentrate on the welding area interaction and can dynamically modify the lase power in response to changes in the interaction area to adapt to changes during the welding process, according to the study's analysis of CNN decision range using gradient weighted class activation mapping (GradCAM) technique.

In terms of research methodology, Božič et al. adopted an end-to-end control architecture, in which CNN is responsible for real-time classification of welding status and transmitting the predicted results to a PID controller to adjust the laser power output [17]. The experimental system consists of Yaskawa GP50 industrial robot, HighYag RLSK scanning head, and IPG YRL-400-AC fiber laser, and uses FLIR Flea3 industrial camera for welding process monitoring. The research team collected welding images at different welding speeds and annotated the corresponding welding states. The CNN model is constructed using the Keras framework and extracts features using three convolutional layers, each layer including convolution, batch normalization, ReLU activation, and pooling operations. During the training process, in order to reduce data correlation, the research team introduced an interval of about 50 frames when dividing the datasets, and removed images located within 5% of the power boundary to ensure that the model can more accurately identify different welding states. In addition, researchers randomly added surface defects to about 30% of the images to prevent CNN from relying on irrelevant visual features for classification [17].

7 Challenges and Developments

Although deep learning technology has made many breakthroughs in the field of welding automation, there are still many challenges and room for improvement. Based on the results of the above research, traditional CNNs rely on large-scale annotated datasets, while obtaining high-quality defect data in industrial welding environments is costly [14]. This issue still needs further optimization to reduce the need for manual annotation. In addition, the "black box" nature of deep learning

models restricts their usage in safety critical fields, so future research can combine explainable artificial intelligence (XAI) technology to increase the transparency of model decisions. Meanwhile, the industrial welding environment is often accompanied by complex interference factors such as high temperature, vibration, smoke, and light reflection, which may lead to a decrease in the robustness of CNN models in practical applications. Future research can further combine Transformer or Graph Neural Network (GNN) to improve the generalization capability of the model. In addition, the delay in predicting the welding state by CNN may lead to power overshoot in the PID control system, affecting the welding quality [17]. Future research can combine feed-forward control or state estimation methods based on Kalman filtering to improve the response speed of welding process control. In addition, by increasing the frame rate of industrial cameras or optimizing the CNN computing architecture, such as using lightweight Transformer structures, prediction latency can be further reduced and the real-time performance of welding control systems can be improved.

The current research is mainly based on a single data source, such as radio-graphic images or ultrasonic inspection images, for welding defect detection [14]. Future research can explore Multi Modal Learning, such as combining optical images, ultrasound data, and temperature sensor data, to improve the detection accuracy and reliability of welding defects. At the same time, more energy will be invested in researching potential enhancement mechanisms for CNN construction methods and final diagnostic performance, in order to reduce the consumption cost of CNN models and enable more effective processing of large-scale industrial models in the future.

8 Conclusion

This article reviews the application progress of deep learning technology in the fields of welding defect detection, welding fault diagnosis, and remote welding power control. Research has shown that welding defect detection techniques based on CNN, the accuracy and resilience of detection are greatly increased by using techniques like enhanced Faster R-CNN, which combines FPN with DCN. In addition, incorporating self supervised learning (SSL) and Transformer mechanisms into CNN methods effectively reduces reliance on large amounts of annotated data and enhances the adaptability of the model in industrial environments. CNN does not require manual feature search or definition of welding defect features in classification tasks, as features are automatically extracted through convolution processes, which improves the accuracy of data processing compared to previous studies. In terms of intelligent welding fault diagnosis, CNN achieves high-precision fault classification by combining data preprocessing techniques such cyclic spectral coherence, wavelet transform (WT), S-transform (ST), and Fourier transform (FFT). The model's generalization ability is further improved by data augmentation techniques including noise addition, signal translation, and mirror transformation, which allow it to adjust to different welding settings. The integration of CNN and PID control in remote laser

welding power control allows for adaptive laser power adjustment to respond to real-time welding status changes and guarantee weld quality stability.

CNN deep learning technology has shown great potential in automated welding industry. Future research should focus on further improving the generalization ability and real-time performance of the model, combined with multi-modal data fusion and end-to-end automation control, to achieve a more intelligent welding system. By optimizing reinforcement learning and self supervised learning techniques, it is expected to further improve the intelligence level of welding automation, providing more efficient, accurate, and stable solutions for the industrial manufacturing field.

References

1. CCOHS: Welding - Overview of Types and Hazards, <https://www.egr.msu.edu/~pkwon/me477/welding.pdf>, n.d.
2. Ariefa, I., Wikarta, A.: Convolutional Neural Network (CNN) technology to detect welding defects in motorcycle frames using transfer learning and optimizer, 2023 Int. Workshop Artif. Intell. Image Process. (IWAIP), 2023, pp. 331–336
3. Yang, L., Wang, H., Huo, B., et al.: An automatic welding defect location algorithm based on Deep Learning, *NDT & E Int.*, 120, 102435(2021).
4. Hartl, R., Bachmann, A., Habedank, J.B., et al.: Process monitoring in friction stir welding using convolutional neural networks, *Metals*, 11(4), 535(2021)
5. Tang, D., Zhang, J., Wang, P., He, Y.: Weld TOFD defect classification method based on multi-scale CNN and cascaded focused attention, *J. Manuf. Process.*, 138, 157–168(2025)
6. Kumaresan, S., Aultrin, K.S., Kumar, S.S., et al.: Deep learning based simple CNN weld defects classification using optimization technique, *Russ. J. Nondestruct. Test.*, 58(6), 499–509(2022)
7. Khumaidi, A., Yuniarno, E.M., Purnomo, M.H.: Welding defect classification based on Convolution Neural Network (CNN) and Gaussian Kernel, 2017 Int. Semin. Intell. Technol. Appl. (ISITIA), 2017.
8. Singh, A., Kalaichelvi, V., Karthikeyan, R.: Application of convolutional neural network for classification and tracking of weld seam shapes for Tal Brabo manipulator, *Mater. Today Proc.*, 28, 491–497(2020)
9. Gillis, A.S., Craig, L., Awati, R.: What is a Convolutional Neural Network (CNN)?: Definition from TechTarget, Search Enterp. AI, 2024, <https://www.techtarget.com/searchenterpriseai/definition/convolutional-neural-network>
10. Dai, D.: An introduction of CNN: Models and training on neural network models, 2021 Int. Conf. Big Data Artif. Intell. Risk Manag. (ICBAR), 2021
11. Ma, D., Jiang, P., Shu, L., Geng, S.: Multi-sensing signals diagnosis and CNN-based detection of porosity defect during Al Alloys Laser Welding, *J. Manuf. Syst.*, 62, 334–346(2022)
12. Ren, S., He, K., Girshick, R., Sun, J.: Faster R-CNN: Towards real-time object detection with region proposal networks, *IEEE Trans. Pattern Anal. Mach. Intell.*, 39(6), 1137–1149(2017)
13. Wang, J., Mu, C., Mu, S., et al.: Welding seam detection and location: Deep Learning Network-based approach, *Int. J. Press. Vessels Pip.*, 202, 104893(2023)

14. Tang, S., Yuan, S., Zhu, Y.: Data preprocessing techniques in convolutional neural network based on fault diagnosis towards rotating machinery, *IEEE Access*, 8, 149487–149496(2020)
15. Chen, Z., Gryllias, K., Li, W.: Mechanical fault diagnosis using convolutional neural networks and Extreme Learning Machine, *Mech. Syst. Signal Process.*, 133, 106272(2019)
16. Liu, T., Zheng, P., Liu, X.: A multiple scale spaces empowered approach for welding radiographic image defect segmentation, *NDT & E Int.*, 139, 102934(2023)
17. Božič, A., Kos, M., Jezeršek, M.: Power control during remote laser welding using a convolutional neural network, *Sensors*, 20(22), 6658(2020)

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