Deep Learning in Manufacturing: A Focus on Welding Defect Classification with CNNs

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Abstract

Welding is integral to modern manufacturing, yet the complex process often leads to defects, impacting the quality of the final product. Recent advances in deep learning, particularly Convolutional Neural Networks (CNNs), have shown remarkable results in applications like defect recognition. This study evaluated AlexNet, ResNet-18, ResNet-50, ResNet-101, MobileNet-v2, ShuffleNet, and SqueezeNet for their effectiveness in identifying welding defects, using accuracy, precision, sensitivity, specificity, and F-score as metrics. The dataset covered defects like cracks, lack of penetration, porosity, and a no-defect class. Our analysis shows that most of these architectures deliver promising results in accuracy, sensitivity, specificity, precision, and F1-score, highlighting their potential in defect recognition.

Keywords: Convolutional neural network, Classification, Deep learning, Welding defects

1. Introduction

Welding is a crucial industrial process integral to various production sectors, including high-performance industries like aerospace, automotive, marine, and power generation. This complex process involves multiple parameters that directly impact the quality of the weld joint. Factors such as welding procedures, methods, environmental conditions, and the operator's skill level can lead to various defects during the welding of pipelines and pressure vessels [1]. Common defects include blowholes, cracks, incomplete fusion, incomplete penetration, slag inclusions, and undercutting, which significantly compromise the sealing and strength of the products. In addition to welding parameters, unforeseen events in the manufacturing process can also cause weld defects. Therefore, rigorous welding quality inspection and testing are essential during manufacturing, especially for products like pipelines and pressure vessels. This is critical to identify the root causes of welding defects and implement targeted corrective measures to ensure product quality and safety [1].

Considerable research has been devoted to addressing the challenges of weld defect detection and identification. These defects are typically detected using non-destructive testing (NDT) techniques, favored for their non-invasive interaction with specimens. Common NDT methods for weld defect detection fall into various categories, including visual or manual inspection, radiographic testing with ionizing radiation sources (such as gamma rays or X-rays), eddy current testing, ultrasonic testing, and dye penetrant testing [2], [3]. However, each of these techniques has inherent limitations. For example, eddy current testing is only applicable to metallic specimens, while X-ray radiographic testing poses potential health risks due to prolonged exposure to radiation. Additionally, the majority of current weld surface defect recognition relies on manual inspection by NDT experts analyzing these radiographic images. This manual process of interpreting and evaluating images can be complex, subjective, inconsistent, time-consuming, labor-intensive, and prone to errors, particularly when distinguishing between defects with similar features [4]. Consequently, developing an automated inspection solution that offers more efficient and accurate recognition of weld surface defects is essential to overcome the drawbacks of manual inspections.

The adoption of automated machine vision systems, integrating deep learning techniques, offers a promising solution for weld surface image classification challenges. Convolutional Neural Networks (CNNs), renowned for their ability to learn nonlinear relationships between inputs and outputs, mimic the human brain's learning process and have been effectively applied in various real-world scenarios. These applications include signal/image classification [5], [6], [7], cybersecurity [8], [9], medical diagnosis [10], [11], [12], fault detection [13], [14], [15] and prediction [16], [17]. Encouraged by deep learning's success, numerous network architectures have been developed, such as AlexNet [18], ResNet-18 [19], ResNet-50 [19], ResNet-101 [19], MobileNet-v2 [20], ShuffleNet [21], and SqueezeNet [22]. Transfer learning, a method for adapting these existing CNN architectures to new tasks, has gained popularity. It utilizes smaller datasets and reduces training time, making it an efficient approach for training CNNs in new application domains.

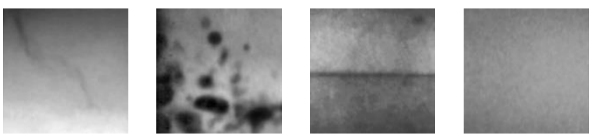
While previous studies [4], [23], [24], [25], [26], [27] have explored welding defect classification using deep learning, the optimal selection of CNN architectures remains relatively unexplored, leaving many architectures yet to be assessed. Addressing this gap, our paper presents an extensive study evaluating the performance of seven popular CNN architectures: AlexNet, ResNet-18, ResNet-50, ResNet-101, MobileNet-v2, ShuffleNet, and SqueezeNet, in classifying weld defects from digital radiographic images. Our aim is to objectively identify the most effective CNN architecture using various performance metrics. This study could lead to replacing manual inspection methods with a more accurate automated weld defect classification system, potentially reducing production costs and increasing throughput.

2. Methodology

2.1. *Data acquisition and preprocessing*

This study focuses on training and evaluating a deep learning model using the RIAWELC welding defect dataset [28]. Unlike other commonly used datasets such as GDXRay [29] and WDXI [30], RIAWELC offers a larger, open-source dataset, which is beneficial for training CNNs without the risk of overfitting.

The RIAWELC dataset comprises 24,407 radiographic images, each of size 224×224 pixels, categorized into four classes of welding defects: lack of penetration (LP), cracks (CR), porosity (PO), and no defect (ND). A representative image for each defect type is displayed in Fig. 1, and Table 1 details the distribution of images across these classes. The substantial size of RIAWELC dataset supports the development of automated methods for identifying and classifying welding defects, crucial for reliable inspection and quality control.



(a) (b) (c) (d)

Fig.1 Sample of radiographic images for each welding defect class from RIAWELC dataset: (a) LP, (b) CR, (c) PO and (d) ND.

Table 1. Data distribution of RIAWELC dataset for each welding defect class.

Defect Types	CR	PO	LP	ND
No. of Image	7,635	6,320	4,452	6,000

To facilitate deep learning model training, the RIAWELC dataset is divided into three subsets: 70% for training, 10% for validation, and 20% for testing. Additionally, all radiographic images from the dataset are resized to match the input requirements of the selected pretrained network, as outlined in Table 2, ensuring compatibility with the network architectures.

Table 2. Summary of seven pretrained networks

Pretrained Networks	Depth	Size (MB)	Parameter (Millions)	Input Size
AlexNet	8	227	61.0	224×224
ResNet-18	18	44	11.7	224×224
ResNet-50	50	96	25.6	224×224
ResNet-101	101	167	44.6	224×224
MobileNet-v2	53	13	3.5	224×224
ShuffleNet	50	5.4	1.4	224×224
SqueezeNet	18	5.2	1.24	227×227

2.2. *Transfer learning of pretrained networks*

Training CNNs from scratch for specific tasks presents challenges due to significant resource requirements, such as training time, infrastructure, and input datasets. Transfer learning offers a viable solution by transferring knowledge from one or more source domains to a different target domain. In this study, we utilize transfer learning to extract the learnable parameters from selected pretrained network architectures (namely, AlexNet, ResNet-18, ResNet-50, ResNet-101, MobileNet-v2, ShuffleNet, and SqueezeNet) for the welding defect radiographic images classification tasks.

Specifically, the last three layers of these pretrained networks are replaced with a new fully-connected layer, a SoftMax layer, and a classification output layer. Additionally, the original output layers are substituted with new output layers tailored to four classes: lack of penetration (LP), cracks (CR), porosity (PO), and no defect (ND). These modified networks are then trained using the RIAWELC dataset, as detailed in Table 1.

2.3. *Hyperparameter tuning*

Stochastic Gradient Descent (SGD) is a popular optimizer in deep learning training, valued for its ability to effectively balance accuracy and efficiency. In this study, SGD is employed to train selected pretrained network architectures with the RIAWELC dataset, aiming to minimize the cross-entropy loss function. However, the performance and convergence of SGD are influenced by various training hyperparameters, including momentum, initial learning rate, L2 regularization, maximum epoch, and batch size.

Specifically, the initial learning rate dictates the step sizes in the parameter update process. L2 regularization helps to prevent network overfitting by adding a penalty term to the loss function. The maximum epoch limits the number of iterations to avoid overfitting, and the batch size determines the number of samples used per iteration, impacting the stability, speed, and memory usage of SGD.

To facilitate a fair comparison in performance evaluations, the hyperparameters for all selected pretrained networks are standardized. This includes setting the momentum to 0.9, the initial learning rate to $\mathbf{2 \times 10^{-3}}$, L2 regularization to 0.5, the maximum epoch to 5, and the batch size to 32.

2.4. *Performance metrics*

The overall performance of all pretrained CNN networks in classifying welding defect radiographic images is evaluated using five key metrics: accuracy, sensitivity, specificity, precision and F1 score. These metrics are derived from the true positive (TP), true negative (TN), false positive (FP), and false negative (FN) outcomes produced during the testing phase of the CNN architectures. The mathematical formulations for each performance metric employed in this study are as follows.

Accuracy, indicating the overall correctness of the CNN architecture's predictions, is calculated as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \qquad (1)$$

Sensitivity, measuring the CNN architecture's ability to correctly identify positive results, is computed as:

$$Sensitivity = \frac{TP}{TP + FN} \qquad (2)$$

Specificity, gauging the CNN architecture's capacity to accurately identify negative results, is determined as:

$$Specificity = \frac{TN}{TN + FP} \qquad (3)$$

Precision, assessing the accuracy of positive predictions among all positive cases identified, is calculated as:

$$Precision = \frac{TP}{TP + FP} \qquad (4)$$

F1 Score, the harmonic mean of precision and sensitivity, is defined as:

$$F1\ Score = 2 \times \left(\frac{Sensitivity \times Precision}{Sensitivity + Precision}\right) \qquad (5)$$

The abovementioned five performance metrics provide a comprehensive assessment of the CNN architectures' capabilities in distinguishing different classes of welding defects.

3. Results and Discussions

The performance of all selected pretrained networks, including AlexNet, ResNet-18, ResNet-50, ResNet-101, MobileNet-v2, ShuffleNet, and SqueezeNet, in classifying radiographic images of welding defects is comprehensively evaluated. To facilitate a quantitative comparison, each CNN architecture's effectiveness in the welding defect classification task is assessed using the five performance metrics previously mentioned, namely accuracy (Acc.), sensitivity (Sens.), specificity (Spec.), precision (Prec.) and F1 score. The simulation results are detailed in Table 3, where the highest values attained by each CNN architecture for these metrics are highlighted in boldface.

Table 3. Quantitative performance evaluation of all selected CNN architectures for welding defect classification task

CNN architecture	Acc. (%)	Sens. (%)	Spec. (%)	Prec. (%)	F1 (%)
AlexNet	71.43	71.43	90.48	80.21	70.92
ResNet-18	78.57	78.57	92.86	80.56	78.92
ResNet-50	82.14	82.14	94.05	83.93	82.49
ResNet-101	**85.71**	**85.71**	**95.24**	**87.50**	**86.06**
MobileNet-v2	71.43	71.43	90.48	69.00	69.06
ShuffleNet	75.00	75.00	91.67	80.63	75.98
SqueezeNet	71.43	71.43	90.48	75.00	70.92

Table 3 reveals a significant observation across all CNN architectures: the identical values of accuracy and sensitivity when classifying the RIAWELC dataset. This uniformity implies that the models' ability to correctly predict positive instances (sensitivity) significantly impacts their overall accuracy. Among these, ResNet-101 (85.71%) and ResNet-50 (82.14%) stand out with the best and second-best performance in both accuracy and sensitivity, highlighting their superior detection capabilities for welding defects in radiographic images. Conversely, architectures with lower complexity, such as AlexNet, MobileNet-v2, and SqueezeNet, demonstrate less effectiveness, each recording 71.43% in both accuracy and sensitivity.

Moreover, Table 3 indicates that all selected CNN architectures consistently achieve higher specificity and precision compared to their accuracy and sensitivity. This suggests they are more effective in correctly identifying true negatives (specificity) and ensuring accurate positive predictions (precision). Specifically, ResNet-101 exhibits the highest specificity (95.24%), while AlexNet shows the lowest (90.48%), indicating a broad capability across these models to identify non-defective instances accurately. Precision, however, varies more across the models, with ResNet-101 leading at 87.50%, suggesting its higher accuracy in classifying weld defects. Conversely, MobileNet-v2, despite similar accuracy and sensitivity to other models, records the lowest precision (69.00%), implying a higher rate of false positives.

The F1 score, reflecting the harmonic mean of precision and sensitivity, offers a more balanced evaluation of model performance. ResNet-101 and ResNet-50 achieve the highest F1 scores (86.06% and 82.49%, respectively), confirming their robust overall performance in classifying the radiographic images of welding defects. In contrast, AlexNet, MobileNet-v2, and SqueezeNet exhibit lower F1 scores (70.92%, 69.06%, and 70.92%, respectively), indicating a compromise between sensitivity and precision in these models.

Analysis of the simulation results in Table 3 reveals that more complex CNN architectures, such as ResNet-101 and ResNet-50, consistently outperform simpler ones like AlexNet and SqueezeNet across all performance metrics. This superior performance of advanced models like ResNet-101 and ResNet-50 highlights the significance of choosing the right model for complex image classification tasks, such as welding defect classification. It suggests that deeper networks are more adept at extracting essential features necessary for accurately identifying welding defects. The enhanced capability of these complex CNN models to discern intricate patterns in data meets the expectations associated with deeper network architectures.

However, it is important to note that while these sophisticated CNN architectures offer improved classification accuracy, they also demand greater computational resources. In contrast, simpler CNN models, despite being less precise, are more computationally efficient and may be preferable in scenarios with limited resources. In practical applications, factors like available computational power, latency considerations, and the criticality of accurately detecting defects should guide the selection of CNN architectures. Balancing these considerations is key to effectively deploying CNNs in real-world tasks.

4. Conclusions

This paper introduces a deep learning-based machine vision inspection algorithm that combines pretrained CNN architectures and transfer learning for classifying four types of welding defects—lack of penetration, cracks, porosity, and no defect—using radiographic images from the RIAWELC dataset. The objective is to thoroughly analyze the efficacy of seven different pretrained CNN architectures: AlexNet, ResNet-18, ResNet-50, ResNet-101, MobileNet-v2, ShuffleNet, and SqueezeNet, in addressing welding defect classification tasks. This analysis employs various performance metrics, including accuracy, sensitivity, specificity, precision, and F1 score. Simulation studies reveal that these pretrained networks exhibit diverse performance levels in defect classification, with ResNet-101 emerging as the most effective, achieving 85.71% accuracy, 85.71% sensitivity, 95.24% specificity, 87.50% precision, and an F1 score of 86.06%. In contrast, MobileNet-v2 shows the least effectiveness, with the lowest scores across all metrics: 71.43% accuracy and sensitivity, 90.48% specificity, 69.00% precision, and an F1 score of 69.06%. These results offer valuable insights into the applicability of pretrained deep learning networks for welding defect classification, providing a significant benefit to manufacturing companies seeking to enhance their quality control processes. In this study, the hyperparameter settings for all pretrained networks are manually configured. It is anticipated that their classification performance could be further improved by employing advanced metaheuristic search algorithms to optimize these hyperparameter settings, thereby refining the training process of the pretrained networks.

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