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A Study on the Development of Deep Learning Algorithm for Determining External Quality of Welded Parts Using Transfer Learning

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Abstract

Recently, deep learning has been applied to various welding techniques, such as laser welding, gas metal arc welding (GMAW), and resistance spot welding, and research on automation and quality prediction is being conducted. Even for GMAW, many researchers have attempted to predict quality through X-ray, current, and voltage measurements. If judgment in real time is not necessary, it is most effective to judge the quality of a welded part using an exterior image. Therefore, in this study, a welded appearance quality judgment model was analyzed using image deep learning. Welding defects were classified into pores, overlaps, craters, melting of the base material, cracks, and undercuts, and were divided into 7 categories including normal ones. In constructing the deep-learning model, transfer learning was performed using existing networks, such as ResNet and AlexNet. To improve the accuracy of deep learning, tests were performed while the optimization technique, maximum number of epochs, and minibatch size were changed. It was confirmed that the accuracy of weld defect prediction improved as the minibatch size increased, and the stochastic gradient descent model had the highest accuracy. Increasing the number of data for learning should make the technique of using images to judge the quality of GMAW welds using the proposed model more widely applicable.

Key Words: Weld quality, Weld appearance, Deep learning, CNN (Convolution Neural Network), ResNet

1. Introduction

Machine learning (deep learning) is being utilized in a variety of industries. It is being applied to autonomous cars as a way to distinguish between objects, as well as to medical devices, games, color restoration, and the creation of new objects. In production and manufacturing, machine learning is being used to automate processes, inspect quality, and ensure user safety. Among the many different methods of applying machine learning, deep learning is widely used in machine learning using time series data measured by sensors, machine learning through pre-processing of measured data, and processes that use images to inspect quality or automation processes.

Likewise, there are many applications of machine learning and deep learning in the field of welding[1–3]: shape extraction from laser vision sensing images[4], weld line tracking using laser sensors[5], quality and weld line tracking using image sensors[6], weld line tracking through time series data analysis[7], and quality prediction through analysis of acoustic signals[8]. J. H. Kim et al. developed an algorithm to judge the quality of a welded part by learning the resistance in resistance spot welding[9]. T. W. Kim et al. verified the possibility of utilizing deep learning for non-destructive welding quality inspection by applying it to quality judgment in the joining technology of Al-Cu dissimilar materials using green laser[10]. H. Deng et al. developed a deep learning model to detect defects through image pre-processing in asymmetric laser welding images[11].

As shown in the above examples, there are many application cases of deep learning in welding for quality judgment and automation. Moreover, deep learning has been applied to the gas metal arc welding (GMAW) process. M. S. Kim et al. proposed a deep learning model for judging the formation of backbead in GMAW[12]. R. T. Martinez et al. developed a deep learning technique for predicting the shape of GMAW welded parts[13]. S. Q. Moinuddin et al. suggested an algorithm to predict weld defects based on current and voltage data in GMAW process[14]. S. Shin et al. presented a deep learning method to predict pores after measuring current and voltage data in real time[15]. H. Zhu et al. performed image classification for pores, spatter, and overlap by monochromatizing images[16]. Furthermore, there are various methods to apply deep learning for quality judgment, such as analyzing defects by capturing X-ray images[17,18].

There are many studies on quality prediction in GMAW, but there is a lack of papers related to appearance quality. Moreover, there are papers that analyze weld defects, but they do not cover various defects. In addition, in the case of actual welded part images, there are many changes in the image depending on the lighting, curved welded part, slag, and shooting angle. This makes it difficult to predict the quality. As a result, most industrial sites are performing visual quality inspection. Therefore, to automate the inspection of external quality of welded parts in this study, image data of defective and normal parts of weld appearance were obtained and labeled, and deep learning algorithms were applied to predict the quality. Here, the hidden layer was constructed through transfer learning, and the accuracy of deep learning was analyzed by applying multiple models. Finally, the best model was selected and a proposal was made to improve the accuracy of weld defect judgment.

2. Experimental Method

First of all, the welded part was photographed to secure a database for judging the quality of the welded part. Fillet welding was performed using the IGM welding robot, and a wide bead width was secured by weaving. Based on the weld appearance photos, the algorithm for judging the welding quality was configured as shown in Fig. 1. Fig. 1(a) shows the images of six types of weld defects: pores, base metal greening, undercut, overlap, crack, and crater. These were categorized into seven categories, including the normal weld

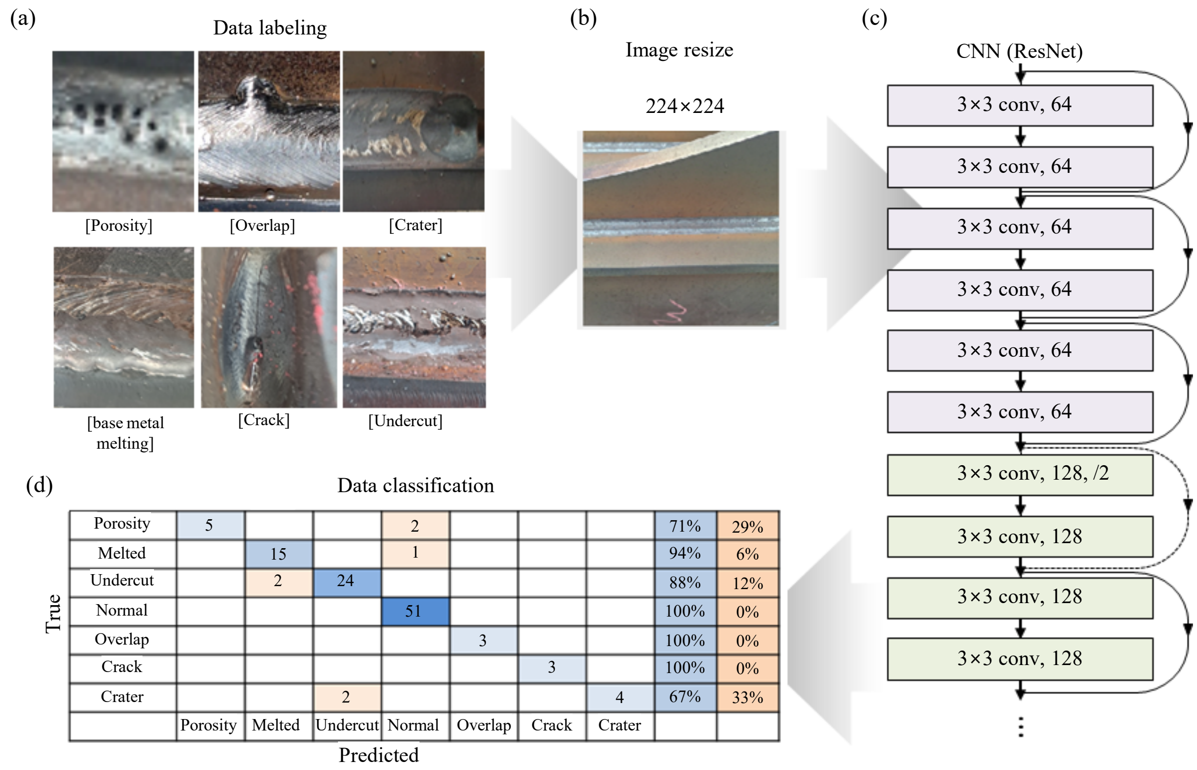


Fig. 1 Weld defect prediction deep learning algorithm workflow (a) Weld defect image and categories, (b) Image resizing for application in transfer learning, (c) Part of CNN based ResNet 101, (d) Predicted test data confusion chart based on the trained model

condition. As shown in Fig. 1(b), the size of the images was varied to apply transfer learning. As shown in Fig. 1(c), a convolutional neural network (CNN) was used to predict the welded part quality, and the data was trained using transfer learning. The existing models for transfer learning are Alexnet and ResNet101. In Fig. 1(c), only ResNet is representative. AlexNet is a CNN architecture with a total of 8 layers, including 5 convolutional layers and 3 fully connected layers. ResNet is also a CNN architecture and consists of blocks with multiple convolutional layers and connections that bypass the convolutional layers. ResNet's bypassing connections allow it to train a much deeper network without suffering from the gradient vanishing problem that is common in deep neural networks. Finally, the performance of the classification model was evaluated after testing with the trained model as shown in Fig. 1(d). All data trainings were performed using Matlab. As shown in Table 1, the optimization algorithms used were Adam, Rmsprop, and SGDM. Among the optimization algorithms, Gradient Descent (GD) is a time-consuming method that calculates the gradient of the loss function in all directions and then updates the data in the direction with the highest gradient.

To improve the GD, the Gradient Descent (SGD) method was created, which uses probabilistic calculations to learn, and is faster. However, it moves in a random direction, which causes oscillations when learning. To improve this, the Stochastic Gradient Descent with Momentum (SGDM) method was proposed, which adds momentum. This method avoids oscillations by learning with inertia in the direction of the gradient of the previously moved loss function. While SGDM can be faster to learn, it can sometimes slow down training because it can lead to many trainings in the wrong direction. The Root Mean Square Propagation (RMSprop) is similarly trained by adjusting the learning rate based on the average of the gradient magnitudes of the loss functions executed to reduce oscillations, an issue with SGD. Adaptive Moment Estimation (Adam) combines the ideas of RMSprop and SGDM and adjusts the learning rate based on moment estimation. It is computationally efficient and is most commonly used for high-dimensional parameter spaces.

Table 1 Deep learning parameter settings for welding defect detection

Parameter		Input value
Initial learning rate	Optimization algorithm: Adam	0.001
	Optimization algorithm: RMSprop	0.001
	Optimization algorithm: SGDM	0.01
Mini-batch size		64, 128
Max epoch		10, 30
Data		Train: 70%, Test 30%

The performances of the classification models were compared by varying some of the parameters required for training. The tests were conducted by varying the minibatch size and epoch. The minibatch size was set to 64 and 128 because it is recommended to use powers of 2, which is the unit of bits. The epoch was set to a maximum of 30, as there is a problem with overfitting if the epoch is too large. The minimum was set to 10 to avoid stopping when the training was not complete. We shuffled all the training data randomly after each epoch to prevent overfitting. In total, 380 images were taken, with 70% of them used for training and 30% for testing.

3. Experiment Results

The results of training with the weld defect photos were expressed in a confusion chart as shown in Fig. 2. The confusion chart is shown in Fig. 2. The results of correctly predicting the defective or normal parts are colored in blue, and the incorrect results are colored in red. Parts with a large amount of data in the corresponding cells are expressed in darker colors. For cracks, craters, and overlaps, not much data was obtained because such defects rarely occur. The transfer learning model was ResNet101, and the optimization technique was Adam. Fig. 2 shows the variation of accuracy with the maximum number of epoxies and minibatch size. It can be seen that the accuracy improves more when the minibatch size is larger. Similarly, it can be seen that increasing the maximum number of epoxies to 30 improves the accuracy for the test data. Since increasing the epoch further would likely result in overfitting, we did not further train the model by increasing the maximum epoch. When using Adam to predict weld defects, the minibatch size of 128 and the maximum epoch of 30 resulted in the most accurate prediction at 90.2%.

Similar to the above methods, the prediction accuracy of the optimization method was checked. The optimization techniques used were SGDM, which is supported by Matlab, RMSprop, and Adam. Fig. 3 shows the changes of the loss as the epoch increased. RMSprop showed the largest loss, while the SGDM method had the smallest loss. For SGDM and Adam, the loss decreased sharply when the epoch was above 10.

As the epoch increased, the loss decreased and the accuracy improved. However, RMSprop showed an in-

■ Adam, Maxepoch: 10, MiniBatchSize: 64 ➡ accuracy: 83.93%

True

Porosity	6						1	86%	14%
Melted		14		1				93%	7%
Undercut			26					100%	0%
Normal	2	1	3	44			1	86%	14%
Overlap				1	1		1	33%	67%
Crack		1	1				1	0%	100%
Crater	2		1				3	50%	50%
	Porosity	Melted	Undercut	Normal	Overlap	Crack	Crater		

Predicted

■ Adam, Maxepoch: 10, MiniBatchSize: 128 ➡ accuracy: 88.4%

True

Porosity	7							100%	0%
Melted		14		2				88%	12%
Undercut	2		21	3				81%	19%
Normal	1	3		47				92%	8%
Overlap					3			100%	0%
Crack						3		100%	0%
Crater		1	1				4	67%	33%
	Porosity	Melted	Undercut	Normal	Overlap	Crack	Crater		

Predicted

■ Adam, Maxepoch: 30, MiniBatchSize: 64 ➡ accuracy: 87.5%

True

Porosity	7							100%	0%
Melted		14	1	1				88%	12%
Undercut			26					100%	0%
Normal			1	48	2			94%	6%
Overlap			1	2				0%	100%
Crack						3		100%	0%
Crater		3	2	1				0%	100%
	Porosity	Melted	Undercut	Normal	Overlap	Crack	Crater		

Predicted

■ Adam, Maxepoch: 30, MiniBatchSize: 128 ➡ accuracy: 90.2%

True

Porosity	4	1	2					57%	43%
Melted		15		1				94%	6%
Undercut			24	2				92%	8%
Normal		1		50				98%	2%
Overlap					1			100%	0%
Crack						3		100%	0%
Crater			2				4	67%	33%
	Porosity	Melted	Undercut	Normal	Overlap	Crack	Crater		

Predicted

Fig. 2 Confusion chart of predicted results according to changes in max epoch and batch size

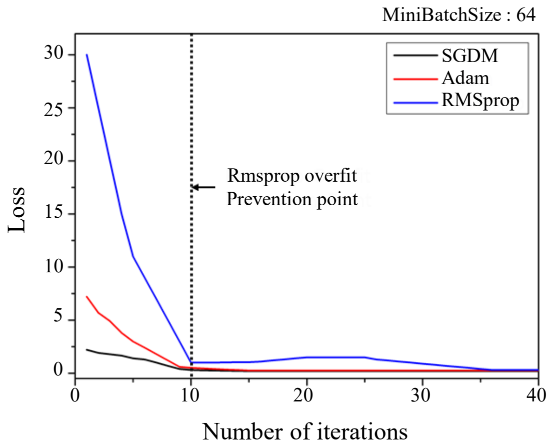


Fig. 3 Graph of loss change according to optimization technique

crease in loss when the epoch is higher than 10, indicating that the possibility of overfitting. Therefore, the prediction accuracy was compared for the case of 10 epoch. The prediction accuracy for the test data is shown in Fig. 4. The prediction accuracy of Adam in comparison to SGDM and RMSprop is shown in Fig. 2. SGDM, the optimization technique with the smallest loss shown in Fig. 3, had the highest accuracy of about 93%. Similar to the above methods, the transfer learning model was tested using Alexnet instead of ResNet101.

The results are shown in Fig. 5, which shows a slight increase in accuracy over ResNet. Finally, a comparison graph for all results is shown in Fig. 6. Fig. 6(a) shows that the optimization technique using SGDM has the highest prediction accuracy, and RMSprop has the lowest accuracy. Fig. 6(b) shows that increasing the minibatch size and the number of epoxies contributes to the accuracy improvement. However, randomly increasing the number of epoxies can reduce the accuracy of the validation data due to overfitting. Using all the previous processes, it was determined that the current SGDM model is the most accurate at 92%. Based on this, we checked the test model and obtained the results shown in Fig. 7. Fig. 7(a) shows 100% probability of base material melting. Similarly, Fig. 7(b) shows a 36.5% probability of a crater, which is not an accurate prediction. However, the probability of a crater is greater than that of any other defect, so it was predicted to be a crater. Similarly, the prediction accuracy is over 90% in Fig. 7(c) and (d). Currently, the amount of data is not large enough to obtain perfect prediction results,

■ SGDM, Maxepoch: 10, MiniBatchSize: 64 ➡ accuracy: 93.75%

True \ Predicted	Porosity	Melted	Undercut	Normal	Overlap	Crack	Crater		
Porosity	5			2				71%	29%
Melted		15		1				94%	6%
Undercut		2	24					88%	12%
Normal				51				100%	0%
Overlap					3			100%	0%
Crack						3		100%	0%
Crater			2				4	67%	33%

■ RmsProp, Maxepoch: 10, MiniBatchSize: 64 ➡ accuracy: 57.14%

True \ Predicted	Porosity	Melted	Undercut	Normal	Overlap	Crack	Crater		
Porosity			3	4				0%	100%
Melted		4	6	6				25%	75%
Undercut		1	18	7				69%	31%
Normal		3	6	42				82%	18%
Overlap		1	2					0%	100%
Crack			3					0%	100%
Crater			2	4				0%	100%

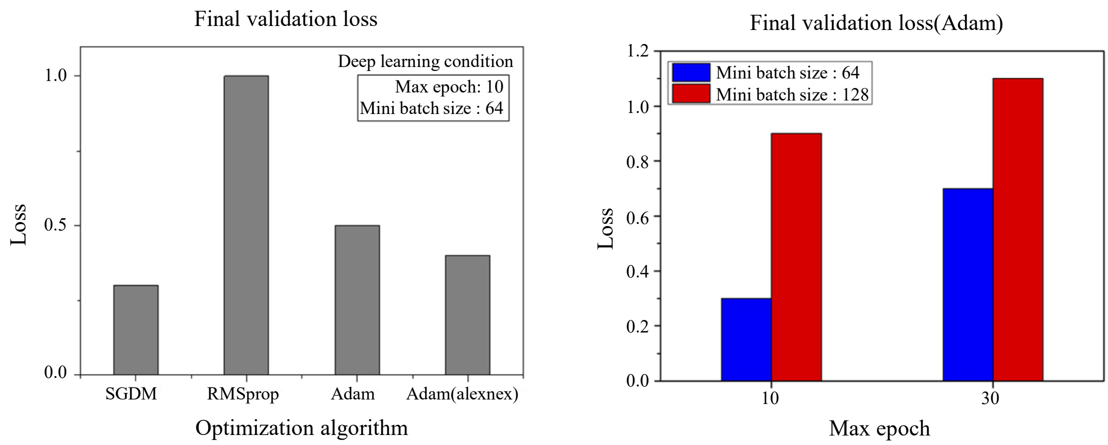
Fig. 4 Confusion chart of prediction results by optimization method

■ Alexnet, Adam, Maxepoch: 10, MiniBatchSize: 64 ➡ accuracy: 85.71%

True									
Porosity	4		1	2				57%	43%
Melted		15	1					94%	6%
Undercut			24	2				92%	8%
Normal		5	1	44	1			86%	14%
Overlap			1		2			67%	33%
Crack						3		100%	0%
Crater			2				4	67%	33%
	Porosity	Melted	Undercut	Normal	Overlap	Crack	Crater		

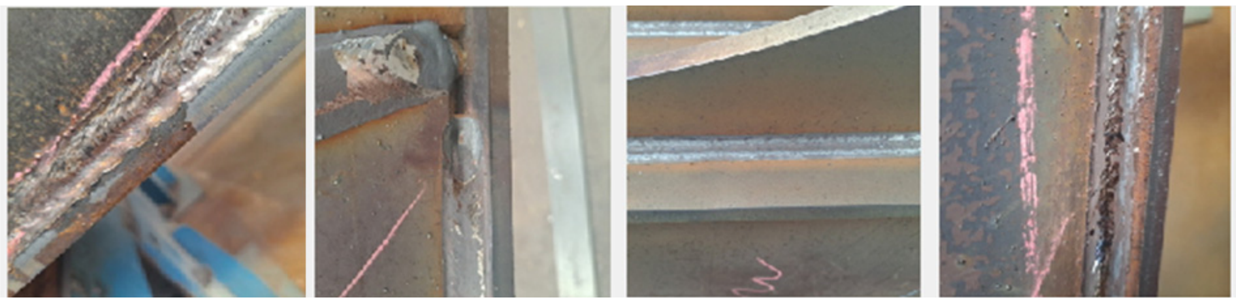
Predicted

Fig. 5 Confusion chart of prediction results by transfer network



(a) (b)

Fig. 6 Loss change graph according to deep learning conditions (a) Loss change according to optimization technique, (b) Loss change according to maximum epoch and mini-batch size



(a) Base metal melting, 100% (b) Crater, 36.8% (c) Normal, 94.5% (d) Undercut, 99.5%

Fig. 7 Weld defect prediction results and probability for test data (a) 100% probability of base metal melting, (b) The probability of being a crater is 36.8%, which is the most probable state compared to other defects, (c) 94.5% chance of being normal, (d) 99.9% chance of undercut

but the prediction accuracy will improve when the amount of data is sufficient.

4. Conclusions

A deep learning algorithm was built to determine the appearance quality of fillet welded parts used in industrial sites. Images of normal and defective parts of fillet welded parts were obtained and labeled. The algorithm was trained to recognize a total of six types of defects in the welded parts: pores, overlaps, cracks, undercuts, base metal melting, and craters. The hidden layer of deep learning was constructed through transfer learning, and the existing models ResNet 101 and Alexnet were used. Tests were conducted by varying the optimization technique, maximum epoch number, and minibatch size to improve the accuracy of deep learning. The results showed that the larger the minibatch size, the better the weld defect prediction accuracy. The accuracy of the validation model was higher at 30 than at 10, and the SGDM model showed the highest accuracy among the optimization techniques when the maximum epoch was 10.

In this study, we proposed a deep learning model for determining the appearance quality of welded parts. The SGDM model showed the best results, and the accuracy of weld defect judgment could be improved through various optimization techniques and changes in learning variables. However, the analysis of the results was insufficient due to a lack of publicly available images or data for weld defects. In the future, we plan to improve the accuracy of defect judgment by securing a large amount of data.

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전이학습을 이용한 용접부 외관 품질 판단 딥러닝 알고리즘 개발에 관한 연구

A Study on the Development of Deep Learning Algorithm for Determining External Quality of Welded Parts Using Transfer Learning

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1. 서 론

최근 다양한 산업분야에서 기계학습(딥러닝)이 많이 활용되고 있는데, 자율주행 자동차에서 사물을 구분하는 방법으로 적용하거나 의료기기, 게임, 색복원, 새로운 개체를 생성하는 방법 등에서 다양하게 응용되고 있다. 생산 및 제조 공정에서는 공정 자동화, 품질 검사, 사용자 안전 확보 등에 적용하기 위해 기계학습이 많이 이용되고 있다. 기계학습을 적용하기 위한 다양한 방법으로, 센서로 측정되는 시계열 데이터를 이용하는 머신러닝, 측정된 데이터의 전처리를 통한 머신러닝, 이미지를 활용하여 품질을 검사하거나 자동화하는 공정 등에 딥러닝이 많이 이용되고 있다.

이와 마찬가지로 용접 분야에서도 머신러닝과 딥러닝이 많이 응용되고 있다[1-3]. 레이저 비전센싱 이미지에서의 형상 추출[4], 레이저센서를 이용한 용접선 추적[5], 이미지 센서를 이용한 품질 및 용접선 추적[6], 시계열 데이터 분석을 통한 용접선 추적[7], 음향 신호의 분석을 통한 품질 예측[8]. 등 다양하게 응용되고 있다. Kim 등은 저항점용접에서의 저항을 학습하여 용접부의 품질을 판단하는 알고리즘을 개발하였다[9]. Kim 등은 그린레이저를 이용한 Al-Cu 이종소재의 접합기술에서 품질 판정에 딥러닝을 접목하여 비파괴 용접 품질검사에 활용 가능성을 확인하였다[10]. Deng 등은 비대칭 레이저 용접 영상에서의 이미지 전처리를 통해 결함을 검출하는 딥러닝 모델을 개발하였다[11].

위와 같이 용접에서 품질 판단, 자동화를 위해 딥러닝이 적용된 사례가 많이 존재한다. 그리고 GMAW공정에도 딥러닝이 많이 적용되고 있다. Kim 등은 GMAW에서 백비드의 형성 유무를 판단하기 위한 딥러닝 모델을 제시하였다[12]. Martinez 등은 GMAW 용접부 형상을 예측하기 위한 딥러닝 기술을 개발하였다[13]. Moinuddin 등은 GMAW 공정에서 전류, 전압 데이터를 바탕으로 용접부 결함을 예측하는 알고리즘을 제시하였다[14]. Shin 등은 실시간으로 전류, 전압 데이터를 측정한 후 기공을 예측하는 딥러닝 방법을 제시하였다[15]. Zhu 등은 이미지를 흑백화 하여 기공, 스패터, 오버랩에 대한 이미지 분류를 수행하였다[16]. 이 외에 X-ray 이미지를 촬영하여 결함을 분석하는 등 품질 판단을 위해 딥러닝을 적용하는 다양한 방법이 존재한다[17,18].

GMAW에서의 품질 예측을 위한 연구는 많이 수행되고 있으나 외관 품질과 관련된 논문은 부족하다. 또한 용접부 결함에 대해 분석한 논문은 존재하지만 다양한 결함에 대해 다루지 못하였다. 그리고 실제 용접부 이미지의 경우 조명, 곡선형태의 용접부, 슬래그, 촬영각도에 따라 이미지의 변화가 많이 발생하게되고 이런 현상에 의해 품질 예측이 어려운 경우가 많다. 그로 인해 대부분의 산업현장에서는 육안으로 품질검사를 진행하고 있다. 따라서, 본 연구에서는 용접부 외관품질 검사를 자동화하기 위해 용접부 외관의 결함과 정상 부분의 이미지 데이터를 확보하여 라벨링을 진행한 후 딥러닝 알고리즘을 적용하여 품질을 예측하고자 하였다. 이때 은닉층은 전이학습을 통해 구성을 하고 여러 모델을 적용하여 딥러닝 학습의 정확도를 분석하고자 하였다. 최종적으로 가장 우수한 모델을 선정하고 용접부 결함 판단 정확도를 높이기 위한 방안을 제시하고자 한다.

2. 실험 방법

먼저 용접부 품질 판단을 위한 데이터베이스를 확보

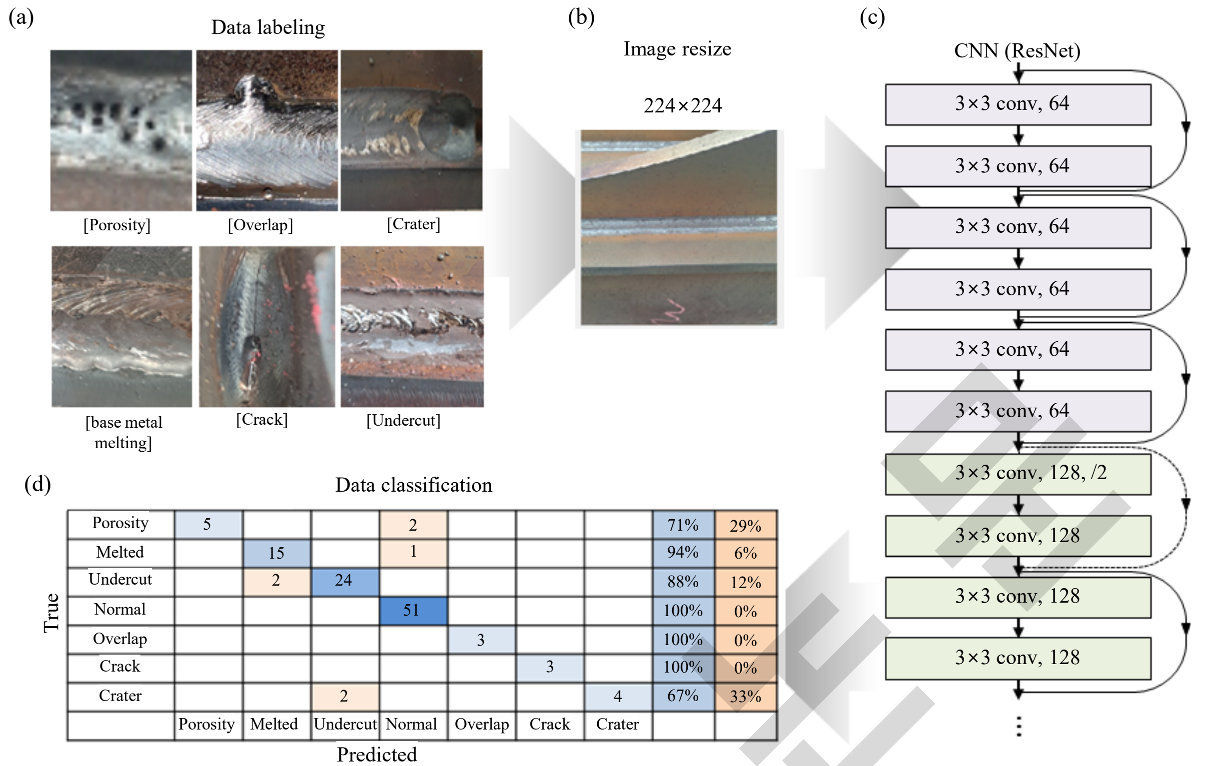


Fig. 1 Weld defect prediction deep learning algorithm workflow (a) Weld defect image and categories, (b) Image resizing for application in transfer learning, (c) Part of CNN based ResNet 101, (d) Predicted test data confusion chart based on the trained model

하기 위해 용접부를 촬영하였다. IGM 용접 로봇을 이용하여 필렛용접을 진행하였으며 위빙을 통해 넓은 비드폭을 확보하였다. 용접 외관 사진을 바탕으로 용접 품질을 판단하는 알고리즘을 Fig. 1과 같이 구성하였다. Fig. 1(a)와 같이 용접 결함은 기공, 모재녹음, 언더컷, 오버랩, 크랙, 크레이터로 총 6가지 결함에 대한 이미지를 확보하였으며 정상 용접 상태를 포함하여 총 7가지 카테고리로 분류하였다. Fig. 1(b)와 같이 전이학습에 적용하기 위해 이미지의 크기를 변화시켰다. Fig. 1(c)와 같이 용접부 품질을 예측하기 위해 CNN (Convolution neural network)을 이용하였으며 전이학습(transfer learning)을 이용하여 데이터를 학습을 진행하였다. 전이학습을 위한 기존의 모델은 Alexnet과 ResNet101을 이용하였으며 Fig. 1(c)에서는 대표적으로 ResNet만 표현하였다. AlexNet은 심층 컨볼루션 신경망(CNN) 아키텍처로 5개의 컨볼루션 레이어와 3개의 완전 연결 레이어를 포함해 총 8개의 레이어로 구성되어있다. ResNet은 또한 CNN 아키텍처로 여러개의 컨볼루션 레이어와 컨볼루션 레이어를 우회하는 연결이 포함된 블록으로 구성되어 있다. ResNet의 우회하는 연결을 사용하면 심층 신경망에서 흔히 발생하는 기울기 소실 문제 없이 훨씬 더 깊은 네트워크를 훈련할 수 있다. 최종적으로 Fig. 1(d)와 같이 학습된 모델을 이용하여 테스트한 후 분류 모델의 성능 평가를 진행하였다.

모든 데이터의 학습은 매트랩을 이용하여 진행하였다. Table 1에서 보는 바와 같이 최적화 알고리즘은 Adam, Rmsprop, SGDM 방법을 이용하였다. 최적화 알고리즘 중 GD (Gradient descent)는 경사하강법으로 손실 함수의 모든 방향으로의 기울기를 계산한 후 가장 기울기가 높은 방향으로 데이터를 업데이트 하는 방식으로 시간이 오래 걸리는 방식이다. 이를 개선하기 위해 확률적인 계산을 통해 학습을 하는 SGD

Table 1 Deep learning parameter settings for welding defect detection

Parameter		Input value
Initial learning rate	Optimization algorithm: Adam	0.001
	Optimization algorithm: RMSprop	0.001
	Optimization algorithm: SGDM	0.01
Mini-batch size		64, 128
Max epoch		10, 30
Data		Train: 70%, Test 30%

■ Adam, Maxepoch: 10, MiniBatchSize: 64 ➡ accuracy: 83.93%

True	Porosity	Melted	Undercut	Normal	Overlap	Crack	Crater		
Porosity	6						1	86%	14%
Melted		14		1				93%	7%
Undercut			26					100%	0%
Normal	2	1	3	44			1	86%	14%
Overlap				1	1		1	33%	67%
Crack		1	1				1	0%	100%
Crater	2		1				3	50%	50%

Predicted

■ Adam, Maxepoch: 10, MiniBatchSize: 128 ➡ accuracy: 88.4%

True	Porosity	Melted	Undercut	Normal	Overlap	Crack	Crater		
Porosity	7							100%	0%
Melted		14		2				88%	12%
Undercut	2		21	3				81%	19%
Normal	1	3		47				92%	8%
Overlap					3			100%	0%
Crack						3		100%	0%
Crater		1	1				4	67%	33%

Predicted

■ Adam, Maxepoch: 30, MiniBatchSize: 64 ➡ accuracy: 87.5%

True	Porosity	Melted	Undercut	Normal	Overlap	Crack	Crater		
Porosity	7							100%	0%
Melted		14	1	1				88%	12%
Undercut			26					100%	0%
Normal			1	48	2			94%	6%
Overlap			1	2				0%	100%
Crack						3		100%	0%
Crater		3	2	1				0%	100%

Predicted

■ Adam, Maxepoch: 30, MiniBatchSize: 128 ➡ accuracy: 90.2%

True	Porosity	Melted	Undercut	Normal	Overlap	Crack	Crater		
Porosity	4	1	2					57%	43%
Melted		15		1				94%	6%
Undercut			24	2				92%	8%
Normal		1		50				98%	2%
Overlap					1			100%	0%
Crack						3		100%	0%
Crater			2				4	67%	33%

Predicted

Fig. 2 Confusion chart of predicted results according to changes in max epoch and batch size

(Stochastic gradient descent) 방식이 만들어졌으며 속도가 빨라지는 효과가 있다. 하지만 이는 랜덤한 방향으로 움직이다 보니 학습할 때 진동하는 현상이 나타나기 때문에 이를 개선하기 위해 Momentum을 추가한 SGDM (Stochastic Gradient Descent with Momentum)방법이 나왔으며 이는 이전에 움직였던 손실함수의 기울기 방향으로 관성을 줘 학습하는 방식으로 진동하는 현상을 피할 수 있는 방식이다. SGDM은 학습 속도가 빨라질 수 있으나 잘못된 방향으로의 학습이 많이 될 수 있기 때문에 학습을 늦게하는 경우가 있습니다. RMSprop (Root mean square propagation) 역시 마찬가지로 SGD에서 발생하는 문제점인 진동을 줄이기 위해 실행된 손실함수의 기울기 크기 평균을 기반으로 학습률을 조정하며학습하는 방식으로 구성되었다. Adam (Adaptive moment estimation)은 RMSprop과 SGDM의 아이디어를 합친 방식으로 모멘트의 추정치를 기반으로 학습속도를 조정하는 방식이다. 이는 계산효율이 뛰어나며 고차원 매개변수 공간에 적합한 방식으로 가장 많이 활용되는 방식이다.

학습 시 필요한 변수들 중 일부를 변경하며 분류모델의 성능을 비교하였다. 미니배치 사이즈와 에폭(epoch)을 변경하며 테스트를 진행하였으며 미니배치 사이즈의 경우 비트의 단위인 2의 제곱수로 하는 것이 좋기 때문에 64, 128로 설정하였다. 에폭을 너무 크게 설정할 경우 과적합이 발생하는 문제가 있기 때문에 최대 30으로 설정하여 진행하였으며 학습이 다 되지 않았을 때 멈추지 않게 하기 위해 최소 10으로 설정하였다. 그리고 매 에폭마다 모든 훈련 데이터를 랜덤하게 섞는 방법을 이용하여 과적합을 방지하였다. 총 이미지는 380장을 촬영하였고 학습을 하기 위한 훈련 데이터를 70%, 테스트를 위한 데이터는 30%로 구성하였다.

3. 실험 결과

용접부 결합 사진을 바탕으로 학습 한 결과를 Fig. 2와 같이 confusion chart로 표현하였다. 결함 또는 정상인 부분과 동일하게 예측한 결과는 파란색, 틀린 경우는 빨간색으로 표시하였다. 해당되는 셀의 데이터의 수가 많은 부분은 진한 색으로 표현하였다. 크랙, 크레이터, 오버랩의 경우 결함이 발생하는 경우가 거의 없기 때문에 많은 데이터를 확보하지 못하였다. 전이학습 모델은 ResNet101을 이용하였으며 최적화 기법은 Adam을 이용하였다. Fig. 2는 최대 에폭 수와 미니배치 사이즈에 따라 변하는 정확도의 변화를 확인하였다. 미니배치 사이즈가 크면 정확도가 더 향상되는 것을 확인할 수 있다. 마찬가지로 최대 에폭을 30으로 증가시켰을 때 테스트 데이터에 대한 정확도가 더 향상되는 것을 확인할 수 있다. 에폭을 더 증가시킬 경우 과적합이 될 가능성이 크기 때문에 최대 에폭을 늘려 더 학습을 진행하지 않았다. Adam을 이용하여 용접부 결함을 예측하는 경우 미니배치 사이즈는 128, 최대 에폭은 30으로 한 결과의 예측정확도가 90.2%로 가장 정확하게 나타났다.

위 방법과 마찬가지로 최적화 기법에 따른 예측 정확도를 확인하였다. 최적화 기법은 매트랩에서 지원하는 SGDM, RMSprop, Adam을 이용하였다. Fig. 3은 에폭이 증가함에 따라 변하는 손실(Loss)의 변화를 보여주고 있다. RMSprop의 손실이 가장 크게 나타났으며 SGDM 방법이 가장 손실이 작게 나타났다. SGDM와 Adam의 경우 에폭이 10 이상일 때 손실이 감소하는 폭이 급격히 줄어들었다.

에폭이 증가함에 따라 손실이 감소하며 정확도가 향상되지만 RMSprop은 에폭이 10보다 높을 때 손실이 증가하는 것을 확인할 수 있어 과적합이 되었을 가능성이 있음을 알 수 있다. 따라서 에폭이 10일 경우에 대해 예측정확도를 비교하였으며 테스트 데이터에 대한 예측 정확도는 Fig. 4와 같이 나타내었다. Adam의 경우 Fig. 2에 표현이 되어있으며 SGDM, RMSprop에 대해 나타내었다. Fig. 3에서 나타난 손실이 가장 작은 최적화 기법인 SGDM가 정확도가 약 93%로 가장 높게 나타났다. 위 방법들과 유사하게 전이학습 모델을 ResNet101이 아닌 Alexnet을 이용하여 테스트를 수행하였다.

그 결과 Fig. 5와 같이 나타났으며 ResNet보다 정확도가 약간 상승하는 것을 확인할 수 있다. 마지막으로 모든 결과에 대해 비교하는 그래프를 Fig. 6에 표현하였다. Fig. 6(a)에서 보는바와 같이 최적화 기법은 SGDM를 사용하는 것이 예측 정확도가 높게 나타

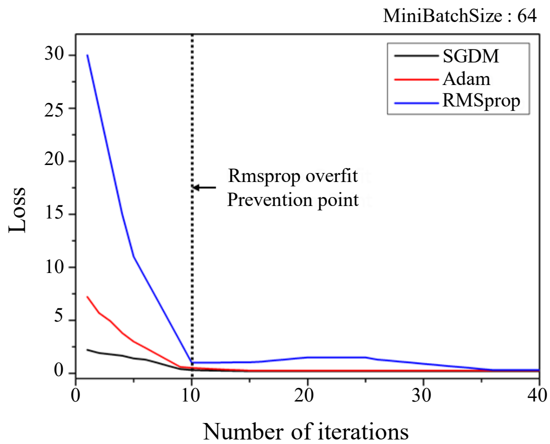


Fig. 3 Graph of loss change according to optimization technique

■ SGDM, Maxepoch: 10, MiniBatchSize: 64 ➡ accuracy: 93.75%

Porosity	5			2				71%	29%
Melted		15		1				94%	6%
Undercut		2	24					88%	12%
Normal				51				100%	0%
Overlap					3			100%	0%
Crack						3		100%	0%
Crater			2				4	67%	33%
	Porosity	Melted	Undercut	Normal	Overlap	Crack	Crater		

True

Predicted

■ RmsProp, Maxepoch: 10, MiniBatchSize: 64 ➡ accuracy: 57.14%

Porosity			3	4				0%	100%
Melted		4	6	6				25%	75%
Undercut		1	18	7				69%	31%
Normal		3	6	42				82%	18%
Overlap		1	2					0%	100%
Crack			3					0%	100%
Crater			2	4				0%	100%
	Porosity	Melted	Undercut	Normal	Overlap	Crack	Crater		

True

Predicted

Fig. 4 Confusion chart of prediction results by optimization method

■ Alexnet, Adam, Maxepoch: 10, MiniBatchSize: 64 ➡ accuracy: 85.71%

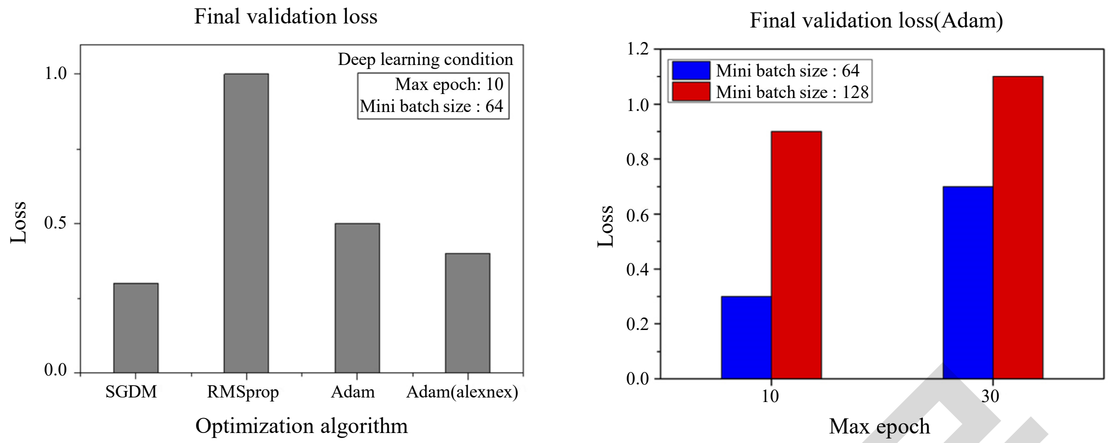
Porosity	4		1	2				57%	43%
Melted		15	1					94%	6%
Undercut			24	2				92%	8%
Normal		5	1	44	1			86%	14%
Overlap			1		2			67%	33%
Crack						3		100%	0%
Crater			2				4	67%	33%
	Porosity	Melted	Undercut	Normal	Overlap	Crack	Crater		

True

Predicted

Fig. 5 Confusion chart of prediction results by transfer network

났으며 RMSprop을 이용하는 것이 가장 정확도가 떨어지는 것을 확인할 수 있다. 그리고 Fig. 6(b)에서 보는바와 같이 미니배치 사이즈와 에폭수를 늘리는 것이 정확도 향상에 기여하는 것을 확인할 수 있다. 하지만, 무작정 에폭수를 늘리는 것은 과적합에 의해 검증 데이터의 정확도를 떨어뜨릴 수 있다. 앞의 모든 공정을 이용하여 판단한 결과 현재 SGDM 모델이 92%로 가장 정확하게 나왔으며 이를 바탕으로 테스트 모델을 확인한 결과 Fig. 7과 같은 결과를 얻었다. Fig. 7(a)는 모재가 녹았을 확률이 100%라는 것을 나타낸다. 이와 마찬가지로 Fig. 7(b)는 크레이터일 확률이 36.5%라는 것을 나타내며 정확한 예측은 아니다. 하지만 다른 결함일 확률보다 크레이터일 확률이 가장 크기 때문에 크레이터로 예측하였다. Fig. 7(c), (d)에서도 마



(a) (b)

Fig. 6 Loss change graph according to deep learning conditions (a) Loss change according to optimization technique, (b) Loss change according to maximum epoch and mini-batch size

(a) Base metal melting, 100% (b) Crater, 36.8% (c) Normal, 94.5% (d) Undercut, 99.5%

Fig. 7 Weld defect prediction results and probability for test data (a) 100% probability of base metal melting, (b) The probability of being a crater is 36.8%, which is the most probable state compared to other defects, (c) 94.5% chance of being normal, (d) 99.9% chance of undercut

찬가지로 예측 정확도가 90% 이상인 것을 확인할 수 있다. 따라서, 현재 데이터의 양이 많지 않아 완벽한 예측 결과를 얻지 못하였지만 데이터의 양이 충분할 경우 예측 정확도가 향상될 것으로 생각된다.

4. 결 론

산업현장에서 사용되는 필렛 용접부의 외관 품질을 판단하기 위한 딥러닝 알고리즘을 구축하였다. 필렛 용접부의 정상부분과 결함부분의 이미지를 확보한 후 라벨링을 진행하였다. 용접부의 기공, 오버랩, 크랙, 언더컷, 모재녹음, 크래이터로 총 6가지의 결함에 대해서 판단하도록 하는 학습을 진행하였다. 딥러닝의 은닉층은 전이학습을 통해 구성하였으며 기존의 모델인 ResNet 101과 Alexnet을 이용하였다. 딥러닝 학습 정확도 향상을 위해 최적화 기법, 최대 에폭수, 미니배치사이즈를 변화시키며 테스트를 수행하였다. 그 결과, 미니배치사이즈가 클수록 용접부 결함 예측 정학도가 향상하는 것을 확인할 수 있었다. 에폭수가 10일 때 보다 30일 때 검증 모델의 정확도가 높으며 최대 에폭이 10일 때 최적화 방법 중 SGDM 모델이 가장 정확도가 높게 나타났다.

본 논문에서는 용접부의 외관 품질을 판단하기 위한 딥러닝 모델을 제시하였다. SGDM모델이 가장 우수한 결과를 나타내었으며 다양한 최적화 기법과 학습 변수의 변화를 통해 용접부 결함 판단 정확도를 향상시킬 수 있었다. 용접부 결함의 경우 공개된 이미지 또는 데이터가 부족하여 결과 분석 역시 부족한 점이 있지만 향후 많은 양의 데이터 확보를 통해 결함 판단 정확도을 개선할 예정이다.

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