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Towards an automatic classification of welding defect by convolutional neural network and robot classifier

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ABSTRACT

The control process of welding requires manual operations, and this consumes time. Robot classifier can help by automatic detection of welding defect and by taking rapid actions to correct in situ the defect. This paper presents a convolutional neural network (CNN) model developed to classify the welding defect like splash, twisty, overlap, edge and copper adhesion based on machine vision. Using a resistance spot welding (RSW) dataset the CNN model was trained and evaluated to achieve the best performance. The batch size was varied to quantify its effect on the precision of the model. The model can predict the type of welding surface by confidence of 99.86%.

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1. INTRODUCTION

Non-destructive Testing technics are recently more applied, especially in manufacturing thanks to their multiple advantages. To assess the integrity of a mechanical part, we can use multiple non destructive test (NDT) technics like ultrasonic [1]–[3] or radiographic images [4] which have been the most applied in Machine vision [5]. Welding is a process of joining two parts of metal (sometimes other materials) to form a strong and continuous bond. There are several different welding processes, each with its own characteristics, advantages, and limitations.

A welding defect refers to an undesirable quality or characteristics of a welded joint. Welding defects can arise due to various factors such as improper welding techniques, material issues, equipment problems, or environmental conditions. Detecting and addressing welding defects is crucial to ensure the integrity, strength, and safety of the welded components. Some common welding defects include:

– Porosity defect: it occurs when the weld metal contains the gas pockets or voids. This weakens the joint and this brings about structural integrity reduction. Incomplete penetration defect: it occurs when the joint does not full by the weld metal, resulting in a weak connection. This can be caused by inadequate welding parameters or improper joint preparation.
– Incomplete fusion: Incomplete fusion occurs when there is a lack of proper bonding between the weld metal and the base metal, leading to weak and unreliable joints.
– Undercutting: Undercutting is a groove that forms along the edge of the weld, typically due to heat increasing or bad choosing of the appropriate method. It leads to the weakness of the the joint and promote stress concentration.

- Overlap: overlapping happens when the joint bead does not properly insert with the base metal, resulting in a surface layer that is not securely attached.
- Cracks: it can happens in the zone of weld or the surrounding metal caused by the increasing of the stress, inappropriate preheating, or rapid cooling. Cracks can severely demonstrate the quality of the welding. Excessive heat affected zone (HAZ): Improper heat management can lead to an excessively large heat-affected zone, causing changes in material properties and potentially weakening the joint.
- Burn-through: Burn-through occurs when the welding process melts through the base metal, creating holes or voids. This can weaken the joint and lead to structural failure. To control the welded parts, many technics can be employed such as: visual or manual inspection, radiographic, ultrasonic testing [6], [7], control by eddy current, evaluating the defects is difficult due to fact that it requires an experimented operator, time consuming and subjective.

In our paper, we focus on six types of surface defect: twisty, splash; mutilation, overlap copper-adhesion and edge as presented in the Figure 1. We aim to develop a robot classifier in our project. The robot classifier [8], [9] will use the data set of differnts type of welding captured by the camera vision [10]. The robot will be propgarmed to put the scaned piece in the specified area depending on the detected type of defect. We focus fisrt on the development of the convolutional neural network (CNN) model.

Figure 1. Six Surface welding defects and normal surface welding (first image on the left)

The present article is organized as follows: in the first section, we introduce the type of welding defect. After that, a review of previous papers is conducted to list different classifiers of welding defect. The method and the model are presented in the next part. The proposed model is evaluated and discussed regarding the batch size parameter. In the last section, the robot classifier is used to capture the welding image. The validation of the prediction permit to verify the perofmormance of CNN model.

2. STATE OF THE ART

Previous works have been conducted to develop the welding defect classification. Liangliang in [11] has proposed a weld defect detection technic by designed wandering Gaussian. The authors in [12] have proposed an algorithm YOLOv5 to detect weld defect in steel pipe, and have discussed the two-stage representative object detection algorithm Faster R-CNN.

Others have shown that using machine-learning programs can also improve the precision of welding defect identification as reported in [13]–[18]. Many models have used logistic regression (LR), adaptive cascade boosting (AdaBoost), random forest (RF), k-N neighbor (k-NN), support vector machine (SVM) and neural network (NN). More than that, deep learning methods are more suitable at identification and classification of weld flaws in radiographic images. The Table 1 resumes some models developed to classify the welding defect.

Table 1. Welding defect classifiers

Reference	Model	Precision
Hou *et al*. [19]	deep neural network + sparse auto-encoders	90,27
Mery and Berty [20]	-	90,91%
Silva *et al.* [21]	ANN–Non linear	-
Kumar *et al*. [22]	ANN	86,1
Wang and Liao [23]	Multi-layer perceptron (MLP), fuzzy (K-NN)	-
Zapata [24], Vilar *et al.* [25]	Adaptive-network-based fuzzy inference system (ANFIS)	-
Naddaf and Zargaradeh [26]	VGG-16, VGG- 19, AlexNet, ResNet	96%
Thakkallapally [27]	VGG-19	91%
Valavanis and Kosmopoulos [28]	Sequentiel backward selection (SBS)	-
Yang and Jiang [29]	Unifed DNN	91,36%

More models have been developed to classify the welding defect. They are different in terms of architecture and thus they have a different accuracy. Choosing a suitable classifier is very important to ensure a best detection.

3. PROPOSED METHOD

The method as illustrated in Figure 2, is divide into three main steps, namely the data set preparation, training the model and evaluation. In the first step we collect the data. Data set is taken from resistance spot welding (RSW) datasets [30]. It includes information on seven types of welding surface: normal, splash, twisty, overlap, edge and copper adhesion. The data set file contains 7892 images with a size of 2.12 Go.

After that the pre-processing is carried out and finally the scaling the features by normalizing the input data between 0 and 1. In the second step, the model is trained by 80% of the data set and validated by 20%. The data set augmentation is applied in order to feed the model with all possible positions of the defect. At last, the obtained output is evaluated and the accuracy is calculated by varying the batch size. Four cases are considered, batch size equals to 10, 15, 20, and 25.

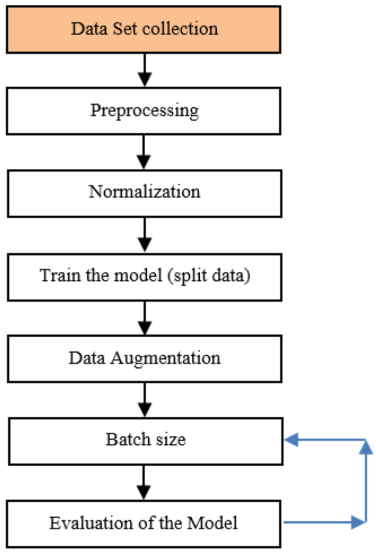


Figure 2. Methodology of the proposed model

4. MODEL

As illustrated in the Figure 3, the sequential model is constituted by three of convolutional blocs with layer of maximum pooling for each layer of convolution. The model is fully connected layers of size 128. The function of activation is Relu (1). The rectified linear units is a non-lineair function that equals:

$$ReLU = max(0, x) \tag{1}$$

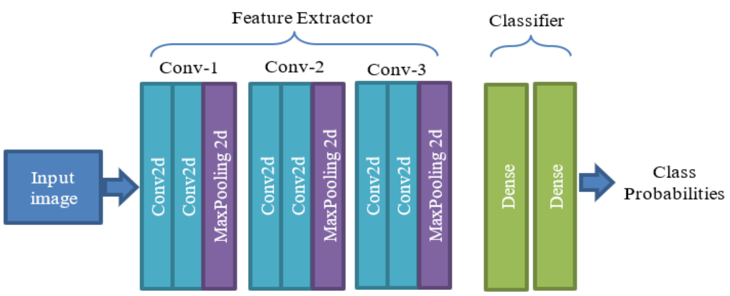


Figure 3. Architecture of CNN implemented model

5. RESULTS AND DISCUSSION
5.1. Data set augmentation
The model is fed by a random transformation of the images. This helps in increasing the performance of the model. The Figure 4 shows the increasing accuracy for two cases. The Figure 4(a) and Figure 4(b) illustrate the variation of the loss and the accuracy in the case of data augmentation. The Figure 4(c) and Figure 4(d) show the variation of loss and accuracy for non-augmented data. By comparing the two cases, we conclude that the augmented data allow increasing the accuracy.

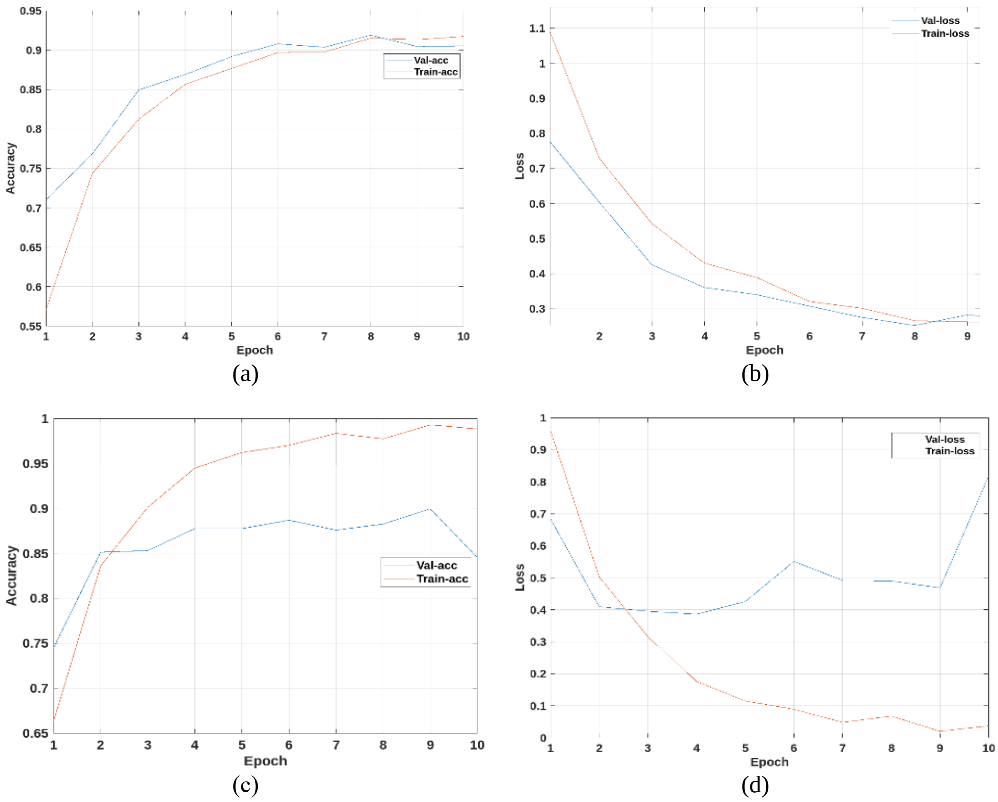


Figure 4. Learning curves of the proposed model; (a) and (b) for augmented data, (c) and (d) for non-augmented data

5.2. Effect of batch size on the model accuracy
To find the effect of the batch size on the performance of the model, we calculate the accuracy variation for different batch sizes. The Figure 5 presents the variation of validation accuracy for four cases of batch size. As shown in the figure, the validation accuracy does not depend on the batch size. The four curves are slightly different.

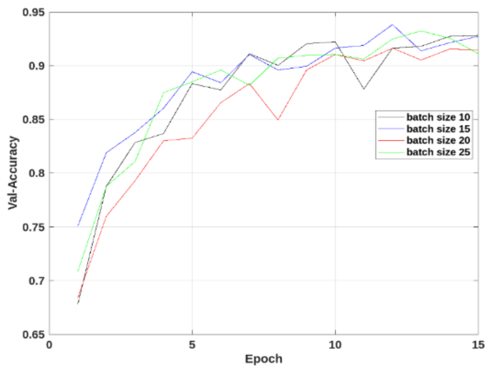


Figure 5. Validation accuracy for different cases of batch size

5.3. Evaluation of the model for different batch size

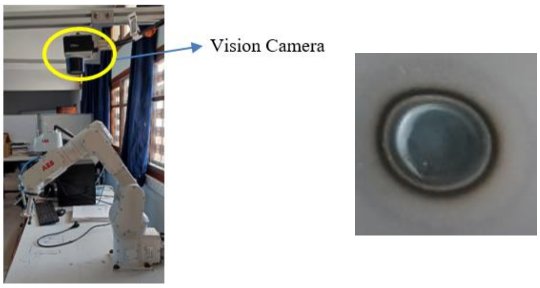
To evaluate the proposed model, we try to predict the type of welding surface by 4 batch sizes for the same number of epochs. The Table 2 demonstrates that as the size of batch increases the time of computation also increases. Concerning the confidence, it does not depend on the batch size. It appears that using the batch size of 10 let the model to be more precise.

Table 2. Confidence for different batch size

Batch size	Time (ms/step)	Confidence (%)
10	357	99,72
15	396	98,86
20	472	99,53
25	707	99,63

5.4. Experimental validation

The idea is to feed the classifier robot presented in Figure 6. The robot presented in the Figure 6(a) is equipped with a precise-vision camera that scans the part. The captured image Figure 6(b) is then inserted into the program. The proposed method is accurate by predicting the type of welding with a precision of 99%.



(a) (b)

Figure 6. Experimental validation (a) robot with vision camera and (b) tested welding image

6. CONCLUSION

This study aims to develop a CNN model to predict the type of welding surface by radiographic images. We found that the data augmentation helps a lot to earn more accuracy. In addition, the batch size does not affect the accuracy. Moreover, we demonstrated that the batch size affects the computational time. The automation of weld defect detection is possible by deep learning. The performance of the model depends on the architecture of the classifier. The robot classifier development will be studied in the next articles.

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REFERENCES

[1] S. Shi, S. Jin, D. Zhang, J. Liao, D. Fu, and L. Lin, "Improving ultrasonic testing by using machine learning framework based on model interpretation strategy," *Chinese Journal of Mechanical Engineering*, vol. 36, no. 1, p. 127, Oct. 2023, doi: 10.1186/s10033-023-00960-z.

[2] S. Nissabouri, "Conversion of ultrasonic waves with symmetric notches in isotropic plate," in *2023 3rd International Conference on Innovative Research in Applied Science, Engineering and Technology (IRASET)*, IEEE, May 2023, pp. 1–5. doi: 10.1109/IRASET57153.2023.10152994.

[3] S. Nissabouri, M. El Allami, and E. H. Boutyour, "Quantitative evaluation of semi-analytical finite element method for modeling Lamb waves in orthotropic plates," *Comptes Rendus. Mécanique*, vol. 348, no. 5, pp. 335–350, Nov. 2020, doi: 10.5802/crmeca.13.

[4] B. Hena, Z. Wei, C. I. Castanedo, and X. Maldague, "Deep learning neural network performance on NDT digital X-ray Radiography Images: Analyzing the Impact of Image Quality Parameters—An Experimental Study," *Sensors*, vol. 23, no. 9, p. 4324, Apr. 2023, doi: 10.3390/s23094324.

[5] P. Y. Mahajan, A. Bajwa, and A. Bansal, N. Dua, G. Kaur, A. Varora, "Infrared machine vision for detection and characterization of defects present in a mild steel material," *Journal of Non Destructive Testing and Evaluation (JNDE)*, vol. 20, no. 1, 2023.

[6] S. Nissabouri, M. El allami, E. H. Boutyour, and A. Errkik, "Delamination localization in sandwich skin using lamb waves by finite element method," *Advances in Acoustics and Vibration*, vol. 2018, pp. 1–11, Nov. 2018, doi: 10.1155/2018/9705407.

[7] S. Nissabouri, M. El Allami, E. Boutyour, and A. Errkik, "Lamb wave interaction with delamination in orthotropic plate," in *ACM International Conference Proceeding Series*, in ICCWCS'17. New York, NY, USA, NY, USA: ACM, Nov. 2017, pp. 1–5. doi: 10.1145/3167486.3167545.

[8] T. Song, Z. Yan, S. Guo, Y. Li, X. Li, and F. Xi, "Review of sEMG for robot control: techniques and applications," *Applied Sciences*, vol. 13, no. 17, p. 9546, Aug. 2023, doi: 10.3390/app13179546.

[9] H. Li *et al.*, "A novel robotic-vision-based defect inspection system for bracket weldments in a cloud–edge coordination environment," *Sustainability*, vol. 15, no. 14, p. 10783, Jul. 2023, doi: 10.3390/su151410783.

[10] M. Abdullah-Al-Noman, A. N. Eva, T. B. Yeahyea, and R. Khan, "Computer vision-based robotic arm for object color, shape, and size detection," *Journal of Robotics and Control (JRC)*, vol. 3, no. 2, pp. 180–186, Feb. 2022, doi: 10.18196/jrc.v3i2.13906.

[11] L. Li *et al.*, "Defect detection method for high-resolution weld based on wandering Gaussian and multi-feature enhancement fusion," *Mechanical Systems and Signal Processing*, vol. 199, p. 110484, Sep. 2023, doi: 10.1016/j.ymssp.2023.110484.

[12] D. Yang, Y. Cui, Z. Yu, and H. Yuan, "Deep learning based steel pipe weld defect detection," *Applied Artificial Intelligence*, vol. 35, no. 15, pp. 1237–1249, Dec. 2021, doi: 10.1080/08839514.2021.1975391.

[13] F. Duan, S. Yin, P. Song, W. Zhang, C. Zhu, and H. Yokoi, "Automatic welding defect detection of X-Ray images by using cascade AdaBoost with penalty term," *IEEE Access*, vol. 7, pp. 125929–125938, Jul. 2019, doi: 10.1109/ACCESS.2019.2927258.

[14] N. Boaretto and T. M. Centeno, "Automated detection of welding defects in pipelines from radiographic images DWDI," *NDT & E International*, vol. 86, pp. 7–13, Mar. 2017, doi: 10.1016/j.ndteint.2016.11.003.

[15] S. Sambath, P. Nagaraj, and N. Selvakumar, "Automatic defect classification in ultrasonic NDT using artificial intelligence," *Journal of Nondestructive Evaluation*, vol. 30, no. 1, pp. 20–28, Mar. 2011, doi: 10.1007/s10921-010-0086-0.

[16] Y. Huang, D. Wu, Z. Zhang, H. Chen, and S. Chen, "EMD-based pulsed TIG welding process porosity defect detection and defect diagnosis using GA-SVM," *Journal of Materials Processing Technology*, vol. 239, pp. 92–102, Jan. 2017, doi: 10.1016/j.jmatprotec.2016.07.015.

[17] B. Das, S. Pal, and S. Bag, "Torque based defect detection and weld quality modelling in friction stir welding process," *Journal of Manufacturing Processes*, vol. 27, pp. 8–17, Jun. 2017, doi: 10.1016/j.jmapro.2017.03.012.

[18] J. Kumar, R. S. Anand, and S. P. Srivastava, "Flaws classification using ANN for radiographic weld images," in *2014 International Conference on Signal Processing and Integrated Networks (SPIN)*, IEEE, Feb. 2014, pp. 145–150. doi: 10.1109/SPIN.2014.6776938.

[19] W. Hou, Y. Wei, J. Guo, Y. Jin, and C. Zhu, "Automatic detection of welding defects using deep neural network," *Journal of Physics: Conference Series*, vol. 933, no. 1, p. 012006, Jan. 2018, doi: 10.1088/1742-6596/933/1/012006.

[20] D. Mery and M. A. Berti, "Automatic detection of welding defects using texture features," *Insight - Non-Destructive Testing and Condition Monitoring*, vol. 45, no. 10, pp. 676–681, Oct. 2003, doi: 10.1784/insi.45.10.676.52952.

[21] R. R. da Silva, L. P. Calôba, M. H. S. Siqueira, and J. M. A. Rebello, "Pattern recognition of weld defects detected by radiographic test," *NDT & E International*, vol. 37, no. 6, pp. 461–470, Sep. 2004, doi: 10.1016/j.ndteint.2003.12.004.

[22] J. Kumar, R. S. Anand, and S. P. Srivastava, "Multi - class welding flaws classification using texture feature for radiographic images," in *2014 International Conference on Advances in Electrical Engineering (ICAEE)*, IEEE, Jan. 2014, pp. 1–4. doi: 10.1109/ICAEE.2014.6838443.

[23] G. Wang and T. W. Liao, "Automatic identification of different types of welding defects in radiographic images," *NDT & E International*, vol. 35, no. 8, pp. 519–528, Dec. 2002, doi: 10.1016/S0963-8695(02)00025-7.

[24] J. Zapata, R. Vilar, and R. Ruiz, "An adaptive-network-based fuzzy inference system for classification of welding defects," *NDT & E International*, vol. 43, no. 3, pp. 191–199, Apr. 2010, doi: 10.1016/j.ndteint.2009.11.002.

[25] R. Vilar, J. Zapata, and R. Ruiz, "An automatic system of classification of weld defects in radiographic images," *NDT & E International*, vol. 42, no. 5, pp. 467–476, Jul. 2009, doi: 10.1016/j.ndteint.2009.02.004.

[26] S. Naddaf-sh and H. Zargaradeh, *Next-Generation of Weld Quality Assessment Using Deep Learning and Digital Next-Generation of Weld Quality Assessment Using Deep Learning and Digital Radiography*, no. March. 2020.

[27] B. C. Thakkallapally, "Defect classification from weld radiography images using VGG-19 based convolutional neural network," *Ndt.Net*, vol. 1, no. 18, pp. 1–6, 2019, [Online]. Available: https://www.ndt.net/article/nde-india2019/papers/CP017.pdf

[28] I. Valavanis and D. Kosmopoulos, "Multiclass defect detection and classification in weld radiographic images using geometric and texture features," *Expert Systems with Applications*, vol. 37, no. 12, pp. 7606–7614, Dec. 2010, doi: 10.1016/j.eswa.2010.04.082.

[29] L. Yang and H. Jiang, "Weld defect classification in radiographic images using unified deep neural network with multi-level features," *Journal of Intelligent Manufacturing*, vol. 32, no. 2, pp. 459–469, Feb. 2021, doi: 10.1007/s10845-020-01581-2.

[30] M. Xiao, B. Yang, S. Wang, Z. Zhang, and Y. He, "Fine coordinate attention for surface defect detection," *Engineering Applications of Artificial Intelligence*, vol. 123, p. 106368, Aug. 2023, doi: 10.1016/j.engappai.2023.106368.

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