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Welding defects classification through a Convolutional Neural Network

Stefania Perri [a,*], Fanny Spagnolo [b], Fabio Frustaci [b], Pasquale Corsonello [b]

[a] Department of Mechanical, Energy and Management Engineering, University of Calabria, Italy
[b] Department of Informatics, Modeling, Electronics and Systems Engineering, University of Calabria, Italy

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A B S T R A C T

This letter presents a Convolutional Neural Network (CNN), named WelDeNet, customized to classify welding defects, such as lack of penetration (LP), cracks (CR), porosity (PO) and no defect (ND), by inspecting digitalized radiographic images. A new dataset that collects 24,407 images representing welding defects is also presented. WelDeNet consists of 14 cascaded convolutional layers and achieves a test accuracy of 99.5 %. When hardware implemented within the Raspberry Pi 3B + board, WelDeNet exhibits an inference time of only 134 ms, with CPU and memory utilizations of just 51 % and 47 MB, thus offering a promising solution easy-to-integrate in a real industrial environment.

1. Introduction

Welding is crucial in a large variety of manufacturing processes and several efforts have been spent in the past to make it even more precise and reliable. High-quality products can be yielded through non-destructive visual inspection methods that can employ artificial intelligence (AI) algorithms, like CNNs, to inspect radiographic images and to classify welding defects accurately [1–13]. However, enabling these technologies for Industry 4.0 and 5.0 presents several technical challenges. In fact, there is the need for easy-to-integrate digital solutions that reach real-time performances and can be efficiently combined to existing productive apparatus without requiring any complex re-engineering. Moreover, these automated systems must comply with timing and geometrical constraints imposed by the specific application. Last, but not least, customized CNN models are required. They must be trained and validated through appropriate datasets collecting a considerable volume of annotated images representing a wide variety of operating conditions and welding defects. In fact, as it is well known, small datasets cause overfitting. Unfortunately, just a few collections of radiographic images related to welding defects can be found in literature. The GDXRay [12] contains only 68 images of welds, whereas the WDXI [13] collects 13,766 X-ray images of welding defects, but it is not released freely.

In this letter, we present both a dataset collecting 24,407 radiographic images of welding defects (freely released at https://github.com/stefyste/RIAWELC) and a customized CNN, named WelDeNet, for the accurate classification of these defects. Experimental results demonstrate that the proposed CNN achieves a classification accuracy of 99.5 %, which is quite better than [7–10,13]. Moreover, at a comparable accuracy, it uses much less convolutional layers and is significantly simpler than [11].

2. The inspection methodology

The non-destructive inspection method based on radiographic images is referenced to enable efficient technologies based on CNNs that can classify reliably welding defects. To this aim, a new set of annotated images has been collected to be used for training, validating and testing customized CNN models.

2.1. The new dataset

X-ray weld images have been captured in a real industry-manufacturing environment, using the equipment described in Fig. 1a, and digitalized in images consisting of 2000 $\times$ 8640 8-bit pixels, like those visible in Fig. 1b. From each image, the weld bead has been sliced by discarding the background area and the regions of interest have been extracted. Then, the windows of pixels where weld defects could be located have been tiled. Several tests performed with tile sizes ranging from 32 $\times$ 32 to 150 $\times$ 150 have shown that tiles of 80 $\times$ 80-pixel size is a good compromise to clearly visualize both small and/or close defects, like PO, and large

* Corresponding author at: University of Calabria, Via P. Bucci Cubo 42C, 87036 Rende, Italy.

E-mail address: s.perri@unical.it (S. Perri).

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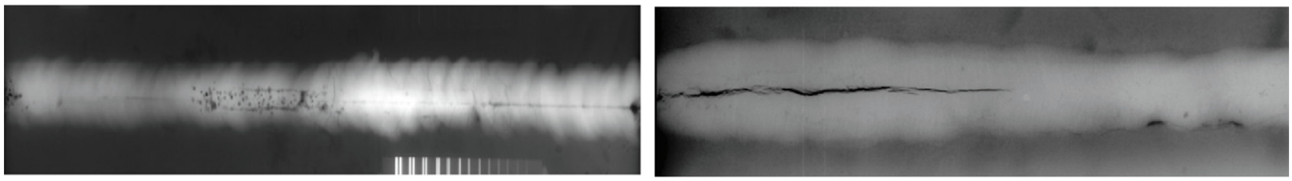
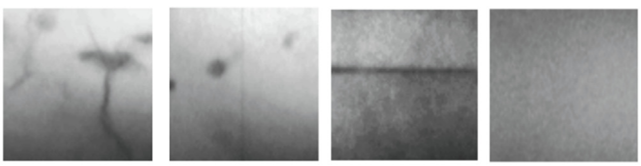
Welding technique	Welder	X-ray source	X-ray scanner
Submerged arc	Lincoln Electric POWER WAVE® AC/DC 1000	COMET EVO 300P	Array 2905 HD

a)



b)



c)

Defect	Total	Train	Validation	Test
CR	7635	4962	1908	765
PO	6320	4108	1580	632
LP	4452	2893	1113	446
ND	6000	3900	1500	600
Total	24407	15863	6101	2443

d)

Fig. 1. The main characteristics of the new dataset: a) the equipment used; b) samples of digitalized weld images; c) examples of images collected in the dataset; d) the organization of the new dataset.

defects, such as CR and LP. The tiles have been enhanced by means of the contrast-limited adaptive histogram equalization [14] and scaled to the 224 × 224-pixel size in the jpeg format. Finally, 24,407 images have been collected and annotated into four categories: LP, CR, PO and ND, appearing as reported in Fig. 1c. The resulting dataset has been organized as summarized in Fig. 1d, thus guaranteeing that, for each defect, train, validation and test datasets collect 65 %, 25 % and 10 % of the annotated images, respectively.

To validate the dataset, among several well-known CNN models (i.e. VGG16, ResNet50, MobilNet, SqueezeNet, and many others [15-20]), SqueezeNet V1.1 [15] has been chosen for its lower complexity. After being re-trained on the proposed dataset by using the transfer learning and the fine tuning [21,22], the referred CNN showed a test accuracy of 99.84 %. With the aim of reducing the overall computational complexity, thus obtaining a solution even easier to integrate in a real industrial environment, a novel CNN model has been carried out.

2.2. The proposed CNN model

The proposed WelDeNet model has been constructed by removing from SqueezeNet V1.1 two Fire layers. Its architecture is depicted in Fig. 2a that also reports the input size of each computational layer. Each Fire level is conventionally structured as illustrated in Fig. 2b; the generic convolutional layer (Conv) performs either 1 × 1 or 3 × 3 convolutions; the rectified linear units (ReLUs) and the down-sampling max pooling layers (Max Pool) run as schematized in Fig. 2c and 2d; the Dropout is applied with a ratio of 50 % to prevent the CNN from overfitting by randomly nullifying the contribution of some neurons [23]; the global average pooling layer (GA Pool) averages the pixels within each received input feature map (Fig. 2e).

WelDeNet has been described by a Python code exploiting the Keras library. Then, the Google Colab suite has been used with the Tensorflow framework to perform the transfer learning and the fine tuning with the following training settings: learning rate 0.001; epochs 50; batch size 32; dropout 0.5; optimization algorithm “Adam”; cost function “Categorical CrossEntropy”. The latter is reported in (1) for d training images and c classified defects, with y and $\hat{y}$ being the target and the predicted probability distributions. In these steps, the new dataset above presented has been used, thus making WelDeNet able to classify the four welding defects of interest. The model performances are summarized in Fig. 3, where the accuracy/loss curves and the normalized confusion matrix are illustrated. The fluctuations observable for the loss curve in the initial epochs are due to the Stochastic Gradient Descent optimization technique used for the training.

$$CCE = -(1/d) \cdot \sum_{j=1}^{d} \left(\sum_{i=1}^{c} \left(y_i^d \cdot \log \widehat{y_i^d} \right) \right) \quad (1)$$

3. Results and discussions

Table 1 compares WelDeNet to several representative counterparts in terms of model complexity and classification accuracy. Some of the referenced competitors exploit custom CNN models [7,9,13], whereas the others modify existing CNNs by adding or removing computational layers. It is worth noting that, even though each CNN referenced as a competitor classifies different categories of welding defects and it is trained using a different dataset, Table 1 provides a big picture of the state-of-the-art and shows that WelDeNet achieves a quite better accuracy than its counterparts. The main reasons of this advantage are: 1) the larger dataset used for the training prevents overfitting issues; 2) differently from [8], [10] and [11], which adopt the transfer learning with the aim of compensating for the small dataset volume, the fine tuning adopted here is application-oriented and aims at improving the ability of customized layers to correctly classify welding defects. In terms of complexity, WelDeNet utilizes less convolutional layers than [8,10,11] and SqueezeNet. Moreover,

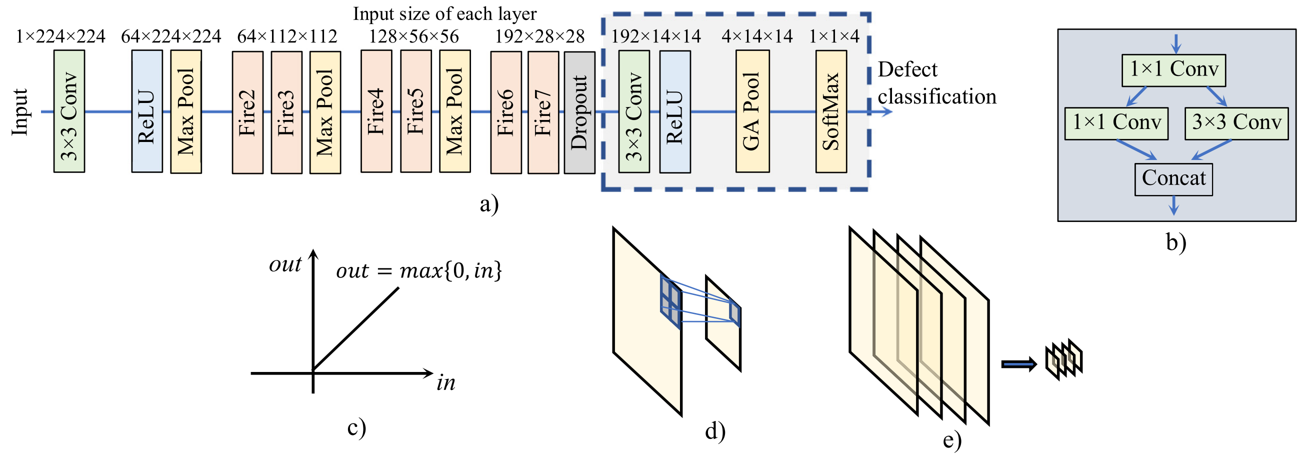


Fig. 2. The proposed WelDeNet: a) the model; b) the Fire layer; c) the ReLU function; d) the max pooling; e) the GA pooling.

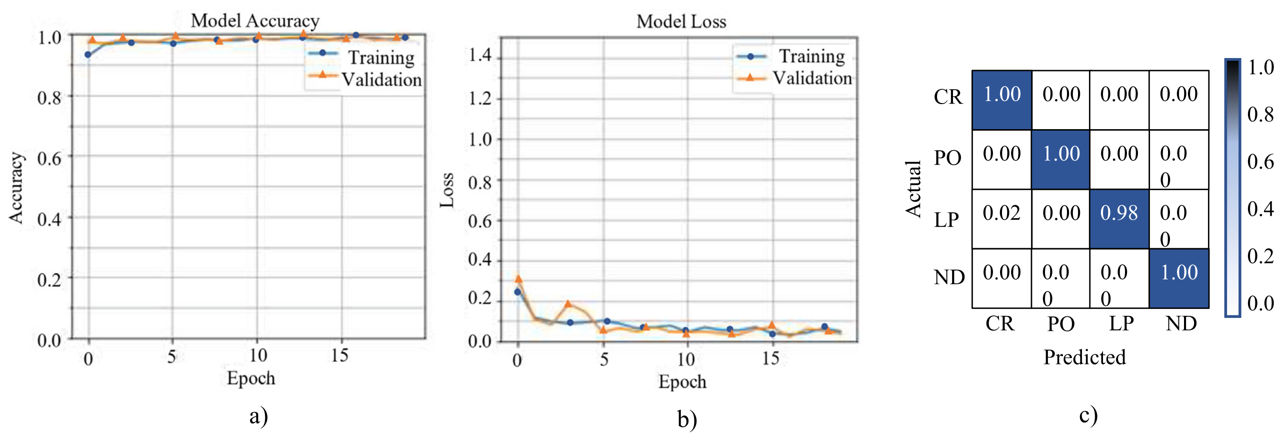


Fig. 3. WelDeNet performances: a) the accuracy curve; b) the loss curve; c) the normalized confusion matrix.

Table 1
Comparison results.

Reference	[7]	[8]	[9]	[10]	[11]		[13]	This Work	This Work
CNN model	Custom	TL-MobilNet	Custom	VGG16	ResNet50		Custom	SqueezeNet V1.1	WelDeNet
# CONVs	0	26	2	13	49		4	18	14
# Fully Connected or GA Pool	5	3	3	3	1		1	1	1
Input Image size	32 × 32	96 × 96	320 × 240	224 × 224	224 × 224		400 × 400	224 × 224	224 × 224
# Classified defects	2	5	4	3	9	14	4	4	4
Dataset volume	400	6,208	120	3000	940	940	13,766	24,407	24,407
Test Accuracy	91.84 %	97.69 %	95.83 %	97.6 %	99.4 %	97.8 %	46.6 %	99.8 %	99.5 %

while SqueezeNet consists of 724,548 parameters, WelDeNet is described by only 386688. Finally, the classification accuracy of the novel CNN is higher than [7-10,13] and it is comparable with [11] and SqueezeNet.

Comparison results show that, while the model presented in [7] allows just the presence/absence of defects to be distinguished, the classification of welding defects within more than two classes is made possible by the other CNNs. As a final remark, WelDeNet can be made able to classify even more than four categories by accordingly modifying the layers enclosed in the dashed box of Fig. 2a (i.e. increasing the number of features processed by the layers 3 × 3 Conv, ReLU and GA Pool, as well as the number of categories classified by the SoftMax) and re-training the updated model using again the transfer learning and the fine tuning.

4. Hardware implementation

With the aim of demonstrating that WelDeNet offers an actual opportunity to integrate an artificial neural network in a real industry-manufacturing environment, it has been translated in the TensorFlow Lite format and then hardware implemented within the Raspberry Pi 3B + platform [24]. The latter provides a 1.4 GHz 64-bit general-purpose quad-core ARM Cortex-A53 processor, a 1GByte SDRAM memory and several interfacing ports (e.g. USB, Bluetooth, HDMI, etc.). In our implementation, we installed the 32-bit Raspbian operating system.

Several tests performed on the proposed model have shown that WelDeNet achieves an inference time of only 134 ms. Moreover, during the inference task, it utilizes the on-board CPU at most at 51 % and uses at most 47 MB of the available memory.

5. Conclusions and future works

This letter presented a new dataset collecting 24,407 annotated greyscale images of size 224 $\times$ 224 pixels and a novel CNN model, named WelDeNet, able to classify four classes of welding defects, namely lack of penetration, cracks, porosity and no defect, with an accuracy of 99.5 %. The comparison with state-of-the-art competitors has shown that, when trained on the dataset here released, the proposed CNN behaves better than its counterparts either identifying defects with a higher accuracy or exploiting less convolutional layers. Results obtained from the hardware implementation within the Raspberry Pi 3B + board, suggest that the proposed CNN can be integrated within real industrial inspection systems.

Future work will focus on several aspects. First, in order to achieve even more robust and accurate CNN models, the dataset will be extended introducing further annotated images and WelDeNet will be made able to classify more than four categories of welding defects. Finally, the design of a heterogeneous embedded system will be carried out using Field Programmable System on Chips (FPSoCs). In such an implementation, additional computational capabilities will be introduced either with custom purposely designed hardware circuits or with software routines executed by the embedded general-purpose processor on-chip available.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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