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Deep Learning for Quality Prediction in Dissimilar Spot Welding DP600-AISI304, Using a Convolutional Neural Network and Infrared Image Processing

Bárbara Dora Ross Veitía [1], Alejandro Espinel Hernández [1], Louriel Oliveira Villarinho [2], Mario Sánchez Orozco [3], Angel Sánchez Roca [3], Hipólito Carvajal Fals [4] and Emilio Jimenez Macias [5,*]

[1]National Center for Applied Electromagnetism, University of Oriente, Santiago de Cuba, Cuba. Ave Las América s/n. 90400
[2]Faculty of Mechanical Engineering. Federal University of Uberlândia, Minas Gerais, Uberlândia, Brazil.
[3]Faculty of Mechanical and Industrial Engineering. University of Oriente, Santiago de Cuba, Cuba. Ave Las América s/n. 90400. Santiago de Cuba. Cuba
[4]Federal Technological University of Paraná. Rua Doutor Washington Subtil Chueire, 330 - Jardim Carvalho. CEP 84017-20 - Ponta Grossa. PR. Paraná. Brazil
[5]Department of Electrical Engineering, University of La Rioja, Av. de la Paz, 93, 26006 Logroño, Spain

[*]Corresponding author. Email address: emilio.jimenez@unirioja.es

Abstract

In face of the dizzying progress of Industry 4.0, the application of Artificial Intelligence in manufacturing processes is a challenging task. In this research, a Convolutional Neural Network (CNN) was implemented to determine the quality of dissimilar joints DP 600-AISI 304. Infrared images obtained during the process of resistance spot welding were processed. The idea of applying a CNN focuses on filtering infrared images before training the deep neural network, for the detection of certain hidden features in the data, as well as extracting patterns and classifying welded joints. For its implementation, open source tools such as Anaconda, libraries such as Tensorflow and Keras, high-level Application Programming Interface (APIs) were used to work with neural networks in Python language. After processing and training with infrared images, a neural model was obtained and the metrics obtained from the training were analysed. It was found that the use of deep learning and in particular CNN are techniques that can be considered as predictive methods for the classification of welded joints and computer vision supervision. Data processing was possible on very small timescales, facilitating optimization and efficiency improvement in manufacturing processes.

Keywords: Artificial Intelligence; Deep Learning; Convolutional Neural Network; Infrared Image Analysis

1. Introduction

With the rise of the industrial revolution, the so-called Industry 4.0, there is a tendency to apply Artificial Intelligence (AI) in the different scenarios of industry. Systems based on computer vision are

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strongly linked to the development of industries that are in continuous transformation of their processes with the aim of optimizing and increasing production.

There are solutions for the visual inspection of online processes such as supervised and unsupervised learning machines, which have proven to be effective methods with application in the automotive, pharmaceutical, and microelectronic industries, among others. The electric resistance spot welding (RSW) process is considered the leading welding type in the automotive industry, used to join two or more metal sheets. There are studies (Espinel et al., 2016) that report that the number of welding points made during the manufacturing process of a vehicle is estimated between 3,000 and 10,000 points.

Environmental impact, energy saving and safety are three very important aspects to be considered by car manufacturers. The production of the different parts that structure the vehicle are inspected online and more and more studies are being conducted by the scientific community every day in search of models that further foster the optimization these processes, as well as the location of possible defects in the welded joints found in different parts of the vehicle, allowing to obtain a higher quality and competitive product.

Non-destructive tests (NDT) are considered in the characterization of welded joints, because their practice does not permanently alter their physical, chemical, mechanical, or dimensional properties and can be applied at any stage of the process (Gutiérrez, 2017). Infrared Thermography (IT), due to its application, is considered a non-invasive technique, since it can be used to quantify the temperature of a surface without direct contact with the material, based on the measurement of infrared radiation of the electromagnetic spectrum. The use of IT and artificial neural networks (ANN) can be applied to the inspection and maintenance of manufacturing processes (Garrido et al., 2020).

Researchers like Martín et al. (Martín et al., 2010), use an ANN to predict the influence of the pitting corrosion behavior (PCB) of joints obtained in the RSW process, using as material an austenitic steel 304 (AISI304). They designed an ANN considering that the phenomena that relate the heat generated in the RSW process with the PCB are highly complex. They consider that to train the network it is important to consider a good number of input data, as well as the number of neurons that will make up the hidden layer of the network. The results obtained confirm that the use of ANN is effective for prediction.

Similar studies were conducted by Gavidel et al. (2019), though in this case using deep neural networks (DNN). They determined, from the analysis of different algorithms of machine learning equipment that DNNs can be used as predictive models, and can be considered non-destructive methods to evaluate the quality of the weld, as well as to predict the diameter of the weld point. For the analysis, they collect data from studies made by other authors with different predictive models and establish a comparison between them, concluding that DNNs are more efficient for this type of task.

On the other hand, He and Liu (2020) designed a deep regression and classification model for the detection of surface defects in generic industrial products. The method was validated on three public data sets. From the analyzes, the authors built a total of six class groups and then designed a convolutional neural network (CNN), obtaining good results in terms of detection precision and efficiency.

A high performance index is obtained in the studies made by Guo et al. (2019), from the use of a CNN to classify the quality of the welded joint from images of cross sections of joints obtained by RSW. They employ 50 epoch training, reaching a precision for classification of 99.01%. In this case, a destructive method is used to characterize the quality of the welded joint.

Studies conducted by Mayr et al. (2018) use different learning machine techniques to assess the quality of the weld from the analysis of the defects of each one of the weld joints analyzed. The CNNs appeared to be more efficient when classifying from processed images.

The studies made have focused on the detection of defects, however, no work has been reported related to the application of CNN in the RSW process using dissimilar materials DP600 - AISI304. Similarly, no CNN-type neural models have been found that process IR images in this type of process. In this work, the aim is to classify the quality of the dissimilar joints obtained by the RSW process, using IR images, with the use of CNN.

2. Materials and Methods

For the development of this work, two 1.2 mm thick metal sheets were used, a Dual Phase steel (DP600) and an austenitic stainless steel (AISI304). They were lap-welded on a direct current medium frequency machine (MFDC), consisting of a Bosch PSG 3100 transformer, a Bosch PSI600.100L controller and a water-cooled pneumatic clamp. In this case, depending on the polarity used, the DP 600 steel is placed in contact with the positive electrode and the AISI 304 with the negative electrode of the welding clamp (DP600 / AISI 304). Table 1 shows the levels of the RSW process variables during the experimental design.

Table 1. Experimental design.

Parameter	Low level (-1)	Central level (0)	High level (+1)
Welding current, kA	3	4	5
Welding time, ms	300	400	500

2.1. Preparation of the data set

The quality of the welded joint is influenced by the levels of the process variables (Table 1), and mechanical tests were performed for its evaluation in order to obtain data on the characteristics and properties of the welded joints. Mechanical resistance tests were made using a SHIMATSU universal testing machine, model AGX 50 kN. In this process, mechanical resistance is closely related to point diameter and indentation, therefore, these were considered to build the classes.

The tests were performed according to the norm (Zuniga & Sheppard, 1997) that standardizes the tests for the RSW process. The maximum failure force and failure mode of the welded joint were also selected as variables that influence the quality of the welded joints. The measurement of the diameters of the welding points was made in accordance with ISO 14373 (2007) and the indentation measurements were made from the cross sections of the welded joint.

The data set with the IR images used was extracted from a private dataset, presented in a study made by Espinel et al. (2016). For this study, the authors worked with dissimilar welded joints of the DP600 / AISI304 type, considering the higher mechanical resistance obtained for this position of the sheets or polarity. The quality indicators were considered: the presence or not of defects, formation of pores and the occurrence or not of expulsions. All the data generated from the mechanical tests were organized and the welded samples were classified into three classes: good, acceptable and bad welds.

The IR images extracted during the RSW process were tagged and class groups were formed corresponding to the properties obtained from the welded joint to train the neural network and obtain a model with good performance and high classification values. The images, to be processed in the CNN input layer, were resized to be processed by the neural network, adjusting to a size of 100x100x3 pixels while maintaining the 3 channels of RGB colors.

2.2. Model creation

The CNN-type network model is intended to simulate the way the human brain learns and works thanks to the ANN architecture and the optimization routine applied to it. It was decided to use this network model because it is possible to work with structured data such as images, in order to classify them and their proven efficiency in previous research.

When the CNN model is faced with a stimulus, certain neurons activate, evaluate the information they have received, react and communicate with other neurons. In subsequent stimuli, they add new data to those they already know, evaluate the result of the previous actions and correct their operation to achieve the best possible reaction.

The difference with other traditional neural network models is that this one has a higher number of layers, between 5 and 50 layers or even more. Figure 1 shows the basic structure of a CNN (Convolutional Neural Network).

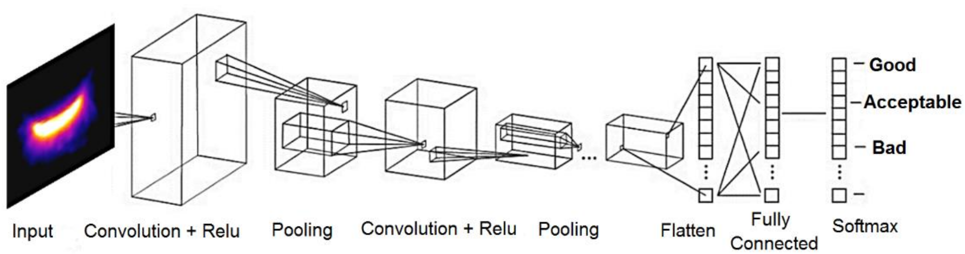

Figure 1. Basic structure of a CNN.

The first step of creating and training the CNN is to define the network architecture. The architecture of a CNN varies depending on the types and numbers of layers included. In figure 1, it can be seen that the highest level layers study the characteristics of the object, and the lowest layers, classify and decide the characteristics of the image. To conduct a good training process, the weights of all the layers must be well adjusted, as they will be trained at the same time.

The image input layer defines the size of the input images of a convolutional neural network and contains the raw pixel values of the images. A convolutional layer consists of neurons that connect to subregions of the input images. A convolutional layer learns the features localized by these regions while scanning through an image. In this case, the image size used was 100x100x3. A rectified linear unit (ReLU) layer follows the convolutional layer. A nonlinear activation function performs a threshold operation to each element, where any input value less than zero is set to zero, see Equation 1.

$$f(x) = \begin{cases} x, & x \geq 0 \\ 0, & x < 0 \end{cases} \qquad (1)$$

The pooling layers follow the convolutional layers, performs down-sampling by dividing the input into rectangular pooling regions, and computing the maximum of each region, reducing the number of connections to the following layers. They do not perform any learning themselves, but reduce the number of parameters to be learned in the following layers contributing to reduce overfitting. The size of the rectangular regions is determined by the pool size. The the output of a pooling layer is defined by Equation 2.

$$(\text{Input Size} - \text{Pool Size} + 2 * \text{Padding})/\text{Stride} + 1 \quad (2)$$

The software calculates the size of the padding at training time so that the output has the same size as the input when the stride equals one.

The upper layers are formed by a sequence of layers with a convolution function ReLu (Rectified Linear Unit Layers) that do not add complexity to the network and Pooling. The latter reduce the dimension of the data and the number of parameters, calculating the maximum of a region, the mean values and other descriptors. Groups of these layers are normally concatenated, which are responsible for learning the characteristics of the images.

At the end of this phase, there is a volume, which will be flattened and converted into a vector by the layer called Flatten, which makes it possible to work with the neural networks, which are fully connected.

Finally, for classification a Softmax layer follow the final fully connected layer. The output unit activation function is the Softmax function (Equation 3).

$$y_r(x) = \frac{e^{a_r(x)}}{\sum_{j=1}^{k} e^{a_j(x)}} \quad (3)$$

where, $0 \le y_r \le 1$ and $\sum_{j=1}^{k} y_j = 1$.

2.3. Implementation of the CNN network

The implementation of the convolutional neural network was performed through Anaconda-environment software Jupyter developed in Python, using the Keras API and the Tensorflow framework, which allow the implementation of neural networks using sequential models. The models are built considering the layers that the neural network will have. Figure 2 shows the sequence followed to create and validate the proposed neural network model.

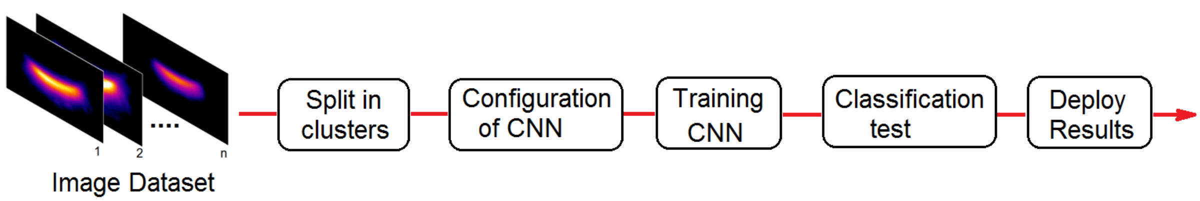

Figure 2. Diagram of CNN network approach implementation.

```
cnn=Sequential()

cnn.add(Convolution2D(32, (3, 3),padding='same',input_shape=(100,100,3), activation='relu'))
cnn.add(MaxPooling2D(pool_size=tamano_pool))

cnn.add(Convolution2D(64, (2,2), padding='same', activation='relu'))
cnn.add(MaxPooling2D(pool_size=tamano_pool))

cnn.add(Flatten())

cnn.add(Dense(256,activation='relu'))
cnn.add(Dropout(0.2))

cnn.add(Dense(clases, activation='softmax'))


cnn.compile(loss='categorical_crossentropy', optimizer='adam',metrics=['accuracy'])
```

Figure 3. Structure of the CNN network model.

As shown in Figure 2, once the images were read from the directory where they were housed, they were normalized, dividing each element by the number of pixels, that is, 255, obtaining an array with values between 0 and 1.

Once the images are pre-processed, the convolutional network model is defined to then do the compilation specifying the functions: optimization, cost or loss, and the metrics to use. In this case, the Adam optimization function, the categorical-crossentropy loss function and for the metrics, the accuracy function are used, as shown in Figure 3.

As shown in Figure 3, the Conv2D instruction introduces a convolutional layer and the MaxPooling instruction, the pooling layer. Two convolutional layers were created in this model. For each convolution, the ReLu function was used as the activation function. The Flatten layer guarantees to flatten the volume of data and convert it into a vector, which allows working with neural networks, which are fully connected. Then a Dense layer is added, which it is going to have 256 neurons that are going to be connected to the previous layer and also the activation function to be used is the ReLu.

The Dropout instruction (Figure 3) does the Dropout regularization function. With the passage of the convolution, it will be possible for the model to extract features from the image. Finally, the last Softmax layer will indicate the label to which the image corresponds, applying a probability of similarity. These last layers make the classification of the IR images.

2.4. CNN Training

The first results of the initial training with the dataset used were not good due to a slight imbalance between the images belonging to the different defined classes. To solve this, it was necessary to use the Data Augmentation technique, which is one of the most used in these cases. This technique consists of processing each one of the images, generating for each one of them N variations. These new images are created following several principles such as: turning the original image, rotating it, increasing it or modifying the color space, and in this way avoiding possible cases of overfitting.

Finally, the network was trained, saving the training result in a variable in order to extract the history of the training data. The metrics obtained were evaluated graphically, and the Matplotlib library was used to visualize them. Although it has already been evaluated during training, it can be evaluated with another dataset that contains characteristics similar to the source images.

3. Results and Discussion

The appearance of defects such as pores, expulsion, very low or very high values of indentation and point diameter, together with the failure mode, affect the quality of the welded joint. Figure 4 shows representative images of factors that were considered to evaluate the quality of the dissimilar joints according to the three defined classes.

Mechanical resistance is the property with the highest incidence when evaluating the quality of the welded joint. Figure 4 shows that the images that belong to the Bad class, present an interface failure mode (IF) and may have pores. The Acceptable class has a larger weld point diameter, pull-out failure mode (PO) and may or may not have pores, with a greater mechanical resistance than the bad ones. For the joints classified into the Good class there is no occurrence of pores. These are joints where the failure mode is PO and have an adequate point diameter with a mechanical resistance much higher than that of the previous cases.

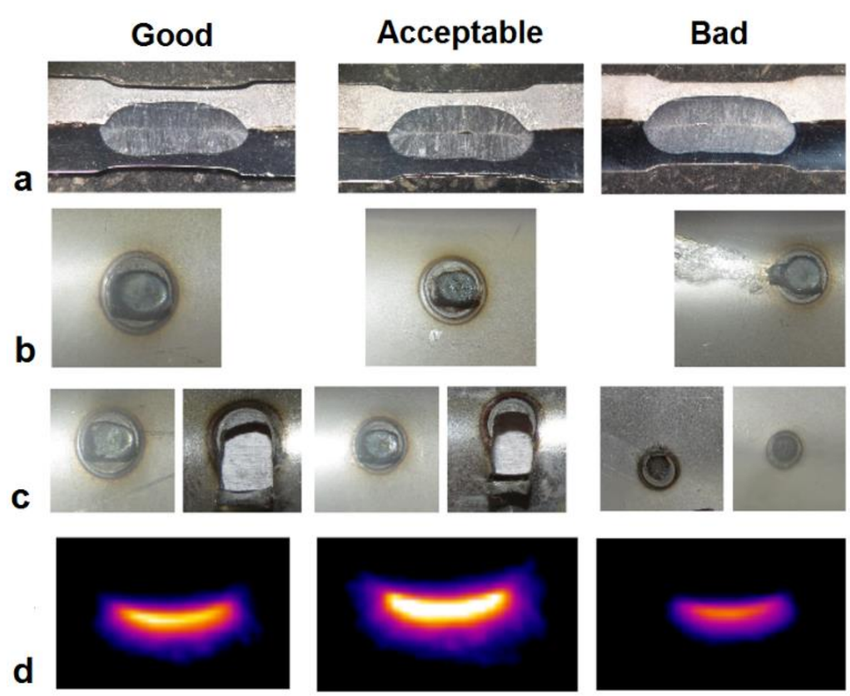

Figure 4. Defined classes to label the images of the dissimilar joints a) presence of pores, b) presence of expulsion, c) failure mode. d) IR image.

The preparation of the data set for the model construction, the structure of the convolutional network model, the techniques applied to balance the data of each class and the image normalization, all contributed to the increase in accuracy of the classifier. Figure 5 shows the performance of the network model during training and validation, based on the evaluation of the precision with which IR images are classified during training periods.

An accuracy of 99.98% was obtained for the training set and 97.33% for the validation set. The increase of the stages for the training and validation set guarantees a higher index of precision during the classification. Furthermore, there is a minimal difference between the two groups, and this is due to loss during training.

Figure 6 shows this loss behavior and the model fit during training. The loss is nothing more than the sum of the errors made for each data in the training or validation sets. For the training dataset, from the second epoch the model loss begins to decrease significantly, until reaching minimum values of 0.003 and remaining stable around this value, which indicates correct learning. As this value decreases, greater adjustment is achieved in the model classification task.

In a similar way, it happens for the validation (Figure 7), observing a slight increase in loss compared to the training phase, which starts to decrease with the increase of the iterations from the 17th epoch.

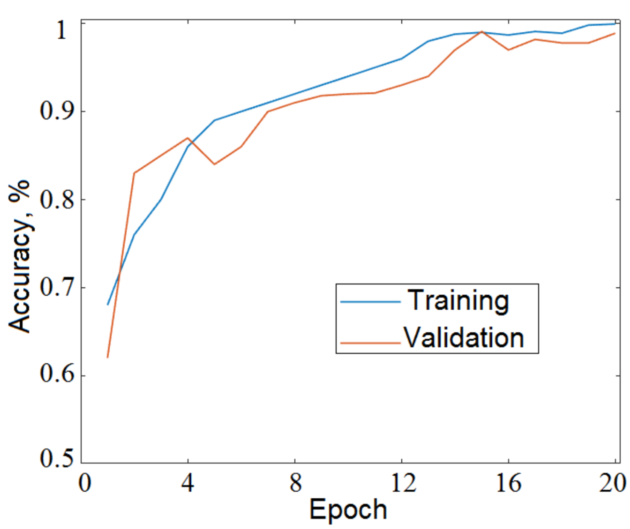

Figure 5. Performance of the CNN model during the training and validation phases.

A first approach to the construction of the CNN-based model allows satisfactory results to be obtained and the validity of the use for the classification of the images analyzed to be demonstrated. Future works will focus on increasing the set of images to improve its classification capacity.

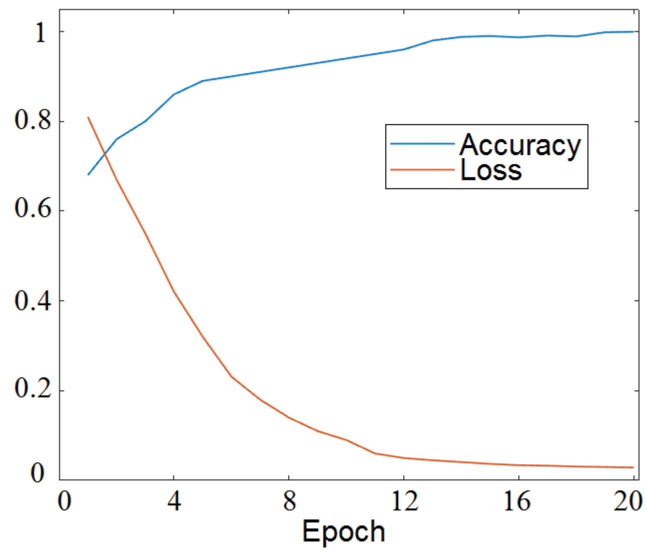

Figure 6. Performance evaluation for training and model loss during each training epoch.

4. Conclusions

From the analysis of the results achieved during this research, it is possible to reach the following conclusions:

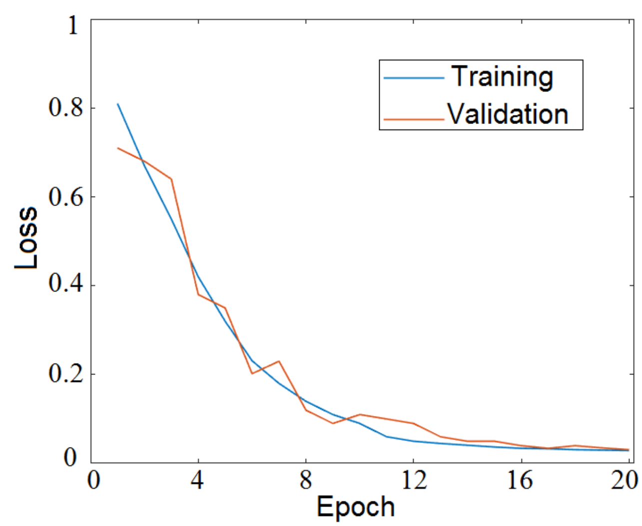

Figure 7. Model loss function in the training phase for training dataset and validation.

- The validity of the use of convolutional neural networks (CNN) for the analysis and classification of the quality of RSW welded joints of dissimilar materials DP600 / AISI30 was demonstrated from IR images obtained online from the process.
- The use of techniques to avoid overfitting in network training guaranteed a model accuracy of 97.33%.

- The CNN network model can be considered a non-invasive method for the classification of the quality of the weld; allowing to perform data processing in very small timescales, thus facilitating the optimization and improvement of the productivity of industries.

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