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Machine Learning for Automatic Classification of Defective Automobile Parts Images

Jose Ruiz-Pinales, Rafael Guzmán-Cabrera, Maricarmen Peña-Gomar, Miguel Torres-Cisneros

Abstract—**In this work, we use deep learning to automatically classify images of automotive parts, which could have or have no defects. Particularly, we analyzed an automotive part which is indeed composed of two different pieces welded in 8 specific points. The absence of one or more welding points on the piece is considered a defective part. We generate a database with 51 images of several parts containing up to eight welding points. We used a SegNet convolutional neural network with 14 layers. The neural network was trained using hand-labelled defect images. The results of the training stage are the specific weights corresponding to the characteristics of the images. Our results show that our method can locate accurately the welding points.**

Index Terms—**Defective automobile parts, machine learning, image processing, classification.**

I. Introduction

Control quality in the industry is an important issue that usually is carried on by human operators or by visual-based automatic classification systems. As it is known, the first one involves some problems from which we can highlight that their perception can change during the workday while the second method does not. Nevertheless, automatic defect detection must deal with different issues such as big databases, time machines, precision, and several methods to choose from, among others [1].

In industrial settings, where large volumes of parts are inspected at high speeds, it is essential that the machine learning models can process images in real-time and scale to handle a high throughput. Training deep learning models such as CNNs can be computationally intensive, and inference times can be long if the model is not optimized [2].

Techniques such as model compression, hardware acceleration using GPUs, and the use of lightweight models (e.g., MobileNet, SqueezeNet) can help optimize inference speed and enable real-time defect detection in industrial applications [3].

In the automotive industry, the quality of parts is crucial to ensuring the safety, efficiency, and reliability of vehicles. Traditional methods of inspecting automobile parts for defects often rely on manual labor, which can be time-consuming, prone to errors, and inefficient. To address these challenges, machine learning (ML) has emerged as a powerful tool for automating the classification of defective automobile parts based on image data. Machine learning algorithms, particularly those in the domain of computer vision, can automate the identification and classification of defects in parts such as engines, body panels, wheels, and other critical components [4].

Machine learning models for image classification rely on large datasets of labeled images to train algorithms to automatically identify patterns and anomalies indicative of defects. These models can identify a wide range of defects, including cracks, dents, scratches, surface irregularities, and other imperfections that might otherwise go unnoticed by human inspectors. This report discusses the role of machine learning in the automatic classification of defective automobile parts images, exploring the key techniques involved, the benefits of using machine learning for such tasks, challenges, and real-world applications in the automotive industry.

Starting decades ago, but with a strong emphasis in the last years, research groups around the world have dedicated their efforts to using deep learning techniques for different tasks [5]. Even when deep learning is used in object recognition with good results some authors have reported its use in difficult tasks such as surface inspection [6], this is one of the reasons we propose the use of convolutional neural networks (CNN) to solve our problem.

Machine learning-based defect detection is already being used in several areas of the automotive industry. For example, automakers use machine learning models to inspect parts such as body panels, wheels, and engines for imperfections during manufacturing. By automating the inspection process, manufacturers can reduce human error, increase inspection speed, and ensure higher-quality products.

Some notable applications include:

- Automated Visual Inspection: In assembly lines, cameras equipped with machine learning models can capture images of parts and classify them as defective or non-defective in real-time.
- Quality Control in Manufacturing: Automated systems can detect surface defects such as dents, scratches, and cracks in parts during the production process, ensuring that only parts meeting quality standards proceed to the next stage.
- Predictive Maintenance: Machine learning models can also be used to analyze images of parts to predict when a component might fail, enabling proactive maintenance and reducing downtime.

Our tasks consist of an automobile piece produced of two different metal parts welted in 8 specific points. Because the welding process is manual, some welded points could be missing, and this modified the mechanical resistance of the piece. Then, if there are one or more missing welding points in

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J. Ruiz-Pinales, R. Guzmán-Cabrera, M. Torres-Cisneros are with the Universidad de Guanajuato, Engineering Division, CIS, Mexico (cisneros@ugto.mx).

M.C. Peña-Gomar is with Universidad Michoacana de San Nicolás de Hidalgo; FCFM, Mexico.

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Fig. 1. Automobile part with 8 welding points

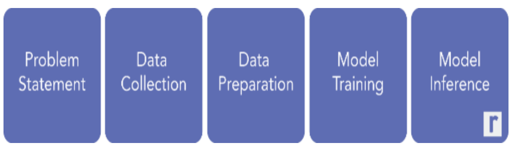

Fig. 2. Solution stages for a machine learning problem

the piece, it is considered a defective item. Figure 1 shows the image of one of the automobile parts, where the welding points have been manually marked with a red square.

As we can see from Figure 1, the welding points are hard to detect (because of the piece color and the image background), and this problem could be considered a surface defect detection.

In this work, we propose the use of a convolutional neural network (CNN), to automatically classify a non-defective automobile part.

II. Method and Results

In a learning system, training is maybe the most important task. In a visual recognition based on neural networks, the training is carried on manually marking the regions of interest (ROI) in the images, then the system "learns" the expected output from it. Figure 2 shows the different solution stages for a problem like ours.

Convolutional Neural Networks (CNNs) are a class of deep learning algorithms that have proven to be highly effective for image classification tasks. CNNs automatically learn to identify relevant features in images without the need for explicit human intervention. CNNs are composed of multiple layers, including convolutional layers that detect edges, textures, and patterns, pooling layers that reduce the spatial dimensions of the image, and fully connected layers that classify the image based on the features extracted from the preceding layers.

CNNs have revolutionized the field of computer vision due to their ability to handle raw pixel data and automatically learn hierarchical representations of images. In the context of defective automobile parts, CNNs can be trained to recognize various defects, such as cracks, dents, and corrosion. By providing the network with a large and diverse set of labeled images, the model can generalize to identify defects in new, unseen images with high accuracy.

In our case, we have a clear statement of the problem; identify the welding points in the automotive piece. The next step was to generate a database of images of different pieces and identify and mark the welding points in each image. In this stage, we used a neural network architecture known as a convolutional encoder-decoder to segment the image in regions that contain the welding points. This network has 14 layers, 7 of these are convolutional, 3 are max-pooling and 3 more are upsampling. The convolutional type used a ReLU activation function, while the convolutional filters for each layer were 3×3 size. The number of the maps were 4, 8, 16 and 32 for the first 4 convolutional layers and 16, 8 and 1 for the last 3 layers. The image operations in this stage were carried out with a GPU RTX 2080. The average time consumed for test images was around 5 ms. This time value implies that the system can operate in real-time. The input for this neural network was an automotive piece image and the output was the segmented image where we can easily identify the regions where are located the welding points, as we can see in Fig. 3.

For the data collection and preparation stage, we designed a GUI in Matlab® to segment the images of the automobile parts with welding points. To prove our proposal, we took 51 pictures of the pieces with a resolution of 3024×4032 pixels. The output of this GUI was a grayscale image with a white spot located in the place where welding points are located, as we can see in Fig. 3. The preparation stage finished scaling the images to 1/6 of their original size and converting to gray levels. 46 Images were selected for training and 5 for testing.

We used Python to implement the neural network using Keras and Tensorflow in a workstation with windows 10, an i7 core processor, and a GPU RTX 2080. The NN was trained using the mean squared error loss function and the Nadam optimization algorithm. The number of epochs was fixed at 3000 and the learning rate at 0.0001. We used the Xavier algorithm for setting the values of the initial weights, while because of the big image size, the batch size was fixed at 1.

Finally, in Figure 5 it is possible to observe: (a) a training image, (b) the obtained output from the trained network, and (c) the welding points detection.

The performance of machine learning models heavily depends on the quality and quantity of labeled data available for training. In the case of defective automobile parts, collecting a sufficiently large and diverse dataset that covers various types of defects, lighting conditions, and viewing angles is a significant challenge. Moreover, accurately labeling the defects in the images can be time-consuming and costly, especially in large-scale industrial settings.

To mitigate this issue, techniques such as data augmentation (e.g., rotating, flipping, or adjusting the brightness of images) can be used to artificially increase the size of the dataset and introduce more variability. Additionally, semi-supervised learning and transfer learning approaches, where models are pre-trained on large datasets and fine-tuned on specific defect detection tasks, can help overcome data scarcity.

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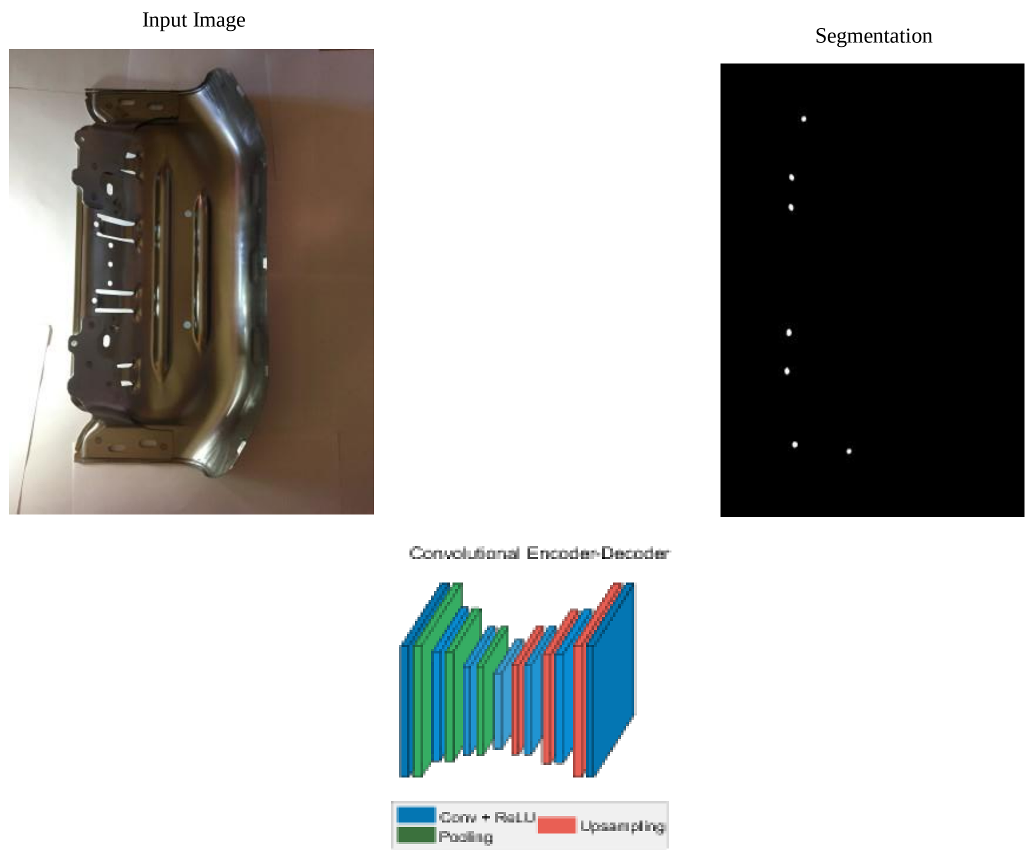

Fig. 3. Image segmentation using encoder-decoder convolutional neural network

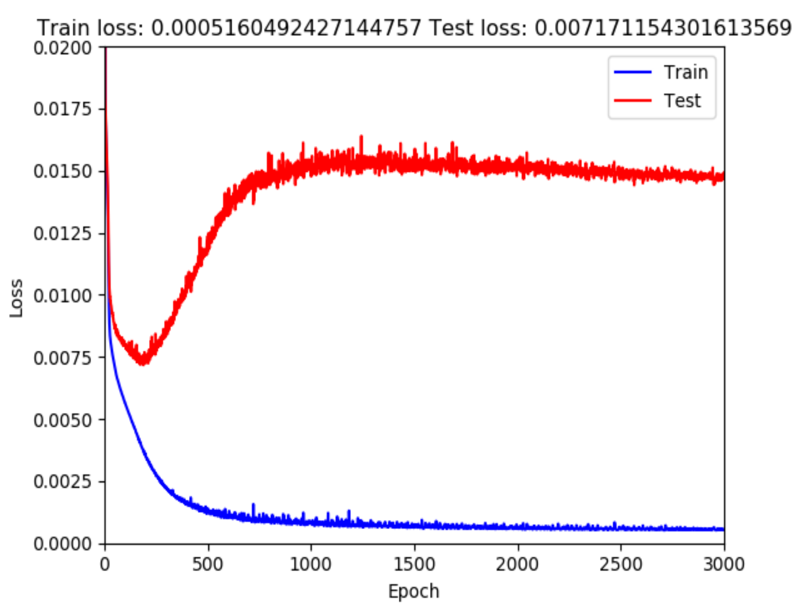

Fig. 4. Loss function for training and test stages versus Epoch number.

III. CONCLUSIONS

Our proposal was able to process each image in real time, where the image preparation stage was implemented in Matlab and the neural network was trained in Python. The results prove that all welding points can be detected in each piece, independently of how many welding points are in the automobile part.

We found that the neural network required only three max-pooling layers to be able to segment the image. We attributed this to the fact that welding points are relatively small. In fact,

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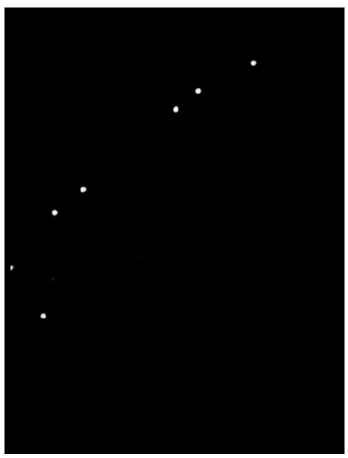
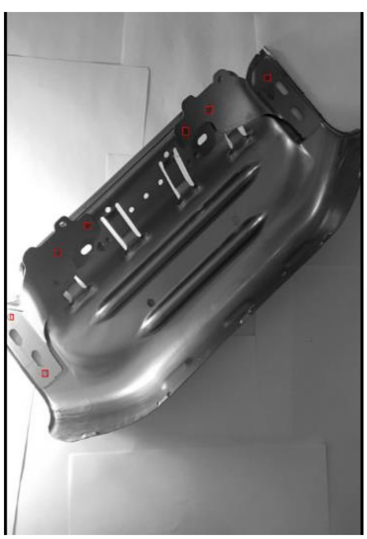
(a)



(b)



(c)

Fig. 5. (a) A training image, (b) the obtained output from the trained network, and (c) the welding points detection

the SegNet architecture is a large network containing many max-pooling layers as well as convolutional layers.

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