THE ANNALS OF "DUNĂREA DE JOS" UNIVERSITY OF GALAŢI
FASCICLE V, TECHNOLOGIES IN MACHINEBUILDING,
ISSN 2668-4829 (PRINT) 2668-4888 (ONLINE)
https://doi.org/10.35219/tmb.2019.1.07

MACHINE LEARNING TECHNIQUE TO DETECT DEFECTS ON THE STEEL SURFACE

Florin BogdanMARIN, Carmela GURAU, MihaelaMARIN

Department of Material Science and Engineering, "Dunărea de Jos" University of Galați, România
email: florin.marin @ugal.ro

ABSTRACT

In this paper is presented a technique concerning the machine learning using computer vision data for the detection of defects on the steel surface. The early detection of defects can reduce the product damage and manufacturing cost. Moreover, it provides information that will provide data concerning quality of products and correct classification and this means that the product will not be rejected by the customer and avoid other costs. The non-contact inspection of the surface defects using the computer vision has become very popular in manufacturing industrial systems as it provides reliable and fast results. The machine learning achieved impressive results in image classification tasks, though it requires the previous learning phase to be completed. The proposed machine learning technique allows fast identification of defects and also permits learning during the process.

KEYWORDS: machine learning, steel surface, computer vision

1. INTRODUCTION

Steel is the industry's most important material. Flat steel products are used in a wide area of steel products. Surface defects detection are of paramount interest for production, in order to decide if the product is accepted by customers and decide the use taking into account level of quality.

Defect detection using the image processing is a field of machine vision largely used in industry in industry. The main advantages are high quality control as well as high speed, continuous control. There are numerous applications in control, such as the steel surfaces in control such as steel surfaces. Scholars and industry have developed very reliable systems for the automatic inspection of surfaces of all kind of mass produced goods [1][2][3].

The image processing is composed of several steps. First, the system the image is acquisitioned usually from video streams. This needs suitable cameras and a lighting system, which requires special attention when choosing camera as well as the type of lighting.On the market there is a wide number of cameras with different specifications, such as frame rate up to 10 000 frames/s or multispectral camera. Also, there are wide commercial offers for different types of lighting system. Once the images are acquisitioned, the next step is the computer vision processing to extract the features required for the specific application for identification of specific defects. The algorithm returns the presence of a specific defect [4][5][6].

The state-of-the-art development shows that Support Vector Machines (SVM)algorithm [9] achievevery good performance in the classification of defect [10]. The SVM uses the idea of finding a hyper plane to separate "good" solutions in respect to the "not good" solutions. This algorithm is used when various defects are separable, as seen in Fig.1.

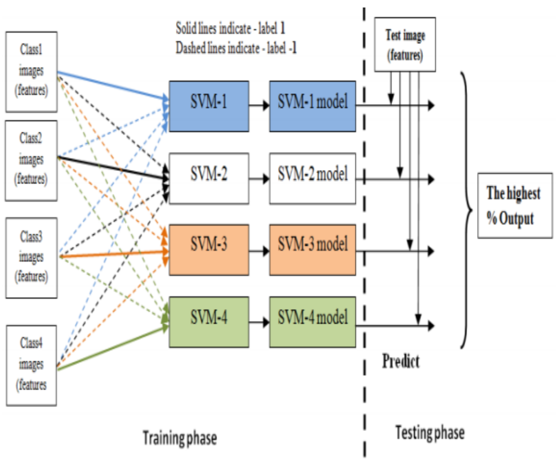

Fig.1. *The diagram of our proposed voting strategy for 4 classes [10]*

There are also research teams that use the Artificial Neural Networks (ANN) [5] that require training using previously trained data.

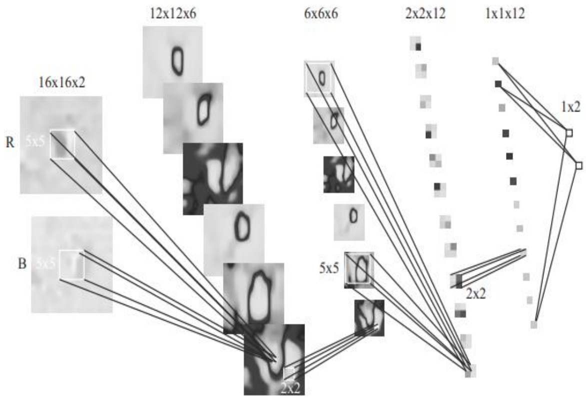

Fig.2. *CNN architecture for surface defect detection: two convolutional and pooling layers and a fully connected layer [11]*

A CNN is a multi-layer neural network architecture that is able to learn using previous data in order to achieve the identification of a specific feature (Figure 3).

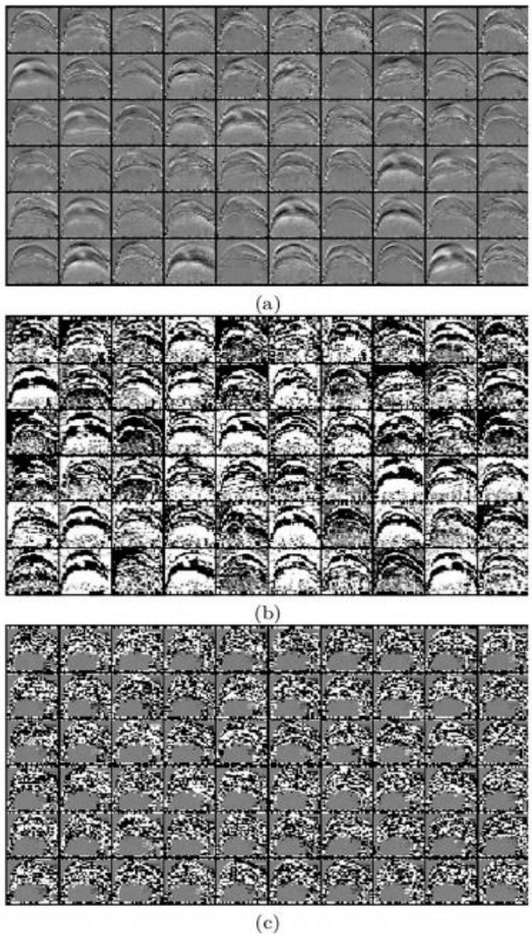

Fig.3.*Visualization of the output features from the second hidden layer when applying an autoencoder on: (a) grayscale images, (b) gradient images, and (c) the binary images [12]*

The convolutional neuronal networks are widely used to achieve satisfactory results. Important advances can be achieved by learning the discriminative features that are representing a specific defect (see Fig.2) [11].

The concept of neural networks is the basic algorithm for many deep learning algorithms, which means that deep learning networks are composed of many layers thatcontinuous transforminput data to further forward information to the next level in the network.

The choice of a neural architecture depends on the application required taking into account the features to be detected.

This paper presents a technique concerning the machine learning using the computer vision data for the detection of defects on the steel surface. The machine learning achieved impressive results in image classification tasks using supervised learning. The proposed machine learning technique allows the fast identification of defects and also permits learning during the process.

2. THE PROPOSED SOLLUTION

This research aims to propose intelligence algorithm along with the computer vision in order to allow the user to define the defect in a very fast way, intuitive, without the need for a programmer or an image processing expert. Consequently, we want the user to use the software interface to define the defects by selecting the rectangle areas where defects are present and introduce some basic information.

There are several descriptors which are used to compare.

1)The Local Binary Patterns (LBP) are used to define the spatial structure of greyimages that are the output after thresholding algorithm.

2)The Local Binary Pattern Histogram Fourier (LBP-HF)] Have the advantages that area rotation invariant descriptor which takes input from LBP. In case of most steel defects rotation invariance is of utmost importance.

3) Histogram of Oriented Gradients (HOG): is analgorithm that is evaluatingthe normalized local histograms of image gradient.

As described in Figure 4, the user needs to define the defect concerning two aspects. One is considering the shape description and the other is colour detection. The user should define in a very intuitive manner if a certain defect is described better by colour, such as in case of rust, or is described by shape, such in case of scratches. Also, the user might define a defect as described by both manners (see Figure 4).

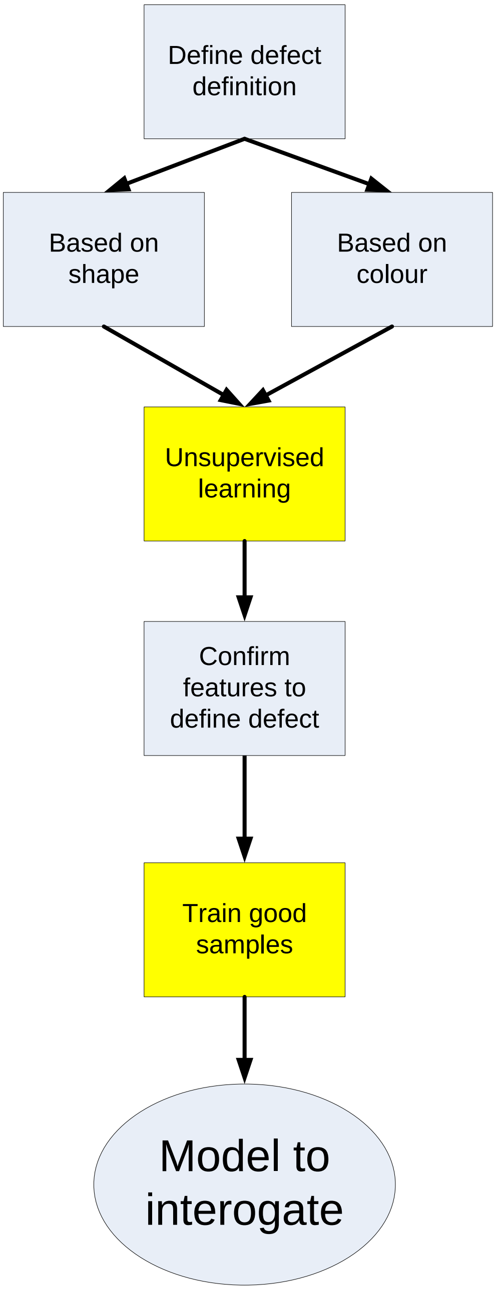

Fig.4. *The steps of the proposed technique*

Though the user defined some defects, the algorithm is capable ofnovelty detection, and this is done usingthe support vectorsalgorithm. We are aiming the user to use software with simple interface in order to detect novel defects even no previous training or indication. In the SVM model there are left several free parameters, which can be determined automatically.

Rust is one of the most common surface damages of steel structures.As the rust has a specific colour, the detection is not a very difficult aim, however, the characterisation in an automated way is quite challenging.

We used in our application the detection of rust, using this defect as novelty detection, without previous training.There are authors who havecomputed several statistic variables of RGB colour channels from one image aiming to define a multivariate discriminant to detect rusts. We used the RGB space as well as CMYK for the detection based on colour.

To eliminate and compensatethevariation of results due to light condition, we used pattern classifiers based onthe K-means method. SVM is used for finding the optimal separating areas for rust to non-rust areas.

Figure 5 shows the results of the rust areas detecting, with the rust used as novelty detection, with no previous definition of features.

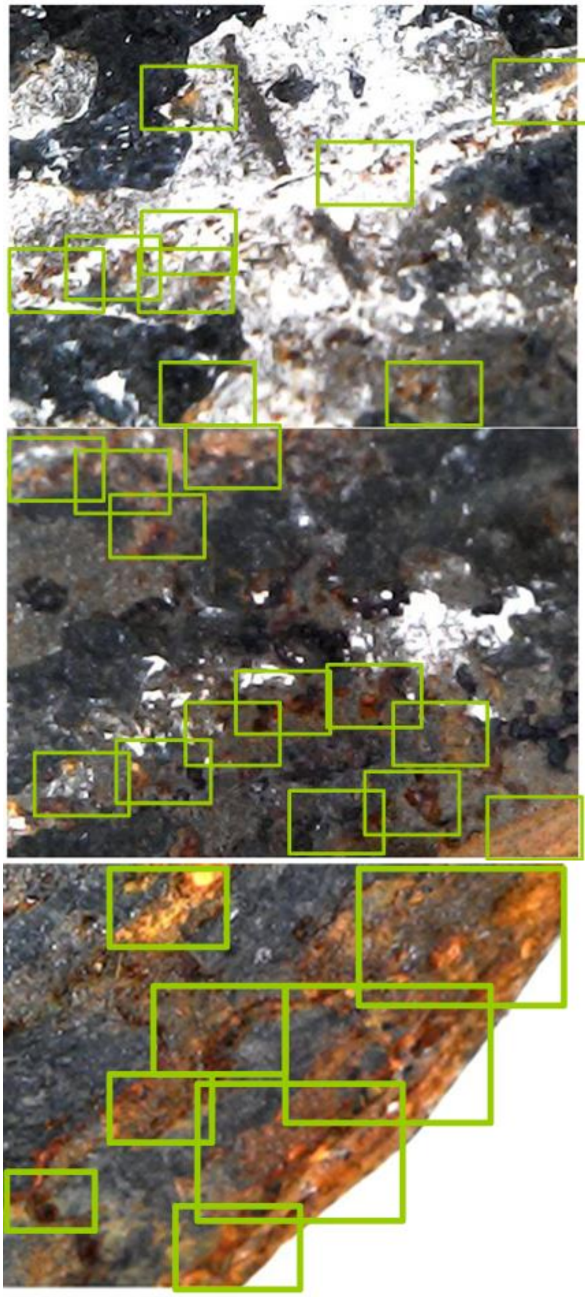

Fig.5. *Detection of rust areas – defined as novelty detection*

Figure 6 displays a classic transformation of images using the thresholding followed by contour detection and deleting the blobs with minimum areas.

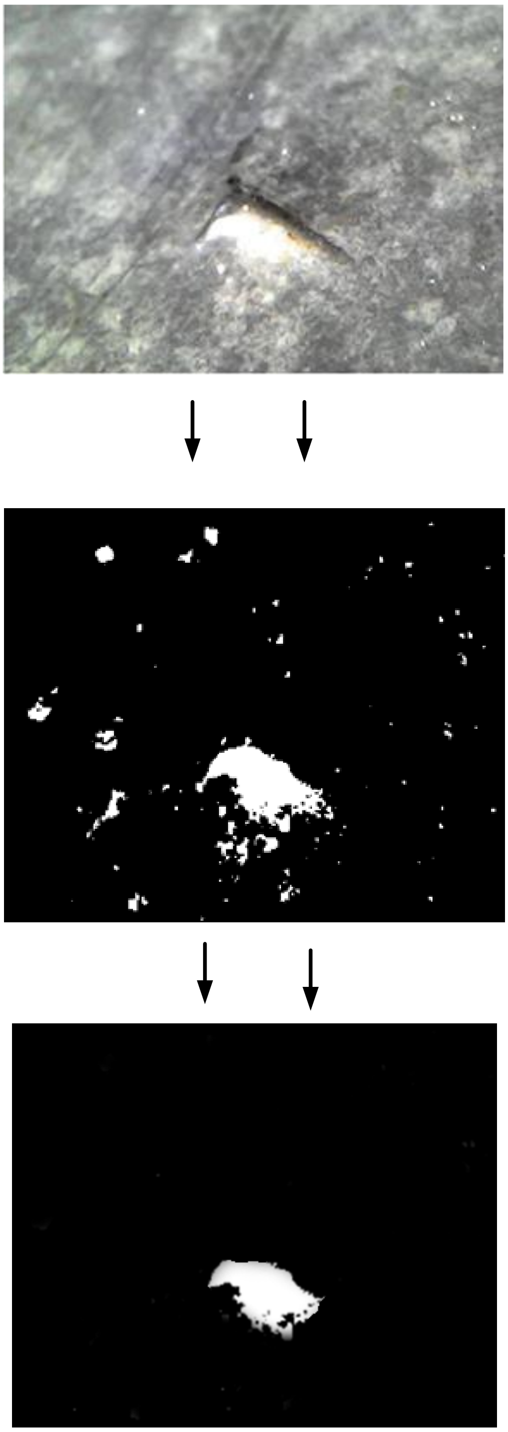

Fig. 6.*Basic image processing*

This basic transformation from the computer vision algorithm is used in order to extract features. The algorithm allows detecting novel defects without the user to select magnification or to perform measuring the scale of magnification.This is an important feature for an intelligent algorithm, to be highly adaptable to wide area of settings (Figure 7).

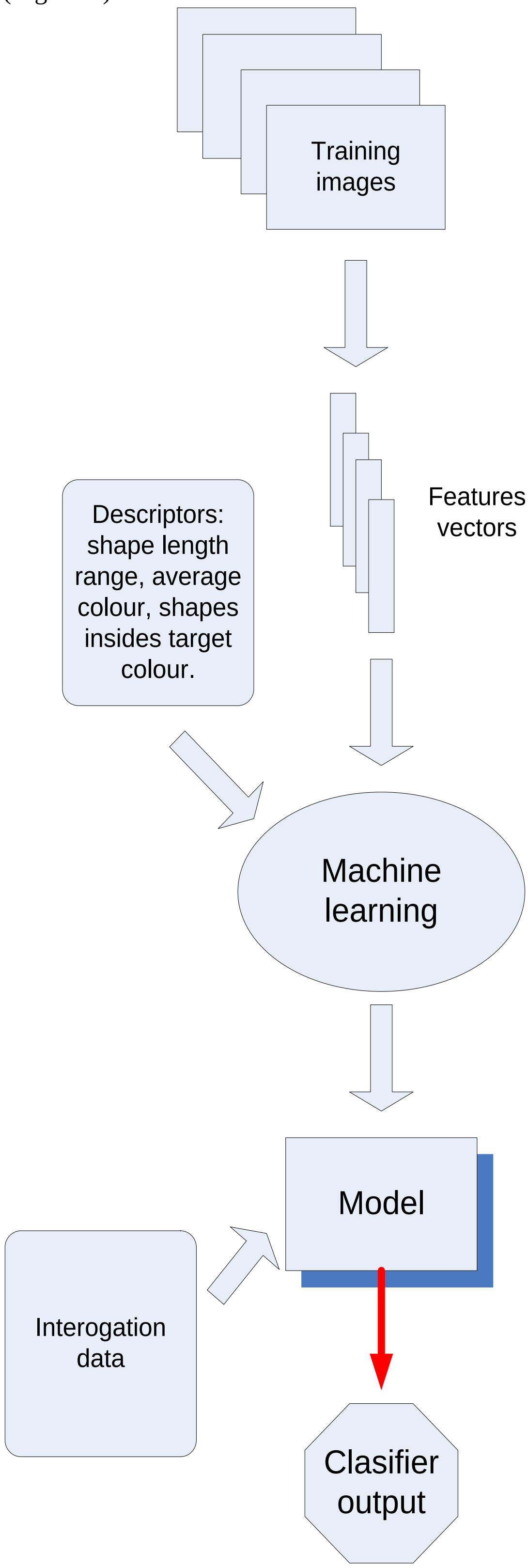

Fig. 7.*Proposed algorithm for training*

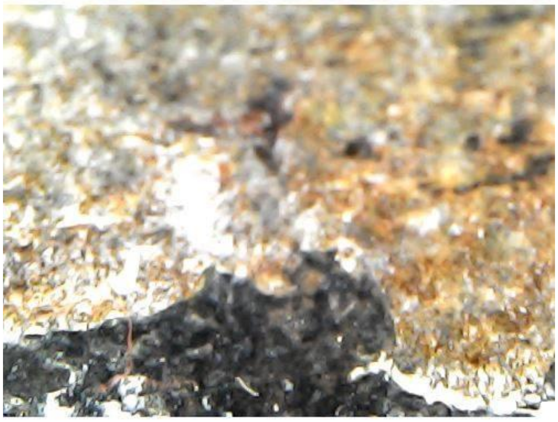

Fig. 8.*Image aspect of rust area*

The rust areas detection and novelty defect detection can be detected even though a partial focused image, where closer areas are visible and we can extract features while some areas are blurred due to non-focus of cameras. This emerges when camera position is altered or steel surface is not plane and parallax errors are present.

The software used is Visual Studio along with Opencv computer vision library for computer vision basic image processing algorithm.

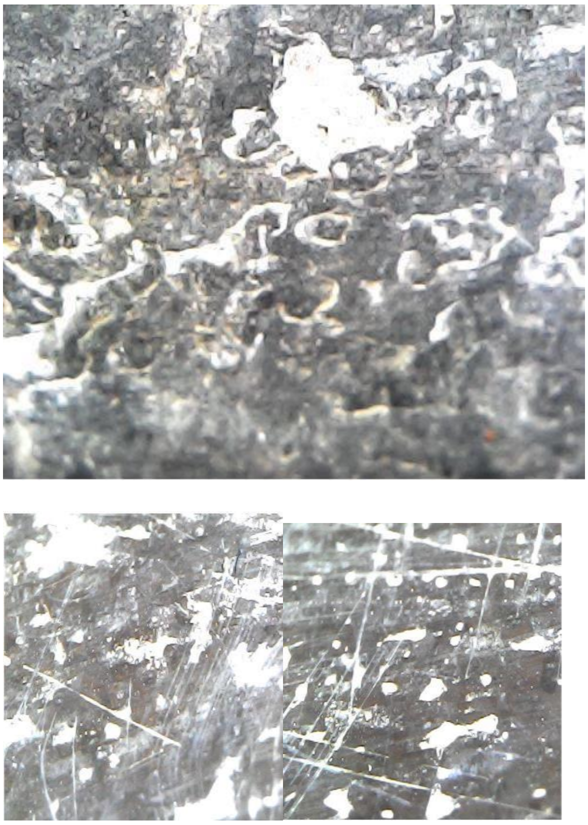

Fig. 9.*Different aspects of steel, provided as input for non-deffective*

Fig. 10.*Detection of defect as novelty defect*

We evaluate the performance and efficiency of the proposed approach using 2000 real images. The database contains only 30 images of defective. First, we will assessthe ability of our algorithm to classify the defective images using the training of non-defective.

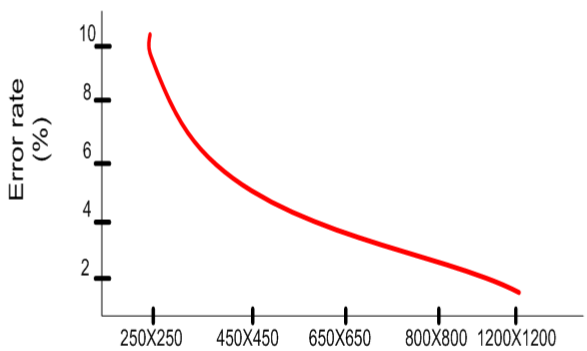

Fig. 11.*Error rate in case of image variation*

The results demonstrate that the proposed algorithm can be successfully applied using different magnification scale. Second, we evaluate the sizes of images for detecting and localizing defects in images. We compare, see Fig.11 the performances of different size of images.

3. CONCLUSIONS

This paper presented an intelligent-based algorithm in order to detect defects on steel. We propose an algorithm to define in a very intuitive manner for the user of defects. Besides, the artificial intelligence algorithm allows for detection of novelty defects that are not defined by the user. The algorithm that uses classic approaches incomputer vision and artificial intelligence need to be further developed in order to detect a wide spectrum ofdefects.

REFERENCES

[1] Y. Frayman, H. Zheng, and S. Nahavandi, “Machine vision system for automatic inspection of surface defects in aluminum die casting,” Journal of advanced computational intelligence, vol. 10, no. 3, pp. 281–286, 2011

[2]F. Pernkopfand P. O’Leary, “Image acquisition techniques for automatic visual inspection of metallic surfaces,” NDT & E International, vol. 36, no. 8, pp. 609–617, 2003.

[3]R. Gonzalez and R. Woods, “Digital image processing. 1992,” Reading, Mass.: Addison-Wesley, vol. 16, no. 716, p. 8.

[4]S. Kotsiantis, “SupervisedMachineLearning: A Review of ClassificationTechniques,” in Proceeding of the 2007 conference on Emerging Artificial Intelligence Applications in Computer Engineering: Real Word AI SystemswithApplications in eHealth, HCI, Information RetrievalandPervasive Technologies, 2007.

[5] L. Martins, F. Panddua, and P. Almeida, “Automatic detection of surfacedefects on rolledsteelusing computer visionand artificial neural networks,” in IECON 2010 - 36th AnnualConference on IEEE Industrial Electronics Society, 2010

[6]A. Kumar and G. K. Pang, “Defect detection in textured materials using gabor filters,” IEEE Transactions on Industry Application, vol. 38, no. 2, pp. 425–440, 2002.

[7]T. Ojala, M. Pietikinen, and D. Harwood, “A comparative study of texturemeasureswithclassificationbased on featureddistributions,” Pattern Recognition, vol. 29, no. 1, pp. 51 – 59, 1996

[8] Tomaso Poggio, Vincent Torre, andChristof Koch. Computationalvisionandregularizationtheory. In Readings in Computer Vision, pages 638–643. Elsevier, 1987

[9]Leopoldo Armesto, Josep Tornero, Alvaro Herraer “Inspection system based on artificial vision for paint defect detection on car bodies” IEEE conference. 2014

[10]B.Suvdaa, J. Ahn, and J. Ko, Steel Surface Defects Detection and Classification, Semantic scholar 2018.

[11]Soukup and R. Huber-Mork, Convolutional Neural Networks for Steel Surface Defect Detection from Photometric Stereo Images, Springer International Publishing Switzerland 2014

[12] Oumayma Essid,Hamid Laga,Chafik Samir, Automatic detection and classification of manufacturing defects in metal boxes using deep neural networks, PLOS One Journal , 2018.