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GPU Cuda JSEG Segmentation Algorithm associated with Deep Learning Classifier for Electrical Network Images Identification

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Abstract

An automatic recognizer system based in Artificial Intelligence for thermographic images of the electric power distribution network is proposed in this article. The infrared thermography is usually used to conduct inspections in electrical power distribution lines, assisted by a human operator, which is usually responsible for operating all the equipment, selecting the hottest spots in the image (corresponding to the places needing maintenance), making reports and calling the technical team, which will do the repairs. The proposed automatic diagnosis system aims to replace the manual inspection operation using image processing algorithms. An old method of segmentation for thermal images known as JSEG is implemented and tested and a Deep Learning Neural Network is responsible to recognize the segmented elements. A comparison between the exclusive Deep Learning based image recognition with the same method preceded by the JSEG segmentation algorithm is done in this article, showing better performance with this previous segmentation of the thermographic images.

Keywords: Thermography; Image Processing; Deep Learning; CUDA JSEG Segmentation; Preventive Maintenance; Infrared Photo.

1. Introduction

The thermography is a non-destructive and non-invasive inspection technique, based on the detection of infrared radiation, naturally emitted by bodies, with the intensity proportional to its temperature. Using this technique, it is possible to identify regions or hotspots where the temperature is altered in relation to a pre-adjusted pattern. It is based on the measurement of the electromagnetic radiation emitted by a body in certain temperature above the absolute zero [1][2]. Thermographic images are useful in non-destructive technologies for building diagnostics, with the concerns of energy consumption minimization in the building sector, and in energy related building defects [2].

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Karvelis et al. 2014 described an approach using thermographic images in the development of reliable systems for fault detection in induction machines, using image segmentation [3]. The work of Bagavathiappan et al. is related to a review of infrared thermography for condition monitoring [4].The infrared thermography is an effective tool in monitoring the condition of electrical equipments, since it has the capability to detect the thermal abnormality in such equipments. The common approach, that is used in monitoring systems, can be divided in: image pre-processing, segmentation, classification and decision making [5][6]. The Thermovision Project, developed by a brazilian electric distribution company, consists of the construction of a vehicle equipped with four thermographic cameras provided by Flir, model A-612, and five optical cameras provided by Dalsa. These cameras are mounted on automatic positioning system called 'pantilt', which can be adjusted automatically by stepper motors. A tracking algorithm is responsible for proper automatic positioning of all cameras. The camera positioning is done so that when it locates an electric pole, this image object remain in the center of view of the cameras. Figure 1 illustrates the aspect of the thermographic inspection vehicle under development: (A) Thermovision Project inspection vehicle, (B) details of the cameras at the top, (C) and (D) are photos of the real vehicle assembled.

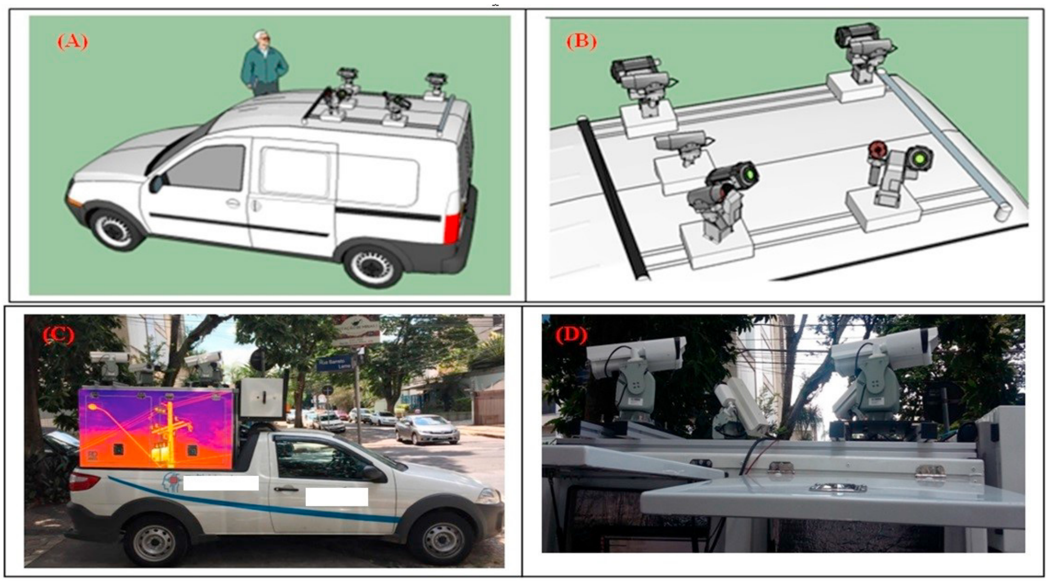

Figure 1- Thermovision thermographic inspection vehicle appearance, showing details of the cameras at the top.

Figure 2- (A) Pantilt and cameras mounted on the top of vehicle; (B) Infrared thermal camera inside the container.

The set of cameras and 'pantilts' are assembled on the top of the vehicle, as showed in figure 2, at left (A). The Flir infrared camera can be viewed in figure 2(B), with the switch board functioning for multiplexing the signals from the thermal camera and the optical camera and delivering these signals on the same cable that is connected externally to the pantilt. The four *pantilts*, as showed in 2(A), are part of this project, controlled by automatic tracking software, written in C language, and based on Faster-RCNN Detector and KCF Tracker developed by Yingjie and Yang [7][8]. This tracker system uses the optical image to centralize the electric poles.
At figure 3 it is shown an illustration of the display of the PC computer, inside the vehicle, during maintenance routine of the Thermovision Project.

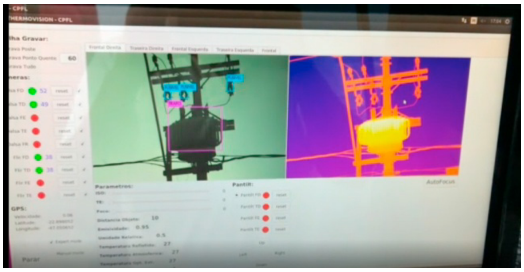

Figure 3 – Software running at PC computer in the Thermovision Project vehicle, with JSEG and Deep Learning functions activated. The segmentation lines do not showed to users. An optical image can be watched side by side of thermographic image.

It is proposed in this paper a software for automatic segmentation and recognition of hot spots in thermographic images obtained in the Thermovision Project. Two approaches are described. The first approach uses the JSEG segmentation algorithm, that uses the concept of J-images to conduct the segmentation process; then it is used the Deep Learning with Convolutional Neural Network technique to recognize the hot spots in the image, as one of four objects: transformer, electric bushing, knife-wrench and electrical splice connector. The second approach uses only the Deep Learning with Convolutional Neural Network technique to the segmentation and recognition process. The rest of the paper is organised as follows. Section 2 is used to the description of the JSEG segmentation algorithm. Section 3 refers to implementation of the JSEG algorithm. Then, at Section 4 it is presented Deep Learning and Convolutional Neural Network implementation aspects. Section 5 is dedicated to the experimental results, and Section 6, to the conclusions.

2. JSEG Algorithm

The implemented algorithm, tested and described in this work, is known as JSEG in the image processing specialized literature. The word 'JSEG' means J-segmentation, because it produces J-images, a kind of transformed image [9]. It was developed and initially presented by Yining, Manjunath et al. [10] in 2001.The JSEG main idea is to split the segmentation process into two stages, processed in an independent way: color quantization and spatial segmentation [11]. Figure 2 shows the scheme adopted by the JSEG Algorithm for color image segmentation. In the color quantization of the first stage, the colors of the image are quantized into some representative classes, which may be used to differentiate the regions in an image. This quantization is applied only in the color space, without considering the spatial distribution. After that, the colors of the pixels are replaced by the so called class labels, to form the class map, generating a quantized color image with a reduced number of colors for the next stage. The spatial segmentation, uses as a criterion of 'good-segmentation' the class labels from the previous stage. Applying the criterion of local windows to the class map, it is obtained the 'J-image', where high and low values of the J-value correspond to the boundaries (hills) and interiors (valleys) of the color regions (separated by different textures), respectively. A region growing method is then used to segment the image, based on images in multi-J scale. The J-images correspond to local homogeneity measures in different scales, which can indicate potential outlines localizations. A region is part of the image compounded by a group of pixels that have some level of similarity. In the region-based segment methods, it is assumed that the near pixels of a region have similar values.The ordinary procedure is to compare a pixel to its neighbors, and then group them following a similarity criterion.

2.1 Spatial Segmentation Algorithm

The non-supervised segmentation of color and texture consists in considering the spatial arrangement of the pixels using a region-growing technique based on morphological operators, whereby a mode of homogeneity is defined with pixels grouped in the segmented region. In the other hand, it should be considered different scales of images. The JSEG algorithm segments images in pseudo-color produced by the thermal vision cameras, without adjusting manual parameters for each image and it simplifies the texture and color. The segmentation with this algorithm goes through three sub-stages, which are called: color space quantification, hit rate in regions and blend of regions with similar colors.

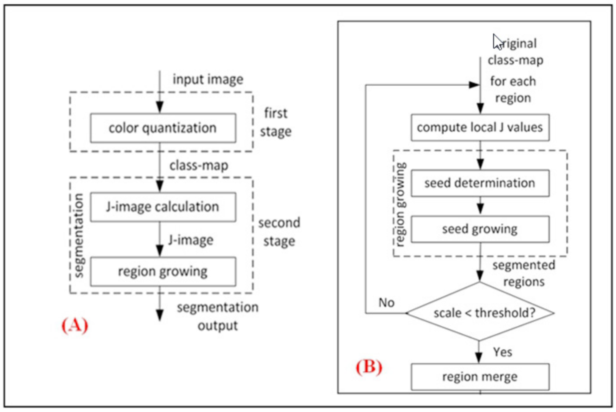

Figure 3- (A) JSEG Algorithm to segment colored images; (B) A flowchart illustrating the spatial segmentation algorithm [12].

With this aim, it is assumed that each region in image has a uniform distribution of color and texture patterns. The color information of each image can be represented by its color counting. In general, considering a natural scene color image, the colors among near regions can be differentiated. In the first stage, the color space is quantized with little degradation using the perceptive algorithm of quantization. The aim of this stage is to define the regions on the image using a minimum number of colors. Each color is associated with a class. In the original image, there are pixels that are replaced by classes in the first stage, that origin the class map, which will be used in a next stage. Before proceeding with the region growing (using morphological operators), the J-image must be created. The pixel values of the J-image are used as a criterion of similarity by the region-growing algorithm. The pixel values of the J-image will be called J-values and are calculated from a window positioned over the quantized image, where the J-value to be calculated is from the pixel in the center of the window. To calculate the J-value, it is defined firstly Z as the set of all the spots of the quantized image, then $z = (x,y),\ z \in Z$, and m is the average in all Z elements. C is the number of classes obtained in the color quantization. Therefore, Z is classified in C classes. The Zi is the Z elements that belong to i class, where $i = 1, \ldots, C$; and m_i are the average of the elements in Zi. The J-value is given by the equations (1), (2) and (3) as follows:

$$J = \frac{S_B}{S_W} = \frac{(S_T - S_W)}{S_W} \tag{1}$$

$$S_T = \sum_{z \in Z} \|z - m\|^2 \tag{2}$$

$$S_W = \sum_{i=1}^{C} \sum_{z \in Z} \|z - m_i\|^2 \tag{3}$$

where S_T represents the sum of the quantized image spots, considering the standard diversion in all Z elements. By this way, the relation between S_B and S_W denotes distance measures of this class relation for distributions of arbitrary non-linear class. S_W is an estimator that calculates the sum of the standard diversion inside the classes. The distance and, consequently, the J-value decreases to images that have color classes more uniform. Further information can be obtained in the book cited in [12]. Several sizes of windows are used: the largest ones detect the borders of the regions with textures; the smaller ones detect changes on colors and light intensity. Each size of window is associated to a scale of image analysis. The concept of J-image, with the several scales, enables the segmentation of textured regions. The J-image regions with the smallest values are called **valleys**. The smallest ones are found with a heuristic proposed by Manjunath et al. [11]. Therefore, it is possible to determinate the initial points of the growth in an efficient way. So, the algorithm adds the regions that are more alike to the valleys. The end of the algorithm is reached when there are no more pixels to be added to the regions. The J-image is recalculated for each one of the new regions with a smaller window than the previous employed one. After using the smallest window, the algorithm groups the regions with similar colors. This algorithm needs only three parameters to run. The first, the threshold of the color quantization algorithm, is related to the number of groups in which the colors are grouped. The second, scale numbers, influences how the JSEG algorithm deals with the details of the image. The last parameter is the threshold used by the algorithm that groups the regions with similar colors. More than those parameters, it is necessary to define the spatial resolution of the images. As one of the classes corresponds to the hottest point in the image, it is necessary to choose a resolution that enables the JSEG algorithm to distinct the hottest points (hotspots) from the another segmented regions. As the image segmentation is a subjective process, choosing the great parameters is a hard task, hence the parameters and the image resolution in this work are chosen manually with the assistance of the visual inspection of the segmented images and previously adjusted in the software. Once those parameters are chosen manually, it is expected that they keep constant to the proposal of the thermographic image analysis. J-images allow to use a regions growth method to segment the image. The original image is an initial region. The algorithm begins segmentation of the image with a rough initial scale. Then it repeats the same process on the new segmented regions on a finer scale. Figure 3-B shows a flowchart of the steps used in the Spatial Segmentation Algorithm.

3. Methodology and Implementation of JSEG algorithm

In this section it is described some implementation detail of the methodology used in this project. In this paper, the goal of thermal images processing is to detect the hottest areas. Therefore, the algorithm can be implemented more fruitfully under an assumption that there are not many hot spots in outdoor electrical energy distribution thermal images. The reduction of duration is one of the main problems of JSEG algorithm. In order to solve this problem, a modified GPU CUDA JSEG implementation have been selected, based in [13]. The result was a fast and robust algorithm. The time of segmentation was 73 ms (9x9 grid size) in this example, using NVIDIA GeForce GTX1080 GPU video-board implementation and 970ms running at CPU, for the same grid size. The JSEG segmentation time in 65x65 grid was 2,456 ms in average.

4. Deep Learning Classifier

In order to recognize the overheated elements that were segmented by the previous JSEG stage, a supervised type classifier based on deep learning convolution network was implemented. This classifier also works in the GPU and was written in C and CUDA language and is based on YOLO algorithm [14][15]. The input of this classifier is the segmented image from JSEG algorithm and the output is a region in the box and a label that represents the class of the classified image. Figure 4 shows the architecture of Deep Learning (DL) convolution neural network tested and it is based on Alexnet [16] .

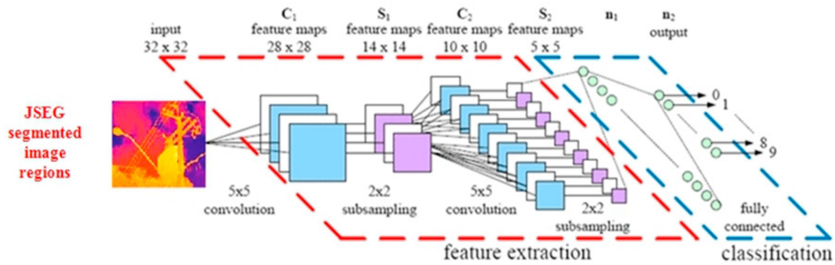

Figure 4- YOLO Convolution Neural Architecture, based in Alexnet [14].

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5. Experimental Results

Figure5 shows the main electrical line components, which frequently need maintenance. In (A) is showed the electric transformer, (B) electric bushings; (C) knife-wrenches and (D) electrical splice connectors. After segmentation, all these same components are used to training a deep learning neural network to recognize automatically the elements, and it is the second stage of the developed software.

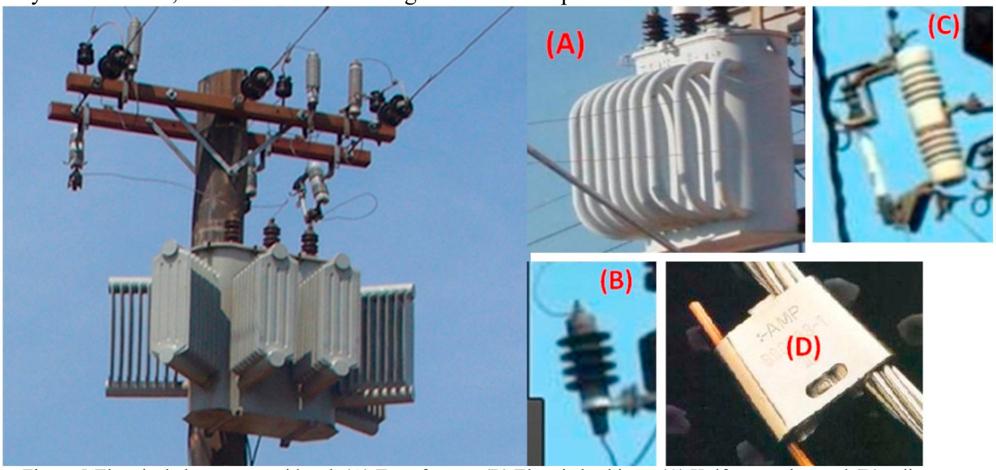

Figure 5-Electrical elements considered: (A) Transformer; (B) Electric bushings; (C) Knife-wrenches and (D) splice connectors.

Two results of the JSEG algorithm implementation are shown in figure 6, in two rows. The leftmost image of both rows of figure 6 refers to the original thermographic image. During tests, four distinct scales were used, employing rounded windows of the size 9x9, 17x17, 33x33, and 65x65 pixels per radius, which are shown from the second to fifth figures, in two rows, from left to right of figure 6.

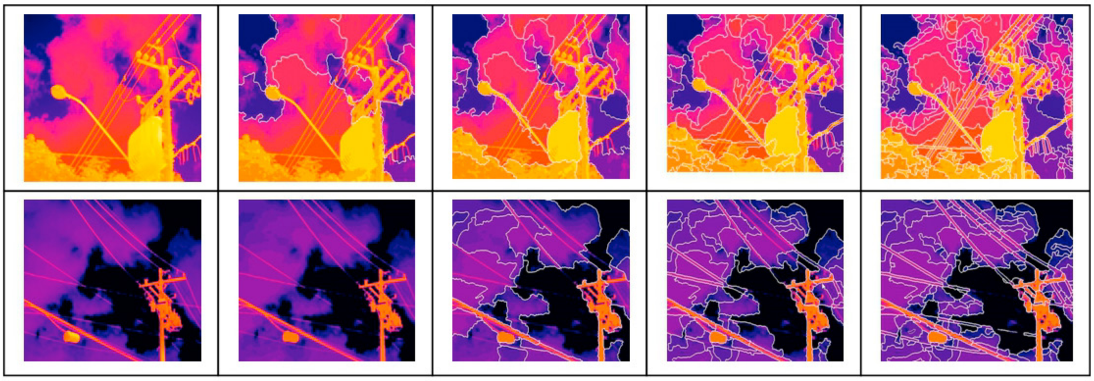

Figure 6- Examples JSEG segmentation in scales 9x9, 17x17, 33x33 and 65x65. Just hot spots (clearer colors regions) go to the DL training.

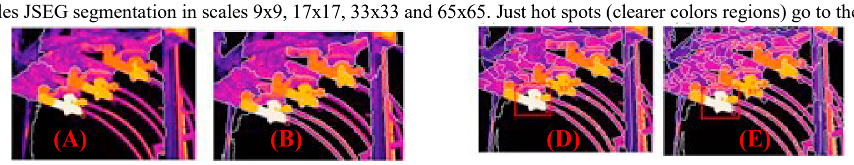

Figure 7-DL recognition, in JSEG scales 9x9, 17x17, 33x33, and 65x65, from left to right.In (C) and (D) the hot spots are recognized by DL.

Figure 7 shows the segmentation of the hottest part in these four scales, respectively, from (A) to (D), using DL. In particular, it is noted the importance of segmenting automatically by a specific software for image analysing and processing, regions of different colors: in a thermographic image generated in pseudo-colors, different colors represent regions of the image that have distinct temperatures. Therefore, the hottest element can be segmented, which facilitates the electric component recognition by another software module, based in DL. It can be seen that the region where the temperature is higher is shown in white color (clearer) and it is properly segmented in scale 33x33 (figure 7-C) and scale 65x65 (figure 7-D). Figure 8 shows another thermographic image: wires with the splice-connector (Ampact© provided by TE Connectivity manufacture), where there is an abnormal heating. The photographic image shown was taken using FLIR camera, model A-615, equipped with 7 degree lens, about 12 meters of distance of the pole. The regions in white color correspond to the area with the locally highest temperatures, that are printed in the image.

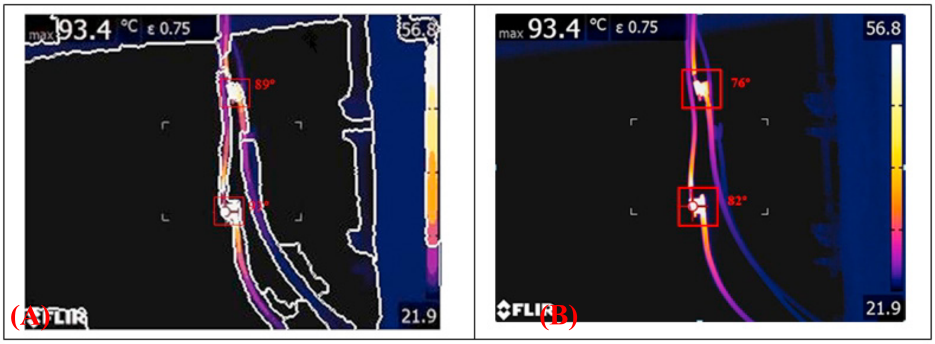

Figure 8- (A) Image classified, with contour box, after JSEG segmentation of the hot spots; (B) DL contour box around hot spots.

Figure 9 shows another example of JSEG segmentation followed by DL hot region recognition, confirming the effectiveness of the proposed method.

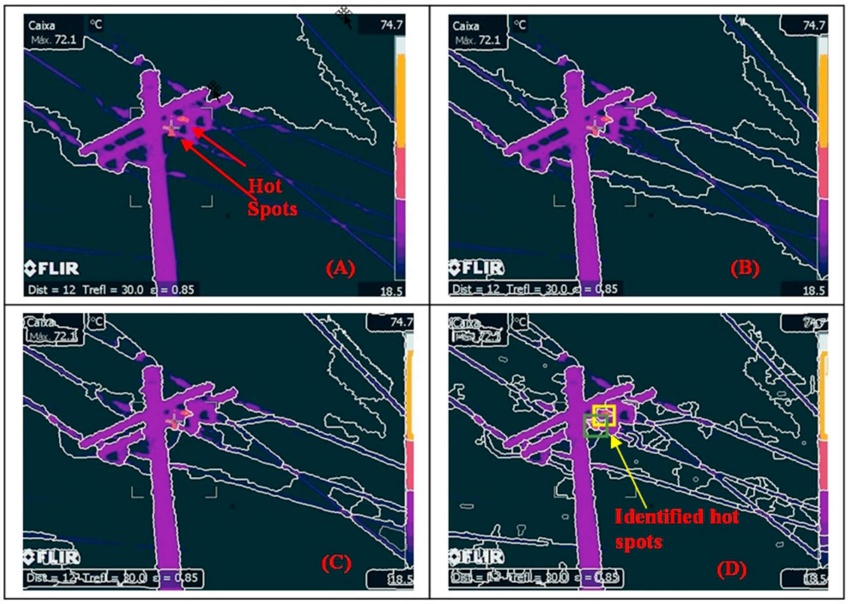

Figure 9 – Detected hot spots in photo 9(D), after JSEG segmentation. The DL network recognized the segmented region easier than non segmented regions. The time for hot spot identification in this image was 580ms, with NVIDIA GTX1080 GPU implementation.

The graph showed in figure 10 represents the variation of performance of the trained DL when the number of neurons was varied. It was measured for one hidden layer, using only the DL network, and using DL with JSEG segmentation (JSEG+DL), with "learning_rate": 3.0, "num_epochs": 60, "mini_batch_size": 64, and on each iteration, changing the number of hidden neurons by 10, starting with 10 neurons.Figure 11 shows how the accuracy varies according to the number of epochs and batch size, in two cases: with and without JSEG segmentation, running at NVIDIA GeForce GTX1080 GPU video-board and Asus Intel “i7” 3.8 GHz CPU.

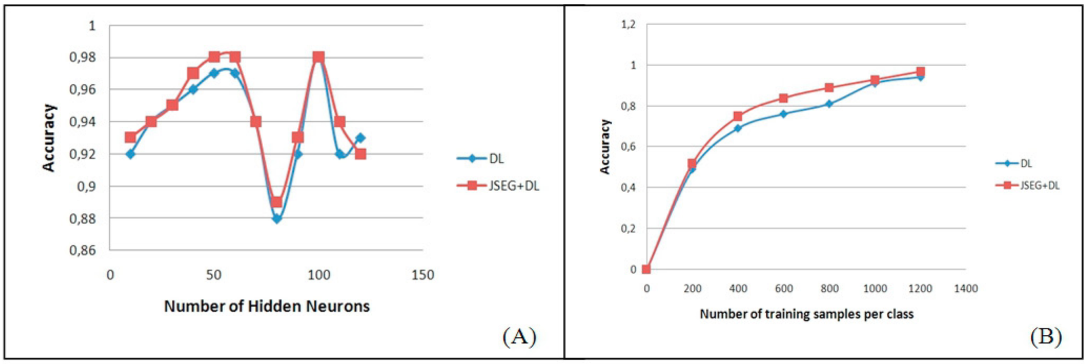

Figure 10- (A) Accuracy of DL and JSEG+DL, varying the number of hidden neurons, "learning_rate" 3.0, "num_epochs": 60, "mini_batch_size: 64";(B) Accuracy comparative graph between DL and JSEG+DL, varying the number of samples in training set.

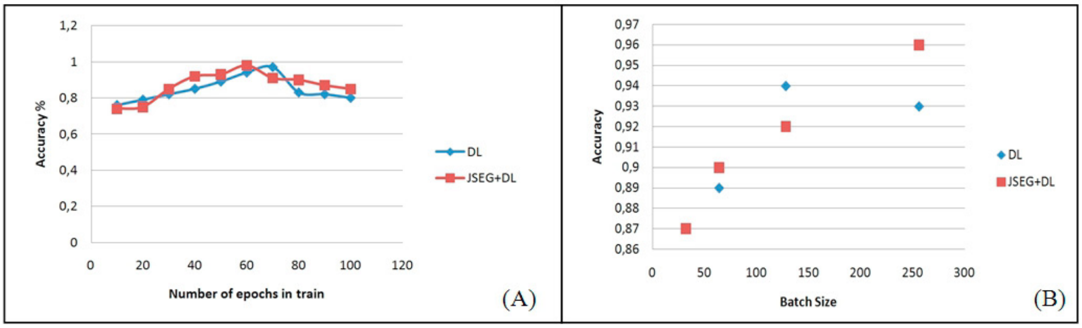

Figure 11- (A) Accuracy of DL and JSEG+DL, varying the number of epochs during training process;(B) Accuracy comparative graph between DL and JSEG+DL varying the batch size: 32, 64, 128 and 256.

Varying the batch size with 32, 64, 128 and 256 values, the best values found were 256 for JSEG+DL and 128 for DL. The Confusion Matrix for the four classes of elements is shown in Table I, where the DL performance is showed between parentheses for the same set of images, DL with 100 neurons and 2 hidden layers, using ReLu activation function. The best performance after the JSEG was obtained with the detection of electrical splice connectors, which are the components that present the most frequent faults [17].

TABLE I CONFUSION MATRIX FOR THE 4 CLASSES

	Transformer	**Electric bushings**	**Knife-wrenches**	**Electrical splice connectors**
Transformer	1152 (1151)	29 (21)	7 (15)	12 (13)
Electric bushings	27 (34)	898(642)	35 (157)	56 (183)
Knife-wrenches	21 (14)	59(84)	942 (819)	89(194)
Electrical splice connectors	0 (10)	76(73)	111(104)	873 (741)

6. Conclusions

Nowadays, several algorithms have been proposed for image segmentation, many of them based on Deep Learning and CNN [18][19]. However, the authors thought it interesting to test the old JSEG because of previous experience with this algorithm. There are several versions of pre-trained YOLO algorithm models available in different Deep Learning frameworks. This model was trained in 4 classes. There are also a number of regional CNN (R-CNN) algorithms based on a selective regional proposal, which were not discussed in this article. In this paper it was shown that the use of the JSEG algorithm can improve the performance of DL network in the recognition of thermographic images in pseudo-color and is possible to implement a fast JSEG with GPU and CUDA technologies.

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