International Journal of Applied Engineering Research ISSN 0973-4562 Volume 12, Number 17 (2017) pp. 6814-6820

Comparison between Backpropagation and CNN for the Recognition of Traffic Signs

Jorge Enrique Zafra
Mechatronic Engineer, Faculty of Engineering, Nueva Granada Military University, Bogotá D.C, Colombia.

Robinson Jimenez Moreno
Assistant Professor, Department of Mechatronics Engineering, Nueva Granada Military University, Bogotá, Colombia.

Ruben Dario Hernández
Assistant Professor, Department of Mechatronics Engineering, Piloto University, Bogotá D.C, Colombia.

Abstract

In this article, it is presented the development of two algorithms of neural networks, which allow the recognition of traffic signs from the realization of a training of neural networks through Backpropagation and another training using neural convolutional networks, in order to compare them and to know which of the two methods is more efficient in terms of execution time and precision, with respect to the same amount of input images that contain the three classes to classify: Regulatory, Warning and Informative. Once the networks were trained, random-image tests were performed achieving 98.33% accuracy for the Backpropagation algorithm and 94.44% accuracy with convolutional neural networks.

INTRODUCTION

Because technology has become one of the most important elements that are present in the daily life of a human being, it is evolving exponentially in day to day, with the same speed with which human needs grow. That is why there are many technological solutions to the same problem, making some of them become obsolete over the years, either due to the time required for execution, sophistication, precision or simply for economic ease or facility of use of new technologies.

In the last decades, several works have been carried out in the field of artificial intelligence, specifically with neural networks, since these have generated interest both in the development of its theoretical part as in its practical part due to its implementation of solutions to complex problems [20], such as robotics, computational control, approximation of functions, among others, where neural networks are frequently used for pattern recognition, and with high performance in the development of optical devices for character recognition [11].

Another kind of objects that are being recognized are the recognition of traffic signs, which are very essential when using advanced driving assistance systems and also in the use of autonomous vehicles [18]. In general, traffic signs are those posters placed alongside the streets, which contain useful information for drivers, pedestrians and cyclists. These signs are divided in Colombia into 3 groups: regulatory, warning and informative. Regulatory are those signs that generate information of prohibition, restriction and priority. The warning ones generate information of possible dangers, and of physical information which allow the driver to know characteristics of the road. Finally informative signs that give the drivers information of destination, distances, services and tourist information. Recently, many of the advances achieved in autonomous vehicles have been carried out in the field of detection, segmentation and task recognition [18], where their main focus has been on traffic signs, roads [16,17], vehicles and floor signs that are painted on the road.

This article presents a comparison between two methods of pattern recognition that are part of the area of neural networks. One of the methods is the convolutional neural network which has been recently implemented, due to its effectiveness in results in multiple tasks of classification of images, for which it has been winner of different challenges of image recognition such as the ImageNet image recognition contest [22], besides being one of the few methods that has been able to surpass the human capacities in certain tasks of recognition of patterns in images [21]. The other method is the Backpropagation (BP) algorithm is one of the main methods that have been used in pattern recognition and has been a fundamental pillar for the development of new methods due to its adaptability since many of the investigations and projects carried out have adapted the BP method to other existing ones, such as the counter propagation to generate improvements in learning abilities [24], in addition to this it has been used due to its simplicity, speed [23] and to its main characteristic of being able to recalculate their weights by epoch due to an error generated at the exit of the neuron for the minimization of the error.

The comparison of these two methods will be carried out by means of its implementation for image recognition with the three types of traffic signs: Regulatory, Informative and Warning, in order to know which of these two is more efficient, for a future development and possible implementation in the autonomous vehicles or in the advanced systems of assistance of conduction.

BACKGROUND

Building and designing machines capable of performing processes with a certain intelligence has been one of the primary objectives of scientists throughout the ages. At the beginning, studies were focused on the development of automata, which are machines whose function is to perform a typical human task, without its intervention, with greater or lesser success. Sometime later they directed the studies in similar tasks oriented to the area of the artificial intelligence.

The beginnings of artificial intelligence (AI) were thanks to Warren McCulloch and Walter Pitts, who launched a theory of how to work with neurons, making a breakthrough in modeling a simple neural network through electrical circuits. Shortly thereafter, Frank Rosenblatt succeeded in creating a *Perceptron*, a name given to the first accurate neural network, made entirely in a computational way. With this new advance was achieved tasks such as prediction climatological, and simulations of logical gates such as AND.

Since the perceptron is able to discriminate linearly, i.e. it is able to select two subgroups from a group of components, taking into account that this group can be separated as long as there is one or more straight lines that separate the components into two subgroups, as can be observed in figure 1. However it was found that the perceptron could not solve all tasks, so many scientists left the field of Artificial Intelligence and only a few remained in this area, such as Teuvo Kohonen, Stephen Grossberg and James Anderson, who after many efforts succeeded in creating the Multilayer Neurons, which overcame the limitations of the perceptron, generating a new impulse in the area of artificial neural networks and in to Artificial Intelligence [1].

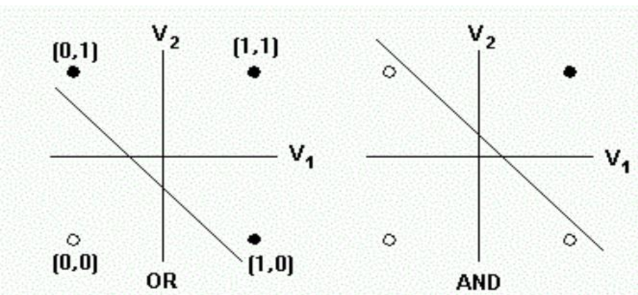

Figure 1: *OR* and *AND* gates [2].

Neural networks

To be able to address the topic of neural networks, it is necessary to define that it is a neuron. A neuron in the biological realm is defined as the ones in charge of the information processing, since they somehow elaborate an exit signal from a stimulus, whose process goes from the dendrites that are the input way of the signals, that combine in the body of the neuron where a processing is carried out, and finally goes to the axon which is the path of the output signal generated by the neuron, as can be seen in figure 2.

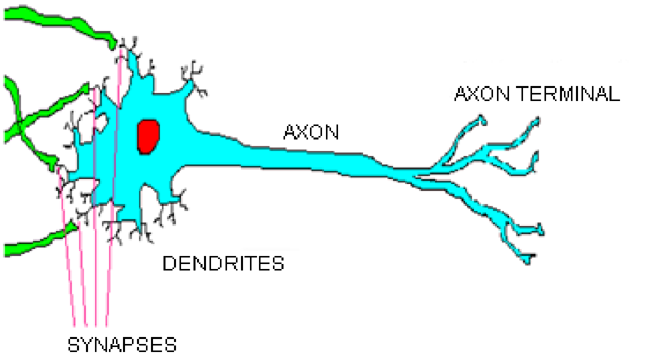

Figure 2: Parts of a Neuron [3].

Artificial Neural networks aim to reproduce the behavior of the human brain, which can generate specific representations such as numbers or objects. These are composed of input layers, hidden layers and output layers, where the input layer is where information enters, the set of elements in the hidden layer is where information processing takes place and the output layer is where the processed information arrives so that it can be viewed [3].

The network architecture might be constituted as shown in figure 3, by an input layer, two hidden layers and one output layer, where the number of hidden layers may vary according to the problem being solved indeed [4].

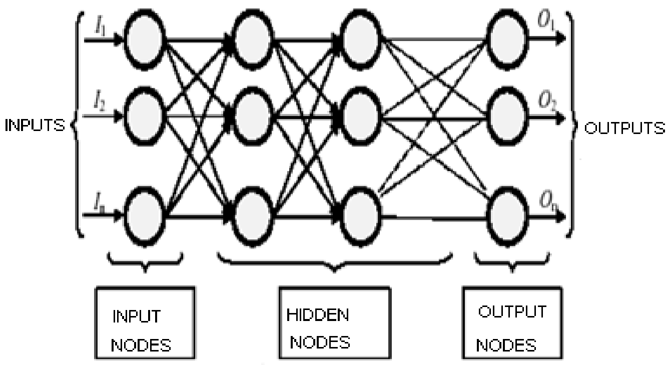

Figure 3: Neuronal Network Scheme [4].

International Journal of Applied Engineering Research ISSN 0973-4562 Volume 12, Number 17 (2017) pp. 6814-6820

Figure 4 shows how a neural network can mimic the behavior of a brain, and this is achieved because the artificial neurons have parts that fulfill the same functions as those of a biological neuron [3].

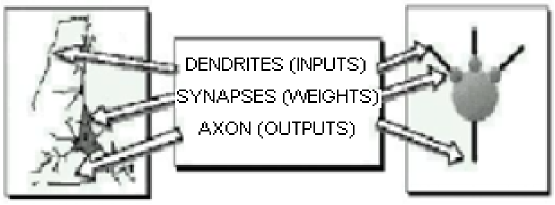

Figure 4: Comparison of neurons [3].

Convolutional Neural Networks

A convolutional neural network is very similar to a conventional neural network as the multilayer perceptron, this network is composed of weights and biases that can be learned. What differentiates convolutional neural networks is that their inputs are usually images, which allows to encode certain properties, allowing to gain efficiency and reduce network parameters [5]. These networks work by consecutively modeling small pieces of information and then combining this information into the hidden layers.

One way to understand how they work is that the first layer will try to detect the edges of the input images and try to set edge detection patterns. Then, the hidden layers of the network will try to combine them in simpler forms and, finally, in patterns of the different positions of objects, lighting, scales, etc. The final layers will attempt to match an input image with all patterns and arrive at a final prediction as a weighted sum of all of them [6].

Backpropagation

The Backpropagation method is one of many and main methods of multi-layer networks, this algorithm works by a propagation-adaptation cycle which consists of giving an input pattern to stimulate the network, so that this pattern can be propagated from the first to the output layer through hidden layers [7]. Once the output is obtained, it is compared to the output to be obtained and an error is found for each of the outputs of the network. Upon obtaining the error of these, the error propagates in direction of exit towards entrance, going layer by layer until all the neurons of the network have received the signal of error, then based on this signal they modify their neuronal weights until the network allows to correctly classify all the training patterns [8].

The most important of this method is that as the network is trained, the hidden neuronal layers are organized so that the neurons can recognize characteristics of the input pattern [7] and the output error is minimized.

DEVELOPMENT

The algorithms to be compared were implemented in the software MATLAB 2016a where two image databases were loaded, so that one is the patterns used to train the different networks and the other to contain the test images of the two methods and to evaluate the network.

At the beginning of the programs, the image folder to be trained was loaded, which contains 20 different images for each type of traffic sign in this case: 20 images for Regulatory, 20 for Warning and 20 for Informative signs, separated by folders.

Convolutional Neural Network (CNN)

Having already loaded the training images, a distribution of the information stored by each of the folders was carried out, i.e. it would be possible to obtain different repeated characteristics in the images, for each type of traffic sign.

Once this separation is made, one looks at how often patterns or characteristics are repeated in each of the elements belonging to the different categories, as shown in figure 5.

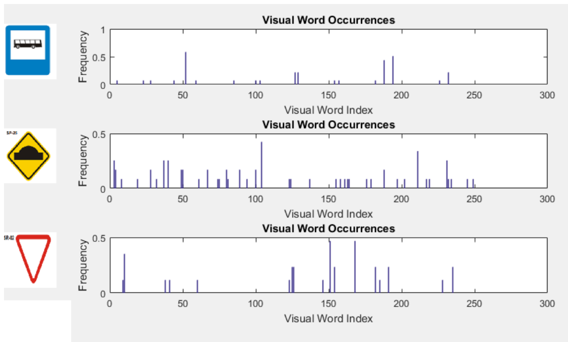

Figure 5: Frequency of repetition of characteristics.

Having the characteristics with their specific frequency, these are saved and organized into tables for use in the toolbox of Matlab "classificationLearner". Once the Matlab tool is opened, the information obtained from the CNN network is loaded, as shown in Figure 6, where all the characteristics segmented by the different types are loaded in order to train the network.

Name	Type	Range	Import as
enaldata1	double	0 .. 0.19518	Predictor
enaldata2	double	0 .. 0.137361	Predictor
enaldata3	double	0 .. 0.323381	Predictor
enaldata4	double	0 .. 0.235702	Predictor
enaldata5	double	0 .. 0.5	Predictor
enaldata6	double	0 .. 0.275371	Predictor
enaldata7	double	0 .. 0.180907	Predictor
enaldata8	double	0 .. 0.181818	Predictor
enaldata9	double	0 .. 0.297044	Predictor
enaldata10	double	0 .. 0.351123	Predictor

Figure 6: Information on the characteristics obtained.

Once the information is loaded, a classifier is chosen, in this case "All SVMs" are selected. Once the training is completed, it is observed which of all these classifiers can be more useful seeing both the matrix of confusion and the precision that each of them generates and with it to perform the training of the neural network as shown in figures 7 and 8 respectively.

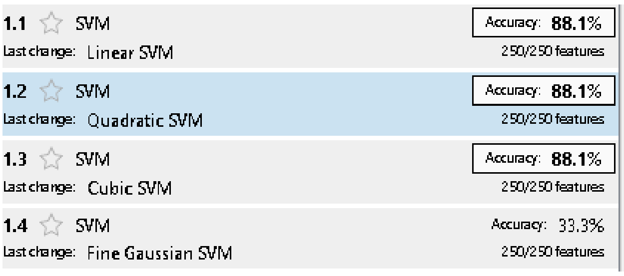

Figure 7: Classifier with more precision.

By obtaining the model and the most important confusion matrix, the model is exported, in order to train the neural network and obtain its precision.

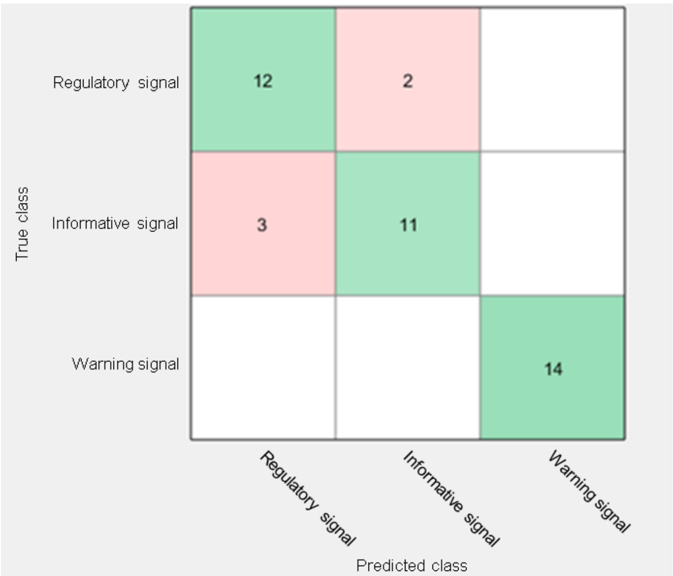

Figure 8: Confusion Matrix Model 1.2.

In this case the exported model has an architecture of 7 layers of neurons, the first layer is the input layer containing the "senaldata" or features that were entered to train the network, contains 5 hidden layers where the processing of the image occurs through filters, and finally there is an output layer that is in charge of classifying the image according to the three categories of traffic signs. After the training, the accuracy generated by the exported model was observed, which produced an accuracy of 94%, as shown in figure 9.

```
validationAccuracy =

    0.9444
```

Figure 9: Convolutional neural network accuracy.

Once the network was trained, several tests were carried out loading images of the test image database, which were separated by folders according to their type of traffic sign.

When performing the different tests, the following results were found:

Figure 10 shows how the CNN method was able to classify the traffic signs of successive curves (first to the left), in its category of Warning signs.

Figure 10: CNN Warning Sign Prediction.

Figure 11 shows how the CNN method was able to classify the service station transit sign in its Informative category.

Figure 11: CNN Informative Sign Prediction.

Finally, Figure 12 shows how the CNN method was able to classify the transit sign of banned forward, in its category of Regulatory signs.

Figure 12: CNN Regulatory Sign Prediction.

As shown in Figures 10, 11 and 12, the CNN network method was able to classify the different images into their respective categories. Although the previous images show that the convolutional network is effective classifying, as it has an accuracy of 94% there is a degree of confusion of classes as can be observed in figure 13.

Figure 13: CNN Misclassification of a Warning Sign.

Backpropagation (BP) algorithm:

Having already loaded the training images, one by one of the images belonging to each of the different types of signs was read, making a resize of 20x20. After performing this procedure, each image was converted into a vector column with a dimension of 1200x1 and the images have dimensions of 20x20x3 since they were worked in RGB.

Once this was done, an input matrix with 1200x60 dimensions was created, because its rows are the column vectors of each image and 60 by the total number of images loaded. Once the matrix was made, it was normalized by dividing by 255 which is the maximum value that a pixel can obtain.

After having the normalized input matrix, it was proceeded to create the Target matrix which is the matrix of desired outputs, having dimensions of 3x60, since the output signal to be obtained is a 3-row column vector for each of the input images.

Upon obtaining the Input and Target Matrices, it was proceeded to use the characteristic equations of the Backpropagation algorithm which are:

$$w1 = a + (b - a) * rand(S1, R) \quad (1)$$

$$w2 = a + (b - a) * rand(S2, S1) \quad (2)$$

$$b1 = a + (b - a) * rand(S1,1) \quad (3)$$

$$b2 = a + (b - a) * rand(S2,1) \quad (4)$$

$$w1 = a + (b - a) * rand(S1, R) \quad (5)$$

$$n1 = W1 * P \quad (6)$$

$$A1 = logsig(n1) \quad (7)$$

$$n2 = W2 * A1 \quad (8)$$

$$A2 = logsig(n2) \quad (9)$$

In addition to these equations, a minimum error of 0.01, a number of epochs of 10000 to make training faster, the number of output neurons given by the number of types of traffic signs that in this case is 3 and a number of hidden neurons of 6 were set, since with this number was sufficient to obtain a satisfactory result in the training. It was also taken into account the equations to be used when performing the recalculation of neuron weights, in order to obtain an output according to the desired.

$$df1 = dlogsig(n1, A1(:, i)) \quad (10)$$

$$df2 = dlogsig(n2, A2(:, i)) \quad (11)$$

$$s2 = -2 * diag(df2) * e(:,1) \quad (12)$$

$$s1 = diag(df1) * w2' * s2 \quad (13)$$

$$W2 = W2 - 0.1 * s2 * A1(:, i)' \quad (14)$$

$$b2 = b2 - 0.1 * s2 \quad (15)$$

$$W1 = W1 - 0.1 * s1 * P(:, i)' \quad (16)$$

$$b1 = b1 - 0.1 * s1 \quad (17)$$

$$A1(:,1) = logsig(W1 * P(:, i), b1) \quad (18)$$

$$A2(:,1) = logsig(W2 * A1(:, i), b2) \quad (19)$$

When performing the configuration in the BP algorithm, the neuron training was performed, where for each epoch the error or "mse" in this case was decreasing, until it reached a minimum error or its maximum number of epochs, as seen Figure 14.

```
Iteration : 5426        mse :     0.058720
Iteration : 5427        mse :     0.060548
Iteration : 5428        mse :     0.049385
Iteration : 5429        mse :     0.049710
Iteration : 5430        mse :     0.059526
Iteration : 5431        mse :     0.059445
Iteration : 5432        mse :     0.049032
Iteration : 5433        mse :     0.050477
Iteration : 5434        mse :     0.060262
Iteration : 5435        mse :     0.058153
Iteration : 5436        mse :     0.048779
```

Figure 14: Training epoch and error.

International Journal of Applied Engineering Research ISSN 0973-4562 Volume 12, Number 17 (2017) pp. 6814-6820
© Research India Publications. http://www.ripublication.com

After performing the network training with Backpropagation algorithm, its accuracy was obtained from the desired output where it generated 98.3% precision as shown in figure 15.

```
precision =

   98.3333
```

Figure 15: Backpropagation Network Precision.

Once the network was trained, several tests were performed loading images of the test image database, which were separated by folders according to their type of traffic sign. The tests done generated the following results:

Figure 16 shows how the BP method was able to classify the traffic sign of public restrooms in its Informative category.

Figure 16: Informative Sign Prediction through Backpropagation.

Figure 17 shows how the BP method was able to classify the landslide sign in its category of Warning signs.

Figure 17: Warning Sign Prediction through Backpropagation.

And finally, Figure 18 shows how the BP method was able to classify the traffic sign of right turn forbidden, in its category of Regulatory signs.

Figure 18: Regulatory Sign Prediction through Backpropagation.

As previously mentioned the outputs obtained were column vectors with 3 rows. And the results depended directly on the output neurons, since the type of output said to what type of traffic sign the input image would correspond.

The configuration of the output that was programmed was the following:

- Regulatory = [1; 0; 0].
- Warning = [0; 1; 0].
- Informative = [0; 0; 1].

Although the previous images show that the Backpropagation network is efficient classifying images, as it has a precision of approximately 98%, it has misclassifications as shown in Figure 19.

Figure 19: BP Network Misclassification.

In the previous image it can be seen how the program was not able to recognize what type of sign was the image of Figure 19, since it did not generate any title for this one. This is because the output signal from the network was [1; 0; 1], an output for which there was no programming and thus a type of traffic sign.

CONCLUSIONS

In training times, the backpropagation neural network can be much faster, reaching good results, but its training may have to be repeated several times to obtain a high percentage of accuracy, compared to the convolutional networks, which have a much higher training time but their accuracy is high at the beginning, so that the re-training of the same network is not necessary.

Backpropagation neural networks may reach very high precisions such as 98% as well as they may have very low precisions such as 50% accuracy, which means that the accuracy of the backpropagation network depends directly on the random values with which its training begins, while the convolutional networks always round its accuracy by 80%, in all the times that the network was trained.

The neural networks that should be used for future development and implementation in autonomous cars or advanced driving assistants, should be the convolutional neural networks, since these have excellent effectiveness and great precision at any time and, in addition to this, are the networks that are better adapted to having images as input, since its information classification feature makes the landscape may be irrelevant while backpropagation will not be, aspect that would be very important since the landscapes vary along a route but the traffic signs do not.

REFERENCES

[1] Felipe Lara Lozano, “Fundamentos de redes neuronales artificiales”, Laboratorio de cibernética aplicada, Centro de Instrumentos, Unam, PDF.

[2] Cristian Segura, “IA redes Neuronales”, PDF.

[3] S.Y. Kung, “Digital Neural Networks”, Prentice Hall, 1993.

[4] José R. Hilera y Victor J. Martínez, “Redes Neuronales Artificiales”, Alfaomega-Rama, 2000.

[5] Hana Hosoe, Shinji Sako and Bogdan Kwolek, “Recognition of JSL Finger Spelling Using Convolutional Neural Networks”, 2017 Fifteenth IAPR International Conference on Machine Vision Applications (MVA) Nagoya University, Nagoya, Japan, May 8-12, 2017.

[6] Raul E.Lopez Briega, “Redes Neuronales con TensorFlow”.

[7] Redes Multicapa, “Algoritmo Backpropagation”, PDF.

[8] Antonio J. Serrano, Emilioo Soria, Jose D. Martin, “Redes Neuronales Artificiales”, Escola Tecnica Superior d’Enginyeria, Curso 2009-2010.

[9] T. Serre, L. Wolf, S. Bileschi, M. Riesenhuber, and T. Poggio, “Robust object recognition with cortex-like mechanisms,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 29, no. 3, pp. 411–426, 2007.

[10] Mohamed Chemsi, Kodjo Agbossou, Senior Member IEEE, and Alben Cardenas,” Neural Network Backpropagation Algorithm Control for PEM Fuel Cell in Residential Applications” IEEE Electrical Power and Energy Conference, 2016.

[11] Nadir Murru, Rosaria Rossini, “A Bayesian approach for initialization of weights in backpropagation neural net with application to character recognition”, Neurocomputing 2016.

[12] W.S. McCulloch, W.H. Pitts, A logical calculus of the ideas immanent in nervous activity, Bull. Math. Biophys. 1943.

[13] Y. Liu, J. Yang, L. Li, W. Wu, Negative effects of sufficiently small initial weights on back-propagation neural networks, J. Zhejiang Univ.-Sci. C (Comput. Electron.) 2012.

[14] P. Dollar, C. Wojek, B. Schiele, and P. Perona: Pedestrian Detection: An Evaluation of the State of the Art. IEEE Transactions on Pattern Analysis and Machine Intelligence, 34(4):743–761, 2012.

[15] J. M. Alvarez, Y. LeCun, T. Gevers, and A. M. Lopez: Semantic Road Segmentation via Multi-scale Ensembles of Learned Features. In European Conference on Computer Vision (ECCV), 2012.

[16] G. Oliveira, W. Burgard, and T. Brox: Efficient Deep Models for Monocular Road Segmentation. In IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2016.

[17] C-A. Brust, S. Sickert, M. Simon, E. Rodner, and J. Denzler: Convolutional Patch Networks with Spatial Prior for Road Detection and Urban Scene Understanding. In International Conference on Computer Vision Theory and Applications (VISAPP), 2015.

[18] Touqeer Ahmad, David Ilstrup, Ebrahim Emami, George Bebis, “Symbolic Road Marking Recognition Using Convolutional Neural Networks”, IEEE Intelligent Vehicles Symposium (IV), Redondo Beach, CA, USA, 2017.

[19] J. Long, E. Shelhamer, and T. Darrell, “Fully Convolutional Networks for Semantic Segmentation”. In IEEE International Conference on Computer Vision and Pattern Recognition (CVPR), 2015.

[20] Y. LeCun, Y. Bengio, G. Hinton, “Deep learning, Nature”, 2015.

[21] He, K., Zhang, X., Ren, S., & Sun, J, “Delving deep into rectifiers: Surpassing human-level performance on imagenet classification”. In Proceedings of IEEE international conference on computer vision (ICCV), Santiago, Chile, 2015.

[22] Krizhevsky, A., Sutskever, I., & Hinton, G. E, “ImageNet classification with deep convolutional neural networks”, In Proceedings of neural information processing systems (NIPS), Nevada, USA, 2012.

[23] S. Abid, F. Fnaiech, and M. Najim, “A fast feedforward training algorithm using a modified form of the standard backpropagation algorithm,” IEEE Trans. Neural Networks vol. 12, 2001.

[24] M. Sornam, Muthu Subash Kavitha, M.Poornima Devi, “An Efficient Morlet Function Based Adaptive Method for Faster Backpropagation for Handwritten Character Recognition”, IEEE International Conference on Advances in Computer Applications (ICACA), 2016.