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CHECKING THE HOMOGENEITY OF CONCRETE USING ARTIFICIAL NEURAL NETWORK

BY

ALEXANDRINA ELENA PANDELEA*, MIHAI BUDESCU, GABRIELA COVATARIU and RAREŞ GEORGE ȚĂRAN

"Gheorghe Asachi" Technical University of Iași,
Faculty of Civil Engineering and Building Services

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Abstract. This paper proposes a manner to verify the concrete samples homogeneity using artificial neural networks. This method determines the percentages of different areas of component materials visible at top and bottom of a concrete cylinder having 20 cm diameter and 20 cm height. The materials that have been achieved are rubber grains, aggregates and mineral matrix.

The training of the neural network was realise by using backpropagation algorithm and then, in order to separate the regions of interest was used Levenberg – Marquardt algorithm. As a neural network input data were used photos having 258 ×170 pixels resolution achieved both on the both sides of the cylinder.

Key words: neural network; backpropagation algorithm; concrete; rubber; computing percentage; Levenberg – Marquardt algorithm.

1. Introduction

Artificial neural networks (ANN) have been used in Civil Engineering since 1989. They are applicable in practice as a result of testing older model

*Corresponding author: *e-mail:* alexandrina_pandelea@yahoo.com

biological neurons and brain activities. Compared with biological support which is largely unknown, the operation support of neural networks is specific mathematic having an artificial intelligence heuristics.

ANN phrase suggest that their function is inspired by biological neural networks and represent an informational processing device, with advantages / disadvantages common with any other device projected by human being for knowing purposes. It must avoid any confusion to correct understand of the role and limits of use of neural networks, which would create the impression that neural networks can be substitutes whenever and wherever a human brain (Flood *et al.*, 1997).

Nowadays, networks application in construction is a very studied because its allow solving problems in a limited time and with fewer resources.

Engineering problem solving involves:

a) analysis of the problem, establishing network architecture, data input and output thereof.

b) choosing training algorithm (supervised learning, reinforcement learning and self-organizing).

c) data sets collected for problem sets are divided into training and test sets.

Correctness network operations, by introducing input data not contained in the training set but the correct answer is known (Covatariu, 2010).

2. Percentage Calculation Using ANN with Backpropagation Algorithm

2.1. Introduction in Neural Networks for Classification Problem

In order to build a neural networks are used as input a set of images. For this, there are use images that can be taken from the satellite (Iounousse *et al.*, 2015) or performed under a microscope (Hage & Hamade, 2013), depending on the issue. The images consist of a number of pixels, each pixel of the colour image p being characterized by:

a) a vector with two components, denoted $g(p)$ which contains the geometric coordinates of the pixel;

b) a three – component vector, $c(p)$ expressing the colour coordinates of the RGB cube.

Using the geometric coordinates we can define the set of pixel G_k, disjoint sets that correspond to the regions occupied by the colour e_k, k = 1, 2, 3, 4, where: e_1 – means black, e_2 – signifies red, e_3 – means green and e_4 – signifies blue. In the RGB cube scaled to [0, 1] × [0, 1] × [0, 1] defines the set of colours associated with each element e_k, k = 1, 2, 3 or 4.

Consider the set:

$$C_k = \left\{ U_k c(p) | g(p) \in G_K \right\}. \quad (1)$$

Select colour samples representative of the three types of regions and defined sets of samples C_1^*, C_2^*, C_3^* and C_4^*. They are the best way to get partial information about colour sets C_1, C_2, C_3 and C_4 which are unknown as concrete values into RGB cube. After that, delete identical vectors in each lot of colour. In considered working assumption $C_1^* \subseteq C_k$, k = 1, 2, 3, 4, sets C_1^*, C_2^*, C_3^* and C_4^* are disjoint. Fulfilment of this hypothesis depends on the sharpness of image.

Its training the neural network with an appropriate architecture to classify colours into three classes of sets of samples C_1^*, C_2^*, C_3^* and C_4^*. It is used backpropagation algorithm for network training, information is processed in the opposite direction from output to input of the network.

The trained network is used to classify all pixels in the image in three classes, corresponding to C_1^*, C_2^*, C_3^* and C_4^*. It builds a new digital image that defines four regions which estimates ideal areas of interest G_k.

It uses three colours to represent different regions G_1^*, G_2^*, G_3^* and G_4^* expected to provide a better view. Estimate ideal regions will get by segmentation of image. Separating the region of interest is performed using a neural network trained by Levenberg – Marquardt algorithm.

Levenberg – Marquardt algorithm is one of the fastest methods used in practice, it ensures numerical solutions in minimization problems of nonlinear functions. The algorithm is an interpolation between Gauss – Newton algorithm and the method of gradient descent.

It brings improvements Newton's method through an approximation of the Hessian with a singular and symmetrical matrix:

$$\left[\nabla^2 \varepsilon(w) + vI\right] \tag{2}$$

where: v is the positive parameter that provides rapid convergence of the algorithm; I – the identity matrix; $\varepsilon(w)$ – cost function.

Finally, measure the area of estimated regions, G_1^*, G_2^*, G_3^* and G_4^* and calculate the percentage held by each (Matcovschi & Păstrăvanu, 2008).

2.2. Case Study

It is considered as test sample a cylinder having 10 cm diameter and 20 cm height. The materials used to manufacture the test sample was rubber grains, aggregate and mineral matrix.

The rubber grains was obtained by recycling the used tires through a grinding process. The size of the aggregates are 0,…,4 mm and 4,…,8 mm and type of cement used is C30/37. For better workability of the composition were used SIKA 20HE additives. Reinforced concrete with recycled rubber mixes includes a 30% rubber.

After casting composition in a cylindrical shape, a vibrating procedure was achieved in order to eliminate the air from concrete sample and also to ensure uniformity, to increase the strength and eliminate segregation. It was obtained through vibration on concrete's shaking table.

A neural network was designed in order to determine the percentage of the mineral matrix's area, aggregate and rubber on both sides of the element.

Fig. 1 *a* – Cylinders made of concrete and rubber.

To obtain the rates matrix, rubber and aggregate following steps:

1. Enter the initial image in neural network (Figs. 1 *a* and 6).

2. Select in image the following regions: black for rubber, red for aggregate, green for cement and blue for background.

3. The network generates a new image with that 4 chosen colours (Figs. 2 and 7).

4. Choose the colour samples of image representative regions.

5. Placing colours in sample sets C_1^*, C_2^*, C_3^* and C_4^* in RGB cube, scaled to $[0, 1] \times [0, 1] \times [0, 1]$ (Figs. 3 and 8);

6. The network generates as output data that the regions of interest (Figs. 4 and 9).

7. Train the network using multiple neurons and a large number of periods (Figs. 2, 5 *a*, 5 *b*, 5 *c*, 5 *d*, and Figs. 7, 10 *a*, 10 *b*, 10 *c*, 10 *d*).

8. Using a program developed in MATLAB (Beale *et al.*, 2015) to determine all the percentages of areas of interest, a program that has as main parameters resulting matrix as output date and number of colours (Tables 1 and 2).

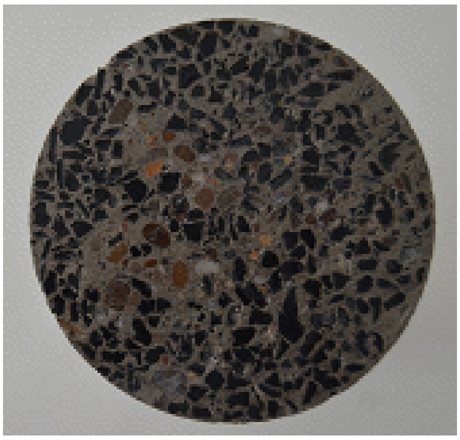

Fig. 1 *b* – Initial image (upperside).

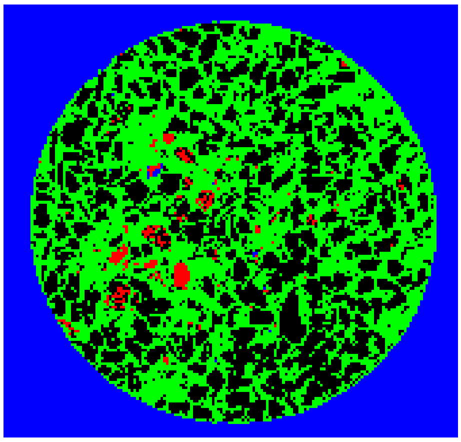

Fig. 2 – The image segmented in 4 colors.

The following are the results generated by neural networks for studied cylinder.

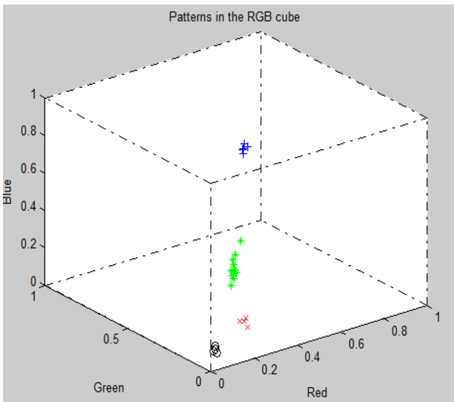

Fig. 3 – Placing colours in the cube RGB

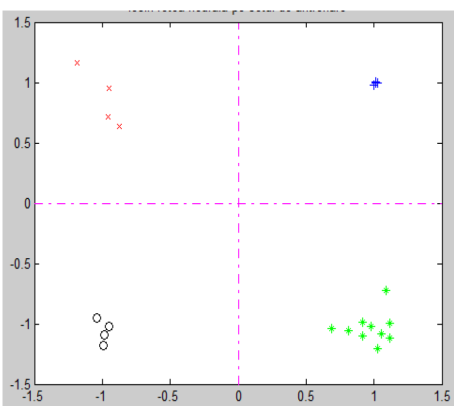

Fig. 4 – Output networks with the training set.

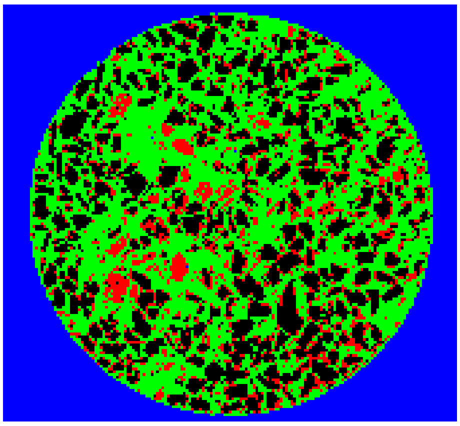

Fig. 5 *a* – 20 neurons, 10 epochs.

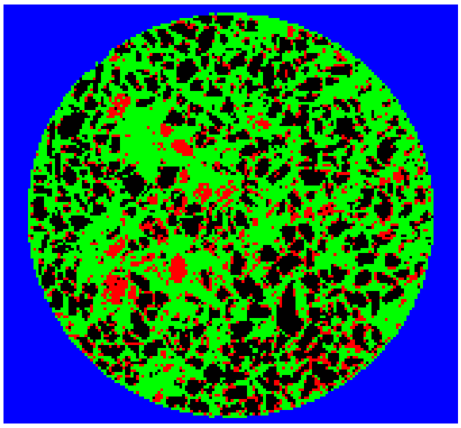

Fig. 5 *b* – 20 neurons, 100 epochs.

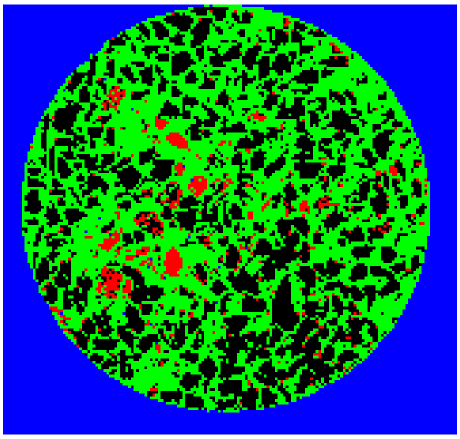

Fig. 5 *c* – 25 neurons, 250 epochs.

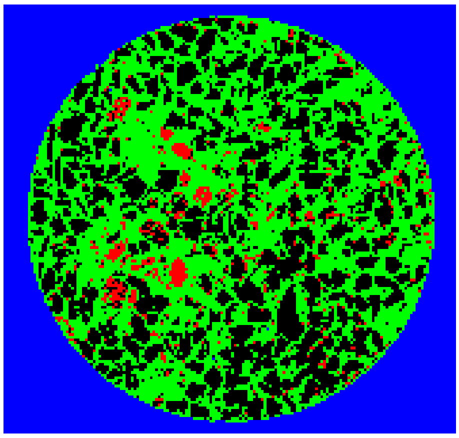

Fig. 5 *d* – 30 neurons, 1,000 epochs.

Table 1
Determining the Percentage of Material in Various Cases of Training of Neural Network on the Upperside of the Cylinder

Number of neurons	No. of training epochs	Rubber %	Aggregate %	Matrix %	No. of figure
10	10	54.45	1.89	43.57	2
20	10	33.4593	13.8812	52.6595	5 *a*
20	100	33.0249	14.3236	52.6515	5 *b*
25	250	41.1319	14.3236	52.6515	5 *c*
30	1,000	40.8866	4.7264	52.6515	5 *d*

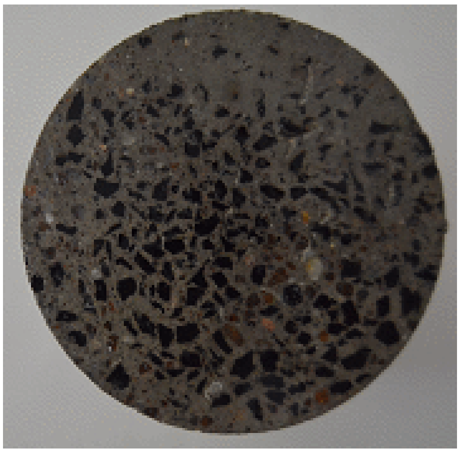

Fig. 6 – Initial image (underside).

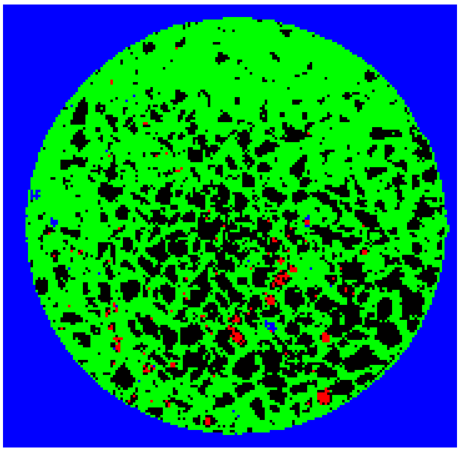

Fig. 7 – The image segmented in 4 colors.

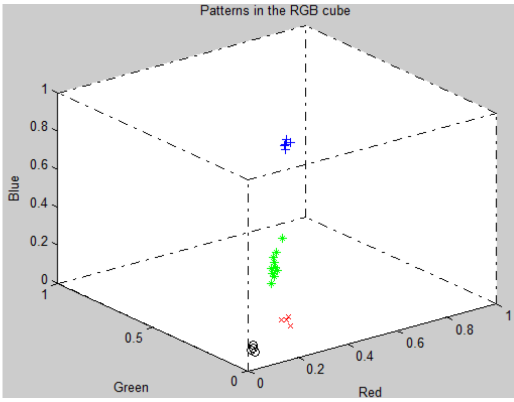

Fig. 8 – Placing colours in the cube RGB.

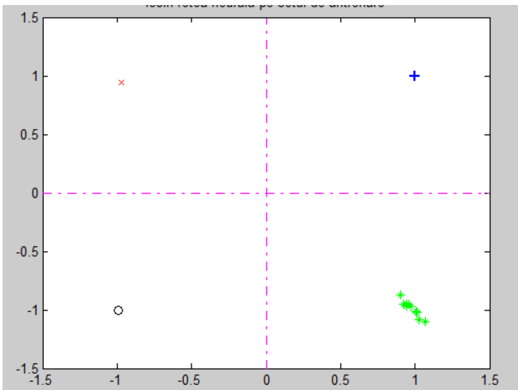

Fig. 9 – Output networks with the training set.

Table 2
Determining the Percentage of Material in Various Cases of Training of Neural Network on the Underside of the Cylinder

Number of neurons	No. of training epochs	Rubber %	Aggregate %	Matrix %	No. of figure
10	10	31.1863	0.9878	67.82589	7
20	10	29.245	0.9882	69.7668	10 *a*
20	100	28.0683	0.9768	70.9549	10 *b*
25	100	27.487	3.8728	68.6402	10 *c*
30	1,000	28.5572	4.1619	67.2809	10 *d*

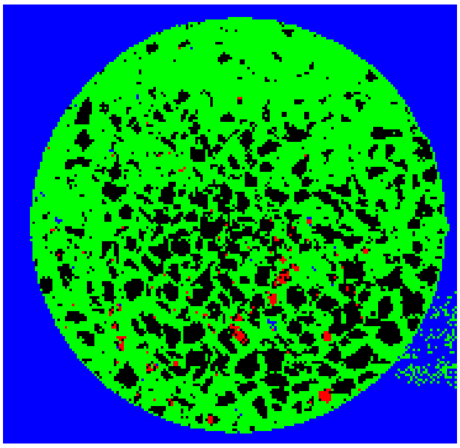

Fig. 10 *a* – 10 neurons, 10 epochs.

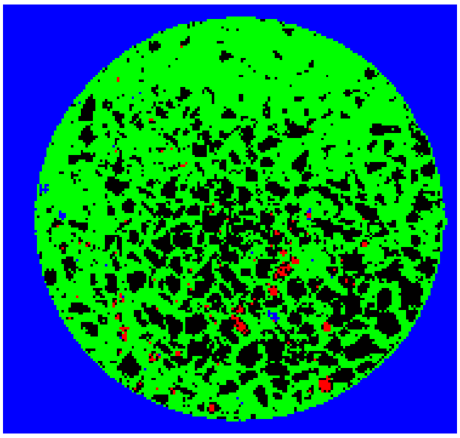

Fig. 10 *b* – 20 neurons, 100 epochs.

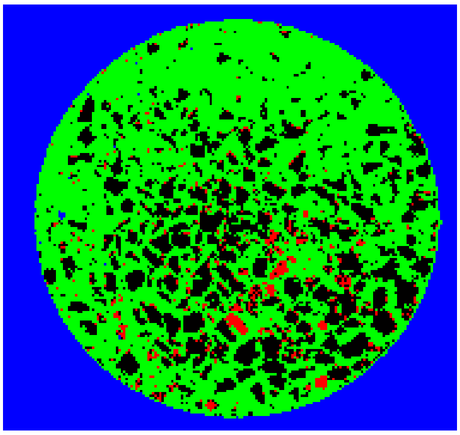

Fig. 10 *c* – 25 neurons, 100 epochs.

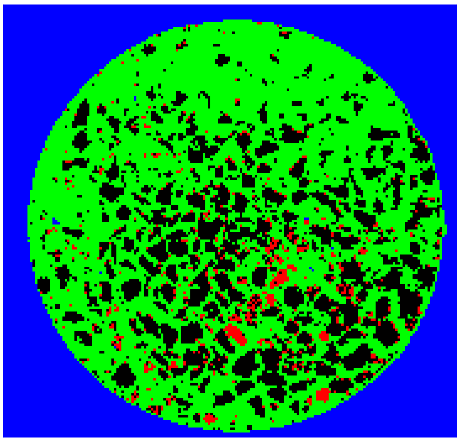

Fig. 10 *d* – 30 neurons 30, 1000 epochs.

3. Conclusions

After the network training with a number of neurons that varies between 10 to 30 and 10 to 1,000 iterations were obtained different percentages of component materials. For the upperside of the cylinder, neural network with 30 neurons and 1000 iterations generated a percentage of 40.8866% rubber, 4.7264% aggregate and 52.6515% matrix.

To the underside of the cylinder network with the same number of neurons and iterations like upperside generated the results: 28.5572% rubber, 4.1619% aggregate and 67.2809% matrix.

The percentage is different between the both sides, 12.3294% for rubber, 0.5645% for aggregate and 14.6294% for matrix.

So, on the upperside is about 12% more rubber than underside. The cause of these differences in percentages between the two sides is caused by the improper vibration procedure.

Vibration for a longer period of time than that provided led to the creation of a less homogeneous concrete, the rubber is present in a greater amount on the upperside. Theoretically vibration range is 5-30 seconds.

In practice, regarding this period must be taken into account the following factors: the thickness layer of vibrated materials, concrete consistency and performance of vibrating device. Although vibration was terminated when the element surface became horizontal, without air bubbles and when the grout has appeared on the surface, and it wasn't taken into account the thickness of layer to vibrate.

Uniformity is an important parameter for increasing the element's strength.

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VERIFICAREA OMOGENITĂȚII BETONULUI UTILIZÂND REȚELE NEURONALE ARTIFICIALE

(Rezumat)

Se propune un mod de a verifica omogenitatea probelor de beton folosind rețele neuronale artificiale. Această metodă determină procentajele diferitelor arii ale materialelor componente vizibile în partea de sus şi de jos a unui cilindru de beton cu diametru de 20 cm şi 20 cm înălțime. Materialele care au fost utilizate sunt bucati mici de cauciuc, agregate şi matrice minerală.

Antrenarea rețelei neuronale a fost facută cu algoritmul backpropagation, apoi a fost utilizat algoritmul Levenberg - Marquardt pentru a separa regiunile de interes. au fost folosite ca date de intrare în rețeaua neuronală fotografii cu rezoluție 258 × 170 pixeli de pe ambele părți ale cilindrului