doi: 10.22564/rbgf.v13i3.1200

RECOGNITION OF FORMATIONS OF VOLCANIC ORIGIN IN SATELLITE IMAGES USING NEURAL NETWORKS

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Here, we are trying to relate the formations of volcanic origin with data from satellite image (Landsat MSS). With this in mind, we approached the problem with the neural network technique. The area under study is La Payunia, in the province of Mendoza, Argentina. The satellite image used is centered at 35°55'12" south and 68°55'48" west. The neural network approach implies a minimization of the square error between the desired output and the actual output obtained. We were faced with a problem of optimization that was handled by the Simplex algorithm. The network used consists of four neurons at the input layer, four neurons at the hidden layer and one neuron at output. This structure matches the four spectral bands of the Landsat MSS data as input and the geological map as output. The neural network is trained over an area of known lithology. Therefore, it relates radiometric with geologic characteristics. In the present case the results are quite coincident with the aerial-photographs interpretation of the area. The good results indicate the potential for the identification of volcanic formations in regions of arduous access.

Key words: Satellite images; Lava field; Supervised classification; Artificial Neural networks.

RECONHECIMENTO DE FORMAÇÕES DE ORIGEM VULCÂNICA EM IMAGENS DE SATÉLITE COM O USO DE REDES NEURAIS – *Tentamos relacionar, neste trabalho, os afloramentos de rochas vulcânicas com os dados de imagens de satélite (Landsat MSS). Com este propósito, utilizamos a técnica de redes neurais como instrumento de classificação da informação obtida por satélites. A área de estudo é La Payunia, província de Mendoza, Argentina. A imagem de satélite utilizada está centralizada em 35° 55'12" S e 68° 55'48" W. A aplicação da rede neural implica a minimização do erro quadrático entre a saída que se deseja obter e a saída que realmente se obtém. Este é um problema de otimização que solucionamos, implementando o algoritmo Simplex. A rede usada consiste de quatro neurônios na camada de entrada, quatro neurônios na camada oculta e um neurônio na camada de saída. Esta estrutura corresponde às quatro bandas espectrais dos dados de satélite (Landsat MSS) como entrada e aos dados do mapa geológico como saída. A rede é calibrada em uma área de litologia conhecida. Portanto, ela relaciona características radiométricas com geológicas. Neste caso, os resultados obtidos foram coincidentes com a interpretação aerofotográfica e geológica. A aplicação desta técnica e os resultados obtidos são promissores para a identificação automática de litologias de interesse em áreas de difícil acesso.*

Palavras-chave: *Imagens de satélite; Derrames vulcânicos; Classificação supervisionada; Redes Neurais artificiais.*

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INTRODUCTION

The aim of the present work is to apply a classification scheme that discriminates different lithologies in satellite images, in our case, formations of volcanic origin. Artificial Neural Networks (ANNs) have been widely applied in classifying tasks (Touretzky & Pomerleau, 1989), as well as in pattern recognition (Bebis & Papadourakis, 1992). Hepner et al (1990), used ANNs for land cover classification. Comparing the results with other conventional classification methods, they found that the ANNs acted better. Lee et al (1990), used ANNs for a textural classification of clouds. Benediktsson et al (1990), included multisource data in an ANNs classification scheme.

ANNs learn from examples and can predict situations not included in the examples. In this sense, they have been used in robotics, learning of English words, and in the navigation of an autonomous vehicle. ANNs link input with output disregarding the physical laws connecting them.

In our case, the classifying problem is to link a configuration of spectral response with a lithology. Therefore, in this paper, gray level intensities of each of the four satellite's spectral bands act as input to the network. The output is given by the geological information available. A logical variable is used with such objective: It will show, or not, the occurrence of a lava formation. The available data are: (a) the geological maps of the area (Gonzalez Díaz, 1979;1972); (b) an aerial photograph interpretation; and (c) the Landsat MSS images of the area, taken on February, 1982.

GEOLOGY AND VEGETATION COVER OF LA PAYUNIA AREA

La Payunia is a desert plain where the Payún Matrú Volcano is inserted. The eolic activity has deposited sands at the east of the volcano. Fig. 1 is a simplified version of the geological map (Gonzalez Díaz, 1979;1972). Tab. 1 resumes their characteristics.

The vegetation consists of bushes of little leafs, thorny shrubs, and covers the area as sporadic patches. There are no trees and the vegetation is discontinued by extensive uncovered areas.

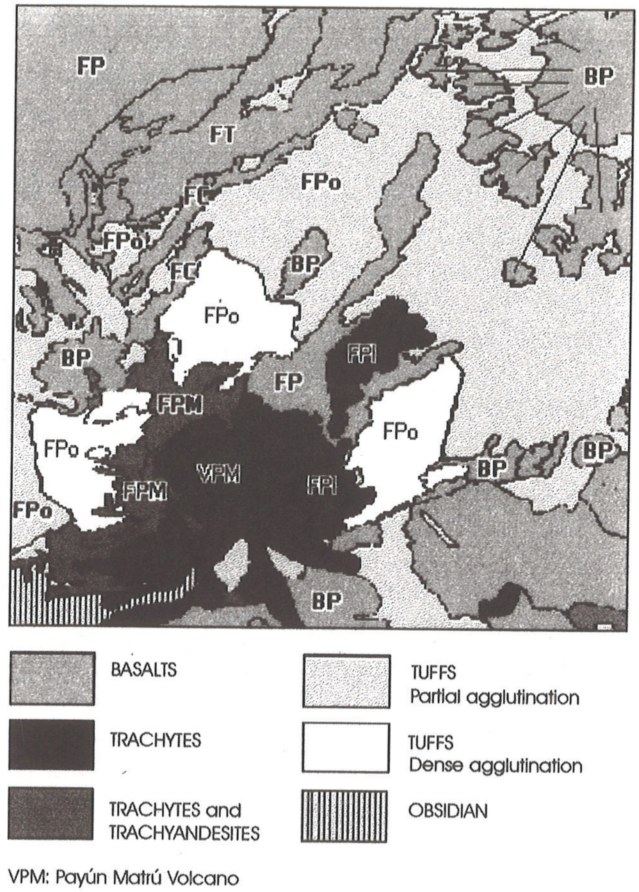

Figure 1 - Geological map.

Figura 1 - *Mapa geológico*

Formation	Ab.	Description
C° Carbonilla	FC	Olivine-Pyroxenic basalts
Tromen	FT	Olivine-Pyroxenic basalts
El Puente	FP	Pyroxenic-olivinic basalts
La Planchada	FPl	Trachytes with pyroxene and olivine
El Portezuelo	FPo	Andesitic-trachytic ignimbrites
Basaltos Pleistocenos	BP	Olivine basalts and trachybasalts
Payún Matrú	FPM	Trachytes, trachyandesites and andesites

Table 1 - Characteristics of the units of the geologic map of Fig. 1.

Tabela 1 - *Características das unidades do mapa geológico da Fig. 1.*

ARTIFICIAL NEURAL NETWORK (ANN)

ANNs reproduce in a very simplified way the complex behaviour of the brain. This complex behaviour is due partially to the kind of interconnections between neurons and to the number of them (Touretzky & Pomerleau, 1989).

It can be considered that the real neurons are roughly composed by a soma, axon and dendrites (Churchland, 1989):

1. Soma is the body of the cell containing the nucleus and responsible for the metabolic activity;
2. Axon extends from the soma to some distance. It is a long fiber several times the diameter of the soma and has terminal branching;
3. Dendrites are a set of fibers diverging from the soma.

Dendrites collect information as electrical pulses from the environment and transfer them to the soma. The soma integrates (sums) this information providing two possible outputs: If the sum of the pulses is lower than a reference triggering level, there is no reaction; if the sum is greater than the reference level, an electrical pulse is generated. This pulse travels through the axon to a neighbor cell via a special junction called synapses: a point where an axon branch is very close to a dendrite of a different cell.

This behaviour is very easy to reproduce with computers where the input connections (synapses), sum and threshold function (soma), and output connections (axon) characterize each neural unit (Jones & Hoskins, 1987).

STRUCTURE OF THE NETWORK

Our problem is to find different volcanic lithologies: e.g. lavas and non lavas formations as, for example, tuffs of different types of agglutination. Although, geologically speaking, these classes are easily separated, they cannot be set apart in the satellite information due to factors such as the noise created by vegetation cover and atmospheric effects which mask the radiometric signal from the lavas. Therefore, some pixels will be erroneously interpreted.

The most elementary structure of an ANN model is the "perceptron" (see e.g. Hertz et al, 1991, pp 89) which consist of a single layer of neurons, one for every different input, connected to the output. However, for a simple case of not linearly separable classes it does not work. Nonetheless, the addition of a hidden layer solves the problem. As in our case the classes are not linearly separable, we use here a structure with hidden layers (Jones & Hoskins, 1987).

A structure with four neurons in the hidden layer provided the lower error in a least squares sense.

There is one extra neuron in each layer that is always turned on and acts as a threshold regulator for each neuron in the next layer (Touretzky & Pomerleau, 1989). Therefore, the neural network used in this paper has an input layer of five neurons, one hidden layer of five neurons and one neuron as output. In order to simulate the electric response of the neurons, we use an activation function. This function must give a bounded positive output if the argument is greater than a reference level and a bounded negative output for the opposite case. Hyperbolic tangent has such characteristics.

Fig. 2 shows the diagram of connections where:

U_i: Reflectance level for each spectral band. It is the information that enters to the network through the i^{th} neuron;

X_i: Response of the input neuron;

W_{ij}: Synapses or interconnecting weights between the i^{th} neuron of the input layer and the j^{th} neuron of the hidden layer;

W_{jk}: Synapses or interconnecting weights between the j^{th} neuron of the hidden layer and the k^{th} neuron of the output layer (k=1 in our case);

h_j: Internal field for each hidden neuron;

h_k: Internal field for each output neuron;

S_j: Output of each hidden neuron;

S_k: Output of the network for a given input

Y_k: Desired output.

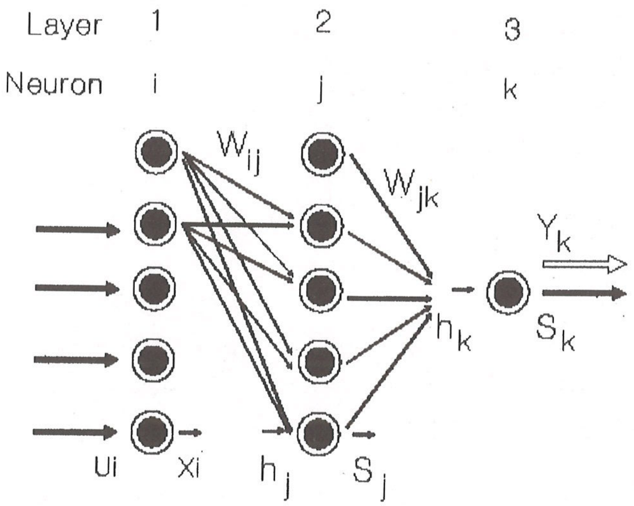

Figure 2 - Scheme of connections between neurons for the present ANN.

Figura 2 - *Esquema de conexões entre neurônios para o presente ANN.*

The computational sequence is as follows:

$$x_i = \tanh(U_i) \quad (1)$$
$$h_j = \Sigma X_i \cdot W_{ij} \quad (2)$$
$$s_j = \tanh(h_j) \quad (3)$$
$$h_k = \Sigma S_j \cdot W_{jk} \quad (4)$$
$$s_k = \tanh(h_k) \quad (5)$$

Then, for each set of weights, the output S_k is calculated and compared with the desired output Y_k, which coincides with the geological map and the error is:

$$\varepsilon_k = S_k - Y_k \quad (6)$$

LEARNING STAGE

In this stage the parameters (Wij, Wjk) of the network are adjusted in a least square sense.

As the problem of minimization is not dependent of the particular algorithm used to calculate the parameters (Hertz et al, 1991, pp 124-129), in this paper, we use the well established Simplex optimization method (Nelder & Mead, 1965; Branham, 1990).

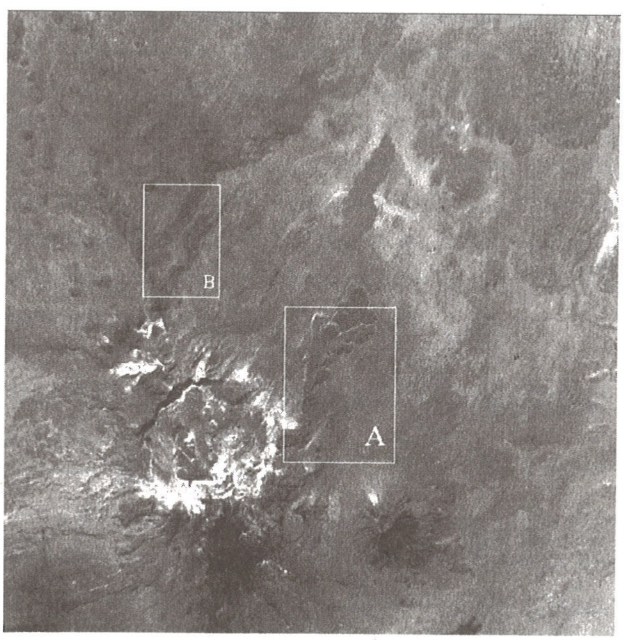

Figure 3 - Composite satellite image of the zone (Bands 4, 5 and 7). Window "A": training area. Window "B": testing area.

***Figura 3** - Imagem de satélite composta (Bandas 4, 5 e 7). Janela "A": área de treinamento. Janela "B": área teste.*

A Landsat MSS image is composed of four subsets, each subset gives information related to a spectral band (4, 5, 6 in the visible range and 7 in the near infrared). The network structure used is adapted to this kind of data arrangement.

Fig.3 is the composite satellite scene of the area.

It covers an area of roughly 30km x 40km (512x512 pixels) centered at 67° 07' 00" W, 36° 30' 00"S. The highlighted windows were selected for training the network ("A"), and for controlling the prediction of the trained network ("B"). Fig. 4 is the aerial photograph corresponding to window "A".

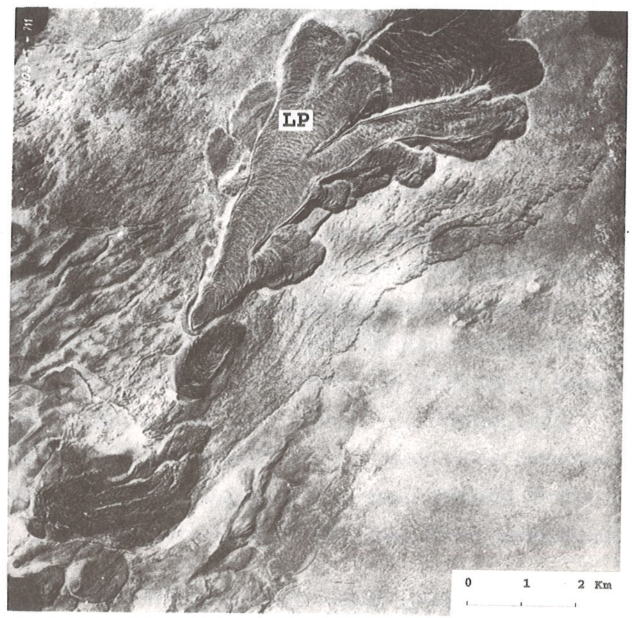

Figure 4 - Aerial photograph of the southeastern sector of Payún Matrú volcano. 'LP': Lava flow known as La Portada de Abajo escorial (La Planchada formation).

***Figura 4** - Fotografia aérea do setor sudeste do vulcão Payún Matrú. 'LP' : Fluxo de lava conhecido como "Escorial de la Portada de Abajo" (Formação "La Planchada")*

For the learning process, we selected a small area of approximately four thousand pixels from the satellite images of the area. This includes part of a lava formation (La Planchada), composed by scoriaceous trachytes and hyalotrachytes.

These data, four for each training pixel, were entered into the network for learning purposes, together with the desired output.

The desired output (presence or not of lava formations) is obtained as follows:

- On the aerial photograph (Fig. 4) a masking cover was placed on the lava formation;
- This mask, obtained by scanning the aerial photograph and scaling, was superimposed on the satellite image;
- The corresponding area in the image is marked by "Y", for the presence of basalt, and by "N", in the absence of basalt, as shown in Fig.5.

A value "1" was given to all pixels corresponding to the formation of interest and value "-1" to the others. In this way, the already mentioned logical output variable is obtained.

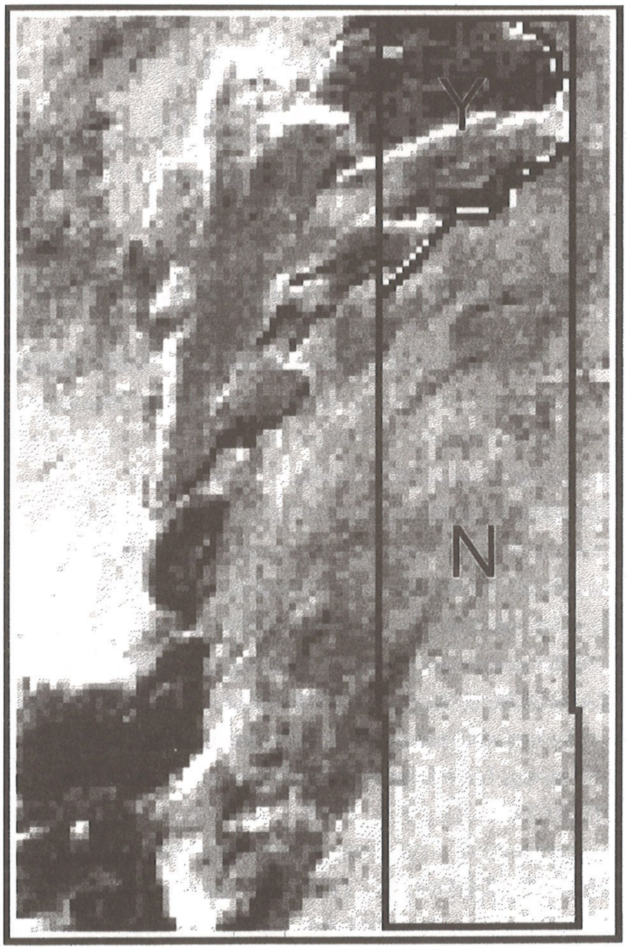

Figure 5 - Satellite image depicting the lavic outcrop of La Planchada formation (La Portada de Abajo escorial). This is window "A" of Fig. 3.

Figura 5 *- Imagem de satélite mostrando o afloramento de lava da formação La Planchada (Escorial de la Portada de Abajo). Corresponde à janela "A" da Fig. 3.*

As usual, small random numbers (<.1) are used for the initial weight vector.

Since, from the geological map, we know the areas with basalt we can calculate the percent agreement:

$$\textit{Percent agreement} = \frac{\textit{number of hits}}{\textit{total number of pixels}} \qquad (7)$$

After convergence of the minimization procedure, the percent agreement for this four thousand selected pixels was 90.68 %.

PREDICTION

After training the network, the best set of parameters Wij and Wjk (interconnecting weights) is used to predict an unknown area. Initially, it was used to predict a larger section in the same training area, to test the performance of this network as a predicting key. The whole area depicted

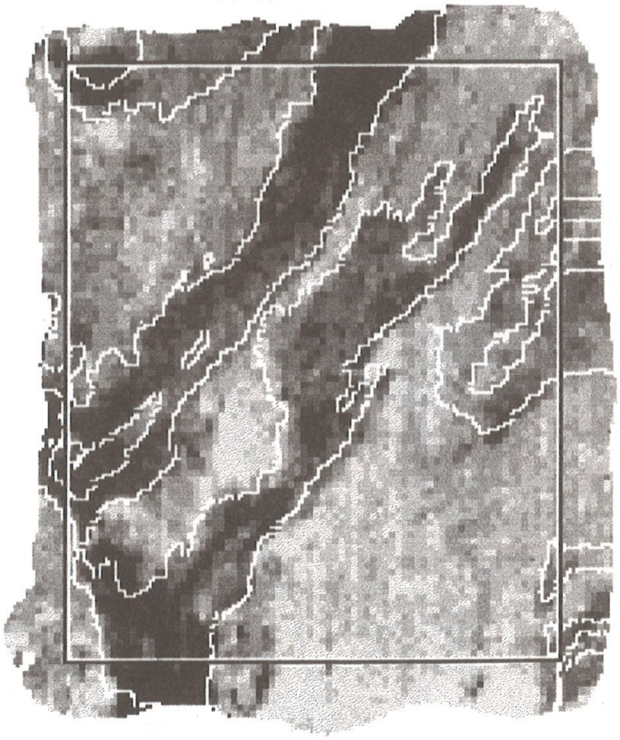

Figure 6 - Satellite image depicting the lavic outcrop of C° Carbonilla formation (Matrú escorial). This is window "B" of Fig. 3.

Figura 6 *- Imagem de satélite mostrando o afloramento de lava da formação C° Carbonilla (Escorial del Matrú). Corresponde à janela "B" da Fig. 3.*

in Fig. 5 (window "A" of Fig. 3) was used for such purpose. It includes the lava outcrop, part of which was used in the training. In this case, the percent agreement, defined in Eq. (7), was 81.24%.

For testing the quality of the prediction, an area controlled by aerial photograph (Fig. 6) was considered (window "B" of Fig. 3). The border of the lava formation is delineated by a white line. The calculated percent agreement in this case turned out to be P_r=80.1%.

Finally, the prediction was extended to the entire satellite image.

The prediction for the entire scene is shown in Fig. 7. It provides a remarkable coincidence with the geological map of the area, clearly delineating the zones of volcanic origin and scoriaceous macrotexture.

The output of the network indicates those areas of volcanic origin corresponding to "aa" lava and blocks lava whose common characteristic is a very irregular surface. Our ANN doesn't distinguish the basic from the meso-siliceous or acidic lithologies.

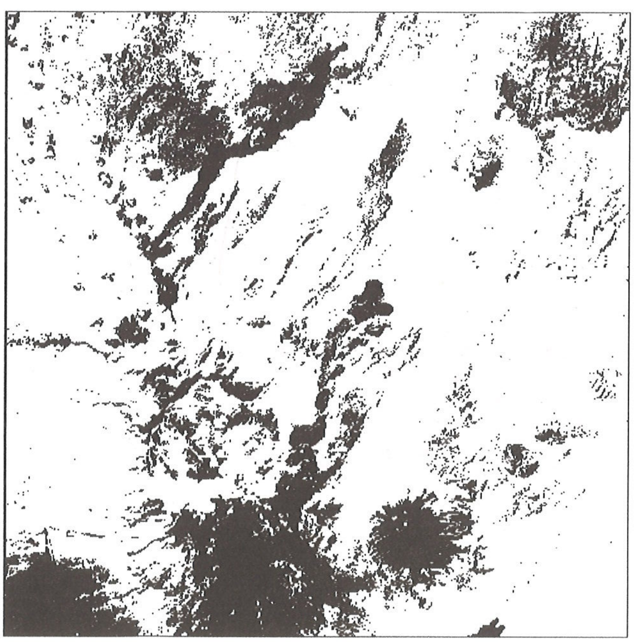

Figure 7 - Network's prediction over the whole scene.

***Figura** 7 - Prognóstico da ANN para toda a cena.*

CONCLUSIONS AND PERSPECTIVES

ANN's are used as a tool for classifying images. This is a simple way to approach the classifying problem.

The Simplex algorithm for minimization of the error during the learning rate was used with success.

The output of the network indicates the areas of that volcanic origin have a very irregular surface.

It is important to note that ANNs techniques allow one to work without statistical assumptions on the classes to be analized.

Obviously, this methodology is not restricted to our problem but it can be applied to other types of problems (e.g., agricultural surveys), as well as other types of images (e.g.,TM, SPOT).

ACKNOWLEDGEMENT

Enrique Miranda is acknowledged for helpful discussions. This work has been subsidized by PIA # 162/90 from CONICET.

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Submetido em: 16/08/94
Revisado pelo(s) autor(es) em: 21/06/95
Aceito em: 28/06/95

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