Classification of remote sensing data by neural networks

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Abstract

Classification based solely on classical satellite imagery methods sometimes remains unable to give relevant results. These shortcomings have therefore prompted specialists to use the bio-inspired classification for interesting results. In our work, we used a neural classification with the backward propagation algorithm of the gradient integrating the raw data of the three Thematic Mapper channels TM1, TM3, TM4. This will allow us to identify and extract the information contained in the satellite images. The results obtained show that the classification supervised by neural network allowed a better discrimination between the themes (forest, saline 1) having strong spectral similarity.

Keywords: *Neural network, Satellite image, clustering, Perceptron Multi Layer.*

1. Introduction

The first views of the earth from space date back to 1946. They were taken by cameras carried on rockets. The first manned flights showed the interest of being able to have space observation bases. In the 1960s, the Gemini and Apollo flights brought back the first color photographs of the ocean and the land. With the appearance of remote sensing, observation satellites regularly provide a large number of images, data and information inaccessible from the ground. Remote sensing has thus become a very important discipline, because it is now a very valuable and essential decision-making tool for the management of terrestrial resources [1].

The analysis and interpretation of these remote sensing images constitute an important field of research and scientific studies [2]. Several applications take advantage of this, for example, the monitoring of deforestation, the evolution of desertification, the evolution of water resources, the mapping of land cover, inventory of agricultural resources, construction and updating of topographic maps, updating of cadastral plans, discovery of forest diseases, the location of areas of pollution, vegetation, industry, etc [3].

Similarly, current databases whose objective is to study local changes in territories are increasingly based on spatial images. Remote sensing allows the improvement of perception for visualizing and analyzing objects. For example, we can perceive objects such as cars, buildings, and trees, which generate very heterogeneous images. The increasing amount of images available and the increase in their size generate masses of data.

Indeed, the resolution of civilian observation images reaches metric and infra levels metrics. These advances were made in a very short period of time and image processing techniques have not evolved as quickly as acquisition technologies [4].

The classification of satellite images is a discipline in which advances are essential in order to achieve efficient processes for extracting relevant knowledge. It consists of grouping data into homogeneous classes. In imaging, it consists of identifying groups of pixels that have the same spectral similarities in order to provide easily interpretable information[5]. Two types of classification can be distinguished:

1. Unsupervised classification such as: Kmeans [6] and ISODATA [7] (Iterative Self - Organizing Data Analysis Techniques)

2. Supervised classification such as: Maximum Likelihood [8], Minimum Distance [9], and SVM [10] (Support Vector Machine).

In this paper, we are interested in the supervised classification of remote sensing data by Multi Layer Perception Neural Networks (MLPNN). This paper is structured in sections. The second section presents the state of the art on multi-layer perceptual neural networks. The principle of MLPNN classification based on gradient back propagation learning is presented in the third section. The results obtained by the application of our method on satellite images will be presented in the fourth section.

2. Multi-Layer Perception

Formal neural networks are theoretical models of information processing inspired by the functioning of biological neurons. The first work on cognitive neuroscience carried out in the 1940s by the Canadian psychologist and neuropsychologist neuropsychologist Hebb led to the invention of the perceptron by Rosenblatt (1957). The perceptron is one of the simplest neural classifiers, as it has only one hidden layer [11].

In contrast to classical classifiers, neural classifiers, such as the neural classifiers, such as the single layer perceptron, are of practical interest. On the one hand, they do not require input data, fitting a parameterisable statistical distribution, and on the other hand, the parameters of the neural network gradually adapt to the properties of the input data, as it is provided with known examples. These advantages have made these networks the most popular in image classification, for more complex classification problems, simple perceptrons cannot provide satisfactory results.

The solution given by Bishop (1995) of combining several perceptrons has proven to be effective in dealing with such problems and has resulted in good accuracy of the classification results. Such a neural network is called a multilayer perceptron (Figure 1). Indeed, in the general case, the decision boundaries separating the classes in a single hidden neuron network are half-planes or half-spaces separated by a hyperplane. When increasing the number of hidden layers, the first hidden layer can create as many separating lines as it has neurons. This increase in layers also implies an increase in the complexity of the regions identifying the different classes [12].

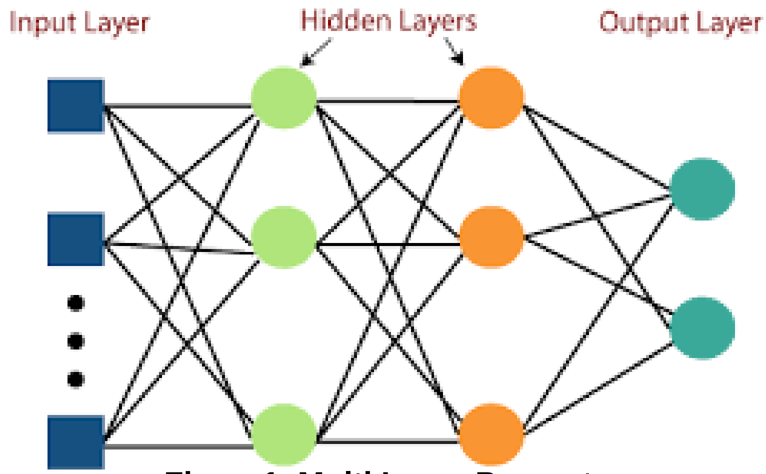

Figure1. Multi Layer Perceptron

The learning of the multilayer perceptron is supervised, in the sense that the network is forced to converge towards a specific final state. This is done by creating a learning base. Each example in the base consists of the input vector and the appropriate output vector. The principle of this training is described in section 3.

3. Learning Back propagation of the gradient

An artificial neural network, like the brain, learns to react correctly to an external stimulus. The principle of learning consists of subjecting the network to a stimulus whose desired response is known, as many times as necessary to modify the weights of the connections, until the correct response is obtained. To perform the learning, three elements are essential. Signal Strength, Error and Learning Rate. However, it is important to know that there are some basic concepts involved in learning a multilayer perceptron model. Recall that the gradient back-propagation algorithm is one of the most common algorithms in feedforward neural networks [13]. This algorithm has two main phases:

1. Propagation or Forward Pass: In this first phase, at each iteration, the network is given a set of inputs. These inputs are propagated to the output layer with an output $\hat{\boldsymbol{y}}$. If this output does not correspond to the target y, the algorithm will backtrack (from the output layer to the input layer) to correct this error by progressively modifying the weights found in each neuron of each layer.
2. Fixing the Backward Pass error: In the first iteration, the network often does not provide exactly what is expected as a result. It has to learn first. The error between the output value and the target value is calculated. In general, the root mean square sum of the errors (*MSE*) is calculated for all output neurons that are back-propagated in the network.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(\hat{\boldsymbol{y}}_{\boldsymbol{i}} - \boldsymbol{y})^2 \qquad (1)$$

The weights of the network will be changed at each iteration. This change is done in such a way as to minimise the error between the desired output, the target and the result of the network at one input $\boldsymbol{x_i}$. This change is thus performed via the gradient descent method. In fact, starting from two phases above, the algorithm propagates the input signal in the network at each iteration in the direction of the output in order to obtain an output and the error between this output and the desired output is calculated (figure 2).

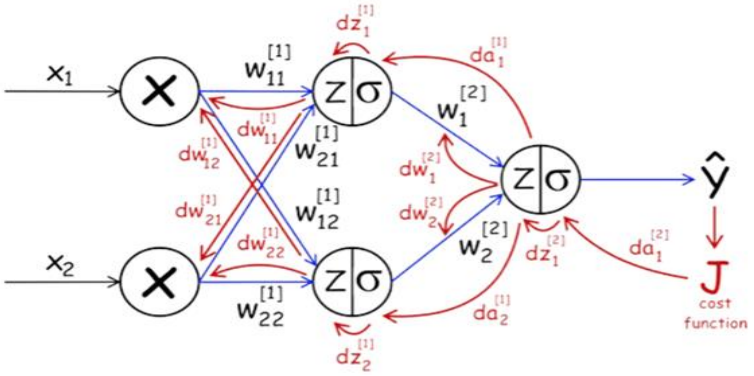

Figure 2. Learning principle Gradient back propagation

Then, by back-propagation, intermediate errors are calculated which correspond to the hidden layers. Finally, we adjust the weights $\boldsymbol{w_{jl}^{h}}$. The aim of the learning process is to find the correct weights for the connections, i.e. to give the network behaviour as close as possible to that of the target. Hence, the back-propagation algorithm consists in performing several iterations until the error is small enough [14].

4. Experimental results and discussion

In this section, we present the guidelines for achieving the objective of this paper which consists in a supervised classification of satellite images by MLPNNs with gradient back propagation learning. To do this, the methodology chosen with the raw data is defined, as well as the system allowing the fusion of these data. We also discuss the results obtained by making a comparison between the different classifications carried out which combine the raw radiometry channels.

4.1 Study Site

Our classification procedures were tested on digitised LANDSAT 5 -TM satellite image data of the Oran region, Algeria, dated 15 March 1993 (Figure 3).

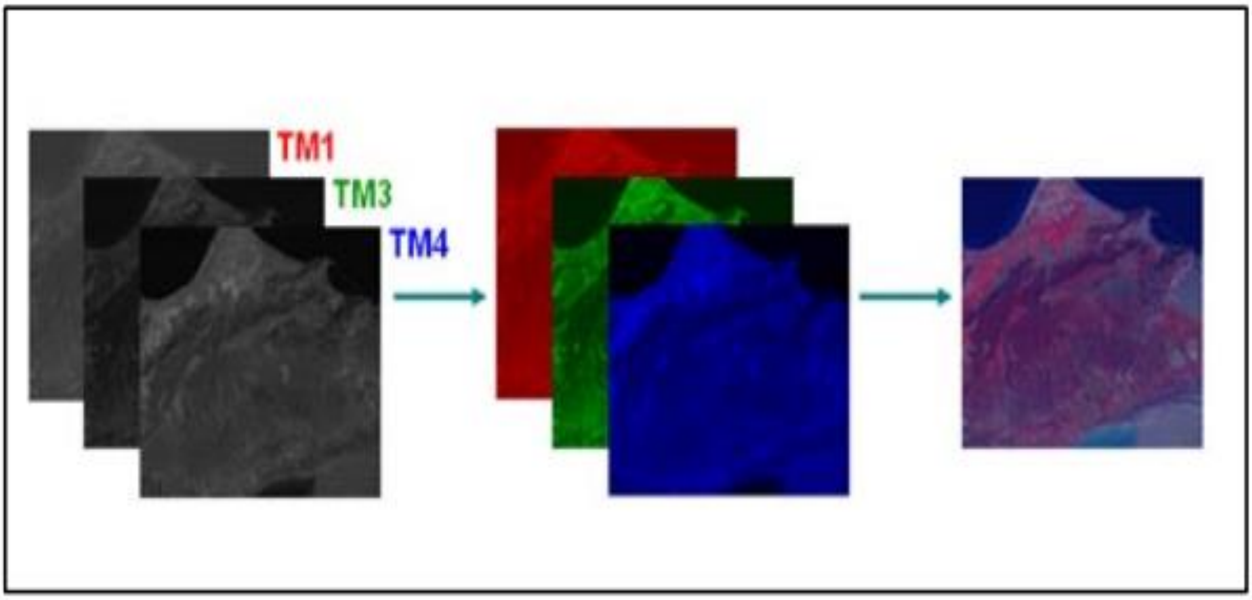

Figure 3. Study Site

The study area is known for its diversity of terrain, the presence of several themes and the problems of confusion between the different classes, which provides an ideal platform for examining the effectiveness of the classifier used.

Confusions appear in the image due to the shadow effect and some different themes with similar spectral responses. This situation is of great interest for the test in the classification tests performed.

4.2 Méthode Utilisée

We aim to improve the quality of classified images using data from three channels: TM1, TM3 and TM4. A set of samples used in our application representing the following themes of interest (10 classes):

Sea, Surf, Fallow land, Forest, Burns, Maquis, Urban, Cereals, Saline 1, Saline 2.

Our approach consists of five phases:

Loading image TM1, TM2, TM3 phase.
Colouring and enhancement phase.
Sampling phase.
Learning phase.
Classification phase.

After loading the images, we will apply a very specific treatment to the image which is colouring to better interpret the image. To do this, we assign the red to channel TM1 channel, green to TM3 channel and blue to TM4 channel. Then we apply an enhancement, by a set of well-defined coefficients, in order to facilitate the taking of the samples.

Sampling is the most important part of our approach; it requires learning as the results are weighted. The training data are pixels of each class, chosen using thematic knowledge of the classes present in the study area, therefore the sample size is taken according to the nature of each class.

The training is carried out by using the MLP back propagation algorithm mentioned above. Once the learning phase is completed, a supervised neural MLPNN classification can be applied. This phase also allows us to obtain the confusion matrix which allows us to calculate the classification rate and to visualise the confusions between the different classes. This classification uses the MLPNN algorithm with gradient back propagation illustrated in Figure 4.

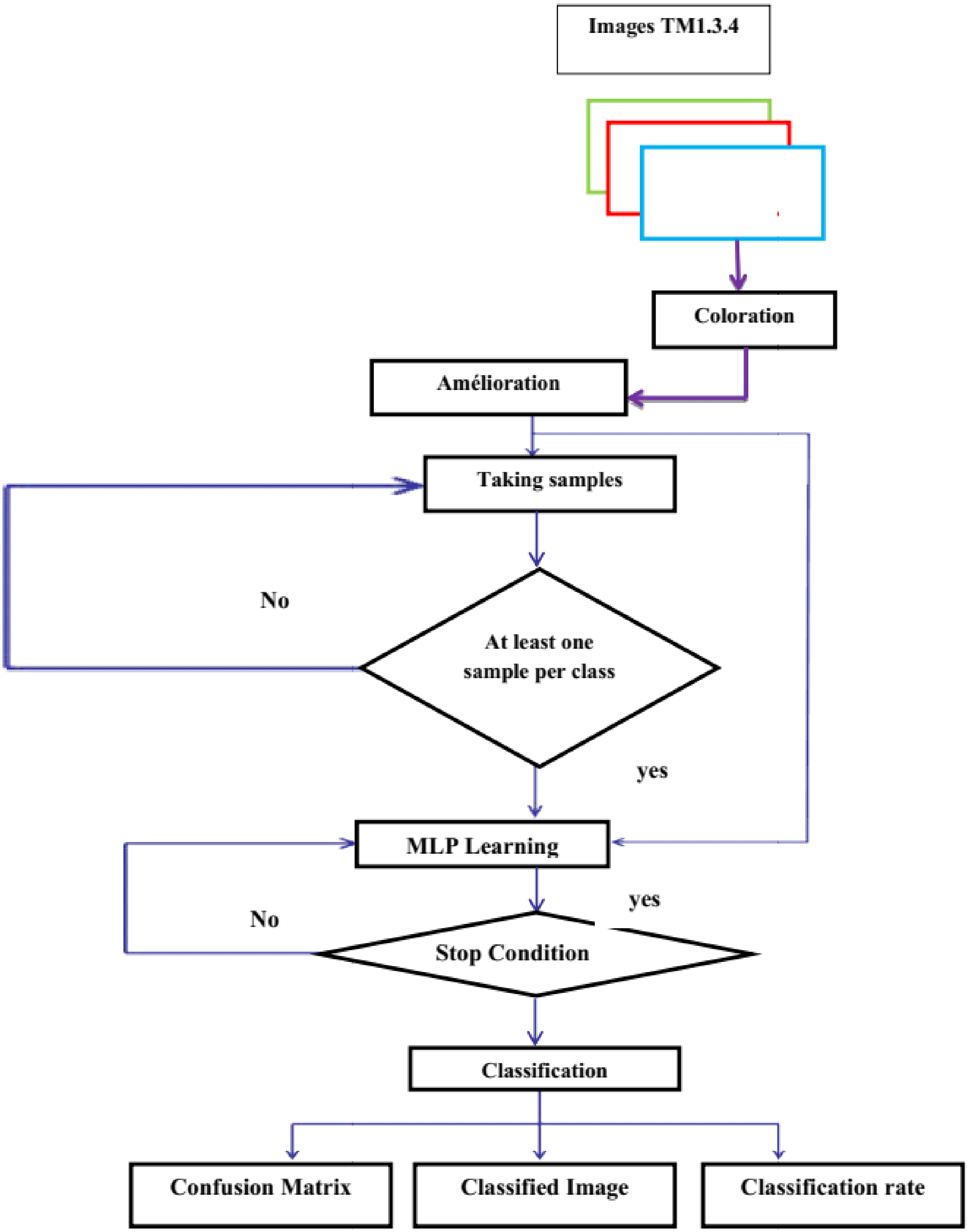

Figure 4: Flow chart of our classification approach

4.3 Classification results

4.3.1. Test 1

Regarding the architecture parameters of the neural network used are fixed at :
Number of neurons in the input layer: 03
Number of neurons in the hidden layer: 05
Number of neurons in the output layer: 10
Number of iterations: 1000 iterations.
The activation threshold: 0.03
The learning step: 0.5

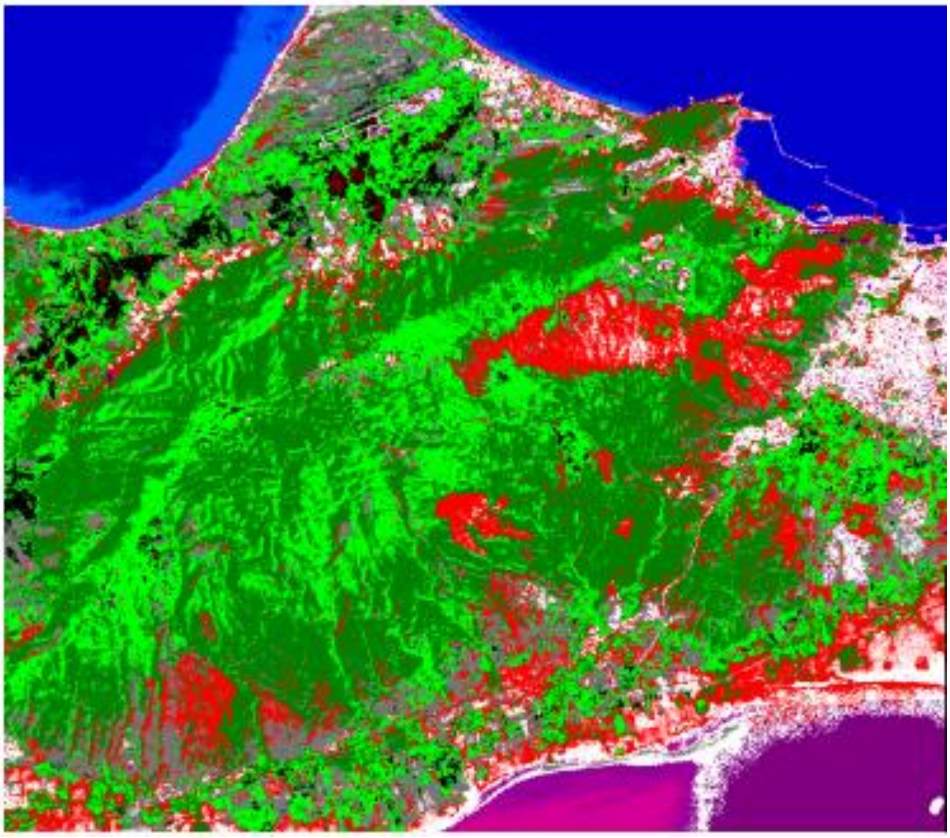

Figure 5: Classified image of the 1st Test

Table 1. Confusion matrix of the 1st Test

	Sea	Surf	Cereal	Fallow	Forest	Maquis	Urban	Burned	Saline 1	Saline 2
Sea	**100**	0	0	0	0	0	0	0	0	0
Surf	0	**100**	0	0	0	0	0	0	0	0
Cereal	0	0	**73**	0	0	27	0	0	0	0
Fallow	0	0	0	**100**	0	0	0	0	0	0
Forest	0	0	0	0	**83.16**	16.84	0	0	0	0
Maquis	0	0	0	0	0	**100**	0	0	0	0
Urban	0	0	0	0	0	0	**66.43**	0	**33.57**	0
Burned	0	0	0	0	0	0	0	**100**	0	0
Saline 1	0	0	0	0	0	0	0	0	**79.82**	20.18
Saline 2	0	0	0	0	0	0	0	0	0	**100**
Classification rate : 90.25%										

We notice in this result, despite the high classification rate of 90.25, some conflicts such as: the appearance of urban in saline 1 and cereal in the maquis class. To compensate for this degradation, we modified the learning step to 0.75 and the activation threshold of the neurons to 0.06 in order to improve the quality of the classification (2nd test).

4. 3.2 Test 2

Regarding the architecture parameters of the neural network used are fixed at :
Number of neurons in the input layer: 03, Number of neurons in the hidden layer: 05
Number of neurons in the output layer: 10, Number of iterations: 1000 iteration,
The activation threshold: 0.06, the learning step: 0.75

Figure 6: Classified image of the 2nd Test

Table 2. Confusion matrix of the 2nd Test

	Sea	**Surf**	**Cereal**	**Fallow**	**Forest**	**Maquis**	**Urban**	**Burned**	**Saline 1**	**Saline 2**
Sea	**100**	0	0	0	0	0	0	0	0	0
Surf	0	**100**	0	0	0	0	0	0	0	0
Cereal	0	0	**100**	0	0	0	0	0	0	0
Fallow	0	0	0	**100**	0	0	0	0	0	0
Forest	0	0	0	0	**100**	0	0	0	0	0
Maquis	0	0	23.66	0	0	**71**	5.34	0	0	0
Urban	0	0	0	0	0	0	**100**	0	**0**	0
Burned	0	0	0	0	0	0	0	**100**	0	0

Saline 1	0	0	0	0	0	0	0	0	**100**	0
Saline 2	0	0	0	0	0	0	0	0	0	**100**
Classification rate : 97.1%										

Using these parameters, we obtained a classification rate of 97.1%, we noted some conflicts between: The Maquis and Ceréal class and the Maquis and Urban class.

4.4 Discussions

In Figure 5, the image of the classification obtained by the MLPNN is given, and as shown in the table 1, this method gives an overall classification rate of 90.25% calculated on the set of samples chosen for verification.

In Figure 6, we show the image of the classification obtained by the MLPNN, as shown in Table 2, this method gives a classification rate equal to 97.1 using a learning step equal to 0.75 calculated on the set of samples chosen for the verification.

The comparison between the two classifications by increasing approximately the value of the activation threshold and learning step shows an improvement of 6.85% on the overall classification rate.

A field recognition campaign allowed us to observe that the classification based on multi-layer neural networks was globally satisfactory.

5. Conclusion

Image analysis encompasses a multitude of areas; here we have addressed one which is the classification of satellite images by multi-layer neural networks. This is a difficult problem, mainly due to the choice of the network architecture and the initialization of parameters such as the number of hidden layers, the activation threshold and the learning step.

The main contribution of this paper was to develop a neural MLP classification with a retro gradient propagation algorithm that integrates the raw data of the three channels TM1, TM3 and TM4. This classification also offers a high discriminatory power between themes with strong similarities and gives satisfactory results.

From a research perspective, it would be interesting to use other classification methods on other types of images, different resolutions and from other types of sensors.

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