Satellite remote sensing classification with Artificial Neural Networks and Support Vector Machines

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Abstract. Image classification is used to group multispectral pixels into different land cover classes. This is important for cartographic updating, since it is possible to compare an old, thematic land cover map with information from a recent image. In this paper we focus on comparing two methods of supervised classification, Artificial Neural Network (ANN) and Support Vector Machine (SVM), for the classification of SPOT5 satellite images. The training of both algorithms was carried out with a randomized 10% of the total number of pixels; the remaining 90% of the pixels were used to evaluate the algorithms. The results of the evaluation show that ANN outperforms SVM; the accuracy of the former is of 97.7% while the latter is only 90.5%.

Keywords: supervised classification, Artificial Neural Network, Support Vector Machine, SPOT5

1 Introduction

Due to a territory's change in vegetation and other cartographic features over the passage of time, cartographic updating is an important task that should be performed periodically. Currently, this task is carried out manually by an operator who analyzes the cartographic features on orthophotos. This is a time consuming job, and for this reason the industry needs automatic, or semiautomatic, methods that facilitate this task. The segmentation of an image is usually the first landmark in most automatic classification methods. When dealing with multispectral satellite images this segmentation is initially carried out by classification methods. We are interested in finding a good classification method for a specific type of satellite imagery, SPOT5. In this paper we compare two classification methods: ANN and SVM.

There are many papers comparing different classifications methods of remote sensing imagery ([7] and [3]). Yet, few papers have been written comparing ANN and SVM. Byvatov et al. [2] found that SVM outperformed ANN by only a 2%; SVM had an 82% correct prediction accuracy while ANN had 80%. The results of García-Orellana et al. [4] show similar performance records for SVM and ANN in the diagnosis of microcalcification clusters in mammograms, although the ANN detection was slightly better. Muniz et al. [6] found that ANN performed better than SVM for the classification of medical data, although they used a variant called probabilistic neural network. To the author's knowledge, the comparison of SVM and ANN for remote sensing imagery has never published, specifically for SPOT5 satellite imagery.

2 Materials

In this study we used images from the satellite SPOT5 corresponding to the university campus of Alcalá and its surroundings, about 30 Km east of the city of Madrid, where the terrain is relatively flat. The SPOT5 imagery is made up of four multispectral bands plus a panchromatic one; the frequencies are: Green B1 0.50-0.59 µm; Red B2 0.61-0.68 µm; near infrared B3 0.78-0.89 µm; Infrared B4 half 1.58-1.75 µm; Panchromatic 0.50-0.73 µm. The first three had a resolution of 10 m and the fourth had a resolution of 20 m. The panchromatic band had a resolution of 2.5 m. The image was taken from an altitude of 822 km with a digitalization of a byte per pixel. The width of field for the complete scene is 60 km x 60 km. The image we have used in our work (figure 1) corresponds to a scene of about 2 km x 2.5 km.

Fig. 1. A false color image of pansharpened SPOT5 of the study area. B1 for red, B2 for blue and B3 for green.

This scene corresponds to a pansharpened image using the Principal Component method, which merges the high resolution 2.5 panchromatic band with the lower, 10 m and 20 m, resolution multispectral imagery to create a single high resolution image of 2.5. First, a principal component is performed on the multispectral bands, then the first component band is replaced by the panchromatics and finally the inverse principal transformation is performed.
We used two supervised classification methods: ANN and SVM, and a brief introduction to each of these methods is given in the following sections.

2.1 ANN

Artificial neuronal networks (ANN) consist of a simulation of the properties observed in biological neuronal systems through recreated mathematical models by means of artificial mechanisms (like an integrated circuit, a computer or a set of valves). The objective is for the machines to give answers similar to those given by the brain, which are characterized by their generalization and robustness. A neuronal network is composed of units called neurons. Each neuron receives a series of entrances through interconnections (also called weights) and emits an exit (see figure 2). This exit is given by three functions:

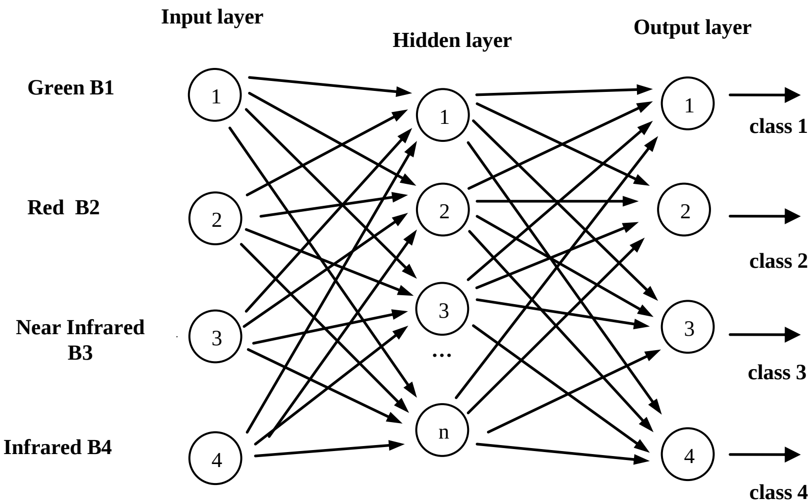


Fig. 2. ANN for lineal separable data

- *A propagation function (also known as an excitation function) generally consists of the summation of each entrance multiplied by the weight of its interconnection (net value).*
- *An activation function modifies the previous one. It is not necessary in this case, since the exit is the same function as the propagation.*
- *A transition function is applied to the value given by the activation function. It is used to limit the exit of the neuron and it is generally defined by the interpretation that we want to give these exits.*

There are four neurons for the input layer, one for each band of the pansharpened SPOT5 image. In our case, the output layer also has four neurons since we are considering four classes. For each pixel each neuron in the output layer is given a probability of belonging to each class. The pixel is finally assigned to the class with the highest probability. The number of neurons in the hidden layer is a parameter to be tuned in order to obtain the best performance. The higher the non-linearity of the problem at hand, the greater the number of hidden neurons the network is going to need. We tried several neuron amounts and obtained the best results with three neurons.

2.2 SVM

The SVM is a supervised classification method. The idea of a SVM initially appeared in a 1992 article [1], where it was applied to a problem of character recognition. Different variants from a SVM algorithm have recently been developed by Vladimir Vapnik and a research group at AT&T laboratories. The SVM belongs to the family of linear separators since they induce linear or hyperplane separators in spaces with very high dimensionality. This high dimensionality is obtained by applying nucleus or kernel functions. The objective is to find hyperplanes g with the maximum separation between both margins (see figure 3). For more details see Vapnik [8].

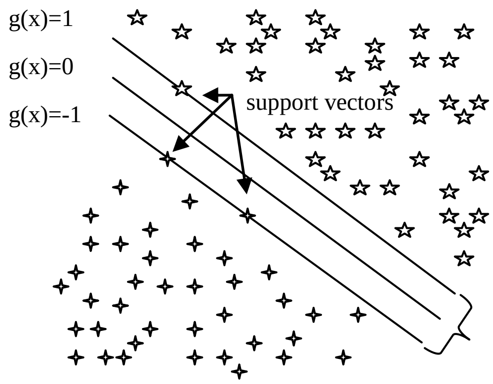


Fig. 3. SVM for lineal separable data

2.3 Differences and similarities between ANN and SVM

ANNs are close related to SVMs. When the latter uses a sigmoid kernel function it is equivalent to a two-layer or perceptron neural network. A difference is that in standard neural network training the weights of the network are found by solving a non-convex, unconstrained minimization problem, while in SVM they are found by solving a quadratic programming problem with linear constraints. Another difference is that the development of ANNs followed a heuristic path, with applications and extensive experimentation preceding theory, while the development of SVMs was first theoretical, with sound mathematics, and then followed by implementation with experiments.

3 Classification

3.1 Training

We have chosen four classes: vegetation without chlorophyll, vegetation with chlorophyll, buildings, roads and highways. The following zones of interest were chosen for the phase of training (Figure 4):

Fig. 4. Training samples

The training was performed with 10% of pixels from each training class.

Table 1. Number of pixels per class.

Classes	areas	Color	Total Pixels	Training pixels
Vegetation without chlorophyll	4	Reed	2.442	244
Vegetation with chlorophyll	4	Green	2.312	231
Building	5	Blue	1.124	112
Roads	3	Yellow	608	61

Due to the characteristics of SPOT5 imagery, such as the existence of two infrared bands, it is suitable for vegetations studies. Therefore two classes of vegetation were defined: one considering chlorophyll and the other not considering it.

3.2 Results

The classification results for the ANN algorithm is presented in Figure 5. Figure 5(a) represents the probability layer for the first class, vegetation without chlorophyll, the brighter the pixel the higher the probability. The others images (Figures 5(b), 5(c) and 5(d)) represent the probabilities for the vegetation classes with chlorophyll, buildings, and roads, respectively. Similar to ANN, Figure 6 represents the probability layers for the four classes, except for the SVM algorithm. Finally, in Figure 7 the classification for both algorithms (7(a) for ANN and 7(b) for SVM) can be observed.

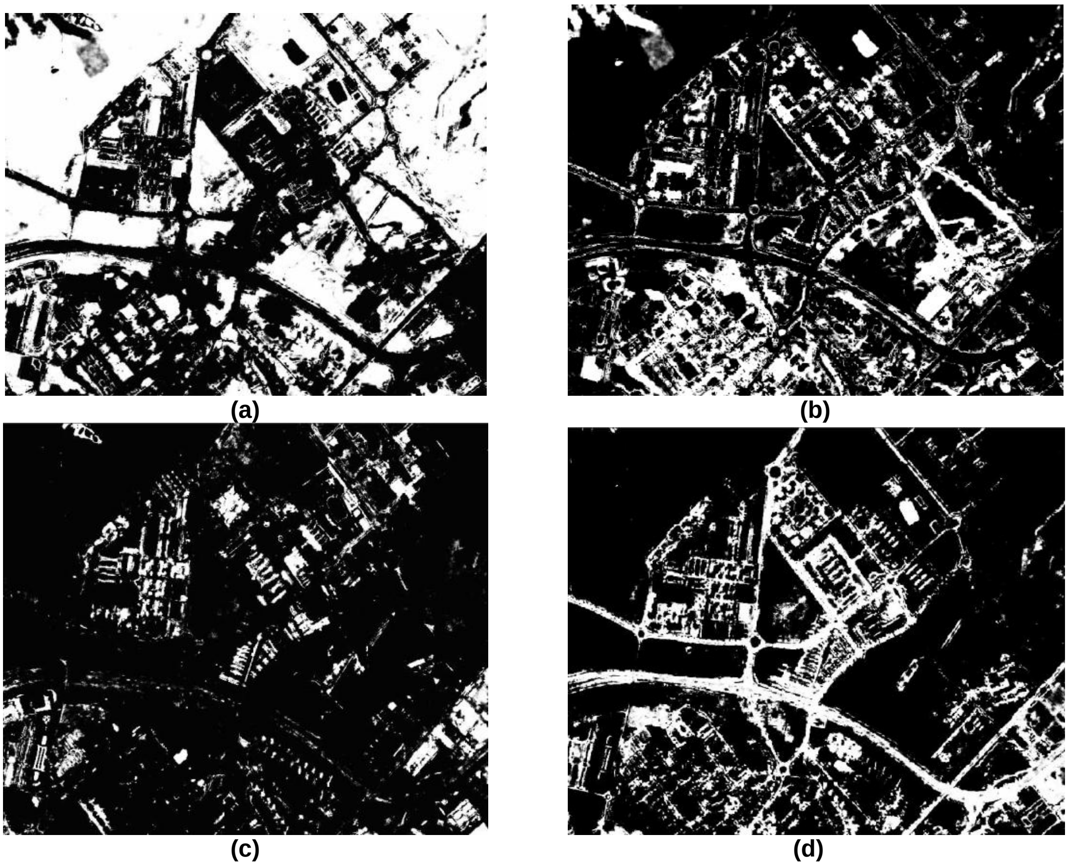


Fig. 5. Probability layers for classes 1, 2, 3 and 4 for the ANN algorithm.

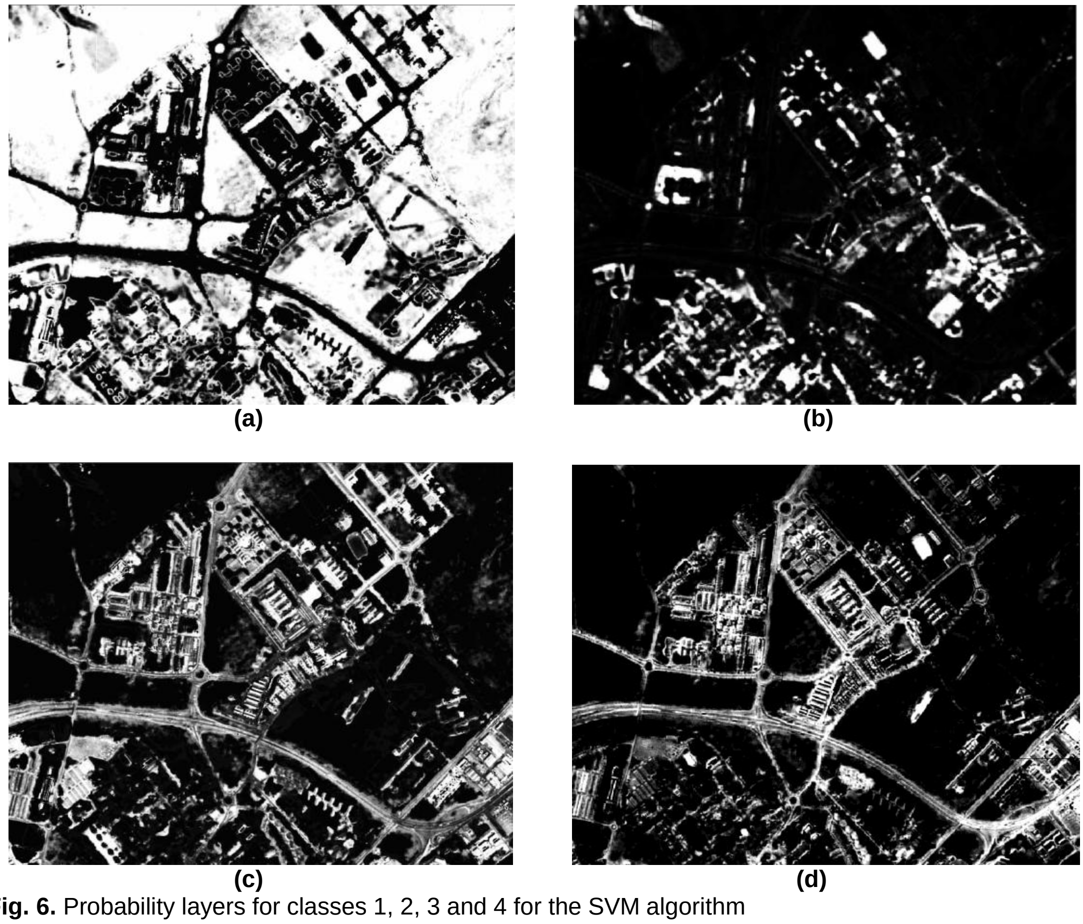
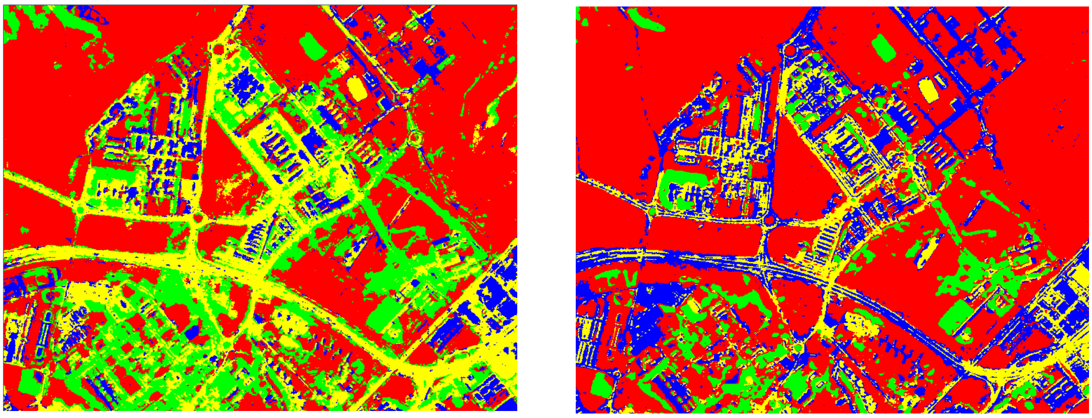


Fig. 6. Probability layers for classes 1, 2, 3 and 4 for the SVM algorithm



(a) (b)

Fig. 7. Classification images for the ANN and SVM algorithms.

The confusion matrices have been calculated comparing the layer of probabilities obtained with the total numbers of the pixels.

Table 2. Confusion matrix for the ANN algorithm.

Overall Accuracy = (6341/6486) 97.7644%
Kappa Coefficient = 0.9676

	Ground Truth (Pixels)				
Class	Region #1	Region #2	Region #3	Region #4	Total
Unclassified	0	0	0	0	0
Vegetation without chlorophyll	2.442	0	66	0	2.508
Vegetation with chlorophyll	0	2.312	5	1	2.318
Building	0	0	1.001	21	1.022
Roads	0	0	52	586	638
Total	2.442	2.312	1.124	608	6.486

Class	Commission (Percent)	Omission (Percent)	Commission (Pixels)	Omission (Pixels)
Vegetation without chlorophyll	2.63	0.00	66/2.508	0/2.442
Vegetation with chlorophyll	0.26	0.00	6/2.318	0/2.312
Building	2.05	10.94	21/1.022	123/1.124
Roads	8.15	3.62	52/638	22/608

Table 2. Confusion matrix for the SVM algorithm.

Overall Accuracy = (5875/6486) 90.5797%
Kappa Coefficient = 0.8633

	Ground Truth (Pixels)				
Class	Region #1	Region #2	Region #3	Region #4	Total
unclassified	0	0	0	0	0
Vegetation without chlorophyll	2.442	0	36	0	2.478
Vegetation with chlorophyll	0	2.312	0	0	2.312
Building	0	0	882	369	1.251
Roads	0	0	206	239	445
Total	2.442	2.312	1.124	608	6.486

Class	Commission (Percent)	Omission (Percent)	Commission (Pixels)	Omission (Pixels)
Vegetation without chlorophyll	1.45	0.00	36/2.478	0/2.442
Vegetation with chlorophyll	0.00	0.00	0/2.312	0/2.312
Building	29.50	21.53	369/1.251	242/1.124
Roads	46.29	60.69	206/445	369/608

In both algorithms the part corresponding to vegetation seems to be better classified than the one corresponding to buildings and roads. With a very low number of false positives in both algorithms, it is interesting to note the 2.63% of the false positives obtained in the case of vegetation without chlorophyll for the ANN algorithm were mainly assigned erroneously to the class of vegetation with chlorophyll. In the case of SVM this percentage is only of 1.45%.

In the SVM there was an important amount of false positives between the buildings and roads classes. There were 369 pixels from the building class to which the road class was assigned, and there were 206 pixels of the road class assigned to the buildings class. While in the case of the ANN algorithm there were 21 pixels and 52 pixels, respectively, which represented a far lower percentage. This is the reason why the ANN performs better than the SVM for this paper. Possibly this occurred because ANNs have a greater nonlinear potential than SVMs. Actually, there is a theorem, the Kolmogorov theorem [5], that states that any function can be approximated by a neuronal network. But it is a typical existence theorem which says that something exists but does not say how to do it.

One disadvantage of an ANN compared to a SVM is that the former takes more time to run than the later. Another disadvantage is that an ANN is like a black box, it is difficult to know why it does what it is supposed to do. Therefore, it is a trial and error process to decide how many hidden neurons to use, or how to tune the other parameters.

4 Conclusions

For this type of imagery the ANN outperforms the SVM, the accuracy for the ANN is of 97.7% while that of SVM is 90.5%.

The scientific literature and our work show that the ANN outperforms SVM. However, the big disadvantage of the ANN is finding the right parameters; it is a long trial and error process.

Future work should try to run the algorithms for other types of satellite images with different kinds of classes since the results for vegetation are very similar for both algorithms.

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