Natural Texture Classification: a Neural Networks Models Benchmark

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Abstract

In this paper a natural texture classification study was developed employing neural network models. The objective of this study was to assess the accuracy of each model for the classifying natural texture problem. Multi-layer Perceptron (MLP) network, Hopfield network, Self-organizing feature map (SOFM) network and a Radial Basis Function (RBF) network were the models studied, analyzed using the Neurosolutions version 5.0 (trial version) software and Weka version 3.4 software, in this work. A file, with more than 700 records of natural texture characteristics, which were obtained by the analysis of digital photographs of real landscapes, was used for the experiments. These natural textures were divided in 9 classes: water, ground-sand, grass, stones, sky, tree, mountain, snow and flowers. The experimental results showed that Multilayer Perceptron network was the best neural network model in the natural texture classification.

1. Introduction

Texture plays an important role in computer vision and pattern recognition, since most real worlds objects consist of different kinds of texture surfaces [1].
The analysis of natural textures is an important topic in the field of image processing and pattern recognition. Artificial neural networks have been studied for many years in the hope of achieving human-like performance in the fields of speech and image recognition [2]. One of he simplest tasks that neural nets can be trained to perform is pattern classification [3]. In pattern classification problems, each input vector (pattern) belongs, or does not belong, to a particular class or category [3]. There are many researches in natural texture classification using neural networks [4] [5].

In this paper, the performance of four neural network models in the natural texture classification is analyzed using the Neurosolutions version 5.0 (trial version) software [6] and Weka version 3.4 software[7]. The neural network models are: Multi-layer Perceptron (MLP) network, Hopfield network, Self-organizing feature map (SOFM) network and a Radial Basis Function (RBF) network. MLP is analyzed using Weka 3.4 software[7] and the other models are analyzed using Neurosolutions version 5.0 software [6].

Neurosolutions is a neural network development software that combines a modular, icon-based network design interface with an implementation of advanced learning procedures, such as conjugated gradients and back propagation through time. Also includes several neural networks models which can be easily implemented [8].

Weka is a collection of machine learning algorithms for data mining tasks. The algorithms can either be applied directly to a dataset or called from your own Java code. Weka contains tools for data pre-processing, classification, regression, clustering, association rules, and visualization. It is also well-suited for developing new machine learning schemes. Weka is open source software issued under the GNU General Public License [9].

The rest of this paper is organized as follows. The theory of the neural network models, used in this work, is explained in section 2. Section 3 explains the data used in the experiments and how the experiments were made. Section 4 shows the experimental results. Finally the conclusions are given in section 5.

2. Neural networks models

In this section, a brief description of each neural network model, used in this paper, is presented.

A. Multilayer Perceptron

Multilayer perceptron is a feed forward network in which vertices can be numbered so that all connections go from a vertex to one with a higher number. In practice the vertices are arranged in layers with connections only to higher layers [10].

MLPs are networks with one or more layers of nodes between the input and the output nodes. These additional layers contain hidden units or nodes then are not directly connected to both the input and output nodes. The capabilities of this network stem from the nonlinearities used within nodes. If nodes were linear elements, then a single-layer network with appropriately chosen weights could exactly duplicate those calculations performed by any Multi-layer network [2]. The structure of this neural network is shown in figure 1.

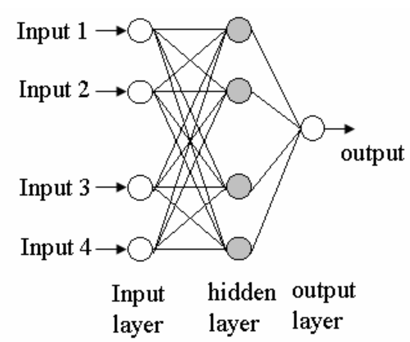

Figure 1. Multi-layer Perceptron network

B. Hopfield Network

An iterative auto-associative network has been developed by Hopfield. This network is a fully interconnected neural network, in the sense that each unit is connected to every other unit. The network has symmetric weights with no self-connections [3].

Hopfield conceptualizes a network in terms of its energy and the physics of dynamic systems. A processing element will change state if doing so will reduce the "frustration level" of the network [11]. The output of each processing element in the binary, symmetrically weighted model is fully connected by weights to the inputs. This recurrency provides the nonlinearity. Positive weights are excitatory and will strengthen connections; negative weights are inhibitory, weakening connections [11]. The structure of this neural network is shown in figure 2.

C. Self-organizing feature map (SOFM) network

Self-organizing feature maps (SOFMs) transform the input of arbitrary dimension into a one or two dimensional discrete map subject to a topological (neighborhood preserving) constraint. The feature maps are computed using Kohonen unsupervised learning. The output of the SOFM can be used as input to a supervised classification neural network such as the MLP. This network's key advantage is the clustering produced by the SOFM which reduces the input space into representative features using a self-organizing process. Hence the underlying structure of the input space is kept, while the dimensionality of the space is reduced [12].

Kohonen network assume a topological structure among the cluster units. This property is observed in the brain, but is not found in other artificial neural networks [3].

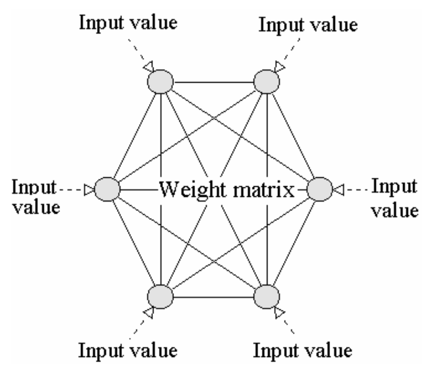

Figure 2. Hopfield network

Kohonen network is an auto-associative network that is a single layer, recurrent and highly connected. Weights must be initialized, and both weights and inputs must be normalized or adjusted to some standard reference. Processing elements compete for the privilege of learning. In a "winner-takes-all" learning rule, the node with the highest response and its nearest neighbors all adjust their weights. As time passes, the size of the neighborhood may be reduced. Neighborhoods become similar in their response properties, and a global organization begins to take shape [11]. The structure of this neural network is shown in figure 3.

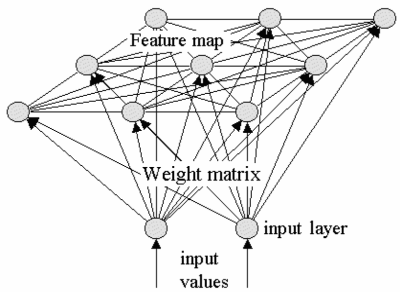

Figure 3. Kohonen network

D. Radial basis function

Radial basis functions emerged as a variant of artificial neural network in late 80's. However, their roots are entrenched in much older pattern recognition techniques as for example potential functions, clustering, functional approximation, spline interpolation and mixture models [12] The output units of RBF network implement a weighted sum of hidden unit outputs. The input into a RBF network is nonlinear while the output is linear. Their excellent approximation capabilities have been studied in [13] [14].

Radial basis functions are embedded into a two-layer feed-forward neural network. Such a network is characterized by a set of inputs and a set of outputs. In between the inputs and outputs there is a layer of processing units called hidden units. Each of them implements a radial basis function. In a pattern classification application the inputs represent feature entries, while each output corresponds to a class [15]. The structure of this neural network is shown in figure 3.

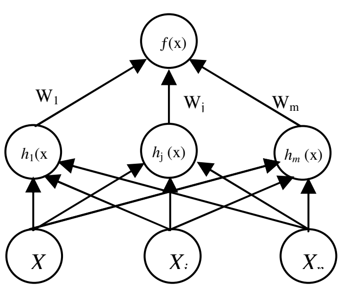

Figure 4. Radial Basis network

3.Experiment design

For the experiments, training file and testing file were built by extracting 19 characteristics of some several digital images. This characteristics are: mean of band color R, mean of band color G, mean of band color B, variance of band color R, variance of band color G, variance of band color B, standard deviation of band color R, standard deviation of band color G, standard deviation of band color B [16], Hu moments [17], maximum probability [18], entropy[18] and uniformity[18].

Training file contains 742 instances which are divided in 9 texture classes: water, ground-sand, grass, stones, sky, tree, mountain, snow and flowers. Figure5 shows some examples of the natural textures used in this work.

Training file is organized as follows:

- Water: 132 instances.
- Ground-sand: 48 instances.
- Grass: 58 instances.
- Stones: 40 instances.
- Sky: 102 instances.
- Tree: 74 instances.
- Mountain: 46 instances.
- Snow: 88 instances.
- Flowers: 154 instances.

Every network model (MLP, Hopfield, Kohonen and RBF) was trained using training file. After training, each network model was tested, to analyze the performance of every network model in the natural texture classification, using a testing file. Testing file was built taking 5 instances of each class, of the training file.

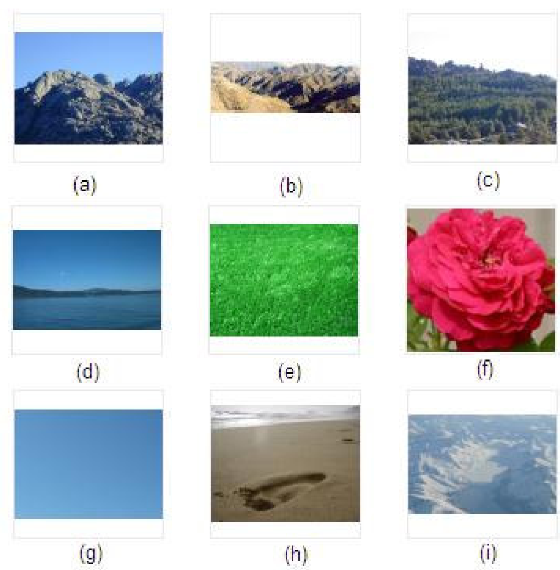

Figure 5: Natural textures used in classifications experiments: (a)Stones, (b)Mountain, (c)Tree, (d)Water, (e)Grass, (f)Flower, (g)Sky, (h)Ground-Sand and (i)Snow.

4. Experimental results

In this section the performance of each neural network model in the classification, following the methodology described in the previous section, is presented. The confusion matrix, in which each cell contains the percentage of exemplars classified for the corresponding combination of desired and actual outputs, relative to the total number of exemplars for the given desired output class, and the average accuracy are presented for every neural network model as follows.

A. Multilayer Perceptron

The accuracy in the classification using Multilayer Perceptron model is 95.5%. The accuracy details are shown in Table 1. The training time with this neural network was 1.05 minutes.

Table 1. Classification accuracy using Multilayer Perceptron network

%	W	Gro	Gra	St	Sky	Tr	Mo	Sn	Fl
Water	100	0	0	0	0	0	0	0	0
Ground	0	80	20	0	0	0	0	0	0
Grass	0	0	100	0	0	0	0	0	0
stones	0	0	0	100	0	0	0	0	0
Sky	0	0	0	0	100	0	0	0	0
Tree	0	0	0	0	0	100	0	0	0
Mountain	20	0	0	0	0	0	80	0	0
Snow	0	0	0	0	0	0	0	100	0
flower	0	0	0	0	0	0	0	0	100

The average accuracy per class for the testing file classification, using this neural network model is:

- Water: 100%
- Ground-sand: 80%
- Grass: 100%
- Stones: 100%
- Sky: 100%
- Tree: 100%
- Mountain: 80%
- Snow: 100%
- Flowers: 100%

B. Hopfield Network

The accuracy in the classification using Recurrent Networks model is 86.6%. The accuracy details are shown in Table 2. The training time with this neural network was 2.44 minutes.

Table 2. Classification accuracy using Hopfield network

%	W	Gro	Gra	St	Sky	Tr	Mo	Sn	Fl
Water	100	0	0	0	0	0	0	0	0
Ground	0	60	40	0	0	0	0	0	0
Grass	0	0	100	0	0	0	0	0	0
stones	0	0	0	100	0	0	0	0	0
Sky	0	0	0	0	100	0	0	0	0
Tree	20	0	0	0	0	80	0	0	0
Mountain	60	0	0	0	0	0	40	0	0
Snow	0	0	0	0	0	0	0	100	0
flower	0	0	0	0	0	0	0	0	100

The average accuracy per class for the testing file classification, using this neural network model is:

- Water: 100%
- Ground-sand: 60%
- Grass: 100%
- Stones: 100%
- Sky: 100%
- Tree: 80%
- Mountain: 40%
- Snow: 100%
- Flowers: 100%

C. Self-organizing feature map (SOFM) network

The accuracy in the classification using Kohonen Network model is 60%. The accuracy details are shown in Table 3. The training time with this neural network was 3 minutes.

Table 3. Classification accuracy using Kohonen network

%	W	Gro	Gra	St	Sky	Tr	Mo	Sn	Fl
Water	60	0	0	0	0	0	0	0	40
Ground	0	0	100	0	0	0	0	0	0
Grass	0	0	100	0	0	0	0	0	0
Stones	0	0	0	0	0	0	0	0	100
Sky	0	0	0	0	100	0	0	0	0
Tree	0	0	0	0	0	0	0	0	100
Mountain	20	0	0	0	0	0	80	0	0
Snow	0	0	0	0	0	0	0	100	0
Flower	0	0	0	0	0	0	0	0	100

The average accuracy per class for the testing file classification, using this neural network model is:

- Water: 60%
- Ground-sand: 0%
- Grass: 100%
- Stones: 0%
- Sky: 100%
- Tree: 0%
- Mountain: 80%
- Snow: 100%
- Flowers:100 %

D. Radial Basis function network

The accuracy in the classification using RBF network model is 88.8%. The accuracy details are shown in Table 4. The training time with this neural network was 1.40 minutes.

Table 4. Classification accuracy using RBF network

%	W	Gro	Gra	St	Sky	Tr	Mo	Sn	Fl
Water	80	0	20	0	0	0	0	0	0
Ground	0	60	0	0	0	0	0	0	40
Grass	0	20	80	0	0	0	0	0	0
Stones	0	0	0	100	0	0	0	0	0
Sky	0	0	0	0	100	0	0	0	0
Tree	0	0	0	0	0	100	0	0	0
Mountain	20	0	0	0	0	0	80	0	0
Snow	0	0	0	0	0	0	0	100	0
Flower	0	0	0	0	0	0	0	0	100

The average accuracy per class for the testing file classification, using this neural network model is:

- Water: 80%
- Ground-sand: 60%
- Grass: 80%
- Stones: 100%
- Sky: 100%
- Tree: 100%
- Mountain: 80%
- Snow: 100%
- Flowers: 100%

5. Conclusions

The average accuracy in the classification for each neural network model and each natural texture is presented in table 5, which summarizes the information presented in the other tables. The four neural network models studied in this paper can classify sky, snow and flower completely.

Based on the experimental results, the best neural network model in the classification of natural texture is MLP network with 99.5% of accuracy in the classification.

However, is notable that each network model has its advantages in specific natural textures. Therefore we can't say that some network is the best one.

For general applications based on these kinds of textures the MLP network is recommended, but you must check the other neural networks advantages for specific problems.

As future work we will realize experiments at a larger scale, with much more digital photographs instances. Finally we will obtain and add the Precision/ Recall and F-measure results to our experiments.

Table V. Accuracy (%) for each model and each class

	MLP	Hopfield	SOFM	RBF	Accuracy (%)
Water	100	100	60	80	85
Ground-sa	80	60	0	60	50
Grass	100	100	100	80	95
stones	100	100	0	100	75
Sky	100	100	100	100	100
Tree	100	80	0	100	70
Mountain	80	40	80	80	70
Snow	100	100	100	100	100
flower	100	100	100	100	100
Accuracy (%)	95.5	86.6	60	88.8	

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