CLASSIFICATION OF SATELLITE IMAGES USING CONTEXT FEATURES AND BASED ON NEURAL NETWORK METHODS

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ABSTRACT **:** *One of the important techniques for interpretation of remote sensing images is classification, which is frequently used in evaluation of landscape changes. The key issue is how to precisely classify the satellite images at high spatial resolution. This study attempts to examine an optimal classification method versus other classification methods based on neural networks. Having compared the employed methods so far, it can be asserted that a suitable neural network can be designed so as to achieve a high precision classification. The results of this study indicated that combination of the proposed algorithm and the SVM can yield much better outputs.*

Keywords: Image Classification, Neural Network, SVM Algorithm.

1. INTRODUCTION

Using an image classification, a pixel is determined from a certain class. Generally, such classification entails two monitored and unmonitored methods. In the former, the type and place of certain types of land covers such as urban, agricultural and blue areas are identified through a combination of field work, interpretation of aerial photographs, map analysis and personal experience. It is essential that the user specify certain locations in the image data representing uniform land covers. Due to their spectral characteristics, these locations are usually called training spots in classification terms for final map preparation. In the latter method, the types of places of different land covers are supposed to be determined as class, usually unknown in advance. That is because reference land information are either absent or the landscape has not been well defined in the imaging scene. Therefore, the algorithm is required to categorize the pixels with similar spectral characteristics in terms of a certain statistical measures into a unified cluster. Afterwards, the user will label and incorporate the spectral clusters and finally place within information classes.

2. ROPOSED METHOD

The implementation of the program generally takes several stages as follow:

1. Reading the current image at the neural network training database.
2. Image conversion from RGB into Gray Level.
3. Applying a 3x3 average filter.
4. Drawing the input image feature vector.
5. Juxtaposing the total feature vector and forming the final feature vector.
6. Forming the target vector.
7. Construction of neural network.
8. Training the neural network through the final feature vector and target vector.

METHODOLOGY

As one of the various properties attributed to the components of an image such as color, shape and motion, texture is a prominent image feature from the perspective of both human sight and computerized process. The texture of an image depends on the spatial distribution of values for the grey tint, entailing some information about folding, flatness, uniformity, contrast, etc. The texture analysis provides interesting options for detection of structural heterogeneity in each class.

The various types of texture classification can be divided into four methods: statistical, structural, model-based and conversion. The gray level co-occurrence matrix (GLCM) is unique due to its crucial characteristics for distinguishing objects in different directions.

Equations 1 to 3 illustrate how the texture parameters are calculated.

Contrast

$$f_1 = \sum_i \sum_j (i-j)^2 p(i,j) \quad (1)$$

Entropy $$f_2 = \sum_i \sum_j \left(\frac{p(i,j)}{\log p(i,j)} \right) \quad (2)$$

Homogeneity

$$f_3 = \sum_i \sum_j \left(\frac{p(i,j)}{1+|i-j|} \right) \quad (3)$$

Generally, the classification methods perform more ideally when incorporated with GLCM statistical features. The texture classification in synthetic spectral response classes leads to higher accuracy (e.g. fallow areas and anywhere determined by plant density) [1].

UTILIZATION OF NEURAL NETWORK

1.4 MLP Neural Network

Having calculated the GLCM, features should be extracted from the matrix. For each image, a corresponding feature vector is obtained. All the feature vectors obtained for the images form a total vector, which is used in the training segment of the neural network [2].

Based on their information process method, the neural networks can be divided into two groups: feed forward and recursive [3].

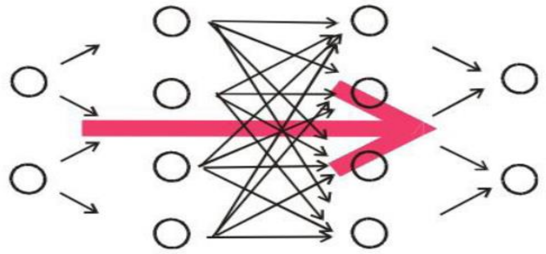

Fig.1 A representation of feed forward architecture.

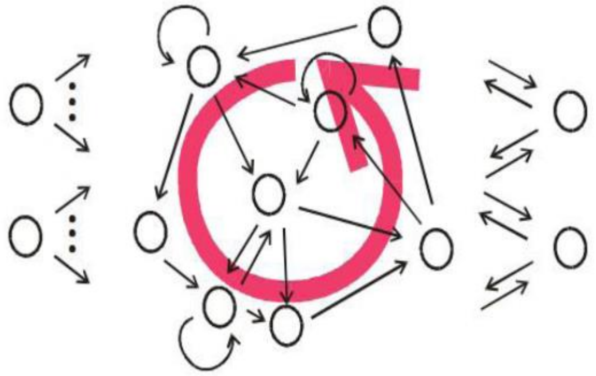

Fig.2 A representation of recursive architecture.

One of the most commonly used and most efficient networks is back propagation. The feed forward networks usually have one or more hidden neuron layers, i.e. neurons are arranged in a layered structure where neurons of each layer link completely to the next.

The MLP neural network used in this study has been displayed the figure blow:

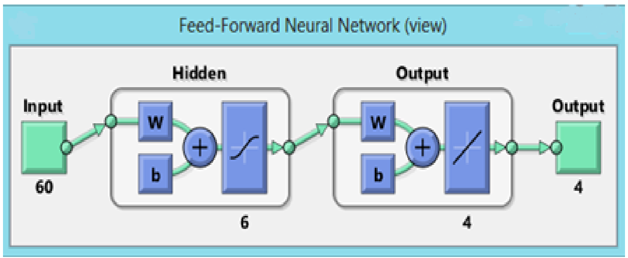

Fig.3 The MLP neural network used in this study.

One of the key parameters in the MLP neural network is the number of neurons in hidden layers. In order to find out the number of suitable neurons in each hidden layer, the hidden layers were raised from 1 to 13 while the categorization percentage was calculated. The highest value was for six neurons in the hidden layer. Figure 4 illustrates the results of neuron modification in the hidden layer.

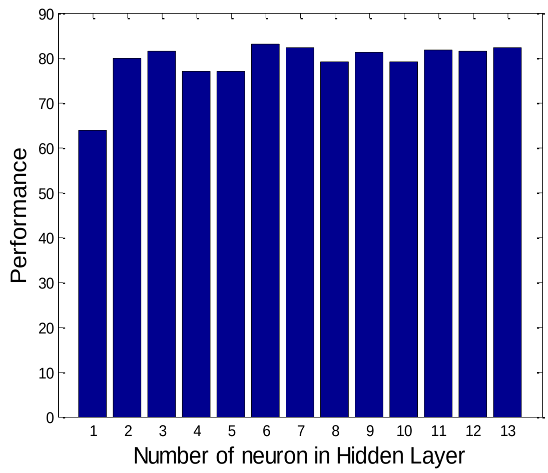

Fig.4 The results of neuron modification in the hidden layer of MLP neural network.

The highest categorization percentage was 82.9 for 6 neurons in the hidden layer, whereas the lowest categorization percentage was 63.8 for one neuron in the hidden layer.

The modification made in the Mean Square Error (MSE) throughout the training procedure has been shown in Figure 5.

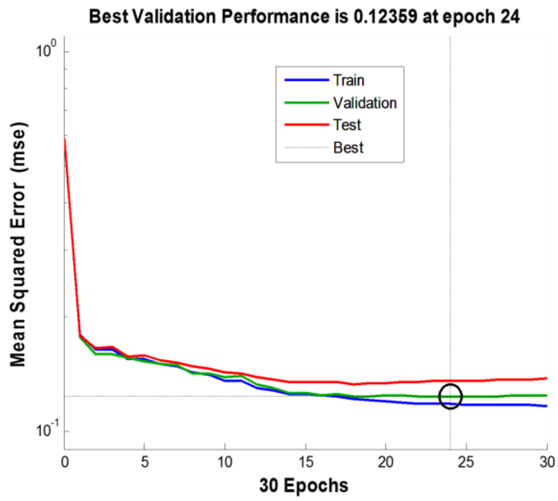

Fig.5 Curves for modification made in the Mean Squared Error (MSE) throughout the training procedure.

2.4 Radial Basis Function (RBF) Neural Network

Unlike the MLP entailing multiple consecutive layers, the RBF neural network has three fixed layers: input, hidden and output. The construction of an RBF has been illustrated in Figure 6.

Unlike the MLP, the hidden layers in the RBF network have Gaussian nonlinear function. The link between the input neurons and the hidden layer is not as solid as that in the MLP network. The hidden layer neurons are multidimensional units, where the number of dimensions is equal to how many inputs there are inside the network. The RBF training takes place in two monitored and unmonitored stages. The training procedure involves an initial adjustment of Gaussian function parameters of the hidden layer through one of the cluster methods, followed by regulation of the linking weights between the hidden and output layers by means of a monitored learning algorithm such as the post standard error diffusion steepest descent and conjugate gradient.

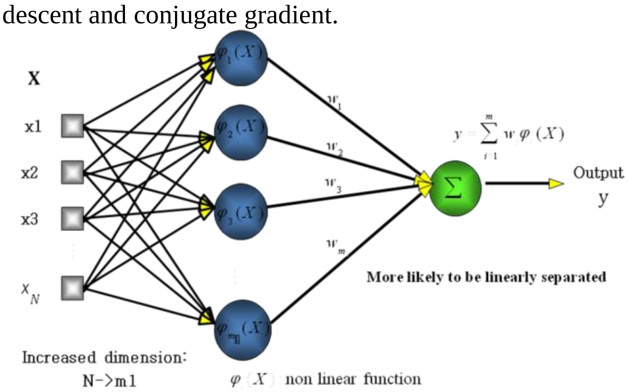

Fig.6 Construction of the RBF network.

3.4 Support Vector Machine (SVM)

The SVM method has been proposed for solving the monitored classification methods. Normally, the classifiers obtain the decision boundaries through detecting several different class distributions. In hyperspectral images, the estimation of density function for distribution classes yields a great deal of error due to little number of training points. Hence, such images require certain algorithms for downsizing the bands prior to the classification phase.

The SVM algorithm is a classifier different from the alternative classifier in that it does not require lower number of image bands for processing and classifying the hyperspectral data. In this procedure, the pixels specifying the class boundaries are determined by the entire bands and an optimization algorithm,. These samples are called support vectors. Needless to say, there is constantly a subset among the training samples capable of specifying the decision boundaries. For instance, the samples of training points with the shortest distance from the decision boundaries can be considered as a subset for definition of the decision boundaries.

At first, the SVM algorithm is evaluated to detect the interclass boundaries separately. Then, it will be extended to more complicated modes. If two classes are completed separated from one another, the decision boundary will fall between. For example, such boundary is a straight line in 2D, whereas it is a plane in 3D.

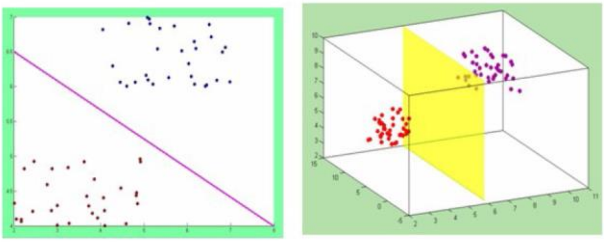

Fig.7 Representation of the decision boundaries within 2D and 3D spaces.

3. RESULTS OF SIMULATION

1.5 MLP Neural Network

Once of the ideal criteria in categorization is the confusion matrix. Generally, such indication applies to the monitored learning algorithms, even though it is still useful in the unmonitored learning. The application of this matrix in the unmonitored algorithms is usually called compliance matrix, where every column represents a sample of the predicted values, while every column entails an actual sample. Outside the realm of Artificial Intelligence, this is normally called a contingency matrix or error matrix.

The confusion matrix for a 6-neuron network in hidden layer has been illustrated in the following:

Table .1 Confusion matrix for the MLP neural network.

	other	**Class1**	**Class2**	**Class3**	**Class4**
other	0	0	0	0	0
Class1	2	102	4	3	5
Class2	3	1	15	0	1
Class3	2	2	5	48	1
Class4	6	10	8	7	115

Four classes were selected in this research. As for calculation of the confusion matrix, one image was selected and various classes were specified on by coloring each segment.

If you look closer at the confusion matrix, there are five rows and columns, each corresponding with one of the work classes taking into account due to certain spots in the reference image not belonging to any one of the four classes. These spots are not associated in the reference image to any color.

The accuracy percentage of the categorization can be obtained through the confusion matrix. For that purpose, the sum values of the core diameter are divided by the total matrix below:

Performance=$\frac{0+102+15+48+115}{340} = 83.35\ \%$

2.5 Radial Basis Function (RBF) Neural Network

Another neural network employed in this research involves the RBF, the categorization percentage of which is 71.47.

Table .2 Confusion matrix for the RBF neural network.

	other	**Class1**	**Class2**	**Class3**	**Class4**
other	0	0	0	0	0
Class1	1	29	3	3	14
Class2	0	0	2	0	0
Class3	11	35	42	169	31
Class4	0	0	0	0	0

3.5 Support Vector Machine (SVM)

Yet another classifier employed in this research involves the SVM. The results obtained from the support vector machine for the RBF kernel, linear kernel and polynomial kernel were 72.17, 87.94 and 55.84 percent, respectively.

Table .3 Confusion matrix for the SVM classifier with linear kernel.

	other	**Class1**	**Class2**	**Class3**	**Class4**
other	0	0	0	0	0
Class1	9	171	6	0	6
Class2	0	0	0	0	0
Class3	2	3	2	57	3
Class4	2	6	2	0	71

Performance=$\frac{0+171+0+57+71}{340} = 87.94\ \%$

As can be seen clearly, the support vector machine scored the highest categorization percentage at 87.94. Next to it, the MLP and the RBF neural networks scored 83.5 and 71.4 for the categorization percentage, respectively.

Fig. 8 Reference image.

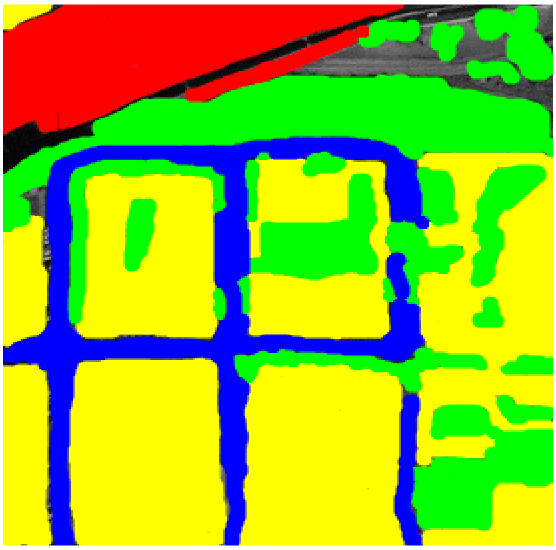

Fig. 9 The image obtained through application of MLP algorithm.

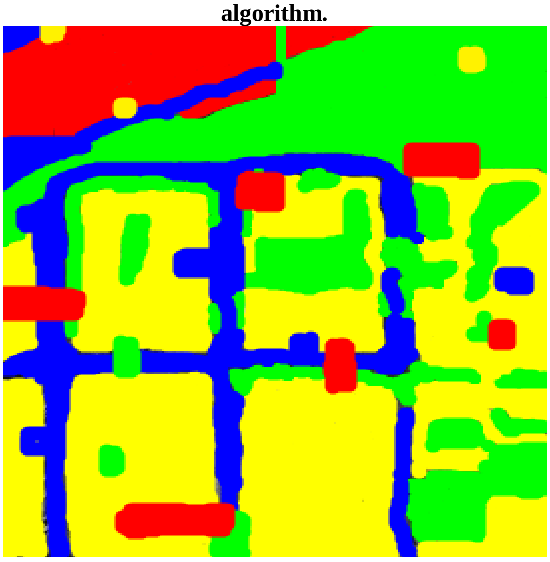

Fig. 10 The image obtained through application of RBF algorithm.

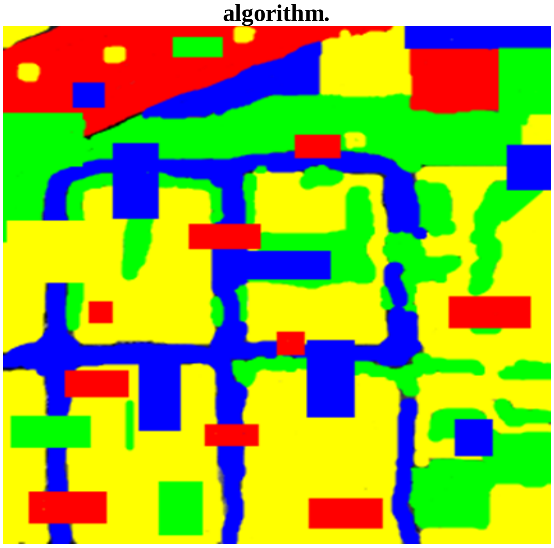

Fig. 11 The image obtained through application of SVM algorithm.

4. CONCLUSION

Texture analysis plays a key role in any digital image processing, which in turn can provide the extra information for handling satellite images. The concept of texture implies that various region levels on a satellite images have different textures. Additionally, the co-occurrence matrix was used to obtain the features of these regions. As mentioned earlier in the case of support vector machine, there is a function called kernel engaged in this type of categorization. In fact, the SVM does not categorize the data inside their input space, but transfers them into a new space by means of the kernel function. The data in this new space adopt more dimensions, thus performing the categorization more optimally. In other words, should the application of the linear categorization in the input vector space have a low categorization percentage, it will be boosted through transfer into a new space with more dimensions.

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