

## *Artificial Neural Network Based Classification using Textural Features for Remotely Sensed Data*

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### **Abstract**

*Image Classification plays an important role in the fields of Remote sensing, Image analysis and Pattern Recognition. Digital image classification is the process of sorting all the pixels in an image into a finite number of individual classes. The conventional statistical approaches for land cover classification use only the gray values. However, they lead to misclassification due to strictly convex boundaries. . Texture is one of the most important properties of visual surface that helps in discriminating one object from another or an object from background. One of the main tasks of texture analysis is the recognition of image regions using their textural properties. Textural features can be included for better classification but are inconvenient for conventional methods. Artificial Neural Networks can handle non-convex decisions. The uses of textural features help to resolve misclassification. This paper describes the design and development of a Hierarchical Neural Network by incorporating textural features. The effect of inclusion of textual features on classification is also studied. This image classification is a two step process in which initial stage involves K means clustering technique followed by Expectation – Maximization algorithm. The second stage involves the computation of texture features using Gray level Co-Occurrence matrix followed by classification using Neural Networks. Thus this work aims to study Neural Networks used for the classification of natural texture images and suggest the Neural Network Architecture leading towards the goal of attaining high accuracy Image Classification.*

**Keywords:** *Texture Classification, EM algorithm, Feature Extraction, Neural Networks.*

## I INTRODUCTION :

Image classification is the process of creating thematic maps from satellite imagery. A thematic map is an informational representation of an image which shows the spatial distribution of a particular theme. Themes can be diversified as their areas of interest. Example of themes is soil ,vegetation ,water depth and atmosphere. Inside a theme , there can be defined sub themes , and thus the process of classification needs to become more refined.

Remotely sensed data and the land cover/land use classification of urban areas set their own requirement for feature extraction. Features should be easily computed, robust, insensitive to various distortions and variations in the images, and they should support the discrimination of the land cover/land use classes. In this paper the following two basic feature groups are used:

- Statistical features showing the intensities and intensity variations of pixels(mean, standard deviation, energy and entropy)
- Texture features based on gray level cooccurrence matrix.(autocorrelation ,covariance, inertia, inverse difference)

This is an optional step on the classification process which serves only as a low level pre-processing of the image to reduce its spectral , or spatial dimensionality. It can be accomplished by using any type of spatial filters or spectral transforms to reduce the data and/or enhance its multispectral features, or even by simply selecting a subset of bands. In this stage ,the multispectral image is transformed into a feature image.

In order to approach higher classification accuracies it is necessary to consider texture information around each pixel. We can compare the performance of several texture measures for classifying land cover classes in satellite images. One of these texture measures is cooccurrence matrices. Neural network have been applied in many applications such as : automotive, aerospace, banking , medical, robotics, electronics and transportation. An another application of neural network is in remote sensing for classification of images .Given enough hidden units and enough data, neural networks can approximate any function to any desired accuracy. Neural networks are valuable tools in problems when one has little or no knowledge about the form of the relationship between input vectors and their corresponding outputs.

In this paper, artificial neural network for classification of remotely sensed data has been implemented. The back propagation algorithm is applied for the classification of the images. The main stages of the proposed system are Image segmentation, Feature Extraction and Classification using Neural Network. Image segmentation considered here is a two step process-Kmeans clustering technique followed by Expectation Maximisation algorithm. Feature extraction involves the computation of texture features to improve the classification of satellite images using Neural Network. The back propagation algorithm is applied for the classification of the images. A good method of training is an important problem in the classification of remotely sensed data. The overall system has segmentation process and feature extraction discussed in section 2, the lassification using Neural Network in section 3 and Results & conclusions in section 4.

## II SEGMENTATION AND FEATURE EXTRACTION :

### a) IMAGE SEGMENTATION: *K means clustering technique:*

Image segmentation[3][4] is the process of division of the image into regions with similar attributes. K means clustering technique is performed on the collection of remotely sensed data. In our trials we have used 5 clusters. Centroids are initialized by finding the mean vector and looking for those K vectors that are farthest from the mean. Euclidean distance in the feature space is used as the measure of dissimilarity. The convergence criteria is that the difference in the centroids in successive iteration is less than a predefined threshold. At the end of this run we get a class label for each of the pixels and the centroids for each of the classes. For the  $K^{\text{th}}$  cluster , the mean is given by,

$$\mu_k = \frac{1}{n_k} \sum_{i=1}^{n_k} x_i$$

where  $\mu_k$  is the mean vector and  $n_k$  is the number of vectors in the  $K^{\text{th}}$  cluster. For the  $K^{\text{th}}$  cluster , the covariance matrix is given by

$$C^k = \frac{1}{n_k} \sum_{i=1}^{n_k} (x_i - \mu_k)^2$$

where  $n_k$  is the number of vectors in the  $K^{\text{th}}$  cluster ,  $x_i$  is the vector in the cluster k and  $\mu_k$  is the mean vector of cluster K. Mean and covariance values are refined in the Expectation Maximisation algorithm

### *Expectation maximization algorithm:*

The EM algorithm consists of two steps : an Expectation step followed by Maximization step. The Expectation is with respect to the unknown underlying variables , using the current estimate of the parameters and conditioned upon the observations .The maximization step then provides a new estimate of the parameters. These two steps are iterated until convergence.

### *E step:*

The E step computes the probability  $S_{ik}$  associated with the labeling the  $i^{\text{th}}$  pixel ,  $x_i$  as belonging to the  $K^{\text{th}}$  cluster ,

$$S_{ik} = \frac{1}{2\pi |C^k|^{\frac{3}{2}}} e^{-\frac{1}{2}(x_i - \mu_k)^T (C^k)^{-1} (x_i - \mu_k)}$$

where  $C^k$  is the covariance matrix associated with cluster  $K$ ,  $\mu_k$  is the mean vector of the cluster  $K$ ,  $i$  and  $k$  take values  $1, 2, \dots, N$  and  $1, 2, \dots, K$  respectively. Here  $N = \text{width} * \text{height}$  and  $K = \text{number of clusters}$ .

### *M step:*

The M step refines the model parameters given the clustering arrived at E step. The weighted mean of the  $K^{\text{th}}$  cluster is updated as:

$$\mu_k = \frac{\sum_{i=1}^{n_k} S_{ik} x_i}{\sum_{i=1}^{n_k} S_{ik}}$$

The weighted variance of the feature in the  $K^{\text{th}}$  cluster is updated as:

$$C^k = \frac{\sum_{i=1}^{n_k} S_{ik} (x_i - \mu_k)^2}{\sum_{i=1}^{n_k} S_{ik}}$$

where,  $x_i$  is the  $i^{\text{th}}$  vector of cluster  $k$  and  $\mu_k$  is the mean vector of cluster  $K$ . Both E and M steps are carried out iteratively. The convergence criteria is taken as,

$$|\mu_k^{(n+1)} - \mu_k^{(n)}| < \text{Threshold}$$

### b) TEXTURE FEATURE EXTRACTION :

Many land cover/land use classes in urban areas can be distinguished from each other via their shape or structure characteristics. Therefore, it is important to extract features that are able to describe relevant "texture" properties of classes.

Texture [2][4] is an important characteristic for the analysis of many types of images such as an image obtained from aircraft or satellite platforms. It is the visual effect, which is produced by spatial distribution of tonal variations over relatively small areas. The concept of texture can be investigated through its relationship with spectral data; in fact, textural and spectral information can both be present in an image or either one can dominate the other classification accuracy.

In the proposed algorithm for classification, the cooccurrence features are selected as the basic texture feature detectors due to their good performance in many pattern recognition applications including remote sensing. A gray level cooccurrence matrix is defined as a sample of the joint probability density of the gray levels of two pixels

separated by a given displacement. The features based on GLCM are energy, entropy and correlation . Gray-scale co-occurrence matrix  $P_d$  is obtained by

$$P_d = |(r, s), (l, v): I(r, s) = i, I(l, v) = j|$$

The features computed are :

$$* \textit{Energy} = \sum_i \sum_j P_d^2(i, j)$$

$$* \textit{Entropy} = -\sum_i \sum_j P_d^2(i, j) \log P_d(i, j)$$

$$* \textit{Correlation} = \sum_i \sum_j \frac{(i - \mu)(j - \mu)P_d(i, j)}{\sigma_x \sigma_y}$$

$$* \textit{Inertia} = \sum_i \sum_j (i - j)^2 P_d(i, j)$$

$$* \textit{Inversedifference} = \sum_i \sum_j \frac{P_d(i, j)}{1 + (i - j)^2}$$

$$* \textit{Autocorrelation} = \sum_i \sum_j ij P_d(i, j)$$

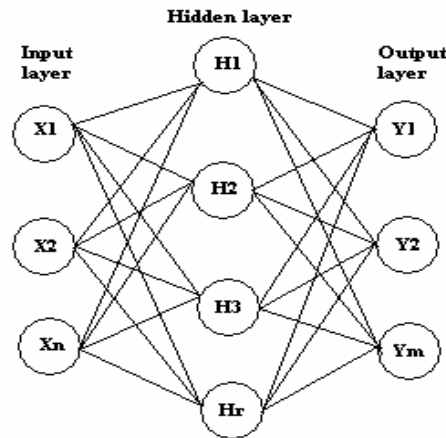
where  $\mu$  is the mean of  $P_d$  and  $\sigma_y$  are the standard deviations of  $P_d(x)$  and  $P_d(y)$  respectively .These statistical features and texture features computed serve as inputs to the Neural Network.

### III NEURAL NETWORK CLASSIFICATION :

Classification is the process of sorting pixels into a finite number of individual classes or categories of data based on their original values. If a pixel satisfies a certain set of criteria, then the pixel is assigned to the class that corresponds to that criterion. The most widely used neural classifier is multiplayer perceptron network.

Artificial neural networks[6][8] can be seen as highly dynamical systems consisting of multiple simple units that can perform transformation by means of their state response to their input information. How the transformation carried out depends on the Neural Network (NN) model and its way of learning the transformation. Neural network learns by example. In a typical scenario, a neural network is presented iteratively with a set of sample, known as the training set, from which the network can learn the values of its internal parameters.

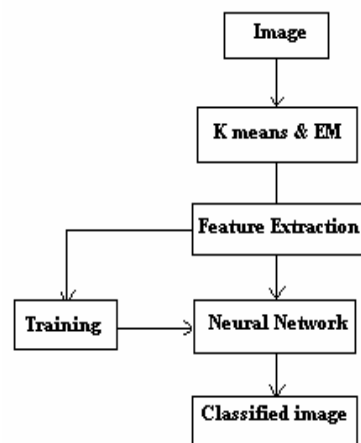
The multi-layer perceptron neural network model consists of a network of processing elements or node arrangement in the layers. Typically it requires three or more layers of processing nodes: an input layer which accepts the input variables used in the classifier procedure, one or more hidden layers, and an output layer with one node per class. Number of neurons in the input layer depends on the features vector and in the output layer is based on the number of classes.



**Fig 1: Neural Network**

The patterns available for the design have been separated into two sets: the training set and the test set. The networks are trained through successive epochs by using the training set as inputs. After each epoch the mean squared error (MSE) over the validation set is computed. The training goes forth for one more epoch until the MSE starts increasing. After training the network performance is estimated by applying the testing set on the network input and computing the classification error. The activation function used in both layers is the *log-sigmoid*, which holds outputs always between 0 and 1.

The classification process stages that have been explained in previous sections are implemented. Figure 2 shows the overall performance of the system.



**Fig 2: flowchart of classification using Neural Network**

Remotely sensed data is first segmented by applying K means clustering and Expectation Maximisation algorithm. Feature vectors are computed for each clustered data. Neural network is first trained for feature vectors extracted from sample images and then its classification performance is analysed using a test image.

## IV RESULTS AND CONCLUSIONS :

The above methodology is tested using a subimage of bhuj\_guarat\_coastline4mfc400 .Five major landuse/landcover classes are identified from the image, viz, forest , water , vegetation , urban area and open area. This image was initially segmented using K means clustering technique and its value were improved using Expectation-Maximisation algorithm. The segmented data has five clusters and feature vectors are computed for each cluster of image. The tabulation in figure 3 shows the feature vectors extracted for each cluster in the segmented Bhuj image.

Cluster	I	II	III	IV	V
Mean	0.2672	0.5104	0.5088	0.4704	0.3120
S_deviation	0.1322	0.1083	0.0487	0.0637	0.0594
Energy	177986	122186	93302	95158	157542
Entropy	1.0e+006 * 1.5088	0.9579	0.6909	0.7091	1.3074
Correlation	1.0e+004 * 0.0574	5.7339	4.3969	1.7654	0.0874
Inertia	59	91	189	186	73
Inv_difference	546.5000	530.5000	481.5000	483.0000	539.5000
Autocorrelation	977	1387	1353	1263	1051

Fig 3 : Feature vectors computed for the segmented image

The feature vectors that were computed include statistical features like mean, standard deviation , energy and entropy and textural features like correlation , inertia , inverse difference and autocorrelation. Features extracted from the image were applied to the Neural Network that was designed to have 8 neurons in the input layer ,10 neurons in the hidden layer and 5 neurons the output layer. The original image is shown in figure 4a and the output image of the proposed method is shown in figure 4b.

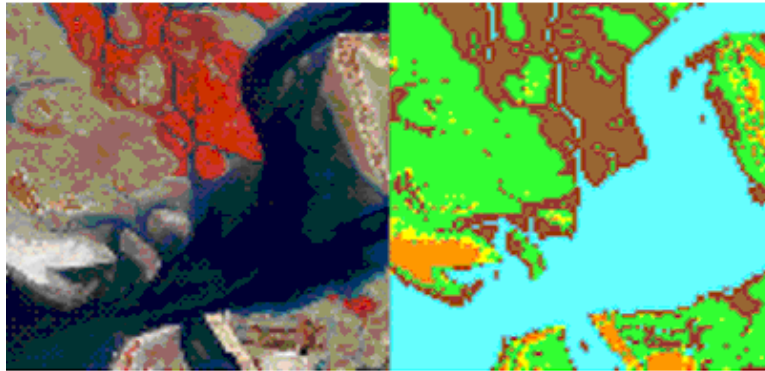


Fig 4: a)Original image of Bhuj in Gujarat coastline b) Segmented image using K means clustering and EM algorithm

## CONCLUSION :

The potential of combining classifiers in order to improve classification accuracy of remotely sensed images has been investigated. A classification system was proposed, which combines the results from a statistical classifier and from a feed-forward neural network. Texture features extracted from clustered image were used as a combination strategy. The system was evaluated on a satellite image of Bhuj near Gujarat coastline. In the experiments for performance evaluation the combination attained an average performance considerably higher than that of individual classifiers. The experiments have also shown that the combination tends to equalize the performance among all classes, while improving the overall recognition rate. Results encourage a deeper research of combined classifiers for this kind of application as well as the procedure to produce expert net networks.

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