Classification of IRS LISS-III Images by using Artificial Neural Networks

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ABSTRACT
The purpose of this paper is to classify the LISS-III satellite images into different classes as agriculture, urban and water body. Here pixel based classification is used to classify each pixel of the satellite image as belonging to one of those three classes. To perform this classification, a neural network back propagation technique is used. The neural network consists of three layers: Input layer, hidden layer and output layer. During training of a network, the sample inputs are given to the input layer which then propagate the hidden layer and then later to the output layer. Each neuron in hidden layer will receive the inputs from all the neurons of the corresponding synoptic weights and summed up. Each neuron of output layer will also get the input from all the neurons of hidden layer which are also multiplied with their corresponding weights. The outputs of the output layer are compared with desired result. The error between desired output and actual output is calculated to obtain error matrix. For each input, both local and global classification is obtained. In local classification, the neural network is trained using a particular image and that same image is given as input. In global classification, a new input is given for the network rather than the images with which it has been trained. Accuracy is then calculated for both the local and global classification.

General Terms
Image Mining, Classification Technique, Neural Networks, Pattern Recognition

Keywords
Image classification, Neural Networks, back propagation algorithm, LISS-III Multispectral images

1. INTRODUCTION
Neural networks are used as statistical tools in a variety of fields, including Psychology, Statistics, Engineering, Economics and even Physics. They are used also as models of cognitive processes by neuro and cognitive scientists. Basically, Neural networks are built from simple units, sometimes called neurons or cells, by analogy with the real thing. These units are linked by a set of weighted connections. Learning is usually accomplished by modification of the connection weights. Each unit codes or corresponds to a feature or a characteristic of a pattern that we want to analyze or that we want to use as predictor. These networks usually organize their units into several layers. The first layer is called the input layer; the last one is the output layer. The intermediate layers are called the hidden layers. The information to be analyzed is fed to the neurons of the first layer and then propagated to the next layer and so on until the last layer. Each unit receives some information from other units and processes this information, which will be converted into the output of the unit. The goal of the network is to learn or to discover some association between input and output patterns, or to analyze, or to find the structure of the input patterns. The learning process is achieved through the modification of the connection weights between units. Bischof et al. [1992] describes multi spectral classification of land-sat images using neural networks. Heerman et al. [1992] describes the classification of multi spectral remote sensing data using a back propagation Neural network. Hepner et al.[1990] have given a comparison to conventional supervised classification by using minimal training set in Artificial Neural Network. Mohanty [1996] have classified remotely sensed data by using Artificial Neural Network based on software package. In this paper, Artificial Neural Network is used for classification of IRS-1D data, which has been implemented. The back propagation algorithm is applied for classification of image for each input in both local and global classifications are applied. In local classification, the neural network is trained using a particular image and that the same image is given as input. In global classification, a new input is given for the network rather than the images with which it has been trained. Accuracy is calculated for both local and global classification.

2. STUDY AREA AND CHARACTERISTICS
Indian Remote Sensing (IRS-1D) satellite gives PAN(Panchromatic) high spatial resolution and LISS-III [Linear Imaging self scanning sensor] gives high spectral resolution data. Indian Remote Sensing Satellite (IRS)-1C/1D gives high resolution PAN, LISS-III, WiFS data. Topographic maps on 1:50000 scale are used. Classified landuse / landcover [level III] map generated from LISS-III data is used to assess the damage to agriculture crops. The two data sets acquired for this research were collected via IRS-1D satellites using LISS-III sensors in the multispectral (MS) mode by NRSA, Hyderabad, Andhra Pradesh (A.P) , India. The characteristics of IRS-1D, LISS-III data are summarized in Table1.

3. METHODOLOGY
The purpose of this study is to classify satellite image by both local and global classifications and compare the accuracy of each of the classifications. In addition, the accuracy of the training is improved by finding the saturation point, where regardless of the number of Indian epochs through the training data, the accuracy will not increase further. The methodology is:

- To apply local classification to the input image for each of the training data sets 100, 500 and 1000 respectively.

- To apply global classification to the input image, for one image, two images and three images.
- To assess the accuracy of both local as well as global classification.

To calculate the accuracy of the classified images as the number of epochs increase until saturation point is reached.

Table1. Characteristics of Satellite image IRS-1D

Satellite/Sensor	IRS-1D,LISS-III
SpatialResolution at Nadir	23.5 m
Swath	127 km(bands 2,3,4) 134 km(bands 5-MIR)
Repetetivity	25 days
Spectral Bands	0.52-0.59 microns(B2) 0.62-0.68 microns(B3) 0.77-0.86 microns(B4) 1.55-1.70 microns(B5)
Primary Application	These data has a diverse range of applications viz. Land use and Land cover, urban planning, biodiversity characterization, Forest survey, wet land mapping environmental impact, crop acreage and production estimation of major crops, drought monitoring and assessment based on vegetation condition, snowmelt runoff estimation and so on.

The following flow chart represents the steps involved in satellite image classification. Once a satellite image is given as input, the first and the most important step is feature extraction. In this, features like mean, Euclidean distance and RGB values are extracted for each pixel in the image. Then these extracted features are given to the neural network which is designed and trained by training data to classify each pixel as belonging to one of the output classes and a classified image is produced.

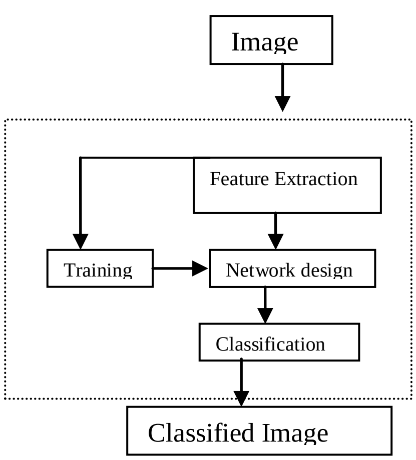

Figure1. Flow chart for satellite image classification using neural networks

4. NEURAL NETWORK MODEL

One of the most popular architectures in neural networks is the multi-layer preceptor shown in Figure 2. Most of the networks with the architecture use the window –hoff rule as their learning algorithm and the logistic function as the transfer function of the units of the hidden layer. These networks are very popular because they can appropriate any multivariate function relating the input to the output. In statistical framework, these networks are akin to Multivariate Non-linear Regression .when the input parameters are the same as the output patterns, and these networks are called auto-associators. They are closely related to linear [if the hidden units are linear] and non linear (if any) Principal Component Analysis and other statistical techniques linked to the General Linear Model, such as Discriminant Analysis or Correspondence Analysis.

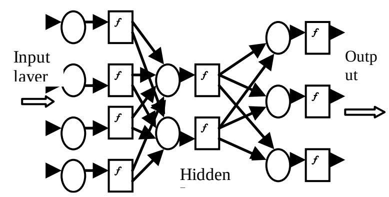

Figure 2. A Multi-layer perception

4.1 Back Propagation Algorithm

The back propagation algorithm is used in layered feed forward Artificial Neural Networks. This means that the artificial neurons are organized in layers and send their signals forward and then the errors are propagated backward. The network receives inputs by neurons in the input layer and the output of the network is given by the neurons on an output layer. Feed forward networks often have one or more hidden layers of sigmoid neurons followed by output layer of linear neuron. Multiple layers of neurons with non linear transfer functions allow the network to learn non linear and linear relationships between input and output vectors. The linear output layer gets the network produced values outside the range -1 to +1.

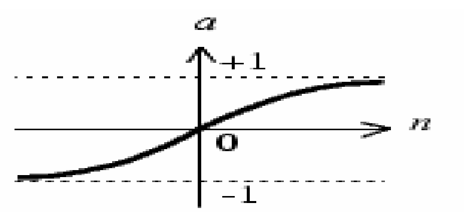

Figure 3. Sigmoid Transfer Function

On the other hand, if we want to confirm the outputs of network between 0 and 1, then the output layer should use a log-sigmoid transfer function. Before training a feed forward network, the weights and biases must be initialized. Once the network weights and biases have been initialized, the network is ready for training. We used random numbers around zero to initialize weights and biases in the network. The training process requires a set of proper inputs and targets as outputs. During training, the weights and biases of the network are iteratively adjusted to minimize the network performance function. The default performance function for feed forward networks is mean square errors, the average squared errors between the network outputs and target output.

5. IMAGE CLASSIFICATION USING BACK PROPAGATION

In order to classify the satellite images, the first step is feature extraction. In feature extraction, certain features are calculated for each pixel. Then, the network is trained by computing the input matrix and the target vector. The input matrix is obtained from the features and the target vector is manually calculated. Once training is completed, the network is simulated with an input image, for which classification should take place, to specify agriculture, urban and water body.

5.1. Feature Extraction

Classification of multi-spectral remote sensing data may be considered as mapping, F, from a multidimensional gray value space into a discrete vector space of feature classes given by

$$F : [a,b,c,d,...] M*N \rightarrow \{A, B, C, ...\} M*N \qquad (1)$$

where: a, b, c, d,…are gray value of the pixel in different spectral bands

A, B, C, …are the feature classes ,

M*N is the total number of pixels in the image, in any of the spectral bands.

The most basics of all image features are some measures of image amplitude in terms of luminance, spectral value, etc. One of the simplest ways to extract texture features in an image is to use the first-order probability distribution of the amplitude of the quantized image. They are generally easy to compute and largely heuristic. The first order histogram estimate of p(b) is simply

$$p(b) = N(b)/M \qquad (2)$$

where b=grey level in an image

M= the total number of pixels in a neighborhood window centered about an expected pixel,

N(b) = the number of pixels of gray value b in the same window that $0 \le b \le L-1$.

5.2. Mean

The mean indicated by μ (a lower case Greek mu), is the statistician's jargon for the average grey-level of image or each region. The mean is calculated for each image or region

$$\mu = \bar{b} = \sum_{b=0}^{L-1} b p(b)$$

In MATLAB, the function MEAN2 is used to compute mean of matrix elements.

5.3. Euclidean Distance

For each pixel in the image, Euclidean distance is the distance between that pixel and the nearest nonzero pixel of that image. In order to calculate this, the image must first be converted into black and white. The function BWDIST is used to calculate the Euclidean distance of all the pixels.

5.4. RGB

For a colour image, each pixel has RGB values associated to it. To extract these values, the function IMPIXEL which returns the red, green, and blue colour values of specified image pixels.

5.5. Network Design, Training and Classification

The neural network is designed to be a feed forward BP network. For this purpose, NEWFF function is provided in MATLAB. The MATLAB function LOGSIG is the Logarithmic sigmoid transfer function, which is used to calculate a layer's output from its net input. TRAINLM is Levenberg-Marquardt back propagation. It is a network training function that updates weight and bias values according to Levenberg-Marquardt optimization. TRAINLM can train any network as long as its weight, net input, and transfer functions have derivative functions. Training stops when any of the following conditions occurs:

1) The maximum number of EPOCHS (repetitions) is reached.

2) The maximum amount of TIME has been exceeded.

3) Performance has been minimized to the GOAL.

4) Validation performance has increased more than MAX_FAIL times since the last time it decreased [when using validation].

5.5.1. Network Design

The neural network is designed with 3 layers. The first layer is the input layer, which consists of 5 neurons. The hidden layer is the second layer also consisting of 5 neurons. The output layer, on the other hand, consists of a single output neuron specifying the output class of a particular pixel. The input layer takes the five features as input: one feature for each input neuron. These features propagate into the hidden layer and finally to the output neuron, which gives the output class.

5.5.2. Training

Training is performed to obtain local as well as global classifications.

5.5.3. Classification

5.5.3.1. Local Classification

In local classification, the neural network is trained with the input satellite image for which the classification should take place. Training takes place with three sets of training data: 100, 500 and 1000.

5.5.3.2. Global Classification

In this classification, the neural network is trained with sample images that are different from the inputs given to it. Here, the network is trained using 3 different images. First, it is trained with one image, then with two images and finally with three images.

5.6. Accuracy Assessment

Once a satellite image has been classified, the accuracy is computed by comparing it with desired output, which is produced manually. The overall accuracy is calculated from the correct number of agriculture, urban and water body pixels present in the actual output. The output class of the pixel (i, j) in the actual output is compared with its class in the desired output. If both match, then that pixel (i, j) is correctly classified. This is used to

obtain the correct number of agriculture, urban and water body pixels. Once they are known, their sum is divided by the total number of pixels, to obtain the accuracy. The following example shows how accuracy is calculated.
Example:

CD	UCD	Wt	Ag	Gr	Ur	Op	RT
Unclassified	0	0	0	0	0	0	0
Water	0	9	1	6	1	11	28
Agricultural Field	0	0	4	0	0	0	4
Greenery Field	0	0	0	2	0	0	2
Urban	0	0	1	0	2	0	3
Open Area	0	0	0	0	2	11	13
Colum Total	0	9	6	8	5	22	50

Note:-CD-Classified Data, UCD-Unclassified Data, Wt-Water, Ag-Agriculture, Gr-Greenary Field, Ur-Urban, Op-Open area, RT-Row Total.

User's Accuracy (%) is computed as shown below:

Water = 9/28= 32.14

Agricultural Field = 4/4 = 100

Greenery Field = 2/3 = 66.67

Open Area = 11/13 = 84.62

Urban = 2/2 =100.00

Overall Accuracy = (9+4+2+2+11)/50 =.56

6. EXPERIMENTAL RESULTS

When a LISS-III satellite image was given as input, classified images were produced. These images were dependent on the type of classification. For local classification, the outputs were closer to the desired output compared to global classification. In order to show this, accuracy was calculated for all of the classified images of local and global classifications. Then, the accuracy values were plotted as bar graphs.

6.1. Classification Results of Image 1

The original image for which classification is to be performed is shown in Figure 6.1

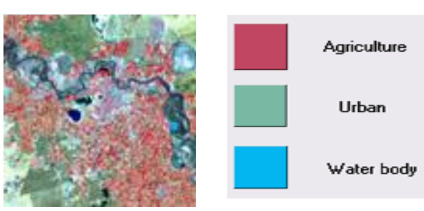

Figure 6.1. LISS-III Original Image (Image 1)

6.1.1. Local Classification

(a) (b) (c)

Figure 6.2. Classified image of Image 1 with (a) Training data =100, (b) Training data =500, and (c) Training data=1000

6.1.2. Local Accuracy of Image 1

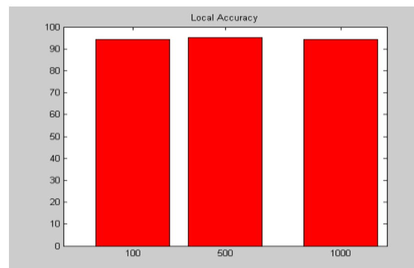

Figure 6.3. Local Accuracy of Image 1 with Training Data

6.1.3. Global Classification of Image 1

(a) (b) (C)

Figure 6.4. Classified image of Image 1 with (a) Training with 1 image (b) Training with 2 images, (C) Training with 3 images

6.1.4. Global Accuracy of Image 1

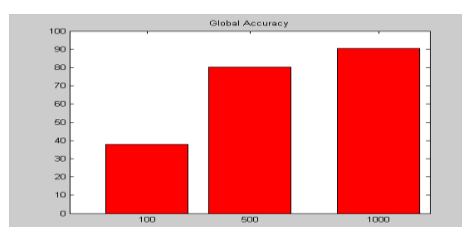

Figure 6.5. Global Accuracy of Image 1 with Training Data

The following graph shows the accuracy as the number of epochs increase. The figure 6.6 shows, beyond a certain point, the accuracy does not increase further. This is called saturation point.

When saturation point is reached at 40 epochs, regardless of the increase in the number of epochs, the accuracy will not increase.

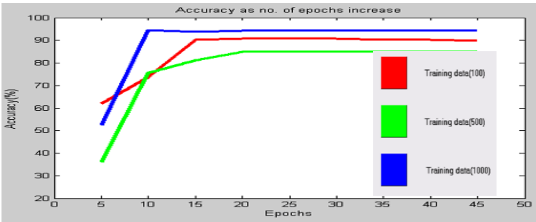

Figure 6.6. Number of Epochs vs. Accuracy Graph of Image 1

6.2. Classification Results of Image 2

The second original image for which classification is to be performed is shown in Figure 6.7

Figure 6.7 LISS-III Original Image (Image 2)

6.2.1. Local Classification of Image 2

(a) (b) (c)

Figure 6.8 Classified image of Image 2 with (a) Training data =100, (b) Training data =500, and (c) Training data=1000

6.2.2. Local Accuracy of Image 2

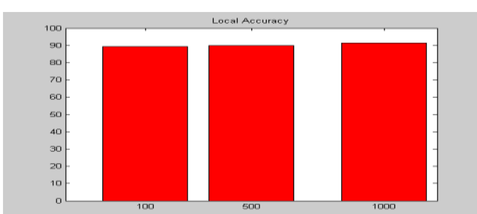

Figure 6.9. Local Accuracy of Image 2 with Training Data

6.2.3. Global Classification of Image 2

Figure 6.10 Classified image of Image 1 with (a) Training with 1 image (b) Training with 2 images, (C) Training with 3 images

6.2.4. Global Accuracy of Image 2

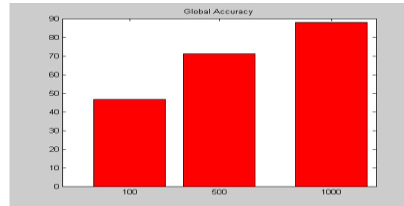

Figure 6.11 Global Accuracy of Image 2 with Training Data

The following graph shows the accuracy as the number of epochs increase. The figure 6.12 shows, beyond 40 epochs, the accuracy does not increase further.

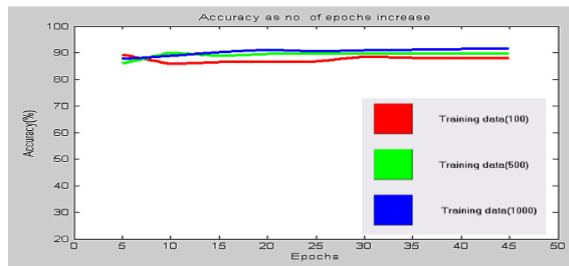

Figure 6.12 Numbers of Epochs vs. Accuracy Graph of Image 2

7. CONCLUSION

In this paper BP neural network has been used for classifying satellite images and accuracy is calculated for each output. The results show that the accuracy of the classified images increased as the training data increased. In case of local classification, as the training data increased from 100 to 500 and to 1000, the accuracy also increased. Similarly, there was an increase in accuracy as the network was trained with more and more images. In addition, the line graphs demonstrated that for LISS-III images, the saturation point is reached at 40 epochs. Beyond this value, the accuracy will not increase further. Further, if features like Digital Elevation Model (DEM) and slope are also calculated for each pixel, along with the other five features, the accuracy of the classified images will increase and the classified images will be closer to the desired outputs. The use of DEM provides the basis in modeling and analysis of spatio-topographic information, whereas slope is used to differentiate one particular area from another. The accuracy can further be improved by using various techniques for classification, such as fuzzy logic and genetic algorithms.

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