Performance Analysis of ANN for Satellite Image Pixel Classification

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ABSTRACT
This paper presents a thorough experimental analysis to investigate the behavior of neural network classifier for classification of multispectral satellite images. For this series of experiments have been performed to study the effect of various neural network parameters upon classification accuracy. It is per pixel supervised classification using spectral bands (original feature space). The parameters considered are: initial weight, training set size, number of hidden layer neurons and number of input layer nodes. Based on 1050 number of experiments, it is concluded that for good classification accuracy and speed, following two critical issues needs to be addressed: 1) selection of most discriminative spectral bands and 2) determination of optimal number of nodes in hidden layer. The accuracy obtained with ANN classifier is compared with that of traditional classifiers like MLC and Euclidean classifier using Xie-*Beni* and β indexes.

General Terms
Pattern Recognition, Classification.

Keywords
Artificial Neural Network; Land Cover Classification; Multispectral Satellite Imagery, Neural Network Structure.

1. INTRODUCTION
Multispectral satellite images consist of images of Earth's surface taken into few spectral bands [1]. These images are used to for various applications such as land cover mapping, crop estimation, draught monitoring and urban planning etc. For preparing land cover map, each pixel is classified into land cover class like vegetations, waterways, man-made structures and road network. In nonparametric approach, artificial neural networks are popular choice due to their ability to learn from given data though training. In literature survey, we found that different neural network architectures are used for unsupervised and supervised classification [2]-[6].

For supervised classification, feed forward neural network with only one hidden layer is widely used. The performance of any classification system depends on the set of features used and the classifier also. The aim of this paper is to investigate the behavior of neural network classifier for classification of multispectral satellite images. For this series of experiments have been performed to study the effect of various neural network parameters upon classification accuracy. The parameters considered are: initial weight, training set size, number of hidden layer neurons and number of input layer nodes.

The rest of paper is organized as follows. In section 2, we present experimental setup for analysis of neural network to study its behavior for multispectral image classification. In section 3, we discussed the analysis of experimental results and ANN classifier comparison & conclusion is presented in section 4 & 5 respectively.

2. EXPERIMENTAL FRAMEWORK
The following section, describes the detail of experiments carried out to study the behavior of neural network for satellite image classification.

2.1 Neural network and its topology
In our experiments three layered (single hidden layer) neural network is employed as a classifier. It is trained by back propagation algorithm [7]. After learning, the network is used as a classifier to classify the whole image. One input node is used to represent the each spectral band or features. Thus the number of input nodes is determined by the number of spectral bands i.e. by dimension of the input pattern. The input pattern consists of normalize grey scale value of a pixel in selected spectral bands. Also one output node per ground cover class is used i.e. the number of output nodes is equal to the number of classes in the image. The number of hidden layer nodes is varied from 2 to 8 for experimental analysis. The block diagram is shown in fig. 1.

2.2 Multispectral data
The Landsat satellite images of Washington DC city area is used for experiments [8]. The six images are of size 512 x 512 pixels each and corresponding to six spectral bands: b1: visible blue (450 – 520 nm), b2: visible green (520 – 600nm), b3: visible red (630 – 670 nm), b4: near infrared (760 – 900 nm), b5: middle infrared (1550 – 1750 nm) & b6: thermal infrared (10,400 – 12500 nm). The four major classes identified in the images are: water, urban area, vegetation & roads. Fig. 2 shows two images corresponding to band 3 and band 4.

2.3 Training & test Set
In our work, the samples of each class are randomly selected by visual inspection of the image with the help of Matlab software. Total 50 samples of each class were selected and equally divided into 25 samples each to form training & test set. For training & testing input patterns, the desired output vector was obtained by setting the low value of 0.1 for output node that do not corresponds to the pixels assign class & high

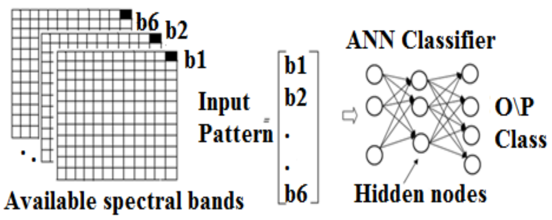

Fig 1: System block diagram.

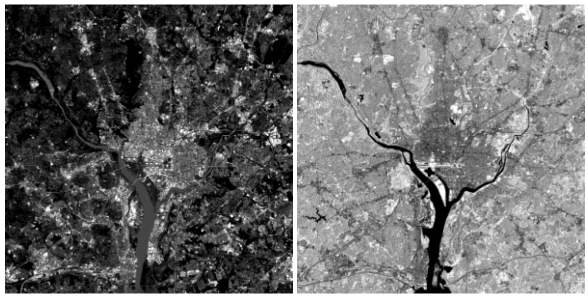

Fig 2: Multispectral images (a) visible red (630 – 670 nm), b3 (b) near infrared (760 – 900 nm), b4.

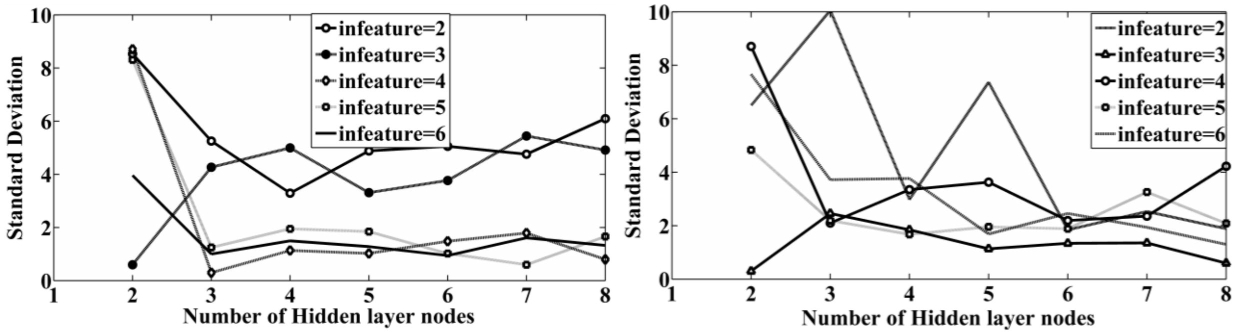

Fig 3: Variation in accuracy with initial weights (a) sample size=25. (b) sample size=5.

value of 0.9 for the node that does corresponds to the pixels assigned class i.e. for the input pattern of class 1, the desired output vector will be [0.9, 0.1, 0.1, 0.1], for class2, it is [0.1, 0.9, 0.1, 0.1] and so on.

2.4 Experimental framework

The number of experiments is performed to study the behavior of neural network for given classification problem. The numbers of spectral bands are increased from 2 to 6. Initially spectral band combination of visible blue and red i.e. band b1 & b2 is used. Then remaining bands are added one by one. The number of hidden layer nodes is changed from two to eight for each of the above input feature combination. Each network is then trained with training data set sizes of 5, 10 and 25 pixels. Also for each of the network, ten different initial weights were selected for training. Thus total 1050 experiments are conducted with all combinations of above variables. Based on the result of above experiments, in following section the effect of these variables are discussed one by one.

3. RESULT ANALYSIS

3.1 Effect of different initial weights

From the confusion matrices, it is observed that for input features combination b1, b2 and b1, b2 and b3 (any number of hidden node & sample size), test sample classification insufficient input feature, there is considerable change in accuracy due to the initial weights. The increase in number of hidden nodes beyond minimum does not have effect on the variation in accuracy due to initial weights. See fig. 3.

3.2 Effect of training sample set size

The investigation of confusion matrices for the training sample size revealed following facts. Up to three spectral band (any number of hidden nodes), increase in sample size does not improves classification accuracy and overall test sample accuracy is very low (40% to 60%) as seen in Fig. 4 (b). This may be because of inadequate input features. With four spectral bands & hidden layer nodes more than two, increase in training sample set size from 5 to 15 and then to 25 do improve the accuracy. But the improvement is insignificant (2%) for increase in samples from 15 to 25. See Fig. 4 (a). That is, the rate of improvement in accuracy decreases with increase in the sample size. It is also observed that for the given neural network architecture, the training time increases & variation in accuracy due to the change in the initial weights reduces with increase in sample size.

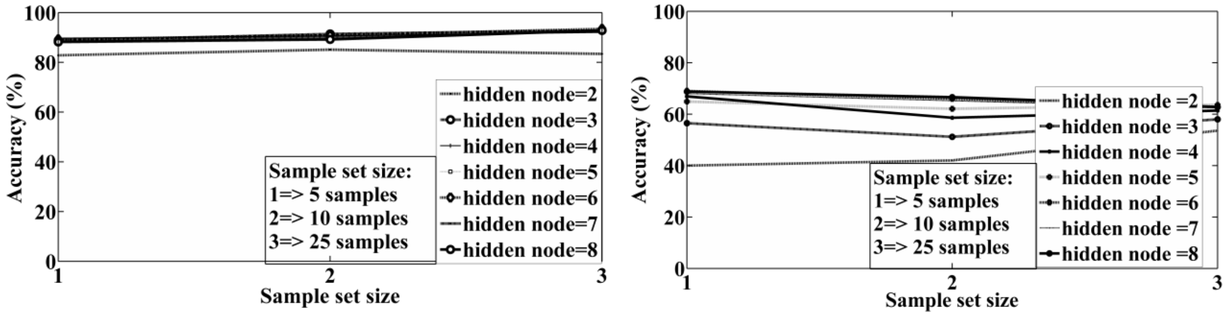

Fig 4: Variation in classification accuracy for different sample size
(a) Number of spectral band used=5. (b) Number of spectral band used=3.

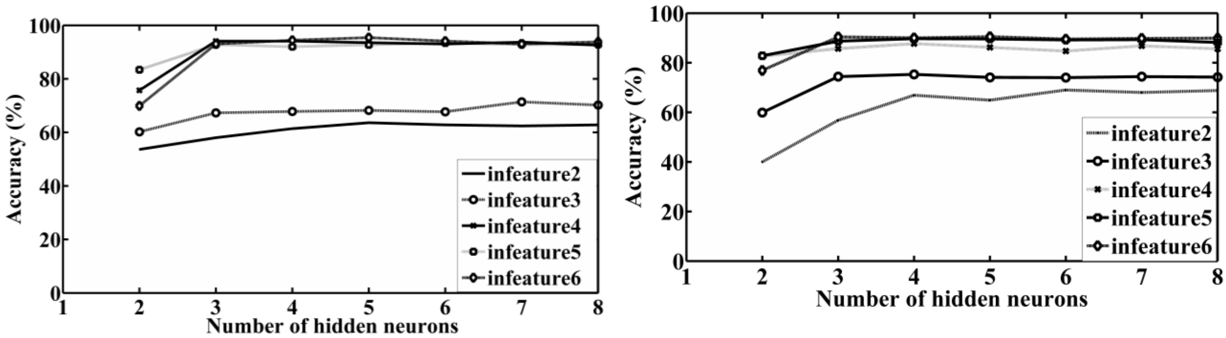

Fig 5: Variation in classification accuracy for different number of hidden nodes
(a) sample set size = 25 (b) Sample set size = 5

Thus with inadequate number of input & hidden layer nodes, increase in sample size does not improves classification accuracy and overall accuracy remains low. With proper network architecture, accuracy increases with sample size but the rate of improvement decreases with increase in the sample size. Thus training sample set must be prepared not keeping in mind the size but the quality representation of the classes to be identified.

3.3 Effect of hidden layer nodes

Regarding the hidden layer nodes following observations are made. With two nodes in the hidden layer (any input feature combination), accuracy is very low and varies greatly with initial weights. This is because network does not have enough flexibility to adjust the weights. The classification accuracy increases significantly as the hidden nodes are increased from two to three as shown in Fig. 5 (a) and (b). After that, increase in hidden node size does not have significant effect on the accuracy. It seems that the network with two hidden nodes is not suitable for this problem since it does not have enough flexibility to adjust the weights.

3.4 Effect of input spectral bands

It is observed that with input feature combination b1, b2 and b1, b2 and b3, accuracy is very less (60 to70%). This is because that network does not train properly for class 3 & class 4, due to inadequate number of input features or due to inadequate information about that land cover classes. The addition of spectral band b3 does not improve the accuracy. As seen in Fig. 6 (a) and (b), for input feature combination b1, b2, b3 & b4 accuracy jumps to 90 % as the network is well trained for all classes. Thus it seems that spectral band b4 brings additional information to improve the accuracy.

After this, increase in input features does not improve the accuracy. Thus inadequate input features results in poor classification. Addition of some input feature brings the more information and helps to improve the accuracy but some may not. The spectral band that does not bring any discriminating information should not be used. This also indicates that good classification can be achieved by using the subset of the available features or spectral bands. The effect of increasing the number of input features is not necessarily results into the increased accuracy but surely increases the computing time requirements.

4. ANN CLASSIFIER COMPARISON

For comparative study, the classification was also done by traditional supervised classifiers: the Euclidean classifier and maximum likelihood classifier (MLC). As shown in Table 1, accuracy obtained by MLC is comparable to that obtained by our algorithm, but qualitatively classification provided by our algorithm is much better than that of MLC. MLC fails to classify finer details in the image and its accuracy varies over different runs of algorithm, due to lower number of training sample. On contrarily, even with lower sample the performance of neural classifier remains robust compared to both traditional classifiers. The XB index are 3.5, 9 and 1 for Euclidean, MLC, ANN classifier respectively. The values of β index are 2.2, 2 and 2.3 respectively as shown in Table 1. Figure 7 shows classified gray scale image.

5. CONCLUSION

Form above experimental analysis, this work conclude that the dependency upon initial weights can be reduced to great extent with proper input features, sufficient number of hidden nodes and adequate sample size. Also the increase in sample size does not improve the accuracy but consumes time. It is also observed that for proper classification, minimum number of hidden node is must. Beyond that, increase in hidden nodes does not improve the accuracy. On the contrarily, network may lose its capacity to generalize and increases the training time.

Also the classification accuracy is not function of the number of input features but depends upon the 'information' provided by the features. Therefore input features should be selected so that they contain distinct information for each output class. So there must be some method to select the useful features. Thus in this paper through experimental study, it is established that selection of most discriminative spectral bands and determination of the number of hidden layer neurons are the two most critical issues for the use of ANN in classifying the satellite images.

We believe that the number of hidden layer neuron depends on the classification problem in hand and must be determined methodologically. From our experimental analysis, it is observed that both the input feature and the number of hidden layer nodes together affect the classification accuracy and therefore must be considered simultaneously.

6. FUTURE SCOPE

The authors plan to solve this complex problem within multiobjective particle swarm optimization framework to simultaneously estimate the most discriminative spectral band and to determine the number of nodes in hidden layer.

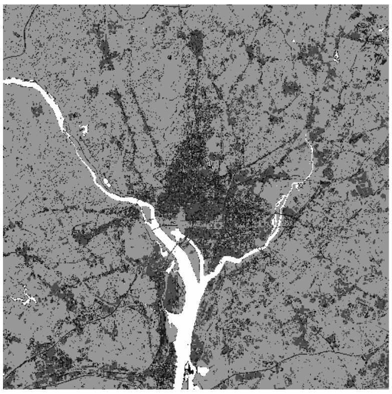

Fig 7: Classified grey scale image

Table 1. Comparison of different classifiers

Classifiers	% Accuracy	XB Index	β index
Euclidean	90	3.5	2.2
MLC	94	9	2
ANN	94	1	2.3

7. ACKNOWLEDGMENT

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