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Performance Analysis of Artificial Neural Network Based Land Cover Classification

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Abstract**—**Landcover classification using automated classification techniques, while employing remotely sensed multi-spectral imagery, is one of the promising areas of research. Different land conditions at different time are captured through satellite and monitored by applying different classification algorithms in specific environment. In this paper, a SPOT-5 image provided by SUPARCO has been studied and classified in Environment for Visual Interpretation (ENVI), a tool widely used in remote sensing. Then, Artificial Neural Network (ANN) classification technique is used to detect the land cover changes in Abbottabad district. Obtained results are compared with a pixel based Distance classifier. The results show that ANN gives the better overall accuracy of 99.20% and Kappa coefficient value of 0.98 over the Mahalanobis Distance Classifier.

Keywords**—**Landcover classification, artificial neural network, remote sensing, SPOT-5.

I. Introduction

IMAGE classification is one of many problems of concern in image processing. The goal of image classification is to predict the categories of the input image using its features. Remotely sensed imagery can be made use of in a number of applications such as encompassing reconnaissance, creation of mapping products for military and civil applications, evaluation of environmental damage, monitoring of land use, radiation monitoring, urban planning, growth regulation, soil assessment, and crop yield appraisal [1].

Land use and land cover classification is important for many decisions making and management activities related to the earth surface like hydrological modeling and environmental management [2]. Generally, remote sensing offers imperative coverage, mapping and classification of land-cover features, namely vegetation, soil, water and forests. Remotely sensed data can be used for classification map of the features that are meaningful in land cover scene [3]. Therefore, thematic map with themes like land use, geology, and vegetation types is the principal product. [4]. Remote sensing based on image classification has attracted the remote sensing community for a long time as many environmental and socioeconomic applications are based on the classification results.

Image classification problem can be solved by many approaches such as Maximum Likelihood, Mahalanobis, and ANN. ANN is an information processing model, that is inspired from the information processing mechanism of human brain, and has been employed for many applications [18]. Many structures of ANN have been developed by the researchers according to the need of their problem. Furthermore, researches [5]-[9] have proved that the classification accuracy is improved by neural network in comparison to the classical approach because the data distributions are strongly non-Gaussian in ANN, whereas the non-ANN based techniques use Gaussian distribution parameter [10].

The paper has the following sections: Section II describes the pilot region; Section III briefly explains the methodology, the training and testing pixels. Brief overview of the two classification algorithms is presented in Section IV. Section V discusses the generated curves and plots. Section VI explains accuracy assessment and describes result and findings. Finally, Section VII concludes the paper.

II. Study Area

The location of our study area includes forest intensive area in Abbottabad districts of Khyber Pakhtunkhwa province, Pakistan. Approximately 4599 km^2 area is studied which is a subset of the acquired SPOT-5 imagery. This area has wide arable lands and covers approximately 40% forest of Pakistan. It includes densely populated urban as well as rural areas.

III. Methodology

A. Pre-Processing

Target image of SPOT-5 high resolution was obtained from SUPARCO. SPOT-5 satellite is cable of capturing 2.5-meter panchromatic and 10-meter multispectral imaginary. With its short wave infrared band, it is well suited for geological applications and vegetation. The objective of the research is the locations of forestry in experimental region. So, for image enhancement, Normalized Difference Vegetation Index (NDVI) was calculated. And to increase the homogeneity in the scene, a median filter is used [11], [12].

Originally five different classes including agriculture land, settlements, forest, water bodies, and barren land were taken. After classification, it was observed that agriculture land also had vegetation and reaped crops, and the same class was assigned. In order to remove the mix-up, the unsupervised classifier k-mean was used and based on the k mean output classes, the original ROIs were refined so the agriculture land was separated into two classes shrubs and bushes and sparse vegetation. Finally, classes were verified through separability analysis after selecting them visually in the image. Training classes are distinguished from each other by applying TD

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(transformed divergence) and JM (Jeffries-Matusita) algorithms. Their range is [0, 2]. Higher values of TD and JM give better separation between classes than lower values. Table III shows the TD and JM separability values with the same class and the other classes' spectral bands. The separability values for the training and testing data of the same class is minimum, which implies that the training and testing data have similar spectral characteristics and are not distinguishable. The classes which have the low separability factor are often merged in a single class because of similar spectral characteristics and low distinct ability of remote sensor used.

B. Training and Testing Data:

The pixel of classes was divided into train and test pixel. Each training class has more than 10N pixels with N = total number of bands. The remaining pixels are used for the accuracy testing of the classifier and are not used in training because then the accuracy results of Kappa coefficient are unwarranted, and the independent assessment of classifier is violated [13].

TABLE I
TRAINING DATA DETAILS BASED ON SPOT-5 IMAGER

NAME	TRAINING DATA		TESTING DATA	
	(Number of pixels)	NDVI Mean (DN Value)	(Number of pixels)	NDVI Mean (DN Value)
Shrubs & Bushes	17750	0.2844	7607	0.2841
Sparse Vegetation	14217	0.2258	6031	0.2259
Settlements	8443	0.1855	3616	0.1856
Forest	62515	0.2980	26795	0.2981
Water Bodies	8569	0.2325	3520	0.2313
Barren Land	56464	0.1357	24209	0.1357

IV. CLASSIFIERS

A. ANN

A multi-layered feed-forward ANN is used to perform non-linear classification and uses back propagation for supervised learning. The BP ANN with a nonlinear mapping function can give good classification results for complex areas [16]. Feed forward model consists of an input layer, output layer, and a hidden layer. The performance of the network is improved by adjusting the weights of the interconnected nodes to minimize the difference between the desired and actual output. The error feedbacks through the network and weight are adjusted using recursive method [14]. The neuron excitation level is represented by the weighted sum of input values:

$$g(x) = \sum_{1=1}^{n} w_i x_i \tag{1}$$

where, w_i= synaptic weights; x_i= inputs and i=1,2,3,…..,n and here the activation function is logistic function.

$$f(x) = \frac{1}{1+e^{-x}} \tag{2}$$

where x = excitation level of neurons.

The operation of ANN is controlled through various parameters that are used in this study and are briefly defined as:

- **Training Threshold Contribution**: Determines the size of the contribution of the internal weight with respect to the activation level of the node.
- **Training Rate:** It specifies the magnitude of the weight adjustment for the nodes.
- **Training Momentum:** The momentum parameter is used to prevent the system from converging to a local minimum.
- **Training RMS Exit Criteria:** Root mean Square error at which the training should stop.
- **Number of Hidden Layers:** Provides additional computational power.
- **Number of Training Iterations:** Determines when training will stop once the number of iterations
- **Min Output Activation Threshold:** Pixel values less than this threshold value are labeled as unclassified.
- **Mahalanobis Distance:** The Mahalanobis distance classification uses statistics for each class and is direction sensitive classifier [17]. It is similar to Maximum likelihood. It assumes that all class covariances are equal, and therefore, it is a faster method than maximum likelihood. Unless a distance threshold is specified, all pixels are classified to the closest ROI class. If some pixels do not meet the threshold value, they may be unclassified. Mathematically [15],

$$d(x, m_i)^2 = ((x - m_i)t\Sigma - 1(x - m_i)) \tag{3}$$

where, i= class; x= n-dimensional data (where n is the number of bands); mi= mean vector; Σi-1= Inverse covariance matrix.

V. ROC CURVES

TABLE II
OPTIMUM THRESHOLD VALUE FOR EACH CLASS IN EACH CLASSIFIER

Neural net classifier		Mahanalobis distance classifier	
Class name	Optimum threshold values	Class name	Optimum threshold values
Shrubs& bushes	0.94	Shrubs& bushes	1.633
Sparse vegetation	0.94	Sparse vegetation	1.633
Settlements	0.05	Settlements	2.14
Forest	0.94	Forest	2.14
Water bodies	0.68	Water bodies	2.14
Barren land	0.94	Barren land	2.14

ROC curve is a three-dimensional curve between the probabilities of detection vs false alarm vs the threshold values. To get the optimum threshold value for each class, the curve is calculated. There combination gives the 3D graph for the Probability of Detection vs. Probability of false Alarm vs. threshold (PDT). The optimum operating point in the graph is selected where 80% of the detection lies, and the false alarm probability is least as it is the least distance from (0,1) in a 2D graph of ROC plane. By using the selected operating point the threshold values for each class from PDT, curve has been calculated. Exporting the ROC and PDT values in ASCII to MS Excel, Maximum PD value (threshold value which lies in convex hull of PD graph) is calculated. The optimum threshold values for each class for both the classifiers have been shown in Table II.

TABLE III
TD AND JM SEPARABILITY FACTORS BETWEEN ANY TWO CLASSES OF SURVEYED TRAINING DATA, AND BETWEEN TESTING AND TRAINING DATA OF IDENTICAL CLASSES

	Training pixels						Testing pixels of same class
	Shrubs & bushes	Sparse vegetation	Settlements	Forest	Water bodies	Baren land	
Shrubs & bushes	-	1.907,1.936	1.999,2	1.999, 1.999	1.999,2	1.999,2	0.00089, 0.00089
Sparse vegetation	1.907, 1.936	-	1.990,1.999	1.999,2	1.999, 1.999	1.990, 1.999	0.00089, 0.00089
Settlements	1.999,2	1.990,1.999	-	2,2	1.996 ,1.999	1.990, 1.999	0.0029, 0.0029
ForestS	1.999, 1.999	1.999,2	2,2	-	2,2	2,2	0.0003, 0.0003
Water bodies	1.999,2	1.999,1.999	1.996,1.999	2,2	-	1.999,2	0.0047, 0.0047
Barren land	1.999,2	1.990,1.999	1.999,1.999	2,2	1.999,2	-	0.0003, 0.0003

JM is represented by the first value, and TD is represented by the second value in each cell

TABLE IV
CLASSIFIERS' RESULTS FROM CONFUSION MATRIX

		Before post Processing	Majority Filter	Median Filter	Majority+Seive+Clump
Mahalanobis Distance	Overall Accuracy	85.97%	87.57%	87.53%	89.03%
	Kappa Coefficient	0.81	0.83	0.83	0.85
	Shrubs & Bushes PA,UA	70.28, 61.55	70.50, 62.53	70.32, 62.66	70.03, 64.52
	Sparse Vegetation PA,UA	78.43, 46.84	79.90, 51.18	79.80, 50.80	80.72, 55.84
	Settlement's PA,UA	94.03, 89.24	96.54, 91.27	96.76, 90.95	96.35, 92.93
	Forest PA,UA	83.72, 98.35	85.84, 98.57	85.77, 98.58	88.44, 98.52
	Water Bodies PA,UA	92.87, 94.29	94.97, 96.65	94.94, 96.76	96.70, 96.43
	Barren Land PA,UA	93.07, 98.36	94.37, 98.61	94.36, 98.66	95.53, 98.54
Neural Net	Overall Accuracy	99.20%	99.26%	99.30%	99.39%
	Kappa Coefficient	0.98	0.99	0.99	0.99
	Shrubs & Bushes PA,UA	97.62, 99.85	97.90, 99.85	98.05, 99.72	98.12, 99.88
	Sparse Vegetation PA,UA	96.04, 98.54	96.37, 98.51	96.32, 98.47	96.9, 98.48
	Settlements PA,UA	98.70, 99.44	98.95, 99.44	98.98, 99.36	99.00, 99.47
	Forest PA,UA	99.94, 100.00	99.96, 100.00	99.96, 100.00	100.00, 100.00
	Water Bodies PA,UA	99.55, 99.18	99.55, 99.26	99.55, 99.32	99.57, 99.26
	Barren Land PA,UA	99.71, 99.96	99.75, 99.96	99.73, 99.96	99.77, 99.96

VI. RESULTS AND DISCUSSION

Classification has been done for 70% ROI as training samples for both the classifier for specific threshold value, and the ROC and PDT curves have been generated. Optimum threshold values for each classifier are found with the help of these ROC and PDT curves.

Final classification based on optimum threshold values for each class, has been applied on training data. To find the accuracy and Kappa coefficient of the results, the test samples are used to generate Confusion matrix. Table III shows the overall accuracy, kappa coefficient, user and producer, and accuracy. From the results, it is clear that ANN with overall accuracy = 99.20%, Kappa coefficient 0.98, performed better than Mahanolobis Classifier having overall accuracy 85.97%, and Kappa coefficient 0.81. Final classification results are generated while considering specific parameter values for ANN and are discussed as follows.

Number of hidden layer for the ANN was considered to be 1, as higher value will only increase the complexity without having significant performance gain. Training RMS exit criterion was selected to be 0.1 value. This exit criterion was achieved by the ANN within first 100 iterations, therefore within our considered experimental setup we considered the 100 iteration for the ANN. Training threshold contribution value adjust node weight adjustment. And low value could result in inaccurate outputs. And its value was considered to be 0.9. Higher training rate increases the training speed but also has risk of non-convergence of result. So, for training accuracy, a value of 0.2 is considered. And the training momentum which helps in setting higher training rate value without oscillating was considered to be 0.5.

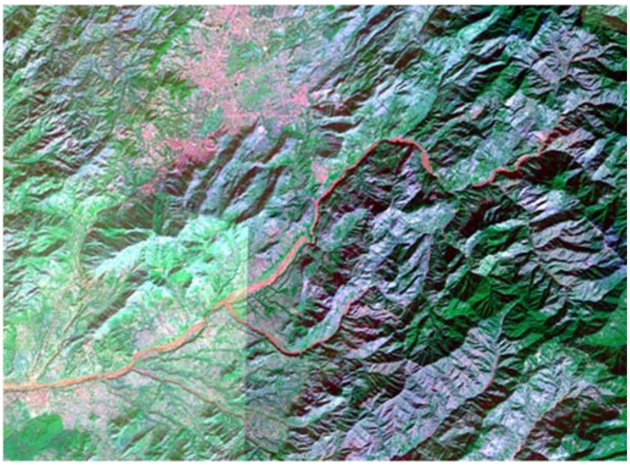

Fig. 1 Original Spot-5 Image

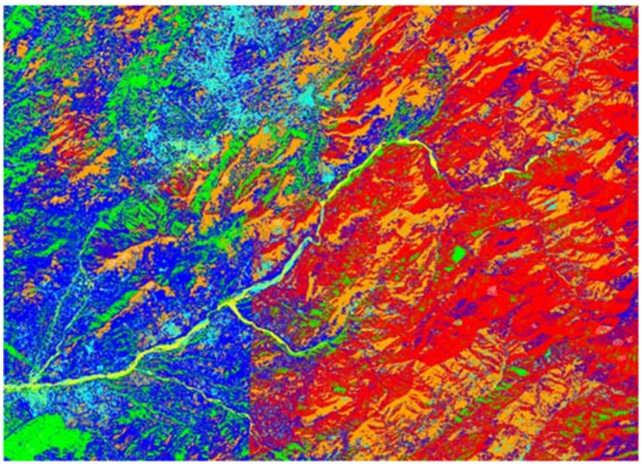

Fig. 2 Thematic map of Mahanolobis distance classifier

Unclassified Settlements Water Bodies
Shrubs & Bushes Sparse Vegetation Forest
Barren Land

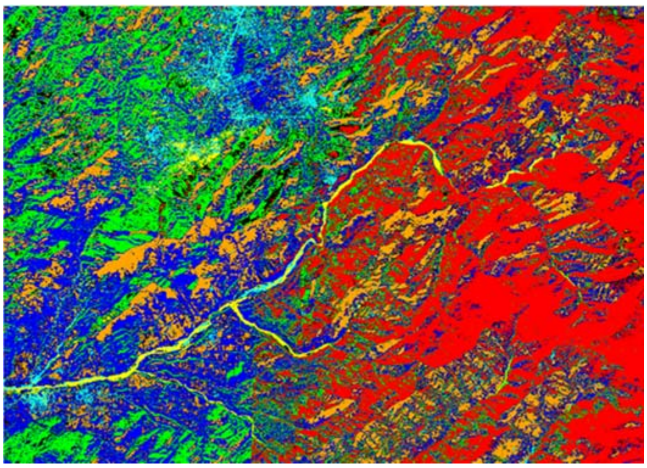

Fig. 3 Thematic map of neural network

VII. Conclusion

In this paper, two classification methods are used, namely, ANN and Mahanolobis distance (md) for classification of land cover types in Abbottabad district. The highest classification accuracy was obtained by ANN which is 99.2% with reference to Mahanolobis classifier which results in classification performance of 85.97%. It was concluded that the spot-5 image classified using ANN method is the best option for land cover classification. Furthermore, it is found that Mahanolobis distance classifier is a simpler classifier but is not preferred for non-real time application due to its less accurate nature in critical applications where there is high demand of classification accuracy.

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