Land cover Classification and Crop Estimation using Remote Sensing Techniques

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ABSTRACT
Due to the rapid growth of population the food need also increases which is the center of focus for various researchers and governments. For this purpose crop information system has been made, the aim of crop information system is to monitor the crop health and estimate the needs for the next four to five years. Geo graphic information system plays an important role in crop estimation and identification. GIS uses remote sensing technique to identify various crops and their yield. In this paper novel approaches are used for the identification and estimation of tobacco. SPOT 5 imagery having resolution of 2.5m is used for the estimation and identification of tobacco. For post processing, statistics like kappa coefficients and Receiver operating curves are utilized. This study mainly focuses on the Mardan region in KPK Pakistan. Classification is done for four categories, these categories are then classified using state of the art machine learning classifiers and the accuracy of these various classifiers has been compared.

Keywords
Remote sensing, Receiver operating curves, kappa coefficient, SVM, Maximum likelihood, Minimum distance, Mahalanobis distance.

1. INTRODUCTION
Remote sensing is used to obtain the information from the earth surface at a distance i.e without any physical contact. Remote sensing becomes very helpful in crop estimation and identification. The imagery obtained from these satellites is used for the various observations. Remote sensing with combination of machine learning techniques helps to accurately estimate the yield of various crops. Machine learning techniques which has been used for various purposes also comes handy when processing the imagery achieved through remote sensing. The hyper spectral imagery obtained usually contains various bands; these bands are widely for various analyses for Crop vegetation index such as Normalized difference vegetation index (NDVI) and Temperature condition index (TCI). These index obtained are used for crop yield estimation and classification in conjunction with linear regression the residual obtained by these methods for soya bean and corn were 0.86 and 0.78 which were very close to the actual obtained values [1]. Remote sensing based approaches are used to measure the surface flux, with the help of remote sensing water consumption can be related to crop yield. A case study carried out for wheat and soybeans using land sat imagery to map the indexes like Bowen ,latent heat and wetness index, the relationship between these index were obtained, strong correlation was found between these indexes which was mapped to crop yield [2]. The hyper spectral imagery obtained from satellite requires pre processing such as geometric which removes distortion due to the geometry, atmospheric to compensate the atmospheric noise and radiometric correction. Beside the vegetation index such as NDVI newly generated vegetation index General yield unified reference index (GYURI) has been introduced which is obtained from Gaussian curve. The correlation for the corn using these techniques were found to be 0.93 [3]. The reflection of various crops has been noticed in the infra red regions, these reflections of various crops can be obtained by various satellite imageries. Landsat and MODIS data obtained were compared with the actual field measurement Leaf area index (LAI) was obtained based on the reflectance to measure the grain yield for wheat [4]. In irrigation water management systems crop coefficients are the most commonly used methods. Linear regression is used to derive the correlation between vegetation index (NVDI) obtained from hyper spectral MODIS imagery and Crop coefficient, strong correlation was found between these two the correlation factor was 0.91 and the actual estimated crop coefficient was 0.90, the root mean square error was 0.16 respectively [5]. Estimation of crop Eva transportation based on crop coefficient is the most widely used technique, the crop coefficient estimated from remote sensed data. The crop coefficient estimated for corn, sorghum, soya beans, alfalfa has been estimated using regression model the correlation between them is found to be 0.74 [6]. Crop yield estimation helps in forecasting the estimates recent advancement has achieved the yield estimation of tobacco the current yield estimation which is based on statistical technique and survey report, the remote sensing technique which obtain the estimate based on geo spectral reflectance from vegetation indexes helps in differentiating the crops and non crops fields since each crop has its own spectral signature [7]. The spectral signature are used in identification and estimation of crop yield parameters such as leaf area index, these spectral signatures helps in monitoring the crop conditions using remote sensing which helps in the assessment of the final yield and quantity of crops such as maize [8]. The wavelength at which these reflectance is measured is mostly different and these different wavelength is used to measure crop energy, to discern between closely related species several techniques can be used for hyper spectral imagery in which the wavelength are selected with the help of sensors which is associated with the identification of desired specie [9]. Various researchers are been able to explore the multi spectral imagery and obtain the vegetation indices to determine the crop coefficient using remote sensing for maize, cotton and soya bean [10-14]. Other researchers has been used the vegetation indices for edicting the crop coefficient and used these indices to predict best coefficient for agriculture crops [15-21]. The core objective of this paper is to identify and estimate the tobacco in Mardan region Pakistan, for

classification and evaluation we have used the kappa statistics which could be found in the rest of the sections.

2. METHODOLOGY

For the purpose of tobacco identification, the imagery used is, hyper spectral imagery of SPOT5, having resolution of 2.5m which shows that 2.5m area would be represented by a single pixel. Recent work which have used SPOT5 imagery can found in [22, 23, and 24]. Four ROI which are hills, tobacco, settled areas and Water has been utilized. These ROIs were obtained by visiting these various field and then finding their spectral location through GPS. After obtaining ROIs the imagery that were obtained, were used for experiment. Initially the imagery was very large, then by field survey a subset of fields in the given imagery were selected for further classification. For classification of this imagery, state of the art machine learning techniques are utilized. For post classification utilization of kappa coefficients, receiver operating curves and confusion matrix have been made. The following section shows the classifiers that are used in this work.

2.1. Classification

For classification of hyper spectral imagery, various classifiers are utilized which are described below:

2.1.1. Mahalanobis Distance

Mahalanobis classifier is supervised learner which use the distance from the training data and the unknown pixel to classify the unknown pixels. Varying the distance of the classifier have significant effects on the results and hence it can also be called threshold. The correlation between known and unknown pixels can be obtained by using the covariance matrix. The following equation shows how the classifier in a matrix forms.

$$d(X,m_i)= \sqrt{(m_{i-X_l})^T \textstyle\sum_i^{-l} m_{i-X_l}}$$

The $\sum_i^{-1}$ is known as the covariance matrix. The classifier can be tuned by varying the threshold T value.

2.1.2. Minimum Distance

Minimum distance is another simple supervised classifier which used Euclidian distance to calculate the correlation amongst the known and unknown pixels. The minimum distance is same like the maximum likelihood but with less computational cost. Like mahalanobis classifier the minimum distance also require the thresholds. Following equation shows the matrix form of the minimum distance classifier.

$d(X,m_i)= \sqrt{(m_{i-X_l})^T (m_{i-X_l})}$.

2.1.3. Parallel Piped.

Parallel piped is supervised learning classifier which is also known as multi level classifier since it slices the feature space the boundary of each feature space is defined by highest and lowest values on particular axis. Based on these two values the statistics of each class is calculated ,compared to other classifiers the computation time is very low and schematics of parallel piped classifier is very easy. When the region has dependencies then the accuracy of the classifier is low, the preprocessing required for consideration of othogonalizaiton used the principal component analysis.

2.1.4. Maximum Likelihood

Maximum likelihood is so far the most popular classifier used in remote sensing. The maximum likelihood calculates the posterior probability based on which the unknown pixel is classified into the a class the posterior probability can be found as

Lc = P(C/X) = P(C)*P(X/C) / ΣP(i)*P(X/i).

The maximum likelihood calculates the prior and posterior of class(c). there some case for maximum likelihood such as when the variance and the co-variance matrix are symmetric then the maximum likelihood calculates the Euclidian distance and based on these distance class is assigned to pixel, when both the determinants are equal then the maximum likelihood is like mahalanobis distance.

2.1.5. Binary Encoding

The binary encoding classifier assigns binary codes to each of the classification segments. These codes are assigned based on the means since if the pixels are above certain mean it is assigned 1 else it is assigned 0. It uses exclusive-OR to classify the image the greatest number of bands that resembles unless minimum threshold value is assigned.

2.1.6. Support Vector Machine

Support vector machine is one of the most popular machine learning classifier which is used in almost every classification problem i.e. image classification, text classification and audiovisual data classification. Since support vector is always driven by kernels it has many types of kernels which is used for classification. Here we have used the following kernels.

2.1.6.1. Linear Kernel

Linear SVM can be described by the following equation given a training data T.

T= {(Xi, Yi) |Xi ε R, Yi ε {-1, 1}.

Since a linear relation can be found between the input and output based on which the class is assigned either 1 or -1. To find a hyper plane which divides the plane in 1 and -1 can be written as

w. x – b= 0.

w. x – b = 1.

And

w. x – b =-1.

2.1.6.2. Polynomial Kernel

In SVM polynomial kernel is used to represent the training vector in the form of polynomials. Since we have used for polynomial of degree 2. Polynomial kernels not only use the input data to form a linear space but it also uses regressions for iterative analysis. The feature space of polynomial kernel and that of polynomial regression is the same.

2.1.6.3. Radial Basis Function

The radial basis function for two inputs x1 and x2 can be written as

R(x1, x2) =exp(r$||x1 - x2||^2$)

Where r= -1/2α^2. Since the RBF kernel decreases with distance and it approaches to zero.

2.1.6.4. Sigmoid Kernel

The sigmoid kernel is equivalent to the multi-layer perceptron the activation function of the sigmoid function can be written as

$$K(x, y) = \tanh(\alpha x^T y + c)$$

The two parameter for sigmoid function are alpha which has the value equal 1/N, where N is the dimension of data and the intercept c.

2.1.7. Neural Network

Neural network consist of an activation function which is always known as neuron. Each input is applied to the neural network then the neural network applies a non linear function to produce the result. The neural network always consists of layers the output of one layer is input to the other layer and so on.

2.2. Result and Discussion

The results were obtained using these various classifiers for some of them such as minimum distance and mahalanobis , minimum distance and parallel piped we evaluated the result using different thresholds while for others such as SVM, Neural Net. For post classification different parameters such as ROC (Receiver operating curves) and kappa statistics are utilized. The minimum distance classifier performs well in identification and estimation of the tobacco and other region to get the best result we evaluated it using up to 12 thresholds, the ROC curve shows that the accuracy of the system increase up to threshold 8 and after 8 threshold the accuracy of the system remains the same the kappa coefficient obtained using minimum distance classifier is 0.98 and the overall accuracy of the system is 99.2%. The mahalanobis classifier also showed the same statistics and we evaluated the classifier performance on 10 thresholds the best accuracy noted was 99 % and the kappa statistics was 0.99 which was better than the previous i.e. the minimum distance. The classifier accuracy becomes constant when the threshold reaches the threshold 10. The parallel piped classifier showed the same accuracy as the previous one and the best result were obtained when the threshold applied was 4 for other coefficient the classifier showed poor accuracy and kappa coefficient below threshold 4 and above this threshold the result were very weak the accuracy and the kappa statistics obtained at threshold four was 99% and 0.98 respectively. Binary encoding classifier showed poor accuracy and were unable to detect the four ROI's that we have used, the binary encoding classifier only detected hills and tobacco for others it failed. The neural network also showed weak detection and classification it only classified the hills for the rest it was unable to detect and classify the rest of the classes. Maximum likelihood which is always known for his accuracy perform the best and showed overall accuracy of 100% and kappa coefficient of 1 which shows strong agreement, it correctly classified each classes and the error ratio was zero noted for all the classes. For SVM, we used four kernels i.e. linear, polynomial, radial basis and sigmoid. The statistics for these various kernels were obtained like maximum likelihood the SVM also perform the best and the results of these two classifiers were almost the same except for sigmoid function in which we obtained accuracy of 99% and kappa coefficient of 0.99, for the rest of the kernels the accuracy and the kappa coefficients were the same.

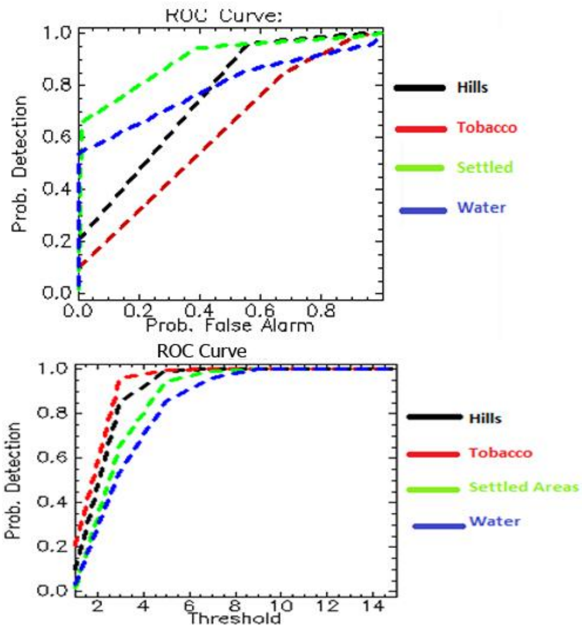

Figure 1. Mahalanobis distance a) probability of false alarm b) probability of detection.(the figure in part a shows that error converges in part b it clearly shows that when the threshold reahces 8 then the probability of detection remains constant if we increase the threshold it has no effect on the accuracy of the classifier it will still remain the same)

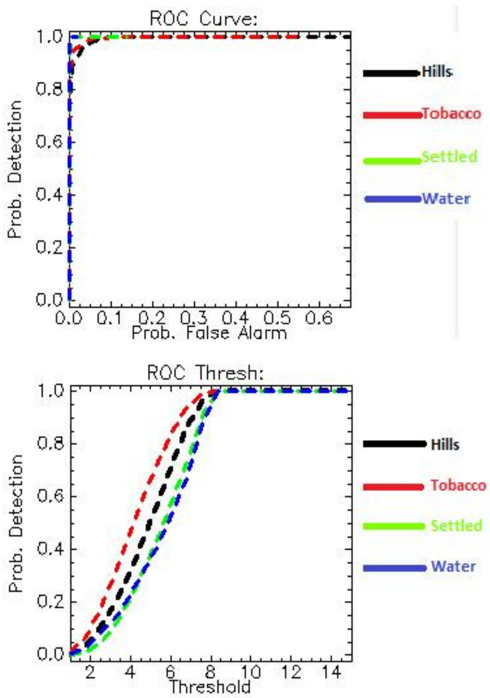

Figure 2. Minimum distance Classifer a) probability of false alarm b) Probability of detection.(the figure in part a shows that the error/false alarm vanishes as the threshold increase in part b it clearly reveals that when the threshold reaches at 8 then the accuracy remains constant further increase in the coefficient will not change the accuracy/detection of the classsifier.

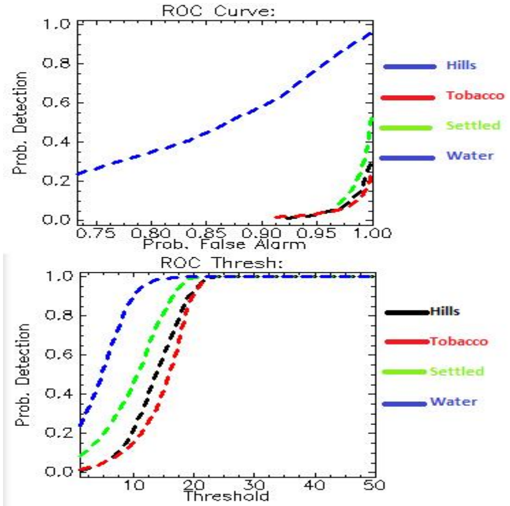

Figure 3. Maximum likelihood a) Probability of false alarm b) Probability of detection. (the accuracy obtianed using maximum likelihood is the one which is achieved by the actual measurements part b of the figure shows that when threshold reaches 20 then the accuracy of the system remains constant.

The following table shows the accuracy which is obtained by dividing the number of pixel obtained for particular class to the whole number of pixels in the truth image, Error of omission which shows the misclassified pixels i.e. pixels belonging to other class and is classified in some other class. Error of Commission shows the classifier error i.e. classifier failed to classify the pixels of particular class. Producer accuracy measures the probability that the classifier has classified pixel in class I given the actual total pixels of the ground truth class. User accuracy is the probability of a pixel classified into class I given total number of pixels in the class. The kappa statistics (Kappa coefficient) is another statistical measure and is defined by the following equation

$$K= N\sum_{i=1}^{k} Xkk - \sum_{i=1}^{k} Xt * Xc \,/\, N^2 - \sum_{i=1}^{k} Xt * Xc.$$

Where N represents the sum of all the pixel in class. Xkk represents the diagonal of the confusion matrix, Xt represents the sum of all the ground pixels in the class and Xc represents the sum of all the pixels of the class.

Classifier	Accuracy %	Kappa Coefficient	Error of Omission and commission							
			Tobacco		Hills		Settled		Water	
			Commission	omission	commission	omission	commission	omission	commission	omission
Parallel Piped	99.41	0.98	0.0	0.01	0.04	0.07	16.35	0	0.64	11.54
Minimum Distance	99.21	0.98	0.00	0.00	0.25	0.00	8.37	1.25	0.34	15.67
Maximum likelihood	100.0	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Neural network	92.45	0.85	0.00	0.00	16.40	0.00	0.00	100.00	0.00	100.00
Binary encoding	91.30	0.83	0.00	2.13	18.44	0.00	0.00	100.00	0.00	100.00
Mahalanobis distance	99.53	0.99	0.01	0.57	1.16	0.00	0.26	2.51	0.00	1.85
Support Vector Machine										
1. Linear Kernel	100.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2. Polynomial kernel	100.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
3. Radial Basis function	100.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
4. Sigmoid	99.99	0.99	0.00	0.00	0.02	0.00	0.00	0.25	0.00	0.00

Figure 4. Accuracy and Error of omision and commisions

Classifier	Accuracy	Kappa Coefficient	Error of Omission and commission							
			Tobacco		Hills		Settled		Water	
			Producer Accuracy	User Accuracy	Producer Accuracy	User Accuracy	Producer Accuracy	User Accuracy	Producer Accuracy	User Accuracy
Parallel Piped	99.41	0.98	99.99	100	99.93	99.96	100	83.65	88.46	93.36
Minimum Distance	99.21	0.98	100.00	100.00	100.00	99.75	98.75	91.63	84.33	99.66
Maximum likelihood	100.00	1.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Binary encoding	91.30	0.83	97.87	100.00	100.00	81.56	0.00	0.00	0.00	0.00
Neural network	92.45	0.85	100.00	100.00	100.00	83.60	0.00	0.00	0.00	0.00
Mahalanobis distance	99.53	0.99	99.43	99.99	100.00	98.84	97.49	99.74	98.15	100.00
Support Vector machine										
1. Linear Kernel	100.00	1.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
2. Polynomial kernel	100.00	1.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
3. Radial Basis function	100.00	1.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
4. Sigmoid	99.99	0.99	100.00	100.00	100.00	99.98	99.75	100.00	100.00	100.00

Figure 5. User Accuracy and producer Accuracy.

3. CONCLUSION

In this paper, comparison of seven classifier on hyperspectral imagery obtains from SPOT 5 imagery is performed. Various statistical parameters for results validations such as ROC (Receiver operating curve), Accuracy and kappa coefficients which is shown in table 4 and table 5 are calculated. Four ROI's are used for the purpose of classification. Based on comparison of these classifier, it is found that maximum likelihood and support vector machine perform the best and showed the less error as compared to other classifiers. Other classifiers like minimum distance and Mahalanobis also did good predication while neural network and binary classifiers failed to detect all the four regions.

4. FUTURE WORK

So far calculation for various fields such as tobacco, hills, settled areas and water have been done by visiting the sites. Since it is evident that these parameter/ROI's can also be obtained by using there spectral signatures as NDVI, LAI and other indices. One possible approach for estimating the yield of these crops would be using the vegetation indexes instead of visiting the fields also to make an accurate crop fore warning system certain parameters comes very helpful such as temperature index, irrigation index and soil index. Based on these indexes an accurate system would be designed which not only helps in the prediction of the tobacco crop but will also helps in monitoring their health and improving the crop yield. Such techniques which has previously done for various crops can be found in [1-3]. Based on these parameters the crop information system will be able to accurately estimate the yield of particular soil for next five years but it will also help in increasing the soil fertility in case the soil index is low it would tends to improve index to improve the crop quality.

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