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Classification of Hyperspectral Satellite Images Using Ensemble Techniques for Object Recognition

K. M. Sharavana Raju[1], V. Karthikeyani[2]

[1]Research Scholar, Department of Computer Science, Bharathiar University, Coimbatore – 641 046, Tamilnadu, India.
[2]Assistant Professor, Department of Computer Science, Thiruvalluvar Government Arts College,Rasipuram, Tamilnadu, India.

Abstract-- **Image classification is one of the most important tasks of remote sensing information processing used for object recognition. In this paper, a novel scheme is proposed to improve the accuracy of hyperspectral image classification by amalgamating multiple feature vector sets and ensemble methods with different classifiers. Extracting the texture, color and object features of the satellite images, an ensemble classifier is built for object recognition which recognizes the type of objects present in it. Effective use of feature set and the selection of suitable classification methods with different combination methods are applied for improving classification accuracy. Classifiers such as Multi Layer Perceptron (MLP), k-Nearest Neighbour (KNN) and Support Vector Machine (SVM) are used. This combination shows high performance in terms of Classifier Accuracy (CA), Object Recognition Rate (ORR) and False Alarm Rate (FAR). Results obtained from the ensembling classification give better solution when compared with single classification system.**

Keywords-- **Hyperspectral satellite images; ensemble classification; Object Recognition Rate, False Alarm Rate, Classifier Accuracy.**

I. INTRODUCTION

Hyperspectral imaging is a spectral imaging technique deals with imaging narrow spectral bands over a continuous spectral range while multispectral imaging deals with discrete narrow bands. Hyperspectral remote sensing is defined as the technique of obtaining information about earth's surface or objects through the analysis of data collected by hyperspectral sensors. Hyperspectral image analyses have been used for many purposes such as land cover classification, remote sensing, environmental monitoring and vegetation. Nowadays land cover classification is used to recognize different types of earth's surface. Classifying the types of different heterogeneous classes present in the hyperspectral image is one of the research areas in remote sensing [1]. Classifying the pixels in the hyperspectral image and identifying their relevant class belongings depends on the feature extraction and classifier selection process.

A feature is a characteristic element that differentiates one class from other and the method of transforming the input data into the set of features is called feature extraction. Ensemble classifier approach for spectral-spatial classification of hyperspectral images is proposed.

II. CLASSIFICATION APPROACHES

With the development of remote sensing data acquisition tools, more complex classification methods to generate accurate and consistent results are on the increasing demand. A set of classification algorithms and techniques have been promoted to improve remote sensing image classification accuracy. Many advanced approaches, such as artificial neural networks (ANN) [2], SVM [3], expert systems [4] and fuzzy set [5] and have been extensively used. However, lot of factors, such as remote sensing data, complexity of the landscape, a prior knowledge and classification approaches and some image pre-processing methods affect the performance of a classification task [6]. Therefore, a sequence of new methods can be aimed for improving the performance of remote sensing image classification.

Image ensembling performs well in enhancing the classification accuracy because ensembling the images provides abundant textural, spectral, spatial and object related information for image interpretation [7]. Adequate and good training samples are also the key factor of image classifications [8]. It has also been demonstrated that ensemble learning technique and multiple classifier system can improve classification accuracy effectively as well [9]. Although great progresses have been made on classification techniques, the previous studies have suggested that there is no existing approach is applicable and optimal to all cases [10]. Therefore, it is always significant to propose some advanced classification schemes with high accuracy and reliability.

Ensemble methods are learning algorithms that construct a set of classifiers and then classify new data points by taking a vote of their predictions as illustrated in Figure.1.

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A set of classifiers with similar training performances may have different generalization performances, combining outputs of several classifiers reduces the risk of selecting a poorly performing classifier. It has been discovered that a classifier ensemble can often outperform a single classifier. A large body of research exists on classifier ensembles and why ensemble techniques are effective. [11]. In order to make the ensemble more efficient, there should be some type of *diversity* between the classifiers [12]. Two classifiers are diverse if they make unusual errors on new data points. In ensemble classifiers, diversity can be found by using different types of classifiers. Ensembles create many classifiers, and combine their outputs to improve the performance of a single classifier. If each classifier commits different errors, so their planning combination can lessen the total error. Therefore we need base classifiers whose decision boundaries are sufficiently different from those of others, such a set of classifiers is said to be diverse**.**

In the framework of pattern recognition, there is no guarantee that some or one specific classifier can always accomplish the best performance on every situation. But better predictive performance than any single classifier might be achieved through extreme learning algorithms. This is the main methodology of extreme learning, also named as classifier ensemble in terms of classification task. Due to its strength in computation, statistics and expression extreme learning has been widely applied in machine learning and pattern recognition fields [13], [14].

Researchers have developed many EL methods such as Bagging, Boosting, Multi-boost, Random Forest, Rotation Forest, etc., and most of them have been used in remote sensing image processing with effective performance [11], [15], [16]. The vital component of constructing an effective extreme learning system is producing base classifiers with high diversity. In order to reach that, many techniques such as resampling, label switching, and feature space partitions have been developed. In this work, ensembling integrates with two or more classifier and with various combination methods are used to recognize the objects present in the satellite images based on the label classification.

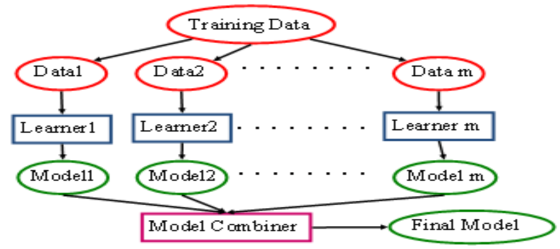

Figure I. Learning Ensembles Classification process

III. METHODOLOGY

The huge dimensionality of the hyperspectral image features makes it harder for classification. Convolution lies in the nature of high dimensional hyperspectral data and the consequent ground truth demand for supervised classification [17]. Several unsupervised and supervised algorithms have been developed for classification of hyperspectral images. In this research work, satellite images are used and their GLCM texture, color and object features are selected and extracted. Multi layer Perceptron (MLP), k-Nearest Neighbour (KNN) and Support Vector Machine (SVM) classifiers are used for ensembling purpose. After segmenting and clustering the satellite images based on the color reflectance, the proposed system extracts the different features embedded in the satellite images. 12 texture features namely contrast, energy, homogeneity, entropy, sum average, sum of variances, sum entropy, sum variance, correlation, autocorrelation, difference variance and difference entropy; 3 color features namely cluster prominence, cluster shade and dissimilarity and 4 object features namely mean, median, mode and standard deviation are extracted and feature data sets are created. In addition to the basic feature vector sets, three more feature vector sets are created with different combinations.

Ensemble classifier models are built to recognize the type of objects in the satellite images. Using the ensemble techniques forty different ensemble models from the seven vector sets are generated and evaluated for obtaining the performance metrics. The proposed ensemble classifier uses the hold-out method for splitting the dataset into training and testing samples.

The hold-out method procedure is given in the Figure 6.7. The hold-out method randomly partitions the dataset into two independent sets, training and testing. Generally, two-thirds of the data are allocated to be the training set and remaining one-third is allocated as test set. Majority voting scheme is used as the aggregation algorithm during ensembling. The advantage of using ensemble classification is that they provide more freedom, allowing solutions that would be difficult to reach with only a single classifier. Results obtained from the ensembling classification give better solution when compared with single classification system. Most of the existing solutions are based on building ensemble model that generate a Pool of Classifiers (PoC) belonging to the same classifier. Aggregation methods are selected along with a classifier that produces best results with high diversity, high accuracy and low error rate.

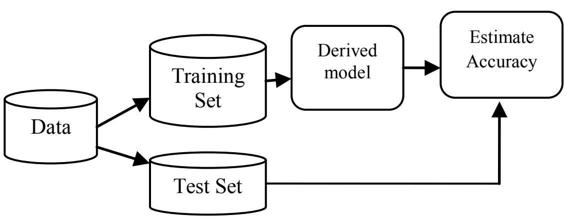

Figure II. Hold-out Method

IV. Performance Evaluation Measures

The choice of standard performance assessment measures enables appropriate evaluation of proposed technique with other existing techniques. The performance of the object recognition system to identify objects in satellite images can be determined by the computation of total classification accuracy (CA), Object Recognition Rate (ORR) or sensitivity, False Alarm Rate (FAR) or specificity and confusion matrix.

A. Classification accuracy (CA)

Classification accuracy (CA) is the most common evaluation technique to measure the performance of the data in the feature vector sets for classifying objects present. The higher the classification accuracy, the better the system is performing. The advantage of this measure lies in its simplicity; the disadvantage is that it can be misleading.

Classification accuracy is calculated as

$$CA = \frac{\text{Correct classified patterns}}{\text{Total number of patterns}}$$

B. Object Recognition Rate (ORR) - Sensitivity

The Object Recognition Rate (ORR) or the sensitivity ensures the test ability of the classifier. ORR or sensitivity regards only positive cases, for instance, it can be used to recognize the objects present in the satellite images. ORR or sensitivity was computed as for each object

$$ORR = \frac{\textit{number of true positive decisions}}{\textit{number of actual positive cases for each class}}$$

In otherwords, Sensitivity = [TP / TP+FN *(%)*]
where, TP = True Positive cases and
FN = False Negative cases.

C. False Alarm Rate (FAR) – Specificity

The False Alarm Rate (FAR) or specificity and it deal only with negative cases. FAR is computed as

$$FAR = \frac{\textit{number of true negative decisions}}{\textit{number of actual negative cases for each class}}$$

In otherwords, Specificity = [TN / FP+TN *(%)*]
where, TN = True Negative cases and
FP = False Positive cases.

D. Confusion matrix

A confusion matrix represents information about actual and classified cases produced by a classification system. Performance of such a system is commonly evaluated by demonstrating the correct and incorrect patterns classification. The typical construction of the confusion matrix for the two classes is represented in Table 1. Row (X1 and X2) represents the actual patterns and column (Y1 and Y2) represents the classified patterns for a class particular class. The difference between the actual patterns and the classified patterns is used to determine the performance of the proposed techniques.

TABLE I.
REPRESENTATION OF CONFUSION MATRIX

Actual	Predicted	
	Positive	Negative
Positive	X1	X2
Negative	Y1	Y2

V. Experimental Results

The performance of the proposed system was evaluated using 385 images from which 19 features were extracted. Seven different feature vector sets are formed and 40 classification models have been constructed with three different classifiers namely, MLP, KNN and SVM. Ensemble classification is performed with nine combination methods on the feature vectors to create different feature subsets. The performance metrics like object recognition rate (ORR), false alarm rate (FAR) and classifier accuracy (CA) are found using the ensemble classifiers for the image feature vector sets. The results are found for three different cases namely, before preprocessing, segmentation and clustering and finally using preprocessed, segmented and clustered feature vector sets. The proposed ensemble classifier uses the hold-out method for splitting the dataset into training and testing samples.

The average accuracy of single classifiers and the average accuracy of ensemble system with different combination methods are found. While comparing the overall results of the ensemble classifiers, single classifier, 2-classifier and 3-classifer models, the 2-classifier ensemble models MLP and SVM showed high classification accuracy than the other 2-classifier models and 3-classifier models. This combination shows high performance in terms of object recognition rate (ORR), false alarm rate (FAR) and classifier accuracy (CA). Texture features showed very high performance when compared with the color and object feature vectors. Tables II-V shows performance metrics for SFSC, SFMC, MFSC and MFMC classifier models is given as below. Figures III-VI illustrates the graphically output of the performance metrics.

VI. Conclusion And Scope For Future Works

Nowadays, satellite images are widely used in agriculture, geology, forestry, biodiversity conservation, regional planning, education, intelligence and warfare to identify the exact locations and to analyze objects present, which will increase in the forthcoming years. In such a situation, users can be provided with GUI tools that can be utilized by different types of people to discover reliable knowledge from the satellite images.

Different types of objects are embedded on the satellite images which can be analyzed to identify valuable resources found on the earth, protect the earth and human lives from disasters, plan the urban land developments, utilize and control the water resources, save forest wealth etc.

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TABLE II.
Single Feature – Single Classifier (SFSC)

Features & classifiers	CA			ORR			FAR		
	BPP	**BSC**	**PSC**	**BPP**	**BSC**	**PSC**	**BPP**	**BSC**	**PSC**
T1	82.65	63.23	89.96	79.65	69.35	82.64	6.27	7.98	4.78
T2	80.9	65.21	87.44	76.74	64.53	79.12	6.98	8.32	5.25
T3	83.76	63.64	93.93	83.28	72.82	85.75	5.78	7.62	4.19
C1	84.23	69.98	87.87	82.24	65.52	81.65	5.99	6.46	3.12
C2	83.53	63.9	84.55	78.86	58.73	73.87	6.89	6.75	3.98
C3	86.21	72.91	90.39	84.82	69.15	84.62	5.32	6.2	2.62
O1	79.12	76.73	86.24	80.52	62.85	80.54	5.31	4.89	2.65
O2	76.23	73.75	79.51	75.22	59.76	75.12	6.41	5.67	3.52
O3	81.57	79.01	91.52	83.65	65.52	83.96	4.63	4.26	2.53

TABLE III.
Multiple Feature - Single Classifier (MFSC)

Features & classifiers	CA			ORR			FAR		
	BPP	**BSC**	**PSC**	**BPP**	**BSC**	**PSC**	**BPP**	**BSC**	**PSC**
TC1	71.23	64.87	87.63	67.56	52.62	82.15	5.36	6.73	4.06
TC2	63.86	58.15	75.06	64.63	46.18	78.43	5.08	6.66	3.87
TC3	73.91	69.62	92.59	68.43	61.33	86.42	4.77	5.94	3.33
TO1	72.52	60.94	85.64	67.87	54.71	77.5	5.29	6.12	4.45
TO2	65.15	56.78	76.39	64.95	53.77	75.63	4.89	5.95	4.07
TO3	75.26	69.81	93.59	69.63	57.64	83.73	4.35	5.38	3.87
CO1	73.29	62.64	87.49	67.22	53.74	77.42	5.43	5.99	4.76
CO2	60.62	57.92	77.89	62.34	47.84	71.51	5.25	6.23	4.93
CO3	77.81	73.25	94.82	69.74	57.63	88.97	4.78	5.78	4.12

TABLE – IV.
Single Feature - Multiple Classifier (SFMC)

Features & classifiers	CA			ORR			FAR		
	BPP	**BSC**	**PSC**	**BPP**	**BSC**	**PSC**	**BPP**	**BSC**	**PSC**
T12	88.57	75.74	95.36	84.19	65.32	82.34	2.63	4.03	1.56
T13	90.63	78.35	97.08	86.87	69.34	89.43	3.81	4.26	1.87
T23	89.12	76.16	96.43	85.24	67.75	87.45	2.77	4.46	1.65
C12	87.21	73.24	93.65	81.91	63.17	80.23	3.39	4.28	1.89
C13	91.53	80.48	96.28	86.25	67.62	90.98	3.65	4.54	2.07
C23	88.98	78.76	95.73	84.34	63.64	86.85	3.73	4.98	2.54
O12	86.9	72.42	91.11	79.22	59.46	79.14	3.92	5.39	2.56
O13	91.22	78.31	96.93	84.86	69.23	88.65	4.06	5.43	2.64
O23	87.91	73.12	91.28	82.15	65.23	84.23	4.38	5.68	2.72
T123	76.98	71.09	87.07	76.72	59.89	82.98	4.74	5.93	3.05
C123	74.45	69.64	85.29	75.65	57.87	80.74	4.91	6.24	3.57
O123	72.23	68.87	84.06	74.54	54.12	78.31	5.25	6.19	3.89

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TABLE V.
Multiple Feature - Multiple Classifier (MFMC)

	CA			ORR			FAR		
	BPP	BSC	PSC	BPP	BSC	PSC	BPP	BSC	PSC
TC12	92.65	75.23	95.96	83.65	69.35	92.64	6.27	7.98	4.78
TC13	95.9	79.21	97.44	87.74	74.53	94.12	6.98	8.32	5.25
TC23	93.76	78.64	96.93	85.28	72.82	93.75	5.78	7.62	4.19
TO12	89.23	76.98	89.87	82.24	65.52	81.65	5.99	6.46	3.12
TO13	93.53	78.9	94.55	88.86	78.73	93.87	6.89	6.75	3.98
TO23	92.21	75.91	90.39	84.82	69.15	88.62	5.32	6.2	2.62
CO12	89.12	73.73	86.24	80.52	62.85	80.54	5.31	4.89	2.65
CO13	92.23	76.75	89.51	87.22	69.76	87.12	6.41	5.67	3.52
CO23	89.57	74.01	87.52	83.65	65.52	86.96	4.63	4.26	2.53
TCO123	87.45	72.41	92.76	83.12	64.67	83.98	4.09	4.89	2.45

CA - Classifier Accuracy, ORR - Object Recognition Rate, FAR - False Alarm Rate
BPP – before preprocessing; BSC – with preprocessing, without segmentation & clustering;
PSC – with preprocessing, segmentation and clustering

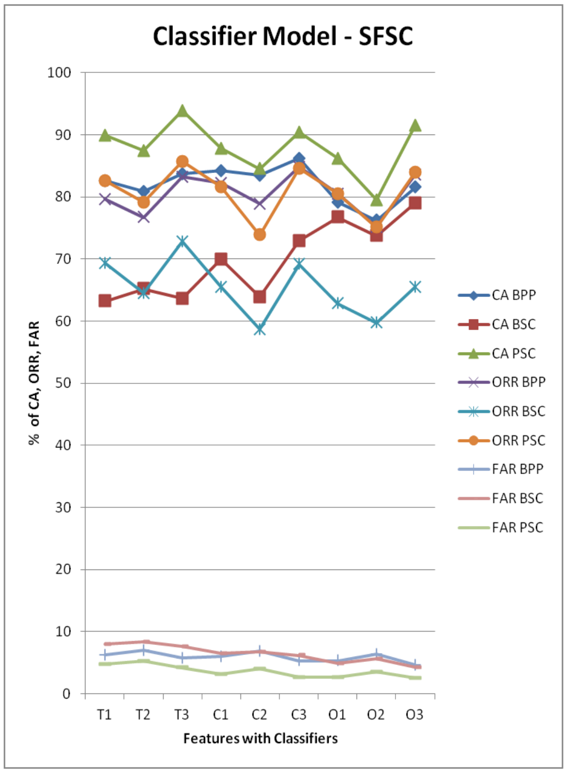

Figure III. Performance metrics of SFSC model

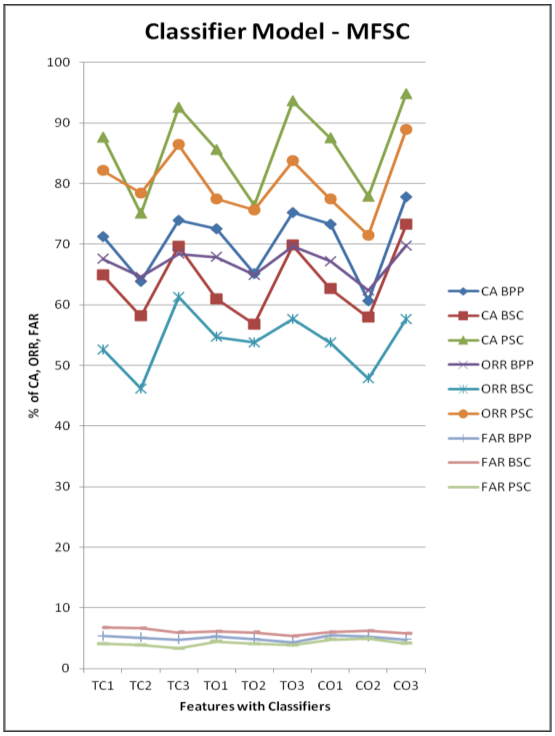

Figure IV. Performance metrics of MFSC model

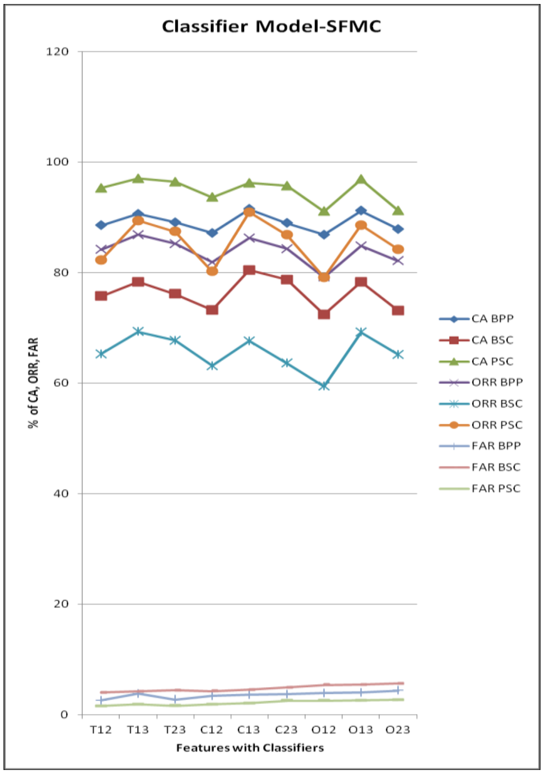

Figure V. Performance metrics of SFMC model

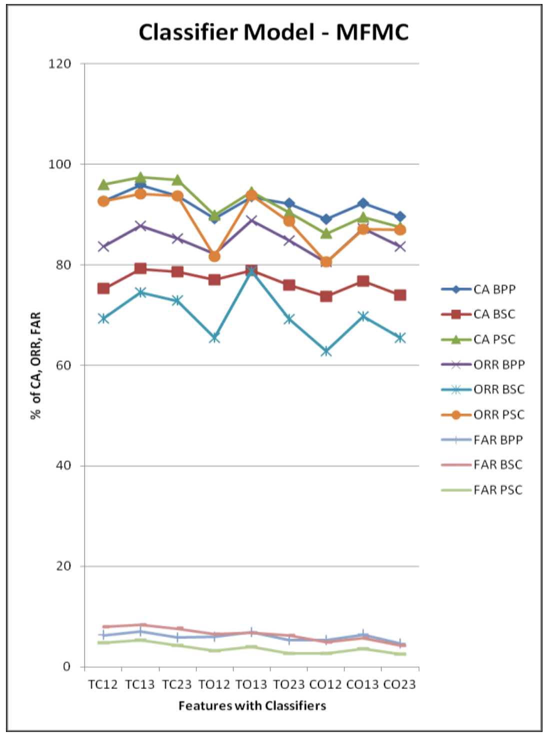

Figure VI. Performance metrics of MFMC model