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## ELECTRICAL & ELECTRONIC ENGINEERING | RESEARCH ARTICLE

# A neural network based classification of satellite images for change detection applications

K. Radhika<sup>1\*</sup> and S. Varadarajan<sup>2</sup>

**Abstract:** Detecting changes on the earth surface are vital to predict and avoid several catastrophes being occurring. In many situations, change detection techniques aids in detecting such changes being taking place. The changes can be noticed from different kinds of low- and high-resolution satellite images of multi-spectral and multi-temporal images. There are different kinds of change detection techniques to observe changes in the images, like principal component analysis method, spectral change vector analysis, post-classification method, kernel method, etc. Machine learning (post-classification) method based change detection provides better accuracy, because these methods are based on pixel comparison in multi-temporal satellite images. The change detection accuracy depends on the classifier used for classification of multi-temporal images. Any misclassification in either images leads to poor detection in change, hence classifier selection is very important in this case. In the recent past, the performance of classification techniques is improved by combining the advantages of some of the classifiers as ensemble methods. In this work, ensemble based classifier is explored for images classification. Different parameters are considered to estimate the performance of ensemble based classifier. Finally, the changed pixels in two temporal images are observed and listed. The images are also shown in zoomed for easy observation of changes in the images.

### ABOUT THE AUTHORS

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### PUBLIC INTEREST STATEMENT

Image classification is an imperative system utilised as a part of remote sensing. Extraction of land cover data is generally accomplished through a classification process which is one of the most intense tools in satellite image processing. Different information partitions inferred by various methods can be gathered into a new solution by ensemble the different classification methods. The accuracy of satellite image plays an interesting role to utilise the images. Utilization of good classifier leads to accurate change detection.

The goal of the work is to utilise the information contained in remotely sensed data to extract information and identify targets into a defined number of thematic classes. The analysis of satellite imagery can be used for multiple applications including water canal planning, land-use monitoring, under-cover operation missions, monitoring disasters, estimate of environmental figure, urban planning, aurora particle monitoring, growth regulation, soil inspection, mining and crop production assessment.

**Subjects: Electrical Engineering Communications; Communications & Information Processing; Radar & Navigation; Radio; Satellites; Television & Audio; Telecommunication**

**Keywords: classification; satellite image; high resolution; ensemble; low resolution**

## 1. Introduction

Changes occurring on the earth surface are important to know the environment and surrounding changes. The information provided by traditional methods and air photos is time consuming and ineffective. However, it is possible to observe the changes with the up-to-date analysis of satellite images (Doroodgar, Liu, & Nejat, 2014; Li, Xiao, Xia, Tang, & Li, 2014; Zhong & Zhang, 2012). In remote sensing, two important procedures used for the analysis of land use and land cover are classification and change detection. Classification is a powerful tool to extract accurate information in the satellite images; it is divided into two types: supervised classification and unsupervised classification. Every classification method has its own advantages and disadvantages. Unsupervised classification does not require prior data, and some automated methods are used to do the classification (De Morsier, Tuia, Borgeaud, Gass, & Thiran, 2013; Epstein, Payne, & Kramer, 2009; Hemissi, Farah, Etabaa, & Solaiman, 2013). Supervised classification method on the other hand requires prior data to validate the performance of the classifier. If ground truth data is available, supervised classification method provides better results. To classify large data sets, clustering is to be performed before the classification for improvement of accuracy.

Several types of image classification techniques were explored in the past decade. Some of the popular methods are K-Nearest neighbour (KNN) classifier, Support Vector Machine (SVM) classifier (Bruzzone & Cossu, 2002; Celik, 2010; Chang & Lin, 2011), Maximum Likelihood (ML) classifier (Bruzzone & Prieto, 2001), etc., The accuracy of classification is further improved by considering the benefits of different classifiers and combining them to form a classifier that have all the merits of different classifiers (Bahirat, Bovolo, Bruzzone, & Chaudhuri, 2012; Rizvi & Mohan, 2011). This kind of combining different classifiers is called ensemble method. In ensemble method, clustering and classification process can be combined (Murali Mohan Babu, Subramanyam, & Giriprasad, 2015; Radhika & Varadarajan, 2015). One of the applications of classification is change detection of land use and land cover data. Change detection in temporal images is observing changes related to the area at different time-spans. Weak classifier results in poor change detection, w leads to the wrong analysis of the ground surface. The selection of an appropriate classifier is very important in satellite image processing to get accurate change detection.

There are various change detection techniques for the observation of changes in satellite images. To measure the difference between images, the methods used are image rationing and change vector analysis. Based on feature extraction, the conventional detection methods use vegetation index, spectral mixture analysis, scale-invariant feature transform operator and forest canopy variables. These methods are useful to notice the changes in the image. Other change detection related methods are multivariate alteration detection, principal component analysis and Gram-Schmidt transformation. These methods project the original image into the feature space to assign labels to the areas.

## 2. Ensemble of different classifiers

Several methods have been combined to get the ensemble method. The ensemble method performs exact classification thereby detecting exact change that has taken place. The main aspect of ensemble methodology is to get the benefits of several classifiers individually. By mixing the good features and characteristics of different classifiers, the resulting classifier can achieve better results.

The general steps to be considered in framing ensemble method are: (i) training set; (ii) base inducer; (iii) diversity generator; (iv) combiner.

Ensemble methods are of two types: the dependent framework and the independent framework. In the dependent framework, the classifier composer gets inputs from all the considered classifiers for ensemble along with the unlabelled tuples to provide predicted labels. Here each classifier stage depends on each other. Individually, every classifier is trained with input sets, and finally their outputs are combined together as shown in Figure 1.

Here unlabelled tuples are given to classifier composer consisting of different classifiers that are applied with the training set. First, the training set is applied to the dataset manipulator and the obtained datasets are given to the corresponding classifiers. Based on the unlabelled tuples and classifiers results, the classifier composer will produce predicted labels. The different classifiers that can be used are SVM, ML, K-NN, etc.

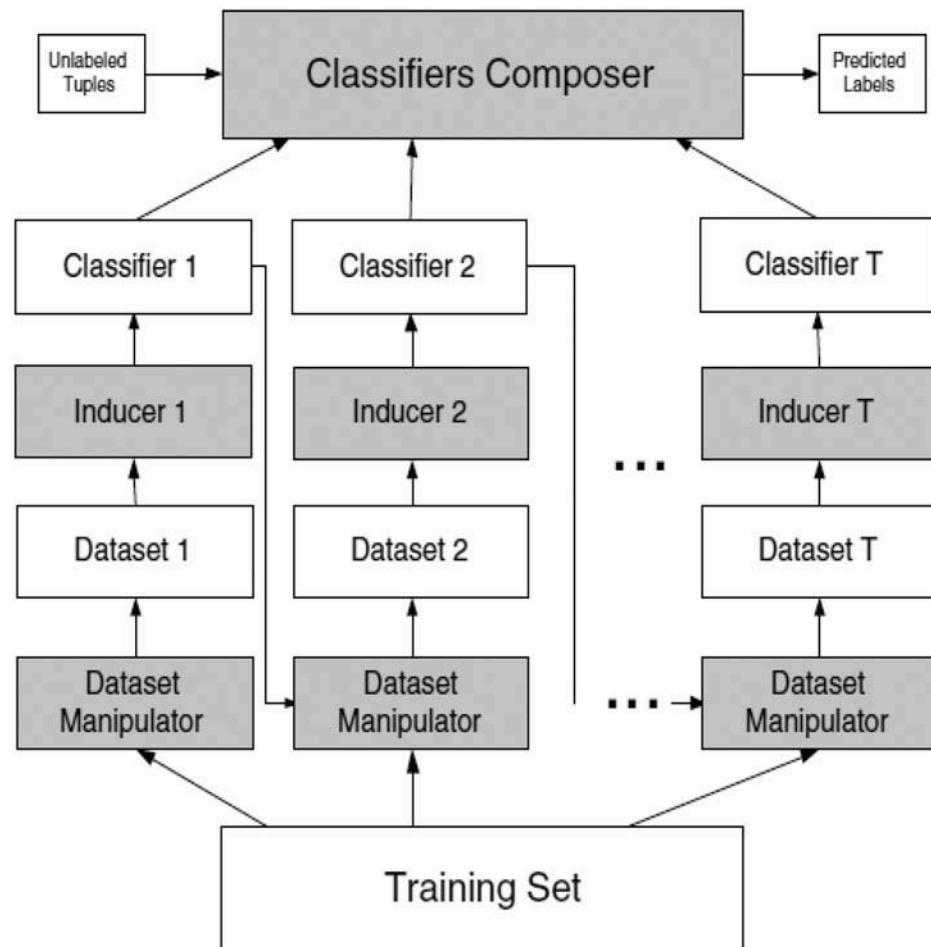
The independent framework method follows the framework as shown in Figure 2.

The general classifiers used in the ensemble method to extract the information content in the satellite image are discussed below.

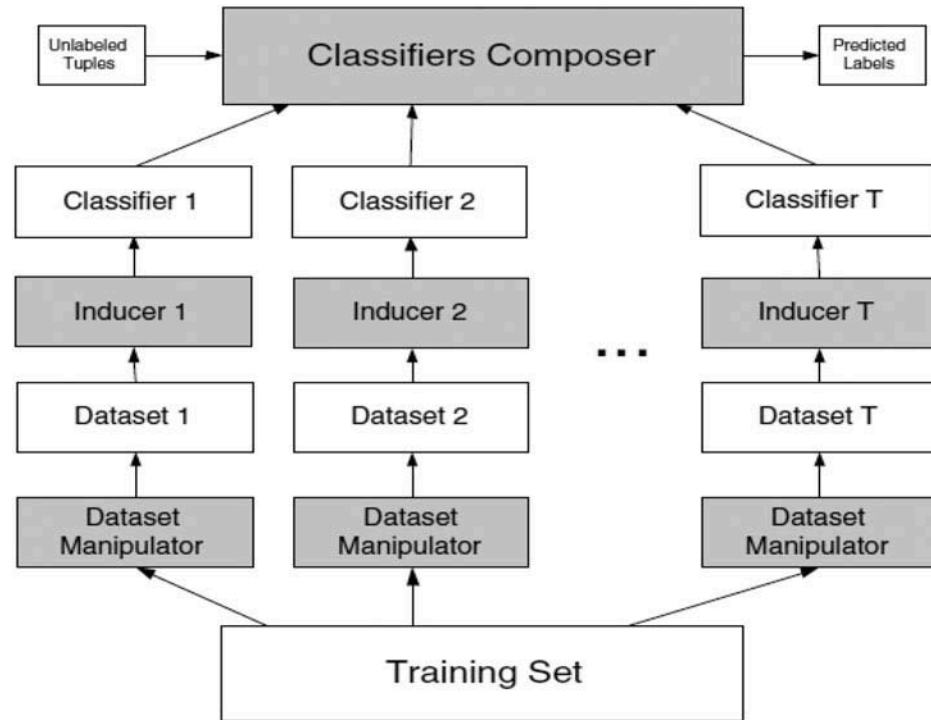
**(i) ML-classifier**

It is useful to classify the under lying data in remote sensing images, where classification is based on the ML of the pixel. For  $i$ th class, the posterior probability of a pixel is denoted by  $Y_i$ .

**Figure 1. Ensemble of different classifiers (dependent framework).**



**Figure 2. Ensemble of different classifiers (independent framework).**



$$Y_i = P(i/X) = P(i) \cdot P(X/i) / \sum P(j) \cdot P(X/j) \tag{1}$$

Where  $P(i)$  is the prior probability of class  $k$ .

$P(X/i)$  is the conditional probability to observe  $X$  from class  $i$ .

For normal distributions, the likelihood can be expressed as follows:

$$Y_i(X) = \frac{1}{(2\pi)^{\frac{a}{2}} |\Sigma_i|^{\frac{1}{2}}} \exp \left\{ -\frac{1}{2} (X - \mu_i) \Sigma_i^{-1} (X - \mu_i)^t \right\} \tag{2}$$

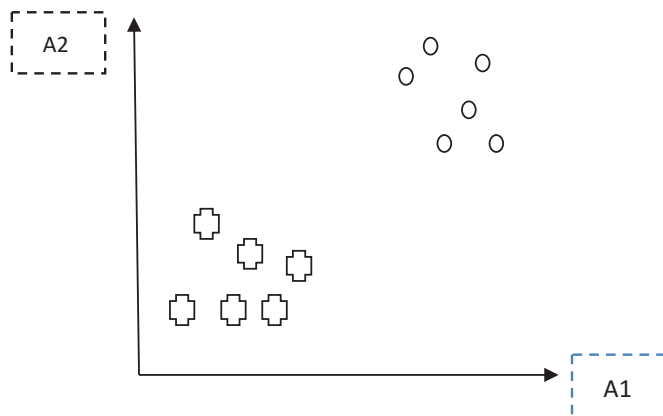
Where  $a, X, Y_i(X), \mu_i, \Sigma_i, |\Sigma_i|$  are different parameters of ML classifier

For symmetric variance-covariance matrix, the  $Y_k$  is the same as the Euclidian distance, whereas the determinants are same, the  $Y_k$  becomes the same as the Mahalanobis distances.

**(ii) SVM classifier**

SVM classifier working is based on hyperplanes, which are efficient for classification. It transforms low dimension space into high dimension space. SVM classifiers find applications in text categorization, time series analysis, database mining and face identification. This method is generally considered as the state of art classification method in the classification of medical images and satellite images. Linear and non-linear data can be classified using SVM based classification efficiently. Here non-linear mapping is the better way to convert original information into higher order data or dimension. Support vector is the base to identify the hyperplanes in SVM. Consider an example of a two-class SVM based on two input attributes as shown in Figure 3. It shows two input attributes of two classes SVM.

Figure 3. The 2-D training data.



### 3. Results and discussions

The change detection is based on post-classification approach and is performed on two temporal images. Ensemble subspace technique is used for classification of images. Ensemble technique is preferred because it results in better quality of classifier through which accurate change detection is possible. These methods can be applied for both low resolution and high resolution images. Table 1 gives confusion matrix containing four classes. The actual number pixels and predicted number of pixels produce the confusion matrix of the classification (Stanistaw, 2006). The correctly classified pixels appear in diagonal elements. Individual accuracies are calculated along with overall or final accuracy, and it is tabulated in Table 2. Table 3 shows different quality parameters for given satellite image like precision, recall, specificity and F1 score kappa values for the particular classifier.

The classes defined here are: agriculture fields, water, green land and barren land. These classes are shown with colours as Water (A)—Cyan, Agriculture (B)—Green, Barren Land (C)—Yellow, Green Land (D)—Blue. The tables contain A, B, C and D notations instead of defined classes for

Table 1. Confusion matrix

		Predicted				
		Class	A	B	C	D
Actual	A	38	10	0	0	48
	B	0	40	0	1	41
	C	0	3	51	3	57
	D	0	0	1	53	54
	Total	38	53	52	57	200

Table 2. Accuracy measurement for first image

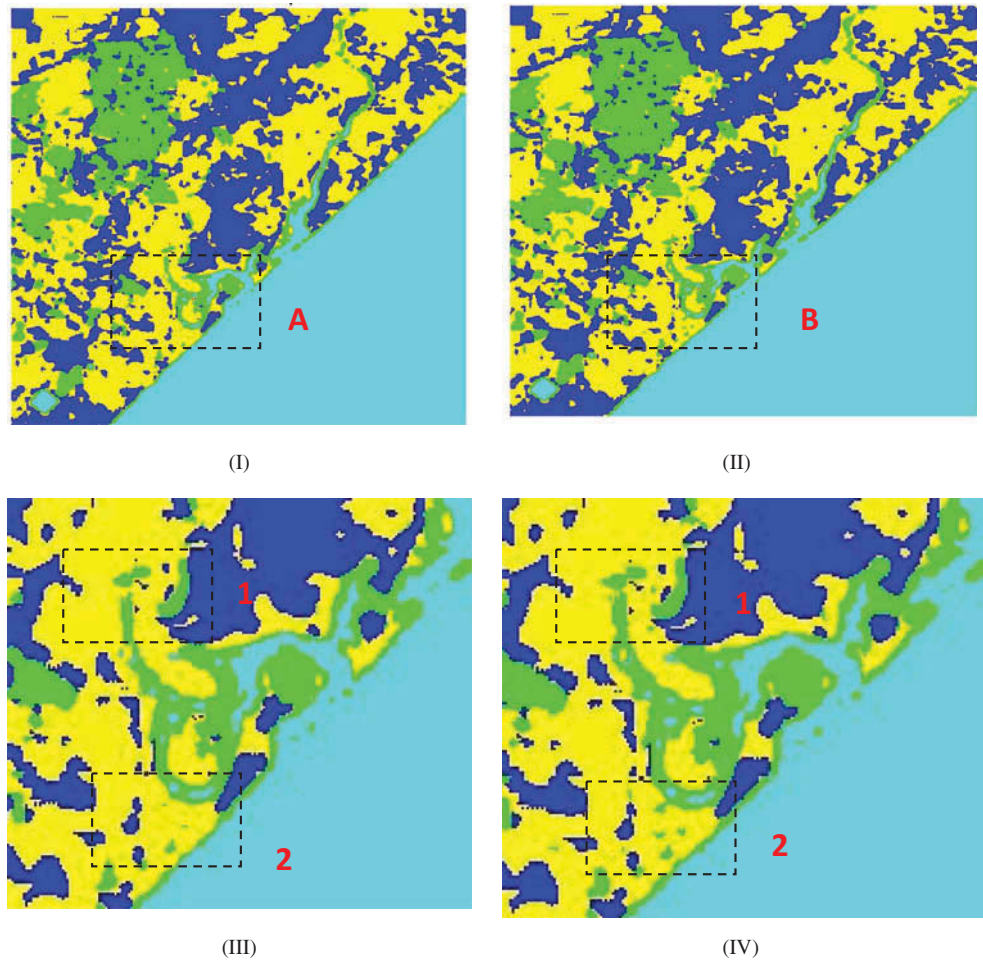
Type of land cover	Reference pixels	Classified pixels	Matching	Accuracy type	
				Procedures	Users
A	38	48	38	100.00%	79.17%
B	53	41	40	75.47%	97.56%
C	52	57	51	98.08%	89.47%
D	57	54	53	92.98%	98.15%
Total	200	200	182	91%	
Overall classification accuracy					

Table 3. Different quality parameters for first image						
	Accuracy	Precision	Recall	Specificity	F1 score	Kappa
A		1	0.791667	1	0.883721	0.742798
B		0.754717	0.97561	0.918239	0.851064	0.966816
C	0.91	0.980769	0.894737	0.993007	0.93578	0.857752
D		0.929825	0.981481	0.972603	0.954955	0.9741
Over all		0.916328	0.910874	0.970962	0.90638	0.879844

ease. Though 200 points are considered for getting the accuracy measurement for better comparison, these points are not the small number for 512\*512 images. From these points both user's and producer's accuracies are calculated. The various standard quality parameters used for deciding any classification process are calculated (Murali Mohan Babu & Radhika, 2016). From the ground truth values Kappa values are calculated. Kappa coefficient is a deciding value to specify whether the classifier is accurate or not. Better results are achieved for high resolution images compared with low resolution images (Lillesand & Kiefer, 2000).

Figure 4 shows Classified first image, Classified second image, Zoomed image of (I) and Zoomed image of (II). Table 4 gives the list of classes and corresponding pixels of first image. Table 5 gives

Figure 4. (I) Classified first image; (II) Classified second image; (III) Zoomed image of (I); and (IV) Zoomed image of (II).





**Table 4. List of classes and corresponding pixels of first image**

	Class	Pixels in class after classification Proposed method
1	Class1	86,405
2	Class2	33,555
3	Class3	79,340
4	Class4	62,844
Total		2,62,144

**Table 5. List of classes and corresponding pixels of second image**

	Class	Pixels in class after classification proposed method
1	Class1	86,838
2	Class2	33,275
3	Class3	81,259
4	Class4	60,772
Total		2,62,144

**Table 6. Change detection in pixels and area**

		First image		Second image		Change	
Class		Pixels	Area (m <sup>2</sup> )	Pixels	Area (m <sup>2</sup> )	Pixels	Area (m <sup>2</sup> )
Class1	Water	86,405	34,562,000	86,838	34,735,200	433 (Increase)	1,73,200 (Increase)
Class2	Agriculture	33,555	13,422,000	33,275	13,310,000	280 (Decrease)	1,12,000 (Decrease)
Class3	Barren Land	79,340	31,736,000	81,259	32,503,000	1,919 (Increase)	7,67,000 (Increase)
Class4	Green Land	62,844	25,137,000	60,772	24,308,800	2,072 (Decrease)	8,28,200 (Decrease)
Net						0	0

list of classes and corresponding pixels of second image. Table 6 contains change detection in pixels and area. Here both classified images pixels are compared and the changed areas are obtained. The table shows the total number of pixel change related to water, which is 433 and the area change, which is 1,73,200 m<sup>2</sup> (increased); total number of pixels change related to agriculture is 280 and the area change is 1,12,000 m<sup>2</sup> (decreased); total number of pixels change related to barren land is 1919 and the area change is 7,67,000 m<sup>2</sup> (increased); total number of pixels change related to green land is 2072 and the area change is 8,28,200 m<sup>2</sup> (decreased).

#### 4. Conclusion

In this work, the discussions are carried-out on ensemble techniques for better accuracy and standard quality assessment parameters. Different ground truth points (200 points) were considered with four classes: water, green land, barren land and agriculture for validation of classified output. Different quality parameters like accuracy, precision, recall, specificity, F1 score, kappa value, omission error and commission error were evaluated for individual class and for the overall classifier. Finally, pixels of each class were compared in the two classified images and the

corresponding area is also calculated. This analysis provided good change detection based on ensemble method. This analysis has been carried out for 512\*512 sized images. The results could be exactly analysed, if the considered satellite image is of high or good resolution. This analysis can be used in agriculture for crop monitoring, forest deformation, urban areas for developments and disaster management. This process and analysis can be extended to more number of classes and to bigger sized images with suitable processing speed of computer.

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No potential conflict of interest was reported by the authors.

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