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Monitoring Land Cover of Google Web Service Images through ECOC and ANFIS Classifiers

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***Abstract*—** Image classification is one of the most significant applications for remote sensing imagery which is used in a wide range of applications from military to farm development by the government and private agencies. The proposed work focuses on the land use / land cover classification using advanced supervised classification techniques, Error Correcting Output Code (ECOC) multiclass model classifier and Adaptive Neuro-Fuzzy Inference System (ANFIS) classifier. The samples of different classes such as, vegetation, quarry, water, wasteland and urban area were collected from different locations, refined, and trained on RGB, Gray and HSV color spaces based on the features mean, standard deviation, energy, contrast, entropy, and homogeneity. In ANFIS classifier when the number of inputs is more, the construction of FIS structure causes excessive propagation of number of rules which leads to memory overhead. Owing to this limitation, the number of features was restricted to mean and standard deviation in HSV and RGB color spaces. Based on the performance measures overall accuracy and kappa coefficient, it has been observed that the ECOC classifier produces better results in RGB color space and hence it has been applied on different locations of Tamil Nadu in Google Maps. From the results it has been proved that the ECOC classifier performs well when the ground cover nature is heterogeneous in nature.

***Keywords*—**Error Correcting Output Code (ECOC) multiclass model, True Color Composite Filter, Statistical Features, Textural Features, Google Maps' Images, Adaptive Neuro-Fuzzy Inference System (ANFIS) classifier

I. INTRODUCTION

The science and technology of Remote Sensing (RS) is the most fascinating and challenging subject for the past three decades, which offers unique capabilities for understanding, monitoring, forecasting, managing and decision making about our planet's resources via classification. Owing to the complexity of landscape, availability of reference data, selected remotely sensed data, and analyst's experiences the classification of remote sensing images is a challenging one. Supervised Classification techniques require training areas defined by the analyst in order to determine the characteristics of each category whereas the Unsupervised Classifications search for natural groups of pixels, called clusters, present within the data by means of assessing the relative locations of the pixels in the feature space. These techniques have some limitation in image classification without compromising the classification accuracy [1].

For environment conservation and land resource management, the recent advances in satellite imaging technology and classification methods have been acknowledged as the most successful techniques. Recently, more precise data have become available widely in digital form for urban land use/land cover mapping from high resolutions to moderate resolutions and hence the detailed mapping should be possible with high accuracy potential [2]. This paper focuses on Google Maps' image classification based on statistical and textural features such as mean, standard deviation, energy, contrast, entropy, and homogeneity using Error Correcting Output Code (ECOC) multiclass model classifier, and Adaptive Neuro-Fuzzy Inference System (ANFIS) classifier.

The rest of the paper is organized as follows. Section II describes the related works carried out on remote sensing image classification. The methodology of ECOC and ANFIS classifiers is described in section III. Results and performance evaluation have been carried out in section IV and the final section concludes this paper.

II. RELATED WORK

Contents of image such as color, texture, shape and size plays an important role in semantic image classification.

Many researchers apply various classification approaches for land cover classification.

Vegetation area that is surrounded by desert, urban, and road-street zones have been extracted by Mohamed (2012) from Google Earth images based on back propagation neural networks. In his work samples were collected from different vegetation scenes scattered across the Google Earth images of the desert surfaces of Qatar. The statistical features mean and standard deviation have been calculated for each Hue (H) and Saturation (S) components with its eight neighbours and has been trained to detect the vegetation [3].

Recently a promising pattern classification approach, Support Vector Machine (SVM) has been frequently used in the field of land use/land cover classification. Initially it was designed for two-class problems, which finds the hyperplane that maximizes the distance to the closest training data points in both classes. From binary SVMs several algorithms have been proposed to generate multiclass SVMs and the most suitable one is one-against-one (OAO) [4, 5].

Even though SVMs have peculiar advantages in the problems with small sample size, nonlinearity, and high dimensionality, it is less applicable to solve land use/land cover multiclass classification problems. An Error Correcting Output Coding (ECOC) framework has been proposed by Dietterich to convert multiclass problem into several two-class problems. The combination of ECOC with SVM OAO is a powerful tool which enhances the fault tolerance of multiclass classification models. It has error-correcting properties and also it reduces the bias and variance produced by the learning algorithm. So it has been used in multiclass categorization problems for improving the performance of inductive learning programs [4, 6, 7, 8].

For environmental modelling, artificial neural network (ANN) is a powerful tool with the ability to capture the non-linear relationships present in many geographic phenomena. Madhubala et al. (2010) describes the classification of Linear Imaging Self Scanning sensor (LISS-III) images using ANN by local classification and global classification based on the features mean, Euclidean distance and RGB values. In local classification the training and testing were performed on same image whereas on different images in global classification. From the result it was observed that the accuracy is improved by increasing the number of samples and also training with more and more images [9].

ANFIS is the integration of ANN and fuzzy logic models to fuse the capabilities of ANNs self-learning with the linguistic expression function of fuzzy inference system (FIS). Also it obviates many of their shortcomings such as the lack of flexibility in ANN and finding out the correct positions and shapes for membership functions in FIS [10].

Mojedifar (2013) investigated the potential of an ANFIS by classifying the Advanced Space-borne Thermal Emission and Reflection Radiometer (ASTER) data based on the spectral properties of rocks in mapping the distribution of hydrothermally altered areas. The authors demonstrated that the ANFIS method yielded the best classification than the Maximum Likelihood Classifier (MLC) and ANN [11].

Bernabe and Plaza (2010) have developed a tool to select the location in Google Maps at the maximum zoom level, and classify it using unsupervised k-means technique, and view the classified area in different zoom levels [12].

Hypergim, a new web platform, enables the users to perform the classification of satellite images from Google Maps using unsupervised Isodata and k-means algorithms. Agustin et al., (2016) improved the classification results of Hypergim using supervised Random Forest algorithm which is trained through the tool and allow the users to label the samples directly on the image [13].

Now Google Maps provides regularly updated high resolution satellite and aerial images with good quality and high zooming level from many locations around earth. Owing to the lack of a guideline for selection and the availability of suitable classification algorithms in hand, it is difficult to identify the best classifier for Google Maps' images [1, 12, 13, 14, 15]. With these considerations in mind, this study attempts to examine the Google Maps remote sensing data to extract the land covers using the two powerful supervised classifiers, ECOC and ANFIS.

III. METHODOLOGY

III.I Study Area

Web mapping services have become a key tool for remote sensing image analysis which can now be used as a powerful source of high resolution satellite/airborne imagery across the entire world. A popular web mapping service is a Google Maps which is developed by Google and launched in February 2005 to offer the remote sensing images freely. The study areas used in this work are pallipalayam – near Erode, Kodangipalayam – near Palladam, Sulur Lake – near Coimbatore, located within Tamil Nadu, the southern India were captured from Google Maps (CNES/Airbus, DigitalGlobe, Map data 2017). The block diagram of the proposed system is shown in Figure 1.

III.II Pre-processing

In a 'true color' image the three visual primary color bands red, green and blue are assigned to the R, G, and B colors for display so that it resembles closely what the human eyes would observe. The true color composite has very little contrast and the colors are unbalanced. The data concentrated within a small part of an available dynamic range makes it to appear dull. Another reason for the dull appearance is the highly correlated visual bands. So de-correlation stretch has been applied to enhance the true color composite image followed by a linear contrast stretch.

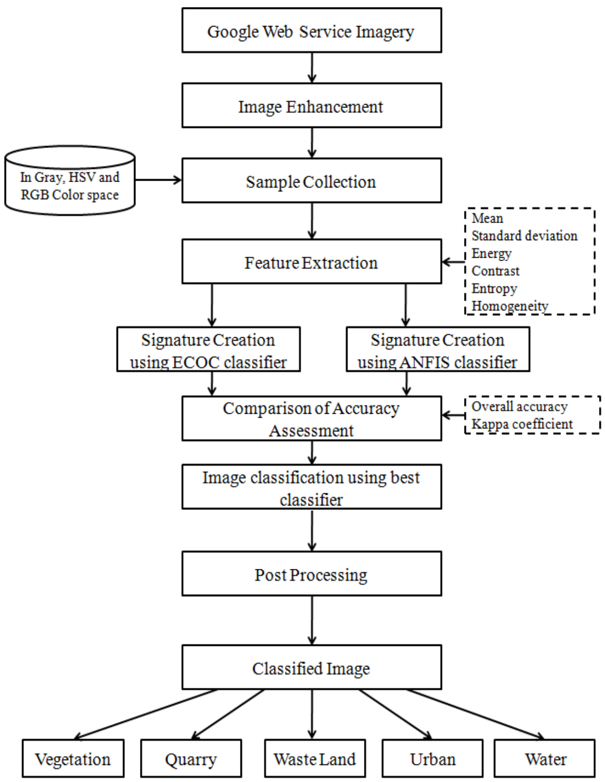


Figure 1. Block diagram of the proposed system

De-correlation stretch enhances the color separation across highly correlated channels so that the surface features have become more clearly visible and been exaggerated. In linear contrast stretch the data has been spread much more of the available dynamic range to recognize the surface features easier.

III.III Data Set

Ground reference data for the land covers, namely, vegetation, quarry, wasteland, urban area, and water body have been chosen in a random manner from the image to guarantee that there is no bias in the selection. For each of the land cover types, 5x5-pixel sub-images of dispersed samples were selected from the three images in RGB, HSV and Gray color spaces (refer Table 1). After collecting the samples, the six feature vectors mean, standard deviation, energy, contrast, entropy, and homogeneity for each region in R, G, B, H, S, and Gray colors were calculated and the corresponding classes were identified. Before classifying the full scene, a preliminary classification is made on the training set pixels, to determine the percentage of the pixels which are actually classified as expected.

Algorithm

a) *Capture snapshots of a location*
b) *Enhance the true color composite image.*
c) *Collect the samples for each class in RGB, HSV and Gray color space*
d) *Compute the features for each band in all color space*

III.IV Feature vectors Extraction

In texture training, the feature database is created from each sample (X) of three colour space. The mean and standard are calculated from original values of gray, H, S, R, G, and B bands. Whereas the other features such as contrast, energy, entropy and homogeneity are calculated from their co-occurrence matrix C(i,j) using the Eq. (1) to Eq. (6).

$$Mean = \frac{1}{N^2}\sum_{i=1}^{N}\sum_{j=1}^{N} x_{i,j} \quad (1)$$

$$Std\ Dev = \sqrt{\frac{1}{N^2}\sum_{i=1}^{N}\sum_{j=1}^{N}\left(x_{ij}-\bar{x}\right)^2} \quad (2)$$

$$Contrast = \sum_{i,j=1}^{N}(i-j)^2 C(i,j) \quad (3)$$

$$Energy = \sum_{i=1}^{N}\sum_{j=1}^{N} C(i,j)^2 \quad (4)$$

$$Entropy = -\sum_{i=1}^{N}\sum_{j=1}^{N} C(i,j)\log(C(i,j)) \quad (5)$$

$$Homogeneity = \sum_{i,j=0}^{N}\frac{1}{(1+(i-j)^2)} * C(i,j) \quad (6)$$

III.V Training Phase

The representative training area has been identified and the numerical description for the texture attributes in each land cover types of interest present in a scene has been developed. Success of the classification is determined by the quality of training process. For delineating the training set pixels throughout the scene, it is important to analyze the dispersion of the sites present in the scene to increase the chance of all variations in the cover types. The accuracy has been improved by adding the important spectral classes and omitting the redundant spectral classes through self classification.

III.VI Classification Phase

The classification stage determines the identity of each pixel by evaluating the spectral patterns in the data set using ECOC and ANFIS classifier. The most closely resembled pixels in the data set are categorized and labelled into the land cover class and recorded in the corresponding cell of an interpretation data set.

III.VI.I ECOC classifier

In this approach, ***m(m-1)/2*** binary SVM classifiers are generated for ***m*** classes and assigns the instance to one of the two classes, then increase the vote for the assigned class by one. An error correcting code, a bit vector, is assigned to each class and the right class for a given unknown tuple can be identified by having additional bits. The 'closest' class of errors has been identified using Hamming distance measurement. Coding is required to determine the classes that the binary learners train and decoding scheme is required to aggregate the predictions of the binary classifiers. It reduces the problem of classification with three or more classes to a set of binary classifiers using one-versus-one in coding design and Hamming distance in decoding design (Figure 2). For each binary learner, one class is positive, another is negative, and ignores the rest. This design exhausts all combinations of class pair assignments.

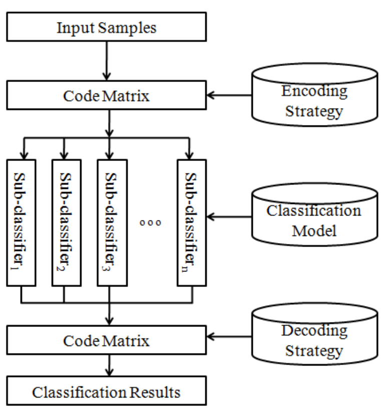


Figure 2. ECOC algorithm framework

Algorithm

a) *Generate m by n -1/0/1 coding matrix C*
b) *Construct n binary SVM OVO classifier*
c) *Aggregate the predictions of the classifiers*

III.VI.II ANFIS classifier

An adaptive network consists of nodes which are connected by the collection of modifiable parameters as directional links whose values determine the overall input-output behaviour. ANFIS is the Sugeno-type fuzzy model, a framework of the adaptive system, whose parameters have been identified by a hybrid learning algorithm (Figure 3). For the given set of input-output parameters, the ANFIS method build a FIS model and tune its membership function parameters by a back propagation algorithm alone, or in permutation with a least squares type of method [16].

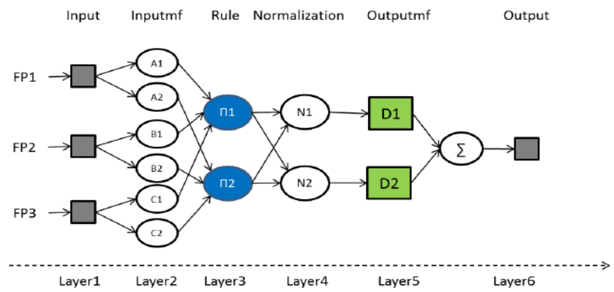


Figure 3. ANFIS architecture.

Algorithm

a) *Generate FIS*
b) *Choose the FIS model parameter optimization method: back propagation or a mixture of back propagation and least squares*
c) *Choose the number of training epochs and the training error tolerance.*
d) *Train the FIS model to adjusts the membership function parameters*

III.VII Testing Phase

For the three images the signatures were created by ECOC and ANFIS classifiers using 70% of the training data based on the features. The 30% of the testing samples were classified based on the signatures and the accuracy has been calculated from the error matrix.

III.VIII Evaluation Measures

Classification performance can be evaluated by the preparation of error matrix with number of rows and columns are equal to the number of categories that has been classified. Error matrix compares the relationship between the results of the classifier and the corresponding known reference data on a category-by-category basis.

The ratio between the sum of elements along the diagonal and the total number of reference pixels gives the overall accuracy of classification. The overall statistical agreement of an error matrix can be measured by Kappa coefficient which takes non-diagonal elements into account and computed as

$$\hat{k} = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}(x_{i+} \, . \, x_{+i})}{N^2 - \sum_{i=1}^{r}(x_{i+} \, . \, x_{+i})} \qquad (1)$$

where

r = number of rows in the error matrix

x_{ii} = number of observations in row i and column i

(on the major diagonal)
x_{i+} = total of observations in row i
x_{+i} = total of observations in column i
N = total number of observations included in matrix

III.IX Post processing

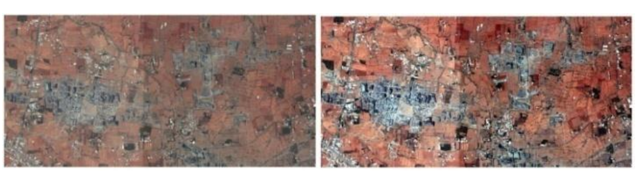
Due to the inherent spectral variability encountered by the classifier, the salt-and-pepper appearance of the classified output to be smoothed on the basis of logical operations to show only the dominant classification. In majority filter the moving window is passed through the classified dataset and the central pixel value has been set as majority class present in the window, if it exist [17].

IV. RESULT AND PERFORMANCE EVALUATION

Google Maps service has been used as a baseline for this study. 200m spatial resolution of different locations were captured from the Google Maps images within Tamil Nadu, India which includes the five land covers, namely, vegetation, quarry, water body, wasteland, and urban area. The input images and their corresponding enhanced images are shown in the Figures 4, 5, and 6. The reference data of 5 x 5 pixel size were collected from each enhanced image is shown in the Table 1. The six features were calculated for RGB, HSV, and Gray colour spaces.

a) Original Image b) Enhanced Image
Figure 4. Pallipalayam

a) Original Image b) Enhanced Image
Figure 5. Sulur Lake



a) Original Image b) Enhanced Image
Figure 6. Kodangipalayam

The samples of each class were split into two groups randomly of size 70% for training and 30% for testing. ECOC multiclass model and ANFIS classifiers are used to train and test the samples. In ANFIS back propagation with least squares is chosen for FIS parameter optimization and trained for 60 epochs. Using measures overall accuracy and kappa coefficient the results are evaluated. The best training group for each class in each image has been selected based on the accuracy. Finally the training sets for each class has been created by combining each best group and refined by removing the duplicate entries.
The samples of each class were split into two groups randomly of size 70% for training and 30% for testing.

Table 1. Reference Data Set

Pallipalayam				
Class	*Type*	*Test*	*Train*	*Total*
C1	Vegetation	53	122	175
C2	Quarry	30	70	100
C3	Wasteland	60	140	200
C4	Urban	23	52	75
			Total	550
Sulur Lake				
C1	Vegetation	120	280	400
C3	Wasteland	98	227	325
C4	Urban	135	315	450
C5	Water	90	210	300
			Total	1475
Kodangipalayam				
C1	Vegetation	12	28	40
C2	Quarry	26	62	88
C3	Wasteland	32	76	108
C4	Urban	19	45	64
			Total	300

In ANFIS back propagation with least squares is chosen for FIS parameter optimization and trained for 60 epochs. Using measures overall accuracy and kappa coefficient the results are evaluated. The best training group for each class in all images have been selected based on the accuracy. Finally the training sets for each class has been created by combining the best group and refined by removing the duplicate entries.

Since the image is classified based on samples of the classes, the actual quality should be checked by sampling approach. In which, number of raster elements are selected and the classification results are computed. This result is compared with the true class and the error matrix is created to calculate the accuracy measures. The accuracy assessment of the ANFIS and ECOC classifiers have been discussed in three different colour spaces based on statistical features mean and standard deviation. Improvement of the accuracy has been studied by increasing the number of features such as energy, contrast, entropy, and homogeneity.

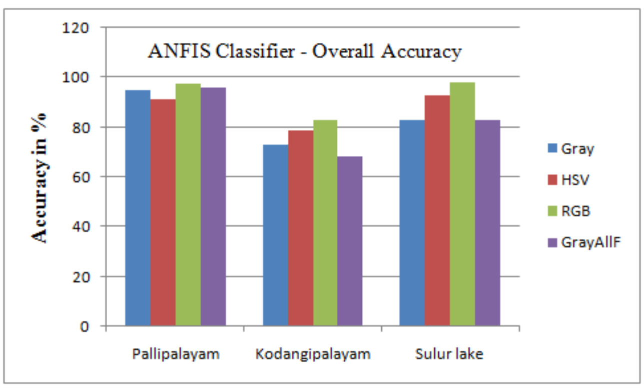
For each feature, construction of FIS structure in ANFIS causes excessive propagation of number of rules, when the number of inputs is moderately large that is more than four or five, which leads to memory overhead due to curse of dimensionality problem. Also the tuning process is repeated for every feature which results in more time complexity.

Table 2: Overall accuracy and kappa coefficient of three different images using ANFIS and ECOC classifier

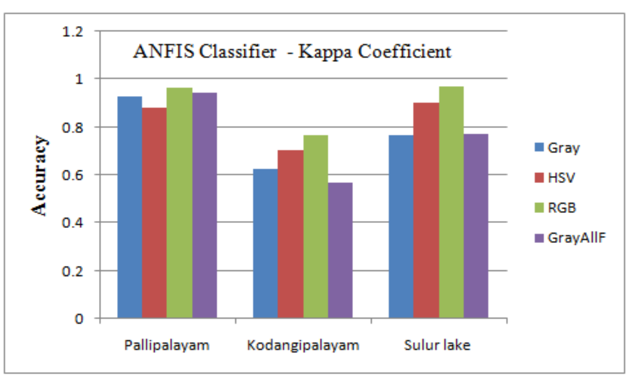
Images	Accuracy	ANFIS				ECOC					
		Using Mean and STD			Using all features	Using Mean and STD			Using all features		
		Gray	HSV	RGB	Gray All F	Gray	HSV	RGB	Gray All F	HSV All F	RGB All F
Palli palayam	Overall accuracy	94.77	91.5	97.39	96.08	86.27	88.89	92.81	97.39	88.24	**98.69**
	Kappa coefficient	0.9274	0.8803	0.9638	0.9448	0.8010	0.8457	0.8973	0.9638	0.8344	**0.9818**
Kodangi palayam	Overall accuracy	73.03	78.65	83.15	68.54	52.81	88.76	86.52	67.42	94.38	**95.51**
	Kappa coefficient	0.6254	0.7035	0.766	0.5690	0.3161	0.8439	0.8128	0.5537	0.922	**0.9376**
Sulur Lake	Overall accuracy	82.73	92.81	97.84	83.21	70.74	79.38	92.57	76.26	86.33	**98.8**
	Kappa coefficient	0.7666	0.9028	0.9708	0.7731	0.6046	0.7214	0.8996	0.6792	0.8153	**0.9838**

Thus ANFIS classifier is applied to only gray colour space when all six features are considered, whereas while considering the features mean and standard deviation, ANFIS is applied to all three colour spaces gray, HSV and RGB. To evaluate, overall accuracy and kappa coefficient are computed and the same are summarized in Table 2.

From the Figure 7, it can be easily identified that ANFIS classifier gives better overall accuracy and kappa coefficient in RGB colour space with minimum features in all the three images. In ECOC classifier, multiclass problem is converted into several two-class problems and run in parallel leads to less time complexity and needs less memory. So it works in all colour spaces and the results are shown in the Table 2.

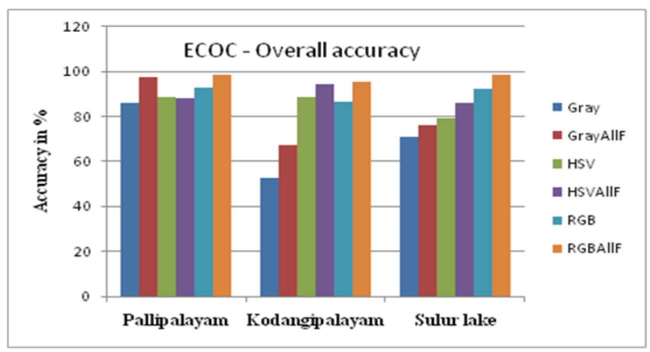


a) Overall Accuracy

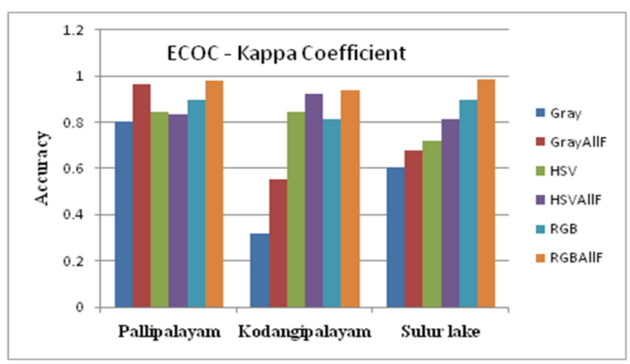


b) Kappa Coefficient

Figure 7. Accuracy of ANFIS classifier

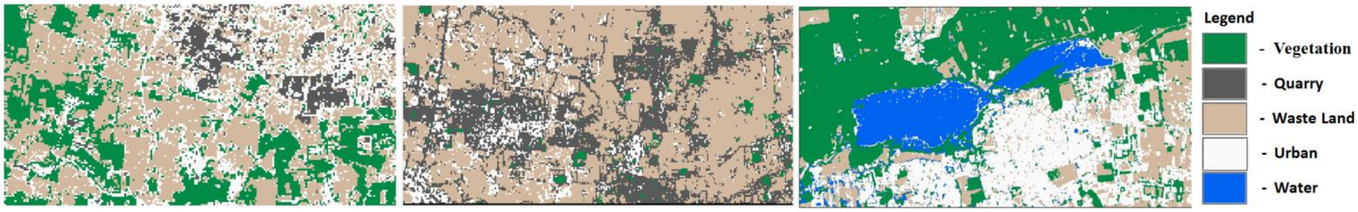


a) Overall Accuracy



a) Kappa Coefficient

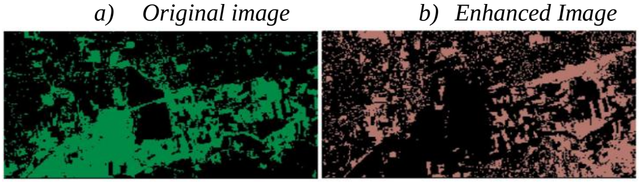
Figure 8. Accuracy of ECOC classifier



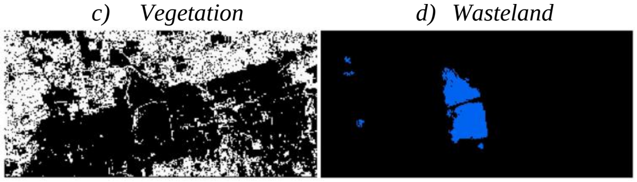
a) Pallipalayam *b) Kodangipalayam* *c) Sulur Lake*

Figure 9. Classified Image of Figure 4,Figure 5, and Figure 6.

a) Original image *b) Enhanced Image*



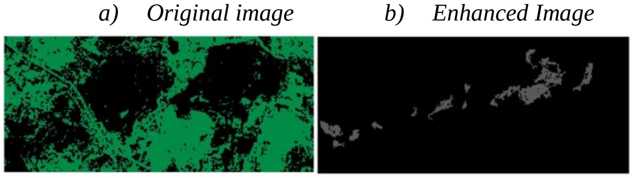
c) Vegetation *d) Wasteland*



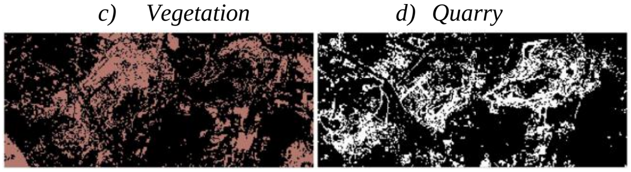
e) Urban Area *f) Water*

Figure 10. Singanallur Lake Area

a) Original image *b) Enhanced Image*



c) Vegetation *d) Quarry*



e) Wasteland *f) Urban Area*

Figure 11. Manipal Hospital Area

From the Figure 8, it has been observed that ECOC classifier produce better accuracy on RGB colour space with all features. For each 5x5 non-overlapping test samples from the original image, calculate all the features in each R, G, and B band and classify the pixel based on the trained set. Based on training and testing phase results, the Google Maps' image has been classified using ECOC classifier with the best training samples and the classified image is post-processed and is shown in Figure 9.

The global training set is constructed by combining the samples collected from the three images and tuned by removing duplicate with wrong classified entries. This training set and ECOC classifier is applied on new Google maps' images, Manipal Hospital area, near Salem and Singanallur Lake area, near Coimbatore and the classified results are shown in the Figures 10 and 11.

The visual inspection of the classified images indicates that ECOC algorithm is generally capable to detect the patterns present in the image. In the case of Singanallur Lake area, ECOC classification technique performs well when the actual ground cover is heterogeneous in nature. But in Manipal Hospital area, the water bodies which constitute less than 1% of the total area are misclassified indicating requirement of adequate training sites representing water category. Other classes are classified correctly which indicates better behaviour of ECOC classifier.

V. CONCLUSION

Recent advances in satellite imaging technology and classification methods have increasingly been acknowledged as the most successful techniques for environment conservation and land resource management. Recently, more precise data have become available widely in digital form for urban land use/land cover mapping from high resolutions to moderate resolutions. This paper uses the Google Maps as a source of satellite imagery for extracting urban land cover in Tamil Nadu, India.

Land use / land cover classification by ANFIS and ECOC techniques with the features mean, standard deviation, energy, contrast, entropy, and homogeneity is proposed in this paper. On different location with 200m spatial resolution the samples for different classes were collected, refined, and trained on RGB, HSV and Gray colour spaces. Due to storage overhead and high time complexity ANFIS classifier is not applicable when all the six features are considered. Based on the evaluation measures overall accuracy and kappa coefficient, it has been proved that the ECOC classifier with six features (statistical and texture) generate better results in RGB colour space. Hence ECOC classifier is applied on two different locations from Google Maps' images and it produces more accurate results. Since this work is purely based on the intensity values, the water body and vegetation areas are similar in some locations which may lead to misclassification. In future, it is proposed to reduce the errors in classification and is also planned to focus on the usability of this information in the urban planning.

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