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Comparative Study on Detection and Classification Approaches on Man-Made Objects from Satellite Images

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Abstract**—** Automatic extraction of buildings and change detection of buildings from satellite images is an important tool for city management and planning. The discovery of changes is the process of identifying differences in the state of the objects extracted from the remote image by observing different time periods. The main objective of this paper is to extract the manmade objects (buildings) from the given input satellite images and detect the changes in the extracted building map. This work presents the Region of Interest (ROI) and extraction of the building using K-Nearest Neighbor (KNN), Support Vector Machine (SVM) and Extreme Learning Machine (ELM) techniques. Initially, the input satellite image is de-noised by using the Wavelet Shrinkage de-noising approach. Then the K-Means, Fuzzy C-Means (FCM) and Artificial Bee Colony (ABC) approaches are applied to the de-noised image to segment the vegetation and non-vegetation areas and then extract the features using Local Binary Pattern (LBP) Technique. Finally, the extracted features are given to the KNN, SVM and ELM classifier to get the building map and then the change detection process is applied. In this paper, the comparison is made on three clustering approaches and three classifier approaches to find the best approach for manmade object extraction. From the experimental result, it is shown that the ABC approach performs better than K-Means and FCM in clustering and ELM provides the best result than the KNN and SVM in classifiers.

Keywords**—** Building Extraction, Vegetation, Non-Vegetation, Wavelet Shrinkage, FCM, K-Means, ABC, LBP, KNN, SVM, ELM

I. INTRODUCTION

Urban areas are one of the most exquisite regions of the globe due to the rapid expansion of the city and urbanization. The modern world needs accurate information about these changes for updating the databases of geographical information systems (GIS). GIS update information is used for major applications such as city planning, business planning, road networking, asset valuation, disaster management, etc. With the rapid progress of a recognized image sensor remotely from satellite are become the most important data source for tracking and updating GIS maps. The discovery of changes is the process of identifying differences in the state of the objects extracted from the remote image by observing different time periods. This thesis relates to the collection of artificial objects (in particular, buildings) in the urban areas and to identifying the exchanges of these objects using high-quality satellite imagery.

The main aim of this paper is to compare various steps used to find the changes in human-made objects such as building using high-resolution satellite images in order to update GIS. The objective can be subdivided into the following tasks:

1. implementation of existing methods such as segmentation and classification approaches;
2. studying the limitations and advantages of these implemented methods, and
3. detect the best method for development of a new automated technique for the segmentation, and classification of man-made objects such as buildings.

The remainder of the paper is organized as follows Section I contains the introduction of man-made object extraction and its uses, Section II contains the related work of man-made object extraction methods. In Section III, the proposed method is specifically depicted, including its design idea and practical implementation approach. In Section IV, the performance of the proposed method is evaluated. Finally, conclusions are made with future directions in Section V.

II. RELATED WORK

Building detection from 2–D images has been achieved using a variety of methods, where a building can be described either as a group of pixels sharing some common properties or as an object described by specific features or geometric properties. Pixel-based methods attempt to extract buildings by appropriately clustering image pixels into homogeneous regions. An overview of the most popular among these methods follows.

They proposed an active contour algorithm to segment buildings from the background. The initialization of the active contour algorithm was made using a circular cast algorithm [1]. A level set segmentation approach to the building detection task, based on the notion that buildings can be described by certain characteristics (shape, colour, texture, etc.) that allows the construction of a suitable energy function, was suggested in [2]. Unfortunately, it is often hard or even impossible to construct an energy function that can characterize every building in an urban area, due to colour and shape variations buildings demonstrate. As in our approach, several other methodologies take advantage of the normalized difference vegetation index (NDVI) to separate man-made objects from vegetation. Singh et al. employed NDVI to remove vegetation and filtered the remaining image regions to keep only those with sizes in a range capable to represent building candidates [3]. A similar strategy was followed in [4] with the addition of an object-based classification procedure after the vegetation removal to differentiate blobs that belong to buildings from blobs that do not.

On the other hand, object-based methods identify features or extract shapes from an image that can characterize buildings. Sirmacek and Unsalan [5] employed a building detection method based on the combination of scale-invariant feature transform keypoints and graph theory. They used subgraph matching to detect urban areas and graph cuts to identify separate buildings in an urban environment. In another work, the same authors developed a method to extract corners [Harris, features from accelerated segment test (FAST)], Gabor features, and gradient-magnitude-based support regions (GMSR) from satellite and aerial images. They computed the kernel density estimation of these features and merged those using data and decision fusion schemes to locate building centres [6]. In several studies, lines proved to be significant features for the task of building detection. Lines can either be found by Hough transform [7] or by detecting edges and forming edge chains. Edge chains were employed in [8] to identify lines, which were used at a later stage to form building candidates. Possibly missing lines were inferred and rectangles were formed.

Another building detection method based online grouping was attempted in [9], while in [10], the authors combined line grouping and corner labelling to form building hypothesis. Parameterized shapes, namely templates, are used as an alternative way to solve the task of building detection. Vinson et al. [11] used deformable templates of arbitrary scale and orientation to fit with the blobs extracted after applying a height threshold to a digital elevation model. Karantzalos and Paragios [12] combined a level-set segmentation approach driven by 2–D shape priors to achieve building segmentation in urban areas. They demonstrated that the introduction of shape templates in a data-driven approach can improve the building detection results. Shadow detection has also been incorporated into several building detection methods, as a way to denote the existence of tall structures, which can be candidate buildings [4], [13]. However, shadow detection techniques can be significantly affected by the position of the sun the time the image is captured. The advances in the field of artificial intelligence have sparked the use of machine learning techniques to solve the problem of building detection. Superpixels, the smallest clusters of pixels with similar multispectral information that can be formed, were employed in [14].

The authors used conditional random fields to label superpixels and form building candidates. Shackelford and Davis [15] employed a pixel-based fuzzy classifier to label pixels in a multispectral image and a region merging segmentation procedure to split an image into meaningful disjoint sets of pixels. Afterwards, they used skeletonization and polygon approximation procedures to infer the boundaries of the identified buildings. Similarly, fuzzy logic inference with texture and line features was employed in [16] to detect buildings in an aerial image. To identify building regions, Scenarios et al. [17] extracted various spectral, texture, and shape features trained a base-layer fuzzy classifier for each feature and fused these classifiers' decisions by a meta-layer fuzzy classifier. Chai et al. [18] used a Markov random field (MRF) for low-level modelling of spectral data and marked point processes for high-level modelling of buildings.

They combined these two models and optimized the results using simulated annealing in order to segment buildings from the background. An MRF framework that exploits knowledge specific to the particular appearance of buildings, such as shadow, rectangularity, and vegetation, was also employed in [19] to detect buildings. Finally, Femiani et al. [20] took advantage of shadow information and vegetation constraints to drive a graph-cut algorithm toward a successful building segmentation. The methodology proposed in this paper is an object-based approach to the problem of building detection. It is a continuation and extension of our previous work [21], where histograms of oriented gradients (HOG) features [22] are extracted and trained using a support vector machine (SVM) classifier. In this study, however, the HOG features are enhanced with the concatenation of local binary patterns (LBP) features [23], [24]. The combination of HOG and LBP features has been previously employed in various human detection tasks with great success [25], [26].

One of the main contributions of this paper is the use of a novel special de-noising measure that computes the distance between the HOG–LBP features in the SVM classifier. A cosine-based distance function was initially introduced by Fitch et al. in an attempt to robustly and accurately compute the translational displacements between video frames [27]. This distance function was found to allow for a suppression of the effects of noise and outliers and be more robust than its l2 -norm counterpart. Therefore, in this paper, the SVM classifier is trained on the HOG–LBP descriptors using the above-mentioned cosine-based distance function. Furthermore, we propose a novel and accurate region refinement procedure that receives the output of the HOG–LBP detector and outputs candidate building regions. To achieve this, image segmentation is performed using the expectation-maximization (EM) algorithm [28] and then image regions are selected as most probable to contain buildings. The selected regions are further processed and final building candidates are formed, while false alarms are rejected.

III. METHODOLOGY

In this procedure, first, the input satellite image is pre-processed. The schematic diagram of this work is shown in Fig.1.In the segmentation step, the input image is segmented into vegetation and non-vegetation regions. After that, vegetation regions are eliminated and only non-vegetation candidate regions are left. In the feature extraction step, multiple features are extracted to describe each non-vegetation regions. Once the features are generated, the previously trained classifier model is employed to classify the vegetation candidate regions into buildings. After that, the change detection is done on the classified building images based on distance metrics. In the end, the detection results are validated and analysed by using the performance metrics. In the rest of the section, the proposed method is explained in a detailed manner. The proposed work is divided into five steps. They are

1. Pre-processing
2. Segmentation
3. Feature Extraction
4. Classification
5. Change Detection

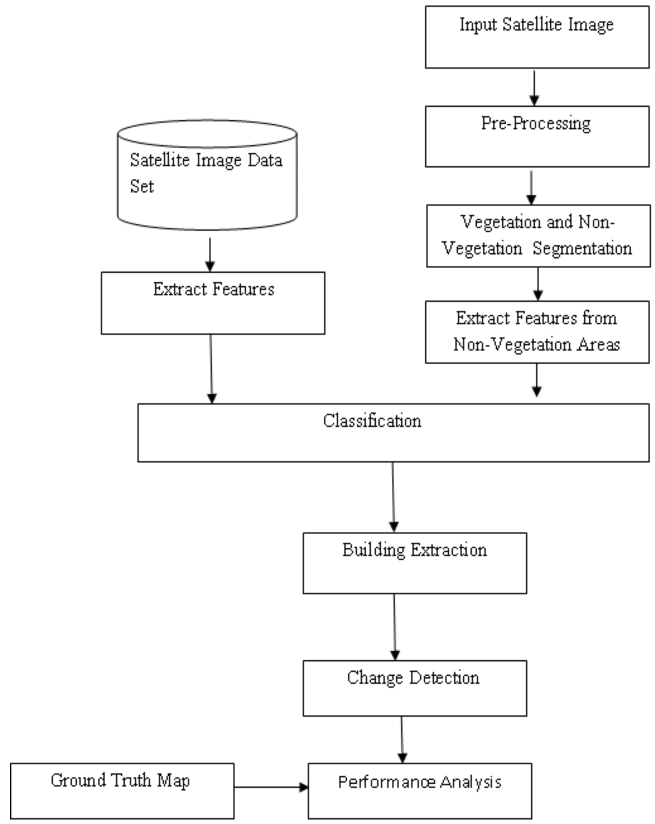

Figure. 1. Overall Flow Diagram of Classification Methods

A. *Pre-Processing*

This is the first step of change detection of man-made objects. Our change detection technique is based on the detection of the boundaries of each building. The results of our algorithm are very much dependent on the clarity of the input satellite images. Noisy information in the satellite image is one of the great reasons to reduce the accuracy of the detection of changes. So this work uses the speckle noise reduction method. Standard speckle reduction methods tend to blur the image. In particular, edges are smoothed and strongly isolated scatterers are removed. Because these two features are very important, Pizurica developed a speckle reduction method based on context-based locally adaptive wavelet shrinkage [24]. The idea is to estimate the statistical distributions of the wavelet coefficients representing mainly noise and representing useful edges.

In particular, it was noted that in high-resolution satellite images, the magnitudes of the wavelet coefficients representing mainly noise follow an exponential distribution while those representing a useful signal follow a Gamma distribution. This information is used to find a threshold that allows distinguishing useful signal from noise. Prior knowledge about possible edge configurations is introduced using a Markov Random Field.

B. Segmentation

This is the second step of the proposed work. After completing the pre-processing step the vegetation and non-vegetation area needs to be divided from the pre-processed image to detect the rough location of the buildings. To do this work, the segmentation approaches are used. Among several segmentation approaches, this chapter only deals with the K-Means, Fuzzy C-Mean Clustering and Artificial Bee Colony approach.

K-Means Clustering

1. Place K points into the space represented by the objects that are being clustered. These points represent initial group centroids.
2. Assign each object to the group that has the closest centroid.
3. When all objects have been assigned, recalculate the positions of the K centroids.
4. Repeat Steps 2 and 3 until the centroids no longer move. This produces a separation of the objects into groups from which the metric to be minimized can be calculated. It is calculated by using the below formula

$$J = \sum_{j=1}^{k} \sum_{i=1}^{n} \left\| x_i^{(j)} - c_j \right\|^2 \quad ,(1)$$

where $\left\| x_i^{(j)} - c_j \right\|^2$ is a chosen distance measure between a data point $x_i^{(j)}$ and the cluster centre c_j, is an indicator of the distance of the *n* data points from their respective cluster centres.

Fuzzy C-Means Clustering

Clustering involves dividing the image pixel from the given input pre-processed image into different classes based on intensity value. So that pixel in the same class is similar as possible and the pixel in the different classes is as dissimilar as possible. Many clustering algorithms have been introduced in the earlier. Since clusters can formally be seen as subsets of the data set, one possible classification of clustering methods can be according to whether the subsets are fuzzy or crisp. In general, the performance of fuzzy clustering methods is superior to that of the other existing clustering approaches. Because of Fuzzy c-means (FCM) groups the image pixel into n clusters with every pixel in the input image belonging to every cluster to a certain degree.

The key idea of FCM is to represent the similarity of a point to a cluster with a function (membership function) whose values (memberships) are between zero and one. These indicate the strength of the association between that data element and a particular cluster. FCM Algorithm is developed by Dunn. FCM introduced a membership of each sample point in all clusters by a membership function which ranges between zero and one. Thus, points on the edge of a cluster may be in the cluster to a lesser degree than points in the centre of the cluster. The sum of the memberships for each sample point must be unity.

FCM Algorithm

The fuzzy c-means algorithm is very similar to the k-means algorithm:

- Choose a number of clusters.
- Assign randomly to each point coefficients for being in the clusters.
- Repeat until the algorithm has converged (that is, the coefficients' change between two iterations is no more than ε, the given sensitivity threshold) :
- Compute the centroid for each cluster
- For each point, compute its coefficients of being in the clusters.

Artificial Bee Colony Clustering

ABC was originally presented by Dervis Karaboga under the inspiration of collective behaviour of honey bees with better performance in function optimization problem. There are three essential components of ABC optimization model of food source selection that leads to the emergence of the collective intelligence of honey bee swarms: food sources, employed foragers and unemployed foragers. There are two basic behaviours: recruitment to a food source and the abandonment of a food source.

1. Food sources: these are simulated by the position of a solution of the optimization problem, the profitability of food source is expressed as the fitness of the solution.

2. Unemployed foragers: these are of two types, scouts and onlookers. Their responsibility is exploring and exploiting food source.

3. Employed foragers: these search for and are equal to the number of food sources. The employed bees store the food source information and share with others according to a certain probability. The employed bee will become a scout when food source has been exhausted. All the information about the currently rich food sources is available on the dance area and the onlooker watches numerous dances performed by the employed bees and chooses the profitable source. The onlooker bee decides the profit using the probability values of the food sources. The recruitment is thus proportional to the profitability of a food source.

ABC Algorithm

1. First get each subset. Consider each subset as the initial food sources
2. Repeat
3. Send the employee bee onto the food sources and determine their nectar amounts
4. Calculate the probability value of the sources with which they are preferred by the onlooker bees
5. Send the onlooker bees onto the food sources and determine their nectar amounts

6. Stop the exploitation process of the sources exhausted by the bees
7. Send the scouts into the search area for discovering the new food sources, randomly
8. Save the best food source found so far

Until the requirements are met

C. Feature Extraction

This is the third step of the proposed work. After completing the segmentation step the vegetation and non-vegetation area are divided from the pre-processed image and it gives the location of the non-vegetation objects. From that, it is necessary to find the accurate location of the buildings. Then only we find the changes. To do this work, the feature extraction is used. Among several feature extraction approaches, this paper only deals with Local Binary Pattern approach.

Local Binary Pattern

The local binary pattern (LBP) texture operator was first introduced as a complementary measure for local image contrast1. The first incarnation of the operator worked with the eight-neighbours of a pixel, using the value of the centre pixel as a threshold. An LBP code for a neighbourhood was produced by multiplying the threshold values with weights given to the corresponding pixels and summing up the result. Since the LBP was, by definition, invariant to monotonic changes in grayscale, it was supplemented by an independent measure of local contrast.

LBP Algorithm

Apply the below steps for all pixel in an input image

1. Get the neighbouring pixels of current pixel based on the pixel Distance
2. Then compare the current pixel with that the neighbouring pixels
3. If the centre pixel is greater than the neighbouring pixel put the value 1
4. Else put the value 0
5. Then convert these binary number into the decimal value
6. This is called a local binary pattern description
7. Then store the description into the array. This array is called bin.

D. Classification

This is the fourth step of the proposed work. Only feature extraction step is not sufficient for finding the exact location of the building from the given pre-processed satellite image. After extracting the features it must be given as input to the classification approaches then only it gives the accurate location of the buildings. Among several classification approaches, this chapter only deals with the K-Nearest Neighbour, Support Vector Machine and Extreme Learning Machine approaches.

K-Nearest Neighbor

In pattern recognition, the K-Nearest Neighbours algorithm (or KNN for short) is a non-parametric method used for classification. The input consists of the k closest training examples in the feature space. In K-NN classification, the output is a class membership. An object is classified by a majority vote of its neighbours, with the object being assigned to the class most common among its k nearest neighbours (k is a positive integer, typically small). If K = 1, then the object is simply assigned to the class of that single nearest neighbour. The training examples are vectors in a multidimensional feature space, each with a class label. The training phase of the algorithm consists only of storing the feature vectors and class labels of the training samples. In the classification phase, k is a user-defined constant, and an unlabelled vector (a query or test point) is classified by assigning the label which is most frequent among the k training samples nearest to that query point. A commonly used distance metric for continuous variables is Euclidean distance

Support Vector Machine

The idea of the SVM classifier appeared initially in a 1992 article by Boser, Guyon, and Vapnik (1992), where it was applied to a problem of recognition of characters. The authors demonstrated the superiority of the SVM against other algorithms for character recognition. SVMs are essentially binary classifiers by their inherent nature; however, they can be used to handle the multiple classification problems commonly needed in remote-sensing applications.

SVM Algorithm:

1. In the training phase, the training data and its labelling are given as the input
2. And then the training data is normalized by subtracting the average value of the trained data
3. Finally, they find the decision value of each label and marked these as the trained value
4. The decision function is calculated by using the below formula

$$d(v)=\sum w_i L_i v_i^T v + n \quad (2)$$

5. The test data is normalized and find out it margin value
6. This decision value is checked with the trained data to find the corresponding label using below formula

$$v \in \begin{cases} C1, & d(v) > 0.5 \\ C2, & \text{otherwise} \end{cases} \quad (3)$$

7. Then the matched class label is given as the output

ELM – Extreme Learning Machine

ELM works for the “generalized” single-hidden layer feedforward networks (SLFNs) but the hidden layer (or called feature mapping) in ELM need not be tuned. Such

SLFNs include but are not limited to support vector machine, polynomial network, RBF networks, and the conventional (both single-hidden-layer and multi-hidden-layer) feedforward neural networks. Different from the tenet in neural networks that all the hidden nodes in SLFNs need to be tuned, ELM learning theory shows that the hidden nodes of generalized feedforward networks needn't be tuned and these hidden nodes can be randomly generated. All the hidden node parameters are independent of the target functions or the training datasets. All the parameters of ELMs can be analytically determined instead of being tuned.

ELM Algorithm

Given a training set $\mathbb{N} = \{ (s_i, lt_i) | s_i \in R^n, l_i, \in R^m, i = 1, \dots\dots, N\}$, activation function g, and the number of hidden nodes L,

Assign randomly input weight vectors or centres a_i and hidden node bias or impact factor f_i, i= 1,….. , V.

Find the hidden layer output matrix M.

Find the output weight τ = M^+ T.

M+ is the Moore-Penrose generalized inverse of hidden layer output matrix M.

$$M+ = (M^T M)^{-1} M^T \quad (4)$$

D. Change detection

This is the last step of the proposed work. In this step, the change of the building map is detected from the output of the classifiers. In order to obtain the map of changes, the algorithm compares the mask of buildings obtained from the SVM and ELM with the new image of the buildings obtained from SVM and ELM by using the Euclidean distance measure of Equation (5)

$$CV(M_i, M_j) = \sqrt{\sum_{i=1}^{n} (q_i - r_i)^2} \quad (5)$$

Here is the change value between the reliable old building map V_i and new building map V_j. q_i is the feature value of the old building map V_i. r_i is the feature value of the and n is the total number of points in building the map.

IV. RESULTS AND DISCUSSION

A. Experimental Images

Dataset is used in our experiments are collected from the Calcutta. The dataset cover over three cities like Chennai, Mumbai and Calcutta. From the full dataset, 1000 subsamples are extracted with a size of 512 x 512. From the total 1500 subsample images, 800 samples are given into the training process. The remaining 700 subsample images are given into the testing process. Some samples images of training and testing are depicted in Figure.2.

Figure. 2. Experimental Images

B. Performance Metrics

To evaluate the performance of the change detection techniques of man-maid objects, several performance metrics are available. This chapter uses Detection Accuracy, Precision Rate, Recall Rate, Error Rate and F-Measure to analyses the performance.

Detection Accuracy

Detection Accuracy is the measurement system, which measures the degree of closeness of measurement between the original detected buildings and the detected buildings by the change detection method.

$$\text{Accuracy} = (TP+TN)/(TP+FP+TN+FN) \quad (5)$$

Where, TP – True Positive (building regions that are identified as a building)

FN – False Negative (building regions that are identified as non-building)

TN – True Negative (non-building regions that are identified as non-building)

FP – False Positive (non-building regions that are identified as buildings)

Error Rate

Error Rate is the measurement system, which measures no of falsely detected buildings form the given input satellite images.

$$\text{Error Rate} = \frac{\text{No of Images of Falsely Detected Buildings}}{\text{Total No of Images}} \quad (6)$$

C. Experimental Results

The result of the proposed work is shown in this section as image format. In this section, the result of the pre-processing, segmentation and classified steps are displayed.

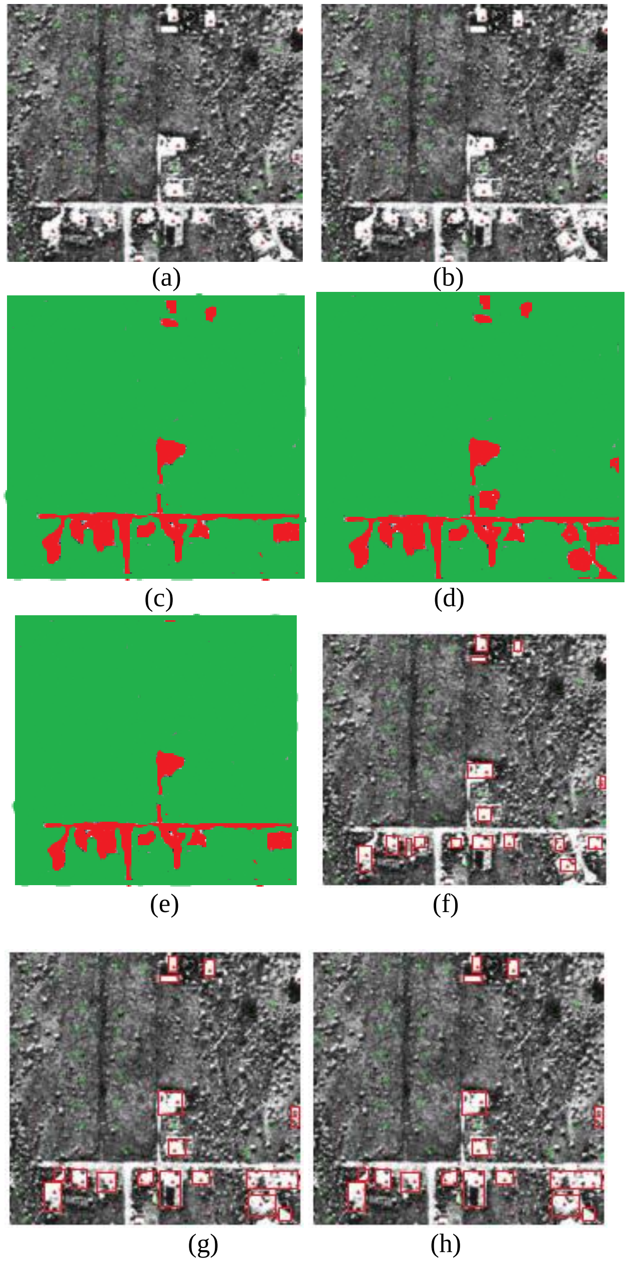

Figure 3 (a) Input Image (b) Pre-processed Image (c) Vegetation and Non-Vegetation Segmentation using FCM (d) Vegetation and Non-Vegetation Segmentation using ABC (e) Vegetation Segmentation using KMeans (f) Building Detection using KNN (g) Building Detection using SVM (h) Building Detection using ELM

D. Result and Analysis

To analyse the performance of the classifier system, it is compared with various techniques by using the performance metrics which are mentioned above. This is shown in the below tables and graphs.

Experiment No # 1: Performance Analysis of Classifiers

In this experiment, this work will evaluate the contribution of each type of classifier in the change detection of building task. This experiment takes KNN, SVM and ELM are the classifiers. Table 1 shows the detection accuracy analysis of the KNN, SVM and ELM.

Table 1: Detection Accuracy Analysis of Classification Methods

Test Data	**Detection Accuracy Analysis**		
	KNN	***SVM***	***ELM***
Test1	0.68	0.81	0.86
Test2	0.71	0.84	0.88
Test3	0.69	0.82	0.87
Test4	0.73	0.86	0.91
Test5	0.72	0.85	0.90
Test6	0.7	0.83	0.89
Test7	0.74	0.87	0.93
Test8	0.75	0.88	0.94
Test9	0.77	0.90	0.95
Test10	0.76	0.89	0.94

From Table 1, it is shown that the detection accuracy value of the ELM method is higher than the KNN and SVM approach. So the ELM method is best than the KNN and SVM approach. The graph of detection accuracy analysis is shown in Figure.4.

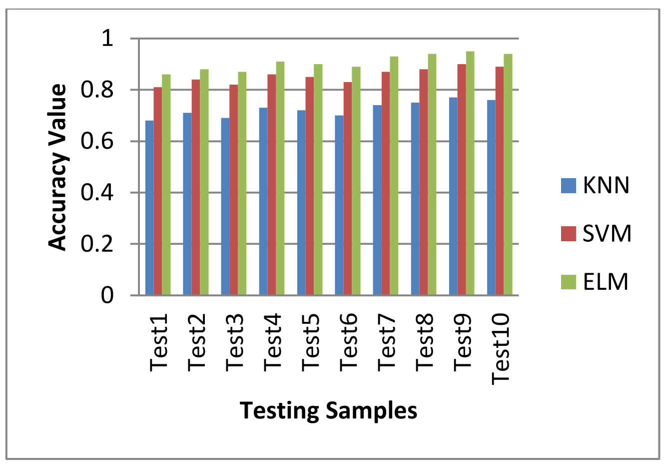

Figure.4 Detection Accuracy Analysis of Classification Method

From Figure 4, it is shown that the detection accuracy value of the ELM method is higher than the KNN and SVM approach. So the ELM method is best than the KNN and SVM approach.

Table 2: Error Rate Analysis of Classification Methods

Test Data	Error Rate Analysis		
	KNN	*SVM*	*ELM*
Test1	0.32	0.19	0.14
Test2	0.29	0.16	0.12
Test3	0.31	0.18	0.13
Test4	0.27	0.14	0.09
Test5	0.28	0.15	0.1
Test6	0.3	0.17	0.11
Test7	0.26	0.13	0.07
Test8	0.25	0.12	0.06
Test9	0.23	0.1	0.05
Test10	0.24	0.11	0.06

From Table 2, it is shown that the error rate value of the ELM method is lower than the KNN and SVM approach. So the ELM method is best than the KNN and SVM approach. The graph of detection error rate analysis is shown in Figure.5.

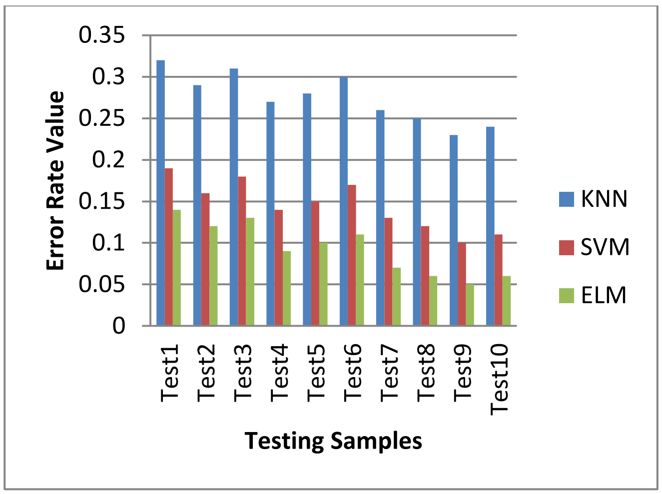

Figure.5 Error Rate Analysis of Classification Method

From Figure 5, it is shown that the error rate value of the ELM method is lower than the KNN and SVM approach. So the ELM method is best than the KNN and SVM approach.

Experiment No # 2: Performance Analysis of Segmentation Approaches

In this experiment, this work will evaluate the contribution of each type of segmentation approaches in the change detection of building task. This experiment takes K-Means, FCM and ABC are the segmentation approaches. For classifier, this experiment uses the ELM approach as the classifier because it gives the best result in experiment 1. For extract features, LBP is used. Among five performance metrics, this experiment takes only detection accuracy and error rate as the performance metric. In Table 3.6 shows the detection accuracy analysis of the K-Means, FCM and ABC.

Table 3: Detection Accuracy Analysis of Segmentation Methods

Test Data	Detection Accuracy Analysis		
	K-Means	*FCM*	*ABC*
Test1	0.709	0.799	0.849
Test2	0.739	0.829	0.869
Test3	0.719	0.809	0.859
Test4	0.759	0.849	0.899
Test5	0.749	0.839	0.889
Test6	0.729	0.819	0.879
Test7	0.769	0.859	0.919
Test8	0.779	0.869	0.929
Test9	0.799	0.889	0.939
Test10	0.789	0.879	0.929

From Table 3, it is shown that the detection accuracy value of the ABC method is higher than the K-Means and FCM approaches. So the ABC method is best than the K-Means and FCM approaches. The graph of detection accuracy analysis is shown in Figure.6.

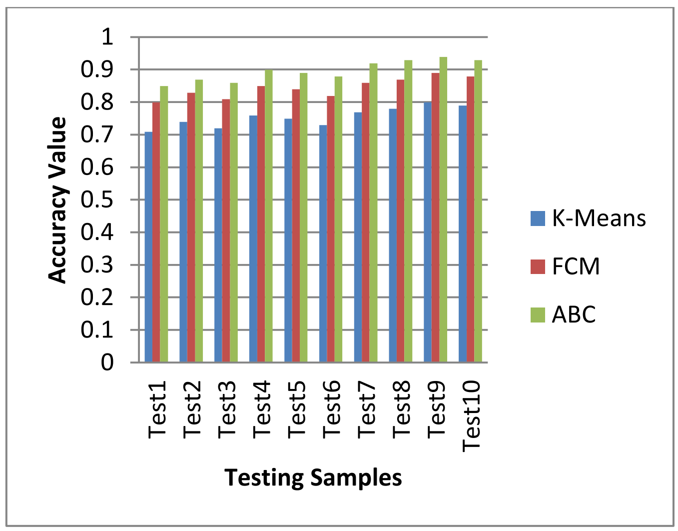

Figure.6 Detection Accuracy Analysis of *Segmentation* Method

From Figure 6, it is shown that the detection accuracy value of the ABC method is lower than the K-Means and FCM approaches. So the ABC method is best than the K-Means and FCM approaches.

Table 4 Error Rate Analysis of Segmentation Methods

Test Data	Detection Accuracy Analysis		
	K-Means	*FCM*	*ABC*
Test1	0.291	0.201	0.151
Test2	0.261	0.171	0.131
Test3	0.281	0.191	0.141
Test4	0.241	0.151	0.101
Test5	0.251	0.161	0.111
Test6	0.271	0.181	0.121
Test7	0.231	0.141	0.081
Test8	0.221	0.131	0.071
Test9	0.201	0.111	0.061
Test10	0.211	0.121	0.071

From Table 4, it is shown that the error rate value of the ABC method is lower than the K-Means and FCM approaches. So the ABC method is best than the K-Means and FCM approaches. The graph of detection error rate analysis is shown in Figure 7.

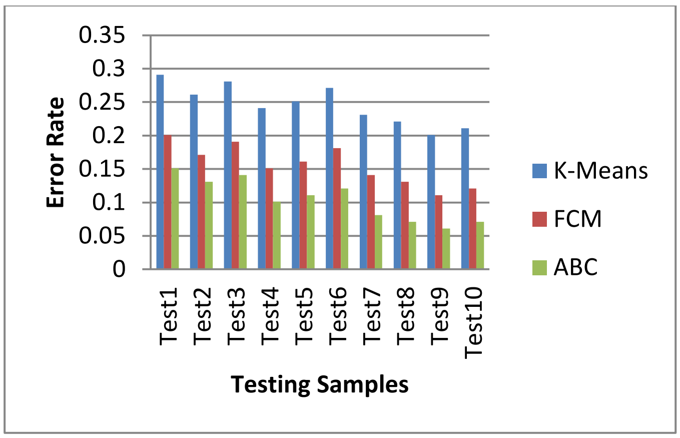

Figure.7 Error Rate Analysis of *Segmentation* Method

From Figure 7, it is shown that the error rate value of the ABC method is lower than the K-Means and FCM approaches. So the ABC method is best than the K-Means and FCM approaches.

V. CONCLUSION AND FUTURE SCOPE

In this paper, the comparison process is carried for two clustering approaches and two classifier approaches to find the best segment and classifier approach for manmade object extraction from given satellite images. Initially, the input satellite image is de-noised by using the Wavelet Shrinkage de-noising approach. And then the K-Means, Fuzzy C-Means (FCM) and Artificial Bee Colony (ABC) approaches are applied to the denoised image to segment the vegetation and non-vegetation areas and then extract the features from that affected area using Local Binary Pattern (LBP) Technique. Finally, the extracted features are given to the SVM and ELM classifier to get the building map and then the change detection process is applied. From the experimental result, it is shown that the ABC approach performs better than FCM and ELM provides the best result than the SVM. In future, the comparison will be made on feature extraction approaches.

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