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Efficient Classification Methodology For Change Detection Using Satellite Imagery

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ABSTRACT

Change detection is an application, which is used in Satellite Image Processing. For Statistical investigation, change detection tries to detect whether or not a change has occurred between two or more time periods. Most of the time we are using arial photographs or satellite photographs to analyze the change detection process. In this paper we propose an interactive object based classification method to solve Change Detection (CD). New object based classification method is a combination of Gray Level Co-occurrence Matrix(GLCM), Support Vector Machine (SVM) and Undirected Graphical model (Markov Net work).During the Feature Extraction GLCM extracts the important feature from Pre event and Post event images. Change detection method depends on the calculation of the difference image (DI) from two co-registered images such as Pre event and Post event images. In classification phase, classification algorithm such as SVM, classify the images into two different classes specifically change region and no-change region. Undirected graphical model (Markov network) is used to enhance the output of Support Vector Machine (SVM).Finally our proposed method produced good accuracy than existing methods. Resourcesat-2 and Landsat-8 images were tested and experimental results generate accurate Change Detection maps with simple and minimal interaction.

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INTRODUCTION

Satellite images are images of the earth taken from the away places with the use of artificial satellite. The process to avoid the effects of haze, clouds and sensor induced with in satellite image and cover the 2 Dimensional Satellite image on 3 Dimensional Surface of the earth is called Satellite image Processing. Satellite Image Processing has various applications on land use land cover classification, mineral exploration application, forestry and agriculture, oceanography, hazard assessment, environmental monitoring, land degradation etc. Land use land cover is a very useful application of Satellite Image Processing (Randen, T., J.H. Husoy, 1999).

Land cover means the physical land type such as forest or water type. Same as land use means how peoples are using the landscape. More over land cover indicating how much of region is covered by building area, forest, agriculture, wasteland and etc. For this type of analysis, one of the main uses of Satellite imagery is detection of changes occurring after a natural disaster.

We can analyze the data into two ways, one is classification and another is Prediction. Generally Classification refers to grouping similar things and prediction refers to predict future data trends (For example if we want to build a different classification model which is to be categorized in to physical material at the surface of the earth as Agricultural land, Building area, water resources, Bare soil, Forest area etc. Change detection using satellite images, debit and credit card fraud detection, performance target prediction of marketing, manufacturing are the numerous applications of the classification and prediction. In 16th June 2013 Uttrahand state, India, affected by natural disaster specifically floods and landslides .Suppose our government wants to analyze that whether the changes has occurred between before the disaster and after the disaster for statistical purposes. Here we can classify as change region and non change region for different time period. The figure 1 describing how the classification algorithm classifies the training data using classification rules (www.tutorialspoint.cpm). In this example, we can use the different multiple set of If-THEN rules for classification. The IF-THEN rules as follows, IF

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condition THEN conclusion .We can apply the training data into the IF-THEN rules as follows

IF Reason = floods and landslides AND Changes Occurred=yes THEN Classification status=change region.

Data classification is a combination of Training phase/Learning phase and Testing phase. It is a two phase process. The following figures describing about the classification process (figure 1 and figure 2). In the first step a classifier can use the predetermined data sets. During the training phase where a classification algorithm formed the classifier by analyzing different training sets made up of set of training samples and their associated class labels (Jie Feng *et al.*, 2015). A Training Sample Ts is represented by an n dimensional attribute vector Ts= (Ts_1, Ts_2, Ts_3, Ts_4…. Ts $_{n)}$, describing n different measurements made on the training samples from set of n database attributes respectively A_1, A_2, A_3, ……… A_n.

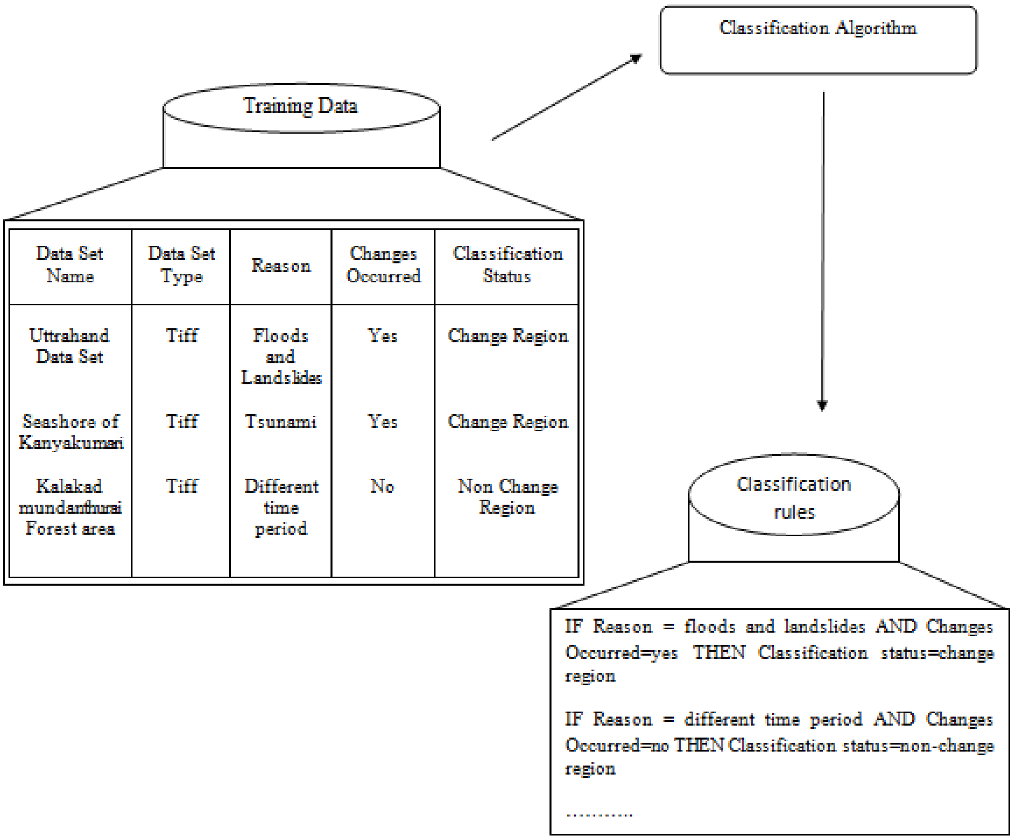


Fig. 1: Learning Phase or Training Phase

In figure 1, Classification algorithms are analyzing the training data. Here Classification rules are formed by set of class label attributes and their associated learned model.

In figure 2, Training data are used to calculate the accurateness of the classification rule. If the accuracy of the classification rule is considered acceptable, the rules can be useful to the classification of new training samples.

In the supervised learning the class label of the each training sample is given. Supervised learning is the one of the prior decision method. Then we have to calculate the accuracy of the classifier. The accuracy of the classifier means training samples that are correctly classified by the classifier.

Basically classification algorithms can be divided in to two ways. First one is supervised learning and second one is Unsupervised learning. In this paper supervised learning methods specifically

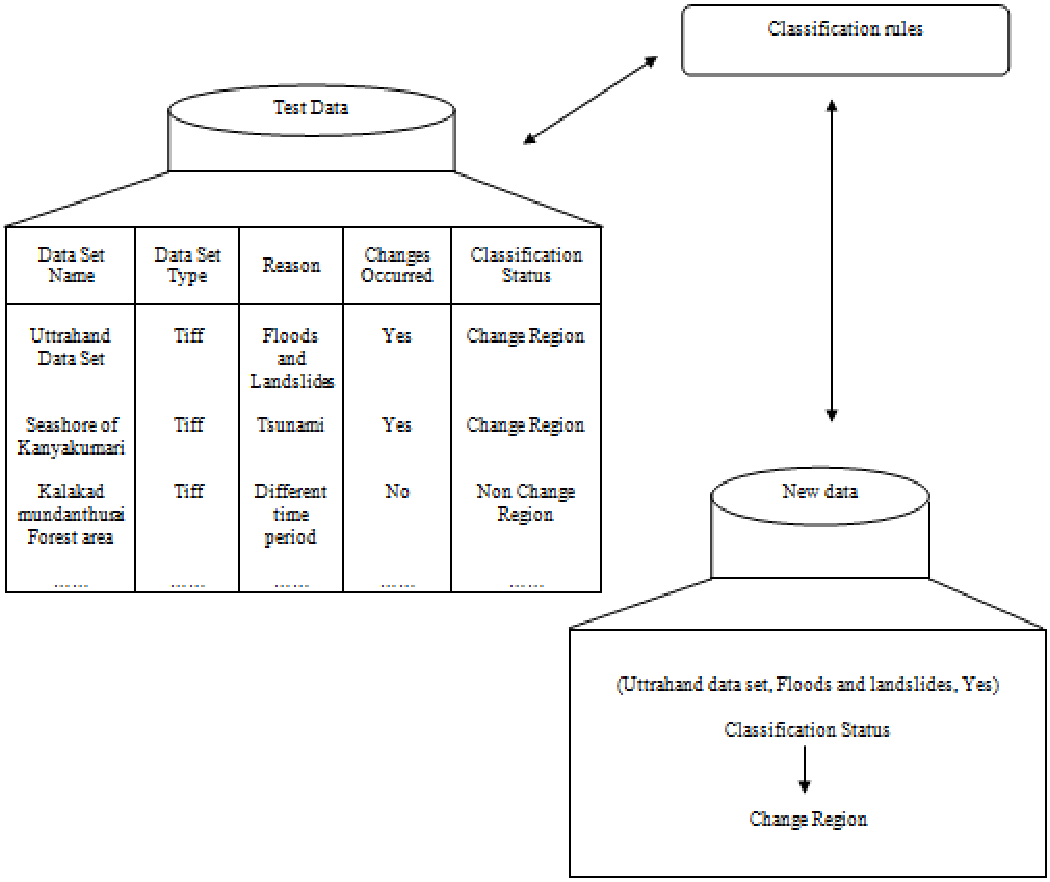


Fig. 2: Classification Phase

Support Vector machine (SVM) are used to classify changed or no changed regions. The class label of each training tuple is provided, this process is also known as supervised learning.

A supervised classification algorithm has prior knowledge about the data (Tuia, D., *et al*., 2011). It uses training samples which represent the different classes and for which the corresponding features are known. The test image is then segmented into different regions and the features of these regions are compared with that of the available training samples. The region belongs to the class of a particular training sample if their features match with each other.

The more advantages of Multispectral Satellite Imagery are its ability to provide change detection with Object Based Image Analysis (OBIA). While comparing with traditional pixel based change detection methods Object Based Change Detection (OBCD) provides a better result for Multispectral Satellite Imagery (Chamundeeswari, V.V., *et al*., 2009). Object based Change Detection has the ability to improve the performance of change detection for land use land cover classification.

In this paper we present new Object Based classification methods for change detection. In particular we focus on images characterized by a single object. This stage users need to give the input markers very close to change and no change classes in the Difference Image(DI).Then the input markers of Differential image are used for training a support vector machine (SVM)classifier in the same way of supervised classification (Kavitha, S., K.K. Thyagharajan, 2012; Bazi, Y., *et al*., 2010; Moujahdi, C., *et al*., 2014). After training the SVM Classifier, it is able to classify pixels in the images as change and no change pixels. Undirected graphical model (Markov Network) provides an enhanced result of SVM classifier. Section 2 explains about our proposed method.

2. Description of Proposed Method:

2.1 Architecture Design:

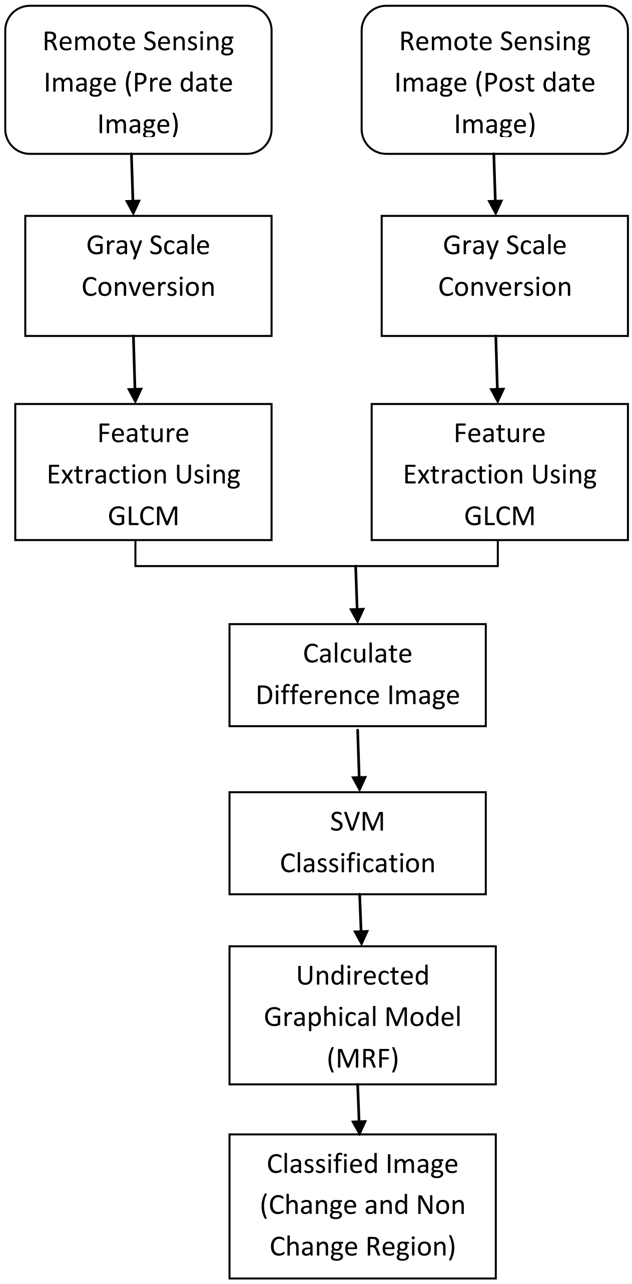


Fig. 3: Architecture Design

Multispectral image is a set of several toneless images of the same view which has been taken by different sensors. Let us consider two images I_1 and I_2 are a multispectral Satellite images of size M× N× d captured by same geological region at different time period. Let I_D is a multispectral Differential Image(DI) (Celik, T., K.K. Ma, 2011) of dimension d generated from I_1 and I_2.Let I_{DM} is the scalar modules image obtained for I_D i.e., $I_{DM} = \sqrt{(I_D^1)^2 + (I_D^2)^2 + \ldots + (I_D^d)^2}$

.The goal of the proposed approach is to provide an accurate classification for change detection map and to identify the changes that occurred between two images captured between two dates (Chen, G., *et al*., 2012). Figure 3 explains our proposed architecture design. The following algorithm explains the interactive object based classification methods for Change detection.

Algorithm: Interactive object based classification for Change Detection

Input : Image I_1 and Image I_2

Output: Classification for Change Detection (CD) map J

Step 1: Read the two Inputs I_1 and I_2

Step 2: GLCM Feature Extraction extracts the important features

Step 3: Calculate Difference Image (DI) using image subtraction method

Let us consider two images, Image 1, Image 2 as P, Q and I, j is the pixels of image P, Q.

```
For (i=1: n)
    {
For (j=1: m)
{
Differential Image [i, j] = P [i, j] - Q [i, j,];
}
}
```

Step 4: Mark the change and no Change Regions in the DI.

Step 5: Make a training set For SVM

Input/ Output set P and Q and Training set (p_1, q_1)……… (P_m, q_m)

So we like to learn the mapping P→ Q, where p$\in$ P is some object and q$\in$ Q is a class label.

Therefore want to learn classifier: q = f (p, α), where α are the parameters of the function.

For example, if we are choosing our model from the set of hyper lanes in R^n then we have

$$f(p,\{w,b\}) = sign(w.p+b)$$

Step 6: Train the SVM

Step 7: Generate an initial classification for change detection

Step 8: Enhance the performance of classification for change detection using undirected graphical model (Markov Networks)

During classification we may get energy minimization problems on a rectangular grid of pixels. Where, energy is a combination of data term and smoothness term.

$$E(u) = E_{data}(u) + E_{smoothness}(u)$$

A Markov Network is a Undirected graph G = (V, E)

V= {1, 2…..N) is the set of nodes each of which is associated with a random variable (RV),

u_j, for j=1…N.

End

3. Methodologies:

3.1. Feature Extraction using GLCM:

For successful land use classification, intensities of an image are usually not sufficient. Thus, a textural feature is evaluated for each pixel based on the pixel and band (Klaric, M.N., *et al*., 2013). Texture provides valuable information such as contrast, uniformity, regularity etc. for the identification of objects in the image. A pattern or patterns may be repeated over a region is a texture. The repetitions may be exact or may vary, with respect to position. The texture is an image can be obtained by indicating it as a 2-D gray level variation (Serpico, S.B., G. Moser, 2006). This matrix is called as Gray Level Co-occurrence Matrix (GLCM).

The Graycomatrix function generates a gray-level co-occurrence matrix (GLCM) by calculating how often a pixel with the intensity (gray-level) value *i* occurs in a particular spatial relationship to a pixel with the value *j*. Each element (*i*, *j*) in the glcm is simply the sum of the total number of times that the pixel with value *i* occurred in the particular spatial relationship to a pixel with value *j* in the input image.

The following table illustrates how graycomatrix calculate the three values in a GLCM. In the following table 1 indicating the pixel value of input image (I) .The table 2 indicating the Gray Level Co-occurrence Matrix (GLCM) value of given Input image. In the output of GLCM, pair element(1,1) having the value 1 because there is only one times in the input image where two horizontally adjacent pixels having the values 1 and 1.In the output of GLCM ,pair element(1,2) having the value 0 because none of the times in the input image where two horizontally adjacent pixels having the values 1 and 2 (www.mathworks.in). Same as In the output of GLCM ,pair element(1,7) having the value 2 because two times in the input image where two horizontally adjacent pixels having the value 1and 7.

Table 2: Processing of calculating GLCM

1	1	4	5	8
3	2	1	7	6
5	3	4	6	1
8	2	1	7	3

Table 1

	1	2	3	4	5	6	7	8
1	1	0	0	1	0	0	2	0
2	2	0	0	0	0	0	0	0
3	0	1	0	1	0	0	0	0
4	0	0	0	0	1	1	0	0
5	0	0	1	0	0	0	0	1
6	1	0	0	0	0	0	0	0
7	0	0	1	0	0	1	0	0
8	0	1	0	0	0	0	0	0

In this paper Co-Occurrence matrix is decided by two important parameters like relative distance between the pixel pair d measured in pixel number and their relative pixel orientation ϕ. Normally ϕ is quantized in four directions (0°, 45°, 90° and 135°).

To demonstrate how the calculation is made, for Image I, let m represent the gray level of pixels(*x*, y) and n represent the gray level of pixels ($x\pm$ dϕ_0, y$\pm$ dϕ_1) with L levels of gray tones where 0≤*x*≤M-1, 0≤y≤N-1 and 0≤m, n≤L-1.From the above representation gray levels Co-Occurrence matrix CM $_{m,\,n}$ for distance d and direction ϕ can be written as follows

$$CM_{m,n,\phi} = \sum_x \sum_y P\{I(x,y) = m \,\&\, I(x \pm d\phi_0, y \mp d\phi_1) = n\} \quad (1)$$

If the argument is true; $P\{.\}=1$; Otherwise P {.}=0.For each ϕ values its, ϕ_0, ϕ_1 value is referred as in the Table 3. The best advantages of GLCM is it is diagonally symmetry where CM $_{m,\,n}$ $_{=}$CM $_{n,\,m}$. Thus the computation of the GLCM can be rewritten in the equation 2, Now instead of the ± and ∓ signs we can use + and – signs.

$$CM_{m,n,\phi} = \sum_x \sum_y P\{I(x,y) = m \,\&\, I(x + d\phi_0, y - d\phi_1) = n\} \quad (2)$$

In this paper Haralick et.al introduced fourteen textural features from the GLCM and in this paper we have used only four of the texture features are considered to be the most applicable. Those textural features are Contrast, Entropy, Correlation and Energy. Energy is sometimes called as Angular Second Movement. Angular Second Movement (ASM) measures textural uniformity of an image. When the image is uniform, its energy will be upper limit. The energy ASM function can be written as equation 3 and 4.

Table 3: Orientation Constant

ϕ	ϕ_0	ϕ_1
0^0	0	1
45^0	-1	-1
90^0	1	0
135^0	1	-1

$$ASM = \sum_{i,j=0}^{N-1} P_{i,j^2} \quad (3)$$

$$Energy = \sqrt{ASM} \quad (4)$$

Entropy could be a measure that is reciprocally related to energy. It measures the disarray or uncertainty of an image.

$$Entropy = \sum_{i,j=0}^{N-1} P_{i,j}(-\ln P_{i,j}) \quad (5)$$

Contrast is sometimes called as sum of squares variance. *Contrast* may be a measure of local gray level variation of an image. This parameter takes low value for a horizontal image and high value for an uncouth image.

$$Contrast = \sum_{i,j=0}^{N-1} P_{i,j}(i-j)^2 \quad (6)$$

Finally *correlation,* measures the linear dependency among neighboring pixels. It gives a measure of abrupt pixel transitions in the image.

$$Correlation = \sum_{i,j=0}^{N-1} P_{i,j}\left[\frac{(i-\mu_i)(j-\mu_j)}{\sqrt{(\sigma_i)^2(\sigma_j)^2}}\right] \quad (7)$$

3.2. Compute DI and Build Training Set for SVM:

During the dissimilarity image calculation Image differencing and rationing, image pixels distribution analysis, image neural network analysis and Change Vector Analysis (CVA) are all typical pixel- or block-based change detection algorithms. (Melgani, F., L. Bruzzone, 2004). In this paper image subtraction method is used to calculate basic difference image from pre dataset and post dataset. To give the training set for SVM we have to mark change and no change region in the DI (Salmon, B.P., *et al*.,2013). In Change detection process change pixels are marked by green marker assigned to"1"whereas no change pixels are marked by blue marker assigned to"-1".Figure 5(f) and 6(f) shows the Change and no change region marking.

3.3. Image Classification with SVM and Undirected graphical model:

In This paper we used Support Vector Machine algorithm to classify the images as change and non change area. The first paper of SVM was presented by Vladimir Vapnic and colleagues Bernhard Boses and Isablle Guyon in 1992. Support vector machine Support Vector machine using a nonlinear mapping to transform the original training samples into a higher dimension.SVM Searches for the separating hyperlane with in this new dimension. Here hyperlane is the "Decision Boundary" that is splitting the tuples (MunozMar, J., *et al*., 2007) of one class from another class. With the use Support Vector and margins SVM decide this hyperlane. To explain the SVM we can take the two case problems where the classes are linearly divisible. Let the data set D be given as (P1, q1), (P_2, q_2)…….. ($P_{|D|}$, $q_{|D|}$), where P_i is the set of training tuples with related class labels q_i. Each q_i can take one of two values either +1 or -1 that is $q_i \in \{+1, -1\}$, Corresponding to the classes classification status=change region (Due to floods and landslides changes has occurred in particular area) and classification status= Non change region(Due to floods and landslides changes has not occurred in particular area), respectively. In the following example figure 4 based on two inputs attributes A_1 and A_2 as follows

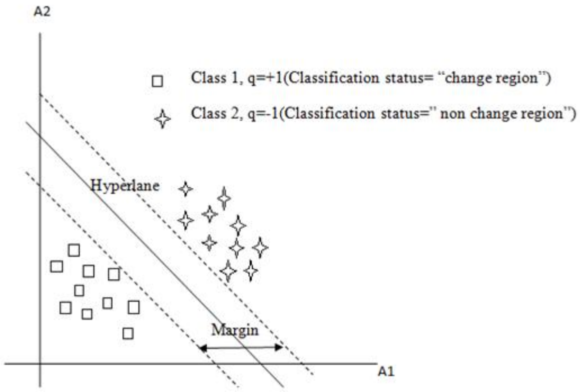


Fig. 4: SVM Classification Process A separating Hyperlane can be written as

$$Wt.P + b = 0 \quad (8)$$

Where Wt is a weight vector, namely Wt= {wt_1, wt_2, wt_3…. wt_n}; n is a number of attributes and b is a scalar. Our training tuples are two dimensional so that P=(p_1, p_2) where p_1 and p_2 are the values of attributes A_1 and A_2 respectively for P. Suppose b is an additional weight wt_0 we can rewrite the equation(2) as follows

$$wt_{0+} wt_1 p_1 + wt_2 p_2 = 0 \quad (9)$$

Thus any point that lies above the separating hyperlane, then satisfies the following condition

$$wt_{0+} wt_1 p_1 + wt_2 p_2 > 0 \quad (10)$$

Thus any point that lies below the separating hyperlane, then satisfies the following condition

$$wt_{0+} wt_1 p_1 + wt_2 p_2 < 0 \quad (11)$$

We can adjust the weights because of hyperlanes defining the sides of the margin can be rewritten as follows,

$$H_1 = wt0 + wt_1 p_1 + wt_2 p_2 \geq 1 for q_i = +1. \quad (12)$$

$$H_1 = wt0 + wt_1 p_1 + wt_2 p_2 \leq 1 for q_i = -1. \quad (13)$$

Therefore any tuple that comes on or above H_1 belongs to class +1 and any tuple that comes on or below H_2 belongs to class -1.we can combine the equations (12, 13) then we get the equation as follows,

$$q_i (wt_0 + wt_1\ p1 + wt_2 p_2) \geq 1 \quad (14)$$

Any training tuples that comes on hyperlane H1 or H2 (that is sides defining the margin) satisfy equation 15.This states are called Support vector.

More over SVM can easily classify the nonlinear separable data. In input space SVM are able to find the nonlinear decision boundaries. For using non linear classification we have to extend the liner approach. For that we have to follows two step process. In the first step using nonlinear mapping transform into the higher dimensional space from original input data. After transforming into the new dimension space, then searches for a linear separating hyperlane in the new space (Okeke, F., A. Karniel, 2010). A decision hyperlane in the new space is d(R) = Wt R + b, where Wt and R are vectors.

When searching for a linear SVM in new area, the training tuples appear only in the form of dot products ϕ (P_i). ϕ (P_j) where ϕ(P) is simply the nonlinear mapping function is used to transform the training tuples. Instead of dot product we can apply a kernel function K (P_i, P_j) as follows

$$K(P_i, P_j) = \phi(P_i).\phi(P_j) \quad (15)$$

The following MATLAB Pseudo code specifying, how the SVM classifier classifies as Changed and Non Changed Region.

```
SVMStruct = svmtrain (M (:, 1),(M (:,2)));
plot ([-1 1], [-1 1]);
plot (SVMStruct. Alpha, SVMStruct. SupportVectors,'ro');
MM=DI (:);
for i=1: length (MM)
Group (i) = svmclassify (SVMStruct,MM (i));
end
Ih=reshape (Group,[256 256])
 XD=DI;
Y=ih;
for i=1:size(DI,1)
   for j=1: size (DI, 2)
```

```
U(i,j)=-
log(length(find(DI==DI(i,j)&Y==Y(i,j)))/length(find
(Y==Y(i,j))));
    end
end
```

The local energy function is as follows

$$U_{mn} = U_{data}(X_D(m,n), Y(m,n)) + U_{smoothness}(Y(m,n), Y^s(m,n)) \quad (17)$$

$$U_{data}(X_D(m,n), Y(m,n)) = -\ell n\left\{\frac{P_{XD(m,n)}}{Y(m,n)}\right\} \quad (18)$$

Where $P_{XD\,(m,\,n)}$ /Y (m, n) is the posterior probabilities to the SVM Outputs during the classification phase.

Under Undirected Graphical model final change detection map J is as follows

$$U_T = \sum_{m=1}^{M} \sum_{n=1}^{N} U_{mn} \quad (16)$$

4. Experimental Results:

4.1 Datasets:

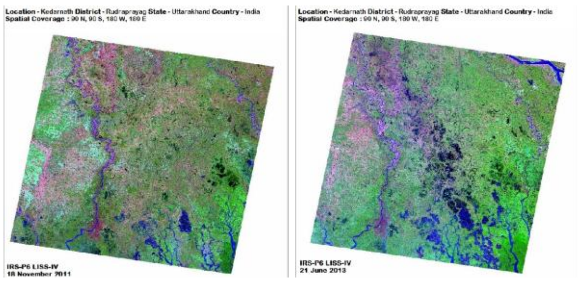
Here Experiments are conducted by the real remote-sensing images of parts of Uttarakhand, India and Paraguay River. We implement using two datasets such as Resourcesat-2 and Landsat-8 Images.

1) First Dataset images taken by Resourcesat-2 on November 18, 2011 and June 21 2013; show the Uttarakhand, India.

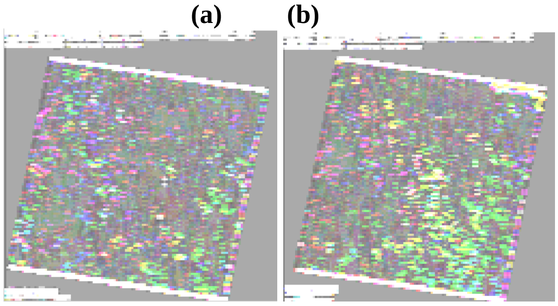
2) Second Dataset images taken by Landsat-8 on April 14, 2014 and July 19, 2014; show the Paraguay River, north of the city of Asuncion.

4.2. Results and Analysis:

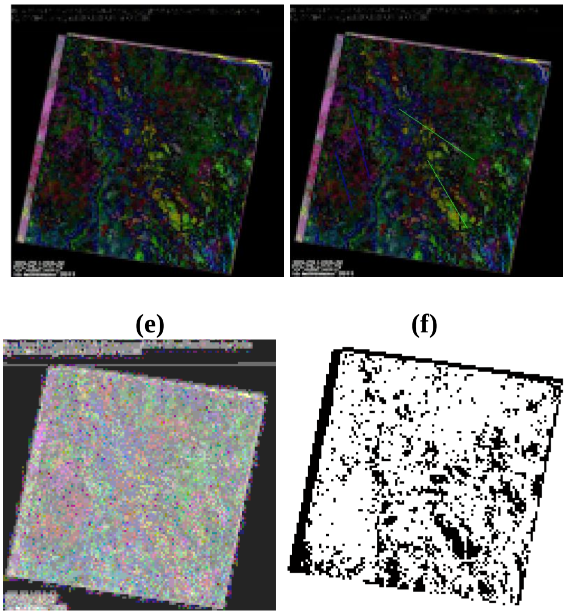
It is evident from the post-event images of Kedarnath town around the temple that the massive destruction was the result of large-scale debris carried by the huge volume of water from the upper reaches above the town. Figure 5 shows the results of Resourcesat-2 images and Figure 6 shows the results of Landsat-8 images. Figure 5(h) and 6(h) shows Final Change map(white color indicating no change region and Black color indicating change region).Figure 7 shows results of our proposed methods compare with some other existing methods. As a result of our proposed method provides more accurate result than other methods. Table 4 and 5 shows the performance evaluation of our proposed methods for Resourcesat-2 and Landsat-8 images.



(a) **(b)**



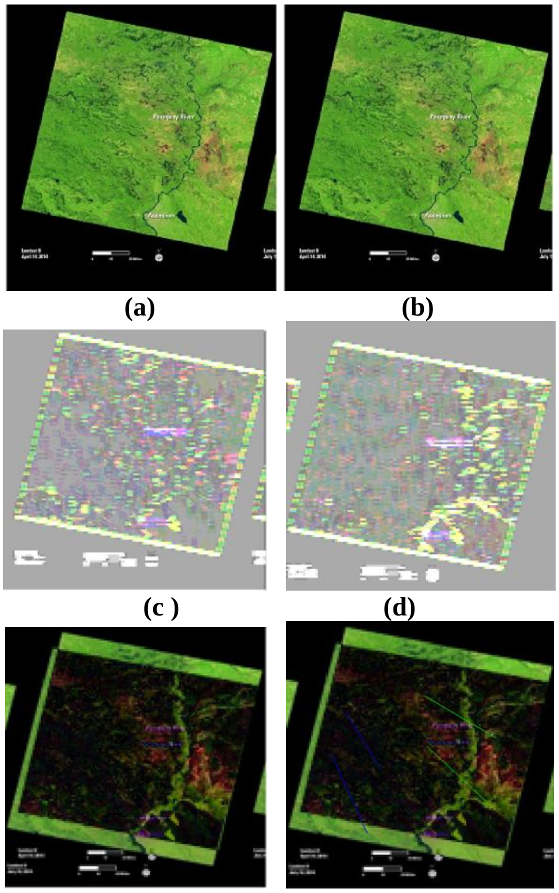
(c) **(d)**



(e) (f)

(g) (h)

Fig. 5: Classification Map of Resourcesat-2 images(a)-(h) (a) Predata Image,(b)Postdata Image,(c)Feature Extraction of Predata Image,(d)Feature Extraction of Postdata Image,(e)DifferenceImage(DI),(f)Region marking, (g)SVMClassification,(h)Final changeMap(white-No change Region,Black-Change Region).



(a) (b)

(c) (d)

(e) (f)

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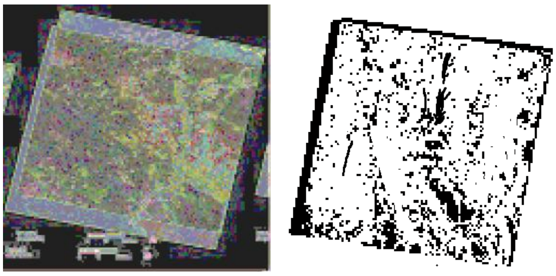


(g) (h)

Fig. 6: Classification Map of Landsat-8 images(a)-(h) (a)Predata Image,(b) Postdata Image,(c) Feature Extraction of Predata Image,(d) Feature Extraction of Postdata Image,(e) Difference Image(DI),(f)Region Marking,(g)SVM Classification,(h)Final ChangeMap(white-No change Region,Black-Change Region).

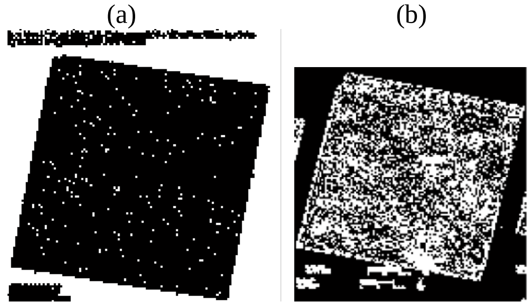
Table 4: Performance evaluation of Landsat-8 images

Classification Method	Total Sample Pixels Taken	Correctly Classified Pixels	Overall Classification Rate	Error Rate	Kappa(K^) Statistics
GLCM+SVM+MRF	512	449	87.69	12.31	0.8399
FCM	512	408	79.68	20.32	0.7607
SVM+MRF	512	318	62.10	37.89	0.3635
MRF	512	97	18.94	81.06	0.1110

Table 5: Performance evaluation of Resourcesat-2 images

Classification Method	Total Sample Pixels Taken	Correctly Classified Pixels	Overall Classification Rate	Error Rate	Kappa(K^) Statistics
GLCM+SVM+MRF	512	436	85.15	14.84	0.8155
FCM	512	423	82.61	17.38	0.7886
SVM+MRF	512	323	63.08	36.91	0.3692
MRF	512	83	16.21	83.78	0.0943

(a) (b)



(c) (d)

Fig. 7: Change Map obtained for the Landsat-8 dataset : (a) GLCM+SVM+MRF, (b) SVM+MRF, (c)SVM, (d) FCM.

Conclusion:

Here we have proposed a new object based classification methodology to solve the Change Detection Problem using the concepts of Feature Extraction, Support Vector Machine, Undirected graph model (Markov Network). Our Proposed approach provides very attractive in generating CD with minimum interaction. The pixels in the image are initially processed using the training set generated using SVM. The usage of Markov Network improves the performance and decision to locate the Change region. This methodology explicitly models the effect of pixels. The main novelty of the proposed methodology is the use of Object-based change detection. After disaster it is evident that the upstream of Mandakini River and Paraguay River and its tributaries have witnessed a drastic change in size of river beds and surrounding area. This is due to flood (rain fall), land slide, human intervention from November 2011 to June 2013 and April 14 2014 to July 19 2014. This improves the visual recognition of Multi spectral Images under realistic imaging conditions and will improve the accuracy rates in future. We have to improve this, so that it will perform well on simulated video data also.

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