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SVM-Based Detection of Miniature Area of LCLU: A False-Damage Assessment Index for Disaster Management Application

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Abstract: ***In this paper, we reflect on changing the detection environment for addressing the difficulty of detecting miniature area of Land Cover Land Use (LCLU) with a technique using Support Vector Machines (SVMs).We then become accustomed and sophisticatedly changing the Support Vector Machine for designing a supervised learning basis detection that enfolds the False Damage Assessment Index(FDAI). Primarily our proposed detection technique is controls easily the FDAI by simply adjusting two parameters() where it can be facilitate to control sensitivity of detection to the binary classifier and numerical supervised learning algorithm. The experimental results demonstrating about ours proposing detector noticeably improving the detection probability on many existing classifiers in both DAI and FDAI cases .***

Keywords : Machine Learning, False Damage Assessment Index (FDAI), Miniature area.

I. INTRODUCTION

SVM is a supervised ML algorithm that is used in classification challenges. Now a days research has been entered into new methods of classification where SVMs have recently enthralled the attention of the remote sensing fraternity. More recently SVMs are applied to machine vision fields like satellite image classification. SVMs like ANN and other non-parametric classifier have a repetition for being robust. Satellite remote sensing is useful tool to monitor earth surface. Particularly in producing land cover and land use classifications. Generally land cover and land use classification builds upon two imaging methods viz..optical and microwave remote sensing. These are having both merits and demerits.

The primary requirement for image analysis is to have effective classification of an image by SVMs technique. Image classification needs a very important and basic operation for significant analysis and interpretation of images. For the purpose of disaster management , it is essential to complete damage detection as fast as possible after the occurrence of disasters in order to make use of the detection result in emergency management. For proper and timely implementation of image detection result in emergency management, it is important that the damage detection procedures be complete as fast as possible. This has led to the need of automated damage assessment system with proper accuracy and required information that would aid in decision making in practical scenarios.

A supervised classification of connected component analysis is employed for assessing the damage. Connected component labeling or connected component analysis or blob extraction region labeling or blob discovery or region extraction, by whatever the name it is known, refers to the graph theory application of algorithm that uses subsets of components that are connected which are labeled depending on a given heuristic. Here, if a pixel p is at coordinate (x,y) and has 4 direct neighbors say N4 (p) and 4 diagonal neighbors say ND(p), This preprocessed image is usually binary and consists of numerous regions against a background. In this work the images classify by different SVMs approaches implemented as a part of this work is considered as input images. Now as the components are connected, each region is assigned a unique label, so that the distinct objects can be distinguished. In the next stage, these regions based on their labels are processed to extract a number of features that is represented by the region for example area, center of gravity, bounding box etc. In the final stage, all these features help in classifying each region into one or more than two classes. There are typically two stages in connected component analysis and labeling.

II. METHODOLOGY

A.Problem statements and overview of the method

By Selecting the Image which is desired area to find Damage Assessment Index (DAI) calling as study area. This can be done by acquisition of LISS-IV Image of that particular area .Then the Image undergoes through various filters for Geometric correction and for the selection of precise band of frequencies as a preparation of the Classification. The methodology to assess damage can be broadly categorized as qualitative and quantitative damage assessment. Qualitative assessment refers to the visual interpretation of mono temporal or multi temporal images of the disaster affected areas. This methodology is costly and takes time and requires high resolution image since the low resolution images will be difficult to interoperate.

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Quantitative damage assessment on the other hand uses digital image processing and has three different methodologies that include detection of change, classification of image and texture analysis. In this research work image classification philosophy is employed in order to quantify and formulate the damage. A supervised classification of connected component analysis is employed for assessing the damage. Connected component labeling or connected component analysis or blob extraction region labeling or blob discovery or region extraction.

The SVMs are chosen to determine damage assessment index for satellite images. Mostly these SVMs to specifying and classifying as the optical images for land, build up land, sand, water body, fallow land, degraded scrub and land with scrub. As an improvement in the average classification accuracy and at the same time for reducing the variance for SVM performance in the classification. "Support Vector Machine" (SVM) is a supervised ML algorithm that can be useful in both classification and regression challenges. However, it is predominantly using a solution for the classification problems. In this algorithm, we plot each data item as a point in n-dimensional space (where n is number of features you have) with the value of each feature being the value of a particular coordinate. Two major categories of image classification techniques include **unsupervised** (done by software) and **supervised** (done manual) classification. Unsupervised classification is that in which the outcomes (collecting of pixels with same properties) are based on the software analysis of an image without human providing sample classes. The techniques used by the computer to determine which pixels are related and groups them into classes. Where as in the supervised classification the user can select the sample pixel in an image that which pixel relate to their respective class. Support Vectors Machines (SVM) have proved recently their ability in pattern recognition and classification [Vapnik, 1995]. The aim of this paper is to evaluate the potentiality of SVM on image recognition and image classification tasks.

B. False-Damage Assessment Index which Controlled by Support Vector Based detector

Return to the problem of detection itself to identify an objective from miniature area of LCLU can be in nature treated as a problem of classification on the basis of this truth, in this part adapts and pleasingly modify the SVM from original SVM referred to as β-SVM(as shown in eqn6) , a conventional and widely using supervised learned basis detection has been utilize in few existing research works to discriminate detection from selected miniature area[refence No], approximately all of those are directly applied SVM Machine Learning techniques and could not considered the FDAI in that. nevertheless making the FDAI controlling is not only can suitably controls the detector sensitivity to the out layers sustain by the factor as the DAI spike but also facilitates to calculate the performance of various detection algorithms. So now it is interesting to design an FDAI-controlled SVM based detector to identify the miniature area of LCLU in the disaster management.

C. For an i sample in the training data set we will construct the subsequent feature vectors, which are support vectors, hyper plane and margin. For handling such problems, non linear kernel functions are introduced in to the SVM. These kernel functions attempts in to mapping as

$$k(x_a, x_b) = \phi(x_a).\phi(x_b) \quad (1)$$

$$g(x) = W^T\phi(x) + b = \sum_{i=sv} \alpha\phi(x_i)^T\phi(x) + b \quad (2)$$

in to a radial dimensional feature area, where in the begin linearly non separable data set which transformed to a separate one linearly. In this paper we are considering the kernel function as the radial basis function, an important choice in this SVM- based detection defines as explained below

$$\gamma^i = y_i(w^T x_i + b) \quad (3)$$

$$\{(x_1, y_1), (x_{2,} y_2), \ldots, (x_m, y_m)\} \quad (4)$$

$$\gamma = \min_{1 \le i \le m} \gamma^i \quad (5)$$

$$\min_{w,b,\xi} \frac{1}{2}\|w^2\| + \beta\sum_{i=1}^{m}\xi_i \quad (6)$$

s.t $y_i[k(w, F_i) - b] \ge 1 - \xi_i; i = 1,2,\ldots m$

Maximize margin width of equation (5)

$\frac{\gamma}{\|w\|}$ subject to;

$$y_i(w^T x_i + b) \ge \gamma \text{ for } i = 1,2, \ldots, m \quad (7)$$

Maximize $\frac{1}{2}\|w^2\|$;

s.t $y_i(w^T x_i + b) \ge 1$ (8)

The next step after mapping is to determine the hyper plane, i.e (eqn**7**), to differentiate miniature area of data in the mapped linearly distinguishable high dimensional feature area according to the Maximum margin principle.(eqn**7**) & (eqn8)

$$x = [x_1, x_2] \quad (9)$$

Let $k(x_i, x_j) = (1 + x_i.x_j)^2$

To show $k(x_i, x_j) = \phi(x_i).\phi(x_j)$ (10)

To handle these type of problems we sophisticatedly customized the β-SVM to substitute yet statistically equivalent version of the β-SVM, that refers as the FDAI controllable SVM(eqn**10**) & (eqn11)

Radial basis function(Gaussian)

$$k(x_i, x_j) = e^{-\frac{\|x_i - x_j\|^2}{2\sigma^2}} \quad (11)$$

$$P_d = \frac{\text{The number of correctly classified target samples}}{\text{The total number of target samples in testing data set}}$$

By adapting the β-SVM as a classifier, then we can construct an FDAI-controlled SVM based detection and the detailed procedure is summarize in the following steps.

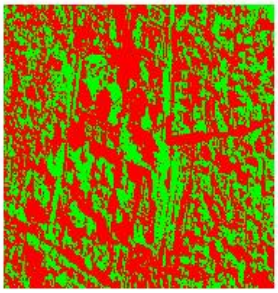
These stages will be executed frequently until the dissimilarity between the SVM and β-SVM is lower than the pre defined porch value (eqn**11**). Treating this algorithm needs to executes for each step by step data individually to build the FDAI for the detection environment of each data set is extensively different.

III. RESULTS AND DISCUSSION

The images are sourced from the open repository of Digital Globe. Some of the images are also sourced from web site which credits the images to Digital Globe. A pre April 2015 Nepal earthquake image of the densely populated area of Katmandu, Nepal is shown in Fig (1). This earthquake which is also known as the Gorkha earthquake had claimed lives of 8800 people while injuring more than 23000. It occurred at 11:56 NST on 25 April, with a magnitude of 7.8. Similarly the figure (2) illustrates the image captured post the occurrence of earth quake.

Figure 1: Katmandu prior the earth quake.

Figure 2: Katmandu post the earth quake.



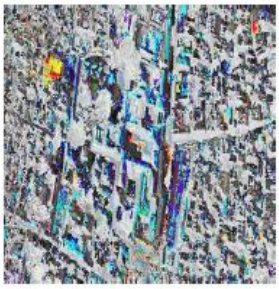


Figure 3: Binary equivalent classification results Figure 4: Binary equivalent classification result

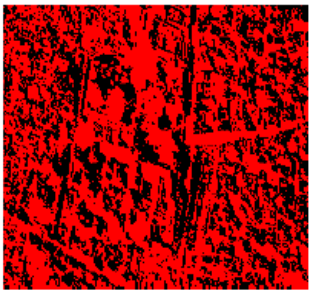


Figure 5: SVM Simplified Results
Figure 6: SVM Simplified Results

$$P_F = \frac{\text{The number of misclassified miniature area}}{\text{The total number of miniature area samples in trainin g data set}}$$

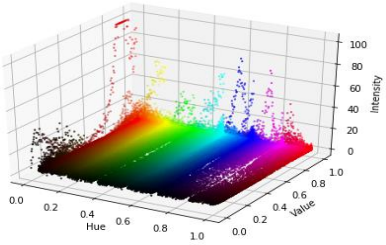


Figure 7: SVM based DAI.

As shown in above Figure (7) is calculate the detection probability is defined as Pd and also calculate the FDAI, which is defined as Pf.

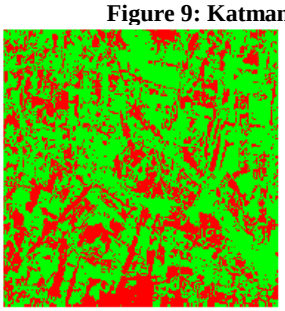
The index size of the resulted image is (200, 200)
The total index values damaged (White) are 137
The total index values undamaged (black) are 116
Based on the above Figures (1) to (6)

The qualitative damage analysis through visual interpretation reveals that even though there is damage, the damage is relatively less and there are lots of standing structures. A connected component analysis for the segmented image through the proposed method reveals the presence of number of labeled components in each image.

The DAI calculated for the above damage represented through Fig (1) and Fig (2) is Figures 3&4

In order to differentiate the damage and to illustrate the suitability and the validity of the DAI another set of **images before and after the** April 2015 Nepal earthquake are considered. These images have relatively high damage when compared to the damage represented by figure (2) for corresponding prevent image illustrated by figure (1).

Figure 8: Katmandu prior to earth quake.
Figure 9: Katmandu prior to earth quake.



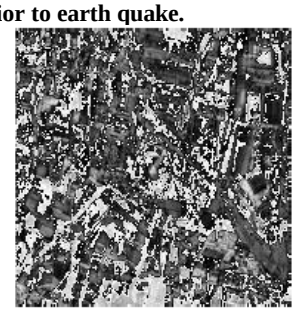


Figure11: Binary equivalent classification result.
Figure 10: Binary equivalent classification result

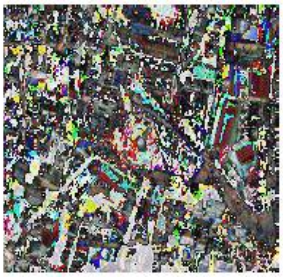


Figure 12: SVM Simplified Results
Figure 13: SVM Simplified Results

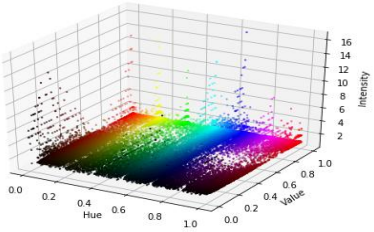
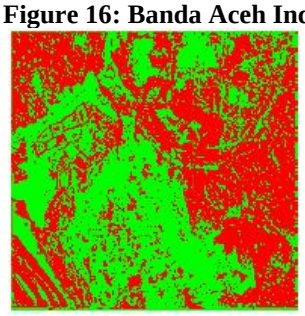


Figure 14: SVM based DAI.

As shown in above Figure (14) is calculate the detection probability is defined as Pd and also calculate the FDAI, which is defined as Pf. The index size of the resulted image is (200, 200), The total index values damaged(White) are 131
The total index values undamaged(black) are 136
Based on the above Figures 8 to 13,
A visual interpretation reveals clear and significant damages to standing structures and relatively the damage is higher in comparison to the region represented by figure (1) and figure (2). Similarly we can observe from the figures that there is lot of people moving around and even we can see vehicles and other small objects. In order to remove the influence of these small objects only those regions having a specific number of pixel counts are considered. This helps in identifying the damage to major structures and helps in reducing false interpretations. The DAI calculated for the above damage represented through Fig (8) and Fig (9) is 5.6 indicating damage for majority of region. The comparison between DAI of the two different regions provides an inference towards the relative damage across the two regions. This provides a very crucial indicator that will aid in the rescue phase.
The images from the 2004 Indian Ocean earthquake that occurred at 00:58:53 UTC on 26 December along the west coast of Sumatra Indonesia have been considered to illustrate the suitability of the DAI by the authors here. Sumatra-Andaman earthquake is the name given to the event by the scientific community. Figure (15) and Figure (16) represent the pre event and post event image after the Tsunami in Band Aceh region of Indonesia.

Figure 15: Banda Aceh Indonesia Prior to 2004 Tsunami
Figure 16: Banda Aceh Indonesia post the 2004 Tsunami



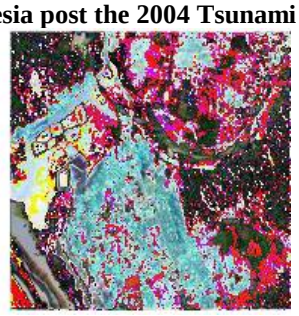


Figure 17: Binary equivalent classification result.
Figure 18: Binary equivalent classification result.

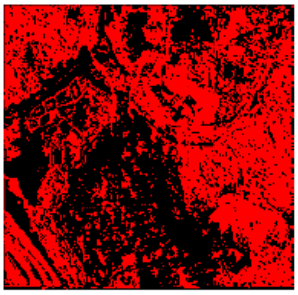


Figure 19: SVM Simplified Results
Figure 20: SVM Simplified Results

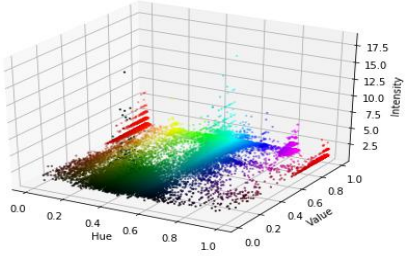


Figure 21: SVM based DAI.

As shown in above Figure (21) is calculate the detection probability is defined as Pd and also calculate the FDAI, which is defined as Pf.
The index size of the resulted image is (200, 200) The total index values damaged(White) are 135
The total index values undamaged(black) are 96
Based on the above Figures 15 to 20,

Visual interpretation and analysis of the images (15) and image (16) reveal extensive damage post tsunami. It can be concluded with utmost confidence that there is collateral damage with both the loss of settlement and
the tree / forest cover. The damage can be categorized as very high. The DAI calculated for the above event is 8.2 and corroborate with the visual interpretation.

To further show the validity of the proposed index, specific cases of damage assessment through field surveys and other methods of calculation available in the literature have been compared. In order to develop an automatic damage detection methodology, the authors observed the characteristics of he buildings that were damaged in area using the high-resolution satellite images that shows pre and post affect of the Haiti earthquake in 2010[13].Based on the results and interpretation of the authors about the accuracy of the prediction it can be inferred that out of a total of 1378 building close to 877 images have suffered different degrees of damage. It comes to around 63 % damage. The before and after event images of the capital city of the republic of Haiti, Port-au-Prince is given in the figure (22) and figure (23).

Figure 22: Haiti prior to earthquake
Figure 23: Haiti post earth quake

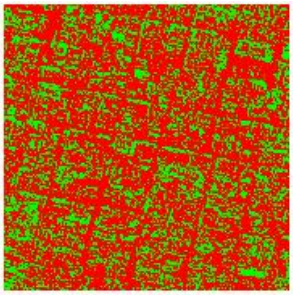


Figure 24: Binary equivalent classification results .
Figure 25: Binary equivalent classification results

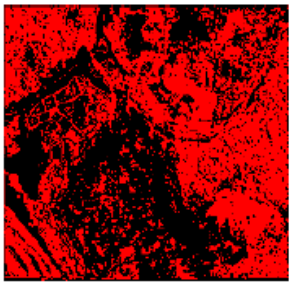


Figure 26: SVM Simplified Results
Figure 27: SVM Simplified Results

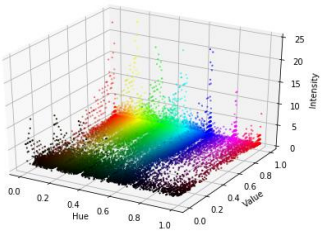
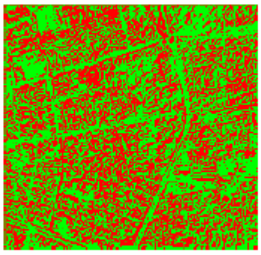


Figure 28: SVM based DAI..

As shown in above Figure (28) is calculate the detection probability is defined as Pd and also calculate the FDAI, which is defined as Pf.

The index size of the resulted image is (200, 200)
The total index values damaged(White) are 155
The total index values undamaged(black) are 126
Based on the above Figures 22 to 27,
The best DAI calculated for images are 5.8. This conforms to the medium damage suggested by results described in [13]. In [24] authors have performed a study to evaluate the damage before and after December 26th 2003 Bam, Iran earth quake. The pre event and post event images are illustrated using figure (29) and figure (30)

Figure 29: Pre event image of the Bam, Iran Earth quake
Figure 30: Post event image of the Bam, Iran Earth quake



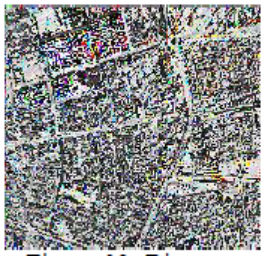
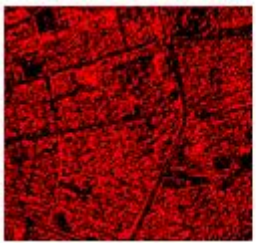


Figure 31: Binary classification results
Figure 32: Binary classification results



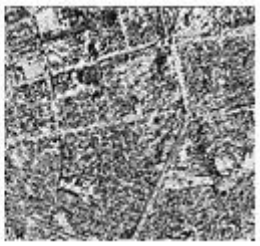


Figure 33: SVM Simplified Results
Figure 34: SVM Simplified Results

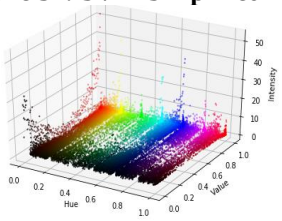


Figure 35: SVM based DAI..

As shown in above Figure (35) is calculate the detection probability is defined as Pd and also calculate the FDAI, which is defined as Pf. The index size of the resulted image is (200, 200)The total index values damaged(White) are150 The total index values undamaged(black) are 104

Based on the above Figures 29 to 34,The authors in [14] through their analysis observed that there is damage to 88.7 % of the buildings in the region and attribute an accuracy of 74.4 % to their proposed method. This assessment puts the damage in high damage category and the DAI arrived in this research work suggests the same *with a DAI of 7.7 indicating a high damage factor.* In [15] authors have attempted to assess damage due to earthquake and subsequent tsunami caused in part of Banda Aceh, Indonesia Prior owing to 2004 Tsunami. The pre and post event images are represented using figure (36) and figure (37). The authors have presented the damage at 40%, suggesting a damage of medium intensity and the DAI arrived by the proposed method stands at 5.4 suggesting a medium to heavy damage.

Figure 36: Banda Aceh - Indonesia (Pre Tsunami Image)
Figure 37: Banda Aceh - Indonesia (Post -Tsunami Image)

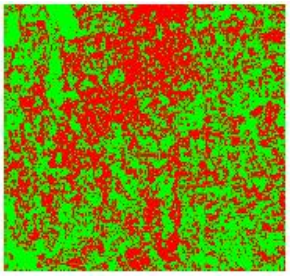
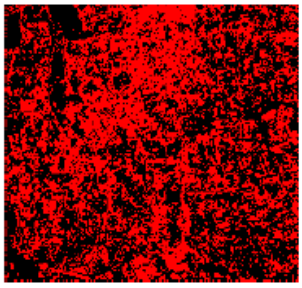


Figure 38: Binary classification results
Figure 39: Binary classification results



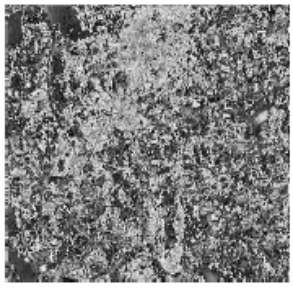


Figure 40: SVM Simplified Results
Figure 41: SVM Simplified Results

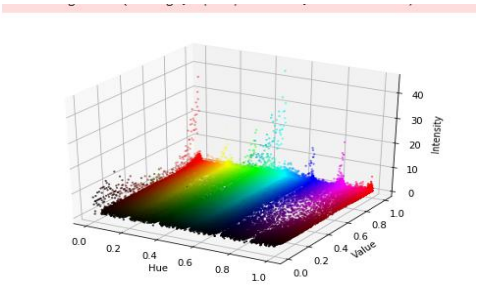


Figure 42: SVM based DAI..

As shown in above Figure (42) is calculate the detection probability is defined as Pd and also calculate the FDAI, which is defined as Pf. The index size of the resulted image is (200, 200)

The total index values damaged(White) are 133

The total index values undamaged(black) are 138

IV. CONCLUSION

In regard to the implementation of the damage assessment index, the simplicity of the algorithm makes it computationally less complex. This reduced computationally complexity enhances the suitability of the proposed index for real time and contiguous analysis. The damage assessment index clearly indicates the degree of damage and can provide the planners with valuable information in directing the rescue and research operations.

This kind of quantification on a scale, helps in easy interpretation of the level of damage and can aid in the decision making process based on fig (7,14,21,35, and 42). The damage assessment index has been validated through visual interpretation and comparing the results with calculation of Pf and Pd for the FDAI. It can be inferred from the results discussed the assessment of damage is in close agreement with that of the visual interpretation and compare DAI with FDAI to get analysis. The significance of index can be observed form the fact that it gives a holistic view about the damage image which shown in figures (1,8,15,22,29and36) by comparing images captured pre and post event.

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