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Sequential Feature Selection Using Hybridized Differential Evolution Algorithm and Haar Cascade for Object Detection Framework

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Abstract: Intelligent systems an aspect of artificial intelligence have been developed to improve satellite image interpretation with several foci on object-based machine learning methods but lack an optimal feature selection technique. Existing techniques applied to satellite images for feature selection and object detection have been reported to be ineffective in detecting objects. In this paper, differential Evolution (DE) algorithm has been introduced as a technique for selecting and mapping features to Haarcascade machine learning classifier for optimal detection of satellite image was acquired, pre-processed and features engineering was carried out and mapped using adopted DE algorithm. The selected feature was trained using Haarcascade machine learning algorithm. The result shows that the proposed technique has performance Accuracy of 86.2%, sensitivity 89.7%, and Specificity 82.2% respectively.

Keywords/Index Terms: Differential Evolution, Haar-cascade, Machine learning, Satellite image

1. Introduction

Object detection is a computer vision approach of identifying objects in an image. It’s an approach that remains a fundamental problem because, real-time images exhibit variation in resolution and when applied to a dynamic world, information about the object can be superseded or corrupted before it is ready for use if the algorithm used is a slow one (Ramisa *et al.*, 2008). Factors such as system or sensor noise, varying brightness, perspective changes, cluttered background, and others, contribute to why humans still have the capacity to recognize objects in images with lesser effort (Kurian, 2011). These factors necessitate the need for a robust model capable of detecting objects within the shortest possible time. The adoption of machine learning algorithm for the use of object detection has enabled process automation thereby making the process less dependent on human subjective procedures. The process takes large object samples as training dataset and compares further inputs with the existing training models to output a result that should look similar to the training set of objects. Common examples of object detection machine learning models include deep learning, Haar-cascades and etc (Kranthi, & Surekha, 2019). The algorithm here take image as an input and output it in the form labels (Kurian, 2011). The classification algorithm is an unsupervised method of learning that take a given data sample and classify them into a group base on the training rules (Sathya & Abraham, 2013). Localization, similar to classification is the training of an object detection algorithm to identify an object in a single image (Cinbis *et al*., 2017).

Object detection in satellite images is a subset of object detection in optical sensing images. This detection entails the determination of an aerial or object contained in an image belonging to a localized area of interest and predictively locating an object in large set image dataset (Cheng & Han, 2016). The choice of a good object detection algorithm should be on the bases of (Kurian, 2011): Reliability, speed, and automation. As the algorithm is required to be robust in handling and image variation so that it will not degrade the image in the process. Speed is essential because the algorithm might be deployed to work online and it should work without human intervention (Leibe *et al.*, 2008).

Differential Evolution (DE) is a meta-heuristic based algorithm (Beheshti & Shamsuddin, 2013; Feoktistov, 2006) that is efficient with an aim to resolve non-linear, non-differential, non-continuous and real-parameters problem (Ecaterina *et al.*, 2011; Nunes *et al.*, 2017). From a randomized general population with a solution, Differential Evolution main objective becomes the selection of the best solution iteratively through some set of instructions. DE has been reported to have parameter that can be adjusted. Mutation factor $f \in [0,2]$, combination factor $c \in [0,1]$ and number of individual population N_{pop}

The challenge with existing machine learning techniques in identifying features or objects in satellite images effectively and accurately in an efficient manner with little or no delay in the processing is the lack of methods that can perform feature selection optimally. Hence, this work core contribution is the hybridization of differential Evolution algorithm for feature selection and classifier (Haar-cascade) for object detection and identification in satellite images.

2. Related Work

Several object detection algorithms exist in the literature (Cheng & Han, 2016). Most work on object detection in aerial image, in the past satellite images were object-oriented (Merchant *et al*., 2019). Methods such as template matching-based object detection, machine learning-based object detection, and object-based image analysis, knowledge-based object detection. (Kim *et al.*, 2004; Leninisha &Vani, 2015; Mayer *et al.*, 2006; Wang *et al.*, 2015) presented methods of detecting road networks and other objects in satellite images. (Zhang *et al.*, 2011) introduced a semi-automatic template matching technique to track roads. The work adopted spoke wheel algorithm to get direction of road width and starting point. Also (Kim *et al.*, 2004) used rectangular template against profile adopted in the work of Zhang to track ribbon road the use of least square correlation template matching. (Zhou *et al.*, 2006) proposed some road tracking techniques using profiles that are orthogonal and parallel to the road direction. (Baltsavias, 2004) present a review of knowledge-based object detection in RSI. Object-based image analysis currently has become the most widely used method for classifying and mapping VHR imagery into a well-defined object. It is a two steps image segmentation and classification (Blaschke *et al.*, 2014)

2.1.1 Haar cascade

Prior to the invention of machine Learning techniques for object detection such as Haar cascade for application in divert field, several other template and object matching algorithm had been actively use. Such as the Scale invariant feature transform (Dalai, 2019), Speed up Robust Feature (Sharma, 2019), oriented fast and rotated binary robust independent elementary features (Gollapudi, 2019). Though, these object detection algorithm have high Accuracy but require longer processing time. On the other hand, Haar-like – feature or Haar cascade is a machine learning object detection method developed by Viola and Jones (Ren *et al.*, 2017) for the purpose of detecting images with speed and accuracy in detection rate. The approach introduces a method of representing an image called Integral Image (Viola & Jones, 2001). This method of representing images allows features trained in another classifier to be computed very fast. When these classifiers are combined in the form of ensemble learning, the approach is called Haarcascade (Phuc, 2019). That is the combination of two or more classifiers trained with haar-like features to produce the best result (Leibe *et al.*, 2008). Haar cascade is an algorithm that operates on the fact that all human face has certain features and these features can be used when trained in a machine to detect objects in images. The feature in relation to human face is (Viola & Jones, 2001): the eyes region is darker than the nose and upper cheek and the nose bridge is brighter than eyes.

$$f\left(x,y\right)=\sum_{a=0}^{x}\sum_{b}^{y}I\left(a,b\right) \quad (1)$$

From (1), the algorithm takes into account the sum difference between pixel value taken from the dark region and compared with the summed integral value f at localized area (x, y) in a rectangle with range of $[0,0]$ to $[x, y]$.The generalized expression for detection and false positive in Haarcascade is given in (2) and (3).

$$w = \prod_{i=1}^{k} w_i \qquad (2)$$

Equation (2) and (3), represents the learning process and the detecting process is shown in equation (3).

$$z = \prod_{i=1}^{k} z_i \qquad (3)$$

Where w is the minimum accepted false positive rate, z is the minimum accepted detection rate, P = set of positive, N = set of negative, Feature Engineering

Features are extracted to give more insight into dataset. The process entails understanding the component and features that are contained in data. For classification related problems (unsupervised learning) classification algorithm is entrusted with interpretation to the dataset as it is expected to classify or cluster the data based on the instructed rules. Haarcasde is a feature rather than pixel-based classifier. Owning to its fastness when compared to pixel extracted features. Extracting features from satellite image will require good knowledge in satellite image processing tools such as ArcGIS, R language, MatLab, etc through the use of Raster library and other in-built libraries specifically dedicated to image processing.

2.1.2 Creating Haar Cascade for Object Dectection: A Theoretical Background

Haar cascade performance can be improved given the efficiency of Adaboost that allow the algorithm to contain a significantly large number of training example that in turn contributes to generalized performance of stronger classifier's error. Consequently, this makes small training image samples containing the need to find feature to be misclassified (Fan, 2019). Adaboost simultaneously associates learning procedures (Wang, 2019). The essence of associating the learning procedure by large was to construct classifiers for object recognition. The choice of the states in the learning process in Adaboost, is designer dependent but the first choice for each state will be created by the system on positive images and tested on negative images which will be used for subsequent use in bulding a second classifiers that mature into better detection rate. The process continues with the next classifer that is then used for the next state. the iterative process ends when the last state is completed (Kyrkou 2010). The cascaded stages discussed, are achieved by l training each classifier by means of Adaboost and minimizing thr error rate with the use of other compiling threshold algorithm.

3. Methodology

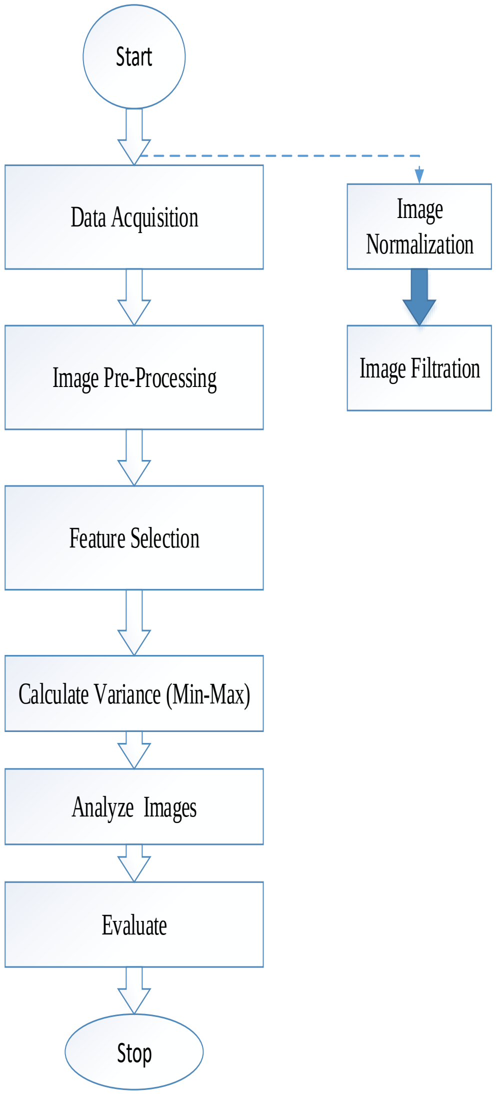

Figure 1: Work Flow chat

3.1.1 Data Collection and Pre-Processing

This work used landsat8 imagery extracted from https://usgs.gov/fm/data/ between the periods of January through June 2018 for Kaduna state Nigeria. Kaduna state capital is a commercial city while other regions of the state predominantly for farming and mining. The state is located in the Northwestern region of Nigeria with a population density of about 6,113,503 according to 2006 population census. The dataset contains satellite images of high resolution and has features such as water bodies, land, vegetation and others such as buildings. The aim of this work is the application of Haar features like machine learning algorithm in identifying objects in the dataset.

After the dataset was collected, it was observed that the images were of different sizes and colour intensity as such, image color channel switch was done and Guassian blur. The reason for guassian blur was to obtain a 2-D distribution fuction which can equally be achieved with convolution. To produce the desired convolution, discrete approximation to Guassian is done to output a weight average of each pixels. The choice of Guassian is because, Guassian output a more smoothing and preserves edge in an improve manner than similar methods. In order to reduce noise in a simpler and effective way, we used binary threshold method (Sezgin 2004; Senthilkumaran 2016).

The pre-processing of data is an essential part of the data mining process. It involves steps like data filtering, replacement of missing information (data cleaning), normalization and feature extraction. In this work, acquired dataset was ensured to be in uniform size, extends and formats. Hence, feature of interest was cropped out. In this work three features were cropped out and thence presents as $C^t = \left(C^t_{ux}, C^t_{uy}, C^t_{uz}\right)$ and C^t_{uc} as the coordinate of each feature in an image $\mathrm{H} \in = \{x, y, z\}$ of features $b \in \{1, ..., k\}$. From our available dataset, a set of features was extracted for water bodies and vegetation.

In order to attenuate noise, introduce into the images, each set of extracted features was first normalized for the purpose of uniformity in training and evaluation.

3.1.2 Feature Normalization

This operation on a dataset is a recurrent operation in machine learning domain (*Forman. et al* 2009). Data normalization for this work is done using the model in equation (4).

$$v_{ij} = \frac{V'_{ij} - \min\left(V'_{m.j}\right)}{\max\left(V'_{m.j}\right) - \min\left(V'_{m.j}\right)} \quad (4)$$

Where V'_{ij} is the feature being normalized, V_{ij} represents values of normalized features respectively and $V'_{m.j}$ is the column of *j* in the matrix V_m which represents the constructive arrangement of the same feature in the dataset, this operation is carried out for both training set and test set thereby resulting in V_m and V_{me} matrices. Hence, the set of features will be *V*. From the previous steps applied, V can be said to be a set-in matrix containing all features in the dataset.

$$V = \left[\left(V^1\right)^T \left(V^2\right)^T ....\left(V^x\right)^T .....\right], \quad (5)$$

where V^x is a related sub-matrix of feature x.

This work assumes that there are reoccurring features in the dataset as it's possible to assume that each feature can be determined by just physical observation. Based on this assumption, this work performed other statistical analyses to determine the variation between the features in terms of variance in the composition of features.

$$\delta_{xy}^{t} = \sqrt{\sum_{d'}\left(g_{xd'}^{t} - g_{yd'}^{t}\right)^{2}} \qquad (6)$$

where g_{xy}^{t} and g_{yd}^{t} represents max and min respectively, the variance values of two features that look alike are therefore combined using equation (7).

$$G^{t} = \frac{1}{2}\sum_{j=1}^{m}\sum_{d}\left(h_{jd}^{t}\right)^{2}, \qquad (7)$$

Where $d \in \{x, y, z\}$ and the combination rule must satisfy equation (8)

$$G^{t} < G_{\min}, \qquad (8)$$

Where $G_{\min}$ is the threshold, the process is able to minimize the noise in the selected feature of dataset. The process, however, will produce a system that will have low computational cost and fast computing since it only requires features that are within the threshold.

For the case of feature selection for training and testing, selected features need to be combined and used to form a uniform set of similar sets of datasets. From equation (5), each set of set instance vector V_{w}^{a} can be constructed as

$$V_{wi}^{a} = \left[V_{wij}^{a} V_{wi}^{b} V_{wil}^{a}\right], \qquad (9)$$

Where V_{wif}^{a} and V_{wil}^{a} represent an instance of the selected features that belong to the same grouping.

3.1.3 Training Cascade Classifiers

Here in this work, it's assumed that the model is made up of several independent classifiers, the final detection rate and false-positive rate are given in equation and (1) and (2) respectively (Mutsuddy, 2019). Where k are the steps in the cascade, for selected, featured, the probability that a set of instance sample X will be trained in a classifier at a given stage of training and mapping task to independent classifiers is given as

$$P(S \cap H \mid X) = P(S) = P(S \mid X).1 = P(S \mid X)P(H \mid X) \quad 10)$$

Where $P(S \mid X)$ represent the posterior probability of our output classifier. When S and X are independent $P(S \cap X) = P(S)P(X)$, likewise $P(S \mid X) = P(S)$. This implies the output of the classifier must not rely upon the input samples of instance. This happens when the instance is on the classifier boundary, where the output of the classifier corresponds to random prediction. This implies condition (a) to the left hand of equation can be forced by methods for the choice of the nearest instance to the boundary of classifier *S*. Then again, condition (b) is forced by the training procedure itself because of the way that the classifier train is fed with the selected training instance.

3.2 Evaluation Matrices

To evaluate the performance of classifiers in this work,five categories of positive image set were used. The categories were represented in percentages (100, 80, 60 ,40 and 20), three categories of negative images were also used. The image sets are of different sizes. Positive image set comprise of image with Water Body and other feature such as Rocks, Vegitation; negative image set has vegetations but no water patches in the image set. At the end of the process, the object correctly detected were saved in a separate location. The results however, showed that, the true positively detected objects represents the positive images with positive features. And the false positive represents images within the positive image set but does not have the object it was trained to detect. In this work, the performance of the classifier was measured using accuracy. For binary classification, accuracy is measured using the expression as follows (Liu, 2019):

$$Accuracy = \frac{T_P + T_n}{T_P + T_n + F_P + F_n} \quad (11)$$

Where T_n represents true negative, which is denoted for correctly classified of negative instances, T_p (true positive) correctly classify positive instance, F_p, F_n represents false positive and false negative respectively. False-positive incorrectly classifies into negative while the false negative classify instances into positive classes and negative sample instances. The accuracy measurement does not consider unbalance dataset. So, therefore, accuracy measurement has a biased tendency towards the majority classes. Other evaluation parameter considered in this work includes precision and Recall as shown in equation (12 and 13) Bharadwaj (2019).

$$precision = \frac{T_p}{T_p + F_p} \quad (12)$$

$$\mathrm{Re}call = \frac{T_p}{T_p + F_n} \quad (13)$$

4.0 Result and Discussion

According to Table 1 and 2, Accuracy rate for object detection is shown in Figure 1 and 2. Results of Haarcascade's implemented on set of satellite images contains water body.The result showed boundary area box drawn around water bodies. The algorithm therefore, has high accuracy in detecting presence of water. Figure 2 represents the accuracy detection result of the algorithm when trained in other sets of datasets containing Vegetation. In the training rule, Green vegetation was denoted by cropping Region of Interest (ROI) that has been selected by equation (6)

Table 1 and 2 illustrate the performance accuracy, *TN*, *TP*, *FN*, *FP*, specificity and the sensitivity of the proposed method. The method achieves an accuracy performance of 85.89% when the training set is 100%. Sensitivity attains a performance of 84.7% and 81.3% for specificity.

Figure 3 illustrates the steady increase in accuracy as the size of the dataset increase from 20% to 100% while sensitivity experience a fall to 60% of the dataset. This, therefore, justify equation (13)

Similarly, Figure 4 illustrates the rise in the Specificity of the proposed methods. The specificity increased from 20% to

100%.

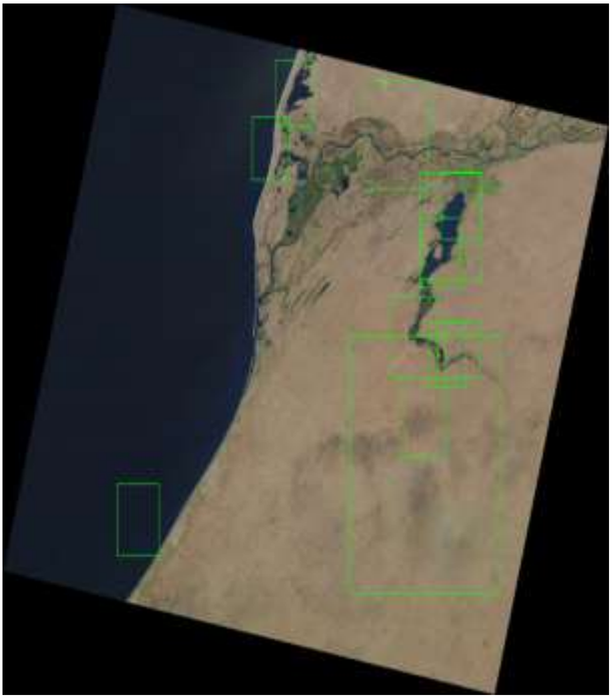

Figure 1: Detection of Water in Satellite Image

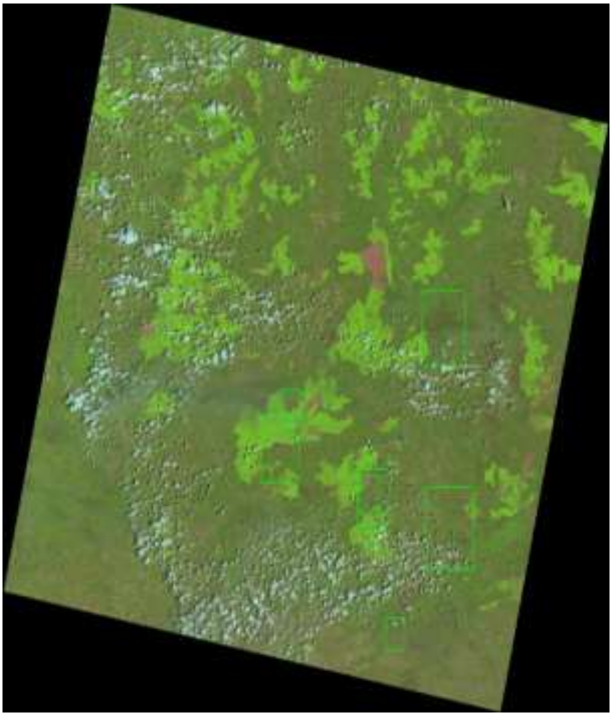

Figure 2: detection of Vegetation in Satellite Image

Table 1: Table of Confusion Matrices

Data size (%)	TP	FP	TN	FN
100	149	4	35	39
80	120	8	38	46
60	52	17	35	31
40	60	17	35	13
20	60	38	18	13

Table 2: Table showing specificity and Sensitivity

Data size (%)	Accuracy	Sensitivity	Specificity
100	86.2	89.7	82.2
80	82.55	82.6	72.2
60	65.1	75.3	63.7
40	63.81	77.9	82.2
20	63.76	77.9	82.2

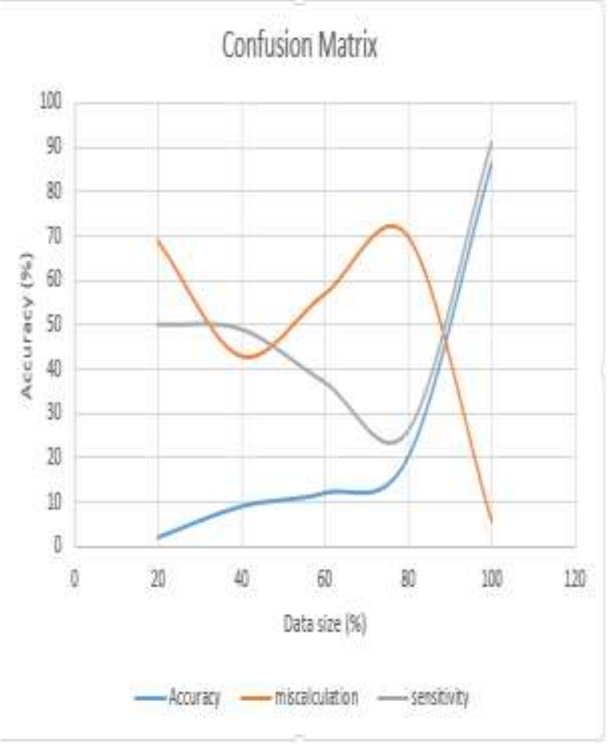

Figure 3: Confusion matrix chart for Haar cascade

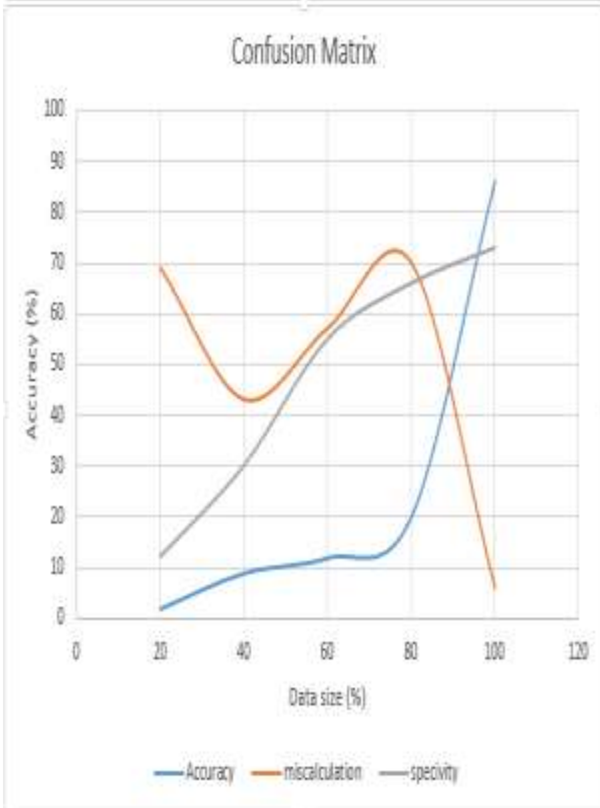

Figure 4: plot of Accuracy and Specificity

4. Conclusion

In this paper, we proposed the use of Differential Evolution algorithm for feature selection and mapping for the purpose of detecting objects and features in satellite images the selected features were trained using HaarCascade machine learning algorithm for detection. The proposed techniques hybridized DE a meta-heuristic algorithm and machine learning to achieve an improvement in reducing computational time and improving the accuracy of the Haar algorithm in detecting objects for satellite image. The result obtained shows that improvement in Accuracy, smaller number of False positive and increased true positive in Table 1 is an indication that the algorithm performed with high efficiency thereby leading Accuracy rate of 86.2,82.5,65.1,63.8 and 63.7 respectively. While Sensitivity and Specificity increases as the size of the training dataset increase which implies our proposed algorithm learn better with large set of data. Comparing the result obtained from this set of Satellite images with other satellite images of the same resolution and but from different location with similar features. This we will consider for future work as this will evaluate the performance of our model giving different location and source of dataset. Secondly, we had recommend the use of Deep Learning Techniques for multiple feature detection from satellite images to further reduce system overhead cost.

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