CLASSIFICATION AND COMPARISION OF REMOTE SENSING IMAGE USING SUPPORT VECTOR MACHINE AND K-NEAREST NEIGHBOUR ALGORITHMS

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ABSTRACT

Remote sensing is collecting information about an object without any direct physical contact with the particular object. It is widely used in many fields such as oceanography, geology, ecology. Remote sensing uses the Satellite to detect and classify the particular object or area. They also classify the object on the earth surfaces which includes Vegetation, Building, Soil, Forest and Water. The approach uses the classifiers of previous images to decrease the required number of training samples for the classifier training of an incoming image. For each incoming image, a rough classifier is predicted first based on the temporal trend of a set of previous classifiers. The predicted classifier is then fine-tuned into a more accurate manner with current training samples. This approach can be further applied as sequential image data, with only a small number of training samples, which are being required from each image. This method uses LANSAT 8 images for Training and Testing processes. First, using the Classifier Prediction technique the Signatures are being generated for the input images. The generated Signatures are used for the Training purposes. SVM Classification is used for classifying the images. The final results describes that the leverage of a priori information from previous images will provide advantageous improvement for future images in multi temporal image classification.

KEYWORDS

Signatures, Prediction, Classifier, Multi temporal, Classification.

1. INTRODUCTION

The information about the particular land area is obtained through Remote Sensing. This is done by rapid monitoring of the land area the classification is based on the Temporal Correlation using Change detection methods. Each object has its own Spectral Characteristics. Remote Sensing images depend on Spectral band which are represented in RGB channels. Their mapping is based on particular purpose of the image. Traditional supervised classification algorithms like Support Vector Machines (SVM) have been widely challenged by the explosive availability of remote sensing images. Whereas, while collecting a sufficient number of training samples it is critical to achieve satisfactory classification results, so it is often labor- and time-consuming which is sometimes practically unfeasible. This problem is more severe for agricultural areas where they are with accuracy of ground reference data that can be quickly outdated due to the frequent land cover changes and spectral characteristic shifts faced by crop phonology and anthropogenic practices like irrigation and harvesting.[2]-[8] Finally, training data sufficiency cannot be guaranteed for each image. Temporal correlation and spectral similarity between multi temporal images have given up an opportunity to reduce the small sample size problem. Where as an incoming image gets classified, existing knowledge provided by previous images is utilized as a priori information. It is not directly applied to the incoming input image, because class data of different images may have different probabilistic distributions in the feature space. This methodology is often termed as cross-image dataset shifts. These shifts originate from changes in the nature of land surface and their properties, for example, they can be induced by the phenology of vegetation, or from the background noise which is caused by varied acquisition and atmospheric conditions and inconsistent sun-target-senor geometries.

Domain adaptation is an important technique which is able to use the dataset shifts among images. This technique aims to adapt a priori information which is extracted from previous images to an incoming image which has shifted their spectral characteristics. These are frequently compared with a complete retraining of the incoming image, the number of required training samples can be frequently reduced if the assistance from previous images is leveraged. Several domain adaptation algorithms have been adopted to use the dataset shifts in multi temporal image classification.[12]-[15] The change-detection-driven algorithm is used in training a classifier of an incoming image with the help of their unchanged samples from a previous image. A change detection step is firstly implemented to identify the number of unchanged pixels, whose labels are then directly transferred to the incoming image.

The SVM-based sequential classifier training (SCT-SVM) method for multi temporal remote sensing image classification is applied. From the information of the set of previous classifiers, this method is able to effectively train classifiers for an incoming image in the same location. This method can be applied continuously to sequential image data, with only a small number of training samples are being required from each incoming image.

2. PROPOSED WORK

The information about the particular land area is obtained through Remote Sensing. This is done by rapid monitoring of the land area the classification is based on the Temporal Correlation using Change detection methods. Each object has its own Spectral Characteristics. Remote Sensing images depend on Spectral band which are represented in RGB channels. Their mapping is based on particular purpose of the image. Traditional supervised classification algorithms like Support Vector Machines (SVM) have been widely challenged by the explosive availability of remote sensing images. Whereas, while collecting a sufficient number of training samples it is critical to achieve satisfactory classification results, so it is often labor- and time-consuming which is sometime practically unfeasible.[18] This problem is more severe for agricultural areas where they are with accuracy of ground reference data that can be quickly outdated due to the frequent land cover changes and spectral characteristic shifts faced by crop phonology and anthropogenic practices like irrigation and harvesting. Finally, training data sufficiency cannot be guaranteed for each image. Temporal correlation and spectral similarity between multi temporal images have given up an opportunity to reduce the small sample size problem. Where as an incoming image gets classified, existing knowledge provided by previous images is utilized as a priori information.[20]-[27] Temporal correlation and spectral similarity between multitemporal images have opened up an opportunity to alleviate the small sample size problem. When an incoming image needs to be classified, existing knowledge provided by previous images can be utilized as *a* priori information. In remote sensing different quality of images are produced based upon their type of sensor. Classification accuracy of an image usually depends upon their image quality. Image classification can be carried out using two ways: supervised classification and unsupervised classification. In supervised classification it is necessary to have prior knowledge about the input data and their location. From the training set of data the features are extracted in supervised classification

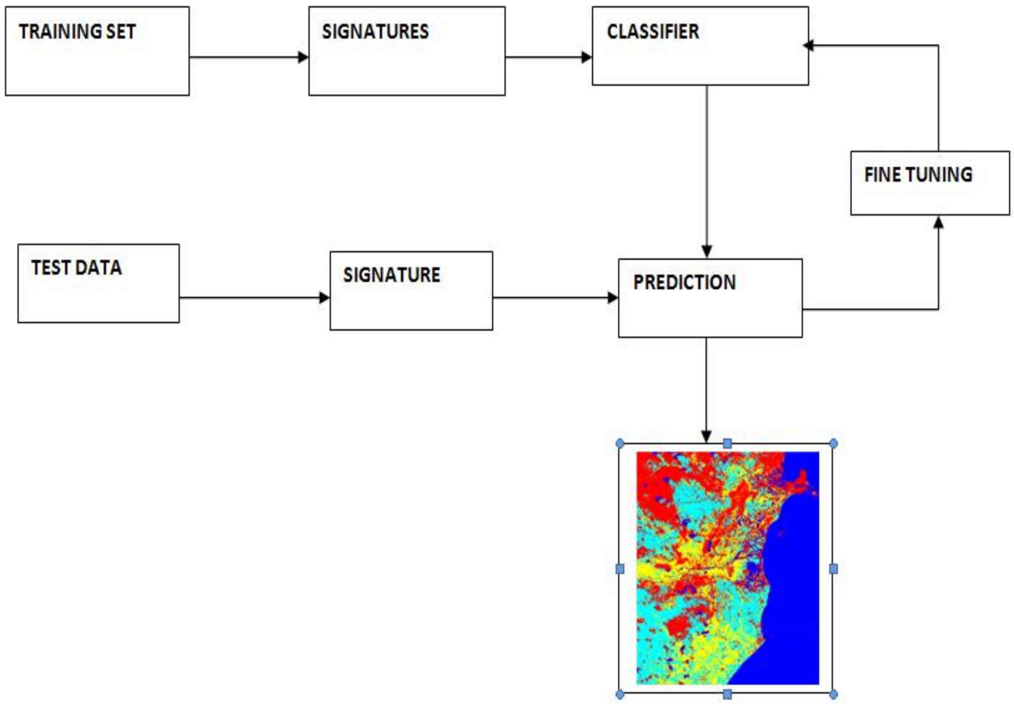

Figure 1: Proposed Work

2.1 Signatures

The amount of solar radiation that is reflected (absorbed, transmitted) will vary with their wavelength. It is an important property of matter that allows us to separate distinct cover types based upon their response values for a given wavelength. When we plot the response characteristics of a certain cover type against wavelength, it is spectral signature of that cover. By comparing the response patterns of different features they are distinguished, where we might not be able to, if we only compared them at one wavelength. For example, water and vegetation may reflect the visible wavelengths but they are almost always separable in the infrared wavelength. [30] Spectral response is a different variable, even for same target type, they vary with time ("green" for leaves) and some location. These features of interest are quite critical in interpreting the interaction of electromagnetic radiation with the surface.

The spectral reflectance characteristics of the earth cover types are used for identifying and mapping them in areas we those are generally unfamiliar with. Even though you are totally unfamiliar with the region we can easily identify the dominant cover types of the area with a high degree of certainty and by utilizing known knowledge about the spectral characteristics of certain surface materials which is the spectral signatures.

2.2 Prediction

The main goal of the classifier prediction is to determine a rough classifier for the current image (Image t). The prediction is based on the temporal trend of a set of previous classifiers. The trend can be due to the background variations under different acquisition conditions or originated from changes in the nature of land surface properties such as the phenology of crops and forests, or both. The former factor causes random and unpredictable changes. The latter factor induces relatively gradual changes, due to the smooth transitions of class data over time. The proposed is to perform a principal component transform, and use the first transformed component to extract the overall temporal trend and suppress the background effects. The first principal component direction captures the maximum temporal dynamics of previous classifiers. The classifier prediction is conducted with the following procedure.

Firstly, the previous classifiers are mean-centralized in the classifier parameter space. Then a principal component transform is applied to transform the mean-centered classifiers from the classifier parameter space into the principal component space. A regression is then performed in order to predict a classifier for Image *t*. [33]-[35] The polynomial fitting function is selected in this work. It is worth noting that the order of the fitting function is selected according to the pattern of the temporal trend of classifiers. In order to achieve better fitting accuracies, higher order polynomials may be adopted, but the over fitting risk will increase as well. So the balance between fitting accuracy and over fitting problem should be considered when choosing the fitting function. The inverse of the principal component transform is then performed, followed by the mean-decentralization (i.e., reverse of the mean-centralization), to obtain the predicted classifier in the original classifier parameter space.

2.3 Fine-Tunning

A domain adaptation algorithm is developed as the second stage of the proposed SCT-SVM. It fine-tunes the predicted classifier $\mathbf{p}\,(t\,)$ to a more accurate position $\mathbf{p}(t\,)$ with training samples of the current image (Image *t*). It is anticipated that classifier prediction errors can be compensated after fine tuning. The algorithm is designed with anticipation that the true classifier should be located not far from the predicted position. This is a reasonable expectation, given that the predicted classifier is based on the historical information extracted from previous images and the changes are often gradual over time. The aim of the fine-tuning is to achieve higher classification accuracy on the training samples of Image *t*.[15] In this way, contributions from the predicted classifier and the training samples are incorporated and balanced in the algorithm.

The a priori information provided by the predicted classifier is utilized by restricting the fine-tuned classifier from departing too far away from the predicted position. The information provided by the training samples of the current image (Image *t*) is utilized by taking into account the classification error of the fine-tuned classifier on the training samples $\{\mathbf{x}i\ ,\ yi\ \}ni{=}1$, where $\mathbf{x}i$ is the feature vector of the i th training sample and $yi \in \{+1,-1\}$ is its corresponding label. [36]Similar to those in the standard support vector machines, a set of non-negative slack variables $\boldsymbol{\xi} = \{\xi i\ \}ni{=}1$ is used to allow soft-margin classification in order to tackle overlapping classes. Consequently, the following constraints are designed. The first term in the objective function accounts for the margin space of the fine-tuned classifier. Like that in the standard support vector machines, the term aims to adjust the separating hyper plane to a position that generates the maximum margin space between classes.[39] The second and third terms aim to minimize their degree of violation of their constraints. The positive constants C and F are regularization parameters, which control the weights of the second and third terms relative to the first term. The values of C and F control the contributions from training samples and previous images, respectively. It is worth noting that the parameters, F and C, need to be preset for the fine-tuning algorithm. The best combination of F and C can be determined through cross validation with a grid search. The dual form of the optimization problem can be obtained by constructing the following Lagrangian function L.

2.4 Classification

The proposed SCT-SVM is a classifier-level approach. SVM transfers the classifier-level knowledge, which is the classifier parameters of a set of previous classifiers, to the incoming image. It is used with the data-level approaches that require the availability of pixels and/or their corresponding labels (raw data) from previous images, such as the Domain Adaptation SVM (DASVM) and the Domain Transfer SVM (DT-SVM), the proposed approach has the following two merits. Firstly, the required computational load can be reduced considering that the size of raw data is usually large. Secondly, the proposed algorithm is applicable even if the raw data of previous images are inaccessible (e.g., private or no longer stored). Therefore, with the data-level approaches, the proposed classifier-level approach is more efficient and more feasible. The second step of the proposed method is fine-tuning. The A-SVM enables the estimation of a fine-tuned target classifier by augmenting a perturbation term to the predicted classifier. However, it has been found that the A-SVM tends to generate a small margin space for the fine-tuned classifier. [19]-[22] The other algorithm, PMT-SVM, is able to estimate a fine-tuned classifier without penalizing its margin maximization.

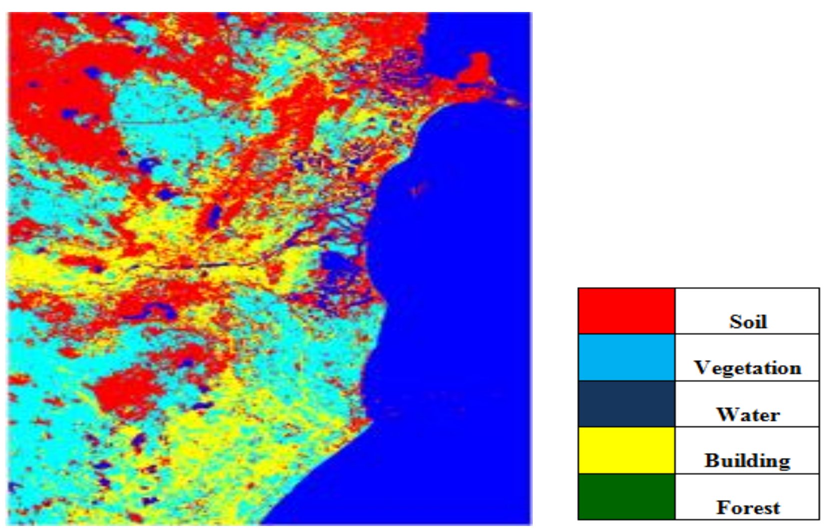

Figure 2: Classification of remote sensing image using SVM algorithm

The limitation, however, is that it restricts the included angle between the predicted and fine-tuned classifiers to a value equivalent to or less than 90◦ in the feature space. This restriction leads to a decreased performance when the underlying optimal classifier is positioned at an angle greater than 90◦ from the predicted position.

The proposed fine-tuning algorithm considers a maximum margin- space term which can alleviate the small-margin-space problem that exists in the A-SVM. The proposed algorithm is also able to fine-tune a predicted classifier into a position larger than 90◦ as no restriction is applied on the fine-tuning angle, which is an improvement from the PMT-SVM.

3. KNN CLASSIFIER

K means is used in partitioning and analysis of the data. K means partitions data is the object inside each cluster will remain closer to each other and some are away from objects in remaining cluster. In K means clustering algorithm they starts with the random number of required clusters K. These numbers of clusters are taken as starting values for grouping. Each and every point is verified and assigned to their nearest cluster. If all the data points are assigned to an cluster then a new K centroids values are recalculated.

KNN is the simplest classification technique. KNN is used to classify the objects based on their similarity or closest training samples in the feature space.[26] Maximum vote of neighboring points is used to classify the object. Example if an unknown sample and known training data are taken and the distances between all training set samples and unknown samples will be calculated. The smallest distance value corresponds to their training set sample which are close to unknown sample. Thus the unknown sample can be classified on the basis of their nearest neighbor. It is highly required for the extraction of edges which is to be completely connected as there are several features values and the objects co-existing in different shapes and sizes in satellite images (LANSAT 8). The measurement of smoothness technique of an image by using Gradian operators and criterion of Euclidean is evaluated. By this method the edge detection is not continuous and their cost of computation becomes large.

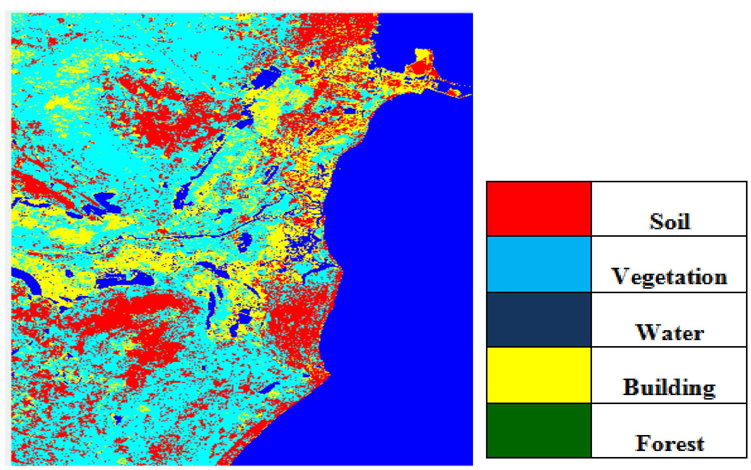

Figure 3: Classification of remote sensing image using KNN algorithm

Optical satellite sensors are used for the detection of relative growing of coral reef. They are found under the water bodies of shallow depth and in clear water. [1],[6] The data of the optical satellite sensor remains available to a great extent.

The most commonly used satellite sensors are the LANDSAT TM and ETM+. The capabilities of these sensors in the spatial and spectral resolutions, represents their inability to differentiate between a coral reef and its various association in some regions. One of the alternative approaches is segmentation process is the objects which are identified for classification by using their pixel combination and this method is termed as an object-based classification. The Object-based classification technique can be widely used and applied for mapping land area with their higher accuracy value. [11] It is a efficient kind of algorithm which can store a huge content of classifiers which are continuously identified by their distance metric functions. They use hamming distance measure which provides the distance function and their value according to the value of K. Many applications have used this classifier and modified it according to their requirements area. This approach opened out to give best accurate results.

4. EXPERIMENTAL RESULTS

The proposed work uses supervised classification algorithm as Support Vector Machine. The Signatures are generated for four classes as Vegetation, Soil, Water and Building. Then the images are predicted and fine tuned and output is displayed with the classified image. The tool MATLAB 2016 is used to implement the proposed methodology. The training and testing were carried out in Windows 7 environment configured by Intel Pentium CPU 1.70GHz, 4GB RAM and 500GB storage.

The GUI displays the training set, Sequential SVM training, Sequential SVM Classification and then the final output is displayed. In the training process the signatures are generated for every image. They are calculated for four classes as Vegetation, Soil, Water and Building. The images are being predicted with the generated signatures. The images are sequentially trained with the SVM with the generated signatures. Finally, the output is displayed with classified LANSAT image as Vegetation, Soil, Water and Building.

The input datasets are collected from Earth Explorer website and the LANSAT 8 images are being downloaded.

The Classified images are obtained for both the SVM and KNN classifiers. Among then the SVM is with the high Sensitivity, Recall and GMean value than KNN classifier.

Table 1: Analysis of LANSAT 8 image using Sequential SVM Classifier

Classifier	Accuracy	Sensitivity	Specificity	Precision	Recall	F-Measure	GMean
SVM	**0.8611**	**0.9458**	**0.7994**	**0.8124**	**0.9458**	**0.7973**	**0.8972**

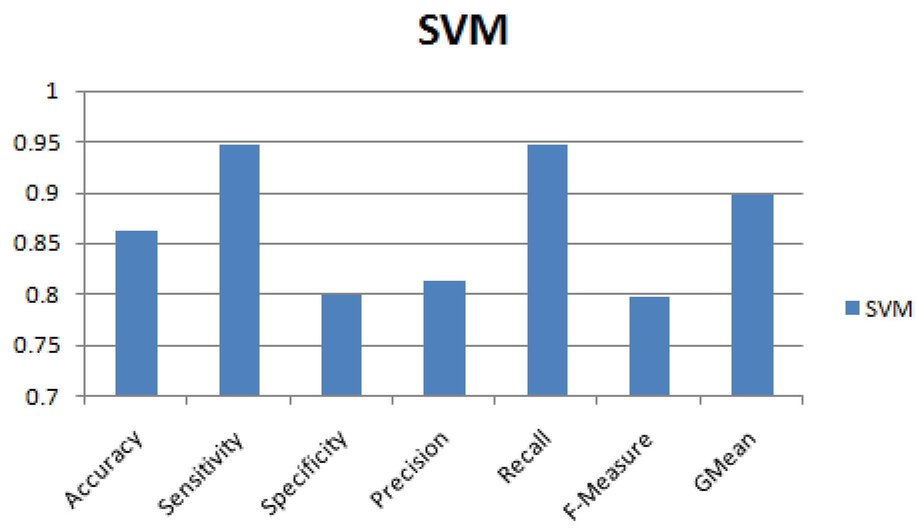

Figure 4: Analysis using SVM Clasifier

Table 2: Analysis of LANSAT 8 image using KNN Classifier

Classifier	Accuracy	Sensitivity	Specificity	Precision	Recall	F-Measure	GMean
KNN	0.8771	1	0.8361	0.8715	1	0.8418	0.9604

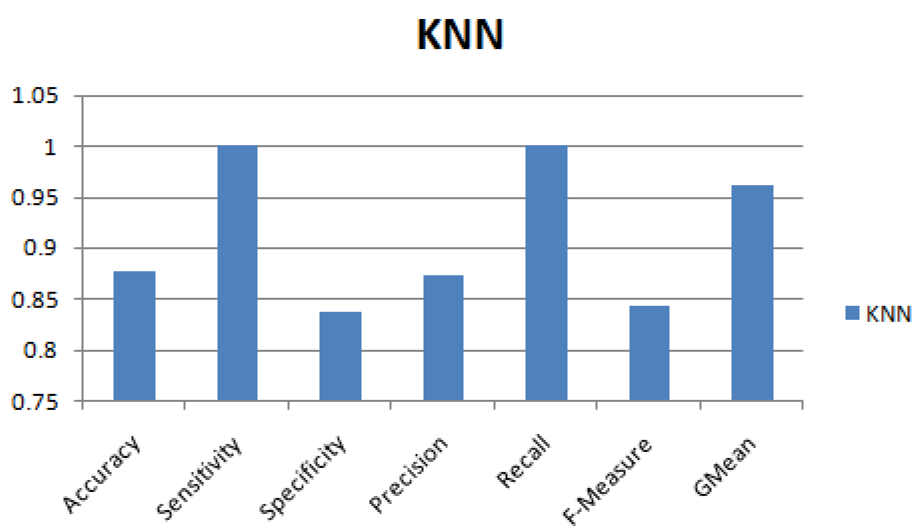

Figure 5: Analysis using KNN Clasifier

Table 3: Classification result of SVM and KNN algorithms

Classifier	Accuracy	Sensitivity	Specificity	Precision	Recall	F-Measure	GMean
SVM	0.8771	1	0.8361	0.8715	1	0.8418	0.9604
KNN	0.8611	0.9458	0.7994	0.8124	0.945 8	0.7973	0.8972

The proposed combinatorial algorithm describes the nearest classes for their testing samples by considering both luminance and their direction measures of the vectors. In the combinatorial algorithm, training samples for every input have been decreased and they are represented by a smaller set of SVs for their classification and only their distances from their testing data point to all their SVs needed to be calculated. Thus the selection of an optimal value of the required parameter in the KNN classifier is not required instead the SVs are determined automatically by the SVM algorithm. The proposed algorithm has less advantages than the conventional KNN for eliminating the parameter selection problem and in reducing their heavy learning time.

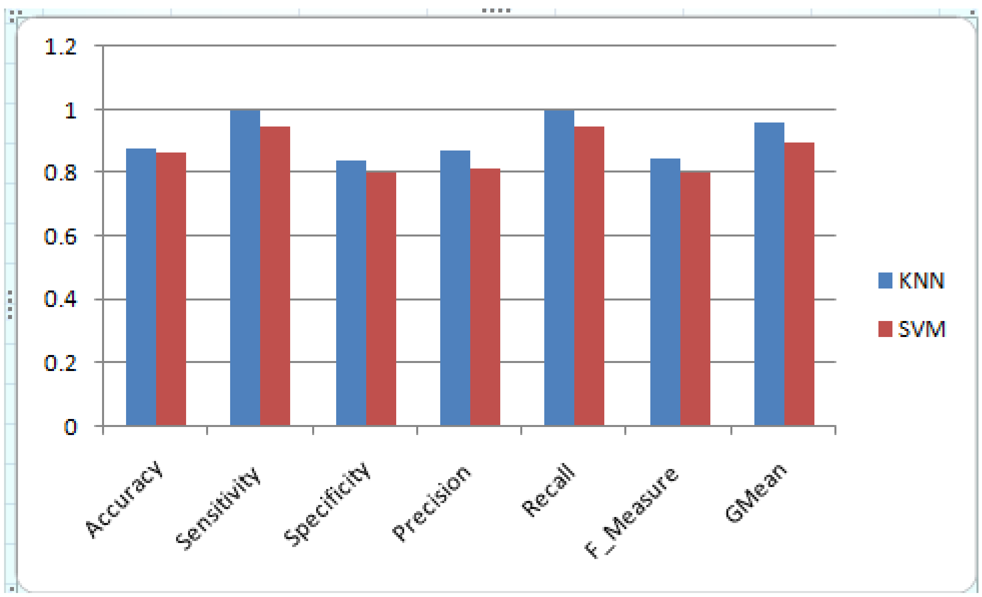

Figure 6: Analysis of remote sensing images using KNN and SVM Classifier

4.1 Comparing The Lansat 8 Images With Google Map Image

The obtainted output of Classified LANSAT image is compared with the Google Map based on their Lattitude and Longitude and then verified. Both SVM and KNN classified images are compared.

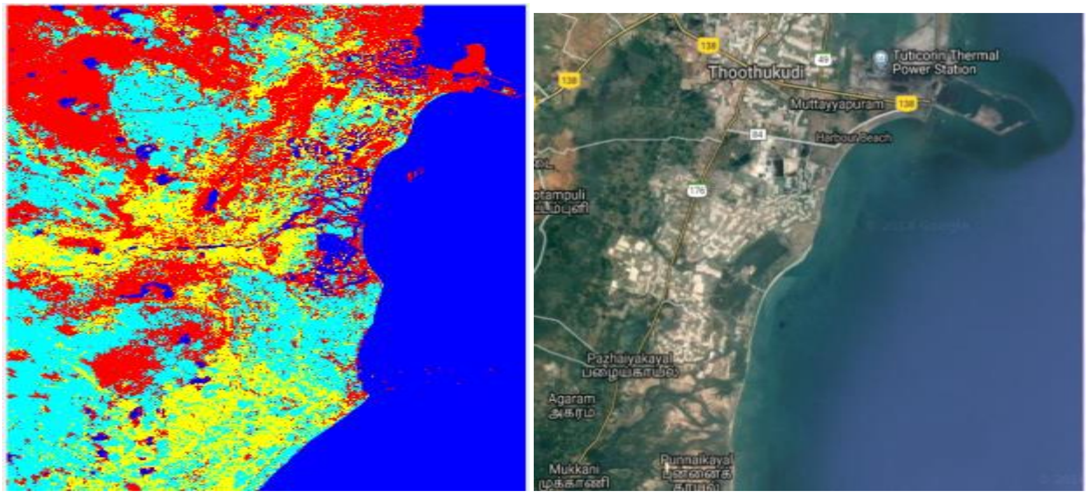

Figure 7: Comparing the SVM classified remote sensing image with google map image

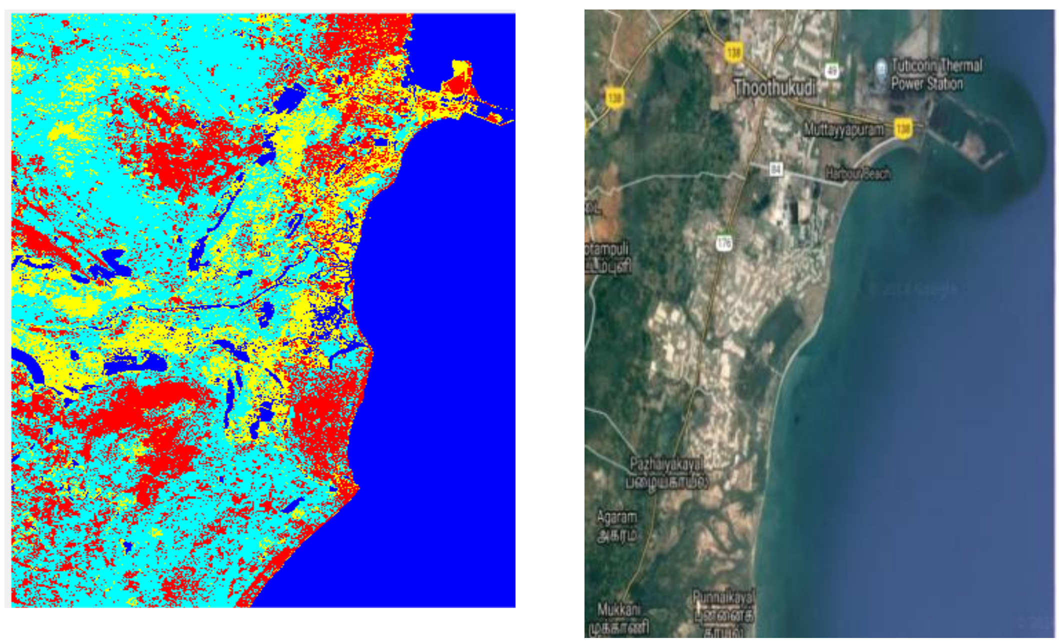

Figure 8: Comparing the KNN classified remote sensing image with google map image

5. CONCLUSION

The SVM-based Sequential Classifier Training (SCT-SVM) is an approach proposed for multitemporal remote sensing image classification. The proposed work leverages the classifiers of previous images to reduce the required number of training samples for the classifier training of a new image. Based on the temporal trend of previous classifiers, classifiers are firstly predicted for the new image. Then, a newly developed domain adaptation algorithm, Temporal-Adaptive Support Vector Machines (TASVM), is used to fine-tune the predicted classifiers into more accurate positions. Experimental results showed that the TASVM outperformed state-of-the-art algorithms in classifier fine-tuning. This method requires the priori information from previous images can provide advantageous assistance for the classification of later images. The proposed approach is suitable for monitoring the quantitative change of a given class, for example, increasing or decreasing of areas, and changes of spatial distributions. Natural changes are often gradual changes, which lead to smooth transitions, especially when the time interval is short. Human activities or disasters, for example, logging or forest fire, often bring abrupt changes. These discontinued cases are not considered in this proposed work as they often needed. The proposed approach is suitable for monitoring the quantitative change of a given class, for example, increasing or decreasing of areas, and changes of spatial distributions. Natural changes are often gradual changes, which lead to smooth transitions, especially when the time interval is short. In this paper multiclass sequential SVM and KNN algorithms are used for classification of data. KNN is more efficient than other algorithms it provides good results while comparing with the Sequential SVM because they consider the prior knowledge about the images. Thus it reduces the number of input images. The accuracy level is more efficient when compared with the SVM algorithm.

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