Land Use Land Cover Classification by applying Ensemble Approaches on Multi Temporal Remote Sensing Images

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Abstract

We have researched in the development of methods and techniques to monitor the modification of land use/land cover (LULC) classes in catchment areas. With the need of fast urbanization and the risk of climatic variations, including a rise in temperature and increased rainfall, this study employs the LULC classification based on cascaded ensemble approaches integrated with high-resolution images of Tilaya catchment areas in the Barakar River Basin (BRB) in West Bengal and Jharkhand states. The Landsat-5 (TM) images for the years 2005, 2010, and 2015 are selected. The results from the classifications provide a consistent accuracy of assessment with a reasonable level of agreement. However, BTEN is found to be more precise than others in the proposed cascading classifier approach. Overall accuracy is 99.99% for 2005 and 2010, and 100% for 2015, with the BTEN classifier values when compared to Coarse kNN accuracy as attained at 99.09%. In addition, 98% and 97.89% accuracy values are obtained in Coarse SVM for 2005 and 2010 with estimated BTEN classifier values as 99.40 and 94.28 respectively. The study is anticipated to assist decision makers for better emergency response and sustainable land development action plans, thus mitigating the challenges of rapid urban growth.

Introduction

The spatial and temporal changes in LULC have proceeded rapidly because of fast urbanization and it's over growing populations. The modification of LULC and the interaction of humans and the environment have caused variability of dynamic changes to the environment and climate [1]. Several floods by river regions are highly vulnerable to flooding due to rapid urbanization and the threat of changed climatic events such as temperature rise, wind storms, and heavy precipitation [2]. Therefore, it is required to monitor the modification of LULC under different circumstances.

An ensemble of two regression models has been developed in early 1977 [3]. At the end of 1980s Hansen and Salamon [4] proved that prediction made by a combination of more than one classifier is accurate than using a single classifier. In 1989 Schapire, [5] proved that boosting of a weak learner to a strong learner can improve the classification accuracy. Ensemble methods are widely used in fields such as finance, bioinformatics, healthcare, manufacturing and geography [3,4,5]. In ensemble based classification method, an ensemble of potentially weak classifier is built to solve complex real world problems. Use of combined classifiers reduces the expected error by reducing the variance component [6]. The more classifier models are build and included, the greater is the reduction in variance. The ensemble classifier model is shown in Fig. 1.

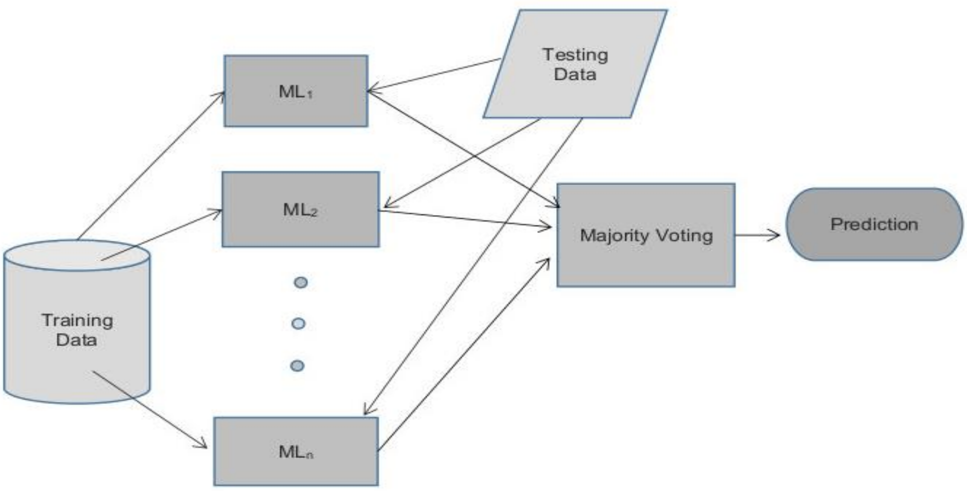

Figure 1: Ensemble classification

Two prominent ensemble classifiers are bagging and boosting [7]. In this study we have used bagging approach of combining different classifier models to classify data items. Bagging stands for Bootstrap aggregation. Each training set is a bootstrap sample. It creates an ensemble of models for a learning scheme where each model gives an equally weighted prediction. Use of bagging can reduce the instability of learned model. Sampling with replacement is used to create the data set. This causes some instances to replicate and some gets deleted.

Backgrounds

Various studies have shown that the application of LULC change detection plays an important role in solving problems related to different domains, such as changes in environmental services [4], urban development [5], and watershed characteristics [6-7]. Currently the use of satellite remote sensing data is considered the most powerful source of information to detect the changes in LULC, because of its wide range of temporal and spatial coverage [8-9]. [10] defined change detection techniques as a method of recognizing changes in LULC with the time variations. Among several methods of image classification, principle component analysis (PCA), Coarse kNN, Coarse SVM are more popular.

Recently finding out significant solutions from the canopy of existing works on remote sensing image analysis, exploiting hybrid intelligences, has become a trend in challenging tasks. Jacobsen identifies hybrid intelligent systems of four categories, based on the systems' overall architecture:

(1) single component systems,

(2) fusion–based systems,

(3) hierarchical systems, and

(4) hybrid systems.

Existing Methods:-

Decision Tree

The principle of the decision tree classifier is to cluster any data into subgroups until all elements of any subgroup have the same class label. Classification rules are defined by clustering the data into the leaves, class labels, in the training stage; while those rules are applied to any test sample and the leaf that the test sample reaches provides the class label of the test sample in the test stage.

Random Forest

The random forest classifier is an ensemble of decision tree classifiers which is developed to improve the classification accuracy. Each tree classifier in this ensemble votes for the best class of any sample, and the resultant class label is then specified via a majority voting technique. Random Forests improve variance by reducing correlation between trees, this is accomplished by random selection of feature-subset for split at each node. `mtry` is the tuning parameter that defines of_features to be selected.

***k*-Nearest Neighbors**

The *k*-nearest neighbor (kNN) classifier assigns any test vector to the respective class that its *k*-nearest neighbors belong at most, considering the distances between the test and training vectors in the feature space. Although it is obvious that classification performance is directly related to the parameter *k*, there is no obvious information on the selection of *k* except that it should be positive and not a multiple of the total number of classes.

Support Vector Machines

Support vector machines (SVMs), also known as maximum margin classifiers, determine the optimal hyperplane that maximizes the distance between the hyperplane and support vectors . Support vectors are the training vectors that are nearest from each class to the hyperplane.

Bagged Tree Ensembled (BTEN) Classifier:

In ensemble approaches, several decision trees are combined to generate more efficient predication solutions than obtained by a single decision tree. In one approach, weak learners are aggregated using Bagged Bootstrap Aggregation method to reduce variance of one decision tree. Some random subsets of data are chosen as replacement for training the model. The solution of this ensemble model comes from the average of all predictions from all decision trees. This Bagging approach improves variance by averaging/majority selection of outcome from multiple fully grown trees on variants of training set. It uses Bootstrap with replacement to generate multiple training sets.

Proposed Cascading Ensemble Classifier approach for catchment analysis

Our proposed method is to improve the performance with the help of cascading ensemble classification by using bagging BTEN classifier for year-wise Tilaya dam catchment analysis. We have chosen Tilaya catchment areas of Barakar river for this analysis, as obtained from Landsat (5) TM for 2005, 2010 and 2015 years. The catchment areas were extracted from our previous works. Figure 2 a)-c) show the catchment areas for three years with 5 years of interval. We have registered all three catchment images using affine registration method to make them similar in intensity and pixel levels. Then we have used layer wise threshold masking to generate LULC (LandUse LandCover) classes for all three catchment areas. For this approach, we have used modified Anderson Land Use/Land Cover Classification Level I classes from landocver.org as the code values for layers, which are shown in Table 1 below.

Figure 2 a) Landsat(5) TM 2005

Figure 2 b) Landsat(5) TM 2010

Figure 2 c) Landsat (5) TM 2015

There are seven Modified Anderson Land Use/Land Cover Classification Level I classes in consideration for this study, namely - 1. Water, 2. Forest, 3. Shrubband, 4. Grassland, 5. Cropland, 6. Urban and 7. Others/Bareground areas.

Table 1: Code Values for 1 km and 8 km data of UMD Land Cover Classification from landcover.org

Value	Label	RGB Red	RGB Green	RGB Blue	Our classes
1	Water	068	079	137	Water
2	Evergreen Needleleaf Forest	001	100	000	Forest
3	Evergreen Broadleaf Forest	001	130	000	
4	Closed Shrubland	255	173	000	Shrubband
5	Open Shrubland	255	251	195	
6	Grassland	140	072	009	Grassland
7	Cropland	247	165	255	Vegetation
8	Urban and Built	000	255	255	Urban
9	Bare Ground	255	199	174	Open/Others

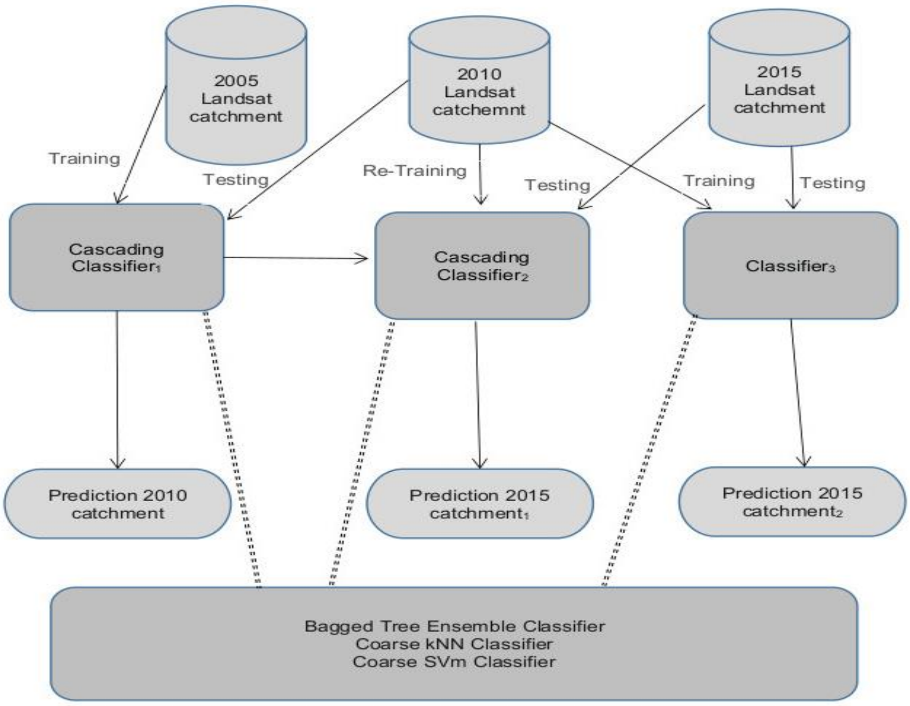

Figure 3 Proposed Cascading Ensemble Classifier approach for Year-wise catchment analysis

Figure 3 shows our proposed approach for cascading classifier analysis over year-wise catchment data using Bagged-Tree Ensemble classifier. We have initially trained the classifier with 2005 catchment data and then tested the model on 2010 catchment data. This generates a prediction for 2010 catchment area. Accuracy and ROC characteristics - Sensitivity and Specificity values for this prediction is shown in Table 2. Then we again re-train the model with 2010 catchment data in cascading way and then tested this model on 2015 catchment data. The prediction of this cascading classifier is also shown in table 2. Finally we train the classifier with 2010 catchment data and tested this model on 2015 catchment data, for comparative ROC analysis with cascading models. We perform comparative executions of coarse SVM, coarse kNN and Bagged Tree Ensemble classifier in this cascading classifier approach, to show the significance of this proposed approach. The statistical values obtained by the solutions of these executed approaches show that this cascading classifier show a comparative accuracy and ROC characteristics values in comparison with the direct classification approaches. The proposed Cascading Ensemble Classifier (CEC) shows the superior performance of 99.99% accuracy when in cascading model in comparison with 100% accuracy in direct model. Therefore, this cascading approach provides a significant prediction method for catchment analysis , as obtained in our experiments here.

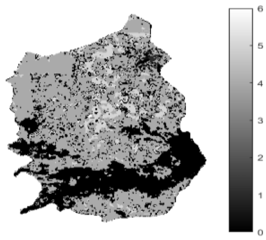

Figure 4 a) LULC classes 05

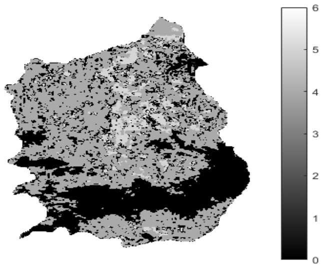

Figure 4 b) LULC classes 2010

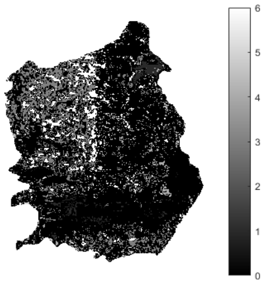

Figure 1 c) LULC classes 2015

Table 2 Comparative ROC characteristics analysis of proposed Cascading Classifier approach over year-wise catchment data

Classifier	Training Year	Accuracy (%)	Sensitivity	Specificity	Testing Year	Accuracy (%)	Sensitivity	Specificity
Bagged Tree Ensemble	2005	99.99	0.9996	0.9999	2010	99.40	0.9710	0.9999
					2015 retrained on 2010)	83.29	0.7278	0.9008
	2010	99.99	0.9999	0.9999	2015	94.28	0.9999	0.9068
	2015	100	0.100	0.100				
Coarse kNN	2005	99.09	97.77	99.66	2010	98.81	95.85	99.72
					2015 (retrained on 2010)	77.21	67.22	83.79
	2010	99.15	97.61	99.68	2015	87.75	95.88	82.59
	2015	98.68	98.87	98.62				
Coarse SVM	2005	97.80	92.70	99.09	2010	97.80	91.86	99.54
					2015(retrained on 2010)	88.01	99.35	80.76
	2010	98.16	94.37	99.28	2015	88.01	99.35	80.76
	2015	94.60	97.60	92.74				

Conclusions

It is clear from the comparative analysis in Table 2 that our proposed cascading BTEN classifier approach provides superior performances than other two well-known existing algorithms in our proposed model. Thus it is identified as best classifier in which ensemble classification is done in year-wise cascading way to improve accuracy. Therefore, this proposed approach shows to be an efficient method for year-wise catchment analysis, as shown for Tilaya catchment areas for 2005, 2010 and 2015 years in this work. Further we have to improve our proposed model to predict LULC classes on different catchment areas as our future research works.

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