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Ensemble Classification of Urban Regions Using Hyperspectral Remote Sensed Scenes

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Abstract: The objective of the proposed work is to classify urban land cover regions, which involves high complexity as the region involves multiple classes and it is a tedious task normally when using any machine learning algorithm. Hence, a decision tree classifier is proposed which classifies efficiently in the case of multi class problems, also it could handle large volume of data. The dictionary of data sets are interactively trained to the classifier from the hyperspectral test sites. The accuracy for the decision tree classifier needs to be analyzed and compared with the other commonly used classifiers. The performance of classifier is analyzed by metrics such as receiver operating characteristics curve and confusion matrices.

Key words: Urban Land Cover · Classification · Decision Tree · Classifier · Predictors · Confusion Matrix and Area Under Curve

INTRODUCTION

The first known efficient work in the area of urban land cover classification is the proposed framework of classifying multispectral data on the basis of spectral knowledge and knowledge base is developed, which analyzes the test categories in terms of spectral relationships. The performance tend to decrease for the data that doesn't meet the criteria specified in the spectral knowledge base. Hence, knowledge base formation is essential in analyzing the wider regions [1]. A new approach is presented which combines classification with linear spectral unmixing. A mathematical model is formed for spectrally similar end members and a new method for pixel based end member estimation is developed. Thus reducing the number of possible end member combination for each pixel and the proposed algorithm is compared with the existing classification techniques [2]. The work proposed emphasis on the existing problems in urban region classification techniques. It employs segmentation of objects from the high resolution color infrared aerial photos and segregates different urban structure types. The urban structure classification is characterized by identifying different attributes. Thus an efficient algorithm for high resolution imagery for urban region classification is carried out [3]. The discrete wavelet transform (DWT) derived contexture and grey-level co-occurrence matrices in the recognition and extraction of selected urban land cover information from very-high spatial resolution Quickbird imagery is proposed. The accuracy results for all the three algorithm proposed is analyzed with respect to the classification of high resolution imagery [4]. The current approaches use disk-shaped structuring elements to derive an morphological profile and this profile contains information about the minimum dimension of objects. The results in a profile containing information about the maximum object dimension and the additional line-based attribute gives a substantial improvement of the classification result and still preserve the shape of objects [5]. The study focuses on a multifaceted accuracy assessment of an urban footprint classification derived from SAR-X image. A pixel-based approach is used to identify the urbanized and non-urbanized areas. Based on this data, the classification result is assessed [6]. A systematic overview of image classification methods, both local filtering-type approaches and global random field models are analyzed. Then a detailed experimental comparison of the presented methods, using two different aerial data sets from urban areas with known ground truth [7].

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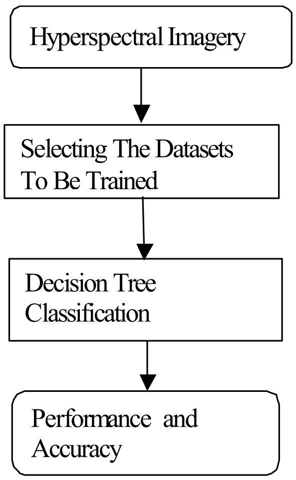

Fig. 1: Block Diagram For The Proposed Work

A decision-tree-based adaptive land cover classification technique is proposed and it uses spatial-statistics-based expressions of best-selected polarimetric indexes on the basis of a separability index criterion and an overall classification accuracy on large number of unknowns is recorded [8]. A new semi-supervised strategy for obtaining finer spatial resolution for urban land cover mapping is proposed. For, semisupervised learning in order to refine the set of initial training samples by the inclusion of additional unlabeled samples, a land cover classification using a probabilistic multinomial logistic regression (MLR) classifier—in both supervised and semi-supervised fashion by considering different numbers of labeled and unlabeled samples [9]. The proposed framework automatically classifies 3-D point clouds generated using oblique aerial image into various urban object classes. A multi camera airborne imaging system is used. The acquired images contain only three RGB spectral bands.The visual and consistency analysis were performed to estimate the proposed classification algorithm's feasibility and reliability [10].

Proposed Methodology: The proposed work is illustrated in the form of block diagram as shown below:

Hyperspectral Satellite Imagery: Hyperspectral imagery is used mainly for its more detailed information in multiple band levels(in the order of 100s) when compared to the multispectral imagery(8-10) band levels. The images are collected as a data cube with spatial information collected in the X-Y plane and spectral information represented in the Z-direction.

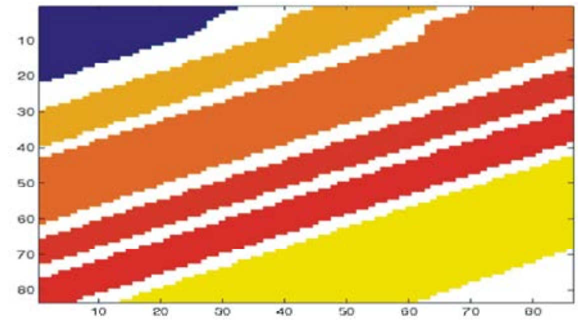

Fig. 2: Ground Truth of Salinas A Dataset.

Selecting The Datasets To Be Trained

Salinas- A Dataset: This scene was collected by the 224-band AVIRIS sensor over Salinas Valley, California with the resolution of 3.7-meter pixels. The ground truth data contains 16 classes.A small sub scene of Salinas image, which is represented as Salinas-A is used. A 86*83 and includes six classes (Brocoli Green Weeds, Corn Senesced Green Weeds, Lettuce Romaine 4th week, Lettuce Romaine 5th week, Lettuce Romaine 6th week, Lettuce Romaine 7th week) with 18 band levels is used for analysis.

The above figure describes the ground truth samples representation of classes considered and illustrated with different color (blue- Brocoli Green Weeds, orange(light)- Corn Senesced Green Weeds, orange (dark)- Lettuce Romaine 4th week, red (light)- Lettuce Romaine 5th week, red(bright)- Lettuce Romaine 6th week, yellow- Lettuce Romaine 7th week.

Indian Pines Dataset: The scene was recorded by AVIRIS sensor across the Indian Pines test site with the resolution of 145\times 145 pixels, 224 spectral reflectance bands in the order of 0.4–2.5 10^(-6) meters (wavelength). The dataset contains mainly agriculture lands and remote terrains like forests and highway lanes, a rail line, low density housing and small roads. Because the scene is taken in June some crops are present with less than 5% coverage. The ground truth data contains sixteen classes.

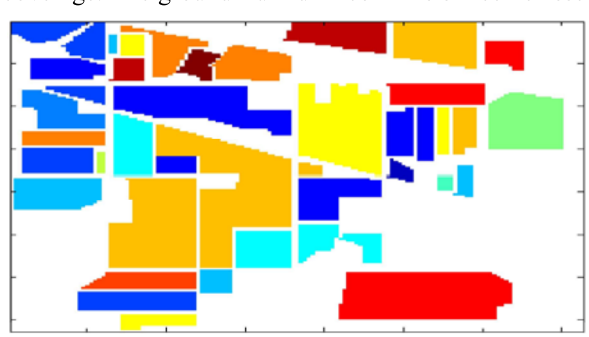

Fig. 3: Ground Truth of Indiana Pines Dataset

Pavia University Dataset: The scene was acquired by the ROSIS sensor over Pavia, northern Italy. The number of spectral bands is 103 for Pavia University and the image is of 610*610 pixels in size used for classification. The geometric resolution is 1.3 meters and 9 classes is represented in the form of ground truth below. (The discarded samples is represented in the form of a broad black strips).

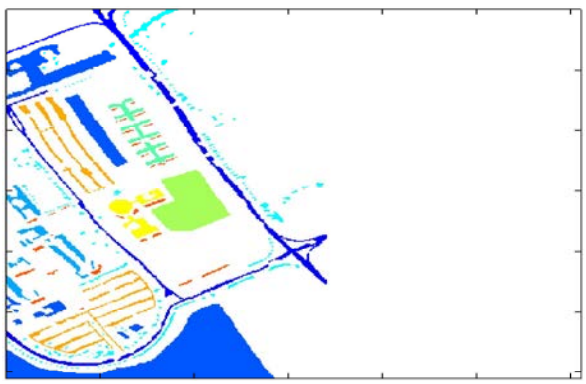

Fig. 4: Ground Truth Of Pavia University Dataset

Decision Tree Classifier: Decision tree classifier uses predictive model which maps observations about an item to conclusions about the item's target values. The incoming data is labelled (which is stored in a buffer).The labelled data once reaches the threshold, the outdated branches are removed and the labelled data in the buffer forms a new branch. Thus, the decision tree classifies multiple class datasets. The parametric analysis of the decision tree is described below:

- Maximum Number of Splits: Maximal number of decision splits (or branch nodes) per tree.

Max Splits size= (X,1)-1 (1)

- Minimum Parent Size: Each splitting node in the tree has atleast 'MinParentSize' observations.

Min Parent Size=max(MinParentSize,2*MinLeafSize)(2)

- Predictor Names: Matrix of predictors used to train the decision tree. It is represented as [X]
- Response Names: Name of the response variable. It is represented as [Y].
- Pruning:Pruning reduces the complexity of the final classifier by cutting down the misclassified and unnecessary branches and thereby improving the predictive accuracy.
- Score Transform – Score Transform function, specified as the comma- separated pair consisting of 'Score Transform' and a function handle for transforming scores. The function should accept matric and return the matrix.

Performance And Accuracy Measurements: Accuracy with respect to classifier is defined as the process of estimating the efficiency of the trained data sets and the performance evaluation techniques, which provides better insights in order to estimate the efficiency of the classifier.

Confusion Matrix: A confusion matrix contains contains information about actual and predicted classifications done by a classification system. Performance of such systems is commonly evaluated using the data in the matrix. Each column of the matrix represents the instances in a predicted class while each row represents the instances of an actual class. Confusion Matrix for the Salinas A Dataset is shown in the below figure:

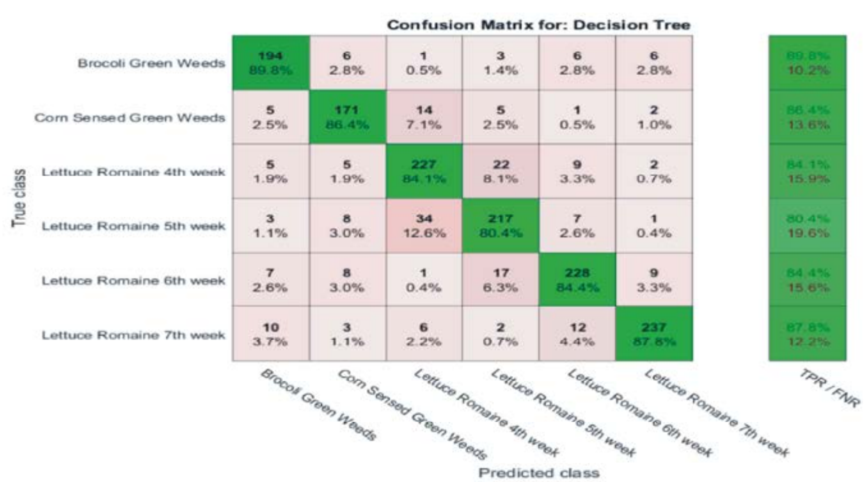

Fig. 5: Confusion Matrix For Salinas A Database

Similarly, Confusion Matrix for the Indian Pines dataset is illustrated below:

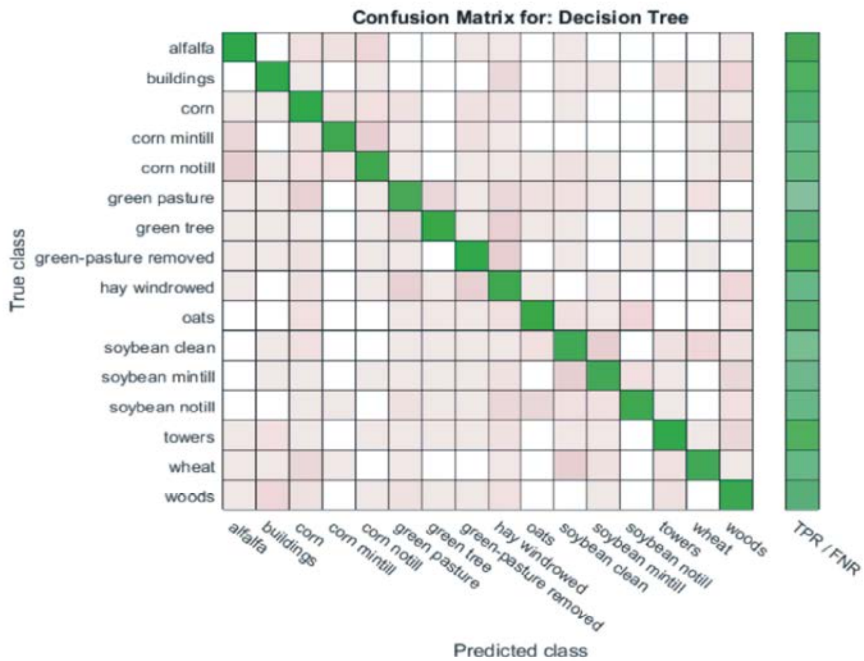

Fig. 6: Confusion Matrix For Indian Pines Data Set

Finally, confusion matrix for the Pavia university dataset is described below:

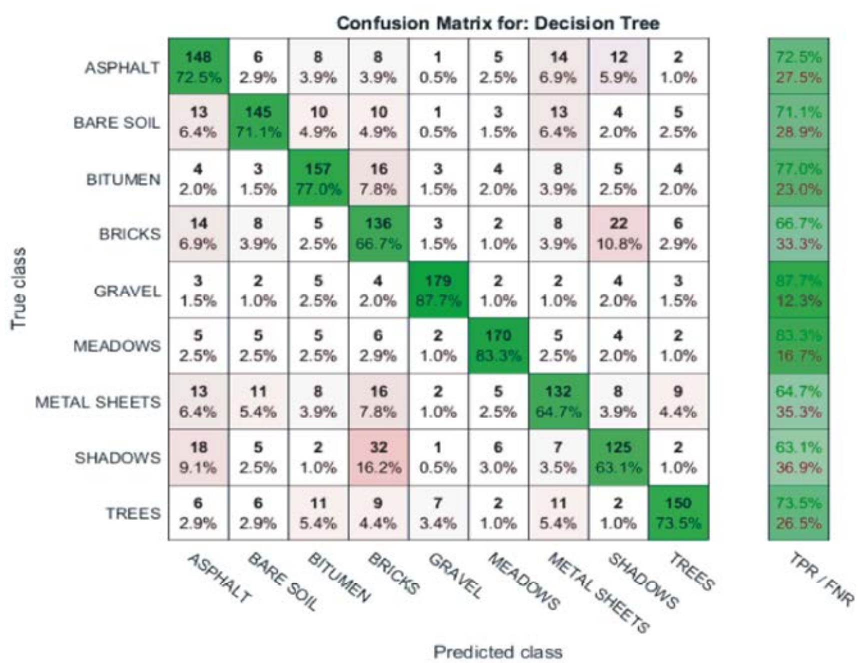

Fig. 7: Confusion Matrix For Pavia University

Receiver Operating Characteristics (ROC) Curve: ROC curve plots between the true positive rate (Sensitivity) as a function of the false positive rate (Specificity) for different cut-off points of a parameter. Receiver Operating Characteristics curve for the Salinas A dataset is illustrated below:

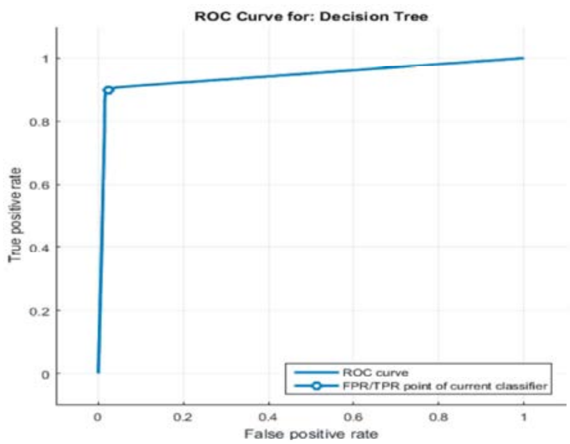

Fig. 8: ROC Curve For The Salinas A Dataset.

Similarly, ROC curve for the Indian Pines Dataset is described below:

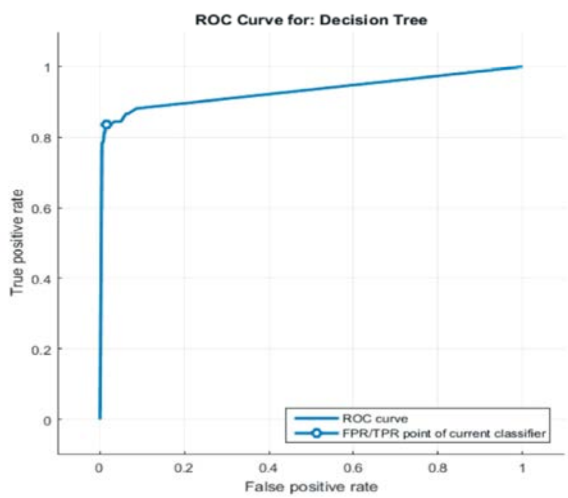

Fig. 9: ROC Curve For The Indian Pines Dataset.

ROC Curve for the Pavia University Dataset is shown above:

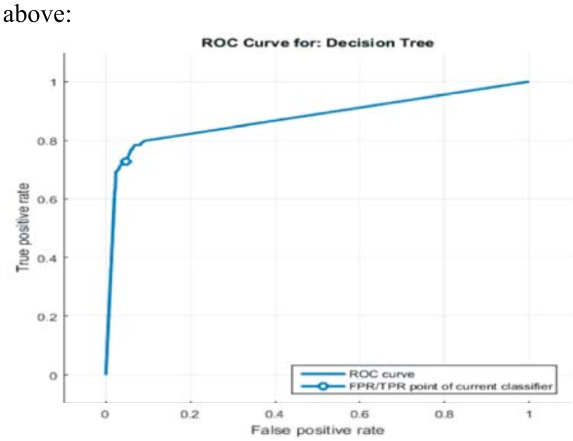

Fig. 10: ROC Curve For The Pavia University Dataset

Validation Accuracy: Validation Accuracy for the Salinas A dataset is shown in the below table:

Table 1: Validation Accuracy Analysis of Decision Tree Classifier with respect to other Classifier for the Salinas A dataset.

S.No.	Classifier Used	Validation Accuracy (%)
1	Quadratic Discriminant	57.4
2	Coarse KNN	68.1
3	Ensemble-Boosted Tree	77
4	Decision Tree	85.3

Similarly, an analysis for the Indian Pines dataset is tabulated below:

Table 2: Validation Accuracy of Decision Tree Classifier with respect to other Classifier for the Indian Pines dataset

S.No.	Classifier Used	Validation Accuracy (%)
1	Quadratic Discriminant	64.4
2	Boosted Tree	73.1
,3	Coarse KNN	73.2
4	Decision Tree	76.5

Validation accuracy analysis for Pavia University dataset is shownbelow.

Table 3: Validation Accuracy analysis for the Pavia University Dataset

S.No.	Classifier Used	Validation Accuracy (%)
1	Linear Discriminant	83.4
2	Boosted Tree	83
3	Coarse KNN	67.3
4	Decision Tree	85.4

CONCLUSION

Thus the urban regions involving multiple classes is efficiently classified for the given Salinas, Indian Pines and Pavia University datasets. The performance analysis such as validation accuracy, Receiver Operating Characteristics Curve and Confusion Matrix is carried out. The Decision Tree Classifier used holds better when compared to other classifiers for the trained datasets. Further, enhancements could be done by training more datasets to increase the efficiency of the classifiers.

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