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Comparative study of hyperspectral imagery classification with SVM and ensemble machine learning methods

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Abstract

Hyperspectral images are usually high-dimensional data consisting of hundreds of spectral bands. Thanks to the spectral details they provide, they are preferred in many ground observation tasks such as forest areas, vegetation, and harvest forecasting. With the widespread use of artificial intelligence in many areas, the use of machine learning algorithms in highly complex data such as hyperspectral data continues to increase. In this study, the Indian Pines dataset was classified using three different machine learning algorithms. In the experiments, the performance of the Support Vector Machines algorithm was compared with the performance of the Random Forest and XG Boost ensemble methods. According to the results obtained, the highest performance was obtained with the XG Boost algorithm as 90.88%. The worst result was obtained with Random Forest as 79.61%. The SVM algorithm, on the other hand, took second place in the performance obtained with an accuracy of 85.12%. The results obtained are presented together with the visuals and the performance metrics are also evaluated as precision, recall, and F1 score.

1. Introduction

Early on in the 1970s, remote sensing was the primary use of hyperspectral imaging then it spread out to other many fields (Amigo et al. 2015). Many methods have been developed to extract information in many fields from data consisting of hundreds of spectral bands. Machine learning is one of the popular methods used in this field. In this study, the performance of the Support Vector Machine algorithm was compared with the other ensemble machine learning algorithms, Random forest and eXtreme Gradient Boosting (XG Boost). While the XG Boost method gave the best results, the lowest accuracies were obtained with the experiments using the RF algorithm. The performances of the items were tested with precision, recall, f1-score and gestational accuracy criteria. The classification maps obtained as a result of the experiments are presented as images.

Experiments in the study were carried out on the Indian Pines data set (URL-1). The dataset image and ground truth are shown in Figure 1. The Indian Pines test site is in Northwest Indiana and the images of the dataset consist of 224 spectral bands and 145 x 145 pixel images in the wavelength range of 0.4–2.5 ± 10 $^{-6}$ meters. The image of the data set includes 16 classes, mostly agriculture, forest and vegetation classes. The class names and sample numbers for each class is shown in Table 1. In the study, 200 bands of the dataset was used in the experiments. The class distribution is showed in Table 1.

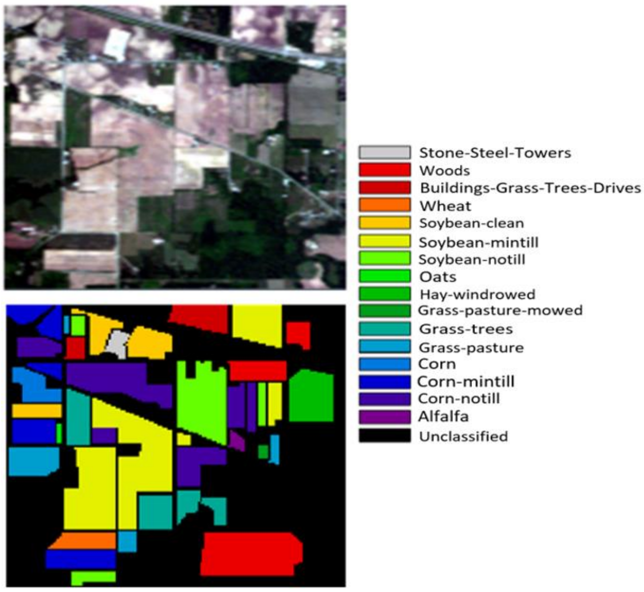

Figure 1. Indian pines dataset image and ground truth with legend

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Table 1. Indian pines class names and sample numbers

Class	Samples
Alfalfa	46
Corn-notill	1428
Corn-mintill	830
Corn	237
Grass-pasture	483
Grass-trees	730
Grass-pasture-mowed	28
Hay-windrowed	478
Oats	20
Soybean-notill	972
Soybean-mintill	2455
Soybean-clean	593
Wheat	205
Woods	1265
Buildings-Grass-Trees-Drives	386
Stone-Steel-Towers	93

The general flowchart of the study is illustrated in Figure 2. The selected samples of the Indian Pines were shown in Figure 3.

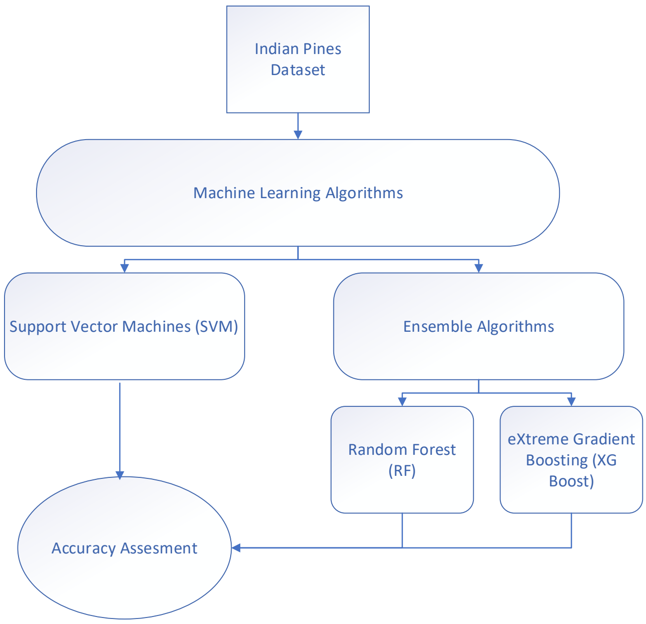

Figure 2. General flowchart of the study

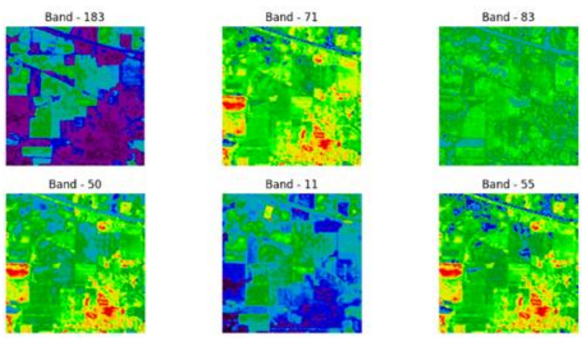

Figure 3. Band Samples of Indian Pines Dataset

2. Method

Machine learning algrithms that are used in the experiments are explained shortly below.

2.1. Support Vector Machines

The supervised machine learning technique Support Vector Machines (SVM) (Cortes and Vapnik, 1995) is utilized for both classification and regression tasks. When the data has distinct boundaries that can be easily separated or when moving the data into a higher-dimensional feature space helps improve separation, it performs particularly well.

In a number of fields, including text classification, image recognition, and bioinformatics, SVM has been shown to be successful. They have effective high-dimensional data-handling skills and good generalization capabilities. SVMs, however, may be sensitive to parameter adjustment and kernel selection.

2.2. Random Forests

A capable and common non-parametric machine learning algorithm, Random Forest (Breiman, 2001) is used for both classification and regression tasks. It functions by building a group of decision trees, then making predictions based on the combined output of these trees. The final prediction is obtained using a voting or averaging method, and each decision tree is trained independently on a part of the data that has been randomly selected.

2.3. Extreme Gradient Boosting (XGBoost)

Extreme Gradient Boosting, or XGBoost(Chen et al., 2015) is a robust and widespread machine learning algorithm that is mainly applied to regression and classification issues. It is an improved version of the machine learning technique known as gradient boosting, which combines the predictions of several weak models (often decision trees) to produce a powerful predictive model (Budholiya et al., 2022). The function is shown in Equation 1.

Objective Function = Loss Function + Regularization Term (1)

2.4. Evaluation Metrics

The evaluation metrics are selected as precision, recall, F1-score and general accuracy. The general formulas are shown in Equations 3-6.

$$Precision = \frac{TP}{TP + FP} \quad (3)$$

$$Recall = \frac{TP}{TP + FN} \quad (4)$$

$$F1\ score = 2 \text{ x} \frac{Precision \text{ x } Recall}{Precision + Recall} \quad (5)$$

$$Overall\ accuracy = \sum_{i=1}^{k} \frac{N_{ii}}{N} \quad (6)$$

TP İS true positive, FP is false positive, FN is false negative and N is the number of samples in the equations.

3. Results

According to the results obtained in the study, the best result was 90,88 % overall accuracy with XG Boost. With the SVM machine learning method, 85, 12 % accuracy was achieved. 79,61 % accuracy has been achieved with the RF algorithm. The performances are listed in Table 2.

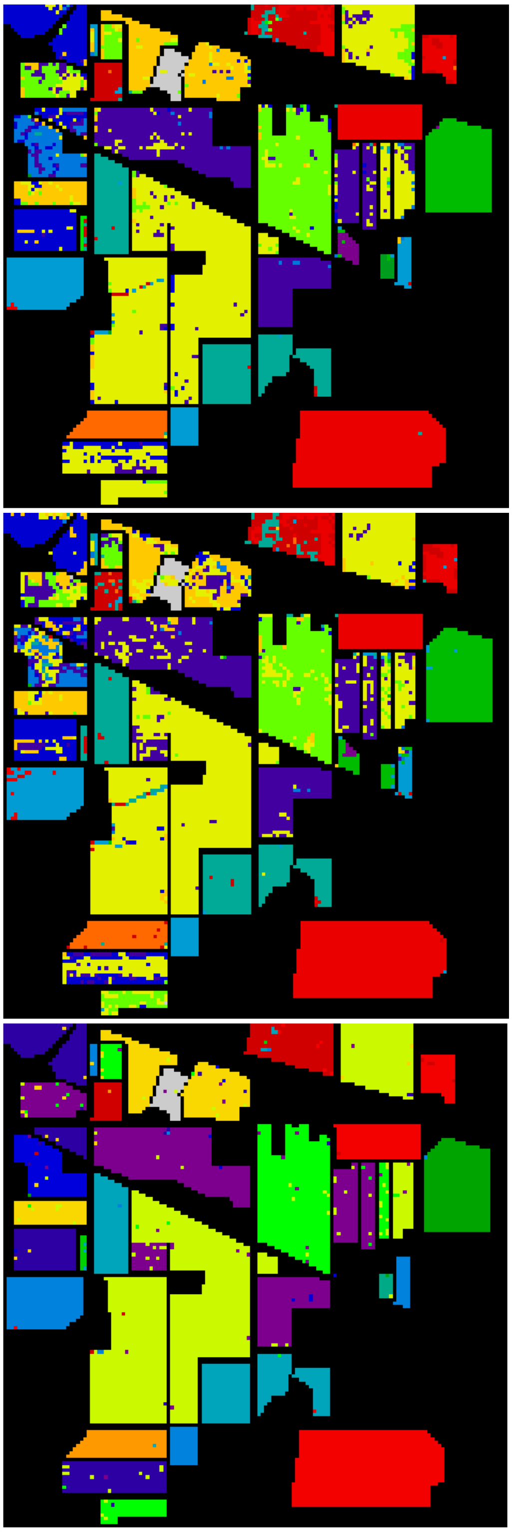

Figure 4. SVM(top), RF (middle) and XGBoost (bottom) classification results by order

Table 2. Performance metrics of the experiments

Methods	Precision	Recall	F1score	Accuracy
SVM	85,94	81,25	83,01	85,12
RF	72,39	64,65	67,20	79,61
XGBoost	90,32	84,49	86,74	90,88

The classification maps are shown in Figure 4. According to classification results generally XG Boost algorithm gave the best performances for most classes. However, in the classification performed using this algorithm, the confusion in the corn no-till and alfalfa classes is remarkable. On the other hand, in SVM and RF results the salt and pepper effect seems to be more common.

4. Discussion

According to the results of the study, one of the ensemble methods was found to be superior to SVM in all conditions, while the other lagged behind the performance of SVM. In this case, it was concluded that it would not be appropriate to generalize the performance of ensemble methods when compared to SVM. The numerical results obtained differ depending on the algorithm used for classification. At the same time, the results obtained may vary depending on the hyperparameter optimization of the algorithms used. In this study, experimentally suitable parameters were sought and used for all three algorithms. The fact that XG boost gives better results than other algorithms may be since it is a new generation technique that includes an iterative optimization.

5. Conclusion

The study can be enriched with more machine learning algorithms and the application of the ensemble method. At the same time, the use of a large number of spectral bands in experiments can be reduced by feature extraction or dimension reduction techniques, and its effect on performance in experiments can be investigated.

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