Assessment of Feature Extraction Methods for Enhanced Hyperspectral Image Analysis

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Abstract

Though Hyperspectral remote sensing offers rich spectral information for in-depth scene interpretation its high dimensionality and small number of labeled samples make classification tasks difficult. This study offers an ANOVA-based feature selection framework intended to extract the most informative spectral features for effective hyperspectral image classification in order to overcome these difficulties. The framework's performance is examined as the number of chosen features, and it is integrated with several supervised machine learning algorithms. Benchmark hyperspectral datasets from AVIRIS and ROSIS sensors, such as Indian Pines, Salinas, Salinas-A, and Pavia University, are used for extensive experiments. The ability of the suggested method to improve classification accuracy while lowering processing complexity is confirmed by evaluation using overall accuracy, precision, recall, F1-score, and computational time.

Keywords:- Hyperspectral images, ANOVA F-test, Spectral features, supervised classifiers.

I. INTRODUCTION

Hyperspectral imagery (HSI) represents one of the most advanced forms of remote sensing technology, providing exceptionally high spectral resolution by capturing reflectance information across hundreds of contiguous and narrow spectral bands. Unlike multispectral images, which contain only a few broad bands, hyperspectral images offer fine spectral granularity that enables precise characterization of materials based on their spectral signatures.[1] Each pixel in an HSI cube can be viewed as a high-dimensional vector, where each dimension corresponds to the reflectance value of a specific wavelength. This rich spectral detail allows for the identification of subtle differences among materials, making hyperspectral imaging indispensable in applications such as mineral exploration, precision agriculture, environmental monitoring, military surveillance, medical diagnostics, and food quality assessment. With the rapid evolution of imaging spectrometers such as AVIRIS, ROSIS, HYDICE, and Hyperion, hyperspectral remote sensing has become a primary and reliable method for large-scale data acquisition. These sensors allow the capture of spatial, spectral, and sometimes temporal information simultaneously, resulting in a three-dimensional data structure known as a hyperspectral data cube.[2] The ability to detect small, low-contrast, or spectrally similar objects—such as crop stress indicators, contaminants, or camouflage materials—makes hyperspectral data highly valuable for both scientific research and real-world decision-making. However, despite its numerous advantages, hyperspectral image

analysis poses significant challenges. The high dimensionality of the data often leads to the "curse of dimensionality," where the large number of spectral bands increases computational complexity and decreases classifier performance if not properly handled. Moreover, acquiring labeled samples for supervised classification is expensive and time-consuming, creating severe imbalances between available training and testing data. Redundant or noisy spectral bands further complicate the classification process, as not all wavelengths contribute meaningful information.To address these issues, effective feature selection becomes an essential step in hyperspectral data processing. Selecting a compact, discriminative set of spectral features helps reduce computational load, mitigate overfitting, and enhance classification accuracy. Statistical feature selection methods, such as the ANOVA F-test, provide a reliable mechanism for identifying bands that offer maximum class separability while eliminating irrelevant or redundant information. In this work, we employ the ANOVA F-test to extract the most informative features from high-dimensional HSI data and evaluate its integration with a collection of widely used supervised classifiers, including Decision Tree, Random Forest, and K-Nearest Neighbor. [3] The remainder of this paper is organized as follows. Section 2 presents a review of related literature relevant to this study. Section 3 describes the ANOVA-based feature selection approach, while Section 4 outlines the supervised classifiers considered in this work. Section 5 details the proposed methodology. Sections 6 and 7 provide the descriptions of the hyperspectral datasets and the performance evaluation metrics, respectively. Section 8 discusses the experimental results, and finally, Section 9 concludes the paper with key findings and future research directions.

II. Literature Review

Hyperspectral image (HSI) classification has been an active research area for several decades due to its ability to capture fine spectral details across hundreds of contiguous bands. Early methods primarily relied on classical pixel-based classifiers such as Support Vector Machines (SVM)[4], K-Nearest Neighbors (KNN)[5], and Maximum Likelihood Classifiers (MLC)[6], which demonstrated strong performance but struggled with high dimensionality and limited training data. To address these limitations, numerous studies have explored feature reduction strategies to enhance classification accuracy and computational efficiency. Feature selection and dimensionality reduction have become essential components of HSI analysis. Traditional techniques such as Principal Component Analysis (PCA)[7] and Independent Component Analysis (ICA) provide effective transformations but often lack interpretability and may discard discriminative spectral features. Consequently, statistical feature selection approaches have gained prominence. The ANOVA F-test, in particular, has been widely used to measure the significance of spectral bands by comparing inter-class and intra-class variance. Studies have shown that ANOVA-based filtering helps reduce redundant information and improves class separability, especially when dealing with highly correlated spectral bands. In recent years, hybrid frameworks combining feature selection with machine learning classifiers have been proposed to handle the curse of dimensionality more effectively. Methods incorporating ANOVA improved classification results on widely used datasets such as Indian Pines, Salinas, Moreover, ensemble-based classifiers—including Random Forest, decision tree have exhibited robustness in high-dimensional environments due to their ability to handle non-linear relationships and variable importance ranking. Recent research trends have also shifted toward deep learning approaches, particularly Convolutional Neural Networks (CNNs) and attention-based architectures. While these methods often achieve high accuracy, they require large labeled datasets and significant computational resources, which remain limiting factors in many practical situations. As a result, classical machine learning models combined with reliable feature selection techniques continue to be a strong choice for many HSI applications,

especially when labeled samples are scarce. Motivated by these findings, the present work focuses on evaluating the effectiveness of ANOVA F-test for spectral feature selection and analyzing its performance with various traditional supervised classifiers. This approach aims to provide an efficient and interpretable framework that addresses the challenges posed by high-dimensional hyperspectral data.

III. Feature selection based on ANOVA F-test

The Two-Way Analysis of Variance (Two-Way ANOVA) is a statistical technique used to examine the influence of two independent categorical variables (factors) on a continuous dependent variable, while also identifying whether there is any interaction effect between the two factors. It extends the basic principles of One-Way ANOVA by allowing the simultaneous assessment of multiple sources of variation within a dataset.

IV. Supervised Learning Techniques

4.1. Decision tree

The Decision Tree classifier provides a simple and interpretable approach for hyperspectral image classification, and its performance is strongly influenced by the high dimensionality and redundancy of spectral bands. Without feature selection, the tree often becomes overly complex and prone to overfitting, reducing accuracy, especially for classes with overlapping spectral signatures. However, when ANOVA F-test–based feature selection is applied, the Decision Tree focuses on the most discriminative bands, resulting in improved accuracy, reduced noise, and faster computation. The classifier performs well for easily separable classes but may show lower precision and recall for minority or spectrally similar classes. Overall, the Decision Tree produces reasonable classification maps with clear boundaries, and its performance significantly benefits from selecting a compact set of relevant features.[8]

4.2. Random forest

The Random Forest (RF) classifier is highly effective for hyperspectral image classification due to its ensemble of decision trees, which enhances robustness and reduces overfitting compared to a single Decision Tree. By aggregating predictions from multiple trees, RF can handle high-dimensional spectral data and complex class boundaries more efficiently. When combined with ANOVA F-test feature selection, the classifier focuses on the most informative spectral bands, improving accuracy, reducing computational time, and mitigating the effects of noisy or redundant bands. Random Forest generally achieves high precision, recall, and overall accuracy across both dominant and minority classes, producing smoother and more reliable classification maps than a single Decision Tree. Its inherent capability to manage spectral variability and imbalanced data makes it particularly suitable for hyperspectral datasets.[9]

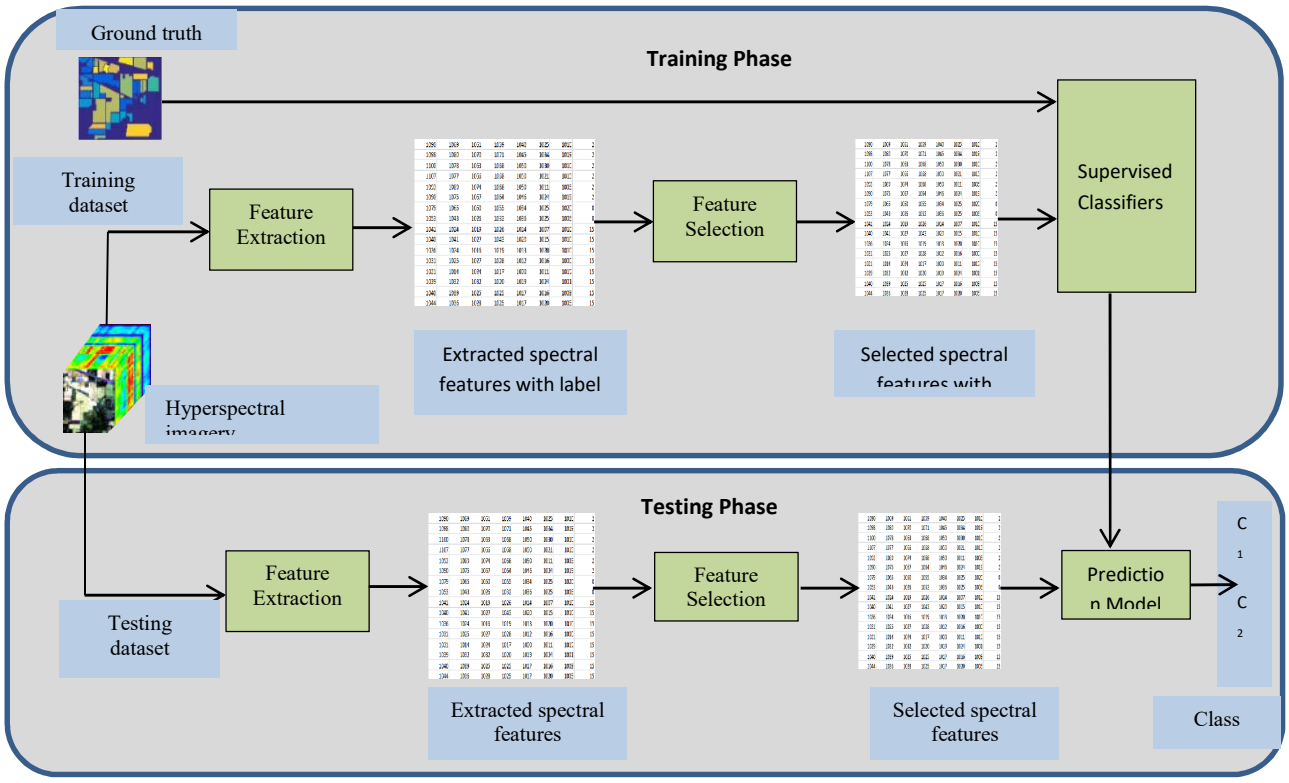
4.3. K- Nearest neighbour

The K-Nearest Neighbors (KNN) classifier is a simple yet effective non-parametric method for hyperspectral image classification, relying on the similarity between pixel spectra to assign class labels. Its performance is highly sensitive to the choice of k (number of neighbors) and the high dimensionality of hyperspectral data, which can lead to the “curse of dimensionality” if irrelevant or redundant bands are included. Applying ANOVA F-test–based feature selection helps KNN focus on the most discriminative spectral bands, improving classification accuracy and reducing computational cost. KNN generally performs well for classes with distinct

spectral signatures but may misclassify pixels in regions where class spectra overlap. Despite its simplicity, KNN provides competitive results and produces smooth classification maps, especially when combined with a carefully selected subset of features.[4]

V. Proposed method

This section describes the design of Hyperspectral classification using ANOVA based spectral features. In general, spectral features holds the valuable details for differentiating the materials or objects present on the land area. Hence, it results to redundancy of similar bands with mild changes. First step of this framework is to removal of unwanted noise present in the data. Then Feature selection extracts the required significant features from the high dimensional data. Here, we use ANOVA F-test statistical method to refine the required features. Here, we are using all the raw data of selected spectral bands and its resembling ground label values as an input. Fig.1. represents the general structure of the proposed supervised classification. This proposed classification process has training and testing phases. Here, we have selected 70% of the data to train the model and remaining 30% for testing the model



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During training, all the spectral bands in the hyperspectral imagery with its respective ground truth image are given into the model as an input. Feature extraction phase removes all noisy and irrelevant features present in the dataset. Noise removed spectral features are processed by ANOVA and most significant features are selected. After that, selected spectral features with their corresponding ground value are fed into any supervised classifier as discussed in Section 4. Then, classifier learn itself by using available ground truth. Lastly, the trained model is formed. In the testing part, remaining 30% of samples are given as input. Like training phase, in testing also irrelevant features are removed in the feature extraction phase and most relevant features are selected by the ANOVA, from this data feature vector is formed. Then, the feature vector is given into the learned model and it is known as predictive model. This predictive model creates the correct class label for each and every pixel. The performance of the FS is evaluated by the performance of classifiers, using the evaluation parameters such as Overall accuracy, Precision, Recall and F1-score and the evaluation time of all the classifiers is calculated.

VI. Dataset description

In this study, four widely used hyperspectral datasets are employed for experimentation. The Indian Pines dataset, captured by the AVIRIS sensor over northwestern Indiana, consists of 145 × 145 pixels with 200 spectral bands (after removing 20 water-absorbed bands) and 16 classes covering agricultural and forest areas. The Salinas dataset, also from AVIRIS, contains 512 × 217 pixels with 224 spectral bands and 16 classes, while Salinas-A is a subscene of Salinas comprising 86 × 83 pixels and six classes. Additionally, the University of Pavia dataset, acquired by the ROSIS sensor in northern Italy, includes 610 × 610 pixels across 103 spectral bands and 9 classes, with missing pixels removed prior to analysis. Tables 1–4 summarize the number of samples per class for each dataset.

VII. Performance metrics

The experimental results of each dataset were assessed using the evaluation metrics such as Accuracy, Precision, Recall and F1-score [10] and the result of each classifier is compared with each other.

7.1. Accuracy: It is the average between number of true prediction and total number of predictions.

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ predictions}$$

7.2. Precision: It gives the number of true positive values from the total number of positive results predicted by the classifier.

$$Precision = \frac{True\ positives}{True\ positives + False\ positives}$$

7.3. Recall: It calculates the true positive results out of number of all relevant samples.

$$Recall = \frac{True\ positives}{True\ positives + False\ neagtives}$$

7.4. F1-score: F1 Score is the average between precision value and recall value. F1 Score ranges from [0, 1]. From that we can infer, how many cases it classifies correctly, and also how robust the classifier is.

$$F1 - score = 2 * \frac{(Recall\ X\ Precision)}{(Recall + precision)}$$

VIII. Experimental result and Analysis

This section compares the performance of results obtained using ANOVA feature selection method with the results obtained without using any feature selection (using full features) on dataset. In order to check the performance of FS method, classification is carried out using different number of features. Different feature combination was obtained using ANOVA. We let the first trial consist of 5 spectral features; second contains 10; subsequently the trials had number of features 50, 100, 150 and 180. The reason for selecting different combination of features is to ensure that, fewer features could also obtain the comparable classification accuracy. From Table 1, it is evident that the overall classification accuracy is increases with number of features and beyond certain number of features, accuracy is not increasing. Hence, the features with highest accuracy is selected and compared with full features. For Indian Pines dataset we consider 180 number of features like that, for Salinas and Salinas-A. We took 180 features and for University of Pavia dataset we considered 100 selected features.

Table 1. Accuracy performance of different number of features on Indian Pines

	5 Features	**10 Features**	**50 Features**	**100 Features**	**150 Features**	**180 Features**	**200 Features**
KNN	52.69%	54.61%	68.37%	71.30%	72.54%	73.35%	71.2%
Decision tree	46.33%	46.98%	54.56%	62.30%	66.89%	67.67%	67.97%
Random Forest	55.19%	56.76%	64.01%	71.70%	76.09%	76.80%	77.45%

Table 2. Experimental results of Indian Pines dataset with 180 features

Metrics	**K-NN**	**Decision Tree**	**Random Forest**
Accuracy	**72**	**67**	**80**
Recall	**54**	**52**	**61**
precision	**60**	**54**	**74**
F1-score	**55**	**53**	**66**
Training time	**0.7**	**2.8**	**8.3**
Testing time	**3.0**	**0.5**	**0.1**

Table 3. Experimental results of Salinas dataset with 180 features

Metrics	**K-NN**	**Decision Tree**	**Random Forest**
Accuracy	89	88	**92**
Recall	90	86	91
precision	86	86	91
F1-score	88	86	91
Training time	5.5	12.5	56.5
Testing time	28.5	0.3	0.9

Table 4. Experimental results of Salinas A dataset with 180 features

Metrics	K-NN	Decision Tree	Random Forest
Accuracy	83	85	85
Recall	87	87	87
precision	84	86	86
F1-score	85	87	87
Training time	0.8	0.2	0.2
Testing time	0.2	0.6	0.6

The performance evaluation conducted across varying feature dimensions and multiple hyperspectral datasets demonstrate the consistent superiority of the Random Forest classifier compared to K-NN and Decision Tree algorithms. From the table 2, For the Indian Pines dataset, increasing the number of selected features from 5 to 200 resulted in a steady improvement in classification accuracy for all models, with Random Forest achieving the highest accuracy of 77.45% at 200 features. From the table 2-4 Detailed analysis at 180 features further confirmed this trend, where Random Forest attained the best accuracy (80%), precision (74%), recall (61%), and F1-score (66%), outperforming K-NN and Decision Tree, though at the cost of higher training time. In contrast, the Salinas dataset exhibited significantly higher accuracies overall, where Random Forest again delivered the highest accuracy of 92% along with balanced precision, recall, and F1-score values around 91%. K-NN showed competitive accuracy (89%) but suffered from extremely slow testing time, highlighting its computational inefficiency for high-dimensional hyperspectral data. For the Salinas A dataset, Decision Tree and Random Forest achieved comparable accuracy (85%) and F1-score (87%), indicating that this dataset presents a more balanced difficulty level for tree-based models. Across all datasets, Random Forest consistently demonstrated robust performance due to its ensemble structure and capability to model complex spectral–spatial relationships, whereas K-NN exhibited sensitivity to high-dimensional feature spaces and Decision Tree, despite its lower training cost, generally produced lower accuracy. Overall, these findings affirm that Random Forest is the most reliable and accurate classifier for hyperspectral image classification when a sufficiently high number of discriminative features is employed.

IX. Conclusion

The proposed method employs ANOVA-based feature selection for hyperspectral image classification. Compared to using the full set of spectral features, this approach improves classification accuracy while reducing computational time. Our results indicate that the quality and quantity of training samples significantly enhance classifier performance. Among the classifiers evaluated, Random Forest achieve the highest accuracy across the tested datasets. For large training datasets, the Random Forest classifier is recommended as an efficient and accurate choice for hyperspectral image classification.

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