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A Comprehensive Review: Classification Techniques on Hyperspectral Remote Sensing

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ABSTRACT

Many topics discuss the processing of remote sensing hyperspectral imagery and its various application applications. This is because the hyperspectral image can easily distinguish between several materials that share the same spectral features. The amount of information contained in the hyperspectral image requires a special method to extract the information. The classification method is one solution to extract information contained in the hyperspectral image. Hyperspectral image classification method consists of supervised classification, unsupervised classification and semi-supervised classification. Classification is a big challenge in remote sensing because of many factors that affect its success. These factors include images with low spatial resolution due to data quality, a complex area, homogeneous areas, and Hughes Phenomenon. Based on these problems, this study aims to review various classification methods used to solve existing classification problems. The results of this study recommend classification techniques that can be used based on performance parameters.

Key words: Remote Sensing, Hyperspectral Image, Classification, Performance Parameters.

1. INTRODUCTION

In the early 1980s hyperspectral remote sensing was the most superior technology in remote sensing. Promising technology in studying the material of the earth's surface spectrally and spatially. To obtain inaccessible geochemical information from the earth's surface. The developing remote sensing technology was worked by dividing visible and infrared broadband into hundreds of spectral parts [1]. Technology that provides detailed spectrum information for individual pixels of images that mostly refers to remote sensing is hyperspectral remote sensing (HRS) [2].

Hyperspectral remote sensing technology in the past two decades has significantly improved [3]. New capabilities using hyperspectral images but in the analysis and processing of hyperspectral image classifications have several levels of difficulty [4].

Hyperspectral imagery has many bands, so the information obtained is richer and is able to distinguish objects with the principle of spectral analysis that has different characteristics. Because of high resolution, or often called super-resolution, the processing techniques for hyperspectral imagery must use strategy. For example, by downsampling or extracting features [5]. The hyperspectral image has a number of bands of up to hundreds. Whereas when it is compared with multispectral imagery it only has dozens of bands. Hyperspectral processing usually uses spectral features that affect objects [6].

"Hyper" in hyperspectral means "over" as in the word "too much", which refers to the number of channels that have a spectrum which is denser than the multispectral [7]. Accuracy of spectral and radiometric calibrations in the hyperspectral remote sensing estimation data set has a very high level of performance. Often the problems that arise in the field of remote sensing are errors in distinguishing objects. By using hyperspectral, the information obtained is continuous spectral at intervals of 10 to 20 nm. This spectral hyperspectral model is very widely used, for example, in the fields of agriculture, petroleum exploitation, minerals, forests, geology, ecology, disaster, environmental monitoring and so forth [4]

The use of classification methods is very necessary for analyzing spectral [8]. Pattern recognition and feature extraction methods are often used to solve problems that arise in the analysis process [9].

There are two ways of classification, namely: supervised and unsupervised learning. In an unattended method, computers or algorithms automatically group pixels with similar spectral characteristics (medium, standard deviation, etc.) into unique clusters according to some criteria that are statistically determined.

The purpose of hyperspectral classification is to classify pixels which have the same spectral characteristics into the same class automatically. But the main research problem of the hyperspectral classification process is a very large dimensional that is also called the Hughes phenomenon. The other problems that arise in the hyperspectral classification are the low spatial resolution, a complex area, and homogeneous areas.

From these research problems, four research questions can be drawn up, namely how to overcome the problems of low spatial resolution, complex areas, homogeneous areas and Hughes Phenomenon. So, what is the best classification method for overcoming these research problems.

In this paper will discuss the classification techniques which are supervised and unsupervised to described some issues such as images with low spatial resolution due to data quality, a complex area, homogeneous areas, and Hughes Phenomenon. Then recommend classification techniques that has/have a powerful performance in hyperspectral classification.

2. METHODS

2.1 Application Of Classification On Hyperspectral Data

In the field of data remote sensing, the most powerful to use is hyperspectral imaging (HSI) [10]. Many disciplines utilize and use hyperspectral data for a variety of applications such as environmental monitoring, agriculture, mineralogy, chemical imaging, food processing and more.

Nowadays, agriculture land change is a very important concern. The drastic change in agricultural land has changed the world order like food security, regional economic change, natural resource, free land use, public open land, and so on. Many researchers concerned with the application of techniques to extract information systems from land change. One of them used remote sensing methods [11].

Hyperspectral is used for agriculture by using a supervised HSI classification algorithm to extract agricultural areas in the Al-Kharj region of Saudi Arabia specializing in wheat crops and to obtain secret images [12].

Hyperspectral data combined with LiDAR data can be utilized in environmental monitoring. In research [13], eight common savanna tree species were classified using random forests and KHAT on 23 hyperspectral image data.

The connection method of the MSAM (Modified Spectral Angle Mapper) technique and continuum removal technique was applied to reflection data in the infrared shortwave region by hyperspectral air sensors, HyMap. In South African, mineral index map was made using hyperspectral data and was found a lot of pegmatite and porphyry sediments. In South Nambia, one of the MSAM classification techniques namely continuum removal techniques can precisely distinguish hydrothermal alteration minerals such as pyrophyllite and kaolinite, and minerals related to pegmatites such as lepidolite and high aluminium muscovite [14].

Research conducted by [15] used hyperspectral data (HySpex sensors) to identify the Neodynium (Nd) surface, the way to identify it was to observe the narrow and shallow depth form of absorption. The two sensors used in this case were infrared shortwave: 1000 nm - 2500 nm (SWIR) and visible infrared and close: 350 nm - 1000 nm (VNIR).

Research conducted by [16] takes advantage of existing content from the hyperspectral NIR imaging system in collaboration with multivariate analysis methods to distinguish three types of sheep muscle. The hyperspectral broom pushed imaging system in the 900 nm -1700 nm spectral range was used to image three types of sheep muscle. Hyperspectral can be used for food quality classification and analysis because hyperspectral imaging will not damage the food and the results are accurate. The hyperspectral remote sensing imaging application was used to analyze the level of food quality: estimating the age of stored toast, predict the quality of beef, to classify Chinese tea leaves, and classifying rice grains [17].

To trace the origin of 1.200 samples of Chinese wolfberry originating from Qinghai in China, Ningxia, Sinkiang and Inner Mongolia, the NIR-HSI combination with the chemometric method was used [18].

2.2 Hyperspectral Classification

Remote sensing is a modern approach to observe the surface of the earth. The use of remote sensing has been widely used in the fields of agriculture and land control, for example in the field of precision agriculture. Precision agriculture is used for example for land mapping, identification of plant diseases, observing plant growth, assessing soil fertility conditions and plants and others. The fact is that remote sensing is used as a preventive measure against changes in an object observed for more than two decades [19].

In the study [20] observed that mangrove species in Indonesia and the Asia Pacific generally had various types of families, such as Rhizophora, Avicennia, Sonneratia, and Laguncularia. This very important diversity of mangroves can be correctly classified so that the spread of mangrove species on earth can be known. One method that can be used is remote sensing. This method is very effective because wide area coverage can be observed very quickly without survey fields. Differences in spectral reflections can classify the types of plant species. This method is widely used in the modern era like now to reach difficult areas.

Researchers [21], examined that each pixel has a feature vector in a feature space that can be used as a parameter for classification. In its application, the diversity of factors influences accuracy, for example, object complexity. In an effort to classify an object, there are two approaches, namely unsupervised learning and supervised learning. Furthermore, the classification types can be separated into object-based and pixel-based. Procedure the classification of hyperspectral images can be done as in figure 1.

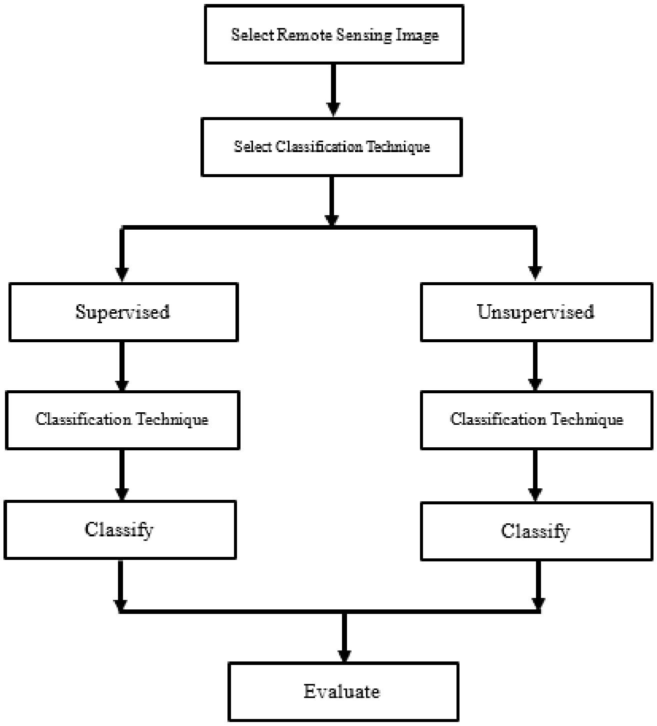

Figure 1: Steps of Image Classification Procedure

Based on Figure 1, each step explains the process involved in the research that has been conducted. First, it was important to select suitable hyperspectral remote sensing image data about the field of study concerning the type of sensor use, date of data collection, spatial and spectral resolution, and available spectrum bands, spatial and spectral resolution.
Second, it involved two processes of classification; supervised and unsupervised. Knowledge from users about the spectral characteristics of pixels and areas studied was the basis of training samples in the supervised classification method. Different in unsupervised classification, classes are defined in the number of clusters which will be generated. Based on research [21], general steps of supervised classification are:

a. Define agriculture land classes;
b. Select training samples;
c. Evaluate the signatures;
d. Decide the decision rules.

Third, this step involved selecting a classification algorithm for the guided classification method and depending on the final objective of image data classification and the characteristics of the image data. The method of classifying works without supervision was by dividing the image into groups that have been determined based on spectral similarities.
Fourth, the process of classification hyperspectral remote sensing image data was conducted during this step. The output was the classification value of each agriculture land and was compared with the supervised classification.
Fifth, this final process involved evaluating the accuracy of the classification results both in terms of the appearance of quality and quantity. The classification image was compared with ground truth data and generating the error matrix.
Different classification methods can give a different percentage of errors on predetermined classification projects. It is very important for remote sensing sensors to choose the classification method that best fits the number of classifications used to provide a very minimal number of errors. Implementation of classification techniques for hyperspectral remote sensing images is briefly described below.
In this paper, several methods are evaluated to solve problems related to low spatial data, a complex area, homogenous areas, and Hughes phenomenon.

3. DISCUSSION AND COMMENTS

Based on previous sessions, this section discusses some important things related to hyperspectral classification techniques, the limitation of the hyperspectral image, the classification process on the hyperspectral imagery, performance parameter and evaluation, best practice of hyperspectral classification, and software availability platform.
The study areas are based on hyperspectral issues raised, they are low spatial data, a complex area, homogenous areas, and Hughes phenomenon. These problems are always haunted when a classification process is performed on hyperspectral data.

3.1 Limitation of Hyperspectral Imaging

In remote sensing image classifiers, a highly accurate classification system is needed and requires a very complicated process. The hyperspectral image is segmented into several homogeneous regions to derive class characteristics needed for mixed pixel decomposition which allows extracting the spectral and spatial features associated with each homogeneous region. One pixel from a multispectral and hyperspectral imagery possibly include more than one object on the ground. Furthermore, there is the problem of recognizing and classify a geographical pixel object due to the overlapping of two or more spectral properties or the different object in one pixel. The mixed problem may include uncertainty indicated by low classification accuracy [22].

3.2 Advantages of Hyperspectral Imaging

Hyperspectral sensors have advantages over multispectral sensors in their ability to identify objects on the ground with more detailed features. The higher spectral resolution of hyperspectral data is suitable for identification and quantification of surface materials, the detection, as well as identifying natural, biological and chemical events. The resolution of a hyperspectral image can also affect accuracy of classification. the complexity of an area can also be the cause of the problem. However, HIS data has a large narrow bands, so based on this specification it can be a challenge in the classification process [23].

3.3 Methods and The Best Practice on Hyperspectral Classification

The classification method discussed in this study is composed of the unsupervised and supervised method. Both of these classification methods rarely stand-alone without pre-process. The number of bands that make up the 3D cube is a limitation contained in hyperspectral remote sensing images that are overcome in pre-process. This large and multiple spectral numbers makes high computation requiring supercomputers to process.

The classification methods using unsupervised are rarely used compared to those supervised because supervised methods are more suitable to be applied in analyzing problems in remote sensing. The most classification attempt is made to facilitate the work of humans with data labels or targets that can be ascertained. So that supervised use is done to facilitate the processing of large hyperspectral data. The guided learning method is one of the most widely used and popular hyperspectral classification methods.

Improved hyperspectral data in the supervised classification method uses pre-processes to improve computational accuracy and efficiency such as stochastic, feature extraction, and feature selection, as shown in Table 1 below.

Table 1: Core and Pre-process Method

Ref.	Core Methods	Pre-process Method
[24]	Support Vector Machine (SVM)	PCA, MNF
[25]	SVM & Random Forest (RF)	SFFS
[26]	CART, Random Forest	PCA
[12]	Parallelpiped	PCA
[27]	SVM	BRDF
[28]	Maximum Likelihood, Mahalanobis Distance, LDA, QDA, ANN	PCA, PLS, MNF, PPI, MR-MIA
[29]	Knn	SNV, PCA, PLS
[30]	SVM	PCA, Data Normalization
[31]	SVM & RBF	KFS, BAHSICp, FSFS, and RFE
[32]	DE-ELM, DE-SVM	PCA
[33]	SC-MK, SVM	PCA, Sobel Edge, ERS
[34]	Structured Sparse Logistic Regression	3-D discrete wavelet transform
[35]	MLR, SVM	EMAP
[36]	SVM	PSO, PCA

In Table 1, the most widely used classification method is SVM, because this method has several advantages they are, firstly SVM has parameters that can be determined by the user, so users can avoid overfitting errors. Secondly, SVM is an algorithm that can be combined with several kernel tricks, so users can experiment in finding the best accuracy by changing the kernel trick. Thirdly, SVM does not have local minima, so this method is very efficient. Fourthly, SVM has a definite algorithm mechanism, unlike deep learning, SVM can be arranged in such a way as to produce the best output. In research [31], SVM is a powerful technique that can be implemented in the kernel like RBF, in this research the highest accuracy is 0.947. In another study, the method that is developed based on ANN (Artificial Neural Network) is the RBF Artificial Neural Network method. In the study [37] the results obtained accuracy reached 100% by using RBFN. So, this is a potential method that can be used in hyperspectral classification.

3.4 Classification Techniques for Hyperspectral Imaging

Classification is a big challenge in hyperspectral remote sensing because of a common problem in HIS data. These factors include images with low spatial resolution due to data quality, a complex area, homogeneous areas, and Hughes Phenomenon. Based on these problems, various classification techniques have been proposed to solve existing classification problems. The four common problems in HIS data will be discussed in the next section below.

3.4.1 Object-based Classification versus Pixel-based

The complexity of the high differences of spectral reflectance is the factor that involves in pixel-based classification. It may produce the “noise” in classification result. This problem can be overcome thru object-based classification. Object-based classification analyzes images was based on segments of the image and then extracted the original word object from the segment. Therefore the target analysis or the area right in the field makes more sense.

There are two main steps included in the object-oriented classification, the classification of images and image segmentation. In the process of image segmentation, there are several strategies for producing objects; first is to integrate vector data and vector-raster data as thematic layers. They divide images into segments and the classification process is based on this segmentation [38]. In addition, pixels can be merged into objects depending on the homogeneity of pixel values within an area, if there is no vector data available the classification based on objects will follow.

Object-based classification in image analysis involved extracting objects in the real world based on their properties such as size and shape. It cannot be performed through the pixel-based classifier. Therefore, to analyze objects and get better results, for features related to objects can be grouped and used as topological features, context features and physical features. The disadvantages of using this method are proven in dealing with meaningful image objects. That is because in image segmentation there are no standard rules.

3.4.2 Unsupervised Classification

Unsupervised Classification is one of common method and usually used in of hyperspectral classification imagery. In research [39] has researched the unsupervised method with NLTV (Nonlocal Total Variation) and PDHG (Primal-Dual Hybrid Gradient Algorithm). This study aimed to overcome convex optimization that was problematic in linear and quadratic models. The NLTV algorithm applied in urban data sets and synthetic data sets consistently worked with high accuracy, in both data producing smoother results by identifying easier visual segmentation, and differentiating material classes that failed to distinguish other algorithms and worked well in the anomaly detection scenario with the correct initialization. This method can maintain the edge of the image well when minimizing and in the iteration, no matrix invasion was involved, but NLTV and other unsupervised classification methods in datasets with a large number of clusters did not satisfy the achieved results.

Classification of hyperspectral data with low resolution can be performed. K-means clustering is used to overcome problems that highlight structural detection and classify hyperspectral data without supervision that has a low level of spatial resolution. From the experiments conducted on the proposed method obtained results that were superior to the classical unsupervised classification method both from the quantitative side and from the perspective of the visual point of view when the area with mixed materials was located at the scene. It took a higher number of iterations, higher resolution improvement factors and a larger pixel count in this study. The advantage of this method is that no other source is needed in addition to HSI [40]

AVIRIS was used to take hyperspectral remote sensing images. To classify HIS, unsupervised classification can be combined with feature extraction methods. Experiments on two hyperspectral images obtained using the BCFE technique were superior in simplifying dimensions compared to conventional feature extraction methods such as the PCA method and the LDA method [41].

3.4.3 Supervised Classification

The supervised classification method has been studied for classification in hyperspectral images using two sensor data. The evaluation process used an accurate method to classify boreal forests. The spectral range used ranges from 400 nm to 1700 nm. Evaluation which was carried out at two spatial levels, pixel maps versus tree-level maps obtained: 1) Working effectively on the classification of boreal tree species with HySpex VNIR 1600 sensors obtained kappa accuracy of more than 0.8 (accuracy obtained by producers was higher than 95% in Pine and Spruce); 2) HySpex-SWIR 320i sensors had a limited role, but these bands can precisely separate species of Fir and Fir; 3) The strong influence possessed by spatial resolution affected the level of classification accuracy which results in a reduction of 20% accuracy at spatial resolutions between 0.4 m and 1.5 m; 4) In the SVM or RF classification method there was no significant difference [42]. The density of various points on different data, analyze by comparing LIDAR, multispectral and hyperspectral data. In the future it is used to map types of trees in the Alps. Hyperspectral remote sensing data is very effective against forest types, single species and general macro-classes, obtained high kappa accuracy values namely forest type 82.1%, single species 76.5% and general macro class 93.2%. Multispectral settings in the general macro class were still very accurate at 85.8% [25].

In other ways, Support Vector Machines (SVM) was a powerful method often used in HIS classification. Many researchers [27], [31], [35], [43] have used the SVM method for the classification process on hyperspectral imagery. This is because SVM produces very good classification accuracy values, even in minority classes. SVM is free from distribution algorithms that can overcome poor statistical estimates. SVM method performs well when training spectra are selected from the same data population that is in the classification process (for example, both of these data are obtained in the same terms and use the same sensor). Many problems of hyperspectral imaging can be solved by SVM such as a complex area [27], Hughes Phenomenon Problem [31], [30], homogenous area [24], and low-density data problem [25].

However, SVM also has many disadvantages. SVM method is very sensitive to its performance against training samples. SVM method functions as a black box and in the model solution for nonlinear cases does not have any important features. Therefore, various methods to improve accuracy have been developed by combining various support methods such as feature selection for enhancing the accuracy or dimension reduction, and statistical improvement method. The combination SVM with feature selection method, many researchers [24], [30], [33], [36] have proposed to avoid the common problem in hyperspectral classification such as a large narrow bands.

Computational complexity in image classification can be reduced based on Rotation Forest. This method can be used to analyze structures and supervised classifying hyperspectral images with low spatial resolution. Rotation Forest method was used to classify hyperspectral images and compared them with other methods in examples SVM, AdaBoost, Bagging, and Random Forest. The experimental results showed that the Rotation Forest technique combined with the PCA Transformation method had more accurate results compared with SVM, AdaBoost, Bagging, and Random Forest methods. In this research that Rotation Forests were good classifier ensembled for hyperspectral imaging [26].

The land cover classification was a very complex method. Random Forest (RF) method was used to resolve a complex area in HIS. Classification of land cover with Random Forest (RF) technique obtained accurate results with Kappa index

0.92 and overall accuracy 92%. The Random Forest (RF) method was strong for training noise and data reduction because there is a very significant difference in the kappa value only observed for the addition of data reduction and noise values each greater than 20% and 50%. Testing using McNemar obtained significant results of 0.00001 indicating that overall performance was better than random forest model algorithms in a single decision tree. The features of non-parametric statistics-based probabilities had the ability to determine important variables. Understanding the rules applied to produce the final classification because there are many classification trees produced from the same resampling dataset is a weakness of the RF method [44].

In hyperspectral classification, Hughes phenomenon and dimension problem are common problems. One of the methods was by using Principal Component Analysis (PCA) [30], [36], [28], [29]. The main components of the hyperspectral image system and features for classification and quality assessment can be found using the PCA method. Large data or a narrow number of bands and high HIS computation time can be solved by the PCA method. The main feature of the spectral image was extracted by the PCA method.

In the same research [45], feature mining very important rule and was commonly used as a recommendation method. This study proposes conventional and sophisticated feature reduction techniques, with details of several common techniques for hyperspectral data analysis. Feature mining methods that have been developed were non-supervised and supervised, nonparametric and parametric, nonlinear and linear techniques, all of which attempted to identify informative subspaces.

Mining features can be simplified measurements including important data. It can be ascertained that classifiers avoided Hughes issues, work well and this process was easy to do if there was sufficient expert knowledge or laboratory research. Difficulty in feature mining such as overfitting in noise sensitivity, learning, overload calculation, and meaning full curves physical interpretation has been researched and spatial information should be incorporated into 3D-DWT texture features [34].

The challenge of the classification of hyperspectral images was that spectral variations in class could lead to over-classification of homogeneous spectral areas, producing salt and pepper noise on this area classification map [36], but this problem was better solved using segmentation method. Segmentation is usually used as a pre-classification process.

The Differential Evolution (DE) method, the ELM Extreme Learning Machine (ELM) method, extraction of hyperspectral remote sensing image features has been carried out[32]. DE-ELM aims to minimize training errors and output weight norms. Compared with existing learning techniques, ELM techniques are characterized by integrated formulations for multiclass, regression and binary problems. The number of nodes must be equal to the number of classes is the multi-output node configuration used by the DE-ELM method. The DE-ELM technique is very effective in the classification and timeliness of computing. ELM provides better accuracy than the faster SVM and ELM methods because this method is simple and also because it provides a simple solution, only requires the inverse of the kernel matrix calculated from a training sample.

Statistical method in hyperspectral classification can be done by using partial least squares regression (PLS), Discriminant PLS, Stepwise MLR, Gaussian blur radius, and rolling ball radius [28], [29], [46], [47], [48], [49], [50]. The advantages of using statistical method are easy computational, but limited availability of the number of bands, and difficult to be used for online inspection.

3.5 Performance Parameter and Evaluation

In the procedure of classification of satellite images, an assessment of accuracy is very important. This evaluation method is definitely used to assess how well the results and algorithms are applied. Evaluation can also mean comparing the results of the image after being analyzed with the reference image. Usually, reference images are obtained from experts who have examined and observed directly on the object, also known as field surveys. The difference between the image of the analysis process and the reference image will produce an accuracy level that is the end-user confidence level. For example, this accuracy evaluation process is used in classification and segmentation methods. Such evaluation methods are known as qualitative evaluation methods. During the evaluation process, usually the resolution of the data used is quite large, so there needs to be a random sampling method so that computing does not take a long time. The confusion matrix is one method that is often used in the process of assessment and evaluating the results of satellite image processing.

4. CONCLUSION

The hyperspectral image has the advantage that the image has more spectral and detail than multispectral, it does not need the previous sample for assessment, and have more solid and accurate information. However, hyperspectral also has disadvantages that hyperspectral has a number of narrow bands that have many or even hundreds of channels. This causes the hyperspectral becomes heavy computation. So, the transmission from the hyperspectral camera requires a lot of resources associated with big data that is also called the Hughes Phenomenon. In other cases, low spatial data, a complex area, region growing is an approach to segmentation in which neighbouring pixels are examined and added to a region class if are detected also called homogenous areas.

The most popular methods of classification on hyperspectral imagery are to use SVM, MLP and RBFN with accuracy above 90%. Because there are powerful methods that can be used in combination with other methods such as feature extraction, feature selection, statistical methods, which are useful for avoiding existing issues of hyperspectral data.

In the next study will discuss the search for a combination of good methods related to segmentation and classification associated with mixed pixels in hyperspectral images and how to improve the results of accuracy on pre-processing or post-processing.

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