

Deep Learning Applications for Hyperspectral Imaging: A Systematic Review

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Abstract

Since the acquisition of digital images, scientific studies on these images have been making significant progress. The sizes and quality of the images obtained have increased greatly from past to present. However, when the information contained in these images remains on the visible band (RGB band), the results that can be obtained are limited. For this reason, the need to acquire images with more broadband information has emerged. Hyperspectral Imaging (HSI) method has been developed to meet this need. A hyperspectral image consists of reflections in hundreds of different bands of the electromagnetic spectrum. Each object exhibits a unique reflection characteristic. Due to this characteristic, objects can be separated from each other using hyperspectral imaging.

Hyperspectral cameras are used to obtain this image. The information it contains is much more than an RGB image, so deeper results can be achieved than the human eye can see.

In this respect, it has great importance. Artificial intelligence technologies are used extensively in image processing as well as in many other fields. As a result, classification studies are carried out on hyperspectral images with machine learning methods. Machine learning methods can be considered as the most general terms of supervised machine learning, unsupervised machine learning, and reinforced machine learning. Supervised machine learning methods mainly: Support Vector Machines(SVM), k-Nearest Neighborhood(k-NN), Decision Trees, Random Forest, Linear Regression and Neural Networks(NN). Neural networks are also used as an unsupervised learning method. However, Deep Learning, a specialized method of artificial neural networks, is highly preferred due to its unique structure. Artificial intelligence methods have been widely used in recent years, especially for the classification of hyperspectral images containing complex information. Considering the studies, it is seen that especially deep learning is used intensively. At this point, studies have revealed different types of models. The number of models and their successes are increasing day by day.

Keywords

Hyperspectral Imaging, HSI, HSI classification, Hyperspectral Image Classification, Deep Learning, HSI with Deep Learning

1. Introduction

1.1. Definition of Hyperspectral Imaging

A hyperspectral image is obtained by recording the reflections of hundreds of different bands of the electromagnetic spectrum. The human eye can only see the reflections in the visible (RGB) band, but a hyperspectral image contains reflections in bands such as infrared (infrared, IR), near-infrared (near-infrared, NIR), which cannot see by the human eye. Figure 1 shows the complete electromagnetic spectrum.

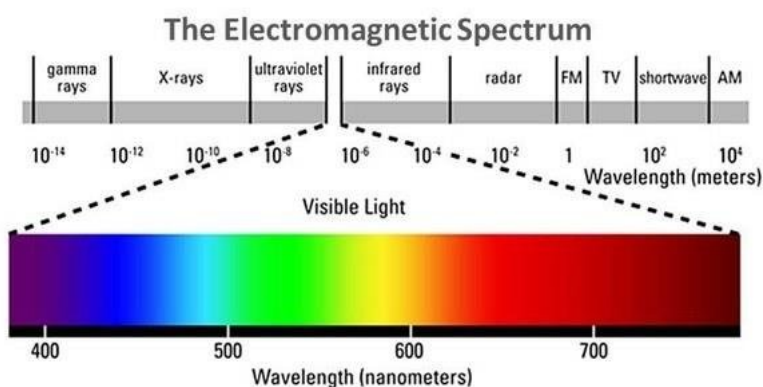


Figure 1. Electromagnetic spectrum

A standard RGB image consists of 3 subcomponents; on the other hand, the hyperspectral image consists of hundreds of subcomponents. After the image is acquired, a data cube (hypercube) consisting of spatial and spectral information appears. The dimensions of the data cube are the resolution of the image and the number of bands in the image. The 'X' and 'Y' components of the hyperspectral data cube are derived from the resolution of the image and the depth is related to the number of bands in the image. In Figure 2, the comparison between RGB and Hyperspectral Images can be seen.

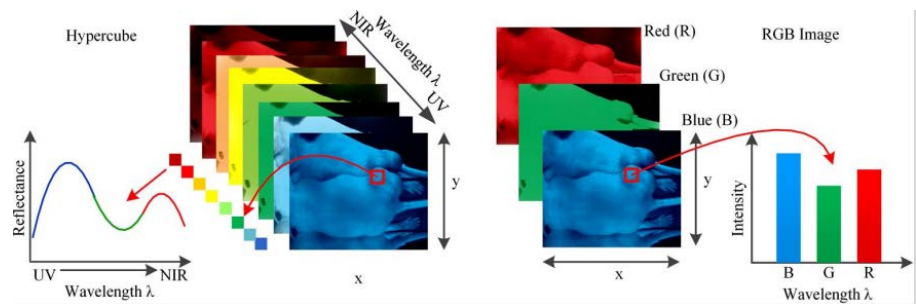


Figure 2. Hyperspectral and RGB Image Components [18]

For each pixel in the hyperspectral image, there is a vector consisting of reflections in each electromagnetic band. At the same time, this vector expresses a spectral signature for each pixel in the hypercube. Figure 3 shows a sample pixel vector and a sample spectral signature.

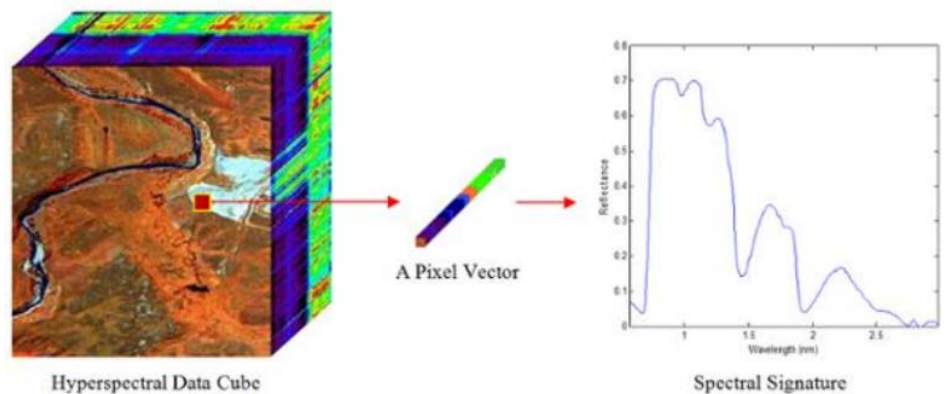


Figure 3. Hyperspectral data cube, pixel vector, and spectral signature

The spectral signature of any pixel contains a piece of characteristic information about the content of the pixel. By using this information, pixels can be dissociated. A basic signal processing has four steps of signal acquisition, preprocessing, feature extraction and selection, classification [32].

To acquire hyperspectral images, customized special ‘Hyperspectral Camera’ is used.

This camera has the ability to decompose the electromagnetic components according to the wavelengths. This camera contains spectroscopy [60]. Spectroscopy is a science related to light emission or reflection occurring in different materials [28].

There are four methods to obtain a hyperspectral cube: spatial scanning, spectral scanning, snapshot hyperspectral imaging, and spatial-spectral scanning [17].

1.2. Hyperspectral Imaging Applications

Hyperspectral imaging has a widespread use since the information it contains and the available results are quite high. Being an expensive method limits its use. However, day by day, new usage areas emerge with a decrease in costs.

The main usage areas are listed below.

- **Remote Sensing:** This technique is successfully implemented in many areas, like classification and change detection [12]. With the images acquired from the hyperspectral cameras located on planes, satellites or UAVs, soil properties, vegetation or rivers, or other natural elements can be detected [48].

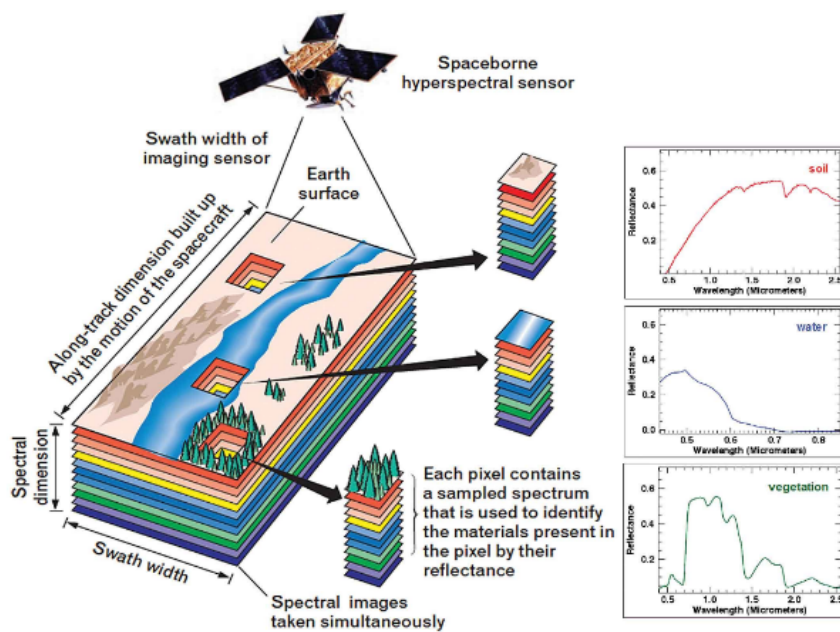


Figure 4. Hyperspectral Imaging concept in Remote Sensing [13]

- **Food:** In this industry, especially in the quality control processes, hyperspectral imaging provides useful information. In Figure 5, the contents of pizza are detected with hyperspectral imaging. The rotten sections can easily be detected in the hyperspectral image [43,44]. In the food industry, hyperspectral imaging can be used to count products [37].

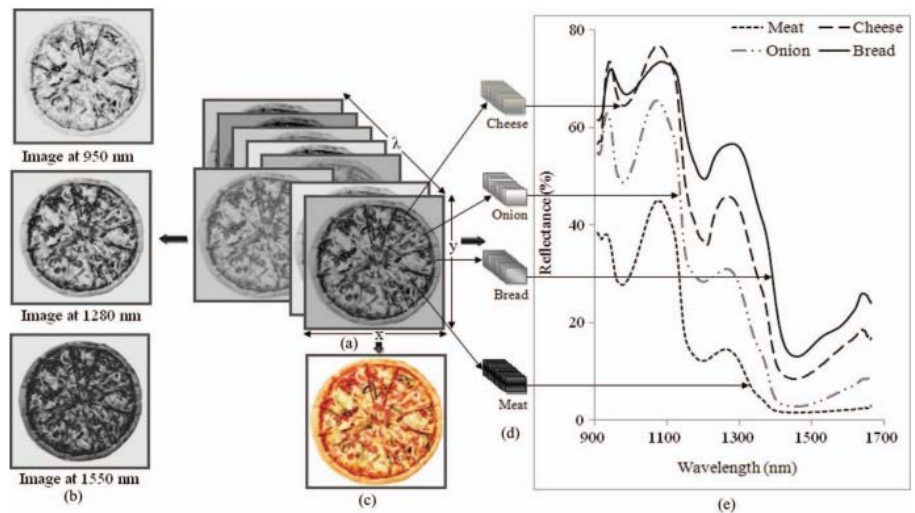


Figure 5. Hyperspectral Imaging in the food industry [15]

- **Agriculture:** A very detailed information about crops on the field can be gathered from hyperspectral images acquired from the cameras located on Drones. It is also possible to gather images at the field level, by fixing a camera on a vehicle such as a tractor [20]. Soil quality can be detected by measuring the carbon level [47]. Non-destructive techniques in the agricultural sector are becoming widespread every day due to technological developments in imaging [36,41,42,45,46]. Diseases can be determined and healed in advance [40,61]. Also, maturing crops can be harvested at the optimum time. Thanks to these advantages, the efficiency is increased.

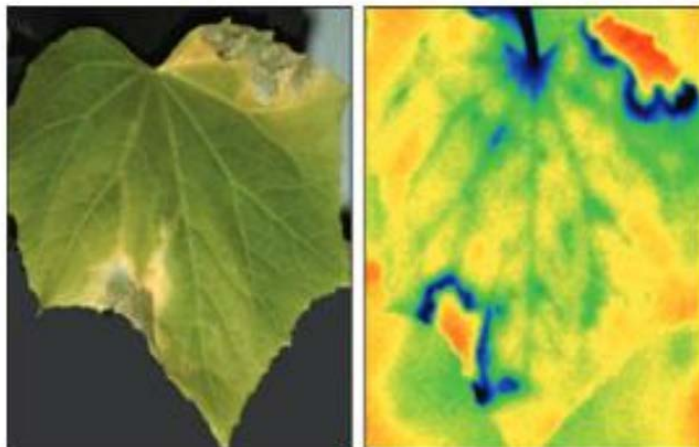


Figure 6. Sample image of cucumber leaf [14]

- **Medical:** A wound at the finger of the patient is shown in Figure 7. Detailed information about this wound can be obtained with hyperspectral imaging. Thus the exact boundaries or the effects under the skin can be investigated. Hyperspectral imaging is a noninvasive mapping method for the parameters of the biological samples examined. [19]

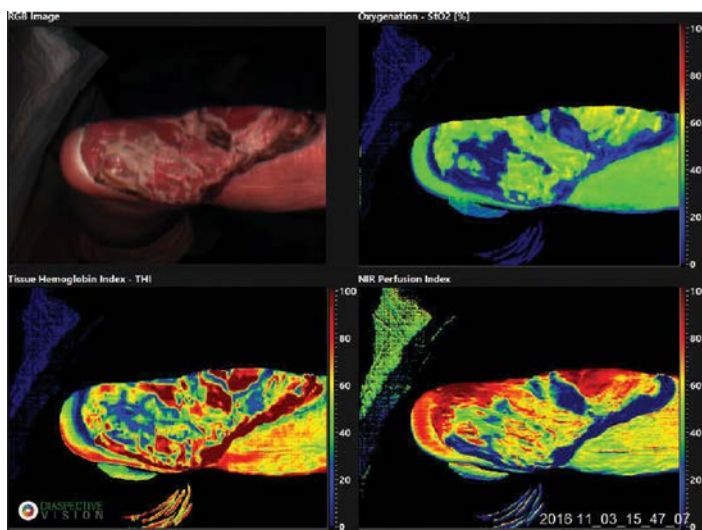


Figure 7. Hyperspectral imaging in medical applications [16]

- **Criminal Investigations:** Hyperspectral imaging is used to detect the clues which cannot be seen with the human eye. In Figure 8, the explosive residues on a banknote, uncovered by the hyperspectral image analysis. Thus, explosive types of manufacturing style information can be accessible.

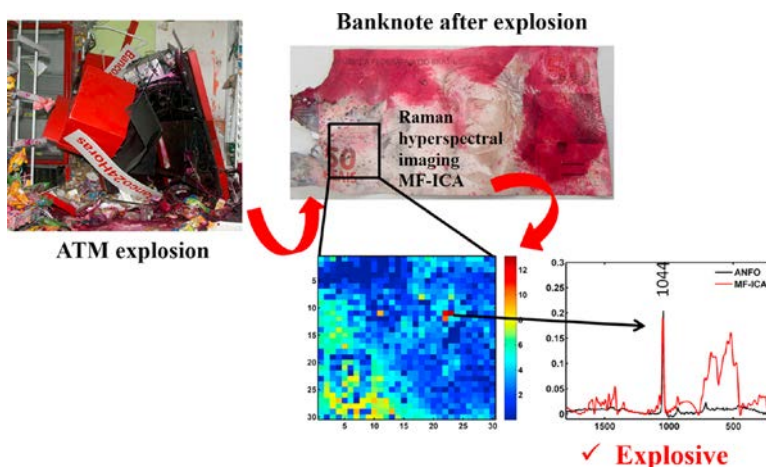


Figure 8. Sample usage of hyperspectral imaging in criminal investigations

1.3. Recent Studies

In recent years, deep learning and hyperspectral imaging have become widespread due to the ever-increasing usage areas and successes. This spread also triggers scientific research on these topics. As a result, both topics intersect. Considering the deep learning studies in the field of hyperspectral imaging, there is a continuous increase in the number of studies performed after 2010. According to ScienceDirect(www.sciencedirect.com, last access 17 Feb. 2020), the graph of the number of publications in the last five years is seen in Figure 9, and with this momentum, it is estimated that the number will exceed thousand in 2020.

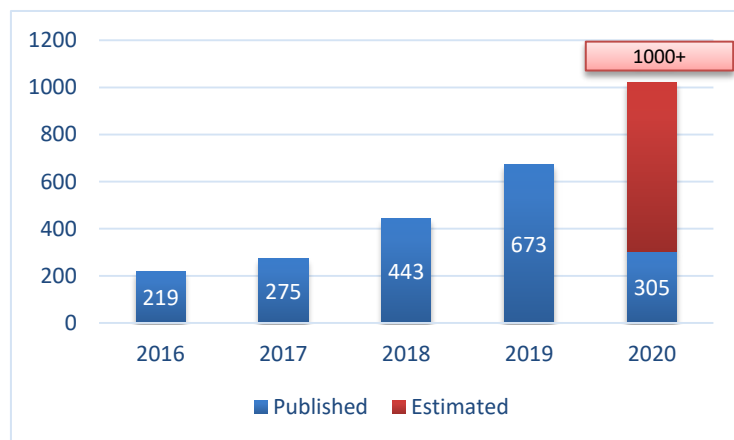


Figure 9. The number of publication in the last five years according to ScienceDirect

1.4. Datasets of Hyperspectral Images

Because of hyperspectral imaging is an expensive method, it is tough to obtain a dataset. In the studies carried out, a limited number of data sets that are accessible to common use are used. The low number of samples in hyperspectral imaging poses a major challenge for implementing machine learning methods [27]. Deep networks usually need a great number of training samples to optimize the model parameters [29]. However, creating ground truth and pixel-labeling are expensive and require much time [38].

The most widely used of these datasets:

- Indian Pines Dataset: Resolution is 145x145 pixels and a total of 220 spectral bands [55].

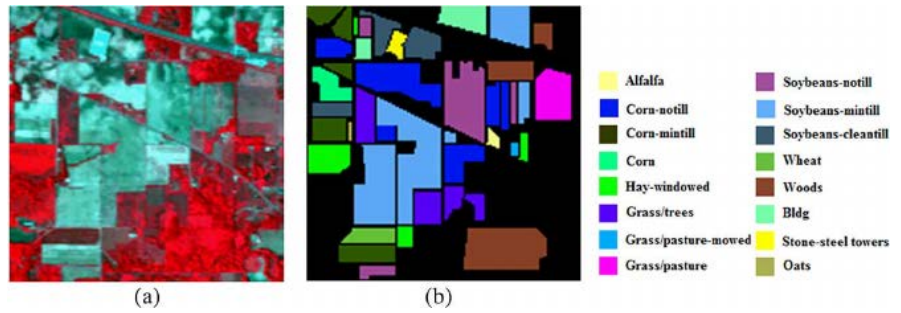


Figure 10. (a) Color image of Indian Pines; (b) Ground truth image of Indian Pines

- Pavia Centre Dataset: Resolution is 1096x1096 pixels and total 102 spectral bands [56].

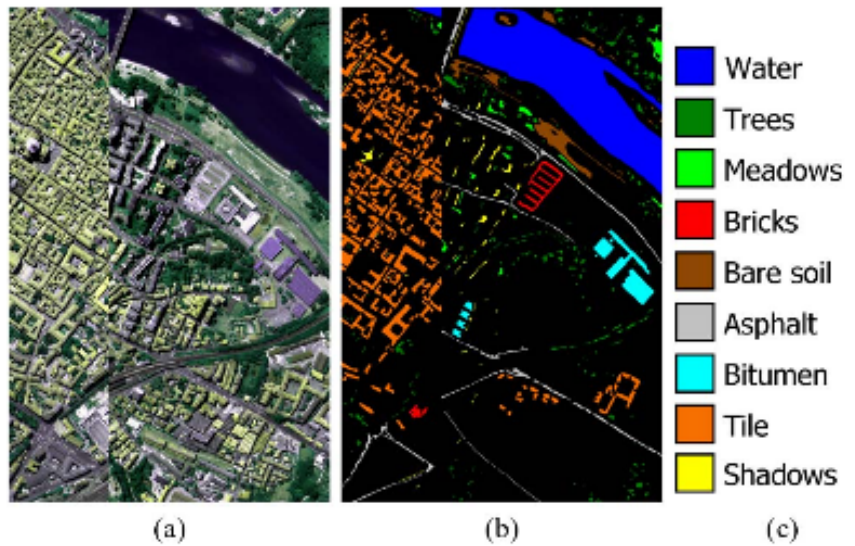


Figure 11. (a) Color image of Pavia Centre; (b) Ground truth image of Centre

- Pavia University Dataset: Resolution is 610x640 pixels total 115 spectral bands [57].

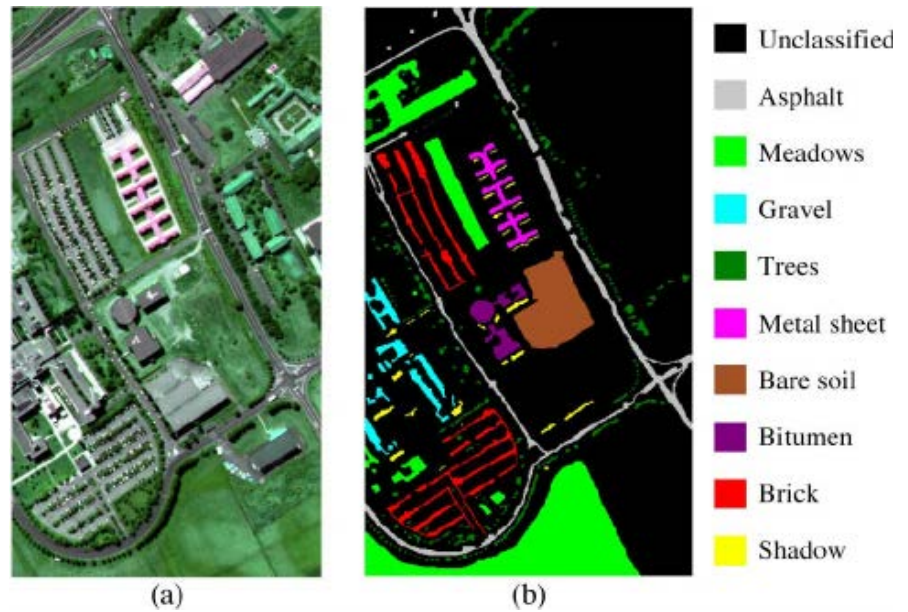


Figure 12. (a) Color image of Pavia University; (b) Ground truth image of Pavia University

- Salinas Dataset: Resolution is 517x217 pixels and a total 224 spectral bands [58].

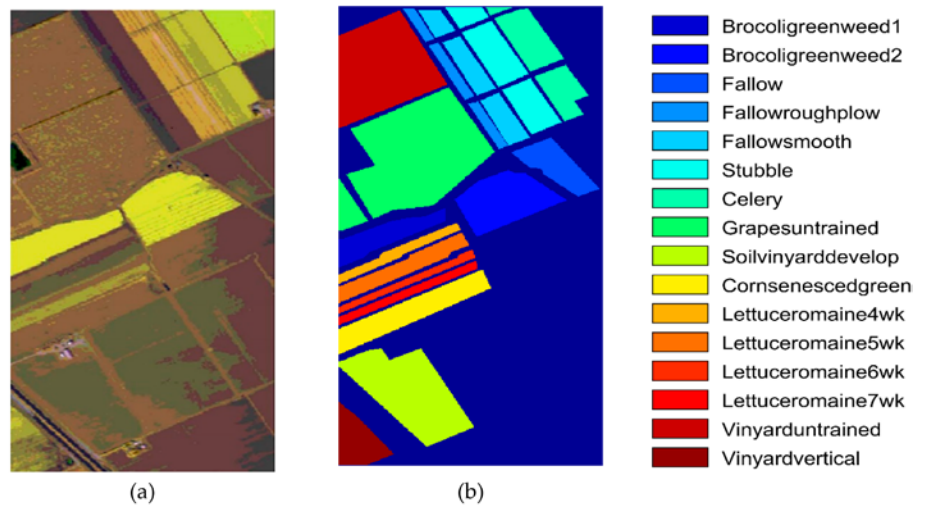


Figure 13. (a) Color image of Salinas; (b) Ground truth image of Salinas

- Xuzhou Dataset: Resolution is 500x260 pixels and total 436 spectral bands [59].

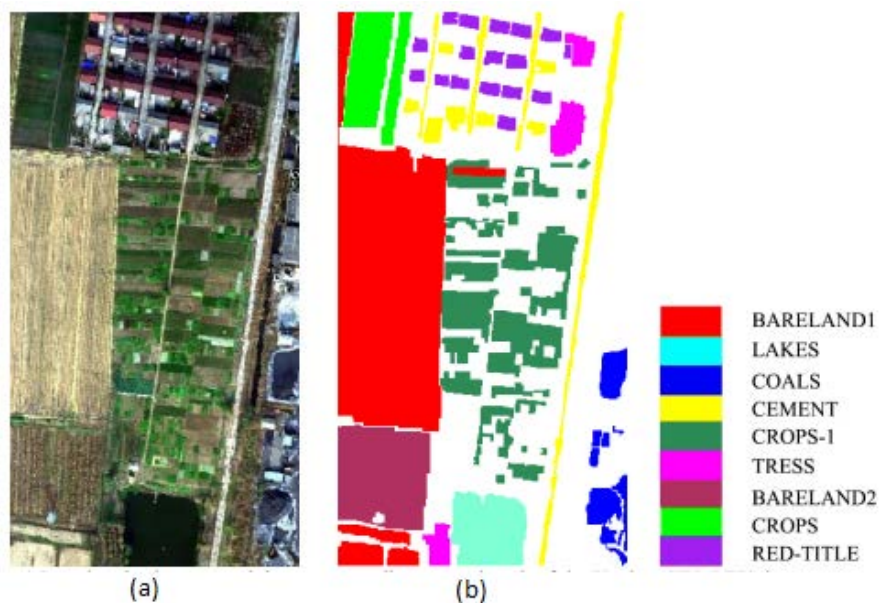


Figure 14. (a) Color image of Xuzhou; (b) Ground truth image of Xuzhou

2. Models

Artificial neural networks play a major role in hyperspectral imaging analysis. In the initial HSI classification studies, most methods focused on investigating the role of spectral signatures of HSIs [21]. Later on, it was determined that the spatial properties reveal important attributes and increase classification success. [22], [23]. It is proposed to combine the spectral and spatial features to increase the success rate [33,35].

Since data points are not linear in hyperspectral images, the success of linear classification methods is low [24]. Because of the high dimensions of hyperspectral images, there are some significant challenges for creating the necessary training examples for statistical classifiers [25]. For this reason, it reduces the size of the image by selecting information from only important bands with principal component analysis (PCA) [26].

In this study, especially deep learning methods will be discussed. 4 different models that emerged within the scope of deep learning were examined. Respectively Convolutional Neural Networks(CNN), Deep Belief Networks(DBN), Auto Encoders(AE), Residual Networks(ResNet) models are explained below.

2.1. Model-1: Convolutional Neural Networks

CNN's are a multi-layered deep learning model that uses a neural network, from raw pixel values to classifier outputs, and is also inspired by biological structures [7]. The CNNs do not require much-preprocessing data to reveal the features from the hidden layer [1]. CNN's provide very successful results in image processing [31].

A sample model is shown in Figure 15. This proposed model is called HybridSpectralNet. In this structure, 2-D and 3-D CNN structures are used together. In this model, both spatial and spectral features are revealed. First, with Principal Component Analysis(PCA), the useless bands are removed from the original dataset. Moreover, respectively 3-D and 2-D convolution operations are utilized.

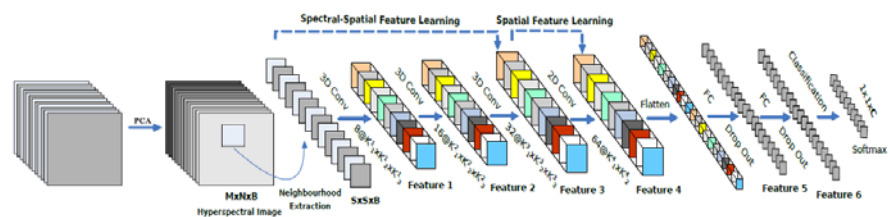


Figure 15. HibridSpectralNet architecture [11]

2.2. Model-2: Deep Belief Networks

In the deep belief network (DBN) structure, a pre-trained model is created with unsupervised learning methods, and then the parameters of this model are improved with the labeled data [10]. The DBN is becoming more popular in nonlinear deep learning applications day by day [51]. In this model, firstly, the texture enhancement is achieved with Guided Filter(GF). Then training sample vectors are applied to the input layer. There are two hidden layers to avoid the overfitting problem. DBN is formed as visible and hidden layers and trained layer by layer [49]. The training procedure requires a long time [50].

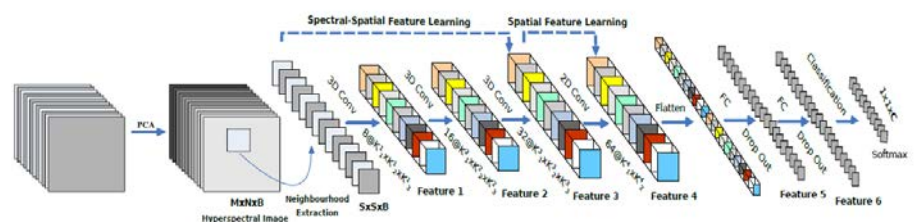


Figure 16. Proposed DBN structure [10]

2.3. Model-3: Auto Encoders

An autoencoder(AE) is a type of a Multi-Layer Perceptron (MLP), in this type, the input layer and output layers are regressed [6]. In AE output data is usually created from input data with the same size [52]. Autoencoder is one of the deep-architecture models; the features are extracted with unsupervised ways [5]. In Figure 17 the proposed model by [3] is shown. This model is called Multi-Scale Relational Collaborative Auto Encoder (MS-RCAE). With this model original data is prepared for classifier SVM.

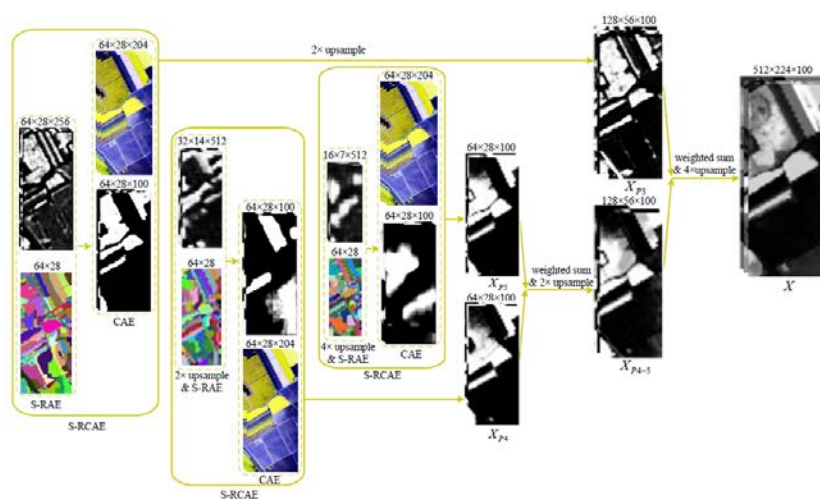


Figure 17. AE model [3]

2.4. Model-4: Residual Networks

A spectral-spatial residual Network(SSRN) is used with precision spectral and spatial properties extraction from HSI and achieves high success in HSI classification in a wide variety of fields. [8]. In Spatial-Spectral Squeeze-and-Excitation Residual Network(SSSERN), Batch normalization is used to regulate the distribution in each layer and increase the speed of Training [9]. At [30,54] it is stated that the residual networks are easy to optimize. However residual networks have less parameter than other deep learning methods [53].

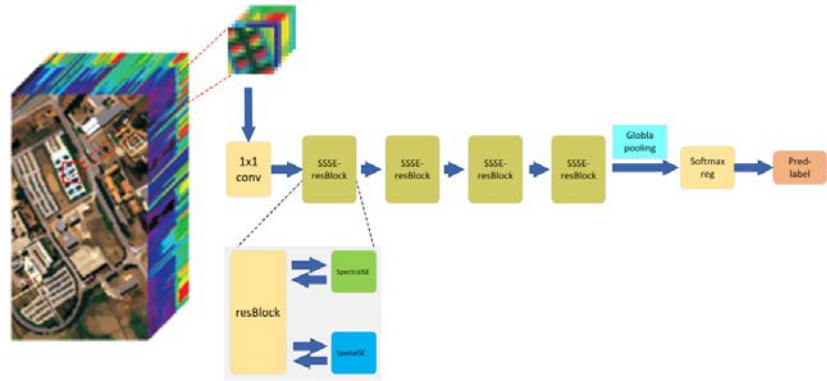


Figure 18. ResNet model [4]

3. Results and Comparisons

Since the common datasets used by all models are Indian Pines and Pavia University, the results and comparisons were made on these datasets. Overall Accuracy (OA), Average Accuracy (AA) and Kappa coefficient will be provided to evaluate the results. Values are represented in percentage (%). OA means the number of correct classifications in the total samples; AA means the average classification accuracies of each class, and Kappa is the measure between the ground truth and classification results [11]. More significant the value of OA, AA, or Kappa means better performance [39].

Table 1. Accuracy&Kappa Values of proposed models for Indian Pines.

	Model			
	CNN[11]	DBN[10]	AE[3]	ResNet[4]
OA	99.39	97.56	97.47	99.44
AA	98.01	97.93	97.53	98.89
Kappa	98.16	96.94	97.18	99.03

Table 2. Accuracy&Kappa Values of proposed models for the University of Pavia.

	Model			
	CNN[11]	DBN[10]	AE[3]	ResNet[4]
OA	99.72	96.96	97.07	99.62
AA	99.20	97.57	95.63	99.13
Kappa	99.64	95.90	94.35	99.35

When the results are examined, it can be seen that the proposed models achieve different successes in different data sets. The ability of models to dimension reduction and feature extraction is different from each other. The difference

between the results is also directly related to the number of samples in the data sets used.

4. Conclusions

In this study, some of the deep learning methods are discussed after necessary information about hyperspectral imaging, which has become quite common recently. 4 new methods that have emerged in the last five years have been examined and the results obtained in the common data sets used have been revealed. This study does not aim to prove the superiority of any method over another.

Undoubtedly, hyperspectral imaging and deep learning techniques are developing day by day. As a result, new methods of feature extraction and classification will continue to emerge for hyperspectral images. In the future, we may encounter an intermingled state of the structures examined in this study.

Conflicts of Interest

There is no conflict of interest

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