TEST Engineering & Management

May-June 2020
ISSN: 0193-4120 Page No. 4458-4462

Hyperspectral Satellite Image Classification using Deep Learning

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Article Info
Volume 83
Page Number: 4458-4462
Publication Issue:
May - June 2020

Article History
Article Received:*19 November 2019*
Revised: *27 January 2020*
Accepted: *24 February 2020*
Publication: *12 May 2020*

Abstract

Hyperspectral images are utilized to provide adequate spectral information so as to acknowledge and differentiate spectrally distinctive materials. Optical analysis techniques are utilized to detect and identify the objects from a scale of images. Hyperspectral imaging technique is one among them. Hyperspectral image classification research is an intense field of study and an outsized number ofrecent approacheshave been developed to enhance the performance for specific applications that exploit both spatial and spectral image content. The goal of hyperspectral imaging is to obtain the spectrum for each and every pixel within the image of a scene, with the intent of detecting processes, identifying materials or finding objects. In this particular study, a strategy for the classification of Hyperspectral satellite images is asserted using deep learning framework. Thisframeworkinvolves inception module architecture containing 1x1, 3x3 and 5x5Convolutional layers which gives an overallclassification accuracy of 97.30%.

Keywords: *Hyperspectral imaging technique, convolutional layers.*

1. Introduction

Remote sensing methods are any methods where information/data is extracted or interpreted by indirect measurement of the thing under study (I.e. there's no physical contact with the object). The data is obtained via non-particulate radiation.

Remote sensing allows coverage of very large areas which enables regional surveys on a spread of themes and identification of extremely large features. It allows repeated coverage which proves to be veryuseful when accumulating data on varied dynamic themes like water, agricultural fields and so on.

Hyperspectral images are volumetric image cubes that encompass many spatial images. Each spatial image, or spectral band, captures the responses of ground objects at a selected wave length. Due to its rich spatial and spectral information contents, hyperspectral imagery has become a vital tool for a spread of remote sensing and scanning applications. It's widely employed in the sensing and discovering of ground minerals, in monitoring of the Earth's resources, and in military surveillance.

In the approach discussed here an Inception module [1] is used in order to perform the classification. Using this model we can extract features and classify Indian pines hyperspectral images more efficiently and easily.

2. Literature Survey

Lokman G. & Yilmaz, G. in their paper on hyperspectral image classification using SVM [2] have designed the classifier using the vector neural network for Hyperspectral image which the neural network is trained for Eigen-value decay. The pre-processed hyperspectral image data is used as the input to the system. It contains classification of the image in matrix form as the output of the system. The output of the target class is in negative values and the background data with other values. To test the classifier they used Hyperion sensor on NASA EO-1 satellite to classify the airborne visible/infrared imaging

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spectrometer (AVIRIS) image of Okavango Delta and image of Salinas Valley**.**

In this paper [3], Ido Faran, Nathan S. Netanyahu, Maxim Shoshany, Fadi Kizel, Eli (Omid) David, Jisung Geba Chang, Ronit Rud have proposed a novel method, to overcome the problem of lack of adequate data by training a deep neural network for classification. For training the convolutional neural network pixel based classification, they used simulated ground truth from hyperspectral, high resolution FENIX image.

[4] In this paper to improve the performance of the hyperspectral image classification based on Siamese convolution neural network (S-CNN) using supervised deep feature extraction method they use labelled samples for training. It is separated into different classes by training the S-CNN [5]. The feature of hyperspectral cube is extracted from five layer Convolution neural network of nonlinear transformation function. The classification task is extracted discriminative by using supervised margin ranking loss function. Thus the support vector machine provides the better classification performance than the conventional method

In this paper [6], Lu, Y., Perez, D., Dao, M., Kwan, C., & Li, J. have collected the image from WorldView-2 satellite for soil detection by combination of original 8 multispectral bands and 80 synthetic hyperspectral bands. The CNN model is used for soil detection over the curved surface area has increased its average of 7.42% in average from 76.26 to 83.48. Soil detection performance can also be increased by pan-sharpening and morphological post processing. For improving the performance of classifying the remote sensing application and object detection can perform synthetic hyperspectral bands of CNN model.

In this paper[7], Shen, Y., Xiao, L., Chen, J., & Pan, D. have used for novel deep ELM neural network for Indian Pines dataset, Pavia University dataset and Salinas dataset for testing. The fully connected deep ELM network and two branch convolutional learning module within hidden nodes are the two part of framework. The generating random weight to Hyperspectral image spectral and spatial features are extracted, concentrated and fed into the fully connected ELM networks. The classified result is obtained from ELM network.

In this paper [8], AVIRIS and ROSIS hyperspectral datasets of developed framework of deep learning are used for experimentation and validation. The spatial and spectral information are encoded using the high level features of CNNs and MLPs. They compared the performance of SVM based classifier and deep learning approach. For every data set given for the validation, deep learning approach has the superior performance.

3. Methodology

In this approach (Figure1) to classify the satellite image data hyperspectral satellite images (HSI) are provided as input. These hyperspectral images are composed of multiple bands/channels which contain spectral and special information about the pixels. By considering a single hyperspectral image (Figure2) and its ground truth image (Figure 3) as input data, classification is performed to classify each pixel into its corresponding class. Ground truth data gives information about the different predefined classes of the pixels.

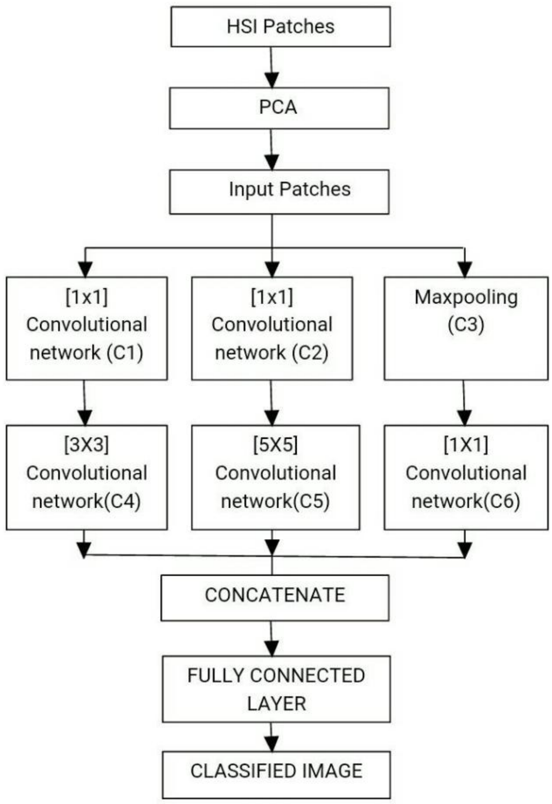

Figure 1: Block diagram of overall system architecture

The hyperspectral image is represented as a 3 Dimensional tensor of WxHxB dimension, where W is the width, H is the height of the image and B denotes the number of spectral bands/channels consisting of several spectral and spatial information. This image is further decomposed into numerous patches of dimension SxSxB. To classify a pixel at location (x, y) to the corresponding class label L(x, y), a patch P(x, y) of dimension SxSxB centred at that pixel is used. Hence the dataset contains pixel's information in the form {P(x, y), L(x, y)} where x=1,2,….,W and y=1,2,….,H

Figure 2: Hyperspectral Image

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Dimensionality reduction of the input image:

The input patches containing hundreds of spectral bands lead to high dimensionality which may result in more training time and high computational costs. From an analysis made on spectral response patterns of pixels, it is observed that the pixels which belong to same class have a very small variance in their response patterns. This predicts that these pixels have similar properties and almost the same pixel values in every channel, while the pixels belonging to different classes have different properties due to large amount of variance. Taking this into account dimensionality reduction is achieved by employing PCA (Principal Component Analysis) [9]approach along the spectral dimension to abridge the entire image into lower dimension.PCA reduces few spectral properties which possess less variance by preserving the spatial properties.

In this experimentation process the first 30 principle components are retained to preserve most of the initial information. After the application of PCA, the input patch which is also a 3D tensor of dimension SxSxB is reduced to SxSxBr, where Br is the number of bands after the application of PCA and S is kept minimum as 5 to have the neighbouring pixels as minimum as possible during classification process which else may increase the computational cost of training data.

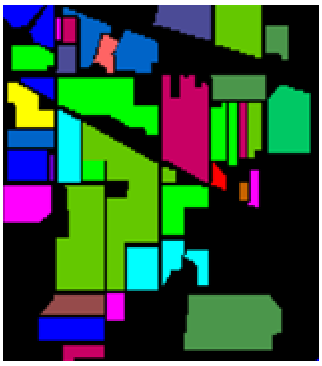

Figure 3: Ground Truth Image

Classification model:

Input patches obtained after applying PCA with reduced dimensions are sent to the deep learning classification structure.25% of the dataset is used for testing and remaining data is used to train the classification model. The model has to train all kinds of samples with maximum accuracies. The Convolutional Neural Network (CNN) architecture which is used here is similar to inception module. It consists of convolutional layers C1, C2 with trainable filters of dimension 1 x 1 and C3 as maxpooling layer. The C1 and C2 convolutional layers are followed by a second set of convolutional layers C4 and C5 with 60 trainable filters, the filters are of dimension 3x3 and 5x5 respectively. By adding 1x1 Convolutional layer before the 3x3 and 5x5 Convolutional layers, while keeping the height and width of the feature map, the number of computations are reduced by a factor of 10. This reduces the computational requirements and in turn maximum efficiency is also obtained. C3 which is maxpooling layer is followed by convolution layer C6 with dimension 1x1.The output from each of C4, C5 and C6 layers is concatenated to form output of the inception module. The output obtained is then flattened into one dimensional set of neurons which is further used to create a fully connected neural network layer for final classification. The model was trained for 25 epochs. The training accuracy of the model increased to a maximum in every epoch. A classified image with each pixel classified into its respective predefined class labels is obtained as the final output.

4. Experimental Results

Dataset:

In this experiment the Indian Pines data set gathered by the AVIRIS sensor over the Indian Pines test site in North-western Indiana is used. It consists of 224 spectral reflectance bands within wavelength ranging between 0.4 and 2.5 10 ^ (-6) meters and 145x145 pixels. Here 75% of data set sample is randomly selected as training dataset and remaining 25% as testing dataset. The Indian Pines data consists oftwo-third of agriculture and one-third of forest/other natural vegetation. The ground truth image of the dataset is designated into 16 classes. Once the classification is done, the results are obtained as discussed below.

Result:

For each class in the designated sixteen classes of the ground truth image which is obtained after classification, the model evaluation matrices are calculated. These evaluation matrices are used to check theprecision, recall (the sum of true positives and false negatives), f1-score (harmonic mean of the precision and recall) and support (the number of samples of the true response that lie in the class).The same is showed in Figure4.

	precision	recall	f1-score	support
Alfalfa	1.00	1.00	1.00	11
Corn-notill	0.97	0.94	0.95	357
Corn-mintill	0.97	0.98	0.97	208
Corn	0.97	0.97	0.97	59
Grass-pasture	1.00	0.97	0.98	121
Grass-trees	0.99	0.99	0.99	183
Grass-pasture-mowed	1.00	1.00	1.00	7
Hay-windrowed	1.00	1.00	1.00	120
Oats	0.83	1.00	0.91	5
Soybean-notill	0.95	0.95	0.95	243
Soybean-mintill	0.96	0.98	0.97	614
Soybean-clean	0.95	0.95	0.95	148
Wheat	1.00	1.00	1.00	51
Woods	1.00	1.00	1.00	316
Buildings-Grass-Trees-Drives	0.95	0.97	0.96	97
Stone-Steel-Towers	1.00	1.00	1.00	23
accuracy			0.97	2563
macro avg	0.97	0.98	0.98	2563
weighted avg	0.97	0.97	0.97	2563

Figure 4: Statistical Analysis of Classification

Values obtained by calculating precision, recall, f-score and support are used to build a confusion matrix.

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This matrix gives information about thenumber of correct and incorrect predictions with count values and also shows how our classification model is confused during predictions. It also gives us information about the errors being made and their types. The confusion matrix obtained for the classification model employed in this study is shown in the Figure5.

```
[[ 11   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0]
 [  0 337   2   1   0   0   0   0   0   3  13   1   0   0   0   0]
 [  0   1 203   0   0   0   0   0   0   0   3   1   0   0   0   0]
 [  0   1   1  57   0   0   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0 117   0   0   0   0   0   0   1   0   0   3   0]
 [  0   0   0   0   0 182   0   0   0   0   0   0   0   0   1   0]
 [  0   0   0   0   0   0   7   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0 120   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   5   0   0   0   0   0   0   0]
 [  0   3   1   0   0   0   0   0   0 230   7   2   0   0   0   0]
 [  0   4   1   1   0   0   0   0   0   7 600   0   0   0   1   0]
 [  0   3   1   0   0   0   0   0   1   2   0 141   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0  51   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0 316   0   0]
 [  0   0   0   0   0   1   0   0   0   0   0   2   0   0  94   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0  23]]
```

Figure 5: Confusion Matrix obtained during Classification

TABLE 1summarizes the result of the classification showing the loss percentage and the accuracy percentage.It is observed that the Inception module of CNN model achieves significant detection performance as the average accuracy is 98.08%.

Table 1: Result of the Classification

Metrics Accuracy	In Percentage (%)
1. Test loss	7.55130105622482
2. Test accuracy	97.30784237222005
3. Kappa accuracy	96.92939627277772
4. Overall accuracy	97.30784237222005
5. Average accuracy	98.0812132164497

The Classification map for the ground truth image (Figure 3) which is designated into 16 classes is obtained as shown in Figure 6.

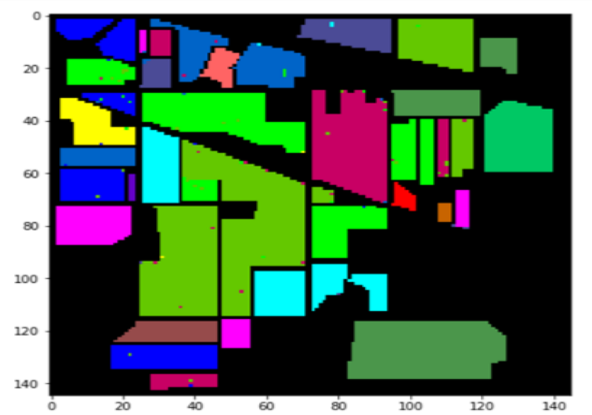

Figure 6: Classification map obtained after applying classification model on Indian pines data set

5. Conclusion and Future Scope

In this paper, an Inception module architecture of CNN model using deep learning tools is implemented for the classification task. Inception module convolves the input tensors with multiple number of filters and connects the obtained results into one block which results in higher performance of the classification model. This approach systematically constructs superior features that encodes pixel's spectral and spatial details and presents high-level performance for every hyperspectral satellite image data. Although PCA has done a good job in case of dimensionality reduction, there are other methods which can be implemented to yield better accuracy depending upon the use case. The above approach can be used in performing classification of satellite images of a particular area considered for study to observe the different resources in that area such as agricultural land, water, built-up areas, etc.

As a part of future work, we would like to gather the dataset of a particular region fora particular time period, say 10 years, on which the discussed classification approach can be applied to the dataset collected for every year and the changes in land use/land cover patterns can be detected. By studying these patterns, observations can be made on following factors such as vegetation changes which will help in taking measures for improving cultivation patterns, change in built-up areas which denotes the rate of urbanization on which several actions can be taken to control the rate, changes in water covered areas which will help in reducing water scarcity. This land use/land cover pattern describes the impact of human activities on the environment which plays a major role in the planning and development of a region.

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