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Research Article

Improved Convolutional Neural Networks for the Classification of the Hyperspectral Image

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Abstract: In recent times, convolutional neural network (CNN) provides improved performance on various image processing analysis. This includes classification of images even with redundant information over various imaging application. With such aim, in this paper, the hyperspectral images are classified using CNN in spectral domain. The CNN architecture includes five different layers enables the classification of data samples by the CNN classifiers and discards redundant information. The experimental results test the efficacy of the model, where the results show that the CNN obtains higher classification accuracy than other methods.

Keywords: CNN, Hyperspectral Image, Classification, Deep Learning

1. Introduction

Remote sensors are used to collect hyperspectral images (HSI) (Landgrebe, 2002), which are distinguished by hundreds of spectral resolution monitoring networks. A variety of conventional classification methods, for example nearest neighbors and logistic regression (Foody &Mathur, 2004), were created to benefit from the rich spectral knowledge. Any more efficient methods of extraction of functional features and specialized classifiers (Tarabalka, Benediktsson&Chanussot, 2009)and Fisher local discrimination analyses (Li, Prasad, Fowler& Bruce, 2011)have recently been proposed. In current documents, SSM (Melgani&Bruzzone, 2004; Gualtieri & Chettri, 2000)has been regarded for hyperspectral classification role, particularly in small sample sizes, as a cost-effective and stable process. SVM aims to distinguish two-class information that tends to obtain optimal prediction hyperplane that better differentiates the workout samples in high-dimensional space with the kernel. In order to enhance classification accuracy, some SVM extensions in the hyperspectral image classification have been presented (Tarabalka, Benediktsson&Chanussot, 2009; Mountrakis,Im&Ogole, 2011; Li, Bioucas-Dias&Plaza, 2012).

The data description of remote sensing is already examined by the Neural Network (NNs), such as Multilayer Perceptron (MLP) (Atkinson&Tatnall, 1997; Bruzzone&Prieto, 1999). In (Ratle, Camps-Valls&Weston, 2010), semi-supervised HSI classification NN system. SVM is in fact higher than the traditional NN with respect to classification accuracy and computing costs for remote sensing classification activities. A deeper NN architecture was considered in (Hinton&Salakhutdinov, 2006)a strong classification model, which is competing with SVM for its classification results.

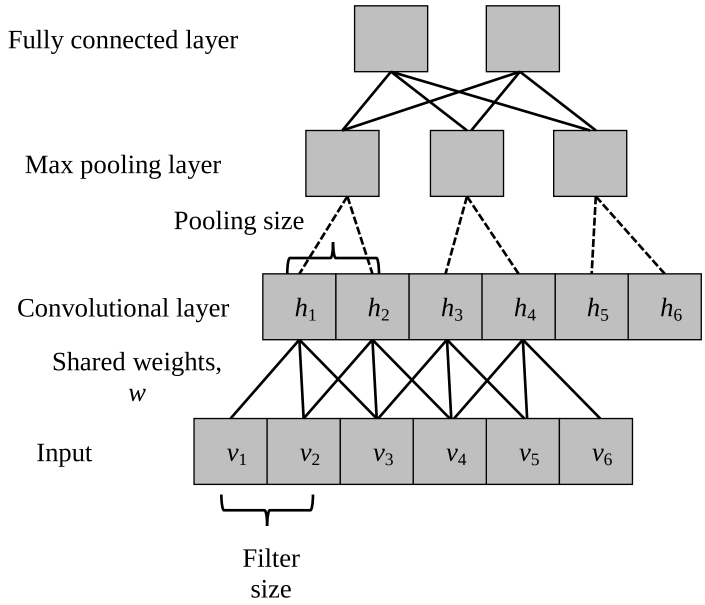
In several areas, profound learning approaches attain promising results. Deep learning involves the analysis of visual problems by the convolutional neural networks (CNNs). CNNs are biological and multi-layered deep learning groups using a single neural network trained from raw pixel values to output classification. Initial introduction to the concept of CNNs was (Fukushima, 1988) and improved in (LeCun, Bottou, Bengio&Haffner, 1998), while (Ciresan, Meier,Masci, Gambardella&Schmidhuber, 2011; Simard, Steinkraus &Platt, 2003)has been streamlined and condensed. CNNs recently outperformed several other traditional approaches, including human performance, in several tasks related to perception, such as image classification (Krizhevsky,Sutskever&Hinton, 2012; Ciregan, Meier&Schmidhuber, 2012), scene marking, object identification, face recognition and digit classification through the widespread data sources and a GPUs implementation. CNNs were also used for other fields, as were voice recognition, in addition to the tasks of vision. It is a proven method of interpreting the quality of visual images as an important class of models, providing some cutting-edge findings on the classification of visual images and on other visual problems.

The classification efficiency of CNNs has been shown to be much higher than that of standard SSM classifiers and deep-CNN (Krizhevsky,Sutskever&Hinton, 2012) in the visual field. However, although CNNs have only been taken into account for visual difficulties, uncommon littoral material is available on the HSI classification technique with several layers. In this article, the use of CNNs for hyper-spectral data can be effectively classified after suitable layer architectures have been defined. Our observations suggest that standard CNNs like LeNet-5 (LeCun, Bottou,Bengio& Haffner, 1998) are not currently valid for hyperspectral data in two convolutional layers. Otherwise, the CNN architecture containing 5 layers with weights for the supervised HSI classification is simple but efficient.

2. CNNs

CNNs represents FFNN consisting of combinations of layers including convolutional, max-pooling and connected layers. It tends to exploit local correlation in spatial distribution using local pattern with its neurons. Figure 1 illustrates a standard convergence network architecture.

Figure.1 A typical CNN architecture.



The neuron linked with its adjacent neurons in the next layer in ordinary profound neural networks. CNNs differ from regular NNs because, depending on their relative position, neurons in convolutions are only sparingly bound to the next levels. In other words, any secret activation in a completely connected DNN is calculated by multiplying the whole weight of the input in this layer. In CNNs, however, any hidden functions are estimated by multiplying a local input. As shown in Figure 1, weight is then divided across the total input area.

A function can be found through the input data due to duplication of weights in a CNN. The neuron detected by the feature is changed as well as the image is moved. The pooling is used to make the characteristics invariant and to summarize the output of many neurons via a pooling mechanism in convolutional layers. Maximum typical pooling function. The maximum value of the input is generated by a Max Pooling function. Max divides the input data and the maximum value for each subregion into a non-overlapping series of windows, reducing statistical complexity for high latitudes and creating a type of translation invariance. The calculation chain of a CNN is used for classification and ends up in a completely linked network, which incorporates information across all sites and all the characteristics of the next stage.

The lower layers consisting of different convolutional and maximum pooling layers are often image-identifying CNNs while the upper layers are entirely bound to the standard MLP NNs. In this article, we will discuss what is the appropriate CNN-based HSI classification architecture and policy.

3. CNN Classification

Gradually, CNNs hierarchy is effective for learning the visual depictions. We can see that the curve of any class is visually distinct from other classes, but certain classes with a human eye are relatively difficult to discern. We know that CNNs can compete in certain visual tasks and perform far better than humans. It encourages us to research the feasibility of using spectral signatures to add CNNs to HSI classification.

Training Strategies

This is how we can learn the CNN classifier parameter space. The forward propagation helps to calculate current parameters for the final classification outcome of the entries. The back propagation is used to adjust workable parameters to reduce difference between the original nad predicted classified outputs.

Algorithm 1: Our CNN-based method

```
function cnnmodel
Type_Layer = CL, MPL, FCL, OL
Set Activation function
    Set m = Model();
        for i=1:4 do
            Set L = new L();
            t_l = T_L
            Size_input = n_i
            params = θ_i
            n = new Neuron;
            add_L();
        end for
    return M;
end
Initialize min error, learning rate, number of max iteration, batch size
Generate random weights
set Model = InitCNNModel;
err = +; iter = 0
while err  > min(err) and iter< max(iter) do
err = 0;
for batch i=1:training_batches
        train_cnnModel with TrainingData and TrainingLabel
        Update params θ
        err = mean + err;
end for
```

3.4. Classification

Built the CNN classification for HSI image classification, since we specify the architecture and all corresponding trainable parameters. The classification method is much like the move forward in which the outcome will be calculated.

4. Experiments

The Python language and Theano [30] were used to execute all the programming. Theano is a Python library which makes mathematical expressions using multi-dimensional arrays easy to describe, optimize and evaluate on GPUs efficiently and conveniently. This results in a PC with a 2.8 GHz Intel Core i7 and a GTX 465 graphics card Nvidia GeForce.

4.1. The Data Sets

The efficacy of the proposed approach is assessed by 3 HSI data that includes Salinas, Indian Pines and Pavia University scenes. In the ground real-world map for testing, we randomly pick 200 labeled pixels per course from all the results. Development statistics are drawn from the training data, divided into training and evaluation samples in order to adjust the criteria of the proposed CNN classification. In addition, every pixel is evenly scaled.

The Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) sensor in North-West Indiana has collected the Indian Pines data collection. The study eliminates classes with a labelled samples and picks classes as in Table 1.

Table.1. Indian Pines - Training/test samples.

Dataset	Training	Testing
Corn-notill	1228	200
Corn-mintill	630	200
Grass-pasture	283	200
Hay-windrowed	278	200
Soybean-notill	772	200
Soybean-mintill	2255	200
Soybean-clean	393	200
Woods	1065	200
Total	6904	1600

The AVIRIS sensor was also used to capture the second data, capturing a 3.7m space resolution area over the Salinas Valley in California. Pixels with 220 bands are used in the shot. It consists primarily of herbs, naked soil and fields of vineyards. There are also 16 main grades, and Table 2 lists the numbers of samples for preparation and research.

Table.2. Salinas - Training/test samples

Class	Training	Test
Broccoli green weeds 1	1809	200
Broccoli green weeds 2	3526	200
Fallow	1776	200
Fallow rough plow	1194	200
Fallow smooth	2478	200
Stubble	3759	200
Celery	3379	200
Grapes untrained	11071	200
Soil vineyard develop	6003	200
Corn senesced green weeds	3078	200
Lettuce romaine, 4 wk	868	200
Lettuce romaine, 5 wk	1727	200
Lettuce romaine, 6 wk	716	200
Lettuce romaine, 7 wk	870	200
Vineyard untrained	7068	200

Vineyard vertical trellis	1607	200

The imaging scene was collected under DLR's HySens project with a geographic coverage of pixels. Until removing the water belt, the data collection had 103 spectral bands. It covers from 0.43 to 0.86m in spectrum and has an output of 1.3m in space. The ground truth map contains approximately 42776 pixels of 9 groups and the numbers of the preparation and research samples are presented in Table 3.

Table.3. Pavia data - Training/test samples

Class	Training	Testing
Asphalt	6431	200
Meadows	18449	200
Gravel	1899	200
Trees	2864	200
Sheets	1145	200
Bare soil	4829	200
Bitumen	1130	200
Bricks	3482	200
Shadows	747	200
Total	40976	1800

4.2. Results and Comparisons

The classification efficiency comparison between the system being suggested and the standard SVM classifier is given in Table 4. The classification results from the CNN classifier are shown in Figures 4, 5 and 6. In addition in Figure 7, the CNN classification is higher for individual groups as seen relative to the SVM.

Table.4. Comparison of Accuracy

Data set	The proposed CNN	RBF-SVM
Indian Pines	91.23%	89.52%
Salinas	93.54%	90.24%
University of Pavia	93.48%	90.66%

Figure.4. Indian Pines dataset [26] - Composition maps

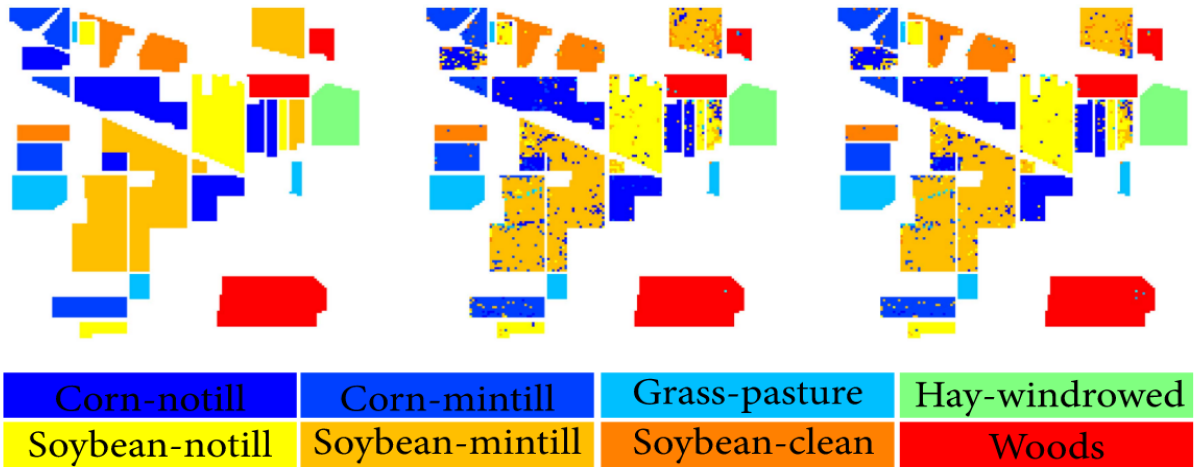


Figure.5. Salinas - Composition maps

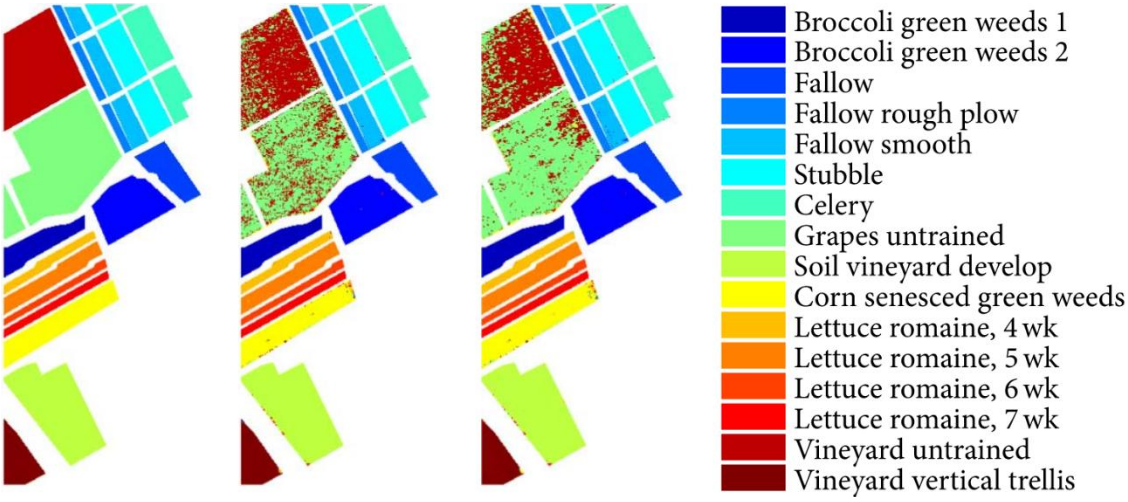
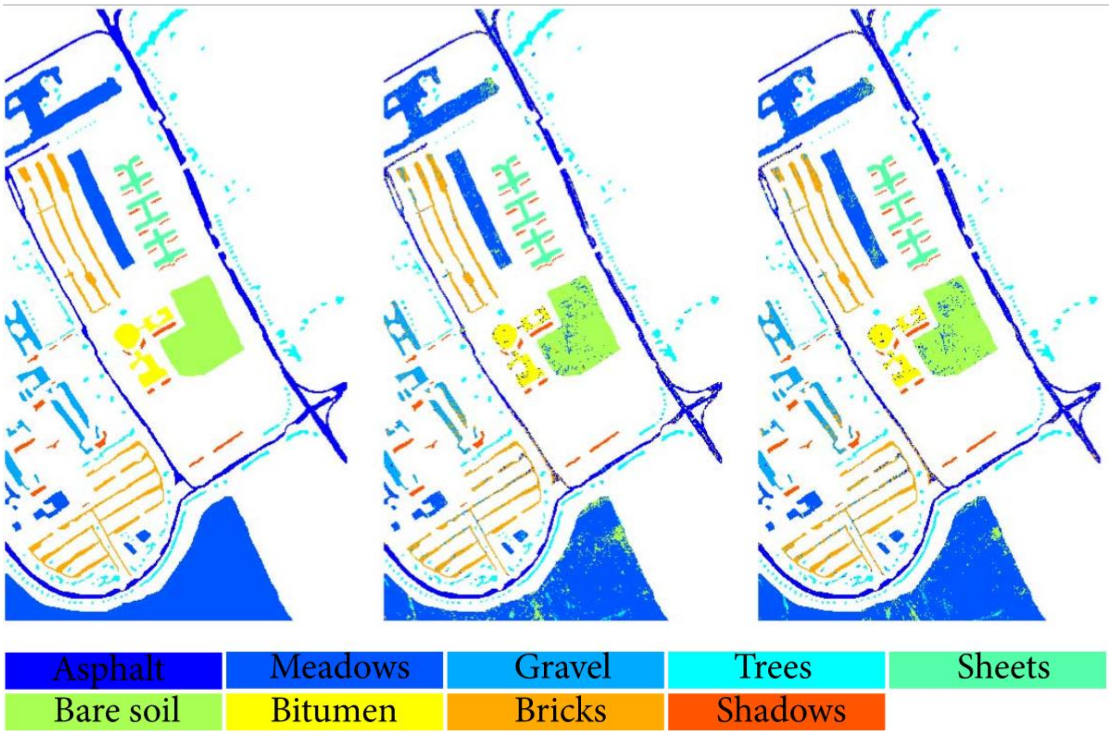


Figure.6. Pavia dataset - Composition maps



The rating accuracy of any data will be more than 90% due to rising training time. However, the CNN classification proposed has the same benefits as deep learning algorithms (see Table 5).

Table.5. Indian Pines – NN Performance

Method	Accuracy	Training Time (s)	Testing Time (s)
Two-layer NN	87.84%	2834	1.69
DNN	88.01%	6562	3.32
LeNet-5	88.99%	5245	2.45
Our CNN	91.12%	4385	1.99

With a growing number of iterations, our network convergence is demonstrated by only 200 training samples per class, the size of the loss function is decreased. Furthermore, after the 5-minute training phase, the cost benefit is lowered, but the appropriate test precision is reasonably stabilised, which shows that this network is overfitting.

Our proposal for CNN is obviously more accurate than SVM. It is clear. Although the standard deep-learning approach will outstrip the SVM classifier, a lot of training samples for building self-encoders are needed.

5. Conclusion

In this paper, we develop a CNN classification model that is developed for classification of HIS images. The result of simulating shows that the proposed model achieves improved classification accuracy than the exiting SVM. We are exploring the use and performance of CNNs for HSI classification. A network architecture known as the Siamese Network may be used in the future and is proven resilient when the number of training samples per group is limited. In addition, recent profound learning research has shown that uncontrolled education may be used for training CNNs, which significantly reduces the need for labelled samples. In the future, deep learning, in particular deep CNNs, could have considerable potential for HSI classification. We still may not take the spatial correlation into account in the present research and focus solely on the spectral signatures.

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