Hyperspectral Image Classification with CNN

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Introduction to Deep Learning

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1 Introduction

Most computer vision applications such as image classification or object recognition have made use of image datasets with a single color or primary colors like the RGB spectrum. Whereas, hyperspectral imaging (HSI) is a sensing technique that contains images of a large number of closely spaced wavelengths which is widely used in remote sensing [1]. In other words, each pixel in an image scene is divided into many different spectral bands instead of three as it is in RGB images. Therefore the data establishes a so-called hyperspectral which is shown in the figure 1. Therefore the data can be seen as a 2D image with λ spectral bands. Because of the emergency and my interests in optics, I propose my final project of "Introduction to Deep Learning" course a classification method with CNN in hyperspectral data. This project can be a pioneer for my further researches in HSI data so that the developed model can be used in different fields such as food quality assessment which is a very big research and application concern because of the lack of automation in this field. The food quality assessment mostly in some fruits and vegetables are still in the stone age in that manner. Sensing and computer vision systems might be a promising field in the food industry also with these types of researches and applications.

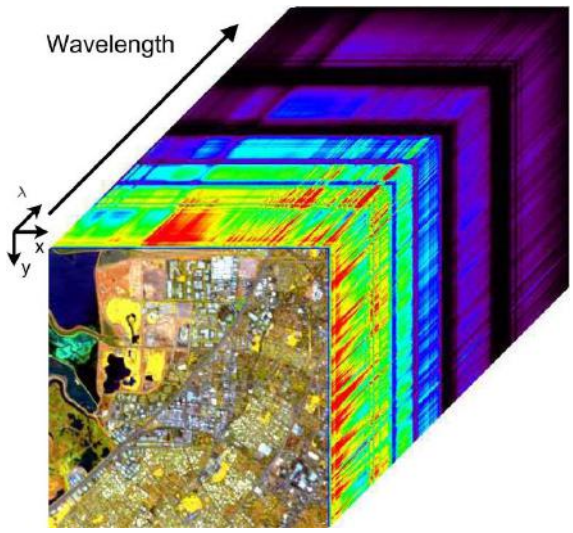

Fig. 1. Example of a hyperspectral cube data [2]

2 Related Works

HSI has arisen from remote sensing, NASA has conducted different researches and became a pioneer in this regard [3]. Recently, deep learning has been used in HSI because of its advantages in image processing for this kind of data. Besides this, HSI is an emerging method in remote sensing and has been used in various areas such as archaeology, autonomous vehicles, vegetation, and water resource control [4], food quality and safety control [5], forensic medicine [6], biomedicine [7] [8]. For my project, I will consider different types of papers that are based on different types of machine and deep learning methods. Some of the standard approaches in the HSI analysis are based on the supervised statistical learning models. In this regard the classification of HSI has been modeled with decision trees and random forests, SVMs [9]. On the other hand, it seems like deep learning methods such as CNN has become more successful for this classification which was shown in [10].

3 Dataset

HSI datasets mostly consist of a scene with a big number of spectral bands. For the project, two different datasets will be used: the Indian Pines dataset and Pavia University dataset. These are the datasets that are generally used for learning models in HSI. The scene in Indian Pines, which can be seen as a satellite scene, was collected by an AVIRIS sensor. The scene that is a test site image from North-western India consists of 145*145 pixels with 224 spectral bands. Besides that, the dataset has a labeled ground reference data which is shown in the figure 2.

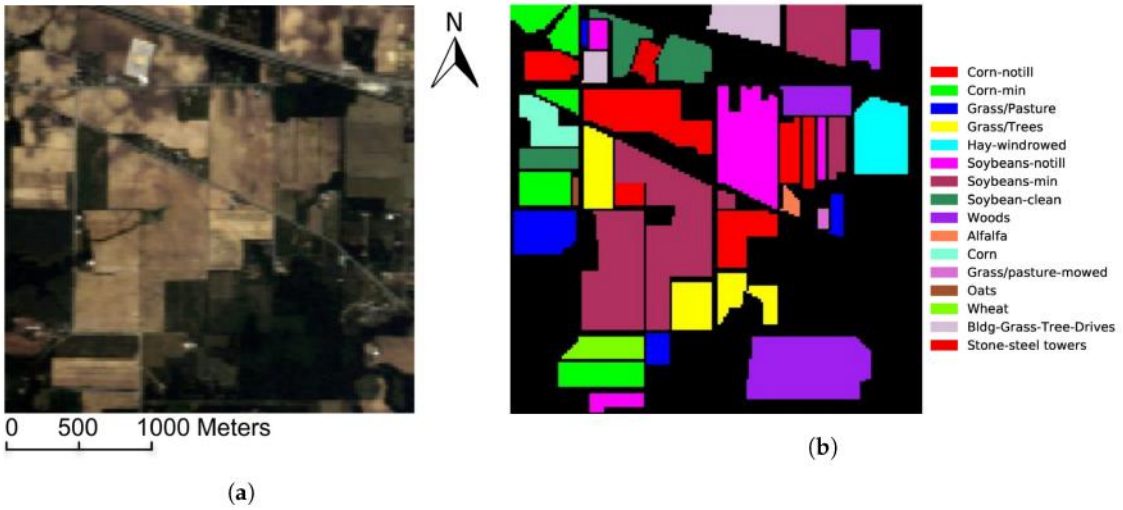

Fig. 2. a) Indian Pines scene b) ground reference data with labels [11]

The Pavia University dataset consists of 610*340 pixels with 103 spectral bands. It has nine classes of interests which show different types of materials which is shown in the figure 3. The samples of both datasets are the pixels that have a vector size of the spectral band. They will be divided into training and test data sets according to the studies and applications so far. As shown in the previous papers both datasets comprise noise in some spectrums. Therefore a proper preprocessing is very important.

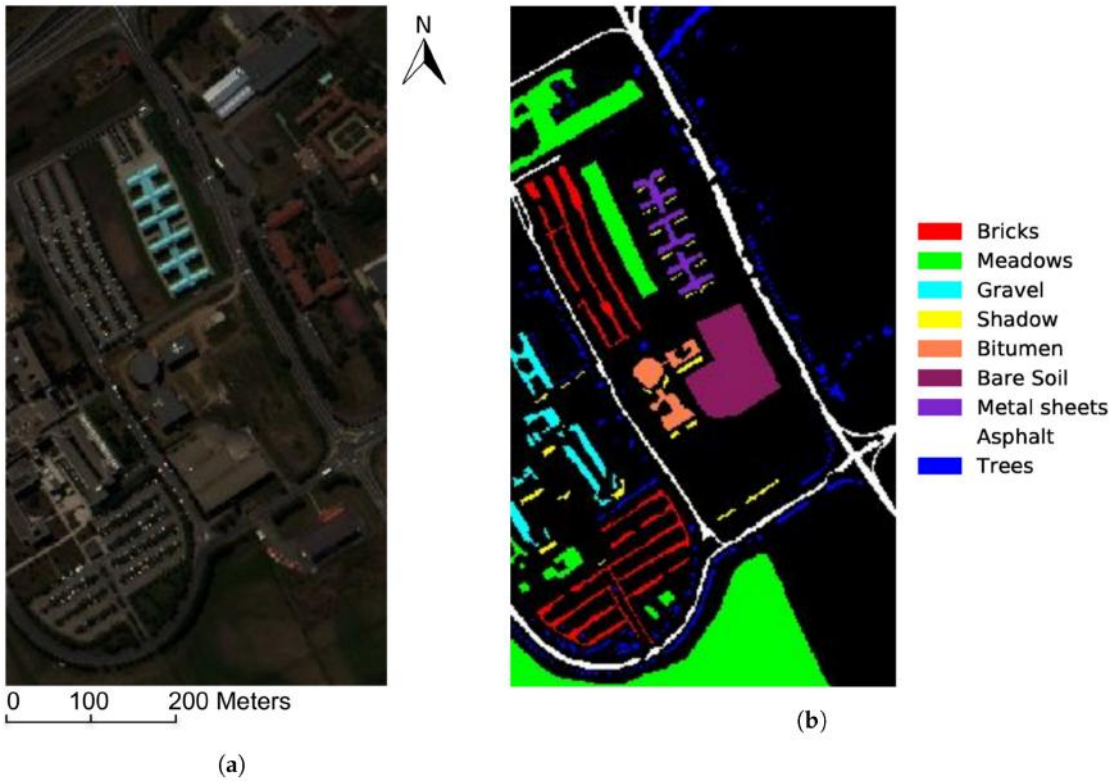

Fig. 3. a) Pavia University scene b) ground reference data with labels [11]

The datasets can be obtained from the website (see http://dase.grss-ieee.org/)of IEEE Geoscience and Remote Sensing Society (GRSS). Through this website, the researchers can upload their classification maps and accuracy and compare themselves with others.

4 Expected Model Structure

As mentioned in the section 2 the CNNs seem to be the state-of-the-art solution for HSI classification. Therefore CNNs will be mostly considered in the project. Until now it has been some applications CNNs that have different dimensions. The dimension of the CNN has not already been decided. It is planned to be decided empirically during the project. But it can be foreseen that the most probable solution will be a 3D-CNN which will be presented in the final report with more details.

Besides this, the sample size for the datasets might be prone to overfitting because of the low spatial resolution of the scene. This is the case for almost all the hyperspectral image datasets where the band size so the feature is large. In contrast the resolution so the number of pixels is low. This overfitting problem might be also solvable by implementing several strategies such as regularization or reducing the architecture complexity. According to the results of these strategies, the feature selection process will be considered. In this manner, a feature selection in this case a band selection might be a solution. This feature extraction might be first applied by using PCAs which is the solution for most of the previous researches. In this regard, an autoencoder might also be used for the feature extraction if needed. One other important aspect is the generalization of the training set. More detailed research will be made and presented for this concept. But at least a basic randomization will be made for the selection of the training set.

5 Evaluation Method

As explained above, the model needs to classify the pixels according to their spectral band. Therefore for evaluation, a test set should be given into the model. Each pixel will be classified to a label according to its spectral band. The accuracy will be calculated through the number of successful classification of the samples i.e. pixels in this regard. The obtained accuracy will be based on several models that will be implemented in 2D or 3D CNNs. Besides, the results will also be compared with the other models that are uploaded to the GRSS website and papers.

6 Detailed Schedule

The project will last 5 weeks until the 5th of March 2021. The task distribution according to weeks is as follows:

- Week 1: Research in current applications in these datasets
- Week 2: Data preparation and preprocessing
- Week 3: Training with CNNs with various depths and kernel sizes
- Week 4: Fine-tuning of the hyperparameters
- Week 5: Documentation and final report

7 References

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