Transfer Learning for HSI with ImageNet Pre-Trained Models

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***Abstract*—Hyperspectral image classification is a widespread application used for the analysis of images in remote sensing. Hyperspectral imagery includes many bands but has a narrow bandwidth. The Convolutional Neural Network is one of the most commonly used deep learning-based methods for computer vision. The use of CNN for HSI classification is can be seen in the latest works. One of the keys of the success of CNN is that the models can be trained in Graphics Processing Units. The truth is that GPUs can offer much faster training, so that allows the use of larger datasets. Pavia University dataset is the remote sensing data for hyperspectral image classification, which has 610x340 pixels and 103 channels. In this work, four ImageNet basic pre-trained models, VGG16, DenseNet121, ResNet50V2, and InceptionResNetV2 have used for HSI classification. The aim of Transfer Learning is to transfer the knowledge to the target domain from the source domain. Transfer Learning allows CNN to be appropriately trained using limited labeled data. After we loaded pre-trained models, we freeze models' layers and made them non-trainable layers. Then we added one flatten and dense layers to the model, which are trainable. Then, we took image cubes in different sizes and resize them to the size of 224x224x3 which is standard input shape for models. The results that we got were close. But in different image cubes sizes, 11x11 image cubes mostly gave us better accuracy in very few epochs.**

Keywords Inductive Transfer Learning - HSI Classification - Pavia University Dataset - Hyperspectral Image - Convolutional Neural Network

I. Introduction

Hyperspectral image (HSI) classification is a widespread application used for the analysis of images in remote sensing. Hyperspectral imagery includes many bands but has a narrow bandwidth [1]. The Convolutional Neural Network (CNN) is one of the most commonly used deep learning-based methods offered for computer vision. Also, the use of CNN for HSI classification is can be seen in the latest works.

One of the keys of the success of CNN is that the models can be trained in Graphics Processing Units (GPUs). The truth is that GPUs can offer much faster training, so that allows the use of larger datasets.

In this work, the Pavia University dataset is the remote sensing data for hyperspectral image classification. The data contains 610x340 spatial size (pixels) and 103 channels (bands) with 9 classes. The dataset also contains two test data, the first has 3921 available samples, and the second is 42776 samples which are labeled for the 610x340 pixels. We use only 3921 samples for training (fine-tuning) and we use 42776 samples for evaluation.

A. *HSI Classification*

HSI classification has been tried with the Pavia University dataset which includes 103 channels. Also, in this work, Principal Component Analysis (PCA) is used as a Feature Extraction technique.

Because the HSI has too many bands, PCA will be a solution for the heavy calculating problems. After applying PCA to the 103 channels raw dataset, only a few bands need to be calculated, i.e. 3, 10, 20, etc.

B. *Transfer Learning*

The aim of Transfer Learning is to transfer the knowledge to the target domain from the source domain. In recent years, many transfer learning methods have been presented [2], [3].

And the recent advances have shown that deep learning has been successfully applied to transfer learning tasks [3].

Transfer Learning allows CNN to be appropriately trained using limited labeled data. As above mentioned, the Pavia University dataset has only 3921 labeled data for training.

We used the below-mentioned models to get the best accuracy by using Python Keras Library and Google Colab. The detailed work explained at the System Model Section.

C. *Pre-Trained Models*

The four basic pre-trained models have used for HSI classification in this work. These are VGG16, DenseNet121, ResNet50V2 and InceptionResNetV2, and they have trained with the ImageNet dataset.

The accuracy and kappa results and their comparisons are shown in the Numerical Results Section.

II. System Model

The used Transfer Learning process [4] has shown at Fig.1. In the Inductive Transfer Learning, the target task is different from the source task, even though the source and target domains are the same or not [5].

Here, firstly pre-trained models [6], [7] were loaded and models' layers were frozen to make them non-trainable layers. Then one flatten and 3 fully connected layers were added to

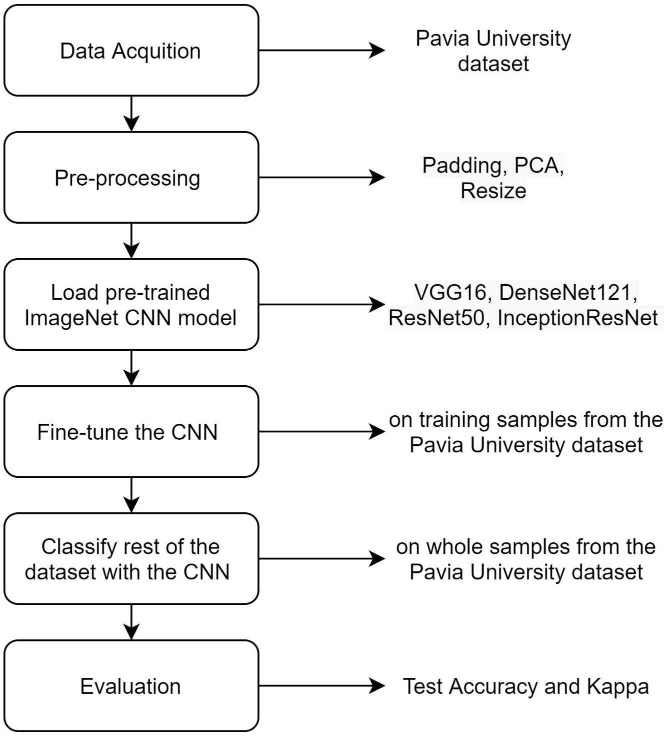

Fig. 1. The flowchart of the system

the model, which are trainable. The models we would use became ready.

The Pavia University dataset [8] information has shown in Table I. There are 9 different labeled classes with different numbers of samples.

TABLE I
CLASSES AND NUMBER OF SAMPLES FOR THE PAVIA UNIVERSITY DATASET

Class	Number of Samples
Asphalt	6631
Bare Soil	5029
Bitumen	1330
Gravel	2099
Meadows	18649
Painted Metal Sheets	1345
Self-blocking bricks	3682
Shadows	947

Pavia University images 3-band false-color composite, for all 9 classes ground truth data and all available training data [9] have shown in Fig.2.

After the dataset was loaded, image cubes are taken in different sizes and resized them to the size of 224x224x3. Because the usage of the optional input shape tuple was not chosen, and the models' standard input size was 224x224x3.

The used models' information as layers, shape, and number of parameters are shown in Fig.3

We get image cubes from the dataset, which were 3x3, 5x5, 7x7, 9x9, and 11x11. And then, we compared the results to find the best test accuracy and kappa.

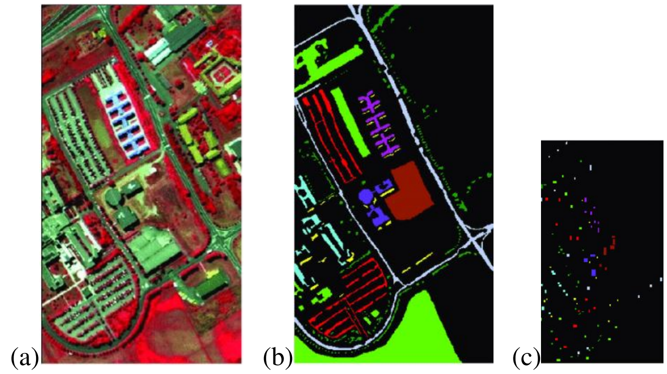

Fig. 2. Pavia University images, (a) 3-band false color composite; (b) for all 9 classes ground truth data; (c) all available training data.

III. Numerical Results

In this work, we tried from 5 to 350 epoch if training accuracy is appropriate for improvement. For all models, the best results are chosen. The results are shown in Table II.

TABLE II
THE NUMERICAL RESULTS THAT WE GET FROM THE MODELS

Model	Image Cubes	Epoch	Accuracy	Kappa
VGG16	11x11	10	75.90	68.91
DenseNet121	11x11	50	77.47	70.54
ResNet50V2	11x11	10	76.99	70.16
InceptionResNetV2	3x3	150	68.32	59.40

%77,5 accuracy will not be assumed as a success. But there is one thing which makes these results to be considerable; only the pre-trained models have been used in the work. Some of them may classify almost 1000 image classes but they have trained with ImageNet dataset, not with the HSIs. The usage of these models in the HSI classification will make the results better if very few data is available.

IV. Conclusion and Discussion

As you can see in Table II, the results were close. But 11x11 image cubes mostly gave us better accuracy and kappa. We got almost %77,5 accuracy and %70,54 kappa on DenseNet121 with 11x11 image cubes in 50 epochs. That assumed to be the best accuracy for this work.

Solving the classification problem with the raw dataset has not tried to due to the available RAM size in Google Colab. When the RAM and GPU problems are solved, the raw data and other channel sizes will be tested. The results will be more reliable then.

Layer (type)	Output Shape	Param #
vgg16 (Model)	(None, 7, 7, 512)	14714688
flatten_3 (Flatten)	(None, 25088)	0
dense_7 (Dense)	(None, 512)	12845568
dense_8 (Dense)	(None, 512)	262656
dense_9 (Dense)	(None, 9)	4617

Total params: 27,827,529
Trainable params: 13,112,841
Non-trainable params: 14,714,688

(a)

Layer (type)	Output Shape	Param #
densenet121 (Model)	(None, 7, 7, 1024)	7037504
flatten_4 (Flatten)	(None, 50176)	0
dense_10 (Dense)	(None, 512)	25690624
dense_11 (Dense)	(None, 512)	262656
dense_12 (Dense)	(None, 9)	4617

Total params: 32,995,401
Trainable params: 25,957,897
Non-trainable params: 7,037,504

(b)

Layer (type)	Output Shape	Param #
resnet50v2 (Model)	(None, 7, 7, 2048)	23564800
flatten_5 (Flatten)	(None, 100352)	0
dense_13 (Dense)	(None, 512)	51380736
dense_14 (Dense)	(None, 512)	262656
dense_15 (Dense)	(None, 9)	4617

Total params: 75,212,809
Trainable params: 51,648,009
Non-trainable params: 23,564,800

(c)

Layer (type)	Output Shape	Param #
inception_resnet_v2 (Model)	(None, 5, 5, 1536)	54336736
flatten_2 (Flatten)	(None, 38400)	0
dense_4 (Dense)	(None, 512)	19661312
dense_5 (Dense)	(None, 512)	262656
dense_6 (Dense)	(None, 9)	4617

Total params: 74,265,321
Trainable params: 19,928,585
Non-trainable params: 54,336,736

(d)

Fig. 3. Pre-Trained Models, (a) VGG16; (b) DenseNet121; (c) ResNet50V2; (d) InceptionResNetV2.

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