Agricultural Crop Hyperspectral Image Classification using Transfer Learning

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***Abstract*—In recent years, there is increasing interest around developing efficient Deep learning methods using convolutional neural networks (CNNs) in classifying Hyperspectral images (HSI). The performance of these networks highly depends on the availability of ample amount of labelled samples for training. To solve the problem of insufficient training samples, Transfer Learning (TL) is currently being incorporated in deep networks. The main objective and purpose of this paper is to implement a model that performs classification task quickly with high performance and is also both resource and data efficient. VGGNet and ResNet networks trained on benchmark ImageNet dataset are considered as source models and learned features from these networks, are transferred to new model that is to be trained on target data. The proposed model is tested on two popular datasets (i.e., Indian pines and Salinas) along with a novel dataset containing field crop data of Kota region in Rajasthan. Experimental results demonstrate that TL based model can achieve remarkable accuracy even with small-training samples on target data.**

***Index Terms*—Deep Learning, VGGNet, ResNet, Hyperspectral image classification, Transfer learning.**

I. Introduction

In recent times, Hyperspectral images(HSI) play a prominent role in providing valuable information for natural resource management [1]. This is because of the availability of in-depth reflectance data over large electromagnetic spectrum. The applications of HSI include crop discrimination, urban and peri-urban area characterization, river water quality assessment, mineral exploration, etc. Hence, analysing remotely sensed HSI has become a new research topic.

Traditional machine learning techniques, such as k-nearest neighbor (k-NN) [2], Support Vector Machine (SVM) [3], Decision Trees [4], Multinomial Logistic regression [5] etc., have been used for HSI classification. These methods do not consider spectral information in HSI and thus making it difficult to improve their classification accuracy. To efficiently classify HSI, deep learning techniques are being preferred.

Deep learning methods incorporating convolutional neural networks (CNNs) have achieved satisfying performance in HSI classification. In one-dimensional CNN (1D CNN) classifier [6], [7] spectral information alone is used in classification process, 2D CNN considers spatial information only and thus discriminating features from spectral information cannot be extracted, while 3D CNN incorporates both spatial and spectral information [8], [9] but the model is more computationally complex. To achieve satisfactory classification accuracy with these networks, adequate amount of training samples are required. Obtaining labelled samples for HSI is both expensive and time consuming. Thus, HSI classification with limited training samples has become a challenging task.

To address the challenge in HSI classification, unsupervised learning algorithms and Transfer Learning (TL) based approaches are observed as possible solutions. In unsupervised learning, auto encoders (AE) [10] or Generative Adversial Networks (GAN's) [11], [12] are guided with a loss function which decides the performance of the network. Although, these methods achieved satisfactory performance in HSI classification, large number of training parameters in these networks makes it difficult and time consuming to train the model in practice.

TL based methods are popular in recent times to significantly reduce the number of training samples as well as time required for training in HSI classification. However, TL works only if dimensions of target dataset is similar to the dataset on which the network is pre-trained. In [13], VGGNet [14] which is pre-trained on ImageNet [15] dataset is considered and a mapping network is designed to convert HSI containing multiple bands to optical images containing three bands(i.e., R,G, B channels). A 3D-CNN structure is used in [16] to learn parameters of HSI of different sensors and RGB images. The objective of this paper is to propose a simple, fast and efficient deep network using transferred parameters to perform agricultural crop HSI classification. The main contributions of this paper are summarised as follows:

- Simple and effective Principle Component Analysis (PCA) [17] dimensionality reduction (DR) technique is used to map the HSI image to a three-band image.
- Experimented the proposed model on a novel field crop dataset in Kota region of Rajasthan [18] along with existing popular datasets Indian pines [19] and Salinas [20]. Validate the classification efficiency of the network.

The rest of this paper is organized as follows: Section-II summarizes the steps involved in HSI classification using transfer learning; Section-III demonstrates an insight into its effectiveness by presenting some experimental results; Section-IV concludes the paper.

II. Proposed Method

Dimentionality reduction (DR), object detection and classification are usually the steps followed in HSI processing. The architecture of the model proposed is shown in Fig 1. This framework contains four core blocks: PCA, patch extraction, CNN and TL.

A. Dimensionality Reduction

HSI, unlike optical images, captures data of object to be measured in multiple bands with different spectral resolutions and enables analysis of data in both spatial and spectral domains. This enhances and expands the applications of these remotely sensed HSI. DR techniques play a prominent role in analysing HSI images [21], usually for reducing computational complexity. DR is additionally used in proposed model to match the dimensions of trained/source dataset with that of test/target dataset. Here, PCA, a simple yet effective DR technique, has been used to reduce the number of bands for the input HSI image. It extracts spatial features by averaging along spectral channel indirectly eliminating redundant bands and thereby reducing the dimension of input.

Benchmark ImageNet dataset is considered as source dataset in this paper. It is a huge dataset containing a large number of images belonging to hundreds of different classes. However, these images contain only three channels i.e., R, G and B. In order to use HSI, usually containing multiple bands, in place of ImageNet dataset, PCA is used to translate HSI to a three channel dataset. First three principle components obtained from PCA are chosen and the proposed model is trained on this three band dataset. From early researches and also from general understanding, it is clear that, using PCA is efficient when compared to selecting randomly three bands from HSI or extracting direct R,G,B channel data from HSI. A complex mapping algorithm may also be used for this purpose but this leads to increase in computational complexity and execution time.

B. Patch extraction

Most of HSI classifiers based on CNN use patches as input classifier. HSI after PCA is considered as patches before giving as input to fine tune the network. Learning process based on patches ensures efficient feature extraction even with small sized labelled samples.

C. Transfer Learning

TL is a process in which base network is trained with source dataset like ImageNet and these learned weights are transferred to new model which can be trained on target dataset (HSI). In this paper, networks pre-trained on ImageNet dataset such as VGG16, ResNet50 [22] are considered for TL. Trained parameters of these networks, except for fully connected layers are considered and are transferred to new model defined. The new model defined uses first layers in the architecture similar to that of pre-trained networks. A new set of fully connected layers have been concatenated and the weights were updated during fine tuning the network with the considered HSI dataset.

III. Experimental Results

In this section, transfer learning based HSI classification on agricultural lands is presented. In order to validate the accuracy of the model, initial testing is done on standard datasets, Indian pines - data on mixed vegetation agriculture and Salinas - data of crop agriculture in Salinas valley, for which groundtruth data is available. A novel dataset with data belonging to crops in Kota region of Rajasthan is also experimented on proposed model.

A. Datasets

a) Indian pines dataset: Indian pines dataset was captured by AVIRIS (Airborne Visible/Infra-red Imaging Spectrometer) sensor over the Indian pines test site in North-western Indiana. The dataset consists of 145 x 145 pixels and has 224 spectral reflectance bands in the wavelength range of 400 to 2500 nm. Of the 224 spectral bands 200 bands are considered after removing the absorption bands. The scene consists of two thirds agriculture and remaining forest data categorized into 16 classes.

b) Salinas dataset: Salinas dataset was also captured by AVIRIS Sensor on Salinas Valley, California. The area covered was 512 × 217 pixels in 224 spectral bands with 54,129 samples, divided into 16 features. The 20 water absorption bands were discarded resulting in 200 spectral bands

c) Field crop data of Kota region, Rajasthan: Dataset is collected by AVIRIS-NG (AVIRIS-New Generation) sensor over Indian sub-continent region. Its spatial and spectral resolutions are 10766x710 pixels and 425 bands respectively. Dataset is cropped to 390 X 330 pixels resolution and after removing absorption bands a total of 375 bands are considered for experimentation. As the labelled data for this dataset is not available, a report from Indian Space Research Organization (ISRO) on analysis of different dataset from AVIRIS-NG data is considered as reference. Based on this, Region of Interest(RoI) is obtained over the cropped Kota region and is given as ground truth. The selected Kota region has 5 classes namely; Bare Soil, Wheat, Peas, Methi (Fenugreek), and Coriander.

B. Results and Analysis

For all three datasets, 25 percent of total samples are considered for fine tuning the model. 25% of training samples results in 7,535 out of 30,140 samples for Kota, 2,562 out of 10,249 samples for Indian Pines and 13,532 out of 54,129 samples for Salinas datasets. In order to test the performance of proposed model in case of minimum training samples, experimentation is done with 400 training samples also. The learning rate of 0.001, 0.0005 and 0.001 is considered for

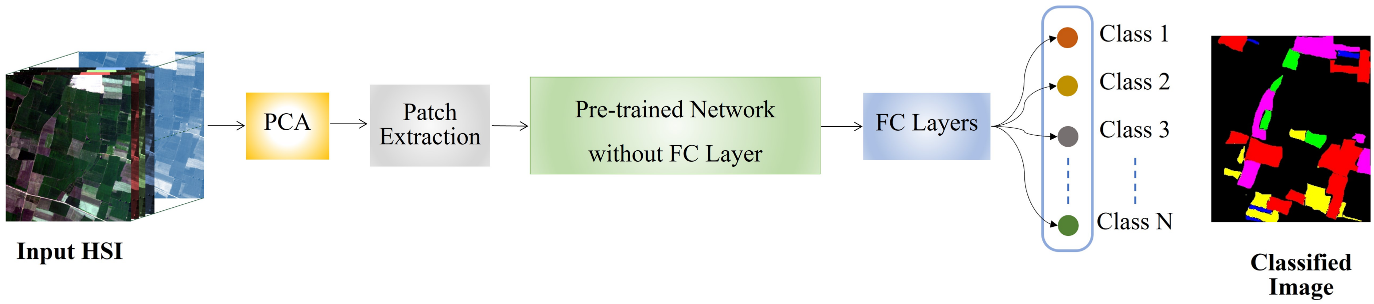

Fig. 1. Architecture of the considered model.

Indian pines, Salinas and Kota datasets respectively. For ease of comparison, training epochs and batch size parameters were maintained the same. Results obtained are demonstrated in Fig. 2. Testing accuracy obtained for each case is shown in Table I. From the results obtained, it can be observed that even with minimum training samples, the network is able to classify efficiently. The comparison of classified images from VGG and ResNet for Kota dataset has been shown in Fig. 3.

TABLE I
CLASSIFICATION RESULTS

Dataset	VGGNet		ResNet	
	400 Samples	25% Samples	400 Samples	25% Samples
Kota	90 %	99 %	93 %	98 %
Indian Pines	90.9 %	99 %	93 %	99 %
Salinas	93 %	98.9 %	96 %	99 %

IV. CONCLUSION

In this paper, a novel dataset for field crop discrimination is considered and successfully classified with a deep network modelled with transferred parameters from a network pre-trained on another dataset. The results show that with limited samples the transfer learning performed effectively. Though the network was not trained on a HSI, with limited training samples of 400 samples and 25% of the total samples, the TL based approaches performed well. The model proposed above is simple, fast, and shows promising results even with minimum training samples.

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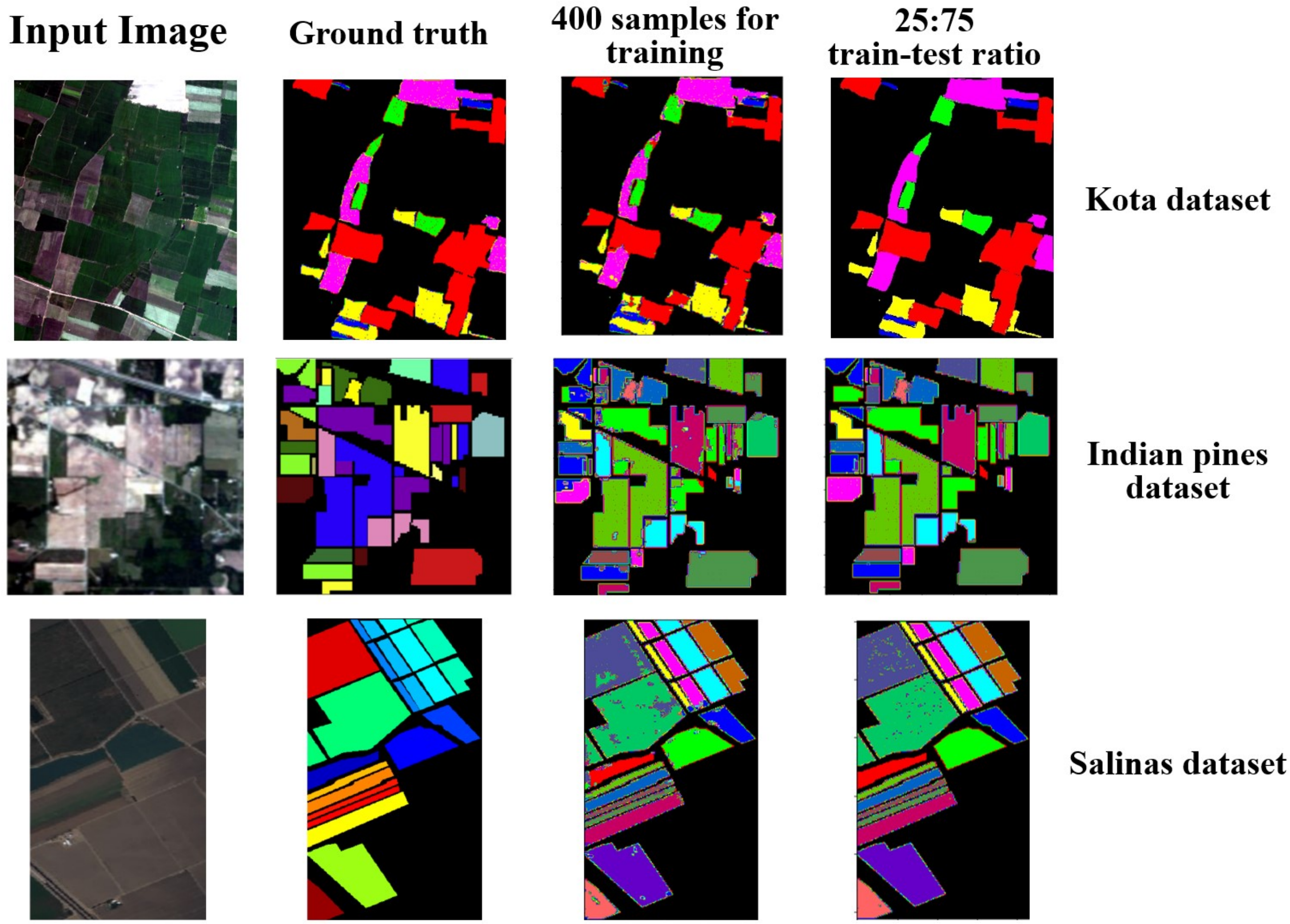

Fig. 2. Classification Maps

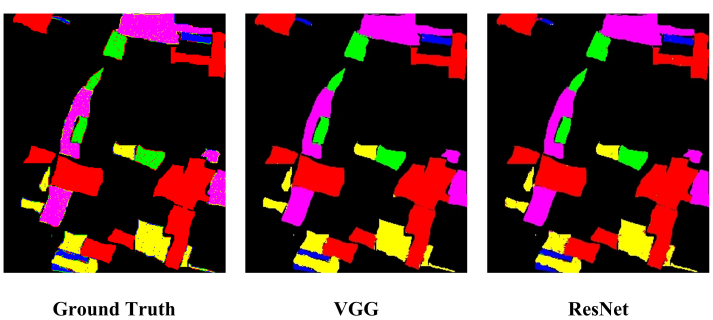

Fig. 3. Comparison of VGG and ResNet on Kota Dataset

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