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Hyper Spectral Image Classification Using Deep Learning Method

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Abstract: *Hyper-spectral photo class is a famous subject matter withinside the subject of faraway sensing. Hyperspectral pix seize mild statistics from throughout the electromagnetic spectrum. This offers a substantially massive quantity of facts to carry out type tasks. With the arrival of Deep Learning, many neural networks were proposed for Hyperspectral Image Classification. Recently, many Convolutional Neural Networks primarily based totally fashions were proposed. However, a lot of those frameworks use the most effective 3D-CNN or most effective 2D CNN or use trade 3D-2D CNN. They do now no longer completely seize the spectral, spatial, and spectral-spatial features. To clear up this problem a Novel 3DCNN with spectral-spatial function extraction, spatial function extraction, and a spectral function extraction approach is proposed. Specifically, we use Principal Component Analysis to lessen the scale alongside the spectral dimension, later for every pixel, the encircling community pixels are formed into a data cube and fed into the 3D convolutions to hierarchically extract high-level spectral-spatial features.*

Keywords: *Hyperspectral Image Classification*

I. INTRODUCTION

Hyperspectral photos in contrast to everyday photos may be visualized as a 3-Dimensional hyper dice that includes a 2-Dimensional pixel photo called a Spatial picture and a 1-Dimensional array for every pixel referred to as the spectral variety that collects records from throughout the electromagnetic spectrum. The 1-Dimensional array is similarly divided into slim channels or bands that have a width of 4 - 10nm over the variety of 400nm – 2500nm. Unlike everyday pictures, Hyperspectral pictures are wealthy in spectral facts, and these spectral facts can reflect the bodily shape and chemical composition of the items of interest, and as a result, offer excessive discrimination ability. And with the improvement of faraway sensing technology, studies looking at using hyperspectral pics have ended up famous over the years. Although, it is not feasible for someone to have enough money for this technology, authorities' businesses can have enough money. It has been determined to have an extensive variety of programs in the environment, medicine, military, and mining fields. Mote sensing is the manner of detecting and tracking the bodily traits of an area, with the aid of using measuring the radiation meditated from a distance, normally from an aerial automobile like a drone or from a satellite. Hyperspectral faraway sensing, additionally called imaging spectroscopy, is an incredibly new generation this is presently being investigated with the aid of using researchers and scientists about the detection and identification of minerals, terrestrial vegetation, and man-made materials based on their spatial and spectral characteristics.

II. LITERATURE SURVEY

Paper 1: Zilong Zhong, Jonathan Li, Lingfei Ma, Han Jiang, And He Zhao worked on DEEP RESIDUAL NETWORKS FOR HYPERSPECTRAL IMAGE CLASSIFICATION. Deep neural networks can research deep characteristic illustrations for hyperspectral image (HSI) interpretation and acquire excessive category accuracy in one-of-a-kind datasets. However, counterintuitively, the classification performance of deep learning models degrades as their depth increases. To study the influence of the deep learning model on HSI classification accuracy, this Paper carried out ResNets and CNNs with special intensity and width in the usage of tough datasets. Moreover, they tested the effectiveness of batch normalization as a regularization method with different model settings. The experimental consequences screen that ResNets mitigate the declining accuracy.They followed the stepped-forward residual networks for HSI classification. In these paintings, it turned into proven that batch normalization complements the HSI interpretation overall performance of each CNNs and ResNets. The ResNets have alleviated but not fully overcome the decreasing- accuracy effect. the proposed ResNets have learned a more discriminative representation of HSIs than those of CNNs.Moreover, the deep studying fashions with wider architectures tend to supply better class accuracy beneath Neath the same regularization methods, but the increase is not obvious when the kernel number is larger than 24. It is well worth noting that the ResNets with four layers carry out the nice in each HSI dataset, owing to small numbers of training samples and land cover categories.

Paper 2: A. N. Abbasi and Mingyi He has worked on Convolutional Neural Networks with PCA and Batch Normalization for Hyperspectral Image Classification. They propose a deep learning method that uses spectral reduction as pre-processing and batch normalization in every layer of the deep network. The PCA is used to reduce the spectral dimensionality, avoid overfitting, and regularize the network, batch normalization and dropout combination are used which also increases the accuracy. Moreover, the data augmentation is used to create further variation (flipping and rotating) in labeled training data for classification improvement and also enhancement of data for the training to overcome the limited training samples to some extent. The training process is regularized and the overfitting is avoided by using a combination of batch normalization and dropout. Moreover, oversampling and augmentation in training data are used to expand the training data and to create some variation in available training data. Finally, the experimental results demonstrated the performance of their method in comparison to other methods, especially for hyperspectral classification tasks.

III. PROPOSED SYSTEM

The HSI classification model developed in this work is based on a feature extraction method that combines a squeeze and excitation network with a deep convolutional neural network. Deep learning is difficult to apply to HSI because HSI's data structure is complicated. In general, the neural network has a strong representation capability and a larger volume of training samples. The primary objective of this work was to create a deep feature extraction model for HSI classification. Deep networks are capable of extracting spatial and spectral characteristics from HSI data simultaneously, which is advantageous for increasing the performances of the presented model. The SE network was combined with CNN (SE-CNN) in this research to increase its performance in extracting features and classifying HSI.

IV. METHODOLOGY

Purpose:

Hyperspectral Images are being researched for their use in remote sensing. Many models have been proposed which do not fully capture the characteristics of hyperspectral images. The purpose of this project is to develop an effective neural network model that can take into consideration the spectral-spatial, spatial, and spectral characteristics.

Scope:

Using Hyperspectral Image Classification, the system will enable government officials to monitor the growth of the urban area by finding the distribution of manmade materials (e. g buildings, roads, etc.) and analyzing the distribution of vegetation.

Work Completed:

Going deeper with Deep CNN for object detection/classification LeCun, et al. introduced the first deep CNN called LeNet5 [15] consisting of two convolutional layers, two fully connected layers, and one Gaussian connection layer with additional several layers for pooling. With the recent advent of large-scale image databases and advanced computational technology, relatively deeper and wider networks, such as AlexNet [16], began to be constructed on

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large scale image datasets, such as ImageNet [17]. AlexNet used five convolutional layers with three subsequent fully connected layers. Simonyan and Zisserman [18] significantly increased the depth of Deep CNN, called VGG-16, with 16 convolutional layers. Szegedy et al. [12] introduced a 22-layer deep network called GoogLeNet, by using multi-scale processing, which is realized by using a concept of "inception module." He et al. [11] built a network substantially deeper than those used previously by using a novel learning approach called "residual learning", which can significantly improve training efficiency of deep networks.

B. Deep CNN for Hyperspectral Image Classification A large number of approaches have been developed to tackle HSI classification problems [4], [19]–[42]. Recently, kernel methods, such as multiple kernel learning [19]–[25], have been widely used primarily because they can enable a classifier to learn a complex decision boundary with only a few parameters. This boundary is built by projecting the data onto a highdimensional reproducing kernel Hilbert space [43]. This makes it suitable for exploiting dataset with limited training samples. However, recent advance of deep learning-based approaches has shown drastic performance improvements because of its capabilities that can exploit complex local nonlinear structures of images using many layers of convolutional filters. To date, several deep learning-based approaches [1]–[6] have been developed for HSI classification. But few have achieved breakthrough performance due mainly to sub-optimal learning caused by the lack of enough training samples and the use of relatively small scale networks.

Deep learning approaches normally require large scale datasets whose size should be proportional to the number of parameters used by the network to avoid overfitting in learning the network.

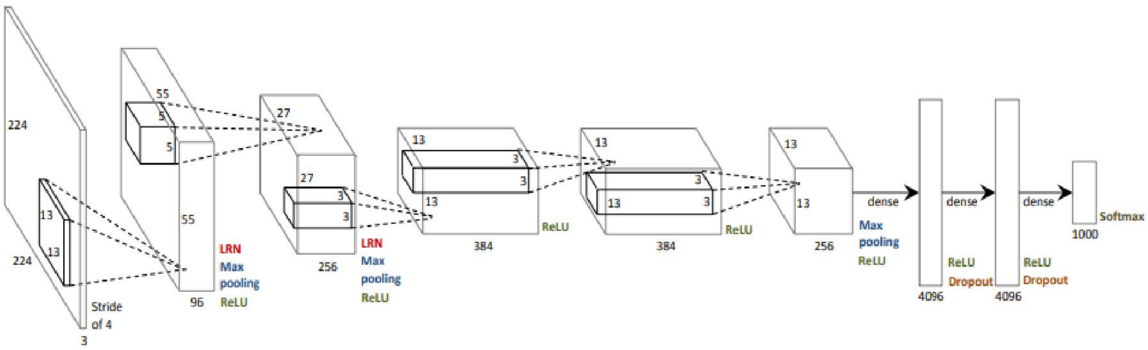

Fig. 2. AlexNet [16]. The network consists of five convolutional layers and three fully connected layers. In the illustration, cubes and boxes indicate data blobs. Several non-linear functions are also used in the network. Non-linear functions are listed beside the output blobs of each layer in order.

Chen et al. [1] used stacked autoencoders (SAE) to learn deep features of hyperspectral signatures in an unsupervised fashion followed by logistic regression used to classify extracted deep features into their appropriate material categories. Both a representative spectral pixel vector and the corresponding spatial vector obtained from applying principal component analysis (PCA) to hyperspectral data over the spectral dimension are acquired separately from a local region and then jointly used as an input to the SAE. In [7], Chen et al. replaced SAE by a deep belief network (DBN), which is similar to the deep convolutional neural network for HSI classification. Li et al. [8] also used a two-layer DBN but did not use initial dimensionality reduction, which would inevitably cause the loss of critical information of hyperspectral images. Hu et al. [2] fed individual spectral pixel vectors independently through simple CNN, in which local convolutional filters are applied to the spectral vectors extracting local spectral features. Convolutional feature maps generated after max pooling are then used as the input to the fully connected classification stage for material classification. Chen et al. [4] also used deep convolutional neural network adopting five convolutional layers and one fully connected layer for hyperspectral classification. Unlike these deep learning-based approaches, we first attempt to build much deeper and wider network using relatively small amounts of training samples. Once the network is effectively optimized, it is expected to provide enhanced performance over relatively shallow and narrow networks.

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V. CONCLUSION

TheHSI is a growing trouble relying upon range inside the location of far-flung sensing. It has wide applications ranging from agriculture, urban area analysis, mining, and even in forest area analysis. Due to the complex nature of Hyperspectral images and spectral-spatial correlation, high dimensionality, and low sample size, it is a challenging classification task. In this work, a framework for Hyperspectral Image Classification using a 3D Convolutional Neural Network is proposed which extracts the spectral-spatial, spatial, and spectral characteristics. It is evaluated with 3 datasets. The proposed approach made use of the spectral and the spatial sub-networks to extract extra specialized features and has obtained good performance.

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