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CNN Model for Land Use Land Cover Classification

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ABSTRACT: Deep learning Convolutional Neural Network (CNN) model is now becomes popular for many applications. It is used for classification, identification of object. The main advantage Deep learning CNN is that it can be used for unstructured video, audio, image data. Remote sensing data is highly unstructured data. Hyperspectral standard Indian Pines data has been used for the study of land use land cover classification. It has been observed that classification accuracy is 82.9 and test loss is 51.11 percent.

KEYWORDS: Convolutional Neural network, Deep learning, Land Use Land Cover.

I. INTRODUCTION

Remote sensing data gives us more information so that we can use it any many applications. Mono chromatic, multispectral, hyperspectral are the categories of remote sensing data [1]. Mono chromatic contains only one band, multispectral contains few number of bands and hyperspectral contains hundreds of bands. Many researchers used hyperspectral data for classification of objects present on earth [2] [3] [4]. Hyperspectral data contains many narrow useful bands. Multispectral gives us less accurate result than Hyperspectral data. Reduction techniques are used by many researchers to extract information from Hyperspectral data [5].

II. RELATED WORK

As Hyperspectral data is affected by atmosphere. Atmospheric correction is required in order to remove affected bad bands. Researchers used QUACK (Quick Atmospheric Correction) method [6]. Here we have used standard Indian Pines data set consist of 16 classes [7]. Alfalfa of 46 samples, Corn-notill os 1428 samples, Corn-mintill of 830 samples, Corn of 237 samples, Grass-pasture 483 samples, Grass-trees of 730 samples, Grass-pasture-mowed of 28 samples, Hay-windrowed of 478 samples, Oats of 20 samples, Soybean-notill of 972 samples, Soybean-mintill of 2455 samples, Soybean-clean of 593 samples, Wheat of 205 samples, Woods of 1265 samples, Buildings-Grass-Trees-Drives of 386 samples, Stone-Steel-Towers of 93 samples are the classes or labels. Many researches has been implemented deep learning neural network for classification, some have used Convolutional neural network and some have used support vector machine and random forest method [8] [9].

III. METHOD USED

We have used standard Indian Pines data set consist of many number of classes. Method used in this study is deep learning CNN. Numbers of bands are reduced or information is extracted using principal component Analysis (PCA). Accuracy has been increased using PCA [10]. Dataset has been processed before applying model. We have converted data set into patches. Similarly ground truth is also divided into number of patches same as dataset has been divided [11]. Then we have model for training purpose. PCA converts data into 30 patches.

We have used sequential model consist of Conv2D as first layer with relu activation function and 3 x 3 filter. Number of filters applied is 3 times number of PCA component that is 90. Second layer of CNN uses same number of

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parameters as first layer used. Regularization has been used by dropping output of first two layers. Threshold used is 0.25. After dropping image, image has been flattened so that we can apply next layer as fully connected layer. In fully connected layer we have used 6 times number of PCA component that is 180 numbers of nodes in hidden layer with relu activation function to get more accuracy. Next to fully connected layer again using regularization techniques, few node output has been dropped out with threshold 0.5. Last layer output layer has been used with 16 nodes same as number of classes and softmax function has been used as number of classes or output is more than 2. Fig 1 shos Indian pines dataset with ground truth of 16 classes [12] [13] [14].

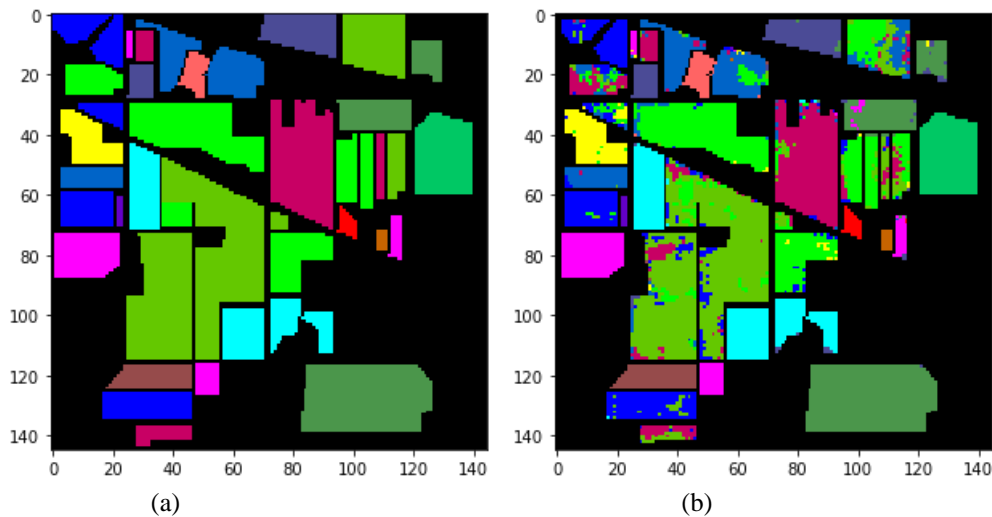


Fig. 1. (a) Indian pines dataset with ground truth (b) Output image after classification

IV. EXPERIMENTAL RESULTS

CNN method has been implemented using python in tensorflow environment [15]. It has been observed that classification accuracy is 82.9 and test loss is 51.11 percent. Table 1 shows precision, recall, f1- score for all 16 classes. It has been observed that precision and recall of wheat is maximum 100 % and Grass-trees and Hay-windrowed classes are 99 %.

Table 1. Precision, Recall, F1-score and support of all classes

	Precision	recall	f1-score	support
Alfalfa	0.91	0.91	0.91	11
Corn-notill	0.73	0.75	0.74	357
Corn-mintill	0.75	0.82	0.78	208
Corn	0.83	0.9	0.86	59
Grass-pasture	0.98	0.96	0.97	121
Grass-trees	0.99	0.96	0.98	183
Grass-pasture-mowed	1	1	1	7
Hay-windrowed	0.99	0.99	0.99	120
Oats	0.83	1	0.91	5
Soybean-notill	0.64	0.82	0.72	243
Soybean-mintill	0.86	0.68	0.76	614

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Soybean-clean	0.68	0.74	0.71	148
Wheat	1	1	1	51
Woods	0.98	0.97	0.98	316
Buildings-Grass-Trees-Drives	0.79	0.95	0.86	97
Stone-Steel-Towers	0.96	1	0.98	23
avg / total	0.84	0.83	0.83	2563

Figure2 showed that comparative graph of all classes and average of precision, recall and f1-score. Following are the equation of precision, recall of class R. C represent other than R class.

Precision of class R= (True Positive of R)/ (True Positive of R +Addition of all wrongly classified as R but was C)

Recall R= (True Positive of R)/ (True Positive of R +Addition of all wrongly classified as C but was R)

F1 Score= (2 * precision * recall) / (precision + recall)

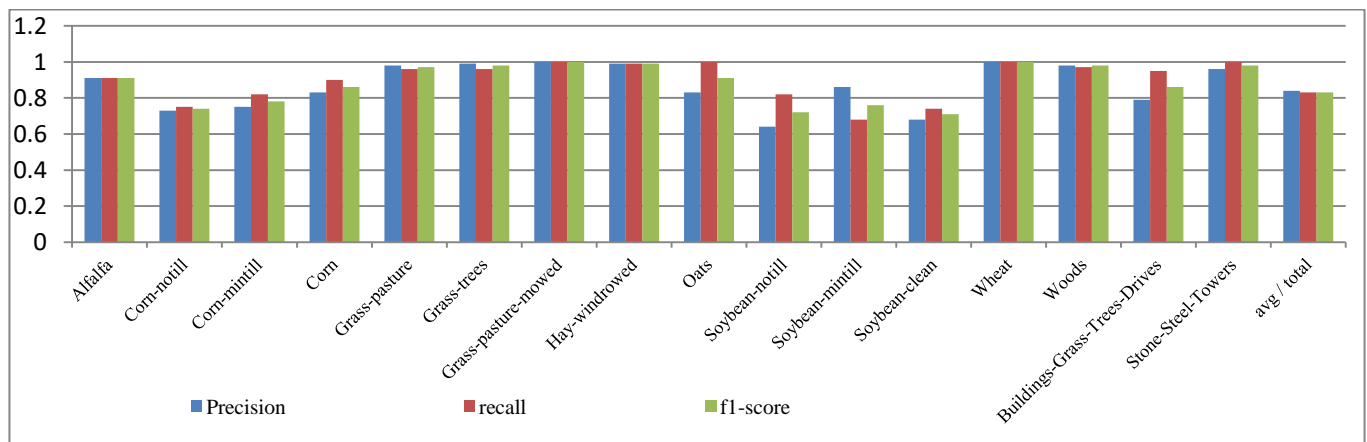


Fig. 2. Comparative graph of all classes and average of precision, recall and f1-score

V. CONCLUSION

This study shows that for classification, identification of object, deep learning Convolutional neural network method gives significance result. The main advantage Deep learning CNN is that it can be used for unstructured video, audio, image data. Remote sensing data is highly unstructured data. Hyperspectral standard Indian Pines data has been used for the study of land use land cover classification. It has been observed that classification accuracy is 82.9 and test loss is 51.11 percent. Precision and recall of wheat is maximum 100 % and Grass-trees and Hay-windrowed classes are 99 %.

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