ISSN No:-2456-2165

Regularized CNN Model for Crop Classification

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Abstract:- In this paper we have compared regularized Convolutional Neural Network (CNN) with without regularized CNN. This 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. EO-1 hyperspectral data has been used for the study of crop classification. It has been observed that classification accuracy is 75 % and test loss is 43.3 %.

Keywords:- *Convolutional Neural Network, Deep Learning, Land Use Land Cover.*

I. INTRODUCTION

Hyperspectral data has more number of significance as it has much number of congruous bands. Remote sensing data gives us more information so that we can use it any many applications. Monochromatic contains single band, multispectral contains 10 to 20 bands and non contiguous, hyperspectral contains hundreds of bands [1]. Many researchers used hyperspectral data for classification of objects present on earth [2].has used for land use land cover classification [3] [4]. Hyperspectral data contains many narrow useful bands. These bands are affected by atmospher so atmospheric correction are required to Hyperspectral images [5].

II. RELATED WORK

In this study, we have used small segment of fulambri village of Aurangabad district, MH, India. 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]. 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 small segment of study area dataset acquired on 24th Dec 2015, from EO-1 hyperion sensor. We have considered two numbers of classes for study purpose. 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 divided whole data into training and testing dataset so that model can be evaluated. Batch size of 10 and 100 epochs have been considered before using model. 101 training sample and 89 testing samples have been used. Mulberry and cotton are two classes.

Image of 1 x 1 and number of channel considered is 155. Our data is multi band data so we have used multichannel CNN.

We have used sequential model consist of Conv2D as first layer with ReLu activation function and 1 x 1 filter. Number of filters applied is 32. Max pooling layer has been used as second layer. Third layer of CNN uses same number of 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 128 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 2 nodes same as number of classes and softmax function has been used as number of classes or output is equal to or more than 2.

IV. EXPERIMENTAL RESULTS

CNN method has been implemented using python in tensorflow environment [15]. It has been observed that classification accuracy is 75 % and test loss is 43.3 %.

Layer (type)	Output Shape	Param #
conv2d_9 (Conv2D)	(None, 1, 1, 32)	4992
max_pooling2d_9	(MaxPooling2 (None, 1, 1, 32)	0
dropout_13 (Dropout)	(None, 1, 1, 32)	0
conv2d_10 (Conv2D)	(None, 1, 1, 64)	2112
max_pooling2d_10	(MaxPooling (None, 1, 1, 64)	0
dropout_14 (Dropout)	(None, 1, 1, 64)	0
flatten_5 (Flatten)	(None, 64)	0
dense_9 (Dense)	(None, 128)	8320
dropout_15 (Dropout)	(None, 128)	0
dense_10 (Dense)	(None, 2)	258
Total Parameter: 15,682		

Table 1:- Shows Layers of CNN, Shape and Parameters

Table 1 shows Layers of CNN, shape and parameters generated. It has been observed that total parameters, trainable parameters are 15682. There are no non trainable parameters generated.

Figure 2 showed that comparative graph of regularized and non regularized CNN. It has been observed that accuracy given by regularized CNN is more compared to non regularised CNN. For non regularised CNN, accuracy is 72.3 and loss is 59.2 percent. Dropout layer has been used for regularization. It removes nodes with less than our threshold. In this case we have used threshold of 0.25 for CNN layer and 0.5 for fully connected layer.

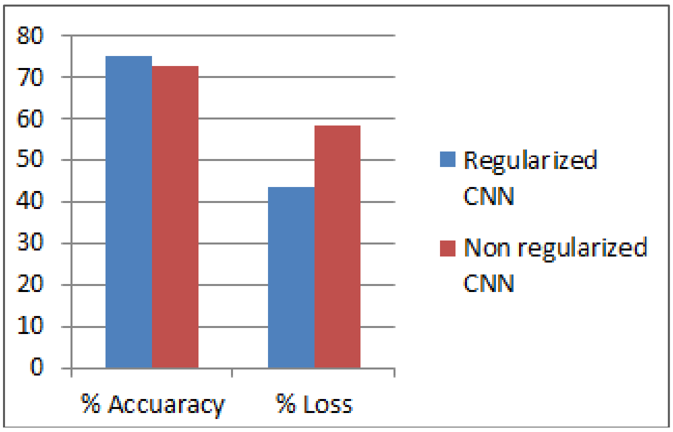

Fig 1:- Comparative Graph of Regularized and Non Regularized CNN

V. CONCLUSION

This study shows that deep learning Convolutional neural network method gives significance result for classification or identification of crops or any material available on earth. 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 EO-1 hyperion sensor data has been used for this study and for crop classification. It has been observed that classification accuracy is 75 % and test loss is 43.3 % using regularized CNN compared with non regularized CNN.

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