J. Integr. Sci. Technol. 2021, 9(2), 70-74 Article

Journal of Integrated
SCIENCE & TECHNOLOGY

# Deep learning Convolutional Neural Network (CNN) for Cotton, Mulberry and Sugarcane Classification using Hyperspectral Remote Sensing Data

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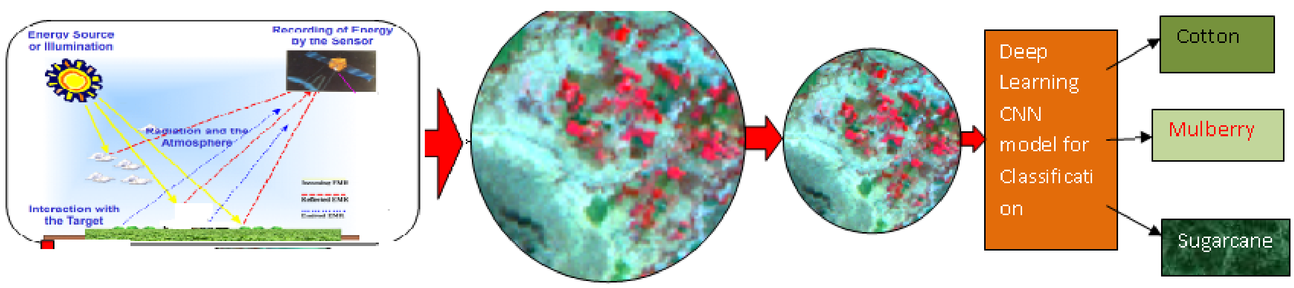
Received on: 20-Sept-2021, Accepted and Published on: 04-Nov-2021

## ABSTRACT




Crop Classification using remote sensing data is important for calculating crop sown area and predicting the crop production. Accuracy in data will help to regulate marketing of the produce. Present study aims to examine the use of deep learning convolutional neural network (CNN) to overcome the difficulties arising in crop identification with satellite images. In the present work, EO-1 Hyperion hyperspectral images have been used for identifying cotton, sugarcane and mulberry crop. Structured data has been extracted from hyperspectral data for performing experiments. Deep learning convolutional neural network (CNN) is compared with deep feed forward neural network (FFNN). It is observed that, deep learning CNN provided 99.33 % accuracy, while deep FFNN gave 96.6 % accuracy. Empirical results demonstrate that CNN works well in practice and compares appreciatively to deep FFNN methods. Moreover, deep learning CNN has demonstrated efficiently for smaller size dataset.

*Keywords: Remote sensing data, Convolutional neural network, Principal component analysis, Hyperspectral data, Deep learning, Deep Feed Forward Neural Network.*

## INTRODUCTION

Deep learning is one of the most versatile modern techniques for feature extraction and classification. This technique has shown promising results and huge potential in the field of agriculture. Use of Hyperspectral and Multispectral remote sensing images for analysing the spectral and spatial classification has been explored widely in recent time.[1,2] In agriculture domain, different crops can be identified and discriminated using remote sensing images.[3] Hyperspectral data needs to be atmospherically corrected to remove the noise. Atmospheric corrections performed using QUACK (Quick Atmospheric Correction) algorithm, is used.[4] In hyperspectral images, hundreds of bands for one scene provide more accurate information. EO-1 Hyperion sensor provides data of 242 bands with a spectral and spatial resolution of 10 nm and 30 m respectively. Only 155 out of 242 bands were selected after atmospheric correction.

PCA plays a significant role to reduce the dimensions or number of bands of hyperspectral images.[5] Kernel PCA is used by numerous researchers to extract the useful bands from a hundreds of hyperspectral.[6–8]

Land cover classification of Remote sensing data has also been studied using convolutional neural.[9,10] For extraction and classification of remote sensing images, deep learning can be employed.[11] The crop can be identified by the reflectance given by the green vegetation area. Each crop has different red edge point in

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Cite as: *J. Integr. Sci. Technol., 2021, 9(2), 70-74.*

 ISSN: 2321-4635 http://pubs.iscience.in/jist

NIR region.[12] Crop type is identified according to its red edge point and the reflectance given by the green vegetation area. Some papers report that the use of CNN improves the accuracy.[13] CNN is also used for scene and region based classification.[14] The research studies have proposed remote sensing image fusion with deep learning CNN.[15] CNN based flexible momentum with PCA and SVM has been used for hyperspectral data classification.[16] Successful proposal of parameter transfer learning and correlation based CNN model have been suggested in literature.[17] CNN has been used by many researchers for hyperspectral image classification. For spectral and spatial classification of hyperspectral imagery, 3D CNN has been implemented.[18] The deep feature extraction and classification of hyperspectral data using CNN have been proposed by Yushi et al.[19] Deep learning features have been extracted by multiscale convolutional auto encoder.[20] A researcher suggested hyperspectral image classification using deep pixel pair features.[10] For crop discrimination, temporal data indices have been used.[21] Very high resolution (VHR) remote sensing (RS) images can be classified using CNN.[22]

## METHODOLOGY

Framework of Deep Learning Classification

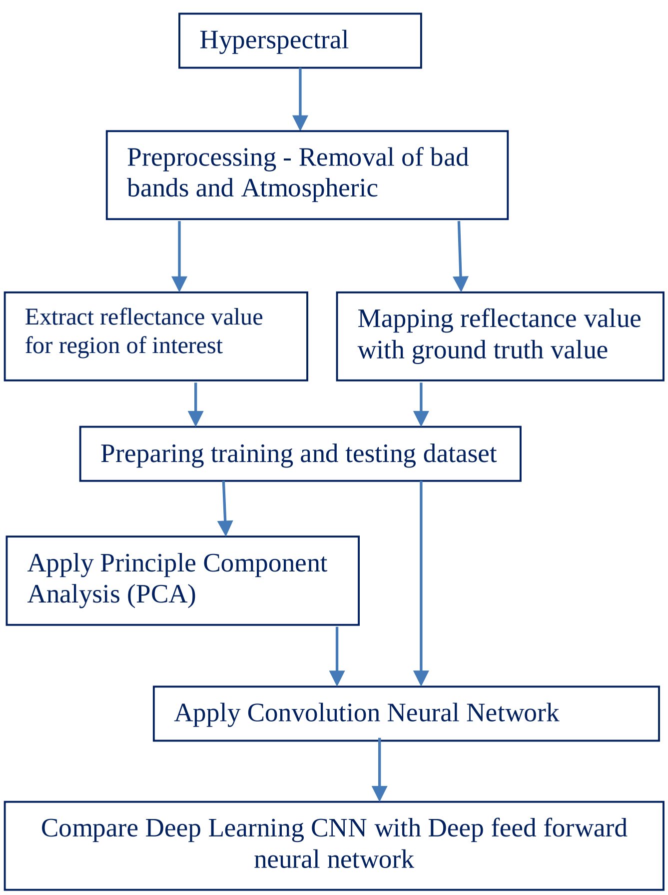


**Figure 1.** Flowchart of the proposed system.

As shown in Figure 1, atmospherically corrected data is provided to the ENVI tool in order to obtain ASCII values of each pixel. ASCII values of region of interest (ROI) are combined with the ground truth and given to the PCA as an input. CNN is further used for pixel classification.[23] Deep learning CNN is compared with deep feed forward NN.[24]

**Principal Component Analysis (PCA)**

Principal Component Analysis (PCA) is a dimensionality-reduction technique that has been used to transform a high-dimensional dataset into a smaller-dimensional subspace prior to running a machine learning algorithm on the data.[25] Hyper spectral data has lots of information in hundreds of bands. In order to get more information and reduce the number of bands, PCA produces informative and significant principal components using the Eigen values and the Eigen vectors.[26]

**Deep Learning Convolutional Neural Network**

Deep learning CNN consist of alternate convolutional layer and max pooling layer connected to the fully connected layer.

**Convolutional layer**

In the present work a n x n square neuron layer is set which is followed by our convolutional layer. If we use an m x m filter w, our convolutional layer output will be of the size (n−m+1) × (n−m+1). It is required to sum up the contributions, weighted by the filter components from the previous layer cells, add bias term and then apply the activation function.

$$F_{ab}^{k} = \sigma\left(\sum_{i=0}^{m-1}\sum_{j=0}^{m-1}\left(w_{ij}\,x_{(a+i)(b+j)}^{k-1}\right) + bias\right)$$

Max Pooling layers

The max-pooling layers are quite simple. They simply take some k x k region and output a single value, which is maximum for that region. For instance, if their input layer is a n x n layer, The output will be a (n/k) x (n/k) layer, as each k x k block is reduced to just a single value via the max function.

An error function L is defined. The error we need to compute for the previous layer is the partial of L with respect to each neuron output (∂L/∂F). Using chain rule, gradient component for each weight is given as below

$$\frac{\partial L}{\partial w_{ij}} = \sum_{a=0}^{n-m}\sum_{b=0}^{n-m}\frac{\partial L}{\partial x_{ab}^{k}}\frac{\partial x_{ab}^{k}}{\partial w_{ij}}$$

We already know the error at the current layer. The deltas at the current layer are computed by using the derivative of the activation function, σ′(x).

$$\frac{\partial L}{\partial x_{ab}^{k}} = \frac{\partial L}{\partial y_{ab}^{k}}\frac{\partial y_{ab}^{k}}{\partial x_{ab}^{k}} = \frac{\partial L}{\partial y_{ab}^{k}}\sigma'(x_{ab}^{k})$$

Multilayer 2D CNN has been implemented by applying ReLU convolution layer and max pooling dropout layer proposed architecture as shown in Figure 2.

The details of each layer of CNN are as shown in Table 1. Similarly proposed deep feed forward neural network is as given in Table 2. The architecture of a convolution layer consists of ReLU kernel of 1 X 1 followed by one max pooling dropout layer.[27]

It has been connected with fully connected dense layer using the softmax function. In an artificial neural network, activation functions decide whether a neuron should be activated or not, whether the information contained by the neuron is relevant or not.

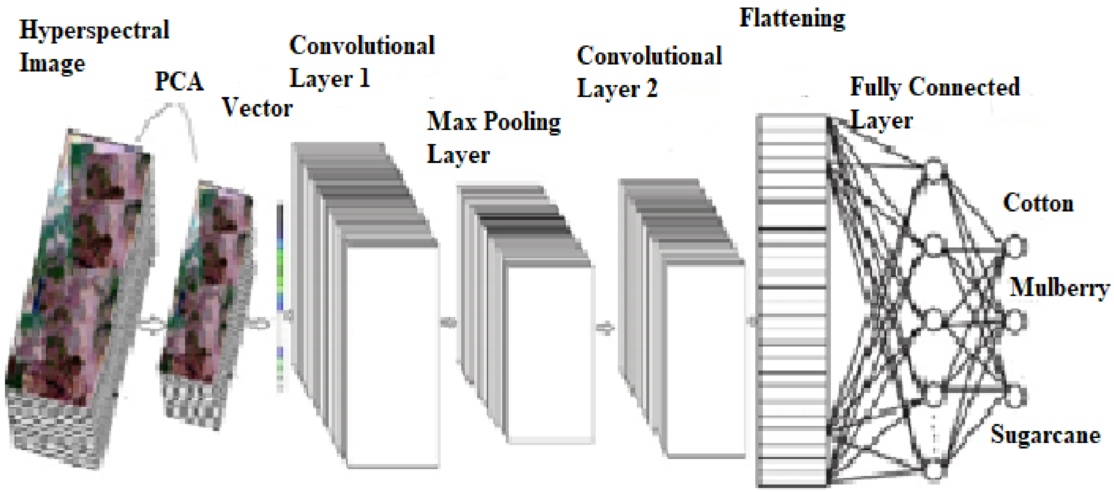


**Figure 2.** Architecture of Deep Learning Convolutional Neural Network.

Rectified linear units (ReLUs) have been used for the hidden layers.[28] A rectified linear unit yields an output x if x is positive and 0 otherwise. single channelled CNN and a 3 x 3 filter have been used. Softmax function has been used in the output layer of CNN. The softmax is used here because more than two classes or crops are to be identified. It has given an equivalent output of each unit between 0 and 1.

**Table1.** Details of Deep learning CNN

| | |
|---|---|
| Input Layer | 6 x 6, 1 channel |
| Convolutional Layer 1 | Stride=1, Padding=0, Filter Size=3 x 3, Number of Filter=25, Bias= 25 |
| Max Pooling Layer 1 | Stride=1, Padding=0, Filter Size=2 x 2, Number of Filter=25 |
| Convolutional Layer 2 | Stride=1, Padding=0, Filter Size=2 x 2, Number of Filter=25, Bias= 25 |
| Flattening | 25X 1 vector |
| Fully Connected Layer | Hidden nodes=10, bias=10 |
| Output Layer | Output node=3 bias=3 |

**Table2.** Details of Deep Feed Forward NN

| | |
|---|---|
| Input Layer | 6 x 6=36 input vector |
| Fully Connected Layer 1 | Hidden nodes=25, bias=25 |
| Fully Connected Layer 2 | Hidden nodes=25, bias=25 |
| Fully Connected Layer 3 | Hidden nodes=25, bias=25 |
| Output Layer | Output node=3 bias=3 |

## Study Area and Test Data

The Area considered in this study is the Aurangabad district region, in Maharashtra, India. The study area lies between upper left corner latitude, longitude (20.31, 75.40), upper right corner latitude, longitude (20.29, 75.47), lower left corner latitude, longitude (19.37, 75.26), lower right corner latitude, longitude (19.39,75.18) in Waregaon village, Aurangabad district of Maharashtra. Required data is collected from space borne hyperspectral remote sensing data (EO-1 Hyperion) acquired on Dec 24, 2015. In the selected study area, the weather is clear and non cloudy and the crop under study attains its middle stage of growth with enough foliage in winter. Hence the crop has been studied in winter season. Same study area of Aurangabad district was used.[21] Mulberry crop have many uses so required to identify plants using remote sensing data.

## Experimental

Crop classification has been performed with the help of hyperspectral USGS EO-1 images.[29] Hyperspctral data needs to be atmospherically corrected to remove noise. In this study, atmospheric corrections are obtained using QUACK (Quick Atmospheric Correction) algorithm.[30] Excluding bad bands and after atmospheric correction, hyperspectral data of 155 bands is used in this study.[31] The crops considered in this study are cotton, mulberry and sugarcane. Signature has been observed by plotting graph of wavelength versus reflectance. Signature of each crop is different as shown in Figure 3(a) (b) (c).

Figure 4 shows graph of cumulative explained variance for each principal component using hyperspectral EO-1 Hyperion data for the region of interest (ROI).[32]

Experiments are conducted in python tensorflow environment for PCA and CNN. 155 bands are given as input to the PCA. Graph shows that after 36 principal components, variance remains constant. First 36 components given more information Therefore these components are considered for conducting the experiment.

Table 3 shows dataset used in classification for training and testing the model. Total 500 records are used, 60 % for training and 40 % for testing.

**Table 3.** Dataset for each class for Deep Learning CNN and Deep FFNN

| Class | Training | Test |
|---|---|---|
| Cotton | 158 | 104 |
| Mulberry | 58 | 40 |
| Sugarcane | 84 | 56 |
| Total | 300 | 200 |

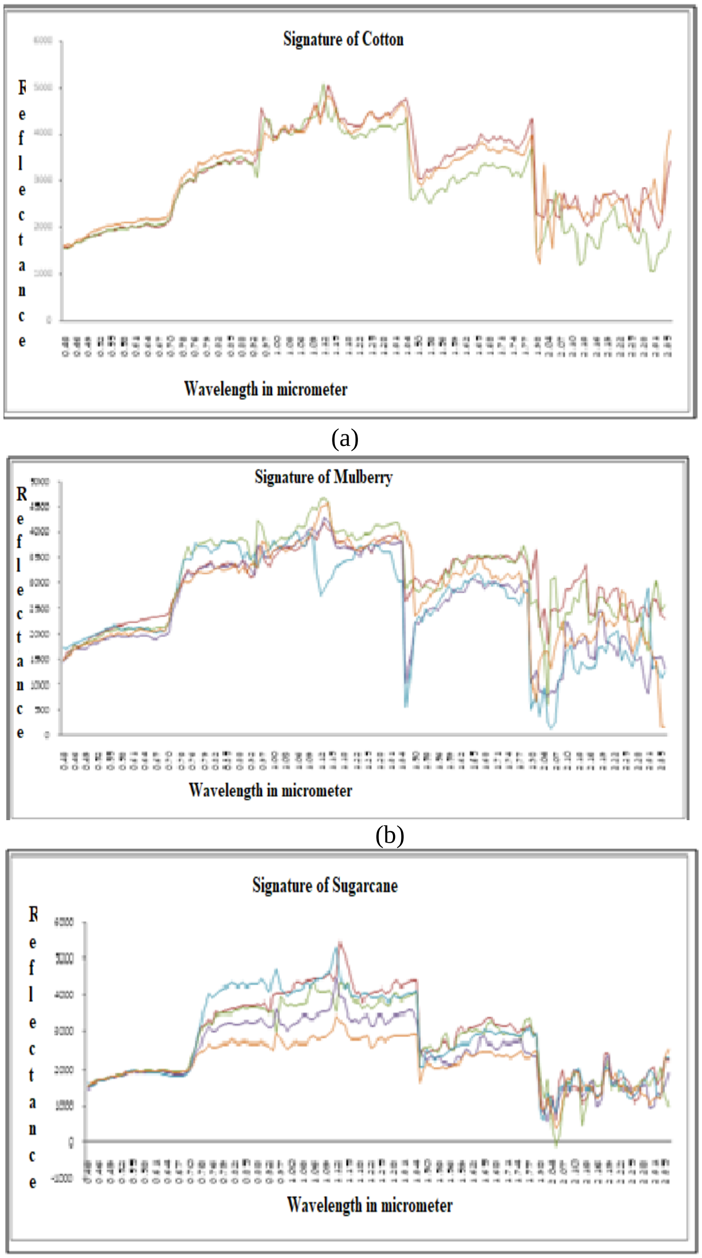


**Figure 3.** (a) Signature of cotton (b) Signature of Mulberry (c) (b) Signature of Sugarcane

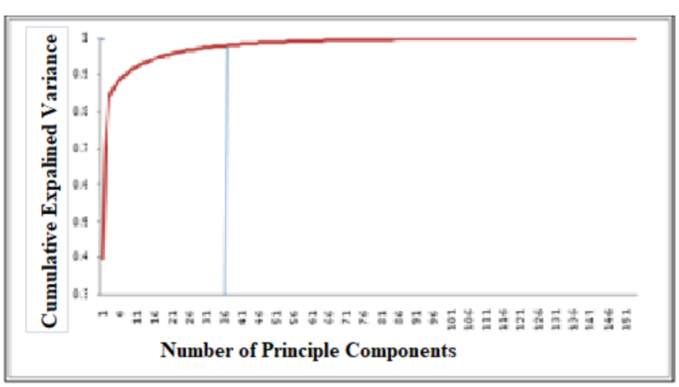


**Figure 4.** Cumulative explained variance of each principal component for hyperspectral EO-1 Hyperion data

As shown in Figure 2, Convolutional neural network with 0.01 learning rate, 16 batch size and Adam optimizer has been implemented. Table 1 shows that deep learning CNN architecture consist of a convolutional layer followed by a max pooling layer and a Convolutional layer, connected to fully connected layer. Deep feed forward network consist of three fully connected hidden layers of 25 nodes each. Table 3 shows comparison between deep learning CNN and deep FFNN on the basis of accuracy, loss and parameters generated in each classifier.[6]

It has been observed that accuracy of DL CNN is 99.3 % whereas accuracy that of deep FFNN is 96.6 %. Loss is less in DL CNN compared to deep FFNN. In the proposed system, storage space depends on parameters generated in each classifier. 3068 parameters are generated in DLCNN, whereas in deep FFNN, parameters are 4053 as shown in Table 4.

**Table 4.** Comparison between Deep Learning CNN and Deep FFNN

| Methods | Accuracy | Loss | #Parameter generated |
|---|---|---|---|
| DL CNN | 99.3 % | 2.49 % | 3,068 |
| Deep FFNN | 96.6 % | 2.74 % | 4,053 |

## Discussion

Deep learning CNN works on structured and unstructured data effectively; this is the main purpose of using it. The features extraction is possible using Convolutional Neural Network. This model uses different parameters and those parameters have to be set while using it. Principal component analysis is important and used many researchers to reduce dimensions and to get more meaningful components. Unstructured Hyperspectral input has been given to the PCA in order to extract useful and informative bands. Spectral signature of crops has been used for classification. The samples of mulberry, cotton and sugarcane plants have been used to perform experiment for crop classification. DL CNN has given good accuracy compare to Deep feed Forward Neural Network. 60 % data has been given for training the model and 40 % data has been given for testing the model. The reason for choosing Hyperspectral dataset is that it has many numbers of continuous spectral bands; therefore we can get more prominent signature of each crop. So it is an effective remote sensing data for crop identification.

## Conclusions

In this study, a CNN approach is proposed for crop identification from EO-1 hyperspectral datasets. Hyperspectral data set has more number of bands so that signature of each crop is more prominent. This feature of Hyperspectral data is useful to identify crops.

Deep learning CNN using multi step convolutional, ReLU, and pooling operators is used to classify three crops, cotton, mulberry, sugarcane which result better accurate result. Further, performance of deep learning CNN compared with Deep FFNN. Deep learning convolutional neural network gives more accurate result compared to deep FFNN. Principal component analysis has been used to reduce dimensions and to get more informative components. In this study we obtained 99.3 % accuracy and 2.49 % loss. In this study, small dataset is used for crop classification using hyperspectral data and deep learning convolutional neural network. It is observed that Deep learning CNN also work effectively with small dataset.

**Conflict of Interest**: Authors declare no conflict of interest.

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