CROPS FINE CLASSIFICATION IN HYPERSPECTRAL IMAGERY BASED ON PRINCIPAL COMPONENT ANALYSIS (PCA) AND DEEP LEARNING

[1]S. JAMALAIAH, [2] Prof. K. MANJULA VANI,

[1] Research Scholar
Department of Spatial Information Technology
Jawaharlal Nehru Technological University Hyderabad UCEST,
Kukatpally, Hyderabad, INDIA- 500085.
[2] Professor
Department of Civil Engineering,
Jawaharlal Nehru Technological University Hyderabad UCEST,
Kukatpally, Hyderabad, INDIA- 500085.

E-mail: [1]satupatijamalaiah@gmail.com, [2]manjulavani@jntuh.ac.in

ABSTRACT

Hyperspectral image classification has been deployed in a number of real-world scenarios, such as agricultural, quality control of agro-food products, and medical fields. Hyperspectral classification is difficult due to inter-class similarities, variability, nested regions, and overlaps. For the classification of hyperspectral data, traditional convolutional neural network (CNN)-based algorithms are applied. CNN primarily employs two-dimensional (2D)-CNN for hyperspectral extracting features, leaving intra band correlation of hyperspectral images ignored. The three-dimensional (3D)-CNN extracts the features by combining spatial-spectral bands of hyperspectral images, which is a complicated model, in order to accomplish this performance. This study proposes a customized 3D-CNN that uses hyperspectral images to integrate both spatial and spectral information. The proposed method first reduces the data by using dimensionality reduction, generates the image cube by using image patching, applies the customized 3D-CNN and, using a softmax classifier, classifies different crops in suburban areas using high-resolution features acquired by the customized 3D-CNN. The customized 3D-CNN model produces maximum overall accuracy of 99.88% and 99.83% for Indian pines and paviaU datasets. The model produces accurate results that are verified against existing solutions. The performance of the proposed method is validated using benchmark hyperspectral datasets from the study area.

Keywords: *Classification, CNN-Convolution Neural Network, Convolution; Deep Learning (DL), Deep Neural Network (DNN), FCL-Fully Connected Layer, HSI-Hyperspectral Image, NN-Neural Network, PCA-Principal Component Analysis, 3D-CNN-3-Dimensional Convolution Neural Network.*

1. INTRODUCTION

In the last two decades, hyperspectral remote sensing has developed considerably. Currently, a large portion of the Earth's surface is covered by airborne and space-born sensors with high spatial, spectral, and temporal resolution. Applications of hyperspectral remote sensing include fine identification of materials and estimation of physical parameters. However, these applications require sophisticated and complex analysis methods. The source of difficulties in hyperspectral remote sensing is the large amount of dimensionality and size of the hyperspectral data [22]. The HSI is made up of hundreds of spectral bands that range from visible to shortwave. This gives a lot of data for applications like target detection and identification. The hyperspectral images

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

contain an abundance of spectral data [3]. This is used to analyze and evaluate materials that have spectrally similar qualities. The classification of hyperspectral data is a significant challenge in the remote sensing world [8]. Due to the high dimensionality and spectrum mixing, classifying hypespectral images is difficult [22]. Hyperspectral image classification has been utilized for many applications, such as precision agriculture [17] and environmental monitoring [18]. Identification and classification of crops are important in the agricultural field [7].

The hyperspectral classification performance depends on both spectral and spatial information [12]. Simple analytical computing and target categorization need high calculation costs and low classification accuracy [22]. The use of CNN in hyperspectral image classification techniques has significantly increased. However, retrieving hyperspectral data remains problematic. The primary cause of poor classification performance is a lack of training cases. The model uses several spatial feature extraction approaches by using DNN to handle these difficulties [23]. Underutilized 1D (speech), 2D (image), and 3D (3D-object) research in DNN and DL has made significant progress. In contrast to 3D-objects, hyperspectral images contain 2D spatial and 1D spectral information. Existing deep neural network approaches are not extended to hyperspectral image (HSI) classification [10]. To represent geographical objects and HSI classification by CNN [8]. Conventional CNN-based approaches extract features largely using 2D-CNN.This allows inter-band correlation of hyperspectral images. Both spectral and spatial properties are used in the majority of hyperspectral images. As a result, a 3D-CNN model can be used instead [11]. However, it depends on a highly complex model [24].

1.1. previous works review

Many methods for hyperspectral image classification have been proposed in the literature. *Yulin Yan and Youngryel Ryu*. proposed a deep leaning method for crop type mapping using Google Street view images [19]. They applied a Convolutional neural network (CNN) to automatically classify the Google Street view images. An overall accuracy of 92% was reported for classifying images into normal ones. *Chunxing Wang et al.* suggested a hyperspectral image classification model based on a 3D CNN model [3] . They classify the hyper spectral image using 3D CNN and J-M distance. There was a 92.50% overall accuracy reported for classifying different crops in both datasets. *Kavita Bhosle and Vijaya Musande*, suggested deep learning methods, such as CNN and convolutional auto encoder have been proposed [7].

They extracted features using both methods before

applying the PCA for dimensionality reduction. An overall accuracy of both methods is 94% and 90%. *Seyyed Ali Ahmadi and Nasser Mehrshad,* for hyperspectral image classification, a Spectral-Spatial Feature Extraction (SEA-FE) approach was presented [13].

In this method, spectral feature reduction using minimum noise fraction (MNF), obtains pixel feature maps, and then computes SEAF. An overall accuracy of 92.13% was reported for classifying the hyperspectral image. *Xin Zhao et al.* suggested a multi-source deep learning technique for hyperspectral image classification [18]. In this approach, train a model with multiple hypespectral images and then transfer that knowledge to the target hyperspectral image. A 98.8% overall accuracy was reported for classifying target hyper spectral images. *Venkata Shashank Konduri et al.* They proposed an approach to map a crop across the United States (USA) before harvest [16]. In this approach, the first step in crop classification was to perform multivariate Spatio-Temporal clustering (MSTC) to create phenoregions. The second step was to assign a crop label to each phenoregion based on spatial concordance between phenoregions and crop classes.

Yanfei Zhong et al. presented a conditional random field classifier for a deep convolutional neural network (CNNCRF) [21]. This frame work is proposed for crop classification with UAV-born high spatial resolution images. The WHU-Hi-Han Chuan dataset had an overall accuracy of 98.50%. *Jinfan Xu et al.* proposed Deep Crop Mapping (DCM) method based on long short-term memory structure with attention mechanism through integrating multi temporal and multi spectral remote sensing data [5]. This method gets 95% accuracy for crop classification. *Vishal Srivastava and Bhaskar Biswas,* suggested Deep CNN feature fusion, manifold learning and regression for pixel classification in hyperspectral images [22]. The main purpose of this work is to improve the classification accuracy for hyperspectral images. This method gets 98.8% classification accuracy. *Ji Zhao et al.* proposed a spectral-

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

spatial agricultural crop mapping method based on conditional random fields (SCRF) [6]. which learns the sensitive spectral information of crops by a spectrally weighted kernel and uses the spatial interaction of pixels to improve the classification performance. 88.24% overall accuracy for crop classification. *Liheng Zhong et al. presented a classification framework based on deep learning for remotely sensed time series data* [9]. This method classifies the summer crops using the land sat Enhanced Vegetation Index (EVI) time series. In this method, they design two deep learning models; one is Long Short-Term Memory (LSTM), and the other one is one-dimensional convolutional layers (conv1D). The highest accuracy (85.4%) was achieved by the conv1D-based model. *Hongwei Zhao et al.* proposed three deep learning models for early crop classification using Sentinel-1A time series data [4]. In deep learning models, one dimensional convolutional neural network (1D CNNs), long-short-term recurrent neural networks (LSTM RNNs), and gated recurrent RNNs (GRU RNNs) are employed. The effective solution combines these three models with an incremental classification approach for early crop classification. This method provides a new perspective on early mapping of croplands in cloudy areas. *Shunping Ji et al.* proposed a novel 3-dimensional (3D) convolutional neural network (CNN) for crop classification [15]. This method uses spatio-temporal remote sensing images. Crop classification accuracy of 79.4% using spatiotemporal remote sensing images.

The primary goal of this research is to present a 3D CNN structure for crop classification based on a hyperspectral standard data set. In terms of classification accuracy, the proposed method outperforms the existing ones. This article's body is outlined: Section 2 discusses the material and methodology. This section addressed the data sets used in the proposed model, data pre-processing, and the 3D CNN model's innovative design. Section 3 contains the results and discussion. Section 4 presents the conclusions.

2. PROPOSED METHODOLOGY

The adapted 3D-CNN is used for hyperspectral image classification. This study is primarily concerned with classifying hyperspectral data using image patching, and creating customized 3D-CNN, and comparing with other NN models.This paper consist of two objectives.

Objectives:

1) Pre-process hyperspectral data using principal component analysis (PCA)
2) Apply neural network model

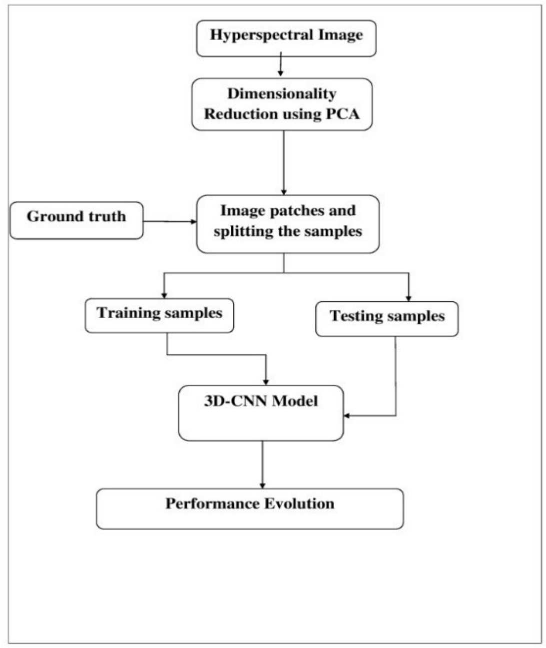


Figure 1: A flow chart for crop fine classification in hyperspectral imagery based on Principle Component Analysis (PCA) and Deep Learning.

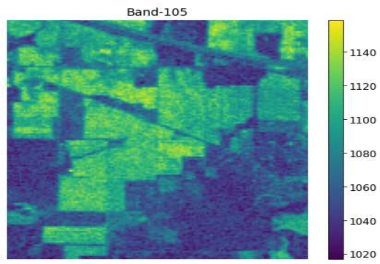
2.1 Datasets

2.1.1 Dataset on Indian pines

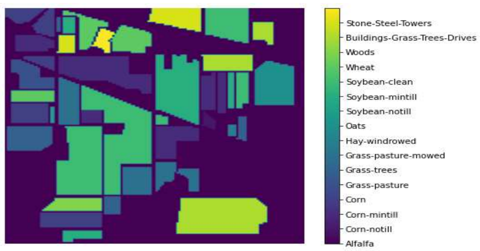
The Indian pines data set was acquired from AVIRIS (Airborne visible Infrared Image Spectrometer) in 1992 at the Indian Pines test site in north-western Indiana, US containing 220 spectral bands ranging from 0.4 µm to 2.5 µm. The data has a geographical resolution of around 20 meters and a spatial dimension of 145 X 145 pixels. The different crops are categorized into 16 classes of interest which forms the data set. The training and testing samples of the data set are shown in the table 1 and the representation of False-Color map and ground truth is shown in Figure.2 (a), Figure.2 (b) given by David Land-greb of purdue University.

Journal of Theoretical and Applied Information Technology
15th June 2023. Vol.101. No 11

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195



(a) False color map



(b) Ground truth map
Figure.2: False color map and Ground truth map for Indian pines data set.

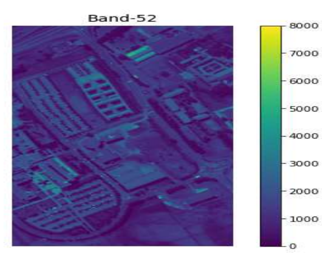
Table 1. The Indian Pines dataset's land cover classes and sample numbers.

S.NO	CLASS	TRAINED SAMPLES	TEST SAMPLES
1	Alfalfa	34	12
2	Corn-notill	1071	357
3	Corn-mintill	622	208
4	Corn	178	59
5	Grass-pasture	362	121
6	Grass-trees	548	182
7	Grass-pasture-mowed	21	7
8	Hay-windrowed	358	120
9	Oats	15	5
10	Soybean-notill	729	243
11	Soybean-mintill	1841	614
12	Soybean-clean	445	148
13	Wheat	154	51
14	Woods	949	316
15	Buildings-Grass-Trees-Drives	289	97
16	Stone-Steel-Towers	70	23
Total		7686	2563

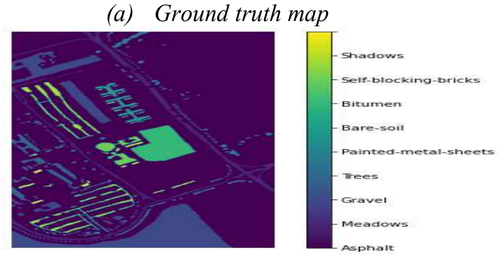
2.1.2 Dataset on Pavia University

The ROSIS sensor captured the PaviaU scene during a flight campaign across Pavia, Northern Italy.103 spectral bands are available in Pavia University. The data has a spatial resolution of about 1.3m and a spatial dimension of 610 X 610 pixels. In above dataset unimportant features need to be removed before analysis. Dataset having 9 different classes in ground tooth image.

The trained and test samples are shown in table 2. The representation of False-Color map and ground truth is shown in Figure 3(a) and Figure 3(b), provided by Prof. Paolo Gamba from the telecommunication and Remote sensing laboratory, Pavia University, Italy.



(a) Ground truth map



(b) False color map
Figure.3: False color map and Ground truth map for Pavia University Dataset.

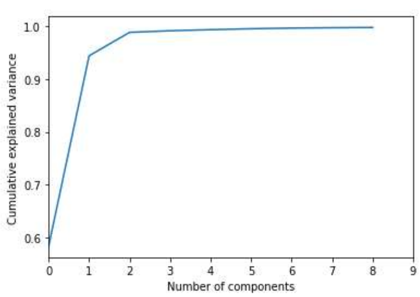
Table 2. The Pavia University dataset's land cover classes and sample numbers.

S.NO	class	Trained samples	Test samples
1	Asphalt	4973	1658
2	Meadows	13987	4662
3	Gravel	1574	525
4	Trees	2298	766

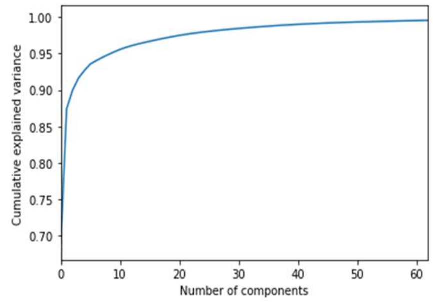
5	Painted metal sheets	1009	336
6	Bare Soil	3772	1257
7	Bitumen	997	333
8	Self-Blocking Bricks	2762	920
9	shadows	710	237
Total		32082	10694

2.1 Dimensionality Reduction

Hyperspectral images contain redundant data due to their high spectral correlation. So, it is useful to dimensions are reduced in these images [2]. Dimensional reduction is a process of reducing features or dimensions of hyperspectral data and simplifies the subsequent process of the classification. Principal component analysis is transformation technique can be utilized for dimensionality reduction of hyperspectral image. Kernel PCA was used to find significant bands among hundreds of hyperspectral bands [3]. This paper proposes a reduction technique that is PCA. PCA is a very accepted method that is used spectrally compact high dimensionally dataset [3]. This selects the important bands for each pixel. The findings of 3D-CNN with PCA were more accurate than the results of 3D-CNN without PCA. Figure 4(a) and Figure 4(b) show PCA for both datasets. The plots show almost above 90% variance by the first 60 components of the Indian pines' dataset and first 20 components of the Pavia University dataset. So, we can drop the other components.



(a) *PCA For Paviau Dataset.*



(B) *PCA For Indian Pine Dataset.*

Figure. 4. PCA For Paviau And Indian Pine Datasets.

2.3 Convolution Neural Network (CNN)

CNN is the most regularly used method for classification and hyperspectral image feature extraction[3]. CNN is an anticipative neural network, the performance for the processing a high dimensional image processing depends on the artificial neurons.

There are two design ideas in convolution neural networks. The first is a 2D structure of image pixels in nearby areas that is correlated, while the second is an architecture that is based on feature sharing. As a result, in all places, the created feature map for each output by convolution employs similar filter [24]

Convolution neural network consist of four components

(1) Convolution layer
(2) Activation function
(3) Pooling layer
(4) Fully connected layer
(5)

2.3.1 Convolution layer

The convolution layer function is calculated from the following equation.

$$a_j^k = \sum_{i=1}^{d} f(x_i^{k-1} * w_{ij}^k + b_j^k) \qquad (1)$$

Where matrix x_i^{k-1} is feature map of the $k-1$ Layer, a_j^k is a jth feature map of the kth layer, d represents the number of input feature maps, w_{ij}^k is the weight parameter and b_j^k is the bias parameter which is randomly initialized.

2.3.2 Activation function

The activation function is calculated from the following equation.

$$f(x_i^{k-1} * w_{ij}^k + b_j^k) \qquad (2)$$

Is the nonlinear activation function where we are utilizing the ReLU activation function in this article.

2.3.3 Pooling layer
It is normally placed following the convolution layer. It is employed in order to minimize the spatial dimension of the data. A pooling procedure reduces the network's parameters and prevents overfitting. In this article, max-pooling is used.

2.3.4 Fully connected layer
The connected layer neuron communicates with all neurons in the preceding layer and sends the target value to the classifier.
To train all parameters in the neural network, the back-propagation technique is utilized. 2D-CNN and 3D-CNN are the CNN methods utilised in the categorization of hyperspectral images. 3D-CNN with PCA and 3D-CNN without PCA and their comparison are our two proposed technique.

2.4 3D- Convolution Neural Network

2.4.1 3D- Convolution
3D-convolution can be used to learn both spectral and spatial information from
Hyperspectral images [4]. As per figure 5 this can be computed by the below equation.

$$c_{abc} = f(\textstyle\sum_{klm} w_{klm} a_{(x+k)(y+l)(z+m)} + b) \quad (3)$$

Where the c_{abc} is the output feature at the position (a,b,c), $a_{(x+k)(y+l)(z+m)}$ represents input at the position (x+k, y+l, z+m) in which (k,l,m) denotes in its offset to (a,b,c) and w_{klm} weighted for the input.$a_{(x+k)(y+l)(z+m)}$With an offset of (k,l,m) in the convolution kernel the feature size is smaller.

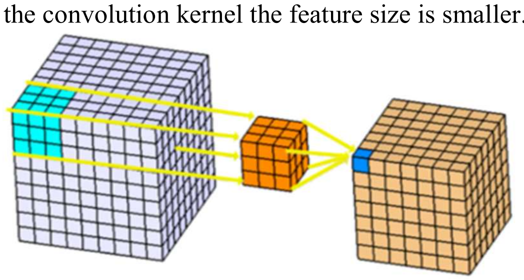


Figure.5: Illustration of 3D convolution.

2.4.2 ReLU activation function
The Rectifier linear unit (ReLU) operates in a nonlinear manner. The ReLU accepts positive neuron input and returns zero if the neuron input is negative. Benefits of the ReLU activation function include rapid gradient progression, sparse activation, and minimal computing load [22].

$$f(x) = \max(0, x) \quad (4)$$

Where x is input data,
The ReLU in 3D-CNN can improve performance in the vast majority of applications.

2.5 Proposed 3D- Convolution network model

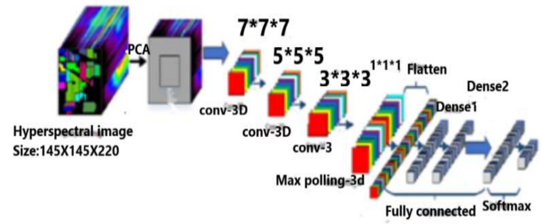


Figure.6: the Architecture of Proposed 3D CNN model for the input hyperspectral image.

Figure 6 depicts the proposed 3D-CNN model for processing of hyperspectral image. This model first uses the PCA for the reduction of data and then its reduced input to the proposed network model to extracts features at different levels of layers such as convolution layers, Maxpooling layers, and dense layers. In the end, fully connected layers and softmax layers are used to classify the data. The number of FCL and 3D convectional layers is referred in table.3 and table.4 for two different widow size datasets.

Table 3. The suggested 3D-CNN model architecture is summarised in Figure 6, with the window size dataset as 11 X 11 pixels for both datasets.

Layer	ıtput shape	# parameters
Input Layer	1, 11,50,1)	0
3D-convolution layer_1 (Conv3D)	), 9, 48, 16)	448
	7, 7, 46, 32)	13856
3D-convolution layer_2 (Conv3D)	5, 5, 44, 64)	55360
3D-convolution layer_3(Conv3D)	2, 2, 22, 64)	0
ıax_pooling layer (MaxPooling3)	(5632)	0
flatten (Flatten)	(512)	2884096
Dense layer_1 (Dense)	(#classes)	8208
Dense layer_2 (Dense)		
total ,2,961,968 trainble prameters are required		

Journal of Theoretical and Applied Information Technology
15th June 2023. Vol.101. No 11

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

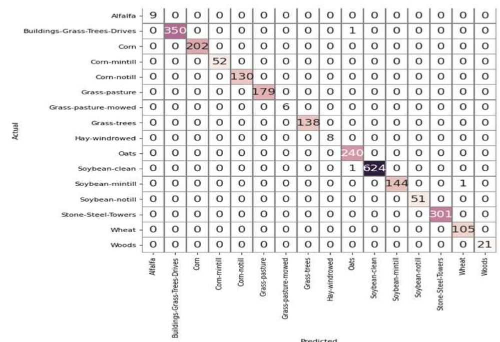
Table 4. The Suggested 3D-CNN Model Architecture Is Summarised In Figure. 6, With The Window Size Dataset As 9 X 9 Pixels For Both Datasets.

Layer	utput shape	#parameters
Input Layer	(9, 9,50,1)	0
3D-convolution layer_1 (Conv3D)	(7, 7, 7, 16)	448
3D-convolution layer_2 (Conv3D)		13856
3D-convolution layer_3 (Conv3D)	(5, 5, 5, 32)	55360
max_pooling layer (MaxPooling3)	(3, 3, 3, 64)	0
flatten (Flatten)	(1, 1, 1, 64)	0
Dense layer_1(Dense)	(64)	33280
Dense layer_2 (Dense)	(512)	4617
	(#classes)	
In total ,107,561 trainble prameters are required		

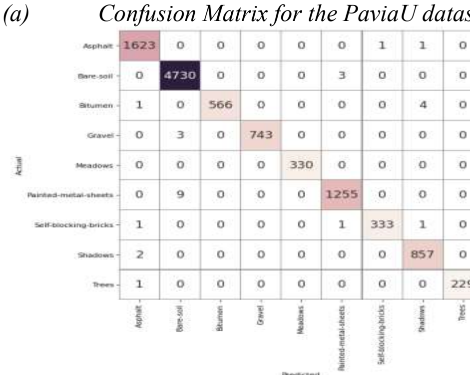
3 RESULTS AND DISCUSSIONS

To categorize crop varieties using the proposed 3D-CNN, 75% of each class's samples are chosen as training samples, with the remaining samples serving as test samples. Some experiments were implemented by using python3 with Anacondas environment and remaining by using an online flat form known as Google co laboratory. Google co laboratory requires a fast internet connection to function in any context. The code can be run on a python3 notebook with 25 GB of RAM and 258 GB of cloud storage for data computation, for efficient execution in Google co laboratory.

To perform a fair comparison for all experiments with a learning rate of 0.001, an activation function Relu is used for all except the last layer with softmax is used, and patch sizes are set as 9×9×9, 11×11×9 for the PaviaU dataset and 9×9×50, 11×11×50 for the Indian pines dataset respectively. The bands chosen by the PCA approach are 9 and 20.Also, for all tests, a learning rate of 0.001 was employed, an activation function Relu was used for all layers except the last layer, which used soft max, and patch size of 9×9×200 pixels , 11×11×200 pixels for Indian pines dataset, 9×9×103 pixels, 11×11×103 pixels for PaviaU dataset respectively were used.103 and 200 selected by a number of bands in the datasets without applying PCA. Average accuracy (AA), Kappa coefficient (K) and Overall accuracy (OA) have been computed from the confusion matrix for evolution purposes. Figure 7(a) and Figure 7(b) shows the confusion matrix of both datasets.



(a) Confusion Matrix for the PaviaU dataset.



(b) Confusion Matrix for the Indian Pines dataset.

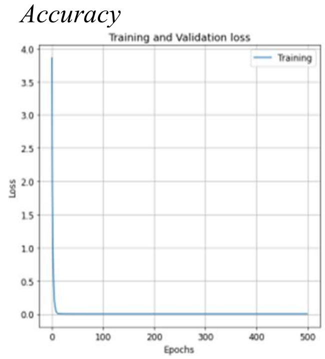
Figure. 7: Confusion matrix for the PaviaU and Indian Pines datasets.

The AA represents an average category-wise classification, the OA represents the number of correctly classified examples from an entire sample, and the kappa coefficient represents the high similarity between the classification and reference maps. The statistical measurement is the kappa coefficient. AA, OA, and Kappa are evolutes from F1-score, support and precision.

Figures.8 and Figures.9 illustrate the convergence of Accuracy and Loss of our proposed 3D-CNN for 500 number epochs with PCA of both datasets. It observes that accuracy of both datasets is 99.83% and 99.68% with no loss.

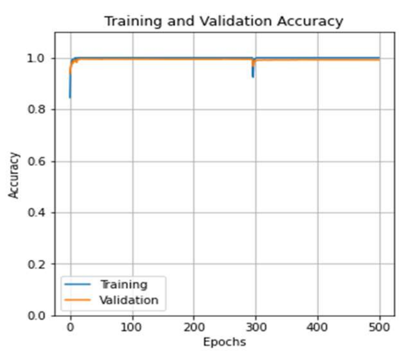
ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

(a) Accuracy

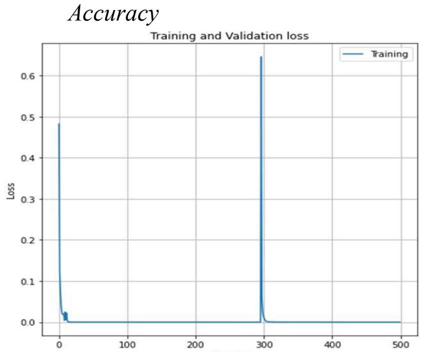


(b) Loss

Figure.8: Accuracy and loss of the proposed 3D-CNN model for the Indian Pines dataset.



(a) Accuracy



(B) Loss

Figure.9: Accuracy And Loss Of The Proposed 3D-CNN Model For The Paviau Dataset.

Table.5 shows the computation time, which is dependent on the internet speed and RAM available. It observes that the model takes less time with PCA compares with without PCA.

Table 5. All Experimental Datasets At Various Window Sizes Take Time To Compute In Minutes.

Dataset	With PCA		Without PCA	
	Window size		Window size	
	9×9 pixels	11×11 pixels	9×9 pixels	11×11 pixels
PaviaU	0.70	0.70	80.75	80.75
Indian pines	0.60	0.60	16.25	35.52

Comparison of customized 3D-CNN with existing methods like RBF (SVM) [10], Hu's (CNN) [10], Mei (CNN) [10], Fast3DCNN [11], 2D3DCNN [24] and, Weihu (DCNN) [10]. All approaches are compared using the same experiment setting, number of training samples, and patch size. The outcomes are shown in the table 6 and Figure 10. As we can see our proposed 3D-CNN has good performance than the other methods.

Table 6. Comparison classification accuracy is based on 75% for training and 25% for test.

S.No	Method	Over all Accuracy %	
		PaviaU	Inadian pines
1	RBF (SVM)	90.59	87.45
2	Hu's(CNN)above same	92.74	90.07
3	Mei(cnn)	98.00	95.7
4	Fast 3D CNN	98.40	97.75
5	2D-3D CNN	99.52	96.07
6	Wei Hu DCNN	92.56	90.16
7	**Proposed method**	**99.83**	**99.68**

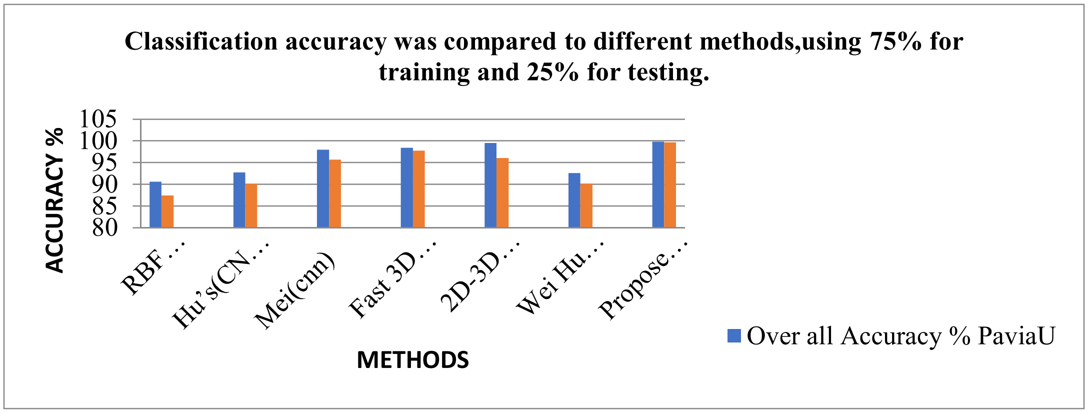


Figure.10: Classification Accuracy Was Compared To Different Methods, Using 75 % For Training And 25% For Testing.

Table 7. The Accuracy Of Each Class For The Indian Pines Dataset Is In Detail.

		With PCA Accuracy %			Without PCA Accuracy %
S.No	Class name	Window size 9×9 pixels	Window size 11×11 pixels	Window size 9×9 pixels	Window size 11×11 pixels
1	Alfalfa	100	100	0	0
2	Corn-notill	99.00	99.70	0	0
3	Corn-mintill	98.50	100	0.99	2.04
4	Corn	100	100	0	0
5	Grass-pasture	100	100	0	0
6	Grass-trees	100	100	0	0
7	Grass-pasture-mowed	100	100	0	0
8	Hay-windrowed	100	100	0	0
9	Hay-windrowed	100	100	0	0
10	Oats	100	100	0	0
11	Soybean-notill	100	99.84	100	100
12	Soybean-mintill	100	99.31	0	0
13	Soybean-clean	100	100	0	0
14	Wheat	100	100	0	0
15	Woods	100	100	0	0
16	Stone-Steel-Towers	100	100	0	0
Test Accuracy		**99.68**	**99.88**	**25.51**	**23.83**
Overall Accuracy		**99.68**	**99.88**	**25.51**	**23.83**
Average accuracy		**99.82**	**99.98**	**6.3**	**6.3**
kappa		**99.64**	**99.86**	**0.12**	**0.23**

Table 7, Table 8, are provide the detail classification each class in the both datasets with different window size and figure 11 and figure 12 shows the Detail class accuracy comparison for Indian pines dataset and PaviaU dataset. It discovers that it obtains high each class accuracy for both data sets with PCA when compared to both data sets without PCA.

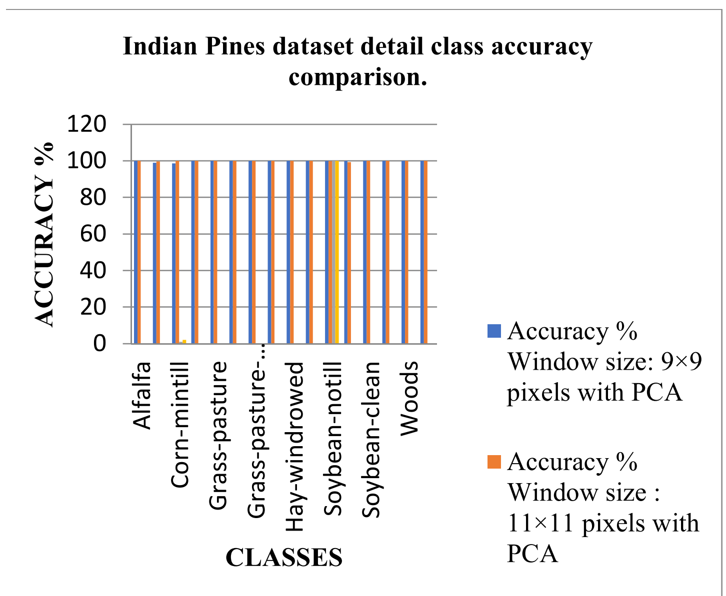


Figure.11: Indian Pines Dataset Detail Class Accuracy Comparison.

Journal of Theoretical and Applied Information Technology
15th June 2023. Vol.101. No 11

ISSN: 1992-8645 | www.jatit.org | E-ISSN: 1817-3195

Table 8. PaviaU dataset detail class accuracy comparison.

		With PCA Accuracy %		Without PCA Accuracy %	
S.No	Class name	Window size 9×9 pixels	Window size 11×11 pixels	Window size 9×9 pixels	Window size 11×11 pixels
1	Asphalt	99.82	99.93	88.66	0
2	Meadows	99.95	99.97	94.50	100
3	Gravel	98.52	100	0	0
4	Trees	99.86	100	58.65	0
5	Painted metal sheets	100	100	97.55	0
6	Bare Soil	99.92	100	0.98	0
7	Bitumen	100	100	0	0
8	Self-Blocking Bricks	99.65	100	0.22	0
9	shadows	100	100	88.64	0
Test Accuracy		**99.83**	**99.98**	**64.71**	44.33
Overall Accuracy		**99.83**	**99.98**	**64.71**	44.33
Average accuracy		**99.75**	**99.99**	**47.69**	11.11
kappa		**99.77**	**99.97**	**49.69**	0.01

[Insert Figure 12 here]

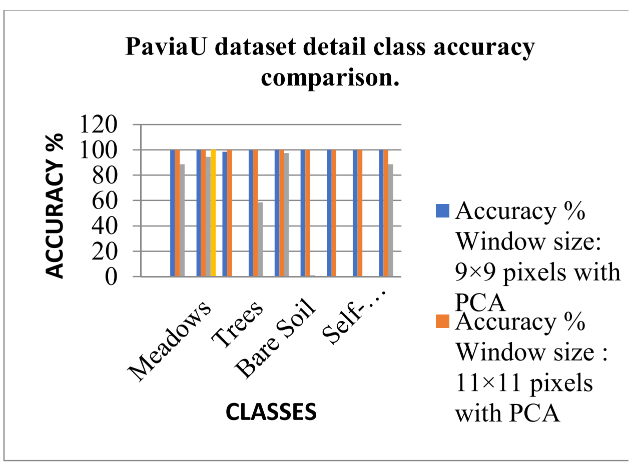
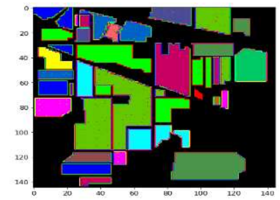
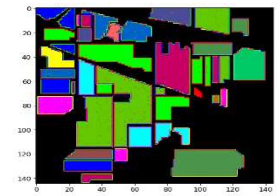


Figure.12: Paviau Dataset Detail Class Accuracy Comparison.

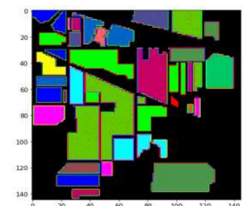
Figures .13 and figure.14 shows the classification images and Ground truth images of Indian pines dataset with different window sizes.



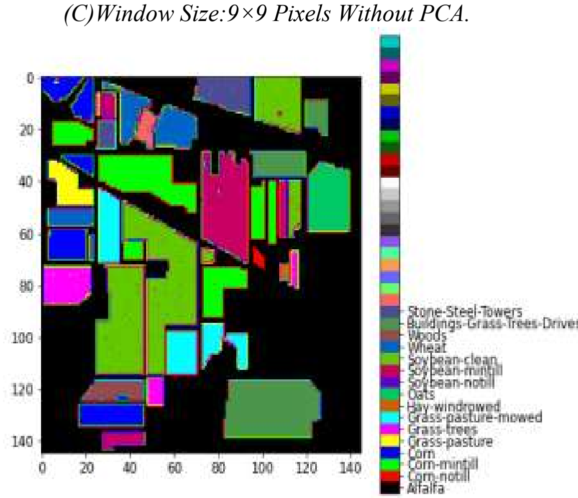
(a) Window Size: 9×9 Pixels With PCA.



(b) (B) Window Size: 11×11 Pixels With PCA.

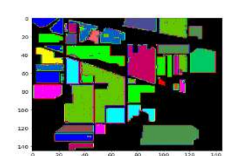


(C)Window Size:9×9 Pixels Without PCA.

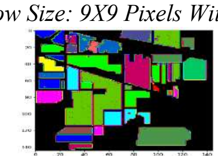


(D) *Window Size: 11×11 Pixels Without PCA.*

Figure.13. Image Of Classification For The Indian Pine Dataset With Various Window Sizes, PCA And Without PCA.



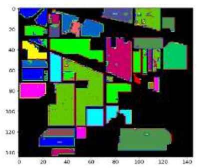
(a) Window Size: 9X9 Pixels With PCA.



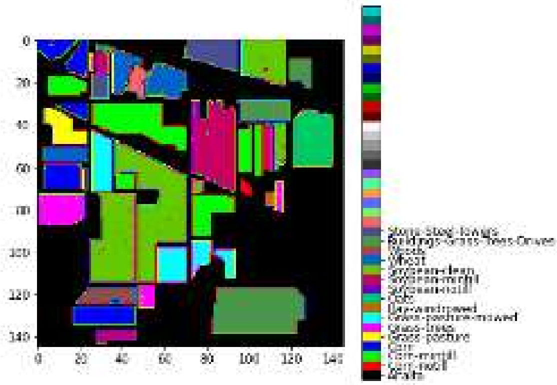
(b) (B) Window Size:11X11 Pixels With PCA

Journal of Theoretical and Applied Information Technology
15th June 2023. Vol.101. No 11

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

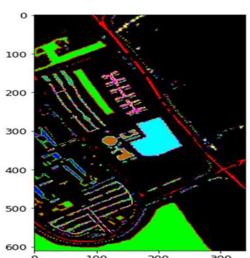


(C) *Window Size: 9X9 Pixels With Without PCA.*

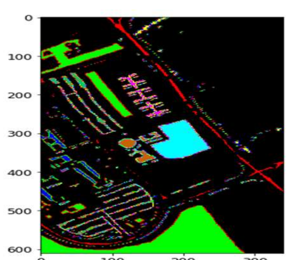


(D) Window Size: 11X11 Pixels Without PCA
Figure.14. Image Of The Ground Truth For The Indian Pines Dataset With Different Window Sizes, With And Without PCA.

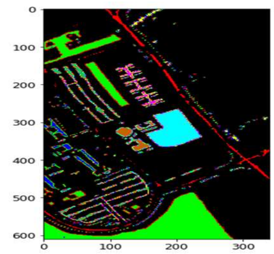
Figures.15 and figure.16 are showing the classification images and Ground truth images with different window Sizes Of Paviau Dataset.



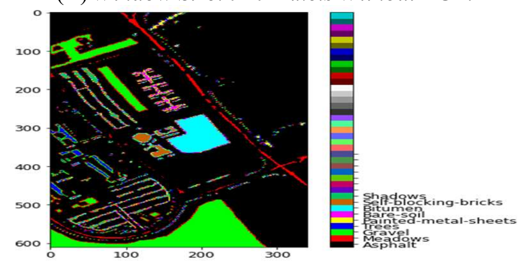
(a) Window Size 9x9and With PCA.



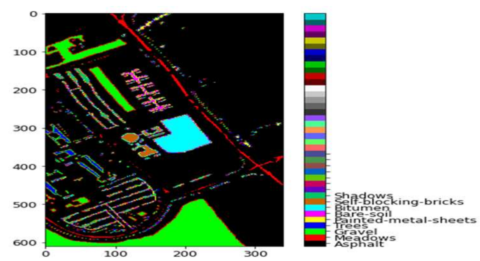
(b) (B) Window Size 11x11and With PCA



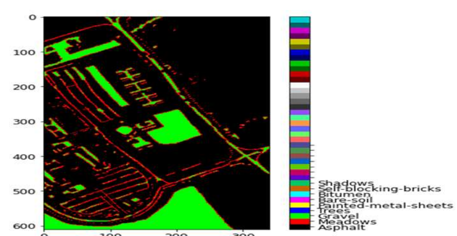
(C) *Window Size: 9X9 Pixels Without PCA.*



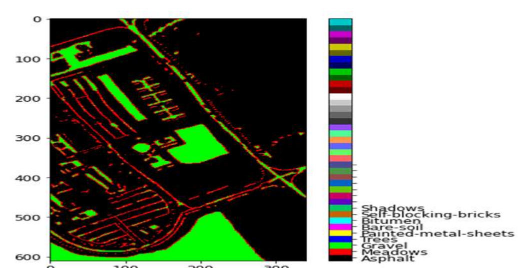
(D) *Window Size 11x11and Without* PCA.
Figure.15. Classification Images Of Paviau Dataset With Different Window Sizes, With PCA And Without PCA.



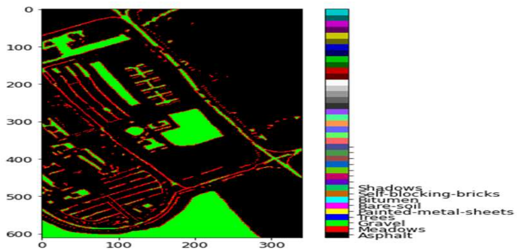
(a) Window Size:9X9 Pixels With PCA



(B) *Window Size:11X11 With PCA*



(C) *Window Size: 9X9 Pixels Without PCA .*



(D) *Window Size: 11X11 Pixels Without PCA*

Figure.16. Ground Truth Images Of The Paviau Dataset With Different Window Sizes, With PCA And without PCA.

4 CONCLUSIONS AND FUTURE SCOPE

The paper classifies the crop type using the 3D-CNN, taking 75% of samples from each class as training samples and the remaining as testing samples from the Indian Pines dataset and the PaviaU dataset. For the purpose of progression, the confusion matrix's average accuracy, overall accuracy, and kappa coefficient were computed. The average accuracy, over all accuracy, and kappa coefficient of the Indian Pines dataset are 98.68%, 99.88%, and 99.86%. The overall accuracy, average accuracy, and kappa coefficient of the PaviaU dataset are 99.75%, 99.83%, and 99.77%. The computational time for all experiments of the Indian Pines dataset and PaviaU dataset is 0.6 minutes and 0.7 minutes, respectively. Furthermore, the 3D-CNN model of deep learning is used for crop identification and crop health detection.

CONFLICT OF INTEREST

The authors declare no conflict of Interest

AUTHOR CONTRIBUTIONS

Mr.S.Jamalaiah conducted research and wrote the paper; Prof.K.Manjulavaniguides the research; Both authors had approved the final version.

REFERENCES:

[1] Ce Zhang ,Peter M. Atkinson,Charles George ,Zhaofei Wen, Mauricio Diazgranados and France Gerard,(October 2020). Identifying and mapping individual plants in a highly diverse high-elevation ecosystem using UAV imagery and deep learning.ISPRS Journal of Photogrammetric and Remote sensing. 169, 280-291.Available:https://doi.org/10.1016/j.isprsjprs.2020.09.025

[2] Chen, K. Zhu, L. Zhu, X. He, J. A. Benediktsson, and P.Ghamisi.(September 2019).Automatic design of convolutional neural network for hyperspectral image classification. *IEEE Trans. Geosci. Remote Sens.* 57(9).pp. 7048–7066

[3] Chunxing Wang , Nan Ma, Yanfang Ming , Quan Wang , Jinfeng Xia.(May 2019).Classification of hyperspectral imagery with a 3D convolutional neural network and J-M distance. Advances in Space Research.64,886–899. Available :https://doi.org/10.1016/j.asr.2019.05.005

[4] Hongwei Zhao, Zhongxin Chen, Hao Jiang , Wenlong Jing , Liang Sun and Min Feng .(November 2019).Evaluation of Three Deep Learning Models for Early Crop Classification Using Sentinel-1A Imagery Time Series—A Case Study in Zhanjiang, China.Remote Sens. 11(2673).pp 1-23.Available:http://doi:10.3390/rs11222673

[5] Jinfan Xu, Yue Zhu ,Renhai Zhong, Zhixian Lin, Jialu Xu, Hao Jiang, Jingfeng Huang, Haifeng Li,Tao Lin,2020.Deep CropMapping: A multi-temporal deep learning approach with improved spatial generalizability for dynamic corn and soybean mapping.Remote Sensing of Environment,247(111946). Available:https://doi.org/10.1016/j.rse.2020.111946

[6] Ji Zhao, Yanfei Zhong, Xin Hu, Lifei Wei, Liangpei Zhang,(January 2020).A robust spectral-spatial approach to identifying heterogeneous crops using remote sensing imagery with high spectral and spatial resolutions**.** Remote Sensing of Environment.239(111605).Available:https://doi.org/10.1016/j.rse.2019.111605

[7] Kavita Bhosle and Vijaya Musande.(March 2020).Evaluation of CNN model by comparing with convolution auto encoder and deep neural network for crop classification on hyperspectral imagery**.**Geocarto International(T&F).35(16),PP 1-15.Available: https://doi.org/10.1080/10106049.2020.1740950

[8] Liang Hong and Meng Zhang(May 2020).Object-oriented multiscale deep features for hyperspectral image classification. International Journal of Remote Sensing.41(14).PP 5549-5572.Available:https://doi.org/10.1080/01431161.2020.1734249

[9] Liheng Zhong, Lina Hu , Hang Zhou, (February 2019.Deep learning based multi-temporal crop classification. Remote Sensing of Environment.221.pp 430–443.Available: https://doi.org/10.1016/j.rse.2018.11.032

[10] Mingyi He, Bo Li, Huahui Chen.(2017). Multi-scale 3d deep convolutional neural network for hyperspectral image classification. IEEE. ICIP.978.pp 3904-3908.

[11] MuhammadAhmad,“A Fast 3DCNN for Hyperspectral Image Classification”.Presented at the IEEE ARXIV,April 29, 2020

[12] Murali kanth ,T.hitendra sarma and C.shobha bindu.(2020). A 3d-deep cnn based feature extraction and hyperspectral image classification. IEEE Trans.Geoscience Remote Sensing Symposium (InGARSS). Pp-229-232.Available:https://doi:10.1109/InGARSS48198.2020.9358920

[13] Seyyed Ali Ahmadi & Nasser Mehrshad, (Mar 2020).Spectral-spatial feature extraction method for hyperspectral images classification using multi scale super pixel and covariance map. GEOCARTO INTERNATIONAL.pp 1-18. Available: https://doi.org/10.1080/10106049.2020.1797188

[14] Shaohui Mei ID , Xin Yuan , Jingyu Ji , Yifan Zhang , Shuai Wan and Qian Du.(November 2017). Hyperspectral Image Spatial Super-Resolution via 3D Full Convolutional Neural Network. MDPI Remote sensing.9(1139). Pp 1-22 Available: doi:10.3390/rs9111139

[15] Shunping Ji ,Chi Zhang, Anjian Xu , Yun Shi 3 and Yulin Duan. (January 2018).3D Convolutional Neural Networks for Crop Classification with Multi-Temporal Remote Sensing Images. MPDI.Remote Sens .10(75).pp.1-17.Available:http://doi:10.3390/rs10010075

[16] Venkata Shashank Konduri, Jitendra Kumar, William W. Hargrove, Forrest M. Hoffman, Auroop R. Ganguly.(December 2020).Mapping crops within the growing season across the United States.Remote Sensing of Environment. 25(1112048) pp.1-14.Available:https://doi.org/10.1016/j.rse.2020.112048

[17] Wei Hu, Yangyu Huang, Li Wei, Fan Zhang, and Hengchao Li.(July 2015). Deep Convolutional Neural Networks for Hyperspectral Image Classification. Journal of Sensors.2015(258619).pp.1-12.Available: http://dx.doi.org/10.1155/2015/258619

[18] Xin Zhao, Yi Liang, Alan J.X. Guo & Fei Zhu.(February 2020).Classification of small-scale hyperspectral images with multi-source deep transfer learning.Remote Sensing Letters.11(4).pp.303–312.Available:https://doi.org/10.1080/2150704X.2020.1714772.

[19] Yulin Yan ,Youngryel Ryu.(January 2021).Exploring Google Street View with deep learning for crop type mapping. ISPRS Journal of Photogrammetry and Remote Sensing,171.pp.278-296.Available:https://doi.org/10.1016/j.isprsjprs.2020.11.022

[20] Zewei Xua , Kaiyu Guanc, Nathan Caslera , Bin Pengc and Shaowen Wanga. (October 2018).A 3D convolutional neural network method for land cover classification using LiDAR and multi-temporal Landsat imagery.ISPRS Journal of Photogrammetry and Remote Sensing,144. pp.423-434.Available:https://doi.org/10.1016/j.isprsjprs.2018.08.005.

[21 Yanfei Zhong , Xin Hu, Chang Luo , Xinyu Wang , Ji Zhao , Liangpei Zhang.(December 2020).WHU-Hi: UAV-borne hyperspdectral with high spatial resolution (H2) benchmark datasets and classifier for precise crop identification based on deep convolutional neural network with CRF.Remote Sensing of Environment.250(112012).pp.1-18.Available:https://doi.org/10.1016/j.rse.2020.112012

[22] Vishal Srivastava & Bhaskar Biswas .(August 2019).Deep CNN feature fusion with manifold learning and regression for pixel classification in HSI images. Journal of Experimental & Theoretical Artificial Intelligence. 1362(3079).pp.1-20.Available: https://doi.org/10.1080/0952813X.2019.1647566

[23] Somenath Bera & Vimal K. 2019.Shrivastava Analysis of various optimizers on deep convolutional neural network model in the application of hyperspectral remote sensing image classification. International Journal of Remote Sensing. 1366(5901). Pp.2665-2683. Available: https://doi.org/10.1080/01431161.2019.1694725

[24] Zixian Ge , Guo Cao , Xuesong Li , and Peng Fu.(january-2020). Hyperspectral Image Classification Method Based on 2D–3D CNN and Multi branch Feature Fusion. IEEE Journal of selected topics in applied earth observations and remote sensing.13.pp.5776-5788.

URLS:

[1] Hyperspectral dataset (weebly.com)