Research Article

Hyperspectral Image Analysis using Principal Component Analysis and Siamese Network

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Abstract: The process of collecting information in hundreds of images having bands with different wavelengths using remotely sensed devices is called Hyperspectral Imaging Technology. So many methods are used for analysis of this hyperspectral information of which Classification is a popular one, which is the process of assigning label to each pixel. For classification of hyperspectral data, many supervised methods are proposed in literature with excellent performance, but the quality the classifier depends strongly on the number of training samples used to construct the model. Data Augmentation (DA) is a strategy that can increase the quantity of training data and effective to overcome the limited training samples problem. The hyperspectral data set suffers with curse of dimensionality with redundant information, influencing the classification accuracy. In this paper, a supervised model for hyperspectral data set is proposed, with dimensionality reduction using Principal Component Analysis and data augmentation using mixed pixels is applied to increase training samples and tested using Siamese network and finally classification is done using CNN.

Keywords: Principal Component Analysis, Convolution Neural Networks, Siamese Network, Image Classification.

1. Introduction

Hyperspectral imaging [1] is the process of collecting and processing of information from across the electromagnetic spectrum. It belongs to a class of techniques commonly referred as spectral imaging or spectral analysis. Human eye sees visible light in three bands, i.e. red, green and blue whereas spectral imaging divides the spectrum into many more bands. It covers more than hundred bands with tremendous spectral resolution which provides detailed information about each pixel. From that captured image dataset, we will get spatial information as well as spectral information. The aim of Hyperspectral image(HIS) classification is to assign a label to each pixel. In general HSI is represented using hyper cube. The problem that arises in classifying or analysing the high dimensional space is called curse of dimensionality. Hyperspectral dataset is one which suffers from curse of dimensionality, where the classification accuracy is degraded after an optimum point of increase in feature space. Figure 1 shows the performance of accuracy with increase in dimensionality or number of features. In this paper, Principal Component Analysis (PCA)[2], an unsupervised linear transformation technique which aims to find the directions of maximum variance in the data and projects it to a new space preserving maximum information.

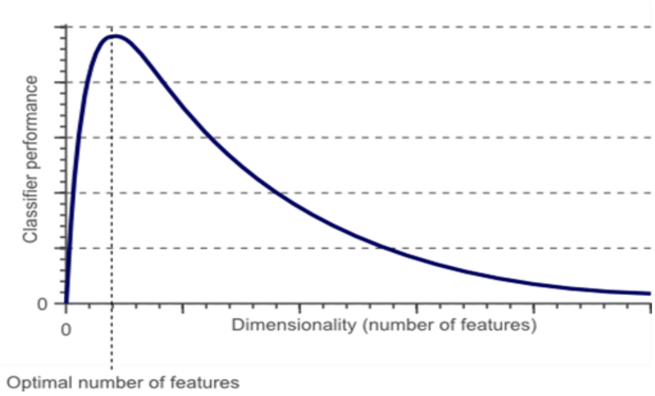

Figure 1: Performance of Classification vs Number of features

Another Dimensionality reduction called Linear Discriminate Analysis(LDA)[3] do not modelnon-linearity in the data andanother limitation of LDA is that the dimensionality of the embeddings is bounded by the number of classes present in the dataset. Other Non-linear methods such as kernel-PCA[4] suffer from prohibitive time complexity.Graph based algorithms such as Locally Linear Embedding (LLE)[5] and Laplacian Eigenmaps do not scale well with addition of new samples as they need to re-compute the Eigen decomposition to obtain new embeddings. To avoid all these problems, Principal Component analysis is best suited especially for Hyperspectral remote sensing images for dimensionality reduction. Another challenge for HSI classification is limited training samples. If the training samples are less, the model may go to over fitting. To avoid over fitting, require more number of training samples, so to increase training samples, mixed pixels technique is proposed in this paper. After generating new sample it will be tested with Siamese network and added to training samples if it satisfies criteria. After that classification technique CNN is applied. Theconcept of principal component analysis is explained elaborately in section2 and proposed methodologyis explained in section 3 and section 4 deals with result and discussion, followed by conclusion in section 5.

2. Principal Component Analysis

Dimensionality reduction is a very important task in hyperspectral image analysis as it helps to tackle the problem of redundant information which reduces the classification accuracy of the model. The dimensionality reduction can be done in two different ways, one is feature selection and second one feature extraction. In feature extraction methods, a new subset of features is created by selecting or combining existing information feature space, while in feature selection, analysis will be done on a subset of features which are selected from the original features. One of the best methods in feature extraction for dimensionality reduction is Principal Component Analysis (PCA). Linear feature based orthogonal transformation technique like PCA is used to find the correlation between spectral wavelength bands of HSI for intrinsic feature extraction. The steps involved in PCA are described below:

1. Centre the data [i.e. mean vector]

- First convert the HSI hypercube to data matrix. Let D be the data matrix of order FxS where (S=X.Y), where F representsthe number of bands in data set and S denotes number of pixels.
- The spectral vector of the pixel is denoted as X_n in the hypercube data matrix.

$X_n = [x_{n1}, \ x_{n2}, \ .. \ .. \ .. \ x_{n-1}, \ x_n]^T$ (1) Where n ε [1,S].

- Zero mean image I can be denoted as

$$I = [I_1, I_2, \ldots\ldots\ldots, I_n]$$

Where I_1 and I_2 …… I_n are images or bands (ınt wavelength

- Mean image vector M is as follows

$M = \frac{1}{S}\sum_{n=1}^{S} X_n$ (3)

- Mean-adjusted spectral vectors

$$I_n = X_n - M = [I_{n1}, I_{n2} \ldots\ldots \ I_{nF}]^T \quad (4$$

2: Covariance matrix denoted as C

$C = \frac{1}{S} I \, I^T$ (5)

3. Calculation of Eigen values:

- If covariance matrix is a diagonal matrix then the each diagonal element represents the each Eigen value.
- Let (E_1, E_2, E_3,......., E_F) be the Eigen values and (V_1, V_2,............,V_F) corresponding to Eigen vectors.

$$\begin{bmatrix} d_{11} & 0 & 0 & 0 & \ldots & 0 & 0 \\ 0 & d_{22} & 0 & 0 & \ldots & 0 & 0 \\ 0 & 0 & d_{33} & 0 & \ldots & 0 & 0 \\ 0 & 0 & 0 & d_{44} & \ldots & 0 & 0 \\ .. & .. & .. & .. & \ldots & .. & .. \\ .. & .. & .. & .. & \ldots & .. & .. \\ 0 & 0 & 0 & 0 & \ldots & .. & d_{nn} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ . \\ . \\ . \\ x_n \end{bmatrix} = \lambda \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ . \\ . \\ . \\ x_n \end{bmatrix} \quad (6)$$

The above matrix equation is used to calculate Eigen vectors, here λ is corresponding Eigenvalue.

4. Now, the data along the Eigen vectors among which K Eigen values which are selected in the descending order.

5. Let V be the matrix of all Eigen vectors, which is calculated with the help of covariance matrix. The equation is as follows

$C=VEV^T$ (7)

Here E is diagonal matrix containing Eigen values (E_1, E_2, E_3, ... E_F)

6.Then 'k' Eigen Vectors are chosen to form dimensional matrix W of size Fxk, where k is the number of dimensions in the new feature subspace with k≤F and often k<<F,

7. Finally projection matrix $Y = W^T I$(8)

where W is formed by the column-wise concatenation of the k Eigen vectors.

3. Proposed Method:

After applying PCA on the original hyperspectral image, only useful images are extracted. After that to increase training samples mixed pixels data augmentation technique is used. After creating it will be tested with Siamese network shown in figure2 , it can be applied for all classes and then classified using Convolution neural network.

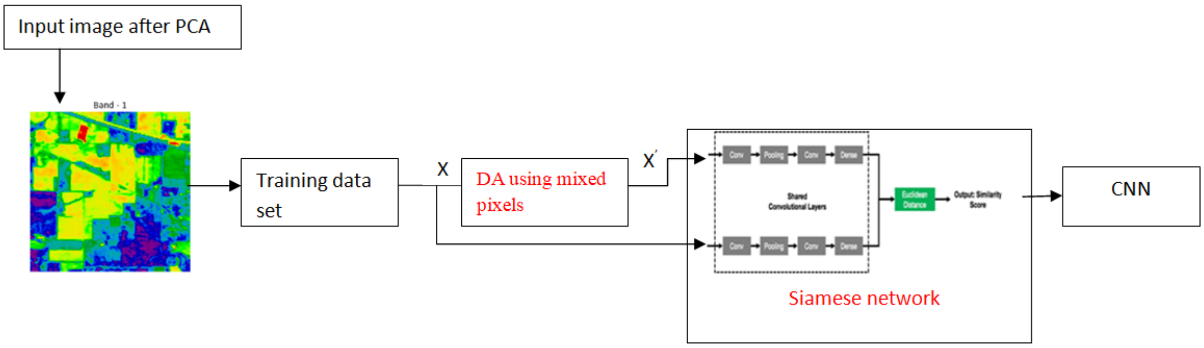

Figure 1: Proposed Architecture for classification of HSI with limited training samples

a. Data Augmentation:

To provide better performance, new data is generated by using mixed pixels technique. As we know that pixels on the image borders of image region are mixed pixels. So for each class by identifying 25% of signatures and are paired with remaining classes to create mixed pixels. For the given class, the abundance values are always above 56% to ensure the mixtures are a majority of the given class. A variety of mixing ratios are utilized to provide more training data. Let X_i be the original image of class i and X_i' be generated image using mixed pixels.

b.Siamese Network

Siamese network architecture is used to check if the two given images are similar or not. It was first introduced for facial recognition and since then it has gained a lot of success. In a Siamese network the two inputs X_i, $X_i'$are fed into two different networks which share their weights and have similar architecture. The input to Siamese network[6,7]are in pair called pixel-pair arethen encoded into feature vectors f_1 and f_2 after a series of convolution, average pooling and fully connected layers. We train the network using backpropagation such that the Euclidean distance of the feature vectors for two similar inputs having same labels tend to be less and the distance for dissimilar images tend to be more. This helps us to learn similarity between the images based on the distance between their feature vectors.Let X_i, $X_i'$are two inputs and $G_w(f)$ is the network.$f_1=(f_{11},f_{12},f_{13},f_{14}\ldots\ldots\ldots\ldots\ldots,f_{1n})$ and $f_2= (f_{21},f_{22},f_{23},f_{24}\ldots\ldots\ldots\ldots\ldots,f_{2n})$ are feature vectors obtained after convolution and pooling. The Euclidean distance after convolution is calculated using the below equation.

$$\text{Euclidean dist}(X_i, X_i') = \sqrt{\sum_{j=1}^{n} |x_{ij} - x'_{ij}|^2}$$

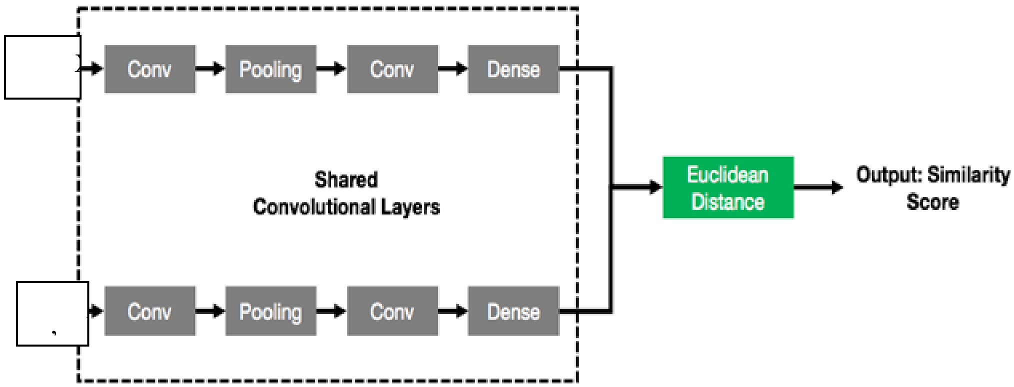

Figure 2: Basic architecture of Siamese Network

The loss function we use here to train our model is the maximum margincontrastive loss[14]. This loss function helps to classify a pair of images with thesame label as more similar than a pair with different labels. The equation for theloss function is as follows:

$$Y_{true} * D^2 + (1 - y_{true}) * \{\max(margin - D\ ,\ 0)\}^2 \quad (9)$$

Here, D is the Euclidean distance between the two feature vectors $f_1$and f_2.Also a margin greater than 0 is used to maintain a lower bound on the distancebetween a pair of inputs with different labels.

C. **Convolution neural network:**

It is one of the deep learning model, which is mainly used for classifying the images. The architecture of a Convolutional neural network (ConvNets or CNN) having three layers. They are convolution layer, pooling layer, fully connected layer. An image classification takes an image as input and processes it and classifies it under certain categories. Deep learning CNN models to train and test, each input image will pass it through a series of convolution layers with filters (Kernals), Pooling, fully connected layers (FC), and apply Softmax function to classify an object with probabilistic values between 0 and 1.

Basically, the CNN model to train and test each input image through the sequence of convolution layer→pooling layer→fully connected layer. Finally, apply the softmax activation function. Then it classifies an image with probabilistic values between 0 and 1.

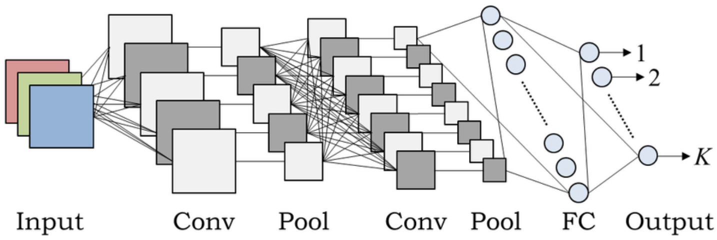

Figure 3: Basic Convolutional Neural Network

1. Convolution Layer : It is the first layer of CNN, used to extract features from an input image. It is a combination of Convolution and activation function(ReLu). Convolution maintains the relationship between pixels by extracted image features using small squares of input data. It is a mathematical operation that takes two inputs such as image matrix and a filter or kernel. Let I is the input image of dimensions NxN and f is the filter dimension fxf . Then the output dimension after performing convolution is represented as

$Z = I * f$ (10)

Dimensions of Z: ((N-F+1) , (N-F+1))

$$M = ReLu(Z) \quad (11)$$

2. Pooling Layer: It is second layer of CNN, used for reduce the number of parameters when the image is too large.It reduces the dimensionality of each object using subsampling or downsampling. There are three types of pooling techniques.

- Max Pooling : It selects maximum value from the rectified feature map.
- Average Pooling : It calculates the average value from rectified feature map.
- Sum Pooling : It calculates the sum value from rectified feature map

Most of the users are preferred Max pooling.

3. Fully Connected Layer: It is the last layer of CNN model. In this layer, the received data from pooling layer i.e generated flattened our matrix into single vector and feed it into a fully connected layer. The linear transformation is

$Z1= W^T.M + b$ (12)

Here M is input image , W is the weight vector and b is the bias value.

Output = softmax(Z1) (13)

4. Experimental results

The proposed methodology is performed on two data sets, Indian Pines [IP] and Pavia University [PU]. The data sets are taken from [], with 16 classes in IP and 9 classes in PU. The number of image bands in IP are 220, with 145 X 145 pixels in each band and the number of image bands in PU are 103, with 610 X 340 pixels in each band. The wavelength of bands in IP ranges from 400 to 2500 nm and the wavelength of bands in PU ranges from 430 to 860 nm. The dimensionality reduction of these two datasets is done using principal component analysis and the components are shown in figure. In PCA, we taken the first principal components / bands having cumulative variance grater than 95%, reducing the number of dimensions of PU data set to 8 and IP dataset to 10, presented in figure 4. The x-axis denotes number of components and y-axis denotes cumulative variance in the graph presented in figure 4 and the principle components is shown in figure 5. After-dimensionality reduction, the components are passed to Siamese network for similarity score. Table 1 shows the accuracy of proposed model compared with other supervised classification methods. Table 2 and Table 3 shows the statistics of training, validation and testing pixels used for the proposed model in each data set.

Table 1: Accuracy of classification

Classification Models	**Accuracy (IP)**	**Accuracy (PU)**
Support Vector Machine	91.8	92.2
Convolutional Neural Network	94.2	95.1
Recurrent Neural Network	96.1	96.9
Proposed model	98.4	98.2

Table 2. Statisticsof Training pixels, Validation pixels and Testing pixels for the Indian Pines DataSet.

No.	Class	Training	Validation	Testing
1	Alfalfa	18	4	24
2	Corn-notill	180	20	1228
3	Corn-mintill	180	20	630
4	Corn	94	23	120
5	Grass-pasture	180	20	283
6	Grass-trees	180	20	530
7	Grass-pasture-mowed	11	2	15
8	Hay-windrowed	180	20	278
9	Oats	8	2	10
10	Soybean-notill	180	20	772
11	Soybean-mintill	180	20	2255
12	Soybean-clean	180	20	393
13	Wheat	82	20	103
14	Woods	180	20	1065
15	Building-Grass-Trees-Drives	154	38	194
16	Stone-Steel-Towers	37	9	47
	Tota	2024	278	7947

Table 3. Statistics of Training pixels, Validation pixels and Testing pixels for the PaviaU DataSet.

No.	Class	Training	Validation	Testing
1	Asphalt	180	20	6431
2	Meadows	180	20	18,449
3	Gravel	180	20	1899
4	Trees	180	20	2864
5	Sheets	180	20	1145
6	Bare Soil	180	20	4829
7	Bitumen	180	20	1130
8	Bricks	180	20	3482
9	Shadows	180	20	747
	Total	1620	180	40,976

PU dataset	IP dataset

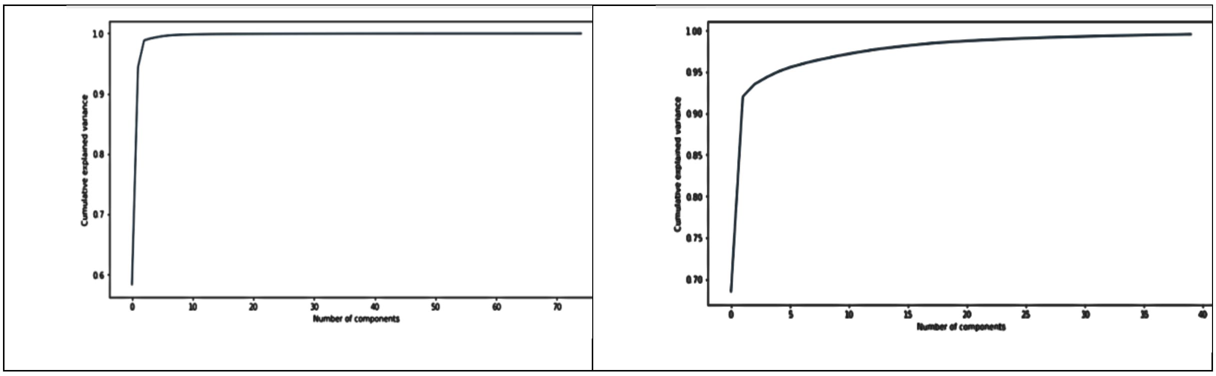

Figure 4: Variance of Components using PCA

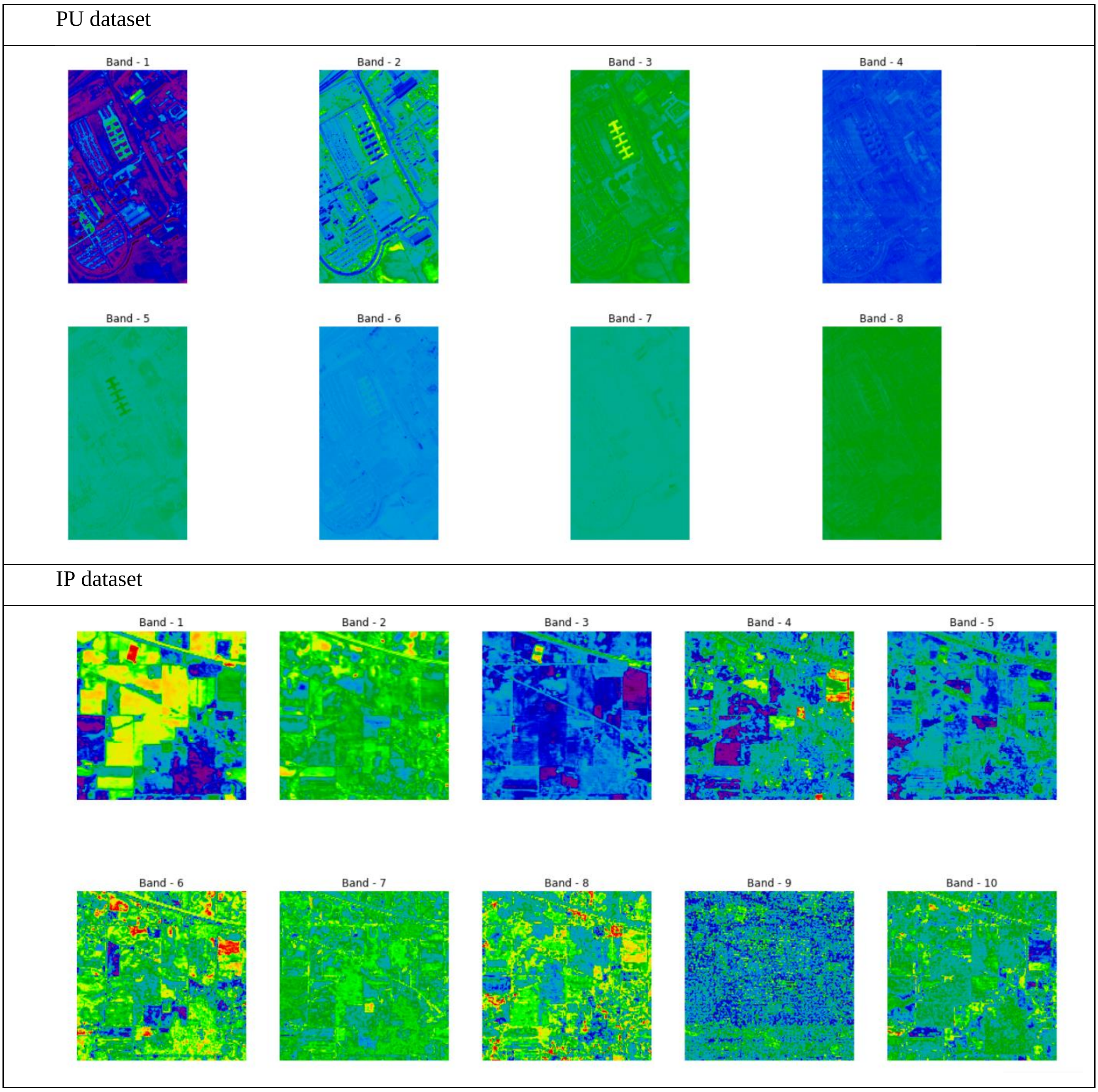

Figure 5: Bands selected using PCA

5. Conclusion:

The proposed model illustrates how a combined mixed pixels and Siamese network architecture can be used to build better models for Hyperspectral Image Classification task where the number of training samples are less. We use PCA for dimensionality reduction and further use mixed pixels and Siamese network for creating new training samples and then CNN is applied for classification.The experimental results show that the proposed model does better in classification of Hyperspectral Images compared to other machine learning models.

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