Hyperspectral Image Classification using Spectral LSTM Networks

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Abstract

The Classification of Hyperspectral images is a famous domain in the remote sensing community. Hyperspectral images constitute large number of bands that contain the captured reflectance spectra values. Most of the existing classification techniques are based on spectral-spatial frameworks and do not take advantage of the fact that the spectral information contained in the hyperspectral images are sequential in nature. The spectral dimensions of hyperspectral are already more significant, and adding the spatial data to it further leads to increase in dimensions. With the recent advances in deep learning, its use is ubiquitous in almost every other domain for big data analytics. The conventional machine learning algorithms cannot able to form deep neural connections as compared to deep learning models. So, in this paper, a novel framework is proposed, which is hybrid of Long Short-Term Memory Networks, a deep learning framework and Principal Component Analysis that give more significance to spectral dimensions of hyperspectral images. Principal Component Analysis is used to reduce the high dimensional image data, which is then passed to Long Short-Term Memory Networks, to classify the images. LSTM is a recurrent neural network which is predominantly performing better on sequential problems. Experiments are performed on standard dataset of Kennedy Space Center and Pavia University. The proposed framework efficiently classify the hyperspectral images and its effectiveness is shown by comparing it with existing state-of-the-art classifiers.

Keywords

Hyperspectral Images, LSTM, PCA, Classification.

1. Introduction

Hyperspectral Images (HSIs) are high dimensional images which are acquired by using satellite sensors. The most popular sensors are NASA's Airborne Visible / Infrared Imaging Spectrometer, Hyperion and ISRO's Bhuvan. These acquired images contain a ton of information which can be used for various useful purposes like mineral mapping, soil mapping, etc. Due to higher dimensions, the existing models are not able to classify the HSIs efficiently (Melgani et al., 2002).
Most of the existing classification models are based on the spectral-spatial frameworks (Yue et al., 2014, Chen et al., 2014, Wang et al. 2019, Zhou et al. 2018). The addition of spatial information to the spectral data increases the classification accuracy of prediction models as shown by various works. But they also add more dimensions to the hyperspectral images, which takes more processing time. So, many researchers tried to use multiple dimensionality reduction algorithms like Principal Component Analysis (PCA), Locality Preserving Projections (LPP) (Singh et al., 2018), etc. Out of which PCA is the most widely used in the field of hyperspectral classification.
With the advent of deep learning, its use is in every domain for data analytics. As HSIs are sequential images, many works used LSTMs for classification of HSI (Mou et al., 2017, Liu et al., 2017, Seydgar et al., 2019, Hang et al., 2019). These works also added spatial dimensions. The

data obtained after the PCA remains sequential as it preserves the global information of the original dataset.

1.1 Motivations of the Proposed work

1. Most of the existing state-of-the-art models are based on spectral-spatial frameworks. The added spatial features add more dimensions to hyperspectral images.
2. The current classification models do not take advantage of the sequential nature of hyperspectral images.

1.2 Contributions of the Proposed Work

1. Only spectral features are used to build a spectral based classification framework. These spectral features are further reduced with the help of Principal Component Analysis.
2. Long Short-Term Memory networks are used to take advantage of the sequential nature of the hyperspectral images.

2. Background of the Proposed Work

2.1 Principal Component Analysis

Principal Component Analysis is one of the most popular dimensionality reduction algorithms. As hyperspectral images have high dimensions, it is mostly used to reduce the high dimensional data for efficient processing. The PCA algorithm is based on eigenvalues, eigenvectors, and covariance matrix. The Principal Components are shown in Figure 1.

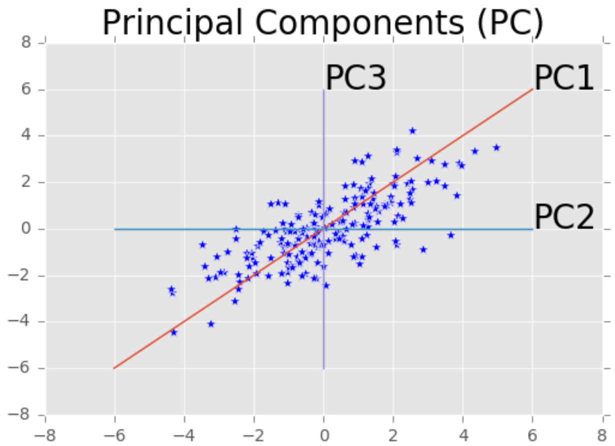


Figure 1: Principal Components

2.2 Long Short-Term Memory Networks

Long Short-Term Memory Networks (LSTM) is a type of recurrent neural network which overcomes the short comings of the previous built RNNs (Hochreiter et al., 1997). The structure of the LSTM is shown in Figure 2.
The forget gate remember only the important part of the information. It takes into account the input x_{it} and previous cell state C_{t-1} and outputs the degree of information which is to be remembered. f_t can be defined as:

$$f_t = \sigma(W_f . [H_{it-1}, x_{it}] + b_f) \tag{1}$$

where H_{it-1} is the output from the previous state.

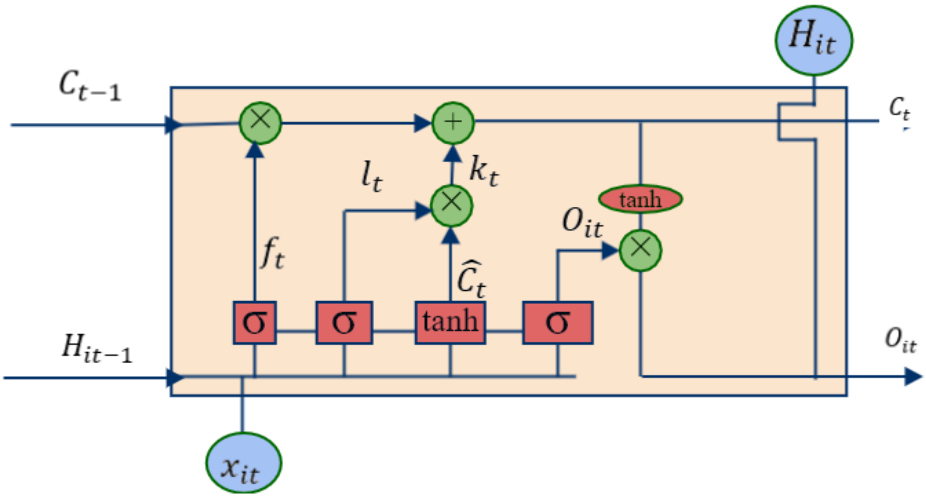


Figure 2: Structure of LSTM

Now, after this, it is important to determine the new information to store it in the cell which makes the new cell state. It is performed in two main steps:

1. A sigmoid layer also known as" input gate layer" determines which values will be selected for updation.

$$l_t = \sigma(W_l.[H_{it-1}, x_{it} + b_i]) \tag{2}$$

2. A tanh layer forms a vector of new candidates values $\hat{C}$ that is selected to add in further states.

$$\hat{C}_t = tanh(W_C[H_{it-1}, x_{it}] + b_C) \tag{3}$$

Now the new information should be added to old cell state C_{t-1} to form new cell state C_t by multiplying C_{t-1} with f_t and adding $l_t \times \hat{C}$:

$$C_t = f_t \circ C_{t-1} + l_t \circ \hat{C}_t \tag{4}$$

where $\circ$ is element wise multiplication (Hadamard product)
Finally, the output is achieved by the final sigmoid and tanh functions:

$$O_{it} = \sigma(W_{output}[h_{it-1}, x_{it}] + b_{output} \tag{5}$$

$$h_{it} = O_t \times tanh(C_t) \tag{6}$$

3. Proposed Framework

In this section, PCA-LSTM based framework is proposed, as shown in Figure 3. Firstly, the Hyperspectral images are given as input to PCA, which reduces the excess spectral dimensions. This framework is based on reduced spectral features. As most of the current work follows the spectral-spatial frameworks, the HSI dimensions are further increased by adding spatial features. The main aim of the PCA is to preserve the spatial information and maximize the variance in the resultant dataset. The PCA components are chosen in such a way that the resultant components explain the 100% variance of the original input dataset. Then, the reduced dataset is divided into training, validation, and testing data.

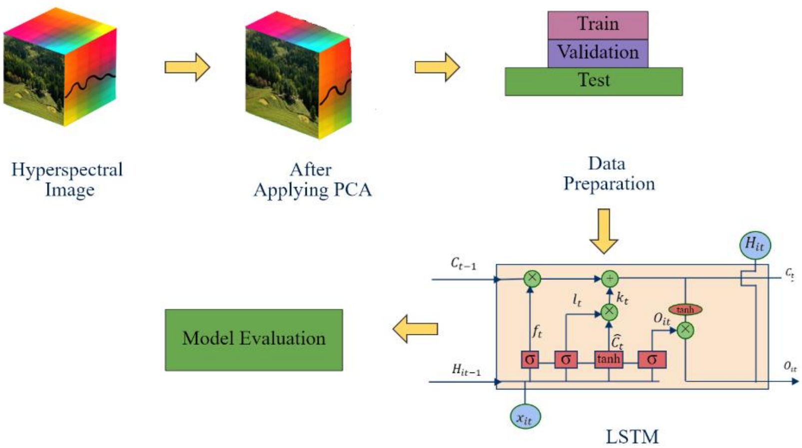


Figure 3: Proposed Framework

Afterwards, the training data is passed to LSTM, which performs better on sequential data for forming meaningful connections based on the sequence. LSTM remembers the essence of the information by remembering a part of essential sequences with the help of forget gate. Then, a trained classifier is obtained, which can classify the hyperspectral images. Afterwards, the testing data is passed to the trained classifier, which predicts the individual class of the input. In the end, the predicted classes are noted and compared with the ground truth to evaluate the performance of the model.

4. Experimental Results and Analysis

Experiments are performed on real hyperspectral images namely—Kennedy Space Center and Pavia University. The image dataset description is given below:

4.1 Kennedy Space Center Dataset

Kennedy Space Center (KSC) dataset, as shown in Figure 4, is captured by NASA's Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) sensor. It contains 224 bands having 10 nm width. This dataset is captured from an approximate altitude of 20km. That's why the resolution of the image is very fine. After performing atmospheric correction, 48 bands are removed due to noise. It contains a total of 13 classes and the total resolution of the corrected final image is 512× 614× 176.

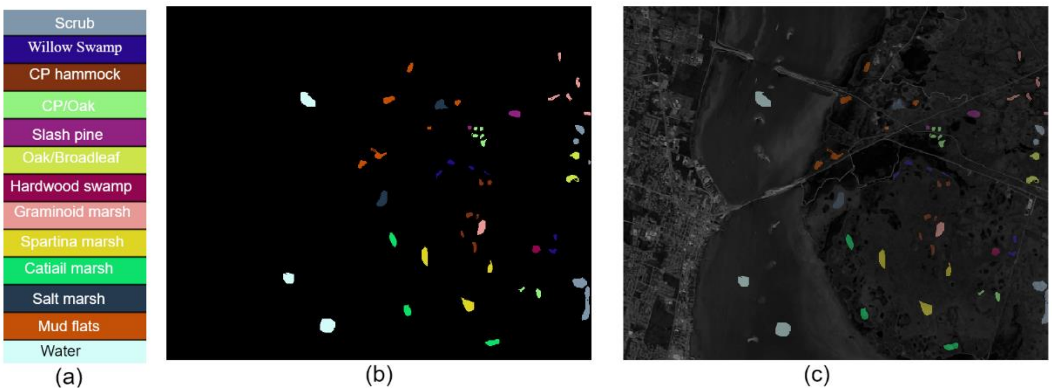
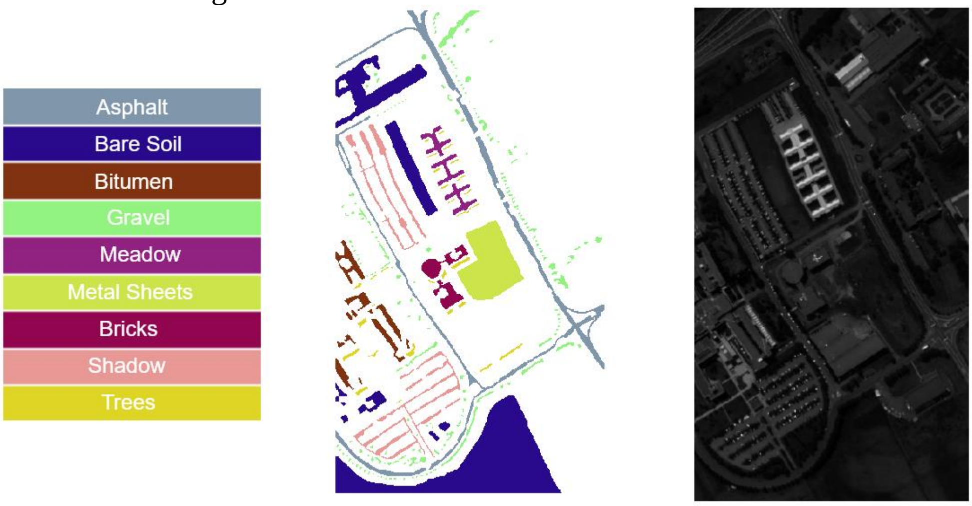


Figure 4: Description of KSC (a) Classes (b) Ground Truth (c) Ground Truth overlayed on spectral band 23

4.2 Pavia University Dataset

Reflective Optics System Imaging Spectrometer (ROSIS) acquired the hyperspectral image of Pavia University, Italy as shown in Figure 5. It is an airborne sensor having a band count of 115. It has a total of 9 classes. After atmospheric corrections, the bands are reduced to 103. Total resolution of corrected image is 610 × 610 × 103.

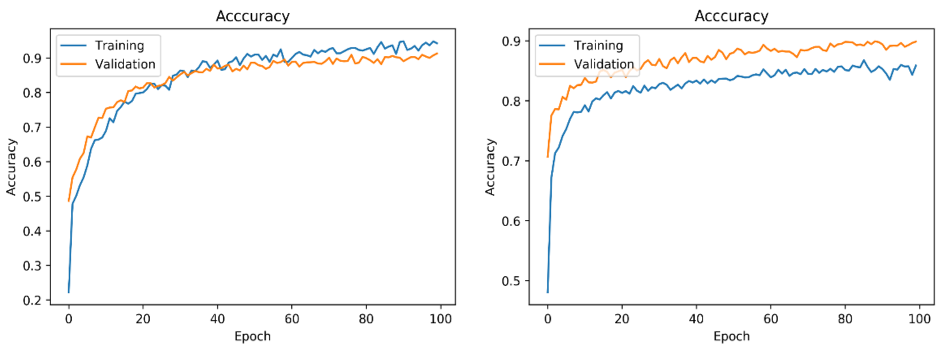


(a) (b) (c)

Figure 5: Description of KSC (a) Classes (b) Ground Truth (c) spectral band 23

4.3 Experimental Results

Experiments are performed on the platform provided by Google named Colaboratory having a powerful GPU. Firstly, the HSIs are passed through PCA to decrease the dimensions. The dimensions are kept in such a way that they can explain 100% of the original dataset. Afterwards, the lower dimension dataset is divided into training, validation and testing. We used 5% training data which is validated by 5% data to avoid overfitting and testing is performed on 100% of the data. The training and validation curves are shown in Figure 6, which shows a near-perfect fit.



(a) (b)

Figure 6: Training and Validation curves of LSTM in case of (a) KSC (b) Pavia

The training and validation data are passed to LSTMs having 'Adam' optimizer. The LSTM can easily form a meaningful connection in case of sequential data. After the training process, a trained leaner is obtained, which can classify the HSI. To this learner, the remaining 100% data is passed for prediction. The predicted values are noted and are compared with ground truth classes for the evaluation of the built proposed framework.

Table 1- Comparison of the Proposed framework with State-of-the-art models on the basis of Overall Accuracy.

Sr. No	Dataset	Proposed (%)	SAE (%)	EN (%)	KNN (%)	SVM (%)
1	KSC	90.00	65.11	66.24	67.70	78.14
2	Pavia	90.00	62.11	59.73	61.19	63.89

The proposed framework is compared with state-of-the-art classification models named Stacked Autoencoders-Deep Networks (SAE) (Singh et al., 2019), Ensemble-Boosted (EN), K-Nearest Neighbor (KNN) and Support Vector Machines (SVM). The proposed framework outperformed all the models on the basis of overall accuracy (OA), as shown in Table 1. The individual class Precision, Recall and F1-score are shown in Table 2. The proposed framework is based on LSTM which can remember important information with the help of forget gate which provides an additional capability to the proposed framework, which is not present in any other existing models. Classification maps are shown in Figures 7 and 8.

Table 2- Individual Class Precision, Recall and F1-Score of the Proposed Framework.

	KSC			Pavia University		
Classes	Precision	Recall	f1-score	Precision	Recall	f1-score
1	0.96	0.95	0.95	0.90	0.90	0.90
2	0.86	0.90	0.88	0.94	0.96	0.95
3	0.89	0.95	0.92	0.71	0.73	0.72
4	0.76	0.63	0.69	0.87	0.89	0.88
5	0.61	0.75	0.67	0.99	0.99	0.99
6	0.72	0.63	0.68	0.91	0.83	0.87
7	0.76	0.90	0.82	0.81	0.70	0.75
8	0.94	0.90	0.92	0.80	0.80	0.80
9	0.95	0.97	0.96	0.98	1.00	0.99
10	0.96	0.96	0.96	--	--	--
11	0.99	0.99	0.99	--	--	--
12	0.92	0.95	0.93	--	--	--
13	1.00	0.98	0.99	--	--	--
	Overall Accuracy		90%	Overall Accuracy		90%

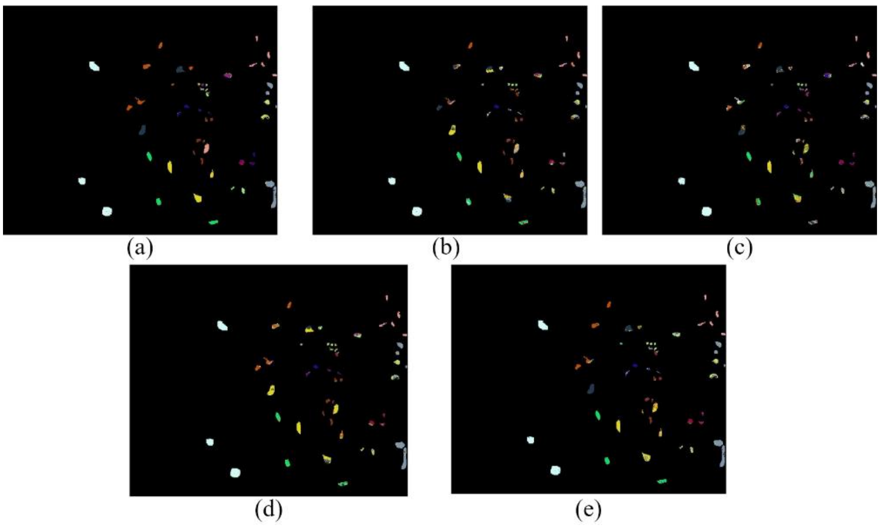


Figure 7: Classification map (KSC) of the (a) Proposed Framework (b) SAE (c) EN (d) KNN (e) SVM

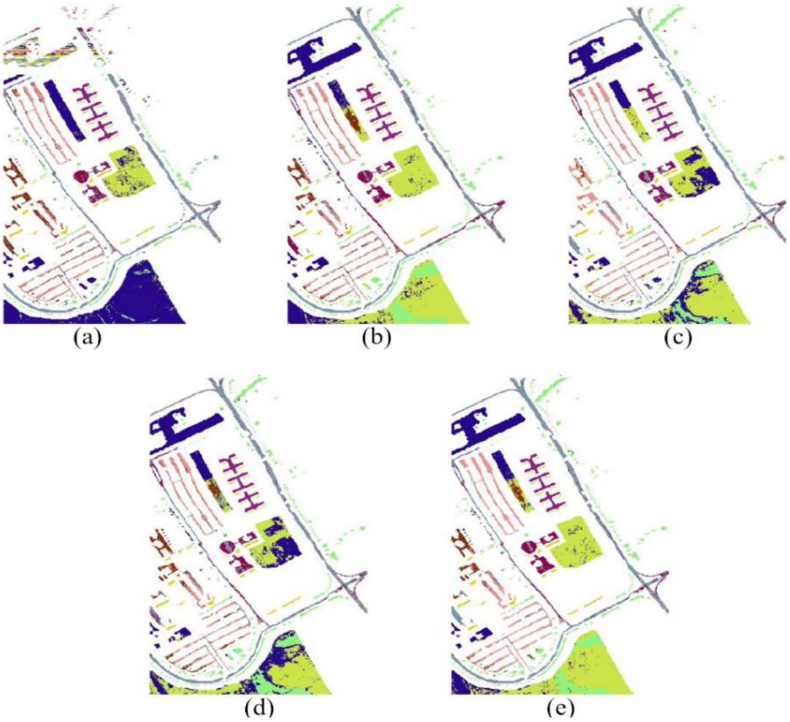


Figure 8: Classification map (Pavia) of the (a) Proposed Framework (b) SAE (c) EN (d) KNN (e) SVM

5. Conclusions

In this work, a PCA-LSTM based hyperspectral classification framework is proposed. PCA is one of the most efficient dimensionality reduction algorithms, which is used to preserve global information. The reduced dataset is passed to LSTM, a deep learning framework which is mostly used for sequential problems. It quickly formed meaningful neural connection with only 5% training. The proposed framework outperformed the existing models. It improves the overall accuracy by 138.23% and 150.68% in case of KSC and Pavia University dataset respectively.

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