Sparse Deep Learning & Hyper Spectral Image Classification

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Abstract: Hyperspectral imaging plays an important role in remote sensing, providing rich spectral information for land cover classification and environmental monitoring. Nevertheless, the complex nature of hyperspectral data with its high-dimensional characteristics poses substantial computational hurdles. In this research, we introduce an innovative solution to tackle this problem, involving the creation of a sparse deep learning model for hyperspectral image classification. The research focuses on the Indian Pines and Pavia University datasets, two widely used hyperspectral datasets with diverse land cover classes. This research explores how using sparse deep learning models can help with the difficulties of classifying hyperspectral images. The research thoroughly examines experimental results from the Indian Pines and Pavia University datasets. The main goal is to assess how well sparse deep learning techniques perform in classifying hyperspectral images. By introducing a new approach, the proposed sparse deep learning model achieves impressive results, with 91% accuracy on the Indian Pines dataset and 89% accuracy on the Pavia University dataset. This model has the potential to provide accurate and efficient analysis of hyperspectral images for remote sensing applications.

Keywords: *Sparse Representation, Deep Learning, Long Short-Term Memory, Hyperspectral Image Classification, Recurrent Neural Network*

1. Introduction

A Hyperspectral Image (HSI) is an image cube with a high dimensionality, where the pixel intensities for each band in the HSI, which has large dimensions, are stored [1]. Using a variety of contiguous spectral bands, hyperspectral imaging represents remote sensing technology that records electromagnetic radiation dispersed or emitted from a scene. Hyperspectral data contains hundreds of spectral bands, as opposed to the three bands used by conventional RGB imaging. Each band represents a specific range of wavelengths, giving each pixel in the picture a thorough spectral description [2].

HSI classification refers to the procedure of precisely forecasting the diverse pixel values linked to the different classes within a remotely sensed hyperspectral image (HSI). The rich information provided by a hyperspectral picture offers considerable benefits to identifying objects and classification in a variety of disciplines, such as agriculture, astronomy, biomedical imaging [3], etc., In addition to locating specific soil patches, HSIs can distinguish between the various soil minerals. This level of specificity has several uses, including astronomy for the study of celestial bodies and agriculture, where it helps with accurate farming. Knowing that HSI comprise both spectral and spatial information is a significant feature [4].

The installation of imaging spectrometers at various locations is essential for capturing hyperspectral images. In order to get electromagnetic wave pictures spanning the near-infrared, visible, ultraviolet, and mid-infrared spectra, imaging spectroscopy was developed in the 1980s [5]. Because imaging spectrometers may collect data in several closely spaced and extremely tiny bands, in this particular wavelength range, each pixel has the capacity to capture the whole spectrum of either reflected or emitted light [6]. Consequently, the excellent spectral accuracy, numerous spectral bands, and availability of data that define hyperspectral pictures, there are several techniques for processing hyperspectral remote sensing pictures, but the ones that are most frequently used include transformation, image correction, dimensionality reduction, noise mitigation, and classification [7].

Deep learning, specifically neural networks, has revolutionized various domains of machine learning by automatically learning hierarchical representations from data. Due to the intrinsic sparsity of the data, conventional deep learning techniques might not be completely appropriate for the hyperspectral domain [8]. The classification of HSI may not be considerably impacted by most spectral bands, which might result in less-than-ideal performance and inefficient computation [9]. In light of these challenges, the primary objective of this study is to integrate a sparse deep learning model into the process of classifying hyperspectral images. We want to improve the precision, effectiveness, and interpretability of hyperspectral picture classification by using the abilities of sparse auto encoders, dropout, and related approaches. In this research, we want to provide a new perspective on how sparse representations might improve the performance of hyperspectral analysis, bridging the gap between the complexity of hyperspectral data and the strengths currently available deep learning architecture.

1.1 Hyperspectral Image Challenges

There are several imaging bands in hyperspectral images, which improve object resolution, especially through higher spectral resolution [10]. However, classification of hyperspectral images is severely restricted by the intrinsic

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high dimensionality of hyperspectral data and the spectral similarity of mixed pixels [11]. As noted in several research the below challenges cover a range of problems that require solutions.

1. ***High Dimensionality:*** Hundreds of spectral bands are comprised in Hyperspectral data, resulting in a high-dimensional dataset. Managing and interpreting this data is complex [12].
2. ***Missing Labeled Samples:*** While collecting hyperspectral image data is relatively easy, obtaining accurate labels for the images is extremely challenging, leading to a scarcity of labeled samples for classification [13].
3. ***Image Quality*:** During hyperspectral data acquisition, factors like noise and background interference may compromise data quality, directly impacting the accuracy of image classification [14].

2. Related Work

The primary objective of HSI classification is to accurately assign a pixel, based on multispectral data, to one of several predefined categories [15]. However, achieving this goal presents significant challenges due to the limited number of training samples and the intricate spectral patterns associated with each pixel. Numerous classifiers have been proposed for HSI classification such as random field-based methods, artificial neural networks, Support vector machines [16]. In addition to these, deep learning-based algorithms have been developed, which, while computationally intensive, have shown impressive results in hyperspectral classification [17]. Deep learning techniques have significantly improved hyperspectral classification outcomes, albeit at the cost of substantial computational resources. Convolutional neural networks (CNNs) are commonly employed for the classification of hyperspectral images (HSIs). Many research efforts focus on the extraction of both spectral and spatial features using cascades of networks [18]. For example, one research [19] extracted the spatial and spectral features, using two consecutive ResNets, while another combines CNN and LSTM models for the extraction of spatial and spectral features, respectively [20].

The processing of hyperspectral images (HSIs) has seen the emergence of the Sparse Representation (SR) methodology as a very successful method. It uses the LMM mathematical framework to handle the classification problem in HSIs [21]. Super-Resolution (SR) is widely embraced in hyperspectral image (HSI) processing due to its robust theoretical foundation and its proven efficacy in various domains, such as signal processing and machine vision applications [22]. Each pixel in an image captured with HSI may be seen as a vector of spectral reflectance values spanning different wavelengths. The mathematical formula for these vectors is x_i ∈ ℝ^n, where 'n' is the number of spectral bands. Finding a sparse representation of these vectors—one in which most of the components in x_i are 0 or almost zero—is the objective [23].

2.1 Sparse Deep Learning

Sparse deep learning techniques offer promising solutions to address the above. Sparse deep learning leverages the inherent sparsity present in hyperspectral data and can significantly benefit hyperspectral image classification in the following ways:

1. ***Efficient Feature Representation*:** Sparse deep learning models can automatically discover and represent relevant features from hyperspectral data, effectively reducing dimensionality and computational demands. Sparse representations allow the network to focus on essential spectral bands, resulting in more efficient processing [24].
2. ***Enhanced Classification Accuracy:*** By exploiting the sparsity of hyperspectral data, sparse deep learning models can potentially improve classification accuracy, especially in scenarios where traditional methods struggle to discern subtle spectral variations.
3. ***Robustness to Noise:*** Sparse representations can help mitigate the effects of noise and outliers, making sparse deep learning models more robust in noisy hyperspectral environments [25].

The concept of sparse neural networks has gained traction in recent years, particularly in the context of high-dimensional data analysis. Pertinent research studies have worked into the realm of sparse neural networks and their diverse applications across multiple domains, encompassing the field of hyperspectral image classification.

3. Methodology

The methodology of our work is briefly explained in this section. Following flowchart of the proposed work which has been followed for sparse deep learning and Hyperspectral image classification.

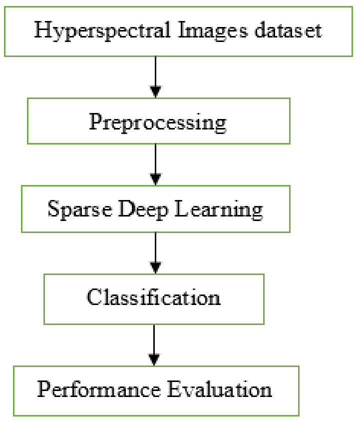


Figure.1. Flowchart of proposed method

3.1 Hyperspectral Images Dataset

In this research, we made use of two established hyperspectral datasets: the Indian Pines dataset and the Pavia University dataset. These datasets are highly regarded and commonly utilized in the realm of remote sensing and hyperspectral image analysis, due to their diverse spectral properties and clearly defined land cover classes [26].

i. ***The Indian Pines dataset:*** The data was acquired using an Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) sensor, covering an agricultural area located in Indiana, USA. It comprises 145x145 pixels, each with a spectral dimension of 224 bands. The dataset encompasses 16 distinct land cover classes, ranging from various crops to urban areas and natural terrains.

ii. ***Pavia University Dataset:*** This dataset, gathered over Pavia, Italy, was captured utilizing Reflective Optics System Imaging Spectrometer (ROSIS) sensors. It comprises 610x340 pixels and contains data from 103 spectral bands. The dataset encompasses nine distinct land cover classes, spanning urban, agricultural, and natural environments.

3.2 Preprocessing

i. ***Data Standardization:*** Prior to model training, standardization was performed on the hyperspectral data. As an integral component of the pre-processing phase, data underwent standardization, involving the deduction of its mean value and subsequent scaling for achieving unit variance. Standardization is crucial to ensure that spectral bands are on a consistent scale and exhibit comparable variance, facilitating the training of deep learning models [27].

ii. ***Conversion to Sparse Matrices:*** Hyperspectral data inherently contain a high degree of redundancy and irrelevance across spectral bands. To harness the benefits of sparse deep learning, we converted the standardized hyperspectral data into sparse matrices. This conversion reduced memory consumption and computational overhead while preserving essential spectral information.

3.3 Sparse Deep Learning

Sparse representation is used to address the inherent dimensionality and computational complexity challenges in hyperspectral data. By focusing on pertinent spectral bands and eliminating redundant information, sparse representations enhance model efficiency and its ability to discern discriminative spectral features [28].

The selection of LSTM as the core architectural component stems from its ability to model temporal dependencies within sequential data, which aligns with the sequential nature of hyperspectral bands over time. LSTM offers a competitive advantage for hyperspectral sequences [29].

Our proposed sparse deep learning model leverages Long Short-Term Memory (LSTM) networks, a type of recurrent neural network (RNN) architecture well-suited for sequential data analysis. The model architecture is detailed as follows:

i. ***Input Layer:*** The input layer accommodates the sparse representations of hyperspectral data. It is designed to accept the sparse matrices obtained during preprocessing.

ii. ***LSTM Layer:*** The LSTM layer includes a variable count of LSTM units, enabling the model to grasp temporal relationships and patterns within hyperspectral data. The utilization of LSTM units is motivated by their capacity to model sequential and time-series information, which aligns with the sequential nature of hyperspectral bands.

iii. ***Dropout Layer****:* We've included a dropout layer with a predetermined dropout rate to reduce the risk of overfitting. A portion of neurons are randomly deactivated during training as part of this regularization technique, which eventually improves the model's classification.

iv. ***Dense Layer:*** To capture intricate relationships and features within the hyperspectral data, a dense layer is added, which utilizes the Rectified Linear Unit (ReLU) activation function.

v. ***Output Layer:*** The output layer utilizes the softmax activation function, which is responsible for producing class probabilities used in hyperspectral image classification. Each output node corresponds to a distinct land cover class.

Table.1. Hyper Parameters used in the model and its values

Hyper Parameters	**Indian Pines**	**Pavia University**
Number of LSTM layers	2	2
Activation Function	ReLU, Softmax	ReLU, Softmax
Optimizer	Adam	Adam
Epochs	50	20
Loss Function	Categorical Cross-Entropy	Categorical Cross-Entropy
Learning Rate	0.001	0.001
Batch Size	64	64

3.4 Classification

The trained sparse deep learning model is applied to the preprocessed hyperspectral data to obtain class predictions. For each pixel, the model output a probability distribution across the available land cover classes. Assigning each pixel in the hyperspectral picture to a particular land cover class or group is known as hyperspectral classification. Once all pixels have been assigned class labels, a classification map is created, where each pixel's color or value corresponds to its assigned land cover class.

4. Results and Discussion

In our research, we thoroughly evaluated the proposed sparse deep learning model utilizing hyperspectral datasets from Indian Pines and Pavia University and rigorously evaluated its performance.

4.1 Indian Pines

When used on the Indian Pines dataset, the sparse deep learning model achieved an accuracy rate of 91%. This high overall accuracy indicates the model's ability to classify land cover categories effectively.

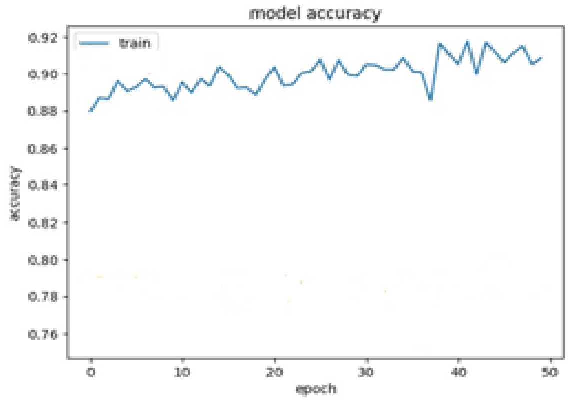


Figure.2. Training accuracy graph for Indian Pines dataset

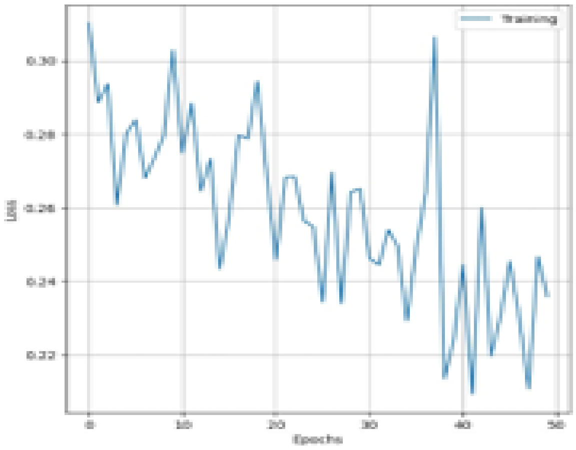


Figure.3. Training loss graph for Indian Pines dataset

To present the classification performance comprehensively, we provide the cassification report below:

Classification Report:

	precision	recall	f1-score	support
Class 0	0.94	0.92	0.93	10776
Class 1	0.95	0.91	0.93	46
Class 2	0.84	0.94	0.88	1428
Class 3	0.77	0.98	0.86	830
Class 4	0.93	0.87	0.90	237
Class 5	0.91	0.93	0.92	483
Class 6	0.95	0.96	0.96	730
Class 7	0.96	0.93	0.95	28
Class 8	0.97	0.97	0.97	478
Class 9	1.00	0.85	0.92	20
Class 10	0.89	0.87	0.88	972
Class 11	0.93	0.90	0.92	2455
Class 12	0.96	0.91	0.93	593
Class 13	0.98	0.97	0.98	205
Class 14	0.78	0.73	0.75	1265
Class 15	0.85	0.85	0.85	386
Class 16	0.89	0.99	0.94	93
accuracy			0.91	21025
macro avg	0.91	0.91	0.91	21025
weighted avg	0.91	0.91	0.91	21025

Figure.4. Classification report for Indian Pines dataset

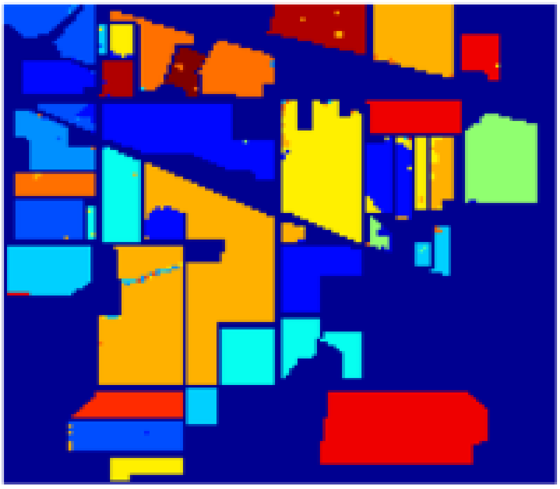


Figure.5. Obtained Classification Map for Indian Pines

4.2 Pavia University

On the Pavia University dataset, the model showed accuracy of 89%. This demonstrates the model's robustness in handling diverse land cover types.

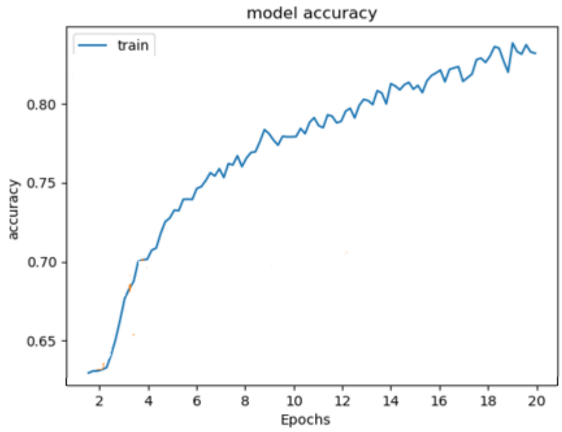


Figure.6. Training accuracy graph for Pavia University data

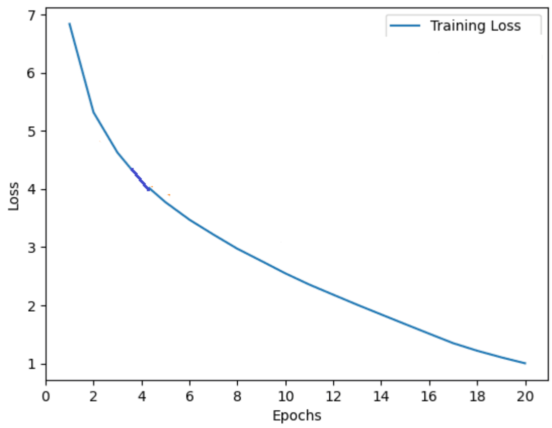
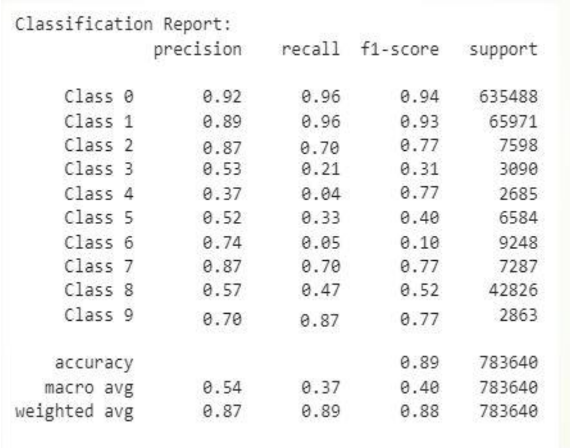


Figure.7. Training loss graph for Pavia University dataset

To present the classification performance comprehensively, we provide the cassification report below:



Classification Report:

	precision	recall	f1-score	support
Class 0	0.92	0.96	0.94	635488
Class 1	0.89	0.96	0.93	65971
Class 2	0.87	0.70	0.77	7598
Class 3	0.53	0.21	0.31	3090
Class 4	0.37	0.04	0.77	2685
Class 5	0.52	0.33	0.40	6584
Class 6	0.74	0.05	0.10	9248
Class 7	0.87	0.70	0.77	7287
Class 8	0.57	0.47	0.52	42826
Class 9	0.70	0.87	0.77	2863
accuracy			0.89	783640
macro avg	0.54	0.37	0.40	783640
weighted avg	0.87	0.89	0.88	783640

Figure.8. Classification report for Pavia University dataset

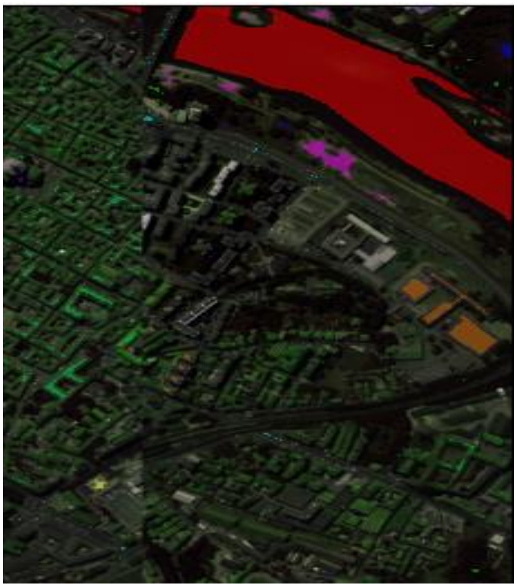


Figure.9. Obtained Classification Map for Pavia University

The results of both the datasets are shown in the table below:

Table.2. Obtained Training and Testing accuracies for both datasets.

Results	**Indian Pines**	**Pavia University**
No. of Epochs	50	20
Training Accuracy	91%	89%
Training Loss	0.26	0.26
Testing Accuracy	88%	84%
Testing Loss	0.33	0.41

5. Conclusion

In this paper, our proposed methodology encompasses a series of meticulous data preprocessing steps, the construction of an LSTM-based sparse deep learning model, and the implementation of regularization techniques and optimization strategies. This approach is designed to enhance classification accuracy, effectively manage high-dimensional hyperspectral data, and ultimately advance the capabilities of hyperspectral image analysis in remote sensing applications.

The experimental results, drawn from two benchmark datasets and comparative studies, demonstrate the better results of the Sparse Representation based LSTM classification method over traditional technique and even standalone LSTM architectures. Our proposed model provides a better result having 91% accuracy for Indian pines dataset and 89% accuracy for Pavia university dataset.

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