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Review Article

Hyperspectral Image Classification using Deep Learning Techniques: A Review

Syeda Sara Samreen[1], Hakeem Aejaz Aslam[2]

[1, 2] *Department of Electronics and Communication, Osmania University, Telangana, India.*

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Abstract *- Hyperspectral image classification is a salient topic of research in the domain of remote sensing. The major problems faced during hyperspectral image classification are the curse of dimensionality and the availability of limited samples during training. It was originally developed for mining and geology purposes to identify hidden minerals. Hyperspectral Imaging has various applications in geosciences, agriculture, astrology, and surveillance. The advancement in computing technology has led to the development of significant deep-learning techniques that play an important role in successfully classifying remotely sensed data. This paper reviews the various deep-learning methods used for hyperspectral image classification. Then the research gaps and methodology for every paper have been highlighted. This paper aims to benefit and support other researchers in further research in this field.*

Keywords *- Convolutional Neural Network, Deep Belief Network, Generative Adversarial Network, Recurrent Neural Network, Remote Sensing.*

1. Introduction

Hyperspectral Imaging is popular for identifying the earth's objects on its surface. It takes and processes information from the electromagnetic spectrum. Hyperspectral imaging mainly aims to take the spectrum of each pixel of the image or scene to identify objects, find materials and detect processes. The normal human eye sees colours of visible light in three bands: red, green, and blue. However, hyperspectral imaging can divide the spectrum into more bands and extend beyond the visible spectrum. Every object has its spectral signature, the same as human fingerprints. It is unique to every object. These fingerprints help in the identification of the materials in the scanned object.

Deep learning techniques are more useful in representing complex features and extracting feature information than other machine learning techniques. Deep learning classification techniques give effective results since the learning mechanism is automatic. The main motive of this literature review is to focus light on the deep learning models and their implementation.

2. Abbreviations

HSI	Hyperspectral Images
CNN	Convolutional Neural Network
RNN	Recurrent Neural Network
CRNN	Convolutional Recurrent Neural Network
RBF	Radial Basis Function
SVM	Support Vector Machine
MMSC	Multi Manifold Spectral Clustering
BP	Bayesian Prediction
DBN	Deep Belief Network
TFE	Texture Feature Enhancement
MNF	Maximum Noise Fraction
CAE	Contractive Auto Encoder
DCGAN	Deep Convolutional Generative Adversarial network

3. Literature Review

The authors in the paper [1] have represented data normalization and CNN as an approach for remote sensing HSI. Firstly, data normalization is done by reducing the scalar values and reserving total information. Probabilistic principal component analysis and Gabor filtering extract spectral and spatial information. This information is then unified to form features, and classification is performed using simple CNN. A comparative study is carried out with different methods. It is observed that the proposed method outperforms the state-of-art-methods.

As per the paper [2], the proposed method does not rely on pre-processing and post-processing and extracts combined features. It brings the HSI cube together. Convolution of input data and the 3D kernel is performed, and its result is run through activation layers. Then, SoftMax loss is used as the loss function to train the classifier. The 3D CNN model performs well and exploits spectral and spatial features. It is lighter, faces less than fitting, and trains easier. The results reveal that the proposed method achieves an overall accuracy of 99.07% compared to 2D CNN, whose accuracy is 95.97%

The authors in paper [3] have proposed an RNN network for the first time. This method analyses hyperspectral pixels in sequential data and uses network reasoning to determine information categories. The proposed RNN method uses a parametric rectified activation function to analyze hyperspectral image sequential data. To reduce the number of parameters in the recurrent layer, the authors have used modified gated recurrent units with PRetanh for hidden representation. The results show higher accuracy than SVM-RBF and CNN and consider the sequential data structure of the hyperspectral pixel. It also achieves higher learning rates. Compared with RBF-SVM and CNN, the suggested method improves the overall accuracy by 10.34% and 8.34%, respectively.

In paper [4], the authors have considered RNNs since they are better for modelling sequence dependency. CRNN is also used along with RNN. The convolutional layers are used before recurrent layers to extract the local features from the input sequence. CRNNs consist of several convolutional layers for HSI classification. The results reveal that combining both convolutional and recurrent layers makes the CRNN model able to extract more feature representation and outperforms the other state-of-art methods. A run time of 158 minutes is achieved, which is slower than just CNN used alone, which is 15 minutes.

In the paper [5], the authors have explained a deep model called deep belief networks to overcome the problem of many labelled training samples. It allows unsupervised pretraining and a supervised fine-tuning method over labelled and unlabeled samples. The method introduces diversity promotion before the pretraining and fine-tuning procedures of DBN. It improves the classification and representation of HSI. The proposed method can be implemented using recursive greedy and BP learning frameworks. The experiments reveal that diversified DBNs bring better results than other HSI classification methods.

In another paper [6], the authors developed a hyperspectral classification method based on DBN and texture feature enhancements using band grouping, selection, and guided filtering. The texture features of the data are improved. After TFE, DBN is applied to the reconstructed data for feature extraction and classification. The results show that the proposed method outperforms most of the classification algorithms. It plays an important role in improving classification accuracy. The algorithms with TFE excel over those without TFE. A classification accuracy of 94.58% is achieved.

Authors in [7] have undertaken a parallel layers method of a Gaussian Bernoulli-restricted Boltzmann machine. It is used to extract high-level features and also non-linear features. It is then used with a logistic regression classifier. The results reveal the suggested method gives better performance than other classification methods.

In the paper [8], the authors have suggested a method to overcome the pre-treatment fuss, simplifying feature extraction and having large data processing difficulty. The method is based on deep learning. It combines maximum noise fraction (MNF) with a multilayer autoencoder, which reduces the high spectral dimensionality of data. SoftMax logistic regression function is used for extracting high-level features. A comparison is performed between traditional linear SVM and the method proposed. It is observed that a classification accuracy of 90.54% is obtained using the suggested method, whereas a classification accuracy of 79.22%is obtained for linear SVM.SVM performs slower by taking 32.5 seconds to process data, and the proposed method takes 4.3 seconds.

The authors in the paper [9] have considered a method that is a CAE-based MMSC algorithm. It uses general multifold clustering. However, it utilizes contractive autoencoders for tangent space estimation. The proposed method envelopes only single-layer CAE. The experiments reveal that the proposed algorithm outperforms spectral clustering, the local weighted PCA, and the MMSC with local PCA and the basic autoencoder. An overall accuracy of 89.3% is obtained for the algorithm proposed.

In the paper [10], the authors have introduced deep convolutional generative adversarial networks (DCGAN), showing that it is a strong contender for unsupervised learning. During training, the deep convolutional adversarial pair grasps a ranking of representations, including parts of objects and different scenes in both the generator and discriminator. The filters obtained by generative adversarial networks and other learned features show their uses as general image portrayals for supervised learning.

The authors in the paper [11] have considered training a customized GAN using a semi-supervised classification algorithm. The framework is based on 1D GAN. It allows spectral features to be extracted automatically for classification. The generator generates hyperspectral samples which resemble the real data, and the discriminator has features that use only a small number of samples to classify hyperspectral data. The results show that the proposed method outperforms several conventional and state-of-the-art classifiers.

Table 1. Research Gap and Methodology Table

Paper ID	DL Methodology	Research Gaps
1	Spectral-Spatial based	The run time can be reduced, and the proposed method can be applied to another dataset
2	Spectral-Spatial based	Fails to make full use of unlabeled samples. Combining supervised and unsupervised classification methods based on 3D CNN will give even better results.
3	Spectral based	Requires longer training time compared to other vector-based classification methods. Accuracy can be improved by using the spatial-spectral network architecture
4	Hybrid	Expensive to get labeled data. Can explore semi-supervised deep learning and reduce run time.
5	Spectral-Spatial based	It can be improved by introducing a determinant point process. The computational efficiency can be improved.
6	Spectral-Spatial based	The proposed method is more suitable for data in practical applications when a limited number of training samples are used.
7	Hybrid	Classification results can be improved by jointly taking advantage of spectral and spatial information
8	Spectral-Spatial based	Other deep learning methods can bring out higher features without increasing the number of layers.
9	Hybrid	It can be extended for the multifold structure, which has intersections. It can be applied to other hyperspectral data.
10	Hybrid	If the model is trained for a long time, it collapses a subset of filters and faces instability.
11	Spectral-Spatial based	A smaller set of unlabeled data can achieve better performance and accuracy.

4. Conclusion

Hyperspectral image classification is a very important part of remote sensing. Deep learning algorithms have been gaining more attention because of their ability to deal with unstructured data and their capability to process a greater number of features. In this paper, we have discussed the different deep learning techniques and their methodology. This work aims to serve the researchers in this area and contributes information to the forthcoming study in this field.

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