Hyperspectral Image Classification Using Deep Learning Models: A Review

Deepak Kumar1* and Dharmender Kumar1
1Guru Jambheshwar University of Science and Technology, Hisar, Haryana, India.

*E-mail: deepakjanghu018@gmail.com

Abstract. Hyperspectral image (HSI) classification is one of the important topic in the field of remote sensing. In general, HSI has to deal with complex characteristics and nonlinearity among the hyperspectral data which makes the classification task very challenging for traditional machine learning (ML) models. Recently, deep learning (DL) models have been very widely used in the classification of HSIs because of their capability to deal with complexity and nonlinearity in data. The utilization of deep learning models has been very successful and demonstrated good performance in the classification of HSIs. This paper presents a comprehensive review of deep learning models utilized in HSI classification literature and a comparison of various deep learning strategies for this topic. Precisely, the authors have categorized the literature review based upon the utilization of five most popular deep learning models and summarized their main methodologies used in feature extraction. This work may provide useful guidelines for the future research work in this area.

Keywords: Deep Learning, Remote Sensing, Hyperspectral Image Classification, Deep Belief Network, Convolutional Neural Network, Generative Adversarial Network, Recurrent Neural Network, Auto Encoder.

1. Introduction
Hyperspectral imaging is a remote sensing technique concerned with extraction of useful information from the images captured by hyperspectral imaging sensors. The HSI sensors collect reflective portion of electromagnetic spectrum containing more than hundreds of very narrow spectral bands from the same area on surface of earth [1]. Every pixel, in a hyperspectral image, can be considered as a vector containing spectral reflectance of a material in a specific wavelength. This spectral reflectance creates a unique spectral signature for each pixel in the hypercube and the spectral signature can be utilized to identify various materials on the earth surface [2]. Hence, HSI has been used in various fields like remote sensing [3], land-cover [4], agriculture [5] [6], medical science [7] etc. Based upon recent research studies in [8], HSI classification has been the most sparkling area for research in remote sensing field.

In the early stages of research work on HSI classification, the main focus has been on exploring spectral signatures of HSIs using pixel-wise classification methods like support vector machines (SVM) [9] [10], neural networks (NN) [11] [12], logistic regression (LR) [13] [14]. Furthermore, other classification techniques have targeted the extraction of high-level features and dimensions reduction methods like independent component analysis-(ICA) [18], linear component analysis-(LDA) [15] and principal component analysis-(PCA) [16] [17]. However, the classification accuracies have not been satisfactory since the spatial information has not been considered in these methodologies. Lately, the spatial information has been incorporated along with spectral information and reported to be quite helpful to improve the classification accuracies in many approaches [19]-[23]. Nevertheless, extraction of discriminative features from HSIs has been a very crucial task in the mentioned approaches.
Recently, deep learning (DL) based methodologies have become a fast-growing drift in computer-vision domain and has achieved remarkable results, e.g., object detection [24], image classification [25] [26]. The application of DL in HSI classification has emerged with very encouraging results. Figure 1 exhibits the exponentially growing trend in the DL based HSI Classification literature published in last ten years according to www.app.dimensions.ai. From this trend, it can be concluded that this area will further be explored with DL based methods and more research studies will be carried out in the coming years. As compared with traditional machine learning (ML)-based methods, DL techniques are quite capable to represent more complicated features and can extract informative features from HSIs using a sequence of hierarchical layers. As the learning mechanism is totally automatic, DL based methodologies have become more appropriate for subsisting with varieties of situation in comparison to ML techniques.

![Figure 1. DL-based HSI Classification literature published in past 10 years (till February 2, 2021) [Source: www.app.dimensions.ai]](image)

In this paper, the authors have focused on DL-based approaches for HSIs classification and pointed at conferring a comparative review of five most popular deep learning models viz. generative adversarial network (GAN), convolutional neural network (CNN), deep belief network (DBN), auto encoder (AE) and recurrent neural network (RNN). The main motivation of this literature review is to illuminate the mechanism behind DL-based models. The authors have categorized the relevant literature into five categories with respect to the type of DL-based models adopted for HSI classification. The authors have intended to provide some insights, including selection of the most suitable DL-based model for HSI classification depending upon the type of features to be extracted, for the future studies in this area.
The remainder of the work has been organized into different sections as follows. The various HSI datasets have been briefly discussed in section-2. In section-3, the authors discussed the relevant literature in five aspects with respect to the type of DL-based model utilized to classify HSIs. The comparison of the published work is done section-4. In the last, conclusions are conferred in section-5.

2. Datasets of Hyperspectral Images (HSIs)

HSIs captured by airborne and spaceborne sensors are very useful in many applications like remote sensing [3], land-cover [4], agriculture [5] etc. These sensors collect reflective portion of electromagnetic spectrum containing hundreds of narrow spectral bands and this reflective portion creates a unique spectral signature for an object. This allows the identification of various materials on earth surface by the unique spectral signature. As the sensors capture HSIs are very expensive, only few HSI datasets are publicly available [65]. Also, the task of creating groundtruth and pixel-labelling is exorbitant and time-demanding [81] and consequently only a few labelled HSIs samples are available for research work. Moreover, the DL-based models need an adequate number of training samples for parameter tuning during the training phase [82]. Thus, the availability of very less number of HSI samples makes the classification task very challenging [83]. Nevertheless, some of the HSI datasets are publicly available and in this section three most popular datasets i.e., Pavia University, Indian Pine, and Salinas are discussed.

2.1. Dataset of Indian Pine

Dataset of Indian Pine has been captured as first dataset by airborne-visible-infrared-imaging-spectrometer (AVIRIS) sensor over a site in northwestern, Indiana, USA [84]. The spatial resolution of image is 20m with a spatial size of 145×145 pixels. The spectral range of the acquired image is 0.4-2.5μm with a sum of 224 number of spectral bands. However, after removing water absorbed and noisy bands, only 200 spectral bands are utilized in experiments. Also, the image contains 16-classes with total 10366-samples in the dataset as depicted in Table 1.

| Sr. No. | Class                   | Samples |
|---------|-------------------------|---------|
| 1       | Oats                    | 20      |
| 2       | Corn                    | 237     |
| 3       | Woods                   | 1265    |
| 4       | Wheat                   | 205     |
| 5       | Alfalfa                 | 46      |
| 6       | Grass-trees             | 730     |
| 7       | Soybean-mintill         | 2455    |
| 8       | Corn-mintill            | 830     |
| 9       | Grass-pasture           | 483     |
| 10      | Soybean-clean           | 593     |
| 11      | Soybean-notill          | 972     |
| 12      | Corn-notill             | 1428    |
| 13      | Hay-windrowed           | 478     |
| 14      | Stone-steel-towers      | 93      |
| 15      | Grass-pasture-mowed     | 28      |
| 16      | Buildings-grass-trees-drives | 386   |

**Table 1. Samples and groundtruth classes of Indian Pine Dataset**

Total 10366
2.2. Dataset of Pavia University
Reflective-optics-spectroscopic-imaging-system (ROSIS) sensor was used to capture Pavia university dataset over the Pavia University, northern Italy [85]. The image contains a spatial resolution of 1.3m with a spatial size 610×340 pixels. The original image contains total 115 spectral bands in a spectral range 0.43-0.86μm. However, a total of 103 spectral bands are utilized in experiments after discarding noisy bands. Also, total of 9-classes having 42776-samples are available in the dataset as shown in Table 2.

Table 2. Samples and groundtruth classes of Pavia University Dataset

| Sr. No. | Class                  | Samples |
|---------|------------------------|---------|
| 1       | Trees                  | 3064    |
| 2       | Gravel                 | 2099    |
| 3       | Asphalt                | 6631    |
| 4       | Bitumen                | 1330    |
| 5       | Shadows                | 947     |
| 6       | Meadows                | 18649   |
| 7       | Bare soil              | 5029    |
| 8       | Painted metal sheets   | 1345    |
| 9       | Self-blocking bricks   | 3682    |
|         | **Total**              | **42776**|

2.3. Dataset of Salinas
Salinas Dataset has been captured by AVIRIS sensor in southern California, USA over the Salinas Valley [86]. The spatial resolution of the image is 3.7m with a spatial size 512×217 pixels. The image is captured in spectral range 0.4-2.5μm with 224 spectral bands in total. However, after reducing noisy and other redundant bands, total of 204 spectral bands are utilized in experiments. Also, a total of 16-classes with 54129-samples are available in the dataset as outlined in Table 3.

Table 3. Samples and groundtruth classes of Salinas Dataset

| Sr. No. | Class                        | Samples |
|---------|------------------------------|---------|
| 1       | Celery                       | 3579    |
| 2       | Fallow                       | 1976    |
| 3       | Stubble                      | 3959    |
| 4       | Fallow smooth                | 2678    |
| 5       | Lettuce romaine 4wk         | 1068    |
| 6       | Vineyard untrained           | 7268    |
| 7       | Lettuce romaine 5wk         | 1927    |
| 8       | Soil vineyard develop        | 6203    |
| 9       | Lettuce romaine 6wk         | 916     |
| 10      | Fallow rough plow           | 1394    |
| 11      | Vineyard vertical trellis    | 1807    |
| 12      | Lettuce romaine 7wk         | 1070    |
| 13      | Grapes untrained             | 11271   |
| 14      | Broccoli green weeds 2       | 3726    |
| 15      | Broccoli green weeds 1       | 2009    |
| 16      | Corn-sensed-green-weeds      | 3278    |
|         | **Total**                   | **54129**|
3. Related work on Deep Learning Models for Hyperspectral Image Classification

Recently, deep learning (DL) has been the most popular and successful technique in computer-vision domain and has achieved remarkable results [27]. Prompted by these successful applications, DL has been employed in remote sensing area for HSIs classification [28] [29]. If compared with traditional ML-based methods, DL-based methods have an edge as the learning process in DL is fully-automatic. With these discriminatory features, a massive number of DL-based models have been developed to learn and extract HSI-features and demonstrated good classification accuracies. However, paying attention to the fact that the characteristics of all DL-based models are different, in this section, the authors have categorized the related literature into five categories based upon the types of model utilized for feature extraction. These distinguished networks are expected to extract spatial and spectral information for the subsequent classification. Sections 3.1-3.5 will introduce the five categories of DL-based models in further detail.

3.1. Convolutional Neural Network (CNN) Based HSI Models

The architecture of CNN model is inspired by biological visual system [30]. A CNN is employed in [31] to extract the spectral information in order to handle the overfitting problem. In [32], the proposed CNN architecture has transformed 1D spectral-vector into 2D matrix to fully utilize the spectral information. In [33] authors have presented a hybrid approach in which convolutional layers are employed to extract middle level spectral features and recurrent layers are used to extract spectral contextual information for HSI classification. In [34] PCA is employed to reduce the dimensions in HSIs and then a fusion of CNN kernels with Gabor kernels is utilized for classification. Similarly, PCA is utilized to extract spatial information in [35] and then this spatial information is provided to a fully connected CNN framework for classification. Likewise in [36], a 2D-CNN has been trained with spatial information along with spectral information. A data adaptive kernel approach is used in 2D-CNN to learn by itself from 2D HSIs in [37]. In addition, handcrafted features are also utilized along with spectral information to deal with the problem of limited training sample in some research works. For instance, overfitting problem is coped by utilizing 2D-CNN in combination with Gabor filtering method in [38]. Furthermore, some authors have also utilized an integrating spectral-spatial information for HSIs classification. For example, an improved pixel pair feature approach in used in [39] and an efficient 3D-CNN framework is proposed in [40] which exploits spectral and spatial information simultaneously. In [41], instead of independently merging spectral and spatial information, a two-stage hybrid deep framework is proposed for the extraction of spectral-spatial features jointly where CNN is utilized to extract the joint features and Stacked AE is employed to obtain deep hierarchical features. Similarly in [42], the authors have introduced a 3d-CNN model which exhibits good performance and jointly exploits spectral and spatial features. In [43], dual channel CNN based framework is proposed where 1D-CNN and 2D-CNN are used to extract the spectral and spatial features respectively. A novel methodology is explored in [44] where a band attention module is embedded with CNN framework to deal with noise in HSI. In the study [45], a combined metric learning-based framework with CNN is proposed. In this work, CNN is employed to extract spatial features while the metric learning based framework is used to fuse the spectral and spatial features together. In [46], a multiscale filtering is used in CNN framework to obtain multi scale features to increase the HSI representational ability. A three-channel virtual RGB image is utilized to extract spatial features in study [47]. These images are passed to CNN for multi-scale feature extraction. In [48], the authors have proposed a semi-supervised 3D-CNN employing an adaptive band selection strategy to exploit spectral-spatial features jointly. Similarly, spectral-spatial features are jointly extracted using a hybrid unsupervised 3D convolutional-autoencoder in [49]. In study [50], a hybrid approach is used to extract spectral-spatial features together. In the proposed work, a 3D-CNN is used to exploit spectral-spatial features while 2D-CNN model is employed to obtain more abstract spatial features.
3.2. Recurrent Neural Network (RNN) Based HSI Models
An RNN based HSI classification framework has been proposed for the first time in [51]. In this work, a novel activation function is also used and class labels are determined by using sequential properties of HSIs. In [52], a spatial sequential based RNN model is proposed to utilize a fusion of Gabor filters and morphological profiles for HSI classification. A spectral-spatial LSTM based framework is proposed in [53] to utilize the spatial feature along with spectral features as an attempt to improve the classification accuracy further. In this study, an LSTM duo is employed to learn spectral and spatial features of HSI. Similarly, the authors in [54] have proposed LSTM cells based RNN framework which incorporates multi-spectral and multi-temporal information along with spatial information. In many studies, hybrid RNN models are proposed for HSI classification. For example, in [55], a convolutional-RNN is implemented where CNN model is utilized to extract middle level features and RNN is used to extract spectral contextual information for classification of HSIs. Similarly, in paper [56] a hybrid framework composed of CNN and GRU based RNN is proposed to exploit both spectral and spatial information. In [57], a bidirectional convolutional LSTM is proposed in order to jointly exploit spectral-spatial information for HSI classification. A hierarchical RNN in combination with 3D-CNN is implemented in [58] to extract multi-scale spectral-spatial features. Similarly, a hybrid framework, composed of a recurrent 2D-CNN and a recurrent 3D-CNN, is implemented in [59] to exhibit good performance. In study [60], two layers of RNN are utilized to compose a cascaded framework, first layer is employed to reduce the spectral bands and the second layer is used to learn features from HSIs.

3.3. Deep Belief Network (DBN) Based HSI Models
The hierarchical deep layers in DBN learn features from inputs in an unsupervised way and due to these characteristics DBN has been very popular among many researchers in HSI classification. For instance, DBN is used for land cover classification in [61] where spectral and spatial features are jointly used. This approach has to face challenges in learning process as multiple hidden layers respond similarly due to co-adaption. In [62], an improved diversified DBN model is used to improve the classification accuracy by regularizing the pre-training process. Similarly, a combined band selection and band grouping approach is utilized to enhance the texture features of HSIs in the proposed DBN framework [63]. In this study a guided filter is also used to enhance the texture features and then a softmax-classifier is used to obtain the classification results. In the study [64], a parallel layers framework, composed of Gaussian-Bernoulli restricted boltzmann machine (RBM) to extract high level and nonlinear features from HSIs, is effectively utilized with a logistic regression classifier. Further, many researchers have considered exploitation of spectral and spatial information jointly in their works to achieve improved classification results. Like, a logistic regression layer based DBN framework proposed in [65] has demonstrated improved classification results by joint exploitation of spectral and spatial features. Likely, a spectral-spatial graph based RBM approach is proposed in [66] for HSI classification. In this approach, the RBM is trained to extract the joint spectral-spatial features and the extracted features are then passed to regression layer based DBN for classification.

3.4. Auto Encoder (AE) Based HSI Models
AE is another popular DL model in HSI classification community due to its unsupervised feature learning capability. Many variants of AE model have been effectively used in many research works primarily to reduce features of high dimensional HSIs. For instance, in paper [67] multi-layer AEs are used in a combination to reduce dimensionality of HSIs and a softmax logistic classifier is utilized for classification. In [68], an improved unsupervised HSI classification framework is implemented where counteractive autoencoder [69] is combined with the multi-manifold learning framework proposed in [70]. Furthermore, the spatial and spectral features are jointly exploited by an unsupervised feature extracting framework consisting of recursive AEs in [71] and the neighboring pixel features are extracted depending upon the spectral similarity. In the work [72], a two-stream hybrid deep neural network is proposed with a class specific fusion approach to learn the fusion weights adaptively. One stream is employed to extract spectral features using stacked AE and second stream is composed of
CNN to extract spatial features. The classification is completed by combining the class prediction scores of both the streams. Similarly, in [73], another hybrid framework for multi-feature based HSI classification is proposed which uses PCA to reduce dimensionality, guided filters to get spatial features and a sparse AE to extract high level features. The authors in [74], have proposed a batch-based training scheme for AEs to exploit spectral-spatial features and these features are merged via a mean pooling scheme. Likely, a classification framework, exploiting spectral-spatial, is developed in [75] to utilize stacked sparse AE for feature extraction and random forest classifier for final classification. Furthermore in [76], the authors have used a threefold feature learning scheme proposed in [77] to implement an efficient multilayer extreme learning machine-based AE framework. In work [78], the authors have addressed the issue of high inter-class-similarity and high intra-class-variability. Here a stacked AE model is used to learn discriminative features via imposing a local fisher discriminant regularization. In the work proposed in [79], extended morphological profiles are utilized to incorporate spatial information within the spectral information obtained from spectral segments. The proposed scheme has been very effective in terms of time complexity. Recently, [80], a k-sparse denoising AE is knitted with spectral-spatial features is employed for HSI-classification. In this work, the spatial features are obtained through restricted spatial information in order to reduce intra-class variability of spatial features.

3.5. Generative Adversarial Network (GAN) Based HSI Models

GAN is comparatively new but very popular DL model for HSI classification due to its distinguished capability to address the issue of overfitting in deep models [87]. As the HSI training samples are limited, deep models have to face the problem of overfitting and these models exhibit good performance in testing phase but a relatively poor performance during testing phase. In [88], GAN has been introduced for the first time as a hybrid deep convolutional GANs for HSI classification. In this work, the authors have employed GAN to learn hierarchy of representation from object part and demonstrated good performance. In the work [89], an auxiliary classifier GAN is proposed by the authors, in which a softmax classifier is utilized in place of discriminative model to produce multiclass label probabilities. Similarly, authors in [87] have proposed a hybrid GAN based framework, in which two CNNs are employed to discriminate the inputs and generate fake inputs respectively. Further, 3-D GAN is employed as a deep spatial-spectral classifier in [90]. In [91], a semi-supervised framework GAN is developed to extract the spectral-features automatically and has shown a significant improvement in the performance with limited number of labelled samples. In a recent study [92], a semi-supervised adaptive weighting feature fusion GAN framework is implemented. In this work, the authors have focused on combination of unsupervised mean minimum loss and supervised central loss to avoid the situation of model collapse.

4. Comparison of Published Work

DL-based methodologies have been very popular among the researchers in HSI classification for past few years. In comparison with conventional ML-based methodologies, DL-based models have been employed in HSI datasets for feature extraction and demonstrated impressive classification accuracies. Moreover, the characteristics of each DL-based model is different and hence in this section, a summarization of the review of published literature is carried out, based upon five DL-based models as depicted in Table 4. In this section, the authors have strived to find types of methodologies used in the literatures to exploit the HSI features and main tasks performed by DL-based models. Here, the methodologies are divided into four categories viz. spectral-based, spatial-based, spectral-spatial based and hybrid. The pixel-wise spectral features are exploited in spectral-based methodologies. Spatial-based methodologies utilize spectral and spatial features both but exploitation is done separately while in case of spectral-spatial methods spatial and spectral features are exploited jointly. Finally, in the hybrid methodologies two or more DL-based models are employed to perform feature extraction, dimensionality reduction or feature learning tasks. These guidelines will be very helpful in selecting a most suitable model for each task involved in HSI classification. Also, the selection of appropriate model can help in reducing computational complexities of DL-based models along with a remarkable classification accuracy.
Table 4. Comparison of deep learning models based upon different methodologies

| DL Model | Spectral based | Spatial based | Spectral-Spatial based | Hybrid |
|----------|----------------|--------------|------------------------|--------|
| CNN      | [31], [32]     | [34], [35], [36], [37], [38] | [39], [40], [42], [44], [46], [47], [48] | [33], [41], [43], [45], [49], [50] |
| RNN      | [51]           | [52]         | [53], [54], [58]      | [55], [56], [57], [59], [60] |
| DBN      | XXXXX          | XXXXX        | [61], [62], [63], [66] | [64], [65] |
| AE       | XXXXX          | XXXXX        | [67], [71], [74], [75], [76], [78] | [68], [72], [73], [79], [80] |
| GAN      | XXXXX          | XXXXX        | [89], [90], [91]      | [87], [88], [92] |

Based upon the comparison depicted in Table 4, CNN has been the most widely used DL-based model due to its eminent capability to extract and learn most prominent features automatically from the complex non-linear datasets. Another distinguished property of CNN is to utilize fully connected layer for classification purpose along with softmax operator. AEs have also been very popular and used in many studies due to its unsupervised deep feature learning capability. In most of the papers, AE has been utilized as an effective tool for feature compression in high dimensional data. Another widely used unsupervised DL-based model is DBN. DBN is capable of learning prominent features without any loss of important information. In the literature review, RNN has been found as the second most widely used DL-based model after CNN. RNN has a distinct capability to consider spectral feature as time sequence which makes this model very effective in learning sequential data inputs. In most of the paper, the availability of very limited training-samples is recognized as a big challenge in HSI classification. GAN models are used in most of the recent work to deal with this problem and has achieved impressive classification results. Although GANs are not used for classification purposes but utilized in collaboration with CNN/RNN in hybrid frameworks.

5. Conclusions

Hyperspectral image (HSI) classification has been a quite spunky field in remote sensing area and recently DL-based models has drawn a big attention in this area. As compared to traditional ML-based classification methods, DL-based models have demonstrated good performance with a remarkable advantage of learning complex HSI features automatically via a sequence of hierarchical layers. In this literature the authors have briefly discussed about benchmark HSI datasets viz. Pavia University, Indian Pine and Salinas. Then, the authors have focused on various the DL-based HSI classification methodologies available in related literature and provided a comprehensive review of the existing work. Specifically, the literature on HSI classification using DL-based methods is categorized into five categories based upon the type of DL models used viz. CNN, RNN, DBN, AE and GAN. Through this work, it can be clearly observed that CNN model is most popular and has been used very widely for HSI classification tasks. It has also been observed that the DL-based methodologies, utilizing both the spectral and spatial features jointly, have exhibited significant improvement in classification accuracies. Also, the hybrid deep learning model-based approaches utilizing one or more DL models to learn spectral features and employing a separate model to exploit spatial information from HSIs, have been very popular among the researchers working in this area and also demonstrated remarkable classification performances in many works. It has also been observed that high computational complexity of deep learning models is very critical and it is the need of the hour to implement parallel HSI classification architectures. In this direction, specialized high performance computing platforms can be used to develop DL-based HSI classification frameworks. This work may be helpful for the researchers working in this area and provide useful guidelines for the upcoming studies in this context.
References

[1] Ahmad, M., Khan, A., Khan, A.M., Mazzara, M., Distefano, S., Sohaib, A. and Nibouche, O., 2019. Spatial prior fuzziness pool-based interactive classification of hyperspectral images. Remote Sensing, 11(9), p.1136.

[2] Rasti, B., Hong, D., Hang, R., Ghamisi, P., Kang, X., Chanussot, J. and Benediktsson, J.A., 2020. Feature Extraction for Hyperspectral Imagery: The Evolution from Shallow to Deep: Overview and Toolbox. IEEE Geoscience and Remote Sensing Magazine, 8(4), pp.60-88.

[3] Ma, L., Liu, Y., Zhang, X., Ye, Y., Yin, G. and Johnson, B.A., 2019. Deep learning in remote sensing applications: A meta-analysis and review. ISPRS journal of photogrammetry and remote sensing, 152, pp.166-177.

[4] Michael Theodore Eismann., 2012. Hyperspectral Remote sensing. SPIE Press.

[5] Peón, Juanjo & Recondo, Carmen & Fernández, Susana & Fernandez Calleja, Javier & Miguel, Eduardo & Carretero, Laura., 2017. Prediction of Topsoil Organic Carbon Using Airborne and Satellite Hyperspectral Imagery. Remote Sensing. 9. 1211. 10.3390/rs9121211.

[6] Manley, IJ, Paul & Sagan, Vasit & Fritschi, Felix & Burken, Joel,. 2019. Remote Sensing of Explosives-Induced Stress in Plants: Hyperspectral Imaging Analysis for Remote Detection of Unexploded Threats. Remote Sensing. 11. 1827. 10.3390/rs11181827.

[7] Guolan Lu, Baowie Fei, 2014, "Medical hyperspectral imaging: a review," J. Biomed. Opt.19(1)010901 https://doi.org/10.1117/1.JBO.19.1.010901.

[8] P. Ghamisi et al., "Advances in hyperspectral image and signal processing: A comprehensive overview of the state of the art," IEEE Geosci. Remote Sens. Mag., vol. 5, no. 4, pp. 37–78, Dec. 2017.

[9] Moughal, T.A., 2013, June. Hyper spectral image classification using support vector machine. In Journal of Physics: Conference Series (Vol. 439, No. 1, p. 012042). IOP Publishing.

[10] Dong, P. and Liu, J., 2011. Hyperspectral image classification using support vector machines with an efficient principal component analysis scheme. In Foundations of Intelligent Systems (pp. 131-140). Springer, Berlin, Heidelberg.

[11] Ratle, F., Camps-Valls, G. and Weston, J., 2010. Semisupervised neural networks for efficient hyperspectral image classification. IEEE Transactions on Geoscience and Remote Sensing, 48(5), pp.2271-2282.

[12] Abe, B.T., Olugbara, O.O. and Marwala, T., 2012. Hyperspectral image classification using random forests and neural networks.

[13] Li, J., Bioucas-Dias, J.M. and Plaza, A., 2012. Semisupervised hyperspectral image classification using soft sparse multinomial logistic regression. IEEE Geoscience and Remote Sensing Letters, 10(2), pp.318-322.

[14] Qian, Y., Ye, M. and Zhou, J., 2012. Hyperspectral image classification based on structured sparse logistic regression and three-dimensional wavelet texture features. IEEE Transactions on Geoscience and Remote Sensing, 51(4), pp.2276-2291.

[15] Bandos, T.V., Bruzzone, L. and Camps-Valls, G., 2009. Classification of hyperspectral images with regularized linear discriminant analysis. IEEE Transactions on Geoscience and Remote Sensing, 47(3), pp.862-873.

[16] Licciardi, G., Marpu, P.R., Chanussot, J. and Benediktsson, J.A., 2011. Linear versus nonlinear PCA for the classification of hyperspectral data based on the extended morphological profiles. IEEE Geoscience and Remote Sensing Letters, 9(3), pp.447-451.

[17] Prasad, S. and Bruce, L.M., 2008. Limitations of principal components analysis for hyperspectral target recognition. IEEE Geoscience and Remote Sensing Letters, 5(4), pp.625-629.

[18] Villa, A., Benediktsson, J.A., Chanussot, J. and Jetten, C., 2011. Hyperspectral image classification with independent component discriminant analysis. IEEE transactions on Geoscience and remote sensing, 49(12), pp.4863-4876.

[19] He, L., Li, J., Liu, C. and Li, S., 2017. Recent advances on spectral–spatial hyperspectral image classification: An overview and new guidelines. IEEE Transactions on Geoscience and Remote Sensing, 56(3), pp.1579-1597.

[20] Li, J., Marpu, P.R., Plaza, A., Bioucas-Dias, J.M. and Benediktsson, J.A., 2013. Generalized composite kernel framework for hyperspectral image classification. IEEE transactions on geoscience and remote sensing, 51(9), pp.4816-4829.

[21] Fauvel, M., Chanussot, J. and Benediktsson, J.A., 2012. A spatial–spectral kernel-based approach for the classification of remote-sensing images. Pattern Recognition, 45(1), pp.381-392.

[22] Fang, L., Li, S., Duan, W., Ren, J. and Benediktsson, J.A., 2015. Classification of hyperspectral images by exploiting spectral–spatial information of superpixel via multiple kernels. IEEE transactions on geoscience and remote sensing, 53(12), pp.6663-6674.

[23] Fang, L., Li, S., Kang, X. and Benediktsson, J.A., 2014. Spectral–spatial hyperspectral image classification via multiscale adaptive sparse representation. IEEE Transactions on Geoscience and Remote Sensing, 52(12), pp.7738-7749.

[24] Girshick, R., Donahue, J., Darrell, T. and Malik, J., 2014. Rich feature hierarchies for accurate object detection and semantic segmentation. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 580-587).

[25] Krizhevsky, A., Sutskever, I. and Hinton, G., E., 2012. Imagenet classification with deep convolutional neural networks. Advances in neural information processing systems, 25, pp.1097-1105.

[26] Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., Erhan, D., Vanhoucke, V. and Rabinovich, A., 2015. Going deeper with convolutions. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 1-9).

[27] LeCun, Y., Bengio, Y. and Hinton, G., 2015. Deep learning. nature, 521(7553), pp.436-444.

[28] Zhang, L., Zhang, L. and Du, B., 2016. Deep learning for remote sensing data: A technical tutorial on the state of the art. IEEE Geoscience and Remote Sensing Magazine, 4(2), pp.22-40.
[29] Zhu, X.X., Tuia, D., Mou, L., Xia, G.S., Zhang, L., Xu, F. and Fraundorfer, F., 2017. Deep learning in remote sensing: A comprehensive review and list of resources. IEEE Geoscience and Remote Sensing Magazine, 5(4), pp.8-36.

[30] Hubel, D.H. and Wiesel, T.N., 1962. Receptive fields, binocular interaction and functional architecture in the cat's visual cortex. The Journal of physiology, 160(1), pp.106-154.

[31] Yu, S., Jia, S. and Xu, C., 2017. Convolutional neural networks for hyperspectral image classification. Neurocomputing, 219, pp.88-98.

[32] Gao, H., Yang, Y., Li, C., Zhou, H. and Qu, X., 2018. Joint alternate small convolution and feature reuse for hyperspectral image classification. ISPRS International Journal of Geo-Information, 7(9), p.349.

[33] Wu, H. and Prasad, S., 2017. Convolutional recurrent neural networks for hyperspectral data classification. Remote Sensing, 9(3), p.298.

[34] Huang, Q., Li, W. and Xie, X., 2018, June. Convolutional neural network for medical hyperspectral image classification with kernel fusion. In BIBE 2018: International Conference on Biological Information and Biomedical Engineering (pp. 1-4). VDE.

[35] Li, J., Zhao, X., Li, Y., Du, Q., Xi, B. and Hu, J., 2018. Classification of hyperspectral imagery using a new fully convolutional neural network. IEEE Geoscience and Remote Sensing Letters, 15(2), pp.292-296.

[36] Haut, J.M., Paolletti, M.E., Plaza, J., Plaza, A. and Li, J., 2019. Hyperspectral image classification using random occlusion data augmentation. IEEE Geoscience and Remote Sensing Letters, 16(11), pp.1751-1755.

[37] Ding, C., Li, Y., Xia, Y., Wei, W., Zhang, L. and Zhang, Y., 2017. Convolutional neural networks based hyperspectral image classification method with adaptive kernels. Remote Sensing, 9(6), p.618.

[38] Chen, Y., Zhu, L., Ghamisi, P., Jia, X., Li, G. and Tang, L., 2017. Hyperspectral images classification with Gabor filtering and convolutional neural network. IEEE Geoscience and Remote Sensing Letters, 14(12), pp.2355-2359.

[39] Ran, L., Zhang, Y., Wei, W. and Zhang, Q., 2017. A hyperspectral image classification framework with spatial pixel pair features. Sensors, 17(10), pp.2421.

[40] Paolletti, M.E., Haut, J.M., Plaza, J. and Plaza, A., 2018. A new deep convolutional neural network for fast hyperspectral image classification. ISPRS journal of photogrammetry and remote sensing, 145, pp.120-147.

[41] Li, S., Zhu, X., Liu, Y. and Bao, J., 2019. Adaptive spectral-spatial feature learning for hyperspectral image classification. IEEE Access, 7, pp.61534-61547.

[42] Li, Y., Zhang, H. and Shen, Q., 2017. Spectral–spatial classification of hyperspectral imagery with 3D convolutional neural network. Remote Sensing, 9(1), p.67.

[43] Zhang, H., Li, Y., Zhang, Y. and Shen, Q., 2017. Spectral-spatial classification of hyperspectral imagery using a dual-channel convolutional neural network. Remote sensing letters, 8(5), pp.438-447.

[44] Dong, H., Zhang, L. and Zou, B., 2019. Band attention convolutional networks for hyperspectral image classification. arXiv preprint arXiv:1906.04379.

[45] Cheng, G., Li, Z., Han, J., Yao, X. and Guo, L., 2018. Exploring hierarchical convolutional features for hyperspectral image classification. IEEE Transactions on Geoscience and Remote Sensing, 56(11), pp.6712-6722.

[46] Zhong, P., Peng, N. and Wang, R., 2015. Learning to diversify patch-based priors for remote sensing image restoration. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 8(11), pp.5225-5245.

[47] Liu, L., Shi, Z., Pan, B., Zhang, N., Luo, H. and Lan, X., 2020. Multiscale deep spatial feature extraction using virtual RGB image for hyperspectral imagery classification. Remote Sensing, 12(2), p.280.

[48] Sellami, A., Farah, M., Farah, I.R. and Solaiman, B., 2019. Hyperspectral imagery classification based on semi-supervised 3-D deep neural network and adaptive band selection. Expert Systems with Applications, 129, pp.246-259.

[49] Mei, S., Ji, J., Geng, Y., Zhang, Z., Li, X. and Du, Q., 2019. Unsupervised spatial–spectral feature learning by 3D convolutional autoencoder for hyperspectral classification. IEEE Transactions on Geoscience and Remote Sensing, 57(9), pp.6808-6820.

[50] Roy, S.K., Krishna, G., Dubey, S.R. and Chaudhuri, B.B., 2019. HybridSN: Exploring 3-D-2-D CNN feature hierarchy for hyperspectral image classification. IEEE Geoscience and Remote Sensing Letters, 17(2), pp.277-281.

[51] Mou, L., Ghamisi, P. and Zhu, X.X., 2017. Deep recurrent neural networks for hyperspectral image classification. IEEE Transactions on Geoscience and Remote Sensing, 55(7), pp.3639-3655.

[52] Zhang, X., Sun, Y., Jiang, K., Li, C., Jiao, L. and Zhou, H., 2018. Spatial sequential recurrent neural network for hyperspectral image classification. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 11(11), pp.4141-4155.

[53] Zhou, F., Hang, R., Liu, Q. and Yuan, X., 2019. Hyperspectral image classification using spectral-spatial LSTM. Neurocomputing, 328, pp.39-47.

[54] Sharma, A., Liu, X. and Yang, X., 2018. Land cover classification from multi-temporal, multi-spectral remotely sensed imagery using patch-based recurrent neural networks. Neural Networks, 105, pp.346-355.

[55] Wu, H. and Prasad, S., 2017. Convolutional recurrent neural networks for hyperspectral data classification. Remote Sensing, 9(3), p.298.

[56] Luo, H., 2018. Shorten spatial-spectral RNN with parallel-GRU for hyperspectral image classification. arXiv preprint arXiv:1810.12563.

[57] Liu, Q., Zhou, F., Hang, R. and Yuan, X., 2017. Bidirectional-convolutional LSTM based spectral-spatial feature learning for hyperspectral image classification. Remote Sensing, 9(12), p.1330.

[58] Shi, C. and Pun, C.M., 2018. Multi-scale hierarchical recurrent neural networks for hyperspectral image classification. Neurocomputing, 294, pp.82-93.
[59] Yang, X., Ye, Y., Li, X., Lau, R.Y., Zhang, X. and Huang, X., 2018. Hyperspectral image classification with deep learning models. IEEE Transactions on Geoscience and Remote Sensing, 56(9), pp.5408-5423.

[60] Hang, R., Liu, Q., Hong, D. and Ghamisi, P., 2019. Cascaded recurrent neural networks for hyperspectral image classification. IEEE Transactions on Geoscience and Remote Sensing, 57(8), pp.5384-5394.

[61] Ayhan, B. and Kwan, C., 2017. June. Application of deep belief network to land cover classification using hyperspectral images. In International Symposium on Neural Networks (pp. 269-276). Springer, Cham.

[62] Zhong, P., Gong, Z., Li, S. and Schönlieb, C.B., 2017. Learning to diversify deep belief networks for hyperspectral image classification. IEEE Transactions on Geoscience and Remote Sensing, 55(6), pp.3516-3530.

[63] Li, J., Xi, B., Li, Y., Du, Q. and Wang, K., 2018. Hyperspectral classification based on texture feature enhancement and deep belief networks. Remote Sensing, 10(3), p.396.

[64] Tan, K., Wu, F., Du, Q., Du, P. and Chen, Y., 2019. A parallel Gaussian–Bernoulli restricted Boltzmann machine for mining area classification with hyperspectral imagery. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 12(2), pp.627-636.

[65] Li, S., Song, W., Fang, L., Chen, Y., Ghamisi, P. and Benediktsson, J.A., 2019. Deep learning for hyperspectral image classification: An overview. IEEE Transactions on Geoscience and Remote Sensing, 57(9), pp.6690-6709.

[66] Sellami, A. and Farah, I.R., 2019, June. Spectra-spatial Graph-based Deep Restricted Boltzmann Networks for Hyperspectral Image Classification. In 2019 Photonics & Electromagnetics Research Symposium-Spring (PIERS-Spring) (pp. 1055-1062). IEEE.

[67] Zhu, J., Wu, L., Hao, H., Song, X. and Lu, Y., 2017. June. Auto-encoder based for high spectral dimensional data classification and visualization. In 2017 IEEE Second International Conference on Data Science in Cyberspace (DSC) (pp. 350-354). IEEE.

[68] Hassanzadeh, A., Kaarna, A. and Kauranne, T., 2017, June. Unsupervised multi-manifold classification of hyperspectral remote sensing images with contractive Autoencoder. In Scandinavian Conference on Image Analysis (pp. 169-180). Springer, Cham.

[69] Rifai, S., Vincent, P., Muller, X., Glorot, X. and Bengio, Y., 2011, January. Contractive auto-encoders: Explicit invariance during feature extraction. In Icml.

[70] Wang, Y., Jiang, Y., Wu, Y. and Zhou, Z.H., 2010, August. Multi-manifold clustering. In Pacific Rim International Conference on Artificial Intelligence (pp. 280-291). Springer, Berlin, Heidelberg.

[71] Zhang, X., Liang, Y., Li, C., Huyan, N., Jiao, L. and Zhou, H., 2017. Recursive autoencoders-based unsupervised feature learning for hyperspectral image classification. IEEE Geoscience and Remote Sensing Letters, 14(11), pp.1926-1932.

[72] Hao, S., Wang, W., Ye, Y., Nie, T. and Bruzzone, L., 2017. Two-stream deep architecture for hyperspectral image classification. IEEE Transactions on Geoscience and Remote Sensing, 56(4), pp.2349-2361.

[73] He, K., Sun, J. and Tang, X., 2010, September. Guided image filtering. In European conference on computer vision (pp. 1-14). Springer, Berlin, Heidelberg.

[74] Sun, X., Zhou, F., Dong, J., Gao, F., Mu, Q. and Wang, X., 2017. Encoding spectral and spatial context information for hyperspectral image classification. IEEE Geoscience and Remote Sensing Letters, 14(2), pp.2250-2254.

[75] Zhao, C., Wan, X., Zhao, G., Cui, B., Liu, W. and Qi, B., 2017. Spectral-spatial classification of hyperspectral imagery based on stacked sparse autoencoder and random forest. European journal of remote sensing, 50(1), pp.47-63.

[76] Ahmad, M., Khan, A.M., Mazzara, M. and Distefano, S., 2019, February. Multi-layer Extreme Learning Machine-based Autoencoder for Hyperspectral Image Classification. In VISIGRAPP (4: VISAPP) (pp. 75-82).

[77] Ahmad, M., Alqarni, M.A., Khan, A.M., Hussain, R., Mazzara, M. and Distefano, S., 2019. Segmented and non-segmented stacked denoising autoencoder for hyperspectral band reduction. Optik, 180, pp.370-378.

[78] Zhou, P., Han, J., Cheng, G. and Zhang, B., 2019. Learning compact and discriminative stacked autoencoder for hyperspectral image classification. IEEE Transactions on Geoscience and Remote Sensing, 57(7), pp.4823-4833.

[79] Paul, S. and Kumar, D.N., 2018. Spectral-spatial classification of hyperspectral data with mutual information based segmented stacked autoencoder approach. ISPRS journal of photogrammetry and remote sensing, 138, pp.265-280.

[80] Lan, R., Li, Z., Liu, Z., Gu, T. and Luo, X., 2019. Hyperspectral image classification using k-sparse denoising autoencoder and spectral–restricted spatial characteristics. Applied Soft Computing, 74, pp.693-708.

[81] Fang, B., Li, Y., Zhang, H. and Chan, J.C.W., 2020. Collaborative learning of lightweight convolutional neural network and deep clustering for hyperspectral image semi-supervised classification with limited training samples. ISPRS Journal of Photogrammetry and Remote Sensing, 161, pp.164-178.

[82] Hu, F., Xia, G.S., Hu, J. and Zhang, L., 2015. Transferring deep convolutional neural networks for the scene classification of high-resolution remote sensing imagery. Remote Sensing, 7(11), pp.14680-14707.

[83] Audibert, N., Le Saux, B. and Lefèvre, S., 2019. Deep learning for classification of hyperspectral data: A comparative review. IEEE geoscience and remote sensing magazine, 7(2), pp.159-173.

[84] Gao, Q., Lim, S. and Jia, X., 2018. Hyperspectral image classification using convolutional neural networks and multiple feature learning. Remote Sensing, 10(2), p.299.

[85] Luo, F., Huang, Y., Tu, W. and Liu, J., 2020. Local manifold sparse model for image classification. Neurocomputing, 382, pp.162-173.

[86] Chen, Z., Jiang, J., Jiang, X., Fan, X. and Cai, Z., 2018. Spectral-spatial feature extraction of hyperspectral images based on propagation filter. Sensors, 18(6), p.1978.
[88] Radford, A., Metz, L. and Chintala, S., 2015. Unsupervised representation learning with deep convolutional generative adversarial networks. arXiv preprint arXiv:1511.06434.

[89] Odena, A., Olah, C. and Shlens, J., 2017, July. Conditional image synthesis with auxiliary classifier gans. In International conference on machine learning (pp. 2642-2651). PMLR.

[90] Zhang, M., Gong, M., Mao, Y., Li, J. and Wu, Y., 2018. Unsupervised feature extraction in hyperspectral images based on wasserstein generative adversarial network. IEEE Transactions on Geoscience and Remote Sensing, 57(5), pp.2669-2688.

[91] Zhan, Y., Hu, D., Wang, Y. and Yu, X., 2017. Semisupervised hyperspectral image classification based on generative adversarial networks. IEEE Geoscience and Remote Sensing Letters, 15(2), pp.212-216.

[92] Liang, H., Bao, W. and Shen, X., 2021. Adaptive Weighting Feature Fusion Approach Based on Generative Adversarial Network for Hyperspectral Image Classification. Remote Sensing, 13(2), p.198.