Hyperspectral Image Classification: A Review

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Abstract. Hyperspectral imaging technique used to capture image of an objects in multidimensional form it uses technology of imaging and spectroscopic combined to capture multidimensional images. With Hyperspectral imaging (HSI) we can study, inspect external and internal characteristic of any Object. As each and every characteristic of any object has a unique spectral signature which is formed based on variations of reflectance or emittance of object material. Due to non-destructive nature of Hyperspectral imaging (HSI) now a day it is penetrate into food production, medical diagnosis, precision agriculture, pharmaceuticals, recycling, and environmental monitoring industries. We are going to review different HSI classification methods based on traditional, deep learning & pre-trained classifier.

Keywords: Deep learning · CNN · Spectral · Spatial

1 Introduction

Classification is a fundamental technique in Hyperspectral images (HSIs) that assigns a label to each pixel based on its properties. Hyperspectral image classification (HSI) is a technique were similar pixels are clustered into same category. Hyperspectral image classification can be done by either based on pixel information or based on the use of training samples. HSI Images are categorised on the bases of pixel data as Knowledge-based, Sub-Pixel, Per-field, Contextual, Multiple Classifiers or Per-Pixel.

The hyperspectral image classification technique still faces a number of hurdles due to resemblance between the spectra and the mixed pixels and the multi-dimensional properties of hyperspectral data, below are few issues that need more attention:

- Variability in Spatial for spectral data. The spectral data of hyperspectral pictures get modified in spatial dimension as a result of factors like atmospheric conditions, sensors, the composition and distribution of ground features, and the surrounding environment. This results in the ground feature corresponding to each pixel not being a single ground feature.
- Hyperspectral image data are highly dimensional. The equivalent spectral information dimension of hyperspectral images is up to hundreds of dimensions because hyperspectral images are created by using spectral reflectance values gathered by airborne or space-borne imaging spectrometers in hundreds of bands.

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- Missing samples with labels. IN real-world applications, it is quite simple to get hyperspectral image data, but it is very challenging to acquire label information that looks like a images. Consequently, the categorization/classification of hyperspectral images frequently encounter a paucity of labelled samples.
- Image calibre, the interference of background elements and noise during the capture of hyperspectral images has a significant impact on the quality of the data that is gathered. The categorization/classification accuracy of hyperspectral images is directly influenced by the images quality.

HSI images can be categorized as Supervised, Unsupervised and Semi-supervised depending on training classification model.

2 Machine Learning Methods

2.1 Supervised Machine Learning

Building a model from labelled training data to aid in classification or prediction of future data is what supervised learning entails. Supervised samples are those with a known desired output. To put it another way, data labelling is used to direct the machine's search for the exact desired pattern. Regression and classification are subdomains of supervised learning.

Supervised learning tools include:

- Artificial Neural Networks
- Decision Trees
- Random Forest
- Support Vector Machines
- k-Nearest Neighbour
- Logistic Regression
- Nave Bayes
- Linear Discriminant Analysis

2.2 Unsupervised Machine Learning

Unsupervised learning entails working with unlabelled data or unknown data structures. In the absence of a known outcome variable, it investigates the data structure to obtain meaningful information. Using of unsupervised learning we can perform clustering and dimensionality reduction operation.

Unsupervised learning tools include:

- k-means clustering
- Independent Component Analysis (ICA)
- Principle Component Analysis (PCA)

2.3 Semisupervised Machine Learning

Semisupervised classification trains the classifier using both labelled and unlabelled data. It fills in the gaps left by the absence of supervised and unsupervised learning. The same kind of labelled and unlabelled samples on the feature space serve as the foundation for this classification approach. Closer hypotheses, the classifier built with these two examples has superior generalisation.Unlabelled segments of HSI data consist of all properties of target data which is systematically capture. To increase classification accuracy, semisupervised learning blends labelled data with unlabelled data.

Semi-supervised learning tools include:

- Semi-Supervised Support Vector Machines(SVM),
- Graph Based Semisupervised
- Self-Training
- Collaborative Training
- Triple Training

3 Hyperspectral Depiction

1 Dimension spectral and 2 Dimension spatial features combindly of a sample, is used to define hyperspectral data. A 3 Dimension hyper cube mathematically expressed as

$$x \in \mathcal{R}^{b\times(n\times m)} \tag{1}$$

where,

b represents total number of spectral bands.

n and m are the spatial components, or breadth and height, respectively. The hyperspectral data is represented as shown in Fig. 1.

3.1 Spectral Depiction

Spectral depiction is a process by isolating each pixel array from other pixels a processing is taken based on spectral signatures, it means pixel is characterised only in spectral space $xi \in \mathcal{R}^b$, here b represent exact count of spectral channels or just appropriate spectral bands which are extracted by using dimension reduction (DR) technique. In order to succeed with better class separability, without extensive loss of useful data and avoid redundancy, a low dimensional image of HSI is considered instead of considering original

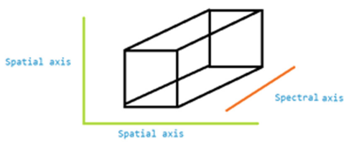

Fig. 1. Hyperspectral Cube.

spectral bands while data processing. Dimension Reduction for spectral depiction of HSI data can be supervised or unsupervised.

Unsupervised
Converting the high dimensional HSI data into a low dimensional HSI data without any class label data, below are few unsupervised methods.

- Principle component analysis (PCA)
- Locally linear embedding

Supervised
Converting the high dimensional HSI data into a low dimensional HSI data need labelled data to learn data distribution, below are few unsupervised methods.

- Linear discriminant analysis (LDA)
- Local Fisher discriminant analysis (LFDA),
- Local discriminant embedding
- Nonparametric weighted FE.

3.2 Spatial Depiction

Spectral Depiction has some limitation due to which classification accuracy is impacted, to overcome this limitation, Spatial Depiction approach is evaluated by extracting the spatial data of the HSI image elements (pixels), here HSI image elements in each band are characterised in the form of a array, $xi \in \mathcal{R}^{n \times m}$ Spatial data has more correlation due to this there is greater likelihoods of image elements (pixels) neighbouring each other belonging to same class. In spectral depiction approach neighbouring pixels data is used and this data is extracted by using Kernel or pixel-centric window process.

Below few processes to extract spatial data from HSI cube.

Morphological Profiles
Morphological profiles are used to extract geometrical properties of spatial data from HSI Image; there are different extensions of morphological profiles for analysis of HIS data as below.

- Extended morphological profiles
- Multiple Structure Element morphological profiles
- Invariant attributes profiles

Texture Features
Texture features provide spatial contextual data of HSI, It can be obtained from texture of the HSI image. Some of below methods are used for texture features extraction.

- Gabor filter: Gabor filter texture exploration method is used for various scales and orientations data extraction.

- Local Binary Pattern: Local Binary Pattern texture exploration method is used for rotation invariant spatial texture image
- Gray Level Co-occurrence matrix: spatial variability of HSI by exploiting the relative positions of neighbourhood pixels

DNN-Based Methods

DNN-based methods are also used to extract spatial data from HSI. In DNN based approach pixels are considered image spot instead of considering it as a spectral array.

The Spatial data of HSI can also be obtained by combining above said methods.

Ex. RNN based HSI Classifier can be created by extracting local spatial sequential features by using Gabor filter and differential morphological profiles method combined.

3.3 Spectral and Spatial Depiction

Both the spectral and spatial information of the data are utilised together in this representation. These methods process a pixel vector based on spectral properties while taking spatial context into account. Below are two different process by which simultaneously uses spectral and spatial representations of HSI.

- Processing the 3-Dimention HSI cube to preserve the real structure and relative information
- Amalgamate spatial information and spectral information.

All of these HSI depiction are used extensively for HSI classification in the literature. The majority of DNNs for pixel-by-pixel classification used HSI spectral depiction. However, numerous attempts have been made to include the spatial information in order to improve the shortcomings of spectral depiction. Combining the use of spatial and spectral information has recently become very popular and enhanced classification accuracy.

4 Hyperspectral Image Classification Methods

4.1 Traditional HSI Classification Methods

Support vector machine (SVM), random forest, and other are conventional HSI classification techniques. The Hughes phenomenon occurs frequently in the HSI categorization/classification because to the HSI spectrum. In order to reduce the dimensionality of HSI, researchers offered a number of techniques, including PCA, PPCA, and ICA. By successfully removing the redundant information in HSI data, dimensionality reduction improves the extraction of HSI characteristics. When using the classic HSI classification approach, the intermediate parameter selection is based on prior experience, which leads to an inadequate classification result and robustness.

4.2 Deep Learning HSI Classification Methods

In contrast to conventional approaches, deep learning techniques may quickly change model parameters via gradient descent and automatically learn features from HSI.Most of the popular DL method are listed below.

- Auto - encoders
- Deep - belief - networks
- Recurrent - neural - networks
- Convolutional – neural- networks

4.3 Pre-trained Model HSI Classification Methods

A stored network that has already undergone training on a sizable dataset, generally for a sizable image-classification job, is referred to as a pre-trained model. Either applies transfer learning to adapt the pretrained model to a specific task, or use the model as is.below are few popular Pre-trained model.

- AlexNet
- VGG16
- GoogleNet

5 Research Gap

Below are few research area were still more work need to be done.

- Manual feature extraction is used in the majority of machine learning algorithms used for hyperspectral data analysis, which significantly increases computation time.
- Extraction of useful information from high-dimensional hyperspectral data is difficult.
- Classification of HSI data based on only considering spectral information has not accomplished satisfactory classification results.

6 Conclusions

HIS datasets are huge and multifaceted it require dynamic more computing power & memory for processing and classification.Cloud computing can provide an innovative solution for processing such data as cloud computing provide greater scalability, flexibility, sustainability & cost effective. Developing classification technique/model by combining spatial information and spectral information for hyperspectral image classification will improve the classification accuracy using DL Pre-trained techniques and make a significant contribution in the field of HSI classification. Most researchers have investigated HSI data classification by focusing on individual spectral information rather than combining spectral and spatial information, and they have created spectral information classification approaches using a) logistic regression b) random forest classifier c) support vector machine algorithm d) neural networks algorithm,etc. but the Classification of HSI data based on only considering spectral information has not accomplished satisfactory classification results.

References

1. M. B. Farrar *et al.*, "A performance evaluation of vis/nir hyperspectral imaging to predict curcumin concentration in fresh turmeric rhizomes," *Remote Sensing*, vol. 13, no. 9, May 2021, doi: https://doi.org/10.3390/rs13091807.
2. Q. Shenming, L. Xiang, and G. Zhihua, "A new hyperspectral image classification method based on spatial-spectral features," *Scientific Reports*, vol. 12, no. 1, Dec. 2022, doi: https://doi.org/10.1038/s41598-022-05422-5.
3. A. Femenias, F. Gatius, A. J. Ramos, I. Teixido-Orries, and S. Marín, Hyperspectral imaging for the classification of individual cereal kernels according to fungal and mycotoxins contamination: A review, vol. 155. Elsevier Ltd, 2022. doi: https://doi.org/10.1016/j.foodres.2022.111102.
4. M. Ahmad *et al.*, "Hyperspectral Image Classification - Traditional to Deep Models: A Survey for Future Prospects," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 15, pp. 968–999, 2022, doi: https://doi.org/10.1109/JSTARS.2021.3133021.
5. J. Jiang, J. Ma, and X. Liu, "Multilayer Spectral-Spatial Graphs for Label Noisy Robust Hyperspectral Image Classification," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 33, no. 2, pp. 839–852, Feb. 2022, doi: https://doi.org/10.1109/TNNLS.2020.3029523.
6. S. Pei, H. Song, and Y. Lu, "Small Sample Hyperspectral Image Classification Method Based on Dual-Channel Spectral Enhancement Network," *Electronics (Switzerland)*, vol. 11, no. 16, Aug. 2022, doi: https://doi.org/10.3390/electronics11162540.
7. D. Saha and A. Manickavasagan, Machine learning techniques for analysis of hyperspectral images to determine quality of food products: A review, vol. 4. Elsevier B.V., 2021, pp. 28–44. doi: https://doi.org/10.1016/j.crfs.2021.01.002.
8. G. Ortac and G. Ozcan, "Comparative study of hyperspectral image classification by multidimensional Convolutional Neural Network approaches to improve accuracy," *Expert Systems with Applications*, vol. 182, Nov. 2021, doi: https://doi.org/10.1016/j.eswa.2021.115280.
9. D. Dai, T. Jiang, W. Lu, X. Shen, R. Xiu, and J. Zhang, "Nondestructive detection for egg freshness based on hyperspectral scattering image combined with ensemble learning," *Sensors (Switzerland)*, vol. 20, no. 19, pp. 1–19, Oct. 2020, doi: https://doi.org/10.3390/s20195484.
10. B. Kumar, O. Dikshit, A. Gupta, and M. K. Singh, *Feature extraction for hyperspectral image classification: a review*, vol. 41. Taylor, 2020, pp. 6248–6287. doi: https://doi.org/10.1080/01431161.2020.1736732.
11. B. Jia et al., Essential processing methods of hyperspectral images of agricultural and food products, vol. 198. Elsevier B.V., 2020. doi: https://doi.org/10.1016/j.chemolab.2020.103936.
12. W. Lv and X. Wang, *Overview of Hyperspectral Image Classification*, vol. 2020. Hindawi Limited, 2020. doi: https://doi.org/10.1155/2020/4817234.
13. O. Yaman, H. Yetiş, and M. Karaköse, "Image processing and machine learning-based classification method for hyperspectral images," *The Journal of Engineering*, vol. 2021, no. 2, pp. 85–96, Feb. 2021, doi: https://doi.org/10.1049/tje2.12012.
14. B. Liu, A. Yu, X. Zuo, Z. Xue, K. Gao, and W. Guo, "Spatial-spectral feature classification of hyperspectral image using a pretrained deep convolutional neural network," *European Journal of Remote Sensing*, vol. 54, no. 1, pp. 385–397, 2021, doi: https://doi.org/10.1080/22797254.2021.1942225.
15. D. Sarwinda, R. H. Paradisa, A. Bustamam, and P. Anggia, "Deep Learning in Image Classification using Residual Network (ResNet) Variants for Detection of Colorectal Cancer," in *Procedia Computer Science*, 2021, vol. 179, pp. 423–431. doi: https://doi.org/10.1016/j.procs.2021.01.025.

16. D. R. Hidalgo, B. B. Cortés, and E. C. Bravo, "Dimensionality reduction of hyperspectral images of vegetation and crops based on self-organized maps," *Information Processing in Agriculture*, vol. 8, no. 2, pp. 310–327, Jun. 2021, doi: https://doi.org/10.1016/j.inpa.2020.07.002.
17. F. Poorahangaryan and H. Ghassemian, "Spectral-Spatial Hyperspectral Image Classification Based on Homogeneous Minimum Spanning Forest," *Mathematical Problems in Engineering*, vol. 2020, 2020, doi: https://doi.org/10.1155/2020/8884965.
18. N. Falco, J. Xia, X. Kang, S. Li, and J. A. Benediktsson, *Supervised classification methods in hyperspectral imaging—recent advances*, vol. 32. Elsevier Ltd, 2020, pp. 247–279. doi: https://doi.org/10.1016/B978-0-444-63977-6.00012-2.
19. S. Velliangiri, S. Alagumuthukrishnan, and S. I. T. Joseph, "A Review of Dimensionality Reduction Techniques for Efficient Computation," in *Procedia Computer Science*, 2019, vol. 165, pp. 104–111. doi: https://doi.org/10.1016/j.procs.2020.01.079.
20. C. K. Gowda, S. Usha, and E. C. J. Jagadeesha, "A research: Hyperspectral image processing techniques," *International Journal of Innovative Technology and Exploring Engineering*, vol. 8, no. 9 Special Issue 2, pp. 577–581, Jul. 2019, doi: https://doi.org/10.35940/ijitee.I1120.0789S219.
21. Y. Zhang, X. Jiang, X. Wang, and Z. Cai, "Spectral-spatial hyperspectral image classification with superpixel pattern and extreme learning machine," *Remote Sensing*, vol. 11, no. 17, 2019, doi: https://doi.org/10.3390/rs11171983.
22. N. Audebert, B. L. Saux, and S. Lefèvre, "Deep Learning for Classification of Hyperspectral Data: A Comparative Review Deep Learning for Classification of Hyper-spectral Data: A Comparative Review. IEEE geoscience and remote sensing magazine Deep Learning for Classification of Hyperspectral Data: A Comparative Review," *IEEE*, vol. 7, no. 2, pp. 159–173, 2019, doi: https://doi.org/10.1109/MGRS.2019.912563.
23. K. Nagasubramanian, S. Jones, A. K. Singh, S. Sarkar, A. Singh, and B. Ganapathysubramanian, "Plant disease identification using explainable 3D deep learning on hyperspectral images," *Plant Methods*, vol. 15, no. 1, Aug. 2019, doi: https://doi.org/10.1186/s13007-019-0479-8.
24. P. Shamsolmoali, M. Zareapoor, and J. Yang, "Convolutional neural network in network (CNNiN): Hyperspectral image classification and dimensionality reduction," *IET Image Processing*, vol. 13, no. 2, pp. 246–253, Feb. 2019, doi: https://doi.org/10.1049/iet-ipr.2017.1375.
25. M. E. Paoletti, J. M. Haut, J. Plaza, and A. Plaza, *Deep learning classifiers for hyperspectral imaging: A review*, vol. 158. Elsevier B.V., 2019, pp. 279–317. doi: https://doi.org/10.1016/j.isprsjprs.2019.09.006.
26. C. Jayaprakash, B. B. Damodaran, V. Sowmya, and K. P. Soman, "Dimensionality Reduction of Hyperspectral Images for Classification using Randomized Independent Component Analysis," in *2018 5th International Conference on Signal Processing and Integrated Networks, SPIN 2018*, Sep. 2018, pp. 492–496. doi: https://doi.org/10.1109/SPIN.2018.8474266.
27. M. Mateen, J. Wen, and M. A. Akbar, "The Role of Hyperspectral Imaging: A Literature Review," 2018. [Online]. Available: www.ijacsa.thesai.org
28. Q. Gao, S. Lim, and X. Jia, "Hyperspectral image classification using convolutional neural networks and multiple feature learning," *Remote Sensing*, vol. 10, no. 2, Feb. 2018, doi: https://doi.org/10.3390/rs10020299.
29. X. Li, R. Li, M. Wang, Y. Liu, B. Zhang, and J. Zhou, Hyperspectral Imaging and Their Applications in the Nondestructive Quality Assessment of Fruits and Vegetables. InTech, 2018. doi: https://doi.org/10.5772/intechopen.72250.

30. S. Paul and D. N. Kumar, "Spectral-spatial classification of hyperspectral data with mutual information based segmented stacked autoencoder approach," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 138, pp. 265–280, Apr. 2018, doi: https://doi.org/10.1016/j.isprsjprs.2018.02.001.
31. O. Arslan, O. Akyurek, and S. Kaya, "A comparative analysis of classification methods for hyperspectral images generated with conventional dimension reduction methods," *Turkish Journal of Electrical Engineering and Computer Sciences*, vol. 25, no. 1, pp. 58–72, 2017, doi: https://doi.org/10.3906/elk-1503-167.
32. M. Li, W. Liu, Z. Zhao, L. Liu, and X. Liu, "Application of hyperspectral imaging technology in nondestructive testing of fruit quality," Nov. 2018, p. 304. doi: https://doi.org/10.1117/12.2506528
33. O. Arslan, O. Akyurek, and S. Kaya, "A comparative analysis of classification methods for hyperspectral images generated with conventional dimension reduction methods," *Turkish Journal of Electrical Engineering and Computer Sciences*, vol. 25, no. 1, pp. 58–72, 2017, doi: https://doi.org/10.3906/elk-1503-167.
34. K. V. Kale, M. M. Solankar, D. B. Nalawade, R. K. Dhumal, and H. R. Gite, *A Research Review on Hyperspectral Data Processing and Analysis Algorithms*, vol. 87. Springer India, 2017, pp. 541–555. doi: https://doi.org/10.1007/s40010-017-0433-y.
35. W. Zhao and S. Du, "Spectral-Spatial Feature Extraction for Hyperspectral Image Classification: A Dimension Reduction and Deep Learning Approach," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 54, no. 8, pp. 4544–4554, Aug. 2016, doi: https://doi.org/10.1109/TGRS.2016.2543748.
36. W. Hu, Y. Huang, L. Wei, F. Zhang, and H. Li, "Deep convolutional neural networks for hyperspectral image classification," *Journal of Sensors*, vol. 2015, 2015, doi: https://doi.org/10.1155/2015/258619.
37. Y. Chen, X. Zhao, and X. Jia, "Spectral-Spatial Classification of Hyperspectral Data Based on Deep Belief Network," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 8, no. 6, pp. 2381–2392, Jun. 2015, doi: https://doi.org/10.1109/JSTARS.2015.2388577.
38. S. Valero, P. Salembier, and J. Chanussot, "Hyperspectral image representation and processing with binary partition trees," *IEEE Transactions on Image Processing*, vol. 22, no. 4, pp. 1430–1443, 2013, doi: https://doi.org/10.1109/TIP.2012.2231687.
39. M. Vidal and J. M. Amigo, "Pre-processing of hyperspectral images. Essential steps before image analysis," *Chemometrics and Intelligent Laboratory Systems*, vol. 117, pp. 138–148, Aug. 2012, doi: https://doi.org/10.1016/j.chemolab.2012.05.009.
40. M. O. Ngadi and L. Liu, *Hyperspectral Image Processing Techniques*. Elsevier Inc., 2010, pp. 99–127. doi: https://doi.org/10.1016/B978-0-12-374753-2.10004-8.
41. Y. Tarabalka, "Classification of hyperspectral data using spectral-spatial approaches." [Online]. Available: https://tel.archives-ouvertes.fr/tel-00557734
42. Y. Luo, J. Zou, C. Yao, T. Li, and G. Bai, "HSI-CNN: A Novel Convolution Neural Network for Hyperspectral Image."