Classification of Hyperspectral Remote Sensing Images for Crop Type Identification: State of the Art

Kawtar El Karfi[1], Sanaa El Fkihi[2], Loubna El Mansouri[3] and Othmane Naggar[4]
[1]*National school For Computer Science (ENSIAS), Rabat, Morocco*
[2]*National school For Computer Science (ENSIAS), Rabat, Morocco*
[3]*The Agronomic and Veterinary Institute Hassan II (IAV), Rabat, Morocco*
[4]*MAScIR - Moroccan Foundation for Advanced Science, Innovation and Research, Rabat, Morocco*

Keywords: Remote sensing data, Hyperspectral image HSI, Classification, Crop type mapping, Machine learning, Deep learning

Abstract: Hyperspectral imagery (HSI) is widely considered to be one of the most used technologies in different remote sensing applications, such as crop mapping, which provides an essential baseline for understanding and monitoring the Earth. Hyperspectral remote sensing, with its multiple narrow and continuous wavebands, allow significant improvements in the understanding of physiological processes of crops and the changes in their phenology, which are indistinct in multi-spectral remote sensing. A generous number of features can be derived from the hyperspectral data, although the classification of crops using high-dimensional and high-resolution data is a challenging task. The main objective of this paper is to list various techniques of machine learning mostly applied for hyperspectral data classification, besides the different hyperspectral open datasets mainly used in various researches.

1 INTRODUCTION

Remote sensing imagery classification gained huge interest (Dou et al., 2018; Lu et al., 2011; Xia et al., 2019) during the past five years,Considerable efforts from different researches have been made to present a variety of approaches for crop type identification using remote sensing images. The identification of cultures as a research field has been widely investigated in several studies (Sitokonstantinou et al., 2018; Lira Melo de Oliveira Santos et al., 2019), most of these studies rely mainly on remotely sensed imaging, as it is an efficient and robust tool for collecting the information needed to produce maps of crops. The generated maps are required in the process of making sustainable decisions to assure the proper management of agricultural areas, reduce costs, and create agrarian policies(Orynbaikyzy et al., 2019).The current available sensors (e.g., multi/hyperspectral, synthetic aperture radar, etc.)(Pandey et al., 2019) are increasingly yielding different types of aerial or satellite images with different resolutions (spatial resolution, spectral resolution, and temporal resolution). For this purpose, significant efforts have been made to develop various datasets (Quinn et al., 2018; El Mansouri et al., 2019). Despite this, accurate crop mapping still a challenging assignment, due to the small size of the plots, the large variety of crops species, and the mixture of different crops and uncultivated areas in some cases(Siachalou et al., 2017). A wide range of studies highly recommends the adoption of HSI as it can provide high-resolution and high-dimensional data to produce high-scale maps (El Mansouri et al., 2018; Khan et al., 2018). HSI is a merging technique of digital imaging and spectroscopy. The concept is as follows: Hyperspectral sensors acquire reflected energy for a wide range of spectral bands, from visible to reflected infrared range (Signoroni et al., 2019). They allow the object in the image to be identified with high precision (Sahoo et al., 2015), using various types of variables, such as spectral signatures, vegetation indices, and textural information. Due to the rich spectral information, HSI can classify objects according to their spectral features (Reshma and Veni, 2017). Despite its ability and high classification accuracy, HSI faces one major challenge that impacts the quality of the hyperspectral data classification, which is handling the enormous amount of features. The main objective of this paper is to highlight current classification approaches applied in the field of remote sensing. Mainly as the literature is very dense with different approaches and methods, each with strengths and weaknesses depending on the case studied, so we aim to develop synthesis and see the impact of HSI with deep learning as an axis of research. The rest of this paper is organized as follows. Section 2 gives a brief overview of HSI. Section 3 examines approaches in the literature that are widely used for crop identification. Our conclusion and summary are drawn in the final section.

2 AN OVERVIEW OF HYPERSPECTRAL IMAGES

2.1 Hyperspectral Imaging

The spectral imaging field can be divided into three domains: multispectral imaging (MSI), hyperspectral imaging (HSI), and ultra-spectral imaging (USI). MSI is a system where the used image has few separated wavelengths. In HSI, the image is obtained with an abundance of continuous wavelengths. USI is a system that uses only one image with a low spatial resolution of several pixels(Khan et al., 2018). Hyperspectral images are hypercube (a three-dimensional shape) containing light intensity measurements where the two first dimensions (X and Y) represent spatial positions, and the third dimension represents spectral variation. The images can be interpreted, typically, as stacks of hundreds of two-dimensional spatial images at different wavelengths, or tens of thousands of spectra, aligned in rows and columns. Hyperspectral narrow bands, typically, contain 100–1500 wavebands and collect data in the near-continuous spectrum from several regions of the electromagnetic spectrum (ultraviolet, visible, near-, mid-, and far-infrared), which offers many opportunities to study specific vegetation variables (Elmasry et al., 2012).

2.2 Public Available Hyperspectral Datasets

The use of different remotely sensed data is according to user requirements and the need for high spatial, spectral, temporal resolution, or a combination of one or more of these and the area of coverage.in this section; we illustrate some datasets that are free and available for use (Table I).

- Indian Pines dataset:Indian Pines data set was gathered by the AVIRIS sensor, over agricultural areas in northwestern Indiana, with 145 pixel *x* 145 pixel images and 224 spectral bands... Sixteen classes (Table I) are labeled (e.g., corn, grass, soybean, woods, and so on).
- Pavia dataset:Pavia Centre and University are two scenes acquired by the ROSIS sensor over the city of Pavia, northern Italy. It is divided into two parts: Pavia University (103 bands, 610 pixels *x* 340 pixels) and Pavia Center (102 bands, 1,096 pixels *x* 715 pixels). Nine labeled classes . They contain various urban materials (such as bricks, asphalt, and metals), water, and vegetation. This dataset has been gained a popularity for a long time and mostly used because it is one of the largest sets of labeled HIS data.
- Botswana dataset: Botswana dataset is collected by The NASA EO-1 satellite over the Okavango Delta, Botswana in 2001-2004. The Hyperion sensor on EO-1 obtain data at 30 m pixel resolution in 242 bands. Preprocessing of the data was led by the UT Center for Space Research to fix the anomalies.
- Salinas dataset: This dataset was collected by the AVIRIS sensor with 224-band over Salinas Valley, California, and is characterized by high spatial resolution (3.7-meter pixels). It includes vegetables, bare soils, and vineyard fields.
- KSC dataset:Kennedy Space Center (KSC) was collected by the NASA AVIRIS (Airborne Visible/Infrared Imaging Spectrometer) over the Kennedy Space Center (KSC) on March 23, 1996, in Florida, the KSC data was gathered with 224 bands, and spatial resolution of 18m.This dataset represents 13 classes of the various land cover types.

3 A CONCEPTUAL OVERVIEW OF MACHINE LEARNING CLASSIFIERS

Remote sensing classification results dependent on many factors such as suitable classifier, selection of training data, image preprocessing, feature extraction, accuracy assessment, the user's need, size of the study area, and analyst's skills. Our contribution is to stress the impact of machine learning methods used to classify HSI. Many studies have been carried out to investigate the performance of classifiers for different remotely sensed data sets and their results in terms of accuracy.

Table 1: public available Hyperspectral Remote Sensing datasets

Dataset	Classes	Labels	Bands	Pixels	Mode
Indian Pines	16	10249	224	21025	Aerial
Pavia	9	50232	103	991040	Aerial
Botswana	14	3248	145	377856	Satellite
Salinas	16	54129	227	111104	Aerial
KSC	13	5211	176	314368	Aerial

3.1 Supervised Algorithms

SVM classification: SVMs were initially designed to identify a linear class boundary (i.e., a hyperplane). The SVM classifier is binary, used to identify a single boundary between two classes. However, this problem is handled by applying the classifier to each possible cluster combination, which means that processing time is expected to increase exponentially as the number of clusters rises (Usha and Vasuki, 2018; Yang et al., 2019). Decision Tree classification: DTs are one of the simplest classifiers. A DT is a recursive division of input data (Salehi et al., 2017). In a classification tree, leaf values constitute classes, leaf values represent a continuous variable. One of DTs advantages,is that the logic of the model can be easily visualized at the end of the classification process. DTs can use categorical data, and once the model is completed, classification is extremely fast because no other complex mathematics is required (Salehi et al., 2017; Maxwell et al., 2018). Random Forest classification: RF is an ensemble classifier because it uses a large number of DTs to overcome the weaknesses of a single DT (Jeon and Kim, 2018). The majority ”vote” of all trees is used to assign a final class to each unknown. This directly overcomes the problem that a single tree is not optimal, but by incorporating several trees, an overall optimum should be obtained. A particular advantage of RF is that due to the presence of several trees, it is not necessary to prune individual trees. A disadvantage is that by having several trees, the possibility of viewing the trees is effectively reduced (Jeon and Kim, 2018). k-NN classification: The k-NN classifier is different from other classifiers. It is an instance-based classifier based on comparing the similarity between each unknown sample with the original training data(Tan et al., 2019). The unknown sample is attributed to one of the k predetermine classes of the training samples containing similar features to the unknown sample. A low number of classes (k) will, therefore, provide a very complicated decision boundary, while a higher k values will lead to greater generalization. Since no trained model is produced, the k-NN classification is expected to require more resources as the number of training samples expands. ANNs classification: ANNs are generally conceptualized as a mathematical analog of the axons of an animal brain and their many interconnections through synapses (Chlingaryan et al., 2018). The elements of an ANN are layered neurons (equivalent to biological axons). An ANN has minimal input and output layers, with one neuron for each input variable and one neuron for each output class. In addition, ANNs usually have hidden nodes arranged in one or more additional layers. One of the main challenges of applying ANN classifiers is the training process that can be time and resources consuming and can produce non-optimal or overfitted models. In this section, we have summarized the algorithms of machine learning that are often used for the classification of remote sensing images. (Table II) gives an overview of the results obtained using the Indian pines dataset, and it can be seen that the SVM has performed well.

Table 2: Classification results using Indian pines dataset (Maxwell et al., 2018).

Algorithm	Overall accuracy(%)	Kappa accuracy(%)
SVM	89,1	0,844
DT	78,3	0,687
RF	87,1	0,814
ANN	85,1	0,787
K-NN	78,6	0,686

3.2 Unsupervised Algorithms

In recent years, unsupervised feature learning algorithms has become an interesting alternative to the traditional methods used for feature extraction and has made significant progress in the classification of remote sensing images (Ragettli et al., 2018). By learning features from images rather than relying on manually engineered features, we can obtain more discriminating features and better fitted to the problem at hand.

The principal component analysis (PCA) (Kang et al., 2019) and k-means clustering (Ratnakumar and Nanda, 2019) are considered to be two of the most popular unsupervised feature learning methods.

PCA could be considered as the first unsupervised feature extraction algorithm that attempts to find an optimal representative projection matrix (need reference), and it is widely used to reduce the size of satellite images (multispec-tral/hyperspectral) (Zhang et al., 2019). Some extensions of PCA have also been introduced in the literature, such as PCANet (Zhang et al., 2019) and sparse PCA.

K-Means Clustering: The k-means clustering is a method of vector quantization that aims to divide a collection of data items into k clusters (Ratnakumar and Nanda, 2019).

3.3 Selection of a Machine-learning Classifier

Selecting the appropriate classifier for Multispectral or hyperspectral data is a challenging assignment because of the large variety of machine-learning techniques. In addition, the existing literature seems to be unstructured and inconsistent concerning the degree of effectiveness of existing algorithms. For instance, the work presented in (Kang et al., 2019) has concluded that SVM and Random forest (RF) algorithms have similar performance in terms of accuracy using the RapidEye satellite imagery data set, while the authors of (Chlingaryan et al., 2018) found that (SVM) outstripped (RF) and (KNN) using the same data set. This contradiction in classification results could be explained by the different procedures used in both studies, according to (Zhao and Du, 2016). In (Elmasry et al., 2012), authors compared the performance of a wide range of machine-learning classification algorithms, using standardized procedures and 30 different datasets from Landsat, Ikonos, and Probe-1 satellites on different dates. They found that (RF) had the highest average classification accuracy of 73.19% , which was significantly better than that obtained by SVM (62.28%). Even though RF was the most efficient classifier for 18 of the 30 datasets, it was not always the most accurate classifier. In the same context, the authors of (Usha and Vasuki, 2018) compared (SVM) and (RF) with 1-D Convolutional Neural Network (CNN) architecture using hyperspectral imagery of the San Francisco Bay Area, California, for the year 2015. The models were trained to classify data under three different seasons of the year (spring, summer, fall). All analyses were completed using simulated hyperspectral infrared imaging (HyspIRI) for the aim of land cover mapping. The obtained results showed that the overall classification accuracy of the CNN architecture reached 89.9%, which is similar to that obtained by SVM 89.5%. The results also showed that the SVM exceeded the RF by an overall accuracy of more than 7%. In the previous case studies, the authors showed the most appropriate classification algorithms that were used with several datasets and yielded different results depending on user requirements.

3.4 Other Useful Applications of Machine Learning Methods in Remote-sensing

Machine learning methods are not limited to classification processes. Many algorithms are also employed for regression. For example, Tree canopy density data were generated using a regression tree method, based on the DT algorithm . The SVM can also be used for regression, known as support vector regression (SVR). For instance, (Wang et al., 2011) used this method for predicting water quality, chemical variables from the SPOT-5 data set and stated that SVR achieved a result better than multiple linear regression. For the prediction of biophysical parameters,(Camps-Valls et al., 2006) found that the implementation of an SVR outperformed regression using ANNs.(Mountrakis et al., 2011) also noted the value of SVR for predicting chlorophyll content, leaf area, and vegetation cover from hyperspectral data. Machine learning has also been used for probabilistic predictions in remote sensing. For example,(Maxwell et al., 2016) used RF to forecast the topographic probability of wetlands based on terrain features (Mountrakis et al., 2011).

3.5 Deep Learning Methods

Most of the current state-of-the-art approaches generally rely on supervised learning to obtain good feature representations. The past decade has witnessed an important growth in using and developing deep learning algorithms. It has become a trend in big data analysis and many computer vision tasks, e.g., image classification, object detection, and natural language processing. It gave birth to a new perspective in the remote sensing field when it has been introduced as a promising method to classify HSI data that has been used in various studies and provided accurate results.

Therefore, we can anticipate that the topic will be further explored, and more and more research works will be published in the next several years.

Since then, several attempts have been made to replace hand-engineered features with trainable multilayer networks, and some deep learning models have shown impressive feature representation capability for a wide range of applications, including remote sensing images classification (Paoletti et al., 2019) (Kussul et al., 2017) (Elnagar et al., 2020).

In comparison with traditional features extraction methods that require a considerable amount of engineering skill and domain expertise, Deep learning features are automatically learned from data using a general-purpose learning procedure via deep-architecture neural networks, which represents the key advantage of deep learning methods. On the other hand, compared with aforementioned unsupervised feature learning methods that are generally weakly structured models (e.g., sparse coding), deep learning models that are composed of multiple processing layers can learn more powerful feature representations of data with multiple levels of abstraction (Kang et al., 2019). In addition, deep feature learning methods can automatically extract features from complex hyperspectral data and can effectively deal with the problem of the large variability of spectral signature. However, the types of features extracted from deep networks are various, e.g., spectral, spatial, and spectral-spatial features, which makes deep learning more suitable for the varieties of situations.

In the existing literature, a number of deep learning models have been proposed, such as Recurrent Neural Network (RNN), Stacked Autoencoder (SAE), and Convolutional Neural Networks (CNNs), (Paoletti et al., 2019) (Kussul et al., 2017) (Liu et al., 2019). Several authors have attempted to give a general review of current advances deep learning techniques for hyperspectral images. For instance, (Liu et al., 2019) listed the most popular deep learning-based algorithms used in the hyperspectral data classification and underlined their ability to deal with a restricted number of training samples and high-dimensional data. Among those approaches, we can cite the widely used CNN-based classifiers. Here we mainly focus on CNN since it is the most used algorithm in HSI classification. CNNs are designed to process data that come in the form of multiple arrays, for example, a multispectral image composed of multiple 2-D arrays containing pixel intensities in the multiple band channels. The learning process of CNNs is computationally efficient and insensitive to data changes. In remote sensing studies, 2D CNNs (Figure 1) have been widely used to extract spatial features from the dimensions of width and height for object detection and semantic segmentation of high-resolution images (He and Chen, 2019). the Hyperspectral image classification is another application of CNNs, in which CNN's were used to extract spatial-spectral features, through either 1D-convolution with spectral features, 2D-convolution with spatial features, or 3D-convolution with a combination of spectral and spatial features (Bhosle and Musande, 2019). (Zhu et al., 2019) found that 2D-convolution provides an accurate result in crop classification than 1D-convolution. (Goodfellow et al., 2016) combined hyperspectral images from three seasons and applied 1D-convolution for land cover classification. In these studies, convolutional layers in CNNs used mostly to extract spatial or spectral features.

4 SUMMARY

The classification of remotely sensed data has made significant progress over the past years. Many factors, such as the spatial resolution of the remotely sensed data, different data sources, and the classification system must be considered when choosing a classification method to use. Various classification methods have their own merits. It is not easy to answer the question of which classification method is suitable for a specific study. For a particular study, it is often difficult to identify the most suitable classifier due to the lack of guidelines in the literature for the selection of appropriate classification algorithms. Also, the combination of different classification approaches has proven to be useful in improving the accuracy of classification (Maxwell et al., 2018). Our objective was to propose a short review of the academic literature to provide some practical considerations for the implementation of machine learning classification in remote sensing data. We suggest that the following points should be highlighted .

- SVM, RF, and enhanced DTs have proven to be very effective methods for classifying remotely sensed data and, in general, these methods seem to produce high overall accuracies compared to other machine classifiers such as simple DTs and k-NN. However, the best algorithm for a specific task may be case-specific and may depend on the classes mapped, the nature of the training data, and the predictive variables provided.
- the quality of training data, generally, have a significant impact on the accuracy of classification. The training data may even have more impact than the algorithm used. Therefore, it is better to obtain a large number of high-quality training samples that fully characterize the class signatures. However, there are practical limitations to collect large training samples. If the training sample is small

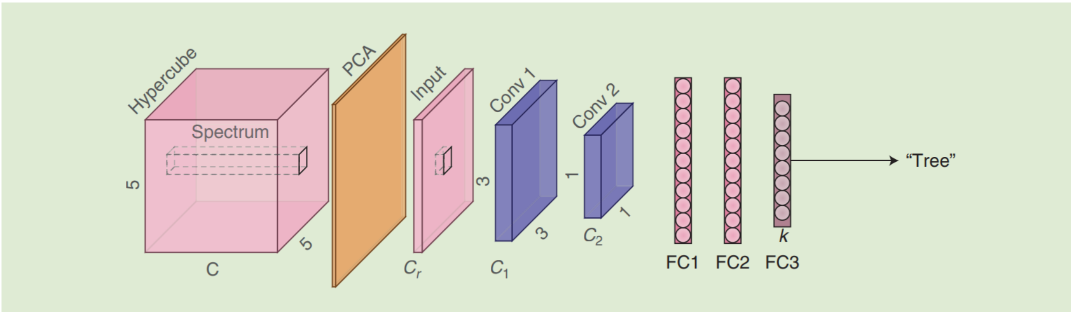

Figure 1: The general 2D CNN architechture for classification of hyperspectral data (Makantasis et al., 2015). Conv: convolution; FC: fully connected.

in number, or if the data quality is ambiguous, an algorithm that is robust to these problems must be used, such as the DT methods.

- The accuracy of the classification may be affected by the imbalance in training data. In general, overall accuracy may not decrease significantly due to imbalance.
- The three input dimensions (spatial, spectral, and temporal) have an impact on the accuracy of crop mapping, individually or in combination. An increase in one of the dimensions increases the accuracy of mapping. Each dimension plays an important role and contributes significantly to the output. From the spatial dimension to the spectral dimension, from the spectral dimension to the temporal dimension.
- Deep learning techniques, including deep neural networks, have already revealed a great promise in the field of remote sensing, and the implementations have been made available in software packages such as MATLAB, R, and scikit-learn.

5 CONCLUSIONS

Earth Observation (EO) sensors are a source of informative data covering the whole globe in spatial and spectral resolution for better and easier land cover classification. They are becoming increasingly attractive as an effective alternative to traditional or conventional methods, and the last years have witnessed a remarkable increase in the use of these technologies in the field of crop mapping or identification. Due to the variable nature of the landscape and multiple sensors, classification techniques also play an essential role in the accuracy of crop mapping for multispectral to hyperspectral data. Indeed, in recent years, many classification machine learning algorithms (supervised or unsupervised) have been used in crop mapping. To implement appropriate methods for HSI classification, several other factors need to be considered to overcome the problems of pixel size and various characteristics to outperform one technique over another. Therefore, it is necessary to know the input data dimensions, types of remotely sensed data, and appropriate classifiers implemented.

ACKNOWLEDGEMENTS

This work is part of the Multispectral satellite imagery, data mining and agricultural applications project, funded by the academy Hassan II of Science and Technology.

REFERENCES

Bhosle, K. and Musande, V. (2019). Evaluation of deep learning cnn model for land use land cover classification and crop identification using hyperspectral remote sensing images. *Journal of the Indian Society of Remote Sensing*, 47(11):1949–1958.

Camps-Valls, G., Bruzzone, L., Rojo-Alvarez, J. L., and Melgani, F. (2006). Robust support vector regression for biophysical variable estimation from remotely sensed images. *IEEE Geoscience and remote sensing letters*, 3(3):339–343.

Chlingaryan, A., Sukkarieh, S., and Whelan, B. (2018). Machine learning approaches for crop yield prediction and nitrogen status estimation in precision agriculture: A review. *Computers and electronics in agriculture*, 151:61–69.

Dou, P., Chen, Y., and Yue, H. (2018). Remote-sensing imagery classification using multiple classification algorithm-based adaboost. *International Journal of Remote Sensing*, 39(3):619–639.

El Mansouri, L., Hadria, R., Lahmer, I., Moutaib, O., Oujemaa, A., and ElGorch, A. (2018). Technologies géo-spatiales pour renforcer les dispositifs de gestion des terres agricoles: Appui à la gestion des surfaces agrumicoles par télédétection dans la plaine de triffa-berkane (maroc). *African Journal on Land Policy and Geospatial Sciences*, 1(3):164–177.

El Mansouri, L., Lahssini, S., Hadria, R., Eddaif, N., Benabdelouahab, T., and Dakir, A. (2019). Time series multispectral images processing for crops and forest mapping: two moroccan cases. In *Geospatial Technologies for Effective Land Governance*, pages 83–106. IGI Global.

Elmasry, G., Kamruzzaman, M., Sun, D.-W., and Allen, P. (2012). Principles and applications of hyperspectral imaging in quality evaluation of agro-food products: a review. *Critical reviews in food science and nutrition*, 52(11):999–1023.

Elnagar, A., Al-Debsi, R., and Einea, O. (2020). Arabic text classification using deep learning models. *Information Processing & Management*, 57(1):102121.

Goodfellow, I., Bengio, Y., Courville, A., and Bengio, Y. (2016). *Deep learning*, volume 1. MIT press Cambridge.

He, X. and Chen, Y. (2019). Optimized input for cnn-based hyperspectral image classification using spatial transformer network. *IEEE Geoscience and Remote Sensing Letters*, 16(12):1884–1888.

Jeon, W. and Kim, Y. (2018). An assessment of a random forest classifier for a crop classification using airborne hyperspectral imagery. *대한원격탐사학회지*, 34(1):141–150.

Kang, X., Zhuo, B., and Duan, P. (2019). Semi-supervised deep learning for hyperspectral image classification. *Remote Sensing Letters*, 10(4):353–362.

Khan, M. J., Khan, H. S., Yousaf, A., Khurshid, K., and Abbas, A. (2018). Modern trends in hyperspectral image analysis: a review. *IEEE Access*, 6:14118–14129.

Kussul, N., Lavreniuk, M., Skakun, S., and Shelestov, A. (2017). Deep learning classification of land cover and crop types using remote sensing data. *IEEE Geoscience and Remote Sensing Letters*, 14(5):778–782.

Lira Melo de Oliveira Santos, C., Augusto Camargo Lamparelli, R., Kelly Dantas Araújo Figueiredo, G., Dupuy, S., Boury, J., Luciano, A. C. d. S., Torres, R. d. S., and Le Maire, G. (2019). Classification of crops, pastures, and tree plantations along the season with multi-sensor image time series in a subtropical agricultural region. *Remote Sensing*, 11(3):334.

Liu, Y., Zhou, S., Han, W., Liu, W., Qiu, Z., and Li, C. (2019). Convolutional neural network for hyperspectral data analysis and effective wavelengths selection. *Analytica Chimica Acta*, 1086:46–54.

Lu, D., Weng, Q., Moran, E., Li, G., and Hetrick, S. (2011). *Remote sensing image classification*. CRC Press/Taylor and Francis: Boca Raton, FL, USA.

Makantasis, K., Karantzalos, K., Doulamis, A., and Doulamis, N. (2015). Deep supervised learning for hyperspectral data classification through convolutional neural networks. In *2015 IEEE International Geoscience and Remote Sensing Symposium (IGARSS)*, pages 4959–4962. IEEE.

Maxwell, A. E., Warner, T. A., and Fang, F. (2018). Implementation of machine-learning classification in remote sensing: An applied review. *International Journal of Remote Sensing*, 39(9):2784–2817.

Maxwell, A. E., Warner, T. A., and Strager, M. P. (2016). Predicting palustrine wetland probability using random forest machine learning and digital elevation data-derived terrain variables. *Photogrammetric Engineering & Remote Sensing*, 82(6):437–447.

Mountrakis, G., Im, J., and Ogole, C. (2011). Support vector machines in remote sensing: A review. *ISPRS Journal of Photogrammetry and Remote Sensing*, 66(3):247–259.

Orynbaikyzy, A., Gessner, U., and Conrad, C. (2019). Crop type classification using a combination of optical and radar remote sensing data: a review. *international journal of remote sensing*, 40(17):6553–6595.

Pandey, P. C., Koutsias, N., Petropoulos, G. P., Srivastava, P. K., and Ben Dor, E. (2019). Land use/land cover in view of earth observation: data sources, input dimensions, and classifiers—a review of the state of the art. *Geocarto International*, pages 1–32.

Paoletti, M., Haut, J., Plaza, J., and Plaza, A. (2019). Deep learning classifiers for hyperspectral imaging: A review. *ISPRS Journal of Photogrammetry and Remote Sensing*, 158:279–317.

Quinn, J. A., Nyhan, M. M., Navarro, C., Coluccia, D., Bromley, L., and Luengo-Oroz, M. (2018). Humanitarian applications of machine learning with remote-sensing data: review and case study in refugee settlement mapping. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 376(2128):20170363.

Ragettli, S., Herberz, T., and Siegfried, T. (2018). An unsupervised classification algorithm for multi-temporal irrigated area mapping in central asia. *Remote Sensing*, 10(11):1823.

Ratnakumar, R. and Nanda, S. J. (2019). A low complexity hardware architecture of k-means algorithm for real-time satellite image segmentation. *Multimedia Tools and Applications*, 78(9):11949–11981.

Reshma, S. and Veni, S. (2017). Comparative analysis of classification techniques for crop classification using airborne hyperspectral data. In *2017 International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET)*, pages 2272–2276. IEEE.

Sahoo, R. N., Ray, S., and Manjunath, K. (2015). Hyperspectral remote sensing of agriculture. *Current Science*, pages 848–859.

Salehi, B., Daneshfar, B., and Davidson, A. M. (2017). Accurate crop-type classification using multi-temporal optical and multi-polarization sar data in an object-based image analysis framework. *International Journal of Remote Sensing*, 38(14):4130–4155.

Siachalou, S., Mallinis, G., and Tsakiri-Strati, M. (2017). Analysis of time-series spectral index data to enhance crop identification over a mediterranean rural landscape. *IEEE Geoscience and Remote Sensing Letters*, 14(9):1508–1512.

Signoroni, A., Savardi, M., Baronio, A., and Benini, S. (2019). Deep learning meets hyperspectral image analysis: a multidisciplinary review. *Journal of Imaging*, 5(5):52.

Sitokonstantinou, V., Papoutsis, I., Kontoes, C., Lafarga Arnal, A., Armesto Andrés, A. P., and Garraza Zurbano, J. A. (2018). Scalable parcel-based crop identification scheme using sentinel-2 data time-series for the monitoring of the common agricultural policy. *Remote Sensing*, 10(6):911.

Tan, K., Zhang, Y., Wang, X., and Chen, Y. (2019). Object-based change detection using multiple classifiers and multi-scale uncertainty analysis. *Remote Sensing*, 11(3):359.

Usha, S. G. A. and Vasuki, S. (2018). Improved segmentation and change detection of multi-spectral satellite imagery using graph cut based clustering and multiclass svm. *Multimedia Tools and Applications*, 77(12):15353–15383.

Wang, X., Fu, L., and He, C. (2011). Applying support vector regression to water quality modelling by remote sensing data. *International journal of remote sensing*, 32(23):8615–8627.

Xia, W., Ma, C., Liu, J., Liu, S., Chen, F., Yang, Z., and Duan, J. (2019). High-resolution remote sensing imagery classification of imbalanced data using multistage sampling method and deep neural networks. *Remote Sensing*, 11(21):2523.

Yang, L., Mansaray, L. R., Huang, J., and Wang, L. (2019). Optimal segmentation scale parameter, feature subset and classification algorithm for geographic object-based crop recognition using multisource satellite imagery. *Remote Sensing*, 11(5):514.

Zhang, L., Su, H., and Shen, J. (2019). Hyperspectral dimensionality reduction based on multiscale superpixelwise kernel principal component analysis. *Remote Sensing*, 11(10):1219.

Zhao, W. and Du, S. (2016). Spectral–spatial feature extraction for hyperspectral image classification: A dimension reduction and deep learning approach. *IEEE Transactions on Geoscience and Remote Sensing*, 54(8):4544–4554.

Zhu, K., Chen, Y., Ghamisi, P., Jia, X., and Benediktsson, J. (2019). Deep Convolutional Capsule Network for Hyperspectral Image Spectral and Spectral-Spatial Classification. *Remote Sensing*, 11:223.