

Hyperspectral Image Compression and Classification: A Survey

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Abstract

The applications of hyperspectral images (HSI) are many, which include agriculture, food quality, remote sensing, medical diagnostics and safety assessment. Hyperspectral image analysis has been used for detecting contaminants and identifying defects in food. It also utilizes advanced software and hardware tools hence allowing users to diagnose and detect pathologies. In this paper an avant-garde investigation about Hyperspectral image compression and classification techniques which can be used in various applications like broadcasting of television, remote sensing via satellite, storage and classification of medical images, pictures and documents has been made. Significant increase in multimedia products has created a need to enhance, extract, store and interpret the information received in the most effective manner. The size of a Hyperspectral image comprises approximately 138.81 megabytes and hence requires large space for storage. Hence, Hyperspectral image compression is of great importance as it reduces the data redundancy and the hardware space required for storage. Hyperspectral image classification has gained great research attention due to the increasing demand of feature information extraction. This survey focuses on describing the recent advances in spectral spatial classification of hyperspectral images and various recent advancements in compression techniques for input HSIs.

Keywords: Hyperspectral image processing, compression, classification, remote sensing

INTRODUCTION

Hyperspectral image is a 3D block, which contains two-dimensional spatial information (image feature) and one-dimensional spectral information (frequency-bands) [1]. Hyperspectral images are characterized by their spatial as well as spectral resolution [2]. Hyperspectral imaging combines the power of digital imaging with a scientific technique called spectroscopy which is basically collecting and processing information from across the electromagnetic spectrum by measuring how light is reflected at hundreds of continuous wavelengths [3]. Ordinary cameras acquire data corresponding to the primary colors - Red, Green and Blue whereas hyperspectral imaging divides the spectrum into

large no. of continuous bands corresponding to different wavelengths. For hyperspectral images, several hundreds of spectral bands of the same scene are typically available, while for multispectral images, up to ten bands are usually provided [4]. Hence, this type of imaging has the ability to acquire information far beyond the spectral range of a human eye.

There is also a growing need for compression of hyperspectral images in order to achieve faster speed and optimize less storage. Key reasons for the compression of hyperspectral images are:

1. *Requires large storage:* The size of a hyperspectral image comprises hundreds and

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thousands of megabytes as acquired from the sensors which need to be compressed.

2. *Bandwidth is limited:* Since HSIs comprise of large amount of data, transmission of this huge data requires higher bandwidth.
3. *Data transmission time is less:* Loss of information and calibration can occur at data centers if data captured using HSI is not transmitted in a limited time.

HSI cameras generate “data cubes”. The information is then processed through a machine-learning algorithm to render a “classified” image, which is labeled and optimized to process data in the future. HSIs are considered as 3D data in compression methods known as third order tensors [5]. HSI classification serves as a phenomenal mechanism to analyze diverse portions in an image. Here, individual pixels are assigned to a set of classes. As HSIs provide great characterization of objects with good accuracy, their classification has become a trending topic of research. Hyperspectral images are a boon in today’s age as they help us see more than what meets the eye.

IMAGE COMPRESSION

The reduction in the size of HSI without a compromise in image quality beyond a desired level is known as image ‘compression’. Decreasing the redundancy is the main aim of the image compression algorithms [6]. HSI compression is one of the crucial steps in an image analysis process. It results in the reduction of storage equipment and bandwidth. A brief overview of the different HSI compression techniques is provided in this paper.

Hyperspectral Image Compressive Sensing Reconstruction (HSI-CSR)

HSI-CSR is an important aspect for applications concerned with remote sensing. In [7], the nonlocal tensor sparse and the Low-rank Regularization (NTSRLR) approach is being discussed. The main steps in the HSI-CSR algorithm are: sensing and reconstruction. Initially a 3rd degree tensor is considered and is divided into 3D full band blocks with overlaps. The blocks are then subjected to KNN clustering.

Then, to ward off the reduction of the high spectral correlation, the 3D cubes are unfolded into their respective 2D matrices. This output can be successfully used for the nonlocal tensor representation.

Hyper Lossy Compression Algorithm (Hyper LCA)

Hyper LCA is designed to provide good compression performance in remote sensing applications. In this method [8], the HSI chosen to be compressed is first segmented into pixel blocks and then each block is compressed independently. The Hyper LCA transform mainly uses integer arithmetic (fixed point concept) for compressing the images. It first selects the most unique pixels from the image block, and then this bunch of pixels is used to represent the image block resulting in spectral correlation and reduction of data. The extracted unique pixels along with the compressed image block formed by these pixels give the output of the Hyper LCA transform.

Discrete Wavelet Transform (DWT)

The DWT is a signal decomposition technique that efficiently breaks down signals into low resolution with fine details. DWT can be interpreted as successive low-pass and high-pass filtering of the discrete time-domain signal in terms of deterministic image processing [9]. DWT is a wavelet transform implementation that uses a discrete collection of wavelet scales and translations that follow certain constraints. This transform disintegrates the signal into batches of wavelets which are mutually orthogonal. This is the main difference between DWT and the continuous wavelet transform (CWT), or its execution for the discrete statistic, sometimes called as the discrete-time continuous wavelet transform (DT-CWT).

Skip Block Based Distributed Source Coding (SB-DSC)

This method [10] is suitable for applications which desire less encoder complexity and higher spectral gain. This method takes into consideration the spectral and spatial redundancies of the

hyperspectral image. Any popular coding principle is taken and two correlation values are obtained from their error measures. These values decide which blocks are supposed to be 'skipped'. The error measure can be used as a strong compression and correction tools at the encoder and decoder sides respectively for reconstruction of skipped blocks without loss of information.

Vector Quantization (VQ)

VQ is one of the quantization methods used to compress a 3-D HSI input image. The two significant stages of VQ as mentioned in [11] are codebook generation (training) and code vector matching (coding). Generally, the algorithms applied on VQ have soaring complexity, so the main intent to avoid the complexity, is to develop a more efficient algorithm that can provide results in a more facile and efficient way. A pioneering algorithm used is Vector quantization principal component analysis (VQPCA).

Initially, the codebooks are generated and then encoding of HSI is done. Here, the HSI is converted into small sets of blocks and then into vectors which are of size n -D. Then the optimal vector is found which results in a minimum amount of distortion. Lastly, we find the vectors which correspond by the index in the codebook, and thereafter the entire image is reconstructed when the code-vectors are regenerated into their original forms.

Sparsification of hyperspectral image and reconstruction—SHSIR ALGORITHM With this algorithm, [12] the image is first represented as with inside of the shape of a 2-D matrix of size $(A \times B)$ dimension. Here, A and B form the range of pixels that corresponds with bands and the range of spectral bands respectively.

Then, a new set of rules based entirely on compression detection is then implemented to reduce the range of samples required to reconstruct the picture thereby substantially and significantly improving the overall compression and execution with proper picture in which the calculations are generated using i.i.d-dimensional arrays with via Gaussian entries. The same is shown in Figure 1. HSI is reconstructed via means of the usage of Bregman iteration, where reconstruction accuracy and noise robustness are optimized.

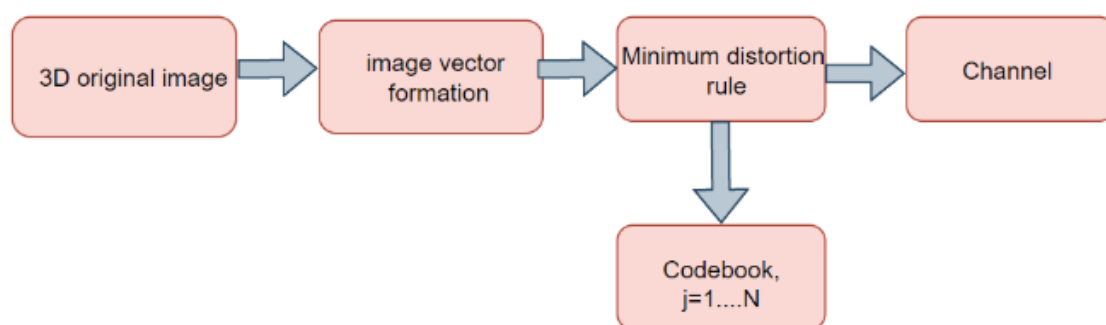


Figure 1. Vector quantization.

Adaptive Spectral Spatial Compression (ASSC)

The hyperspectral image's (ASSC) in [13] provides a new compression method for HSI that makes use of general pixels. To employ spectral and spatial redundancy, the proposed technique divides the authentic HSI pixel into preferred pixels, and then sparsely renders each general pixel by using a simultaneous adaptive sparse rendering scheme. The proposed system divides the HSI pixels which are original into preferred pixels, then modestly represents every preferred-pixel using an adaptive simultaneous sparse illustration approach, conveying the non-zero sparse coefficients. In addition, every well-known-non-zero pixel's coefficients are quantized after which they are preprocessed for

compression. Finally, the Huffman coding algorithm is used to convert all non-zero coefficients, the statistics, and the full dictionary into a binary bit stream. In addition, in each row coefficient, the pulse code differential modulation is purified by the method for compressing the coefficients.

Folded-Principal Component Analysis (PCA) and JPEG2000 Folded PCA and JPEG2000 is an improved approach from the conventional PCA technique as it is more computationally efficient. Here [14], the folded PCA is applied to spectrally decorrelate the HSI dataset and JPEG2000 is used to reduce spatial redundancies. This is achieved by depicting the input HSI as a 2D matrix and then computing its covariance matrix. A partial covariance matrix is obtained upon calculating each transformed 2-dimensional matrix from a HSI pixel. These partial covariance matrices are combined to determine the eigen matrix and data projection. Considering a HSI of dimensions $m \times n$ and b bands whose entire b bands are folded into groups denoted by h , where h is a parameter that decides the amount of assisting information that can be included into PCA. The decorrelated image is then compressed using Kakadu version 7 software which is used to implement JPEG 2000 v2. The encoder then allocates rate automatically to all the PCs to be encoded. FPCA saves h times of computational complexity and requires less storage memory.

Compression Based on Prediction

The technique in [4] uses two predictors, a Huffman coder and a difference coder as shown in Figure 2. Compression techniques based on predictive coding employ either spatial, spectral or hybrid predictors for decorrelation of the image data [15]. There exists a difference between the actual and predicted values of pixels in the HSI. This distinction can be represented by Huffman code words of varied length. In the difference coder, the pixel at (1,1) is assigned as a reference and is not compressed. The difference value of the pixel at location (i,1) for $i > 1$ can be obtained by subtracting the pixel at (i-1,1) and the pixel at (i,1). A similar pattern is followed for the first column. To obtain a different value of a pixel, the pixel at (1, j-1) and (1, j) are subtracted. The Huffman coder is used to produce a short code for values having higher probability and longer codes. These values of the first row and first column are coded using Huffman coding.

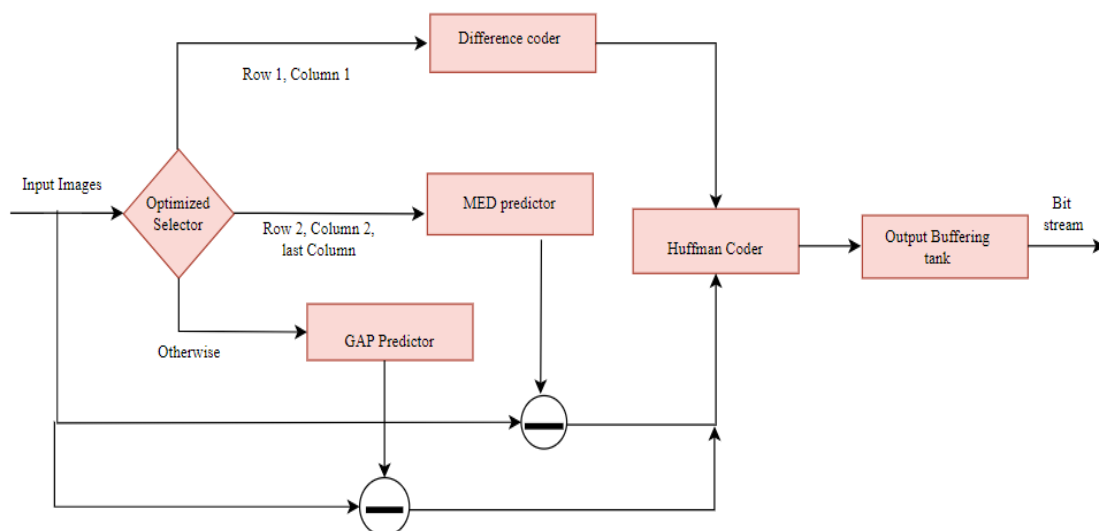


Figure 2. Compression based on prediction.

PCA–Discrete Cosine Transform (DCT) Technology

In [16] PCA is used to obtain the standard from similarities as well as differences in the input image band in an orderly sequential pattern as shown in Figure 3. First, the captured HSI is normalized and its covariance matrix is calculated. The principal component of the normalized image is found using the eigenvalues and eigenvectors. Furthermore, the feature vector (the pattern of

image) is extracted using these principal components hence allowing us to gauge how many features one must select. The image can be reconstructed using inverse transform. By applying DCT to it one can obtain the coefficient of reconstructed HSI by commanding quantization. The DCT is primarily composed of quantization, an encoding and decoding process. By applying both PCA and DCT we obtain an efficiently compressed version of input HSI.

IMAGE CLASSIFICATION

One of the most essential data for remote sensing is hyperspectral imaging due to its high spectral information. For the enormous applications of HSI, a common technique to extract information is classifying each pixel. Classification of a hyperspectral image is a challenging task due to the limited training samples, the large quantity of spectral channels, and large spatial changeability. A large number of methods have been proposed for HSI classification [17]. During the last decade, a number of image processing techniques linked with the machine-learning algorithms have been applied to HSIs. A brief overview of different classification techniques is discussed in this paper.

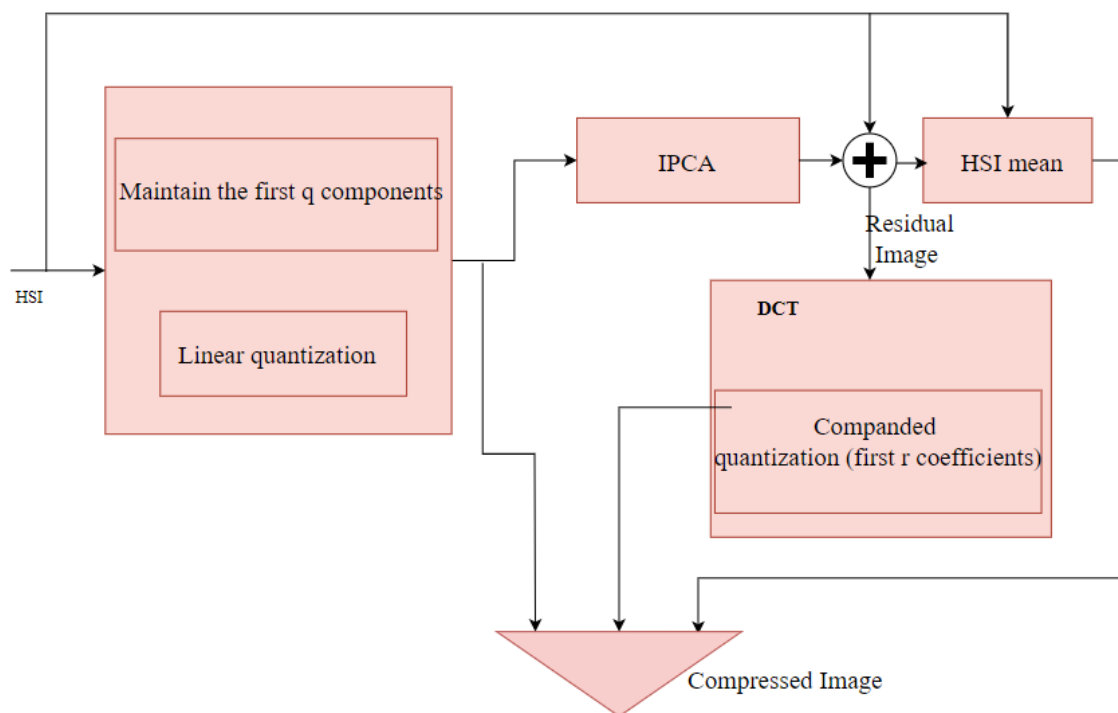


Figure 3. PCA DCT technology.

Convolutional Neural Network-Markov-Random Fields (CNN-MRF)

As discussed in [18], in this algorithm, the hyperspectral image is divided into patches 'Xi'. The data is divided into training and testing data. The data is labeled according to the training data and then classified accordingly with the test data. Each class is known as a 'Markov-random field'. The intermediate probability calculations are done using the 'graph cut' method. The flow chart (Figure 4) of CNN-MRF method is shown below.

Watershed Segmentation

This algorithm is an approach for image segmentation and classification through morphological means. In this method [19] the gradient function of a 2D image is considered which is defined as a measure of shift transition between different regions of an image. It has minimum value in the consistent areas and high values at the edges or borders between the objects. The image is divided into patches by the watershed lines, and then into meaningful classes using further modifications. While

extending this algorithm for hyperspectral images, Feature extraction must be done prior to applying the main transformation. This is necessary for obtaining a single/multi-band image which would be suitable for further processing as shown in Figure 5.

HSEG Segmentation

This algorithm uses unsupervised classification technique and the hierarchical stepwise optimization (HSWO) method. The basic methodology followed is: First, each pixel is assigned a region label. A region is labeled as a unique region if a pre-segmentation is not available. Next, dissimilarity value is found between all pairs of adjoining areas. According to the relation of threshold value and the smallest dissimilarity criteria value, the pairs of regions are merged as discussed in [4].

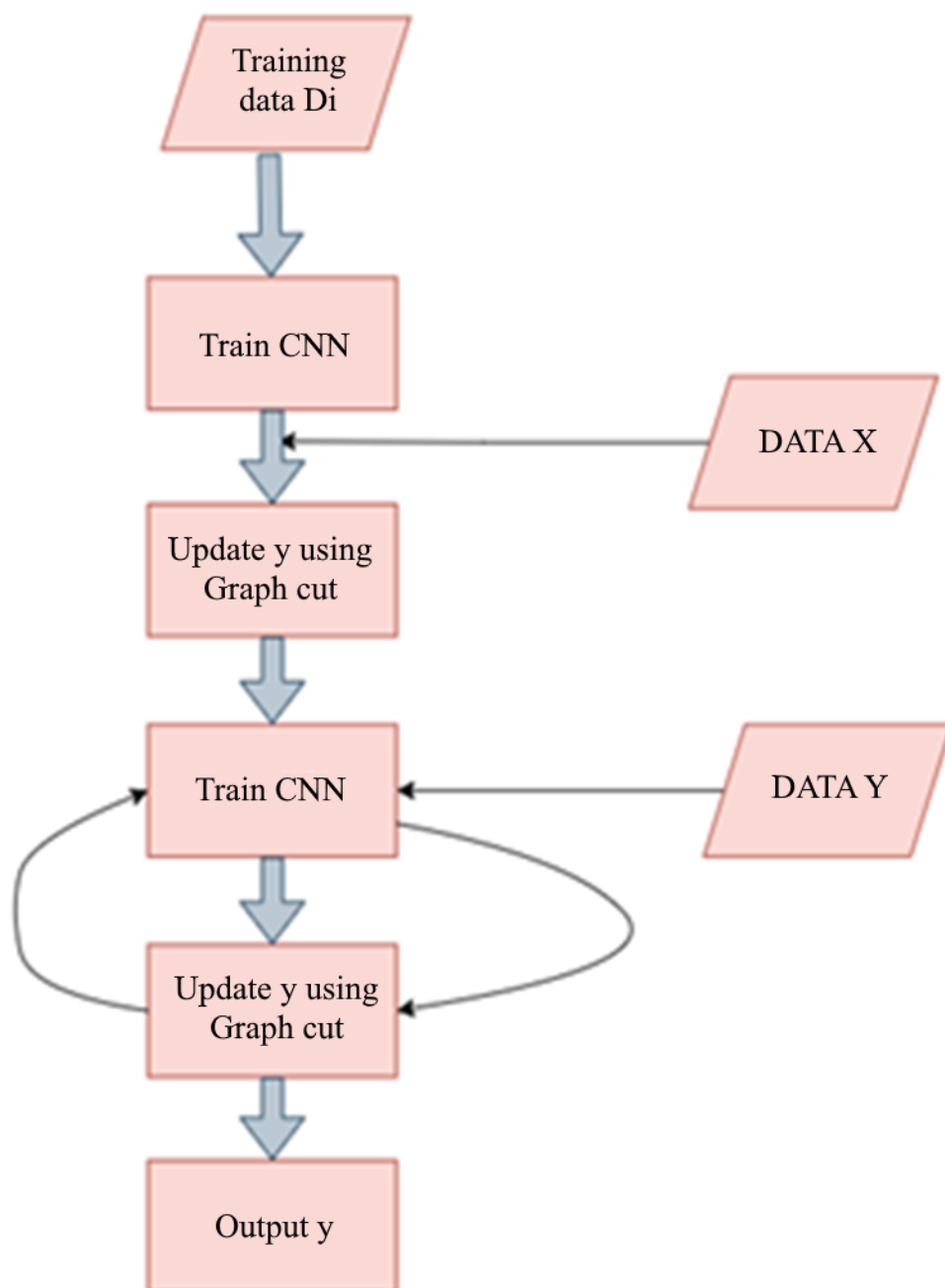


Figure 4. CNN-MRF.

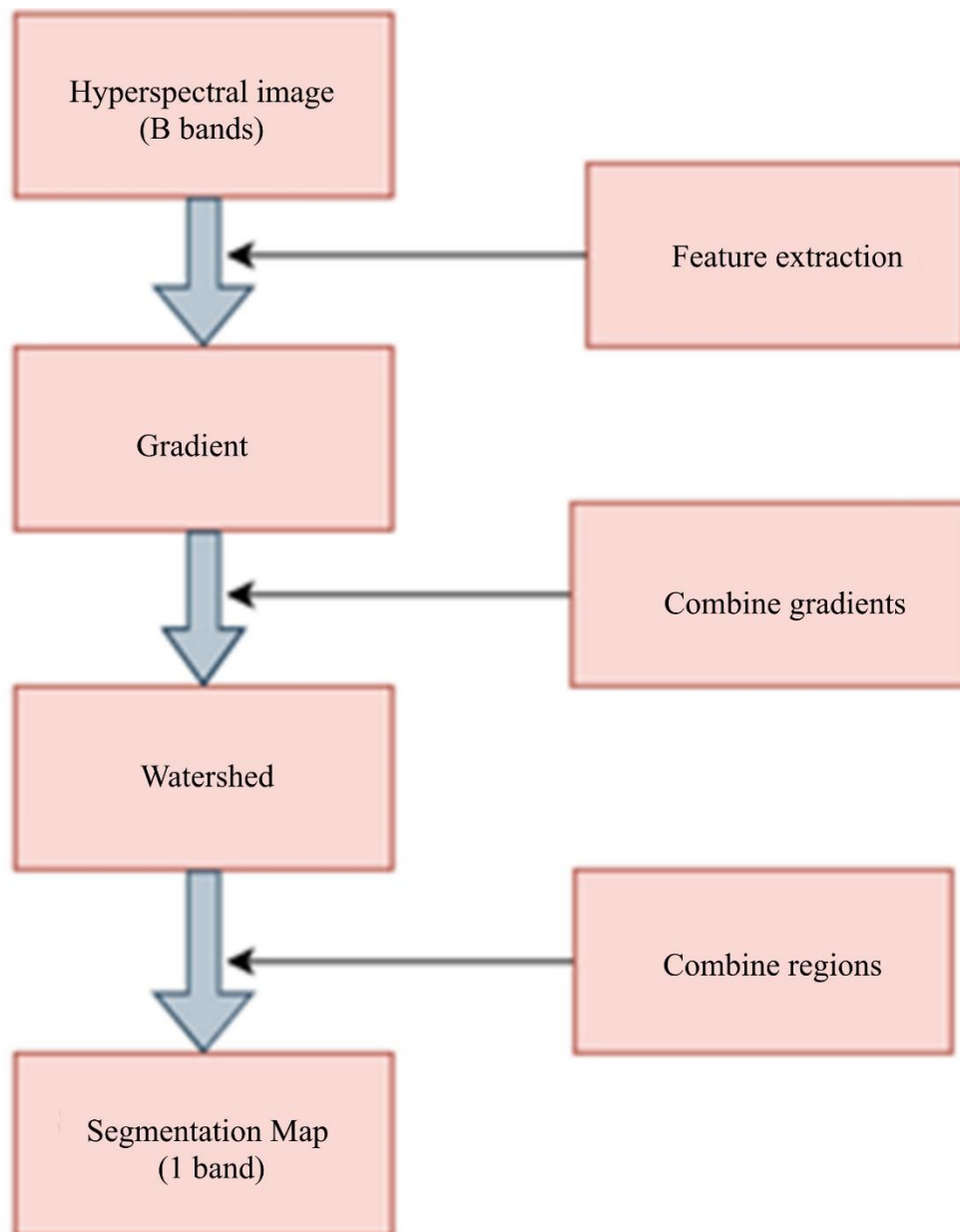


Figure 5. Watershed algorithm.

Multiple Fractal-based Features Classification

This technique in [20] combines spectral and fractal features which include lacunarity, mono fractal and multi-fractal features. First, dimensionality of input HSI is reduced using PCA. The fractal features are then extracted using the following method.

First, a directional method called Pentland method is utilized to get Mono fractal features (intersection and fractal dimension) in which a window that is moving is considered which is of size L , around each pixel of the image. This permits each pixel's nearby area to be examined for spectral changes. To find lacunarity, the gliding box approach is utilized. It surrounds the pixel of interest with an outer window of size L (WL), where WL has a moving window of size m (Wm), and Wm is bordered by another moving window of size r (Wr). The multi-fractal features are obtained using an outer window of size L initially centered on the first pixel of interest. Different combinations of these fractal features (single features, double features, triple features combinations) are classified by SVMs as shown in Figure 6.

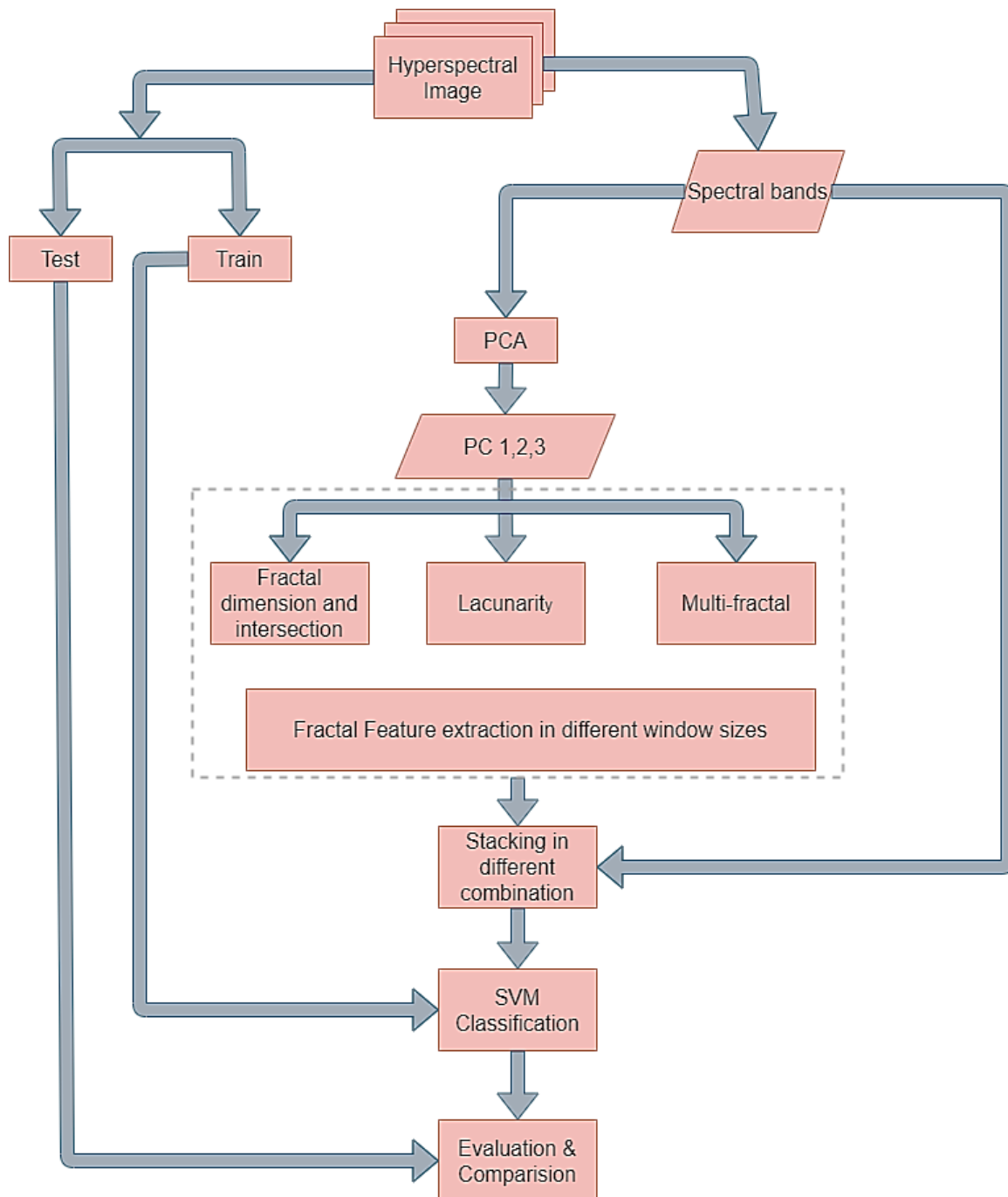


Figure 6. Multiple fractal-based feature classification.

A comprehensive literature survey of various compression techniques is tabulated in Table 1.

Support Vector Machine (SVM) (Linear), (Radial Basis Function) and Convolution Neural Network (CNN)

SVM linear, SVM RBF and convolution neural network model is used in [21] to obtain the useful neighboring spatial regions from the input HSI while PCA- Principal Component Analysis is used to eliminate the redundancies, high Spectral Dimensionality.

First, the neighboring spatial regions are extracted via deep learning, SVM (RBF) and SVM Linear function.

Second, CNN image patches ranging in size from one onwards are created. Experiments with a training dataset are utilized to determine the patch size. SVMs behavior is determined by the changeable width parameter's setting.

Third, the CNN model is trained such that it extracts high level features from each patch. These features are flattened into three 1D feature vectors, which are then concatenated. This is sent into a fully connected network as input. As illustrated in Figure 7, A software classifier is added on top of the two dense layers to predict the label of each pixel as well as the probability of each label.

Table 1. Literature survey: compression techniques.

Title	Authors	Conference/journals	Methods	HSI image	Remarks
Comprehensive review of hyperspectral image compression algorithms	Y. Dua, V. Kumar, and Ravi S. Singh	Optical engineering, issue 9 (2020)	VQPCA and JPEG2000	Indian Pines data set, Salinas data set, Kennedy Space Center data set, Pavia Center and University data set	high processing time is achieved
Nonlocal tensor sparse representation and low-rank regularization for hyperspectral image compressive sensing reconstruction	J. Xue et al, Y. Zhao, W. Liao and J. Cheung-Wai Chan	SILRS (2019)	HSI-CSR and NTSRLR	Indian Pines	HSI recovery quality is improved Better noise suppression
Low-complexity hyperspectral image compression using folded PCA and JPEG2000	S. Mei B. Muhammad Khan, Y. Zhang, Q. Du	IGARSS 2018 - International Geoscience and Remote Sensing Symposium	Folded PCA + JPEG2000	Indian Pines	The complexity of computation and the amount of memory required are both minimal
Compression of hyperspectral image using PCA DCT Tech	R.J. Yadav and M.S. Nag	Lecture Notes in Networks and Systems (2017)	HSI compression using PCA+DCT	Indian Pines, Salinas, Kennedy Space Center, data	Simple, time-efficient, Low computational complexity, high CR
Compressive sensing approach to satellite hyperspectral image compression	K.S. Guna Sheela and H.S. Prasantha	Smart Innovation, Systems and Technologies, issued in 30 December 2018	CS based compression algorithm	URBAN	Less encoder complexity
Hyperspectral image compression based on simultaneous sparse representation and general-Pixels	C. Fua, Y. Yia, F. Luoc, B. Du	Pattern Recognition Letters, Volume 116, p. 65-71	PWSR and SASR	Indian Pines, Jasper Ridge, Moffett and Washington DC	Efficient compression
A hardware friendly algorithm for the on board compression of hyperspectral images	R. Guerra, M. Diaz, Y. Barrios, S. Lopez, R. Sarmiento	Proceedings of the SPIE, Volume 10792, id. 1079208 13 pp. (2018)	Hyper LCA	Yellowstone, Lunar Lake and Moffett Field	More efficient and easily executable in many hardware devices
Skip block based distributed source coding for hyperspectral image compression	M. Banu N.M. Sujatha S., and Al-S.K. Pathan	Multimed tools Appl 75, 11267–11289 (2016)	SB-DSC	AVIRIS data set	Less encoder complexity and higher spectral gain
Lossless hyperspectral image compression based on prediction	Mamatha S. V. Singh	RAICS-IEEE Recent Advances in Intelligent Computational Systems 2013	HSI compression based on prediction	AVIRIS_SC3, Low Altitude Hawaii and Erta Ale	Obtains better CR than OCC scheme

SVM Combined Deep Learning

In [22] a soft max layer used to learn lower-level parameters is replaced with a single class SVM as classifier. This classifier uses output of the third layer of back propagate procedure of DL as input

which are 2000 dimensional vectors. The deep learning combined with SVM recognizes and classifies objects much better as seen in Figure 8.

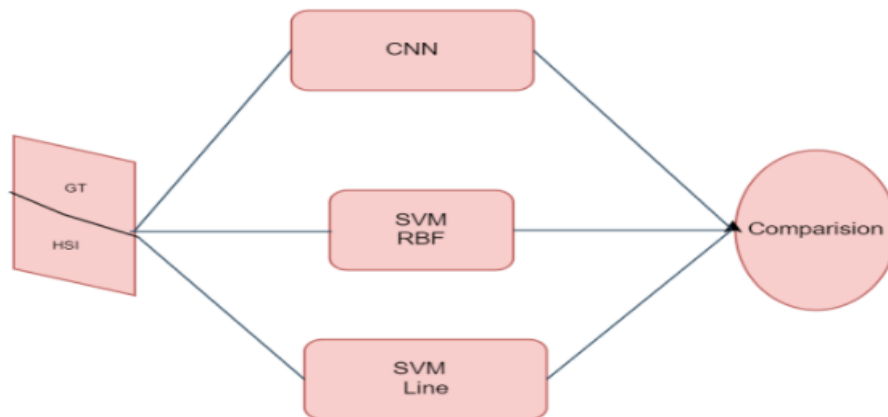


Figure 7. SVM (linear), SVM (RBF) and convolution neural network model.

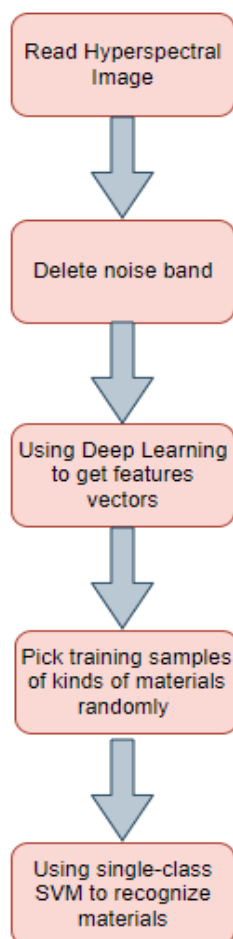


Figure 8. SVM combined deep learning.

RFE-EFS Algorithm

RFE works via means of trying to find a subset of capabilities through beginning with all the functions within side the training dataset and efficiently eliminating features until the preferred

quantity remains. So, that is carried out by instructing and teaching the system by sorting the features by importance and eliminating the less important ones, and readjusting the model. This procedure is repeated till a specific quantity of functions remains.

EFS is known as the Embedded Feature Selection; Typically, it learns which features are best for contributing to a model's accuracy while building the model. This article [23] makes use of an integrated technique to pick out capabilities of the use of SVM. The principal reason for deciding on this approach is that it can improve classification performance; by removing features that hamper the generalizability of the classifier by improving the kernel functionality.

Segmentation by Expectation Maximization (EM)

EM algorithm is a partition clustering approach. In this method [18], the assignment of data points is done partially to different clusters who are spectrally similar rather than assigning an individual cluster. To avoid inaccurate results, feature reduction is applied to the HSI before applying the EM algorithm.

RNN Model

Each input HSI is considered as a vector sequence whose dependencies between central and neighborhood pixels are modeled using RNN. The previous state and current data are fed into the (LSTM)- abbreviated as Long short-term memory. Input and output gates, forget gate, cell input and output are among the five sections of the LSTM. Here [24], at time t , the values of input gates and memory cells' states are computed. Then the forget gate activation is calculated at the same time. This helps us to compute the memory cells' new state. Ultimately, the output gate values can be computed as shown in Figure 9.

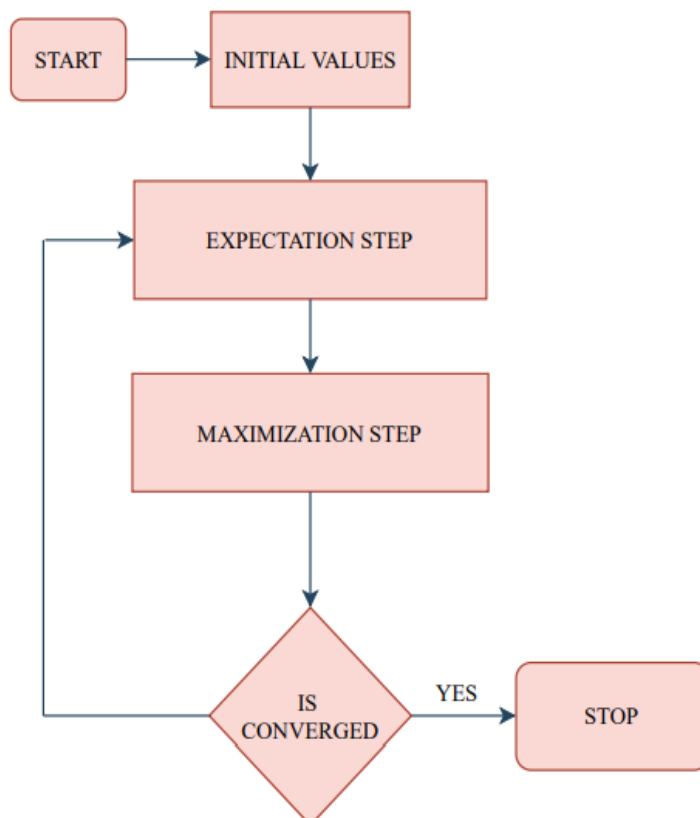


Figure 9. RNN Model.

A comprehensive literature survey of various classification techniques in tabulated in Table 2.

Table 2. Classification techniques survey.

Title	Authors	Conference/Journal	Method	HSI Image	Remarks
Spatial-spectral classification of Hyperspectral Images based on multiple fractal-based features	B. Asghari Beirami and M.M. Zade	Geocarto International Volume 37, issue 1-2020	Spatial-spectral classification based on multiple fractal-based features	Pavia University	Simple framework Best classification accuracy
Hyperspectral image recognition using SVM combined deep learning	Y. Li, J. Li, J.S. Pan	Journal of Internet Technology, vol. 20, no. 3, pp. 851-859, May-2019	SVM combined deep learning	Indian Pines	Excellent feature value extraction is obtained (appx ten times more)
Guided filter based Deep recurrent neural networks for Hyperspectral Image Classification	Y Guo, S Hana, H Cao, Y.U. Zhanga, Q Wanga	Procedia computer science, Volume, 129-2018	RNN Model (Recurrent neural network)	Indian Pines	Excellent performance and high accuracy
A Comparison Between Support Vector Machine (SVM) and Convolutional Neural Network (CNN) Models for Hyperspectral Image Classification	H. Hasan, H. Z.M. Shafri, Md. Habshi	IOP Conference Series: Earth and Environmental Science, Volume 357-2018	SVM and CNN model	The Chikusei dataset	may work with a variety of scales and window sizes
Hyperspectral image classification with Markov-random fields and convolutional neural networks	X. Cao, F. Zhou, L. Xu, D. Meng, Z. Xu, and J. Paisley	IEEE Transactions on image processing-2018	CNN-MRF	Indian Pines	Information on spectral and spatial regions are fully taken into account
Advances in spectral spatial classification of hyperspectral images	M. Fauvel, Y.T. Balka, J. Benediktsson, J. Chanussot, J. Tilton	Proceedings of the IEEE-2013	HSEG Segmentation	Indian Pines	Detailed classification obtained
Advances in spectral spatial Classification of hyperspectral images	M. Fauvel, Y. Tarabalka, Jón. A. Benediktsson, J. Chanussot, J. Tilton	Proceedings of the IEEE-2013	Segmentation by EM Algorithm	Indian Pines	Improvement in classification accuracy and time is significant
Segmentation and classification of Hyperspectral images using watershed transformation	Y. Tara Balka, J. Chanussot, Jón A Bene Diktsson	Pattern Recognition, Elsevier-2010	Watershed Algorithm	University of Pavia	Classification accuracies improved
Feature Selection and Classification of Hyperspectral images with Support Vector Machines	R. Archibald and G. Fann	Geoscience and Remote sensing Letters-IEEE-2007	RFE-EFS Algorithm	Indian Pines	significant reduction in computational time

SIMULATION RESULTS

Compression

In [16], a 16-bit AVIRIS dataset is used. Here, a comparison between the un coded and compressed image in terms of its signature is done. The results of the proposed method are similar to 3D based codecs with reduced encoder complexity for inter band processing. From Figure 10 and Table 3, it can clearly be inferred that the performance is similar to 2D SPIHT.

Table 3. PSNR results for various bit rates for Moffett Scene [16].

Scheme	0.5 bpp	1.0 bpp	2.0 bpp
2D SPIHT	35.98	40.11	47.1321
3D SPIHT	43.1	54.12	57.5
WZ scheme	42.2	52.26	55.0
WZ scheme	46.8	56.0	58.88
Proposed scheme	46.6	55.89	58.39

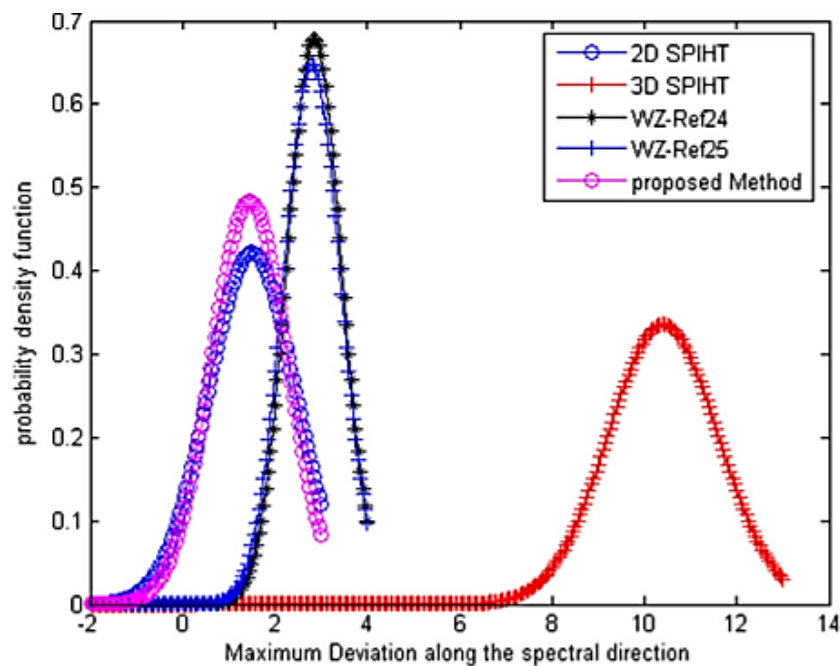


Figure 10. Maximum deviation after compression for low altitude scene [16].

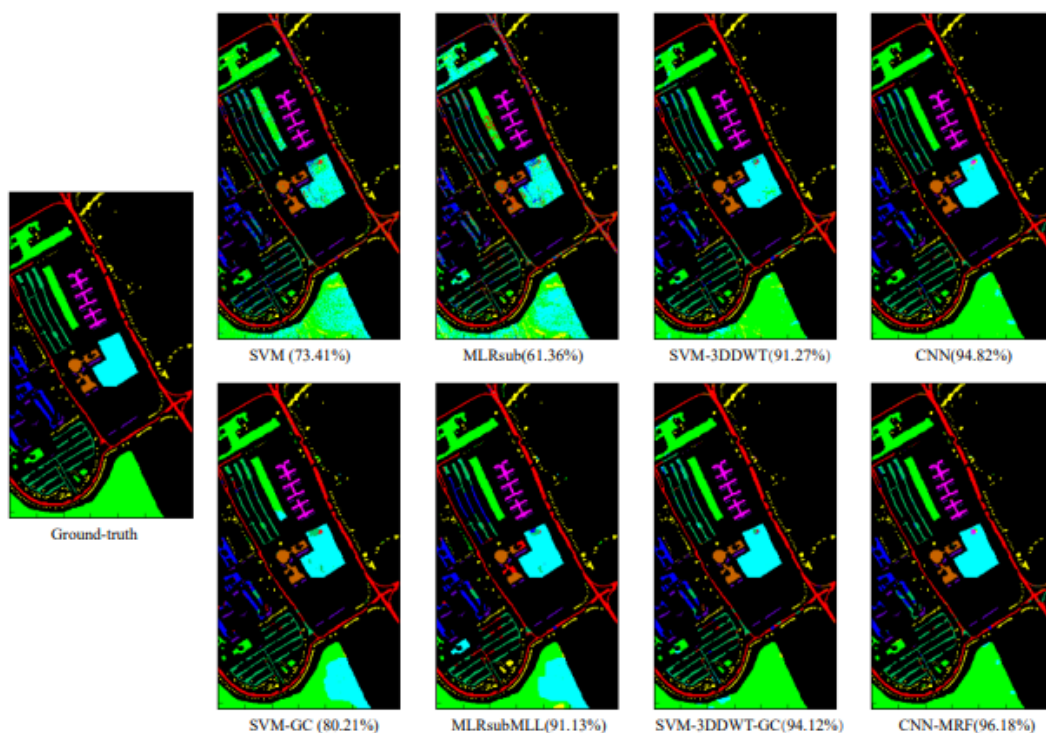


Figure 11. Classification maps for different methods implemented on Pavia University [15].

Classification

In [15], Authors have compared three different HSI classification methods of deep learning with CNN-MRF. The three methods are: SS-DCNN, SPP-DCNN and DC-CNN. These are applied to the Hyperspectral image dataset of Pavia University. This dataset contains 610*610 pixels along 103 spectral bands captured by the ROSIS sensor. The results shown in Table 4 and Figure 11 conclude that CNN-MRF obtains better overall accuracy, average accuracy and kappa coefficient value (Table 4). SVM-GC, MLRsubMLL and SVM-3DDWT-GC, CNN-MRF obtained better and smoother map of classification.

Table 4. Over all accuracy, average accuracy and kappa coefficient (%) of all the deep learning methods on the Pavia University Dataset [15].

Parameter	SS-DCNN	SPP-DCNN	DC-CNN	CNN-MRF
OA	93.34	94.88	99.68	99.71
AA	92.20	93.29	99.50	99.55
kappa	91.95	93.21	99.58	99.63
Time	266.11	333.90	3421.25	1156.43

CONCLUSION

Hyperspectral images are an essential part of earth observation and remote sensing applications. This survey aims to provide an insight on the two important stages of hyperspectral image processing, that is, compression and classification. In this paper, a comprehensive survey of various models of HSI classification and compression is done. A literature survey of both, showcases the merits and demerits of each technique allowing the reader to gauge which technique serves best for a specific application and assists readers in identifying and implementing a fast and effective HSI compression and classification technique.

REFERENCES

1. Gogineni R, Chaturvedi A. Hyperspectral Image Classification. Processing and Analysis of Hyperspectral Data. Book Chapter. Edited. Volume. 2020. doi: 10.5772/intechopen.88925.
2. Khan MJ, Khan HS, Yousaf A, Khurshid K, Abbas A. Modern trends in hyperspectral image analysis: a review. IEEE Access. 2018;6:14118–29. doi: 10.1109/ACCESS.2018.2812999.
3. Sucharitha B, Anithasheela K. Hybrid compression method for hyper spectral images using singular value decomposition and discrete wavelet transform. IEEE International Conference on Intelligent Systems, Smart and Green Technologies (ICISSGT). Nov 13–14 2021; Visakhapatnam, India, US: IEEE Press. Vol. 2022; 2021. doi: 10.1109/ICISSGT52025.2021.00032.
4. Fauvel M, Tarabalka Y, Benediktsson JA, Chanussot J, Tilton JC. Advances in spectral-spatial classification of hyperspectral images. Proc IEEE. Proceedings of the IEEE. 2013, 101 (3):652–75. doi: 10.1109/JPROC.2012.2197589.
5. Sucharitha B, Ather S. Hyper spectral image compression using fractal compression with arithmetic and Huffman coding, International Journal of Emerging Technologies and Innovative Research. June 2019;6(6):90–5.
6. Ugur Toreyin YB, Yilmaz O, Mert YM, Turk F. Lossless hyperspectral image compression using wavelet transform based spectral decorrelation 7th International Conference on Recent Advances in Space Technologies (RAST). Jun 16–19 2015; Istanbul, Turkey. Vol. 2015. IEEE Publications; 2015. p. 251–4.
7. Xue Jize, Zhao Y, Liao W, Chan JC-W. Nonlocal tensor sparse representation and low-rank regularization for hyperspectral image compressive sensing reconstruction. Remote Sens. 2019;11(2):193. doi: 10.3390/rs11020193.
8. Guerra R, Mar´, Íaz D, Barrios Y, Ópez SL, Sarmiento R. A Hardware-Friendly Algorithm for the on-board Compression of hyperspectral Images 9th Workshop on Hyperspectral Image and Signal Processing: Evolution in Remote Sensing (WHISPERS). Sep 23–26 2018; Amsterdam, Netherlands, US. IEEE Publications; 2018. p. 2019.

9. Karami A, Yazdi M, Mercier G. Compression of Hyperspectral Images Using Discrete Wavelet Transform and Tucker Decomposition. *IEEE J Sel Top Appl Earth Observations Remote Sensing*. April 2012;5(2):444–50. doi: 10.1109/JSTARS.2012.2189200.
10. Masoodhu Banu NM, Sujatha S Et al. Sakib Khan Pathan. Skip Block Based Distrib Source Coding Hyperspectr Image Compression. *Multimedia Tools & Applications*. 2016;75(18):11267–89.
11. Dua Y, Kumar V, Singh RS. Comprehensive Review of hyperspectral image compression algorithms. *Opt Eng*. September 2020;59(9). doi: 10.1117/1.OE.59.9.090902.
12. Gunasheela KS, Prasantha HS. Compressive sensing approach to hyperspectral image compression. *ICTACT J Image Video Process*. August 2018;9(1):1849–56. doi: 10.21917/ijivp.2018.0261.
13. Fu C, Yi Y, Luo F. Hyperspectral image compression based on simultaneous sparse representation and general-pixels. *Pattern Recognit Lett*. December 2018;116(1):65–71. doi: 10.1016/j.patrec.2018.09.013.
14. Mei S, Khan BM, Zhang Y, Du Q. Low-Complexity hyperspectral Image Compression using folded PCA and JPEG2000. *IGARSS 2018- IEEE International Geoscience and Remote Sensing Symposium*. July 22–27 2018. Valencia, Spain, US: IEEE Publications.
15. Mamatha AS, Singh V. Lossless hyperspectral image compression based on prediction. 2013 IEEE recent advances in intelligent computational systems (RAICS). 19–21 December 2013. Trivandrum, India, US: IEEE Publications; 2014.
16. Yadav RJ, Nagmode MS. Compression of hyperspectral image using PCA–DCT technology. *Lecture Notes in Networks and Systems*. 2018;7:269–77. doi: 10.1007/978–981–10–3812–9_28.
17. Guo Y, Han S, Cao H, Zhang Y, Wang Q. Guided filter based Deep Recurrent Neural Networks for hyperspectral Image Classification. *Procedia Comput Sci*. 2018;129:219–23. doi: 10.1016/j.procs.2018.03.048.
18. Cao Xiangyong, Zhou F, Xu L, Meng D, Xu Z, Paisley J. Hyperspectral image classification with Markov random fields and a convolutional neural network. *IEEE Trans Image Process*. May 2018;27(5):2354–67. doi: 10.1109/TIP.2018.2799324, PMID 29470171.
19. Tarabalka Y, Chanussot J, Benediktsson JA. Segmentation and classification of hyperspectral images using watershed transformation. *Pattern Recognit*. 2010;43(7):2367–79. doi: 10.1016/j.patcog.2010.01.016.
20. Beirami BA, Mokhtarzade M. Spatial-spectral classification of hyperspectral images based on multiple fractal-based features. *Geocarto Int*. 2022;37(1):231–45. doi: 10.1080/10106049.2020.1713232.
21. Hasan H, Shafri HZM, Habshi M. A comparison between support vector machine (SVM) and convolutional neural network (CNN) models for hyperspectral image classification. *IOP Conf Ser.: Earth Environ Sci*. 2019;357(1). doi: 10.1088/1755–1315/357/1/012035.
22. Li Y, Li Junbao, Pan J-S. Hyperspectral image recognition using SVM combined deep learning. *J Internet Technol*. 2019;20:851–9.
23. Archibald R, Fann G. Feature selection and classification of hyperspectral images with support vector machines. *IEEE Geosci Remote Sensing Lett*. October 2007;4(4):674–7. doi: 10.1109/LGRS.2007.905116.
24. Liu B, Yu X, Yu A, Zhang P, Wan G. Spectral-spatial classification of hyperspectral imagery based on recurrent neural networks. *Remote Sens Lett*. 2018;9(12):1118–27. doi: 10.1080/2150704X.2018.1511933.