Journal of
Data Acquisition and Processing
ISSN: 1004-9037
https://sjcjycl.cn/
DOI: 10.5281/zenodo.777560

A NOVEL COMPRESSION METHODOLOGY FOR HYPER-SPECTRAL IMAGE USING LOSSLESS TECHNIQUE

S .Nithya
Research Scholar JAIN (Deemed –to-be-University) Electronics Engineering, Bengaluru, Faculty of SJB Institute of Technology, Department of ECE, Karnataka, India

Dr. Shweta Gupta
Associate Professor, Department of Electronics and Communication Engineering, JAIN (Deemed-to be University) Bengaluru, Karnataka, India.

ABSTRACT:

In this research, a method is proposed to effectively compress hyper-spectral images in a lossless manner using machine learning techniques. The goal of this method is to enable the storage and transfer of larger amounts of hyper-spectral image data while preserving image details in both the spectral and spatial domains. The proposed system utilizes two consecutive neural layers to predict pixel values efficiently, minimize prediction errors, and keep computational complexity low. This approach has a wide range of applications in remote sensing and image manipulation. . In the proposed system, two consecutive neural layers are defined for performing an efficient compression without any loss of image details. This neural layer has an objective of minimize prediction errors with minimal computational complexity.
Keywords: Concatenation process, hyper spectral image, Neural network, Image manipulation.

1. INTRODUCTION:

In recent years, the field of image processing has become an active area of research, particularly in the area of remote sensing and image manipulation. This is due to the increasing use of image-based devices in various industries, such as military, healthcare, and satellite technology. The ability to produce efficient and accurate image output is crucial in these fields, and as such, various research methodologies have been developed to achieve this goal.

One area of image processing that has gained attention is the field of hyper-spectral imaging. These images contain a wealth of information and can be taken from a variety of sources, such as satellites or aircraft. However, due to the distance from which these images are captured, image processing steps such as compression and enhancement need to be carried out using effective methodologies.

In recent years, advancements in the field of hyper-spectral imaging have led to increased interest in its application in remote sensing. Many researchers have focused on developing new methods for image processing in this domain to improve image quality and accuracy. The sensing based application needs large storage space, expensive spectrometer devices, handy manipulation devices, unmanned space vehicles (1-5). *Figure 1* shows the hyper-spectral sensor and a receiving device flow mechanism.

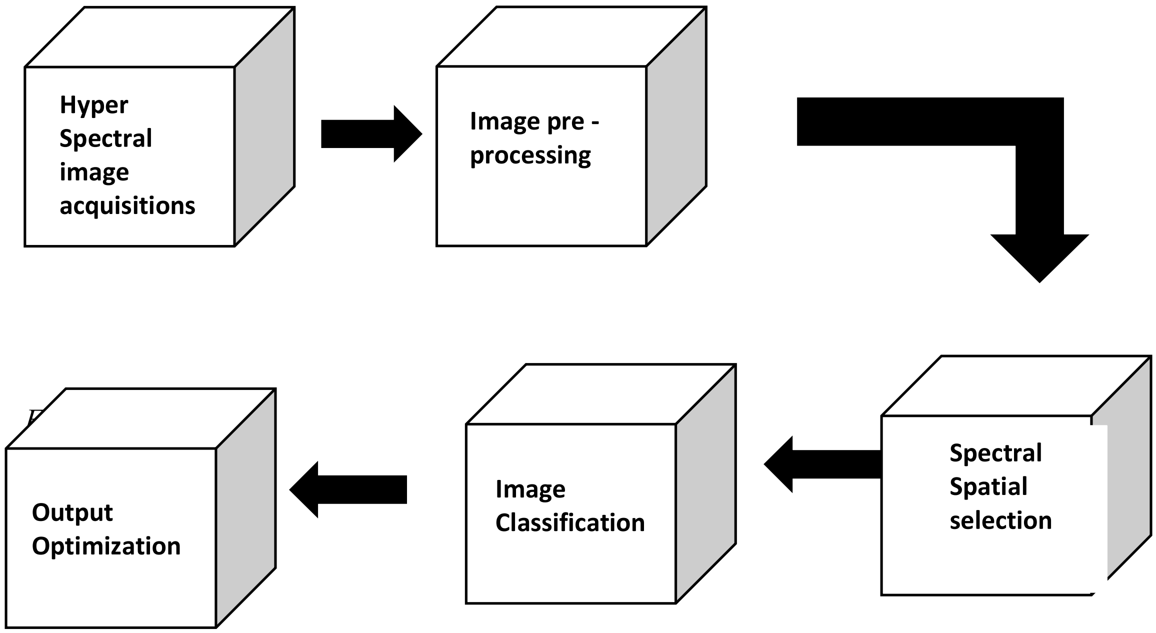

Figure 1. Flow Mechanism of Hyper-Spectral Image.

Hyper spectral imaging is a technique that collects images with high spatial resolution and a narrow bandwidth in the electromagnetic spectrum. These images are represented as a three-dimensional data set, where the first two dimensions represent the spatial details of the image, and the third dimension represents the spectral details of the image. Hyper spectral sensors currently collect images in a range from near field ultraviolet to short wave infrared.

Hyper spectral images have a greater number of spectral bands compared to traditional natural images, which typically only have three channels. Each spectral band in a hyper spectral image can have a higher bit depth, with 12 or 16 bits per pixel, while natural images typically have 8 bits per pixel. This high bit depth allows for greater detail and accuracy in the image data. For example spectral image of Pine region in indian region is shown in *Figure 2.* The images is taken with the help of Infrared region spectrometer devices.

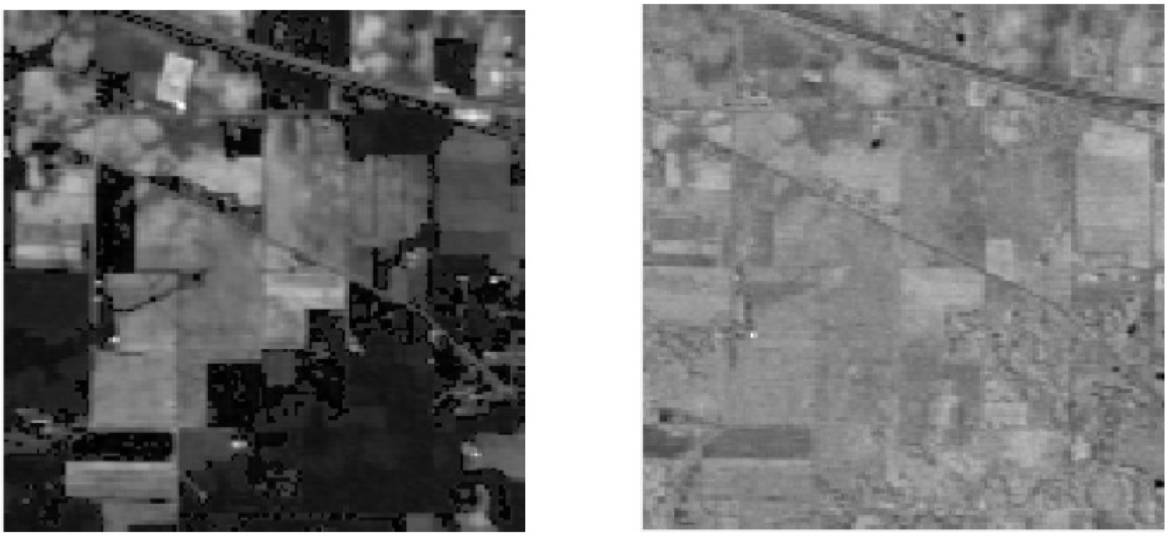

Figure 2 . Spectral Band 30 th and Spectral band 90 th pine region of indian location (140 x140 images of 16 bits/pixel).

Hyper spectral images require more storage and processing resources than traditional natural images due to their high bit depth and the large number of spectral bands. This means that hyper spectral imaging sensors require more resources for image collection and transmission than traditional natural images. However, there is an increasing demand for hyper spectral images in various applications, such as space devices, which makes it important to develop efficient methods for storing and transmitting hyper spectral image data cubes.

The proposed research in this paper aims to address this issue by developing a new image compression method for hyper spectral images. The remaining part of the research paper is organized as section 2 explains supporting research methodology for the proposed work followed by proposed image compression process. The performance of proposed system is depicted in section 4 as results and discussion. Finally, conclusion is described by section 5 and references taken are listed in section 6.

2. SUPPORTING RESEARCH METHODOLOGIES

In past research, various techniques have been proposed for manipulating hyper spectral images, such as transformation-based methods. These methods involve transforming the time-domain details of an image to different domains (such as frequency or wavelet domain) to achieve compression or enhancement (11-13). However, these methods have some limitations. One major limitation is that the conversion to different domains can result in a loss of accuracy in the spatial details of the image (14). Despite these limitations, transformation-based approaches have been found to have a good correlation between the spatial parameters and high image transformation accuracy.

Wavelet transform in three dimensions is a method that allows for the analysis of data in both the spatial and spectral domains. One dimension of the wavelet transform is used to represent the spatial information in the data, while the other dimension is used to represent the spectral information.

In Principal Component Analysis (PCA), the data is transformed to decorrelate the multiple components of the image. This can be useful for analyzing hyper spectral images, as it can help to extract more meaningful information from the data. However, PCA can be computationally complex, and various methods have been proposed to minimize this complexity, such as cluster-based computation and pairing-based computation. These methods are designed to make the analysis of hyper spectral images more efficient

3. PROPOSED IMAGE COMPRESSION.

The manipulation of hyper spectral images can be complex due to the large amount of spectral data they contain. To address this issue, an adaptable algorithm based on prediction methodology can be used to handle complex manipulation in a more efficient manner. This algorithm utilizes neural network techniques to observe the details of the image dataset of a hyper spectral image, both in the spatial and spectral fields, in order to make accurate pixel value predictions.

Unlike traditional neural networks, which require a training dataset to predict output values for an implemented application, the proposed neural network-based algorithm is adaptable and does not require a trained set for hyper spectral image compression processes. This makes it more efficient and useful for handling the complexity of hyper spectral images. There are two stages in the neural network has a capacity for getting the data set both in spatial and spectral correlation for producing a exact image's pixel value in the output image. As it does not need training set it has minimum computational complexity than traditional neural networks.

In general compression either lossy or lossless compression methods dataset must be formed efficiently. For lossy compression images will be dividing into smaller parts, then spectral and spatial details for all parts. This will increase computation complexity. On other hand lossless methods uses predictive technique which spatial and spectral image will be manipulated for entire images or in a cluster format. The lossless prediction of a hyper spectral image is shown in the below *figure 3.*

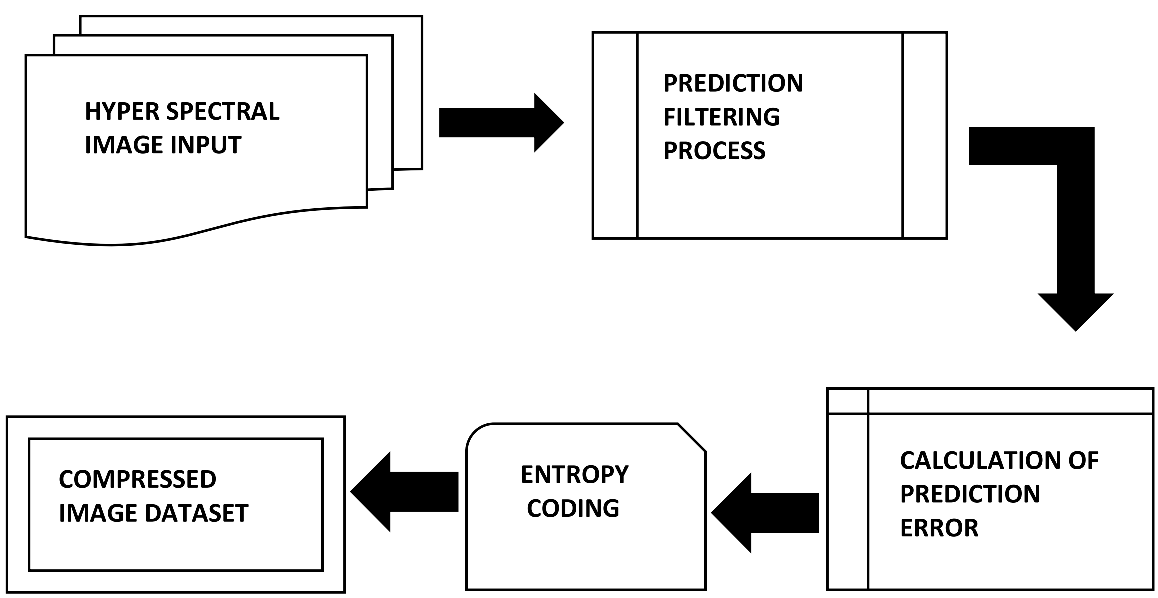

Figure 3. Compression Mechanism of Hyper Spectral Images.

We know that spectral image has both spatial and spectral datasets which can be able to compress in lossless manner using predictive methodology. In spite of spatial similarity presence between the image dataset we achieve efficient prediction output of pixel values. For hyper spectral image assume x_{abc} represents xand y axis with c as a spectral image cube. On the prediction of pixel values x'_{abc} uses previous pixel values will be used. The actual pixel vale and estimated pixel ($x_{abc} \sim x'_{abc}$) value is computed by encode module.

3.1 SELECTION OF CONTEXT IN A IMAGE

Initially selection of context in a image will be carried out before compression process. It is done by performing an average manipulation to encounter a betterment in the spatial correlation metrics as given in relation equation 1.

$$X''_{abc} = (x_{a-1,b,c} + x_{a-1,b-1,c} + x_{a,b-1,c} + x_{a,b+1,c}) \quad - (1)$$

The context for spatial domain in selected between current and previous bands of spectral images. For the formation of each band, 4 neighboring pixel values will be formulated in a one dimensional vector format as ($x_{a-1,b,c}$, $x_{a-1,b-1,c}$, $x_{a,b-1,c}$, $x_{a,b+1,c}$). Hence a combined spatial dataset is format in 3 x 4 matrix format as

($X_{a,b,c-4}$, $X_{a,b,c-3}$, $X_{a,b,c-3}$)

3.2 PREDICTION PROCESS

The efficacy of a prediction process depends on the selection of context metrics of the image. Let Y_i be the two dimensional spectral image data set of a hyper spectral image dataset as i=(1,2,….k) , k represents the total count of spectral band in image data cube. We may reshape the pixel values of Y_i in to a vector format , then the presence of pixel values is consider as a random process. For a hyper spectral image 16 bits/pixel Y_i is defined as $p_j = P(Y=j)$, where j belongs to pixel values in the range of ($0,2^{16}-1$). Then the entropy is given as in equation 2.

$$H(Y_i) = - \sum_j pj \log2 Yi \qquad - (2)$$

$H(Y_i)$ represents the low bit rate for lossless compression achieved using a predefined entropy module.

Further reduction in manipulation complexity is done by performing a first order based information context. The entropy of spectral image is processed as conditional context as shown in equation (3).

$$H (Y_i | C_{spat}, C_{Spec}) = - - \sum_j pj \log2 \text{ (Yi | Cspat, C Spec)} \qquad - (3)$$

Where C_{spat}, C_{Spec} represents spatial and spectral context of a hyper spectral image.

3.3 FRAMEWORK OF PROPOSED WORK.

The processing of proposed methodology has two phase computational stage as shown in *Figure 4* spatial phase and spectral phase. The details will be extracted from each of the phase from the context formation and they will be combined to predict the pixel value of compressed hyper spectral image.

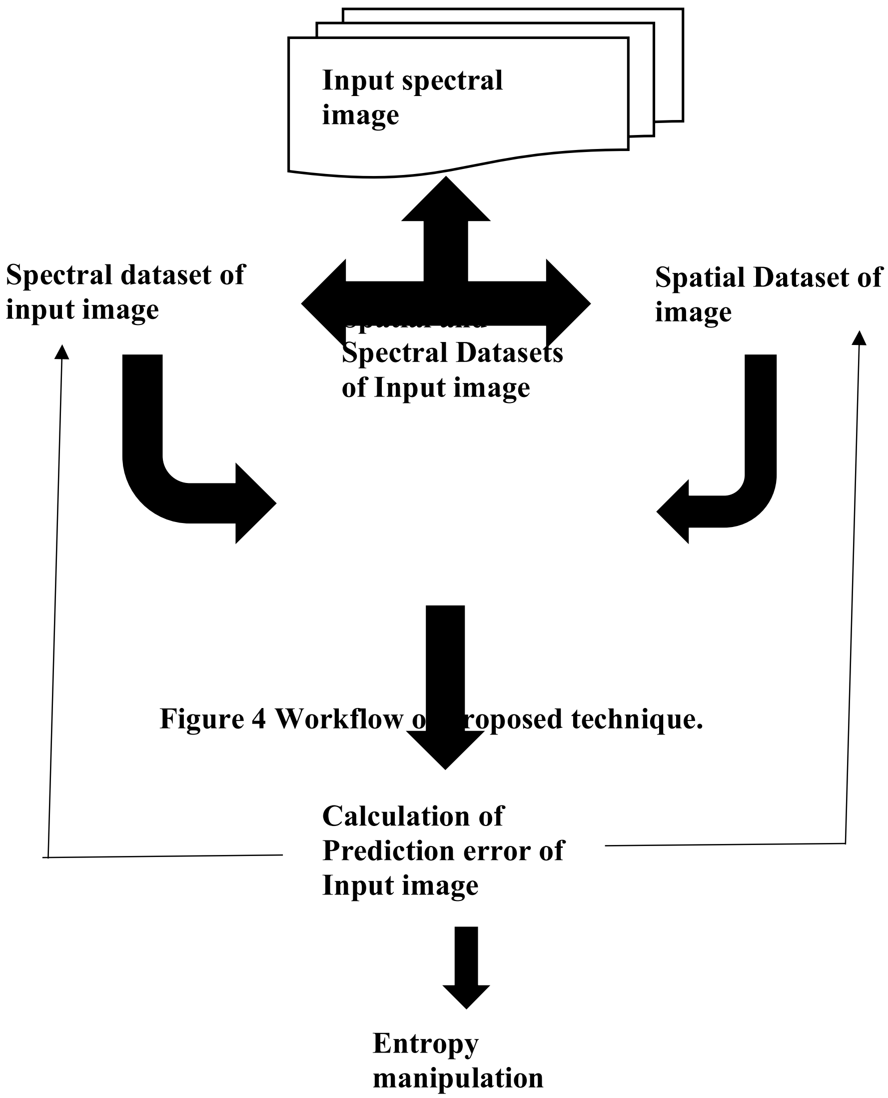

Figure 4 Workflow of proposed technique.

In the proposed system, both spatial and spectral details of input image are parallel correlated with the current pixel value to predict the estimated pixel values. It has two neural stages spatial and spectral correlation separately. To extract the features of spatial dataset of image a nonlinear process in series of mapping processing. The proposed work 3X4 dataset of spatial metrics is formatted into 1X8 dataset of spatial metrics. For spectral dataset same two stage hidden stages is used. But for spectral extraction a Nonlinear process of mapping is used. Algorithm used for the proposed system is given below.

Proposed methodologies Algorithm

Step 1: Initialize the neural networks.

Step 2: Calculate the correlation of spectral using *Equation 1.*

Step 3: Select the number of data sets for a spectral image

Step 4: Extract the spatial and spectral contexts Cspat and Cspec.

Step 5: Prepare the data sets from the contexts using neural networks.

Step 6: Concatenate spatial and spectral dataset of input spectral image

Step 7: Predict the pixel values.

Step 8: Calculate and record the prediction error ex,y,z for further mapping and coding.

Step 9: Compute the spectral image's weight for calculating prediction error

Step 10: Adjusting the parameters: $IMG_{weight} = IMG_{weight} + \Delta IMG_{weight}$.

Step 11: end process.

4. RESULT AND DISCUSSION

4.1 DATASET.

For estimating the performance of proposed system which used 20 hyper spectral images from *Indian Pine (145 X 130 X 200)* dataset.

4.2 MEAN SQUARE ESTIMATION.

In traditional neural network-based image manipulation, a trained dataset is used to make predictions. However, this approach has the disadvantage that the trained dataset is often a random selection of data and may not be representative of the actual image being processed. In contrast, the proposed system uses an adaptive methodology for predicting pixel values by using both the spectral and spatial datasets simultaneously.

To demonstrate the accuracy of the proposed methodology, a linear processing cycle is used to measure the prediction error. Figures 5 and 6 show the mean square error for various hyper spectral images, and it can be seen that the error falls to lower values after the image reaches above 30 bands. This suggests that the proposed system is more efficient at predicting the pixel values of compressed images.

S.no	Spectral Bands	Mean square Error
1	0	50
2	20	24
3	40	32
4	60	57
5	80	17
6	100	65
7	120	77
8	140	44
9	160	30
10	180	19
11	200	11

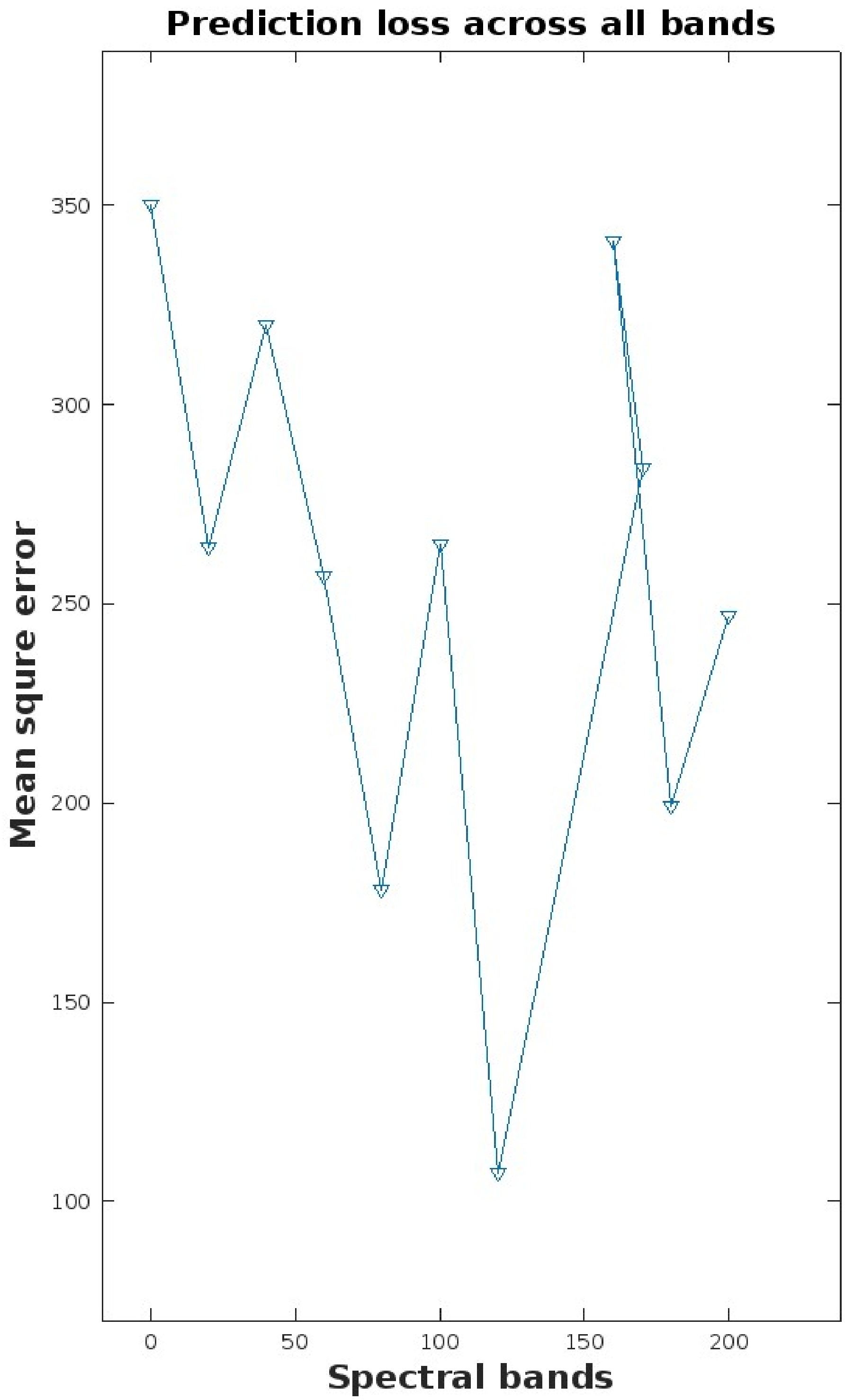

Figure 5 . Mean square variations of all bands for Indian pine dataset

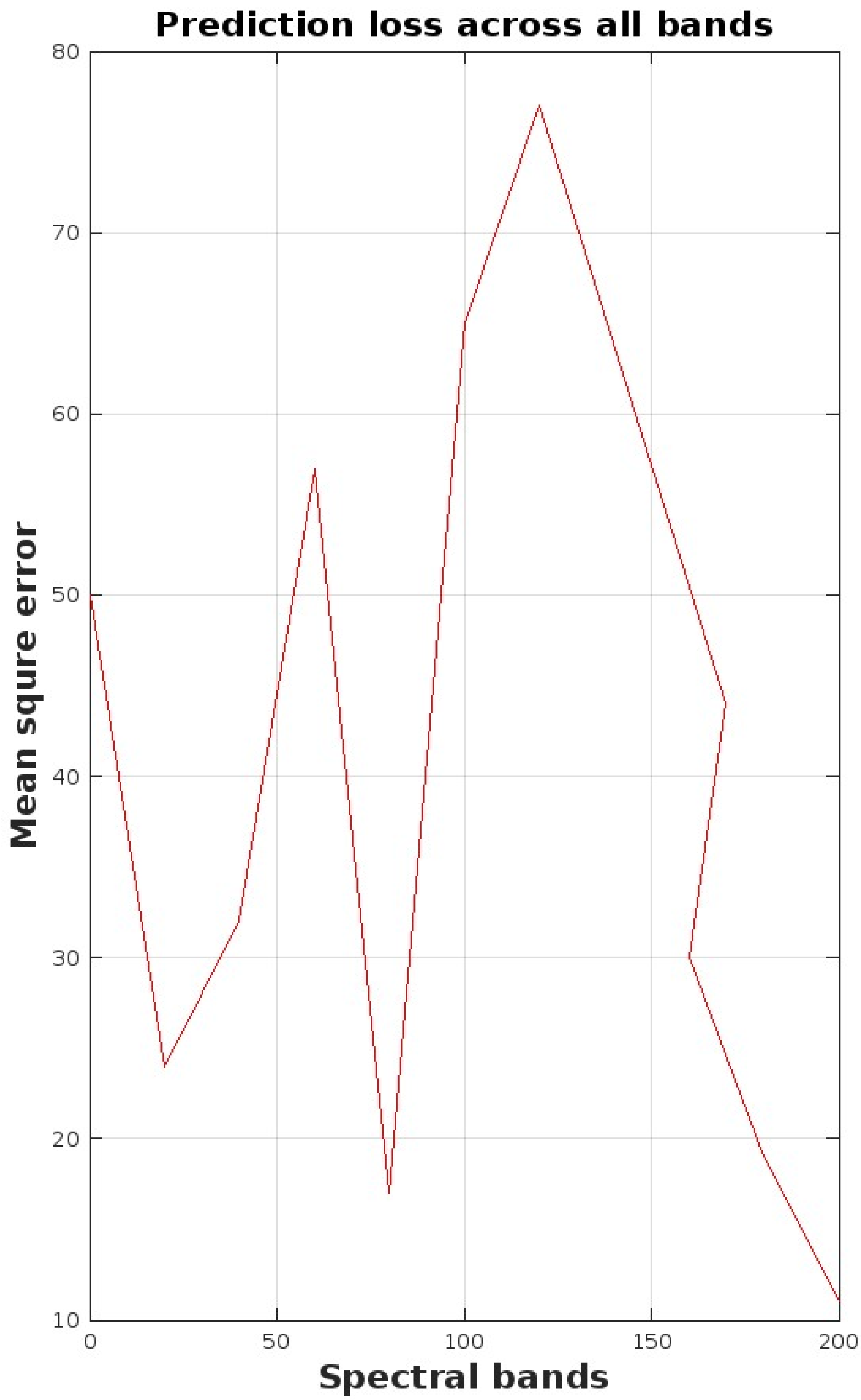

Figure 6. Mean square variations of all bands for Salinas dataset.

4.3 LEAST MEAN SQUARE ESTIMATION.

In general, the least mean square error (LMS) is a commonly used parameter to evaluate the efficacy of lossless image compression systems. For traditional neural network-based systems, the LMS is dependent on the training dataset. However, this can be a limitation as if a complex dataset is introduced during the processing stage, traditional neural networks may struggle to adapt and produce low efficacy values.

The proposed system, however, is adaptable to input datasets of spectral images and has the capacity to change according to the spectral and spatial values of the input images. This allows it to adapt to different types of images and produce more accurate predictions, resulting in a higher efficacy compared to traditional neural networks.

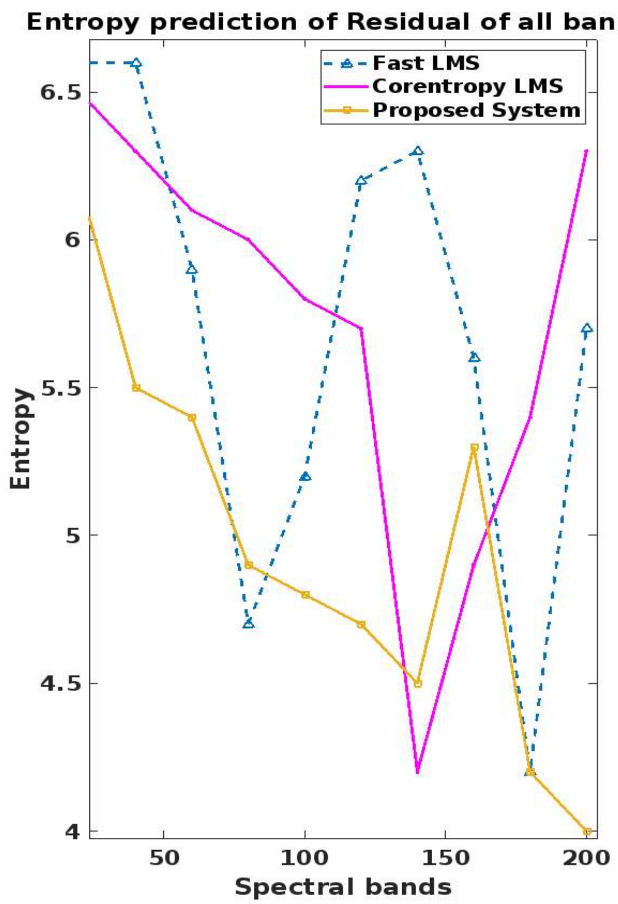

Figure 7. Entropy of prediction Residuals of all bands of Indian pine dataset

4.4 Comparison of Concatenation of two details and spatial details.

We know the proposed system estimated the spatial and spectral dataset parallel manner and then merges the both dataset for the estimation of pixel values of compressed images. The graphical representation shown in *Figure 8* represents the efficiency of concatenation process with actual spectral bands. We may see that both curves pass in a linear manner which implies that the proposed system compressed the given spectral image in a lossless compression method.

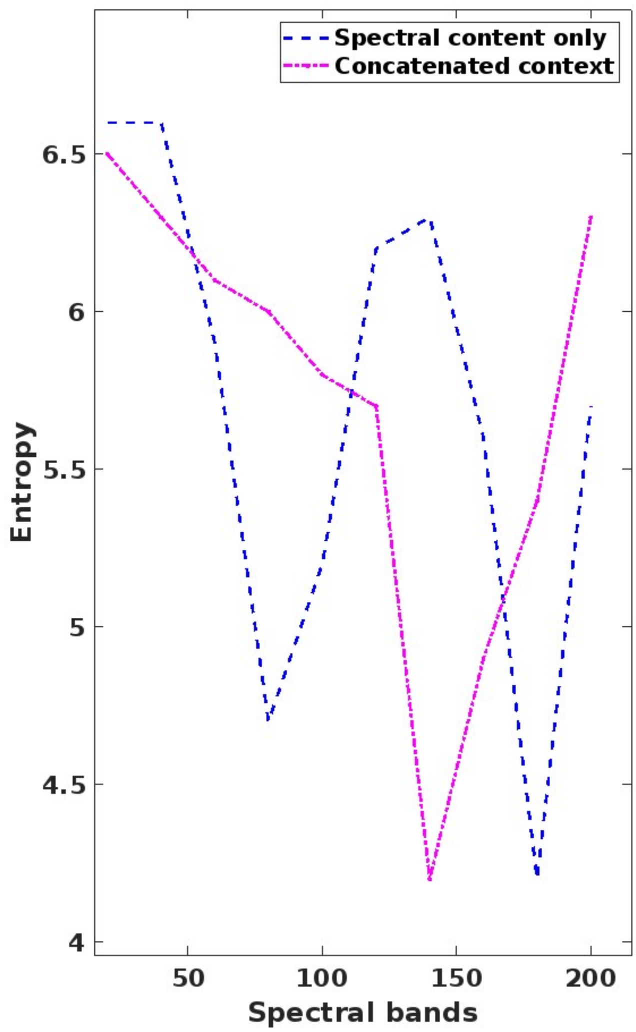

Figure 8. Comparison of Compression and spectral dataset

5. CONCLUSION

In this research, a new approach is proposed to overcome the difficulties in using traditional neural networks for performing lossless compression of hyper spectral images. The proposed technique does not require a training dataset, unlike traditional neural networks which rely on a training dataset for their computation process. The proposed technique employs a unique process for extracting the context details of hyper spectral images in both the spectral and spatial domains by processing both datasets in parallel to minimize computation time. The proposed neural network has two processing layers for the spatial and spectral domains separately. The adaptable nature of the proposed methodology and the absence of a training dataset make it suitable for compression of hyper spectral images. Simulation results have shown that the proposed technique achieves a low bit rate per pixel in the compression process with high compression gains for hyper spectral images.

6. REFERENCES

1. S. Golomb. Run-length encodings. IEEE Transcations on Information Theory,12(3):399{401, July 1966.
2. R. F. Rice. Some practical universal noiseless coding techniques. In Tech. Rep.JPL-79-22, Jet Propulsion Laboratory, Pasadena, California, March 1979.
3. M. Klimesh. Low-complexity lossless compression of hyperspectral imagery via adaptive altering. In The Interplanetary Network Progress Report, Jet Propulsion Laboratory, Pasadena, California, Nov. 2005.
4. A. Kiely. Selecting the Golomb parameter in Rice coding. In The Interplanetary
5. Network Progress Report, pages 1{18, Jet Propulsion Laboratory, Pasadena,California, Nov. 2004.
6. Lossless multispectral & hyperspectral image compression CCSDS 123.0-B-1,ser.Blue Book, May 2012. https://public.ccsds.org/Pubs/123x0b1ec1.pdf, 2012 (accessed September 1, 2016).
7. Z. Jiang, W. D. Pan, and H. Shen. Universal Golomb-Rice coding parameter estimation using deep belief networks for hyperspectral image compression. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing,11(10):3830{3840, October 2018.
8. T. Hastie, R. Tibshirani, and J. Friedman. The Elements of Statistical Learning.Statistics. Springer, New York, 2 edition, 2009.
9. X. Tang and W. A. Pearlman. Three-dimensional wavelet-based compression of hyperspectral images. Hyperspectral Data Compression. Springer, 2006.
10. J. Zhang and G. Liu. A novel lossless compression for hyperspectral images by context-based adaptive classied arithmetic coding in wavelet domain. IEEE Transcations on Information Theory, 4(3):461{465, July 2007.
11. K. Cheng and J. Dill. Lossless to lossy Dual-Tree BEZW compression for hyperspectral images. IEEE Transactions on Geoscience and Remote Sensing,52(9):5765{5770, September 2014.102
12. A. Karami, M. Yazdi, and G. Mercier. Compression of hyperspectral images using discerete wavelet transform and tucker decomposition. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 5(2):444{450, April 2012.
13. B. Penna, T. Tillo, E. Magli, and G. Olmo. Transform coding techniques for lossy hyperspectral data compression. IEEE Transactions on Geoscience and Remote Sensing, 45(5):1408{1421, May 2007.
14. B. Penna, T. Tillo, E. Magli, and G. Olmo. Progressive 3-D coding of hyper-spectral images based on JPEG2000. IEEE Geoscience Remote Sensing letters,3(1):125{129, January 2006.
15. C. L. Chang and B. Girod. Direction-adaptive discrete wavelet transform for image compression. IEEE Transactions on Image Processing, 16(5):1289{1302,May 2007.
16. P. Hill, A. Achim, M. E. Al-Mualla, and D. Bull. Contrast sensitivity of the wavelet, dual tree complex wavelet, curvelet, and steerable pyramid transforms. IEEE Transactions on Image Processing, 25(6):2739{2751, June 2016.

17. J. Zhang, J. E. Fowler, and G. Liu. Lossy-to-lossless compression of hyperspectral imagery using three-dimensional TCE and an integer KLT. IEEE Geo-science and Remote Sensing Letters, 5(4):814{818, October 2008.