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Deep Learning based Techniques on Hyperspectral Imaging

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Abstract:

There are certain challenges when dealing with hyperspectral images including limited training samples, high dimensionality of the data, Hughes phenomena, handling the noisy information, problem of overfitting and information loss. The work presented here describes the various techniques to handle the challenges above while working with the hyperspectral images and their applications. The mostly used classification algorithms are the k nearest neighbor algorithm, the support vector machine, Convolutional neural networks, Decision Trees, Random Forests, and other deep learning algorithms. The work reviews in detail the above algorithms and their performance based on few publicly available hyperspectral images datasets.

Keywords: Hyperspectral images, handling HSI, classification, KNN, CNN, Decision trees, Random Forests.

1. Introduction:

In the recent past, hyperspectral images have shown tremendous rise in its utilization in areas like, military, medicine, e-commerce, logistics, geology, mineralogy to name a few. There is a growing need for advanced tools for hyperspectral image processing in order to utilize the detailed information in the bands. The spectral and spatial information present in the spectrum can be used for solving many deep challenges that the current image handling tools cannot. The amount of information by the processing of the hyperspectral images is growing day by day due to the advances in the remote sensing and image capturing technologies. The large amount of information is leading to challenges including data redundancy, hyperdimensionality of the data, etc. There are certain advancements in the data dimensionality handling methods with the view to find an efficient method.

The Hyperspectral image classification is implemented successfully in many applications where the various techniques for handling the above issues are mentioned including Principal Component Analysis and others. The Paper is distributed in a way that the first part of the paper demonstrates the recent advancements and deep review of the hyperspectral image handling algorithms. The second part of the gives an architecture for hypercspectral image classification, then the later part describes the performance of the various existing technologies and the evaluation results.

2. Literature Review:

The involvement of the machine learning and deep learning algorithms in our day to day have given us opportunities that fuel our future in many ways.The literature mentioned in this work highlights the implementation and utilization of the various learning algorithms in the analysis and applications of the Hyperspectral images information. The Spectral and the spatial information represented over the bands can be utilized for the betterment of the mankind at various levels. The work presented gives an idea about the various applications and features of the deep learning algorithms over the hyperspectral images data from various fields.

2.1 KNN

Giuseppe Bonifazi, Giuseppe Capobianco, Riccardo Gasbarrone, Silvia Serranti [1], In the work, the authors have utilized the Principal Component Analysis method of the K nearest Neighbor algorithm in order to evaluate the quality control of the pistachio nuts. The other methods were applied for the same including the Principal Component analysis- Discriminant Analysis and Partial Least Square- Discriminant Analysis. The PCA-KNN is basically called the mixed classification method that combines the advantages of linear method that is PCA and the non linear method KNN. In this case the KNN uses maximal margin hyperplane to give its best performance for classification task. The implementation cost and the high classification efficiency is the main advantage of this method.

S. KLIBI, K. TOUNSI, Z. B. REBAH, B. SOLAIMAN and I. R. FARAH [2], In the work presented, the authors have worked on soil salinity prediction model. The machine learning approaches applied in the model for improving the efficiency of the system include the mix of auto encoders with methods like KNN, SVM and Decision Trees. The authors have proposed the pixel based approach using spectral signature and the feature vector of the input hyperspectral images. The problem of insufficient data for classification was handled in the work with the help of the neighborhood matrix for each of the image pixels. The accuracy and the efficiency of the method applied by the combination of the auto encoders and other deep learning methods have proved to be better for image classification.

Yanhui Guo, Siming Han, Ying Li, Cuifen Zhang, Yu Bai [3], The authors have used the combination of K-nearest Neighbor along with the guided filter method in order to increase the accuracy of the image classification. Pattern recognition is one of the applications of the non – parametric KNN. The authors have used the integration of the spatial and the spectral information for bettering the classification accuracy. They have also used the guided filter to extract the spatial features of the image for an guided image and then applied a joint representation KNN for the classification task. The joint method have succeeded in improving the classification accuracy.

Huang, K., Li, S., Kang, X. *et al* [4], The authors in the work have introduced KNN based spatio-spectral hyperspectral image classification method in order to improve the classification accuracy. The KNN is applied for image filtering by searching the similar non local pixels. The property of KNN that it can model the spatial co-ordinates and pixel values in the given feature space can help in refining the input image. This can further help for spectral –spatial classification. In the KNN filtering applied for classification in this work uses principal component analysis method in order to generate one band hyperspectral image representation. The KNN based filtering algorithms have generated competitive classification accuracies.

W. Song, S. Li, X. Kang and K. Huang [5], The work mentioned in the paper have concentrated on improving the classification accuracy using the KNN with sparse representation approach. The local region and the non local region of the pixels in the hyperspectral images were explored for detailed pixel information with the help of KNN method. The PCA algorithm has been used for the dimension reduction of the dataset used and further used to generate the new dataset required. The K non-local pixels are identified using KNN search in order to use them for improving the classification accuracy

2.2 SVM:

R. Sunkara, A. K. Singh, G. R. Kadambi and P. K. N [6], The authors have worked over the monitoring the water resources with the help of satellite images captured. For the proposed system, they have applied deep learning based segmentation and SVM classifier approach. This can be used to retrieve the location the water resources. Here the SVM works well improving the accuracy of the classification as compared to the other methods. This can be applied to track the water reservoir with the range of the water in the water reservoirs.

Deepak Kumar Jain, Surendra Bilouhan Dubey, Rishin Kumar Choubey, Amit Sinhal, Siddharth Kumar Arjaria, Amar Jain, Haoxiang Wang [7], The authors have implemented the support vector machine using the SOM that is self organizing maps. Later the classification of the input images can be done based on interior and exterior pixels by comparison of the Posterior Probability of every pixel intensity. For the performance analysis, 16 and 9 classes of plants have been considered and the method outperforms in terms of Accuracy, Kappa and confusion matrix. By the SOM-SVM method it is possible to reclassify the misclassified pixels thus improving the efficiency of the algorithm.

D. K. Pathak and S. K. Kalita [8], The authors have utilized the features of the Support Vector Machine Algorithm to classify hyperspectral images with the help of spectral and spatial features of the image.

They have analysed that the support vector machines can handle large amount of data and noisy samples as well. The approach mentioned in the article shows good performance with respect to accuracy with even small number of uneven training samples. It is mentioned that the method of incorporating the spectral and the spatial features is the main strength of the system and the performance was better than other methods like KNN, Linear Discriminant analysis, etc,

2.3 Conventional Neural Network:

S. Mei, X. Chen, Y. Zhang, J. Li and A. Plaza [9], The authors have observed that the CNN can perform better when it comes to feature extraction capabilities. The CNN has the capability to learn the spectral and spatial features from the given images data.

To further improve the performance of the network, the paper presents a new step activation quantization method. The method discussed here is effective and also reduces memory requirement during the process of classification. The proposed method even proved effective in terms of processing speeds in turn benefitting in the requirements of the hardware implementations by constraining the network layes with the binary weights. .

M. Kanthi, T. H. Sarma and C. S. Bindu [10], The work mentioned in this article concentrates on the implementation of the new approach by utilizing the CNN model to implement 3d deep feature extraction using both the spectral and the spatial information. The input data is divided into 3D patches and is given as an input to the proposed model in order to feature extraction. For implementing the model, two convolutional layers along with two ReLu layers, then, used one- max pooling layer are used. Better overall classification accuracies are obtained over three considered data sets.

C. Yu *et al*., [11], The authors in this work have worked on the CNN method along with an extracted hashing feature for performing hyperspectral image classification. The hash functions are constructed for locality and discriminability of the designed classes. The CNN has been designed to get the hierarchical feature maps including the spatial and the spectral information. The extraction of deep features from the images considered is possible using this approach. Hence, the classification accuracy can be further improved using these extracted features.

J. Li, Q. Du, B. Xi and Y. Li [12], The work presents the approach for hyperspectral image classification where the combination of the CNN architecture along with the orthogonal complement subspace projection balance solution is mentioned in order to handle the problem of few training samples. The authors then have used the synthetic minority oversampling technique for improving the classification accuracy. The benefit of the combined approach is that the classification performance can be improved with the help of more distinctive and refined spectral features.

2.4 Spectral Angle Mapper

S. Chakravarty, B. K. Paikaray, R. Mishra and S. Dash [13], The spectral angle mapper algorithm is a supervised learning algorithm and has been in use for the hyperspectral image classification recently. The algorithm has been widely utilized for the spectral image classification using the spectral angle threshold. The authors in this work have used the method to categorize the satellite image. They explain that Hyperspectral image with multiple bands is captured by the remote sensing satellite. For implementing the spectral angle mapper, hyperspectral images of various bands are first kept over one another in the pattern of three dimensional cube of given images. The SAM then calculates the spectral angle for image classification. Color coding is used to distinguish between the classes and identify the class with good accuracy.

V. S. Sahithi, S. Subbiah and S. Agrawal [14], The authors in the work have evaluated the performance of the three advanced classifiers including spectral angle mapper. They have considered the limitations of the spatial and the spectral dimensions over the hyperspectral and multispectral images data. The fused and unfused both types of images have been used for the evaluation process. The SAM classifier is used to find the spectral similarity between image spectra and the reference spectra by way of calculating the angle between the spectra useful for performing the classification. Over the given data set, SAM classifier output consisted of many unclassified classes and gave less accuracy as compared to ANN and SVM.

B. Tu, C. Zhou, W. Kuang, L. Guo and X. Ou [15], The authors in this work have concentrated on the noisy label detection using a spectral angle along with the local outlier factor (SALOF) algorithm. The training pixel when it is mislabeled causes the noisy label in the hyperspectral images.The SALOF algorithm developed here is used to improve the supervised classification efficiency to a level. This proposed method is cabale of detecting the noisy labels effectively. The overall accuracy is achieved with the help of improved dataset.

2.5 Decision Tree

A. I. Champa, M. F. Rabbi, S. M. Mahedy Hasan, A. Zaman and M. H. Kabir [16], The authors highlighted that the HSI contain many spectral bands containing huge information useful for essential classification applications. The paper presents a Hybrid approach for feature selection used for the image classification. In work dimensionality reduction has been applied over the input dataset and top ten features have been selected. AIRIS sensor data has been utilized where three classifiers have been applied. Based on the concept of Decision trees and random forest, Extremely randomized tree or Extra Tree concept was utilized for the classification efficiency. This outperforms the available classifiers.

Guangxin Ren, Yujie Wang, Jingming Ning, Zhengzhu Zhang [17], The authors in this work have developed a quality assessment method for testing the tea quality without involving humans. The near-infrared hyperspectral imaging has been combined with the multiple decision tree method for the analyzing the quality of the delineating black tea. Various decision tree algorithms including the fine tree, medium tree and course tree were used for testing the modeling effect in the created method. The performance of the system was based on parameters including correct classification rate which has generated 93.13 prediction accuracy.

N. Praditya and A. H. Saputro [18], The authors have concentrated on the hyperspectral image classification application for identifying the beewax over the Rome beauty apples. Here, the hyperspectral images of the wavelength ranging from 400 to 1000 nm was utilized. The reflectance profile measure was used in order to classify the waxed and nonwaxed apples. The dimensionality reduction clustering was applied using the Principal Componenet Analysis. The decision tree model was applied which showed better classification accuracy. The Decision tree model was implemented using 13 essential variables and 13 features for performing the classificationtask.

M. Gupta and S. Minz [19], The authors have worked on a spatial classification information for the classification of the hyperspectral images. The method ID3 decision tree method has been modified for the incorporation of the spatial information of neighboring objects in turn helping predict the actual interested object. The spatial information involved can be nominal or continuous values based on which the splitting criterion was decided. The work has successful implementation of the spatial relationships and have generated reduced error rates. The method was implemented with better classification accuracies and can be applied where spatiality plays a vital role.

2.6 Random Forest

K. M. Sai Kishore, M. Kumar Behera, S. Chakravarty and S. Dash [20], The authors in this work have mentioned that the classification of the features of the hyperspectral image is a crucial task. They have focused on the classification of the complex hyperspectral images with the help of the SVM, Decision tree, Polinomial logistic regression and other classification methods. The method of minimum noise fraction have been used to reduce the un-necessary and noisy data bands for the input data of the hyperspectral images. The authors have observed that the decision trees serve as the one of the best solutions for classification of the hyperspectral images. Over the data considered for the classification, the random forest gives the best overall classification accuracy results.

X. Liu, R. Wang, Z. Cai, Y. Cai and X. Yin [21], The authors have highlighted that the overall performance of the Deep neural

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Networks is dependent on the quality of the input data. The input data dimension is too high and very fine tuned due to which the structural complexity is also increased. The proposed work concentrates on the implementation of the Deep forest for HIS classification task. Later the Deep forest have been extended fo deep multigrained cascade forest in order to implement spatial feature based hyperspectral image classification. The Cascade Random Forest was developed to perform the multigrain scanning over the input data in order to enhance the output. Further, a pooling layer has been added to reduce the generated output dimension.

I. Khosravi and Y. Jouybari-Moghaddam [22], The authors have worked on the implementation of the filter based forest methods for hyperspectral image classification. The methods used are the balanced filter based forest and the other method is the cost sensitive filter based forest for the classification of the high dimensional hyperspectral data. The authors in the work highlighted that the methods have the capability to handle the imbalanced data problems during the classification process. The implementation of the methods have proved to be more efficient than the existing classical forests methods. The SVM served better for handling of the imbalanced data used in the hyperspectral image classification.

Z. Long, M. Xiaoyu, L. Zhigang and L. Yong [23], In the work, the authors have worked on the classification of the tobacco leaves and their impurities. The methods utilized here are smoothing filter, multiplicative scatter correction method and the random forest classifier. The random forest classifier consists of series of decision tree classifiers in which independent random variable exist which is utilized for pixel classification. Here each decision tree required only few training samples to train and only k features randomly extracted are required for the input nodes for classification process. The random forest have shown a better overall classification accuracy.

3. Proposed Methodology:

3.1 Dataset

1. ROSIS Pavia University Hyperspectral Image: Reflective optics spectrographic image system (ROSIS) Pavia University hyperspectral image was acquired with ROSIS optical sensor which provides 115 bands with a spectral range coverage ranging from 0.43 to 1μ. The spatial resolution is 1.3 m. The each image has pixels with 103 spectral channels and 9 classes were considered.

2. Kennedy Space Center (KSC) Hyperspectral Image: KSC hyperspectral image shown in Fig. 1(e) was acquired with airborne visible/infrared imaging spectrometer (AVIRIS) sensor over the Kennedy Space Center (KSC), Florida, USA, on March 23, 1996. This image has 224 bands from 400 to 2500 nm and the

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spatial resolution is 18 m. After removing water absorption and low signal-to-noise (SNR) bands, it has pixels with 176 bands. Thirteen classes are used for this site.

3. Salinas Hyperspectral Image: Salinas scene shown was collected by the 224-band AVIRIS sensor over Salinas Valley, California, and is characterized by high spatial resolution (3.7-m pixels). The area covered comprises 512 lines by 217 samples. After discarding the 20 water absorption bands (108–112, 154–167, 224), 204 bands are used for classification. There are 16 classes in the ground truth image.

4. The Indian Pines (IP) images: It has images with 145 × 145 spatial dimension and 224 spectral bands in the wavelength range of 400 to 2500 nm, out of which 24 spectral bands covering the region of water absorption have been discarded. The ground truth available is designated into 16 classes of vegetation.

3.2 Proposed work

The layers can be identified in given Fig. 1. As the first CNN model is designed to classify a given image into 2 classes, the output layer has two neurons. The last completely associated layer, which is a two-layered highlight vector, is given as an input to softmax classifier, which makes the last prediction whether there is tumor or not. The proposed CNN model for Classification-1 has 13 weighted layers.

- 1 input
- 2 convolutions,
- 2 ReLU,
- 1 normalization,
- 2 max pooling,
- 2 fully connected,
- 1 dropout,
- 1 softmax
- 1 classification layers)

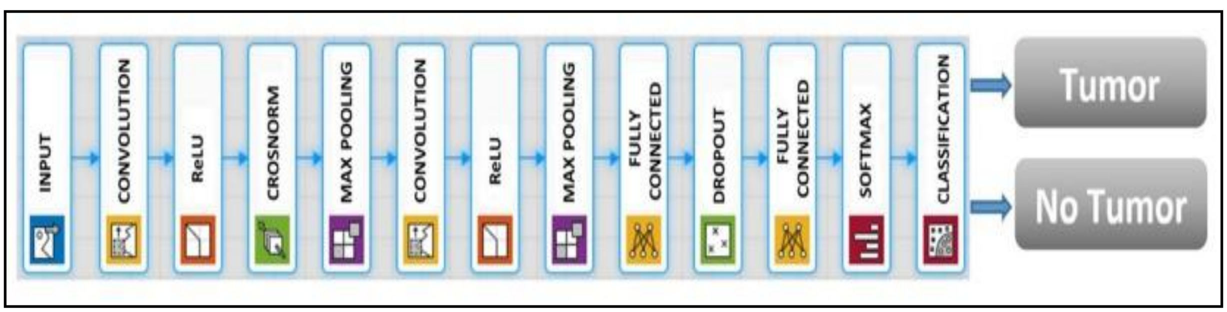

Figure.1 Layered View of CNN Model

Refer to Table 2 for more information about the CNN architecture. As far as the summarized process for proposed work is concerned, first of all the CNN model is designed and implemented for compilation. Afterwards the training data is provided to the model for and the output is analyzed for proper validation of outputs. Total 13

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iterations are considered for complete analysis to find out the iterations with best accuracy results. These results are used for providing the actual input and find out the whether the given image is having a tumor or not. This process provides a good way to draw results with better accuracy.

3.3 CNN Model Description:

Layer	**CNN layer**	**CNN layer Description**	**Layer activations**
1	Input	227 x 227 x 3 input layer	227 x 227 x 3
2	Convolution	128 6 x 6 x 3 convolutions with stride [4 4] and padding [0 0 0 0]	56 x 56 x 128
3	ReLU	ReLU-1	56 x 56 x 128
4	Normalization	Cross-channel normalization	56 x 56 x 128
5	Max pooling	2 x 2 max pooling with stride [2 2] and padding [0 0 0 0]	28 x 28 x 128
6	Convolution	96 2 x 2 x 128 convolutions with stride [1 1] and padding [2 2 2 2]	31 x 31 x 96
7	ReLU	ReLU-2	31 x 31 x 96
8	Max pooling	2 x 2 max pooling with stride [2 2] and padding [0 0 0 0]	15 x 15 x 96
9	Fully connected	512 fully connected layer	1 x 1 x 512
10	Dropout	30% dropout	1 x 1 x 512
11	Fully connected	2 fully connected layer	1 x 1 x 2
12	Softmax	Softmax	1 x 1 x 2
13	Classification	Output with ‘ No tumor’ and ‘tumor’	

3.4 Crop the part of the image representing only the brain.

Resize the image (because the images in the dataset come in different sizes (meaning width, height and # of channels). So, we want all of our images to be (240, 240, 3) to feed it as an input to the neural network.

1. Apply normalization because we want pixel values to be scaled to the range 0-1.

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2. Append the image to X and its label to y.
3. After that, Shuffle X and y, because the data is ordered (meaning the arrays contains the first part belonging to one class and the second part belonging to the other class, and we don't want that).
4. Finally, Return X and y.

4. Prediction Model

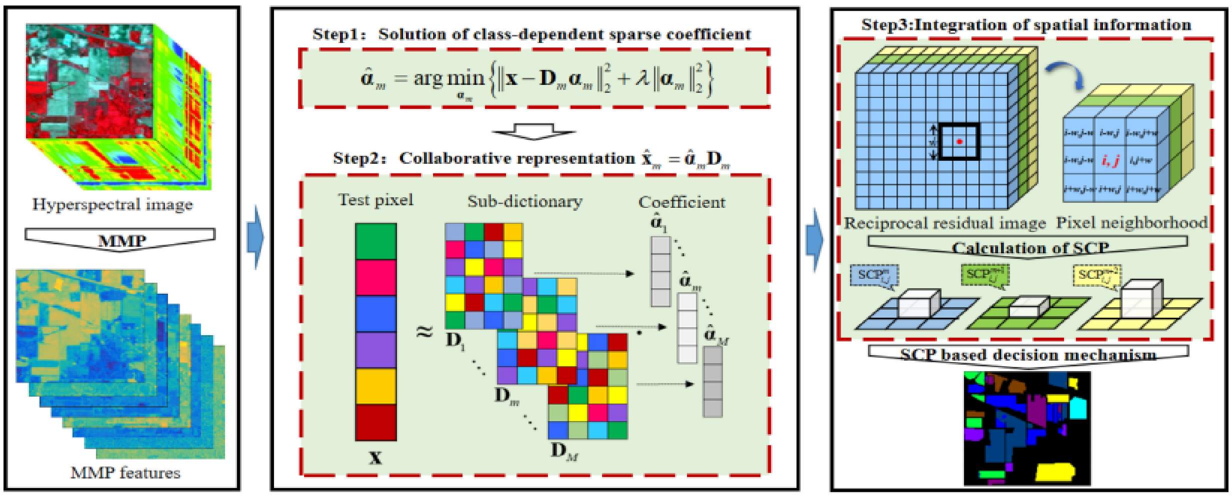

Figure 2. Prediction model

4.1 Implementation

```
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         [(None, 240, 240, 3)]     0

zero_padding2d (ZeroPadding  (None, 244, 244, 3)       0
2D)

conv0 (Conv2D)               (None, 238, 238, 32)      4736

bn0 (BatchNormalization)     (None, 238, 238, 32)      128

activation (Activation)      (None, 238, 238, 32)      0

max_pool0 (MaxPooling2D)     (None, 59, 59, 32)        0

max_pool1 (MaxPooling2D)     (None, 14, 14, 32)        0

flatten (Flatten)            (None, 6272)              0

fc (Dense)                   (None, 1)                 6273

=================================================================
Total params: 11,137
Trainable params: 11,073
Non-trainable params: 64
_________________________________________________________________
```

Figure 3. Prediction model configuration

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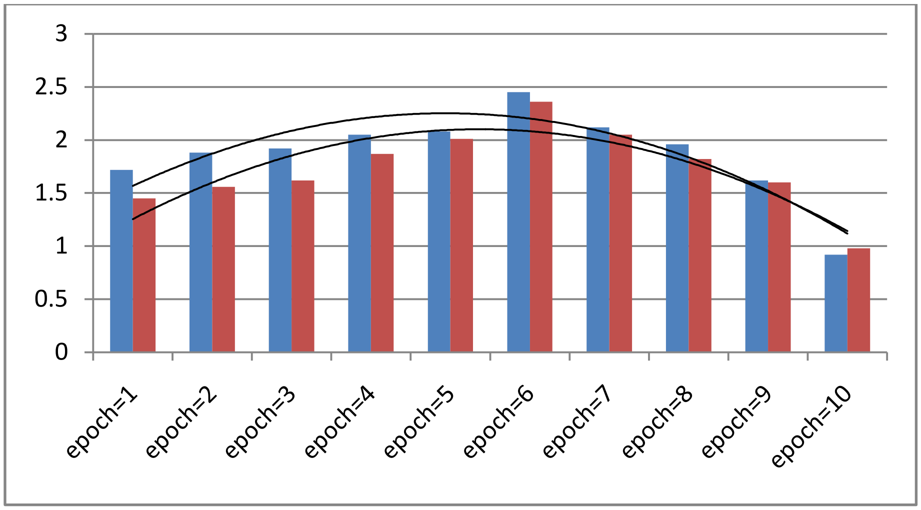

Figure 4. Learning growth

4.2 Model Evaluation & Final Results

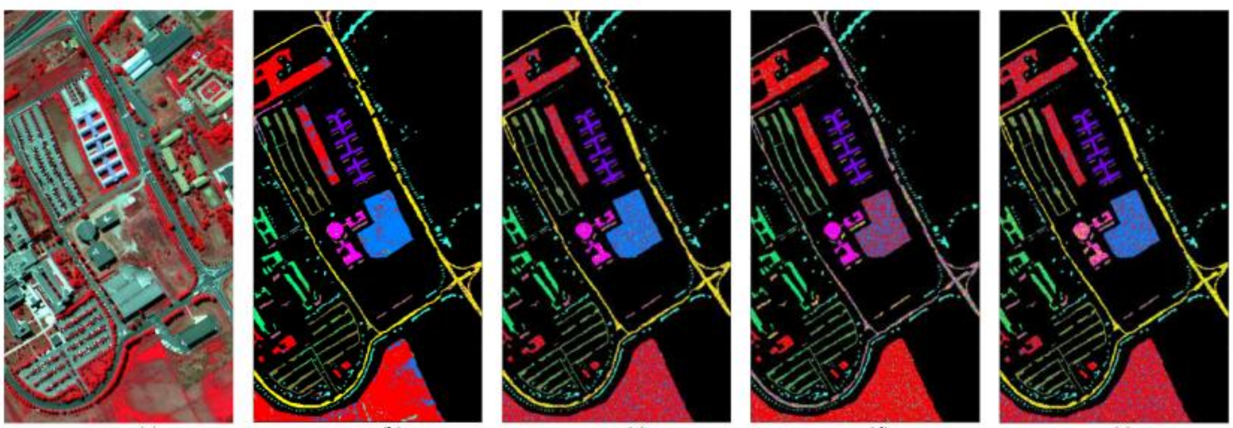

Figure 5. Classification Results

Accuracy of the best model on the testing data:

Test Loss = 0.13098762929439545

Test Accuracy = 0.9806451797485352

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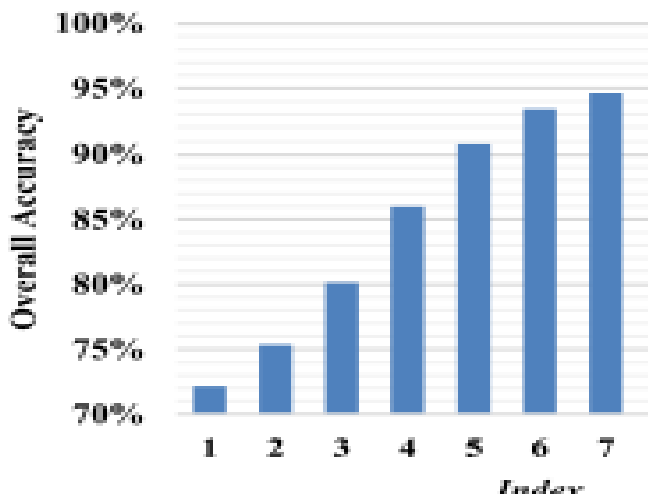

Figure 6. Classifier Accuracy

F1 score for the best model on the testing data:

F1 score: 0.9814814814814815

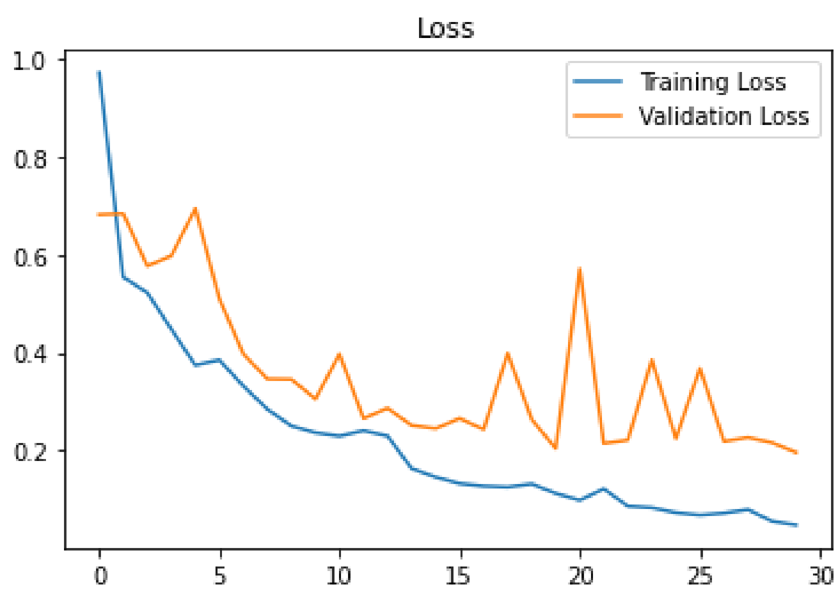

Figure 7. Loss Plot

The f1 score on the validation data:

F1 score: 0.9602446483180428

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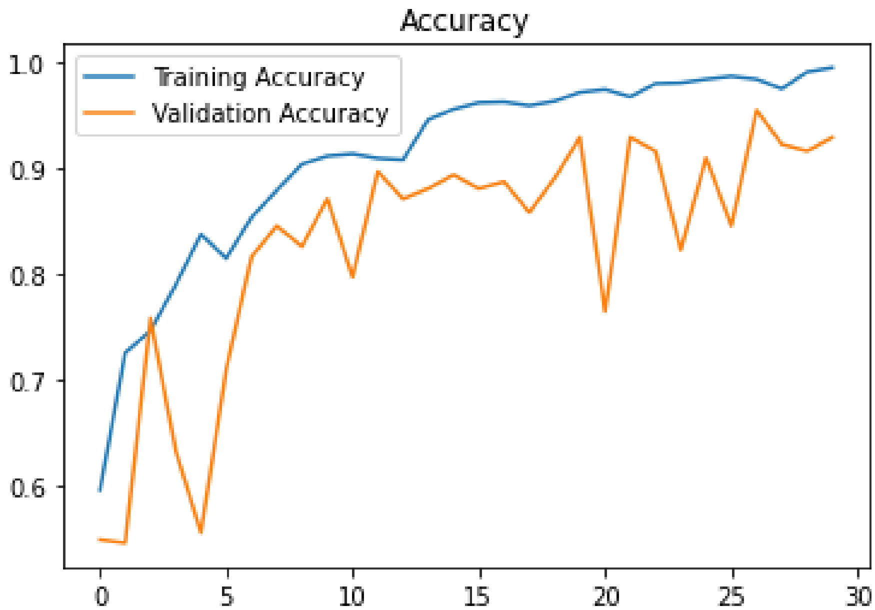

Figure 8. Accuracy Plot

Conclusion:

Multispectral images generate few broad wavelength bands when compared with hyperspectral images which produce more narrower bands . These more number of narrow bands derive continuous spectrum which contains tons of information useful for detailed analysis. Along with the useful information available, there exist challenges while handling the hyperspectral images. The work has discussed the recent advances in various classification techniques in order to handle the issues related to the classification of the hyperspectral images. This work presents a novel CNN-based deep network architecture specifically designed to manage large hyperspectral data cubes. In particular, the proposed new hyperspectral classifier pursues to improve the straightforward residual model formulation by better exploiting the potential of the information available on each unit. The proposed architecture gradually increases the feature map dimension step by step at each pyramidal bottleneck residual blocks, composed of three convolutional layers, as a pyramid, in order to involve more feature map locations as the network depth increases, while balancing the workload among all units and preserving the time complexity per layer. The experimental part of the work, conducted over four well-known hyperspectral data sets and using 10 different classification methods, reveal that the new hyperspectral pyramidal residual model is able to provide a competitive advantage over state-of-the-art classification methods.

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