Classification of high dimensional hyperspectral images using spatial spectral wavelet CNN:SpectralNET

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Abstract— **Hyperspectral images are used in two ways: one is matching the full pixel spectrum with reference spectra for identification of specific target materials based on expected absorption/reflectance in known wavelength bands. The other approach is classification of feature vectors using machine learning algorithms, for which the high dimensionality of the hyper spectral data is a problem. In order to make the classification problem more manageable, dimensionality of the high dimensional datasets needs to be reduced, either by feature selection or feature extraction.**

In this paper we tried to implement the concept of spectral NET which proved to be working better than most of the state of the art algorithms for hyperspectral image classification by making a tradeoff between time and space. A wavelet CNN is a type of SpectralNET that uses layers of wavelet transform to bring out spectral features. Then we connect these spectral features to 2D CNN to bring out spatial features. The experiments were run on the standard/benchmark datasets i.e. Indian Pines, University of Pavia, and Salinas scenes.

***Keywords*— Index terms – Convolutional Neural Network CNN, hyperspectral image, dimensionality reduction, SpectralNET, spectral spatial features.**

I. INTRODUCTION

Hyperspectral sensors measure energy in narrower and more numerous bands than multispectral sensors. So, the dimension of features is sometimes set into hundreds. There is a redundancy of features that are obtained from hyperspectral remote sensing data. So, our task is to eliminate the correlated features and give a representative feature set of the image without any data loss (ie) projecting the data to a lower dimensional subspace which captures the "essence" of the data. We have to find an efficient classification algorithm for our task keeping in mind the cost of computation and the volume of the data that is available for classification of images especially hyperspectral images. There are number of algorithms that scientists have experimented in the past on the classification of hyperspectral images like 2D CNN's, 3D CNN's [1], hybrid based 2D-3D CNN's [2] and FuseNet [3] are among the most frequently used classification algorithms for HSI. 3D-2D CNN's have been proposed in the past where authors have utilized channel wise shift and channel wise weighting to highlight and separate out different spectral bands [4]. RNN's consider spectral signatures of the HSI as a sequence in order to learn discriminative features. Even though there is both spatial and spectral feature extraction from a HSI in 3D-2D CNN's the model is not generalizable to other datasets or is limited. Here in this paper, we used a 2D wavelet CNN for HSI classification. Wavelet transform is understood as one of the best feature extractor for HSI classification task. Once both the spatial and spectral features are extracted from the HSI image they are concatenated channel wise and fed as input to the dense classification layers of 2D CNN's. Factors analysis is used as a preprocessing technique to reduce the dimension of the image. Then patches are extracted and sent into the CNN. This reduces the training time as well. The spectral features coming from wavelet transform are computationally lighter as well compared to a 3D CNN. The model outperforms all previous models and paves the way for wavelet CNN in multi-resolution image classification.

II. OBJECTIVE

1. To develop such a framework for HSI image classification keeping in mind the computational costs and the volume of the data available for training the model and generalising the model to other datasets.

III. MOTIVATION

The computational costs can be reduced significantly if we can classify images with low dimension feature sets and lot of useful applications in the domain of agriculture and health, these techniques can be used to compute different attributes of an image and give predictions to farmers about crop quality etc., real time so that they are more prepared.

IV. PROBLEM STATEMENT

Some image sets, particularly in case of hyperspectral remote sensing, can be of dimension extending into hundreds. The spectral features do have redundancy, so efficient dimensionality reduction algorithms are an active area of research.

V. STUDY APPROACH

This section describes the methods used to complete the project and contains details about data sources and methodologies.

A. Data used (Sources) :

Table 1 Detail description of the data sets used

Name	Spatial Dimension	Spectral Bands	Wavelength Range (nm)	Classes
IP	145*145	224	400-2500	16
UP	610*340	103	430-860	9
SA	512*217	224	360-2500	16

B. Methodology

We will go through the basic literature out there for implementation of dimensionality reduction on high dimensional images and understand different techniques that one can employ. Then, we understand the kind of image data that we are working on and map it to the existing literature, then do some preprocessing of the data. It will help us give a fair idea of the feature set. We will study all the possible and implementable optimization algorithms which are used for dimensionality reduction for high dimensional images and then implement one after another on a sample image. Based on the chosen metric to analyses the output of the dimensionality reduction feature set, we will choose the possible algorithm/model for the data which can give the most optimum solution without any loss in data.

Steps used are:

Step 1: Literature review: Collect papers using Scopus and google scholar.

Step 2: Based on the Literature review, we started defining our project research topic and objectives.

Step 3: Acquiring the databases

Step 4: Analyse the databases and collect only necessary parameters to make the dataset for applying

Step 5: Select the data set and recent advancements in the HSI classification using advanced CNN and deep learning techniques.

Step 6: Chose different metrics for analysing the model developed.

Step 7: Develop a confusion matrix mentioning the details of classification results in terms of precision, recall, F1 score, test loss, overall accuracy, average accuracy and kappa accuracy.

Below mentioned Fig describes the SpectralNET architecture using wavelet CNN model for HSI classification [6].

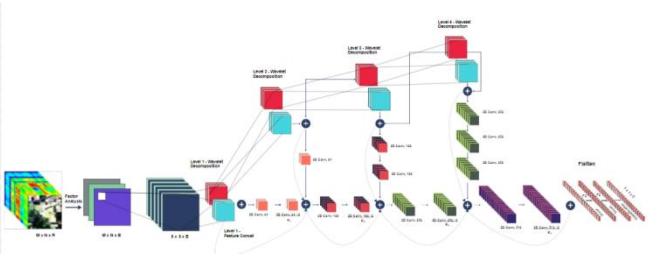

Fig: Proposed SpectralNET (Wavelet CNN) Model for hyperspectral image (HSI) classification.

Detail Model description: The input HSI cube is having a dimension of AXB*R which is sent into the layer of Factor Analysis (FA) to reduce the dimension of the image to A*B*C. The output vector Y has the dimension of 1*AB which take the values C of the categorical variables of different classes of the image chosen. The spectral dimensions are preserved in FA by reducing the number of band without loss of any information unlike PCA from R to C. Using FA in HSI as a pre-processing step is extremely beneficial, as FA is able to describe the variability among the different correlated and overlapping spectrum bands, which helps making the model classify similar examples better. On the other hand, commonly used Principal

Component Analysis (PCA) based reduction does not directly address this objective in HSI. PCA provides an approximation to the required factors which do not help to differentiate similar examples that well. After the FA step is complete, overlapping 3D patches of size SxSxC are extracted from the pre-processed HSI and sent into the SpectralNET. SxS is the window size for patch extraction, for the Indian Pines dataset the patch size has been set at 64x64 and for the University of Pavia and Salinas Scene dataset the window size has been set at 24x24. The truth values for these patches are determined by the center pixel's class category. The values were chosen based on experimentation to maximize the overall accuracy. Relu activation function is used on the hidden deep layers and explored the stochastic gradient descent (SGD) over 150 epochs with a learning rate of 0.01 and momentum of 0.9 to optimize the objective function.

VI. RESULTS AND CONCLUSION

The below tables 2, 3, 4 discuss the results of the classification of the 3 datasets Indian Pines, Salinas scene and University of Pavia respectively

Table: 2 DETAILED CLASSIFICATION RESULTS FOR INDIAN PINES DATASET IN TERMS OF PRECISION, RECALL, F1-SCORE, TEST LOSS, OVERALL ACCURACY, AVERAGE ACCURACY AND KAPPA ACCURACY

Class Labels	Precision	Recall	f1-score	Support
Alfalfa	1.00	1.00	1.00	32
Corn-notill	1.00	1.00	1.00	1000
Corn-mintill	1.00	0.99	1.00	581
Corn	1.00	1.00	1.00	166
Grass-pasture	0.99	1.00	1.00	338
Grass-trees	1.00	1.00	1.00	511
Grass-pasture-mowed	1.00	0.85	0.92	20
Hay-windrowed	1.00	1.00	1.00	335
Oats	0.78	1.00	0.88	14
Soyabean-notill	1.00	1.00	1.00	680
Soyabean-mintill	1.00	1.00	1.00	1719
Soyabean-clean	1.00	1.00	1.00	415
Wheat	1.00	1.00	1.00	143
Woods	1.00	1.00	1.00	886
Buildings-Grass-Trees-Drives	1.00	1.00	1.00	270
Stone-Steel-Towers	0.98	1.00	0.99	65
accuracy			1.00	7175
macro avg	0.98	0.99	0.99	7175
weighted avg	1.00	1.00	1.00	7175
Test loss				0.7%
Average accuracy (%)				99.98%
Kappa accuracy (%)				99.84%
Overall accuracy (%)				99.86%

Table 3: DETAILED CLASSIFICATION RESULTS FOR SALINAS SCENE DATASET IN TERMS OF PRECISION, RECALL, F1-SCORE, TEST LOSS, OVERALL ACCURACY, AVERAGE ACCURACY AND KAPPA ACCURACY

Class Labels	Precision	Recall	f1-score	Support
Brocoli-green-weeds-1	1.00	1.00	1.00	1406
Brocoli-green-weeds-2	1.00	1.00	1.00	2608
Fallow	1.00	1.00	1.00	1383
Fallow-rough-plow	1.00	1.00	1.00	976
Fallow-smooth	1.00	1.00	1.00	1875
Stubble	1.00	1.00	1.00	2771
Celery	1.00	1.00	1.00	2505
Grapes-untrained	1.00	1.00	1.00	7890
Soil-vinyard-develop	1.00	1.00	1.00	4342
Corn-senesced-green-weeds	1.00	1.00	1.00	2295
Lettuce-romaine-4wk	1.00	1.00	1.00	748
Lettuce-romaine-5wk	1.00	1.00	1.00	1349
Lettuce-romaine-6wk	1.00	1.00	1.00	641
Lettuce-romaine-7wk	1.00	1.00	1.00	749
Vinyard-untrained	1.00	1.00	1.00	5088
Vinyard-vertical-trellis	1.00	1.00	1.00	1265
accuracy			1.00	37891
macro avg	1.00	1.00	1.00	37891
weighted avg	1.00	1.00	1.00	37891
Test loss				0.001%
Average accuracy (%)				100%
Kappa accuracy (%)				100%
Overall accuracy (%)				100%

Table 4: DETAILED CLASSIFICATION RESULTS FOR UNIVERSITY OF PAVIA DATASET IN TERMS OF PRECISION, RECALL, F1-SCORE, TEST LOSS, OVERALL ACCURACY, AVERAGE ACCURACY AND KAPPA ACCURACY.

Class Labels	Precision	Recall	f1-score	Support
Asphalt	1.00	1.00	1.00	4642
Meadows	1.00	1.00	1.00	13055
Gravel	1.00	1.00	1.00	1496
Trees	1.00	1.00	1.00	2145
Painted metal sheet	1.00	1.00	1.00	942
Bare soil	1.00	1.00	1.00	3520
Bitumen	1.00	1.00	1.00	931
Self-Blocking Bricks	1.00	1.00	1.00	2577
Shadows	1.00	1.00	1.00	663
accuracy			1.00	29944
macro avg	1.00	1.00	1.00	29944
weighted avg	1.00	1.00	1.00	29944
Test loss				0.07%
Average accuracy (%)				99.98%
Kappa accuracy (%)				99.98%
Overall accuracy (%)				99.99%

VII. FUTURE WORK AND SUGGESTIONS

We would like to explore more deep learning models for HSI image classification and document both pros and cons featuring each dataset that we chose to work on and generalize methods and algorithms to a particular kind of features or image set.

VIII. CHALLENGES AND LIMITATIONS

The dataset has been reduced from 224 spectral bands to 3 using FA on Indian Pines dataset which has some drawbacks. Running the model on the system is difficult unless we have high GPU capacity. So the hyper parameters are not tuned and experimented for multiple times to come up with the most optimum values.

ACKNOWLEDGMENT

We would like to express our gratitude to Tanmay Chakra borty & Utkarsh Tehran the authors of the paper- SpectralNET a 2D wavelet CNN for hyperspectral Image Classification, and the team of PyCK, who guided us throughout this project. We would also like to thank our friends and family who supported us and offered deep insight into the study.

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