Hyperspectral Image Classification using Spatial-Spectral WaveletCNN

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***Abstract*—In contrast to traditional images which consists of just 3 bands of colours(namely red , blue and green colour) , hyperspectral images consists of multiple bands of wavelengths. The broad electromagnetic spectrum is collected and processed during hyper-spectral imaging. Hyper-spectral imaging helps to obtain the spectrum for every pixel in an image, in order to locate objects, detect processes or identify materials.**

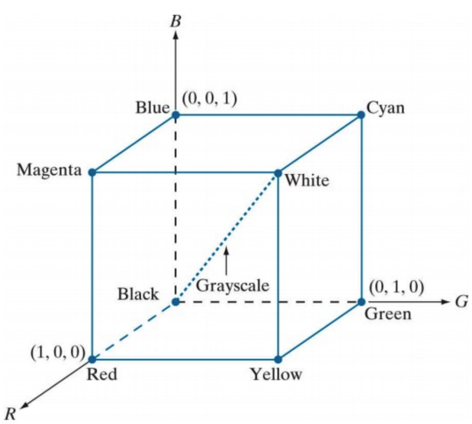
Engineers design and build hyper-spectral sensors and processing systems for a variety of applications such as in astronomy, molecular biology, agriculture, geosciences, physics, and surveillance. These sensors collect data across a wide range of the electromagnetic spectrum and can identify the materials that make up an object by analyzing its fingerprint or spectral signature. For example, spectral signatures of oil can help geologists find new oil reserves.

The study aims at developing a SpectralNET based model for topographical land area classification of Hyper Spectral Images. The model is trained for two datasets namely Kennedy Space Center dataset and Botswana dataset separately and a comparative study has been performed among various optimizers and dimensionality reduction techniques inorder to come up with the most optimized model for each of the two datasets. Kennedy Space Center is a dataset that uses hyperspectral imaging to categorise vegetation in wetland areas at the Florida-based Kennedy Space Center. On March 23, 1996, JPL's Airborne Visible and Infrared Imaging Spectrometer collected hyperspectral data over KSC . 13 classes representing the various land cover types that occur in this ecosystem were defined for the site for classification purposes. Botswana is a hyperspectral image classification dataset.The data used in this study were collected on May 31, 2001, and they are observations from 14 recognised classes that represent the various forms of land cover in the distal Delta's seasonal wetlands, occasional swamps, and dry forests.

***Index Terms*—Hyper-spectral Image (HSI), ML (Machine Learning), DL (Deep learning), Kennedy space center (KSC)**

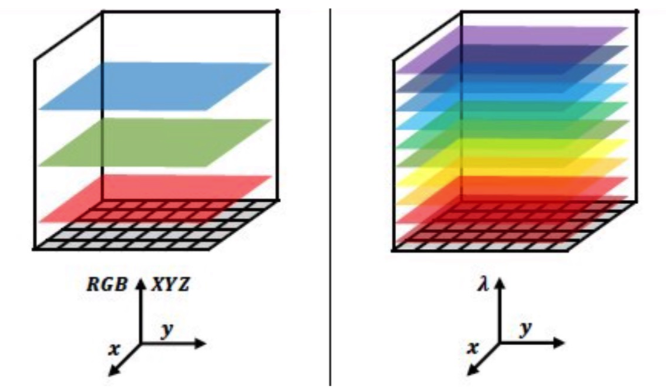
I. INTRODUCTION

Imagine a normal three-channel RGB picture, it is a combination of Red Green Blue. Black lies at the origin and white is at the opposite corner from the origin.The different colors in this model can be thought of as points on or inside the cube,and can be defined by vectors extending from the origin. All the values of R,G and B are assumed to be in the range [0,1]. The reflectance wavelength of a normal RGB image is like a discrete function with only three points which is exactly corresponding to red green blue value.



A normal RGB image has three channels while a hyper spectral image can have hundreds of channels.The reflectance wavelength of a normal hyper spectral image is like a "continuous" function. A variety of applications such as mineral identification, urban planning, precision farming, environmental monitoring and management, and surveillance, have become possible because of the widespread usage of HSI in studying the earth's surface. This is due to HSI's strong capacity to identify and distinguish between various materials. For instance, a remote sensing image can alternatively be thought of as a collection of images captured using several spectral channels at various wavelengths to produce a hyper-spectral image.

The hyper-spectral image is made up of hundreds of spectral channels, each of which has a lot of noise and redundancy, making subsequent HSI analysis complex and time-consuming as well as lowering the effectiveness of subsequent classification algorithms.



Varied applications require channels with different characteristics and properties. It is possible to choose the channel subsets from among these channels that have been categorised based on criteria. For instance, object detection, classification, denoising, noise estimation, and channel selection all require channels with different features.

II. Literature Survey

Convolutional Neural Networks (CNN) are commonly used in the present literature to classify hyperspectral images (HSI). The techniques include SVMs as well as 2D CNNs, 3D CNNs, and 3D-2D CNNs. With the exception of 3D-2D CNNs and FuSENet, the other methods perform poorly since they do not combine spectral and spatial data for the HSI classification problem. While 2D CNNs only evaluate spatial information and do not address multi-resolution image processing, 3D CNNs are computationally intensive and not commonly used. Despite the fact that 3D-2D CNNs attempt to model spectral and spatial properties, their performance appears to be constrained when used across several datasets. For multi-resolution HSI classification, we propose SpectralNET, a wavelet CNN that is a version of 2D CNN, in this article.

To highlight spectral information, a wavelet CNN employs layers of wavelet transform. Compared to a 3D CNN, a wavelet transform is simpler to compute. By fusing the 2D CNN that extracts the spatial information with the spectral characteristics, a spatial-spectral feature vector for classification is produced. Overall, a superior model is produced that can accurately categorise multi-resolution HSI data. The suggested SpectralNET is superior to state-of-the-art approaches.

III. Dataset

We have 2 datsets in our study namely the KSC (Kennedy Space Centre) dataset and the Botswana dataset

A. KSC Dataset

Kennedy Space Center is a dataset that uses hyperspectral imaging to categorise vegetation in wetland areas at the Florida based Kennedy Space Center. On March 23, 1996, JPL's Airborne Visible and Infrared Imaging Spectrometer gathered HSI data over KSC. The spatial resolution of the KSC data, which were collected at an altitude of roughly 20 km, is 18 m. 176 bands were utilised for the analysis after water absorption & low SNR bands were eliminated. 13 classifications representing the various forms of land cover that can be found in this ecosystem were defined for the site for classification purposes.

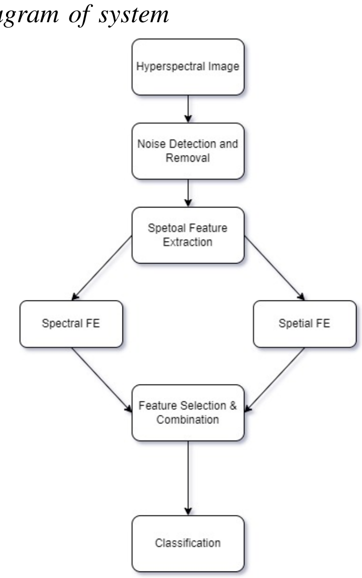
B. BOTSWANA

Botswana is a dataset for the classification of hyperspectral images. Over the Okavango Delta in Botswana, the NASA EO-1 satellite collected a series of data from 2001 to 2004. The EO-1 Hyperion sensor collects data over a 7.7 km strip with a 30 m pixel resolution in 242 bands that cover the 400-2500 nm region of the spectrum in 10 nm intervals. The following 145 bands were included as candidate features instead of the uncalibrated and noisy bands that cover water absorption features: [10-55, 82-97, 102-119, 134-164, 187-220]. The data used in this study were collected on May 31, 2001, and they are observations from 14 recognised classes that represent the various forms of land cover in the distal Delta's seasonal wetlands, occasional swamps and dry forests.

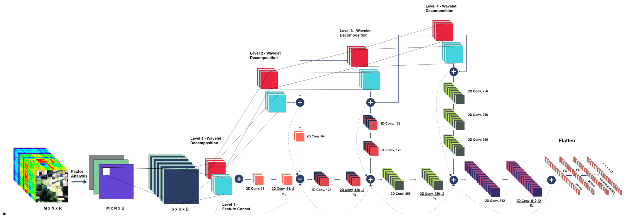
IV. Methodology

We have trained a SpectralNET CNN model using Hyperspectral images obtained from the Air- borne Visible/Infrared Imaging Spectrometer (AVIRIS) over Various Datasets like Kennedy Space Center (KSC), Botswana, and have done a comparative study between various optimizers(such as ADAGRAD, SGD, ADAM) and dimensionality reduction techniques (PCA and FA) used to train the model.

A. Block Diagram of system



B. Model Architecture



C. Dimensionality Reduction Techniques used

- **Factor analysis (FA) :** The common score is created using the largest common variance that can be extracted from all variables using the factor analysis method. It is closely related to data mining as it is the theory used in training machine learning models. The belief behind factor analysis techniques is that the information obtained about the interactions between observed variables can later be used to reduce the set of variables in the dataset.
- **Principal Component Analysis (PCA) :** PCA is a technique used in machine learning to simplify high-dimensional data by identifying patterns in the data and transforming the original set of features into a new set of features, known as principal components. These new features are uncorrelated and are chosen in such a way that they can explain most of the variance in the original data. This approach is unsupervised, and the goal is to find a lower-dimensional representation of the data while retaining as much information as possible.

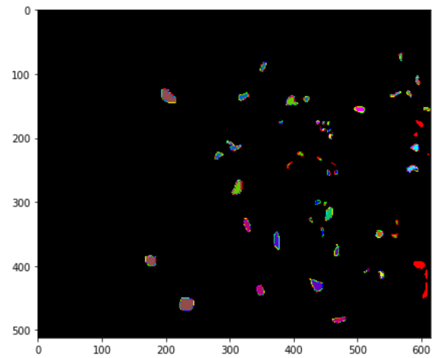
D. Optimizers used

- **SGD :** SGD consistently outperforms the standard stochastic gradient descent approach. The gradient is calculated by the algorithm using exponentially weighted averaging, and the parameters are updated using this gradient. We tweaked the gradient function of SGD by adjusting momentum such that the gradient at present depended on gradients from the past. This speeds up SGD, resulting in faster convergence and less oscillation.
- **Adam :** One of the most favoured optimizers is unquestionably the ADAM optimizer. It is really efficient when working with large problem involving a lot of data or parameters. Adam provides an optimization technique that can manage sparse gradients on noisy problems by combining the best features of the AdaGrad and RMSProp algorithms.
- **Adagrad :** Adagrad adapts the learning rate for each parameter based on the number of iterations. Given that sparse features are more uncommon than dense features, it employs different learning rates for the two types of features. As a result, parameters associated with sparse features must learn at a faster rate than those associated with dense features.

V. Implementation and Results

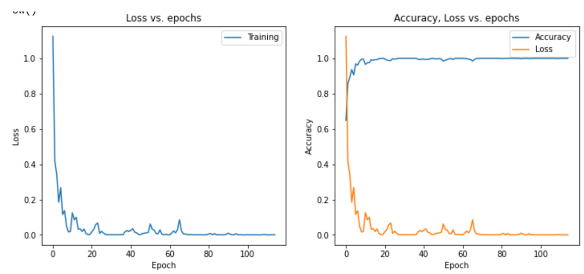
A. Kennedy Space Center (KSC)

The visualization of the Ground Truth of the Kennedy Space Center (KSC) is shown below:

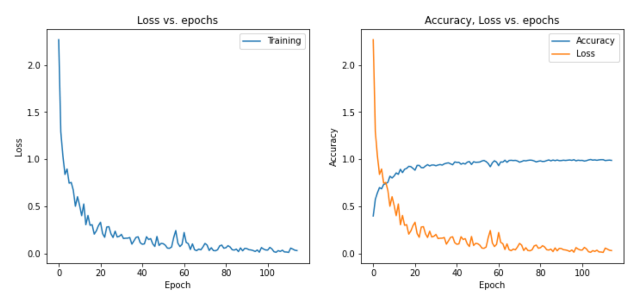


Loss vs Epoch plots for the different combinations of optimizers and dimensionality reduction techniques for KSC dataset are as follows

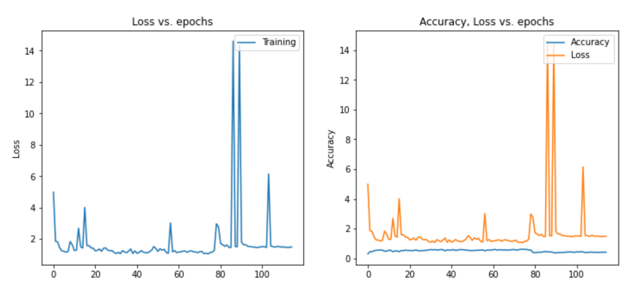
- SGD & FA:



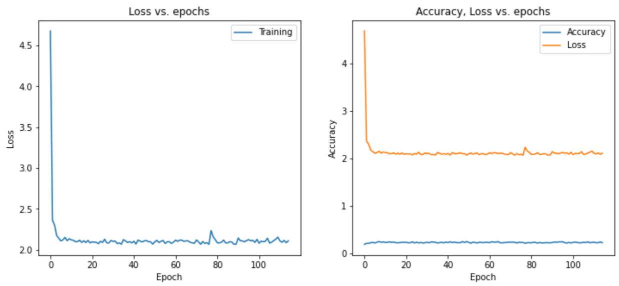
- SGD & PCA:



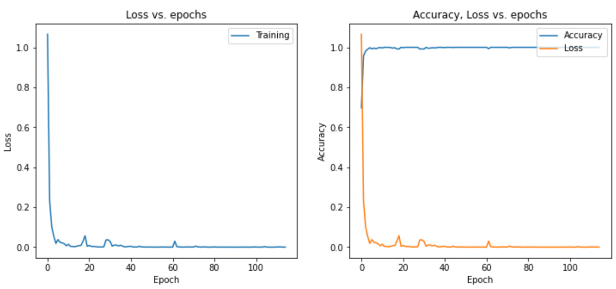
- ADAM & FA:



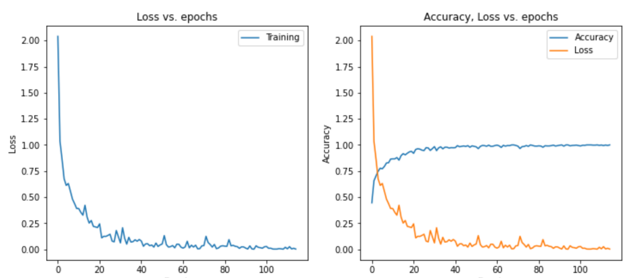
- ADAM & PCA:



- ADAGRAD & FA:



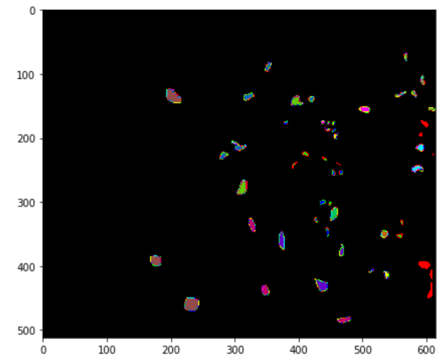
- ADAGRAD & PCA:



Best Accuracy Model (SGD & FA): Visualization:

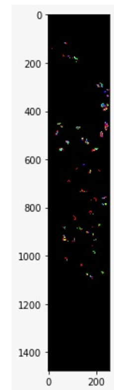
	precision	recall	f1-score	support
0	1.00	1.00	1.00	609
1	0.99	1.00	1.00	194
2	0.99	0.98	0.98	205
3	0.97	0.98	0.97	202
4	1.00	0.96	0.98	129
5	0.99	1.00	0.99	183
6	1.00	1.00	1.00	84
7	0.99	1.00	1.00	345
8	1.00	1.00	1.00	416
9	1.00	1.00	1.00	323
10	1.00	1.00	1.00	335
11	1.00	1.00	1.00	402
12	1.00	1.00	1.00	742
accuracy			1.00	4169
macro avg	0.99	0.99	0.99	4169
weighted avg	1.00	1.00	1.00	4169

Predicted Output:



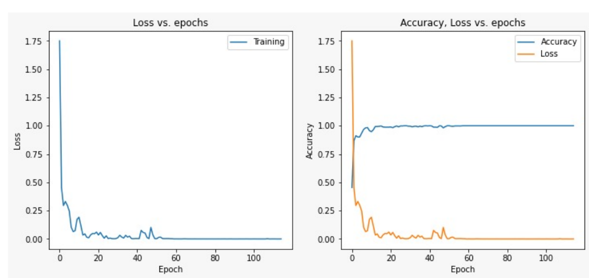
B. Botswanna

The visualization of the Ground Truth of the Botswanna dataset is shown below:

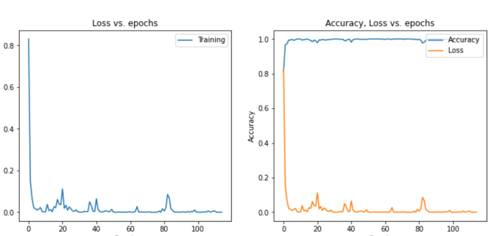


Loss vs Epoch plots for the different combinations of optimizers and dimensionality reduction techniques for Botswana dataset are as follows

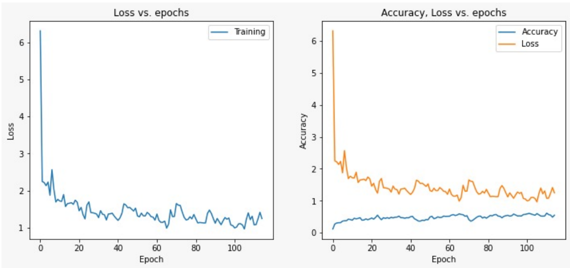
- SGD & FA:



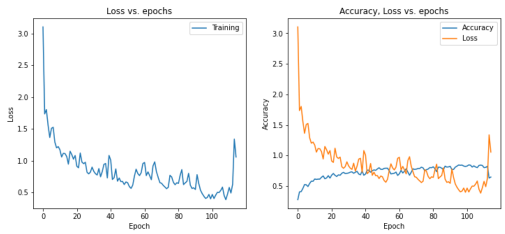
- SGD & PCA:



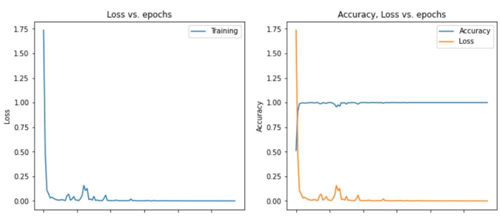
- ADAM & FA:



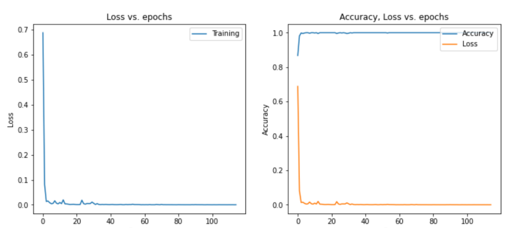
- ADAM & PCA:



- ADAGRAD & FA:



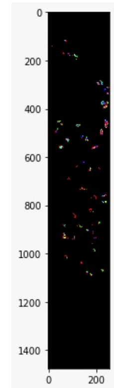
- ADAGRAD & PCA:



Best Accuracy Model (ADAGRAD & PCA): Visualization:

	precision	recall	f1-score	support
0	1.00	1.00	1.00	216
1	1.00	1.00	1.00	81
2	1.00	1.00	1.00	201
3	0.98	1.00	0.99	172
4	1.00	0.98	0.99	215
5	1.00	0.98	0.99	215
6	1.00	1.00	1.00	207
7	1.00	1.00	1.00	162
8	0.98	1.00	0.99	251
9	1.00	1.00	1.00	199
10	1.00	1.00	1.00	244
11	1.00	1.00	1.00	145
12	1.00	1.00	1.00	215
13	0.99	1.00	0.99	76
accuracy			1.00	2599
macro avg	1.00	1.00	1.00	2599
weighted avg	1.00	1.00	1.00	2599

Predicted Output:



Conclusion

As a result, we can say that for the KSC dataset, the best accuracy was obtained when SGD was selected as the optimizer and dimensionality reduction was carried out using Factor Analysis (with an accuracy of 100per.). For the Botswana dataset, however, we discovered that the best accuracy was obtained when ADAGRAD was selected as the optimizer and dimensionality reduction was carried out using PCA(with an accuracy of 100per.).

VI. References

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