Spectral-Spatial Classification of Hyperspectral Imagery Using Deep Learning

University of Wisconsin Eau Claire

[*]Dr. Papia F Rozario, [+]Dr. Rahul Gomes, [*]Laney Ruehmann, [+]Tianqi Sun, [+]Hengrui Jia, [+]Jacob Jensen, [+]Tyler Pham

[+]Department of Computer Science, [*]Department of Geography & Anthropology

ABSTRACT

Classification of hyperspectral images is an important step of image interpretation from high spatial resolution imagery. Different studies demonstrate that spatial features can provide complementary information for increasing the accuracy of hyperspectral image classification. In this study, we propose a method of spectral-spatial classification of hyperspectral images that is based on autoencoders. The resulting high-dimensional vectors of spectral features are classified by several supervised classification algorithms such as support vector machine (SVM), maximum likelihood (ML) and random forest (RF). The experiments are performed on several widely known test hyperspectral images and preliminary results have demonstrated that proposed method provides a higher accuracy matrix than existing traditional models.

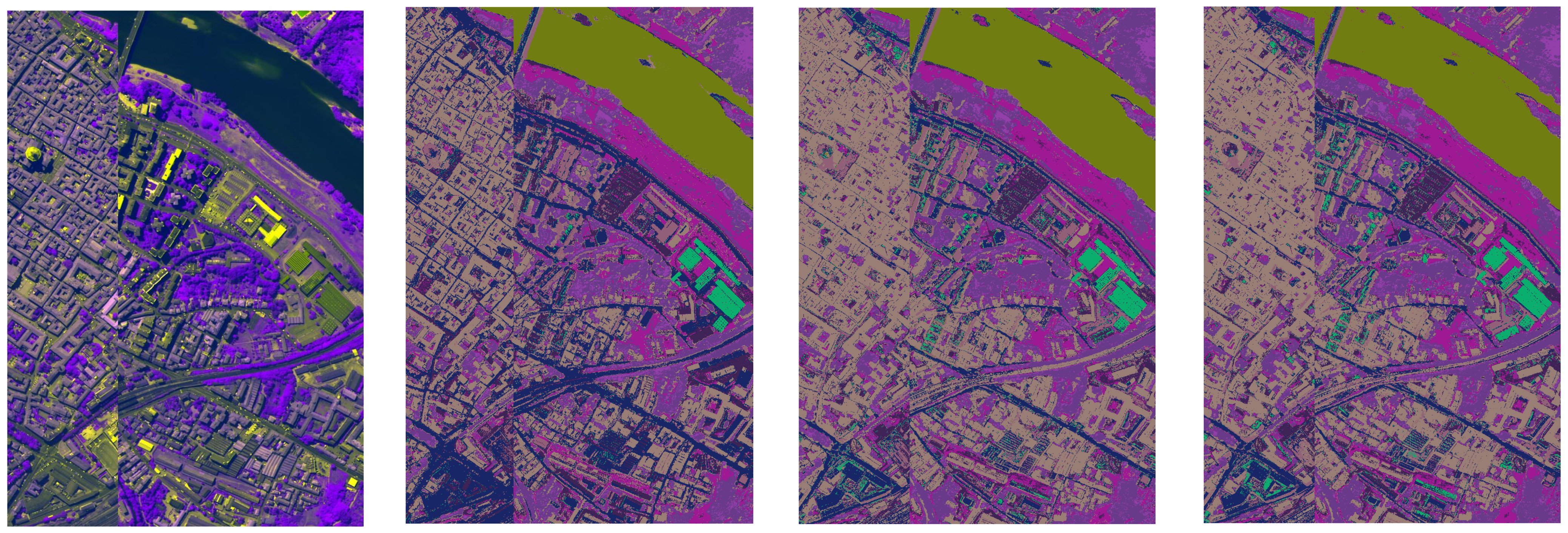
HYPERSPECTRAL IMAGE CLASSIFICATION

Analysis on three datasets, Indian Pines, Pavia Center, and Pavia University, was done. Using Principal Component Analysis (PCA), images for each of these locations was generated with bands ranging from 5 to 10. Classifications were run on each of these images using ML, RF, and SVM. Figure 1 displays the initial PCA image for Pavia Center at 10 bands as well as how the image looks after being classified with the listed classification processes.

These three classification algorithms are machine learning techniques:

- ML utilized labeled data to predict the parameters of the probability distribution. To do that, a mathematical function is applied to ensure that the proposed statistical model has the highest chance of predicting the labeled data.
- RF is a machine learning technique that applies ensemble method for classification, regression, and other tasks. It works by creating multiple decision trees at the training time. The classification result's output is the one class that is selected by most trees.
- SVM analyzes data in regression analysis as well as classification. The model represents instances in space and maps these new instances to the same space. It predicts the class they will belong to based on what interval they are classified into.

Once all classifications are run for each PCA image, they are used to create a confusion matrix to test the accuracy. This produces a table that will define the performance of each algorithm.



Principle Component Analysis *Maximum Likelihood* *Random Forest* *Support Vector Machine*

Figure 1: Image Classification of Pavia Center, Italy

ACKNOWLEDGEMENTS

This research was jointly funded by the National Science Foundation (REU grant #2150191) and the Office of Research and Sponsored Programs (ORSP).

2D-DWT FILTERING

The average relative brightness graph demonstrates of the different categories within a hyperspectral image reflect light at different wavelengths. Graphs like Figure 2 were used to find abnormalities within the HSI. It was also possible to use these graphs for to see which sections of bands had the most variance between the different categories.

To reduce the amount of redundancy in the hyperspectral imagery, a filter called 2D Discrete Wavelet Transform (2D-DWT) was used. To test the effectiveness and proficiency of this filter, four test categories were created:

- 2D-DWT with Adjacent Correlation
- No 2D-DWT with Adjacent Correlation
- 2D-DWT with All Correlation
- No 2D-DWT with All Correlation

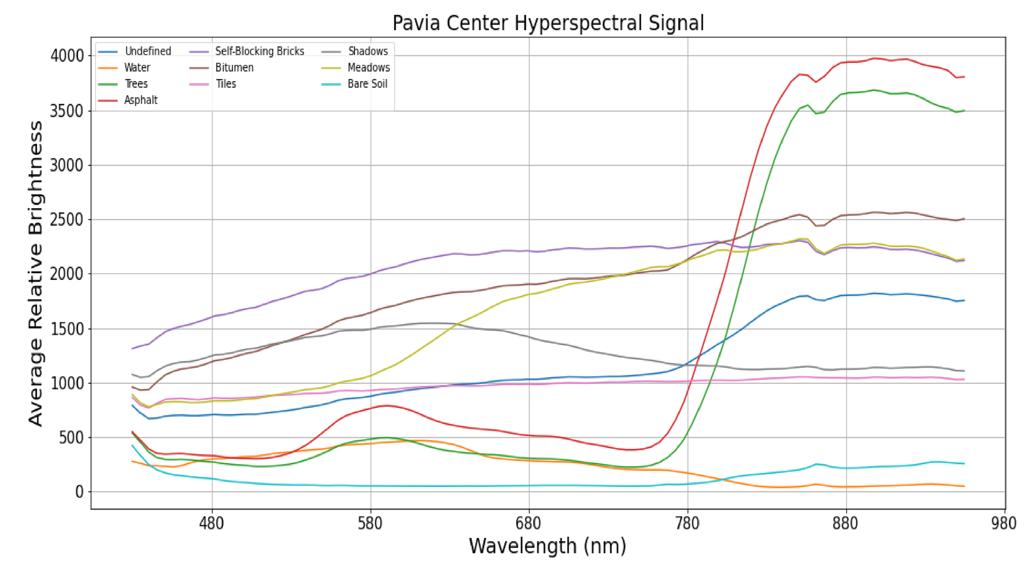


Figure 2: Graph of Pavia Center's Average Relative Brightness

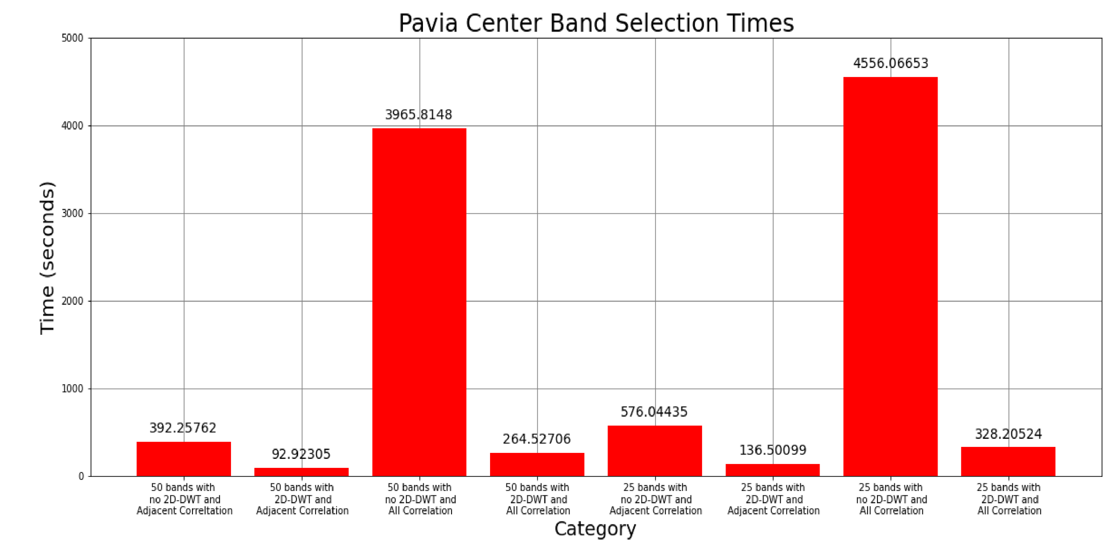


Figure 3: Graph of Processing Times for the 2D-DWT Categories For Pavia Center

AUTOENCODER PROCESS

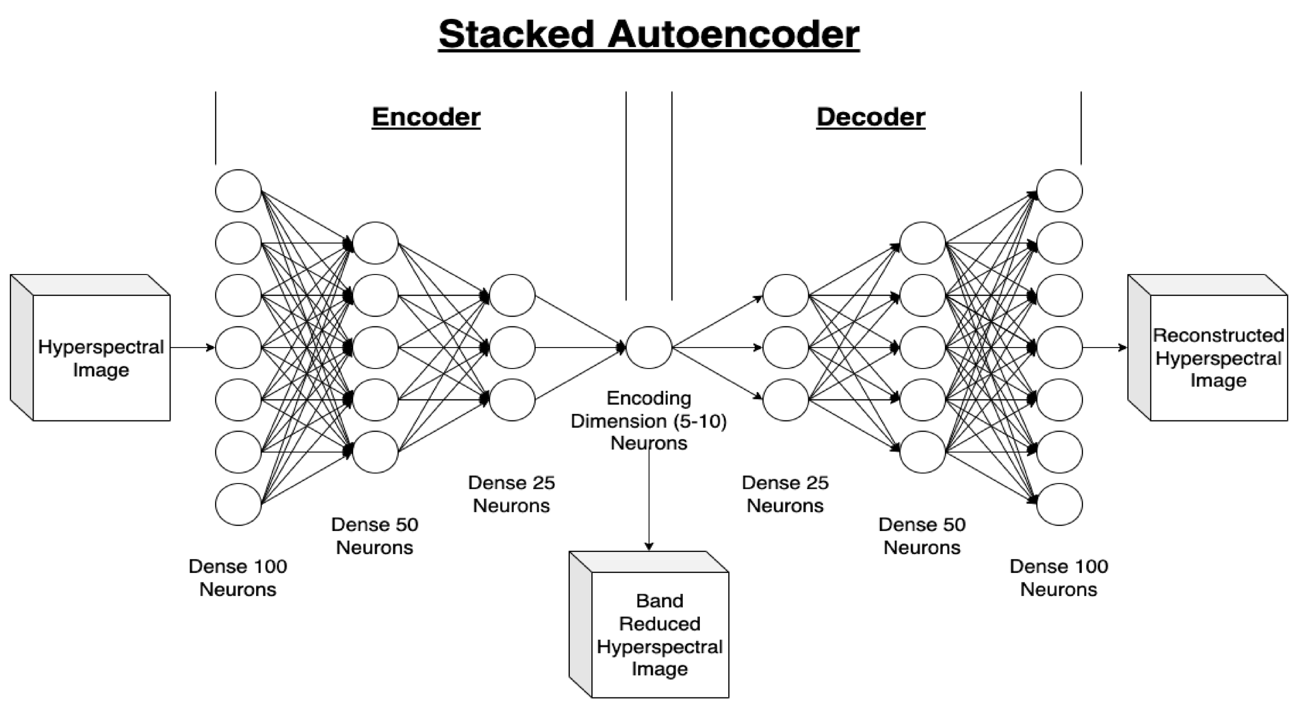


Figure 5: Diagram of Autoencoder Process

An autoencoder is a deep learning technique that uses dense layers, layers of fully connected neurons, for encoding and decoding. It takes an input and encodes it into a smaller dimension and decodes the encoded information back into the same dimension of the original input, hopefully preserving the relevant features of the input. For this project, we used a stacked autoencoder to perform band reduction by encoding the original set of bands of a given image to a smaller set of 5-10 bands for classification.

RESULTS

Differences between these categories was marginal. It was discovered that for selection times, no 2D-DWT with All Correlations had the slowest selection time. For the fastest results, it was found that applying 2D-DWT filter with Adjacent Correlation was most effective (Figure 3).

To compare the different categories within the 2D-DWT filter, accuracy was also tested and compared as well as the processing times. Using all three of the classification algorithms, Figure 4 was created to demonstrate which subset of the 2D-DWT filter had the highest level of accuracy in with classification algorithm. For 25 bands, it appears that adjacent correlation has slightly better results than all correlation. Thus, using less bands and adjacent correlation takes less time but gives comparable accuracy to using more bands.

	25 Bands 2D-DWT-ADJ	25 Bands 2D-DWT-ALL	25 Bands No 2D-DWT-ADJ	25 Bands No 2D-DWT-ALL	50 Band 2D-DWT-ADJ	50 Band 2D-DWT-ALL	50 Band No 2D-DWT-ADJ	50 Band No 2D-DWT-ALL
ML	0.927272114	0.896291047	0.928757045	0.85319429	0.961560528	0.947116196	0.93469677	0.954608349
RF	0.975363639	0.975228646	0.970841349	0.966994027	0.983665755	0.981775843	0.982585805	0.983159529
SVM	0.972292531	0.968681448	0.971178833	0.968748945	0.977489791	0.977219804	0.978097263	0.977489791

Figure 4: Accuracy Assessment at 10 Bands For Pavia Center

We thank the Office of Research and Sponsored Programs for supporting this research, and Learning and Technology Services for printing this poster