# Design and development of Nodel Deep Learning algorithm Hyperspectral Image Classification

*An end-term report submitted towards the partial fulfillment of the degree of*

*Bachelor of Technology*

In

Computer Science and Engineering

by

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KERALA

October 2023

# CERTIFICATE

This is to certify that the work contained in the project entitled "**Design and development of nodel Deep Learning algorithm Hyperspectral Image Classification**" is a bonafide work of **Priyanshu Gupta** (**Roll No. 112001033**), carried out in the Department of Computer Science and Engineering, Indian Institute of Technology Palakkad under my guidance and that it has not been submitted elsewhere for a degree.

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## ❖ Objective

The objective of this project is to utilize hyperspectral imaging technology for the precise estimation of soil nutrient levels. Hyperspectral imagery obtained from satellites, which captures a multitude of narrow, contiguous wavelength intervals, offers a comprehensive spectral dataset that holds great promise for assessing the intricate variations in soil nutrient content. This comprehensive approach involves the systematic collection, meticulous calibration, and sophisticated modeling of hyperspectral data, seamlessly integrating it with measured soil nutrient values from corresponding geographic regions.

Through the establishment of accurate models and thorough validation processes, this study aspires to generate high-resolution nutrient maps. These maps are envisioned to empower precision agriculture and informed environmental decision-making. By creating a more detailed understanding of soil nutrient content and distribution, this project seeks to facilitate sustainable farming practices. It does so by enabling the precise application of fertilizers based on the specific nutrient requirements of localized soil areas, ultimately leading to optimized crop yields while minimizing the environmental impact.

The project's core focus lies in harnessing the potential of hyperspectral imagery to transform the way we assess and manage soil nutrient levels. This innovative approach holds the promise of revolutionizing agriculture by promoting resource-efficient and environmentally conscious farming practices.

## ❖ Dataset

The dataset comprises 1732 hyperspectral train images and 1154 test images, each encompassing 150 wavelength bands within the range of 462 to 492 nm. These images have a spectral resolution of 3.2 nm, facilitating precise spectral analysis for soil nutrient estimation.

To gain a closer insight into the dataset, let's examine an individual image which was plotted to represent a single spectral band. This focused examination allows us to observe the specific spectral characteristics and variations within the dataset, providing valuable information for further analysis and model development.

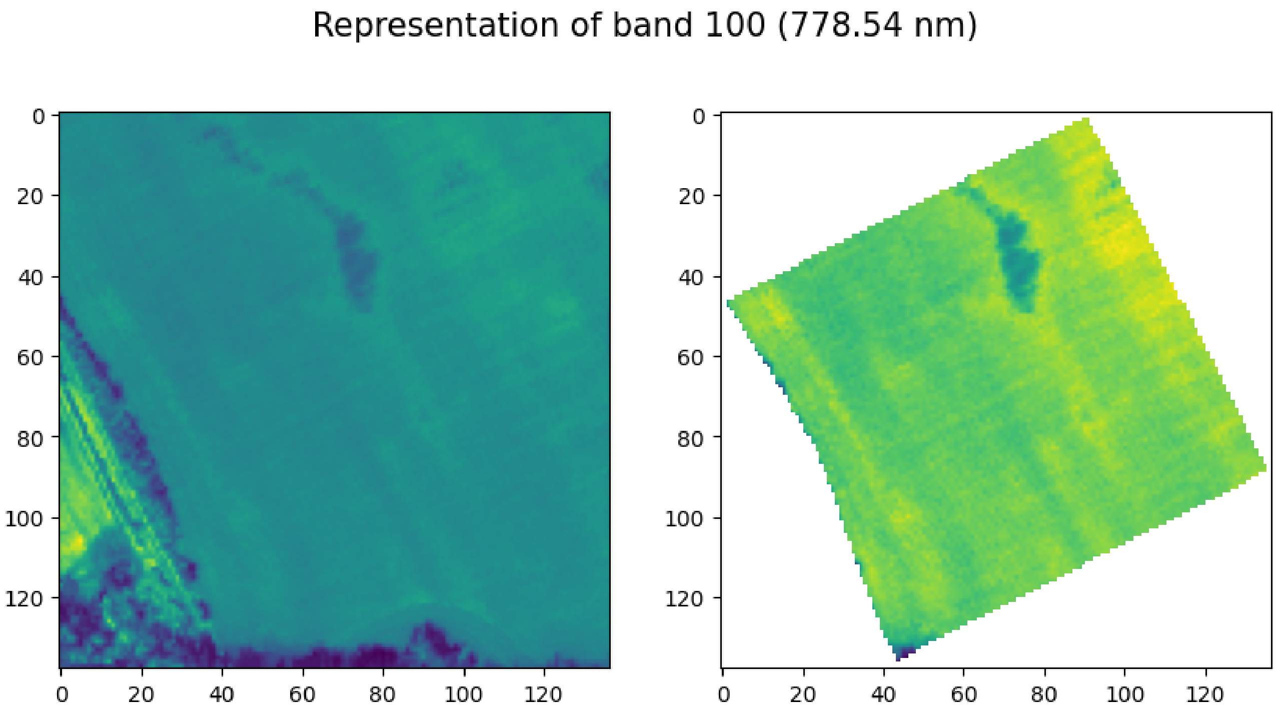


**Fig 1:** Representation of image 1570 corresponding to 778.54 nm band

Upon closer examination of the dataset, a notable pattern emerged in the distribution of pixel sizes within the hyperspectral images. A comprehensive analysis revealed that a significant proportion of the images, specifically close to 40 percent, had dimensions of approximately 11x11 pixels. Interestingly, another segment, accounting for about 10 percent, featured dimensions near 50x50 pixels. This distinctive pattern was consistently observed in both the training and test image sets, reflecting a non-uniform distribution of image dimensions across the dataset. This observation is of critical importance as it may impact subsequent image processing and the development of accurate models.

The training dataset includes information on four essential soil nutrients, namely Phosphorus (P), Potassium (K), Magnesium (Mg), and soil pH.

## ❖ Data Augentation

**Case 1: Finding 11x11 Patch without Masked Values :**

In the first case of data augmentation, the algorithm systematically seeks 11x11 patches within each original sample that are free from masked values, ensuring a pristine representation of the underlying information. For every sample, an attempt is made to locate such a patch. Upon success, the discovered patch is incorporated into the augmented dataset. To introduce variability, the algorithm perturbs the associated y values by introducing controlled noise, thereby enriching the diversity of the training data and enhancing the model's ability to generalize across different scenarios.

**Case 2: Creating Patch with Masked Values :**

In scenarios where a suitable 11x11 patch without masked values cannot be identified by trying typically 10 times, the algorithm resorts to an alternative approach. A square patch is generated, utilizing the minimum pixel dimension of the original sample. To mitigate the presence of masked values, the algorithm intelligently populates the patch by filling masked positions with random pixel values sampled from within the same sample. This newly created patch, although containing masked values, serves as a valuable augmentation, contributing to the model's resilience against diverse input conditions. Similar to Case 1, the algorithm perturbs the y values associated with this patch to further enhance the richness of the augmented dataset.

**Additional Augmentation :** To amplify the diversity introduced through augmentation, the algorithm incorporates an augmentation constant, typically set to 3. This constant determines the number of iterations for which the algorithm seeks to augment each original sample. During each iteration, the algorithm either identifies a pristine 11x11 patch or generates a square patch with masked values, each time perturbing the associated y values. The cumulative effect of these iterations yields a robust augmented dataset, laying the foundation for training a machine learning model capable of capturing intricate patterns and nuances within the input data.

## ❖ Data Preprocessing

In the preprocessing stage, we extract high-level features from raw field data, transforming the original 150-band spectral information into a set of 16 features per sample. The process involves computing the average reflectance across all wavelengths, analyzing reflectance variations through derivatives, and performing Singular Value Decomposition (SVD) to understand dominant spectral components. Additionally, wavelet transformations (cAw1, cAw2) are employed, offering a multi-scale perspective on spectral characteristics. These features collectively capture nuanced patterns and variations in the spectral domain, providing a condensed yet informative representation of the field data for downstream machine learning tasks.

Following are the 16 parts of our features corresponding to each of 150 wavelength bands for each patch.

1. arr: Original filtered data (arr).
2. dXdl: First-order derivative of arr.
3. d2Xdl2: Second-order derivative of arr.
4. d3Xdl3: Third-order derivative of arr.
5. dXds1: Ratio of the first and second singular values.
6. s0: First singular value.
7. s1: Second singular value.
8. s2: Third singular value.
9. s3: Fourth singular value.
10. s4: Fifth singular value.
11. real: Real part of the FFT of arr.
12. imag: Imaginary part of the FFT of arr.
13. reals: Real part of the FFT of the first singular value (s0).
14. imags: Imaginary part of the FFT of the first singular value (s0).
15. cAw1: Concatenation of wavelet coefficients obtained from the w1 wavelet transformation.
16. cAw2: Concatenation of wavelet coefficients obtained from the w2 wavelet transformation.

Next, we appended all of these values as our features which gave us numpy array of 150 x 16 = 2400 length for each sample. Tests were also carried out by normalizing and standardizing the features and values independently.

## ❖ Models Used

I took random 80% samples to be my train data and rest to be the test data but to increase the training data we increased the augmentation layers to be taken into account, so for the training samples, their augmented data was also trained and we had 3 times of the training data, meaning augment constant set to be two.

1. **Random Forest :** Used random forest for predictions with 100 estimators which gave a RMSE of 46.83.

2. **XGBoost :** Used learning_rate=0.1, max_depth=5, alpha=10, n_estimators = 100 and got a RMSE of 46.14.

3. **Support Vector Regression :** Even bad results with RMSE of 54.18 with epsilon to be 0.2.

| Layer (type) | Output Shape | Param # |
|---|---|---|
| input_11 (InputLayer) | [(None, 2400)] | 0 |
| dense_37 (Dense) | (None, 2048) | 4917248 |
| dropout_257 (Dropout) | (None, 2048) | 0 |
| dense_38 (Dense) | (None, 1024) | 2098176 |
| dropout_258 (Dropout) | (None, 1024) | 0 |
| dense_39 (Dense) | (None, 512) | 524800 |
| dropout_259 (Dropout) | (None, 512) | 0 |
| dense_40 (Dense) | (None, 256) | 131328 |
| dropout_260 (Dropout) | (None, 256) | 0 |
| dense_41 (Dense) | (None, 128) | 32896 |
| dropout_261 (Dropout) | (None, 128) | 0 |
| dense_42 (Dense) | (None, 64) | 8256 |
| dropout_262 (Dropout) | (None, 64) | 0 |
| dense_43 (Dense) | (None, 4) | 260 |

```
Total params: 7,712,964
Trainable params: 7,712,964
Non-trainable params: 0
```

**Fig 2:** Model summary.

4. **Deep Learning :** Used sequential models to test RMSE which was 38.54 but it increased on normalizing the parameters to 39.97 and on standardisation to 41.15.

## ❖ Future Work

In the pursuit of advancing hyperspectral soil nutrient estimation, we are presented with promising avenues for further exploration. These paths open up new possibilities for enhancing the accuracy and applicability of our models, driving us towards a deeper understanding of the complex relationships within environmental data.

**Expanding the Dataset :** Firstly, we can expand our dataset by encompassing a broader range of spatial and spectral characteristics. This expansion is vital to capture the diversity of environmental conditions and regional variations. A larger and more diverse dataset not only improves model robustness but also enhances its adaptability to different scenarios.

**Try Alternate Approaches :** Secondly, exploring alternative modeling approaches beyond RF and XGBoost is paramount. This entails a comprehensive examination of various machine learning and statistical techniques tailored to address hyperspectral data's unique challenges. By doing so, we can identify the most effective models for diverse scenarios, ensuring that our soil nutrient estimation approaches are optimized for accuracy and versatility.

In conclusion, these avenues represent exciting opportunities for progress in the field of hyperspectral soil nutrient estimation. They underscore the significance of adaptability, scalability, and the relentless pursuit of more accurate and versatile solutions in the realm of environmental data analysis. Through these explorations, we inch closer to achieving precision and reliability in our environmental parameter estimation endeavors.

## ❖ References


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