

Design and development of Nodel Deep Learning algorithm Hyperspectral Image Classification

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by

Priyanshu Gupta

Roll number: 112001033

Under the kind guidance of

Dr. Satyajit Das



IIT PALAKKAD

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

INDIAN INSTITUTE OF TECHNOLOGY, PALAKKAD

KERALA

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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.

Dr. Satyajit Das
Assistant Professor
Department of Data Science
Indian Institute of Technology Palakkad

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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.

❖ Collected Dataset : Hyperspectral Images

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.

Representation of band 100 (778.54 nm)

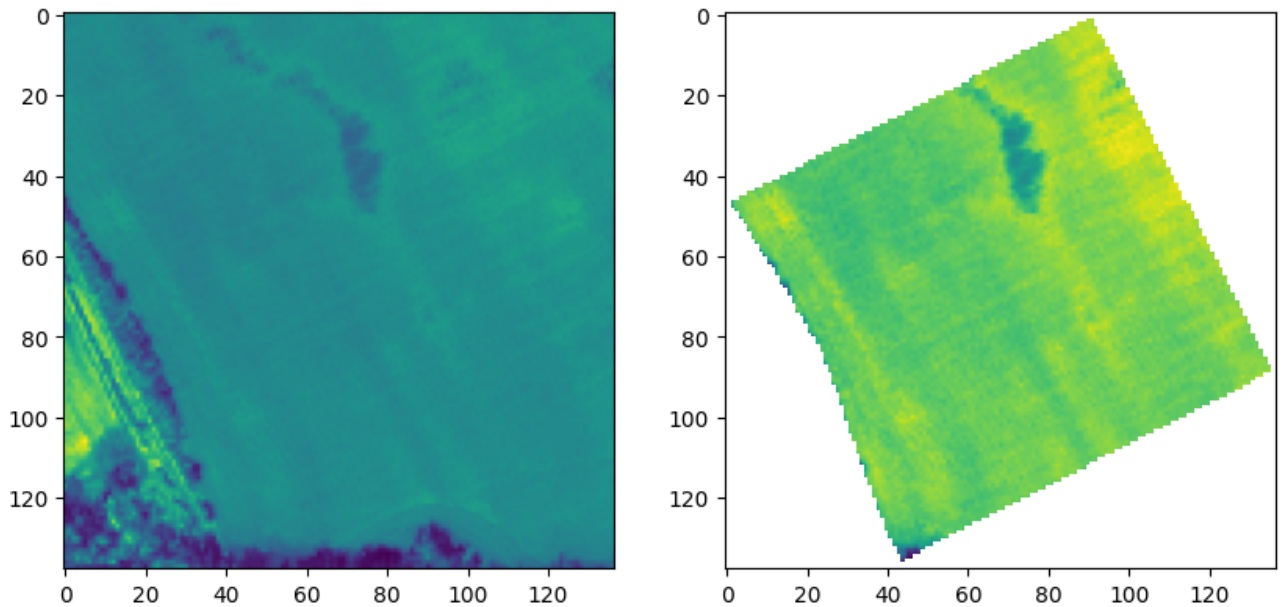


Fig 1: Representation of image 1570 corresponding to 778.54 nm band

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.

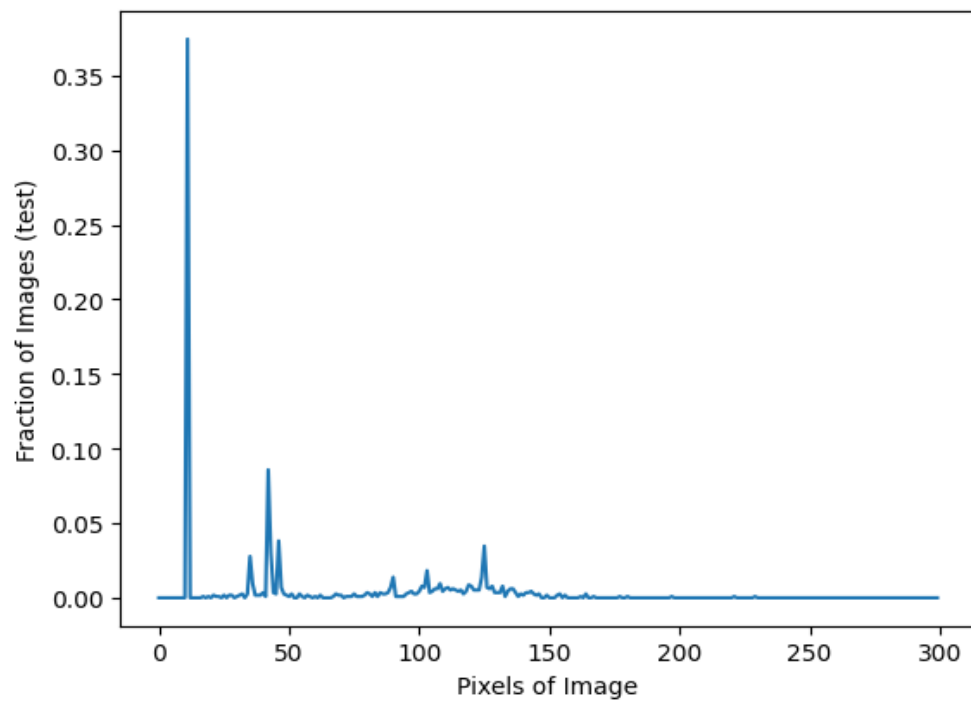
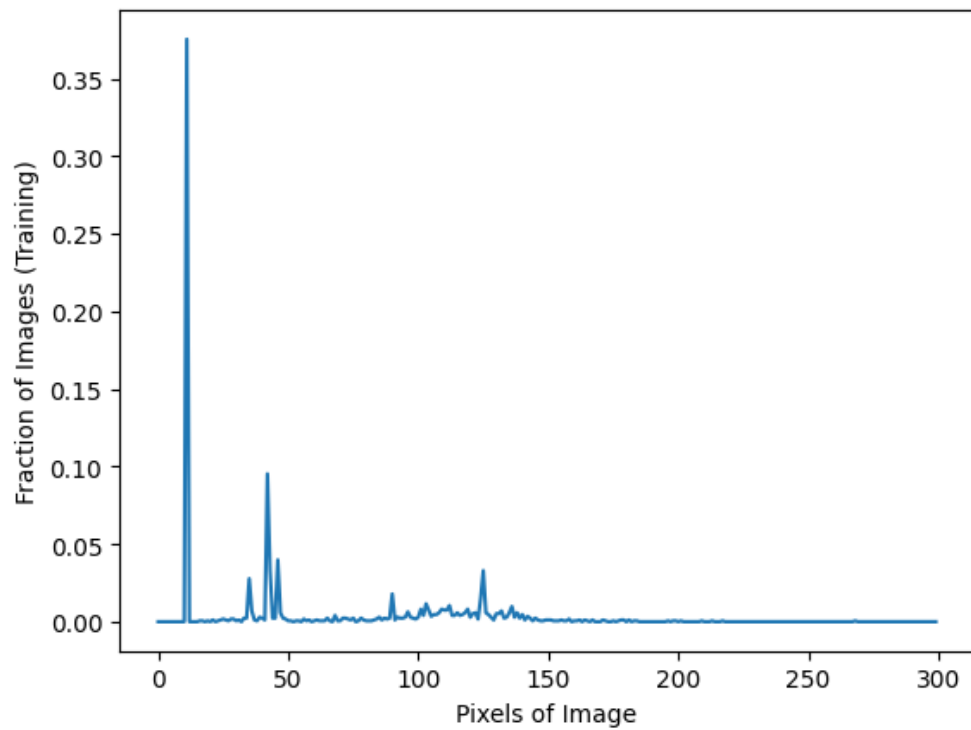


Fig 2: The graph above visually represents this distribution of pixel sizes within the dataset.

❖ Collected Dataset : Soil Nutrients

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

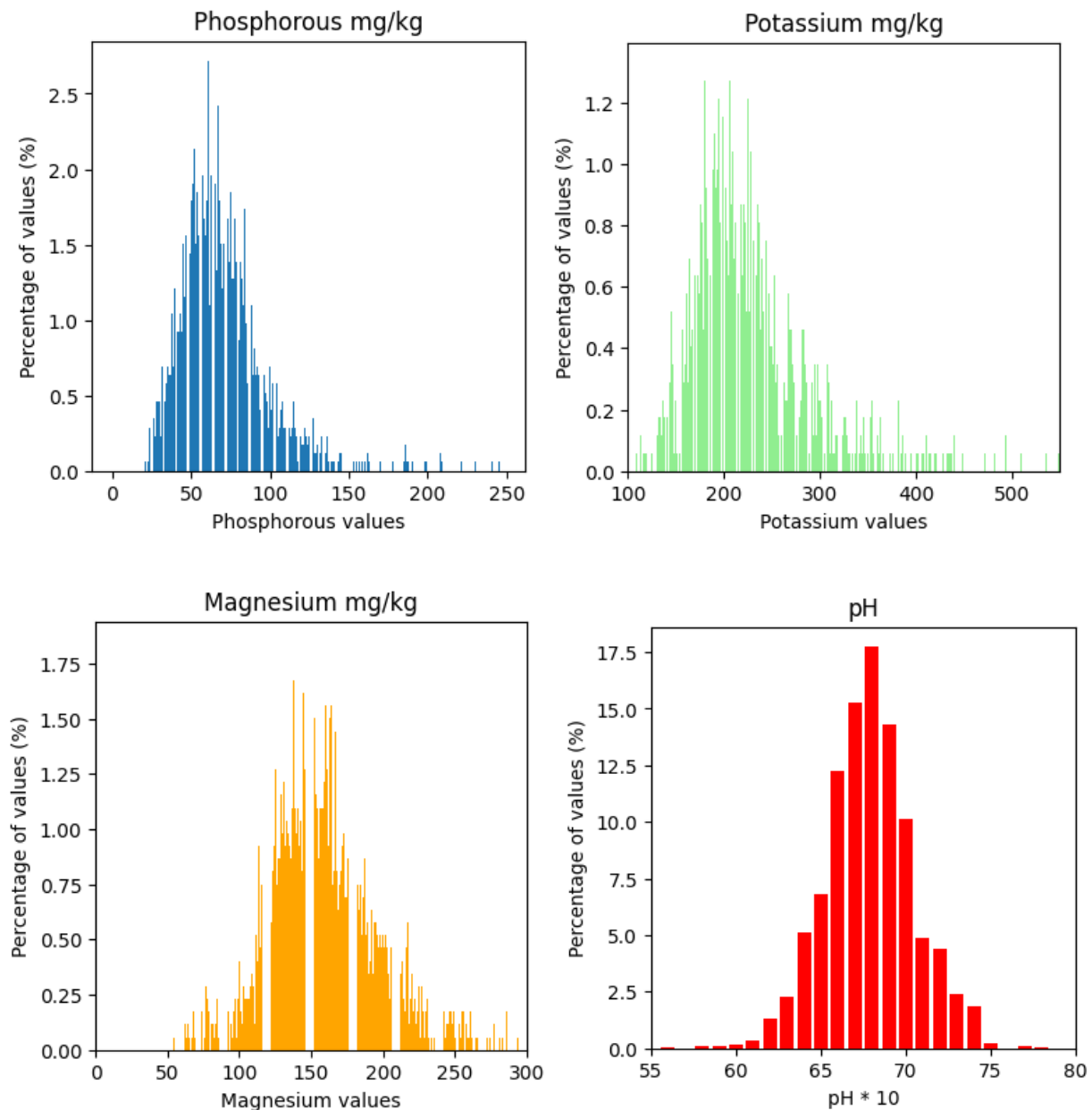


Fig 3: The graph above visually represents the percent distribution of soil contents within the dataset.

Following plotting, the analysis shows the ranges of soil nutrient values: the ranges for phosphorus (P) are 25 to 150, potassium (K) is 100 to 400, magnesium (Mg) is 50 to 300, and land pH is between 6 and 7.5. These established ranges offer a fundamental comprehension of the variance in important soil nutrients.

❖ Literature View

Two basic categories of data are included in hyperspectral imagery: spectral and spatial properties. The layout and placement of objects within the scene serve as the primary means of describing the "where" component of the imagery in spatial data. Spectral data, on the other hand, focus on the "what," obtaining details regarding the emission or reflectance of light at different wavelengths. We are primarily interested in spectral features because they provide important information that is necessary for estimating soil nutrients, such as the average reflectance of the soil.

- ❖ **Study 1:** Their goal was to choose the best screening technique among gradient boosting decision trees (GBDT), least absolute shrinkage and selection operator (LASSO), and Pearson correlation coefficient (PCC). In order to develop a high-accuracy model for soil nutrient estimate, they also attempted to use support vector machines (SVM), ridge regression (RR), backpropagation neural networks with genetic algorithm optimisation (GABP), and multiple linear regression (MLR).

Following a successful trial over the dataset, the most preferred model combinations were GBDT-GABP and LASSO-GABP, which had the highest accuracy out of all the 12 combinations that were attempted.

Lastly, they used HuanJing-1A Hyperspectral Imager (HJ-1A HSI) imagery to map the nutrient levels of soil at a regional scale using this model, and they were able to get an RMSE of 4.01.

- ❖ **Study 2:** Another method adopted a different strategy, focusing on the average reflectance feature. With this technique, more characteristics were derived from the average reflectance using derivatives, wavelet transforms, singular value decomposition (SVD), and Fast Fourier transforms (FFT). With the usage of these features, an extensive feature array was produced for every field patch, providing an abundance of data for study. eXtreme Gradient Boosting (XGBoost), K-Nearest Neighbour (KNN), and Random Forest (RF) models were used.

The most accurate model was, surprisingly, a hybrid model consisting of KNN and RN. This method produced an exceptionally low RMSE of 0.79476, indicating the efficacy of their feature extraction and modelling strategy.

❖ Approach and Algorithms

In study 2, the RF (Random Forest) model and KNN (K-Nearest Neighbor) hybrid model achieved an impressive RMSE of 0.79476 using derivatives and transforms of average reflectance feature.

Average reflectance refers to the average amount of light or electromagnetic radiation reflected by a surface or material across a range of wavelengths. It is a fundamental spectral characteristic that provides insights into the overall reflective behavior of an object or substance in a hyperspectral image.

Random Forest (RF) is an ensemble learning technique that combines the predictions of multiple decision trees to create a robust and accurate model. It's highly effective for handling complex datasets and capturing non-linear relationships.

K-Nearest Neighbor (KNN) is a simple yet powerful algorithm that classifies data points based on their similarity to the nearest neighbors. It's particularly suitable for pattern recognition and can work well with spatial data.

Considering that our dataset shares similarities with study2, where multiple images lie in the 0-11 pixel domain, it's important to note that RF may encounter challenges in this context. RF models tend to perform less optimally when there's a lower number of pixels, as this leads to higher variations in channel-aggregation.

❖ **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 KNN 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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