Soil Classification using Hyperspectral Image Segmentation and Deep Neural Network

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Abstract

In the agriculture industry, soil is the most fundamental entity and the type of soil determines the type of crop that will grow on it. Soils are of different colors depending on their mineral composition, element concentration, organic matter, and moisture content which helps in the segregation of soils based on their color. Soil color is a reflection of these properties and their determination is absolutely essential for cultivators without which the probability of unproductive crops and crop losses will be high. Determination of soil color can become extremely difficult without proper chemical testing due to similar appearances when the soil is wet. In addition, a small patch of soil cannot accurately reflect the properties of the entire soil every time. Soil testing can also become an expensive and redundant affair that might take days to get results. This necessitates the development of a system that can determine the soil color without testing it every time. We introduce a model that can predict the type of soil in terms of its color which can be used to determine soil composition. We gathered soil samples of different colors and scanned them with a hyperspectral camera. This provides information about the samples across the electromagnetic spectrum with 168 spectrum bands compared to a traditional RGB image with 3 bands. We mapped the mean spectrum values across the 168 bands to their color to create a dataset that was fed to the model. We used machine and deep learning techniques to train and test our model. The model was able to predict the type of soil with high accuracy. In the agricultural industry, the model can be applied to a variety of situations. .

Keywords: Hyperspectral Imaging, Pixel wise NIR spectra, Ridge regression, Hyperspectral Image segmentation, Deep Neural Network, Convolutional Neural Network.

1 Introduction

Soil color is determined by element concentration, mineral composition, organic matter, and moisture content. It reflects soil properties and processes and is an invaluable diagnostic feature for soil horizon delineation and classification. Soil colors are used to infer pedogenic processes in soils. The main pigmenting (coloring) agents in soils are organic matter, iron, and, to a lesser extent, manganese. When these agents are not covering the mineral grains, the natural color of the grains is visible. Most mineral grains are naturally gray. Soil color is the property of soil that most reflects its pedogenic environment and history. Organic matter and iron oxides contribute the most to soil color. Organic matter darkens the ground, while iron oxides produce a range of soil colors that depend on iron's oxidation state. Soil color is influenced by mineral composition, water content, and microbial composition. For example, soils high in calcium tend to be white, those high in iron reddish, and those high in humus dark brown to black. Soil needs only about 5% organic material to appear black when wet.

Soil color is also a reflection of its age and the temperature and moisture characteristics of the climate. Cooler regions are more likely to have grayish-to-black topsoil due to the accumulation of humus. In moist, warm conditions, soils tend to be more yellowish-brown to red depending on the hydration of ferric oxide and extensive weathering of the soil's parental minerals. Rapid mineralization of the organic content in warm and moist regions means that humus accumulation is insufficient to have a significant soil color. Arid soils are usually light in color (acute staining from the low organic contents) mainly because of their color. Following rain, water temporarily darkens soil color by increasing light absorption. In addition, moisture can have long-term effects on soil color. For instance, in an anaerobic or water-logged environment, iron oxides occur in the ferrous state. These can give the soil a subtle bluish-gray tint. A mottled rusty or streaked appearance in a grayish matrix may indicate poorly drained soils. A blackish color in the absence of organic material may reflect staining by manganese oxides. Hence, we need a system to determine soil color and composition.

Soil composition determination can also help to determine water drainage, aeration, mineral material composition, and organic matter content. Healthy soils are essential for optimal plant growth, human nutrition, and water filtration. Healthy soil supports a more resilient environment to drought, flood, or fire. The soil regulates the Earth's climate and stores more carbon than the world's forests combined.

Intervals of measured series data (signals) must be assigned a class in a number of engineering problems, such as geotechnics, petroleum engineering, etc., while retaining the constraint of contiguity, and conventional classification methods may not be sufficient. An expert who monitors the signals' size and trends as well as any potential a priori knowledge is required for classification in this situation. In 2006 authors B. Bhattacharya and D.P. Solomatine [1] presents a method for automating this classification process. First, the measured signals are segmented using a segmentation algorithm that has been devised. Second, the boundary energy approach is used to extract the key features from these segments. Decision Trees, ANNs, and Support Vector Machines are used in the classifiers that are developed based on the measured data and extracted features to categorise the segments. Cone penetration testing measurements were used to assess the approach for classifying sub-surface soil, and the findings were satisfactory.

Authors Yushun Zhai et al. (2006) [2] aimed to examine several neural network topologies and assess the performance of artificial neural networks for the classification of bare soils. With either satellite or aerial remote sensing data, a set of classifiers built on feed-forward back-propagation neural networks was trained. As spectral radiance sources, we used panchromatic aerial shots of bare-soil agriculture in the Delta region of Mississippi and Landsat images. By examining the connection between classifier performance and the size of input matrices used to gather spectral radiance data, the effects of contextual information of the sample points were examined. The conclusion of this paper was ANN-based machine-learning techniques appear to be effective for soil texture classification.

In 2009 authors P.Bhargavi and Dr.S.Jyothi's [3] research aimed to use data mining techniques and apply them to a soil science database to establish if meaningful relationships can be found. A database of soil science information was used in this research . The Department of Soil Sciences and Agricultural Chemistry, S V Agricultural College, Tirupati, has pulled a sizable amount of data from their soil database. Measurements of soil profile data from numerous locations in Chandragiri Mandal, Chittoor District, are contained in the database. The study determines whether different data mining approaches are used to classify soils. Additionally, a comparison between the most efficient approach and Naive Bayes classification was done. The results of the study could be very advantageous for agriculture, soil management, and the environment.

Quantitative techniques for prediction and classification in soil survey are developing rapidly. In year 2010 authors Miloš Kovačević et al.[4] introduces application of Support Vector Machines in the estimate of values of soil properties and soil type classification based on known values of particular chemical and physical properties in sampled profiles. Support Vector Machines are the model of choice for estimating values of physical characteristics and pH value when using just chemical data inputs, according to a comparison of the suggested approach with alternative linear regression models. Additionally, they are the model of choice when the estimated property and the chemical data inputs do not have a strong correlation. Their performance in a classification test, however, is comparable to that of the other evaluated approaches, with a growing advantage when a data set only contains a few training samples for each type of soil.

Substantial work has been done in analysing the soil type and based on the classification suggest the crop that should be grown. Authors Aditya M. , Param P. et al. [5] in year 2022 proposed a crop recommendation system to predict the optimal crop to be grown by analyzing various parameters including the region, soil type, yield, selling price, etc.

Authors Sk Al Zaminur Rahman et al. [6] (2018) employed Several machine learning algorithms such as weighted k-Nearest Neighbor (k-NN), Bagged Trees, and Gaussian kernel based Support Vector Machines (SVM) for soil classification. Experimental results show that the proposed SVM based method performs better than many existing methods.

In another paper author Saurabh Gaikwad (2022) [7] presented a system based on agricultural data analysis utilising machine learning techniques and image processing that can be very useful to farmers and the general public to anticipate what kinds of crops can be grown for different sorts of soil series.

Authors (2021) Angu Raj , Dr. Thiyaneswaran Balashanmugam et al.[8] used technologies like machine learning and IOT to collect soil parameters like soil moisture, temperature, humidity and pH are collected from the sensors using IOT and given to Graphical User Interface (GUI). GUI gets the inputs and suggests the suitable crops. In year 2012 authors Sun-Ok Chung et al. [9] did notable work in classifying soil using RGB characteristics of soil.

With time and technological advances people started using deep learning models and hyperspectral imaging in classifying soil types and in other research areas. One of the earliest use hyperspectral data was done in year 2004 by authors M. Pal and P. M. Mather [10] , In their research, the findings of two tests comparing the classification accuracy of multi-class SVMs, maximum likelihood (ML), and artificial neural network (ANN) methods are presented. For test locations in eastern England and central Spain, the two land cover categorization tests use multispectral (Landsat 7 ETM+) and hyperspectral (DAIS) data, respectively. The classification of soil types was performed by Authors Shengyao Jia et al. [11] and used a HSI system with a spectral range of 874–1734 nm. A total of 183 soil samples collected from Shangyu City (People's Republic of China). In order to extract the texture properties of energy, contrast, homogeneity, and entropy from the gray-scale images at the effective wavelengths, the SPA approach was used to choose the effective wavelengths from the entire spectrum. The SVM and PLSR approaches, respectively, were used to create the classification models for soil types and the prediction models for soil TN. The results showed that by using the combined data sets of effective wavelengths and texture features for modelling an optimal correct classification rate of 91.8%. could be achieved. Further , author Shengyao Jia et al. [12] used the same dataset for determining the total nitrogen content of soil. The local models were established for soil TN according to soil types, which achieved better prediction results than the general models. The overall results indicated that hyperspectral imaging technology could be used for soil type classification and soil TN determination There are extremely few hyperspectral images available. It is difficult to create a suitable deep learning model for classifying hyperspectral images. The performance of classification is improved by the combined use of spatial and spectral data. In this study authors Alkha Mohan and Venkatesan M. [13] suggests a brand-new hybrid CNN model that takes both spatial and spectral characteristics into account when classifying hyperspectral images. Using multi-scale receptive fields, it is discovered how dependent on spatial aspects the brain is. The hybrid model shows a reasonable performance with less computational complexity when compared to several cutting-edge CNN-based approaches. In recent years, classification of hyperspectral images (HSI) has seen considerable use of deep neural networks. However, a lot of labelled samples, whose collection requires a lot of time and money, are responsible for its success. In this paper authors Xiangyong Cao et al. [14](2020) provides an active deep learning technique for HSI classification that combines active learning and deep learning into a single framework in order to enhance classification performance while lowering labelling costs. A convolutional neural network (CNN) is first trained using a small set of tagged pixels. Next, we actively choose the most insightful pixels from the labelling candidate pool. The freshly created training set, which incorporates the newly labelled pixels, is then used to fine-tune the CNN. This step is carried out iteratively with the step before it. Finally, class label smoothness is enforced using a Markov random field (MRF) to further improve classification performance. Our suggested methodology outperforms the other cutting-edge classical and deep learning-based HSI classification algorithms on three benchmark HSI data sets while using much fewer labelled samples. The research of authors Xueying Li et al. [15] in 2021 develops a convolutional neural network classification model using six different types of soil (orchards, forests, tea plantations, farmlands, barren land, and grasslands) in Qingdao, China, as examples, based on visible near-infrared spectroscopy technology. The classification outcomes under the constraints of various number label samples are examined, and the shallow network SVM classification outcomes are contrasted. Convolutional neural networks perform better at classifying six different soil kinds and just six soil types than support vector machines when the Kennard-Stone technique divides the calibration set. The test set's categorization accuracy is greater than 95%. The classification outcomes by convolutional neural networks are also better when the calibration set is randomly divided into portions of 1/3 and 1/4. The test set's categorization accuracy is greater than 87The JigsawHSI network, a variant of the Jigsaw network and Geothermal AI networks, both of which are based on the Inception architecture, was introduced in this article by authors Jaime Moraga and H. Sebnem Duzgun [16] (2022). The Indian Pines, Pavia University, and Salinas Valley datasets—three open-source datasets frequently used in the categorization of hyperspectral images—were used to assess the network's performance. Under the same circumstances, the JigsawHSI network produces results that are either identical to or superior to those of HybridSN, demonstrating that when dimensionality reduction is used as a first step, the results of 2D-CNNs are comparable to those of a more sophisticated 3D-2D-CNN.

2 Methodology

2.1 Sample Scanning

Samples of soils were collected from nearby fields and were stored over a period of time to reduce the moisture level. The samples of particular soils were collected from a single source to maintain consistency while recording samples and avoid inaccurate sampling.

These samples were scanned under the Pika-IR hyperspectral camera which functions under the NIR or Near Infrared range spectral range. The samples were scanned in a batch of six.The samples once collected were stored in a natural environment and dry enviornment to keep it unaffected from moisture.

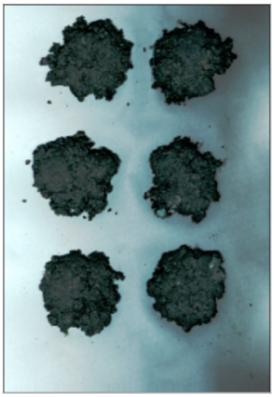

Fig. 1 Hyperspectral Image of a batch of soil

2.2 Hyperspectral Image Camera

The hyperspectral camera used for scanning samples used was a Resonon Pika-IR. It is a high-speed, cost-effective camera that covers the NIR (Near-infrared Range). Our research laboratory consisted of the benchtop system version of this camera.

The highlighting features of the Pika-IR camera are it can capture images high speed images at a maximum frame rate of 521. With a spectral channel of 900-1700nm range and a spectral bandwidth of 4.9mm it also supports spectral resolution of 8.8nm with a bit depth of 14. Figure 1 below shows the benchtop system.

Fig. 2 Benchtop System

First, to prevent the distortion of the HSI, stage speed, exposure duration, and the distance between lens and object are adjusted. These are decided based on the samples size and number of samples to be scanned at a go on the stage.

2.3 Data preprocessing and model preparation

2.3.1 Data Pre-processing for Machine Learning model.

After the step of data acquisition, we move on to data preprocessing wherein we make our data ready for our Machine learning and Deep learning modelc.

In this process the data acquired by the hyperspectral scanning is processed to perform data cleaning , and structure the data in particular format to pass it to the machine learning models for fitting and prediction. We had the .bil file which stored the hyperspectral data. Each sample had its .hdr file which stored its metadata. The hypercube was then processed programmatically using spectral library to generate a .csv file of the mean value of spectrum at each band. As each scan contained information for 168 bands so it represented the number of columns of our dataset and a sample name represented the row consisting data of 168 columns. For the prediction purpose the first column of our dataset contained sample number denoting the type of soil wherein 0 is for black soil, 1 for red soil and 2 for yellow soil.

Table 1 Snapshot of Dataset containing 168 bands as independent variable and first column (i.e sample number which denotes the type of soil) as dependent variable.

Sample	888.71	893.55	898.38	903.22	908.06	912.9
0	2583	2553	2525	2509	2495	2482
0	2779	2747	2715	2700	2681	2665
0	2628	2604	2572	2564	2553	2538
0	2130	2110	2089	2069	2050	2049
0	2515	2487	2460	2446	2430	2414
0	2580	2551	2525	2512	2495	2483
0	2195	2171	2160	2132	2119	2113
1	2392	2364	2346	2320	2303	2303
1	2360	2333	2311	2290	2280	2273

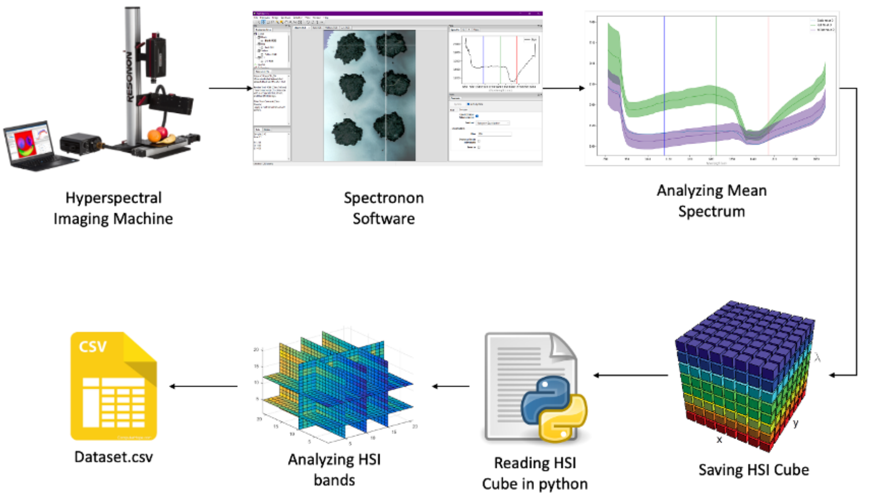

Fig. 3 Data acquisition flow graph for ML model.

Fig 4 depicts the steps required to perform data pre-processing for training machine learning model. First we scan the soil samples under the HSI camera. Further the soil samples are observed and there trend and analysis is observed. The HSI cube is then saved using the software. Further if read the HSI cube using python to perform subsequent operations. After reading the cube in python, noise removal step is done and further the mean is calculated for preparation of dataset.csv.

2.3.2 Data Pre-processing for Deep Learning model.

After the step of data acquisition, we move on to data preprocessing wherein we make our data ready for our CNN model. In fig 6 we can visualise the steps needed for data pre-processing for training the pre- trained CNN models. First and foremost the samples are scanned under the resonon camera with the help of spectronon. Wherein after adequate samples are scanned of all types analysis is done by plotting and observing the differences and similarities in the mean spectrum graph. Further good quality cubes are saved for subsequent operations to be performed in python. The saved cubes are the read in python using required library. The cube read is then further processed to remove noise using appropriate algorithm. After processing the cube the number of hyperspectral bands are reduced and then principal component analysis is done to transform the cube into 3 bands to make it suitable to pass in the pre-trained CNN models.

We can observe that after applying PCA the area which contains the soil acquires a unique colour for its patch which will be helpful for classification as the colour acquired is the resultant combination of its chemical and hyperspectral properties. Thus, as each soil as different chemical and hyperspectral properties will acquire different unique colour for its patches , resulting in accurate classification.

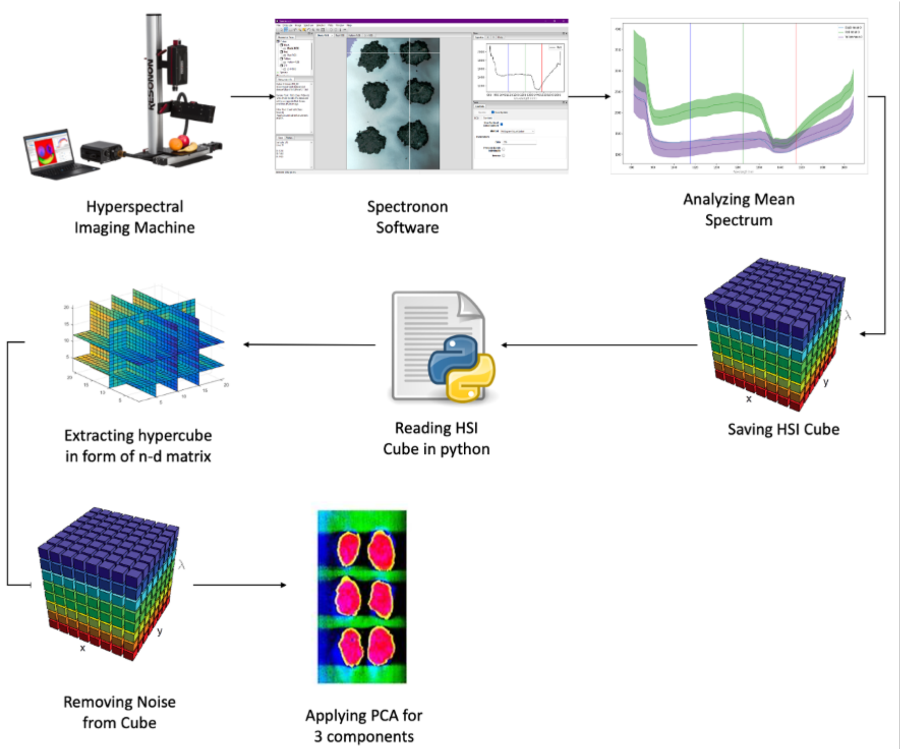

Fig. 4 Data acquisition flow graph for DL model.

3 Model Analysis

3.1 ResNet50

Classification of soil was done by analysing and establishing the relationship between properties of soil obtained after applying PCA along with their class. We have used Resnet50 as our CNN model to classify the soil into different categories. This model was chosen as it overcomes it intelligently handles the problem of vanishing gradient using skip connection which is generally caused in a highly dense CNN model. Skip connection is Resnet is direct connection that skips over some layers of the model. The output is not the same due to this skip connection. Without the skip connection, input 'X gets multiplied by the weights of the layer followed by adding a bias term. In case where dimension of x are different from f(x), the skip connection is padded with extra zero entries to increase its dimension.

Then comes the activation function, F() and we get the output as :

$$H(x) = F(w * x + b) \tag{1}$$

But with skip connection technique, the output is :

$$H(x) = F(x) + x. \tag{2}$$

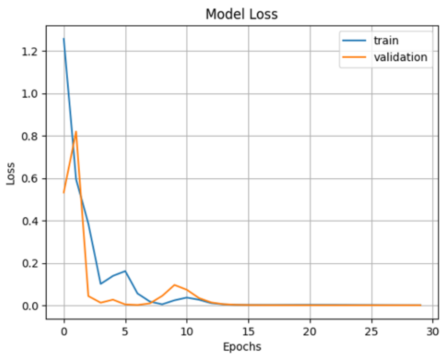

Fig. 5 ResNet50 Model Loss in training and validation

4 Result and Discussion

4.1 Band Selection and Chemical Analysis

We have studied and found that out that in different types of soil we find different chemical composition. Three different categories of soil was scanned i.e Black Soil, Red Soil and Yellow Soil .Figure 10 shows the mean spectrum graph of three different types of soil. This mean spectrum graph is plotted by considering all the values of the sample across all 168 bands. All the values corresponding to the sample are plotted and the mean is calculated for the 168 bands. The highlighted region represents the values covered by a particular sample and the bold coloured line represents their mean. The blue line represents the Black Soil, the green line represents the fruit in eatable stage and the red line represents the fruit in overripe stage. From the figure we can observe that from 1400 nm the graphs start overlapping each other. It represents the 2 overtone of -OH bond. This overlapping represents the different water content in different soils.

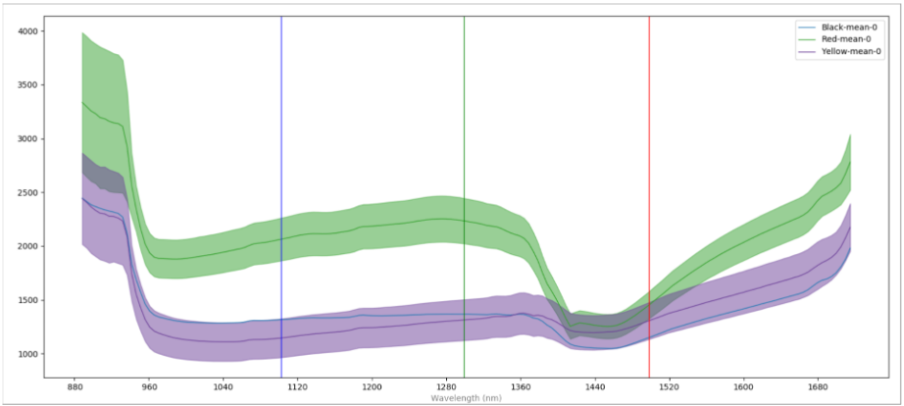

Fig. 6 Mean spectrum comparision of three different types of soil.

4.2 Result of models.

We have done the classification soil using machine learning and various techniques of deep learning. For machine learning model we have used support vector machine algorithm and obtained results for various kernel which are , 62.5% accuracy for sigmoid, 80% percent accuracy for linear , 75% accuracy for polynomial and 87.5% accuracy for RBF kernel. We observed that in machine learning algorithms they performed poor during validation phase.

Various deep learning models were trained including VGG16,VGG19 and Resnet50 along with different parameters. Resnet50 provided us with best accuracy. In table 2 we can observe for different optimizers such as SGD, AdaGrad, RMS-Prop, and Adam we have accuracies as 90.91%, 92.18%, 94.59%, 97.30% respectively. We can observe that we obtain the best accuracy for Adam optimizer. Summarised result of different models are shown in Table 3.

Table 2 Results of ResNet50.

Model	ResNet50			
Optimizer	SGD	AdaGrad	RMS-Prop	Adam
Batch size	32	32	32	32
Epochs	30	30	30	30
Image Size	180x180	180x180	180x180	180x180
Loss	0.6472	0.2422	0.0198	0.0016
Accuracy (%)	90.91	92.18	94.59	97.30
Val_Loss	0.4901	0.1299	0.0942	4.67E-04
Val_Accuracy (%)	91.06	96.87	98.92	99.73

Table 3 Comparison of results of various deep learning models.

Model	VGG16	VGG19	ResNet50
Optimizer	Adam	Adam	Adam
Batch size	32	32	32
Epochs	30	30	30
Image Size	224x224	224x224	180x180
Loss	0.0982	0.2548	0.0016
Accuracy	96.17	91.85	97.30
Val_loss	0.0825	0.2817	4.67E-04
Val_accuracy	97.45	92.89	99.73

5 Conclusion

The methods discussed in this paper are highly dependent on the NIR spectra stored pixel-wise in raster formats. This paper proposed the classification of soil via a non-destructive hyperspectral image system in order to classify them as yellow, red, or black. The obtained results show that by applying ML and DL models, it is possible to efficiently predict soil color and composition.

The results of this project are promising but there is a huge scope for improvements in the project by increasing its scalability and covering as many samples as possible combined with the addition of more properties of the soil to train our model which can be extracted using various testings of soil. This will help determine the exact properties that we need which are difficult to predict using other testing and inspection but will be easier with hyperspectral imaging. This can become a very promising model which can make cultivation very easy with the most efficient prediction about the right crop to grow in that soil.

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