Bachelors of Technology Project

SOIL TYPE CLASSIFICATION FROM SATELLITE IMAGES

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Introduction

Soil is one of the significant natural resources, like air and water. It is a non-renewable resource and hence invaluable. Soil exists throughout the world in different varieties. Different types of soil have different behaviour and physical properties. These diverse behaviour and physical properties of the soil are suited differently to different types of agricultural requirements.

The main information source for sustainable agriculture and land use management are the soil surveys. Soil survey mappings are defined by the soil properties that affect management practices such as drainage, erosion control, tillage and nutrition and thus it requires the whole soil profile.

The traditional methods involving soil surveys are quite expensive and time taking due to the large number of observations. However, the technological advancement in the fields of computer and information technology bring in totally new methods and new tools for carrying out such tasks computationally. The rapid growth in the fields of Remote sensing techniques and Geographical Information System (GIS) have opened new ways for estimating soil types and its spatial distribution with reasonable costs and accuracy. These remote sensing methods provide perspective for spatial and instantaneous measurements of soil content. Also thermal emission data proves helpful in finding soil series and sensitivity of the surface.

So, here we propose a novel idea for combining the remote sensing techniques with image processing tools to classify the different soil types and therefore be able to predict soil behaviour and its physical properties. The main principle of the project is to inspect the possibilities of using remote sensing data with image processing tools to do soil classification.

Problem Statement

The main objective of our work is to implement a classification method for classifying satellite images of soil into different soil types using deep learning methods.

Abstract

Nowadays, with the advancements in the fields of Remote Sensing and Geographical Information Systems (GIS), we have new ways for estimating soil types and its spatial distribution with reasonable costs and accuracy. The innovation of this work is to use LANDSAT satellite image data and GIS to assess land information and perform soil classification using deep neural networks.

Index Terms

Remote Sensing, Geographical Information System (GIS), Soil classification, feature extraction, Image clustering, Image classification, LANDSAT, Natural colour image, Thermal Image, CNN(Convolutional Neural Network), Deep Learning, Temporal difference

Literature Analysis on Previous works

1. Application of Satellite Remote Sensing to find Soil Fertilization by using soil colour : This research paper uses LANDSAT image data and GIS techniques to assess land information and soil classification in the area of Vellore District and uses this information to propose the possible fertilization for the study area. They have firstly used the k-means clustering algorithm for segmentation of the study region based on colour. The segmentation step is basically used as preprocessing for the data. The k clusters obtained from the segmentation step are then used to perform the classification based on the k nearest neighbour decision rule. They have then used the classified data to find out the best fertilization for the best soil using the soil colour.

2. Multi-spectral Image Segmentation based on the k-means clustering : This research paper uses the satellite image from Sentinel 2 remote sensing satellite to perform pixel based clustering using the k-means clustering. The extracted regions obtained from the clustering step are classified using a minimum distance decision rule.

3. Classification of Cluster Area For satellite Image : The objective of this research paper is to develop a classification system for satellite images into clusters. The main steps involved in this are converting the image from RGB color space to L*a*b* color space, then classifying the colors in a*b* space using k-means clustering. Then every pixel is labelled in the image using the results from k-means clustering. Then using these labels, images are created that segment the image by color resulting into different categories(Greenland, water, urban+balance etc.).

Data Collection Phase

We downloaded data from two different sources :

1. OHC | Free GIS Data | Download : Bhuvan, is an Indian web based utility which allows users to explore a set of map based content prepared by Indian Space Research Organisation. The content which the utility serves is mostly restricted to Indian boundaries. It has imageries from the ISRO satellites: Resourcesat and Cartosat. We downloaded the Resourcesat-2 data for different land blocks of differing soil types.

2. USGS EarthExplorer : The USGS EarthExplorer gives a quick and intuitive way to download satellite imagery. It has data from the different NASA satellites such as LANDSAT. We downloaded the satellite images from the LANDSAT-8 satellite.

The data downloaded from the Bhuvan resource center was not usable as most of the image blocks were blank. The pixel values signified the images were totally blank.

So, we proceeded with the data from the USGS EarthExplorer source.

There are 6 major soil types :

1. Alluvial soil
2. Red soil
3. Black soil
4. Arid soil
5. Laterite soil
6. Mountain soil

Out of these 6 major soil types we downloaded data of the top 4 soil types : Alluvial, Red, Black and Arid soil. We did not consider the remaining 2 soil types as individual blocks of these two soil types were not available for download.

We downloaded 200 images each from each soil type. The downloaded images had both temporal and spatial variations i.e. we chose different blocks and downloaded images that were captured at different timings for each soil region.

About the downloaded data

Out of the many different satellite data present on the website, we downloaded the data of the ‘LANDSAT 8’ satellite, “Landsat 8 Operational Land Imager(OLI) and Thermal Infrared Sensor(TIRS)” to be more precise. We considered Landsat 8 over Landsat 7 or other satellites because it is among the latest satellites and has maximum accuracy.

The Landsat-8 satellite has two main sensors : the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS).

OLI collects images using nine spectral bands in different wavelengths of visible, near-infrared, and shortwave light. It has sufficient resolution to distinguish features like urban centers, farms, forests and other land uses. While TIRS is mainly used for measuring water consumption.

The data collected from the Landsat-8 has the following band structure :

Landsat 8 Operational Land Imager (OLI) **and Thermal Infrared Sensor** (TIRS) images consist of nine spectral bands with a spatial resolution of 30 meters for Bands 1 to 7 and 9. New band 1 (ultra-blue) is useful for coastal and aerosol studies. New band 9 is useful for cirrus cloud detection. The resolution for Band 8 (panchromatic) is 15 meters. Thermal bands 10 and 11 are useful in providing more accurate surface temperatures and are collected at 100 meters. Approximate scene size is 170 km north-south by 183 km east-west (106 mi by 114 mi). The instruments on Landsat 9 (launch ready December 2020) are being designed as improved copies of Landsat 8.

View Landsat 7 / Landsat 5 and Landsat 8 Common Band Combinations

Landsat 8-9 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS)

Bands	Wavelength (micrometers)	Resolution (meters)
Band 1 - Coastal aerosol	0.43-0.45	30
Band 2 - Blue	0.45-0.51	30
Band 3 - Green	0.53-0.59	30
Band 4 - Red	0.64-0.67	30
Band 5 - Near Infrared (NIR)	0.85-0.88	30
Band 6 - SWIR 1	1.57-1.65	30
Band 7 - SWIR 2	2.11-2.29	30
Band 8 - Panchromatic	0.50-0.68	15
Band 9 - Cirrus	1.36-1.38	30
Band 10 - Thermal Infrared (TIRS) 1	10.6-11.19	100
Band 11 - Thermal Infrared (TIRS) 2	11.50-12.51	100

Regarding metadata of the downloaded data, the data downloaded follows the following naming convention for easy retrieval of the metadata :

LXSS_LLLL_PPPRRR_YYYYMMDD_yyyymmdd_CC_TX

Where:

- L = Landsat
- X = Sensor ("C"=OLI/TIRS combined, "O"=OLI-only, "T"=TIRS-only, "E"=ETM+, "T"="TM, "M"=MSS)
- SS = Satellite ("07"=Landsat 7, "08"=Landsat 8)
- LLL = Processing correction level (L1TP/L1GT/L1GS)
- PPP = WRS path
- RRR = WRS row
- YYYYMMDD = Acquisition year, month, day
- yyyymmdd - Processing year, month, day
- CC = Collection number (01, 02, …)
- TX = Collection category ("RT"=Real-Time, "T1"=Tier 1, "T2"=Tier 2)

Example: LC08_L1GT_029030_20151209_20160131_01_RT

Means: Landsat 8; OLI/TIRS combined; processing correction level L1GT; path 029; row 030; acquired December 9, 2015; processed January 31, 2016; Collection 1; Real-Time

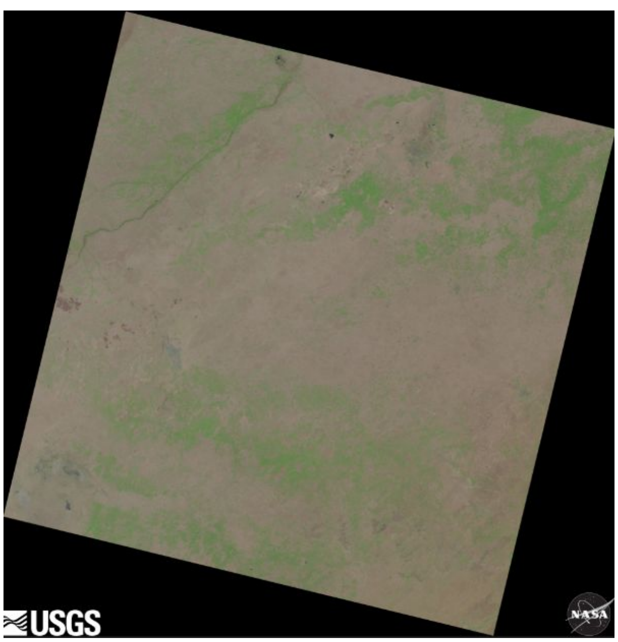
For the mentioned satellite data, the size of each block scaled to ground level is equal to 185 km x 180 km. It is due to these large sizes of blocks that we could not gather independent images of the laterite soil and mountain soil.

Out of the available options, we downloaded LandsatLook Natural Color Image images for each image block:

The natural colour image is a natural-looking false colour composite image that is formed using the bands 6, 5, 4. False color images are a representation of a multispectral image produced using any bands other than visible red, green and blue as the red, green and blue components of the display. False color composites allow us to visualize wavelengths that the human eye can not see (i.e. near-infrared and beyond). Using bands such as near infrared highlights the spectral differences and often increases the interpretability of the data.

The downloaded data had both the temporal and spatial variations i.e. we chose different blocks and downloaded images that were captured at different timings for each soil region.

Sample Data :



Img 1 : Natural Colour Image

File name : LC08_L1TP_149041_20200318_20200326_01_T1

Information about data :

- Satellite : Landsat - 8
- Sensors : OLI/TIRS combined
- Processing correction level : L1TP
- Path : 149
- Row : 41
- Acquisition Date : 18/03/2020
- Processing Date : 26/03/2020
- Collection Number : 01
- Collection category : Tier-1

Traditional Machine Learning Method

We used k-means clustering algorithm using different image features on a set of 200 images each from all soil types.

K-means Clustering Algorithm

K-means clustering is an unsupervised learning algorithm that is used to cluster a given data set into k clusters based on certain features. The main idea behind the algorithm is to define k random centers initially, one for each cluster. These centers need to be defined as far as possible from each other for better results since the results depend on the initial centers selected randomly. The algorithm focuses on minimizing the objective function

$$J(V) = \sum_{i=1}^{c} \sum_{j=1}^{c_i} (\|x_i - v_j\|)^2$$

where,

'||xi - vj||' is the Euclidean distance between xi and vj.

'ci' is the number of data points in ith cluster.

'c' is the number of cluster centers.

K-means clustering follows the following algorithmic steps :

Let X = {x1,x2,x3,……..,xn} be the set of data points and V = {v1,v2,…….,vc} be the set of centers.

1. Randomly select 'c' cluster centers.
2. Calculate the distance between each data point and cluster centers.
3. Assign the data point to the cluster center whose distance from the cluster center is the minimum of all the cluster centers..
4. Recalculate the new cluster center using:

$$v_i = (1 / c_i) \sum_{j=1}^{c_i} x_i$$

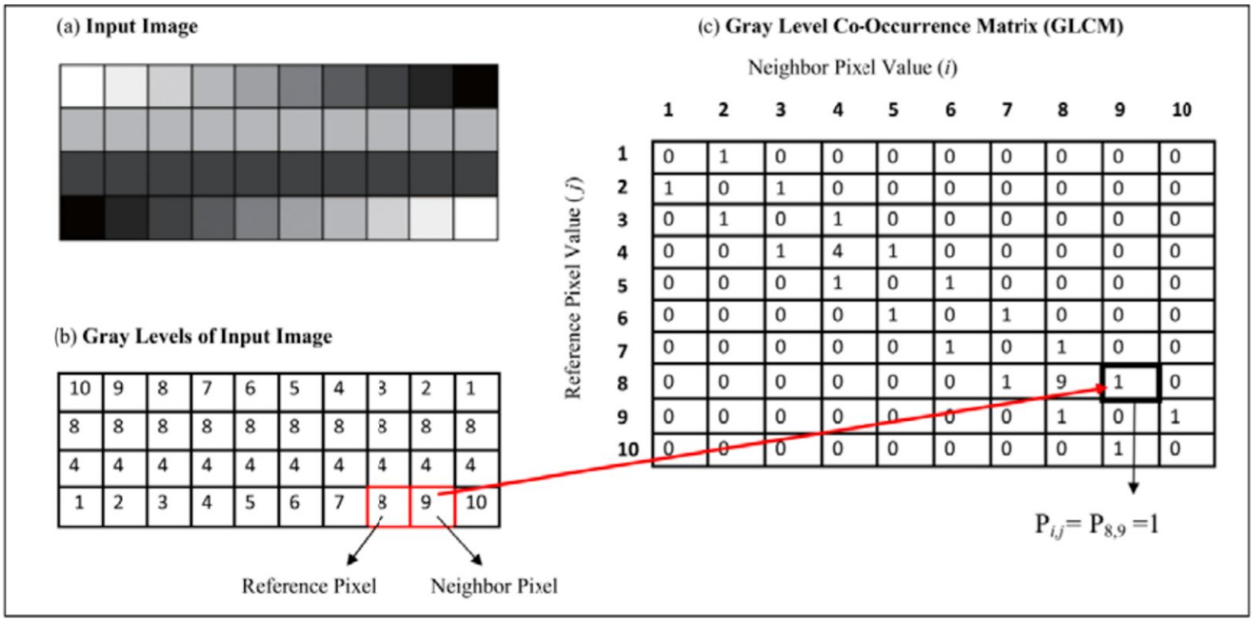
where, 'ci' represents the number of data points in ith cluster.

5. Recalculate the distance between each data point and new obtained cluster centers.
6. If no data point was reassigned then stop, otherwise repeat from step 3).

The time complexity of this algorithm is O(tknd), where n is # objects, k is # clusters, d is # dimension of each object, and t is # iterations. Normally, k, t, d << n.

Texture Feature Extraction using GLCM

Gray Level Co-occurrence Matrix (GLCM) is used to calculate the spatial dependencies of gray levels in an image. Co-occurrence matrices are constructed in four spatial orientations: 0, 45, 90, 135. Another matrix is then constructed by taking the average of preceding matrices. The steps are followed as shown in the below image :



The texture features such as contrast, energy, dissimilarity, homogeneity are then calculated from the GLCM matrix using the following formulas.

Contrast : $\sum_{i,j=0}^{N-1} P_{i,j}\ (i-j)^2$

Energy : $\sum_{i,j=0}^{N-1} P_{i,j}^2$

Dissimilarity : $\sum_{i,j=0}^{N-1} P_{i,j}\ |i-j|$

Homogeneity : $\sum_{i,j=0}^{N-1} \frac{P_{i,j}}{1+(i-j)^2}$

We tried to obtain the clustering results using features such as colour and texture on both natural colour image as well as thermal image.

The best accuracy we achieved in clustering was 0.39 using texture as feature.

We, then, used the k-Nearest Neighbour (kNN) classification algorithm using texture as the feature.

K-Nearest Neighbour(KNN) Classification

This algorithm is a supervised machine learning algorithm that relies on labeled input data to train a function that produces an appropriate output when given with new unlabeled input data. This algorithm relies on the assumption that similar things exist in close proximity.

The algorithmic steps involved in the algorithm are :

1. Load the data
2. Initialize K to your chosen number of neighbors
3. For each example in the data
    a. Calculate the distance between the query example and the current example from the data.
    b. Add the distance and the index of the example to an ordered collection
4. Sort the ordered collection of distances and indices from smallest to largest (in ascending order) by the distances
5. Pick the first K entries from the sorted collection
6. Get the labels of the selected K entries
7. return the mode of the K labels

The training and testing data split was in the ratio 90% to 10%.

The accuracy received in this was 0.37.

Result in this phase is average efficiency obtained in 100 runs with slightly randomised test and train data to have better information on efficiency of algorithm.

Deep Learning Method

There are three important types of neural networks that form the basis for most pre-trained models in deep learning:

- Artificial Neural Networks (ANN)
- Convolution Neural Networks (CNN)
- Recurrent Neural Networks (RNN)

	MLP	RNN	CNN
Data	Tabular data	Sequence data (Time Series,Text, Audio)	Image data
Recurrent connections	No	Yes	No
Parameter sharing	No	Yes	Yes
Spatial relationship	No	No	Yes
Vanishing & Exploding Gradient	Yes	Yes	Yes

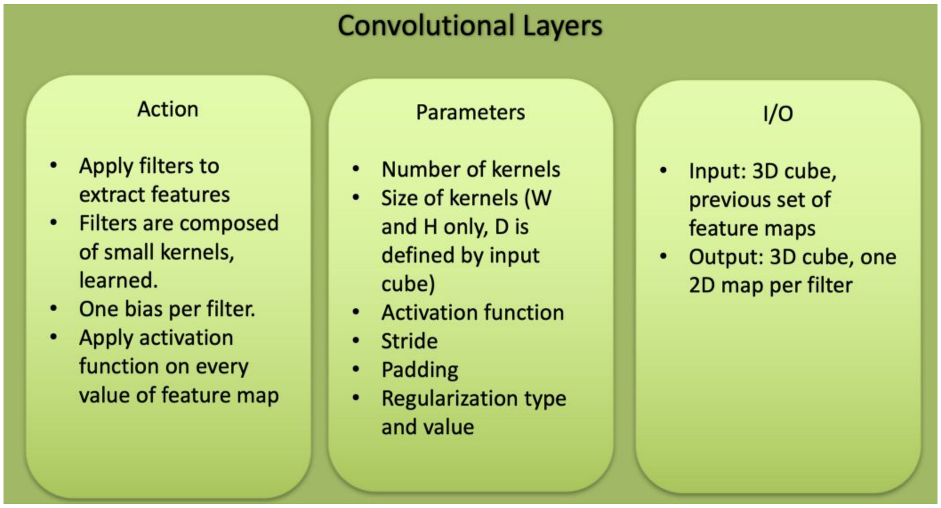
We used Convolution Neural Network for our purpose because of the following reasons:

- The building blocks of CNNs are filters a.k.a. kernels. Kernels are used to extract the relevant features from the input using the convolution operation. Convolving an image with filters results in a feature map which is relevant for classifying images.
- CNN learns the filters automatically without mentioning it explicitly. These filters help in extracting the right and relevant features from the input data.
- CNN captures the spatial features from an image. Spatial features refer to the arrangement of pixels and the relationship between them in an image. They help us in identifying the object accurately, the location of an object, as well as its relation with other objects in an image.
- CNN also follows the concept of parameter sharing. A single filter is applied across different parts of an input to produce a feature map.

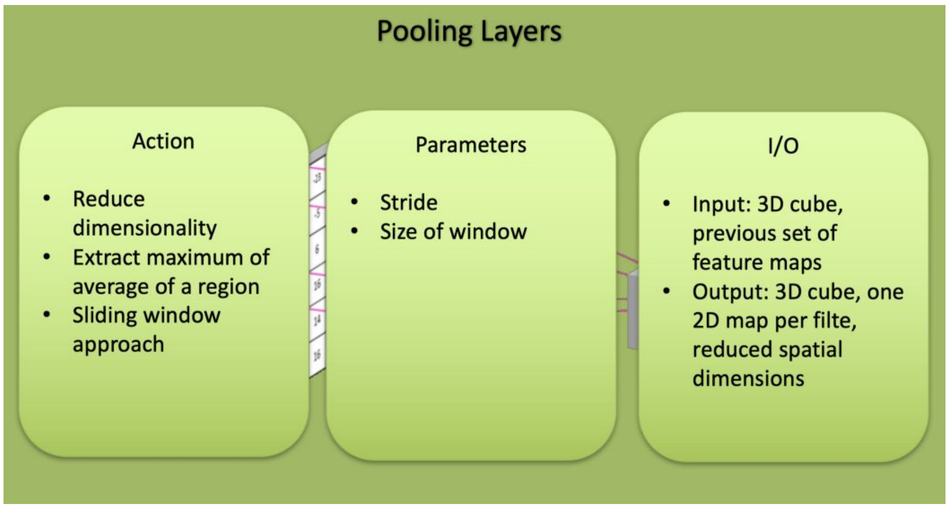
Convolution Neural Network Layers :

There are three types of layers in a convolutional neural network: convolutional layer, pooling layer, and fully connected layer. Each of these layers has different parameters that can be optimized and performs a different task on the input data.

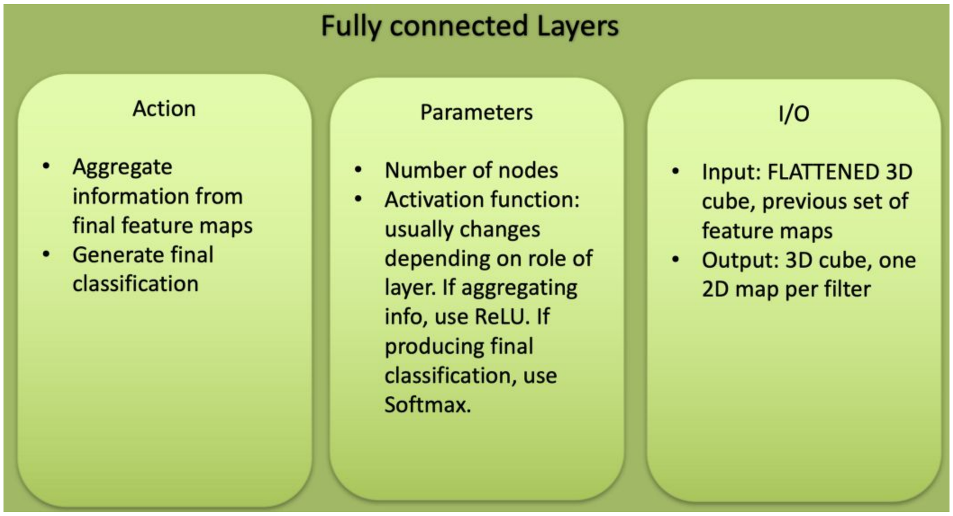
1. Convolutional Layers : Convolutional layers are the layers where filters are applied to the original image, or to other feature maps in a deep CNN. This is where most of the user-specified parameters are in the network. The most important parameters are the number of kernels and the size of the kernels.



2. Pooling Layers : Pooling layers are similar to convolutional layers, but they perform a specific function such as max pooling, which takes the maximum value in a certain filter region, or average pooling, which takes the average value in a filter region. These are typically used to reduce the dimensionality of the network.



3. Fully Connected layers : Fully connected layers are placed before the classification output of a CNN and are used to flatten the results before classification. This is similar to the output layer of an MLP.

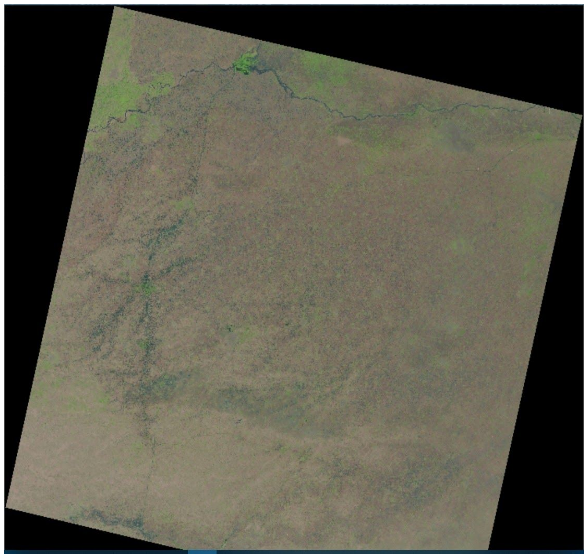


<u>Different Experimentations</u> :

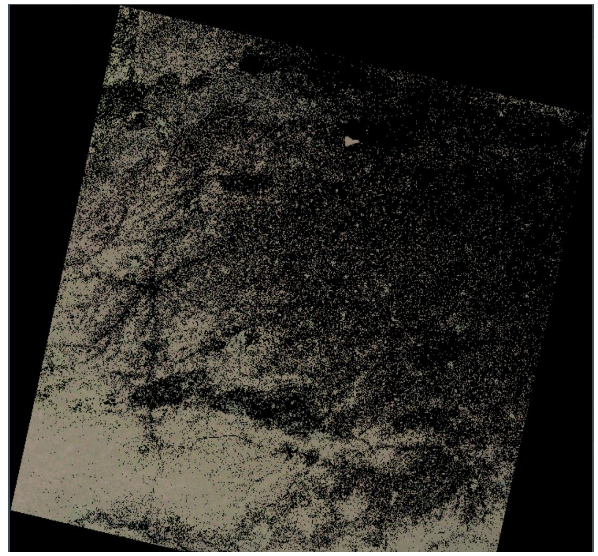
- We used different configurations of CNN layers with raw images as input data and got the best accuracy of average 0.30 in 10 runs of the algorithm where the maximum accuracy obtained was as high as 0.43. The number of internal conv2D layers varied from 3 to 5 along with variations in filter size and the number of filters used.

- We then tried training the model with absolute difference of temporal images of the same block of soil. Absolute difference between temporal images of the same block was used as training and validation datasets Median array was calculated from train images for each block and then the absolute difference of test images with median array were taken for building the test dataset. Accuracy obtained in this method was around 0.34 (average of 10 runs).

- We performed image pre-processing step on the raw images so as to remove vegetation cover before feeding the data to the neural network.



Img 1 : Original Image

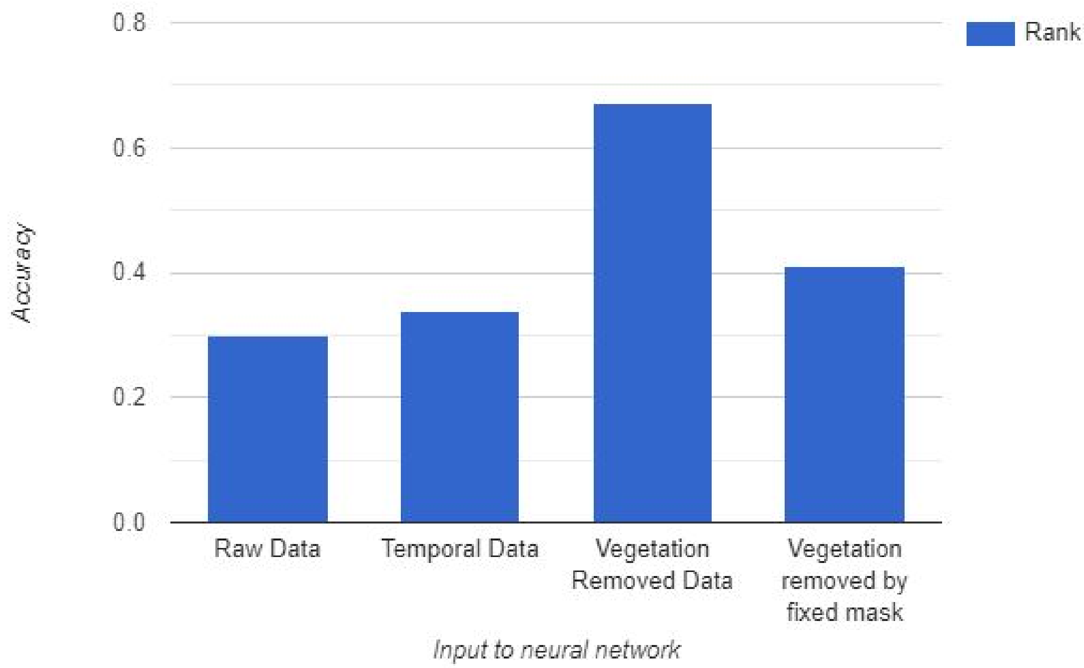


Img 2 : After removing vegetation

We used different configurations of CNN layers with raw images as input data and got the best accuracy of average 0.67 in 5 runs of the algorithm where the maximum accuracy obtained was as high as 0.80. The number of internal conv2D layers varied from 3 to 5 along with variations in filter size and the number of filters used.

- We also tried using vegetation removal step on one image from each block and used it as mask for other images from the same block, but the accuracy decreased to 0.41 because of vegetation fluctuation with time.

Results



Qualitative Results

Name of image	Actual Class	Result
LC08_L1TP_150041_20200426_20200509_01_T1.jpg	2	2
LC08_L1TP_145041_20200930_20200930_01_RT.jpg	0	3
LC08_L1TP_141046_20190612_20190619_01_T1.jpg	3	3
LC08_L1TP_143052_20200324_20200326_01_T1.jpg	3	1
LC08_L1TP_147040_20191129_20191216_01_T1.jpg	0	0
LC08_L1TP_141045_20190527_20190605_01_T1.jpg	3	3
LC08_L1TP_142042_20200214_20200225_01_T1.jpg	0	3
LC08_L1TP_147040_20200217_20200225_01_T1.jpg	0	0
LC08_L1TP_150042_20200629_20200708_01_T1.jpg	2	2
LC08_L1TP_145046_20200118_20200128_01_T1.jpg	1	3
LC08_L1TP_146040_20200703_20200708_01_T1.jpg	0	0
LC08_L1TP_143052_20200409_20200409_01_RT.jpg	3	3
LC08_L1TP_149042_20200521_20200527_01_T1.jpg	2	0
LC08_L1TP_144052_20200721_20200807_01_T1.jpg	3	3
LC08_L1TP_145046_20190523_20190604_01_T1.jpg	1	1
LC08_L1TP_145046_20200219_20200225_01_T1.jpg	1	0
LC08_L1TP_149042_20190519_20190522_01_T1.jpg	2	2

LC08_L1TP_143052_20200221_20200225_01_T1.jpg	3	0
LC08_L1TP_146046_20200109_20200114_01_T1.jpg	1	1
LC08_L1TP_144050_20200228_20200313_01_T1.jpg	3	3
LC08_L1TP_146046_20200125_20200128_01_T1.jpg	1	1
LC08_L1TP_150041_20190713_20190719_01_T1.jpg	2	2
LC08_L1TP_144051_20200228_20200313_01_T1.jpg	3	3
LC08_L1TP_145041_20190827_20190903_01_T1.jpg	0	0
LC08_L1TP_143052_20200104_20200113_01_T1.jpg	3	0
LC08_L1TP_150041_20190526_20190605_01_T1.jpg	2	0
LC08_L1TP_146047_20190327_20190404_01_T1.jpg	1	1
LC08_L1TP_144051_20200315_20200325_01_T1.jpg	3	1
LC08_L1TP_144041_20191108_20191115_01_T1.jpg	0	3
LC08_L1TP_144041_20190617_20190620_01_T1.jpg	0	0
LC08_L1TP_150042_20190323_20190403_01_T1.jpg	2	3
LC08_L1TP_142042_20190518_20190522_01_T1.jpg	0	0
LC08_L1TP_141046_20200411_20200411_01_RT.jpg	3	3
LC08_L1TP_146047_20190412_20190422_01_T1.jpg	1	1
LC08_L1TP_145045_20200219_20200225_01_T1.jpg	1	3
LC08_L1TP_145041_20200525_20200608_01_T1.jpg	0	0
LC08_L1TP_144041_20190601_20190605_01_T1.jpg	0	3
LC08_L1TP_143051_20200205_20200211_01_T1.jpg	3	3
LC08_L1TP_145044_20191217_20191226_01_T1.jpg	1	0
LC08_L1TP_145044_20190421_20190507_01_T1.jpg	1	1
LC08_L1TP_149041_20181226_20190129_01_T1.jpg	2	2
LC08_L1TP_144041_20200416_20200423_01_T1.jpg	0	0
LC08_L1TP_144050_20190516_20190521_01_T1.jpg	3	3
LC08_L1TP_145045_20191030_20191114_01_T1.jpg	1	2
LC08_L1TP_146047_20200313_20200325_01_T1.jpg	1	3
LC08_L1TP_150042_20181217_20181227_01_T1.jpg	2	2
LC08_L1TP_147040_20191028_20191030_01_T1.jpg	0	3
LC08_L1TP_141042_20200411_20200422_01_T1.jpg	0	0
LC08_L1TP_146040_20191208_20191217_01_T1.jpg	0	2
LC08_L1TP_141045_20200529_20200608_01_T1.jpg	3	3
LC08_L1TP_141046_20191103_20191115_01_T1.jpg	3	0
LC08_L1TP_150042_20190408_20190422_01_T1.jpg	2	2
LC08_L1TP_149042_20200215_20200225_01_T1.jpg	2	2
LC08_L1TP_145041_20200509_20200526_01_T1.jpg	0	0
LC08_L1TP_144052_20191226_20200110_01_T1.jpg	3	2
LC08_L1TP_141046_20190425_20190508_01_T1.jpg	3	3
LC08_L1TP_141042_20200310_20200314_01_T1.jpg	0	2
LC08_L1TP_145045_20200407_20200410_01_T1.jpg	1	3
LC08_L1TP_145041_20191115_20191202_01_T1.jpg	0	0
LC08_L1TP_141046_20190511_20190521_01_T1.jpg	3	3
LC08_L1TP_148039_20190613_20190619_01_T1.jpg	0	2
LC08_L1TP_146040_20200210_20200224_01_T1.jpg	0	3
LC08_L1TP_149042_20200606_20200608_01_T1.jpg	2	2
LC08_L1TP_145041_20200219_20200225_01_T1.jpg	0	0
LC08_L1TP_144041_20190516_20190521_01_T1.jpg	0	3
LC08_L1TP_147040_20200201_20200211_01_T1.jpg	0	0
LC08_L1TP_144052_20190124_20190205_01_T1.jpg	3	3
LC08_L1TP_149042_20190127_20190206_01_T1.jpg	2	3
LC08_L1TP_144052_20200111_20200114_01_T1.jpg	3	3
LC08_L1TP_145044_20191201_20191216_01_T1.jpg	1	1
LC08_L1TP_149042_20181226_20190129_01_T1.jpg	2	3

LC08_L1TP_149042_20181108_20181116_01_T1.jpg	2	2

0->Alluvial, 1-> Black 2-> Desert 3-> Red

Conclusion

- Classification into different soil classes using traditional and deep learning methods was successfully performed on the downloaded dataset and the above mentioned results were obtained.
- We got an understanding of the traditional clustering and classification methods as well as the deep learning classification method.
- We also learnt about various data pre-processing techniques.
- The inaccuracy in results can be attributed to the following reasons :
    - Inaccuracy in segmenting soil and vegetation/cloud cover from the images
    - Small data set size (800 images used)
    - Image block size is too large.

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