Individual-Final-Report – Yashwant Bhaidkar

Dataset search:

Our goal is to predict the forest cover type using some variables based on environmental conditions and soil types. We get two datasets available for this problem.

- UCI forest cover prediction dataset: This dataset is imbalanced and it has around 581012 datapoints.
- Kaggle competition: UCI Forest cover prediction: This dataset is balanced –???

We decided to go with the UCI imbalanced data as it is the old dataset with actual entries from the survey.

In this dataset we have,

- 10 Numerical features
- 44 Categorical features

EDA:

I worked on some of the numerical features and categorical features(soil features)

There is no missing information(Null) in this dataset.

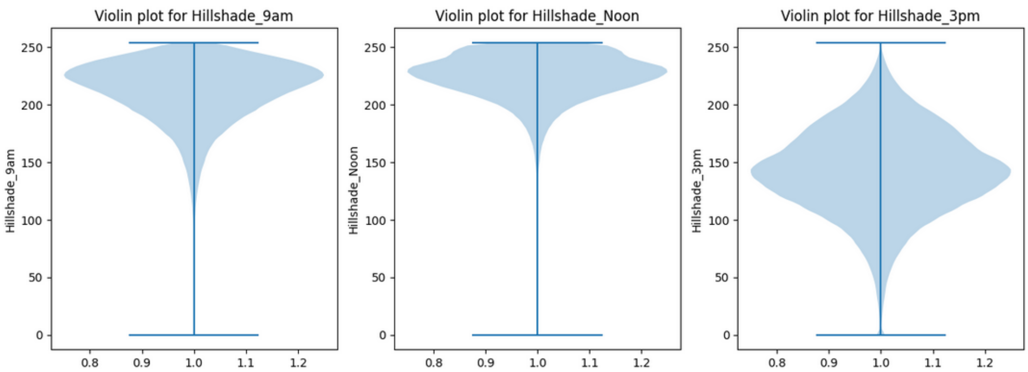
Some of the features which I covered

Hill shade features:

We have 3 features based on the hill shade values for 3 particular times during the day.

This feature is important as it will give us an idea that how much sunlight is available at that spot.

These values range from 0 to 255, so it is giving us the color shade between black and white. (0 is dark and 255 is white)

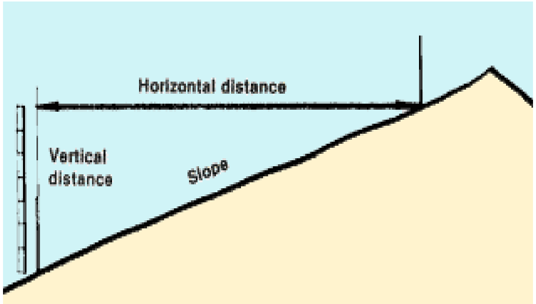


Based on the violin plot, hill shade 3am looks normal and hillshade_9AM and Hillshade_Noon are left skewed. As the range is fixed, we can say that there is no outlier present.

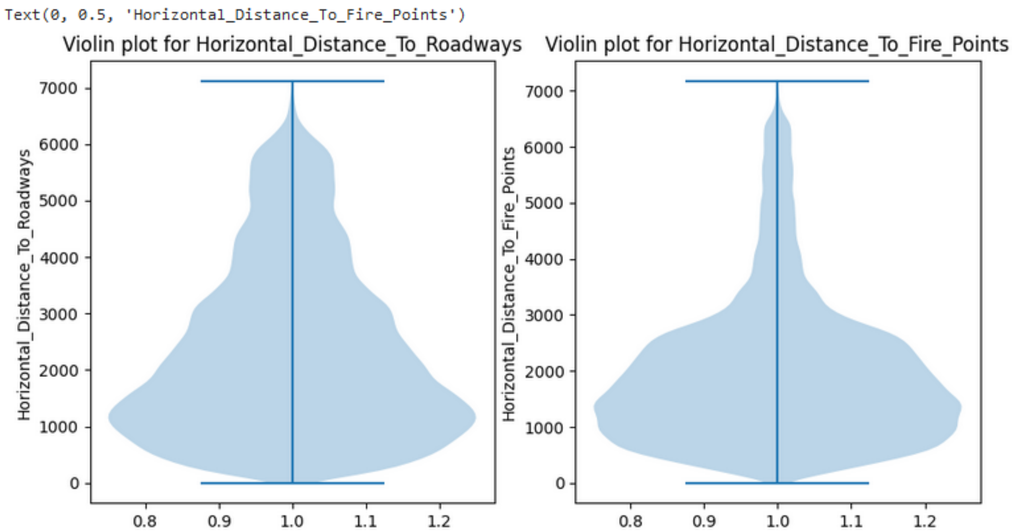
Horizontal distance to roadways and fire points:

Horizontal distance is the distance of the survey spot from the roadways and fire points.

Main impact of this feature is on the forest quality as if the locations are away from the roads and fire points, those spots are more secure and we will get better quality of forest cover as there will be less pollution and the probability of damage from the fire will be very less.



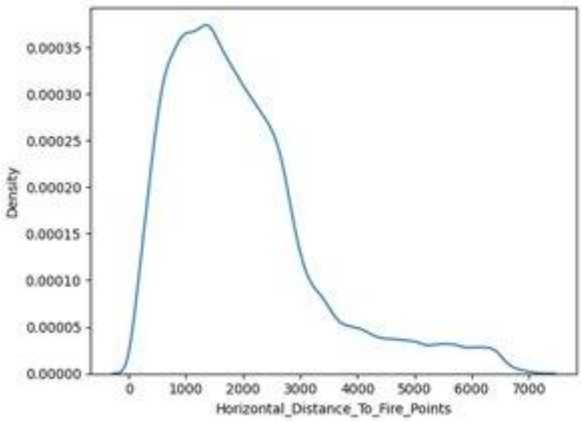
This feature is explaining the horizontal and vertical distance from the survey location to roadways

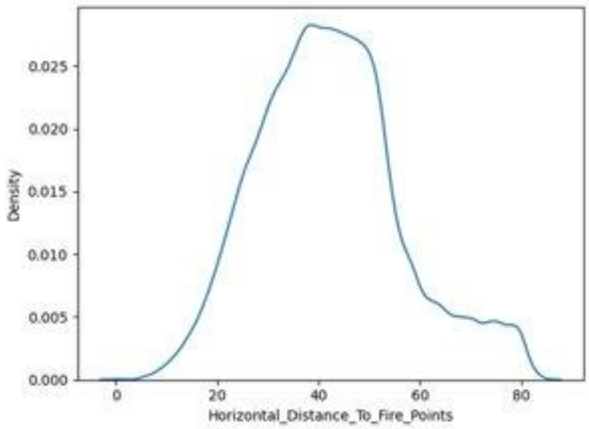


We can clearly see that these features are heavily right-skewed and the value range we have is from 0 to 7000.

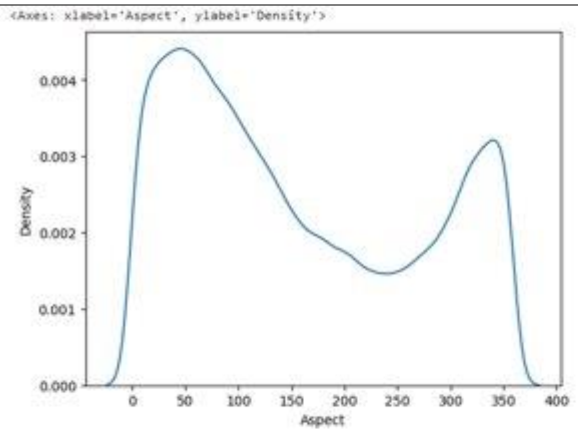
To normalize that, we can apply log on the feature as it will shift the higher range values towards the left and we will get an approximate normal distribution.

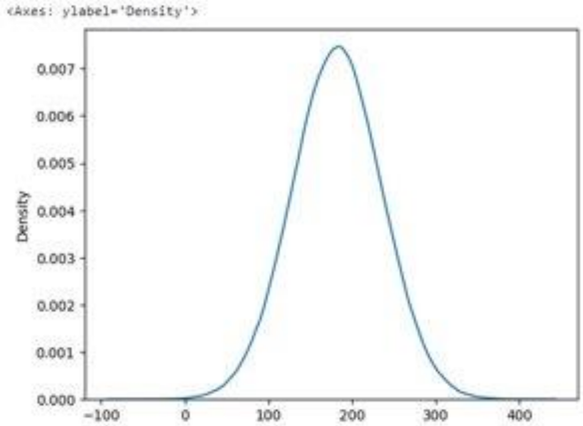
Feature Engineering on Numerical data:





So we normalize the feature which was right skewed to approximate normal feature using sqrt transform.

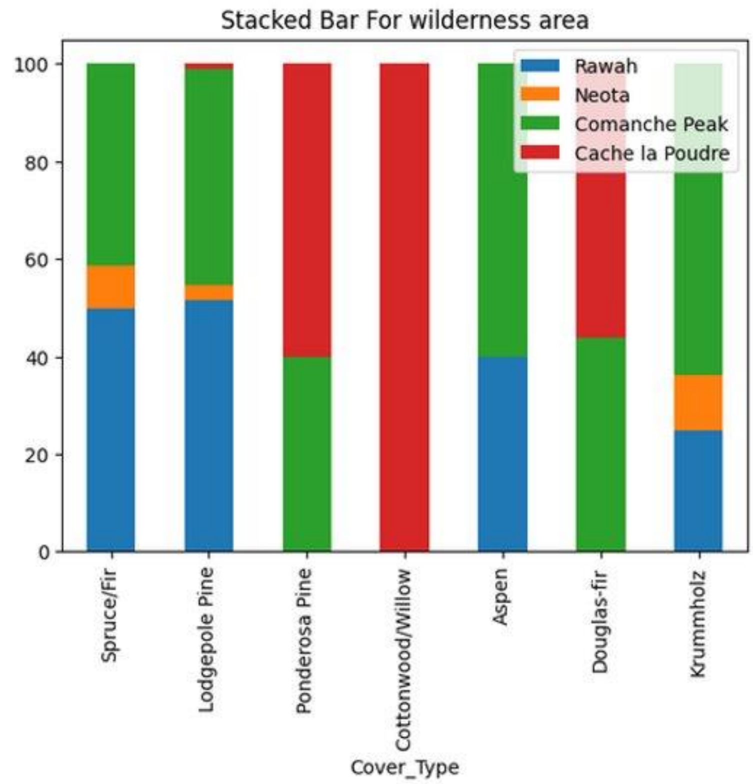




Wilderness area:

We have 4 features based on wilderness area type.

To find the impact of these features on the cover prediction, we mapped the percentage wise class of each wilderness area for particular class type(cover type).



Based on this graph we can say that, Cache la paudre has mostly cottonwood/Willow cover type.

Most of the cover types are observed in wilderness area 3(Comanche peak)

Very small percentage of cover type observed in Neota.

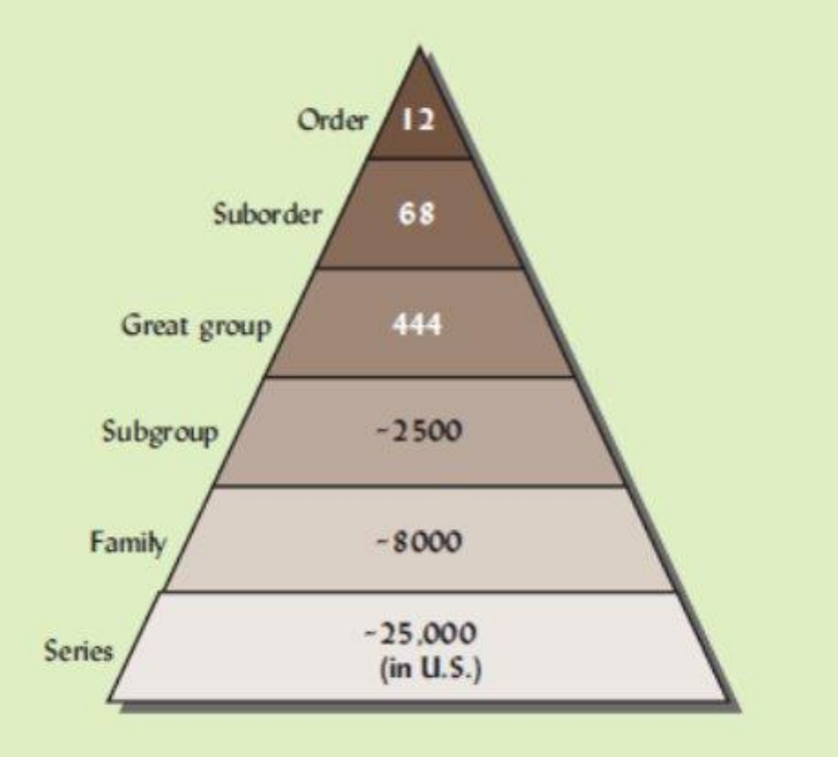
Cover type 1,2,5 and 7 observed in Rawah.

Feature Engineering:

Soil Features:

we have 40 different soil types with the soil texture description.

As we observed that some of the soil description is common, there must be some similarity in these soil types and we can find out the strong relations which are representing the given given types into strong groups.



In case of soil classification, there are 12 main orders of the soil types.

Order – Twelve soil orders are recognized. The differences among orders reflect the dominant soil forming processes and the degree of soil formation. Each order is identified by a word ending in 'sol.' An example is Alfisols.

Suborder - Each order is divided into suborders primarily on the basis of properties that influence soil formation and/or are important to plant growth.

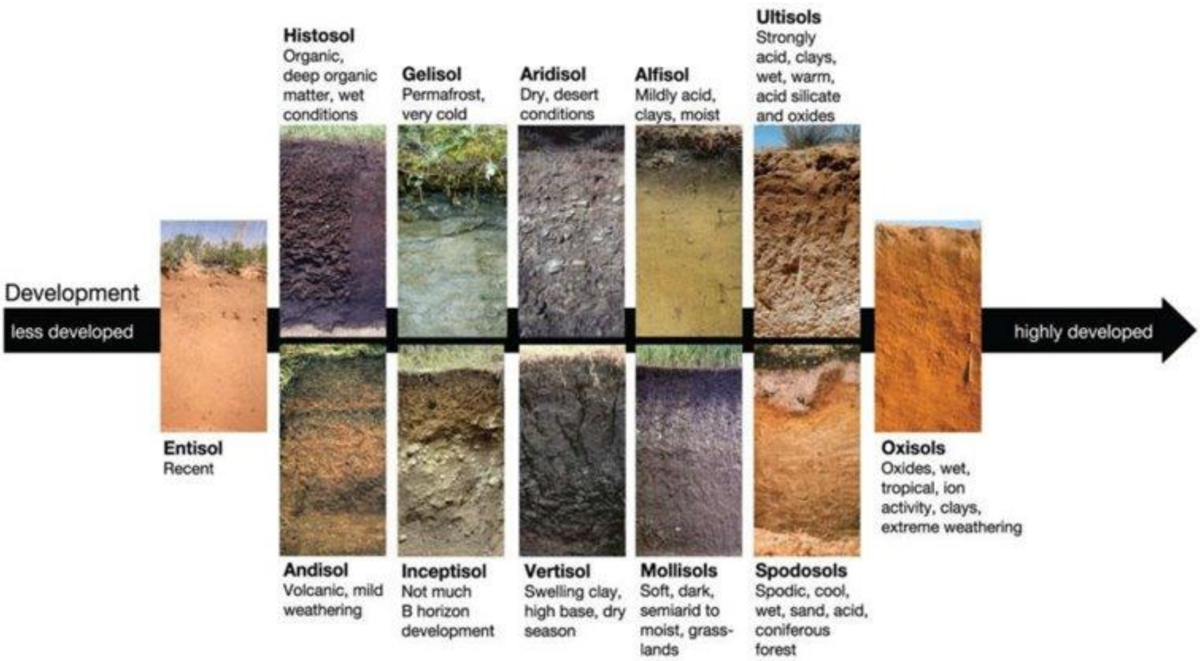
Great Group – Each suborder is divided into great groups on the basis of similarities in horizons present, soil moisture or temperature regimes, or other significant soil properties.

Subgroup – Each great group has a 'typic' (typical) subgroup which is basically defined by the Great Group. Other Subgroups are transitions to other orders, suborders, or great groups due to properties that distinguish it from the great group.

Family – Families are established within a subgroup on the basis of physical and chemical properties along with other characteristics that affect management.

Series – The series consists of soils within a family that have horizons similar in color, texture, structure, reaction, consistence, mineral and chemical composition, and arrangement in the profile.

The main 12 Soil orders are **Entisols, Inceptisols, Andisols, Mollisols, Alfisols, Spodosols, Ultisols, Oxisols, Gelisols, Histosols, Aridisols, and Vertisols**.



Each order is based on one or two dominants physical, chemical, or biological properties that differentiate it clearly from the other orders. Perhaps the easiest way to understand why certain properties were chosen over others is to consider how the soil (i.e., land) will be used.

As we have 40 different soil types in the dataset, it is really hard to manage this many features in the model and we can reduce the by classifying them into main parent classes.

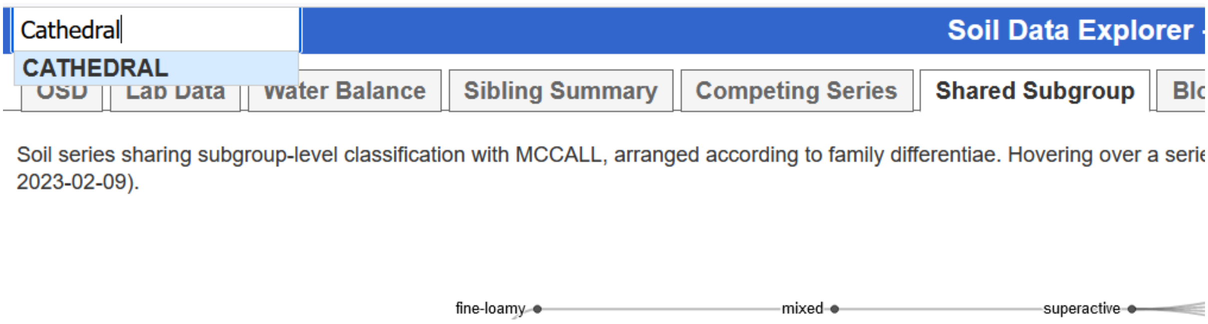
With the help of various survey sites like soilweb.com, we can easily find out the parent type of the given soil family. We can easily find out the order and sub group with the help of survey information.

Example:

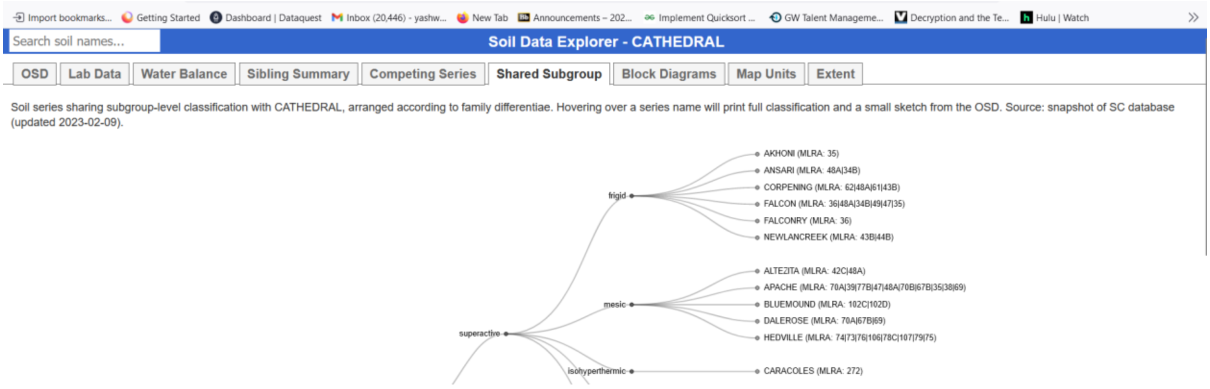
Soil_Type1 is from the Cathedral family.

search the family in

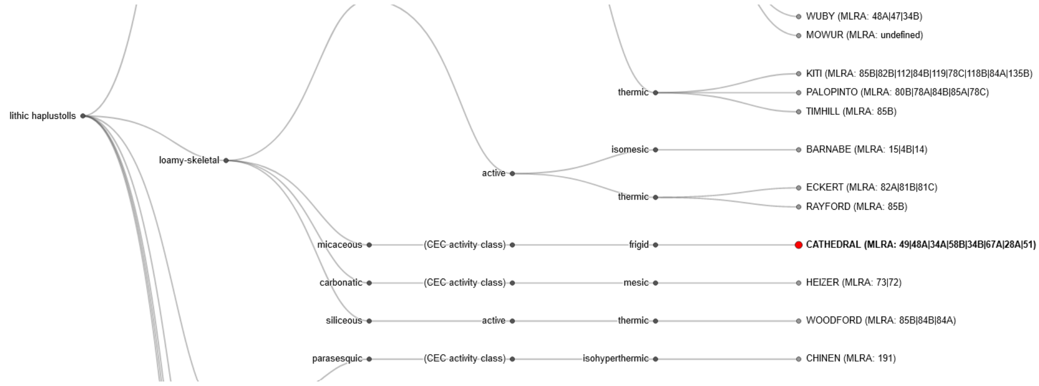
https://soilmap2-1.lawr.ucdavis.edu/sde/?series=mccall#shared-subgroup



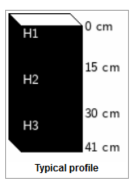
Go to the Shared subgroup option for the hierarchical diagram



In this tab we will get the main parent sub group of the soil family.



Go to soil website and search for sub-group. We will get to see the main order of the soil.



This interface to SoilWeb is now deprecated.
Data are correct but links to documentation are likely broken.
Consider using the current interface to SoilWeb

Soil Taxonomy

Order:	*Mollisols*
Suborder:	*Ustolls* *[Map of Suborders]*
Greatgroup:	*Haplustolls*
Subgroup:	*Lithic Haplustolls*
Family:	*Loamy-skeletal, mixed, mesic Lithic Haplustolls*
Soil Series:	*Lithic Haplustolls* *(Link to OSD)* *(Soil Series Explorer)*
Data:	*[Lab Data]*
Raw Data	*Component* *All Horizons*

Land Classification

Storie Index	*NOT RATED*
Land Capability Class [non-irrigated]	-
Land Capability Class [irrigated]	-
Ecological Site Description	*Woodland Uplands Transition 16-35*
Forage Suitability Group	*n/a*

Soil Suitability Ratings

Waste Related	*Engineering*
Urban/Recreational	*Irrigation*
Wildlife	*Runoff*

Hydraulic and Erosion Ratings

Wind Erodibility Group	*6*

Next, we will check if there is any strong relationship between soil order types and forest cover types.

This is how we got the mapping of 40 soil types into 6 major soil types. There is one type for which we do not have any information hence we categorize that as unknown.

Using the soil order mapping, classifying 40 soil types into 7 main soil orders.

```
[ ] for i in range(0, len(df)):
      mol = ['Soil_Type1','Soil_Type3','Soil_Type4','Soil_Type7','Soil_Type8','Soil_Type1','Soil_Type14','Soil_Type16','Soil_Type17','Soil_Type18']
      alf = ['Soil_Type2','Soil_Type5','Soil_Type6','Soil_Type9','Soil_Type26']
      ent = ['Soil_Type12','Soil_Type34']
      hist = ['Soil_Type19']
      enc = ['Soil_Type10','Soil_Type11','Soil_Type32','Soil_Type28','Soil_Type13','Soil_Type20','Soil_Type21','Soil_Type22','Soil_Type23','Soil_Type24','Soil_Type33','Soil_Type27','Soil_Type25','Soil_Type38','Soil_Type31','Soil_Type29','Soil_Type30']
      spod = ['Soil_Type35','Soil_Type36','Soil_Type37','Soil_Type39','Soil_Type40']
      Unknown = ['Soil_Type15']
      flag = 0

      if i%50000 == 0:
        print(i)

      for x1 in mol:
        if df[x1][i]== 1:
          df['Mollisols'][i] = 1
          flag = 1
          break
```

We are using the above method to map the order types to the respective soil type.

Important soil types based on predicted forest classes:

As per the soil information, it is observed that we have some soil types which are contributing more in the prediction of a particular soil type.

So, we find out the percentage-wise contribution of each soil type in each class prediction.

```
[ ] soil_contri
```

	Cover_Type	Soil_Type1	Soil_Type2	Soil_Type3	Soil_Type4	Soil_Type5	Soil_Type6	Soil_Type7	Soil_Type8	Soil_Type9	Soil_Type10	Soil_Type11	Soil_Type12	Soil_Type13	Soil_Type14	Soil_Type15	Soil_Type16	Soil_Type17
0	1	NaN	NaN	NaN	0.085914	NaN	NaN	NaN	0.020298	0.076001	0.451284	0.352625	1.271242	1.037103	NaN	NaN	0.300227	0.101020
1	2	NaN	0.300740	0.420401	1.147543	NaN	0.321919	0.037063	0.048005	0.348040	3.813259	3.204013	9.628628	4.679828	NaN	NaN	0.615247	0.337803
2	3	5.876266	13.959277	6.743301	20.979471	2.704592	11.167981	NaN	NaN	NaN	32.253734	3.784192	NaN	0.114672	0.324439	NaN	0.360799	1.415226
3	4	6.479796	4.186385	37.058609	6.115763	1.747361	11.649072	NaN	NaN	NaN	8.154350	1.237714	NaN	NaN	5.642519	NaN	1.856571	15.871860
4	5	NaN	2.780997	NaN	6.162435	NaN	NaN	NaN	NaN	NaN	2.738860	7.173707	NaN	13.852312	NaN	NaN	0.368693	6.320447
5	6	4.330051	7.502735	1.168884	3.633328	3.351183	7.773363	NaN	NaN	NaN	51.010537	2.982668	NaN	3.535441	1.888639	0.017274	1.445270	4.082455
6	7	NaN	NaN	NaN	0.380302	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	0.029254	NaN	NaN	NaN	NaN

There are some soil types, which are helpful in predicting the forest cover type and we will include those features in our model

Based on these observations, we can say that Soil_Type29,Soil_Type10,Soil_Type3,So il_Type30,Soil_Type38 are important in cover prediction.

Feature reduction:

Used RFE to get the feature importance with random forest.
Random forest works really well on imbalanced data and it uses entropy or gini to evaluate the node and split it based on information gain.
So if the feature is used multiple times to split the nodes, that feature will the important feature.

```
tf = RFE(RandomForestClassifier(), n_features_to_select=30, verbose=1)
Xt = tf.fit_transform(x_train,y_train)
print("Shape =", Xt.shape)
```

```
Fitting estimator with 61 features.
```

We got top 30 features using get_feature_names_out() method.

```
[ ] tf.get_feature_names_out()
```

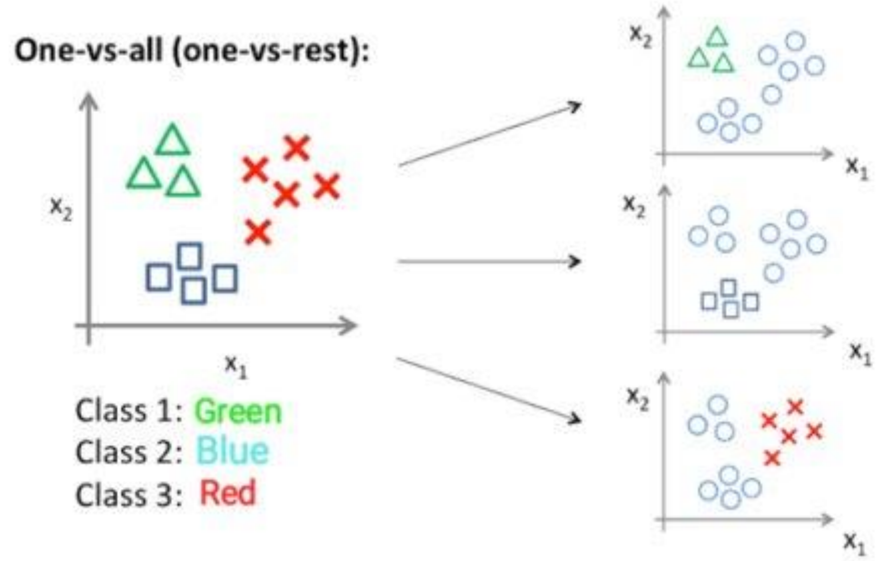
```
array(['Elevation', 'Slope', 'Horizontal_Distance_To_Hydrology',
       'Vertical_Distance_To_Hydrology',
       'Horizontal_Distance_To_Roadways', 'Hillshade_9am',
       'Hillshade_Noon', 'Hillshade_3pm',
       'Horizontal_Distance_To_Fire_Points', 'Wilderness_Area1',
       'Wilderness_Area2', 'Wilderness_Area3', 'Wilderness_Area4',
       'Soil_Type2', 'Soil_Type4', 'Soil_Type10', 'Soil_Type12',
       'Soil_Type22', 'Soil_Type23', 'Soil_Type24', 'Soil_Type29',
       'Soil_Type32', 'Soil_Type33', 'Soil_Type38', 'Inceptisols',
       'Mollisols', 'Spodosols', 'Alfisols', 'Entisols',
       'Aspect_unimodal'], dtype=object)
```

Model Building:

Base model:

Logistic Regression for Multiclass:

Used the logistic regression using one vs all approach for multi-class.
It will create sub-models for each class and provides the output based on the higher probability of the class.



	precision	recall	f1-score	support
1	0.71	0.69	0.70	63717
2	0.75	0.80	0.77	84934
3	0.67	0.80	0.73	10620
4	0.54	0.35	0.43	825
5	0.45	0.04	0.08	2842
6	0.49	0.26	0.34	5230
7	0.73	0.57	0.64	6136
accuracy			0.72	174304
macro avg	0.62	0.50	0.53	174304
weighted avg	0.71	0.72	0.71	174304

Random forest with hyperparameter tuning:

As grid search and randomized cv search were taking too long, we decided to perform the hyperparameter tuning using for loop.

We passed depth and number of estimators in for loop and check the F1 score for each model using CV and Test data.

Hyperparameter tuning using for loop

```
[ ] from sklearn.metrics import f1_score
    depth = [3,5,10,20,50,100]
    cv_f1_score = []
    train_f1_score = []
    for i in depth:
      model = RandomForestClassifier(max_depth = i,n_jobs = -1,n_estimators = 10)
      model.fit(X_train_smote, Y_train_smote)
      CV = CalibratedClassifierCV(model,method = 'sigmoid')
      CV.fit(X_train_smote, Y_train_smote)
      predicted = CV.predict(x_cv)
      train_predicted = CV.predict(x_train)
      cv_f1_score.append(f1_score(y_cv,predicted,average = 'macro'))
      train_f1_score.append(f1_score(y_train,train_predicted,average = 'macro'))
      print('depth {0} is finished'.format(i))
    for i in range(0,len(cv_f1_score)):
      print('f1 value score for depth =' + str(depth[i]) + ' is ' + str(cv_f1_score[i]))
    plt.plot(depth,cv_f1_score,c='r')
    plt.plot(depth,train_f1_score,c='b')
    plt.xlabel('depth(depth of the tree)')
    plt.ylabel('f1 score(train and test)')
```

We got F1 score around .92 which is a stable model.