

Forest Cover Type Prediction - Internship Project

Data Initialization

Dependencies

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from sklearn.metrics import accuracy_score, classification_report,
f1_score

pd.set_option('display.max_columns', None)
```

Merging two data

```
data1 = pd.read_csv('train.csv', index_col="Id") # Got from internship
data2 = pd.read_csv('covtype.csv') # got from internet
forestData = pd.concat([data2, data1], ignore_index=True)
```

Viewing Data

```
forestData.head()
```

	Elevation	Aspect	Slope	Horizontal_Distance_To_Hydrology	\
0	2596	51	3	258	
1	2590	56	2	212	
2	2804	139	9	268	
3	2785	155	18	242	
4	2595	45	2	153	

	Vertical_Distance_To_Hydrology	Horizontal_Distance_To_Roadways	\
0	0	510	
1	-6	390	
2	65	3180	
3	118	3090	
4	-1	391	

	Hillshade_9am	Hillshade_Noon	Hillshade_3pm	\
0	221	232	148	
1	220	235	151	

2	234	238	135
3	238	238	122
4	220	234	150

	Horizontal_Distance_To_Fire_Points	Wilderness_Area1
Wilderness_Area2 \		

0	6279	1
0		
1	6225	1
0		
2	6121	1
0		
3	6211	1
0		
4	6172	1
0		

	Wilderness_Area3	Wilderness_Area4	Soil_Type1	Soil_Type2
Soil_Type3 \				

0	0	0	0	0
0				
1	0	0	0	0
0				
2	0	0	0	0
0				
3	0	0	0	0
0				
4	0	0	0	0
0				

	Soil_Type4	Soil_Type5	Soil_Type6	Soil_Type7	Soil_Type8
Soil_Type9 \					

0	0	0	0	0	0
0					
1	0	0	0	0	0
0					
2	0	0	0	0	0
0					
3	0	0	0	0	0
0					
4	0	0	0	0	0
0					

	Soil_Type10	Soil_Type11	Soil_Type12	Soil_Type13	Soil_Type14	\
0	0	0	0	0	0	
1	0	0	0	0	0	
2	0	0	1	0	0	
3	0	0	0	0	0	
4	0	0	0	0	0	

	Soil_Type15	Soil_Type16	Soil_Type17	Soil_Type18	Soil_Type19	\
0	0	0	0	0	0	
1	0	0	0	0	0	
2	0	0	0	0	0	
3	0	0	0	0	0	
4	0	0	0	0	0	

	Soil_Type20	Soil_Type21	Soil_Type22	Soil_Type23	Soil_Type24	\
0	0	0	0	0	0	
1	0	0	0	0	0	
2	0	0	0	0	0	
3	0	0	0	0	0	
4	0	0	0	0	0	

	Soil_Type25	Soil_Type26	Soil_Type27	Soil_Type28	Soil_Type29	\
0	0	0	0	0	1	
1	0	0	0	0	1	
2	0	0	0	0	0	
3	0	0	0	0	0	
4	0	0	0	0	1	

	Soil_Type30	Soil_Type31	Soil_Type32	Soil_Type33	Soil_Type34	\
0	0	0	0	0	0	
1	0	0	0	0	0	
2	0	0	0	0	0	
3	1	0	0	0	0	
4	0	0	0	0	0	

	Soil_Type35	Soil_Type36	Soil_Type37	Soil_Type38	Soil_Type39	\
0	0	0	0	0	0	
1	0	0	0	0	0	
2	0	0	0	0	0	
3	0	0	0	0	0	
4	0	0	0	0	0	

	Soil_Type40	Cover_Type
0	0	5
1	0	5
2	0	2
3	0	2
4	0	5

Shape

```
print(f"No. of rows: {forestData.shape[0]}")
print(f"No. of cols: {forestData.shape[1]}")
```

No. of rows: 596132
No. of cols: 55

Data Info

```
forestData.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 596132 entries, 0 to 596131
Data columns (total 55 columns):
```

#	Column	Non-Null Count		Dtype
---	-----	-----	-----	-----
0	Elevation	596132	non-null	int64
1	Aspect	596132	non-null	int64
2	Slope	596132	non-null	int64
3	Horizontal_Distance_To_Hydrology	596132	non-null	int64
4	Vertical_Distance_To_Hydrology	596132	non-null	int64
5	Horizontal_Distance_To_Roadways	596132	non-null	int64
6	Hillshade_9am	596132	non-null	int64
7	Hillshade_Noon	596132	non-null	int64
8	Hillshade_3pm	596132	non-null	int64
9	Horizontal_Distance_To_Fire_Points	596132	non-null	int64
10	Wilderness_Area1	596132	non-null	int64
11	Wilderness_Area2	596132	non-null	int64
12	Wilderness_Area3	596132	non-null	int64
13	Wilderness_Area4	596132	non-null	int64
14	Soil_Type1	596132	non-null	int64
15	Soil_Type2	596132	non-null	int64
16	Soil_Type3	596132	non-null	int64
17	Soil_Type4	596132	non-null	int64
18	Soil_Type5	596132	non-null	int64
19	Soil_Type6	596132	non-null	int64
20	Soil_Type7	596132	non-null	int64
21	Soil_Type8	596132	non-null	int64
22	Soil_Type9	596132	non-null	int64
23	Soil_Type10	596132	non-null	int64
24	Soil_Type11	596132	non-null	int64
25	Soil_Type12	596132	non-null	int64
26	Soil_Type13	596132	non-null	int64
27	Soil_Type14	596132	non-null	int64
28	Soil_Type15	596132	non-null	int64
29	Soil_Type16	596132	non-null	int64
30	Soil_Type17	596132	non-null	int64
31	Soil_Type18	596132	non-null	int64
32	Soil_Type19	596132	non-null	int64
33	Soil_Type20	596132	non-null	int64
34	Soil_Type21	596132	non-null	int64
35	Soil_Type22	596132	non-null	int64
36	Soil_Type23	596132	non-null	int64
37	Soil_Type24	596132	non-null	int64
38	Soil_Type25	596132	non-null	int64
39	Soil_Type26	596132	non-null	int64
40	Soil_Type27	596132	non-null	int64

41	Soil_Type28	596132	non-null	int64
42	Soil_Type29	596132	non-null	int64
43	Soil_Type30	596132	non-null	int64
44	Soil_Type31	596132	non-null	int64
45	Soil_Type32	596132	non-null	int64
46	Soil_Type33	596132	non-null	int64
47	Soil_Type34	596132	non-null	int64
48	Soil_Type35	596132	non-null	int64
49	Soil_Type36	596132	non-null	int64
50	Soil_Type37	596132	non-null	int64
51	Soil_Type38	596132	non-null	int64
52	Soil_Type39	596132	non-null	int64
53	Soil_Type40	596132	non-null	int64
54	Cover_Type	596132	non-null	int64

dtypes: int64(55)

memory usage: 250.1 MB

forestData.describe()

	Elevation	Aspect	Slope \
count	596132.000000	596132.000000	596132.000000
mean	2954.037879	155.682674	14.164522
std	286.213696	111.867752	7.523713
min	1859.000000	0.000000	0.000000
25%	2801.000000	59.000000	9.000000
50%	2993.000000	127.000000	13.000000
75%	3163.000000	260.000000	19.000000
max	3858.000000	360.000000	66.000000

Horizontal_Distance_To_Hydrology

Vertical_Distance_To_Hydrology \

count 596132.000000

596132.000000

mean 268.357052

46.536990

std 212.590510

58.376281

min 0.000000

173.000000

25% 108.000000

7.000000

50% 218.000000

30.000000

75% 384.000000

69.000000

max 1397.000000

601.000000

Horizontal_Distance_To_Roadways Hillshade_9am Hillshade_Noon

\

count	596132.000000	596132.000000	596132.000000
mean	2334.012289	212.160208	223.208306
std	1556.966114	26.872779	19.863134
min	0.000000	0.000000	0.000000
25%	1092.000000	198.000000	213.000000
50%	1976.000000	218.000000	226.000000
75%	3304.000000	231.000000	237.000000
max	7117.000000	254.000000	254.000000
Hillshade_3pm Horizontal_Distance_To_Fire_Points			
Wilderness_Area1 \			
count	596132.000000	596132.000000	
596132.000000			
mean	142.339653	1968.392089	
0.443514			
std	38.504181	1321.038719	
0.496800			
min	0.000000	0.000000	
0.000000			
25%	119.000000	1015.000000	
0.000000			
50%	143.000000	1698.000000	
0.000000			
75%	168.000000	2538.000000	
1.000000			
max	254.000000	7173.000000	
1.000000			
Wilderness_Area2 Wilderness_Area3 Wilderness_Area4			
Soil_Type1 \			
count	596132.000000	596132.000000	596132.000000
596132.000000			
mean	0.050967	0.435664	0.069855
0.005680			
std	0.219930	0.495844	0.254903
0.075151			
min	0.000000	0.000000	0.000000
0.000000			
25%	0.000000	0.000000	0.000000
0.000000			
50%	0.000000	0.000000	0.000000
0.000000			

75%	0.000000	1.000000	0.000000		
0.000000					
max	1.000000	1.000000	1.000000		
1.000000					
	Soil_Type2	Soil_Type3	Soil_Type4	Soil_Type5	\
count	596132.000000	596132.000000	596132.000000	596132.000000	
mean	0.013668	0.009704	0.022208	0.002956	
std	0.116109	0.098031	0.147360	0.054286	
min	0.000000	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	0.000000	0.000000	
50%	0.000000	0.000000	0.000000	0.000000	
75%	0.000000	0.000000	0.000000	0.000000	
max	1.000000	1.000000	1.000000	1.000000	
	Soil_Type6	Soil_Type7	Soil_Type8	Soil_Type9	\
count	596132.000000	596132.000000	596132.000000	596132.000000	
mean	0.012120	0.000176	0.000302	0.001941	
std	0.109421	0.013270	0.017374	0.044012	
min	0.000000	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	0.000000	0.000000	
50%	0.000000	0.000000	0.000000	0.000000	
75%	0.000000	0.000000	0.000000	0.000000	
max	1.000000	1.000000	1.000000	1.000000	
	Soil_Type10	Soil_Type11	Soil_Type12	Soil_Type13	\
count	596132.000000	596132.000000	596132.000000	596132.000000	
mean	0.058336	0.021499	0.050657	0.030039	
std	0.234378	0.145039	0.219296	0.170694	
min	0.000000	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	0.000000	0.000000	
50%	0.000000	0.000000	0.000000	0.000000	
75%	0.000000	0.000000	0.000000	0.000000	
max	1.000000	1.000000	1.000000	1.000000	
	Soil_Type14	Soil_Type15	Soil_Type16	Soil_Type17	\
count	596132.000000	596132.000000	596132.000000	596132.000000	
mean	0.001288	0.000005	0.004964	0.006767	
std	0.035870	0.002243	0.070278	0.081983	
min	0.000000	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	0.000000	0.000000	
50%	0.000000	0.000000	0.000000	0.000000	
75%	0.000000	0.000000	0.000000	0.000000	
max	1.000000	1.000000	1.000000	1.000000	
	Soil_Type18	Soil_Type19	Soil_Type20	Soil_Type21	\
count	596132.000000	596132.000000	596132.000000	596132.000000	
mean	0.003286	0.006822	0.015765	0.001433	
std	0.057231	0.082315	0.124565	0.037822	
min	0.000000	0.000000	0.000000	0.000000	

25%	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000	0.000000
max	1.000000	1.000000	1.000000	1.000000
	Soil_Type22	Soil_Type23	Soil_Type24	Soil_Type25 \
count	596132.000000	596132.000000	596132.000000	596132.000000
mean	0.056561	0.098148	0.036125	0.000797
std	0.231003	0.297515	0.186600	0.028216
min	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000	0.000000
max	1.000000	1.000000	1.000000	1.000000
	Soil_Type26	Soil_Type27	Soil_Type28	Soil_Type29 \
count	596132.000000	596132.000000	596132.000000	596132.000000
mean	0.004434	0.001847	0.001602	0.195490
std	0.066437	0.042936	0.039993	0.396578
min	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000	0.000000
max	1.000000	1.000000	1.000000	1.000000
	Soil_Type30	Soil_Type31	Soil_Type32	Soil_Type33 \
count	596132.000000	596132.000000	596132.000000	596132.000000
mean	0.051826	0.043611	0.089257	0.076778
std	0.221675	0.204229	0.285115	0.266240
min	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000	0.000000
max	1.000000	1.000000	1.000000	1.000000
	Soil_Type34	Soil_Type35	Soil_Type36	Soil_Type37 \
count	596132.000000	596132.000000	596132.000000	596132.000000
mean	0.002739	0.003343	0.000216	0.000557
std	0.052267	0.057724	0.014709	0.023593
min	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000	0.000000
max	1.000000	1.000000	1.000000	1.000000
	Soil_Type38	Soil_Type39	Soil_Type40	Cover_Type
count	596132.000000	596132.000000	596132.000000	596132.000000
mean	0.027345	0.024261	0.015448	2.100892
std	0.163086	0.153860	0.123326	1.447781
min	0.000000	0.000000	0.000000	1.000000

25%	0.000000	0.000000	0.000000	1.000000
50%	0.000000	0.000000	0.000000	2.000000
75%	0.000000	0.000000	0.000000	2.000000
max	1.000000	1.000000	1.000000	7.000000

Checking for any Null values

```
forestData.isna().any()
```

Elevation	False
Aspect	False
Slope	False
Horizontal_Distance_To_Hydrology	False
Vertical_Distance_To_Hydrology	False
Horizontal_Distance_To_Roadways	False
Hillshade_9am	False
Hillshade_Noon	False
Hillshade_3pm	False
Horizontal_Distance_To_Fire_Points	False
Wilderness_Area1	False
Wilderness_Area2	False
Wilderness_Area3	False
Wilderness_Area4	False
Soil_Type1	False
Soil_Type2	False
Soil_Type3	False
Soil_Type4	False
Soil_Type5	False
Soil_Type6	False
Soil_Type7	False
Soil_Type8	False
Soil_Type9	False
Soil_Type10	False
Soil_Type11	False
Soil_Type12	False
Soil_Type13	False
Soil_Type14	False
Soil_Type15	False
Soil_Type16	False
Soil_Type17	False
Soil_Type18	False
Soil_Type19	False
Soil_Type20	False
Soil_Type21	False
Soil_Type22	False
Soil_Type23	False
Soil_Type24	False
Soil_Type25	False
Soil_Type26	False

Soil_Type27	False
Soil_Type28	False
Soil_Type29	False
Soil_Type30	False
Soil_Type31	False
Soil_Type32	False
Soil_Type33	False
Soil_Type34	False
Soil_Type35	False
Soil_Type36	False
Soil_Type37	False
Soil_Type38	False
Soil_Type39	False
Soil_Type40	False
Cover_Type	False
dtype:	bool

Columns in the data

```
column = forestData.columns
column
Index(['Elevation', 'Aspect', '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_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', 'Soil_Type18',
       'Soil_Type19', 'Soil_Type20', 'Soil_Type21', 'Soil_Type22',
       'Soil_Type23', 'Soil_Type24', 'Soil_Type25', 'Soil_Type26',
       'Soil_Type27', 'Soil_Type28', 'Soil_Type29', 'Soil_Type30',
       'Soil_Type31', 'Soil_Type32', 'Soil_Type33', 'Soil_Type34',
       'Soil_Type35', 'Soil_Type36', 'Soil_Type37', 'Soil_Type38',
       'Soil_Type39', 'Soil_Type40', 'Cover_Type'],
      dtype='object')
```

Note: There are no null values hence theres no need to do data cleaning

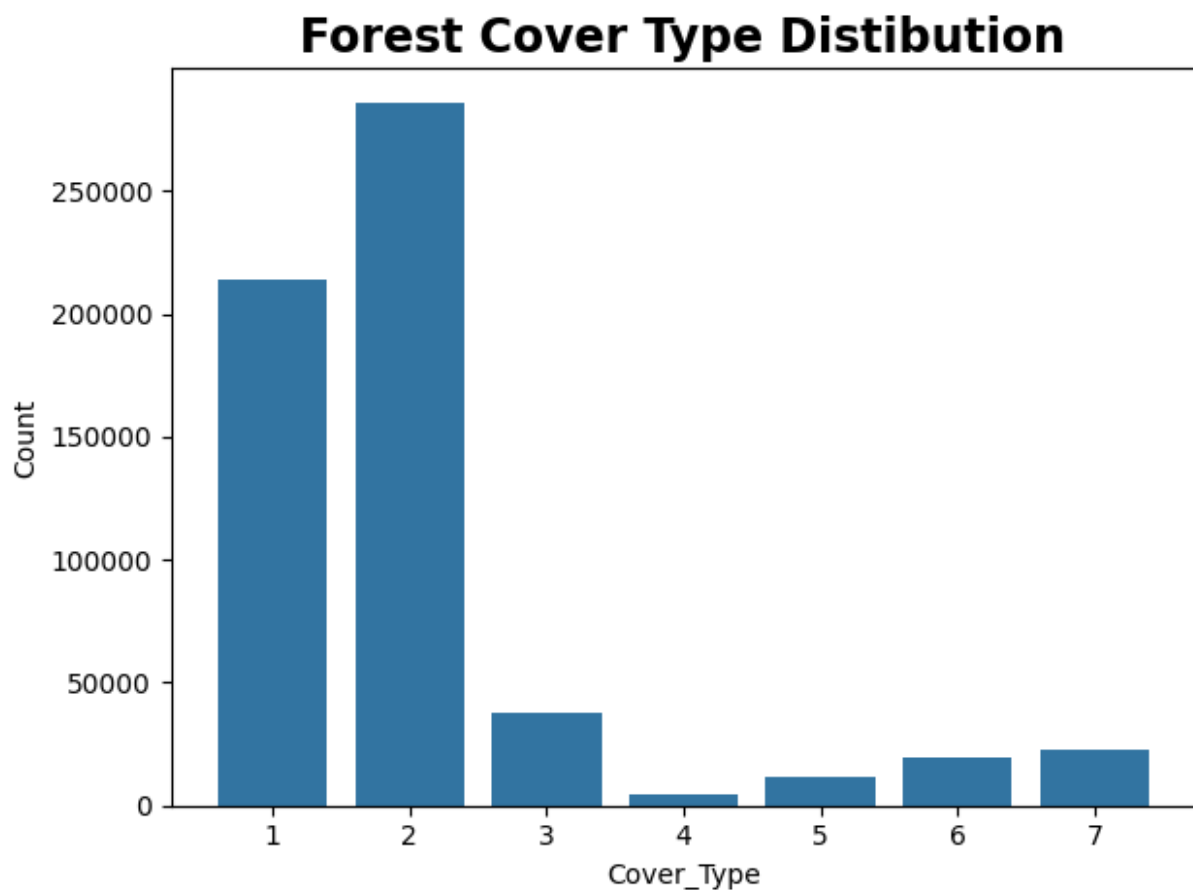
EDA

Target Variable Analysis

- Plot histogram of the forest cover type distribution.
- Check for class imbalance.

```
ax = sns.countplot(data=forestData,x='Cover_Type')
ax.set_xlabel('Cover_Type')
ax.set_ylabel('Count')
ax.set_title('Forest Cover Type
Distribution',fontdict={'weight':'600','size':'17'})
plt.tight_layout()
plt.plot()
```

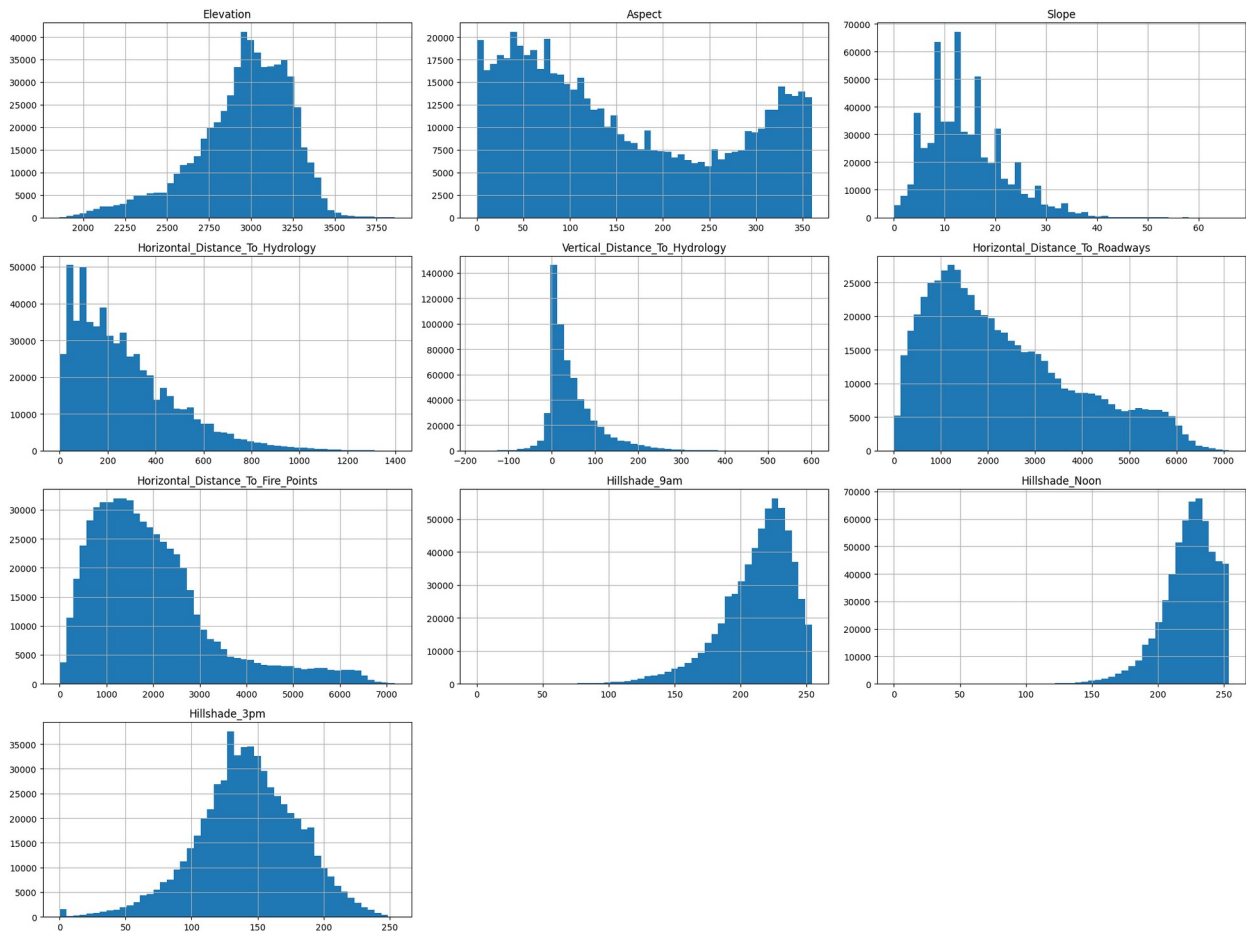
[]



Feature Distributions

Plot histograms for each necessary numerical feature

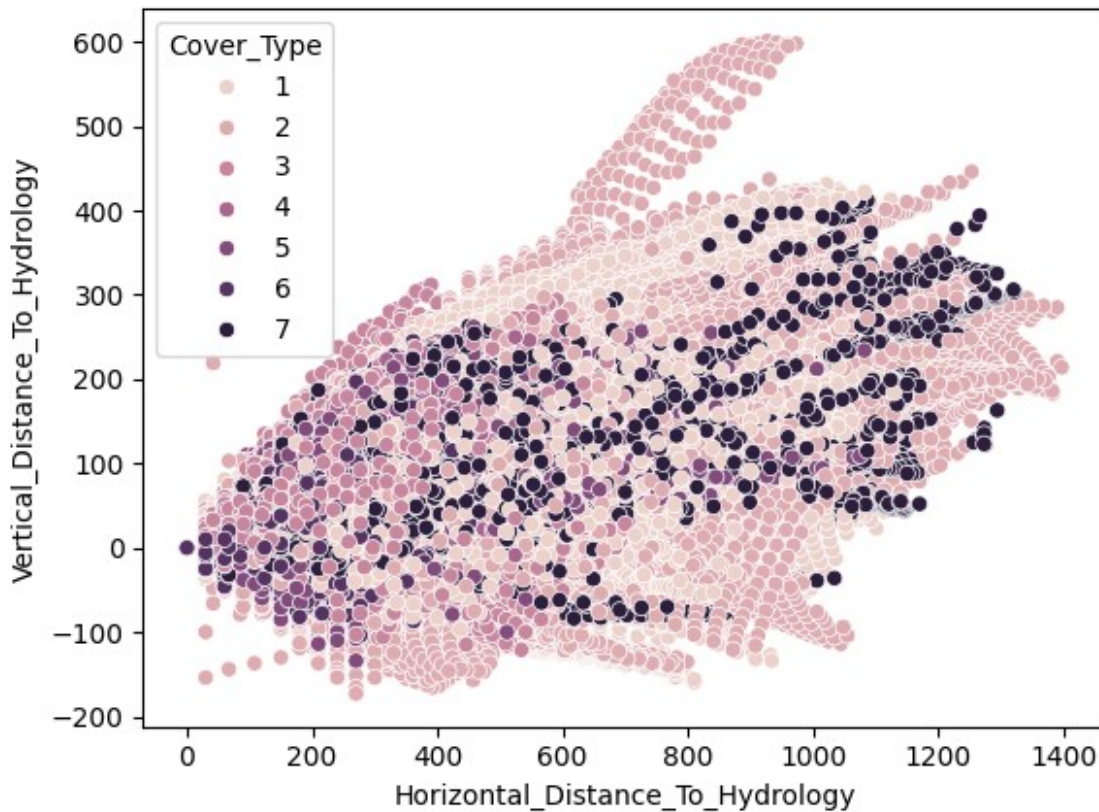
```
forestData[['Elevation', 'Aspect', 'Slope', 'Horizontal_Distance_To_Hydrology', 'Vertical_Distance_To_Hydrology', 'Horizontal_Distance_To_Roadways', 'Horizontal_Distance_To_Fire_Points', 'Hillshade_9am', 'Hillshade_Noon', 'Hillshade_3pm']].hist(bins=50, figsize=(20,15))
plt.tight_layout()
plt.show()
```



Geospatial Relationships

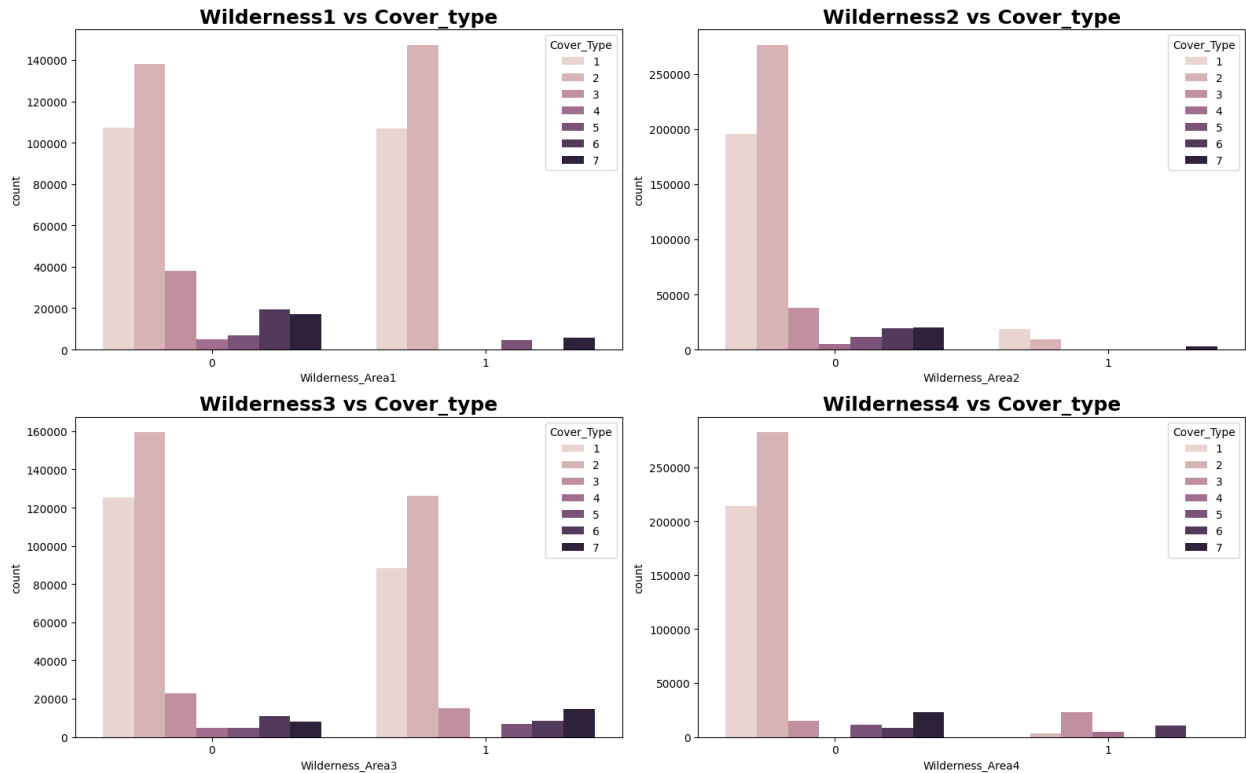
□ Since this is geographical data, features like Horizontal_Distance_To_Roadways, Vertical_Distance_To_Hydrology, etc., may relate spatially.

```
sns.scatterplot(x='Horizontal_Distance_To_Hydrology', y='Vertical_Distance_To_Hydrology', hue='Cover_Type', data=forestData)
plt.show()
```



Wilderness Area vs Cover Type analysis

```
# make it for other wilderness area too
fig, axes = plt.subplots(2, 2, figsize = (16, 10))
ax1 = sns.countplot(x='Wilderness_Area1', hue='Cover_Type',
data=forestData, ax=axes[0, 0])
ax2 = sns.countplot(x='Wilderness_Area2', hue='Cover_Type',
data=forestData, ax=axes[0, 1])
ax3 = sns.countplot(x='Wilderness_Area3', hue='Cover_Type',
data=forestData, ax=axes[1, 0])
ax4 = sns.countplot(x='Wilderness_Area4', hue='Cover_Type',
data=forestData, ax=axes[1, 1])
ax1.set_title('Wilderness1 vs
Cover_type', fontdict={'size': '18', 'weight': '600'})
ax2.set_title('Wilderness2 vs
Cover_type', fontdict={'size': '18', 'weight': '600'})
ax3.set_title('Wilderness3 vs
Cover_type', fontdict={'size': '18', 'weight': '600'})
ax4.set_title('Wilderness4 vs
Cover_type', fontdict={'size': '18', 'weight': '600'})
plt.tight_layout()
plt.show()
```



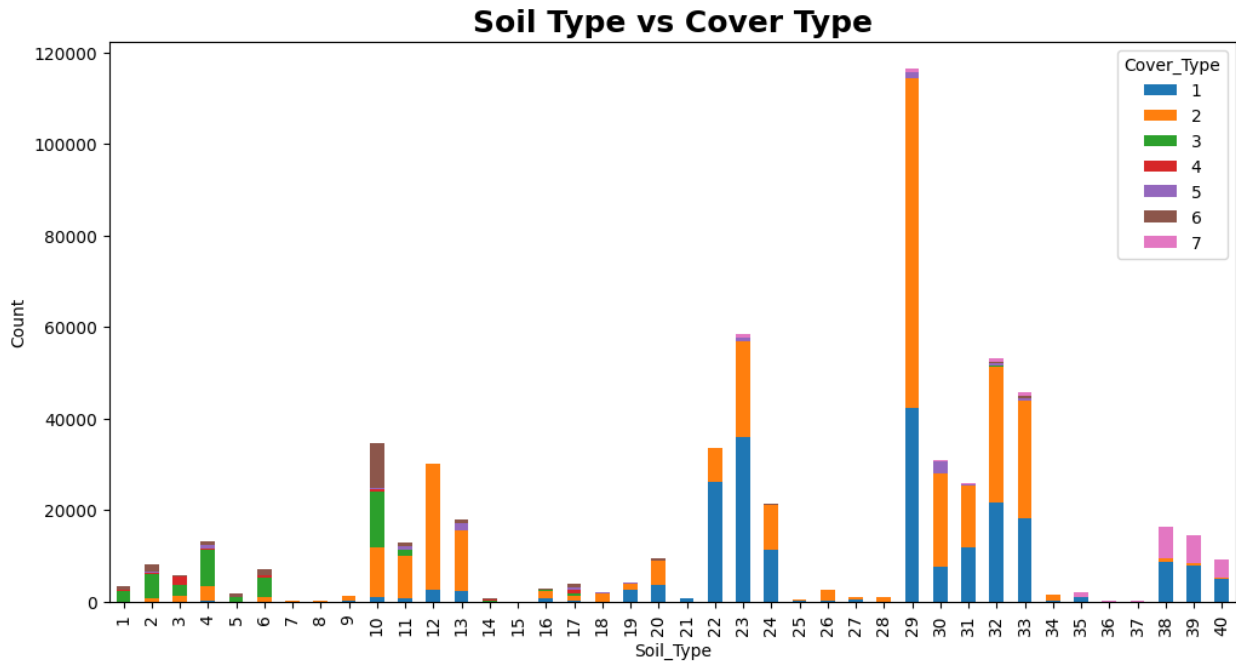
Soil Type vs Cover type relation

Check relationships between soil types and cover types

```
soil_cols = [f"Soil_Type{i}" for i in range(1,41)]
soil_onehot = forestData[soil_cols]

# get soil type label (e.g. 'Soil_Type7') then convert to integer 7
soil_type_series = soil_onehot.idxmax(axis=1).str.replace('Soil_Type',
 '').astype(int)

pd.crosstab(soil_type_series,
forestData['Cover_Type']).plot(kind='bar', stacked=True,
figsize=(12,6))
plt.xlabel('Soil_Type')
plt.ylabel('Count')
plt.title('Soil Type vs Cover
Type',fontdict={'size':'18','weight':'600'})
plt.show()
```



Data Preprocessing

Note: Because we are going to use Tree based models theres no need of Scaling our data

```
X = forestData.drop(['Cover_Type'],axis=1)
y = forestData['Cover_Type']
X_train,X_test,y_train,y_test =
train_test_split(X,y,test_size=0.3,random_state=30)
```

Model Selection

Random Forest Implementation

```
rf_classifier = RandomForestClassifier(n_estimators=100,
random_state=42)

rf_classifier.fit(X_train, y_train)

RandomForestClassifier(random_state=42)
```

XGBoost Implementation

```
xgb = XGBClassifier()
xgb_ytrain = y_train.apply(lambda x: x-1)
```

```
xgb.fit(X_train,xgb_ytrain)

XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None,
              early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None,
              feature_types=None,
              feature_weights=None, gamma=None, grow_policy=None,
              importance_type=None, interaction_constraints=None,
              learning_rate=None, max_bin=None,
              max_cat_threshold=None,
              max_cat_to_onehot=None, max_delta_step=None,
              max_depth=None,
              max_leaves=None, min_child_weight=None, missing=nan,
              monotone_constraints=None, multi_strategy=None,
              n_estimators=None,
              n_jobs=None, num_parallel_tree=None, ...)
```

Model Evaluation

```
y_pred = rf_classifier.predict(X_test)

accuracy = accuracy_score(y_test, y_pred)
classification_rep = classification_report(y_test, y_pred)
weighted_f1 = f1_score(y_test, y_pred, average='weighted')

print(f"Accuracy: {accuracy:.2f}")
print(f"Weighted F1 Score: {weighted_f1}")
print("\nClassification Report:\n", classification_rep)
```

Accuracy: 0.96
Weighted F1 Score: 0.955195331162959

Classification Report:

	precision	recall	f1-score	support
1	0.96	0.94	0.95	64145
2	0.95	0.97	0.96	85642
3	0.95	0.96	0.96	11388
4	0.94	0.97	0.96	1487
5	0.95	0.84	0.89	3417
6	0.94	0.91	0.93	5938
7	0.98	0.96	0.97	6823
accuracy			0.96	178840
macro avg	0.95	0.94	0.94	178840

weighted avg	0.96	0.96	0.96	178840
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```
y_pred = xgb.predict(X_test)
xgb_ytest = y_test.apply(lambda x: x-1)
accuracy = accuracy_score(xgb_ytest, y_pred)
classification_rep = classification_report(xgb_ytest, y_pred)
weighted_f1 = f1_score(xgb_ytest, y_pred, average='weighted')
```

```
print(f"Accuracy: {accuracy:.2f}")
print(f"Weighted F1 Score: {weighted_f1}")
print("\nClassification Report:\n", classification_rep)
```

Accuracy: 0.87
Weighted F1 Score: 0.8737411073859305

Classification Report:

	precision	recall	f1-score	support
0	0.87	0.84	0.86	64145
1	0.87	0.90	0.89	85642
2	0.90	0.90	0.90	11388
3	0.91	0.95	0.93	1487
4	0.89	0.63	0.74	3417
5	0.85	0.82	0.84	5938
6	0.94	0.91	0.93	6823
accuracy			0.87	178840
macro avg	0.89	0.85	0.87	178840
weighted avg	0.87	0.87	0.87	178840

Note: Random Forest performed best in this case