```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import GaussianNB
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.cluster import KMeans
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
from sklearn.preprocessing import StandardScaler
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.naive bayes import GaussianNB
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.cluster import KMeans
from tabulate import tabulate
data = pd.read_csv('/content/Forest Cover Type.csv')
data.head()
```

₹ Elevation Aspect Slope Horizontal_Distance_To_Hydrology Vertical_Distance_To_Hydrology Horizontal_Distance_To_Roadways Hillshad 2596 3 258 0 51 510 1 2590 56 2 212 -6 390 2 2804 139 9 268 3180 65 3 118 2785 155 18 242 3090 4 2595 2 153 391 45 -1 5 rows × 55 columns

data.tail()

₹		Elevation	Aspect	Slope	Horizontal_Distance_To_Hydrology	Vertical_Distance_To_Hydrology	Horizontal_Distance_To_Roadways	Hill
	48642	2561	28	16	390	25	458	
	48643	2557	23	16	390	25	433	
	48644	2554	10	16	391	25	408	
	48645	2554	11	17	395	26	384	
	48646	2551	9	16	400	25	361	
	5 rows ×	55 columns						
	4							•

data.fillna(0)

__

•	Elevation	Aspect	Slope	Horizontal_Distance_To_Hydrology	Vertical_Distance_To_Hydrology	Horizontal_Distance_To_Roadways	Hill
0	2596	51	3	258	0	510	
1	2590	56	2	212	-6	390	
2	2804	139	9	268	65	3180	
3	2785	155	18	242	118	3090	
4	2595	45	2	153	-1	391	
48642	2561	28	16	390	25	458	
48643	2557	23	16	390	25	433	
48644	2554	10	16	391	25	408	
48645	2554	11	17	395	26	384	
48646	2551	9	16	400	25	361	
48647 rd	ows × 55 colu	mns					
4							•

data.shape

→ (48647, 55)

data.info()

```
--- -----
    Elevation
                                        48647 non-null int64
                                       48647 non-null int64
    Aspect
1
2
    Slope
                                        48647 non-null int64
    Horizontal_Distance_To_Hydrology
                                        48647 non-null int64
    Vertical_Distance_To_Hydrology
                                       48647 non-null int64
                                       48647 non-null int64
    Horizontal_Distance_To_Roadways
6
    Hillshade_9am
                                       48647 non-null int64
    Hillshade Noon
                                       48647 non-null int64
                                        48647 non-null int64
    Hillshade_3pm
    Horizontal_Distance_To_Fire_Points 48647 non-null int64
                                        48647 non-null int64
10 Wilderness_Area1
    Wilderness Area2
                                        48647 non-null int64
11
12 Wilderness_Area3
                                       48647 non-null int64
13 Wilderness_Area4
                                       48646 non-null float64
    Soil_Type1
14
                                        48646 non-null float64
15 Soil_Type2
                                       48646 non-null float64
16 Soil_Type3
                                        48646 non-null float64
    Soil_Type4
Soil_Type5
17
                                        48646 non-null float64
                                       48646 non-null float64
18
19
    Soil_Type6
                                       48646 non-null float64
20
    Soil_Type7
                                        48646 non-null float64
    Soil_Type8
21
                                       48646 non-null float64
22
    Soil_Type9
                                        48646 non-null float64
23
    Soil_Type10
                                       48646 non-null float64
24 Soil Type11
                                        48646 non-null float64
                                       48646 non-null float64
25
    Soil_Type12
26
    Soil_Type13
                                        48646 non-null float64
    Soil_Type14
                                        48646 non-null float64
28
    Soil_Type15
                                        48646 non-null float64
                                       48646 non-null float64
    Soil_Type16
29
30 Soil_Type17
                                        48646 non-null float64
31 Soil_Type18
32 Soil_Type19
                                        48646 non-null float64
                                        48646 non-null float64
33
    Soil_Type20
                                        48646 non-null float64
34
    Soil_Type21
                                        48646 non-null float64
35
    Soil_Type22
                                        48646 non-null float64
                                        48646 non-null float64
36
    Soil_Type23
37
    Soil_Type24
                                        48646 non-null float64
38 Soil Type25
                                        48646 non-null float64
39
                                        48646 non-null float64
    Soil_Type26
40
    Soil_Type27
                                        48646 non-null float64
    Soil_Type28
                                        48646 non-null float64
                                       48646 non-null float64
42 Soil_Type29
43 Soil_Type30
                                       48646 non-null float64
44 Soil_Type31
                                       48646 non-null float64
```

data.describe()

₹

7		Elevation	Aspect	Slope	Horizontal_Distance_To_Hydrology	Vertical_Distance_To_Hydrology	Horizontal_Distance_To
	count	48647.000000	48647.000000	48647.000000	48647.000000	48647.000000	486
	mean	2831.526672	141.228544	13.172508	239.109606	39.873538	32
	std	284.219268	106.378387	7.501714	204.272413	50.321057	19
	min	1863.000000	0.000000	0.000000	0.000000	-146.000000	
	25%	2674.000000	56.000000	8.000000	85.000000	6.000000	10
	50%	2854.000000	112.000000	12.000000	190.000000	24.000000	3(
	75%	3021.000000	207.000000	17.000000	342.000000	58.000000	5(
	max	3849.000000	360.000000	61.000000	1343.000000	554.000000	7.
	8 rows ×	55 columns					
	4)

data.columns

```
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',
                    '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_Type32', 'Soil_Type32', 'Soil_Type32', 'Soil_Type32',
                    'Soil_lype19', 'Soil_lype20', 'Soil_lype21', 'Soil_lype22', 'Soil_Type23', 'Soil_Type24', 'Soil_Type25', 'Soil_Type26', 'Soil_Type27', 'Soil_Type28', 'Soil_Type29', 'Soil_Type30', 'Soil_Type31', 'Soil_Type32', 'Soil_Type33', 'Soil_Type35', 'Soil_Type36', 'Soil_Type37', 'Soil_Type38', 'Soil_Type39', 'Soil_Type40', 'Cover_Type'],
                   dtype='object')
X = data.drop(columns='Cover_Type')
y = data['Cover_Type']
                                                                                                                                                                                                                                         data = data.dropna(subset=['Cover_Type'])
X = data.drop(columns='Cover_Type')
y = data['Cover_Type']
                                                                          'Aspect' , 'Slope' , 'Horizontal_Distance_To_Hydrology', 'Vertical_Distance_To_Hydrology',
columns_to_replace_zeros = ['Elevation',
for column in columns_to_replace_zeros:
      median_val = X[column].dropna().median()
      X[column] = X[column].replace(0, median_val)
for column in X.columns:
      X[column] = X[column].fillna(X[column].median())
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_state=42)
#linear regression
lr model = LogisticRegression(random state=42)
lr_model.fit(X_train, y_train)
```

```
🚁 /usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py:469: ConvergenceWarning: lbfgs failed to converge (status=1):
         STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
         Increase the number of iterations (max_iter) or scale the data as shown in:
                 https://scikit-learn.org/stable/modules/preprocessing.html
         Please also refer to the documentation for alternative solver options:
                 https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
             n_iter_i = _check_optimize_result(
                         LogisticRegression
          LogisticRegression(random_state=42)
\label{eq:columns_to_replace_zeros} \textbf{X} [\texttt{columns\_to\_replace\_zeros}]. \textbf{replace} (\textbf{0}, \textbf{X} [\texttt{columns\_to\_replace\_zeros}]. \textbf{median} (\textbf{0}))
from sklearn.metrics import classification_report, accuracy_score
y_pred_lr = lr_model.predict(X_test) # This line is missing, causing the error
lr_report = classification_report(y_test, y_pred_lr,output_dict=True)
lr_accuracy = accuracy_score(y_test, y_pred_lr)
print("Logistic Regression Report:\n", lr_report)
print("Accuracy:", lr_accuracy)
 → Logistic Regression Report:
           {'1.0': {'precision': 0.7701582516955539, 'recall': 0.5331246739697444, 'f1-score': 0.6300863131935882, 'support': 1917.0}, '2.0': {'pr
         Accuracy: 0.8060637204522096
#naive bias classification
nb_model = GaussianNB()
nb_model.fit(X_train, y_train)
 ₹
                 GaussianNB 🗓 🕑
           GaussianNB()
y_pred_nb = nb_model.predict(X_test)
if isinstance(y_test, pd.Series):
       y_test = y_test.fillna(y_test.mode()[0])
elif isinstance(y_test, np.ndarray):
       most_frequent_value = np.nanmax(y_test)
       y_test = np.nan_to_num(y_test, nan=most_frequent_value)
nb_report = classification_report(y_test, y_pred_nb, output_dict=True)
nb_accuracy = accuracy_score(y_test, y_pred_nb)
print("Naive Bayes Report:\n", nb_report)
print("Accuracy:", nb_accuracy)
 → Naive Bayes Report:
           {'1.0': {'precision': 0.16946080652469417, 'recall': 0.1950965049556599, 'f1-score': 0.1813773035887488, 'support': 1917.0}, '2.0': {'precision': 0.16946080652469417, 'recall': 0.1950965049556599, 'f1-score': 0.1813773035887488, 'support': 1917.0}, '2.0': {'precision': 0.16946080652469417, 'recall': 0.1950965049556599, 'f1-score': 0.1813773035887488, 'support': 1917.0}, '2.0': {'precision': 0.16946080652469417, 'recall': 0.1950965049556599, 'f1-score': 0.1813773035887488, 'support': 1917.0}, '2.0': {'precision': 0.16946080652469417, 'recall': 0.1950965049556599, 'f1-score': 0.1813773035887488, 'support': 1917.0}, '2.0': {'precision': 0.16946080652469417, 'recall': 0.1950965049556599, 'f1-score': 0.1813773035887488, 'support': 1917.0}, '2.0': {'precision': 0.16946080652469417, 'recall': 0.1950965049556599, 'f1-score': 0.1813773035887488, 'support': 1917.0}, '2.0': {'precision': 0.16946080652469417, 'recall': 0.1950965049556599, 'f1-score': 0.1813773035887488, 'support': 1917.0}, '2.0': {'precision': 0.16946080652469417, 'recall': 0.1950965049566599, 'f1-score': 0.1813773035887488, 'support': 0.18137730358874888, 'support': 0.1813773035887488, 'support': 0.18137730358874888, 'support': 0.18137730358874888, 'support': 0.18137730358874888, 'support': 0.18137730358874888, 'support': 0.181377303588748888, 'support': 0.18137888888, 'support': 0.18137888888, 'support': 0.18137888888, 'support': 0.181378888888, 'support': 0.181378888888, 'support': 0.1813788888, 'support': 0.18137888888, 'support': 0.1813788888, 'support': 0.181378888, 'support': 0.1813788888, 'support': 0.1813788888, 'support': 0.1813788888, 'support': 0.1813788888, 'support': 0.181378888, 'support': 0.181378888888888, 'support': 0.18137888888, 'support': 0.18137888888888, 'support': 0.1813788888888888, 'support': 0.181378888888, 'support'
         Accuracy: 0.18191161356628982
#KNN CLASSSIFICATION
knn_model = KNeighborsClassifier(n_neighbors=5)
knn_model.fit(X_train, y_train)
                 KNeighborsClassifier (1) ?
          KNeighborsClassifier()
y_pred_knn = knn_model.predict(X_test)
knn_report = classification_report(y_test, y_pred_knn,output_dict=True)
knn_accuracy = accuracy_score(y_test, y_pred_knn)
```

```
print("KNN Report:\n", knn_report)
print("Accuracy:", knn_accuracy)

→ KNN Report:
            {'1.0': {'precision': 0.8480392156862745, 'recall': 0.812206572769953, 'f1-score': 0.829736211031175, 'support': 1917.0}, '2.0': {'precision': 0.8480392156862745, 'recall': 0.812206572769953, 'f1-score': 0.829736211031175, 'support': 1917.0}, '2.0': {'precision': 0.8480392156862745, 'recall': 0.812206572769953, 'f1-score': 0.829736211031175, 'support': 1917.0}, '2.0': {'precision': 0.8480392156862745, 'recall': 0.812206572769953, 'f1-score': 0.829736211031175, 'support': 1917.0}, '2.0': {'precision': 0.8480392156862745, 'recall': 0.812206572769953, 'f1-score': 0.829736211031175, 'support': 1917.0}, '2.0': {'precision': 0.8480392156862745, 'recall': 0.812206572769953, 'f1-score': 0.829736211031175, 'support': 1917.0}, '2.0': {'precision': 0.8480392156862745, 'recall': 0.812206572769953, 'f1-score': 0.829736211031175, 'support': 1917.0}, '2.0': {'precision': 0.8480392156862745, 'recall': 0.812206572769953, 'f1-score': 0.829736211031175, 'support': 1917.0}, '2.0': {'precision': 0.8480392156862745, 'recall': 0.848039216862745, 'recall': 0.84803921686745, 'recall': 0.848039216
          Accuracy: 0.8858170606372046
#DECISION TREE CLASSSIFICATION
dt_model = DecisionTreeClassifier(random_state=42)
dt_model.fit(X_train, y_train)
 ₹
                           DecisionTreeClassifier
           DecisionTreeClassifier(random_state=42)
y_pred_dt = dt_model.predict(X_test)
dt_report = classification_report(y_test, y_pred_dt,output_dict=True)
dt_accuracy = accuracy_score(y_test, y_pred_dt)
print("Decision Tree Report:\n", dt_report)
print("Accuracy:", dt_accuracy)
 → Decision Tree Report:
            {'1.0': {'precision': 0.8709508881922675, 'recall': 0.8695878977569118, 'f1-score': 0.8702688593056643, 'support': 1917.0}, '2.0': {'pr
          Accuracy: 0.9087358684480986
#RANDOM FOREST
rf_model = RandomForestClassifier(random_state=42)
rf_model.fit(X_train, y_train)
 \overline{2}
                           RandomForestClassifier
           RandomForestClassifier(random_state=42)
y_pred_rf = rf_model.predict(X_test)
rf_report = classification_report(y_test, y_pred_rf,output_dict=True)
rf_accuracy = accuracy_score(y_test, y_pred_rf)
print("Random Forest Report:\n", rf_report)
print("Accuracy:", rf_accuracy)
 → Random Forest Report:
            {'1.0': {'precision': 0.9238410596026491, 'recall': 0.8732394366197183, 'f1-score': 0.8978278358809332, 'support': 1917.0}, '2.0': {'pr
          Accuracy: 0.9328879753340185
# k-means cluster for classification
from sklearn.metrics import adjusted_rand_score
kmeans_model = KMeans(n_clusters=2, random_state=42)
kmeans_model.fit(X_train)
 \overline{z}
                                                                             (i) (?)
                                          KMeans
           KMeans(n_clusters=2, random_state=42)
y_pred_kmeans = kmeans_model.predict(X_test)
ari_score = adjusted_rand_score(y_test, y_pred_kmeans)
print("K-Means ARI Score:", ari_score)
 → K-Means ARI Score: 0.02416873487204871
```

```
# comparision table ( basically comparing all the)
results = {
      "Model": ["Logistic Regression", "Naive Bayes", "KNN", "Decision Tree", "Random Forest"],
    "Accuracy": [lr_accuracy, nb_accuracy, knn_accuracy, dt_accuracy, rf_accuracy], # Ensure these variables are defined
}
comparison_df = pd.DataFrame(results)
print(comparison df)
\overline{2}
                      Model Accuracy
     0 Logistic Regression 0.806064
                Naive Bayes 0.181912
     1
                        KNN 0.885817
     3
              Decision Tree 0.908736
              Random Forest 0.932888
     4
# this is the normal overall comparision
# detaild comparision table
models_performance = {
    "Model": ["Logistic Regression", "Naive Bayes", "KNN", "Decision Tree", "Random Forest"],
    "Precision (Class 1)": [
        lr_report['1.0']['precision'], nb_report['1.0']['precision'], # Changed '1' to '1.0' to match the actual key in the dictionaries
        knn_report['1.0']['precision'], dt_report['1.0']['precision'],
        rf_report['1.0']['precision']
    1,
    "Recall (Class 1)": [
        lr_report['1.0']['recall'], nb_report['1.0']['recall'], # Changed '1' to '1.0'
        knn_report['1.0']['recall'], dt_report['1.0']['recall'],
        rf_report['1.0']['recall']
    1,
    "F1-Score (Class 1)": [
        lr_report['1.0']['f1-score'], nb_report['1.0']['f1-score'], # Changed '1' to '1.0'
        knn_report['1.0']['f1-score'], dt_report['1.0']['f1-score'],
        rf_report['1.0']['f1-score']
    ],
    "Accuracy": [
        lr_accuracy, nb_accuracy, knn_accuracy,
        dt_accuracy, rf_accuracy
    ]
}
comparison_df = pd.DataFrame(models_performance)
print(comparison df)
₹
                      Model Precision (Class 1) Recall (Class 1) \
       Logistic Regression
     a
                                        0.770158
                                                          0.533125
     1
                Naive Bayes
                                        0.169461
                                                          0.195097
     2
                        KNN
                                        0.848039
                                                          0.812207
                                        0.870951
                                                          0.869588
     3
              Decision Tree
     4
              Random Forest
                                        0.923841
                                                          0.873239
        F1-Score (Class 1) Accuracy
                  0.630086 0.806064
     0
                  0.181377 0.181912
     2
                  0.829736 0.885817
                  0.870269 0.908736
     3
                  0.897828 0.932888
#RESULT: - THE BEST IS RANDOM FOREST AFTER COMPARING
```