Oil_Spill_Dataset_Analysis

July 23, 2024

[22]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

[2]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

[3]:
```
df = pd.read_csv('/content/drive/MyDrive/colab data file/oil_spill.csv')
df.head()
```

[3]:
```
   f_1    f_2      f_3     f_4  f_5       f_6    f_7   f_8      f_9  f_10  \
0    1   2558  1506.09  456.63   90   6395000  40.88  7.89  29780.0  0.19
1    2  22325    79.11  841.03  180  55812500  51.11  1.21  61900.0  0.02
2    3    115  1449.85  608.43   88    287500  40.42  7.34   3340.0  0.18
3    4   1201  1562.53  295.65   66   3002500  42.40  7.97  18030.0  0.19
4    5    312   950.27  440.86   37    780000  41.43  7.03   3350.0  0.17

   …     f_41      f_42     f_43     f_44   f_45  f_46      f_47   f_48  \
0  …  2850.00   1000.00   763.16   135.46   3.73     0  33243.19  65.74
1  …  5750.00  11500.00  9593.48  1648.80   0.60     0  51572.04  65.73
2  …  1400.00    250.00   150.00    45.13   9.33     1  31692.84  65.81
3  …  6041.52    761.58   453.21   144.97  13.33     1  37696.21  65.67
4  …  1320.04    710.63   512.54   109.16   2.58     0  29038.17  65.66

   f_49  target
0  7.95       1
1  6.26       0
2  7.84       1
3  8.07       1
4  7.35       0

[5 rows x 50 columns]
```

[4]:
```
df.shape
```

[4]: (937, 50)

[5]:
```
df.duplicated().sum()
```

[5]: 0

[6]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 937 entries, 0 to 936
Data columns (total 50 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   f_1     937 non-null    int64
 1   f_2     937 non-null    int64
 2   f_3     937 non-null    float64
 3   f_4     937 non-null    float64
 4   f_5     937 non-null    int64
 5   f_6     937 non-null    int64
 6   f_7     937 non-null    float64
 7   f_8     937 non-null    float64
 8   f_9     937 non-null    float64
 9   f_10    937 non-null    float64
 10  f_11    937 non-null    float64
 11  f_12    937 non-null    float64
 12  f_13    937 non-null    float64
 13  f_14    937 non-null    float64
 14  f_15    937 non-null    float64
 15  f_16    937 non-null    float64
 16  f_17    937 non-null    float64
 17  f_18    937 non-null    float64
 18  f_19    937 non-null    float64
 19  f_20    937 non-null    float64
 20  f_21    937 non-null    float64
 21  f_22    937 non-null    float64
 22  f_23    937 non-null    int64
 23  f_24    937 non-null    float64
 24  f_25    937 non-null    float64
 25  f_26    937 non-null    float64
 26  f_27    937 non-null    float64
 27  f_28    937 non-null    float64
 28  f_29    937 non-null    float64
 29  f_30    937 non-null    float64
 30  f_31    937 non-null    float64
 31  f_32    937 non-null    float64
```

```
 32  f_33    937 non-null    float64
 33  f_34    937 non-null    float64
 34  f_35    937 non-null    int64
 35  f_36    937 non-null    int64
 36  f_37    937 non-null    float64
 37  f_38    937 non-null    float64
 38  f_39    937 non-null    int64
 39  f_40    937 non-null    int64
 40  f_41    937 non-null    float64
 41  f_42    937 non-null    float64
 42  f_43    937 non-null    float64
 43  f_44    937 non-null    float64
 44  f_45    937 non-null    float64
 45  f_46    937 non-null    int64
 46  f_47    937 non-null    float64
 47  f_48    937 non-null    float64
 48  f_49    937 non-null    float64
 49  target  937 non-null    int64
dtypes: float64(39), int64(11)
memory usage: 366.1 KB
```

[7]:
```python
nv = df.isnull().sum()
nv = nv[nv > 0]
nv.sort_values(ascending=False)
```

[7]:
```
Series([], dtype: int64)
```

[8]:
```python
df.duplicated().sum()
```

[8]:
```
0
```

[9]:
```python
df.describe()
```

[9]:
```
              f_1           f_2          f_3          f_4         f_5  \
count  937.000000    937.000000   937.000000   937.000000  937.000000
mean    81.588047    332.842049   698.707086   870.992209   84.121665
std     64.976730   1931.938570   599.965577   522.799325   45.361771
min      1.000000     10.000000     1.920000     1.000000    0.000000
25%     31.000000     20.000000    85.270000   444.200000   54.000000
50%     64.000000     65.000000   704.370000   761.280000   73.000000
75%    124.000000    132.000000  1223.480000  1260.370000  117.000000
max    352.000000  32389.000000  1893.080000  2724.570000  180.000000

                f_6         f_7         f_8          f_9        f_10  …  \
count  9.370000e+02  937.000000  937.000000   937.000000  937.000000  …
mean   7.696964e+05   43.242721    9.127887  3940.712914    0.221003  …
std    3.831151e+06   12.718404    3.588878  8167.427625    0.090316  …
```

```
min    7.031200e+04   21.240000   0.830000     667.000000    0.020000  …
25%    1.250000e+05   33.650000   6.750000    1371.000000    0.160000  …
50%    1.863000e+05   39.970000   8.200000    2090.000000    0.200000  …
75%    3.304680e+05   52.420000  10.760000    3435.000000    0.260000  …
max    7.131500e+07   82.640000  24.690000  160740.000000    0.740000  …

               f_41          f_42         f_43         f_44        f_45  \
count    937.000000    937.000000   937.000000   937.000000  937.000000
mean     933.928677    427.565582   255.435902   106.112519    5.014002
std     1001.681331    715.391648   534.306194   135.617708    5.029151
min        0.000000      0.000000     0.000000     0.000000    0.000000
25%      450.000000    180.000000    90.800000    50.120000    2.370000
50%      685.420000    270.000000   161.650000    73.850000    3.850000
75%     1053.420000    460.980000   265.510000   125.810000    6.320000
max    11949.330000  11500.000000  9593.480000  1748.130000   76.630000

             f_46          f_47        f_48        f_49      target
count  937.000000    937.000000  937.000000  937.000000  937.000000
mean     0.128068   7985.718004   61.694386    8.119723    0.043757
std      0.334344   6854.504915   10.412807    2.908895    0.204662
min      0.000000   2051.500000   35.950000    5.810000    0.000000
25%      0.000000   3760.570000   65.720000    6.340000    0.000000
50%      0.000000   5509.430000   65.930000    7.220000    0.000000
75%      0.000000   9521.930000   66.130000    7.840000    0.000000
max      1.000000  55128.460000   66.450000   15.440000    1.000000

[8 rows x 50 columns]
```

0.1 Selecting Categorical and numerical features

[10]:
```
potential_categorical_features = []
threshold = 15

for column in df.columns:
    unique_values = df[column].nunique()
    if unique_values <= threshold:
        potential_categorical_features.append(column)
        print(f'Feature "{column}" has {unique_values} unique values and might␣
 ↪be categorical.')

if not potential_categorical_features:
    print("No potential categorical features found.")
else:
    print(f"Potential categorical features: {potential_categorical_features}")
```

```
Feature "f_22" has 9 unique values and might be categorical.
Feature "f_23" has 1 unique values and might be categorical.
```

```
Feature "f_25" has 9 unique values and might be categorical.
Feature "f_26" has 8 unique values and might be categorical.
Feature "f_27" has 9 unique values and might be categorical.
Feature "f_33" has 4 unique values and might be categorical.
Feature "f_37" has 3 unique values and might be categorical.
Feature "f_39" has 9 unique values and might be categorical.
Feature "f_40" has 9 unique values and might be categorical.
Feature "f_46" has 2 unique values and might be categorical.
Feature "target" has 2 unique values and might be categorical.
Potential categorical features: ['f_22', 'f_23', 'f_25', 'f_26', 'f_27', 'f_33',
'f_37', 'f_39', 'f_40', 'f_46', 'target']
```

[11]:
```
cat_cols = ['f_22', 'f_23', 'f_25', 'f_26', 'f_27', 'f_33', 'f_37', 'f_39',␣
↪'f_40', 'f_46', 'target']

num_cols = [col for col in df.columns if col not in cat_cols]
```

[12]:
```
df['f_40'].value_counts()
```

[12]:
```
f_40
50    204
55    184
63    135
39    103
73     85
67     79
86     74
85     62
69     11
Name: count, dtype: int64
```

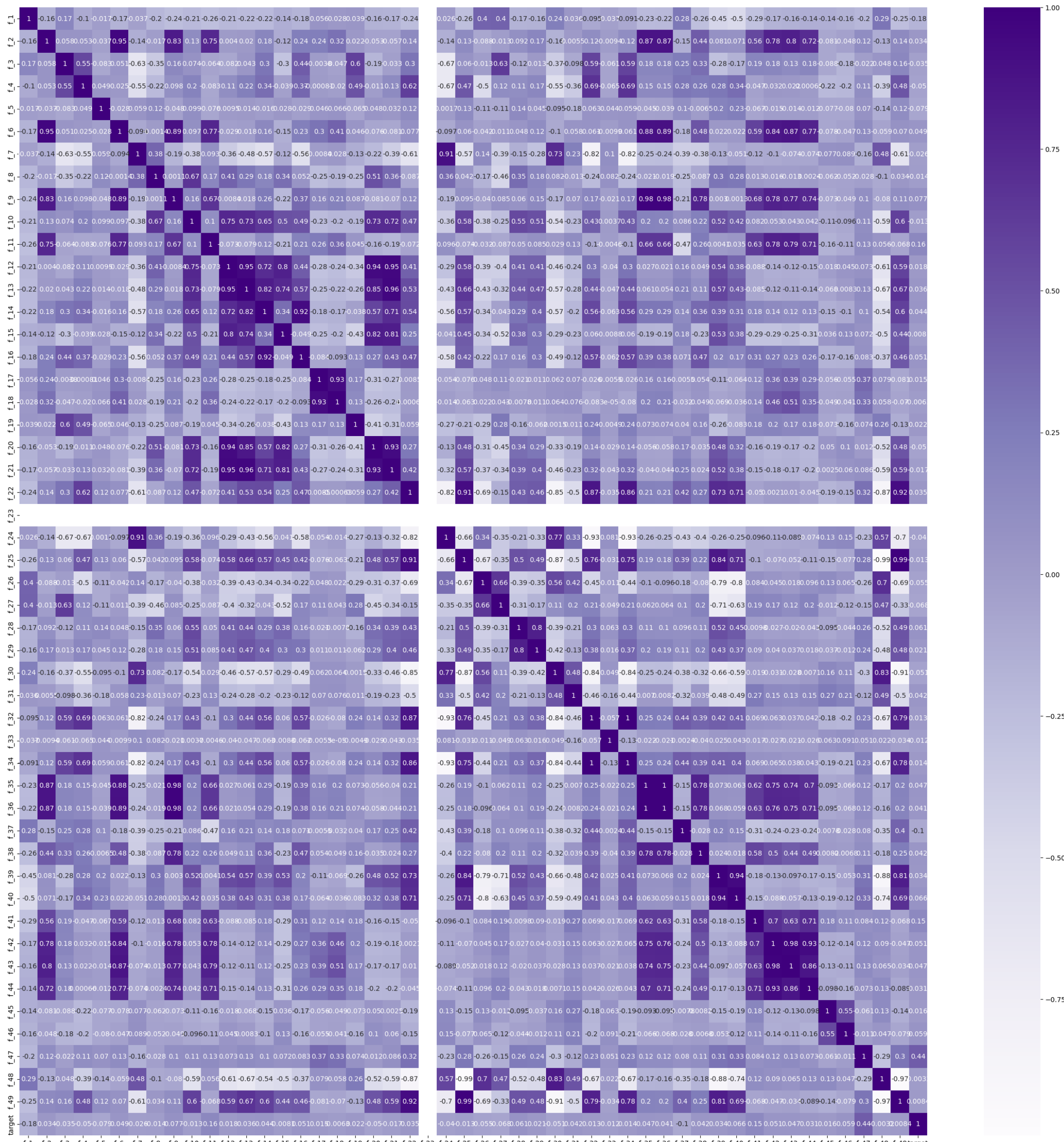
[13]:
```
print(len(cat_cols))
print(len(num_cols))
```

```
11
39
```

0.2 Feature Selection

Feature selection is required here because we have 50 features which are unsuited for the model

[20]:
```
corr = df.corr()

plt.figure(figsize=(30,30))
sns.heatmap(corr, annot=True, cmap= "Purples")
plt.show()
```



[21]:
```
num_cols
```

[21]:
```
['f_1',
 'f_2',
 'f_3',
 'f_4',
 'f_5',
 'f_6',
 'f_7',
 'f_8',
```

```
 'f_9',
 'f_10',
 'f_11',
 'f_12',
 'f_13',
 'f_14',
 'f_15',
 'f_16',
 'f_17',
 'f_18',
 'f_19',
 'f_20',
 'f_21',
 'f_24',
 'f_28',
 'f_29',
 'f_30',
 'f_31',
 'f_32',
 'f_34',
 'f_35',
 'f_36',
 'f_38',
 'f_41',
 'f_42',
 'f_43',
 'f_44',
 'f_45',
 'f_47',
 'f_48',
 'f_49']
```

[23]:

```
def correlation (dataset, threshold):
  corr_col = set()
  corr_matrix = dataset.corr()

  for i in range(len(corr_matrix.columns)):
    for j in range(i):
      if abs(corr_matrix.iloc[i,j]) > threshold:
        colname = corr_matrix.columns[i]
        corr_col.add(colname)
  return corr_col
```

[24]:

```
High_corr_feat = correlation(df, 0.7)
print(len(High_corr_feat))
```

```
27
```

[25]:
```
High_corr_feat
```

[25]:
```
{'f_11',
 'f_12',
 'f_13',
 'f_14',
 'f_15',
 'f_16',
 'f_18',
 'f_20',
 'f_21',
 'f_24',
 'f_25',
 'f_29',
 'f_30',
 'f_32',
 'f_34',
 'f_35',
 'f_36',
 'f_38',
 'f_39',
 'f_40',
 'f_42',
 'f_43',
 'f_44',
 'f_48',
 'f_49',
 'f_6',
 'f_9'}
```

Using Feature importance method of Random Forest bor better decision

[26]:
```python
import pandas as pd
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
```

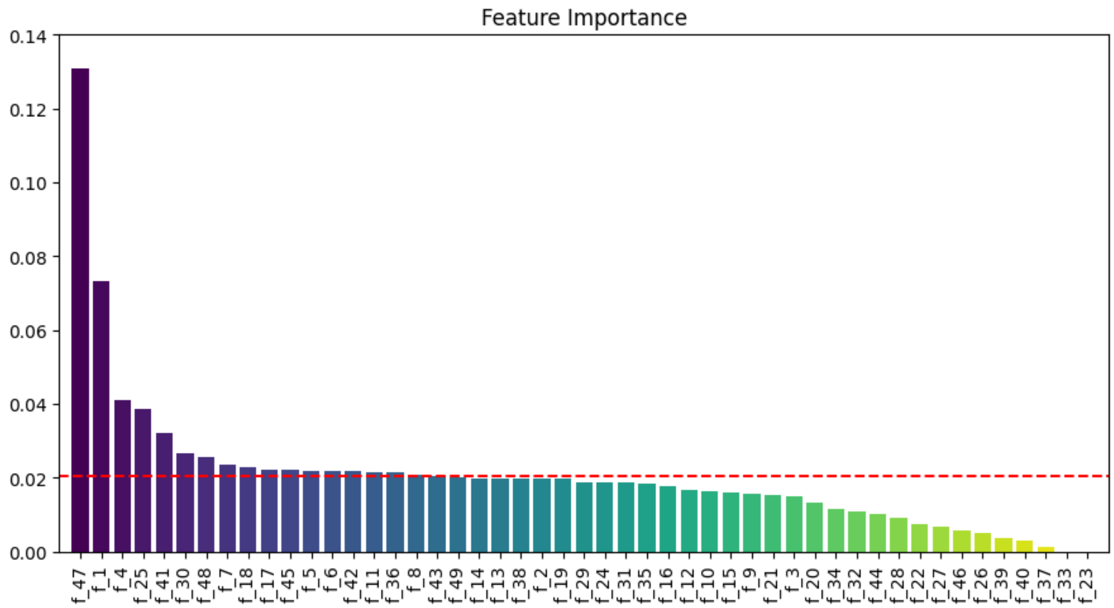
[27]:
```python
# Separate features and target
x = df.drop('target', axis=1)
y = df['target']

# Split the dataset into training and testing sets
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.3,␣
↪random_state=42)

# Create and train the Random Forest model
forest = RandomForestClassifier(random_state=42)
forest.fit(x_train, y_train)
```

```python
# Get feature importances
imp_feat = forest.feature_importances_
mean_importance = np.mean(imp_feat)
std_importance = np.std(imp_feat)
```

[28]:
```python
imp_feat
```

[28]:
```
array([0.07332398, 0.01971647, 0.01506928, 0.04111053, 0.02176426,
       0.02163577, 0.02354695, 0.02084428, 0.01561991, 0.01614662,
       0.02156506, 0.01681376, 0.01984909, 0.01987316, 0.01594908,
       0.01767929, 0.02207773, 0.02288631, 0.01971611, 0.01317309,
       0.01514564, 0.00726373, 0.        , 0.01862542, 0.03859374,
       0.00502522, 0.00662783, 0.00911714, 0.01874776, 0.02655529,
       0.01861299, 0.01064635, 0.        , 0.0115403 , 0.01850997,
       0.02136448, 0.00108966, 0.01977912, 0.00359217, 0.00291329,
       0.03201321, 0.02162046, 0.02029819, 0.00998448, 0.0220041 ,
       0.00549814, 0.13096244, 0.02549836, 0.0200098 ])
```

[45]:
```python
imp_feat = forest.feature_importances_
indices = np.argsort(imp_feat)[::-1]
mean_importance = np.mean(imp_feat)
std_importance = np.std(imp_feat)

# Plot the feature importance of the forest

plt.figure(figsize=(9, 5))
plt.title("Feature Importance")

colormap = plt.cm.viridis
normalize = plt.Normalize(vmin=0, vmax=x_train.shape[1]-1)
colors = colormap(normalize(range(x_train.shape[1])))
plt.bar(range(x_train.shape[1]), imp_feat[indices], color = colors)

# Add mean feature importance line
plt.axhline(y=mean_importance, color='r', linestyle='--', label=f'Mean␣
↪Importance: {mean_importance:.4f}')

plt.xticks(range(x_train.shape[1]), x_train.columns[indices], rotation=90)
plt.xlim([-1, x_train.shape[1]])
plt.ylim([0, 0.14])
plt.tight_layout()
plt.show()
```



[30]:
```
features_below_mean = [x_train.columns[i] for i in range(len(imp_feat)) if␣
    ↪imp_feat[i] < mean_importance]
print(len(features_below_mean))
print(features_below_mean)
```

```
32
['f_2', 'f_3', 'f_9', 'f_10', 'f_12', 'f_13', 'f_14', 'f_15', 'f_16', 'f_19',
'f_20', 'f_21', 'f_22', 'f_23', 'f_24', 'f_26', 'f_27', 'f_28', 'f_29', 'f_31',
'f_32', 'f_33', 'f_34', 'f_35', 'f_37', 'f_38', 'f_39', 'f_40', 'f_43', 'f_44',
'f_46', 'f_49']
```

[31]:
```
features_below_mean = [x_train.columns[i] for i in range(len(imp_feat)) if␣
    ↪imp_feat[i] < mean_importance]
features_below_mean
```

[31]:
```
['f_2',
 'f_3',
 'f_9',
 'f_10',
 'f_12',
 'f_13',
 'f_14',
 'f_15',
 'f_16',
 'f_19',
 'f_20',
 'f_21',
```

```
 'f_22',
 'f_23',
 'f_24',
 'f_26',
 'f_27',
 'f_28',
 'f_29',
 'f_31',
 'f_32',
 'f_33',
 'f_34',
 'f_35',
 'f_37',
 'f_38',
 'f_39',
 'f_40',
 'f_43',
 'f_44',
 'f_46',
 'f_49']
```

[32]:
```
High_corr_feat
```

[32]:
```
{'f_11',
 'f_12',
 'f_13',
 'f_14',
 'f_15',
 'f_16',
 'f_18',
 'f_20',
 'f_21',
 'f_24',
 'f_25',
 'f_29',
 'f_30',
 'f_32',
 'f_34',
 'f_35',
 'f_36',
 'f_38',
 'f_39',
 'f_40',
 'f_42',
 'f_43',
 'f_44',
 'f_48',
```

```
 'f_49',
 'f_6',
 'f_9'}
```

[46]:
```
# Now seleceting the common features from the High corr features and features␣
↪below mean

unwanted_features = set(features_below_mean)
High_corr_feat = set(High_corr_feat)


drop_feat = unwanted_features & High_corr_feat # common elements selected
drop_feat
```

[46]:
```
{'f_12',
 'f_13',
 'f_14',
 'f_15',
 'f_16',
 'f_20',
 'f_21',
 'f_24',
 'f_29',
 'f_32',
 'f_34',
 'f_35',
 'f_38',
 'f_39',
 'f_40',
 'f_43',
 'f_44',
 'f_49',
 'f_9'}
```

[47]:
```
orig_drp ={'f_12',
 'f_13',
 'f_14',
 'f_15',
 'f_16',
 'f_20',
 'f_21',
 'f_24',
 'f_29',
 'f_32',
 'f_34',
 'f_35',
 'f_38',
```

```
 'f_40',
 'f_43',
 'f_44',
 'f_49',
 'f_9'}
```

[48]:
```python
print(len(orig_drp))
```

```
18
```

[49]:
```python
print(len(drop_feat))
```

```
19
```

[50]:
```python
diff = drop_feat - orig_drp
print(diff)
```

```
{'f_39'}
```

[51]:
```python
# From the inference 'f_23' will also be dropped here
```

0.3 Treating Categorical columns

[52]:
```python
plt.figure(figsize=(20,20))
for i in range(len(cat_cols)):
    plt.subplot(4,3,i+1)
    sns.countplot(y=df[cat_cols[i]])
    plt.title(f'Countplot for {cat_cols[i]}')

plt.show()
```

[ ]:
```
## Inference f_23 should be dropped
```

[ ]:
```
df1 = df.copy()
df2 = df.copy()
df3 = df.copy()
```

[ ]:
```
cat_cols.remove('f_23')
df1.drop('f_23', axis=1, inplace=True)
df1.drop(drop_feat, axis=1, inplace=True)
```

[ ]:
```
df1.shape
```

[ ]: (937, 30)

```
[ ]: # Again selecting numcols and cat cols
```

```
[ ]: potential_categorical_features = []
threshold = 15

for column in df1.columns:
    unique_values = df1[column].nunique()
    if unique_values <= threshold:
        potential_categorical_features.append(column)
        print(f'Feature "{column}" has {unique_values} unique values and might␣
↪be categorical.')

if not potential_categorical_features:
    print("No potential categorical features found.")
else:
    print(f"Potential categorical features: {potential_categorical_features}")
```

```
Feature "f_22" has 9 unique values and might be categorical.
Feature "f_25" has 9 unique values and might be categorical.
Feature "f_26" has 8 unique values and might be categorical.
Feature "f_27" has 9 unique values and might be categorical.
Feature "f_33" has 4 unique values and might be categorical.
Feature "f_37" has 3 unique values and might be categorical.
Feature "f_46" has 2 unique values and might be categorical.
Feature "target" has 2 unique values and might be categorical.
Potential categorical features: ['f_22', 'f_25', 'f_26', 'f_27', 'f_33', 'f_37',
'f_46', 'target']
```

```
[ ]: cat_cols = ['f_22', 'f_25', 'f_26', 'f_27', 'f_33', 'f_37', 'f_46', 'target']

num_cols = [col for col in df1.columns if col not in cat_cols]
print(len(cat_cols))
print(len(num_cols))
```

```
8
22
```

```
[ ]: print(len(num_cols))
print(num_cols)
```

```
22
['f_1', 'f_2', 'f_3', 'f_4', 'f_5', 'f_6', 'f_7', 'f_8', 'f_10', 'f_11', 'f_17',
'f_18', 'f_19', 'f_28', 'f_30', 'f_31', 'f_36', 'f_41', 'f_42', 'f_45', 'f_47',
'f_48']
```

```
[ ]:
```

0.4 Treating Numerical Colums

[ ]:
```
print(len(cat_cols))
```

```
8
```

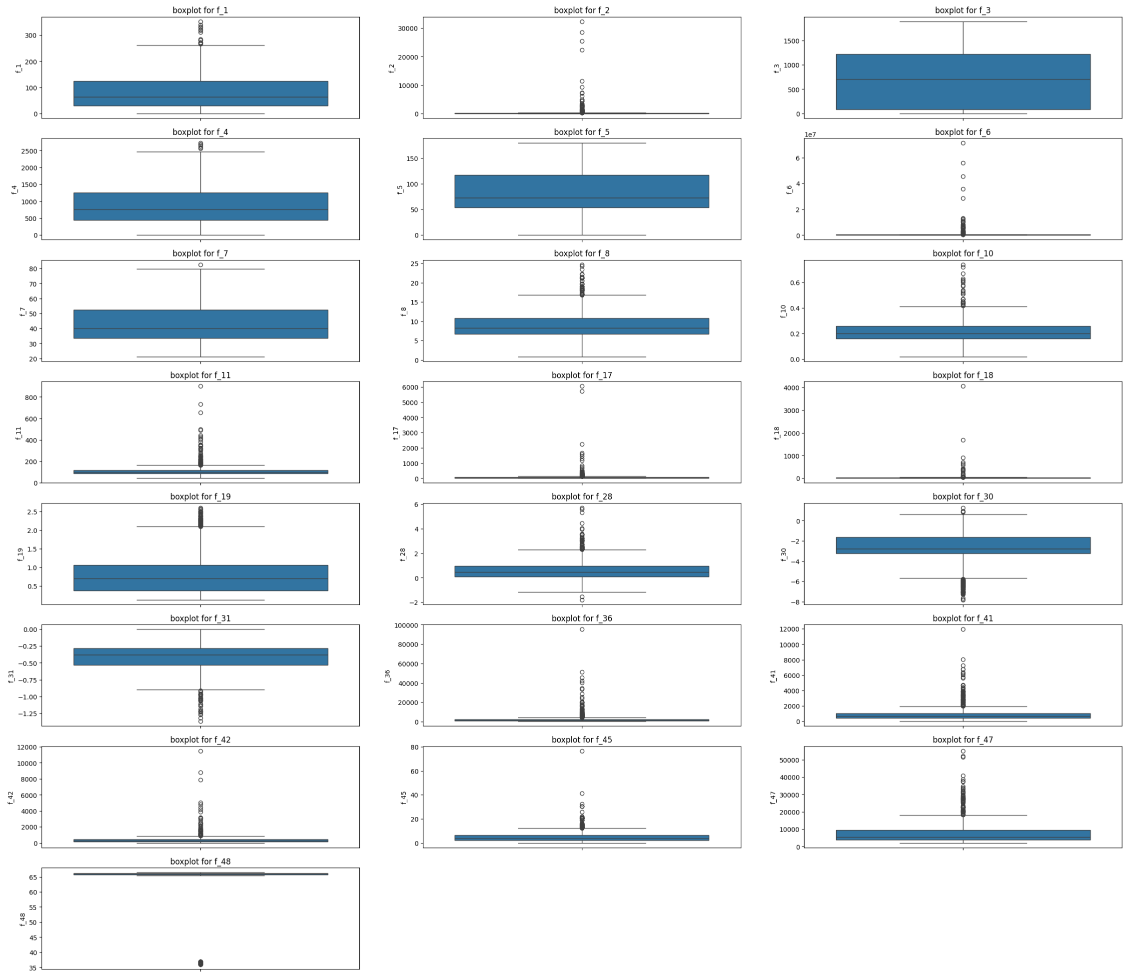
[ ]:
```
num_cols
```

[ ]:
```
['f_1',
 'f_2',
 'f_3',
 'f_4',
 'f_5',
 'f_6',
 'f_7',
 'f_8',
 'f_10',
 'f_11',
 'f_17',
 'f_18',
 'f_19',
 'f_28',
 'f_30',
 'f_31',
 'f_36',
 'f_41',
 'f_42',
 'f_45',
 'f_47',
 'f_48']
```

[ ]:
```
print(len(num_cols))
```

```
22
```

[ ]:
```
plt.figure(figsize=(30,30))
for i in range(len(num_cols)):
    plt.subplot(9, 3, i+1)
    sns.boxplot(y=df1[num_cols[i]])
    plt.title(f'boxplot for {num_cols[i]}')

plt.show()
```



0.4.1 Outlier Treatment

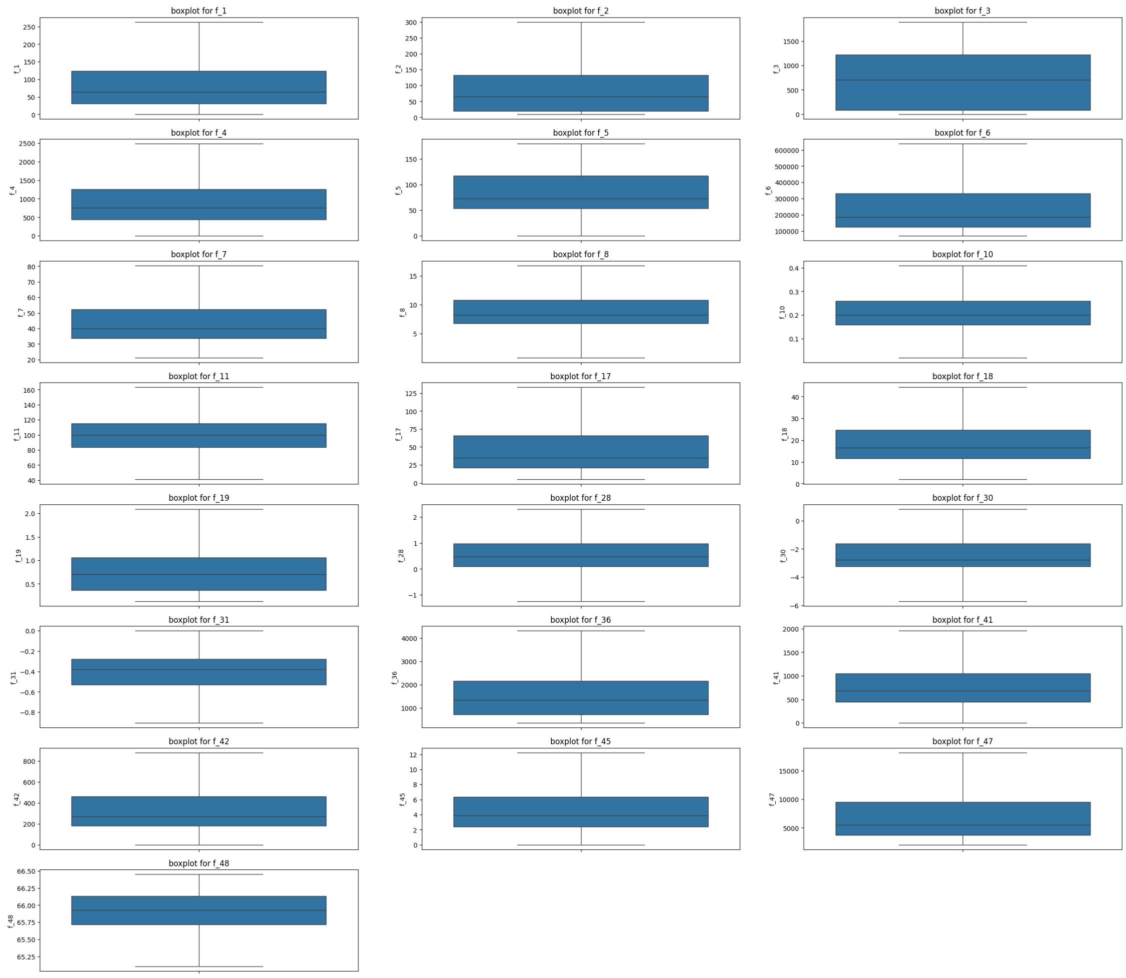
[ ]:
```
num_cols
```

[ ]:
```
['f_1',
 'f_2',
 'f_3',
 'f_4',
 'f_5',
 'f_6',
 'f_7',
 'f_8',
 'f_10',
 'f_11',
 'f_17',
 'f_18',
 'f_19',
```

```
 'f_28',
 'f_30',
 'f_31',
 'f_36',
 'f_41',
 'f_42',
 'f_45',
 'f_47',
 'f_48']
```

[ ]:
```
for col in num_cols:
    Q1 = df1[col].quantile(0.25)
    Q3 = df1[col].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR

    df1[col] = df1[col].clip(lower=lower_bound, upper=upper_bound)
```

[ ]:
```
plt.figure(figsize=(30,30))
for i in range(len(num_cols)):
    plt.subplot(9, 3, i+1)
    sns.boxplot(y=df1[num_cols[i]])
    plt.title(f'boxplot for {num_cols[i]}')

plt.show()
```



[ ]:
```
df1.shape
```

[ ]: (937, 30)

0.5 Splilt into x and y

[ ]:
```
x = df1.drop('target', axis=1)
y = df1['target']
```

[ ]:
```
y.value_counts()
```

[ ]:
```
target
0    896
1     41
Name: count, dtype: int64
```

0.6 Data Balancing

Data is Highly Imbalanced here so we need to balance it

[ ]:
```
!pip install imblearn
```

```
Collecting imblearn
  Downloading imblearn-0.0-py2.py3-none-any.whl (1.9 kB)
Requirement already satisfied: imbalanced-learn in
/usr/local/lib/python3.10/dist-packages (from imblearn) (0.10.1)
Requirement already satisfied: numpy>=1.17.3 in /usr/local/lib/python3.10/dist-
packages (from imbalanced-learn->imblearn) (1.25.2)
Requirement already satisfied: scipy>=1.3.2 in /usr/local/lib/python3.10/dist-
packages (from imbalanced-learn->imblearn) (1.11.4)
Requirement already satisfied: scikit-learn>=1.0.2 in
/usr/local/lib/python3.10/dist-packages (from imbalanced-learn->imblearn)
(1.2.2)
Requirement already satisfied: joblib>=1.1.1 in /usr/local/lib/python3.10/dist-
packages (from imbalanced-learn->imblearn) (1.4.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/usr/local/lib/python3.10/dist-packages (from imbalanced-learn->imblearn)
(3.5.0)
Installing collected packages: imblearn
Successfully installed imblearn-0.0
```

[ ]:
```
from imblearn.over_sampling import SMOTE

smote = SMOTE()

print(x.shape)
print(y.shape)
```

```
(937, 29)
(937,)
```

[ ]:
```
x_res, y_res = smote.fit_resample(x, y)
```

[ ]:
```
print(x_res.shape)
print(y_res.shape)
```

```
(1792, 29)
(1792,)
```

[ ]:
```
y_res.value_counts()
```

[ ]:
```
target
1    896
0    896
```

```
Name: count, dtype: int64
```

0.7 Split Data into train and test and standardize

```
[ ]: from sklearn.model_selection import train_test_split

     x_train, x_test, y_train, y_test = train_test_split(x_res, y_res, test_size=0.
      ↪3, random_state=42)

     print(x_train.shape)
     print(x_test.shape)
     print(y_train.shape)
     print(y_test.shape)
```

```
(1254, 29)
(538, 29)
(1254,)
(538,)
```

```
[ ]: # Now Standardize the dataset
```

```
[ ]: from sklearn.preprocessing import StandardScaler

     scaler = StandardScaler()

     # Fit and transform the training data
     x_train = scaler.fit_transform(x_train)

     # Transform the test data using the same scaler
     x_test = scaler.transform(x_test)
```

Creating evaluaiton metrics

```
[ ]: from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
      ↪classification_report, confusion_matrix
```

```
[ ]: def eval_model(model, mname):
         model.fit(x_train,y_train)
         ypred = model.predict(x_test)

         accuracy = accuracy_score(y_test, ypred)
         precision = precision_score(y_test, ypred, average='binary')
         recall = recall_score(y_test, ypred, average='binary')
         class_report = classification_report(y_test, ypred)
         cm = confusion_matrix(y_test, ypred)
```

```
    train_acc = model.score(x_train, y_train)
    test_acc = model.score(x_test, y_test)

    res_df = pd.DataFrame({'Train_Acc':train_acc,'Test_acc':test_acc,␣
 ↪'Accuracy': accuracy},
                         index=[mname])

    # print('accuracy', accuracy)
    # print('precision', precision)
    # print('recall', recall)
    print('classification_report', class_report)

    return res_df
```

0.7.1 KNN m1

[ ]:
```
from sklearn.neighbors import KNeighborsClassifier

knn_m1 = KNeighborsClassifier()
knn_m1.fit(x_train, y_train)
```

[ ]:
```
KNeighborsClassifier()
```

[ ]:
```
df_knn = eval_model(knn_m1,'KNN')
df_knn
```

```
classification_report               precision    recall  f1-score   support

           0       0.99      0.94      0.96       269
           1       0.94      0.99      0.96       269

    accuracy                           0.96       538
   macro avg       0.96      0.96      0.96       538
weighted avg       0.96      0.96      0.96       538
```

[ ]:

	Train_Acc	Test_acc	Accuracy
KNN	0.980861	0.962825	0.962825

0.7.2 Logistic Regression m1

[ ]:
```
from sklearn.linear_model import LogisticRegressionCV

log_m1 = LogisticRegressionCV()
log_m1.fit(x_train, y_train)
```

[ ]:
```
LogisticRegressionCV()
```

[ ]:
```
df_lg = eval_model(log_m1,'Logistic Regression')
df_lg
```

```
classification_report               precision    recall  f1-score   support

           0       0.97      0.94      0.95       269
           1       0.94      0.97      0.96       269

    accuracy                           0.96       538
   macro avg       0.96      0.96      0.96       538
weighted avg       0.96      0.96      0.96       538
```

[ ]:

	Train_Acc	Test_acc	Accuracy
Logistic Regression	0.951356	0.95539	0.95539

[ ]:
```

```

0.7.3 Decision Tree m1

[ ]:
```
from sklearn.tree import DecisionTreeClassifier

dt_m1 = DecisionTreeClassifier()
dt_m1.fit(x_train, y_train)
```

[ ]: DecisionTreeClassifier()

[ ]:
```
df_dt = eval_model(dt_m1,'Decision Tree') # Overfitting
df_dt
```

```
classification_report               precision    recall  f1-score   support

           0       0.96      0.96      0.96       269
           1       0.96      0.96      0.96       269

    accuracy                           0.96       538
   macro avg       0.96      0.96      0.96       538
weighted avg       0.96      0.96      0.96       538
```

[ ]:

	Train_Acc	Test_acc	Accuracy
Decision Tree	1.0	0.957249	0.957249

0.7.4 Random Forest m1

[ ]:
```
from sklearn.ensemble import RandomForestClassifier

rf_m1 = RandomForestClassifier()
rf_m1.fit(x_train, y_train)
```

[ ]:
```
RandomForestClassifier()
```

[ ]:
```
df_rf = eval_model(rf_m1,'Random Forest') # good results
df_rf
```

```
classification_report               precision    recall  f1-score   support

           0       0.99      0.98      0.99       269
           1       0.98      0.99      0.99       269

    accuracy                           0.99       538
   macro avg       0.99      0.99      0.99       538
weighted avg       0.99      0.99      0.99       538
```

[ ]:

	Train_Acc	Test_acc	Accuracy
Random Forest	1.0	0.986989	0.986989

0.7.5 Bagging Classifier m1

[ ]:
```
from sklearn.ensemble import BaggingClassifier

bag_dt_m1 = BaggingClassifier(base_estimator=DecisionTreeClassifier(),␣
↪n_estimators=100, random_state=42)
bag_dt_m1.fit(x_train, y_train)
```

[ ]:
```
BaggingClassifier(base_estimator=DecisionTreeClassifier(), n_estimators=100,
                  random_state=42)
```

[ ]:
```
df_bag_dt = eval_model(bag_dt_m1,'Bagging Decision Tree')
df_bag_dt
```

```
classification_report               precision    recall  f1-score   support

           0       0.98      0.97      0.98       269
           1       0.97      0.99      0.98       269

    accuracy                           0.98       538
   macro avg       0.98      0.98      0.98       538
weighted avg       0.98      0.98      0.98       538
```

[ ]:
```
                        Train_Acc  Test_acc  Accuracy
Bagging Decision Tree         1.0  0.975836  0.975836
```

[ ]:
```
bag_knn_m1 = BaggingClassifier(base_estimator=KNeighborsClassifier(),
 ↪n_estimators=100, random_state=42)
bag_knn_m1.fit(x_train, y_train)
```

[ ]:
```
BaggingClassifier(base_estimator=KNeighborsClassifier(), n_estimators=100,
                  random_state=42)
```

[ ]:
```
df_bag_knn = eval_model(bag_knn_m1,'Bagging KNN')
df_bag_knn
```

```
classification_report               precision    recall  f1-score   support

           0       1.00      0.94      0.97       269
           1       0.94      1.00      0.97       269

    accuracy                           0.97       538
   macro avg       0.97      0.97      0.97       538
weighted avg       0.97      0.97      0.97       538
```

[ ]:
```
              Train_Acc  Test_acc  Accuracy
Bagging KNN    0.981659  0.966543  0.966543
```

[ ]:
```
bag_rf_m1 = BaggingClassifier(base_estimator=RandomForestClassifier(),
 ↪n_estimators=100, random_state=42)
bag_rf_m1.fit(x_train, y_train)
```

[ ]:
```
BaggingClassifier(base_estimator=RandomForestClassifier(), n_estimators=100,
                  random_state=42)
```

[ ]:
```
df_bag_rf = eval_model(bag_rf_m1,'Bagging Random Forest') # overall good score
df_bag_rf
```

```
classification_report               precision    recall  f1-score   support

           0       0.99      0.98      0.98       269
           1       0.98      0.99      0.98       269

    accuracy                           0.98       538
   macro avg       0.98      0.98      0.98       538
weighted avg       0.98      0.98      0.98       538
```

[ ]:
```
                       Train_Acc  Test_acc  Accuracy
Bagging Random Forest   0.999203  0.983271  0.983271
```

[ ]:
```
bag_log_m1 = BaggingClassifier(base_estimator=LogisticRegressionCV(),␣
↪n_estimators=100, random_state=42)
bag_log_m1.fit(x_train, y_train)
```

[ ]:
```
BaggingClassifier(base_estimator=LogisticRegressionCV(), n_estimators=100,
                  random_state=42)
```

[ ]:
```
df_bag_lg = eval_model(bag_log_m1,'Bagging Logistic Regression')
df_bag_lg
```

```
classification_report               precision    recall  f1-score   support

           0       0.97      0.93      0.95       269
           1       0.94      0.97      0.95       269

    accuracy                           0.95       538
   macro avg       0.95      0.95      0.95       538
weighted avg       0.95      0.95      0.95       538
```

[ ]:
```
                             Train_Acc  Test_acc  Accuracy
Bagging Logistic Regression   0.950558  0.951673  0.951673
```

[ ]:
```
result_df = pd.concat([df_knn, df_lg, df_dt, df_rf, df_bag_dt, df_bag_knn,␣
↪df_bag_rf, df_bag_lg], axis=0).sort_values(by='Accuracy', ascending=False)
result_df
```

[ ]:
```
                             Train_Acc  Test_acc  Accuracy
Random Forest                 1.000000  0.986989  0.986989
Bagging Random Forest         0.999203  0.983271  0.983271
Bagging Decision Tree         1.000000  0.975836  0.975836
Bagging KNN                   0.981659  0.966543  0.966543
KNN                           0.980861  0.962825  0.962825
Decision Tree                 1.000000  0.957249  0.957249
Logistic Regression           0.951356  0.955390  0.955390
Bagging Logistic Regression   0.950558  0.951673  0.951673
```

So, As far as we see **Bagging Random Forest** has the higher results. we can apply hyperparameter tuning to it.

[ ]:
```
from sklearn.model_selection import RandomizedSearchCV
from sklearn.ensemble import RandomForestClassifier
```

```
[ ]: # param_grid = {
     #     'base_estimator__criterion': ['gini', 'entropy'],
     #     'base_estimator__n_estimators': [50, 100, 200],
     #     'base_estimator__max_features': ['auto', 'sqrt', 'log2'],
     #     'base_estimator__max_depth': [None, 10, 20, 30],
     #     'n_estimators': [10, 50, 100]
     # }

     # bag_rf = BaggingClassifier(base_estimator=RandomForestClassifier(),␣
      ↪random_state=42)
```

```
[ ]: # rnd_ht = RandomizedSearchCV(bag_rf, param_grid, cv=5, scoring='accuracy')
     # rnd_ht.fit(x_train, y_train)
```

```
[ ]: # dir(rnd_ht)
```

```
[ ]: # rnd_ht.best_params_
```

```
[ ]: # rnd_ht.best_score_
```

0.8 Model After Hyperparameter Tuning

```
[ ]: bag_rf_m1 = BaggingClassifier(base_estimator=RandomForestClassifier(),␣
      ↪n_estimators=100, random_state=42)
     bag_rf_m1.fit(x_train, y_train)
```

```
[ ]: BaggingClassifier(base_estimator=RandomForestClassifier(), n_estimators=100,
                       random_state=42)
```

```
[ ]: RF = RandomForestClassifier(n_estimators=200, criterion='gini',␣
      ↪max_features='log2', max_depth=20)


     Bag_RF = BaggingClassifier(base_estimator=RF, n_estimators=50, random_state=42)
     Bag_RF.fit(x_train, y_train)
```

```
[ ]: BaggingClassifier(base_estimator=RandomForestClassifier(max_depth=20,
                                                             max_features='log2',
                                                             n_estimators=200),
                       n_estimators=50, random_state=42)
```

```
[ ]: df_Bag_RF = eval_model(Bag_RF,'Bagging Random Forest') # Select this model
     df_Bag_RF
```

```
classification_report                precision    recall  f1-score   support

           0       0.99      0.98      0.98       269
```

```
           1       0.98      0.99      0.98       269

    accuracy                           0.98       538
   macro avg       0.98      0.98      0.98       538
weighted avg       0.98      0.98      0.98       538
```

[ ]:
```
                       Train_Acc  Test_acc  Accuracy
Bagging Random Forest   0.999203  0.983271  0.983271
```

[ ]:
```
Bag_RF.predict(x_test)
```

[ ]:
```
array([0, 0, 1, 0, 1, 1, 0, 0, 1, 1, 0, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1,
       0, 1, 1, 0, 0, 0, 0, 1, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 0, 1,
       1, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1,
       1, 1, 1, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 1, 1, 0, 0, 0, 1, 0,
       0, 1, 0, 1, 1, 0, 1, 0, 1, 1, 0, 1, 0, 1, 1, 1, 0, 1, 1, 0, 0, 0,
       1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1, 1, 0, 0, 1, 0, 1,
       0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 1, 0, 0, 1, 1, 1, 0, 0, 1, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 1, 1, 1, 0, 0, 1, 0, 1, 0, 0, 0,
       0, 1, 0, 1, 1, 0, 0, 0, 1, 1, 1, 0, 0, 1, 1, 1, 0, 1, 0, 0, 1, 0,
       0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 1, 0, 1, 1,
       0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 0, 1,
       0, 0, 1, 1, 0, 0, 1, 1, 1, 1, 0, 0, 1, 0, 0, 1, 1, 1, 0, 0, 1, 1,
       1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 0, 0, 1, 1, 0, 1, 0, 1, 0, 1, 1,
       1, 1, 1, 1, 0, 0, 0, 0, 1, 1, 0, 1, 0, 1, 0, 1, 1, 1, 1, 0, 0, 1,
       1, 1, 1, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0,
       0, 1, 1, 0, 0, 1, 0, 1, 0, 1, 1, 1, 1, 0, 0, 1, 0, 1, 0, 1, 1, 1,
       0, 0, 1, 1, 0, 0, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 0, 0, 0, 1, 0, 1,
       0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 1, 0, 1, 0, 1, 1, 0, 1, 0, 1,
       0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 1, 1,
       1, 1, 1, 0, 0, 1, 1, 0, 1, 1, 0, 1, 0, 1, 1, 1, 1, 0, 0, 0, 1, 1,
       0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 1, 1, 0, 0, 1, 1, 0, 0, 1, 1, 0, 0,
       1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 0, 0, 1, 0, 0, 0, 1, 0, 1, 1, 1,
       0, 0, 1, 1, 1, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0, 1, 1, 1, 0, 1, 0, 0,
       1, 0, 1, 1, 1, 0, 0, 1, 0, 1, 0, 1, 0, 0, 1, 1, 0, 1, 1, 0, 1, 1,
       1, 1, 1, 0, 0, 1, 0, 1, 1, 0])
```

0.9 Making new dataset with 20 samples

[ ]:
```
new_data = df1.sample(20)
new_data.shape
```

[ ]:
```
(20, 30)
```

[ ]:
```
new_data
```

[ ]:

	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8	f_10	f_11	\
447	15.0	210	1111.80	1889.67	137	295312	31.80	8.43	0.27	88.40	
354	71.0	300	1166.82	1832.68	166	638670	40.51	11.27	0.28	116.30	
195	1.0	300	805.86	358.51	60	638670	24.65	6.74	0.27	163.25	
143	133.0	50	1687.60	1498.74	9	125000	37.34	7.30	0.20	63.10	
932	200.0	12	92.42	364.42	135	97200	59.42	10.34	0.17	110.00	
803	71.0	15	11.93	11.13	75	121500	44.40	10.02	0.23	105.30	
296	263.5	75	1117.59	842.47	55	187500	31.95	6.73	0.21	91.90	
601	33.0	12	122.83	578.33	76	97200	50.33	15.02	0.30	91.40	
781	49.0	27	11.74	554.74	68	218700	51.04	9.96	0.20	103.60	
635	67.0	12	356.25	614.92	95	97200	50.58	15.51	0.31	110.00	
734	2.0	98	386.31	292.22	110	638670	50.33	12.73	0.25	113.40	
239	110.0	170	1311.73	582.77	171	425000	30.55	6.98	0.23	95.30	
935	203.0	10	96.00	451.30	68	81000	59.90	15.01	0.25	97.50	
757	25.0	18	78.11	456.00	70	145800	48.94	7.79	0.16	91.80	
663	16.0	18	15.72	556.61	76	145800	69.22	10.98	0.16	100.90	
750	18.0	26	43.62	186.77	69	210600	51.35	6.47	0.13	86.50	
167	158.0	72	1706.17	1314.44	101	180000	34.01	9.15	0.27	71.70	
808	76.0	16	19.00	584.00	62	129600	50.12	7.80	0.16	112.30	
76	66.0	63	1563.17	1399.87	40	157500	37.70	8.34	0.22	97.20	
876	144.0	15	9.73	344.27	92	121500	54.80	16.47	0.30	103.40	

	…	f_33	f_36	f_37	f_41	f_42	f_45	f_46	f_47	f_48	\
447	…	0.0	2340	0.01	0.00	0.00	0.000	0	14192.31	65.105	
354	…	0.0	4320	0.01	1958.55	882.45	3.130	0	10219.05	66.340	
195	…	0.0	4320	0.00	1958.55	882.45	2.850	0	15749.24	65.610	
143	…	0.0	1620	0.01	509.90	304.14	2.460	0	3423.55	66.300	
932	…	0.0	540	0.01	381.84	254.56	4.500	0	2593.50	65.850	
803	…	0.0	450	0.00	569.21	180.00	5.420	0	13587.90	65.350	
296	…	0.0	1260	0.01	860.23	223.61	5.200	0	4866.52	65.870	
601	…	0.0	540	0.01	569.21	90.00	9.490	1	4513.34	66.140	
781	…	0.0	810	0.00	603.74	402.49	2.960	0	3772.43	66.070	
635	…	0.0	450	0.00	360.00	180.00	2.670	0	17382.04	66.280	
734	…	0.0	2160	0.00	1958.55	484.66	12.245	1	15413.42	65.870	
239	…	0.0	2790	0.01	912.41	608.28	2.210	0	7770.70	65.780	
935	…	0.0	540	0.01	402.49	180.00	4.470	0	2421.43	65.970	
757	…	0.0	720	0.00	853.81	180.00	12.200	0	2674.72	65.960	
663	…	0.0	630	0.00	569.21	201.25	4.610	0	3579.04	66.070	
750	…	0.0	990	0.00	1138.42	90.00	12.245	1	4390.92	65.590	
167	…	0.0	1710	0.01	873.21	206.16	6.250	0	4181.97	66.210	
808	…	0.0	720	0.01	649.00	127.28	10.200	1	3862.06	66.110	
76	…	0.0	900	0.01	430.12	320.16	2.070	0	5118.76	66.230	
876	…	0.0	630	0.01	450.00	270.00	3.120	0	2894.48	65.790	

	target
447	0
354	0

```
195         1
143         0
932         0
803         0
296         0
601         0
781         0
635         0
734         1
239         0
935         0
757         0
663         0
750         0
167         0
808         0
76          0
876         0

[20 rows x 30 columns]
```

0.9.1 Apply Preprocessing Steps

[ ]:
```python
new_data['target'].value_counts()
```

[ ]:
```
target
0    18
1     2
Name: count, dtype: int64
```

[ ]:
```python
array1 = new_data['target'].to_numpy()
array1
```

[ ]:
```
array([0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0])
```

[ ]:
```python
test_data = scaler.transform(new_data.drop('target', axis=1))
```

[ ]:
```python
predictions = Bag_RF.predict(test_data)

new_data['predictions'] = predictions
```

[ ]:
```python
new_data['predictions'].value_counts()
```

[ ]:
```
predictions
0    18
1     2
Name: count, dtype: int64
```

[ ]:
```
array2 = new_data['predictions'].to_numpy()
array2
```

[ ]:
```
array([0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0])
```

[ ]:
```
array1 == array2
```

[ ]:
```
array([ True,  True,  True,  True,  True,  True,  True,  True,  True,
        True,  True,  True,  True,  True,  True,  True,  True,  True,
        True,  True])
```

[ ]:
```
# Calculate the number of correct predictions
correct_predictions = np.sum(array1 == array2)

# Calculate the accuracy percentage
accuracy_percentage = (correct_predictions / len(array1)) * 100

print(f'Accuracy: {accuracy_percentage:.2f}%')
```

```
Accuracy: 100.00%
```