Assignment 2

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```
from google.colab import files
uploaded = files.upload()
```

Choose Files Electric_Grid_Stability.csv

- **Electric_Grid_Stability.csv**(application/vnd.ms-excel) - 2417871 bytes, last modified: 5/14/2020 - 100% don

```
Saving Electric_Grid_Stability.csv to Electric_Grid_Stability (4).csv
```

```
# checking the file delimiter format
print (uploaded['Electric_Grid_Stability.csv'][:200].decode('utf-8') + '...')
```

```
"tau1","tau2","tau3","tau4","p1","p2","p3","p4","g1","g2","g3","g4","stab","stabf"
2.95906002455997,3.07988520422811,8.38102539191882,9.78075443222607,3.76308477206316,-0.78
```

1.Importing necessary libraries

```
import numpy as np
import pandas as pd
import io

import matplotlib.pyplot as plt
import seaborn as sns
```

2.Loading data

```
# loading the file in data frame
df= pd.read_csv(io.StringIO(uploaded['Electric_Grid_Stability.csv'].decode('utf-8')))
```

```
# Structure of dataset
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 14 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   tau1    10000 non-null  float64
 1   tau2    10000 non-null  float64
 2   tau3    10000 non-null  float64
 3   tau4    10000 non-null  float64
 4   p1      10000 non-null  float64
 5   p2      10000 non-null  float64
 6   p3      10000 non-null  float64
```

3.Data Preprocessing

- 3.1 Checking for duplicates

```
print('Number of duplicates in dataset : ',sum(df.duplicated()))
```

```
Number of duplicates in dataset :  0
```

- 3.2 Checking for missing values

```
print('Total number of missing values in dataset : ', df.isna().values.sum())
```

```
Total number of missing values in dataset :  0
```

```
# get the number of missing data points per column
missing_values_count = df.isnull().sum()

# look at the # of missing points in the first ten columns
missing_values_count
```

```
tau1     0
tau2     0
tau3     0
tau4     0
p1       0
p2       0
p3       0
p4       0
g1       0
g2       0
g3       0
g4       0
stab     0
stabf    0
dtype: int64
```

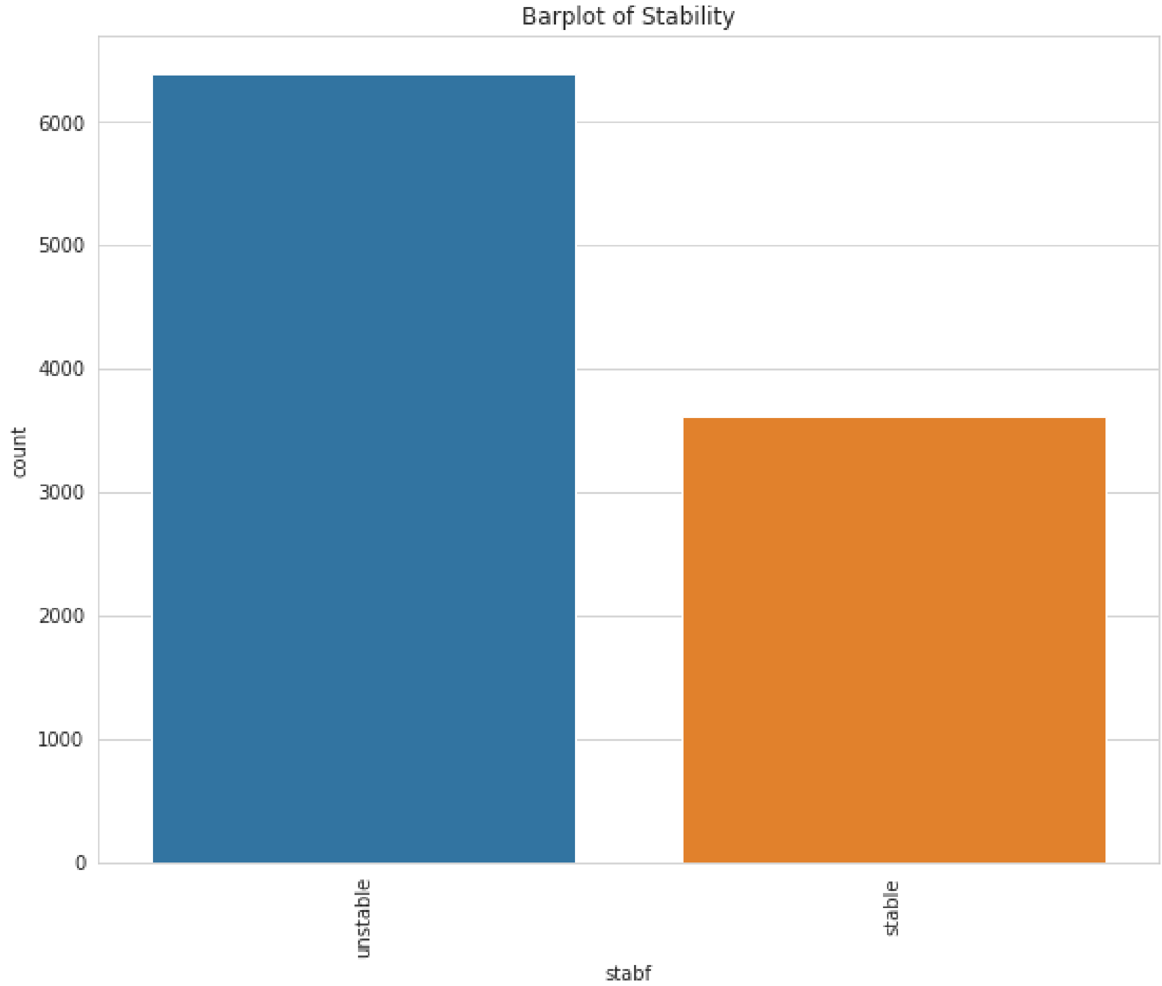
```
# how many total missing values do we have?
total_cells = np.product(df.shape)
total_missing = missing_values_count.sum()

# percent of data that is missing
(total_missing/total_cells) * 100
```

```
0.0
```

- 3.3 Checking for class imbalance

```
# Barplot of Categorical variable stabf
plt.figure(figsize=(10,8))
plt.title('Barplot of Stability')
sns.countplot(df['stabf'])
plt.xticks(rotation=90)
```

```
(array([0, 1]), <a list of 2 Text major ticklabel objects>)
```




```
# Distribution of factors in variable stabf
print('No Stability', round(df['stabf'].value_counts()[0]/len(df) * 100,2), '% of the dataset')
print('Stability', round(df['stabf'].value_counts()[1]/len(df) * 100,2), '% of the dataset')
```

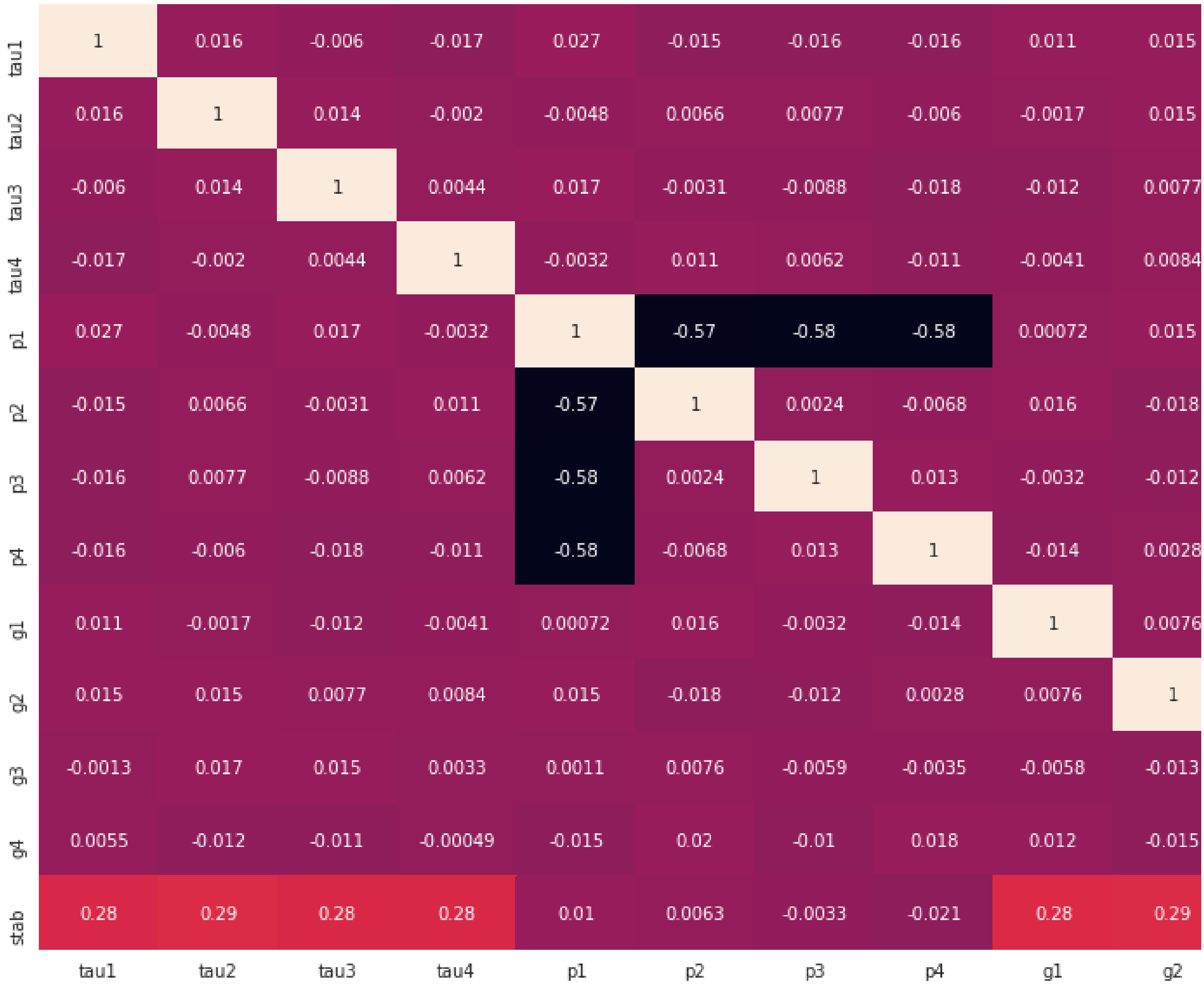
```
No Stability 63.8 % of the dataset
Stability 36.2 % of the dataset
```

As we can see the data is not balanced it will affect the predicting model accuracy.

4.Exploratory Data Analysis

```
# Correlation plot of all varaibles in Dataset
plt.figure(figsize=(20,10))
sns.heatmap(df.corr(),annot=True)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f9788f7d208>
```

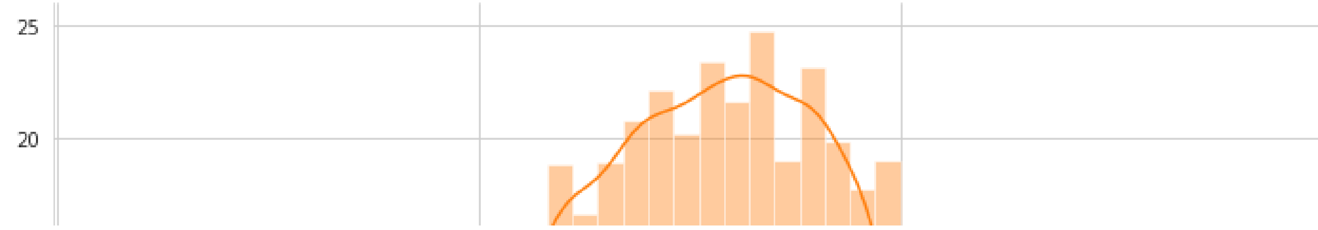


Explanation

So we can see that there is some relationship between “stab” ,” 'tau1' to 'tau4'”and” 'g1' to 'g4'”.variables between them but they have very low correlation with “stab”. So the variable 'p1' to 'p4' will not effect the “stabf”.

```
# Histogram of variable stabf with factors
facetgrid = sns.FacetGrid(df, hue='stabf', height=5,aspect=3)
facetgrid.map(sns.distplot,'stab', hist=True).add_legend()
```

```
<seaborn.axisgrid.FacetGrid at 0x7f978900e400>
```

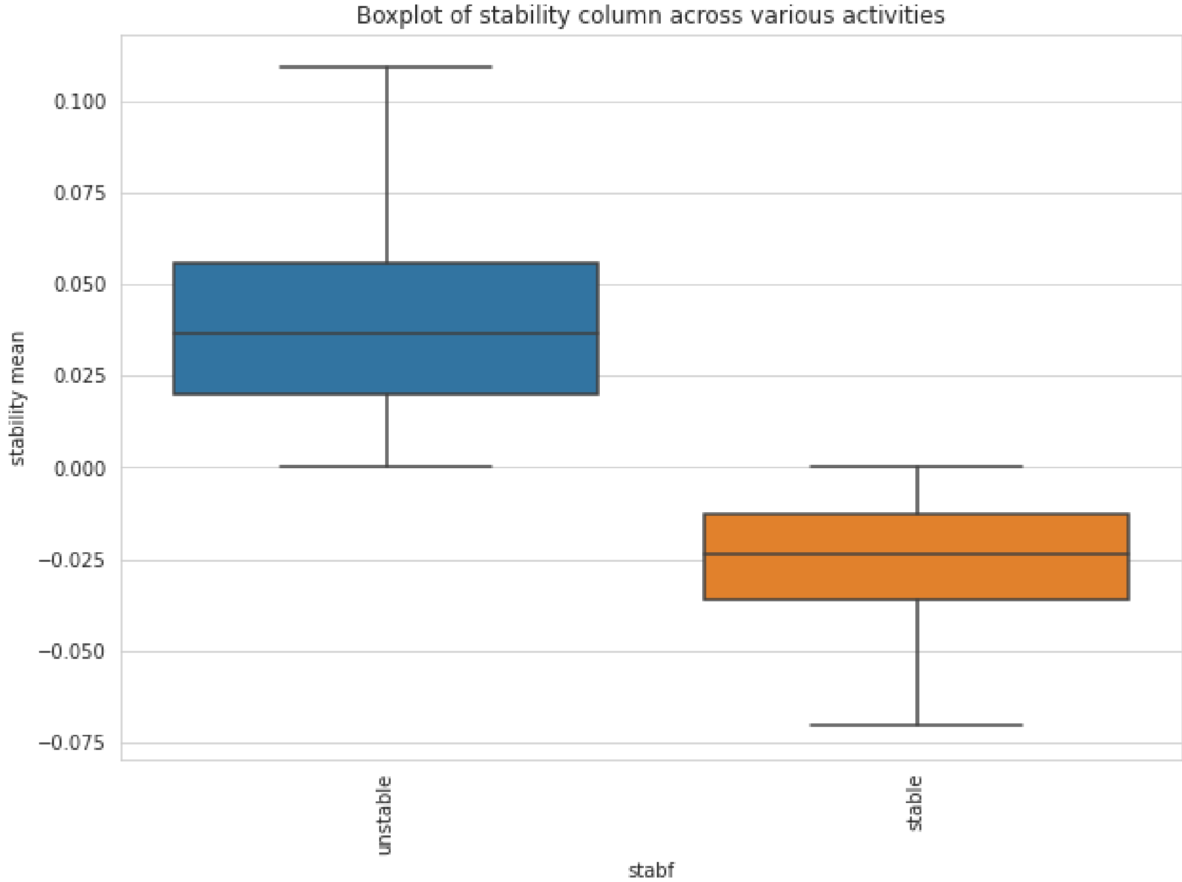


Explanation

As we can see it is some region in factors distribution where both stable and unstable factor share whic differentiate between the stability and unstability of electric grid.

```
plt.figure(figsize=(10,7))
sns.boxplot(x='stabf', y='stab',data=df, showfliers=False)
plt.ylabel('stability mean')
plt.title("Boxplot of stability column across various activities")
plt.xticks(rotation=90)
```

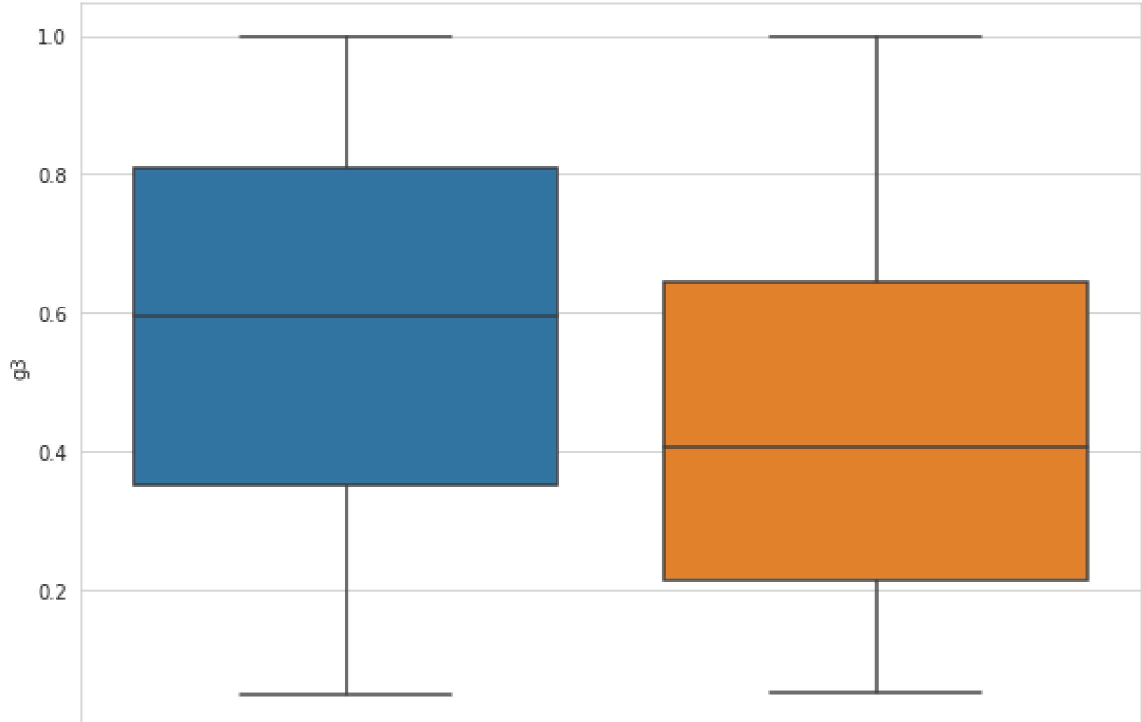
```
(array([0, 1]), <a list of 2 Text major ticklabel objects>)
```



As we can see the median is not same for both stability factor for differential equation root "stab".So the betweendifferential equation root and stability factor.

```
# Boxplot of ge vs stabf variable
plt.figure(figsize=(10,7))
sns.boxplot(x='stabf', y="g3",data=df, showfliers=False)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f9788cb7748>
```



As we can see the median is not same for both stability factor for price elasticity coefficient "g3".So thei between price elasticity coefficient and stability factor.

5.ML models

- 5.1 Defining the train and target

```
X=df.drop(['stabf'],axis=1)
y=df['stabf']
```

```
from sklearn.model_selection import train_test_split

# Split the data into 80% training and 20% testing
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.20,random_state=0)
```

```
print('Training data size : ', X_train.shape)
print('Test data size : ', X_test.shape)
```

```
Training data size :  (8000, 13)
Test data size :  (2000, 13)
```

```
# Data balance
from imblearn.over_sampling import SMOTE

print("Before OverSampling, counts of label 'stable': {}".format(sum(y_train=="stable")))
print("Before OverSampling, counts of label 'unstable': {} \n".format(sum(y_train=="unstable"))

# SMOTE function for balaning the categorical data
sm = SMOTE(random_state=2)
X_train_res, y_train_res = sm.fit_sample(X_train, y_train.ravel())
```

```
print('After OverSampling, the shape of train_X: {}'.format(X_train_res.shape))
print('After OverSampling, the shape of train_y: {} \n'.format(y_train_res.shape))

print("After OverSampling, counts of label 'stable': {}".format(sum(y_train_res=="stable")))
print("After OverSampling, counts of label 'unstable': {}".format(sum(y_train_res=="unstable"))
```

```
Before OverSampling, counts of label 'stable': 2893
Before OverSampling, counts of label 'unstable': 5107

After OverSampling, the shape of train_X: (10214, 13)
After OverSampling, the shape of train_y: (10214,)

After OverSampling, counts of label 'stable': 5107
After OverSampling, counts of label 'unstable': 5107
```

- 5.2 **Logistic regression model** with Hyperparameter tuning and cross validation

```
from sklearn. linear_model import LogisticRegression
from sklearn.model_selection import RandomizedSearchCV
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report

import warnings
warnings.filterwarnings("ignore")
```

Double-click (or enter) to edit

```
parameters = {'C':np.arange(10,61,10), 'penalty':['l2','l1']}
lr_classifier = LogisticRegression()
lr_classifier_rs = RandomizedSearchCV(lr_classifier, param_distributions=parameters, cv=10,rand
lr_classifier_rs.fit(X_train_res, y_train_res)

# Data Imbalance
lr_classifier_rs1 = RandomizedSearchCV(lr_classifier, param_distributions=parameters, cv=10,ran
lr_classifier_rs1.fit(X_train, y_train)

y_pred = lr_classifier_rs.predict(X_test)

y_pred1 = lr_classifier_rs1.predict(X_test)


# Imbalance  Data
lr_accuracy1 = accuracy_score(y_true=y_test, y_pred=y_pred1)
print("Data Imbalance result ")
print("Accuracy using Logistic Regression : ", lr_accuracy1)
cm = confusion_matrix(y_test.values,y_pred1)
print("Confusion Matrix:")
print(cm)
TP =cm[0][0]
TN =cm[1][1]
FN = cm[1][0]
FP = cm[0][1]

precision=TP/(TP+FP)
recall= TP/(TP+FN)
```

```
F1=(2*precision*recall)/(precision+recall)
print("precision:",precision)
print("Recall:",recall)
print("F1_score:",F1)
```

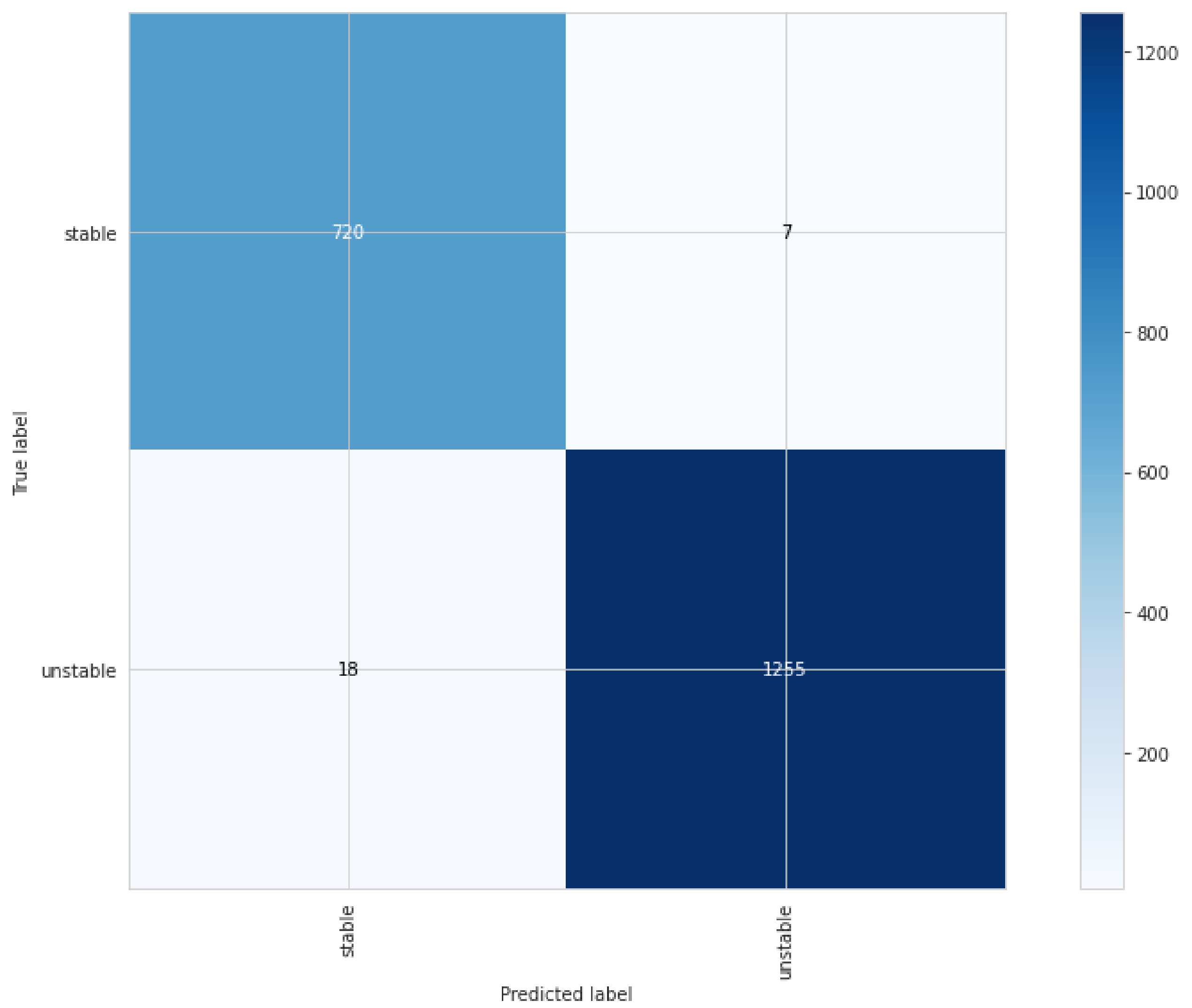
```
Data Imbalance result
Accuracy using Logistic Regression :  0.9875
Confusion Matrix:
[[ 711   16]
 [   9 1264]]
precision: 0.9779917469050894
Recall: 0.9875
F1_score: 0.9827228749136144
```

```
# Balance data
lr_accuracy = accuracy_score(y_true=y_test, y_pred=y_pred)
print("Balance data")
print("Accuracy using Logistic Regression : ", lr_accuracy)
cm = confusion_matrix(y_test.values,y_pred)
print("Confusion Matrix:")
print(cm)
TP =cm[0][0]
TN =cm[1][1]
FN = cm[1][0]
FP = cm[0][1]

precision=TP/(TP+FP)
recall= TP/(TP+FN)
F1=(2*precision*recall)/(precision+recall)
print("precision:",precision)
print("Recall:",recall)
print("F1_score:",F1)
```

```
Balance data
Accuracy using Logistic Regression :  0.9875
Confusion Matrix:
[[ 720    7]
 [  18 1255]]
precision: 0.9903713892709766
Recall: 0.975609756097561
F1_score: 0.9829351535836178
```

```
def plot_confusion_matrix(cm,lables):
    fig, ax = plt.subplots(figsize=(12,8)) # for plotting confusion matrix as image
    im = ax.imshow(cm, interpolation='nearest', cmap=plt.cm.Blues)
    ax.figure.colorbar(im, ax=ax)
    ax.set(xticks=np.arange(cm.shape[1]),
    yticks=np.arange(cm.shape[0]),
    xticklabels=lables, yticklabels=lables,
    ylabel='True label',
    xlabel='Predicted label')
    plt.xticks(rotation = 90)
    thresh = cm.max() / 2.
    for i in range(cm.shape[0]):
        for j in range(cm.shape[1]):
            ax.text(j, i, int(cm[i, j]),ha="center", va="center",color="white" if cm[i, j] > th
    fig.tight_layout()
```

```
plot_confusion_matrix(cm, np.unique(y_pred))
```




```
#function to get best random search attributes
def get_best_randomsearch_results(model):
    print("Best estimator : ", model.best_estimator_)
    print("Best set of parameters : ", model.best_params_)
    print("Best score : ", model.best_score_)


# getting best random search attributes
get_best_randomsearch_results(lr_classifier_rs)
```

```
Best estimator :  LogisticRegression(C=60, class_weight=None, dual=False, fit_intercept=Tr
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='auto', n_jobs=None, penalty='l2',
                   random_state=None, solver='lbfgs', tol=0.0001, verbose=0,
                   warm_start=False)
Best set of parameters :  {'penalty': 'l2', 'C': 60}
Best score :  0.9917763176809504
```

- 5.3 **Decision tree model** with Hyperparameter tuning and cross validation

```
from sklearn.tree import DecisionTreeClassifier

parameters = {'max_depth':np.arange(2,10,2)}
dt_classifier = DecisionTreeClassifier()
dt_classifier_rs = RandomizedSearchCV(dt_classifier,param_distributions=parameters,random_state
```

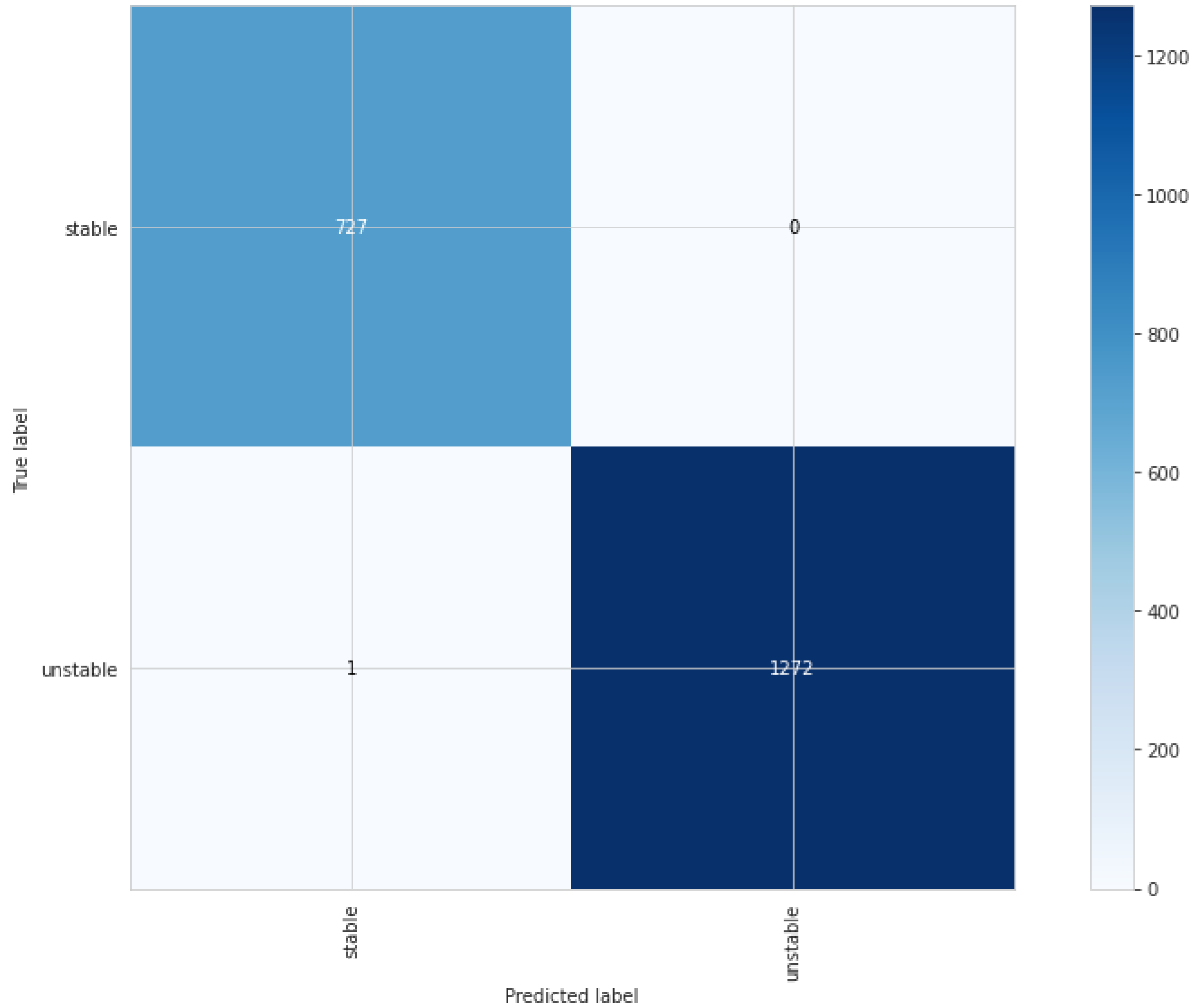
```
dt_classifier_rs.fit(X_train_res, y_train_res)

# Data Imbalance
dt_classifier_rs1 = RandomizedSearchCV(dt_classifier,param_distributions=parameters,random_stat
dt_classifier_rs1.fit(X_train, y_train)

y_pred = dt_classifier_rs.predict(X_test)
# Data Imbalance prediction
y_pred1 = dt_classifier_rs1.predict(X_test)


# Data Imbalance
dt_accuracy1 = accuracy_score(y_true=y_test, y_pred=y_pred1)
print("Data Imbalance result ")
print("Accuracy using Decision tree : ", dt_accuracy1)
cm = confusion_matrix(y_test.values,y_pred1)
print("Confusion Matrix:")
print(cm)
TP =cm[0][0]
TN =cm[1][1]
FN = cm[1][0]
FP = cm[0][1]

precision=TP/(TP+FP)
recall= TP/(TP+FN)
F1=(2*precision*recall)/(precision+recall)
print("precision:",precision)
print("Recall:",recall)
print("F1_score:",F1)
```

```
Data Imbalance result
Accuracy using Decision tree :  0.9995
Confusion Matrix:
[[ 727    0]
 [   1 1272]]
precision: 1.0
Recall: 0.9986263736263736
F1_score: 0.9993127147766323
```

```
# Balance data
dt_accuracy = accuracy_score(y_true=y_test, y_pred=y_pred)
print("Balance Data")
print("Accuracy using Decision tree : ", dt_accuracy)
cm = confusion_matrix(y_test.values,y_pred)
print("Confusion Matrix:")
print(cm)
TP =cm[0][0]
TN =cm[1][1]
FN = cm[1][0]
FP = cm[0][1]

precision=TP/(TP+FP)
recall= TP/(TP+FN)
F1=(2*precision*recall)/(precision+recall)
print("precision:",precision)
print("Recall:",recall)
print("F1_score:",F1)
```

```
Balance Data
Accuracy using Decision tree :  0.9995
Confusion Matrix:
[[ 727    0]
 [   1 1272]]
precision: 1.0
Recall: 0.9986263736263736
F1 score: 0.9993127147766323
```

```
plot_confusion_matrix(cm, np.unique(y_pred))
```




```
# getting best random search attributes
get_best_randomsearch_results(dt_classifier_rs)
```

```
Best estimator :  DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None, criterion='gini
                       max_depth=2, max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort='deprecated',
                       random_state=None, splitter='best')
Best set of parameters :  {'max_depth': 2}
Best score :  0.9998042094958395
```

- 5.4 **Linear SVM model** with Hyperparameter tuning and cross validation

```
from sklearn.svm import LinearSVC
```

```
parameters = {'C':np.arange(1,12,2)}
lr_svm = LinearSVC(tol=0.00005)
lr_svm_rs = RandomizedSearchCV(lr_svm, param_distributions=parameters,random_state = 42)
lr_svm_rs.fit(X_train_res, y_train_res)

# Data Imbalance
lr_svm_rs1 = RandomizedSearchCV(lr_svm, param_distributions=parameters,random_state = 42)
lr_svm_rs1.fit(X_train, y_train)

y_pred = lr_svm_rs.predict(X_test)
# Data Imbalance prediction
y_pred1 = lr_svm_rs1.predict(X_test)


# Data Imbalance
lr_svm_accuracy1 = accuracy_score(y_true=y_test, y_pred=y_pred1)
print("# Data Imbalance")
print("Accuracy using linear SVM : ",lr_svm_accuracy1)
cm = confusion_matrix(y_test.values,y_pred1)
print("Confusion Matrix:")
print(cm)
TP =cm[0][0]
TN =cm[1][1]
FN = cm[1][0]
FP = cm[0][1]

precision=TP/(TP+FP)
recall= TP/(TP+FN)
F1=(2*precision*recall)/(precision+recall)
print("precision:",precision)
print("Recall:",recall)
print("F1_score:",F1)
```

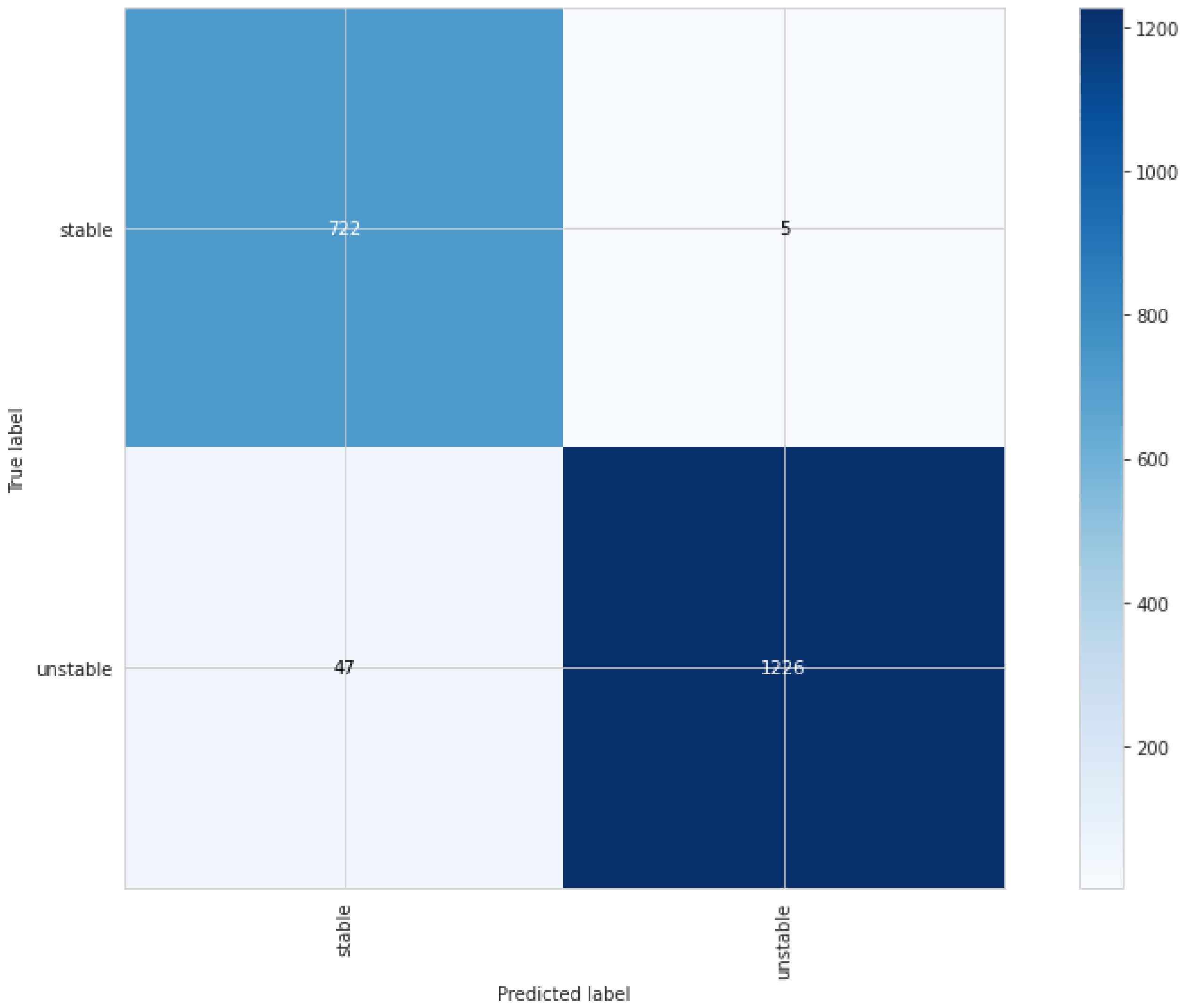
```
# Data Imbalance
Accuracy using linear SVM :  0.9865
Confusion Matrix:
[[ 708   19]
 [   8 1265]]
precision: 0.9738651994497937
Recall: 0.9888268156424581
F1_score: 0.9812889812889813
```

```
# Balance data
lr_svm_accuracy = accuracy_score(y_true=y_test, y_pred=y_pred)
print("Balance Data")
print("Accuracy using linear SVM : ",lr_svm_accuracy)
cm = confusion_matrix(y_test.values,y_pred)
print("Confusion Matrix:")
print(cm)
TP =cm[0][0]
TN =cm[1][1]
FN = cm[1][0]
FP = cm[0][1]

precision=TP/(TP+FP)
recall= TP/(TP+FN)
F1=(2*precision*recall)/(precision+recall)
print("precision:",precision)
print("Recall:",recall)
```

```
print("F1_score:",F1)
```

```
Balance Data
Accuracy using linear SVM :  0.974
Confusion Matrix:
[[ 722    5]
 [  47 1226]]
precision: 0.9931224209078404
Recall: 0.9388816644993498
F1_score: 0.9652406417112299
```

```
plot_confusion_matrix(cm, np.unique(y_pred)) # plotting confusion matrix
```




```
# getting best random search attributes
get_best_randomsearch_results(lr_svm_rs)
```

```
Best estimator :  LinearSVC(C=1, class_weight=None, dual=True, fit_intercept=True,
          intercept_scaling=1, loss='squared_hinge', max_iter=1000,
          multi_class='ovr', penalty='l2', random_state=None, tol=5e-05,
          verbose=0)
Best set of parameters :  {'C': 1}
Best score :  0.9781679685009322
```