```
#Importing necessary libraries
import numpy as np
import pandas as pd
import seaborn as sns
from random import randint
import matplotlib.pyplot as plt

#Importing machine learning algorithms and other modules
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.model_selection import StratifiedKFold
from imblearn.pipeline import make_pipeline as imbalanced_make_pipeline
from imblearn.over_sampling import SMOTE
from sklearn.model_selection import RandomizedSearchCV
from sklearn.metrics import classification_report, confusion_matrix, f1_score,accuracy_score, precision_score, recall_score, roc_auc_scor

#for selecting the top k best features based on statistical analysis
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import f_classif

#Ignore warnings
import warnings
warnings.filterwarnings("ignore")


#Read the dataset and clean column names
data = pd.read_csv("/content/data.csv")
data.columns = [i.title().strip() for i in list(data.columns)]

#Print the number of rows and columns in the dataset
row = data.shape[0]
col = data.shape[1]
print("The number of rows within the dataset are {} and the number of columns is {}".format(row,col))
```

```
The number of rows within the dataset are 6819 and the number of columns is 96
```

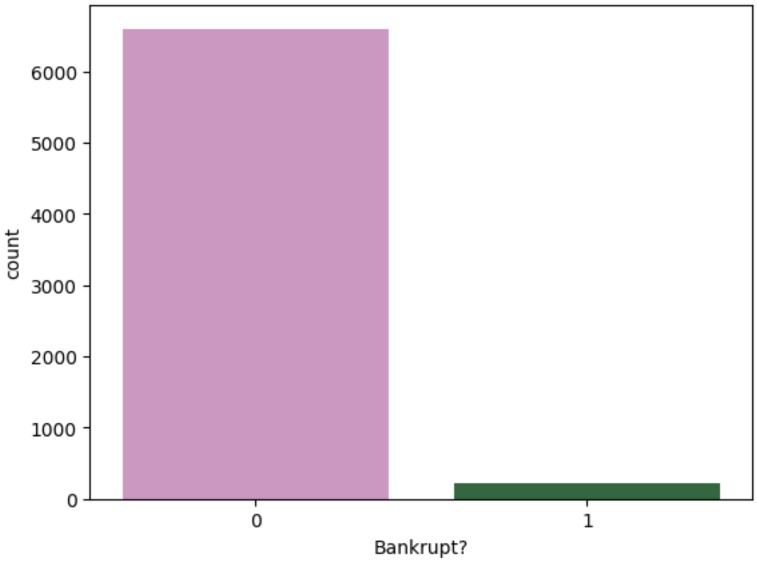
```
#Check for missing values in the dataset
data.isnull().sum().sort_values(ascending=False).head()
```

```
Bankrupt?                                                 0
Roa(C) Before Interest And Depreciation Before Interest   0
Total Expense/Assets                                      0
Total Income/Total Expense                                0
Retained Earnings To Total Assets                         0
dtype: int64
```

```
#Define a list of colors for plotting
colors = ['Accent', 'Accent_r', 'Blues', 'Blues_r', 'BrBG', 'BrBG_r', 'BuGn', 'BuGn_r', 'BuPu', 'BuPu_r', 'CMRmap',
          'CMRmap_r', 'Dark2', 'Dark2_r', 'GnBu', 'GnBu_r', 'Greens', 'Greens_r', 'Greys', 'Greys_r', 'OrRd', 'OrRd_r',
          'Oranges', 'Oranges_r', 'PRGn', 'PRGn_r', 'Paired', 'Paired_r', 'Pastel1', 'Pastel1_r', 'Pastel2', 'Pastel2_r',
          'PiYG', 'PiYG_r', 'PuBu', 'PuBuGn', 'PuBuGn_r', 'PuBu_r', 'PuOr', 'PuOr_r', 'PuRd', 'PuRd_r', 'Purples', 'Purples_r',
          'RdBu', 'RdBu_r', 'RdGy', 'RdGy_r', 'RdPu', 'RdPu_r', 'RdYlBu', 'RdYlBu_r', 'RdYlGn', 'RdYlGn_r', 'Reds', 'Reds_r',
          'Set1', 'Set1_r', 'Set2', 'Set2_r', 'Set3', 'Set3_r', 'Spectral', 'Spectral_r', 'Wistia', 'Wistia_r', 'YlGn', 'YlGnBu',
          'YlGnBu_r', 'YlGn_r', 'YlOrBr', 'YlOrBr_r', 'YlOrRd', 'YlOrRd_r', 'afmhot', 'afmhot_r', 'autumn', 'autumn_r', 'binary',
          'binary_r', 'bone', 'bone_r', 'brg', 'brg_r', 'bwr', 'bwr_r', 'cividis', 'cividis_r', 'cool', 'cool_r', 'coolwarm',
          'coolwarm_r', 'copper', 'copper_r', 'crest', 'crest_r', 'cubehelix', 'cubehelix_r', 'flag', 'flag_r', 'flare',
          'flare_r', 'gist_earth', 'gist_earth_r', 'gist_gray', 'gist_gray_r', 'gist_heat', 'gist_heat_r', 'gist_ncar',
          'gist_ncar_r', 'gist_rainbow', 'gist_rainbow_r', 'gist_stern', 'gist_stern_r', 'gist_yarg', 'gist_yarg_r', 'gnuplot',
          'gnuplot2', 'gnuplot2_r', 'gnuplot_r', 'gray', 'gray_r', 'hot', 'hot_r', 'hsv', 'hsv_r', 'icefire', 'icefire_r',
          'inferno', 'inferno_r', 'jet', 'jet_r', 'magma', 'magma_r', 'mako', 'mako_r', 'nipy_spectral', 'nipy_spectral_r',
          'ocean', 'ocean_r', 'pink', 'pink_r', 'plasma', 'plasma_r', 'prism', 'prism_r', 'rainbow', 'rainbow_r', 'rocket',
          'rocket_r', 'seismic', 'seismic_r', 'spring', 'spring_r', 'summer', 'summer_r', 'tab10', 'tab10_r', 'tab20',
          'tab20_r', 'tab20b', 'tab20b_r', 'tab20c', 'tab20c_r', 'terrain', 'terrain_r', 'turbo', 'turbo_r', 'twilight',
          'twilight_r', 'twilight_shifted', 'twilight_shifted_r', 'viridis', 'viridis_r', 'vlag', 'vlag_r', 'winter', 'winter_r']
```

```
#Visualize the target variable using a countplot
value = randint(0, len(colors)-1)
import seaborn as sns

x = 'Bankrupt?'
y = 'count'

if x is not None:
    sns.countplot(x=x, data=data, palette=colors[value])
elif y is not None:
    sns.countplot(y=y, data=data, palette=colors[value])
```

```
else:
    print("Please specify either x or y for the countplot.")
```

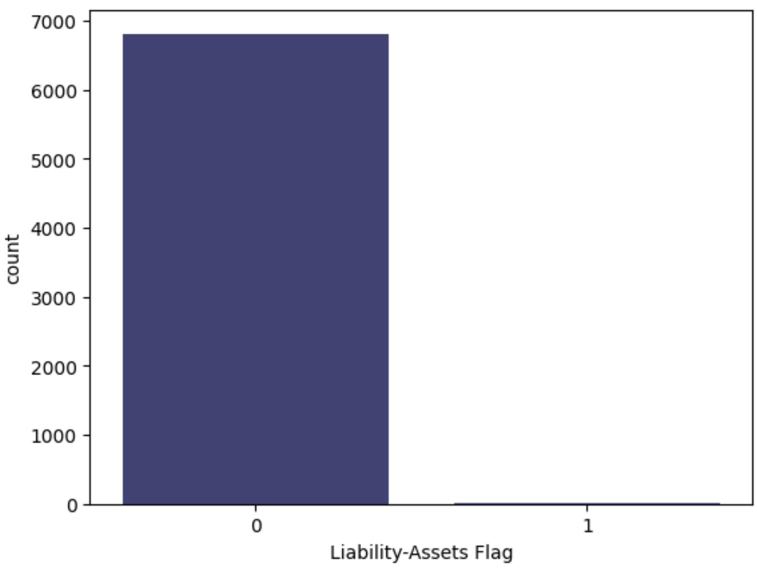



```
#Separate the numeric and categorical features
numeric_features = data.dtypes[data.dtypes != 'int64'].index
categorical_features = data.dtypes[data.dtypes == 'int64'].index

data[categorical_features].columns.tolist()
```

```
['Bankrupt?', 'Liability-Assets Flag', 'Net Income Flag']
```

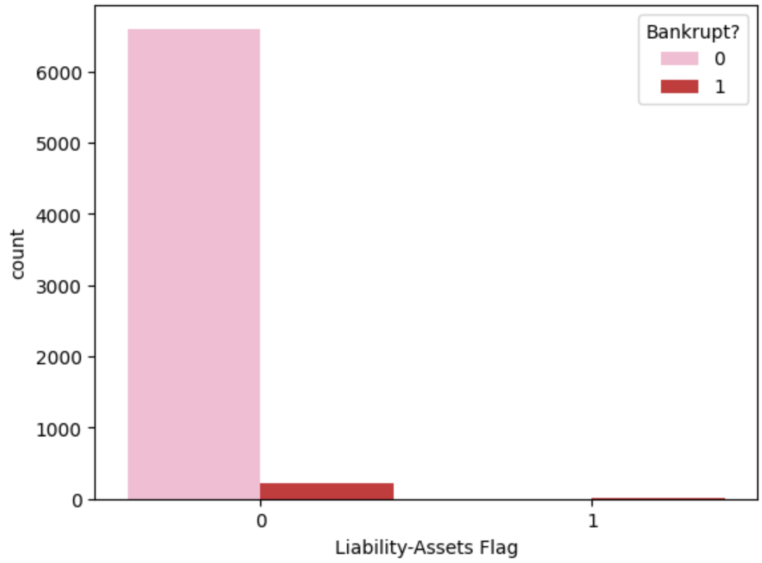
```
#Plot a countplot for a specific categorical feature:Liability-Assets Flag
value = randint(0, len(colors)-1)

print(data['Liability-Assets Flag'].value_counts())

import seaborn as sns

x = 'Liability-Assets Flag'
y = 'count'

if x is not None:
    sns.countplot(x=x, data=data, palette=colors[value])
elif y is not None:
    sns.countplot(y=y, data=data, palette=colors[value])
else:
    print("Please specify either x or y for the countplot.")

numeric_features = data.dtypes[data.dtypes != 'int64'].index
categorical_features = data.dtypes[data.dtypes =='int64'].index
```

```
0    6811
1       8
Name: Liability-Assets Flag, dtype: int64
```



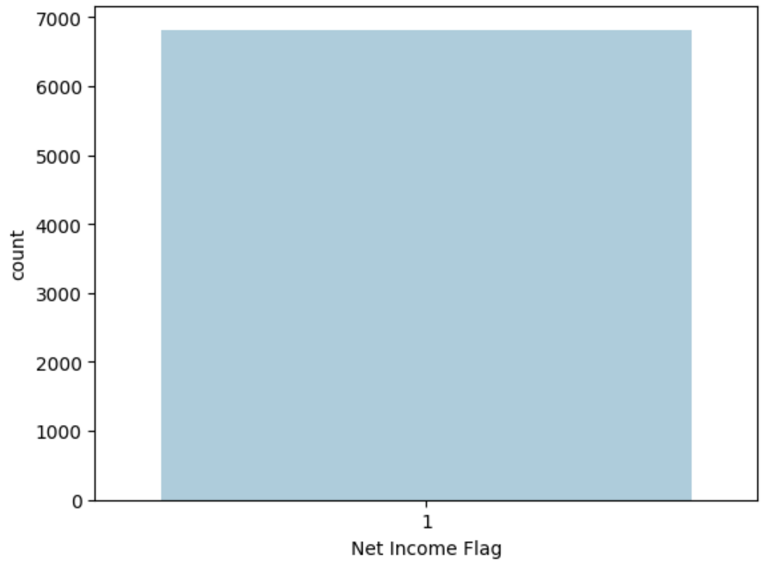
```
#Visualize the relationship between two categorical features using a countplot
value = randint(0, len(colors)-1)

print(data[['Liability-Assets Flag','Bankrupt?']].value_counts())
sns.countplot(x = 'Liability-Assets Flag',hue = 'Bankrupt?',data = data,palette = colors[value])
```

```
Liability-Assets Flag  Bankrupt?
0                      0            6597
                       1             214
1                      1               6
                       0               2
dtype: int64
<Axes: xlabel='Liability-Assets Flag', ylabel='count'>
```



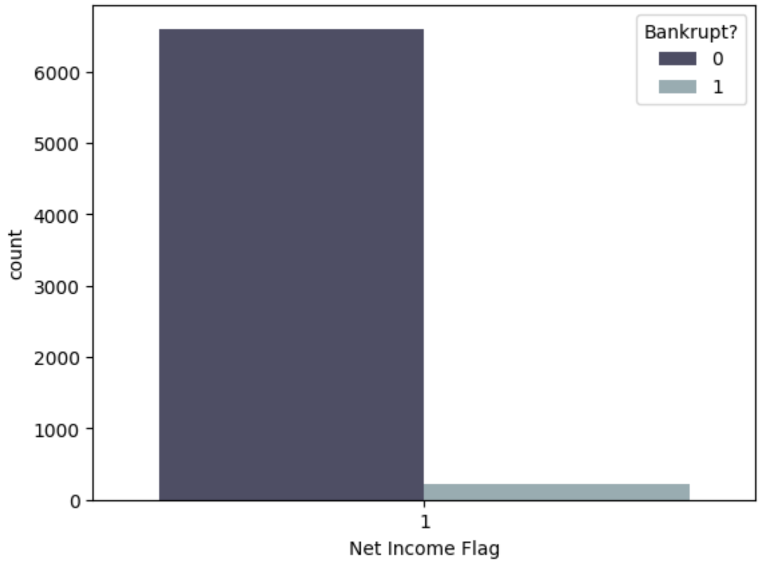

```
#Visualize a numeric feature using a countplot
value = randint(0, len(colors)-1)

print(data['Net Income Flag'].value_counts())
import seaborn as sns

x = 'Net Income Flag'
y = 'count'

if x is not None:
    sns.countplot(x=x, data=data, palette=colors[value])
elif y is not None:
    sns.countplot(y=y, data=data, palette=colors[value])
else:
    print("Please specify either x or y for the countplot.")

numeric_features = data.dtypes[data.dtypes != 'int64'].index
categorical_features = data.dtypes[data.dtypes =='int64'].index
```

```
1    6819
Name: Net Income Flag, dtype: int64
```

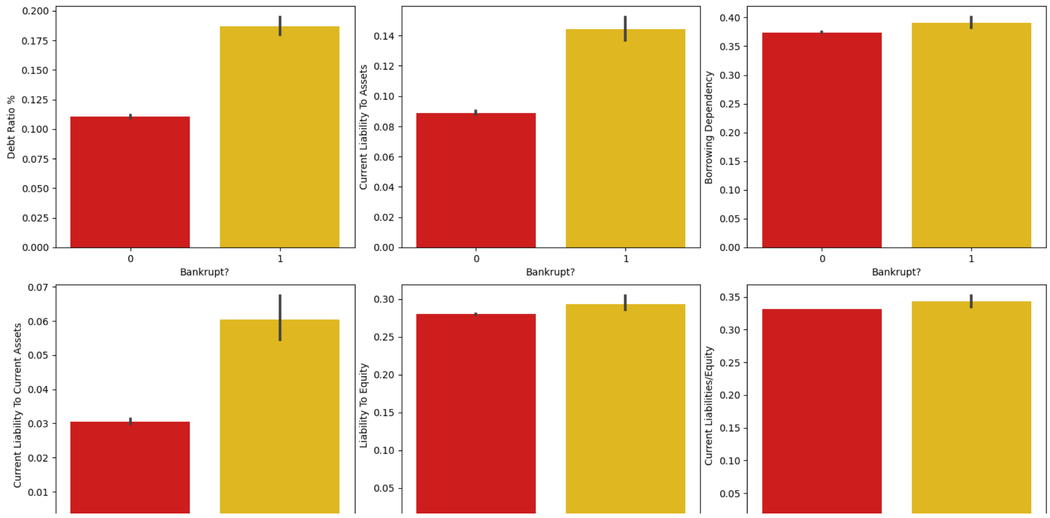


```
#Visualize the relationship between a numeric feature and the target variable using a countplot
value = randint(0, len(colors)-1)

print(data[['Net Income Flag','Bankrupt?']].value_counts())
sns.countplot(x = 'Net Income Flag',hue = 'Bankrupt?',data = data,palette = colors[value])
```

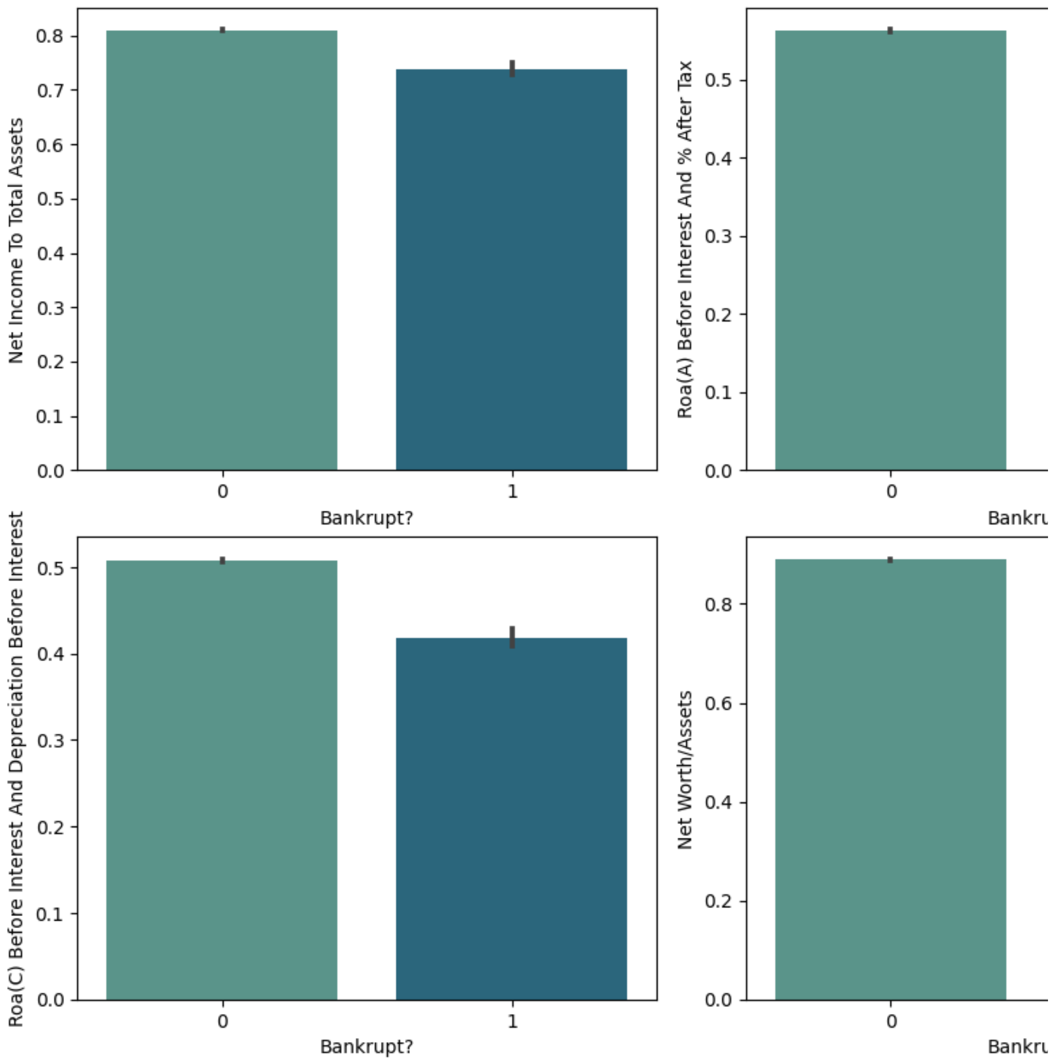
```
Net Income Flag  Bankrupt?
1                0            6599
                 1             220
dtype: int64
<Axes: xlabel='Net Income Flag', ylabel='count'>
```




```
#Identify the top positive and negative correlated features with the 'Bankrupt?' target variable
positive_corr = data[numeric_features].corrwith(data["Bankrupt?"]).sort_values(ascending=False)[:6].index.tolist()
negative_corr = data[numeric_features].corrwith(data["Bankrupt?"]).sort_values()[:6].index.tolist()
#Create new dataframes using the top positive and negative correlated features
positive_corr = data[positive_corr + ["Bankrupt?"]].copy()
negative_corr = data[negative_corr + ["Bankrupt?"]].copy()


#Define a function to create correlation bar graphs
def corrbargraph(x_value, y_value):

    plt.figure(figsize=(15,8))
    value = randint(0, len(colors)-1)

    for i in range(1,7):
        plt.subplot(2,3,i)
        sns.barplot(x = x_value, y = y_value[i-1],data = data,palette = colors[value])

    plt.tight_layout(pad=0.5)


#Plot bar graphs for the positive correlation features
x_value = positive_corr.columns.tolist()[-1]
y_value = positive_corr.columns.tolist()[:-1]

corrbargraph(x_value, y_value)
```

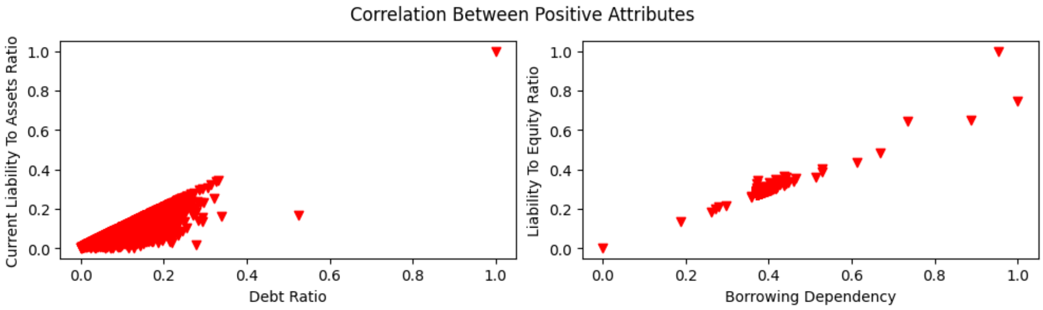



```
#Plot bar graphs for the negative correlation features
x_value = negative_corr.columns.tolist()[-1]
y_value = negative_corr.columns.tolist()[:-1]

corrbargraph(x_value, y_value)
```

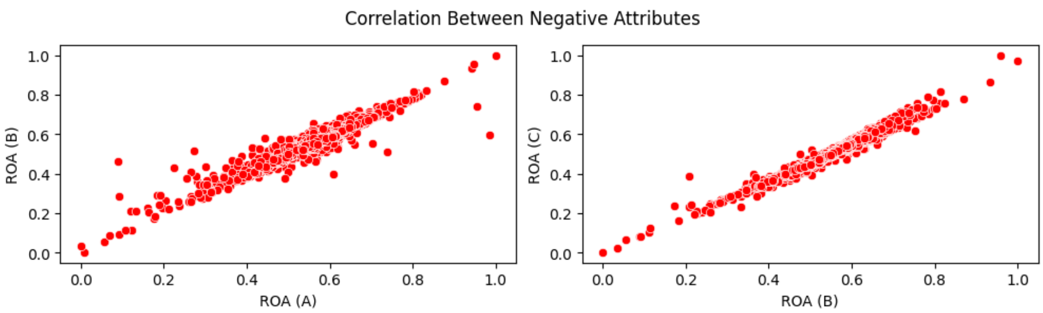



```
#Plot scatter plots for correlations between positive attributes
plt.figure(figsize=(10,3))

plt.suptitle("Correlation Between Positive Attributes")

plt.subplot(1,2,1)
plt.xlabel("Debt Ratio")
plt.ylabel("Current Liability To Assets Ratio")
plt.scatter(data["Debt Ratio %"],data["Current Liability To Assets"], marker='v',color = 'red')
```

```
plt.subplot(1,2,2)
plt.xlabel("Borrowing Dependency")
plt.ylabel("Liability To Equity Ratio")
plt.scatter(data["Borrowing Dependency"],data["Liability To Equity"], marker='v',color = 'red')

plt.tight_layout(pad=0.8)
```

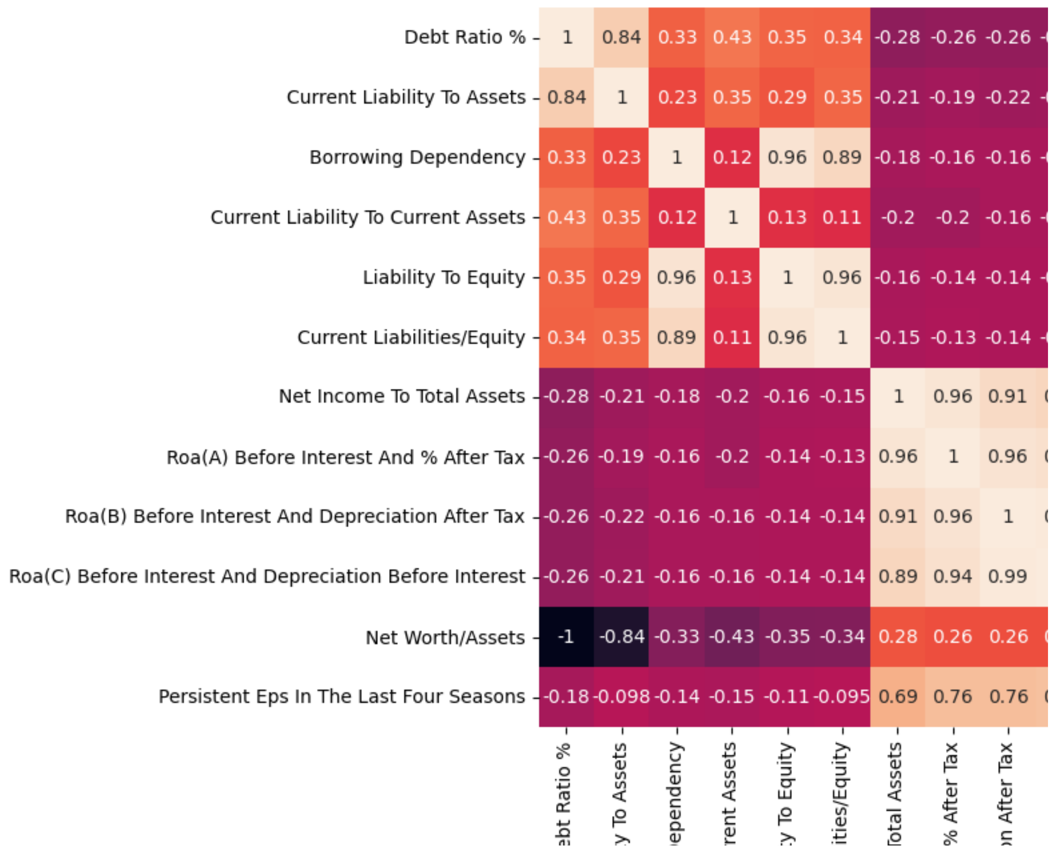



```
##Plot scatter plots for correlations between negative attributes
plt.figure(figsize=(10,3))

plt.suptitle("Correlation Between Negative Attributes")

plt.subplot(1,2,1)
plt.xlabel("ROA (A)")
plt.ylabel("ROA (B)")
sns.scatterplot(data=data, x='Roa(A) Before Interest And % After Tax', y='Roa(B) Before Interest And Depreciation After Tax',color = 'rec

plt.subplot(1,2,2)
plt.xlabel("ROA (B)")
plt.ylabel("ROA (C)")
sns.scatterplot(data=data, x='Roa(B) Before Interest And Depreciation After Tax', y='Roa(C) Before Interest And Depreciation Before

plt.tight_layout(pad=0.8)
```




```
#Plot a heatmap of the correlation matrix between selected attributes
relation = positive_corr.columns.tolist()[:-1] + negative_corr.columns.tolist()[:-1]
plt.figure(figsize=(8,7))
sns.heatmap(data[relation].corr(),annot=True)
```

<Axes: >




```
#data modelling
#Preprocess the numeric features
numeric_features = data.dtypes[data.dtypes != 'int64'].index
data[numeric_features] = data[numeric_features].apply(lambda x: (x - x.mean()) / (x.std()))
#Fill missing values in the numeric features
data[numeric_features] = data[numeric_features].fillna(0)


#Define a DataFrame to store model evaluation metrics
Models = pd.DataFrame(columns=['Algorithm','Model Score','Precision','Recall','F1 score','ROC-AUC score'])
#Define a function for training models without feature selection
def taining_without_feature_selection(Parameters, Model, Dataframe, Modelname):

    data = Dataframe.copy()

    X = data.drop('Bankrupt?', axis=1)
    y = data['Bankrupt?']

#Traditional split of the dataset 80% - 20%
    x_train, x_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

    x_train, x_test, y_train, y_test = x_train.values, x_test.values, y_train.values, y_test.values
#Proportional split of 80% data with respect to the class of the target feature ie. [1,0]
    sf = StratifiedKFold(n_splits=5, random_state=None, shuffle=False)

    for train_index, test_index in sf.split(x_train, y_train):
        sf_x_train, sf_x_test = X.iloc[train_index], X.iloc[test_index]
        sf_y_train, sf_y_test = y.iloc[train_index], y.iloc[test_index]

    sf_x_train, sf_x_test, sf_y_train, sf_y_test = sf_x_train.values, sf_x_test.values, sf_y_train.values, sf_y_test.values

    model_parameter_sm = Parameters

    rand_model = RandomizedSearchCV(Model, model_parameter_sm, n_iter=4)

#Identifying the best parameters through RandomizedSearchCV()
    for train, test in sf.split(sf_x_train, sf_y_train):
        pipeline = imbalanced_make_pipeline(SMOTE(sampling_strategy='minority'), rand_model)
        fitting_model = pipeline.fit(sf_x_train[train], sf_y_train[train])
        best_model = rand_model.best_estimator_
 #Evaluation with against 20% unseen testing data
    print()
    print("Evaluation Of Models")

    sm = SMOTE(sampling_strategy='minority', random_state=42)
    Xsm_train, ysm_train = sm.fit_resample(sf_x_train, sf_y_train)
```

```
    print()
    print("Random Model Evaluation")

    final_model_sm = rand_model.best_estimator_
    final_model_sm.fit(Xsm_train, ysm_train)

    prediction = final_model_sm.predict(x_test)

    print(classification_report(y_test, prediction))
    model = {}

    model['Algorithm'] = Modelname
    model['Model Score'] = str(round((accuracy_score(y_test, prediction)*100),2)) + "%"
    model['Precision'] = round(precision_score(y_test, prediction),2)
    model['Recall'] = round(recall_score(y_test, prediction),2)
    model['F1 score'] = round(f1_score(y_test, prediction),2)
    model['ROC-AUC score'] = round(roc_auc_score(y_test, prediction),2)

    return model
```

```
#Train and evaluate the K Nearest Neighbors model without feature selection:
print("K Nearest Neighbour")
TrainedModel = taining_without_feature_selection({"n_neighbors": list(range(2,5,1)), 'algorithm': ['auto', 'ball_tree', 'kd_tree', 'brute
Models = Models.append(TrainedModel,ignore_index=True)
```

```
K Nearest Neighbour

Evaluation Of Models

Random Model Evaluation
              precision    recall  f1-score   support

           0       1.00      0.98      0.99      1313
           1       0.67      0.94      0.78        51

    accuracy                           0.98      1364
   macro avg       0.83      0.96      0.89      1364
weighted avg       0.99      0.98      0.98      1364
```

```
#Train and evaluate the Logistic Regression model without feature selection
print("Logistic Regression")
TrainedModel = taining_without_feature_selection({"penalty": ['l2'], 'C': [0.001, 0.01, 0.1, 1, 10, 100, 1000]}, LogisticRegression(
Models = Models.append(TrainedModel,ignore_index=True)
```

```
Logistic Regression

Evaluation Of Models

Random Model Evaluation
              precision    recall  f1-score   support

           0       0.99      0.89      0.94      1313
           1       0.23      0.82      0.36        51

    accuracy                           0.89      1364
   macro avg       0.61      0.86      0.65      1364
weighted avg       0.96      0.89      0.92      1364
```

```
#Train and evaluate the Decision Tree Classifier model without feature selection
print("DecisionTree Classifier")
TrainedModel = taining_without_feature_selection({"criterion": ["gini", "entropy"], "max_depth": list(range(2,4,1)),"min_samples_leaf": [
Models = Models.append(TrainedModel,ignore_index=True)
```

```
DecisionTree Classifier

Evaluation Of Models

Random Model Evaluation
              precision    recall  f1-score   support

           0       1.00      0.84      0.91      1313
           1       0.18      0.90      0.31        51

    accuracy                           0.85      1364
   macro avg       0.59      0.87      0.61      1364
weighted avg       0.97      0.85      0.89      1364
```

```
#Train and evaluate the Random Forest Classifier model without feature selection
print("Random Forest Classifier")
```

```
TrainedModel = taining_without_feature_selection({"max_depth": [3, 5, 10, None],"n_estimators": [100, 200, 300, 400, 500]},  RandomForest
Models = Models.append(TrainedModel,ignore_index=True)
```

```
Random Forest Classifier

Evaluation Of Models

Random Model Evaluation
              precision    recall  f1-score   support

           0       1.00      0.96      0.98      1313
           1       0.46      0.96      0.62        51

    accuracy                           0.96      1364
   macro avg       0.73      0.96      0.80      1364
weighted avg       0.98      0.96      0.96      1364
```

```
#Train and evaluate the Support Vector Classifier model without feature selection
print("Support Vector Classifier")
TrainedModel = taining_without_feature_selection({'C': [1,10,20],'kernel': ['rbf','linear']},  SVC(), data, "Support Vector Classifier")
Models = Models.append(TrainedModel,ignore_index=True)
```

```
Support Vector Classifier

Evaluation Of Models

Random Model Evaluation
              precision    recall  f1-score   support

           0       1.00      0.96      0.98      1313
           1       0.47      0.90      0.62        51

    accuracy                           0.96      1364
   macro avg       0.73      0.93      0.80      1364
weighted avg       0.98      0.96      0.96      1364
```

```
#Sort the models based on the F1 score
Models.sort_values('F1 score',ascending=False)
```

	Algorithm	Model Score	Precision	Recall	F1 score	ROC-AUC score
0	K Nearest Neighbour	98.02%	0.67	0.94	0.78	0.96
3	Random Forest Classifier	95.6%	0.46	0.96	0.62	0.96
4	Support Vector Classifier	95.82%	0.47	0.90	0.62	0.93
1	Logistic Regression	89.22%	0.23	0.82	0.36	0.86
2	DecisionTree Classifier	84.68%	0.18	0.90	0.31	0.87

```
#Define a DataFrame to store model evaluation metrics
Models = pd.DataFrame(columns=['Algorithm','Model Score','Precision','Recall','F1 score','ROC-AUC score'])
#Define a function for training models with feature selection
def taining_with_feature_selection(Parameters, Model, Dataframe, Modelname):

    data = Dataframe.copy()

    X = data.drop('Bankrupt?', axis=1)
    y = data['Bankrupt?']

    '''
    Feature Selection Process:
    class sklearn.feature_selection.SelectKBest(score_func=<function>, k=<number of features>
        score_func - Scoring measure
        k - Total features to be returned
    '''
    fs = SelectKBest(score_func=f_classif, k=int((data.shape[1]*85)/100))

    X = fs.fit_transform(X, y)

    X = pd.DataFrame(X)
    y = pd.DataFrame(y)

    x_train, x_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

    x_train, x_test, y_train, y_test = x_train.values, x_test.values, y_train.values, y_test.values

    sf = StratifiedKFold(n_splits=5, random_state=None, shuffle=False)

    for train_index, test_index in sf.split(x_train, y_train):
        sf_x_train, sf_x_test = X.iloc[train_index], X.iloc[test_index]
```

```
        sf_y_train, sf_y_test = y.iloc[train_index], y.iloc[test_index]

    sf_x_train, sf_x_test, sf_y_train, sf_y_test = sf_x_train.values, sf_x_test.values, sf_y_train.values, sf_y_test.values

    model_parameter_sm = Parameters

    rand_model = RandomizedSearchCV(Model, model_parameter_sm, n_iter=4)

    for train, test in sf.split(sf_x_train, sf_y_train):
        pipeline = imbalanced_make_pipeline(SMOTE(sampling_strategy='minority'), rand_model)
        fitting_model = pipeline.fit(sf_x_train[train], sf_y_train[train])
        best_model = rand_model.best_estimator_

    print()
    print("Evaluation Of Models")

    sm = SMOTE(sampling_strategy='minority', random_state=42)
    Xsm_train, ysm_train = sm.fit_resample(sf_x_train, sf_y_train)

    print()
    print("Random Model Evaluation")
    final_model_sm = rand_model.best_estimator_
    final_model_sm.fit(Xsm_train, ysm_train)

    prediction = final_model_sm.predict(x_test)

    print(classification_report(y_test, prediction))

    model = {}

    model['Algorithm'] = Modelname
    model['Model Score'] = str(round((accuracy_score(y_test, prediction)*100),2)) + "%"
    model['Precision'] = round(precision_score(y_test, prediction),2)
    model['Recall'] = round(recall_score(y_test, prediction),2)
    model['F1 score'] = round(f1_score(y_test, prediction),2)
    model['ROC-AUC score'] = round(roc_auc_score(y_test, prediction),2)

    return model

#Train and evaluate the Random Forest Classifier model with feature selection
print("Random Forest Classifier")
TrainedModel = taining_with_feature_selection({"max_depth": [3, 5, 10, None],"n_estimators": [100, 200, 300, 400, 500]},  RandomFor
Models = Models.append(TrainedModel,ignore_index=True)
```

```
Random Forest Classifier

Evaluation Of Models

Random Model Evaluation
              precision    recall  f1-score   support

           0       1.00      0.99      0.99      1313
           1       0.80      0.92      0.85        51

    accuracy                           0.99      1364
   macro avg       0.90      0.96      0.92      1364
weighted avg       0.99      0.99      0.99      1364
```

```
#Train and evaluate the K Nearest Neighbors model with feature selection:
print("K Nearest Neighbour")
TrainedModel = taining_with_feature_selection({"n_neighbors": list(range(2,5,1)), 'algorithm': ['auto', 'ball_tree', 'kd_tree', 'brute']}
Models = Models.append(TrainedModel,ignore_index=True)
```

```
K Nearest Neighbour

Evaluation Of Models

Random Model Evaluation
              precision    recall  f1-score   support

           0       1.00      0.98      0.99      1313
           1       0.64      0.94      0.76        51

    accuracy                           0.98      1364
   macro avg       0.82      0.96      0.88      1364
weighted avg       0.98      0.98      0.98      1364
```

```
#Sort the models based on the F1 score
Models.sort_values('F1 score',ascending=False)
```

	Algorithm	Model Score	Precision	Recall	F1 score	ROC-AUC score
0	Random Forest Classifier	98.83%	0.80	0.92	0.85	0.96
1	K Nearest Neighbour	97.8%	0.64	0.94	0.76	0.96

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