Company Bankruptcy Prediction Report

Introduction

The dataset comprises financial data from the Taiwan Economic Journal, covering the period from 1999 to 2009. The goal is to predict the likelihood of company bankruptcy, defined by the Taiwan Stock Exchange's business regulations. This prediction is crucial for various stakeholders:

- **Loan Institutions:** Assess risk before granting substantial loans.
- **Companies:** Identify and address internal issues to reduce bankruptcy risk.
- **Customers:** Make informed decisions about whether to start or continue doing business with a company.

Attribute Information

The dataset includes various financial ratios and metrics.

Data Overview

- **Shape:** 6819 records, each with 96 financial features.
- **Class Distribution:** Just over 3% of the records indicate bankruptcy.

Oversampling

To address the class imbalance, SMOTE (Synthetic Minority Over-sampling Technique) was applied.

Modeling

Random Forest Classifier

- **Performance:** Achieved a high accuracy of 88.6% on the validation set.

- **Parameters:** The best-performing model used entropy criterion and specific settings for tree complexity and number of trees.

Gradient Boosting Trees

- **Performance:** Achieved an impressive accuracy of 96.1% on the validation set.
- **Parameters:** Utilized squared error as the criterion with optimized learning rate and tree depth settings.

Extreme Gradient Boosting Trees

- **Performance:** The highest accuracy at 96.2% on the validation set.
- **Parameters:** This model used a higher number of trees and a deeper tree structure compared to others.

Extra Trees Classifier

- **Performance:** Accuracy of 94% on the validation set.
- **Parameters:** Focused on maximizing tree depth and number of trees.

Insights

- **Model Performance:** Gradient Boosting and Extreme Gradient Boosting models were more accurate in pinpointing bankruptcy cases compared to Random Forest and Extra Trees models.
- **Trade-offs:** Random Forest and Extra Trees models tended to favour recall (identifying more true bankruptcy cases) at the expense of precision (falsely labelling some non-bankrupt cases as bankrupt).
- **Feature Importance:** In the Extreme Gradient Boost Classifier, the 'After-Tax Net Interest Rate' was significantly more influential than other features.

Conclusions

- **Accuracy vs. Recall:** Tree-based models showed a strong negative correlation between precision and recall. A balance where high recall achieves satisfactory precision is challenging.
- **Model Choice:** For high accuracy in identifying bankruptcies, Gradient Boosting and Extreme Gradient Boosting are preferable. However, for higher recall, Random Forest and Extra Trees might be better suited.
- **Oversampling Effectiveness:** Oversampling enhanced the performance of models prioritizing precision over recall.

This analysis helps stakeholders make informed decisions by predicting the likelihood of bankruptcy, aiding in risk assessment, and identifying potential financial issues within companies.

Module 5 Assignment 2 - Company Bankruptcy Prediction (Kaggle)

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Management/Research Question

In layman's terms, what is the management/research question of interest, and why would anyone care?

Requirements

Conduct your analysis using a cross-validation design and perform or refine previous Exploratory Data Analysis (EDA). Build at least the following models: Random Forest Classifier, Gradient Boosted Trees, and Extra Trees. Conduct hyperparameter tuning for the following parameters: `n_estimators` (number of trees), `max_features` (maximum features considered for splitting a node), `max_depth` (maximum number of levels in each tree), and splitting criteria (entropy or gini). Compare your models using the F1-Score on a 20% validation set. Generate predictions from your models and submit at least two models to Kaggle.com for evaluation, providing your Kaggle.com username and a screenshot of your scores.

Libraries to be loaded:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import KFold, train_test_split,
GridSearchCV, cross_val_score
import seaborn as sns
from sklearn.metrics import confusion_matrix, classification_report,
precision_recall_curve, roc_curve, accuracy_score, mean_squared_error
from sklearn.svm import SVC
from sklearn.naive_bayes import GaussianNB
from imblearn.over_sampling import SMOTE
from sklearn.ensemble import RandomForestClassifier,
GradientBoostingClassifier, ExtraTreesClassifier,
GradientBoostingRegressor
from sklearn.feature_selection import RFE
import xgboost as xgb
pd.set_option('display.max_rows', None)
```

Read Data into Pandas DF

```
train_df = pd.read_csv("data.csv")
train_df.head()
```

```
   Bankrupt?   ROA(C) before interest and depreciation before interest  \
0          1                                           0.370594

1          1                                           0.464291

2          1                                           0.426071

3          1                                           0.399844

4          1                                           0.465022


    ROA(A) before interest and % after tax  \
0                                 0.424389
1                                 0.538214
2                                 0.499019
3                                 0.451265
4                                 0.538432

    ROA(B) before interest and depreciation after tax  \
0                                            0.405750
1                                            0.516730
2                                            0.472295
3                                            0.457733
4                                            0.522298

    Operating Gross Margin   Realized Sales Gross Margin  \
0                 0.601457                      0.601457
1                 0.610235                      0.610235
2                 0.601450                      0.601364
3                 0.583541                      0.583541
4                 0.598783                      0.598783

    Operating Profit Rate   Pre-tax net Interest Rate  \
0                0.998969                    0.796887
1                0.998946                    0.797380
2                0.998857                    0.796403
3                0.998700                    0.796967
4                0.998973                    0.797366

    After-tax net Interest Rate   Non-industry income and
expenditure/revenue  \
0                      0.808809
0.302646
1                      0.809301
```

```
0.303556
2                       0.808388
0.302035
3                       0.808966
0.303350
4                       0.809304
0.303475

   ...   Net Income to Total Assets   Total assets to GNP price  \
0  ...                     0.716845                   0.009219
1  ...                     0.795297                   0.008323
2  ...                     0.774670                   0.040003
3  ...                     0.739555                   0.003252
4  ...                     0.795016                   0.003878

    No-credit Interval   Gross Profit to Sales  \
0             0.622879                0.601453
1             0.623652                0.610237
2             0.623841                0.601449
3             0.622929                0.583538
4             0.623521                0.598782

    Net Income to Stockholder's Equity   Liability to Equity  \
0                             0.827890              0.290202
1                             0.839969              0.283846
2                             0.836774              0.290189
3                             0.834697              0.281721
4                             0.839973              0.278514

    Degree of Financial Leverage (DFL)  \
0                             0.026601
1                             0.264577
2                             0.026555
3                             0.026697
4                             0.024752

    Interest Coverage Ratio (Interest expense to EBIT)   Net Income
Flag  \
0                                            0.564050
1
1                                            0.570175
1
2                                            0.563706
1
3                                            0.564663
1
4                                            0.575617
1

    Equity to Liability
```

```
0               0.016469
1               0.020794
2               0.016474
3               0.023982
4               0.035490

[5 rows x 96 columns]
```

```
train_df.shape
```

```
(6819, 96)
```

```
train_df.describe()
```

```
         Bankrupt?   ROA(C) before interest and depreciation before 
interest  \
count  6819.000000                                        6819.000000   

mean      0.032263                                           0.505180   

std       0.176710                                           0.060686   

min       0.000000                                           0.000000   

25%       0.000000                                           0.476527   

50%       0.000000                                           0.502706   

75%       0.000000                                           0.535563   

max       1.000000                                           1.000000   


        ROA(A) before interest and % after tax  \
count                              6819.000000   
mean                                  0.558625   
std                                   0.065620   
min                                   0.000000   
25%                                   0.535543   
50%                                   0.559802   
75%                                   0.589157   
max                                   1.000000   

        ROA(B) before interest and depreciation after tax  \
count                                        6819.000000   
mean                                            0.553589   
std                                             0.061595   
min                                             0.000000   
25%                                             0.527277   
50%                                             0.552278   
75%                                             0.584105   
```

```
max                                              1.000000

        Operating Gross Margin   Realized Sales Gross Margin  \
count              6819.000000                  6819.000000
mean                  0.607948                     0.607929
std                   0.016934                     0.016916
min                   0.000000                     0.000000
25%                   0.600445                     0.600434
50%                   0.605997                     0.605976
75%                   0.613914                     0.613842
max                   1.000000                     1.000000

        Operating Profit Rate   Pre-tax net Interest Rate  \
count             6819.000000                6819.000000
mean                 0.998755                   0.797190
std                  0.013010                   0.012869
min                  0.000000                   0.000000
25%                  0.998969                   0.797386
50%                  0.999022                   0.797464
75%                  0.999095                   0.797579
max                  1.000000                   1.000000

        After-tax net Interest Rate  \
count                   6819.000000
mean                       0.809084
std                        0.013601
min                        0.000000
25%                        0.809312
50%                        0.809375
75%                        0.809469
max                        1.000000

        Non-industry income and expenditure/revenue  ...  \
count                                   6819.000000  ...
mean                                       0.303623  ...
std                                        0.011163  ...
min                                        0.000000  ...
25%                                        0.303466  ...
50%                                        0.303525  ...
75%                                        0.303585  ...
max                                        1.000000  ...

        Net Income to Total Assets   Total assets to GNP price  \
count                  6819.000000                6.819000e+03
mean                      0.807760                1.862942e+07
std                       0.040332                3.764501e+08
min                       0.000000                0.000000e+00
25%                       0.796750                9.036205e-04
50%                       0.810619                2.085213e-03
75%                       0.826455                5.269777e-03
```

```
max                          1.000000                9.820000e+09

        No-credit Interval   Gross Profit to Sales  \
count          6819.000000             6819.000000
mean              0.623915                0.607946
std               0.012290                0.016934
min               0.000000                0.000000
25%               0.623636                0.600443
50%               0.623879                0.605998
75%               0.624168                0.613913
max               1.000000                1.000000

        Net Income to Stockholder's Equity   Liability to Equity  \
count                          6819.000000           6819.000000
mean                              0.840402              0.280365
std                               0.014523              0.014463
min                               0.000000              0.000000
25%                               0.840115              0.276944
50%                               0.841179              0.278778
75%                               0.842357              0.281449
max                               1.000000              1.000000

        Degree of Financial Leverage (DFL)  \
count                          6819.000000
mean                              0.027541
std                               0.015668
min                               0.000000
25%                               0.026791
50%                               0.026808
75%                               0.026913
max                               1.000000

        Interest Coverage Ratio (Interest expense to EBIT)   Net
Income Flag  \
count                                         6819.000000
6819.0
mean                                             0.565358
1.0
std                                              0.013214
0.0
min                                              0.000000
1.0
25%                                              0.565158
1.0
50%                                              0.565252
1.0
75%                                              0.565725
1.0
max                                              1.000000
1.0
```

```
       Equity to Liability
count          6819.000000
mean              0.047578
std               0.050014
min               0.000000
25%               0.024477
50%               0.033798
75%               0.052838
max               1.000000

[8 rows x 96 columns]
```

EDA

Get dataframe information:

```
train_df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6819 entries, 0 to 6818
Data columns (total 96 columns):
 #   Column                                                    Non-
Null Count  Dtype
---  ------
--------------  -----
 0   Bankrupt?                                                 6819
non-null   int64
 1    ROA(C) before interest and depreciation before interest  6819
non-null   float64
 2    ROA(A) before interest and % after tax                   6819
non-null   float64
 3    ROA(B) before interest and depreciation after tax        6819
non-null   float64
 4    Operating Gross Margin                                   6819
non-null   float64
 5    Realized Sales Gross Margin                              6819
non-null   float64
 6    Operating Profit Rate                                    6819
non-null   float64
 7    Pre-tax net Interest Rate                                6819
non-null   float64
 8    After-tax net Interest Rate                              6819
non-null   float64
 9    Non-industry income and expenditure/revenue              6819
non-null   float64
 10   Continuous interest rate (after tax)                     6819
non-null   float64
 11   Operating Expense Rate                                   6819
```

```
non-null   float64
 12   Research and development expense rate                           6819
non-null   float64
 13   Cash flow rate                                                  6819
non-null   float64
 14   Interest-bearing debt interest rate                             6819
non-null   float64
 15   Tax rate (A)                                                    6819
non-null   float64
 16   Net Value Per Share (B)                                         6819
non-null   float64
 17   Net Value Per Share (A)                                         6819
non-null   float64
 18   Net Value Per Share (C)                                         6819
non-null   float64
 19   Persistent EPS in the Last Four Seasons                         6819
non-null   float64
 20   Cash Flow Per Share                                             6819
non-null   float64
 21   Revenue Per Share (Yuan ¥)                                      6819
non-null   float64
 22   Operating Profit Per Share (Yuan ¥)                             6819
non-null   float64
 23   Per Share Net profit before tax (Yuan ¥)                        6819
non-null   float64
 24   Realized Sales Gross Profit Growth Rate                         6819
non-null   float64
 25   Operating Profit Growth Rate                                    6819
non-null   float64
 26   After-tax Net Profit Growth Rate                                6819
non-null   float64
 27   Regular Net Profit Growth Rate                                  6819
non-null   float64
 28   Continuous Net Profit Growth Rate                               6819
non-null   float64
 29   Total Asset Growth Rate                                         6819
non-null   float64
 30   Net Value Growth Rate                                           6819
non-null   float64
 31   Total Asset Return Growth Rate Ratio                            6819
non-null   float64
 32   Cash Reinvestment %                                             6819
non-null   float64
 33   Current Ratio                                                   6819
non-null   float64
 34   Quick Ratio                                                     6819
non-null   float64
 35   Interest Expense Ratio                                          6819
non-null   float64
```

```
 36   Total debt/Total net worth                                6819
non-null   float64
 37   Debt ratio %                                              6819
non-null   float64
 38   Net worth/Assets                                          6819
non-null   float64
 39   Long-term fund suitability ratio (A)                      6819
non-null   float64
 40   Borrowing dependency                                      6819
non-null   float64
 41   Contingent liabilities/Net worth                          6819
non-null   float64
 42   Operating profit/Paid-in capital                          6819
non-null   float64
 43   Net profit before tax/Paid-in capital                     6819
non-null   float64
 44   Inventory and accounts receivable/Net value               6819
non-null   float64
 45   Total Asset Turnover                                      6819
non-null   float64
 46   Accounts Receivable Turnover                              6819
non-null   float64
 47   Average Collection Days                                   6819
non-null   float64
 48   Inventory Turnover Rate (times)                           6819
non-null   float64
 49   Fixed Assets Turnover Frequency                           6819
non-null   float64
 50   Net Worth Turnover Rate (times)                           6819
non-null   float64
 51   Revenue per person                                        6819
non-null   float64
 52   Operating profit per person                               6819
non-null   float64
 53   Allocation rate per person                                6819
non-null   float64
 54   Working Capital to Total Assets                           6819
non-null   float64
 55   Quick Assets/Total Assets                                 6819
non-null   float64
 56   Current Assets/Total Assets                               6819
non-null   float64
 57   Cash/Total Assets                                         6819
non-null   float64
 58   Quick Assets/Current Liability                            6819
non-null   float64
 59   Cash/Current Liability                                    6819
non-null   float64
 60   Current Liability to Assets                               6819
```

```
non-null   float64
 61   Operating Funds to Liability                                    6819
non-null   float64
 62   Inventory/Working Capital                                       6819
non-null   float64
 63   Inventory/Current Liability                                     6819
non-null   float64
 64   Current Liabilities/Liability                                   6819
non-null   float64
 65   Working Capital/Equity                                          6819
non-null   float64
 66   Current Liabilities/Equity                                      6819
non-null   float64
 67   Long-term Liability to Current Assets                           6819
non-null   float64
 68   Retained Earnings to Total Assets                               6819
non-null   float64
 69   Total income/Total expense                                      6819
non-null   float64
 70   Total expense/Assets                                            6819
non-null   float64
 71   Current Asset Turnover Rate                                     6819
non-null   float64
 72   Quick Asset Turnover Rate                                       6819
non-null   float64
 73   Working capitcal Turnover Rate                                  6819
non-null   float64
 74   Cash Turnover Rate                                              6819
non-null   float64
 75   Cash Flow to Sales                                              6819
non-null   float64
 76   Fixed Assets to Assets                                          6819
non-null   float64
 77   Current Liability to Liability                                  6819
non-null   float64
 78   Current Liability to Equity                                     6819
non-null   float64
 79   Equity to Long-term Liability                                   6819
non-null   float64
 80   Cash Flow to Total Assets                                       6819
non-null   float64
 81   Cash Flow to Liability                                          6819
non-null   float64
 82   CFO to Assets                                                   6819
non-null   float64
 83   Cash Flow to Equity                                             6819
non-null   float64
 84   Current Liability to Current Assets                             6819
non-null   float64
```

```
 85   Liability-Assets Flag                                            6819
non-null   int64
 86   Net Income to Total Assets                                       6819
non-null   float64
 87   Total assets to GNP price                                        6819
non-null   float64
 88   No-credit Interval                                               6819
non-null   float64
 89   Gross Profit to Sales                                            6819
non-null   float64
 90   Net Income to Stockholder's Equity                               6819
non-null   float64
 91   Liability to Equity                                              6819
non-null   float64
 92   Degree of Financial Leverage (DFL)                               6819
non-null   float64
 93   Interest Coverage Ratio (Interest expense to EBIT)               6819
non-null   float64
 94   Net Income Flag                                                  6819
non-null   int64
 95   Equity to Liability                                              6819
non-null   float64
dtypes: float64(93), int64(3)
memory usage: 5.0 MB
```

There are no null values.

```
train_df.isna().sum().sum()

0
```

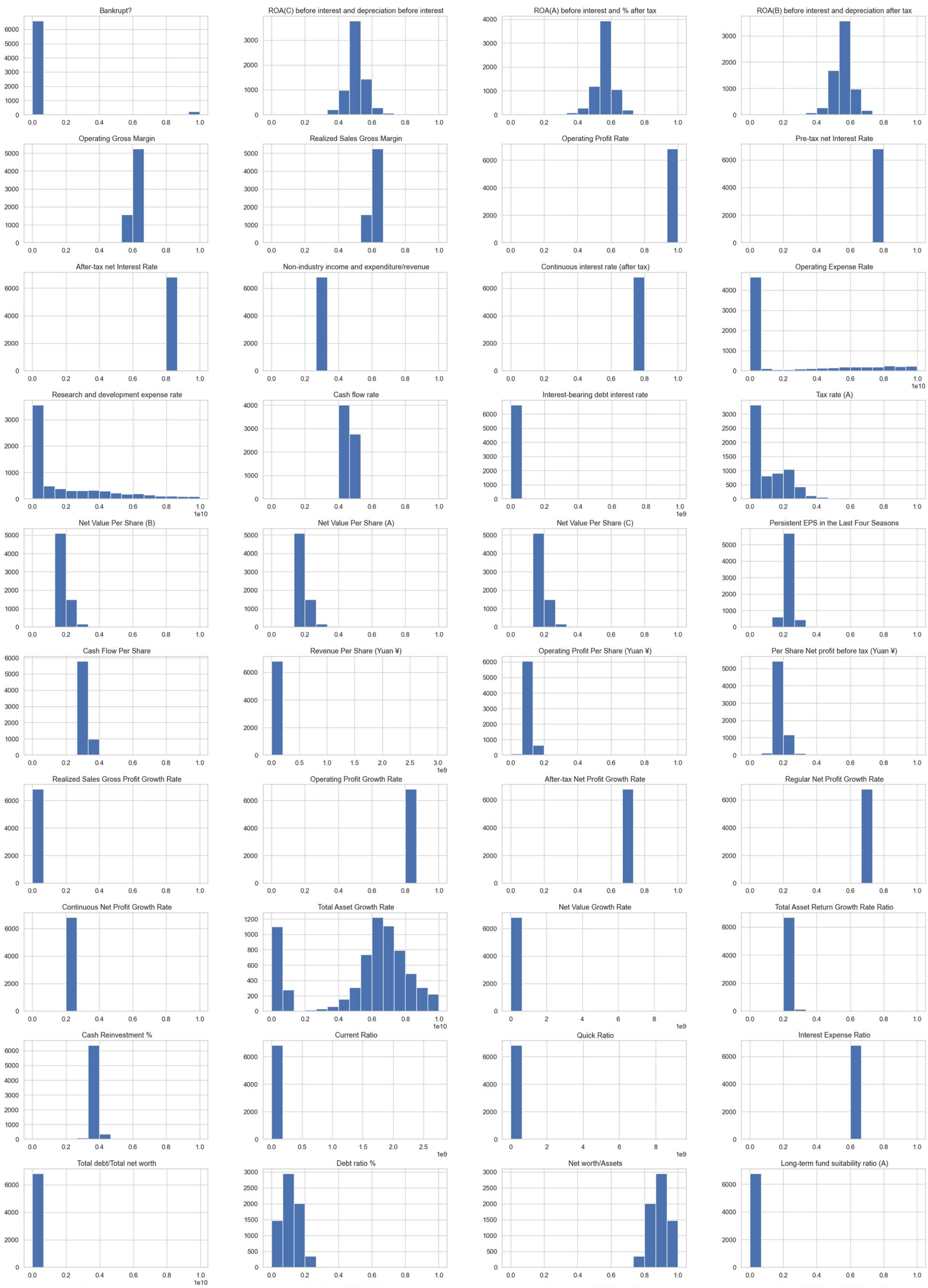
All 96 variables are quantitative variables.

```
# Separate numeric (quantitative) and categorical (nominal) variables
numeric_vars = train_df.select_dtypes(include=['float64',
'int64']).columns.tolist()
categorical_vars =
train_df.select_dtypes(include=['object']).columns.tolist()

print("\nNumeric Variables:")
print(len(numeric_vars))

print("\nCategorical Variables:")
print(len(categorical_vars))


Numeric Variables:
96
```

```
Categorical Variables:
0
```

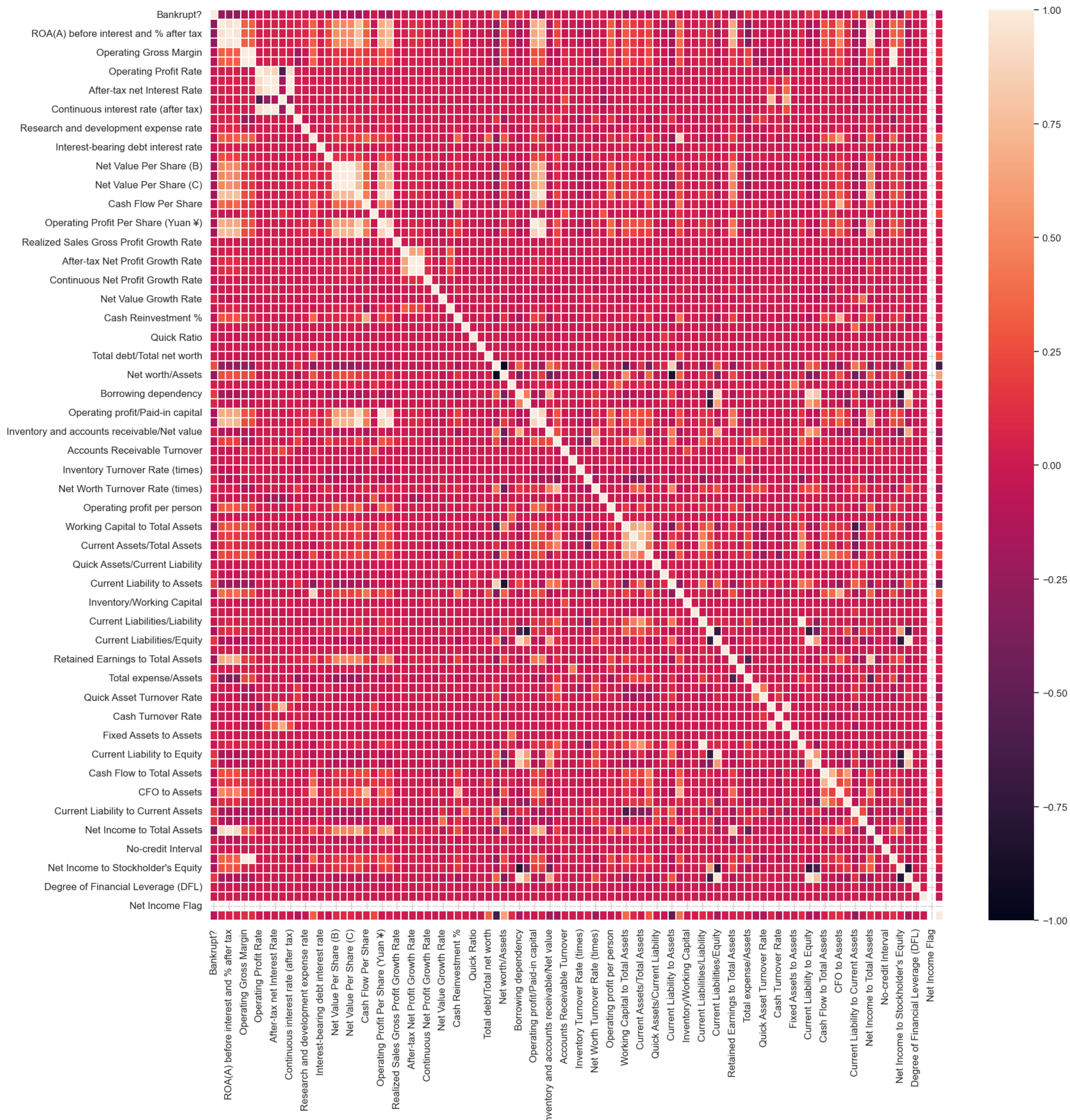
Let's plot a histogram of the variables.

```
sns.set(style='whitegrid', font_scale=1.1, rc={'figure.figsize': [30,
102]})
train_df[train_df.columns].hist(bins=15, layout=(24, 4));
```


Bankrupt?
ROA(C) before interest and depreciation before interest
ROA(A) before interest and % after tax
ROA(B) before interest and depreciation after tax
Operating Gross Margin
Realized Sales Gross Margin
Operating Profit Rate
Pre-tax net Interest Rate
After-tax net Interest Rate
Non-industry income and expenditure/revenue
Continuous interest rate (after tax)
Operating Expense Rate
Research and development expense rate
Cash flow rate
Interest-bearing debt interest rate
Tax rate (A)
Net Value Per Share (B)
Net Value Per Share (A)
Net Value Per Share (C)
Persistent EPS in the Last Four Seasons
Cash Flow Per Share
Revenue Per Share (Yuan ¥)
Operating Profit Per Share (Yuan ¥)
Per Share Net profit before tax (Yuan ¥)
Realized Sales Gross Profit Growth Rate
Operating Profit Growth Rate
After-tax Net Profit Growth Rate
Regular Net Profit Growth Rate
Continuous Net Profit Growth Rate
Total Asset Growth Rate
Net Value Growth Rate
Total Asset Return Growth Rate Ratio
Cash Reinvestment %
Current Ratio
Quick Ratio
Interest Expense Ratio
Total debt/Total net worth
Debt ratio %
Net worth/Assets
Long-term fund suitability ratio (A)
Borrowing dependency
Contingent liabilities/Net worth
Operating profit/Paid-in capital
Net profit before tax/Paid-in capital

Let's create a correlation heatmap.

```
correlation = train_df.corr()
fig, ax = plt.subplots(figsize = (20,20))
sns.heatmap(correlation, ax = ax, linewidth = 0.1);
```

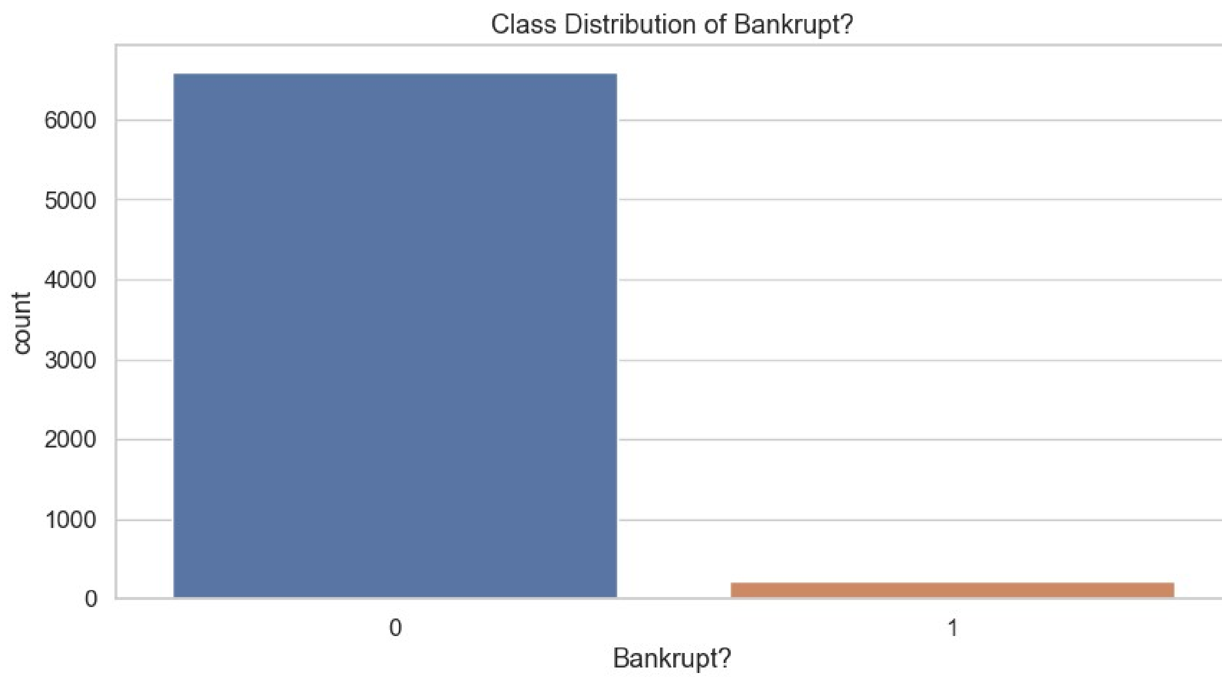


Just over three percent of the data contain rows listed as 'Bankrupt?' (the dependent variable) = 1.

```
total_bankrupt = train_df['Bankrupt?'].sum()
pct_bankrput = total_bankrupt/len(train_df['Bankrupt?'])*100
print('Num bankrupt: %d, %% of sample: %.2f%%' %(total_bankrupt,
pct_bankrput))
```

```
Num bankrupt: 220, % of sample: 3.23%
```

```
sns.set(style='whitegrid', font_scale=1.1, rc={"figure.figsize": [10,
5]})
sns.countplot(x='Bankrupt?', data=train_df);
plt.title('Class Distribution of Bankrupt?')
plt.show();
```




```
print('Financially stable:',
round(train_df['Bankrupt?'].value_counts()[0] / len(train_df) * 100,2)
,'%')
print('Financially unstable:',
round(train_df['Bankrupt?'].value_counts()[1] / len(train_df) * 100,
2), '%')
```

```
Financially stable: 96.77 %
Financially unstable: 3.23 %
```

The data is highly skewed towards financially stable cases. Training a model on this dataset would result in predictions biased towards financial stability.

To address this, we will balance the dataset before training our model.

```
train_df_X = train_df.copy()
train_df_y = train_df_X['Bankrupt?']
train_df_X.drop(['Bankrupt?'], axis=1, inplace=True)

train_df_X.shape
```

```
(6819, 95)
```

Split the train.csv data into 80% training and 20% validation

```
X_train,X_val,y_train,y_val =
train_test_split(train_df_X,train_df_y,test_size=0.2,random_state=42)
```

Oversampling

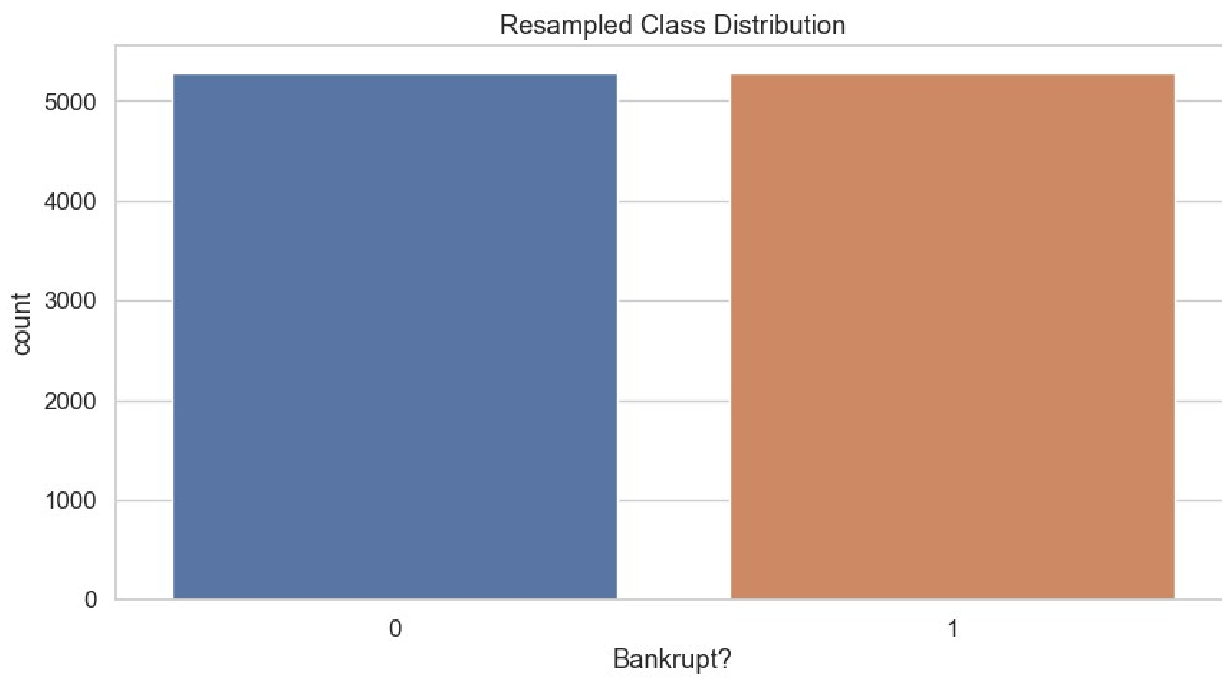
We have the data between 'Bankrupt?' and not 'Bankrupt?'. Let's use Smote for oversampling

```
oversample = SMOTE(random_state=42)
X_train,y_train=oversample.fit_resample(X_train,y_train)

total_bankrupt = y_train.sum()
pct_bankrput = total_bankrupt/len(train_df_y)*100
print('Num bankrupt: %d, %% of sample: %.2f%%' %(total_bankrupt,
pct_bankrput))
```

```
Num bankrupt: 5286, % of sample: 77.52%
```

```
print("Resampled class distribution:\n", y_train.value_counts())
sns.set(style='whitegrid', font_scale=1.1, rc={"figure.figsize": [10,
5]})
sns.countplot(x=y_train)
plt.title('Resampled Class Distribution')
plt.show();
```

```
Resampled class distribution:
 Bankrupt?
0    5286
1    5286
Name: count, dtype: int64
```



MODELING

```
# set up a KFold cross-validation rule
K = 10
kf = KFold(n_splits=K, shuffle=True, random_state=42)
```

Random Forest Classifier

```
rfc_grid = {'n_estimators': [200], 'max_leaf_nodes': [16],
'criterion': ['entropy'],'max_features': ['sqrt']}
rfc_cv = GridSearchCV(RandomForestClassifier(random_state=42),cv=kf,
param_grid=rfc_grid, scoring='r2')
rfc_results = rfc_cv.fit(X_train, y_train)
print("RFC best score", rfc_results.best_score_)
print("RFC best params", rfc_results.best_params_)
```

```
RFC best score 0.7125025858975051
RFC best params {'criterion': 'entropy', 'max_features': 'sqrt',
'max_leaf_nodes': 16, 'n_estimators': 200}
```

```
rfc_n_estimators = rfc_results.best_params_['n_estimators']
rfc_max_leaf_nodes = rfc_results.best_params_['max_leaf_nodes']
rfc_criterion = rfc_results.best_params_['criterion']
rfc_max_features = rfc_results.best_params_['max_features']

score = cross_val_score(RandomForestClassifier(
```

```
            n_estimators=rfc_n_estimators,
max_leaf_nodes=rfc_max_leaf_nodes, criterion=rfc_criterion,
            max_features=rfc_max_features, random_state=42), X_train,
y_train, cv=kf)
print(f'Scores for each fold: {score}')
print("Accuracy: %0.4f " % (score.mean()))
```

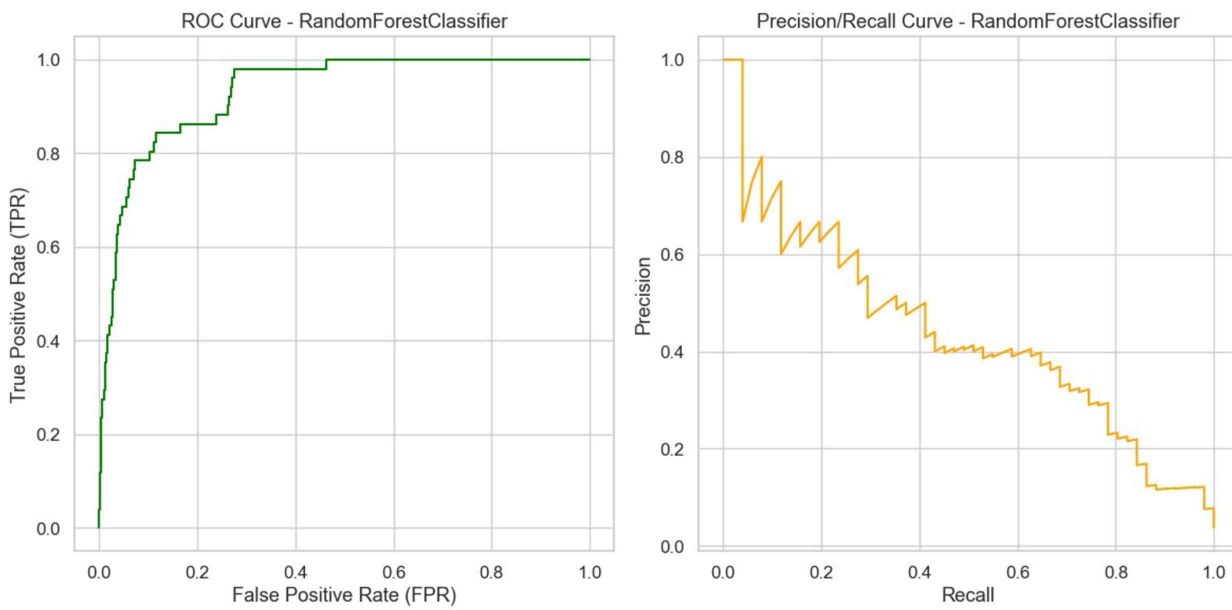
```
Scores for each fold: [0.92060491 0.9168242  0.9243141  0.92999054
0.92999054 0.93472091
 0.92336802 0.94323557 0.92620624 0.93282876]
Accuracy: 0.9282
```

```
rfc_model = RandomForestClassifier(
            n_estimators=rfc_n_estimators,
            max_leaf_nodes=rfc_max_leaf_nodes,
            criterion=rfc_criterion,
            max_features=rfc_max_features,
            random_state=42)
rfc_model.fit(X_train, y_train)
y_pred = rfc_model.predict(X_val)
cm = confusion_matrix(y_val,y_pred)
print('confusion matrix:\n',cm)
print('accuracy score = ',accuracy_score(y_val,y_pred))
print("Classification Report:\n",classification_report(y_val,y_pred))
```

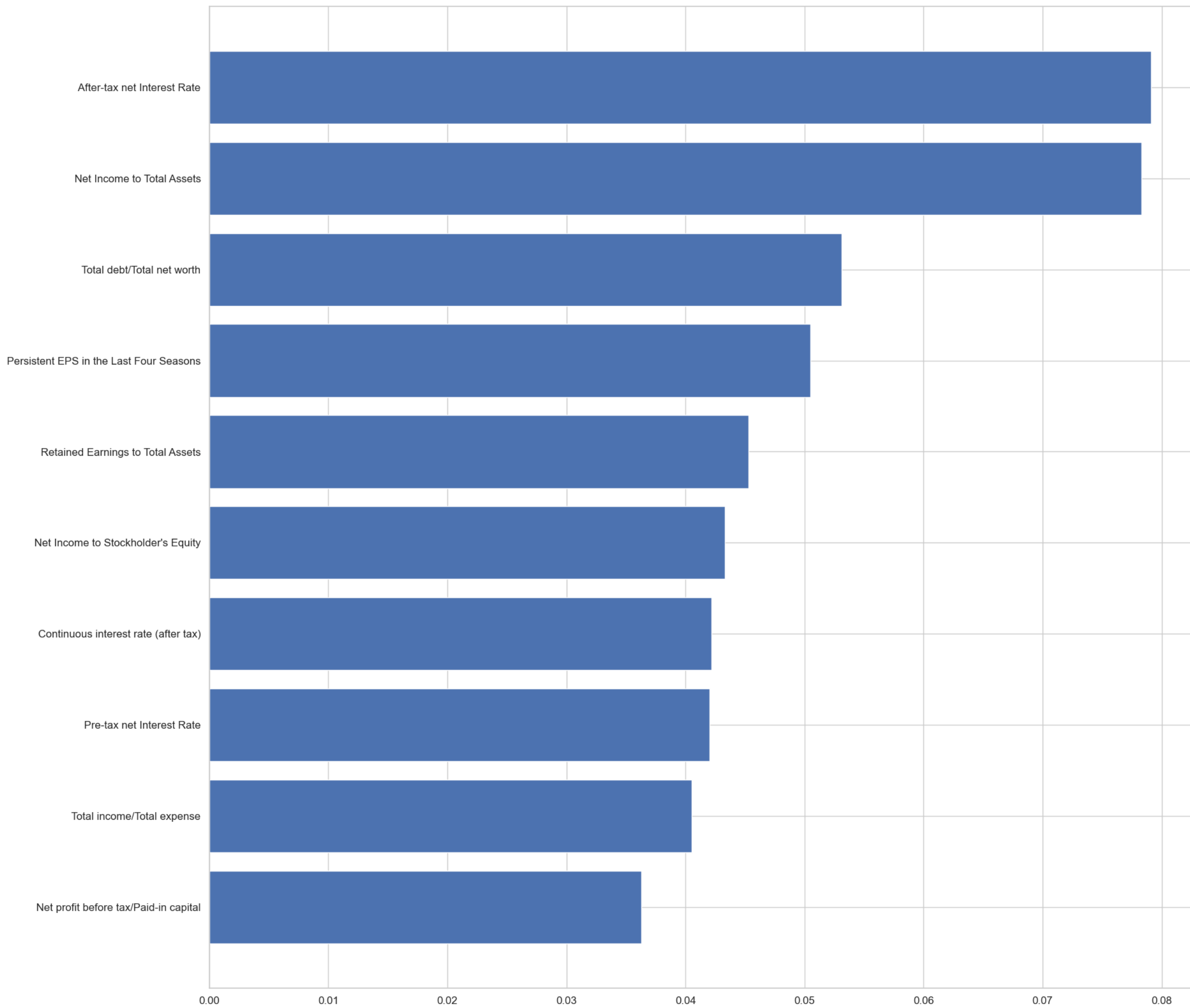
```
confusion matrix:
 [[1168  145]
 [  10   41]]
accuracy score =  0.8863636363636364
Classification Report:
               precision    recall  f1-score   support

           0       0.99      0.89      0.94      1313
           1       0.22      0.80      0.35        51

    accuracy                           0.89      1364
   macro avg       0.61      0.85      0.64      1364
weighted avg       0.96      0.89      0.92      1364
```

```
# Define metrics
y_pred_proba = rfc_model.predict_proba(X_val)[::, 1]
fpr, tpr, _ = roc_curve(y_val, y_pred_proba)
precision, recall, _ = precision_recall_curve(y_val, y_pred_proba)

# Create figure and subplots
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(12, 6))

# ROC Curve
ax1.plot(fpr, tpr, color="green")
ax1.set_title('ROC Curve - RandomForestClassifier')
```

```python
ax1.set_ylabel('True Positive Rate (TPR)')
ax1.set_xlabel('False Positive Rate (FPR)')

# Precision-Recall Curve
ax2.plot(recall, precision, color='orange')
ax2.set_title('Precision/Recall Curve - RandomForestClassifier')
ax2.set_ylabel('Precision')
ax2.set_xlabel('Recall')

# Show plot
plt.tight_layout()
plt.show()
```




```python
#Top 10 features
f_importances_rfc =
pd.Series(np.round(rfc_model.feature_importances_,4),index=X_train.col
umns).sort_values(ascending=False)[:10]
barx=f_importances_rfc.index
bary=f_importances_rfc.values
plt.figure(figsize = (20, 20))
plt.barh(barx, bary)
plt.gca().invert_yaxis()
plt.show()
```



'After-tax Net Interest Rate' accounts for nearly 9% of the oversampled dataset's importance when using the Random Forest Classifier, while 'Net Income to Total Assets' contributes approximately 7% to 8%.

Gradient Boosted Trees

```
gbc_grid = {'n_estimators': [200], 'max_depth': [10], 'learning_rate': [0.5], 'criterion': ['squared_error'], 'max_features': ['sqrt']}
gbc_cv = GridSearchCV(GradientBoostingClassifier(random_state=42), param_grid=gbc_grid, cv=kf, scoring='r2')
gbc_results = gbc_cv.fit(X_train, y_train)
print("GBR best score", gbc_results.best_score_)
print("GBR best params", gbc_results.best_params_)

GBR best score 0.9545422440050235
GBR best params {'criterion': 'squared_error', 'learning_rate': 0.5, 'max_depth': 10, 'max_features': 'sqrt', 'n_estimators': 200}
```

```
gbc_n_estimators = gbc_results.best_params_['n_estimators']
gbc_max_depth = gbc_results.best_params_['max_depth']
gbc_learning_rate = gbc_results.best_params_['learning_rate']
gbc_criterion = gbc_results.best_params_['criterion']
gbc_max_features = gbc_results.best_params_['max_features']

score =
cross_val_score(GradientBoostingClassifier( n_estimators=gbc_n_estimat
ors, max_depth=gbc_max_depth,
            learning_rate=gbc_learning_rate, criterion=gbc_criterion,
max_features=gbc_max_features,
            random_state=42), X_train, y_train, cv=kf)
print(f'Scores for each fold: {score}')
print("Accuracy: %0.4f " % (score.mean()))
```

```
Scores for each fold: [0.98393195 0.98771267 0.98675497 0.98675497
0.98959319 0.98864711
 0.99526963 0.98959319 0.98864711 0.98959319]
Accuracy: 0.9886
```

```
# hypertune n_estimators via early stopping
gbc_model = GradientBoostingClassifier( n_estimators=gbc_n_estimators,
max_depth=gbc_max_depth,
            learning_rate=gbc_learning_rate, criterion=gbc_criterion,
max_features=gbc_max_features, random_state=42)
gbc_model.fit(X_train, y_train)
y_pred = gbc_model.predict(X_val)

errors = [mean_squared_error(y_val, y_pred)
          for y_pred in gbc_model.staged_predict(X_val)]
bst_n_estimators = np.argmin(errors) + 1
bst_n_estimators
```

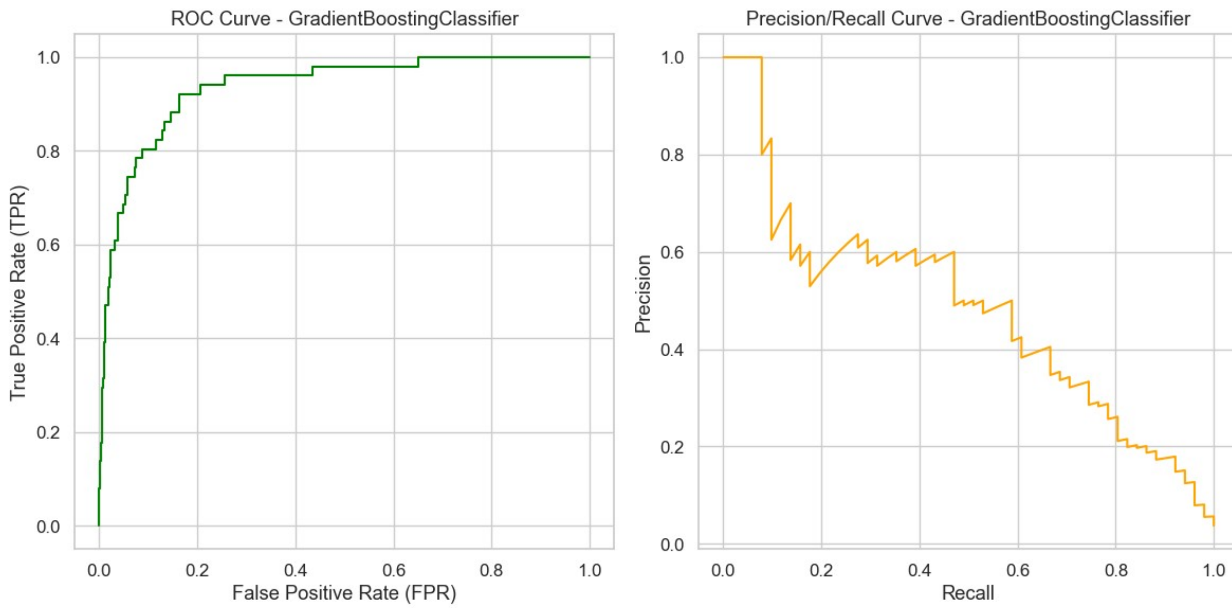
```
63
```

```
gbc_best = GradientBoostingClassifier( n_estimators=bst_n_estimators,
max_depth=gbc_max_depth, learning_rate=gbc_learning_rate,
            criterion=gbc_criterion, max_features=gbc_max_features,
random_state=42)
gbc_best.fit(X_train, y_train)

y_pred = gbc_best.predict(X_val)
cm = confusion_matrix(y_val,y_pred)
print('confusion matrix:\n',cm)
print('accuracy score = ',accuracy_score(y_val,y_pred))
print("Classification Report:\n",classification_report(y_val,y_pred))
```

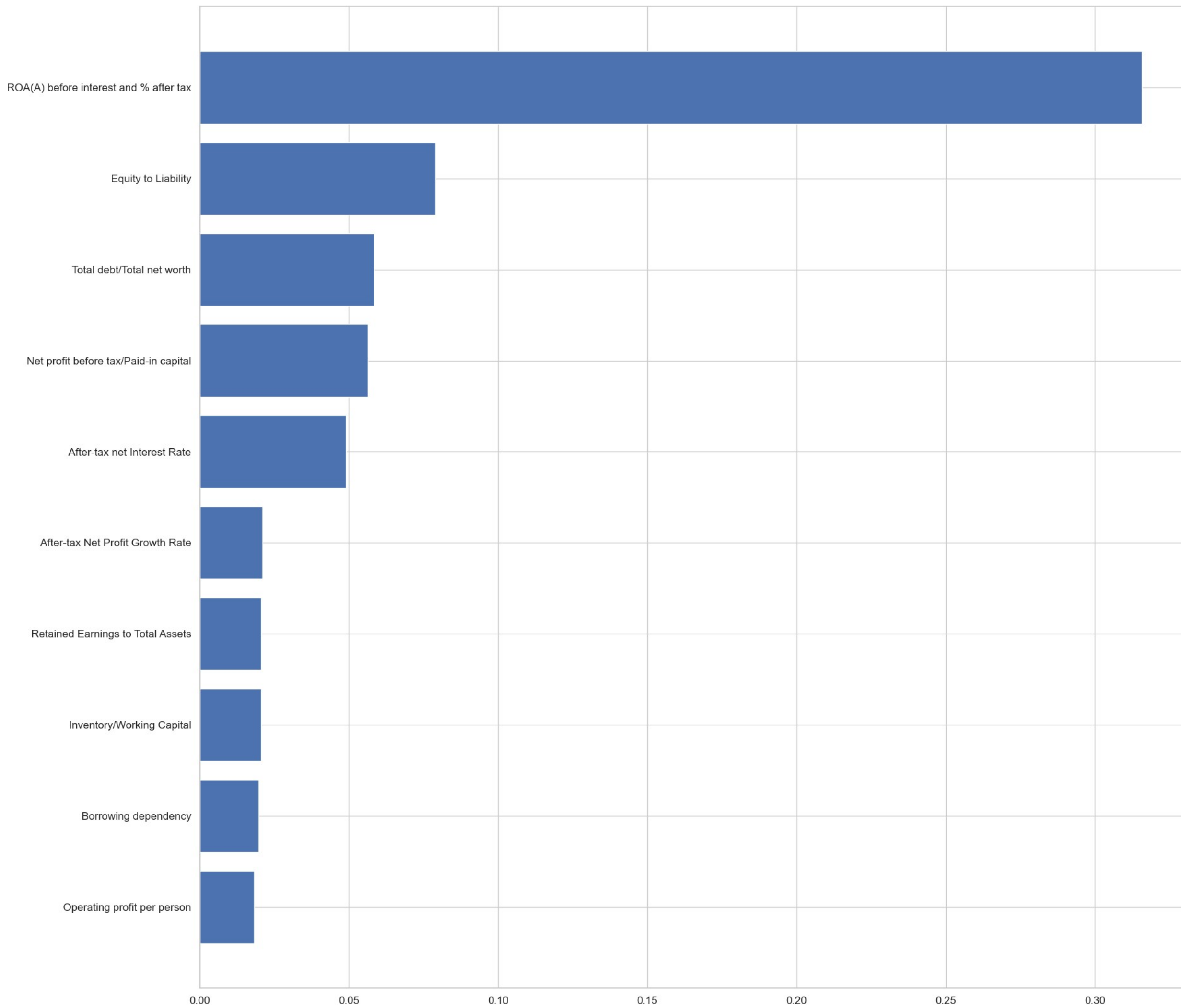
```
confusion matrix:
 [[1282   31]
 [  21   30]]
accuracy score =  0.9618768328445748
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.98      0.98      0.98      1313
           1       0.49      0.59      0.54        51

    accuracy                           0.96      1364
   macro avg       0.74      0.78      0.76      1364
weighted avg       0.97      0.96      0.96      1364
```

```python
# Define metrics
y_pred_proba = gbc_best.predict_proba(X_val)[::, 1]
fpr, tpr, _ = roc_curve(y_val, y_pred_proba)
precision, recall, _ = precision_recall_curve(y_val, y_pred_proba)

# Create figure and subplots
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(12, 6))

# ROC Curve
ax1.plot(fpr, tpr, color="green")
ax1.set_title('ROC Curve - GradientBoostingClassifier')
ax1.set_ylabel('True Positive Rate (TPR)')
ax1.set_xlabel('False Positive Rate (FPR)')

# Precision-Recall Curve
ax2.plot(recall, precision, color='orange')
ax2.set_title('Precision/Recall Curve - GradientBoostingClassifier')
ax2.set_ylabel('Precision')
ax2.set_xlabel('Recall')

# Show plot
plt.tight_layout()
plt.show()
```




```
f_importances_gbc =
pd.Series(np.round(gbc_best.feature_importances_,4),index=X_train.colu
mns).sort_values(ascending=False)[:10]
barx=f_importances_gbc.index
bary=f_importances_gbc.values
plt.figure(figsize = (20, 20))
plt.barh(barx, bary)
plt.gca().invert_yaxis()
plt.show()
```



'ROA(A) before interest and % after tax' represents almost one-third of the oversampled dataset when using the Gradient Boost Classifier.

Gradient Boosted Trees Alternative - Extreme Gradient Boosted Trees

```
xgb_grid = {'n_estimators': [300], 'max_depth': [10], 'learning_rate':
[0.5]}
xgb_cv = GridSearchCV(xgb.XGBClassifier(random_state=42), cv=kf,
param_grid=xgb_grid, scoring='r2')
xgb_results = xgb_cv.fit(X_train, y_train)
print("XGB best score", xgb_results.best_score_)
print("XGB best params", xgb_results.best_params_)
```

```
XGB best score 0.9526467879287847
XGB best params {'learning_rate': 0.5, 'max_depth': 10,
'n_estimators': 300}
```

```
xgb_n_estimators = xgb_results.best_params_['n_estimators']
xgb_max_depth = xgb_results.best_params_['max_depth']
xgb_learning_rate = xgb_results.best_params_['learning_rate']

score =
cross_val_score(xgb.XGBClassifier( n_estimators=xgb_n_estimators,
max_depth=xgb_max_depth,
            learning_rate=xgb_learning_rate, random_state=42),
X_train, y_train, cv=kf)
print(f'Scores for each fold: {score}')
print("Accuracy: %0.4f " % (score.mean()))
```

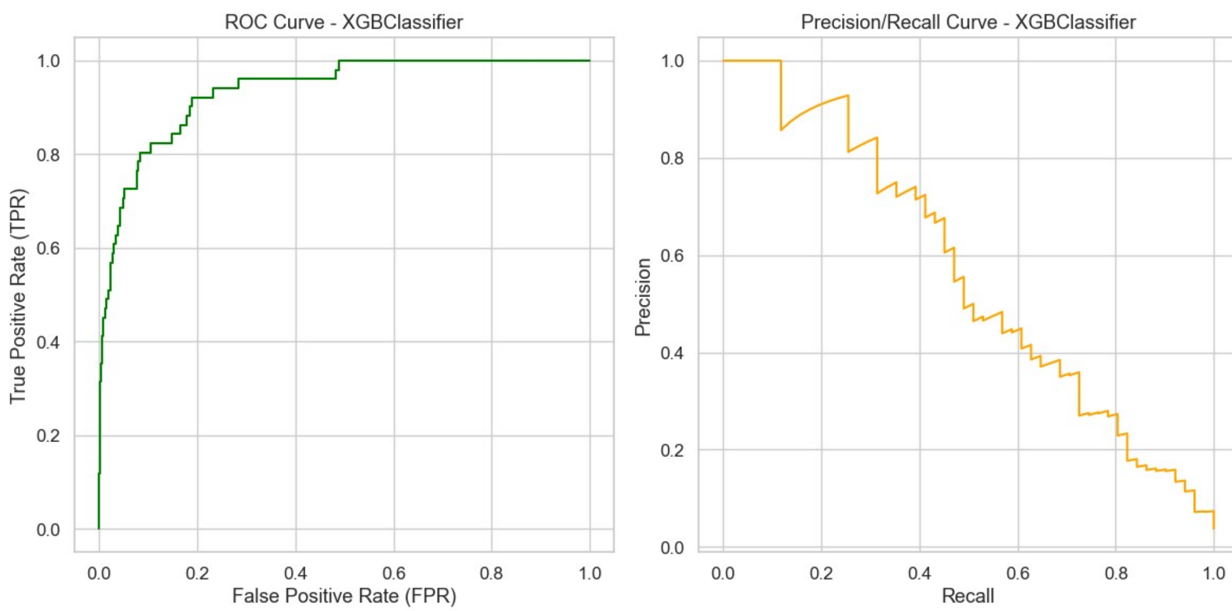
```
Scores for each fold: [0.98582231 0.98582231 0.99053926 0.98486282
0.98675497 0.98959319
 0.99716178 0.98864711 0.98770104 0.98486282]
Accuracy: 0.9882
```

```
xgb_model = xgb.XGBClassifier( n_estimators=xgb_n_estimators,
max_depth=xgb_max_depth, learning_rate=xgb_learning_rate,
random_state=42)
xgb_model.fit(X_train, y_train)
y_pred = xgb_model.predict(X_val)
cm = confusion_matrix(y_val,y_pred)
print('confusion matrix:\n',cm)
print('accuracy score = ',accuracy_score(y_val,y_pred))
print("Classification Report:\n",classification_report(y_val,y_pred))
```

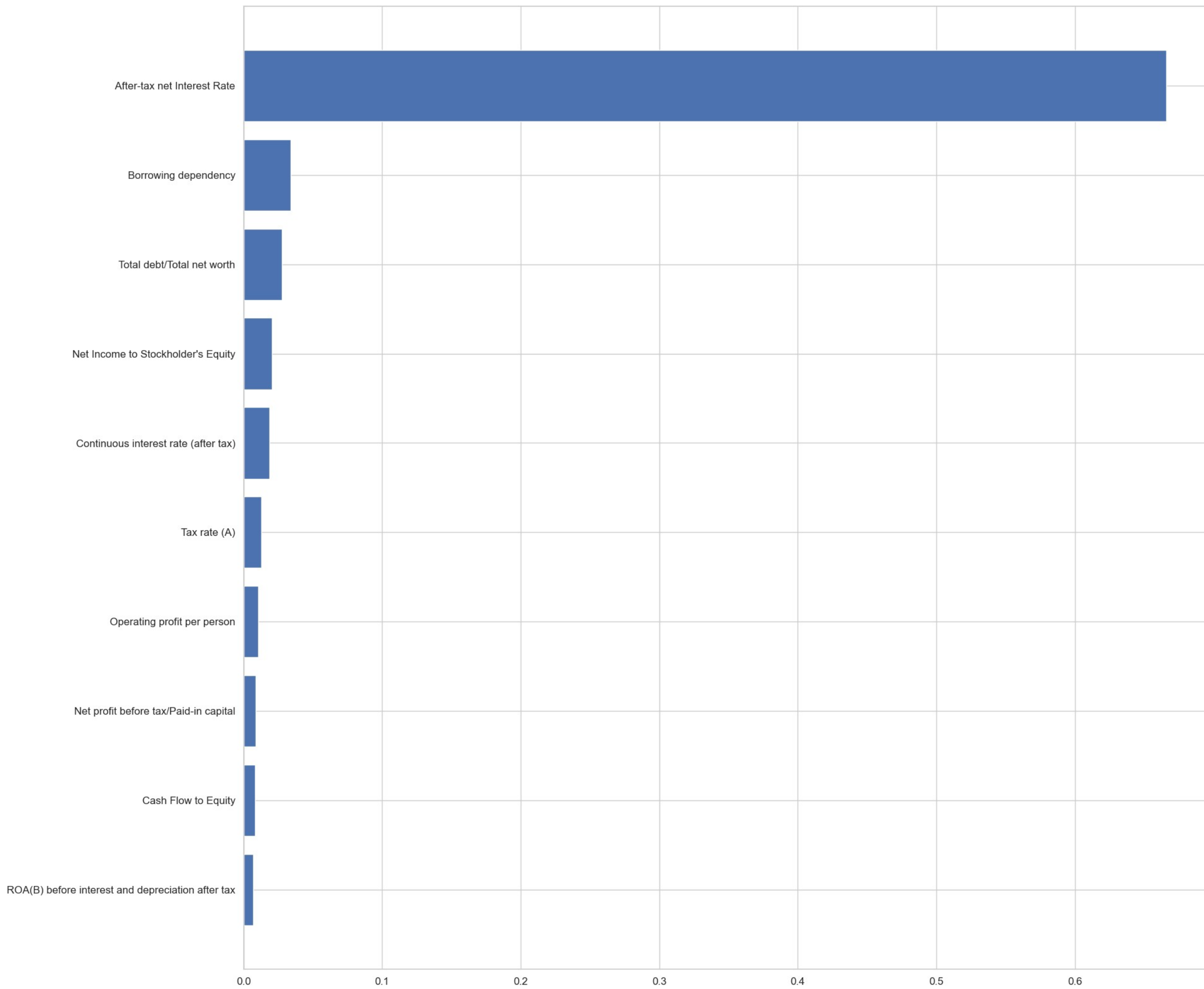
```
confusion matrix:
 [[1285   28]
 [  25   26]]
accuracy score =  0.9611436950146628
Classification Report:
               precision    recall  f1-score   support

           0       0.98      0.98      0.98      1313
           1       0.48      0.51      0.50        51

    accuracy                           0.96      1364
   macro avg       0.73      0.74      0.74      1364
weighted avg       0.96      0.96      0.96      1364
```

```
# Define metrics
y_pred_proba = xgb_model.predict_proba(X_val)[::, 1]
fpr, tpr, _ = roc_curve(y_val, y_pred_proba)
precision, recall, _ = precision_recall_curve(y_val, y_pred_proba)
```

```
# Create figure and subplots
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(12, 6))

# ROC Curve
ax1.plot(fpr, tpr, color="green")
ax1.set_title('ROC Curve - XGBClassifier')
ax1.set_ylabel('True Positive Rate (TPR)')
ax1.set_xlabel('False Positive Rate (FPR)')

# Precision-Recall Curve
ax2.plot(recall, precision, color='orange')
ax2.set_title('Precision/Recall Curve - XGBClassifier')
ax2.set_ylabel('Precision')
ax2.set_xlabel('Recall')

# Show plot
plt.tight_layout()
plt.show()
```




```
f_importances_xgb =
pd.Series(np.round(xgb_model.feature_importances_,4),index=X_train.col
umns).sort_values(ascending=False)[:10]
barx=f_importances_xgb.index
bary=f_importances_xgb.values
plt.figure(figsize = (20, 20))
plt.barh(barx, bary)
plt.gca().invert_yaxis()
plt.show()
```



It's quite interesting how the Extreme Gradient Boost Classifier overwhelming uses the After-Tax Net Interest Rate feature over all other features in the oversampled dataset, representing over two-thirds of the dataset alone. It's more 'extreme' than how 'ROA(A) before interest and % after tax' represents almost one-third of the dataset in the traditional Gradient Boost Classifier.

Extra Trees

```
xtc_grid = {'n_estimators': [200], 'max_depth': [20], 'criterion':
['entropy'], 'max_features': ['sqrt']}
xtc_cv = GridSearchCV(ExtraTreesClassifier(random_state=42), cv=kf,
param_grid=xtc_grid, scoring='r2')
xtc_results = xtc_cv.fit(X_train, y_train)
print("XTC best score", xtc_results.best_score_)
print("XTC best params", xtc_results.best_params_)
```

```
XTC best score 0.9113651260825246
XTC best params {'criterion': 'entropy', 'max_depth': 20,
'max_features': 'sqrt', 'n_estimators': 200}
```

```
xtc_n_estimators = xtc_results.best_params_['n_estimators']
xtc_max_depth = xtc_results.best_params_['max_depth']
xtc_criterion = xtc_results.best_params_['criterion']
xtc_max_features = xtc_results.best_params_['max_features']

score =
cross_val_score(ExtraTreesClassifier(n_estimators=xtc_n_estimators,
max_depth=xtc_max_depth, criterion=xtc_criterion,
            max_features=xtc_max_features, random_state=42), X_train,
y_train, cv=kf)
print(f'Scores for each fold: {score}')
print("Accuracy: %0.4f " % (score.mean()))
```

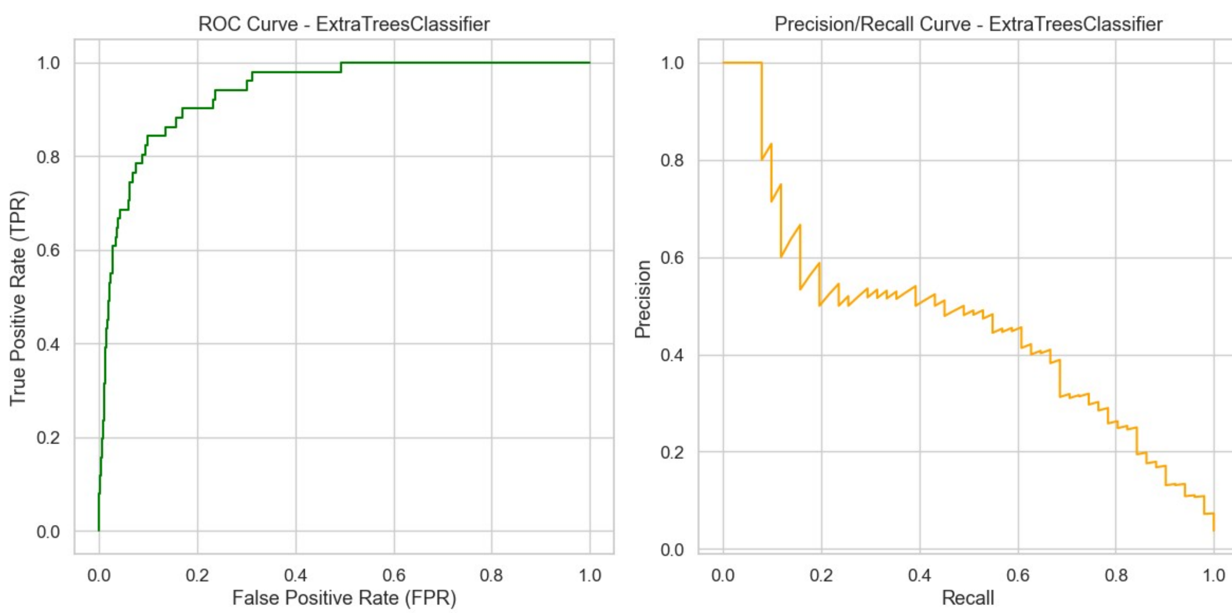
```
Scores for each fold: [0.97164461 0.97637051 0.97350993 0.9820246
0.97729423 0.97540208
 0.9820246  0.98770104 0.97634816 0.97634816]
Accuracy: 0.9779
```

```
xtc_model = ExtraTreesClassifier(n_estimators=xtc_n_estimators,
max_depth=xtc_max_depth, criterion=xtc_criterion,
            max_features=xtc_max_features,random_state=42)
xtc_model.fit(X_train, y_train)
y_pred = xtc_model.predict(X_val)
cm = confusion_matrix(y_val,y_pred)
print('confusion matrix:\n',cm)
print('accuracy score = ',accuracy_score(y_val,y_pred))
print("Classification Report:\n",classification_report(y_val,y_pred))
```

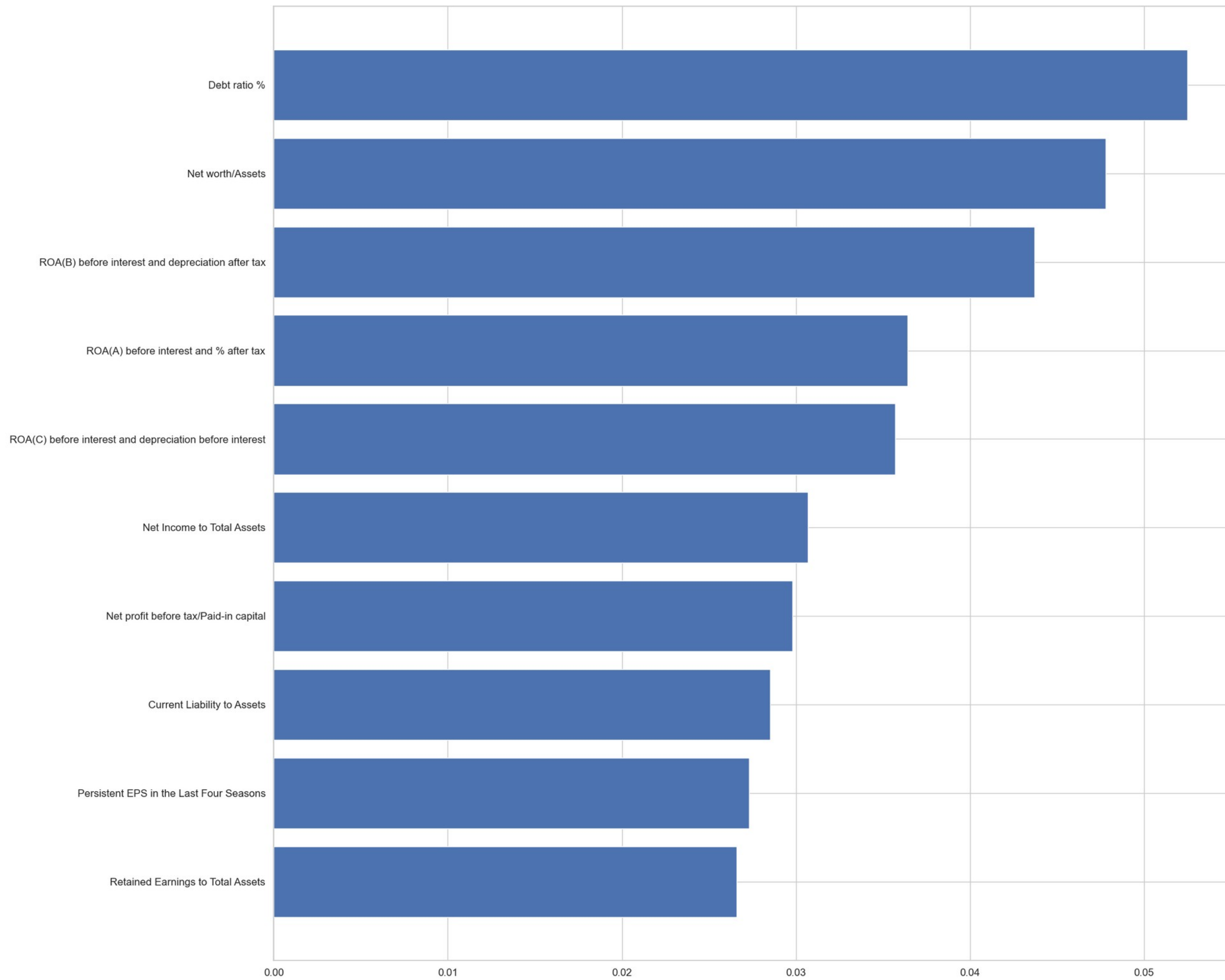
```
confusion matrix:
 [[1248   65]
 [  16   35]]
accuracy score =  0.9406158357771262
Classification Report:
               precision    recall  f1-score   support

           0       0.99      0.95      0.97      1313
           1       0.35      0.69      0.46        51

    accuracy                           0.94      1364
   macro avg       0.67      0.82      0.72      1364
weighted avg       0.96      0.94      0.95      1364
```

```
# Define metrics
y_pred_proba = xtc_model.predict_proba(X_val)[::, 1]
fpr, tpr, _ = roc_curve(y_val, y_pred_proba)
precision, recall, _ = precision_recall_curve(y_val, y_pred_proba)
```

```python
# Create figure and subplots
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(12, 6))

# ROC Curve
ax1.plot(fpr, tpr, color="green")
ax1.set_title('ROC Curve - ExtraTreesClassifier')
ax1.set_ylabel('True Positive Rate (TPR)')
ax1.set_xlabel('False Positive Rate (FPR)')

# Precision-Recall Curve
ax2.plot(recall, precision, color='orange')
ax2.set_title('Precision/Recall Curve - ExtraTreesClassifier')
ax2.set_ylabel('Precision')
ax2.set_xlabel('Recall')

# Show plot
plt.tight_layout()
plt.show()
```




```python
f_importances_xtc = 
pd.Series(np.round(xtc_model.feature_importances_,4),index=X_train.col
umns).sort_values(ascending=False)[:10]
barx=f_importances_xtc.index
bary=f_importances_xtc.values
plt.figure(figsize = (20, 20))
plt.barh(barx, bary)
plt.gca().invert_yaxis()
plt.show()
```



The Extra Trees model does not have a single feature overwhelmingly dominating the dataset. However, the top 15 features collectively represent almost 45% of the oversampled dataset's importance.

Feature Selection

```
feature_selection = []
for i in range (0,10):
    feature_selection.append(f_importances_rfc.index[i])
feature_selection
```

```
[' After-tax net Interest Rate',
 ' Net Income to Total Assets',
 ' Total debt/Total net worth',
 ' Persistent EPS in the Last Four Seasons',
 ' Retained Earnings to Total Assets',
 " Net Income to Stockholder's Equity",
 ' Continuous interest rate (after tax)',
 ' Pre-tax net Interest Rate',
 ' Total income/Total expense',
 ' Net profit before tax/Paid-in capital']
```

```
X_train_fs = X_train[feature_selection]
X_val_fs = X_val[feature_selection]

scaler = StandardScaler().fit(X_train_fs)
X_train_fs_scaled = pd.DataFrame(scaler.transform(X_train_fs),
index=X_train_fs.index, columns=X_train_fs.columns)
X_val_fs_scaled = pd.DataFrame(scaler.transform(X_val_fs),
index=X_val_fs.index, columns=X_val_fs.columns)
```

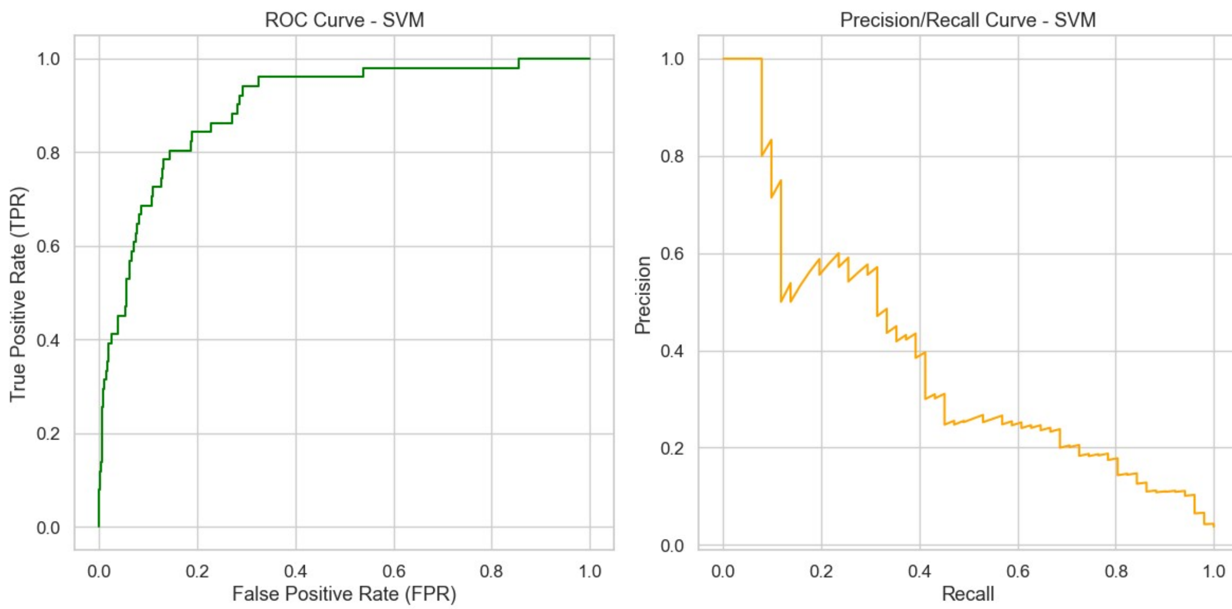
Support Vector Machine

```
svc = SVC(kernel='linear', gamma=0.01, C=2, probability=True,
random_state=42)
svc.fit(X_train_fs_scaled,y_train)

#getting confusion matrix
y_pred = svc.predict(X_val_fs_scaled)
cm = confusion_matrix(y_val,y_pred)
print('confusion matrix:\n',cm)

#checking accuracy
print('accuracy score = ',accuracy_score(y_val,y_pred))
print("Classification Report:\n",classification_report(y_val,y_pred))
```

```
confusion matrix:
 [[1101  212]
 [  10   41]]
accuracy score =  0.8372434017595308
Classification Report:
               precision    recall  f1-score   support

           0       0.99      0.84      0.91      1313
           1       0.16      0.80      0.27        51

    accuracy                           0.84      1364
   macro avg       0.58      0.82      0.59      1364
weighted avg       0.96      0.84      0.88      1364
```

```
# Define metrics
y_pred = svc.predict_proba(X_val_fs_scaled)[::, 1]
fpr, tpr, _ = roc_curve(y_val, y_pred)
precision, recall, _ = precision_recall_curve(y_val, y_pred)

# Create figure and subplots
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(12, 6))

# ROC Curve
ax1.plot(fpr, tpr, color="green")
```

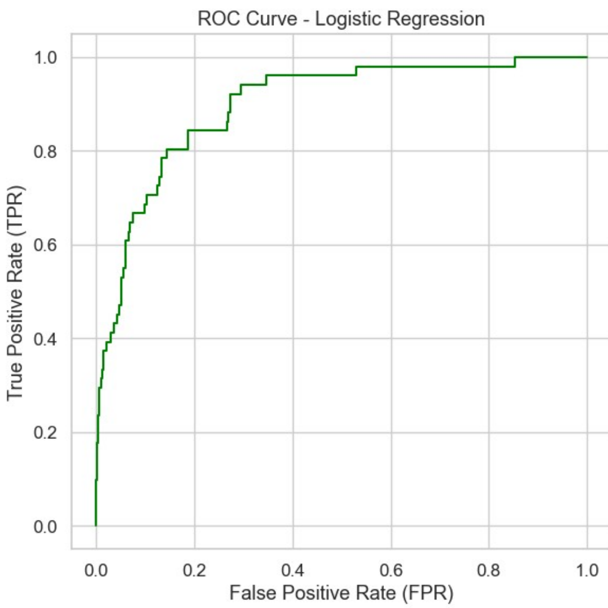
```
ax1.set_title('ROC Curve - SVM')
ax1.set_ylabel('True Positive Rate (TPR)')
ax1.set_xlabel('False Positive Rate (FPR)')

# Precision-Recall Curve
ax2.plot(recall, precision, color='orange')
ax2.set_title('Precision/Recall Curve - SVM')
ax2.set_ylabel('Precision')
ax2.set_xlabel('Recall')

# Show plot
plt.tight_layout()
plt.show()
```

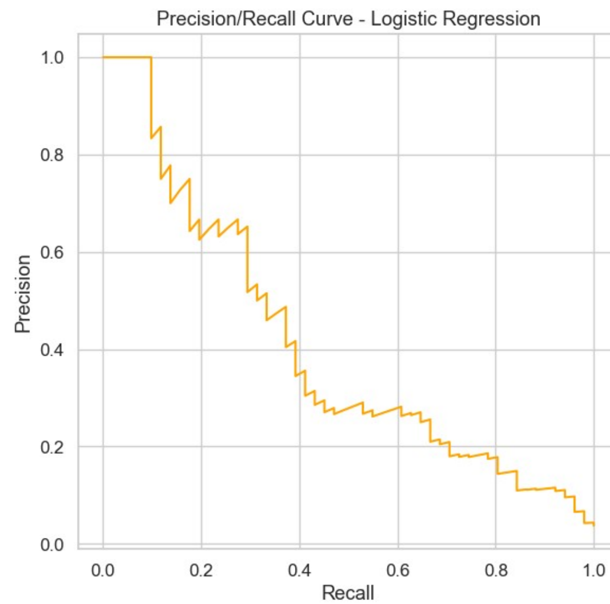


Logistic Regression

```
#training model
lr = LogisticRegression(max_iter = 10000)
lr.fit(X_train_fs_scaled,y_train)

#getting confusion matrix
y_pred = lr.predict(X_val_fs_scaled)
cm = confusion_matrix(y_val,y_pred)
print('confusion matrix:\n',cm)

#checking accuracy
lra = accuracy_score(y_val,y_pred)
print('accuracy score = ',lra)
print("Classification Report:\n",classification_report(y_val,y_pred))
```

```
confusion matrix:
 [[1106  207]
 [  10   41]]
accuracy score =  0.8409090909090909
Classification Report:
               precision    recall  f1-score   support

           0       0.99      0.84      0.91      1313
           1       0.17      0.80      0.27        51

    accuracy                           0.84      1364
   macro avg       0.58      0.82      0.59      1364
weighted avg       0.96      0.84      0.89      1364


# Define metrics
y_pred = lr.predict_proba(X_val_fs_scaled)[::, 1]
fpr, tpr, _ = roc_curve(y_val, y_pred)
precision, recall, _ = precision_recall_curve(y_val, y_pred)

# Create figure and subplots
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(12, 6))

# ROC Curve
ax1.plot(fpr, tpr, color="green")
ax1.set_title('ROC Curve - Logistic Regression')
ax1.set_ylabel('True Positive Rate (TPR)')
ax1.set_xlabel('False Positive Rate (FPR)')

# Precision-Recall Curve
ax2.plot(recall, precision, color='orange')
ax2.set_title('Precision/Recall Curve - Logistic Regression')
ax2.set_ylabel('Precision')
ax2.set_xlabel('Recall')

# Show plot
plt.tight_layout()
plt.show()
```





Naive Bayes

```
#training model
nb = GaussianNB()
nb.fit(X_train_fs_scaled,y_train)

#getting confusion matrix
y_pred = nb.predict(X_val_fs_scaled)
cm = confusion_matrix(y_val,y_pred)
print('confusion matrix:\n',cm)

#checking accuracy
nba = accuracy_score(y_val,y_pred)
print('accuracy score = ',accuracy_score(y_val,y_pred))
print("Classification Report:\n",classification_report(y_val,y_pred))
```

```
confusion matrix:
 [[538 775]
 [  4  47]]
accuracy score =  0.4288856304985337З
Classification Report:
               precision    recall  f1-score   support

           0       0.99      0.41      0.58      1313
           1       0.06      0.92      0.11        51

    accuracy                           0.43      1364
   macro avg       0.52      0.67      0.34      1364
weighted avg       0.96      0.43      0.56      1364
```

unscaled data was used in Naive bayes.

CONCLUSION

Management/Research Question

In layman's terms, what is the management/research question of interest, and why would anyone care?

The primary question of interest is: "Can we accurately predict whether a company will go bankrupt based on its financial data?" This question is crucial for various stakeholders. Loan institutions need to assess the bankruptcy risk of companies to make informed lending decisions. Companies can use the predictions to identify and rectify financial issues, potentially reducing their risk of bankruptcy. Customers, on the other hand, benefit from knowing a company's bankruptcy risk, which helps them decide whether to start or continue business relations with that company.

Using the bankruptcy data from the Taiwan Economic Journal spanning 1999 to 2009, the goal is to predict a company's likelihood of bankruptcy. For loan institutions, this information is crucial to assess the risk before granting substantial loans. Companies can use these predictions to identify and address internal issues to reduce their bankruptcy risk. Customers also benefit by being informed of a company's potential bankruptcy status, aiding in their decision-making about whether to start or continue doing business with the company.

From my observations, both tree-based and non-tree-based models exhibit a nearly strong negative correlation between precision and recall. None of the precision-recall curves indicate a favorable balance where a reasonable recall can achieve a satisfactory precision rate.

When it comes to identifying bankruptcies in the validation dataset, Gradient Boosting and Extreme Gradient Boosting models are more accurate in pinpointing bankruptcy cases. On the other hand, the Random Forest and Extra Trees models tend to favor recall, identifying more true bankruptcy cases at the expense of falsely labeling some non-bankrupt cases. The application of oversampling seems to enhance the performance of models that prioritize precision over recall.