Company Bankruptcy Prediction (Kaggle)

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2024WI_MS_DSP_422-DL_SEC61: Practical Machine Learning

Module 5 Assignment

Company Bankruptcy Prediction

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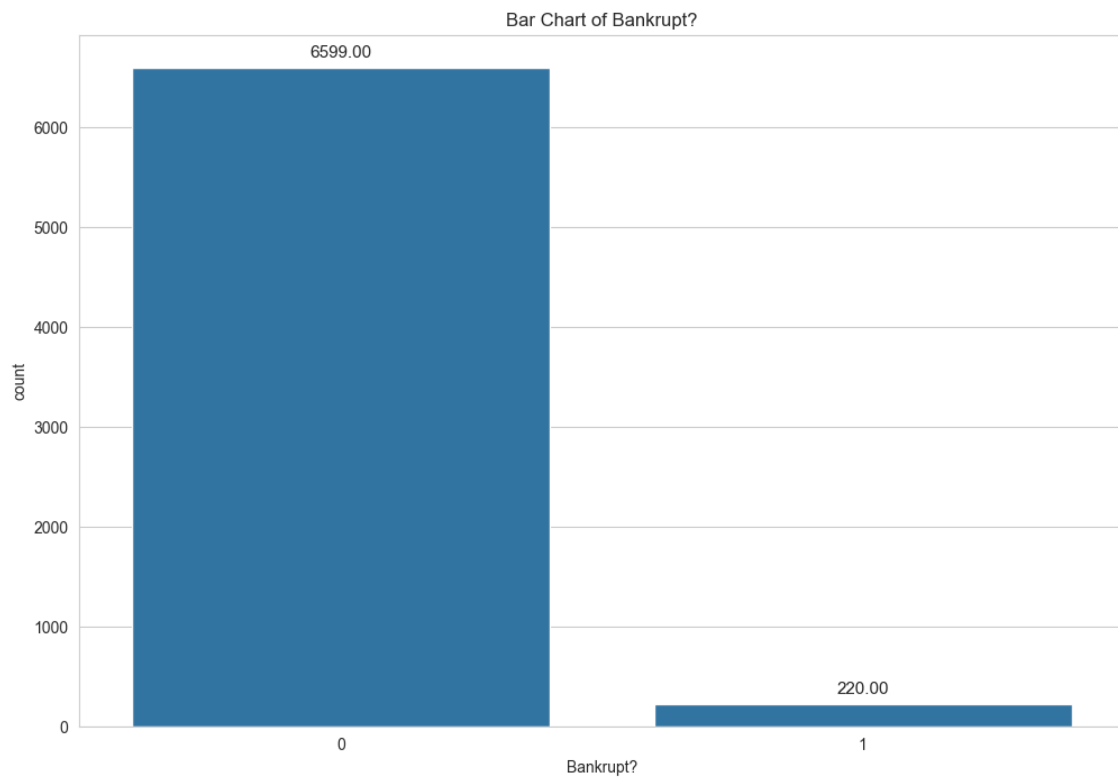
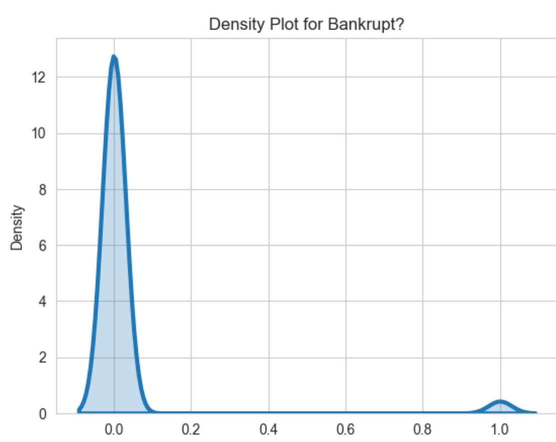
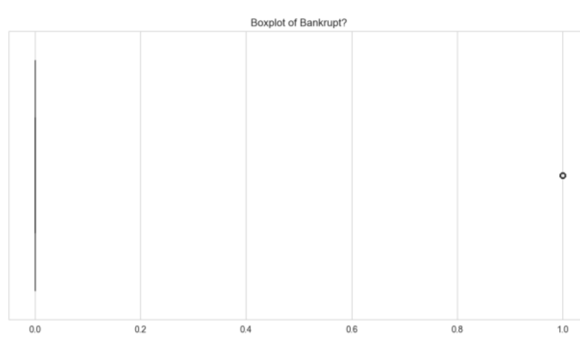
Approach

We start with a comprehensive Exploratory Data Analysis (EDA), commencing with the extraction of descriptive statistics for the 'Bankrupt?' column, serving as the target variable for prediction. We also summarize the dataset by computing the count, mean, standard deviation, minimum, quartiles, and maximum values, for all the 96 columns.







There were no missing values or duplicate rows in the dataset.

Outlier removal in the independent variables for a dataset with a highly imbalanced dependent variable like this one (where bankrupt cases are the minority) could potentially eliminate valuable information. Since bankruptcies are rare events, the characteristics that lead to bankruptcy may be present as outliers in the independent variables. These "outliers" might be critical in predicting the rare event of bankruptcy. If they were removed, the model's ability to generalize and identify the risk of bankruptcy could be significantly impaired. Therefore, we decided to not identify or remove the outliers

Next, we identified the top-20 features that have the highest correlation with Bankrupt, followed it up by plotting a heatmap depicting the strength of these 20 features amongst themselves and with ‘Bankrupt?’. To avoid multi-collinearity, we removed 20 variables that had a significantly high corelation (>0.95) amongst themselves.

We plotted the correlation heatmap of ‘Bankrupt?’ and the new top-20 highly correlated features, and boxplots and distribution-plots of these 20 features.

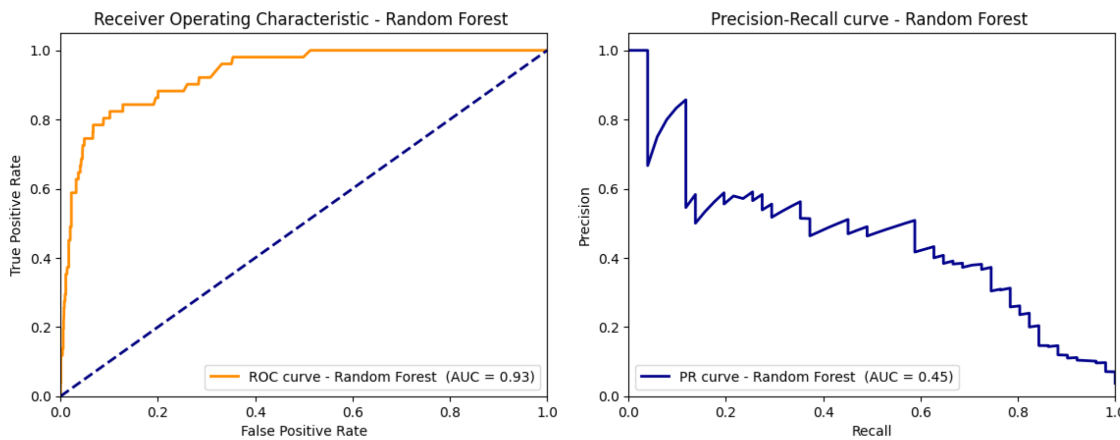
The dataset was split into train and test, in 80:20 ratio, and the data was scaled using StandardScaler.

Our dataset showcases a significant class imbalance with a vast majority of cases being non-bankrupt (6599) and a small minority being bankrupt (220). In such scenarios, logistic regression models tend to be biased towards the majority class, leading to poor classification performance on the minority class. SMOTE (Synthetic Minority Over-sampling Technique) generates synthetic samples for the minority class, helping to balance the dataset. This balance allows the logistic regression model to learn a more generalized decision boundary, improving its ability to correctly identify cases of bankruptcy, which is critical for the model's predictive performance.

By enhancing the representation of the minority class, SMOTE helps in improving the sensitivity (recall) and precision of the model, ensuring that both classes are predicted more accurately, rather than the model overwhelmingly predicting the majority class. We use SMOTE.

We start modelling by deploying the **Random Forest Classifier** and trying different hyperparameters in the model. The best model returns:

```
Best parameters: {'bootstrap': False, 'class_weight': 'balanced', 'criterion': 'entropy',
'max_depth': None, 'max_features': 'log2', 'min_samples_split': 5, 'n_estimators': 100,
'random_state': 42}
Best accuracy score (on the training dataset): 0.9839197881195613
Accuracy:  0.9618768328445748
Precision:  0.49019607843137253
Recall:  0.49019607843137253
F1 Score:  0.49019607843137253
```



The Receiver Operating Characteristic (ROC) curve for this model displays an area under the curve (AUC) of 0.93, signifying a strong discriminative ability of the model to correctly classify the positive cases. This performance is substantially better than random guessing, which would result in an AUC of 0.50, indicating that the model has a high true positive rate while maintaining a low false positive rate.

In contrast, the Precision-Recall (PR) curve has an AUC of 0.45, which is relatively low and signals that the model is not as effective when it comes to precision and recall. The precision of the model is 0.4902, suggesting that when the model predicts a positive class, it is accurate less than half the time. This level of precision can result in a high number of false positives, which may be costly or undesirable depending on the application.

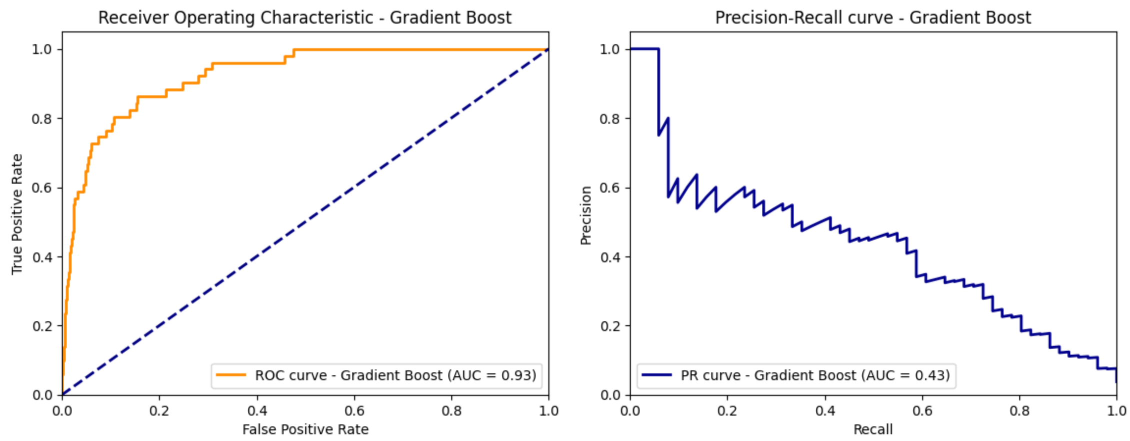
The recall value, also at 0.4902, means the model identifies 49.02% of all actual positive cases. This indicates that the model is capable of detecting nearly half of the positive instances but also misses a substantial portion, which could be critical if the positive class is of particular importance.

The model's accuracy is high at approximately 0.9619, yet this figure may be somewhat deceptive. High accuracy can occur in imbalanced datasets where one class dominates, and it does not necessarily mean the model is effective at classifying the positive class correctly.

Finally, the F1 Score, a measure that balances precision and recall, is 0.4902. This metric confirms the challenges seen in the precision and recall values and underscores the model's moderate effectiveness in classifying the positive class accurately. The identical values for precision, recall, and F1 score suggest a balance between the ability to identify positive cases and the accuracy of these identifications, but it also highlights the need for improvement to enhance the model's performance.

The **Gradient Boost Classifier** returns:

```
Best parameters: {'loss': 'exponential', 'max_depth': 10, 'max_features': 'sqrt',
'min_samples_split': 5, 'n_estimators': 250, 'random_state': 42}
Best accuracy score: 0.9863791146424518
Accuracy:  0.9596774193548387
Precision:  0.46
Recall:  0.45098039215686275
F1 Score:  0.45544554455445546
```



The Receiver Operating Characteristic (ROC) curve for this model displays an area under the curve (AUC) of 0.93, which indicates a strong ability to discriminate between the positive and negative classes, significantly better than random guessing, which would have an AUC of 0.50. This suggests that the model's discriminative ability to correctly classify the positive cases is quite good.

The Precision-Recall (PR) chart, however, shows a lower AUC of 0.43, suggesting that the model has room for improvement in terms of precision and recall. This is corroborated by the model's precision of 0.5217, indicating that when the model predicts a positive outcome, it is correct about 52.17% of the time. This level of precision may lead to a considerable number of false positives.

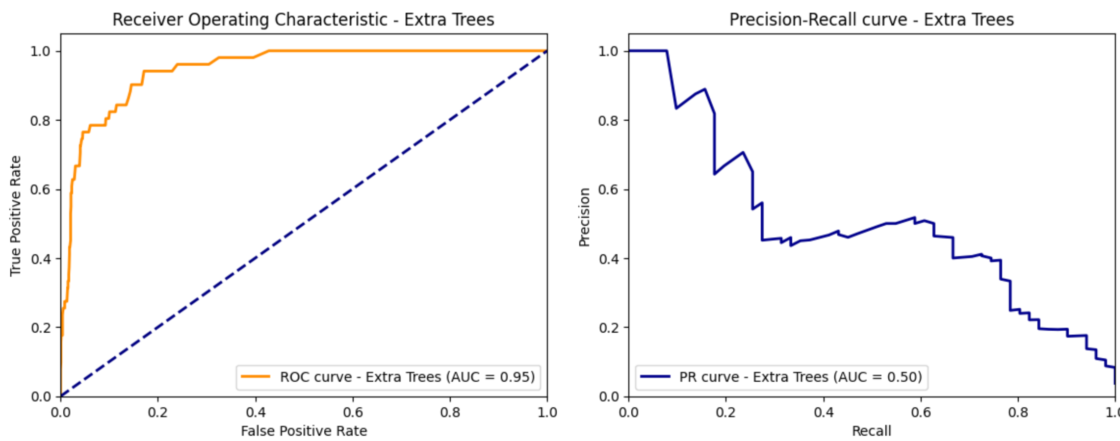
Furthermore, the recall of the model is 0.4706, which means it identifies about 47.06% of all actual positive cases. This moderate recall suggests that the model is missing a significant number of positive instances.

Despite these challenges, the model achieves an accuracy of approximately 0.964, which might be misleading as it does not capture the model's struggles with precision and recall — a common issue in datasets with class imbalance where accuracy is not the most informative metric.

Finally, the F1 Score, which is the harmonic mean of precision and recall, is at 0.4948. This score, being below 0.50, is indicative of the model's inadequate performance in precisely and reliably classifying the positive class.

The **Extra Trees Classifier** returns:

```
Best parameters: {'bootstrap': False, 'class_weight': 'balanced', 'criterion': 'gini',
'max_depth': None, 'max_features': 'sqrt', 'min_samples_split': 2, 'n_estimators': 200,
'random_state': 42}
Best accuracy score: 0.9859061672342037
Accuracy:  0.9596774193548387
Precision:  0.46
Recall:  0.45098039215686275
F1 Score:  0.45544554455445546
```



The Receiver Operating Characteristic (ROC) curve for this model shows an area under the curve (AUC) of 0.95, which is indicative of an excellent ability to distinguish between the positive and negative classes, far surpassing random guessing, which would have an AUC of 0.50. This high AUC value suggests that the model is very effective at correctly classifying the positive cases as compared to a random classifier.

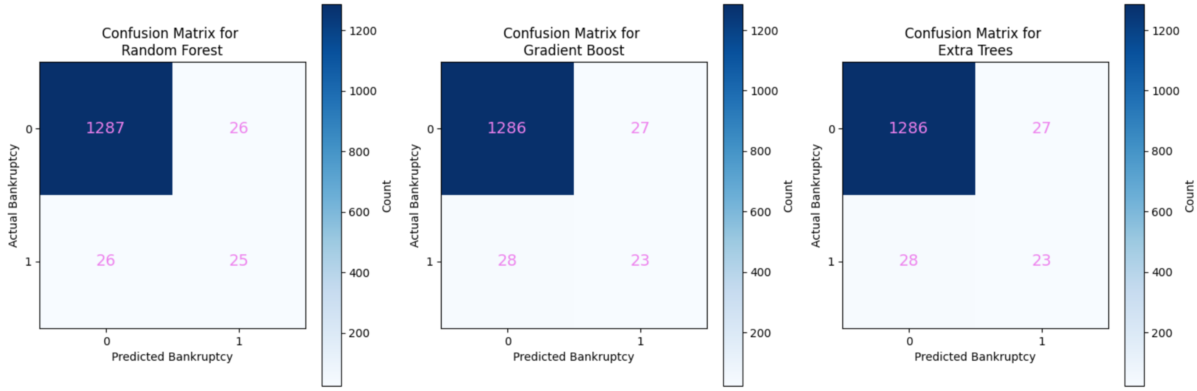
The Precision-Recall (PR) chart, on the other hand, tells a different story with an AUC of 0.50, which is no better than random guessing. This low AUC on the PR curve is indicative of the model's poor performance in terms of both precision and recall. The precision of the model is 0.46, meaning that when the model predicts a positive outcome, it is correct less than half of the time, leading to a significant number of false positives.

Additionally, the model's recall is 0.4509, indicating that it correctly identifies only 45.09% of all actual positive cases. This suggests that the model is missing a substantial number of positive instances, which is concerning for a classifier, especially in contexts where detecting true positives is crucial.

Despite these shortcomings, the model has an accuracy of approximately 0.9597, which can be misleading because it does not account for the model's low precision and recall. This is a typical scenario with imbalanced datasets where a high accuracy doesn't necessarily mean good predictive performance, particularly for the minority class.

Lastly, the F1 Score of 0.4554, which balances precision and recall, is not impressive and reflects the model's suboptimal performance in accurately and consistently classifying the positive class. This score, combined with the low precision and recall, points towards the need for further model tuning or consideration of alternative modeling approaches to improve its predictive power for the positive class.

Management Recommendations: To compare the three models, we plotted the confusion matrices:



Random Forest model exhibits a slightly better balance between false positives and false negatives, with both being equal at 26. Meanwhile, both Gradient Boost and Extra Trees models present a similar performance to each other, with 27 false positives and 28 false negatives, indicating a marginal increase in the false negatives compared to the Random Forest model. In terms of true positives, all three models show relatively close numbers, with Random Forest at 25, and both Gradient Boost and Extra Trees at 23. This suggests that all models have a comparable ability to correctly identify bankruptcies. However, the true negatives, which represent the correct identification of non-bankruptcy cases, are highest for Random Forest at 1287, followed by both Gradient Boost and Extra Trees at 1286, which is an indication of a very slight edge for Random Forest in correctly predicting non-bankrupt cases.

These confusion matrices suggest that while all three models perform similarly, the Random Forest model has a minor advantage in terms of maintaining a balance between type I and type II errors (false positives and false negatives, respectively). This could potentially make it a more reliable choice for scenarios where it’s important to maintain a balance between detecting bankruptcies and avoiding false bankruptcy alarms. However, the differences are marginal, and the choice between these models might also depend on other factors such as model interpretability, computational efficiency, and performance on other metrics not visible in the confusion matrices.

The submission code and results can be viewed at https://www.kaggle.com/code/riteshrk/trees-rf-gb-et.

Code

trees_final_code

February 1, 2024

1 Step 1: Imports

[3]:
```
# Import Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import roc_curve, auc, precision_recall_curve, f1_score,␣
↪confusion_matrix
from sklearn.metrics import accuracy_score, precision_score, recall_score
from sklearn.preprocessing import StandardScaler
from imblearn.over_sampling import SMOTE
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.ensemble import ExtraTreesClassifier
from sklearn.metrics import confusion_matrix

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

[4]:
```
# Read datafile
df = pd.read_csv('data.csv')
```

[5]:
```
# Cleaning the column_names
df.columns = df.columns.str.strip()
```

2 2. Explore Data

[6]:
```
# Get the size of the dataframe
df.shape
```

[6]: (6819, 96)

[7]:
```
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
```

[8]:
```
df.describe()
```

[8]:
```
         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]

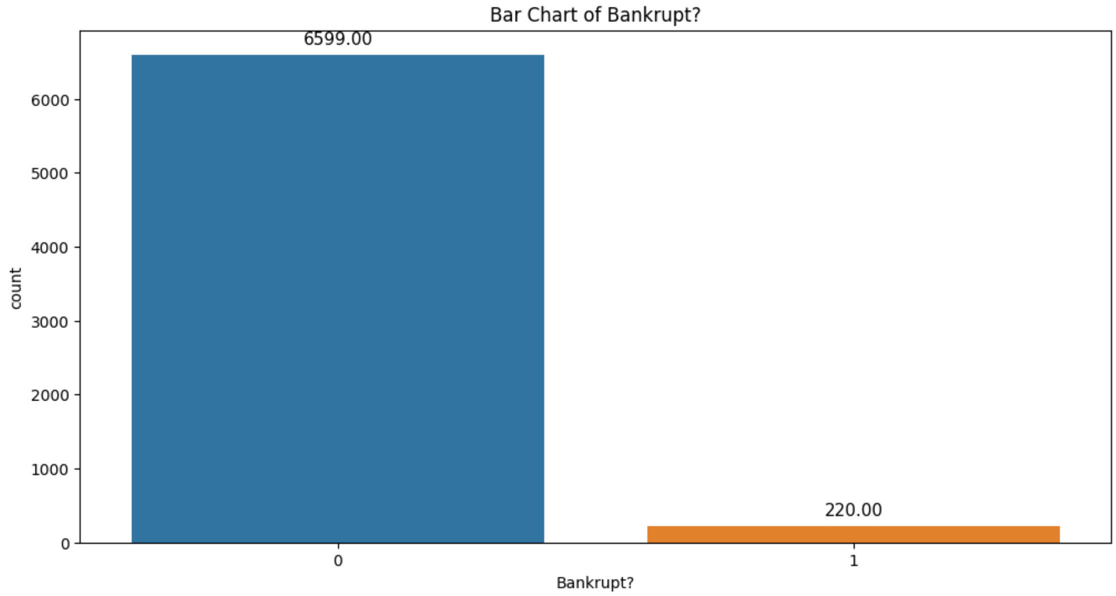
[9]:
```
# Checking for missing values
df.isna().sum().max()
```

[9]: 0

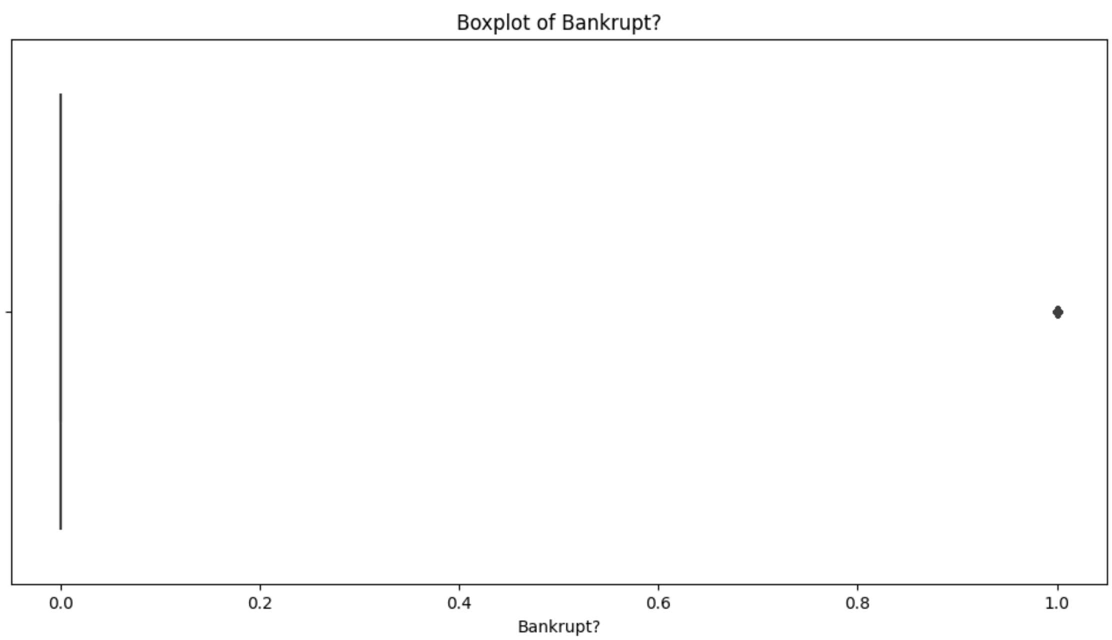
[10]:
```
# Checking for duplicates()
df.duplicated().sum()
```

[10]: 0

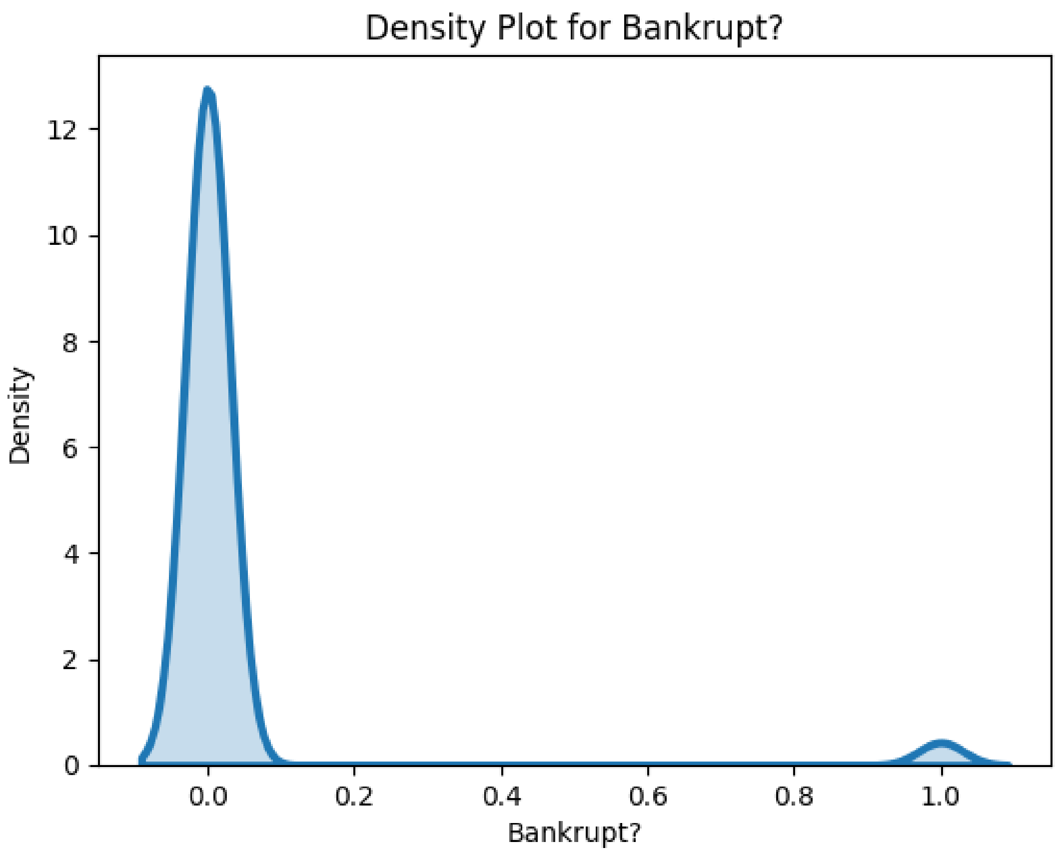
[11]:
```
# Bar chart of Bankrupt?

# Bar chart
plt.figure(figsize=(12, 6))
bar_plot = sns.countplot(x=df['Bankrupt?'])

plt.title('Bar Chart of Bankrupt?')

# Adding data labels
for p in bar_plot.patches:
    bar_plot.annotate(format(p.get_height(), '.2f'),
                      (p.get_x() + p.get_width() / 2., p.get_height()),
                      ha = 'center',
                      va = 'center',
                      fontsize = 11,
                      xytext = (0, 10),
                      textcoords = 'offset points')

plt.show()
```



[12]:
```
# Boxplot of Bankrupt?
plt.figure(figsize=(12, 6))
sns.boxplot(x=df['Bankrupt?'])
plt.title('Boxplot of Bankrupt?')
plt.show()
```



[13]:
```python
# Plot Density Plot
sns.distplot(df['Bankrupt?'], hist = False, kde = True,
             kde_kws = {'shade': True, 'linewidth': 3})

plt.title('Density Plot for Bankrupt?')
plt.xlabel('Bankrupt?')
plt.ylabel('Density')

plt.show()
```



[14]:
```python
# Identify the features that have the highest correlation with Bankrupt?

# Compute the correlation matrix
correlation_matrix = df.corr()

# Get the correlation of 'Bankrupt?' with other features
correlation_with_bankrupt = correlation_matrix['Bankrupt?']

# Get absolute values of correlation for comparison
```

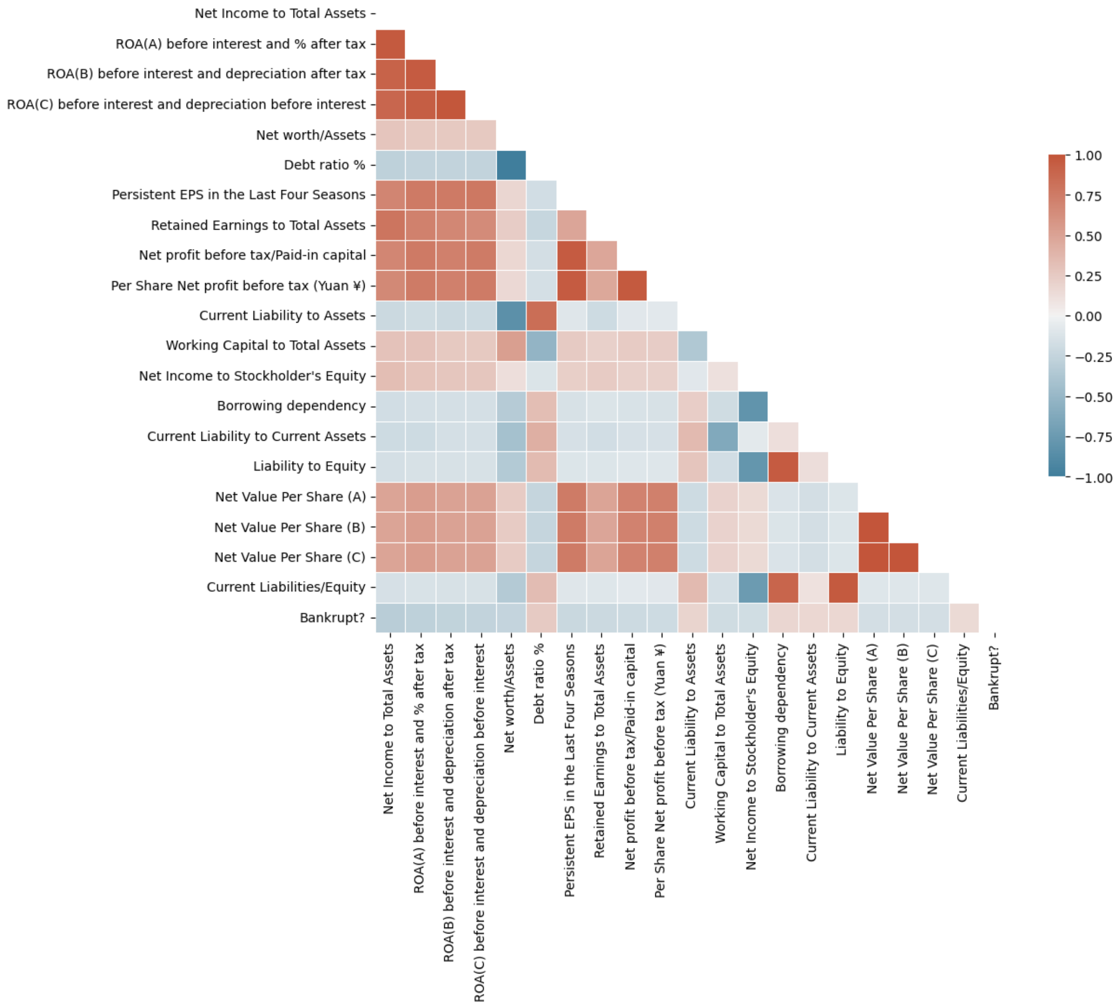
```
absolute_correlation_with_bankrupt = correlation_with_bankrupt.abs()

# Get the twenty features that have the highest correlation with 'Bankrupt?'
top_20_correlated_features = absolute_correlation_with_bankrupt.nlargest(21).
 ↪drop('Bankrupt?', errors='ignore')

print(top_20_correlated_features)
```

```
Net Income to Total Assets                                 0.315457
ROA(A) before interest and % after tax                     0.282941
ROA(B) before interest and depreciation after tax          0.273051
ROA(C) before interest and depreciation before interest    0.260807
Net worth/Assets                                           0.250161
Debt ratio %                                               0.250161
Persistent EPS in the Last Four Seasons                    0.219560
Retained Earnings to Total Assets                          0.217779
Net profit before tax/Paid-in capital                      0.207857
Per Share Net profit before tax (Yuan ¥)                   0.201395
Current Liability to Assets                                0.194494
Working Capital to Total Assets                            0.193083
Net Income to Stockholder's Equity                         0.180987
Borrowing dependency                                       0.176543
Current Liability to Current Assets                        0.171306
Liability to Equity                                        0.166812
Net Value Per Share (A)                                    0.165465
Net Value Per Share (B)                                    0.165399
Net Value Per Share (C)                                    0.164784
Current Liabilities/Equity                                 0.153828
Name: Bankrupt?, dtype: float64
```

[15]:

```
# Plot the heatmap
features_list = list(top_20_correlated_features.index) + ['Bankrupt?']

# Construct a DataFrame with wanted features only
df_subset = df[features_list]

# Compute the correlation matrix for the subset dataframe
correlation_matrix_subset = df_subset.corr()

# Generate a mask for the upper triangle
mask = np.triu(np.ones_like(correlation_matrix_subset, dtype=bool))

# Set up the matplotlib figure
f, ax = plt.subplots(figsize=(11, 9))

# Generate a custom diverging colormap
cmap = sns.diverging_palette(230, 20, as_cmap=True)
```

```python
# Draw the heatmap with the mask and correct aspect ratio
sns.heatmap(correlation_matrix_subset, mask=mask, cmap=cmap, vmax=1, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5}, annot=True)
plt.show()
```



3 3. Address Multi-colinearity

[16]:
```python
# To avoid multi-colinearity, we identify the highly correlated features in df

# Calculate correlation matrix
corr_matrix = df.corr()
# Select upper triangle of correlation matrix
upper = corr_matrix.where(np.triu(np.ones(corr_matrix.shape), k=1).astype(bool))
# Identify pairs with correlation above 0.95
```

```
pairs = [(column, row) for column in upper.columns for row in upper.index if␣
  ↪abs(upper[column][row]) > 0.95]
# Prepare a list containing column pairs and their correlation
output = [(pair[0], pair[1], upper[pair[0]][pair[1]]) for pair in pairs]
# Create a DataFrame from the list
df_output = pd.DataFrame(output, columns=['Feature1', 'Feature2',␣
  ↪'Correlation'])
# Set pandas to display all columns in DataFrame
pd.set_option('display.expand_frame_repr', False)
# Print the output DataFrame
print(df_output)
```

```
                                             Feature1
Feature2  Correlation
0   ROA(B) before interest and depreciation after tax  ROA(C) before interest
and depreciation before…     0.986849
1   ROA(B) before interest and depreciation after tax            ROA(A) before
interest and % after tax     0.955741
2                          Realized Sales Gross Margin
Operating Gross Margin     0.999518
3                          After-tax net Interest Rate
Pre-tax net Interest Rate     0.986379
4                    Continuous interest rate (after tax)
Pre-tax net Interest Rate     0.993617
5                    Continuous interest rate (after tax)
After-tax net Interest Rate     0.984452
6                              Net Value Per Share (A)
Net Value Per Share (B)     0.999342
7                              Net Value Per Share (C)
Net Value Per Share (B)     0.999179
8                              Net Value Per Share (C)
Net Value Per Share (A)     0.999837
9             Per Share Net profit before tax (Yuan ¥)           Persistent EPS
in the Last Four Seasons     0.955591
10                       Regular Net Profit Growth Rate                  After-
tax Net Profit Growth Rate     0.996186
11                                    Net worth/Assets
Debt ratio %    -1.000000
12                     Operating profit/Paid-in capital               Operating
Profit Per Share (Yuan ¥)     0.998696
13               Net profit before tax/Paid-in capital           Persistent EPS
in the Last Four Seasons     0.959461
14               Net profit before tax/Paid-in capital          Per Share Net
profit before tax (Yuan ¥)     0.962723
15                       Current Liability to Liability
Current Liabilities/Liability     1.000000
16                          Current Liability to Equity
```

```
Current Liabilities/Equity     1.000000
17                           Net Income to Total Assets             ROA(A) before
interest and % after tax     0.961552
18                                Gross Profit to Sales
Operating Gross Margin     1.000000
19                                Gross Profit to Sales
Realized Sales Gross Margin     0.999518
20                                  Liability to Equity
Borrowing dependency     0.955857
21                                  Liability to Equity
Current Liabilities/Equity     0.963908
22                                  Liability to Equity
Current Liability to Equity     0.963908
```

[17]:

```
# Drop features to avoid multi-colinearity
# Set the columns we want to drop
columns_to_drop = [
    "ROA(C) before interest and depreciation before interest",
    "ROA(A) before interest and % after tax",
    "Operating Gross Margin",
    "Pre-tax net Interest Rate",
    "After-tax net Interest Rate",
    "Net Value Per Share (B)",
    "Net Value Per Share (C)",
    "Persistent EPS in the Last Four Seasons",
    "After-tax Net Profit Growth Rate",
    "Debt ratio %",
    "Operating Profit Per Share (Yuan ¥)",
    "Persistent EPS in the Last Four Seasons",
    "Per Share Net profit before tax (Yuan ¥)",
    "Current Liabilities/Liability",
    "Current Liabilities/Equity",
    "Operating Gross Margin",
    "Realized Sales Gross Margin",
    "Borrowing dependency",
    "Current Liabilities/Equity",
    "Current Liability to Equity"
]

# Drop the columns
df = df.drop(columns_to_drop, axis=1)
```

[18]:

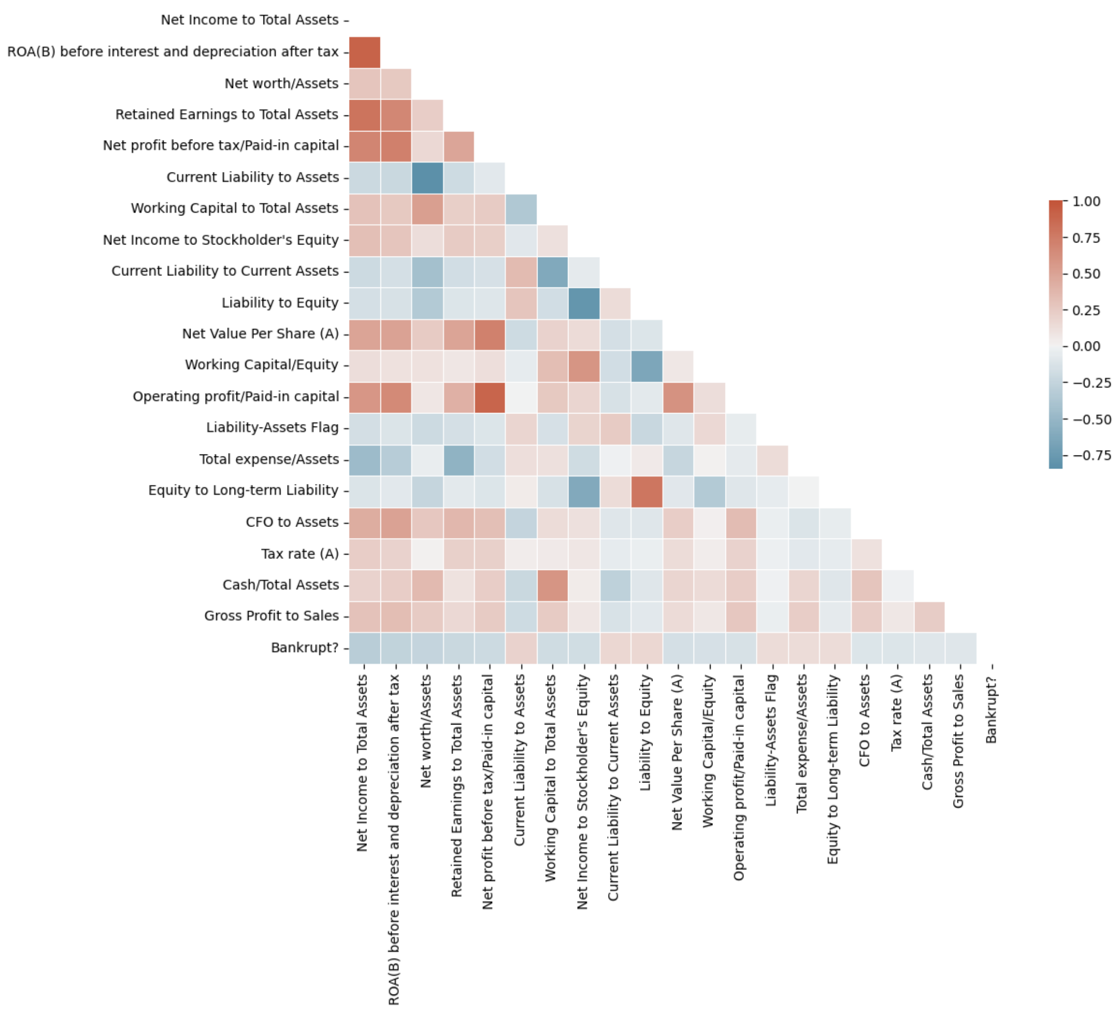
```
# Identify the features that have the hgihest correlation with Bankrupt?

# Compute the correlation matrix
correlation_matrix = df.corr()
```

```
# Get the correlation of 'Bankrupt?' with other features
correlation_with_bankrupt = correlation_matrix['Bankrupt?']

# Get absolute values of correlation for comparison
absolute_correlation_with_bankrupt = correlation_with_bankrupt.abs()

# Get the twenty features that have the highest correlation with 'Bankrupt?'
top_20_correlated_features = absolute_correlation_with_bankrupt.nlargest(21).
↪drop('Bankrupt?', errors='ignore')

print(top_20_correlated_features)
```

```
Net Income to Total Assets                                0.315457
ROA(B) before interest and depreciation after tax         0.273051
Net worth/Assets                                          0.250161
Retained Earnings to Total Assets                         0.217779
Net profit before tax/Paid-in capital                     0.207857
Current Liability to Assets                               0.194494
Working Capital to Total Assets                           0.193083
Net Income to Stockholder's Equity                        0.180987
Current Liability to Current Assets                       0.171306
Liability to Equity                                       0.166812
Net Value Per Share (A)                                   0.165465
Working Capital/Equity                                    0.147221
Operating profit/Paid-in capital                          0.141111
Liability-Assets Flag                                     0.139212
Total expense/Assets                                      0.139049
Equity to Long-term Liability                             0.139014
CFO to Assets                                             0.115383
Tax rate (A)                                              0.109706
Cash/Total Assets                                         0.100130
Gross Profit to Sales                                     0.100044
Name: Bankrupt?, dtype: float64
```

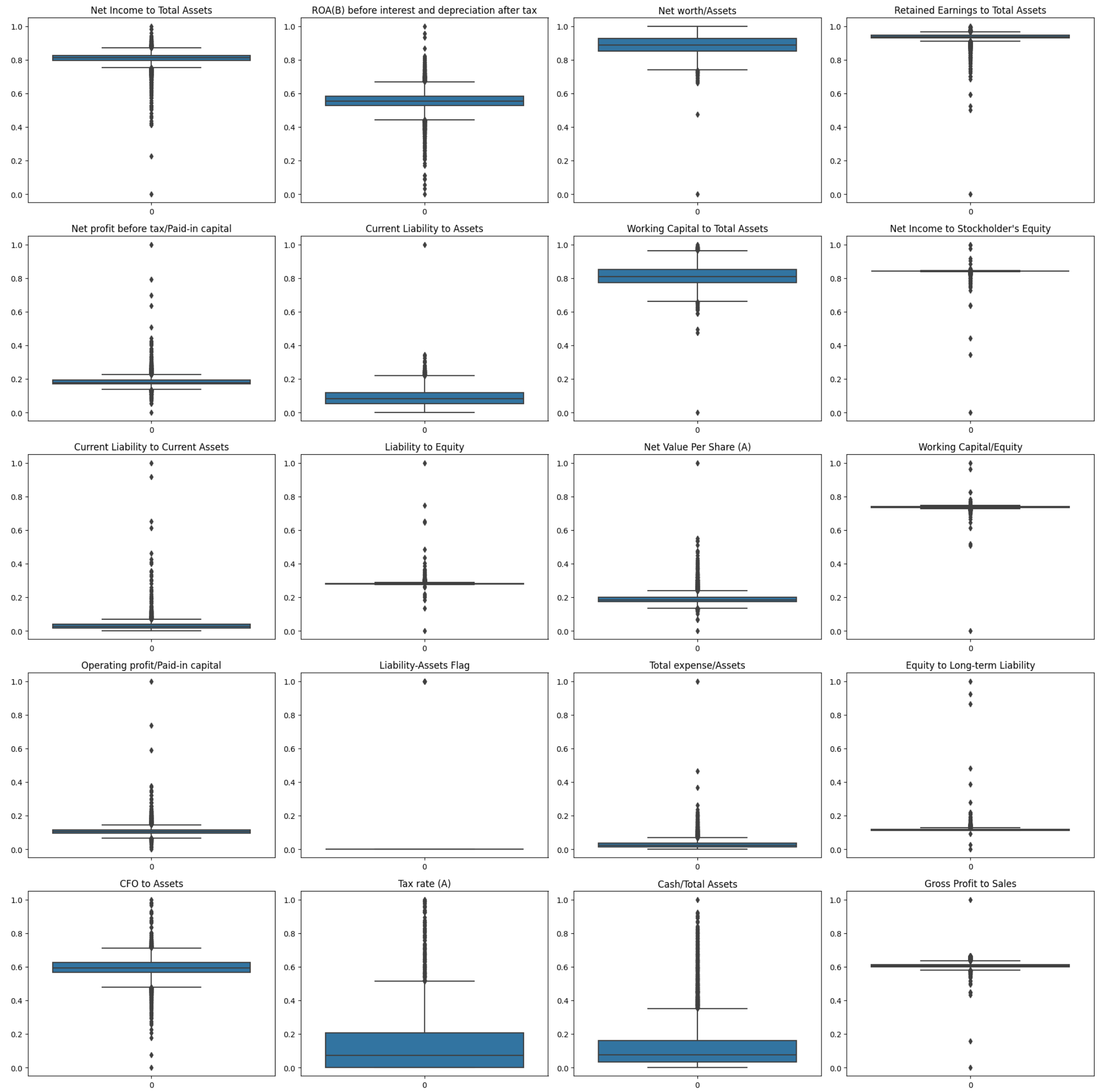
[19]:
```
# Plot the heatmap
features_list = list(top_20_correlated_features.index) + ['Bankrupt?']

# Construct a DataFrame with wanted features only
df_subset = df[features_list]

# Compute the correlation matrix for the subset dataframe
correlation_matrix_subset = df_subset.corr()

# Generate a mask for the upper triangle
mask = np.triu(np.ones_like(correlation_matrix_subset, dtype=bool))

# Set up the matplotlib figure
```

```python
f, ax = plt.subplots(figsize=(11, 9))

# Generate a custom diverging colormap
cmap = sns.diverging_palette(230, 20, as_cmap=True)

# Draw the heatmap with the mask and correct aspect ratio
sns.heatmap(correlation_matrix_subset, mask=mask, cmap=cmap, vmax=1, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .4}, annot=True)
plt.show()
```



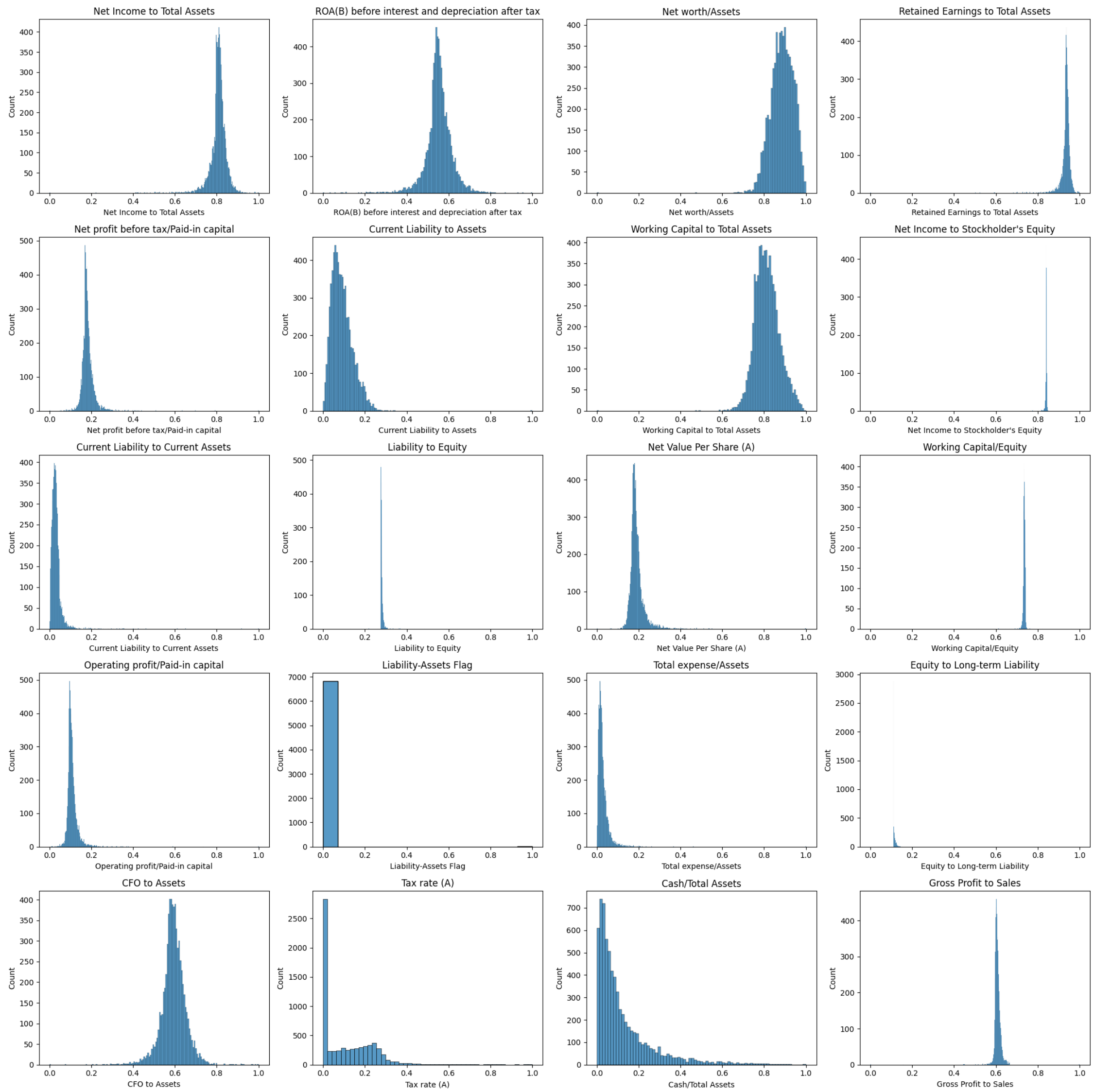
4 4. Explore Most-Important Features

[20]:
```
# Plot the boxplots

fig, axs = plt.subplots(nrows=5, ncols=4, figsize=(20, 20))

# assuming that top_ten_correlated_features index contains feature names
features = top_20_correlated_features.index

for i, feature in enumerate(features):
    # calculate row and column index
    row = i // 4
    col = i % 4

    # plot boxplot on corresponding subplot
    sns.boxplot(df[feature], ax=axs[row, col])
    axs[row, col].set_title(feature)

plt.tight_layout()
plt.show()
```



[21]:
```python
# Plot the distribution plots of top_ten_correlated_features
fig, axs = plt.subplots(nrows=5, ncols=4, figsize=(20, 20))

# assuming that top_ten_correlated_features index contains feature names
features = top_20_correlated_features.index

for i, feature in enumerate(features):
     # calculate row and column index
    row = i // 4
    col = i % 4

    # plot distribution on corresponding subplot
    sns.histplot(df[feature], ax=axs[row, col])
```

```
    axs[row, col].set_title(feature)

plt.tight_layout()
plt.show()
```



5 5. Pre-work for Modelling

[22]:
```
# Define the features and target variable for Modelling
X = df.drop('Bankrupt?', axis=1)
y = df['Bankrupt?']

# Split the data
```

```
X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)
```

[23]:
```
# Initialize the scaler
scaler = StandardScaler()
# Fit and transform the training data
X_train_scaled = scaler.fit_transform(X_train)
# Transform validation data
X_val_scaled = scaler.transform(X_val)  # Note we only 'transform' the␣
↪validation set, not 'fit_transform'
# Initialize SMOTE
smote = SMOTE(random_state=42)
# Fit and resample the training data
X_train_smote, y_train_smote = smote.fit_resample(X_train_scaled, y_train)

# Now you can proceed with your training using: X_train_smote, y_train_smote,␣
↪X_val_scaled and y_val
```

Our dataset showcases a significant class imbalance with a vast majority of cases being non-bankrupt (6599) and a small minority being bankrupt (220). In such scenarios, logistic regression models tend to be biased towards the majority class, leading to poor classification performance on the minority class. SMOTE (Synthetic Minority Over-sampling Technique) is justified in this context as it generates synthetic samples for the minority class, helping to balance the dataset. This balance allows the logistic regression model to learn a more generalized decision boundary, improving its ability to correctly identify cases of bankruptcy, which is critical for the model's predictive performance. By enhancing the representation of the minority class, SMOTE helps in improving the sensitivity (recall) and precision of the model, ensuring that both classes are predicted more accurately, rather than the model overwhelmingly predicting the majority class.

6 6. Modelling

[24]:
```
# Function for plotting ROC and AUC plots
def plot_roc_pr_curves(y_val, y_val_prob, model_name):
    lw = 2

    # ROC curve
    fpr, tpr, _ = roc_curve(y_val, y_val_prob)
    roc_auc = auc(fpr, tpr)

    plt.figure()
    plt.plot(fpr, tpr, color='darkorange',
             lw=lw, label=f'ROC curve - {model_name} (AUC = {roc_auc:.2f})')
    plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
```

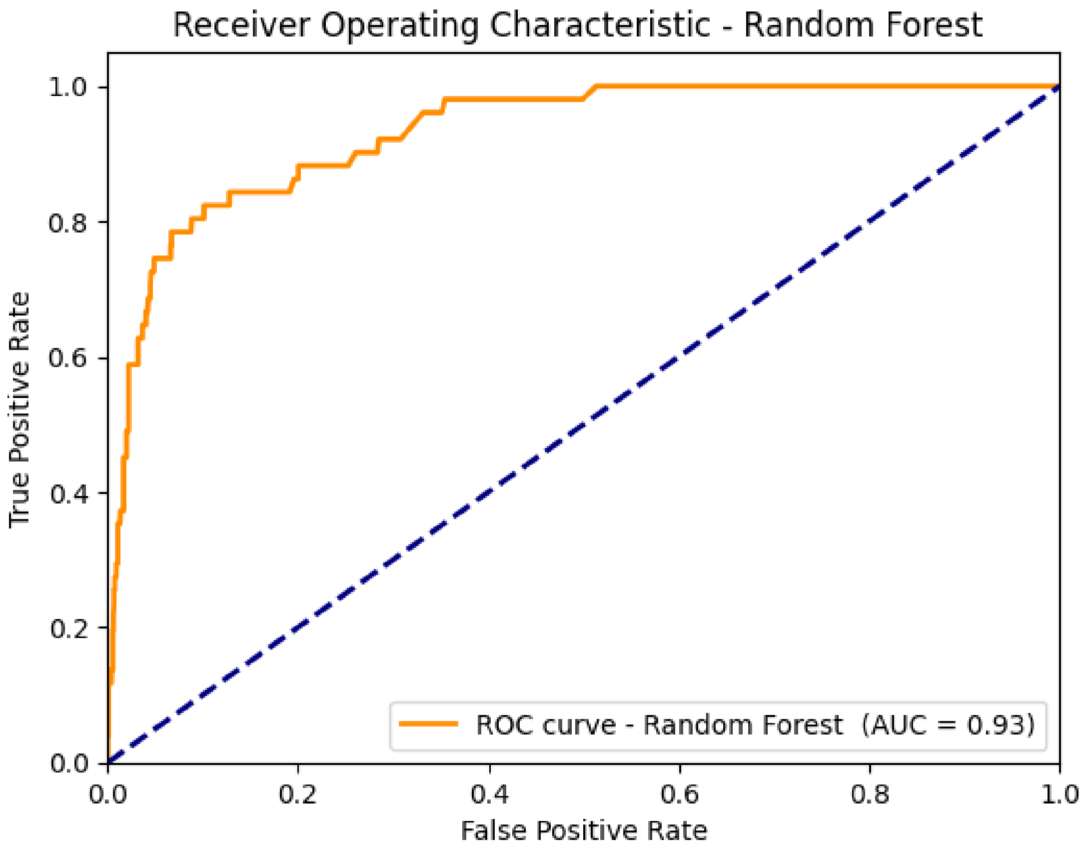
```python
    plt.title(f'Receiver Operating Characteristic - {model_name}')
    plt.legend(loc="lower right")
    plt.show()

    # Precision-Recall curve
    precision, recall, _ = precision_recall_curve(y_val, y_val_prob)
    pr_auc = auc(recall, precision)

    plt.figure()
    plt.plot(recall, precision, color='darkblue',
             lw=lw, label=f'PR curve - {model_name} (AUC = {pr_auc:.2f})')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('Recall')
    plt.ylabel('Precision')
    plt.title(f'Precision-Recall curve - {model_name}')
    plt.legend(loc="lower left")
    plt.show()
```

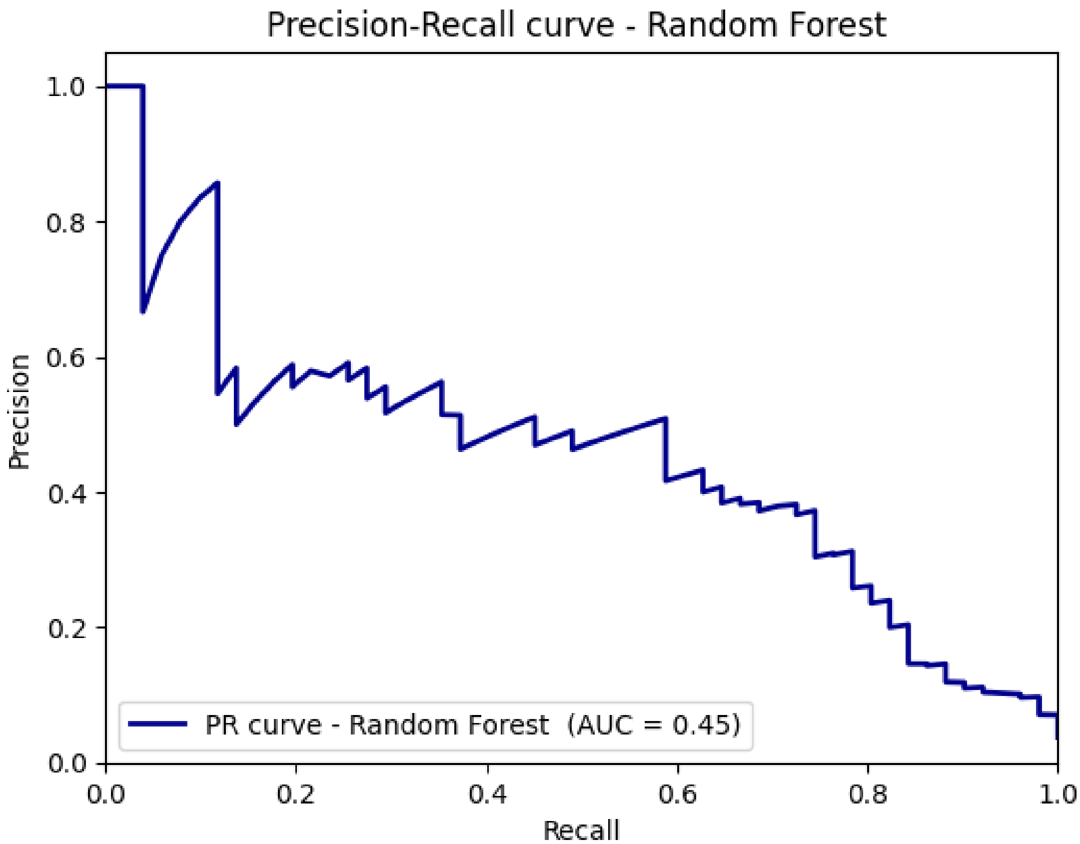
[25]:

```python
## Random Forest Classifier

# Define the parameter grid for hyperparameter tuning
param_grid = {
    'n_estimators': [75, 100, 125],     # number of trees in the forest
    'max_depth': [None, 25, 30, 40],    # maximum depth of the tree
    'min_samples_split': [5, 10, 15],  # minimum number of samples required to␣
 ↪split an internal node
    'max_features' : ['auto', 'sqrt', 'log2'],    # the number of features to␣
 ↪consider when looking for the best split
    'random_state' : [42],     # to make output consistent across multiple␣
 ↪function calls
    'class_weight' : ['balanced','balanced_subsample'],    # weights associated␣
 ↪with classes
    'criterion' : ['gini', 'entropy'],  # function to measure the quality of a␣
 ↪split
    'bootstrap' : [True, False] # whether bootstrap samples are used when␣
 ↪building trees
}

# Initialize the Random Forest Classifier
rf = RandomForestClassifier()

# Initialize the grid search model
grid_search = GridSearchCV(estimator=rf, param_grid=param_grid, cv=3,␣
 ↪scoring='accuracy', n_jobs=-1)
```

```python
# Fit the grid search model
grid_search.fit(X_train_smote, y_train_smote)

# Get the best parameters and best accuracy score
best_params = grid_search.best_params_
best_score = grid_search.best_score_

print('Best parameters:', best_params)
print('Best accuracy score (on the training dataset):', best_score)

# Use the best estimator to make predictions on the validation set
brf_model = grid_search.best_estimator_
y_val_pred = brf_model.predict(X_val_scaled)


# Calculate accuracy, precision, recall, and F1 score
accuracy = accuracy_score(y_val, y_val_pred)
precision = precision_score(y_val, y_val_pred)
recall = recall_score(y_val, y_val_pred)
f1 = f1_score(y_val, y_val_pred)

print('Accuracy: ', accuracy)
print('Precision: ', precision)
print('Recall: ', recall)
print('F1 Score: ', f1)


# Calculate the probabilities of the predictions
y_val_prob = brf_model.predict_proba(X_val_scaled)[:,1]

# Call the funciton to plot the plots
plot_roc_pr_curves(y_val, y_val_prob, "Random Forest ")
```

```
Best parameters: {'bootstrap': False, 'class_weight': 'balanced', 'criterion':
'entropy', 'max_depth': None, 'max_features': 'log2', 'min_samples_split': 5,
'n_estimators': 100, 'random_state': 42}
Best accuracy score (on the training dataset): 0.9839197881195613
Accuracy:  0.9618768328445748
Precision:  0.49019607843137253
Recall:  0.49019607843137253
F1 Score:  0.49019607843137253
```


Receiver Operating Characteristic - Random Forest
True Positive Rate
False Positive Rate
ROC curve - Random Forest (AUC = 0.93)
0.0
0.2
0.4
0.6
0.8
1.0



The Receiver Operating Characteristic (ROC) curve for this model displays an area under the curve (AUC) of 0.93, signifying a strong discriminative ability of the model to correctly classify the positive cases. This performance is substantially better than random guessing, which would result in an AUC of 0.50, indicating that the model has a high true positive rate while maintaining a low false positive rate.

In contrast, the Precision-Recall (PR) curve has an AUC of 0.45, which is relatively low and signals that the model is not as effective when it comes to precision and recall. The precision of the model is 0.4902, suggesting that when the model predicts a positive class, it is accurate less than half the time. This level of precision can result in a high number of false positives, which may be costly or undesirable depending on the application.

The recall value, also at 0.4902, means the model identifies 49.02% of all actual positive cases. This indicates that the model is capable of detecting nearly half of the positive instances but also misses a substantial portion, which could be critical if the positive class is of particular importance.

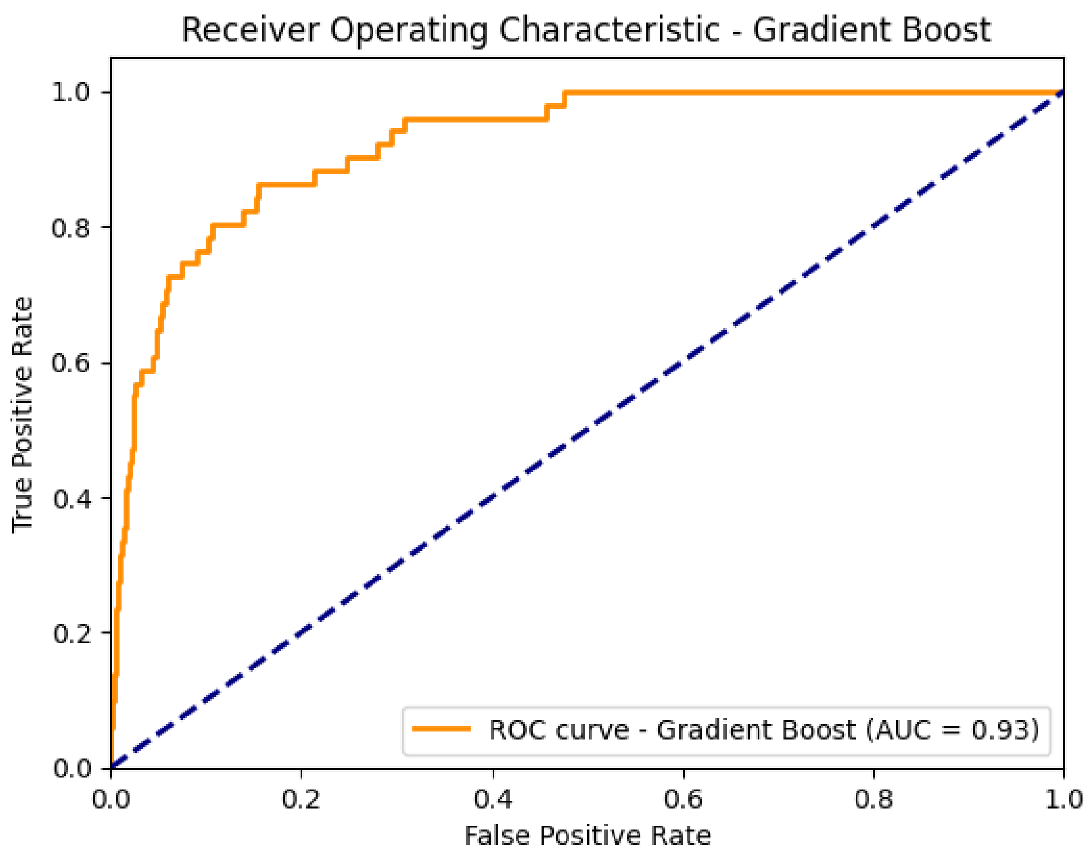
The model's accuracy is high at approximately 0.9619, yet this figure may be somewhat deceptive. High accuracy can occur in imbalanced datasets where one class dominates, and it does not necessarily mean the model is effective at classifying the positive class correctly.

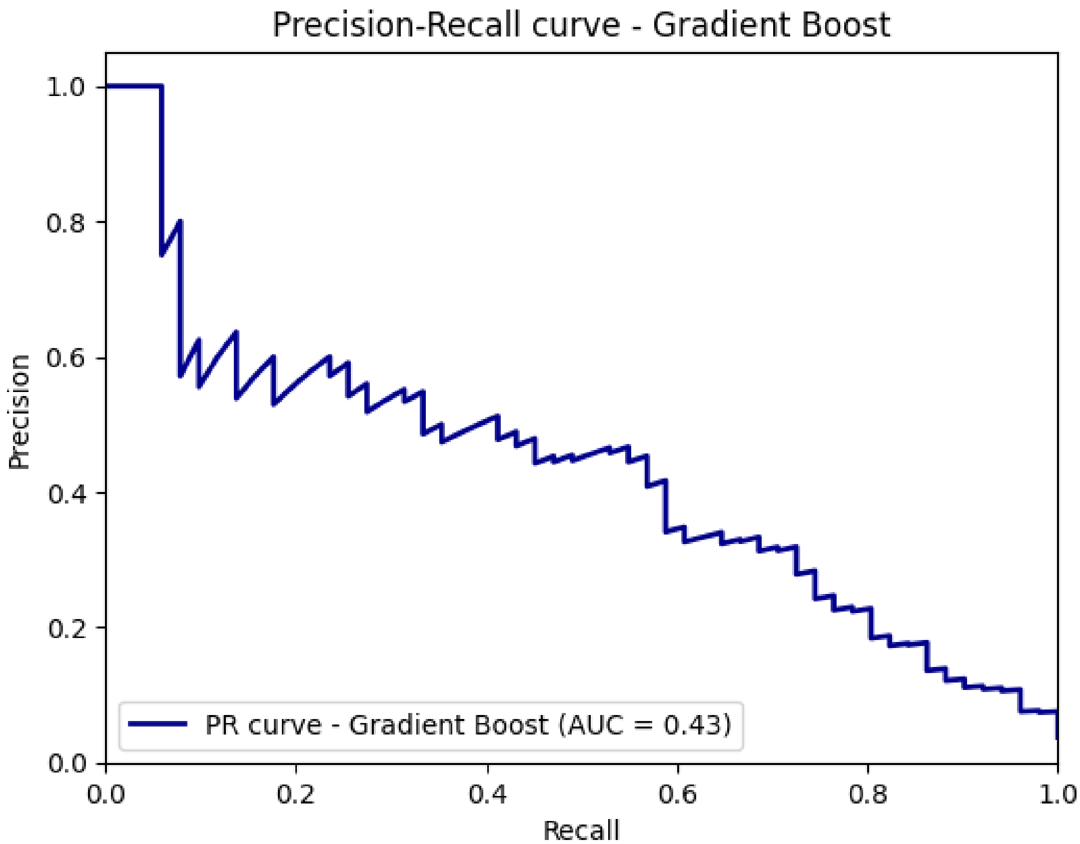
Finally, the F1 Score, a measure that balances precision and recall, is 0.4902. This metric confirms the challenges seen in the precision and recall values and underscores the model's moderate effectiveness in classifying the positive class accurately. The identical values for precision, recall, and F1 score suggest a balance between the ability to identify positive cases and the accuracy of these identifications, but it also highlights the need for improvement to enhance the model's performance.

[26]:
```
#  Gradient Boost Classifier

# Define the parameter grid for hyperparameter tuning
param_grid = {
    'n_estimators': [150, 200, 250],     # number of boosting stages to perform
    'max_depth': [None, 2, 5, 10],    # maximum depth of the individual␣
 ↪estimators
    'min_samples_split': [2, 5, 7],    # minimum number of samples required to␣
 ↪split an internal node
    'max_features' : ['auto', 'sqrt', 'log2'],    # the number of features to␣
 ↪consider when looking for the best split
    'random_state' : [42],  # to make output consistent across multiple␣
 ↪function calls
    'loss' : ['deviance', 'exponential'] # loss function to be optimized
}

# Initialize the Gradient Boosting Classifier
gbt = GradientBoostingClassifier()

# Initialize the grid search model
grid_search = GridSearchCV(estimator=gbt, param_grid=param_grid, cv=3,␣
 ↪scoring='accuracy', n_jobs=-1)

# Fit the grid search model
grid_search.fit(X_train_smote, y_train_smote)

# Get the best parameters and best accuracy score
best_params = grid_search.best_params_
best_score = grid_search.best_score_

print('Best parameters:', best_params)
print('Best accuracy score:', best_score)

# Use the best estimator to make predictions on the validation set
bgb_model = grid_search.best_estimator_
y_val_pred = bgb_model.predict(X_val_scaled)

# Use the best estimator to make predictions on the validation set

# Calculate accuracy, precision, recall, and F1 score
accuracy = accuracy_score(y_val, y_val_pred)
precision = precision_score(y_val, y_val_pred)
recall = recall_score(y_val, y_val_pred)
```

```
f1 = f1_score(y_val, y_val_pred)

print('Accuracy: ', accuracy)
print('Precision: ', precision)
print('Recall: ', recall)
print('F1 Score: ', f1)


# Calculate the probabilities of the predictions
y_val_prob = bgb_model.predict_proba(X_val_scaled)[:,1]
# Plot the plots
plot_roc_pr_curves(y_val, y_val_prob, "Gradient Boost")
```

```
Best parameters: {'loss': 'exponential', 'max_depth': 10, 'max_features':
'sqrt', 'min_samples_split': 5, 'n_estimators': 250, 'random_state': 42}
Best accuracy score: 0.9863791146424518
Accuracy:  0.9596774193548387
Precision:  0.46
Recall:  0.45098039215686275
F1 Score:  0.45544554455445546
```





The Receiver Operating Characteristic (ROC) curve for this model displays an area under the curve (AUC) of 0.93, which indicates a strong ability to discriminate between the positive and negative classes, significantly better than random guessing, which would have an AUC of 0.50. This suggests that the model's discriminative ability to correctly classify the positive cases is quite good.

The Precision-Recall (PR) chart, however, shows a lower AUC of 0.43, suggesting that the model has room for improvement in terms of precision and recall. This is corroborated by the model's precision of 0.5217, indicating that when the model predicts a positive outcome, it is correct about 52.17% of the time. This level of precision may lead to a considerable number of false positives.

Furthermore, the recall of the model is 0.4706, which means it identifies about 47.06% of all actual positive cases. This moderate recall suggests that the model is missing a significant number of positive instances.

Despite these challenges, the model achieves an accuracy of approximately 0.964, which might be misleading as it does not capture the model's struggles with precision and recall — a common issue in datasets with class imbalance where accuracy is not the most informative metric.

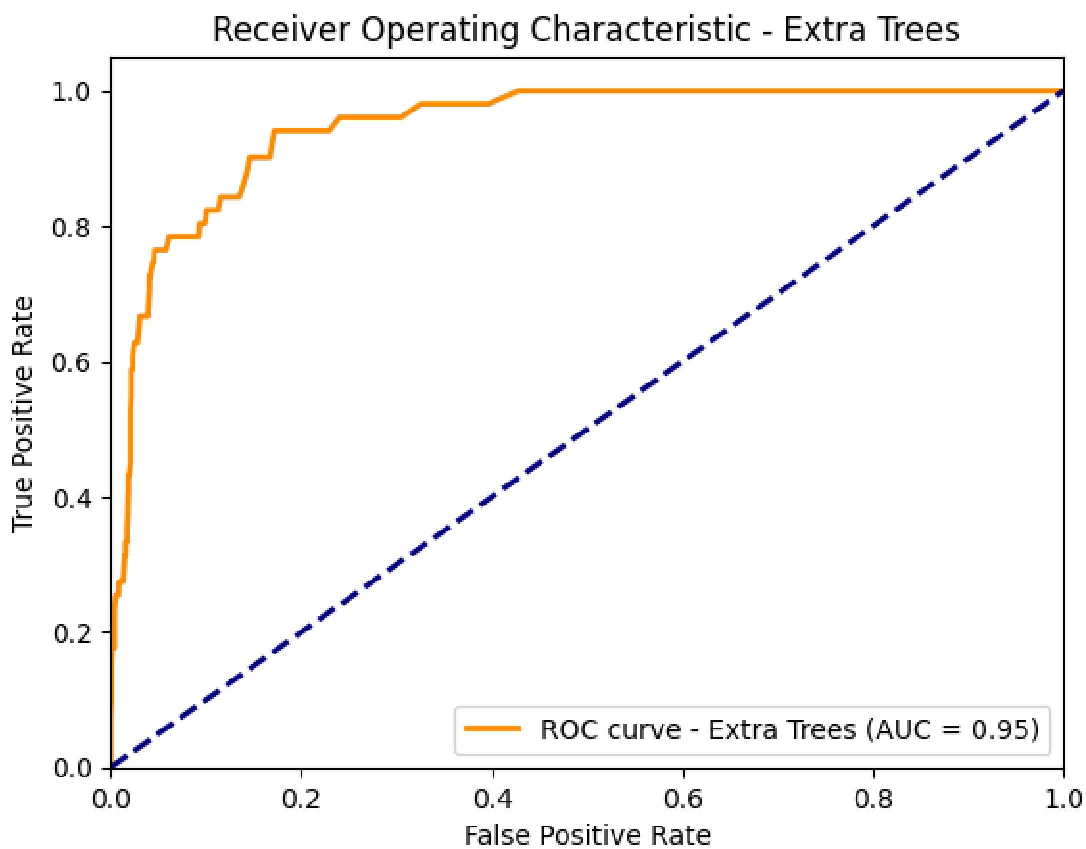
Finally, the F1 Score, which is the harmonic mean of precision and recall, is at 0.4948. This score, being below 0.50, is indicative of the model's inadequate performance in precisely and reliably classifying the positive class.

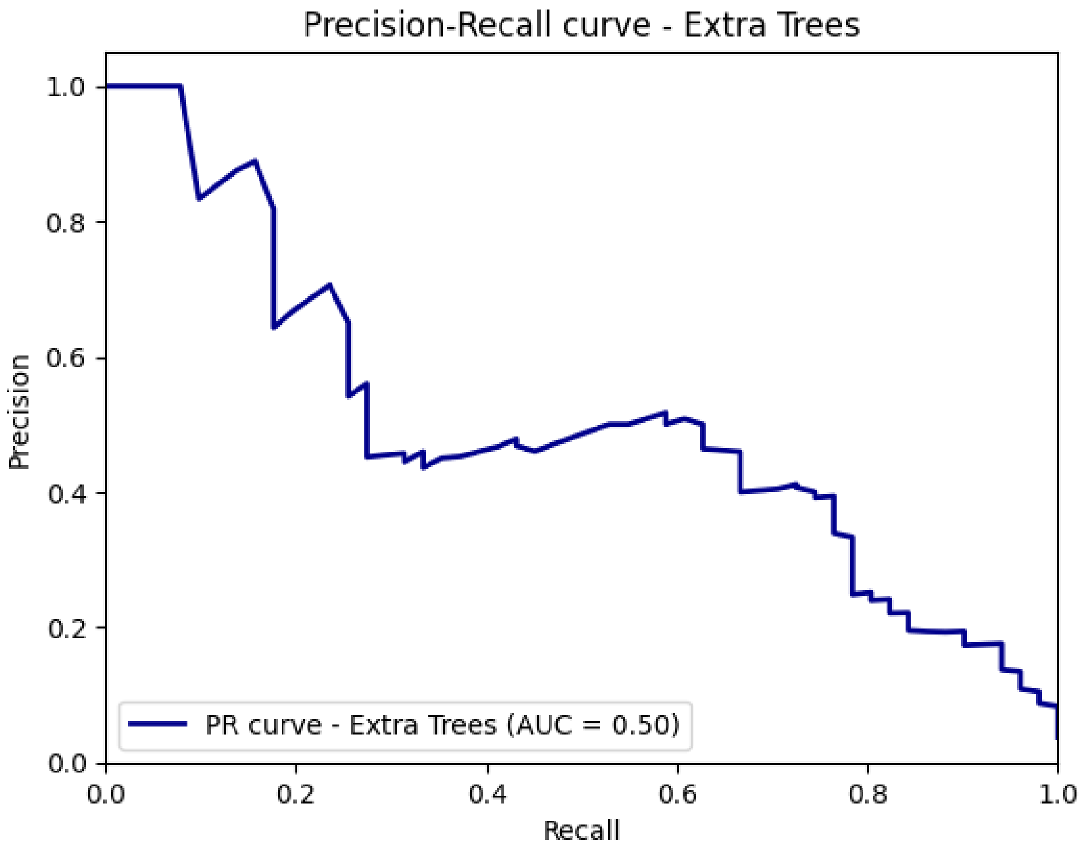
[27]:

```python
## Extra Trees Classifier

param_grid = {
    'n_estimators': [150, 200, 250],     # number of trees in the forest
    'max_depth': [None, 2, 5, 10],    # maximum depth of the individual regression estimators
    'min_samples_split': [2, 5, 7],    # minimum number of samples required to split an internal node
    'max_features' : ['auto', 'sqrt', 'log2'],    # the number of features to consider when looking for the best split
    'random_state' : [42],    # to make output consistent across multiple function calls
    'class_weight' : ['balanced','balanced_subsample'],    # weights associated with classes.
    'criterion' : ['gini', 'entropy'],  # function to measure the quality of a split
    'bootstrap' : [True, False] # whether bootstrap samples are used when building trees
}

# Initialize the Extra Trees Classifier
et = ExtraTreesClassifier()

# Initialize the grid search model
grid_search = GridSearchCV(estimator=et, param_grid=param_grid, cv=3, scoring='accuracy', n_jobs=-1)

# Fit the grid search model
grid_search.fit(X_train_smote, y_train_smote)

# Get the best parameters and best accuracy score
best_params = grid_search.best_params_
best_score = grid_search.best_score_

print('Best parameters:', best_params)
print('Best accuracy score:', best_score)

# Use the best estimator to make predictions on the validation set
etb_model = grid_search.best_estimator_
y_val_pred = etb_model.predict(X_val_scaled)


# Calculate accuracy, precision, recall, and F1 score
accuracy = accuracy_score(y_val, y_val_pred)
precision = precision_score(y_val, y_val_pred)
recall = recall_score(y_val, y_val_pred)
```

```
f1 = f1_score(y_val, y_val_pred)

print('Accuracy: ', accuracy)
print('Precision: ', precision)
print('Recall: ', recall)
print('F1 Score: ', f1)

# Calculate the probabilities of the predictions
y_val_prob = etb_model.predict_proba(X_val_scaled)[:,1]
# Plot the plots
plot_roc_pr_curves(y_val, y_val_prob, "Extra Trees")
```

```
Best parameters: {'bootstrap': False, 'class_weight': 'balanced', 'criterion':
'gini', 'max_depth': None, 'max_features': 'sqrt', 'min_samples_split': 2,
'n_estimators': 200, 'random_state': 42}
Best accuracy score: 0.9859061672342037
Accuracy:  0.9596774193548387
Precision:  0.46
Recall:  0.45098039215686275
F1 Score:  0.45544554455445546
```





The Receiver Operating Characteristic (ROC) curve for this model shows an area under the curve (AUC) of 0.95, which is indicative of an excellent ability to distinguish between the positive and negative classes, far surpassing random guessing, which would have an AUC of 0.50. This high AUC value suggests that the model is very effective at correctly classifying the positive cases as compared to a random classifier.

The Precision-Recall (PR) chart, on the other hand, tells a different story with an AUC of 0.50, which is no better than random guessing. This low AUC on the PR curve is indicative of the model's poor performance in terms of both precision and recall. The precision of the model is 0.46, meaning that when the model predicts a positive outcome, it is correct less than half of the time, leading to a significant number of false positives.

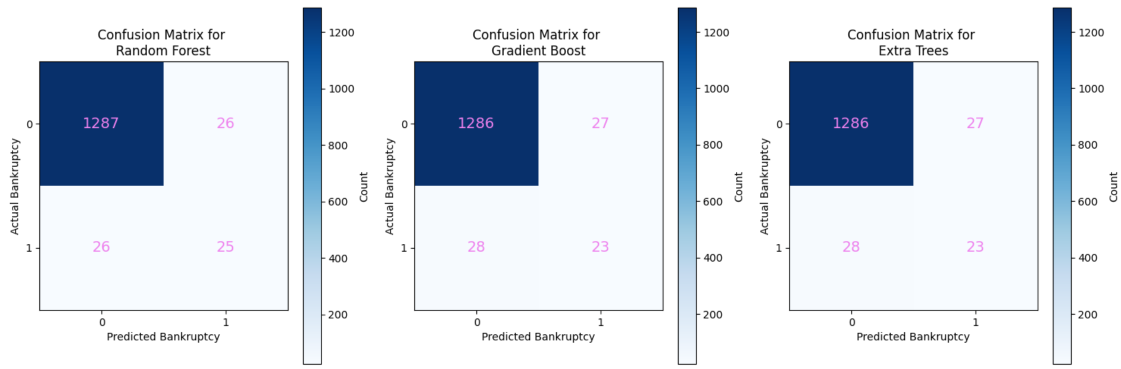
Additionally, the model's recall is 0.4509, indicating that it correctly identifies only 45.09% of all actual positive cases. This suggests that the model is missing a substantial number of positive instances, which is concerning for a classifier, especially in contexts where detecting true positives is crucial.

Despite these shortcomings, the model has an accuracy of approximately 0.9597, which can be misleading because it does not account for the model's low precision and recall. This is a typical scenario with imbalanced datasets where a high accuracy doesn't necessarily mean good predictive performance, particularly for the minority class.

Lastly, the F1 Score of 0.4554, which balances precision and recall, is not impressive and reflects the model's suboptimal performance in accurately and consistently classifying the positive class. This score, combined with the low precision and recall, points towards the need for further model tuning or consideration of alternative modeling approaches to improve its predictive power for the positive class.

7 7. Evaluate Models

[35]:
```python
## Plot the Confusion Matrices

# Define the models and their names
models = [brf_model, bgb_model, etb_model]
model_names = ['Random Forest', 'Gradient Boost', 'Extra Trees']

# Make sure the figure is large enough
plt.figure(figsize=(15, 5))

# Iterate over the predictions and plot their confusion matrix
for idx, (model, model_name) in enumerate(zip(models, model_names)):
    # Get the confusion matrix
    cm = confusion_matrix(y_val, model.predict(X_val_scaled))

    # Create a subplot for each confusion matrix
    plt.subplot(1, 3, idx + 1)  # rows, columns, index

    # Visualize the confusion matrix using matshow
    plt.imshow(cm, cmap=plt.cm.Blues)
    plt.title('Confusion Matrix for \n' + model_name)
    plt.colorbar(label='Count')
    plt.ylabel('Actual Bankruptcy')
    plt.xlabel('Predicted Bankruptcy')
    plt.xticks([0, 1])
    plt.yticks([0, 1])

    # Loop over data dimensions and create text annotations.
    for i in range(cm.shape[0]):
        for j in range(cm.shape[1]):
            plt.text(j, i, cm[i, j], ha="center", va="center", color="violet",␣
 ↪fontsize=14)

    plt.grid(False)

# Adjust the layout so that the plots do not overlap
plt.tight_layout()

# Display the plots
plt.show()
```



Random Forest model exhibits a slightly better balance between false positives and false negatives, with both being equal at 26. Meanwhile, both Gradient Boost and Extra Trees models present a similar performance to each other, with 27 false positives and 28 false negatives, indicating a marginal increase in the false negatives compared to the Random Forest model. In terms of true positives, all three models show relatively close numbers, with Random Forest at 25, and both Gradient Boost and Extra Trees at 23. This suggests that all models have a comparable ability to correctly identify bankruptcies. However, the true negatives, which represent the correct identification of non-bankruptcy cases, are highest for Random Forest at 1287, followed by both Gradient Boost and Extra Trees at 1286, which is an indication of a very slight edge for Random Forest in correctly predicting non-bankrupt cases.

These confusion matrices suggest that while all three models perform similarly, the Random Forest model has a minor advantage in terms of maintaining a balance between type I and type II errors (false positives and false negatives, respectively). This could potentially make it a more reliable choice for scenarios where it's important to maintain a balance between detecting bankruptcies and avoiding false bankruptcy alarms. However, the differences are marginal, and the choice between these models might also depend on other factors such as model interpretability, computational efficiency, and performance on other metrics not visible in the confusion matrices.