In [2]:
```
##Import Libraries
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn import metrics

from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.linear_model import LogisticRegression


from sklearn.preprocessing import StandardScaler, label_binarize, OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.metrics import accuracy_score, classification_report,confusion_matrix, roc_curve, auc
from sklearn.multiclass import OneVsRestClassifier, OneVsOneClassifier
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV

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

In [3]:
```
# load the data
data=pd.read_csv(r"C:\Users\DD\Desktop\ML PROJECTS\Classification\data.csv")
```

In [4]:
```
#read the data
data
```

Out[4]:

Operating Profit Rate	Pre-tax net Interest Rate	After-tax net Interest Rate	Non-industry income and expenditure/revenue	...	Net Income to Total Assets	Total assets to GNP price	No-credit Interval	Gross Profit to Sales	Net Income to Stockholder's Equity	Liability to Equity	Degree of Financial Leverage (DFL)	Inte Cover R (Inte expe to E
0.998969	0.796887	0.808809	0.302646	...	0.716845	0.009219	0.622879	0.601453	0.827890	0.290202	0.026601	0.564
0.998946	0.797380	0.809301	0.303556	...	0.795297	0.008323	0.623652	0.610237	0.839969	0.283846	0.264577	0.570
0.998857	0.796403	0.808388	0.302035	...	0.774670	0.040003	0.623841	0.601449	0.836774	0.290189	0.026555	0.563
0.998700	0.796967	0.808966	0.303350	...	0.739555	0.003252	0.622929	0.583538	0.834697	0.281721	0.026697	0.564
0.998973	0.797366	0.809304	0.303475	...	0.795016	0.003878	0.623521	0.598782	0.839973	0.278514	0.024752	0.575
...	...	...	...	...	...	...	...	...	...	...	...	
0.998992	0.797409	0.809331	0.303510	...	0.799927	0.000466	0.623620	0.604455	0.840359	0.279606	0.027064	0.566
0.998992	0.797414	0.809327	0.303520	...	0.799748	0.001959	0.623931	0.598306	0.840306	0.278132	0.027009	0.566
0.998984	0.797401	0.809317	0.303512	...	0.797778	0.002840	0.624156	0.610441	0.840138	0.275789	0.026791	0.565
0.999074	0.797500	0.809399	0.303498	...	0.811808	0.002837	0.623957	0.607846	0.841084	0.277547	0.026822	0.565
0.998080	0.801987	0.813800	0.313415	...	0.815956	0.000707	0.626680	0.627408	0.841019	0.275114	0.026793	0.565

In [5]:
```
#top 5 column
data.head()
```

Out[5]:

Operating Profit Rate	Pre-tax net Interest Rate	After-tax net Interest Rate	Non-industry income and expenditure/revenue	...	Net Income to Total Assets	Total assets to GNP price	No-credit Interval	Gross Profit to Sales	Net Income to Stockholder's Equity	Liability to Equity	Degree of Financial Leverage (DFL)	Inte Cover R (Inte expe to EI
0.998969	0.796887	0.808809	0.302646	...	0.716845	0.009219	0.622879	0.601453	0.827890	0.290202	0.026601	0.564
0.998946	0.797380	0.809301	0.303556	...	0.795297	0.008323	0.623652	0.610237	0.839969	0.283846	0.264577	0.570
0.998857	0.796403	0.808388	0.302035	...	0.774670	0.040003	0.623841	0.601449	0.836774	0.290189	0.026555	0.563
0.998700	0.796967	0.808966	0.303350	...	0.739555	0.003252	0.622929	0.583538	0.834697	0.281721	0.026697	0.564
0.998973	0.797366	0.809304	0.303475	...	0.795016	0.003878	0.623521	0.598782	0.839973	0.278514	0.024752	0.575

In [6]:
```
#last bottom 5
data.tail()
```

Out[6]:

	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	...	I Inco to To Ass
6814	0	0.493687	0.539468	0.543230	0.604455	0.604462	0.998992	0.797409	0.809331	0.303510	...	0.799
6815	0	0.475162	0.538269	0.524172	0.598308	0.598308	0.998992	0.797414	0.809327	0.303520	...	0.799
6816	0	0.472725	0.533744	0.520638	0.610444	0.610213	0.998984	0.797401	0.809317	0.303512	...	0.797
6817	0	0.506264	0.559911	0.554045	0.607850	0.607850	0.999074	0.797500	0.809399	0.303498	...	0.811
6818	0	0.493053	0.570105	0.549548	0.627409	0.627409	0.998080	0.801987	0.813800	0.313415	...	0.815

5 rows × 96 columns

In [7]:
```
#shape of the data i.e no. of rows and columns
data.shape
```

Out[7]: (6819, 96)

In [8]:
```
# describe :count,max,min
data.describe(include='all')
```

Out[8]:

	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	N i expenditu
count	6819.000000	6819.000000	6819.000000	6819.000000	6819.000000	6819.000000	6819.000000	6819.000000	6819.000000	6
mean	0.032263	0.505180	0.558625	0.553589	0.607948	0.607929	0.998755	0.797190	0.809084	
std	0.176710	0.060686	0.065620	0.061595	0.016934	0.016916	0.013010	0.012869	0.013601	
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	0.000000	0.476527	0.535543	0.527277	0.600445	0.600434	0.998969	0.797386	0.809312	
50%	0.000000	0.502706	0.559802	0.552278	0.605997	0.605976	0.999022	0.797464	0.809375	
75%	0.000000	0.535563	0.589157	0.584105	0.613914	0.613842	0.999095	0.797579	0.809469	
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	

8 rows × 96 columns

In [9]:
```
data.describe()
```

Out[9]:

	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	N(i expenditu
count	6819.000000	6819.000000	6819.000000	6819.000000	6819.000000	6819.000000	6819.000000	6819.000000	6819.000000	6
mean	0.032263	0.505180	0.558625	0.553589	0.607948	0.607929	0.998755	0.797190	0.809084	
std	0.176710	0.060686	0.065620	0.061595	0.016934	0.016916	0.013010	0.012869	0.013601	
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	0.000000	0.476527	0.535543	0.527277	0.600445	0.600434	0.998969	0.797386	0.809312	
50%	0.000000	0.502706	0.559802	0.552278	0.605997	0.605976	0.999022	0.797464	0.809375	
75%	0.000000	0.535563	0.589157	0.584105	0.613914	0.613842	0.999095	0.797579	0.809469	
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	

8 rows × 96 columns

In [10]:
```
#it provides a concise summary of the DataFrame's structure,
#including the number of non-null values, data types of columns, and memory usage.
#It's a useful method for quickly assessing the basic characteristics of your data

data.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                             6803 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                                            6768 non-null   float64
 83   Cash Flow to Equity                                      6803 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                                    6754 non-null   float64
 90   Net Income to Stockholder's Equity                       6806 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
```

In [11]:

```
#it will display information about that object, including its data type, attributes, and methods, if available
#This information is provided interactively to help you understand the object better.
data.info
```

Out[11]:

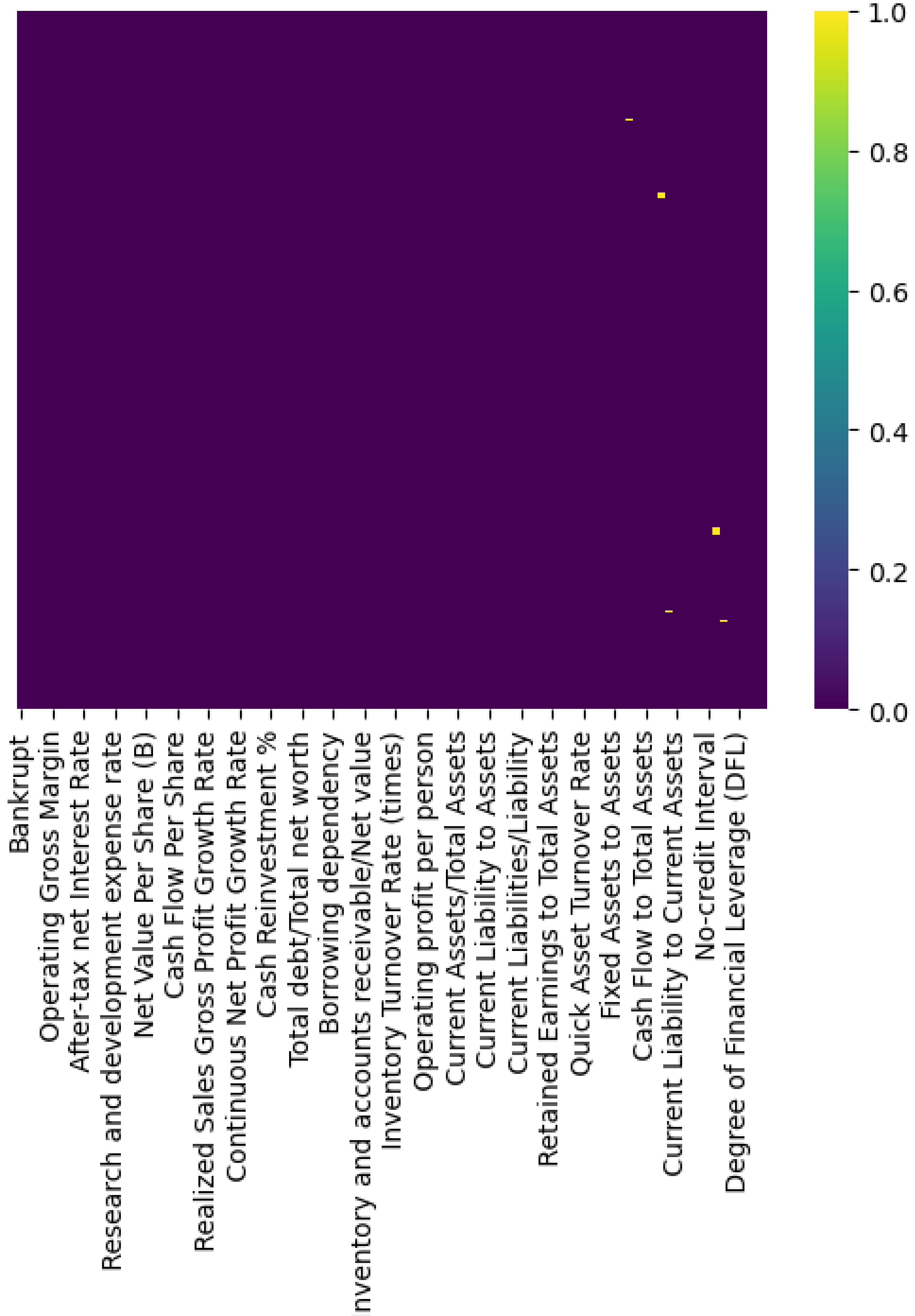
```
<bound method DataFrame.info of       Bankrupt   ROA(C) before interest and depreciation before interest  \
0            1                                           0.370594
1            1                                           0.464291
2            1                                           0.426071
3            1                                           0.399844
4            1                                           0.465022
...        ...                                                ...
6814         0                                           0.493687
6815         0                                           0.475162
6816         0                                           0.472725
6817         0                                           0.506264
6818         0                                           0.493053

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

In [12]:
```
# number of null values in each column
data.isnull().sum()
```

Out[12]:
```
Bankrupt                                                    0
 ROA(C) before interest and depreciation before interest    0
 ROA(A) before interest and % after tax                     0
 ROA(B) before interest and depreciation after tax          0
 Operating Gross Margin                                     0
                                                           ..
 Liability to Equity                                        0
 Degree of Financial Leverage (DFL)                         0
 Interest Coverage Ratio (Interest expense to EBIT)         0
 Net Income Flag                                            0
 Equity to Liability                                        0
Length: 96, dtype: int64
```

In [13]:
```
# to illustrate null values using heatmap
sns.heatmap(data.isnull(), yticklabels=False,cmap='viridis')
```

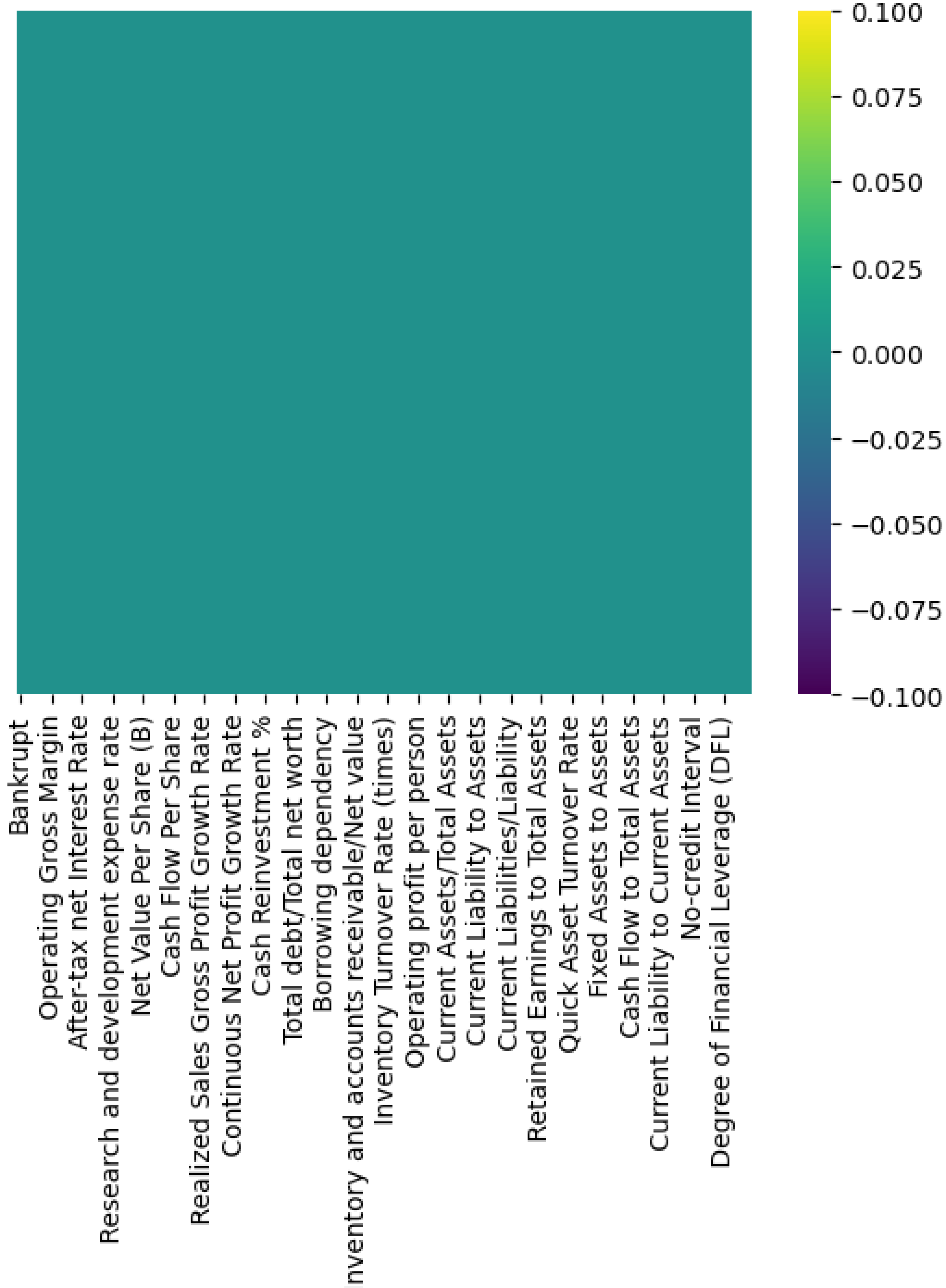
Out[13]:
```
<Axes: >
```


1.0
0.8
0.6
0.4
0.2
0.0
Bankrupt
Operating Gross Margin
After-tax net Interest Rate
Research and development expense rate
Net Value Per Share (B)
Cash Flow Per Share
Realized Sales Gross Profit Growth Rate
Continuous Net Profit Growth Rate
Cash Reinvestment %
Total debt/Total net worth
Borrowing dependency
Inventory and accounts receivable/Net value
Inventory Turnover Rate (times)
Operating profit per person
Current Assets/Total Assets
Current Liability to Assets
Current Liabilities/Liability
Retained Earnings to Total Assets
Quick Asset Turnover Rate
Fixed Assets to Assets
Cash Flow to Total Assets
Current Liability to Current Assets
No-credit Interval
Degree of Financial Leverage (DFL)

In [14]:
```
data[' CFO to Assets'].bfill(axis=0, inplace=True)
data[' Gross Profit to Sales'].bfill(axis=0,inplace=True)

data[' Cash Flow to Equity'].ffill(axis=0,inplace=True)
data[" Net Income to Stockholder's Equity"].bfill(axis=0,inplace=True)

data[' Current Liability to Equity'].fillna(data[' Current Liability to Equity'].mode()[0],inplace=True)
```

In [15]:
```
#after filling the missing data
sns.heatmap(data.isnull(), yticklabels=False,cmap='viridis')
```

Out[15]: <Axes: >


0.100
0.075
0.050
0.025
0.000
−0.025
−0.050
−0.075
−0.100
Bankrupt
Operating Gross Margin
After-tax net Interest Rate
Research and development expense rate
Net Value Per Share (B)
Cash Flow Per Share
Realized Sales Gross Profit Growth Rate
Continuous Net Profit Growth Rate
Cash Reinvestment %
Total debt/Total net worth
Borrowing dependency
Inventory and accounts receivable/Net value
Inventory Turnover Rate (times)
Operating profit per person
Current Assets/Total Assets
Current Liability to Assets
Current Liabilities/Liability
Retained Earnings to Total Assets
Quick Asset Turnover Rate
Fixed Assets to Assets
Cash Flow to Total Assets
Current Liability to Current Assets
No-credit Interval
Degree of Financial Leverage (DFL)

In [16]:
```
data.dtypes# show data types of data
```

Out[16]:
```
Bankrupt                                                      int64
 ROA(C) before interest and depreciation before interest    float64
 ROA(A) before interest and % after tax                     float64
 ROA(B) before interest and depreciation after tax          float64
 Operating Gross Margin                                     float64
                                                             ...
 Liability to Equity                                        float64
 Degree of Financial Leverage (DFL)                         float64
 Interest Coverage Ratio (Interest expense to EBIT)         float64
 Net Income Flag                                              int64
 Equity to Liability                                        float64
Length: 96, dtype: object
```

In [17]:
```
cat_data=data.select_dtypes(include="object")#categoriacl data show in data
num_data=data.select_dtypes(exclude="object")#numerical data show in data
```

In [18]:
```
cat_data
```

Out[18]:

0
1
2
3
4
...
6814
6815
6816
6817
6818

6819 rows × 0 columns

In [19]:
```
num_data
```

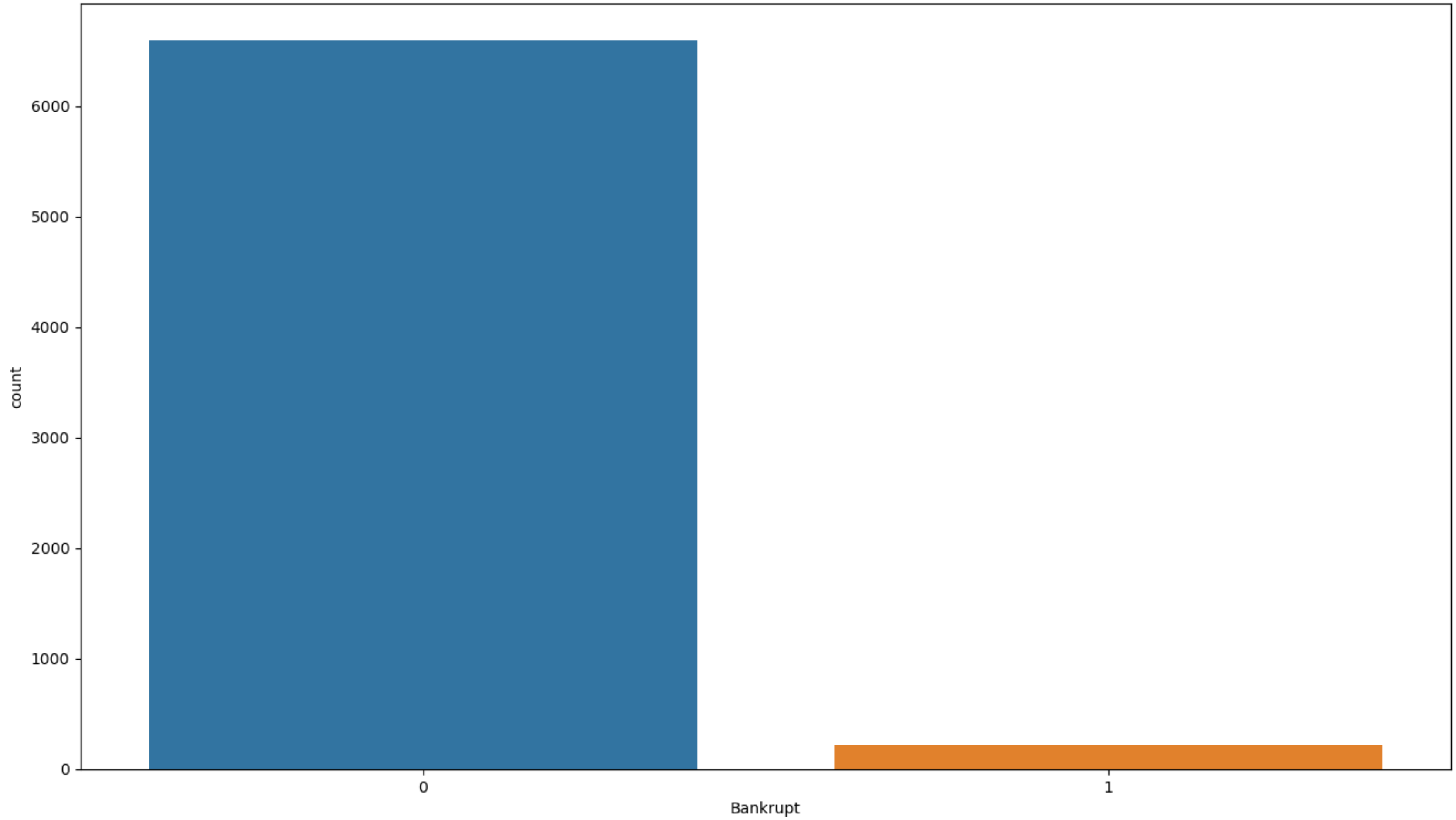
Out[19]:

	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	...	Inco to To Ass
0	1	0.370594	0.424389	0.405750	0.601457	0.601457	0.998969	0.796887	0.808809	0.302646	...	0.716
1	1	0.464291	0.538214	0.516730	0.610235	0.610235	0.998946	0.797380	0.809301	0.303556	...	0.795
2	1	0.426071	0.499019	0.472295	0.601450	0.601364	0.998857	0.796403	0.808388	0.302035	...	0.774
3	1	0.399844	0.451265	0.457733	0.583541	0.583541	0.998700	0.796967	0.808966	0.303350	...	0.739
4	1	0.465022	0.538432	0.522298	0.598783	0.598783	0.998973	0.797366	0.809304	0.303475	...	0.795
...	...	...	...	...	...	...	...	...	...	...	...	
6814	0	0.493687	0.539468	0.543230	0.604455	0.604462	0.998992	0.797409	0.809331	0.303510	...	0.799
6815	0	0.475162	0.538269	0.524172	0.598308	0.598308	0.998992	0.797414	0.809327	0.303520	...	0.799
6816	0	0.472725	0.533744	0.520638	0.610444	0.610213	0.998984	0.797401	0.809317	0.303512	...	0.797
6817	0	0.506264	0.559911	0.554045	0.607850	0.607850	0.999074	0.797500	0.809399	0.303498	...	0.811
6818	0	0.493053	0.570105	0.549548	0.627409	0.627409	0.998080	0.801987	0.813800	0.313415	...	0.815

6819 rows × 96 columns

In [20]:
```
rename column
data.rename(columns = {'Bankrupt?':'Bankrupt'}, inplace = True)
```

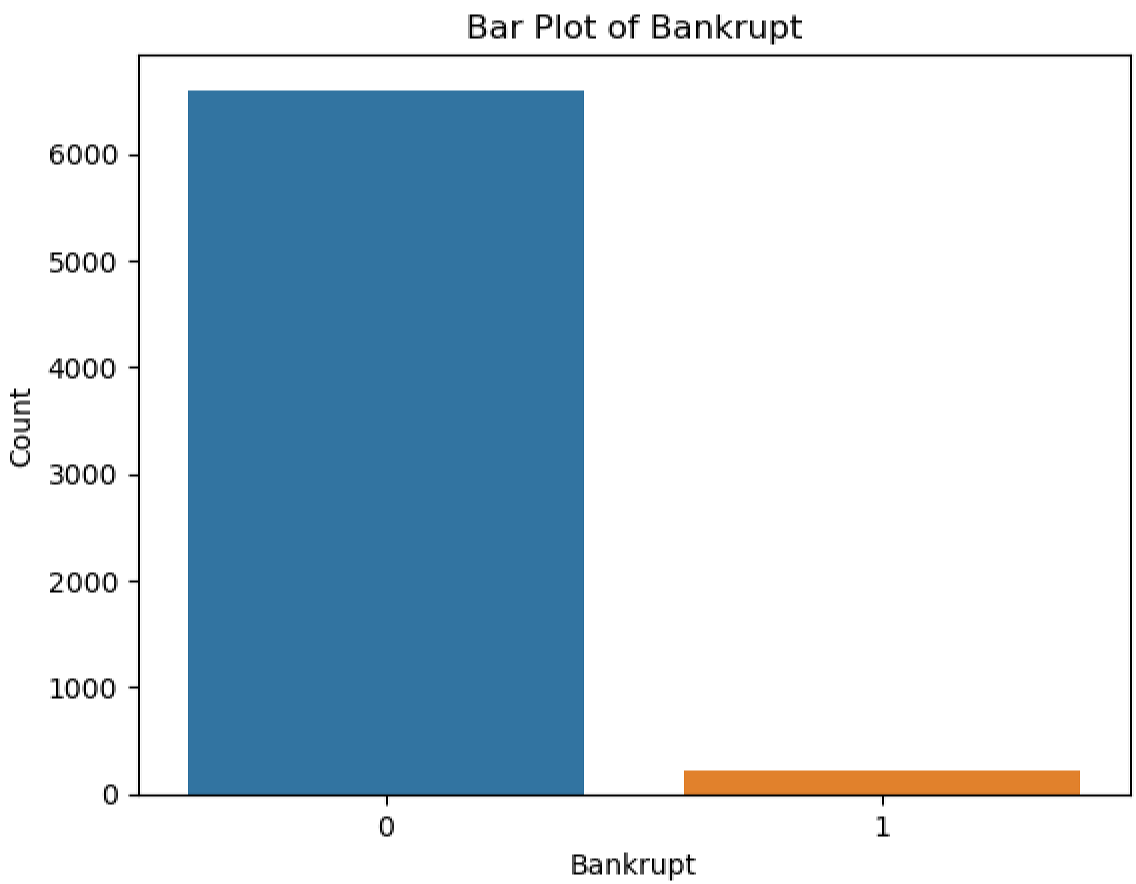
In [21]:
```
plt.figure(figsize=(16,9))# countplot for bankrupt
sns.countplot(x = 'Bankrupt', data = data)
plt.show()
```



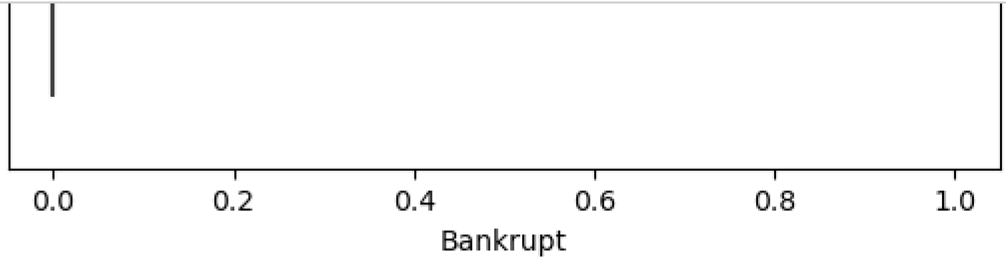
In [22]:
```
corrmat = data.corr()# subplot for all corelated data
plt.subplots(figsize=(18,18))
sns.heatmap(corrmat,cmap="Pastel1", square=True)
plt.show()
```

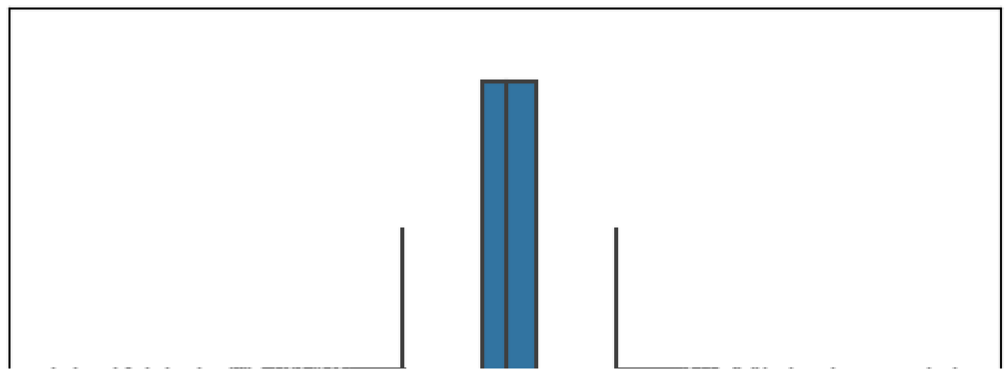

Bankrupt
ROA(C) before interest and depreciation before interest
ROA(A) before interest and % after tax
ROA(B) before interest and depreciation after tax
Operating Gross Margin
Realized Sales Gross Margin
Operating Profit Rate
Pre-tax net Interest Rate
After-tax net Interest Rate
Non-industry income 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
Inventory and accounts receivable/Net value
Total Asset Turnover
Accounts Receivable Turnover
Average Collection Days
Inventory Turnover Rate (times)
Fixed Assets Turnover Frequency
Net Worth Turnover Rate (times)
Revenue per person
Operating profit per person
Allocation rate per person
Working Capital to Total Assets
Quick Assets/Total Assets
Current Assets/Total Assets
Cash/Total Assets
Quick Assets/Current Liability
Cash/Current Liability
Current Liability to Assets
Operating Funds to Liability
Inventory/Working Capital
Inventory/Current Liability
Current Liabilities/Liability
Working Capital/Equity
Current Liabilities/Equity
Long-term Liability to Current Assets
Retained Earnings to Total Assets
Total income/Total expense
Total expense/Assets
Current Asset Turnover Rate
Quick Asset Turnover Rate
Working capcital Turnover Rate
Cash Turnover Rate
Cash Flow to Sales
Fixed Assets to Assets
Current Liability to Liability
Current Liability to Equity
Equity to Long-term Liability
Cash Flow to Total Assets
Cash Flow to Liability
CFO to Assets
Cash Flow to Equity
Current Liability to Current Assets
Liability-Assets Flag
Net Income to Total Assets
Total assets to GNP price
No-credit Interval
Gross Profit to Sales
Net Income to Stockholder's Equity
Liability to Equity
Degree of Financial Leverage (DFL)
Interest Coverage Ratio (Interest expense to EBIT)
Net Income Flag
Equity to Liability
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00

In [23]:
```
sns.countplot(x='Bankrupt', data=data)#count plot for Bankruptlevel
plt.title('Bar Plot of Bankrupt')
plt.xlabel('Bankrupt')
plt.ylabel('Count')
plt.show()
```

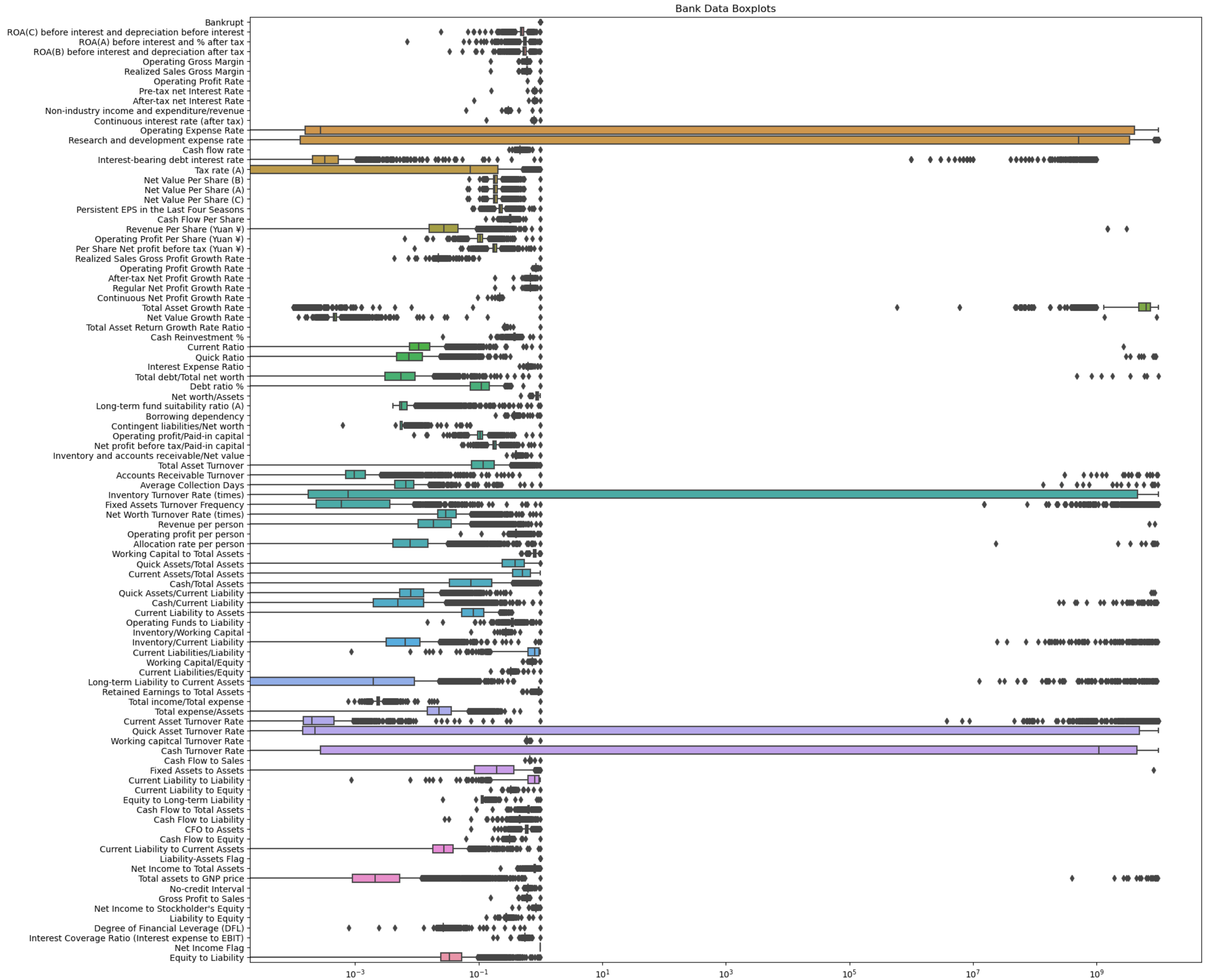


In [24]:
```
for i in num_data.columns:
    sns.boxplot(x=data[i])  # Use 'data' instead of 'num_data'
    plt.show()
```

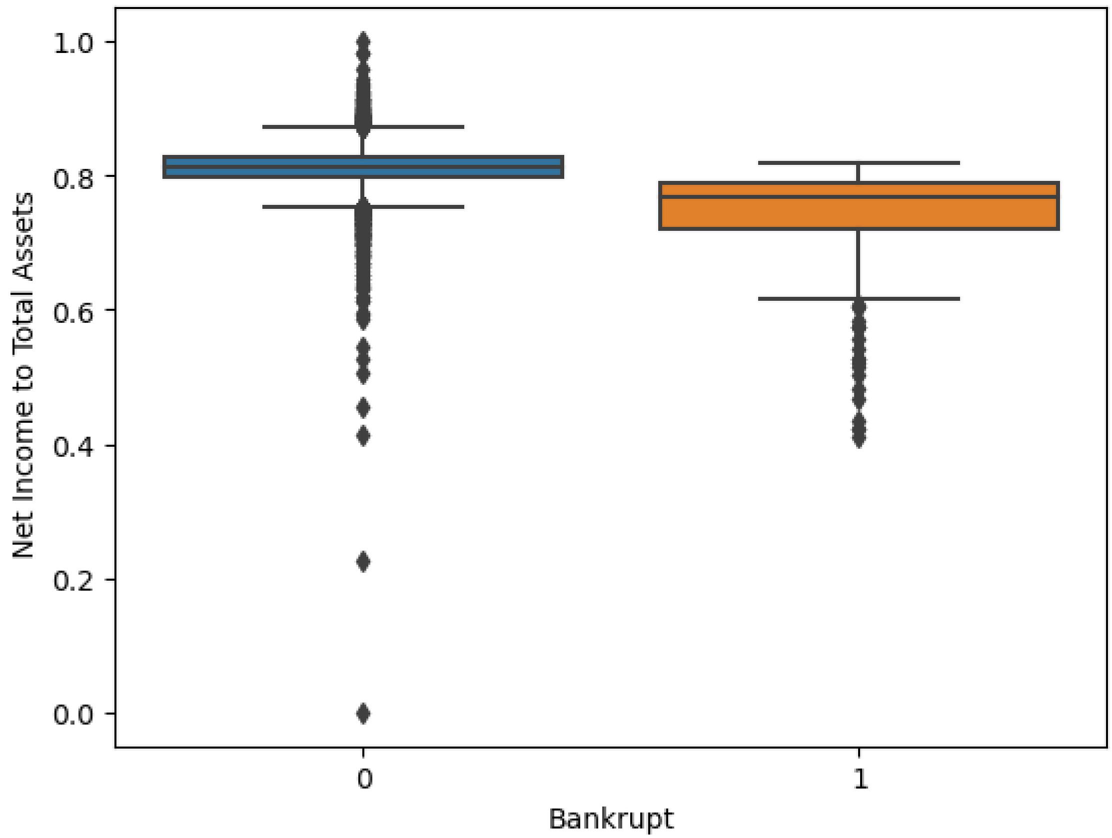




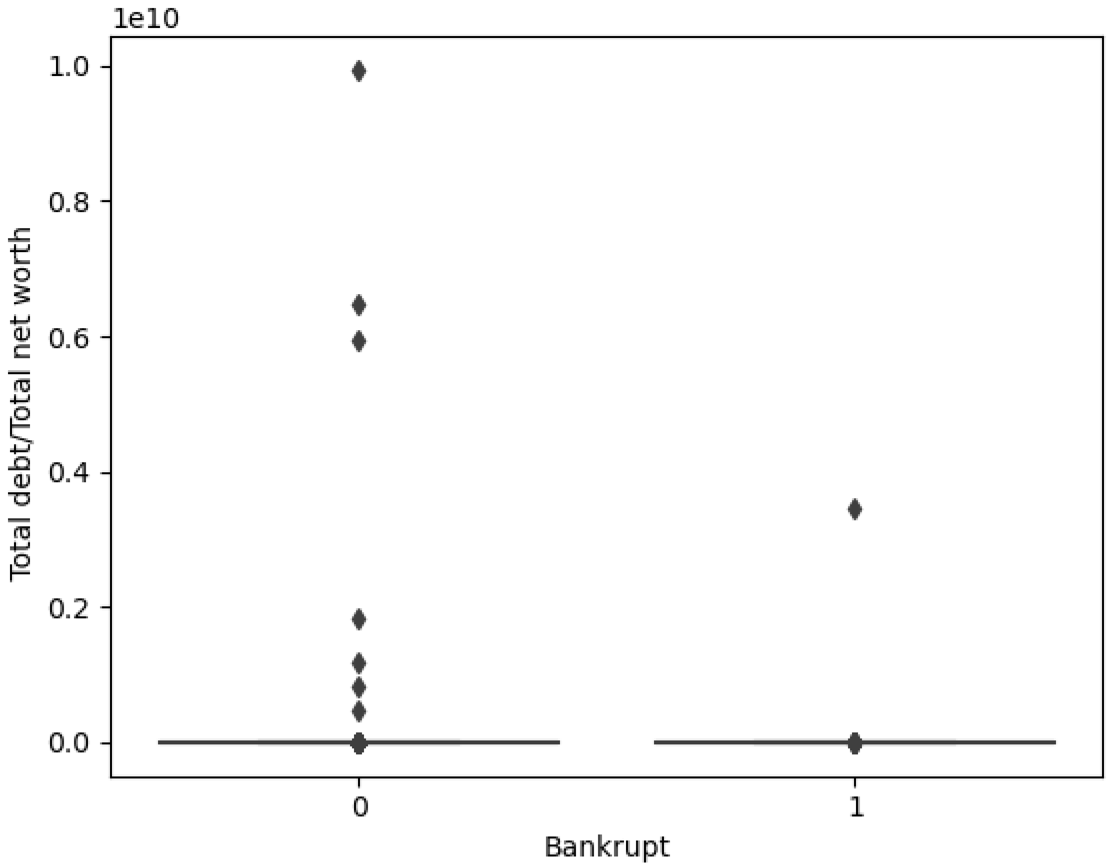
In [25]:
```
plt.figure(figsize = (20,20))
ax =sns.boxplot(data = data, orient="h")
ax.set_title('Bank Data Boxplots')
ax.set(xscale="log")
plt.show()
```


Bank Data Boxplots
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
Inventory and accounts receivable/Net value
Total Asset Turnover
Accounts Receivable Turnover
Average Collection Days
Inventory Turnover Rate (times)
Fixed Assets Turnover Frequency
Net Worth Turnover Rate (times)
Revenue per person
Operating profit per person
Allocation rate per person
Working Capital to Total Assets
Quick Assets/Total Assets
Current Assets/Total Assets
Cash/Total Assets
Quick Assets/Current Liability
Cash/Current Liability
Current Liability to Assets
Operating Funds to Liability
Inventory/Working Capital
Inventory/Current Liability
Current Liabilities/Liability
Working Capital/Equity
Current Liabilities/Equity
Long-term Liability to Current Assets
Retained Earnings to Total Assets
Total income/Total expense
Total expense/Assets
Current Asset Turnover Rate
Quick Asset Turnover Rate
Working capitcal Turnover Rate
Cash Turnover Rate
Cash Flow to Sales
Fixed Assets to Assets
Current Liability to Liability
Current Liability to Equity
Equity to Long-term Liability
Cash Flow to Total Assets
Cash Flow to Liability
CFO to Assets
Cash Flow to Equity
Current Liability to Current Assets
Liability-Assets Flag
Net Income to Total Assets
Total assets to GNP price
No-credit Interval
Gross Profit to Sales
Net Income to Stockholder's Equity
Liability to Equity
Degree of Financial Leverage (DFL)
Interest Coverage Ratio (Interest expense to EBIT)
Net Income Flag
Equity to Liability
10^{-3}
10^{-1}
10^{1}
10^{3}
10^{5}
10^{7}
10^{9}

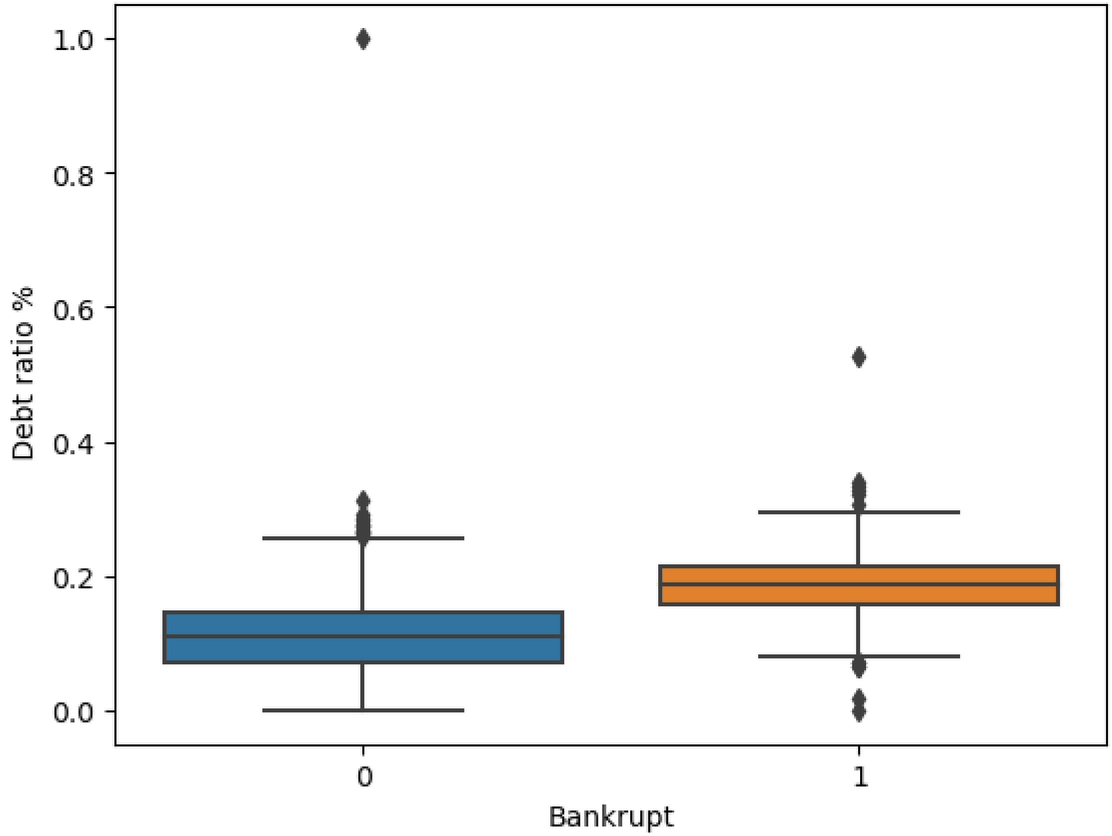
In [26]:
```
sns.boxplot(x="Bankrupt", y=" Net Income to Total Assets", data=data) #boxplot show X and Y
plt.show()
```



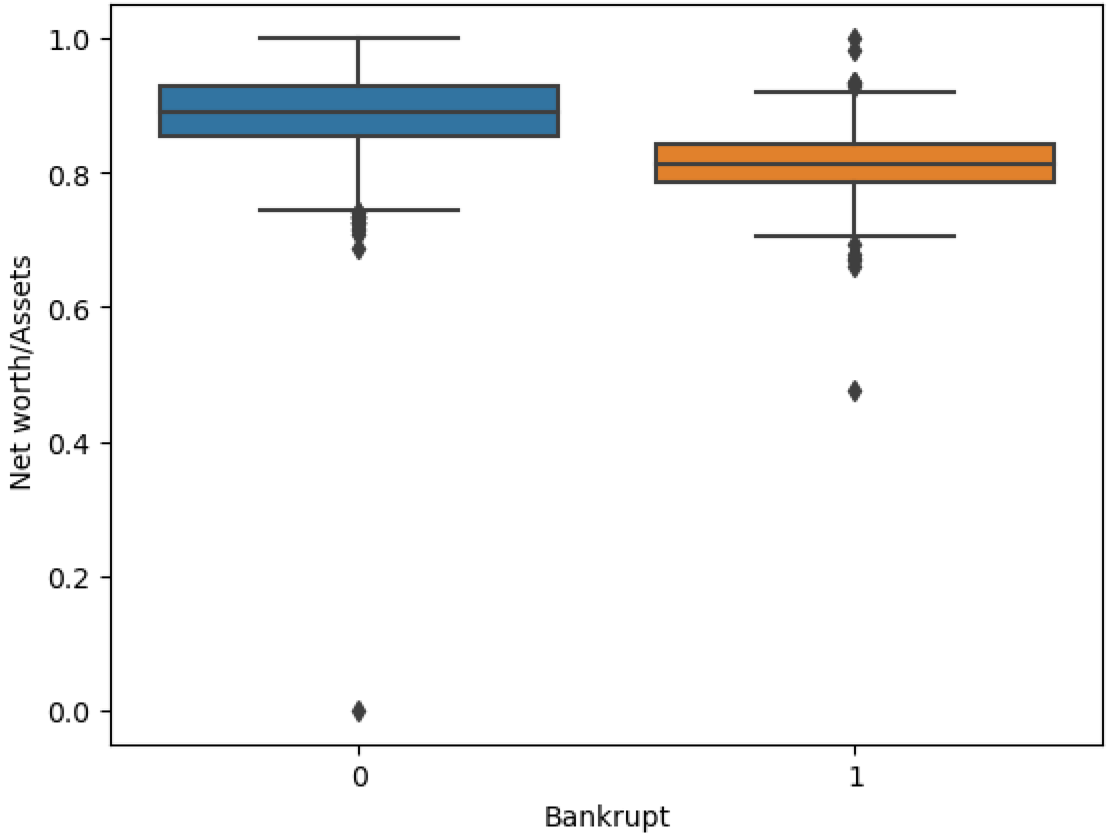
In [27]:
```
sns.boxplot(x="Bankrupt", y=" Total debt/Total net worth", data=data)
plt.show()
```



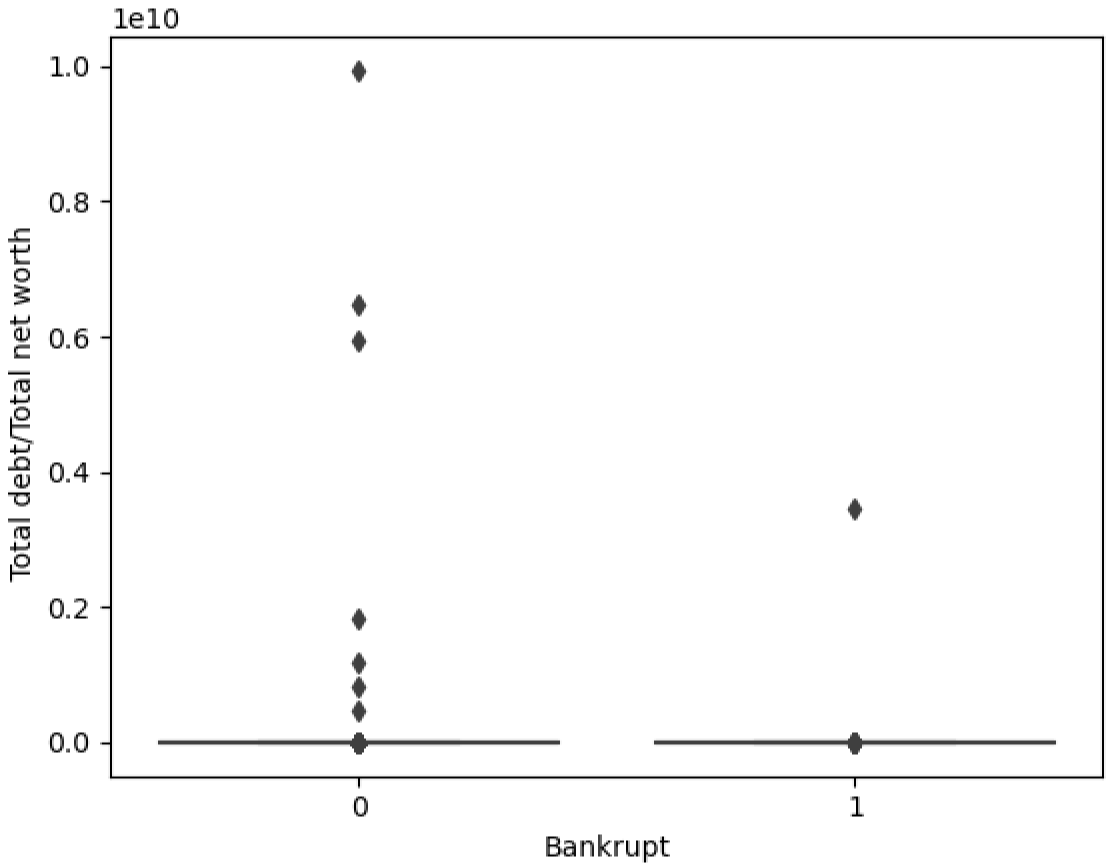
In [28]:
```
sns.boxplot(x="Bankrupt", y=" Debt ratio %", data=data)
plt.show()
```



In [29]:
```
sns.boxplot(x="Bankrupt", y=' Net worth/Assets', data=data)
plt.show()
```

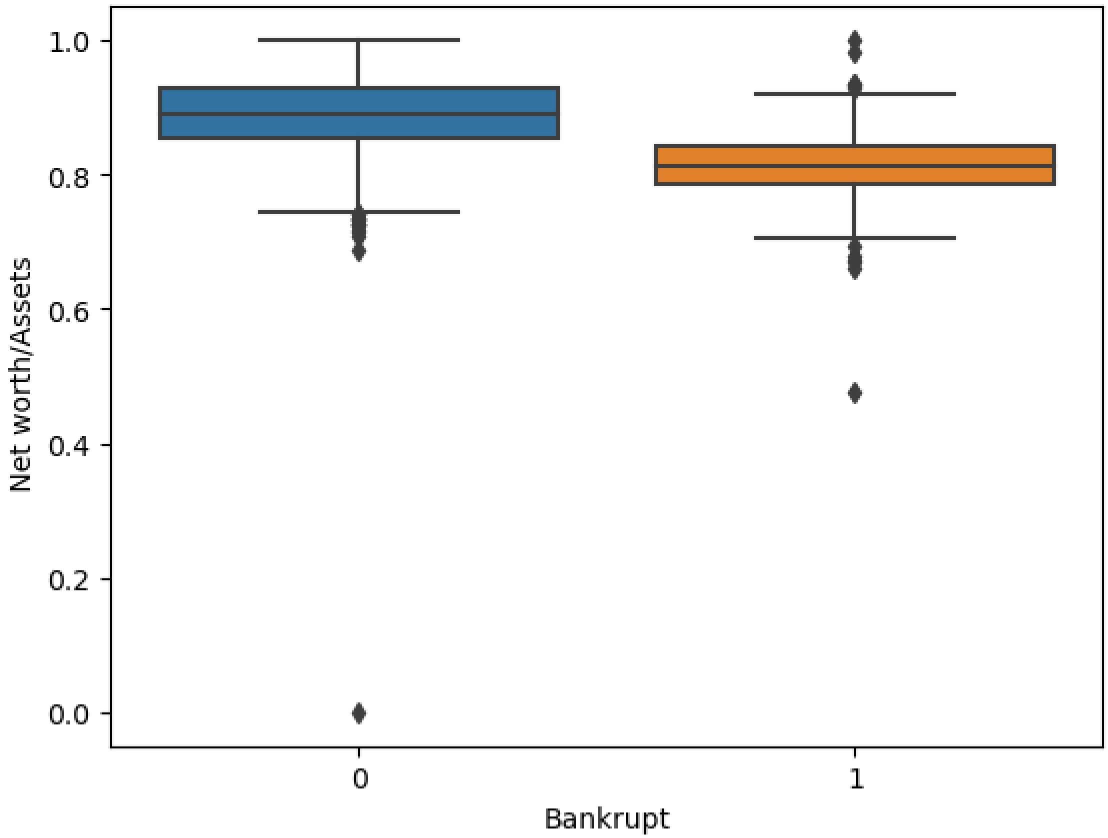


In [30]:
```
sns.boxplot(x="Bankrupt", y=" Total debt/Total net worth", data=data)

plt.show()
```



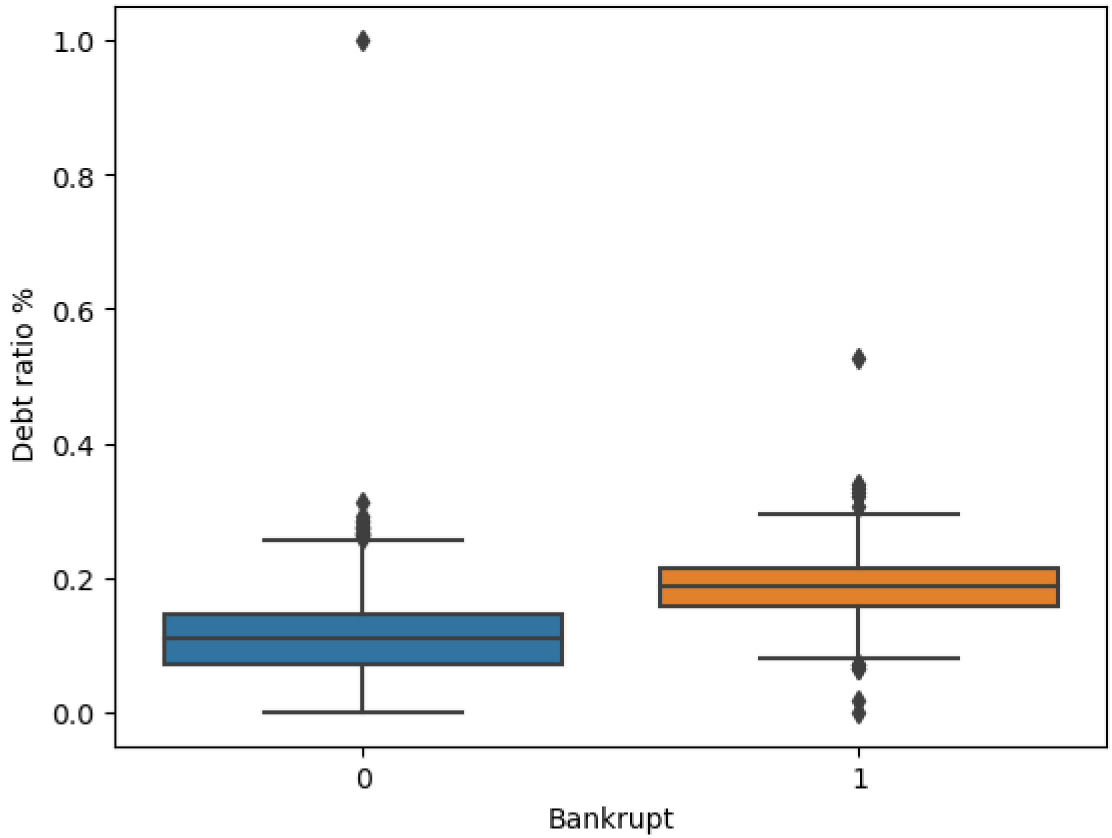
In [31]:
```
sns.boxplot(x="Bankrupt", y=' Net worth/Assets', data=data)
```

Out[31]:
```
<Axes: xlabel='Bankrupt', ylabel=' Net worth/Assets'>
```



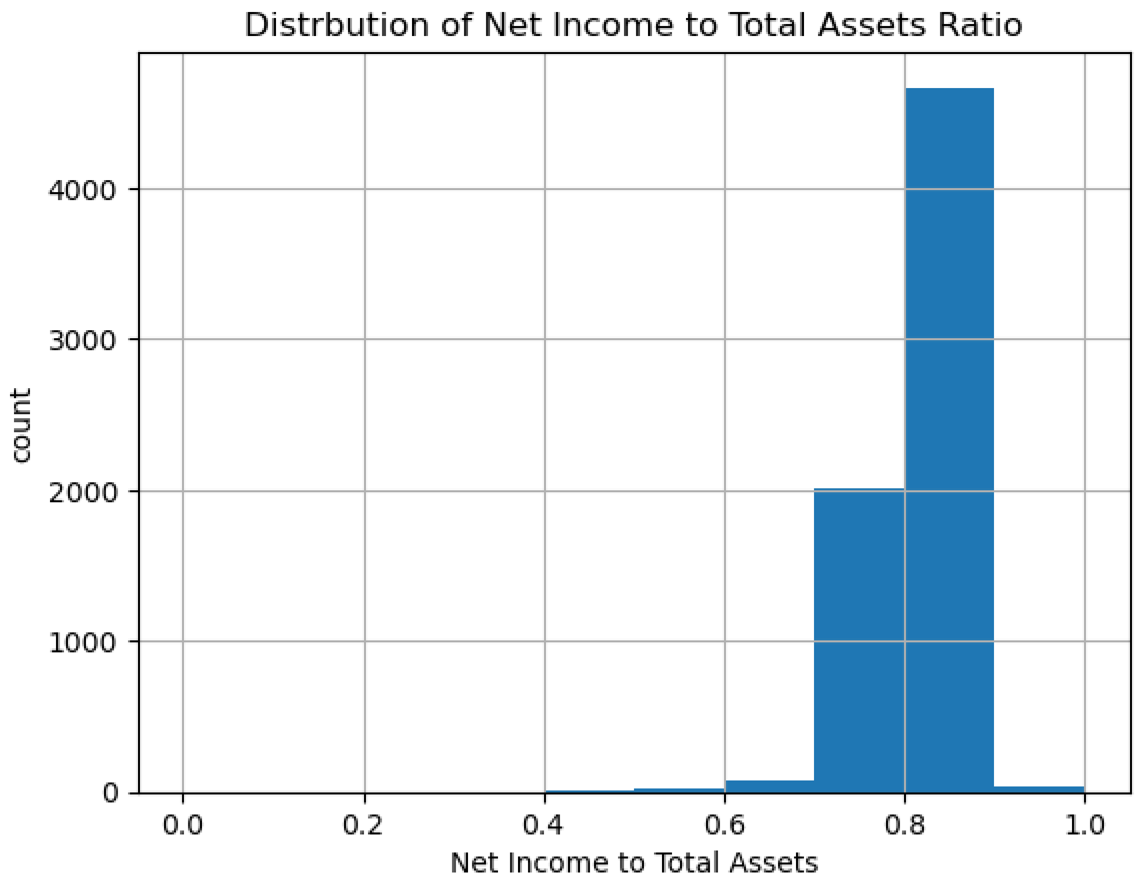
In [32]:
```
sns.boxplot(x="Bankrupt", y=" Debt ratio %", data=data)
```

Out[32]:
```
<Axes: xlabel='Bankrupt', ylabel=' Debt ratio %'>
```

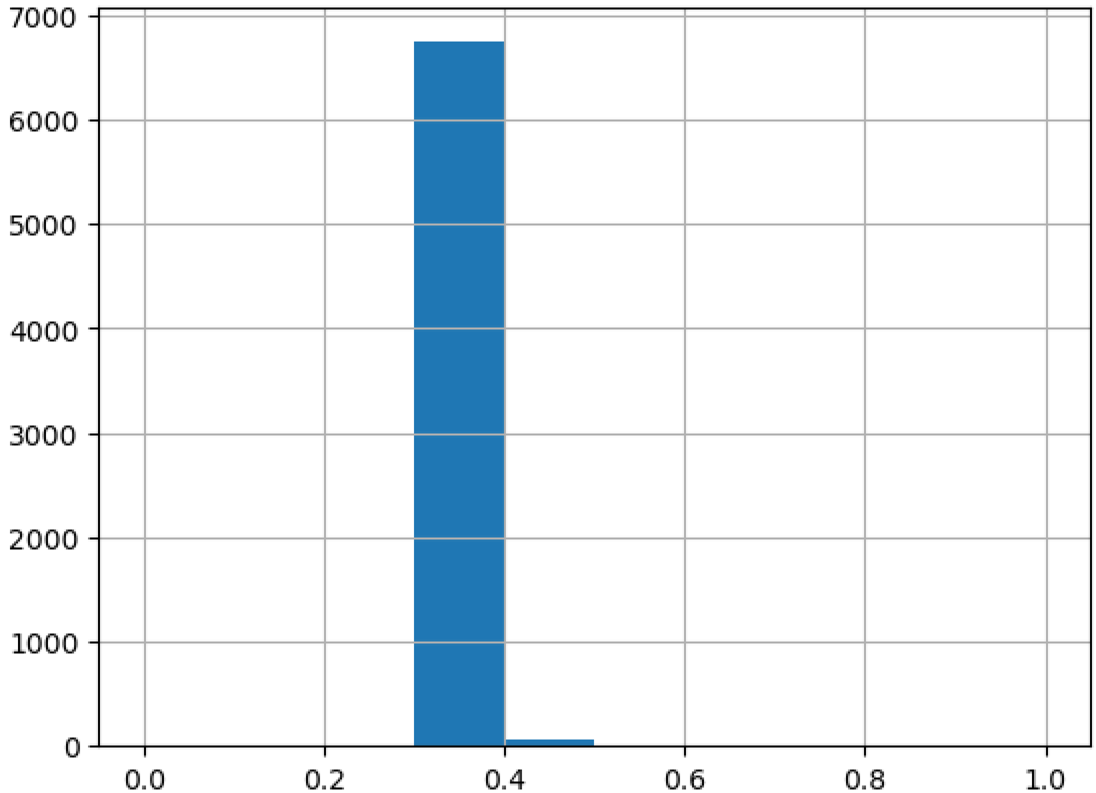


In [33]:
```
sns.boxenplot(x="Bankrupt" , y=" Net Income to Total Assets" , data=data)
plt.xlabel("Bankrupt classes")
plt.ylabel("Net Income to Total Assets")
plt.title("Distribution of Profit/ Net Income Ratio, by Class");
```

In [34]:
```
data[" Net Income to Total Assets"].hist()
plt.xlabel("Net Income to Total Assets")
plt.ylabel("count")
plt.title("Distrbution of Net Income to Total Assets Ratio");
```



In [35]:
```
data[' Borrowing dependency'].hist();
```



Outliers detection and removal

In [36]:
```
from scipy import stats
z_scores = stats.zscore(data['Bankrupt'])
z_score_outliers = (z_scores < -3) | (z_scores > 3)
z_score_outlier_rows = data[z_score_outliers]
print("Outliers Detected by Z-Score:")
print(z_score_outlier_rows)
threshold = 3
new_data = data[(z_scores < threshold) & (z_scores > -threshold)]
```

```
Outliers Detected by Z-Score:
      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
...        ...                                                ...
6591         1                                           0.418515
6640         1                                           0.196802
6641         1                                           0.337640
6642         1                                           0.340028
6728         1                                           0.492176

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

In [37]:
```
new_data
```

Out[37]:

	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	...	Inco to To Ass
6	0	0.390923	0.445704	0.436158	0.619950	0.619950	0.998993	0.797012	0.808960	0.302814	...	0.736
7	0	0.508361	0.570922	0.559077	0.601738	0.601717	0.999009	0.797449	0.809362	0.303545	...	0.815
8	0	0.488519	0.545137	0.543284	0.603612	0.603612	0.998961	0.797414	0.809338	0.303584	...	0.803
9	0	0.495686	0.550916	0.542963	0.599209	0.599209	0.999001	0.797404	0.809320	0.303483	...	0.804
10	0	0.482475	0.567543	0.538198	0.614026	0.614026	0.998978	0.797535	0.809460	0.303759	...	0.814
...	...	...	...	...	...	...	...	...	...	...	...	
6814	0	0.493687	0.539468	0.543230	0.604455	0.604462	0.998992	0.797409	0.809331	0.303510	...	0.799
6815	0	0.475162	0.538269	0.524172	0.598308	0.598308	0.998992	0.797414	0.809327	0.303520	...	0.799
6816	0	0.472725	0.533744	0.520638	0.610444	0.610213	0.998984	0.797401	0.809317	0.303512	...	0.797
6817	0	0.506264	0.559911	0.554045	0.607850	0.607850	0.999074	0.797500	0.809399	0.303498	...	0.811
6818	0	0.493053	0.570105	0.549548	0.627409	0.627409	0.998080	0.801987	0.813800	0.313415	...	0.815

6599 rows × 96 columns

Logistic Regression

In [38]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import mean_absolute_error,mean_squared_error,r2_score
from sklearn.preprocessing import OneHotEncoder,StandardScaler
from sklearn.compose import ColumnTransformer
import joblib

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

In [39]:
```
x=data.drop(['Bankrupt'],axis=1)#x values
y=data['Bankrupt']#y values
```

In [40]:
```
x
```

Out[40]:

	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)	...	In to A
0	0.370594	0.424389	0.405750	0.601457	0.601457	0.998969	0.796887	0.808809	0.302646	0.780985	...	0.7
1	0.464291	0.538214	0.516730	0.610235	0.610235	0.998946	0.797380	0.809301	0.303556	0.781506	...	0.7
2	0.426071	0.499019	0.472295	0.601450	0.601364	0.998857	0.796403	0.808388	0.302035	0.780284	...	0.7
3	0.399844	0.451265	0.457733	0.583541	0.583541	0.998700	0.796967	0.808966	0.303350	0.781241	...	0.7
4	0.465022	0.538432	0.522298	0.598783	0.598783	0.998973	0.797366	0.809304	0.303475	0.781550	...	0.7
...	...	...	...	...	...	...	...	...	...	...	...	
6814	0.493687	0.539468	0.543230	0.604455	0.604462	0.998992	0.797409	0.809331	0.303510	0.781588	...	0.7
6815	0.475162	0.538269	0.524172	0.598308	0.598308	0.998992	0.797414	0.809327	0.303520	0.781586	...	0.7
6816	0.472725	0.533744	0.520638	0.610444	0.610213	0.998984	0.797401	0.809317	0.303512	0.781546	...	0.7
6817	0.506264	0.559911	0.554045	0.607850	0.607850	0.999074	0.797500	0.809399	0.303498	0.781663	...	0.8
6818	0.493053	0.570105	0.549548	0.627409	0.627409	0.998080	0.801987	0.813800	0.313415	0.786079	...	0.8

6819 rows × 95 columns

In [41]:
```
y
```

Out[41]:
```
0       1
1       1
2       1
3       1
4       1
       ..
6814    0
6815    0
6816    0
6817    0
6818    0
Name: Bankrupt, Length: 6819, dtype: int64
```

In [42]:
```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2,random_state=42)
```

In [43]:
```
log=LogisticRegression()
log.fit(x_train,y_train)
```

Out[43]:
```
▾ LogisticRegression
LogisticRegression()
```

In [44]:
```
print("Train Score ",log.score(x_train,y_train))
print("Test Score ",log.score(x_test,y_test))
```

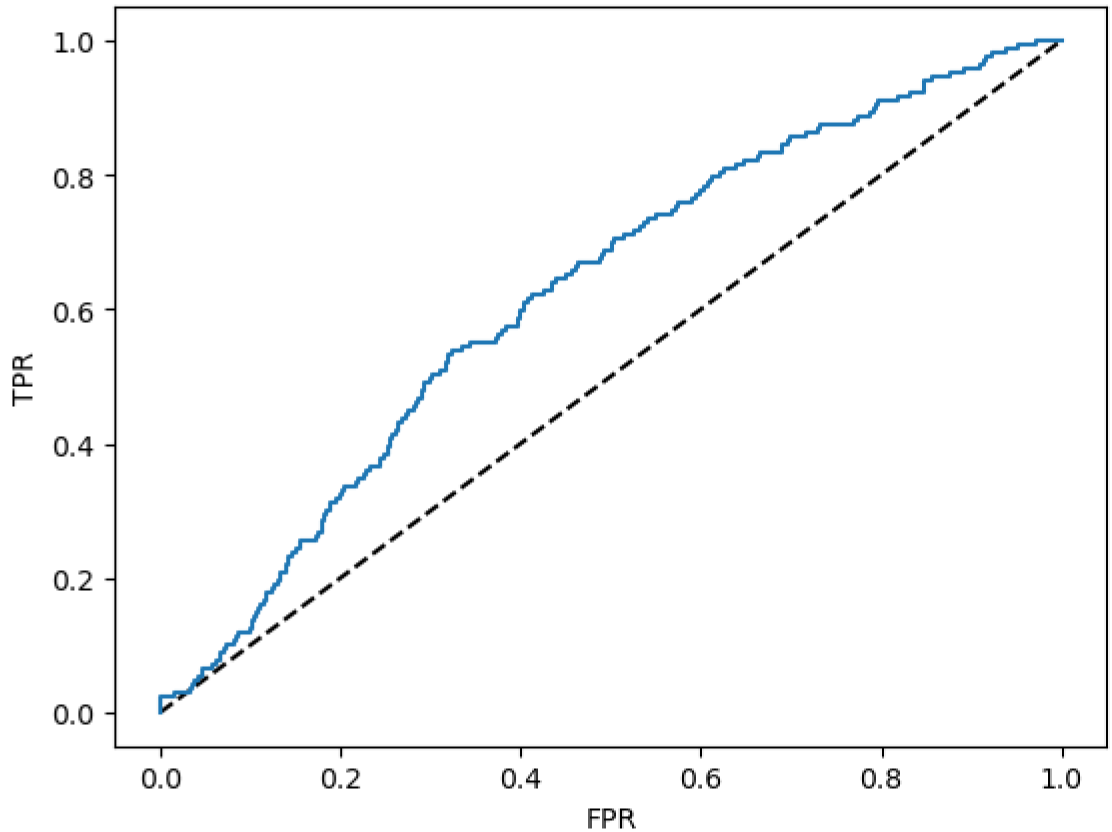
```
Train Score  0.9677360219981668
Test Score  0.9611436950146628
```

In [45]:
```
pred_train=log.predict(x_train)
pred_test=log.predict(x_test)
```

In [46]:
```
from sklearn import metrics
print(metrics.classification_report(y_train,pred_train))
```

```
              precision    recall  f1-score   support

           0       0.97      1.00      0.98      5286
           1       0.27      0.02      0.04       169

    accuracy                           0.97      5455
   macro avg       0.62      0.51      0.51      5455
weighted avg       0.95      0.97      0.95      5455
```

In [47]:
```
roc=log.predict_proba(x_train)[:,1]

fpr,tpr,threshold  = metrics.roc_curve(y_train, roc)
plt.plot([0,1],[0,1],'k--')
plt.plot(fpr,tpr,label='logistic')
plt.ylabel("TPR")
plt.xlabel("FPR")
plt.show()
```



In [48]:
```
metrics.roc_auc_score(y_train,roc)
```

Out[48]: 0.6233704303205744

Grid search

In [48]:
```
param_grid={
    'penalty':['l1','l2'],#lasso ridge
    'C':[0.1,0.5,1,5,10]
}
```

In [49]:
```
from sklearn.model_selection import GridSearchCV
grid=GridSearchCV(estimator=log,param_grid=param_grid,cv=5)
```

In [50]:
```
grid.fit(x_train,y_train)
```

Out[50]:
```
▸ GridSearchCV
▸ estimator: LogisticRegression
    ▸ LogisticRegression
```

In [51]:
```
best_param=grid.best_params_
best_model=grid.best_estimator_
```

In [52]:
```
y_pred=best_model.predict(x_test)
```

In [53]:
```
from sklearn.metrics import accuracy_score , precision_score,recall_score,f1_score,roc_auc_score
acc=accuracy_score(y_test,y_pred)
pre=precision_score(y_test,y_pred)
rec=recall_score(y_test,y_pred)
f1=f1_score(y_test,y_pred)
roc_auc=roc_auc_score(y_test,y_pred)
```

In [54]:
```
print("Best Param: ",best_param)
print("Accuracy:   ",acc)
print("Precision:  ",pre)
print("Recall:     ",rec)
print("f1 Scoer:   ",f1)
print("AUC ROC:    ",roc_auc)
```

```
Best Param:  {'C': 0.1, 'penalty': 'l2'}
Accuracy:    0.9611436950146628
Precision:   0.0
Recall:      0.0
f1 Scoer:    0.0
AUC ROC:     0.4992383853769992
```

RandomizedSearch

In [55]:
```
from scipy.stats import loguniform
from sklearn.model_selection import RandomizedSearchCV
```

In [56]:
```
logistic_random_param={'C':loguniform(1e-4,1e0),
                      'max_iter':(np.arange(100,800,10))}
grid=RandomizedSearchCV(estimator=log, param_distributions=logistic_random_param, cv=5)
```

In [57]:
```
grid.fit(x_train,y_train)
```

Out[57]:
```
▸      RandomizedSearchCV
▸ estimator: LogisticRegression
      ▸ LogisticRegression
```

In [58]:
```
best_param = grid.best_params_
best_model = grid.best_estimator_
y_pred = best_model.predict(x_test)
```

In [59]:
```
acc=accuracy_score(y_test,y_pred)
pre=precision_score(y_test,y_pred)
rec=recall_score(y_test,y_pred)
f1=f1_score(y_test,y_pred)
roc_auc=roc_auc_score(y_test,y_pred)
```

In [60]:
```
print('Best Param: ',best_param)
print('Accuracy:   ',acc)
print('Precision:  ',pre)
print('Recall:     ',rec)
print('F1Score:    ',f1)
print('ROC_AUC:    ',roc_auc)
```

```
Best Param:  {'C': 0.18970209924610734, 'max_iter': 150}
Accuracy:    0.9611436950146628
Precision:   0.0
Recall:      0.0
F1Score:     0.0
ROC_AUC:     0.4992383853769992
```

SVM & Naive Bayes

In [61]:
```
x
```

Out[61]:

	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)	...	In to A
0	0.370594	0.424389	0.405750	0.601457	0.601457	0.998969	0.796887	0.808809	0.302646	0.780985	...	0.7
1	0.464291	0.538214	0.516730	0.610235	0.610235	0.998946	0.797380	0.809301	0.303556	0.781506	...	0.79
2	0.426071	0.499019	0.472295	0.601450	0.601364	0.998857	0.796403	0.808388	0.302035	0.780284	...	0.77
3	0.399844	0.451265	0.457733	0.583541	0.583541	0.998700	0.796967	0.808966	0.303350	0.781241	...	0.73
4	0.465022	0.538432	0.522298	0.598783	0.598783	0.998973	0.797366	0.809304	0.303475	0.781550	...	0.79
...	...	...	...	...	...	...	...	...	...	...	...	
6814	0.493687	0.539468	0.543230	0.604455	0.604462	0.998992	0.797409	0.809331	0.303510	0.781588	...	0.79
6815	0.475162	0.538269	0.524172	0.598308	0.598308	0.998992	0.797414	0.809327	0.303520	0.781586	...	0.79
6816	0.472725	0.533744	0.520638	0.610444	0.610213	0.998984	0.797401	0.809317	0.303512	0.781546	...	0.79
6817	0.506264	0.559911	0.554045	0.607850	0.607850	0.999074	0.797500	0.809399	0.303498	0.781663	...	0.8
6818	0.493053	0.570105	0.549548	0.627409	0.627409	0.998080	0.801987	0.813800	0.313415	0.786079	...	0.81

6819 rows × 95 columns

In [62]:
```
y
```

Out[62]:
```
0       1
1       1
2       1
3       1
4       1
       ..
6814    0
6815    0
6816    0
6817    0
6818    0
Name: Bankrupt, Length: 6819, dtype: int64
```

In [63]:
```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score,classification_report
```

In [64]:
```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2,random_state=42)
```

In [65]:
```
scaler=StandardScaler()
x_train=scaler.fit_transform(x_train)
x_test=scaler.fit_transform(x_test)
```

In [66]:
```
svcm=SVC(kernel='linear')
```

In [67]:
```
svcm.fit(x_train,y_train)
```

Out[67]:
```
SVC
SVC(kernel='linear')
```

In [68]:
```
y_pred=svcm.predict(x_test)
acc=accuracy_score(y_test,y_pred)
acc
```

Out[68]:
```
0.9618768328445748
```

In [69]:
```
print("Accuracy: {:.2f}%".format(acc*100))
```

```
Accuracy: 96.19%
```

In [70]:
```
print(classification_report(y_test,y_pred))
```

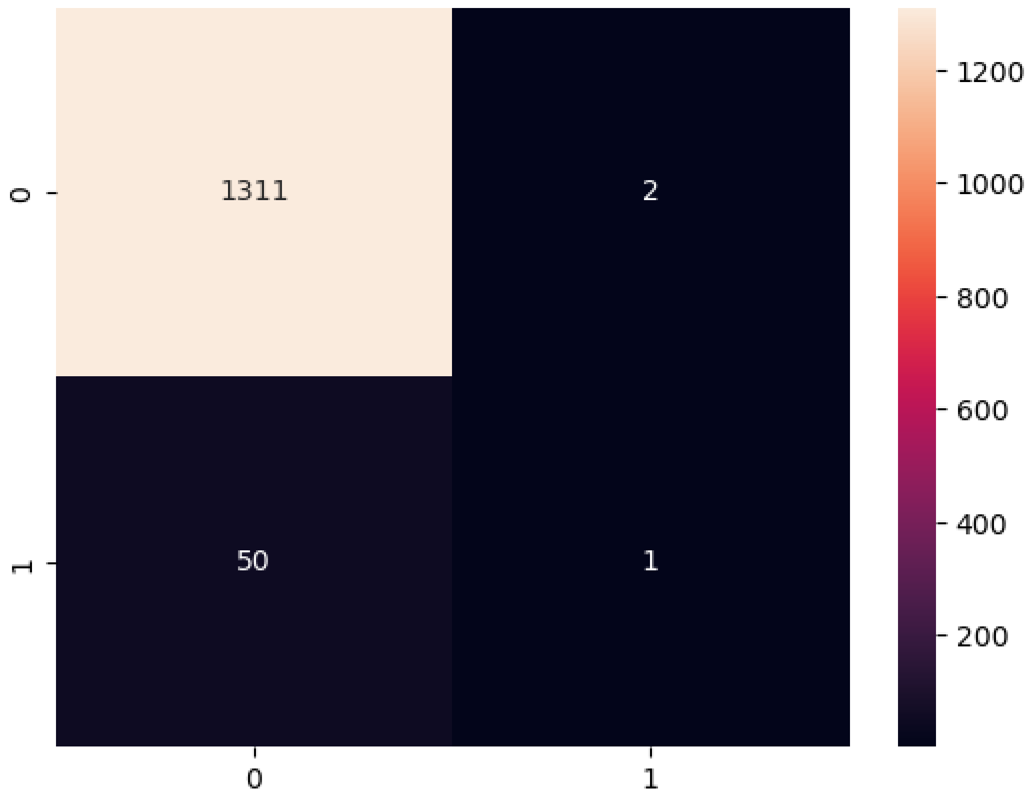
```
              precision    recall  f1-score   support

           0       0.96      1.00      0.98      1313
           1       0.33      0.02      0.04        51

    accuracy                           0.96      1364
   macro avg       0.65      0.51      0.51      1364
weighted avg       0.94      0.96      0.95      1364
```

In [71]:
```
from sklearn.metrics import confusion_matrix
cm=confusion_matrix(y_test,y_pred)
print("Confusion Matrix")
print(cm)
```

```
Confusion Matrix
[[1311    2]
 [  50    1]]
```

In [72]:
```
sns.heatmap(cm,annot=True,fmt='.5g')
```

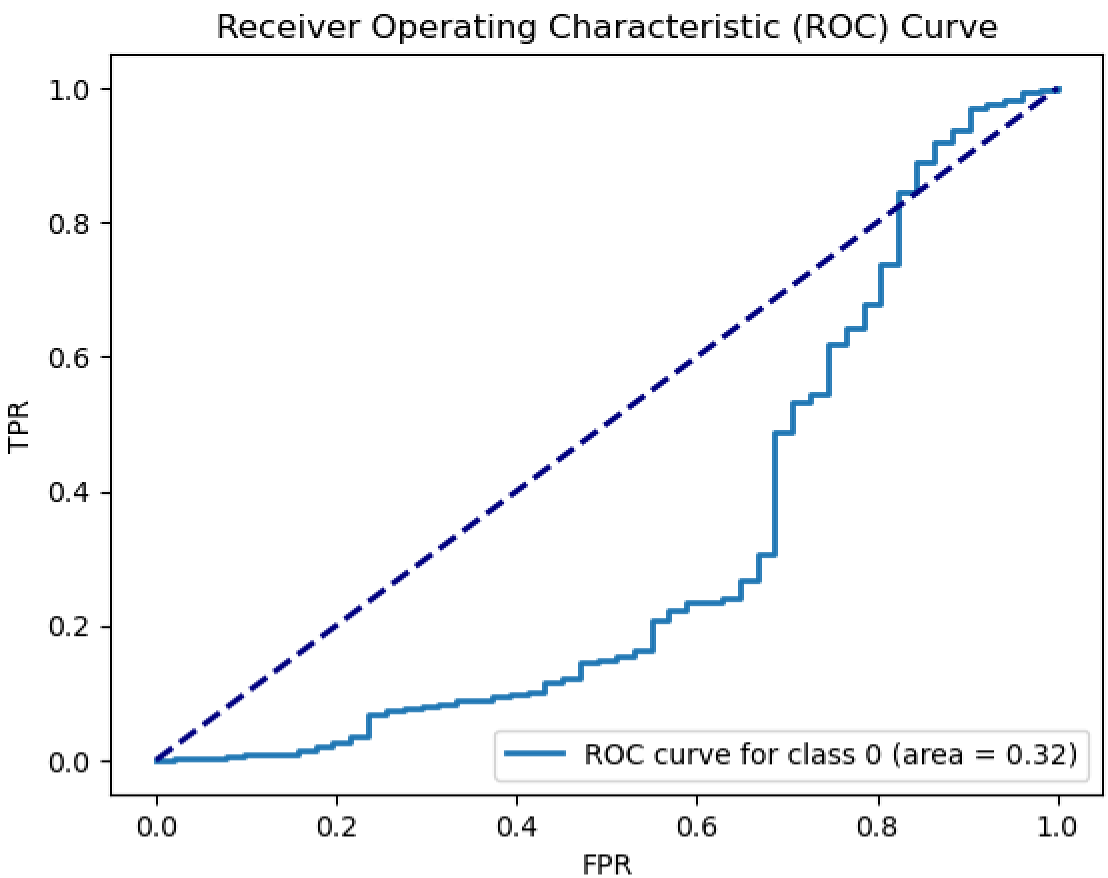
Out[72]:
```
<Axes: >
```



In [73]:
```
from sklearn.svm import SVC
from sklearn.metrics import roc_curve, auc
from sklearn.preprocessing import label_binarize
from sklearn.multiclass import OneVsRestClassifier

yb = label_binarize(y, classes=[0,1])
nc=yb.shape[1]
classifier = OneVsRestClassifier(SVC(kernel="linear", probability=True, random_state=42,decision_function_shap
y_score=classifier.fit(x_train,y_train).decision_function(x_test)
```

In [74]:
```
from sklearn.metrics import roc_curve, auc

fpr = dict()
tpr = dict()
roc_auc = dict()
for i in range(nc):
    fpr[i], tpr[i], _ = roc_curve(y_test, y_score, pos_label=i)
    roc_auc[i] = auc(fpr[i], tpr[i])
```

In [75]:
```
plt.figure()
for i in range(nc):
    plt.plot(fpr[i], tpr[i], lw=2, label='ROC curve for class {} (area = {:.2f})'.format(i, roc_auc[i]))
plt.plot([0, 1], [0, 1], 'k--', lw=2, color='navy')
plt.xlabel('FPR')
plt.ylabel('TPR')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc='lower right')
plt.show()
```



GridSearch

In [76]:
```
from sklearn.model_selection import GridSearchCV
```

In [77]:
```
param_grid = {
'C' : [0.1, 1, 10, 100],
'kernel' : ['linear', 'rbf', 'poly', 'sigmoid']
}
```

In [78]:
```
svcm = SVC()
```

In [79]:
```
grid_search = GridSearchCV(svcm, param_grid, cv=5)
```

In [80]:
```
grid_search.fit(x_train, y_train)
```

Out[80]:
```
▸ GridSearchCV
▸ estimator: SVC
    ▸ SVC
```

In [81]:
```
best_param = grid_search.best_params_
print("Best hyperparameter : ", best_param)
```

```
Best hyperparameter :  {'C': 0.1, 'kernel': 'rbf'}
```

In [82]:
```
best_svm = SVC(C=best_param['C'], kernel=best_param['kernel'])
```

In [83]:
```
best_svm.fit(x_train, y_train)
```

Out[83]:
```
▾ SVC
SVC(C=0.1)
```

In [84]:
```
y_pred = best_svm.predict(x_test)
acc = accuracy_score(y_test, y_pred)
print("Accuracy : {:.2f}%". format(acc * 100))
```

```
Accuracy : 96.26%
```

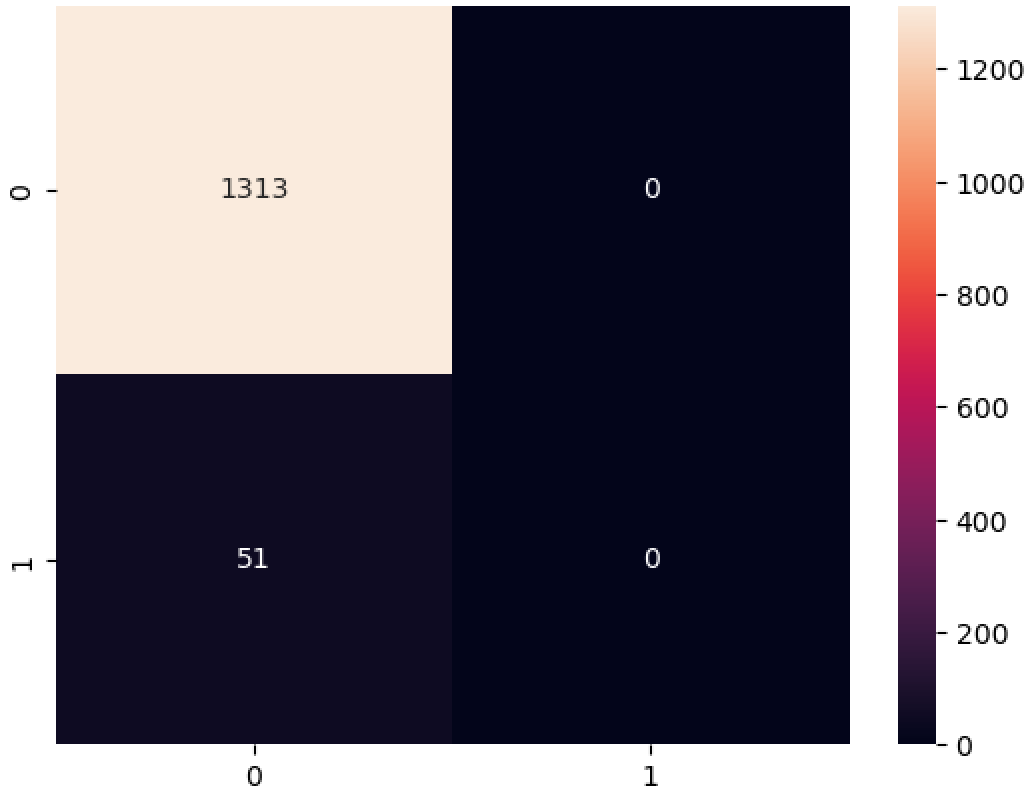
In [85]:
```
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.96      1.00      0.98      1313
           1       0.00      0.00      0.00        51

    accuracy                           0.96      1364
   macro avg       0.48      0.50      0.49      1364
weighted avg       0.93      0.96      0.94      1364
```

In [86]:
```
cm=confusion_matrix(y_test,y_pred)
print("Confusion Matrix : ")
print(cm)
```

```
Confusion Matrix :
[[1313    0]
 [  51    0]]
```

In [87]:
```
sns.heatmap(cm, annot=True,fmt='.5g')
plt.show()
```



Random Search

In [88]:
```
from sklearn.model_selection import RandomizedSearchCV
```

In [89]:
```
 param_grid = {
'C' : [0.1, 1, 10, 100],
'kernel' : ['linear', 'rbf', 'poly', 'sigmoid']
}
```

In [90]:
```
svcm = SVC()
```

In [91]:
```
random_search = RandomizedSearchCV(svcm, param_grid, cv=5)
```

In [92]:
```
random_search.fit(x_train, y_train)
```

Out[92]:

```
▸ RandomizedSearchCV
  ▸ estimator: SVC
      ▸ SVC
```

In [93]:
```
best_parameters = random_search.best_params_
best_model = random_search.best_estimator_
print('Hyperparameters:',best_parameters)
```

```
Hyperparameters: {'kernel': 'rbf', 'C': 1}
```

In [94]:
```
y_pred = best_model.predict(x_test)
```

In [95]:
```
acc=accuracy_score(y_test,y_pred)
print("Accuracy:",acc)
```

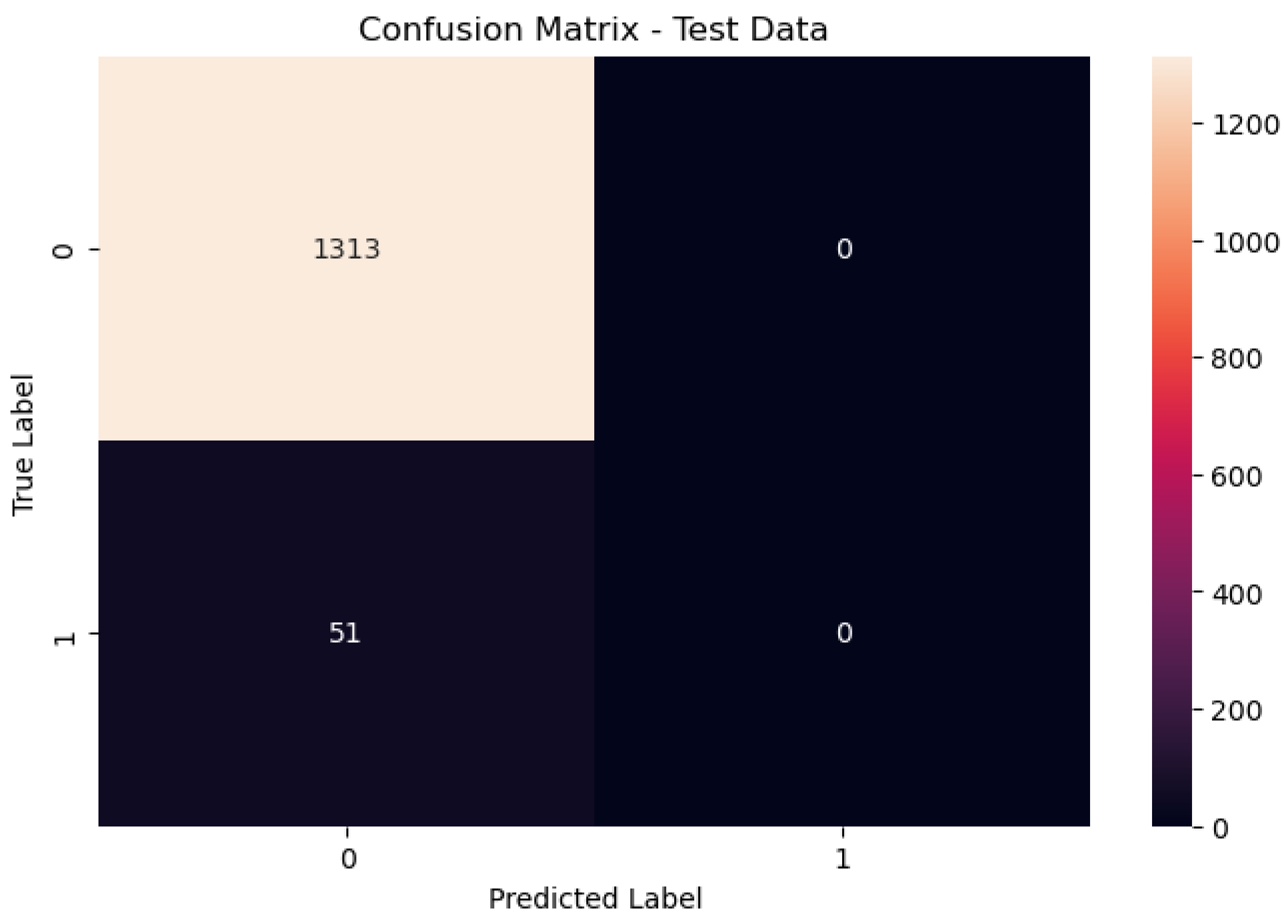
```
Accuracy: 0.9626099706744868
```

In [96]:
```
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.96      1.00      0.98      1313
           1       0.00      0.00      0.00        51

    accuracy                           0.96      1364
   macro avg       0.48      0.50      0.49      1364
weighted avg       0.93      0.96      0.94      1364
```

In [97]:
```
cm = confusion_matrix(y_test,y_pred)
print('Confusion Matrix: ',cm)
plt.figure(figsize = (8,5))
sns.heatmap(cm, annot=True, fmt='.5g')
plt.title('Confusion Matrix - Test Data')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```

```
Confusion Matrix:  [[1313    0]
 [  51    0]]
```



Naive Bayes

In [98]:
```
from sklearn import model_selection, naive_bayes, metrics,feature_extraction
```

In [99]:
```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.25,random_state=42)
```

In [100]:
```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
x_train = scaler.fit_transform(x_train)
x_test = scaler.transform(x_test)
```

In [101]:
```
bayes = naive_bayes.MultinomialNB()
```

In [102]:
```
bayes.fit(x_train,y_train)
```

Out[102]:
```
▾ MultinomialNB
MultinomialNB()
```

In [103]:
```
y_pred_nb=bayes.predict(x_test)
```

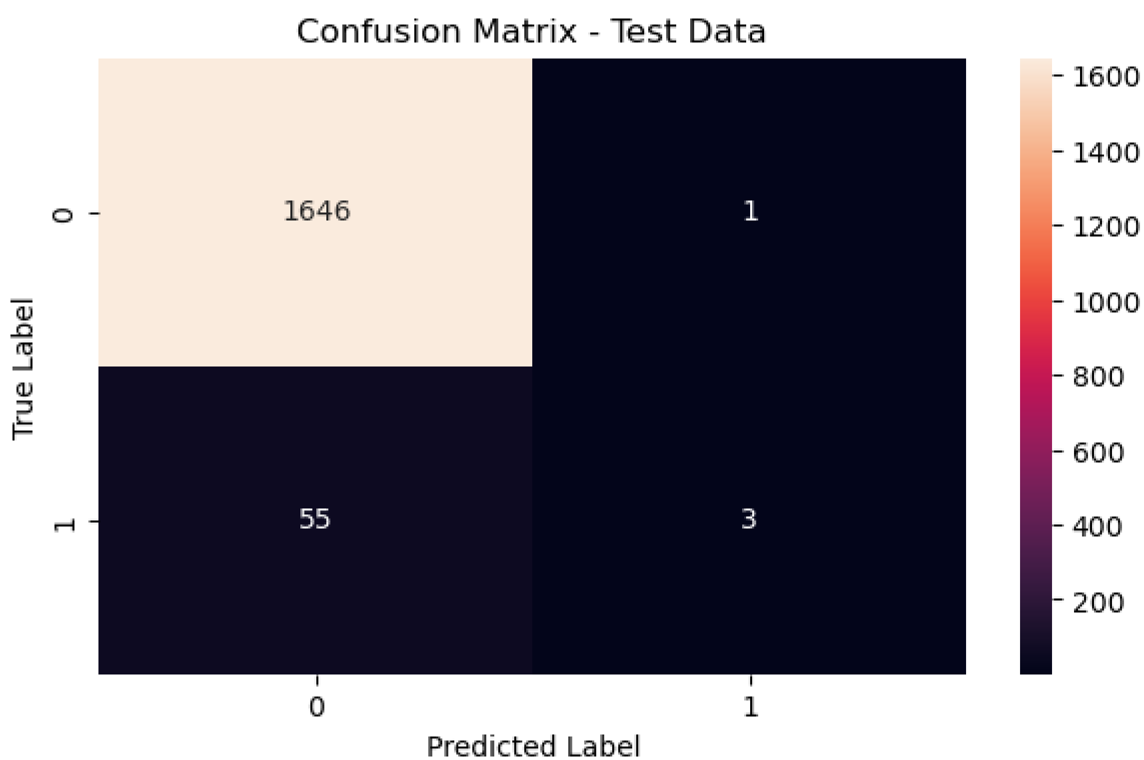
In [104]:
```
accuracy=metrics.accuracy_score(y_test,y_pred_nb)
accuracy
```

Out[104]:
```
0.9671554252199414
```

In [105]:
```
print(metrics.classification_report(y_test, y_pred_nb))
```

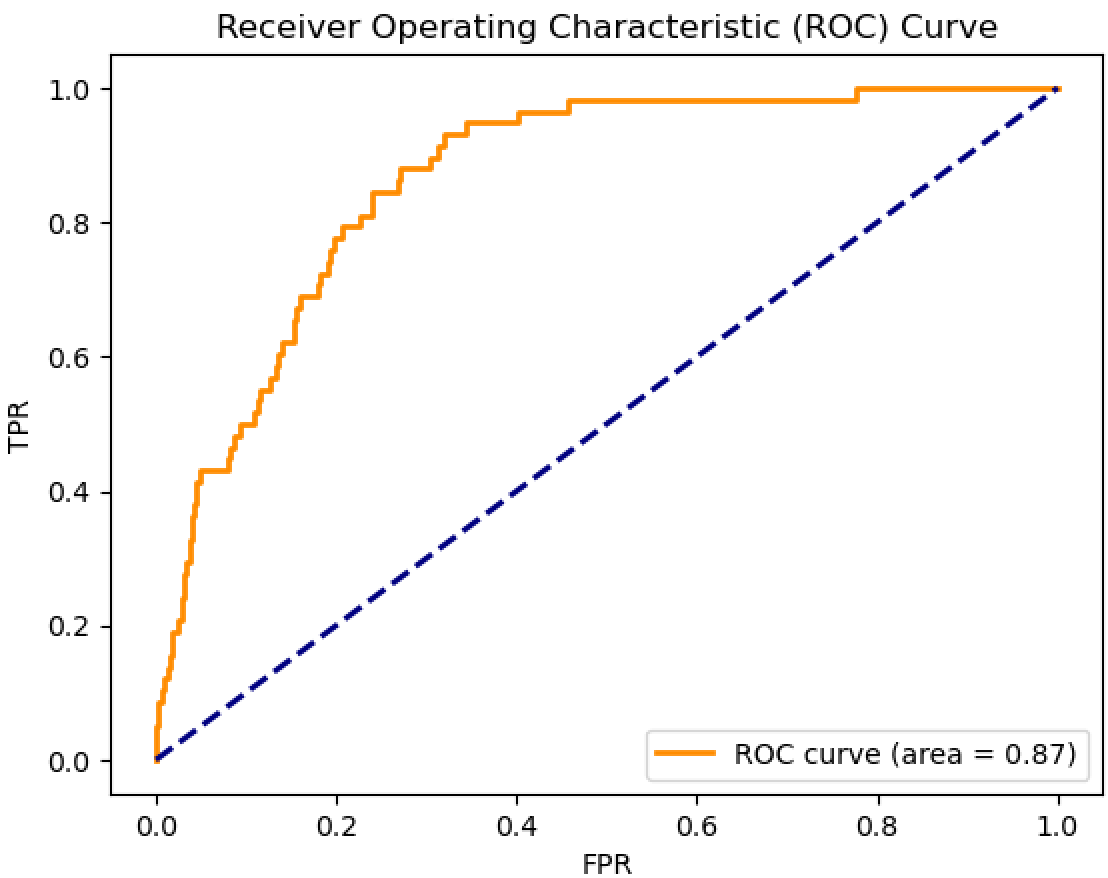
```
              precision    recall  f1-score   support

           0       0.97      1.00      0.98      1647
           1       0.75      0.05      0.10        58

    accuracy                           0.97      1705
   macro avg       0.86      0.53      0.54      1705
weighted avg       0.96      0.97      0.95      1705
```

In [106]:
```
cm=confusion_matrix(y_test,y_pred_nb)
cm
plt.figure(figsize = (7,4))
sns.heatmap(cm, annot=True, fmt='.5g')
plt.title('Confusion Matrix - Test Data')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```



In [107]:
```
from sklearn.metrics import roc_curve, auc

fpr = dict()
tpr = dict()
roc_auc = dict()

for i in range(nc):
    y_score = bayes.predict_proba(x_test)[:, 1]
    fpr[i], tpr[i], _ = roc_curve(y_test, y_score, pos_label=1)
    roc_auc[i] = auc(fpr[i], tpr[i])
```

In [108]:
```
plt.figure()
plt.plot(fpr[0], tpr[0], color='darkorange', lw=2, label='ROC curve (area = {:.2f})'.format(roc_auc[0]))
plt.plot([0, 1], [0, 1], 'k--', color='navy', lw=2)
plt.xlabel('FPR')
plt.ylabel('TPR')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc='lower right')
plt.show()
```



Tuning for Naive Bayes Model

In [109]:
```
 param_grid = {
'alpha': [0.1, 1, 10, 100],
'fit_prior': [True, False]
}
```

In [110]:
```
bayes = naive_bayes.MultinomialNB()
grid_search = GridSearchCV(bayes, param_grid, cv=5)
grid_search.fit(x_train, y_train)
```

Out[110]:
```
▸ GridSearchCV
▸ estimator: MultinomialNB
    ▸ MultinomialNB
```

In [111]:
```
best_param = grid_search.best_params_
best_nb = naive_bayes.MultinomialNB(alpha = best_param['alpha'], fit_prior = best_param['fit_prior'])
best_nb.fit(x_train, y_train)
y_pred = best_nb.predict(x_test)
```

In [112]:
```
print("Best Hyperparameter : ", best_param)
```

```
Best Hyperparameter :  {'alpha': 100, 'fit_prior': True}
```

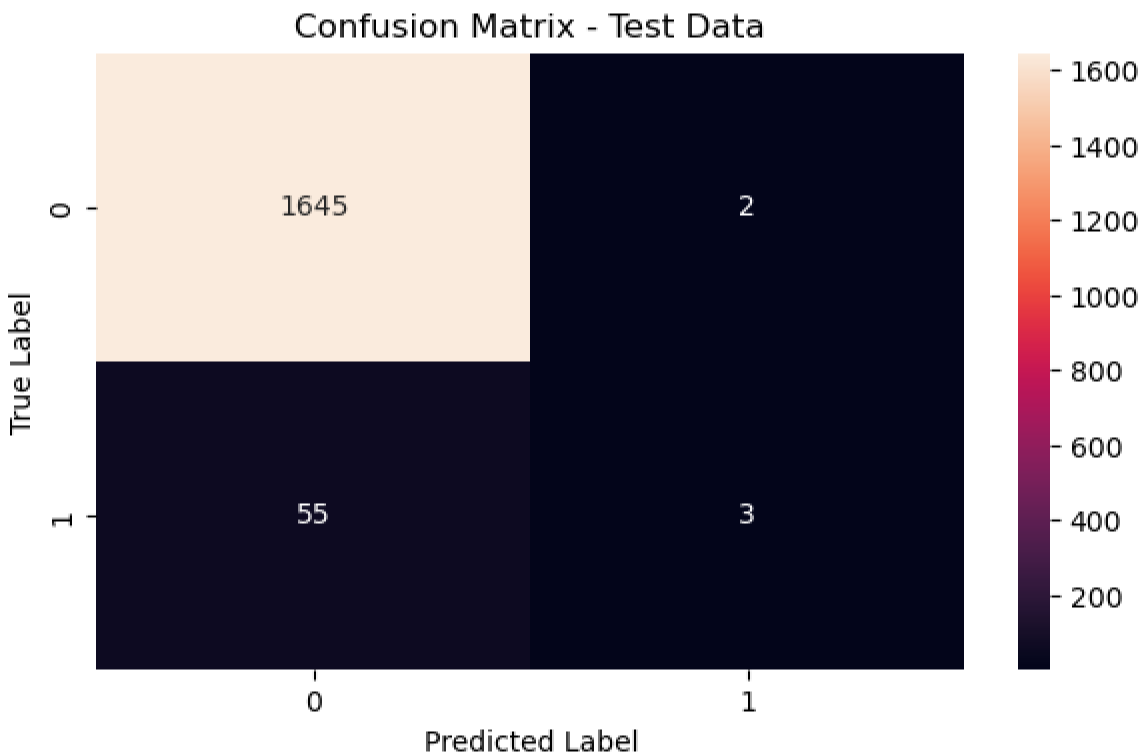
In [113]:
```
acc = accuracy_score(y_test, y_pred)
print('Accuracy',acc)
```

```
Accuracy 0.9665689149560117
```

In [114]:
```
print (classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.97      1.00      0.98      1647
           1       0.60      0.05      0.10        58

    accuracy                           0.97      1705
   macro avg       0.78      0.53      0.54      1705
weighted avg       0.96      0.97      0.95      1705
```

In [115]:
```
cm=confusion_matrix(y_test,y_pred)
cm
plt.figure(figsize = (7,4))
sns.heatmap(cm, annot=True, fmt='.5g')
plt.title('Confusion Matrix - Test Data')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```



Randomized Search

In [116]:
```
from scipy.stats import uniform
param_dist = {
    'alpha': uniform(0.1, 2.0),
    'fit_prior':[True,False]
}
```

In [117]:
```
bayes = naive_bayes.MultinomialNB()
```

In [118]:
```
from sklearn.utils.validation import check_non_negative
check_non_negative(x, "MultinomialNB (input x)")
```

In [119]:
```
randomized_search = RandomizedSearchCV(bayes, param_distributions=param_dist, n_iter=10, scoring='accuracy', c
randomized_search.fit(x, y)
```

Out[119]:
```
▸ RandomizedSearchCV
▸ estimator: MultinomialNB
    ▸ MultinomialNB
```

In [120]:
```
best_param = randomized_search.best_params_
print("Best Hyperparameter : ", best_param)
```

```
Best Hyperparameter :  {'alpha': 1.099238660336462, 'fit_prior': True}
```

In [121]:
```
best_nb = naive_bayes.MultinomialNB(alpha = best_param['alpha'], fit_prior = best_param['fit_prior'])
best_nb.fit(x_train, y_train)
y_pred = best_nb.predict(x_test)
```

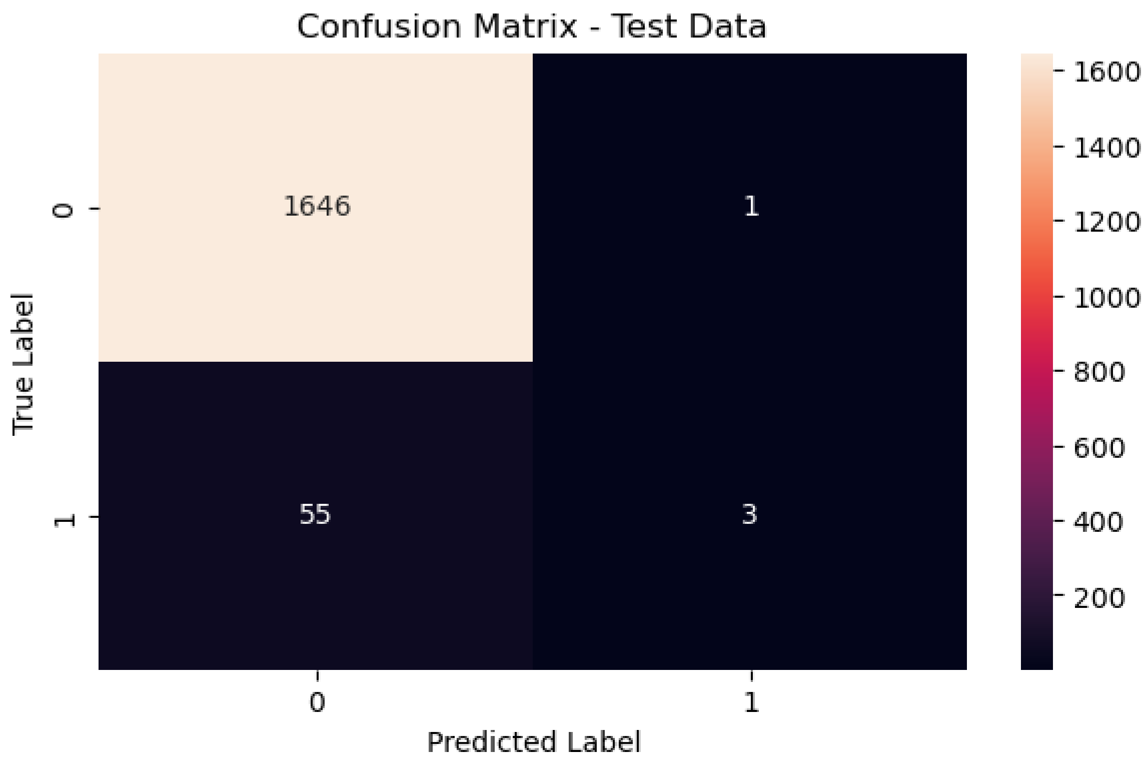
In [122]:
```
acc = accuracy_score(y_test, y_pred)
print('Accuracy',acc)
```

```
Accuracy 0.9671554252199414
```

In [123]:
```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.97      1.00      0.98      1647
           1       0.75      0.05      0.10        58

    accuracy                           0.97      1705
   macro avg       0.86      0.53      0.54      1705
weighted avg       0.96      0.97      0.95      1705
```

In [124]:
```
cm=confusion_matrix(y_test,y_pred)
cm
plt.figure(figsize = (7,4))
sns.heatmap(cm, annot=True, fmt='.5g')
plt.title('Confusion Matrix - Test Data')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```



KNN

In [54]:
```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2,random_state=42)
```

In [55]:
```
from sklearn.neighbors import KNeighborsClassifier
knn= KNeighborsClassifier(n_neighbors=10)
```

In [56]:
```
knn.fit(x_train,y_train)
```

Out[56]:
```
▾ KNeighborsClassifier
KNeighborsClassifier(n_neighbors=10)
```

In [57]:
```
knn.score(x_test,y_test)
```

```
--> 706 return accuracy_score(y, self.predict(X), sample_weight=sample_weight)

File ~\AppData\Local\anaconda3\Lib\site-packages\sklearn\neighbors\_classification.py:266, in KNeighborsCla
ssifier.predict(self, X)
    263         return self.classes_[np.argmax(probabilities, axis=1)]
    264     # In that case, we do not need the distances to perform
    265     # the weighting so we do not compute them.
--> 266     neigh_ind = self.kneighbors(X, return_distance=False)
    267     neigh_dist = None
    268 else:

File ~\AppData\Local\anaconda3\Lib\site-packages\sklearn\neighbors\_base.py:822, in KNeighborsMixin.kneighb
ors(self, X, n_neighbors, return_distance)
    815 use_pairwise_distances_reductions = (
    816     self._fit_method == "brute"
    817     and ArgKmin.is_usable_for(
    818         X if X is not None else self._fit_X, self._fit_X, self.effective_metric_
    819     )
    820 )
    821 if use_pairwise_distances_reductions:
```

In [ ]:

Linear Regression

In [64]:

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error,mean_squared_error,r2_score
from sklearn.preprocessing import OneHotEncoder,StandardScaler
from sklearn.compose import ColumnTransformer
import joblib
```

In [90]:

```
data
```

Out[90]:

Operating Profit Rate	Pre-tax net Interest Rate	After-tax net Interest Rate	Non-industry income and expenditure/revenue	...	Net Income to Total Assets	Total assets to GNP price	No-credit Interval	Gross Profit to Sales	Net Income to Stockholder's Equity	Liability to Equity	Degree of Financial Leverage (DFL)	Inte Cover R (Inte expe to EI
0.998969	0.796887	0.808809	0.302646	...	0.716845	0.009219	0.622879	0.601453	0.827890	0.290202	0.026601	0.564
0.998946	0.797380	0.809301	0.303556	...	0.795297	0.008323	0.623652	0.610237	0.839969	0.283846	0.264577	0.570
0.998857	0.796403	0.808388	0.302035	...	0.774670	0.040003	0.623841	0.601449	0.836774	0.290189	0.026555	0.563
0.998700	0.796967	0.808966	0.303350	...	0.739555	0.003252	0.622929	0.583538	0.834697	0.281721	0.026697	0.564
0.998973	0.797366	0.809304	0.303475	...	0.795016	0.003878	0.623521	0.598782	0.839973	0.278514	0.024752	0.575
...	...	...	...	...	...	...	...	...	...	...	...	
0.998992	0.797409	0.809331	0.303510	...	0.799927	0.000466	0.623620	0.604455	0.840359	0.279606	0.027064	0.566
0.998992	0.797414	0.809327	0.303520	...	0.799748	0.001959	0.623931	0.598306	0.840306	0.278132	0.027009	0.566
0.998984	0.797401	0.809317	0.303512	...	0.797778	0.002840	0.624156	0.610441	0.840138	0.275789	0.026791	0.565
0.999074	0.797500	0.809399	0.303498	...	0.811808	0.002837	0.623957	0.607846	0.841084	0.277547	0.026822	0.565
0.998080	0.801987	0.813800	0.313415	...	0.815956	0.000707	0.626680	0.627408	0.841019	0.275114	0.026793	0.565

In [91]:
```
X=data.drop([' Net Income to Total Assets'],axis=1)
Y=data[' Net Income to Total Assets']
```

In [92]:
```
X_train,X_test, Y_train, Y_test = train_test_split(X,Y, test_size=0.2,random_state=42)
```

In [93]:
```
model=LinearRegression()
model.fit(X_train,Y_train)
y_pred=model.predict(X_test)
print(model.intercept_) #y-intercept of the model
```

```
1.2273167048950069
```

In [94]:
```
print(model.coef_)
```

```
[-5.95841204e-03 -1.47386916e-01  5.04942001e-01  9.22450582e-02
  2.54473615e-02  1.21621058e-01 -1.27124790e+00 -1.77989377e+00
  4.32508322e+00 -4.49676561e-01 -1.65336523e+00 -2.55351296e-13
 -3.61932706e-14 -1.42520543e-01  1.14178111e-12  4.68746400e-03
  1.38506886e-01 -2.15087910e-01  9.90102490e-03  6.97970320e-02
  9.02327680e-03  5.00378038e-11 -2.38582401e-01 -1.36820375e-02
  1.97280813e-02 -6.72088561e-03  2.65307985e-02 -9.38299930e-03
  4.64093554e-03  3.79252185e-13  1.06645869e-10 -8.58471675e-03
 -1.22086402e-01  1.09323054e-11  1.27176047e-13 -4.62723082e-03
  3.68402531e-12 -4.86887704e-02  4.86887704e-02 -1.25888943e-02
 -8.14610923e-02 -4.02218092e-01  2.25744023e-01 -4.40527711e-02
 -2.32106877e-01  2.15574708e-02  8.56675841e-13  1.56089031e-12
 -1.42108547e-14  2.06501483e-14 -3.88388459e-02  7.69267983e-12
 -4.65615298e-03  7.16149362e-13 -2.83380561e-02  3.23201163e-04
  1.19387739e-02  2.11165987e-03  2.93473579e-13  2.08166817e-16
  3.54349371e-02  2.11558009e-02 -2.87379222e-03  2.22100116e-13
 -3.25025328e-03 -1.11387642e-01 -8.92373749e-01  4.96505614e-13
  2.31100177e-01 -9.44874108e-03 -2.05411202e-01  3.33066907e-14
  3.93018951e-14 -1.73202587e+00  6.82787160e-14  5.19886726e-01
 -1.55634632e-04 -3.25025328e-03  3.27515069e-01 -1.63855255e-01
  1.58026159e-03 -5.97240472e-03  5.71643233e-02 -5.93270741e-02
 -3.48945687e-02  2.22673850e-02  1.69342318e-12 -7.79931891e-04
 -5.75511312e-03  4.79272981e-01  1.47604274e+00 -1.03807644e-03
 -4.33978972e-03  0.00000000e+00 -2.51899839e-03]
```

In [95]:
```
mae = mean_absolute_error(Y_test,y_pred)
mse= mean_squared_error(Y_test, y_pred)
rmse = np.sqrt(mse)
r2 = r2_score(Y_test, y_pred)
print('Mean Absolute Error',mae)
print('Mean Squared Error',mse)
print('Root Mean Absolute Error',rmse)
print('R2 Score',r2)
```

```
Mean Absolute Error 949.330580076954
Mean Squared Error 1229262910.4276087
Root Mean Absolute Error 35060.8458316055
R2 Score -767518518399.402
```

In [96]:
```
#adjusted_r2=1-[(1-r2)*(n-1)/(n-k-1)]
adjusted_r2=1-((1-0.52948)*(10169-1)/(10169-13-1))
print('adjusted r2 is :',adjusted_r2)
```

```
adjusted r2 is : 0.5288776602658789
```

In [97]:
```
y_mean=np.mean(Y_test)
SSR = np.sum((y_pred - y_mean) ** 2)
SSR
```

Out[97]: 1676714644764.2239

In [98]:
```
SST = np.sum((Y_test - y_mean) ** 2)
SST
```

Out[98]: 2.184591732480575

In [99]:
```
SSE=SST-SSR
SSE
```

Out[99]: -1676714644762.0393

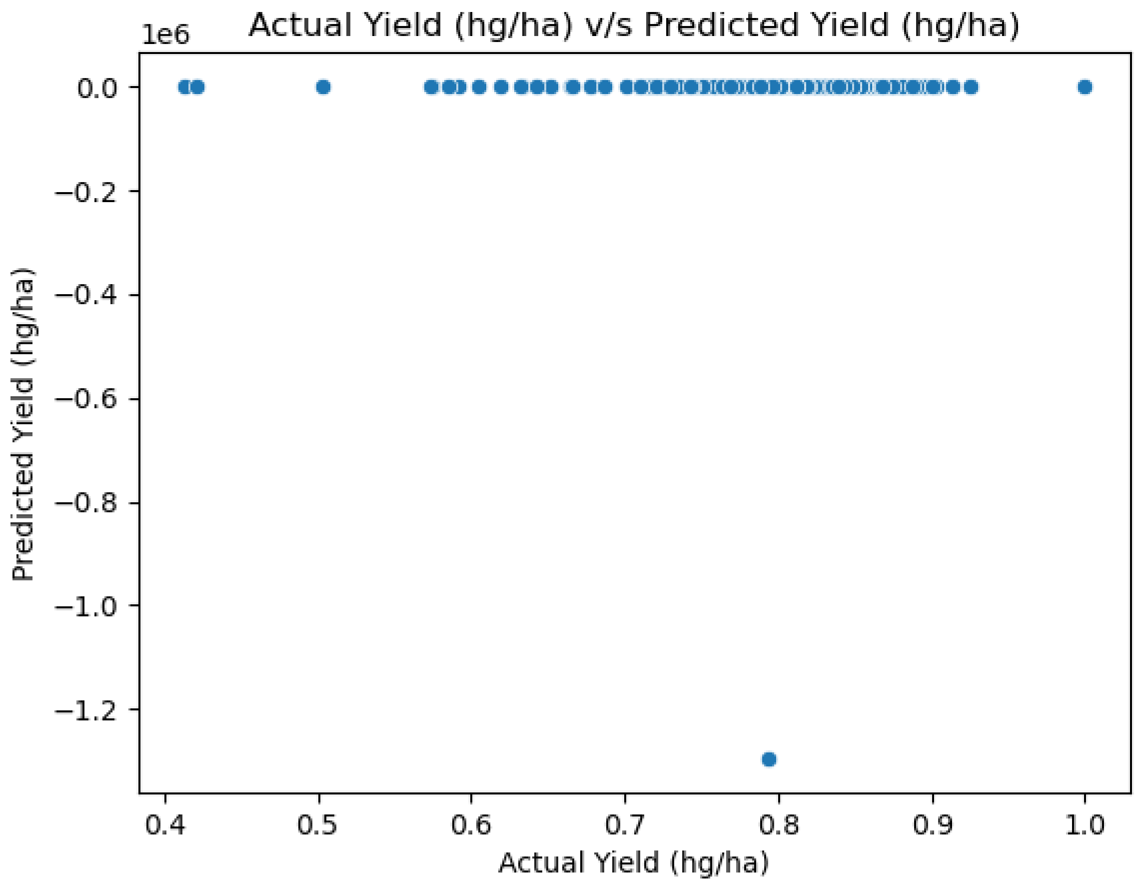
In [100]:
```
b=pd.DataFrame({"Actual":Y_test,"Predicted":y_pred})
b
```

Out[100]:

	Actual	Predicted
239	0.765336	0.770517
2850	0.817797	0.816562
2687	0.847518	0.844501
6500	0.767650	0.759638
2684	0.810394	0.814581
...	...	...
1357	0.811952	0.815805
3946	0.812144	0.810328
5491	0.796622	0.791755
2112	0.787758	0.788186
6423	0.838678	0.835005

1364 rows × 2 columns

In [101]:
```
sns.scatterplot(x=Y_test,y=y_pred)
plt.xlabel('Actual Yield (hg/ha)')
plt.ylabel('Predicted Yield (hg/ha)')
plt.title('Actual Yield (hg/ha) v/s Predicted Yield (hg/ha)')
plt.show()
```



In [ ]: