

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from google.colab import files
```

✓ Uploading and setting up the Polish Dataset

uploading and renaming the columns for further review of the polish dataset.

```
#pulling data from the website.
polishData=pd.read_csv("https://archive.ics.uci.edu/static/public/365/data.csv")
#adding the data into a dataframe
polish_Dataset = pd.DataFrame(polishData)

# Set display options to show all rows and columns
pd.set_option('display.max_rows', None)
pd.set_option('display.max_columns', None)

# Set display width to avoid wrapping of wide DataFrames
pd.set_option('display.width', None)

# Set option to display full content of each column
pd.set_option('display.max_colwidth', None)
polish_Dataset.head(10)
```

	year	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14
0	1	0.200550	0.379510	0.396410	2.0472	32.3510	0.38825	0.249760	1.33050	1.13890	0.50494	0.249760	0.659800	0.166600	0.249760
1	1	0.209120	0.499880	0.472250	1.9447	14.7860	0.00000	0.258340	0.99601	1.69960	0.49788	0.261140	0.516800	0.158350	0.258340
2	1	0.248660	0.695920	0.267130	1.5548	-1.1523	0.00000	0.309060	0.43695	1.30900	0.30408	0.312580	0.641840	0.244350	0.309060
3	1	0.081483	0.307340	0.458790	2.4928	51.9520	0.14988	0.092704	1.86610	1.05710	0.57353	0.092704	0.301630	0.094257	0.092704
4	1	0.187320	0.613230	0.229600	1.4063	-7.3128	0.18732	0.187320	0.63070	1.15590	0.38677	0.187320	0.331470	0.121820	0.187320
5	1	0.228220	0.497940	0.359690	1.7502	-47.7170	0.00000	0.281390	1.00830	1.97860	0.50206	0.286450	0.586910	0.148120	0.281390
6	1	0.111090	0.647440	0.289710	1.4705	2.5349	0.00000	0.111090	0.54454	1.73480	0.35256	0.125750	0.180410	0.309630	0.111090
7	1	0.532320	0.027059	0.705540	53.9540	299.5800	0.00000	0.652400	35.95700	0.65273	0.97294	0.693940	48.966000	1.060200	0.652400
8	1	0.009020	0.632020	0.053735	1.1263	-37.8420	0.00000	0.014434	0.58223	1.33320	0.36798	0.043162	0.033921	0.038938	0.014434
9	1	0.124080	0.838370	0.142040	1.1694	-91.8830	0.00000	0.153280	0.19279	2.11560	0.16163	0.184540	0.182840	0.075411	0.153280

#The orginal dataset did not have named columns. It provided an explantion to each attribute in their reserach paper. The code below is to add replacing the column name with actual names.

```
new_Column_names={
    "A1":'net_profit/total_assets',
    "A2":'Total_Liabilities/total_assets',
    "A3":'Working_Capital_to_Total_Assets_Ratio',
    "A4":'Current_Ratio',
    "A5":'Defensive_Interval_Ratio',
    "A6":'Retained_Earnings_to_Total_Assets_Ratio',
    "A7":'Operating_Income_to_Total_Asset_ratio',
    "A8":'book_value_of_equity/total_liabilities',
    "A9":'Asset_Turnover_Ratio',
    "A10":'Equity_to_Total_Assets_Ratio',
    "A11":'(gross_profit+extraordinary_items+financial_expenses)/total',
    "A12":'gross_profit/short-term_liabilities',
    "A13":'(gross_profit+depreciation)/sales',
    "A14":'(gross_profit+interest)/total_assets',
    "A15":'(total_liabilities*365)/(gross_profit+depreciation)',
    "A16":'(gross profit+depreciation)/total_liabilities',
    "A17":'total_assets/total_liabilities',
    "A18":'gross_profit/total_assets',
    "A19":'gross_profit/sales',
    "A20":'(inventory*365)/sales',
    "A21":'sales(n)/sales(n-1)',
    "A22":'profit_on_operating_activities/total_assets'}
```

```

"A23":'net_profit/sales',
"A24":'gross_profit(in3years)/total_assets',
"A25":'(equity-share_capital)/total_assets',
"A26":'(net_profit+depreciation)/total_liabilities',
"A27":'profit_on_operating_activities/financial_expenses',
"A28":'working_capital/fixed_assets',
"A29":'logarithm_of_total_assets',
"A30":'(total_liabilities-cash)/sales',
"A31":'(gross_profit+interest)/sales',
"A32":'(current_liabilities*365)/cost_of_products_sold',
"A33":'operating_expenses/short-term_liabilities',
"A34":'operating_expenses/_total_liabilities',
"A35":'profit_on_sales/total_assets',
"A36":'total_sales/total_assets',
"A37":'(current_assets-inventories)/long-term_liabilities',
"A38":'constant_capital/total_assets',
"A39":'profit_on_sales/sales',
"A40":'(current_assets-inventory-receivables)/short-term_liabilities',
"A41":'total_liabilities/((profit_on_operating_activities+depreciation)*(12/365))',
"A42":'profit_on_operating_activities/sales',
"A43":'rotation_receivables+inventory_turnover_in_days',
"A44":'(receivables*365)/sales',
"A45":'net_profit/inventory',
"A46":'(current_assets-inventory)/short-term_liabilities',
"A47":'(inventory*365)/cost_of_products_sold',
"A48":'EBITDA_(profit_on_operating_activities-depreciation)/total_assets',
"A49":'EBITDA_(profit_on_operating_activities-depreciation)/sales',
"A50":'current_assets/total_liabilities',
"A51":'short-term_liabilities/total_assets',
"A52":'(short-term_liabilities*365)/cost_of_products_sold',
"A53":'equity/fixed_assets',
"A54":'constant_capital/fixed_assets',
"A55":'working_capital',
"A56":'(sales-cost_of_products_sold)/sales',
"A57":'(current_assets-inventory-short-term_liabilities)/(sales-gross_profit-depreciation)',
"A58":'total_costs/total_sales',
"A59":'long-term_liabilities/equity',
"A60":'sales/inventory',
"A61":'sales/receivables',
"A62":'(short-term_liabilities*365)/sales',
"A63":'sales/short-term_liabilities',
"A64":'sales/fixed assets',
}

```

```
polish_Dataset =polish_Dataset.rename(columns=new_Column_names)
```

```
#based on the intial review of all the attributes type, it was noted that the class ratio was listed as int.
#making the class into a categorial data type from int
polish_Dataset['class']=polish_Dataset['class'].astype('category')
```

```
#snapshot of the features after change in data type 'class'
polish_Dataset.info()
```

```
→ <class 'pandas.core.frame.DataFrame'>
RangeIndex: 43405 entries, 0 to 43404
Data columns (total 66 columns):
 #   Column          Non-Null Count Dtype
 --- 
 0   year            43405 non-null  int64
 1   net_profit/total assets  43397 non-null  float64
 2   Total_Liabilities/total_assets  43397 non-null  float64
 3   Working_Capital_to_Total_Assets_Ratio  43397 non-null  float64
 4   Current_Ratio      43271 non-null  float64
 5   Defensive_Interval_Ratio  43316 non-null  float64
 6   Retained_Earnings_to_Total_Assets_Ratio  43397 non-null  float64
 7   Operating_Income_to_Total_Asset_ratio  43397 non-null  float64
 8   book_value_of_equity/total_liabilities  43311 non-null  float64
 9   Asset_Turnover_Ratio    43396 non-null  float64
 10  Equity_to_Total_Assets_Ratio  43397 non-null  float64
 11  gross_profit+extraordinary_items+financial_expenses)/total  43361 non-null  float64
 12  gross_profit/short-term_liabilities  43271 non-null  float64
```

13	(gross_profit+depreciation)/sales	43278	non-null	float64
14	(gross_profit+interest)/total_assets	43397	non-null	float64
15	(total_liabilities*365)/(gross_profit+depreciation)	43369	non-null	float64
16	(gross_profit+depreciation)/total_liabilities	43310	non-null	float64
17	total_assets/total_liabilities	43311	non-null	float64
18	gross_profit/total_assets	43397	non-null	float64
19	gross_profit/sales	43277	non-null	float64
20	(inventory*365)/sales	43278	non-null	float64
21	sales(n)/sales(n-1)	37551	non-null	float64
22	profit_on_operating_activities/total_assets	43397	non-null	float64
23	net_profit/sales	43278	non-null	float64
24	gross_profit(in3years)/total_assets	42483	non-null	float64
25	(equity-share_capital)/total_assets	43397	non-null	float64
26	(net_profit+depreciation)/total_liabilities	43310	non-null	float64
27	profit_on_operating_activities/financial_expenses	40641	non-null	float64
28	working_capital/fixed_assets	42593	non-null	float64
29	logarithm_of_total_assets	43397	non-null	float64
30	(total_liabilities-cash)/sales	43278	non-null	float64
31	(gross_profit+interest)/sales	43278	non-null	float64
32	(current_liabilities*365)/cost_of_products_sold	43037	non-null	float64
33	operating_expenses/short-term_liabilities	43271	non-null	float64
34	operating_expenses/_total_liabilities	43311	non-null	float64
35	profit_on_sales/total_assets	43397	non-null	float64
36	total_sales/total_assets	43397	non-null	float64
37	(current_assets-inventories)/long-term_liabilities	24421	non-null	float64
38	constant_capital/total_assets	43397	non-null	float64
39	profit_on_sales/sales	43278	non-null	float64
40	(current_assets-inventory-receivables)/short-term_liabilities	43271	non-null	float64
41	total_liabilities/((profit_on_operating_activities+depreciation)*(12/365))	42651	non-null	float64
42	profit_on_operating_activities/sales	43278	non-null	float64
43	rotation_receivables+inventory_turnover_in_days	43278	non-null	float64
44	(receivables*365)/sales	43278	non-null	float64
45	net_profit/inventory	41258	non-null	float64
46	(current_assets-inventory)/short-term_liabilities	43270	non-null	float64
47	(inventory*365)/cost_of_products_sold	43108	non-null	float64
48	EBITDA_(profit_on_operating_activities-depreciation)/total_assets	43396	non-null	float64
49	EBITDA_(profit_on_operating_activities-depreciation)/sales	43278	non-null	float64
50	current_assets/total_liabilities	43311	non-null	float64
51	short-term_liabilities/total_assets	43397	non-null	float64

▼ Variable Additions

This research paper was to introduce financial ratios that can help identify financial stress. This analysis was done by reviewing all attributes and seeing what can be added.

The following additions are based on using existing variables to create these additions. This is based on existing and industry knowledge.

```
#The introduction of this variable is to get an understanding of how much of interest paid is to sales.
#A high proportion of interest to sales will indicate that a good portion of their sales earned will go towards paying the interest and other expenses.

#Variable 1
Interest_to_Sales = (polish_Dataset['(gross_profit+interest)/sales'])-polish_Dataset['gross_profit/sales'])
Interest_to_Sales.replace([np.inf, -np.inf], np.NaN, inplace=True )
Interest_to_Sales
polish_Dataset['Interest_to_Sales'] = Interest_to_Sales

#To gain an understanding on liquidity compared to all assets. Cash is the most liquid asset and can be used to cover debt/interest in the short term.
#variable 2
Cash_to_assets = (polish_Dataset['Total_Liabilities/total_assets'])-(polish_Dataset['(total_liabilities-cash)/sales']) * polish_Dataset['total_liabilities']
Cash_to_assets.replace([np.inf, -np.inf], np.NaN, inplace=True )
Cash_to_assets
polish_Dataset['Cash_to_assets'] = Cash_to_assets

#This is to gain an understanding on how much cash can cover total liabilities. Too high can tell us that the company may have a hard time covering its debts.
#variable 3
Total_liabilities_to_Cash = (polish_Dataset['Total_Liabilities/total_assets'])/ polish_Dataset['Cash_to_assets'] )
Total_liabilities_to_Cash.replace([np.inf, -np.inf], np.NaN, inplace=True )
Total_liabilities_to_Cash
polish_Dataset['Total_liabilities_to_Cash'] = Total_liabilities_to_Cash
```

```

#Tells us how much interest can be covered by cash. A high number gives comfort that the company can cover their interest obligations
#variable 4
cash_to_interest = (polish_Dataset['Cash_to_assets']/ polish_Dataset['total_sales/total_assets']) * (1/polish_Dataset['Interest_to_Sales'])
cash_to_interest.replace([np.inf, -np.inf], np.NaN, inplace=True )
cash_to_interest
polish_Dataset['cash_to_interest'] = cash_to_interest

#After initial analysis, I realized that not all companies have debt/paid interest during their fiscal year.
#This is ratio is taking the inverse.
#variable 5
Interest_to_cash = 1 /(polish_Dataset['cash_to_interest'])
Interest_to_cash.replace([np.inf, -np.inf], np.NaN, inplace=True )
Interest_to_cash
polish_Dataset['Interest_to_cash'] = Interest_to_cash

#This ratio to review how much financial expense is covered by total assets. a high number indicates to me that the company has taken on too
#may not be enough relative to debt. this ratio can be used with asset turnover to provide more direction.
#variable 6
Financial_Expense_To_Total_Asset = (polish_Dataset['profit_on_operating_activities/total_assets'] / polish_Dataset['profit_on_operating_acti
Financial_Expense_To_Total_Asset.replace([np.inf, -np.inf], np.NaN, inplace=True )
Financial_Expense_To_Total_Asset
polish_Dataset['Financial_Expense_To_Total_Asset'] = Financial_Expense_To_Total_Asset

#variable 6
Financial_expense_to_operating = (polish_Dataset['profit_on_operating_activities/total_assets'] / (polish_Dataset["Operating_Income_to_Total
Financial_expense_to_operating.replace([np.inf, -np.inf], np.NaN, inplace=True )
Financial_expense_to_operating
polish_Dataset['Financial_expense_to_operating']=Financial_expense_to_operating

#this ratio gives me an idea on how much operating income can cover the interest for the fiscal period. a high ratio is a good indicator.
#variable 7
Debt_Coverage_Ratio = ((polish_Dataset["Operating_Income_to_Total_Asset_ratio"]*polish_Dataset['profit_on_operating_activities/financial_exp
Debt_Coverage_Ratio.replace([np.inf, -np.inf], np.NaN, inplace=True )
Debt_Coverage_Ratio
polish_Dataset['Debt_Coverage_Ratio'] = Debt_Coverage_Ratio

#operating income can be viewed as cash flow from operating. it is not however, but in its place it can give the reader an idea.
#THis give us the percentage that is available to firm after all expenses are paid from sales for the fiscal
#variable 8
Operating_income_Margin = (polish_Dataset['Operating_Income_to_Total_Asset_ratio'] / polish_Dataset['total_sales/total_assets'])
Operating_income_Margin.replace([np.inf, -np.inf], np.NaN, inplace=True )
Operating_income_Margin
polish_Dataset['Operating_income_Margin'] = Operating_income_Margin

#this ratio tells us how many days cash is received from the moment it is used to pay for inventory and accounts payable, as well as cash
#Variable 9 Cash Conversion Cycle Formula = DIO + DSO - DPO.
Cash_conversion_cycle = ((polish_Dataset['(inventory*365)/cost_of_products_sold']) + (polish_Dataset['(receivables*365)/sales']) - (polish_D
Cash_conversion_cycle.replace([np.inf, -np.inf], np.NaN, inplace=True )
Cash_conversion_cycle
polish_Dataset['Cash_conversion_cycle'] = Cash_conversion_cycle

#This ratio is used to determine how much cash can be used to cover financial expense. since cash is the most liquid asset, a high number in
#the ability to cover financial expenses
#variable 10
Cash_to_Financial_expense = (polish_Dataset['Cash_to_assets'] / polish_Dataset['Financial_Expense_To_Total_Asset'])
Cash_to_Financial_expense.replace([np.inf, -np.inf], np.NaN, inplace=True )
polish_Dataset['Cash_to_Financial_Expense']= Cash_to_Financial_expense

#Used as part of the dupont formula (i.e Return on equity), gives us indication how much leverage is used.

#variable 11
Equity_multiplier= 1/ polish_Dataset['Equity_to_Total_Assets_Ratio']
Equity_multiplier.replace([np.inf, -np.inf], np.NaN, inplace=True )
polish_Dataset['Financial_Leverage'] = Equity_multiplier

#not addition but transforming an existing attribute to 1,0. if working capital is positive, it will be given a 1, if negative it will give
#making working capital into a indicator. 1 = positive values, 0 = negative
polish_Dataset['working_capital_indicator'] =np.where(polish_Dataset['working_capital']<=0,0,1)
polish_Dataset['working_capital_indicator']=polish_Dataset['working_capital'].astype('category')

```

```
#final ratio is return on equity. this is to gauge on management performance on how much they return to shareholders.
#since this ratio is the result of the duPont formula, it helps us determine what goes into the results for shareholders. such as
#asset turnover and financial leverage. a high financial leverage tell us that the results are coming from debt.
#Variable12
Return_On_Equity = polish_Dataset['net_profit/sales'] * polish_Dataset['total_sales/total_assets'] * polish_Dataset['Financial_Leverage']
Return_On_Equity.replace([np.inf, -np.inf], np.NaN, inplace=True)
polish_Dataset['Return_On_Equity'] = Return_On_Equity
```

Start coding or generate with AI.

```
#Review of all financial ratios in the polish dataset
polish_Dataset.info()
```

	Non-Null Count Dtype
0 year	43405 non-null int64
1 net_profit/total_assets	43397 non-null float64
2 Total_Liabilities/total_assets	43397 non-null float64
3 Working_Capital_to_Total_Assets_Ratio	43397 non-null float64
4 Current_Ratio	43271 non-null float64
5 Defensive_Interval_Ratio	43316 non-null float64
6 Retained_Earnings_to_Total_Assets_Ratio	43397 non-null float64
7 Operating_Income_to_Total_Asset_ratio	43397 non-null float64
8 book_value_of_equity/total_liabilities	43311 non-null float64
9 Asset_Turnover_Ratio	43396 non-null float64
10 Equity_to_Total_Assets_Ratio	43397 non-null float64
11 gross_profit+extraordinary_items+financial_expenses)/total	43361 non-null float64
12 gross_profit/short-term_liabilities	43271 non-null float64
13 (gross_profit+depreciation)/sales	43278 non-null float64
14 (gross_profit+interest)/total_assets	43397 non-null float64
15 (total_liabilities*365)/(gross_profit+depreciation)	43369 non-null float64
16 (gross_profit+depreciation)/total_liabilities	43310 non-null float64
17 total_assets/total_liabilities	43311 non-null float64
18 gross_profit/total_assets	43397 non-null float64
19 gross_profit/sales	43277 non-null float64
20 (inventory*365)/sales	43278 non-null float64
21 sales(n)/sales(n-1)	37551 non-null float64
22 profit_on_operating_activities/total_assets	43397 non-null float64
23 net_profit/sales	43278 non-null float64
24 gross_profit(in3years)/total_assets	42483 non-null float64
25 (equity-share_capital)/total_assets	43397 non-null float64
26 (net_profit+depreciation)/total_liabilities	43310 non-null float64
27 profit_on_operating_activities/financial_expenses	40641 non-null float64
28 working_capital/fixed_assets	42593 non-null float64
29 logarithm_of_total_assets	43397 non-null float64
30 (total_liabilities-cash)/sales	43278 non-null float64
31 (gross_profit+interest)/sales	43278 non-null float64
32 (current_liabilities*365)/cost_of_products_sold	43037 non-null float64
33 operating_expenses/short-term_liabilities	43271 non-null float64
34 operating_expenses/_/total_liabilities	43311 non-null float64
35 profit_on_sales/total_assets	43397 non-null float64
36 total_sales/total_assets	43397 non-null float64
37 (current_assets-inventories)/long-term_liabilities	24421 non-null float64
38 constant_capital/total_assets	43397 non-null float64
39 profit_on_sales/sales	43278 non-null float64
40 (current_assets-inventory-receivables)/short-term_liabilities	43271 non-null float64
41 total_liabilities/((profit_on_operating_activities+depreciation)*(12/365))	42651 non-null float64
42 profit_on_operating_activities/sales	43278 non-null float64
43 rotation_receivables+inventory_turnover_in_days	43278 non-null float64
44 (receivables*365)/sales	43278 non-null float64
45 net_profit/inventory	41258 non-null float64
46 (current_assets-inventory)/short-term_liabilities	43270 non-null float64
47 (inventory*365)/cost_of_products_sold	43108 non-null float64
48 EBITDA_(profit_on_operating_activities-depreciation)/total_assets	43396 non-null float64
49 EBITDA_(profit_on_operating_activities-depreciation)/sales	43278 non-null float64
50 current_assets/total_liabilities	43311 non-null float64
51 short-term_liabilities/total_assets	43397 non-null float64
52 (short-term_liabilities*365)/cost_of_products_sold	43104 non-null float64

```
polish_Dataset.head()
```



```
year  net_profit/total assets  Total_Liabilities/total_assets  Working_Capital_to_Total_Assets
```

0	1	0.200550	0.37951
1	1	0.209120	0.49988
2	1	0.248660	0.69592
3	1	0.081483	0.30734
4	1	0.187320	0.61323

```
polish_Dataset.tail()
```



```
year  net_profit/total assets  Total_Liabilities/total_assets  Working_Capital_to_Total_Assets
```

43400	5	0.012898	0.70621
43401	5	-0.578050	0.96702
43402	5	-0.179050	1.25530
43403	5	-0.108860	0.74394
43404	5	-0.105370	0.53629

```
filename='alldata.csv'
polish_Dataset.to_csv(filename,index=False)
```

```
files.download('alldata.csv')
```

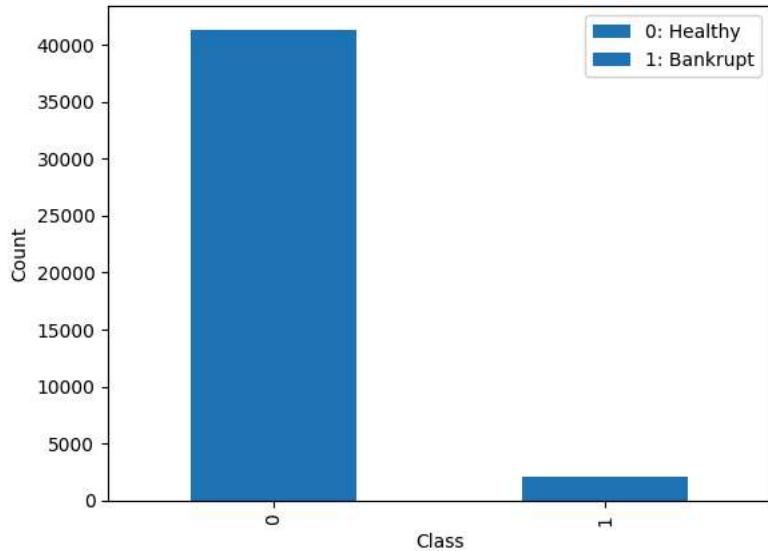


Initial Description Analysis

```
category_counts = polish_Dataset['class'].value_counts()
ax = category_counts.plot(kind='bar')
category_counts.plot(kind='bar')
plt.title('Class Distribution')
plt.xlabel('Class')
plt.ylabel('Count')
plt.legend(['0: Healthy', '1: Bankrupt'])
plt.show()
```



Class Distribution



```
def PlotBarCharts(inpData, colsToPlot):
    %matplotlib inline

    import matplotlib.pyplot as plt

    # Generating multiple subplots
    fig, subPlot = plt.subplots(nrows=1, ncols=len(colsToPlot), figsize=(20, 5))
    fig.suptitle('Bar charts of: ' + str(colsToPlot))

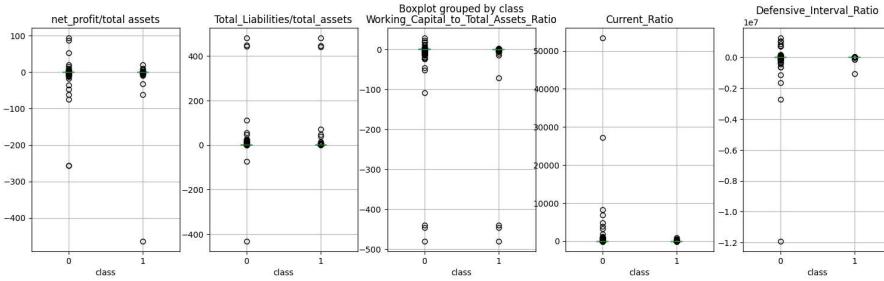
    for colName, plotNumber in zip(colsToPlot, range(len(colsToPlot))):
        inpData.groupby(colName).size().plot(kind='bar', ax=subPlot[plotNumber])

import matplotlib.pyplot as plt

continuous_cols = ['net_profit/total assets', 'Total_Liabilities/total_assets', 'Working_Capital_to_Total_Assets_Ratio', 'Current_Ratio', 'Defer']

fig, axes = plt.subplots(nrows=1, ncols=len(continuous_cols), figsize=(18, 5))

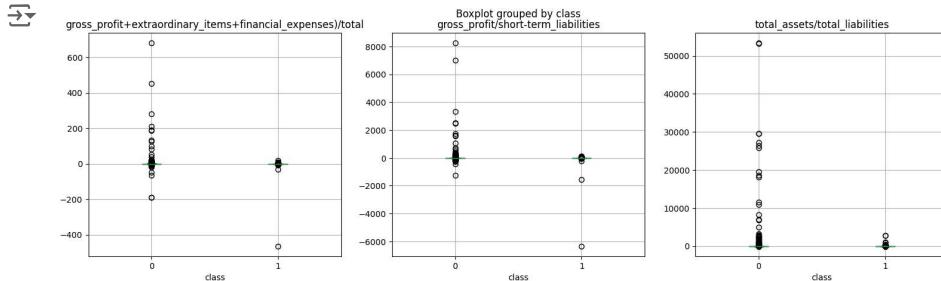
# Creating box plots for each continuous predictor against the Target Variable "class"
for col, ax in zip(continuous_cols, axes):
    polish_Dataset.boxplot(column=col, by='class', figsize=(5,5), vert=True, ax=ax)
    ax.set_title(col)
plt.show()
```



```
continuous_cols = ['gross_profit+extraordinary_items+financial_expenses)/total', 'gross_profit/short-term_liabilities', 'total_assets/total_liabilities']

fig, axes = plt.subplots(nrows=1, ncols=len(continuous_cols), figsize=(18, 5))

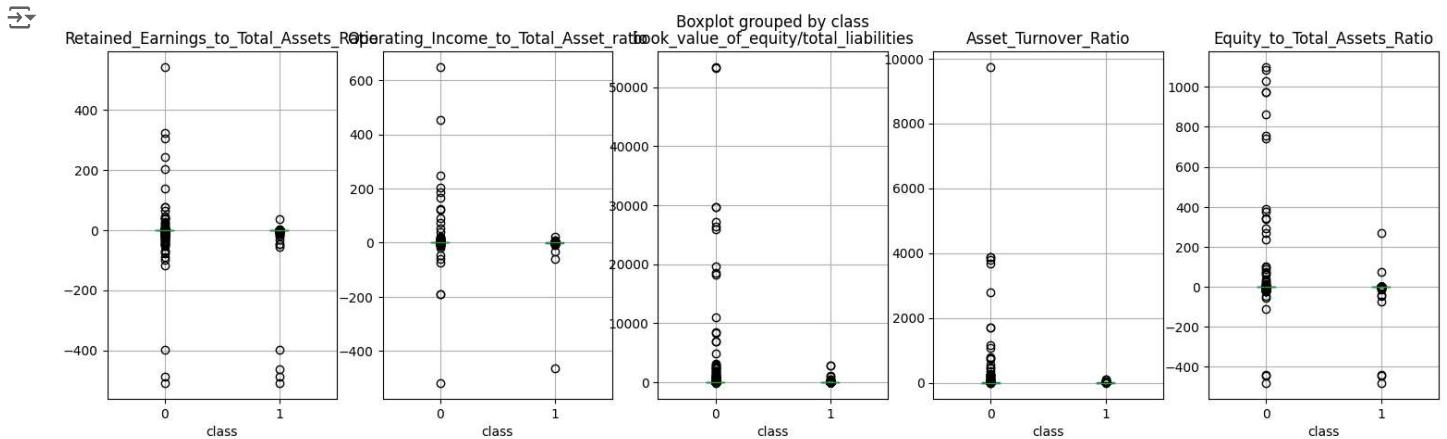
# Creating box plots for each continuous predictor against the Target Variable "class"
for col, ax in zip(continuous_cols, axes):
    polish_Dataset.boxplot(column=col, by='class', figsize=(5,5), vert=True, ax=ax)
    ax.set_title(col)
plt.show()
```



```
continuous_cols = ['Retained_Earnings_to_Total_Assets_Ratio', 'Operating_Income_to_Total_Asset_ratio', 'book_value_of_equity/total_liabilities']

fig, axes = plt.subplots(nrows=1, ncols=len(continuous_cols), figsize=(18, 5))

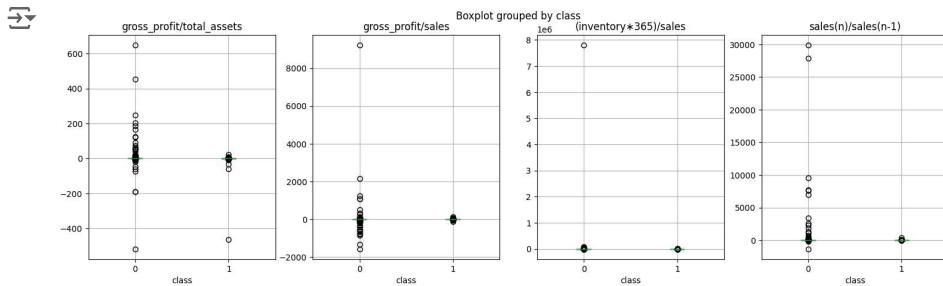
# Creating box plots for each continuous predictor against the Target Variable "class"
for col, ax in zip(continuous_cols, axes):
    polish_Dataset.boxplot(column=col, by='class', figsize=(5,5), vert=True, ax=ax)
    ax.set_title(col)
plt.show()
```



```
continuous_cols = ['gross_profit/total_assets', 'gross_profit/sales', '(inventory*365)/sales', 'sales(n)/sales(n-1)']

fig, axes = plt.subplots(nrows=1, ncols=len(continuous_cols), figsize=(18, 5))
```

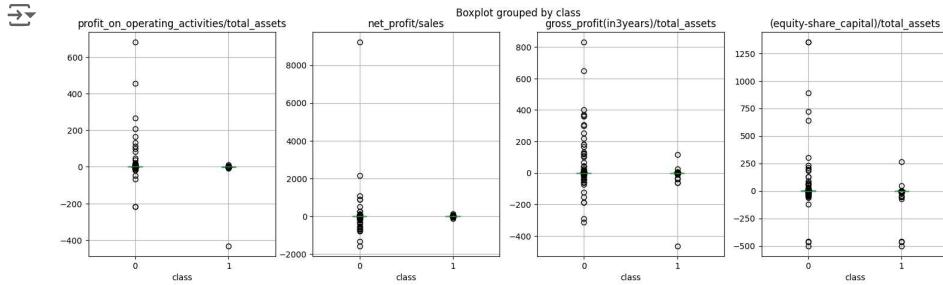
```
# Creating box plots for each continuous predictor against the Target Variable "class"
for col, ax in zip(continuous_cols, axes):
    polish_Dataset.boxplot(column=col, by='class', figsize=(5,5), vert=True, ax=ax)
    ax.set_title(col)
plt.show()
```



```
continuous_cols = ['profit_on_operating_activities/total_assets', 'net_profit/sales', 'gross_profit(in3years)/total_assets', '(equity-share_capital)/total_assets']

fig, axes = plt.subplots(nrows=1, ncols=len(continuous_cols), figsize=(18, 5))

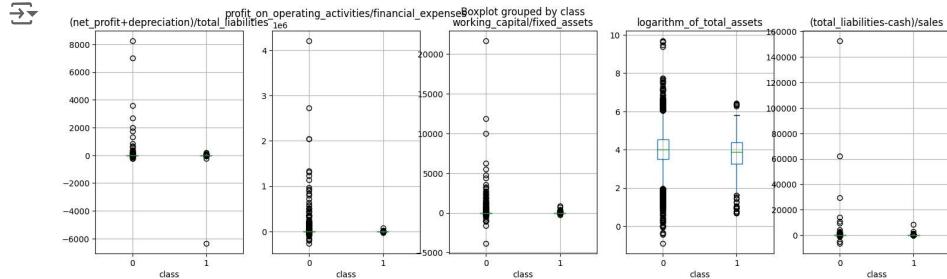
# Creating box plots for each continuous predictor against the Target Variable "class"
for col, ax in zip(continuous_cols, axes):
    polish_Dataset.boxplot(column=col, by='class', figsize=(5,5), vert=True, ax=ax)
    ax.set_title(col)
plt.show()
```



```
continuous_cols = ['(net_profit+depreciation)/total_liabilities','profit_on_operating_activities/financial_expenses','working_capital/fixed_assets']

fig, axes = plt.subplots(nrows=1, ncols=len(continuous_cols), figsize=(18, 5))

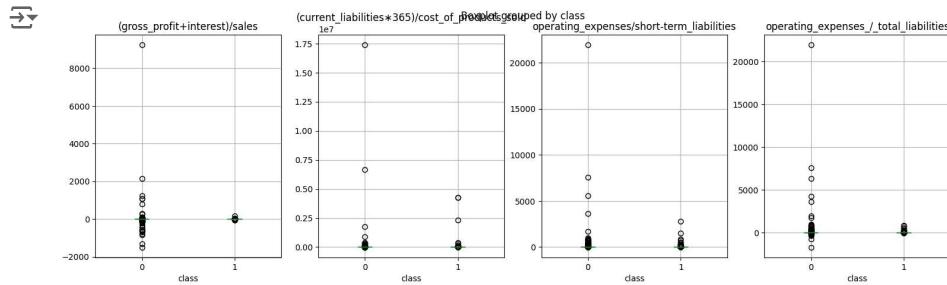
# Creating box plots for each continuous predictor against the Target Variable "class"
for col, ax in zip(continuous_cols, axes):
    polish_Dataset.boxplot(column=col, by='class', figsize=(5,5), vert=True, ax=ax)
    ax.set_title(col)
plt.show()
```



```
continuous_cols = ['(gross_profit+interest)/sales','(current_liabilities*365)/cost_of_products_sold','operating_expenses/short-term_liabilities']

fig, axes = plt.subplots(nrows=1, ncols=len(continuous_cols), figsize=(18, 5))

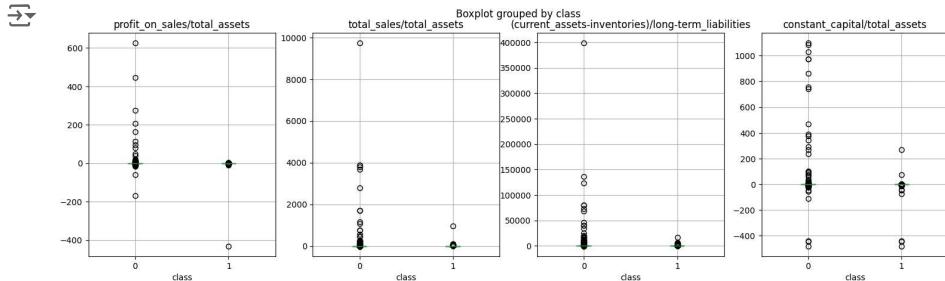
# Creating box plots for each continuous predictor against the Target Variable "class"
for col, ax in zip(continuous_cols, axes):
    polish_Dataset.boxplot(column=col, by='class', figsize=(5,5), vert=True, ax=ax)
    ax.set_title(col)
plt.show()
```



```
continuous_cols = ['profit_on_sales/total_assets','total_sales/total_assets','(current_assets-inventories)/long-term_liabilities','constant_capital/total_assets']

fig, axes = plt.subplots(nrows=1, ncols=len(continuous_cols), figsize=(18, 5))

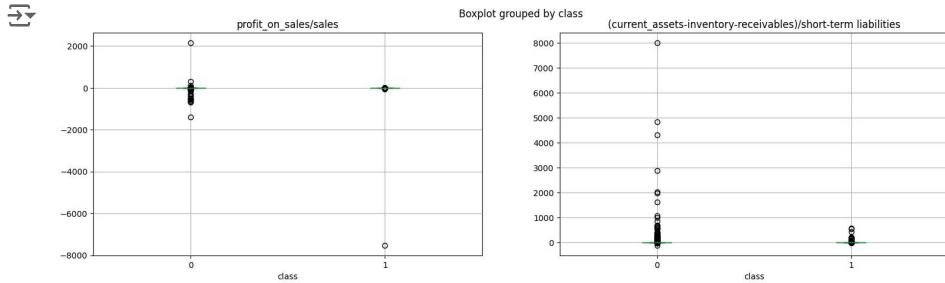
# Creating box plots for each continuous predictor against the Target Variable "class"
for col, ax in zip(continuous_cols, axes):
    polish_Dataset.boxplot(column=col, by='class', figsize=(5,5), vert=True, ax=ax)
    ax.set_title(col)
plt.show()
```



```
continuous_cols = ['profit_on_sales/sales','(current_assets-inventory-receivables)/short-term liabilities']

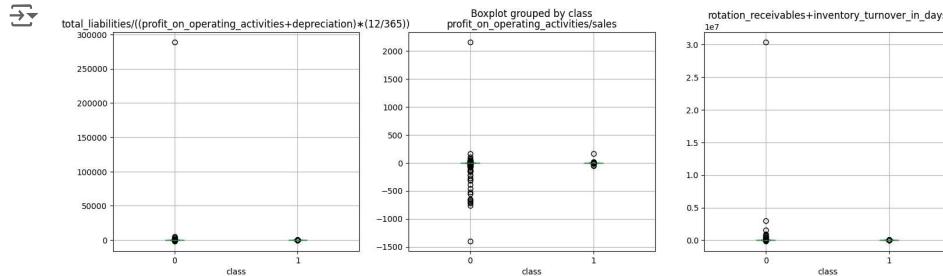
fig, axes = plt.subplots(nrows=1, ncols=len(continuous_cols), figsize=(18, 5))

# Creating box plots for each continuous predictor against the Target Variable "class"
for col, ax in zip(continuous_cols, axes):
    polish_Dataset.boxplot(column=col, by='class', figsize=(5,5), vert=True, ax=ax)
    ax.set_title(col)
plt.show()
```



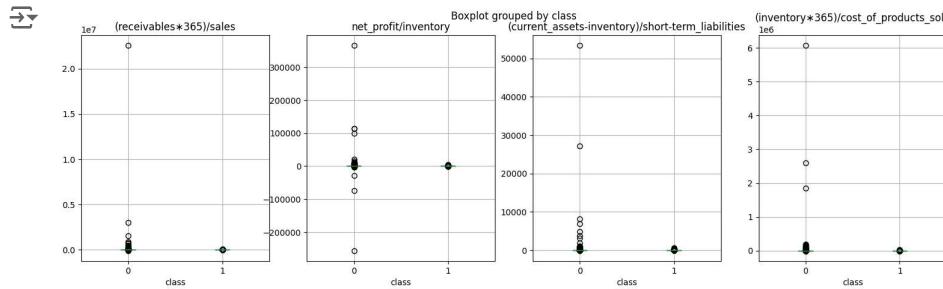
```
continuous_cols = ['total_liabilities/((profit_on_operating_activities+depreciation)*(12/365))','profit_on_operating_activities/sales','rota
fig, axes = plt.subplots(nrows=1, ncols=len(continuous_cols), figsize=(18, 5))

# Creating box plots for each continuous predictor against the Target Variable "class"
for col, ax in zip(continuous_cols, axes):
    polish_Dataset.boxplot(column=col, by='class', figsize=(5,5), vert=True, ax=ax)
    ax.set_title(col)
plt.show()
```



```
continuous_cols = ['(receivables*365)/sales','net_profit/inventory','(current_assets-inventory)/short-term_liabilities','(inventory*365)/cos
fig, axes = plt.subplots(nrows=1, ncols=len(continuous_cols), figsize=(18, 5))

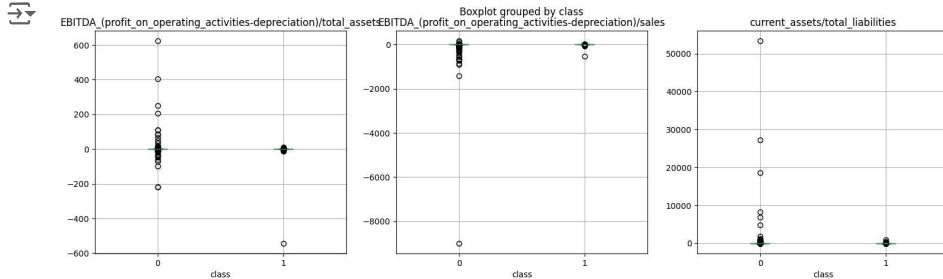
# Creating box plots for each continuous predictor against the Target Variable "class"
for col, ax in zip(continuous_cols, axes):
    polish_Dataset.boxplot(column=col, by='class', figsize=(5,5), vert=True, ax=ax)
    ax.set_title(col)
plt.show()
```



```
continuous_cols = ['EBITDA_(profit_on_operating_activities-depreciation)/total_assets', 'EBITDA_(profit_on_operating_activities-depreciation)']

fig, axes = plt.subplots(nrows=1, ncols=len(continuous_cols), figsize=(18, 5))

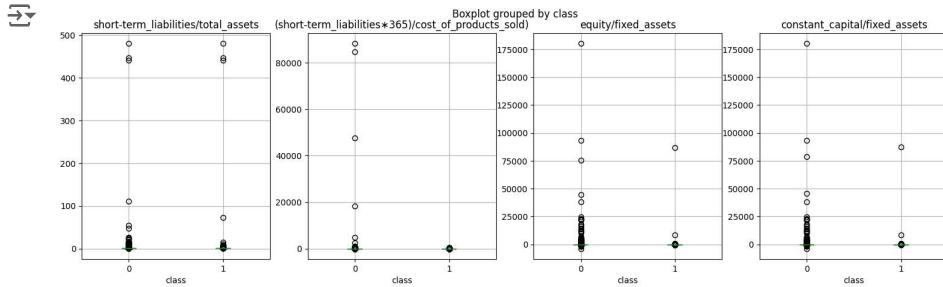
# Creating box plots for each continuous predictor against the Target Variable "class"
for col, ax in zip(continuous_cols, axes):
    polish_Dataset.boxplot(column=col, by='class', figsize=(5,5), vert=True, ax=ax)
    ax.set_title(col)
plt.show()
```



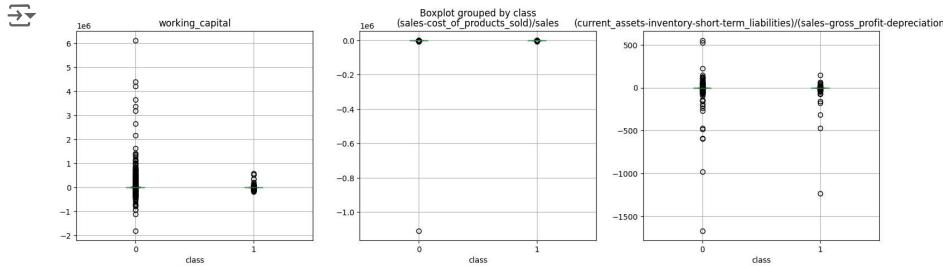
```
continuous_cols = ['short-term_liabilities/total_assets', '(short-term_liabilities*365)/cost_of_products_sold', 'equity/fixed_assets', 'constant_capital/fixed_assets']

fig, axes = plt.subplots(nrows=1, ncols=len(continuous_cols), figsize=(18, 5))

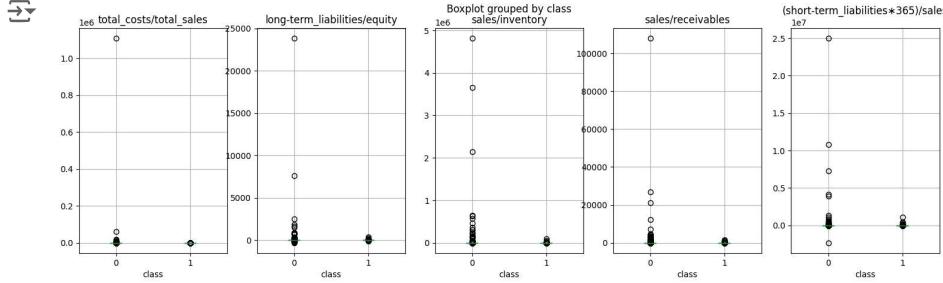
# Creating box plots for each continuous predictor against the Target Variable "class"
for col, ax in zip(continuous_cols, axes):
    polish_Dataset.boxplot(column=col, by='class', figsize=(5,5), vert=True, ax=ax)
    ax.set_title(col)
plt.show()
```



```
continuous_cols = ['working_capital','(sales-cost_of_products_sold)/sales','(current_assets-inventory-short-term_liabilities)/(sales-gross_p  
fig, axes = plt.subplots(nrows=1, ncols=len(continuous_cols), figsize=(18, 5))  
  
# Creating box plots for each continuous predictor against the Target Variable "class"  
for col, ax in zip(continuous_cols, axes):  
    polish_Dataset.boxplot(column=col, by='class', figsize=(5,5), vert=True, ax=ax)  
    ax.set_title(col)  
plt.show()
```



```
continuous_cols = ['total_costs/total_sales','long-term_liabilities/equity','sales/inventory','sales/receivables','(short-term_liabilities*365)/sales'  
fig, axes = plt.subplots(nrows=1, ncols=len(continuous_cols), figsize=(18, 5))  
  
# Creating box plots for each continuous predictor against the Target Variable "class"  
for col, ax in zip(continuous_cols, axes):  
    polish_Dataset.boxplot(column=col, by='class', figsize=(5,5), vert=True, ax=ax)  
    ax.set_title(col)  
plt.show()
```

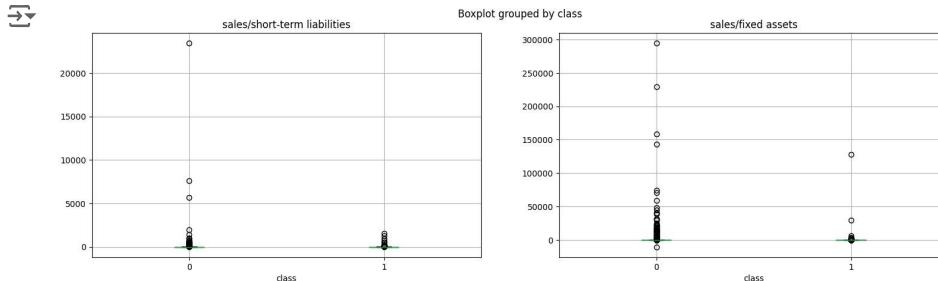


```

continuous_cols = ['sales/short-term liabilities', 'sales/fixed assets']
fig, axes = plt.subplots(nrows=1, ncols=len(continuous_cols), figsize=(18, 5))

# Creating box plots for each continuous predictor against the Target Variable "class"
for col, ax in zip(continuous_cols, axes):
    polish_Dataset.boxplot(column=col, by='class', figsize=(5,5), vert=True, ax=ax)
    ax.set_title(col)
plt.show()

```



```
polish_Dataset.isnull().any()
```

year	False
net_profit/total assets	True
Total_Liabilities/total_assets	True
Working_Capital_to_Total_Assets_Ratio	True
Current_Ratio	True
Defensive_Interval_Ratio	True
Retained_Earnings_to_Total_Assets_Ratio	True
Operating_Income_to_Total_Asset_ratio	True
book_value_of_equity/total_liabilities	True
Asset_Turnover_Ratio	True
Equity_to_Total_Assets_Ratio	True
gross_profit+extraordinary_items+financial_expenses)/total	True
gross_profit/short-term_liabilities	True
(gross_profit+depreciation)/sales	True
(gross_profit+interest)/total_assets	True
(total_liabilities*365)/(gross_profit+depreciation)	True
(gross profit+depreciation)/total_liabilities	True
total_assets/total_liabilities	True
gross_profit/total_assets	True
gross_profit/sales	True
(inventory*365)/sales	True
sales(n)/sales(n-1)	True
profit_on_operating_activities/total_assets	True
net_profit/sales	True
gross_profit(in3years)/total_assets	True
(equity-share_capital)/total_assets	True
(net_profit+depreciation)/total_liabilities	True
profit_on_operating_activities/financial_expenses	True
working_capital/fixed_assets	True
logarithm_of_total_assets	True
(total_liabilities-cash)/sales	True
(gross_profit+interest)/sales	True
(current_liabilities*365)/cost_of_products_sold	True
operating_expenses/short-term_liabilities	True
operating_expenses/_total_liabilities	True
profit_on_sales/total_assets	True
total_sales/total_assets	True
(current_assets-inventories)/long-term_liabilities	True
constant_capital/total_assets	True
profit_on_sales/sales	True
(current_assets-inventory-receivables)/short-term_liabilities	True
total_liabilities/((profit_on_operating_activities+depreciation)*(12/365))	True
profit_on_operating_activities/sales	True

```

rotation_receivables+inventory_turnover_in_days True
(receivables*365)/sales True
net_profit/inventory True
(current_assets-inventory)/short-term_liabilities True
(inventory*365)/cost_of_products_sold True
EBITDA_(profit_on_operating_activities-depreciation)/total_assets True
EBITDA_(profit_on_operating_activities-depreciation)/sales True
current_assets/total_liabilities True
short-term_liabilities/total_assets True
(short-term_liabilities*365)/cost_of_products_sold True
equity/fixed_assets True
constant_capital/fixed_assets True
working_capital True
(sales-cost_of_products_sold)/sales True
(current_assets-inventory-short-term_liabilities)/(sales-gross_profit-depreciation) True

```

```

#number of null
Features_Null=(polish_Dataset.isnull().sum())
Features_Null

```

	0
year	0
net_profit/total_assets	8
Total_Liabilities/total_assets	8
Working_Capital_to_Total_Assets_Ratio	8
Current_Ratio	134
Defensive_Interval_Ratio	89
Retained_Earnings_to_Total_Assets_Ratio	8
Operating_Income_to_Total_Asset_ratio	8
book_value_of_equity/total_liabilities	94
Asset_Turnover_Ratio	9
Equity_to_Total_Assets_Ratio	8
gross_profit+extraordinary_items+financial_expenses)/total	44
gross_profit/short-term_liabilities	134
(gross_profit+depreciation)/sales	127
(gross_profit+interest)/total_assets	8
(total_liabilities*365)/(gross_profit+depreciation)	36
(gross_profit+depreciation)/total_liabilities	95
total_assets/total_liabilities	94
gross_profit/total_assets	8
gross_profit/sales	128
(inventory*365)/sales	127
sales(n)/sales(n-1)	5854
profit_on_operating_activities/total_assets	8
net_profit/sales	127
gross_profit(in3years)/total_assets	922
(equity-share_capital)/total_assets	8
(net_profit+depreciation)/total_liabilities	95
profit_on_operating_activities/financial_expenses	2764
working_capital/fixed_assets	812
logarithm_of_total_assets	8
(total_liabilities-cash)/sales	127
(gross_profit+interest)/sales	127
(current_liabilities*365)/cost_of_products_sold	368
operating_expenses/short-term_liabilities	134
operating_expenses/_/total_liabilities	94
profit_on_sales/total_assets	8
total_sales/total_assets	8
(current_assets-inventories)/long-term_liabilities	18984
constant_capital/total_assets	8
profit_on_sales/sales	127
(current_assets-inventory-receivables)/short-term_liabilities	134
total_liabilities/((profit_on_operating_activities+depreciation)*(12/365))	754
profit_on_operating_activities/sales	127
rotation_receivables+inventory_turnover_in_days	127
(receivables*365)/sales	127
net_profit/inventory	2147
(current_assets-inventory)/short-term_liabilities	135
(inventory*365)/cost_of_products_sold	297
EBITDA_(profit_on_operating_activities-depreciation)/total_assets	9
EBITDA_(profit_on_operating_activities-depreciation)/sales	127
current_assets/total_liabilities	94
short-term_liabilities/total_assets	8
(short-term_liabilities*365)/cost_of_products_sold	301
equity/fixed_assets	812
constant_capital/fixed_assets	812
working_capital	1
(sales-cost_of_products_sold)/sales	127
(current_assets-inventory-short-term_liabilities)/(sales-gross_profit-depreciation)	7

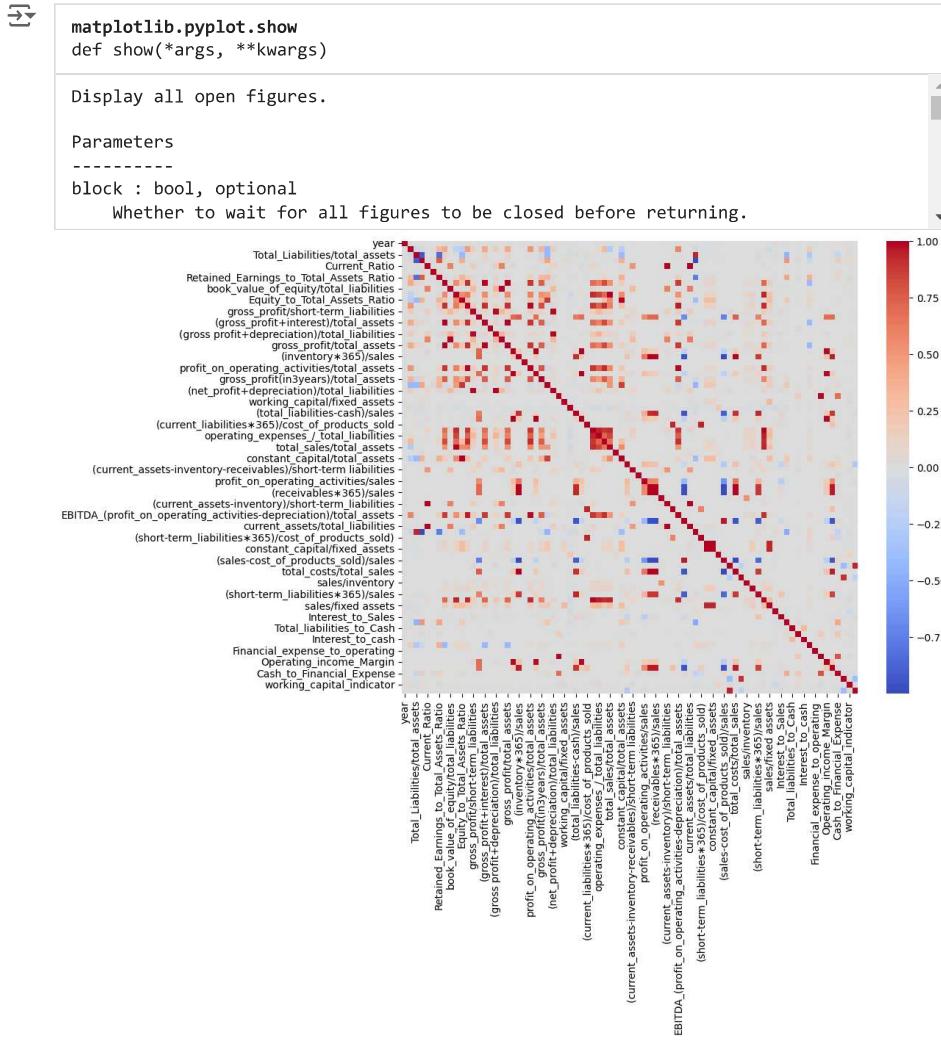
```
polish_Dataset.corr()
```



	year	net_profit/tot asse
year	1.000000	-0.0040
net_profit/total assets	-0.004052	1.0000
Total_Liabilities/total_assets	-0.004834	-0.1041
Working_Capital_to_Total_Assets_Ratio	0.004653	0.0580
Current_Ratio	0.004548	0.0008
Defensive_Interval_Ratio	0.001471	0.0027
Retained_Earnings_to_Total_Assets_Ratio	-0.000409	0.3151
Operating_Income_to_Total_Asset_ratio	-0.019313	0.4084
book_value_of_equity/total_liabilities	0.005614	0.0001
Asset_Turnover_Ratio	-0.017984	-0.2257
Equity_to_Total_Assets_Ratio	-0.021114	-0.2402
gross_profit+extraordinary_items+financial_expenses)/total	-0.019025	0.4921
gross_profit/short-term_liabilities	-0.000910	0.1687
(gross_profit+depreciation)/sales	-0.006130	0.0018
(gross_profit+interest)/total_assets	-0.019312	0.4084
(total_liabilities*365)/(gross_profit+depreciation)	0.002806	0.0002
(gross profit+depreciation)/total_liabilities	-0.000490	0.1639
total_assets/total_liabilities	0.005595	0.0003
gross_profit/total_assets	-0.018880	0.4066
gross_profit/sales	-0.004937	0.0034
(inventory*365)/sales	-0.007237	-0.0000
sales(n)/sales(n-1)	-0.009455	-0.0014
profit_on_operating_activities/total_assets	-0.016220	0.5013
net_profit/sales	-0.005043	0.0036
gross_profit(in3years)/total_assets	-0.011841	0.3348
(equity-share_capital)/total_assets	-0.016473	-0.4139
(net_profit+depreciation)/total_liabilities	-0.000569	0.1690
profit_on_operating_activities/financial_expenses	-0.006109	0.0076
working_capital/fixed_assets	0.013252	0.0028
logarithm_of_total_assets	-0.015942	0.0395
(total_liabilities-cash)/sales	-0.007532	0.0000
(gross_profit+interest)/sales	-0.004699	0.0034
(current_liabilities*365)/cost_of_products_sold	0.001381	-0.0025
operating_expenses/short-term_liabilities	-0.000124	0.0052
operating_expenses/_/total_liabilities	-0.000522	0.0834
profit_on_sales/total_assets	-0.018639	0.3139
total_sales/total_assets	-0.017789	-0.2796
(current_assets-inventories)/long-term_liabilities	-0.006016	0.0015
constant_capital/total_assets	-0.020650	-0.2333
profit_on_sales/sales	-0.005304	0.0009
(current_assets-inventory-receivables)/short-term_liabilities	0.009845	0.0029
total_liabilities/((profit_on_operating_activities+depreciation)*(12/365))	0.000513	0.0001
profit_on_operating_activities/sales	-0.005691	0.0029

	-0.000000	-0.000000
rotation_receivables+inventory_turnover_in_days	-0.006808	-0.000000
(receivables*365)/sales	-0.006808	-0.000000
net_profit/inventory	0.008052	0.000000
(current_assets-inventory)/short-term_liabilities	0.004457	0.000000
(inventory*365)/cost_of_products_sold	-0.002627	-0.000008
EBITDA_(profit_on_operating_activities-depreciation)/total_assets	-0.013376	0.5832
EBITDA_(profit_on_operating_activities-depreciation)/sales	0.006215	0.0011
current_assets/total_liabilities	0.003010	0.000000
short-term_liabilities/total_assets	-0.003462	-0.0564
(short-term_liabilities*365)/cost_of_products_sold)	0.001655	-0.0014
equity/fixed_assets	-0.019033	-0.0317
constant_capital/fixed_assets	-0.018786	-0.0315
working_capital	0.009445	0.0040
(sales-cost_of_products_sold)/sales	0.007262	0.000000
(current_assets-inventory-short-term_liabilities)/(sales-gross_profit-depreciation)	-0.006660	0.0077
total_costs/total_sales	-0.007609	-0.000003
long-term_liabilities/equity	-0.002881	-0.0002
sales/inventory	0.001804	0.0002
sales/receivables	0.000938	0.0005
(short-term_liabilities*365)/sales	-0.006390	0.0003
sales/short-term_liabilities	-0.001623	0.0083
sales/fixed_assets	-0.016681	-0.0690
class	0.043488	-0.0266
Interest_to_Sales	0.005840	-0.000000
Cash_to_assets	0.001698	-0.0343
Total_liabilities_to_Cash	-0.007498	-0.0021
cash_to_interest	0.012476	0.0014
Interest_to_cash	-0.002826	0.0025
Financial_Expense_To_Total_Asset	0.002699	0.1714
Financial_expense_to_operating	-0.009278	0.0001
Debt_Coverage_Ratio	-0.006008	0.0065
Operating_income_Margin	-0.006338	0.0030
Cash_conversion_cycle	-0.007289	-0.0003
Cash_to_Financial_Expense	0.002693	-0.0044
Financial_Leverage	-0.001960	-0.0003
working_capital_indicator	0.013728	0.0336
Return_On_equity	-0.004974	0.0043

```
correlation_matrix = polish_Dataset.corr()
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=False, cmap='coolwarm', fmt=".2f")
plt.show
```



```
# based on initial observations, there are many extreme outliers in this dataset. The outliers are extreme in the 0 dataset.
# I will review each attribute and based on industry and financial experience will narrow the feature selections,
# before conducting any cleaning.
```

Approach

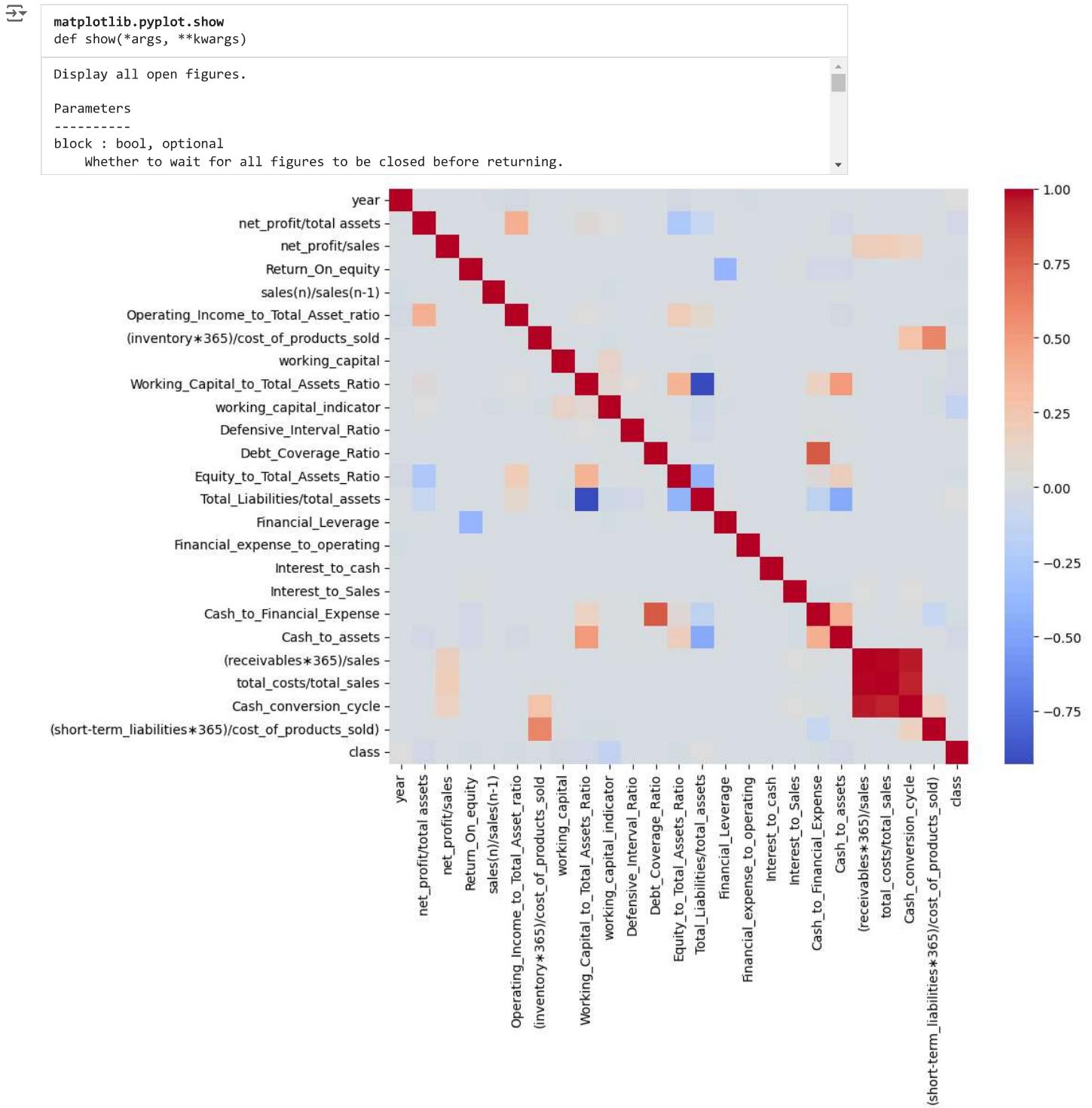
After careful analyzing all the variables. The theme of selection came down to: **Reason for companies to go bankrupt:**

1. **Failure of Business Strategy:** a. Lack of governance i. Failure to understand key metrics can lead to bankruptcy. b. Market trends i. Failing to see what competitors are doing ii. Market sentiment shifts and not adjusting
2. ** Inefficient use of assets** a. Management fails to generate income from assets b. Holding inventory too long c. Negative Working Capital
3. **Too much Debt** a. Debt used to pay for Working capital b. Debt used to pay for equipment, plant c. Operating profits can't cover interest
4. ** Not enough Cash flow** a. Not enough cash on hand b. Not collecting from account receivables c. Sales are not enough to cover expenses d. Cash conversion cycle is too long e. Cash can't cover interest f. Days payable is too high

```
#analysis and data cleaning will be done on this new dataset. The existing dataset, will be used to compare results.
Bankrupt_model = polish_Dataset[['year','net_profit/total assets', 'net_profit/sales','Return_On_equity', 'sales(n)/sales(n-1)', 'Operating_Income_to_Total_Asset_ratio', (inventory*365)]
Bankrupt_model.head()
```

	year	net_profit/total assets	net_profit/sales	Return_On_equity	sales(n)/sales(n-1)	Operating_Income_to_Total_Asset_ratio	(inventory*365)
0	1	0.200550	0.119980	0.413683	1.2479		0.249760
1	1	0.209120	0.123040	0.420018	1.4293		0.258340
2	1	0.248660	0.189960	0.817738	1.4283		0.309060
3	1	0.081483	0.062782	0.148458	1.5069		0.092704
4	1	0.187320	0.115530	0.486231	NaN		0.187320

```
plt.figure(figsize=(10, 8))
sns.heatmap(Bankrupt_model.corr(), annot=False, cmap='coolwarm', fmt=".2f")
plt.show
```



```
pd.options.display.float_format = "{:.3f}".format
Bankrupt_model.describe()
```

	year	net_profit/total assets	net_profit/sales	Return_On_equity	sales(n)/sales(n-1)
count	43405.000	43397.000	43278.000	43266.000	37551.00
mean	2.940	0.035	0.139	0.010	3.88
std	1.284	2.994	48.335	15.320	228.66
min	1.000	-463.890	-1578.700	-1858.486	-1325.00
25%	2.000	0.003	0.002	0.017	0.90
50%	3.000	0.050	0.030	0.123	1.04
75%	4.000	0.130	0.078	0.289	1.20
max	5.000	94.280	9230.500	1031.911	29907.00

```
#extreme outliers are detected with the first analysis. will use a range with a multiplier to remove the extreme outliers.
```

```
Bankrupt_model.info()
```

```
→ <class 'pandas.core.frame.DataFrame'>
RangeIndex: 43405 entries, 0 to 43404
Data columns (total 25 columns):
 #   Column           Non-Null Count  Dtype  
--- 
 0   year             43405 non-null   int64  
 1   net_profit/total assets    43397 non-null   float64 
 2   net_profit/sales        43278 non-null   float64 
 3   Return_On_equity      43266 non-null   float64 
 4   sales(n)/sales(n-1)    37551 non-null   float64 
 5   Operating_Income_to_Total_Asset_ratio 43397 non-null   float64 
 6   (inventory*365)/cost_of_products_sold 43108 non-null   float64 
 7   working_capital       43404 non-null   float64 
 8   Working_Capital_to_Total_Assets_Ratio 43397 non-null   float64 
 9   working_capital_indicator 43405 non-null   category 
 10  Defensive_Interval_Ratio 43316 non-null   float64 
 11  Debt_Coverage_Ratio    37652 non-null   float64 
 12  Equity_to_Total_Assets_Ratio 43397 non-null   float64 
 13  Total_Liabilities/total_assets    43397 non-null   float64 
 14  Financial_Leverage     43393 non-null   float64 
 15  Financial_expense_to_operating 37635 non-null   float64 
 16  Interest_to_cash       23511 non-null   float64 
 17  Interest_to_Sales     43277 non-null   float64 
 18  Cash_to_Financial_Expense 37567 non-null   float64 
 19  Cash_to_assets         43270 non-null   float64 
 20  (receivables*365)/sales 43278 non-null   float64 
 21  total_costs/total_sales 43321 non-null   float64 
 22  Cash_conversion_cycle 42986 non-null   float64 
 23  (short-term_liabilities*365)/cost_of_products_sold 43104 non-null   float64 
 24  class               43405 non-null   category 
dtypes: category(2), float64(22), int64(1)
memory usage: 7.7 MB
```

```
#adjusting for outliers
numeric_cols = Bankrupt_model.select_dtypes(include=[float, int]).columns
numeric_cols
```

```
→ Index(['year', 'net_profit/total assets', 'net_profit/sales', 'Return_On_equity',
       'sales(n)/sales(n-1)', 'Operating_Income_to_Total_Asset_ratio',
       '(inventory*365)/cost_of_products_sold', 'working_capital',
       'Working_Capital_to_Total_Assets_Ratio', 'Defensive_Interval_Ratio', 'Debt_Coverage_Ratio',
       'Equity_to_Total_Assets_Ratio', 'Total_Liabilities/total_assets', 'Financial_Leverage',
       'Financial_expense_to_operating', 'Interest_to_cash', 'Interest_to_Sales',
       'Cash_to_Financial_Expense', 'Cash_to_assets', '(receivables*365)/sales',
       'total_costs/total_sales', 'Cash_conversion_cycle',
       '(short-term_liabilities*365)/cost_of_products_sold'],
       dtype='object')
```

Start coding or generate with AI.

```
#adjusting for outliers
numeric_cols = Bankrupt_model.select_dtypes(include=[float, int]).columns
# Calculate Q1, Q3, and IQR for each column
Q1 = Bankrupt_model[numeric_cols].quantile(0.25)
Q3 = Bankrupt_model[numeric_cols].quantile(0.75)
IQR = Q3 - Q1

# Define the lower and upper bounds for outliers
lower_bound = Q1 - 5 * IQR
upper_bound = Q3 + 5 * IQR

# Create a boolean DataFrame indicating whether each value is an outlier
outliers = (Bankrupt_model[numeric_cols] < lower_bound) | (Bankrupt_model[numeric_cols] > upper_bound)

# Filter rows that contain any outliers
rows_with_outliers = outliers.any(axis=1)
Bankruptcleaned_model = Bankrupt_model[~rows_with_outliers]
```

```
Bankruptcleaned_model.info()
```

```
→ <class 'pandas.core.frame.DataFrame'>
Index: 22828 entries, 3 to 43404
Data columns (total 25 columns):
 #   Column           Non-Null Count Dtype
 ---  -- 
 0   year            22828 non-null  int64
 1   net_profit/total assets 22824 non-null  float64
 2   net_profit/sales    22812 non-null  float64
 3   Return_On_equity   22806 non-null  float64
 4   sales(n)/sales(n-1) 20141 non-null  float64
 5   Operating_Income_to_Total_Asset_ratio 22824 non-null  float64
 6   (inventory*365)/cost_of_products_sold 22822 non-null  float64
 7   working_capital    22827 non-null  float64
 8   Working_Capital_to_Total_Assets_Ratio 22824 non-null  float64
 9   working_capital_indicator 22828 non-null  category
10  Defensive_Interval_Ratio 22820 non-null  float64
11  Debt_Coverage_Ratio   20657 non-null  float64
12  Equity_to_Total_Assets_Ratio 22824 non-null  float64
13  Total_Liabilities/total_assets 22824 non-null  float64
14  Financial_Leverage   22822 non-null  float64
15  Financial_expense_to_operating 20656 non-null  float64
16  Interest_to_cash     10983 non-null  float64
17  Interest_to_Sales   22812 non-null  float64
18  Cash_to_Financial_Expense 20649 non-null  float64
19  Cash_to_assets       22808 non-null  float64
20  (receivables*365)/sales 22812 non-null  float64
21  total_costs/total_sales 22813 non-null  float64
22  Cash_conversion_cycle 22810 non-null  float64
23  (short-term_liabilities*365)/cost_of_products_sold 22820 non-null  float64
24  class              22828 non-null  category
dtypes: category(2), float64(22), int64(1)
memory usage: 4.2 MB
```

```
print(len(Bankrupt_model))
print(len(Bankruptcleaned_model))
```

```
→ 43405
22828
```

```
Bankruptcleaned_model.describe()
```

	year	net_profit/total assets	net_profit/sales	Return_On_equity	sales(n)/sales(n-1)
count	22828.000	22824.000	22812.000	22806.000	20141.00
mean	2.917	0.072	0.040	0.152	1.07
std	1.302	0.126	0.079	0.286	0.28
min	1.000	-0.618	-0.376	-1.338	0.00
25%	2.000	0.015	0.009	0.036	0.92
50%	3.000	0.059	0.034	0.129	1.05
75%	4.000	0.127	0.074	0.269	1.20
max	5.000	0.755	0.457	1.645	2.67

```
Bankruptcleaned_model.corr()
```

	year	net_profit/total assets	net_profit/sales	Retu
year	1.000	-0.099	-0.065	
net_profit/total assets	-0.099	1.000	0.827	
net_profit/sales	-0.065	0.827	1.000	
Return_On_equity	-0.096	0.692	0.582	
sales(n)/sales(n-1)	0.017	0.253	0.220	
Operating_Income_to_Total_Asset_ratio	-0.106	0.986	0.811	
(inventory*365)/cost_of_products_sold	0.032	-0.121	-0.038	
working_capital	0.031	0.180	0.232	
Working_Capital_to_Total_Assets_Ratio	0.030	0.329	0.284	
working_capital_indicator	0.017	0.209	0.203	
Defensive_Interval_Ratio	0.028	0.259	0.312	
Debt_Coverage_Ratio	-0.046	0.526	0.471	
Equity_to_Total_Assets_Ratio	0.016	0.291	0.311	
Total_Liabilities/total_assets	-0.016	-0.282	-0.307	
Financial_Leverage	-0.034	-0.082	-0.105	
Financial_expense_to_operating	0.006	0.060	0.068	
Interest_to_cash	0.003	-0.076	-0.068	
Interest_to_Sales	0.033	-0.103	-0.080	
Cash_to_Financial_Expense	0.027	0.101	0.099	
Cash_to_assets	0.004	0.228	0.192	
(receivables*365)/sales	0.085	-0.064	0.027	
total_costs/total_sales	0.051	-0.566	-0.673	
Cash_conversion_cycle	0.077	-0.132	-0.011	
(short-term_liabilities*365)/cost_of_products_sold	0.024	-0.262	-0.188	
class	0.020	-0.132	-0.140	

```
corr_pairs_negative = Bankruptcleaned_model.corr().unstack().sort_values(ascending=False)
corr_pairs_negative = corr_pairs_negative[corr_pairs_negative < -0.4]
corr_pairs_negative = corr_pairs_negative[corr_pairs_negative < 1].drop_duplicates()
pd.DataFrame(corr_pairs_negative)
corr_pairs_negative
```

Total_Liabilities/total_assets	working_capital_indicator	-0.418
total_costs/total_sales	Debt_Coverage_Ratio	-0.418
Total_Liabilities/total_assets	Defensive_Interval_Ratio	-0.486
(short-term_liabilities*365)/cost_of_products_sold	Equity_to_Total_Assets_Ratio	-0.507
Defensive_Interval_Ratio	Working_Capital_to_Total_Assets_Ratio	-0.540
Operating_Income_to_Total_Asset_ratio	(short-term_liabilities*365)/cost_of_products_sold	-0.559
total_costs/total_sales	total_costs/total_sales	-0.566
Total_Liabilities/total_assets	net_profit/total assets	-0.566
net_profit/sales	Working_Capital_to_Total_Assets_Ratio	-0.637
Total_Liabilities/total_assets	total_costs/total_sales	-0.673
dtype: float64	Equity_to_Total_Assets_Ratio	-0.981

```
for column in Bankruptcleaned_model.columns:
    countzero = (Bankruptcleaned_model[column] == 0).sum()
    print(f"{column} has {countzero} zero values")
```

```
year has 0 zero values
net_profit/total assets has 70 zero values
net_profit/sales has 66 zero values
Return_On_equity has 65 zero values
sales(n)/sales(n-1) has 4 zero values
```

```

Operating_Income_to_Total_Asset_ratio has 9 zero values
(inventory*365)/cost_of_products_sold has 682 zero values
working_capital has 2 zero values
Working_Capital_to_Total_Assets_Ratio has 0 zero values
working_capital_indicator has 3965 zero values
Defensive_Interval_Ratio has 11 zero values
Debt_Coverage_Ratio has 2 zero values
Equity_to_Total_Assets_Ratio has 2 zero values
Total_Liabilities/total_assets has 8 zero values
Financial_Leverage has 0 zero values
Financial_expense_to_operating has 1 zero values
Interest_to_cash has 0 zero values
Interest_to_Sales has 11828 zero values
Cash_to_Financial_Expense has 0 zero values
Cash_to_assets has 1 zero values
(receivables*365)/sales has 26 zero values
total_costs/total_sales has 0 zero values
Cash_conversion_cycle has 10 zero values
(short-term_liabilities*365)/cost_of_products_sold) has 23 zero values
class has 21703 zero values

```

```

length=len(Bankruptcleaned_model['class'])
print(f"total number of rows is: {length}")

```

→ total number of rows is: 22828

```

nulls=Bankruptcleaned_model.isnull().sum()

```

```

nulls

```

year	0
net_profit/total assets	4
net_profit/sales	16
Return_On_equity	22
sales(n)/sales(n-1)	2687
Operating_Income_to_Total_Asset_ratio	4
(inventory*365)/cost_of_products_sold	6
working_capital	1
Working_Capital_to_Total_Assets_Ratio	4
working_capital_indicator	0
Defensive_Interval_Ratio	8
Debt_Coverage_Ratio	2171
Equity_to_Total_Assets_Ratio	4
Total_Liabilities/total_assets	4
Financial_Leverage	6
Financial_expense_to_operating	2172
Interest_to_cash	11845
Interest_to_Sales	16
Cash_to_Financial_Expense	2179
Cash_to_assets	20
(receivables*365)/sales	16
total_costs/total_sales	15
Cash_conversion_cycle	18
(short-term_liabilities*365)/cost_of_products_sold)	8
class	0
dtype: int64	

```

percentage_nulls=nulls/length*100
percentage_nulls
#to determine % of null per attribute. anything over 10% will be removed. The remainder will use random forest imputation.

```

year	0.000
net_profit/total assets	0.018
net_profit/sales	0.070
Return_On_equity	0.096
sales(n)/sales(n-1)	11.771
Operating_Income_to_Total_Asset_ratio	0.018
(inventory*365)/cost_of_products_sold	0.026
working_capital	0.004
Working_Capital_to_Total_Assets_Ratio	0.018
working_capital_indicator	0.000
Defensive_Interval_Ratio	0.035
Debt_Coverage_Ratio	9.510
Equity_to_Total_Assets_Ratio	0.018
Total_Liabilities/total_assets	0.018
Financial_Leverage	0.026
Financial_expense_to_operating	9.515
Interest_to_cash	51.888
Interest_to_Sales	0.070
Cash_to_Financial_Expense	9.545

```
Cash_to_assets          0.088
(receivables*365)/sales 0.070
total_costs/total_sales 0.066
Cash_conversion_cycle   0.079
(short-term_liabilities*365)/cost_of_products_sold) 0.035
class                  0.000
dtype: float64
```

```
percentage_nulls[percentage_nulls>5]
```

```
→ sales(n)/sales(n-1)      11.771
Debt_Coverage_Ratio       9.510
Financial_expense_to_operating 9.515
Interest_to_cash          51.888
Cash_to_Financial_Expense 9.545
dtype: float64
```

```
Bankruptcleaned_model.drop(['sales(n)/sales(n-1)', 'Debt_Coverage_Ratio', 'Financial_expense_to_operating', 'Interest_to_cash', 'Cash_to_Financi
```

```
→ <ipython-input-85-65fb679f6fe4>:1: SettingWithCopyWarning:
  A value is trying to be set on a copy of a slice from a DataFrame
```

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```
Bankruptcleaned_model.info()
```

```
→ <class 'pandas.core.frame.DataFrame'>
Index: 22828 entries, 3 to 43404
Data columns (total 20 columns):
 #   Column           Non-Null Count Dtype
 ---  -- 
 0   year             22828 non-null  int64
 1   net_profit/total assets 22824 non-null  float64
 2   net_profit/sales        22812 non-null  float64
 3   Return_On_equity       22806 non-null  float64
 4   Operating_Income_to_Total_Asset_ratio 22824 non-null  float64
 5   (inventory*365)/cost_of_products_sold 22822 non-null  float64
 6   working_capital         22827 non-null  float64
 7   Working_Capital_to_Total_Assets_Ratio 22824 non-null  float64
 8   working_capital_indicator 22828 non-null  category
 9   Defensive_Interval_Ratio 22820 non-null  float64
 10  Equity_to_Total_Assets_Ratio 22824 non-null  float64
 11  Total_Liabilities/total_assets        22824 non-null  float64
 12  Financial_Leverage        22822 non-null  float64
 13  Interest_to_Sales        22812 non-null  float64
 14  Cash_to_assets           22808 non-null  float64
 15  (receivables*365)/sales 22812 non-null  float64
 16  total_costs/total_sales 22813 non-null  float64
 17  Cash_conversion_cycle    22810 non-null  float64
 18  (short-term_liabilities*365)/cost_of_products_sold) 22820 non-null  float64
 19  class                  22828 non-null  category
dtypes: category(2), float64(17), int64(1)
memory usage: 3.4 MB
```

```
nulls=Bankruptcleaned_model.isnull().sum()
nulls
```

```
→ year                      0
net_profit/total assets     4
net_profit/sales            16
Return_On_equity            22
Operating_Income_to_Total_Asset_ratio 4
(inventory*365)/cost_of_products_sold 6
working_capital              1
Working_Capital_to_Total_Assets_Ratio 4
working_capital_indicator    0
Defensive_Interval_Ratio     8
Equity_to_Total_Assets_Ratio 4
Total_Liabilities/total_assets 4
Financial_Leverage            6
Interest_to_Sales            16
Cash_to_assets                 20
(receivables*365)/sales       16
total_costs/total_sales       15
Cash_conversion_cycle          18
(short-term_liabilities*365)/cost_of_products_sold) 8
```

```
class          0
dtype: int64
```

```
nulls/length*100
```

```
year           0.000
net_profit/total assets   0.018
net_profit/sales        0.070
Return_On_equity       0.096
Operating_Income_to_Total_Asset_ratio 0.018
(inventory*365)/cost_of_products_sold 0.026
working_capital         0.004
Working_Capital_to_Total_Assets_Ratio 0.018
working_capital_indicator 0.000
Defensive_Interval_Ratio 0.035
Equity_to_Total_Assets_Ratio 0.018
Total_liabilities/total_assets 0.018
Financial_Leverage      0.026
Interest_to_Sales       0.070
Cash_to_assets          0.088
(receivables*365)/sales 0.070
total_costs/total_sales 0.066
Cash_conversion_cycle   0.079
(short-term_liabilities*365)/cost_of_products_sold) 0.035
class                  0.000
dtype: float64
```

```
#using 3 different methods of imputation to see which one works best
```

```
Bankrupt_modelMMM=Bankruptcleaned_model.copy()
Bankrupt_modelKNN=Bankruptcleaned_model.copy()
Bankrupt_modelRF=Bankruptcleaned_model.copy()
```

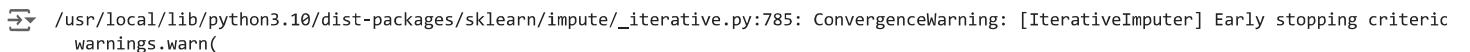
```
from sklearn.impute import SimpleImputer
from sklearn.experimental import enable_iterative_imputer # noqa
from sklearn.impute import IterativeImputer
from sklearn.ensemble import RandomForestRegressor
from sklearn.impute import KNNImputer
```

```
# Columns with missing values in your bankrupt_model dataset
columns_with_missing = [
    'net_profit/total assets', 'net_profit/sales', 'Return_On_equity',
    'Operating_Income_to_Total_Asset_ratio',
    '(inventory*365)/cost_of_products_sold', 'working_capital',
    'Working_Capital_to_Total_Assets_Ratio', 'working_capital_indicator',
    'Defensive_Interval_Ratio', 'Equity_to_Total_Assets_Ratio',
    'Total_liabilities/total_assets', 'Financial_Leverage',
    'Interest_to_Sales', 'Cash_to_assets', '(receivables*365)/sales',
    'total_costs/total_sales', 'Cash_conversion_cycle',
    '(short-term_liabilities*365)/cost_of_products_sold'
]
```

```
# Perform imputation (example using SimpleImputer with mean)
imputer = SimpleImputer(strategy='mean')
Bankrupt_modelMMM[columns_with_missing] = imputer.fit_transform(Bankrupt_modelMMM[columns_with_missing])
```

```
#performing imputation with KNN
imputer=KNNImputer(n_neighbors=5)
Bankrupt_modelKNN[columns_with_missing] = imputer.fit_transform(Bankrupt_modelKNN[columns_with_missing])
```

```
#perfomring imputation with Random Forest
estimator = RandomForestRegressor(n_estimators=3, max_depth= 3)
imputer = IterativeImputer(estimator=estimator, random_state=0)
Bankrupt_modelRF[columns_with_missing] = imputer.fit_transform(Bankrupt_modelRF[columns_with_missing])
```

```

/usr/local/lib/python3.10/dist-packages/scikit-learn/impute/_iterative.py:785: ConvergenceWarning: [IterativeImputer] Early stopping criteric
warnings.warn(
```

```
Bankrupt_modelMMM.isnull().sum()
```

	year	net_profit/total assets	net_profit/sales	Return_On_equity	Operating_Income
	0	0	0	0	0
net_profit/sales	0	0	0	0	0
Return_On_equity	0	0	0	0	0
Operating_Income_to_Total_Asset_ratio	0	0	0	0	0
(inventory*365)/cost_of_products_sold	0	0	0	0	0
working_capital	0	0	0	0	0
Working_Capital_to_Total_Assets_Ratio	0	0	0	0	0
working_capital_indicator	0	0	0	0	0
Defensive_Interval_Ratio	0	0	0	0	0
Equity_to_Total_Assets_Ratio	0	0	0	0	0
Total_Liabilities/total_assets	0	0	0	0	0
Financial_Leverage	0	0	0	0	0
Interest_to_Sales	0	0	0	0	0
Cash_to_assets	0	0	0	0	0
(receivables*365)/sales	0	0	0	0	0
total_costs/total_sales	0	0	0	0	0
Cash_conversion_cycle	0	0	0	0	0
(short-term_liabilities*365)/cost_of_products_sold)	0	0	0	0	0
class	0	0	0	0	0
dtype: int64					

```
Bankrupt_modelMMM.describe()
```

	year	net_profit/total assets	net_profit/sales	Return_On_equity	Operating_Income
count	22828.000	22828.000	22828.000	22828.000	22828.000
mean	2.917	0.072	0.040	0.152	
std	1.302	0.126	0.079	0.286	
min	1.000	-0.618	-0.376	-1.338	
25%	2.000	0.015	0.010	0.036	
50%	3.000	0.059	0.034	0.129	
75%	4.000	0.127	0.074	0.268	
max	5.000	0.755	0.457	1.645	

```
Bankrupt_modelRF.describe()
```

	year	net_profit/total assets	net_profit/sales	Return_On_equity	Operating_Income
count	22828.000	22828.000	22828.000	22828.000	22828.000
mean	2.917	0.072	0.040	0.152	
std	1.302	0.126	0.079	0.286	
min	1.000	-0.618	-0.376	-1.338	
25%	2.000	0.015	0.009	0.035	
50%	3.000	0.059	0.034	0.129	
75%	4.000	0.127	0.074	0.268	
max	5.000	0.755	0.457	1.645	

```
Bankrupt_modelRF.isnull().sum()
```

	year	net_profit/total assets	net_profit/sales	Return_On_equity	Operating_Income
	0	0	0	0	0
net_profit/total assets	0	0	0	0	0
net_profit/sales	0	0	0	0	0
Return_On_equity	0	0	0	0	0
Operating_Income_to_Total_Asset_ratio	0	0	0	0	0
(inventory*365)/cost_of_products_sold	0	0	0	0	0
working_capital	0	0	0	0	0
Working_Capital_to_Total_Assets_Ratio	0	0	0	0	0
working_capital_indicator	0	0	0	0	0
Defensive_Interval_Ratio	0	0	0	0	0
Equity_to_Total_Assets_Ratio	0	0	0	0	0
Total_Liabilities/total_assets	0	0	0	0	0

```

Financial_Leverage          0
Interest_to_Sales           0
Cash_to_assets               0
(receivables*365)/sales     0
total_costs/total_sales     0
Cash_conversion_cycle       0
(short-term_liabilities*365)/cost_of_products_sold 0
class                         0
dtype: int64

```

```
Bankrupt_modelRF['class'].value_counts()
```

```

→ class
 0    21703
 1    1125
Name: count, dtype: int64

```

Preparing to model

This research will be looking at the following algorithms:

1. Logistic Regression
2. Decision Tree
3. Random Forest
4. AdaBoost
5. Gradient Boosting

```
#performing K-Fold cross-validation to split training sets. Using K= 10 as standard
Bankrupt_model_x =Bankrupt_modelRF.drop(['class'],axis=1)
Bankrupt_model_y =Bankrupt_modelRF['class']
```

```
#defining the number of folds
from sklearn.model_selection import KFold
kf = KFold(n_splits=10, shuffle =True, random_state=7)

for train_index, test_index in kf.split(Bankrupt_model_x):
    # Split data into train and test sets
    X_train, X_test = Bankrupt_model_x.iloc[train_index], Bankrupt_model_x.iloc[test_index]
    y_train, y_test = Bankrupt_model_y.iloc[train_index], Bankrupt_model_y.iloc[test_index]
```

```
y_train.value_counts()
```

```

→ class
 0    19537
 1    1009
Name: count, dtype: int64

```

```
import pandas as pd
from sklearn.model_selection import KFold
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier, GradientBoostingClassifier
```

```
# Initialize models
models = {
    'Logistic Regression': LogisticRegression(),
    'Decision Tree': DecisionTreeClassifier(),
    'Random Forest': RandomForestClassifier(),
    'AdaBoost': AdaBoostClassifier(),
    'Gradient Boosting': GradientBoostingClassifier()
}
```

```
#Logistic Regression
classifierLR = LogisticRegression()
classifierLR.fit(X_train, y_train)
```

```
↳ /usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py:458: ConvergenceWarning: lbfgs failed to converge (status=1):  
STOP: TOTAL NO. OF ITERATIONS REACHED LIMIT.
```

Increase the number of iterations (max_iter) or scale the data as shown in:

<https://scikit-learn.org/stable/modules/preprocessing.html>

Please also refer to the documentation for alternative solver options:

https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression

n_iter_i = _check_optimize_result(

↳ LogisticRegression

↳ LogisticRegression()

```
y_predLR = pd.Series(classifierLR.predict(X_test))
```

```
y_predLR
```

```
y_predLR.value_counts()
```

```
→ 0    2282  
   Name: count, dtype: int64
```

```
#Decision tree :
```

```
classifierDT = DecisionTreeClassifier(random_state=7)  
classifierDT.fit(X_train, y_train)
```

```
→ ↴ DecisionTreeClassifier  
   ↴ DecisionTreeClassifier(random_state=7)
```

```
y_predDT = pd.Series(classifierDT.predict(X_test))
```

```
y_predDT
```

```
y_predDT.value_counts()
```

```
→ 0    2155  
   1    127  
   Name: count, dtype: int64
```

```
#Random Forest
```

```
classifierRF = RandomForestClassifier(random_state=7)  
classifierRF.fit(X_train, y_train)
```

```
→ ↴ RandomForestClassifier  
   ↴ RandomForestClassifier(random_state=7)
```

```
y_predRF = pd.Series(classifierRF.predict(X_test))
```

```
y_predRF
```

```
y_predRF.value_counts()
```

```
→ 0    2259  
   1    23  
   Name: count, dtype: int64
```

```
#AdaBoost
```

```
classifierAB = AdaBoostClassifier(random_state=7)  
classifierAB.fit(X_train, y_train)
```

```
→ ↴ AdaBoostClassifier  
   ↴ AdaBoostClassifier(random_state=7)
```

```
y_predAB = pd.Series(classifierAB.predict(X_test))
```

```
y_predAB
```

```
y_predAB.value_counts()
```

```
→ 0    2267  
   1    15  
   Name: count, dtype: int64
```

```
#Gradient Boosting
```

```
classifierGB = GradientBoostingClassifier(random_state=7)  
classifierGB.fit(X_train, y_train)
```

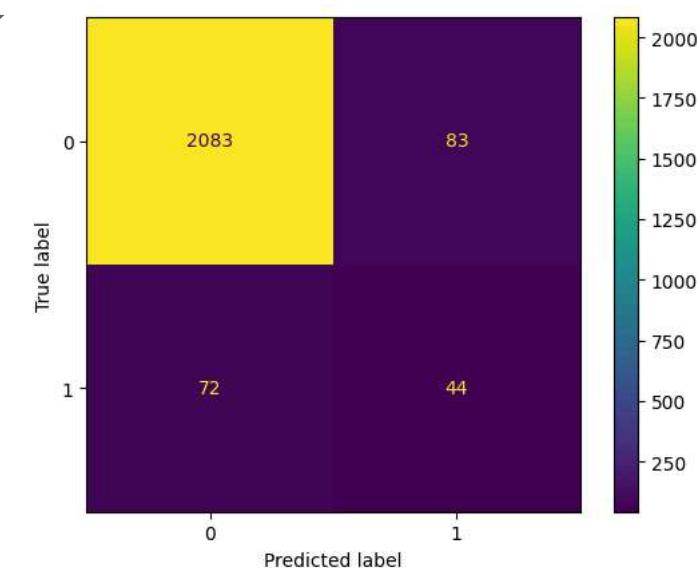
```
GradientBoostingClassifier  
GradientBoostingClassifier(random_state=7)
```

```
y_predGB = pd.Series(classifierGB.predict(X_test))  
y_predGB  
y_predGB.value_counts()
```

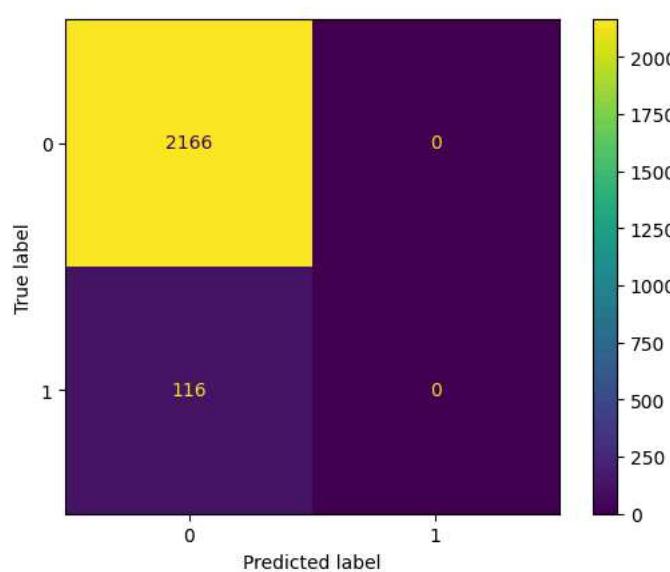
```
0    2259  
1     23  
Name: count, dtype: int64
```

✓ Performance Metrics

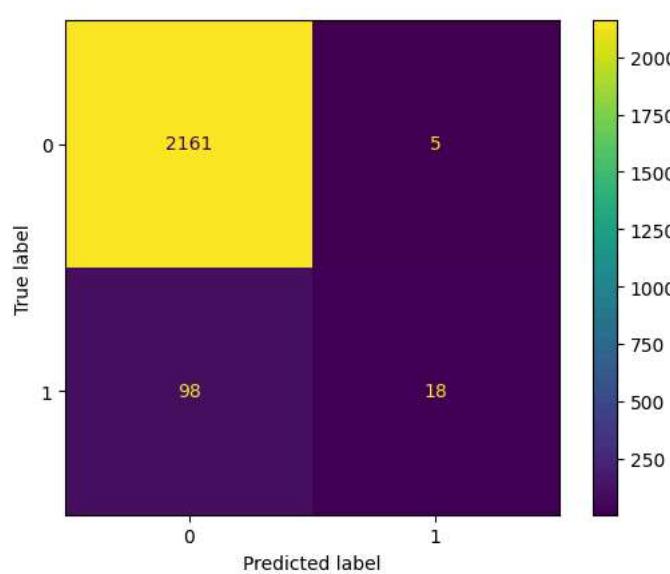
```
#Confusion matrix for Decision Tree  
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay  
cm= confusion_matrix(y_test,y_predDT, labels=classifierDT.classes_)  
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=classifierDT.classes_)  
disp.plot()  
plt.show()
```



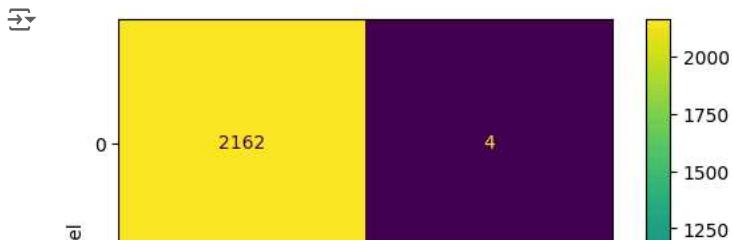
```
#Confusion matrix for Logistic Regression  
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay  
cm= confusion_matrix(y_test,y_predLR, labels=classifierLR.classes_)  
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=classifierLR.classes_)  
disp.plot()  
plt.show()
```



```
#Confusion matrix for Random Forest
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
cm= confusion_matrix(y_test,y_predRF, labels=classifierRF.classes_)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=classifierRF.classes_)
disp.plot()
plt.show()
```



```
#Confusion matrix for AdaBoost
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
cm= confusion_matrix(y_test,y_predAB, labels=classifierAB.classes_)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=classifierAB.classes_)
disp.plot()
plt.show()
```



```
#Confusion matrix for Gradient Boost
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
cm= confusion_matrix(y_test,y_predGB, labels=classifierGB.classes_)
disn = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=classifierGB.classes_)
```