Company bankrupt predictive models

Importing the libraries

In [10]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix, accuracy_score
from sklearn.metrics import f1_score,recall_score,precision_score
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import classification_report
from sklearn.ensemble import RandomForestClassifier
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import PowerTransformer
from sklearn.model_selection  import train_test_split
from sklearn.model_selection import cross_val_score
```

Importing the Dataset

In [11]:
```
df = pd.read_csv(r"C:\Users\hp\Downloads\data.csv")
```

checking the dataset information

In [12]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6819 entries, 0 to 6818
Data columns (total 96 columns):
 #   Column                                                    Non-Null Count
Dtype
---  ------                                                    --------------
-----
 0   Bankrupt?                                                 6819 non-null
int64
 1    ROA(C) before interest and depreciation before interest  6819 non-null
float64
 2    ROA(A) before interest and % after tax                   6819 non-null
float64
 3    ROA(B) before interest and depreciation after tax        6819 non-null
float64
 4    Operating Gross Margin                                   6819 non-null
float64
 5    Realized Sales Gross Margin                              6819 non-null
float64
 6    Operating Profit Rate                                    6819 non-null
float64
 7    Pre-tax net Interest Rate                                6819 non-null
float64
 8    After-tax net Interest Rate                              6819 non-null
float64
 9    Non-industry income and expenditure/revenue              6819 non-null
float64
 10   Continuous interest rate (after tax)                     6819 non-null
float64
 11   Operating Expense Rate                                   6819 non-null
float64
 12   Research and development expense rate                    6819 non-null
float64
 13   Cash flow rate                                           6819 non-null
float64
 14   Interest-bearing debt interest rate                      6819 non-null
float64
 15   Tax rate (A)                                             6819 non-null
float64
 16   Net Value Per Share (B)                                  6819 non-null
float64
 17   Net Value Per Share (A)                                  6819 non-null
float64
 18   Net Value Per Share (C)                                  6819 non-null
float64
 19   Persistent EPS in the Last Four Seasons                  6819 non-null
float64
 20   Cash Flow Per Share                                      6819 non-null
float64
 21   Revenue Per Share (Yuan ¥)                               6819 non-null
float64
 22   Operating Profit Per Share (Yuan ¥)                      6819 non-null
float64
 23   Per Share Net profit before tax (Yuan ¥)                 6819 non-null
```

```
float64
 24   Realized Sales Gross Profit Growth Rate                  6819 non-null
float64
 25   Operating Profit Growth Rate                             6819 non-null
float64
 26   After-tax Net Profit Growth Rate                         6819 non-null
float64
 27   Regular Net Profit Growth Rate                           6819 non-null
float64
 28   Continuous Net Profit Growth Rate                        6819 non-null
float64
 29   Total Asset Growth Rate                                  6819 non-null
float64
 30   Net Value Growth Rate                                    6819 non-null
float64
 31   Total Asset Return Growth Rate Ratio                     6819 non-null
float64
 32   Cash Reinvestment %                                      6819 non-null
float64
 33   Current Ratio                                            6819 non-null
float64
 34   Quick Ratio                                              6819 non-null
float64
 35   Interest Expense Ratio                                   6819 non-null
float64
 36   Total debt/Total net worth                               6819 non-null
float64
 37   Debt ratio %                                             6819 non-null
float64
 38   Net worth/Assets                                         6819 non-null
float64
 39   Long-term fund suitability ratio (A)                     6819 non-null
float64
 40   Borrowing dependency                                     6819 non-null
float64
 41   Contingent liabilities/Net worth                         6819 non-null
float64
 42   Operating profit/Paid-in capital                         6819 non-null
float64
 43   Net profit before tax/Paid-in capital                    6819 non-null
float64
 44   Inventory and accounts receivable/Net value              6819 non-null
float64
 45   Total Asset Turnover                                     6819 non-null
float64
 46   Accounts Receivable Turnover                             6819 non-null
float64
 47   Average Collection Days                                  6819 non-null
float64
 48   Inventory Turnover Rate (times)                          6819 non-null
float64
 49   Fixed Assets Turnover Frequency                          6819 non-null
float64
 50   Net Worth Turnover Rate (times)                          6819 non-null
```

```
float64
 51   Revenue per person                                          6819 non-null
float64
 52   Operating profit per person                                 6819 non-null
float64
 53   Allocation rate per person                                  6819 non-null
float64
 54   Working Capital to Total Assets                             6819 non-null
float64
 55   Quick Assets/Total Assets                                   6819 non-null
float64
 56   Current Assets/Total Assets                                 6819 non-null
float64
 57   Cash/Total Assets                                           6819 non-null
float64
 58   Quick Assets/Current Liability                              6819 non-null
float64
 59   Cash/Current Liability                                      6819 non-null
float64
 60   Current Liability to Assets                                 6819 non-null
float64
 61   Operating Funds to Liability                                6819 non-null
float64
 62   Inventory/Working Capital                                   6819 non-null
float64
 63   Inventory/Current Liability                                 6819 non-null
float64
 64   Current Liabilities/Liability                               6819 non-null
float64
 65   Working Capital/Equity                                      6819 non-null
float64
 66   Current Liabilities/Equity                                  6819 non-null
float64
 67   Long-term Liability to Current Assets                       6819 non-null
float64
 68   Retained Earnings to Total Assets                           6819 non-null
float64
 69   Total income/Total expense                                  6819 non-null
float64
 70   Total expense/Assets                                        6819 non-null
float64
 71   Current Asset Turnover Rate                                 6819 non-null
float64
 72   Quick Asset Turnover Rate                                   6819 non-null
float64
 73   Working capitcal Turnover Rate                              6819 non-null
float64
 74   Cash Turnover Rate                                          6819 non-null
float64
 75   Cash Flow to Sales                                          6819 non-null
float64
 76   Fixed Assets to Assets                                      6819 non-null
float64
 77   Current Liability to Liability                              6819 non-null
```

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

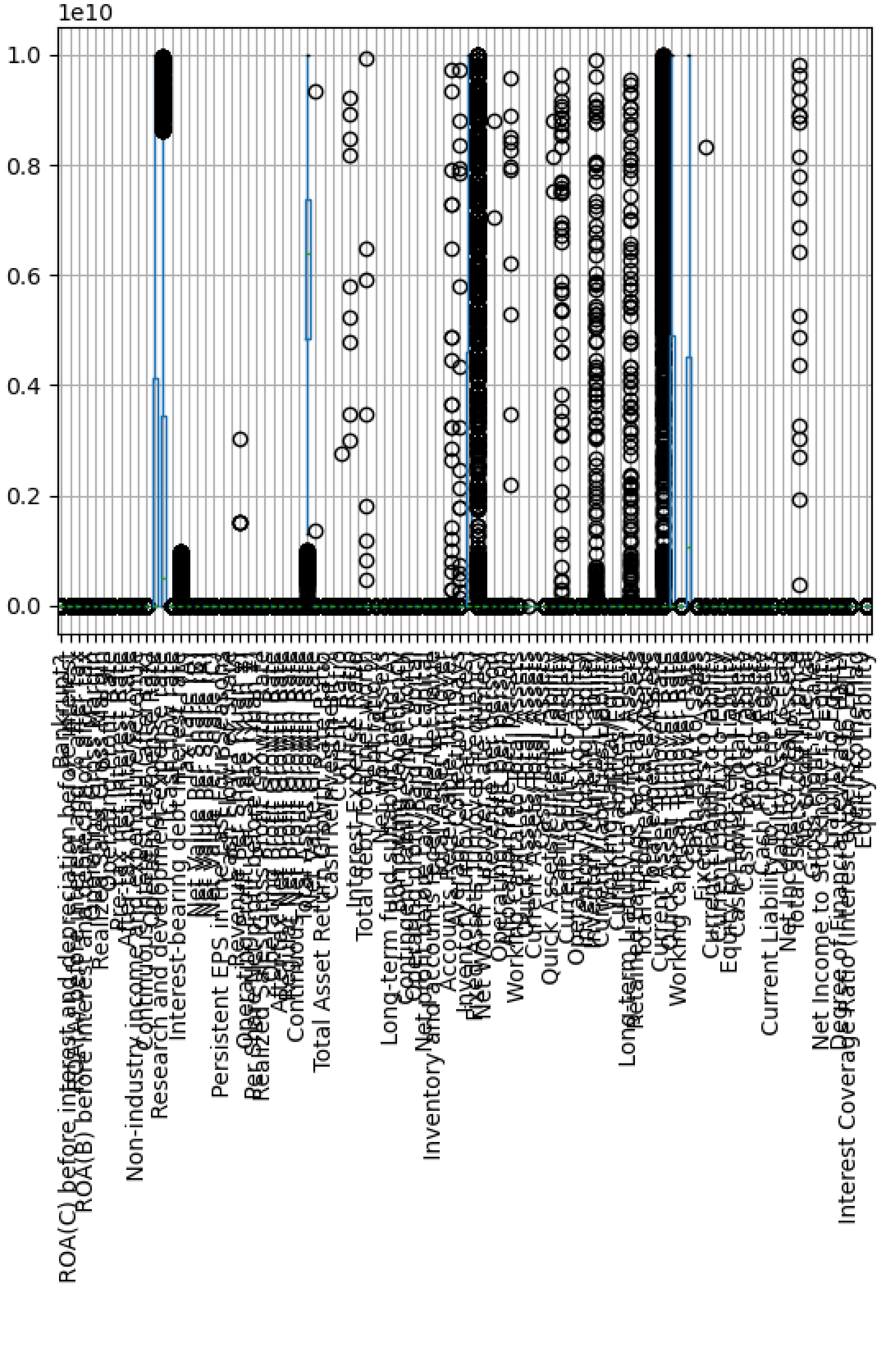
checking the null values in the dataset

In [13]:
```
df.isnull().sum()
```

Out[13]:
```
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
```

checking the Outliers in the dataset

In [14]:
```
df.boxplot()
plt.xticks(rotation =90 )
plt.show()
```


1e10
1.0
0.8
0.6
0.4
0.2
0.0

features Extraction from the main databased

The following all are extracted features

the feature are selected based on the requirement to predict the company are bankrupting so this is the important factores

- Financial Health Indicators : Features like ROA, current ratio, and cash flow measure profitability and liquidity, which directly show if a company is financially stable.
- Risk & Debt Management – Debt ratio and interest rate features capture how much risk the company takes through borrowing.
- Performance Trends – Growth rate and profit margin features show whether the company’s performance is improving or declining over time.
- Predictive Power – These features are proven in finance research to strongly influence bankruptcy likelihood, making them reliable predictors.

In [15]:
```
columns = ['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',
    ' Operating Profit Rate',
    ' Net Income to Total Assets',
    ' Gross Profit to Sales',
    " Net Income to Stockholder's Equity",
    ' Debt ratio %',
    ' Total debt/Total net worth',
    ' Liability to Equity',
    ' Equity to Liability',
    ' Degree of Financial Leverage (DFL)',
    ' Interest Coverage Ratio (Interest expense to EBIT)',
    ' Current Ratio',
    ' Quick Ratio',
    ' Cash/Total Assets',
    ' Cash/Current Liability',
    ' Total Asset Turnover',
    ' Inventory Turnover Rate (times)',
    ' Accounts Receivable Turnover',
    ' Working Capital to Total Assets',
    ' Cash Flow to Total Assets',
    ' CFO to Assets',
    ' Cash Flow to Equity',
    ' Cash Flow to Liability',
```

```
    ' Operating Profit Growth Rate'
]
```

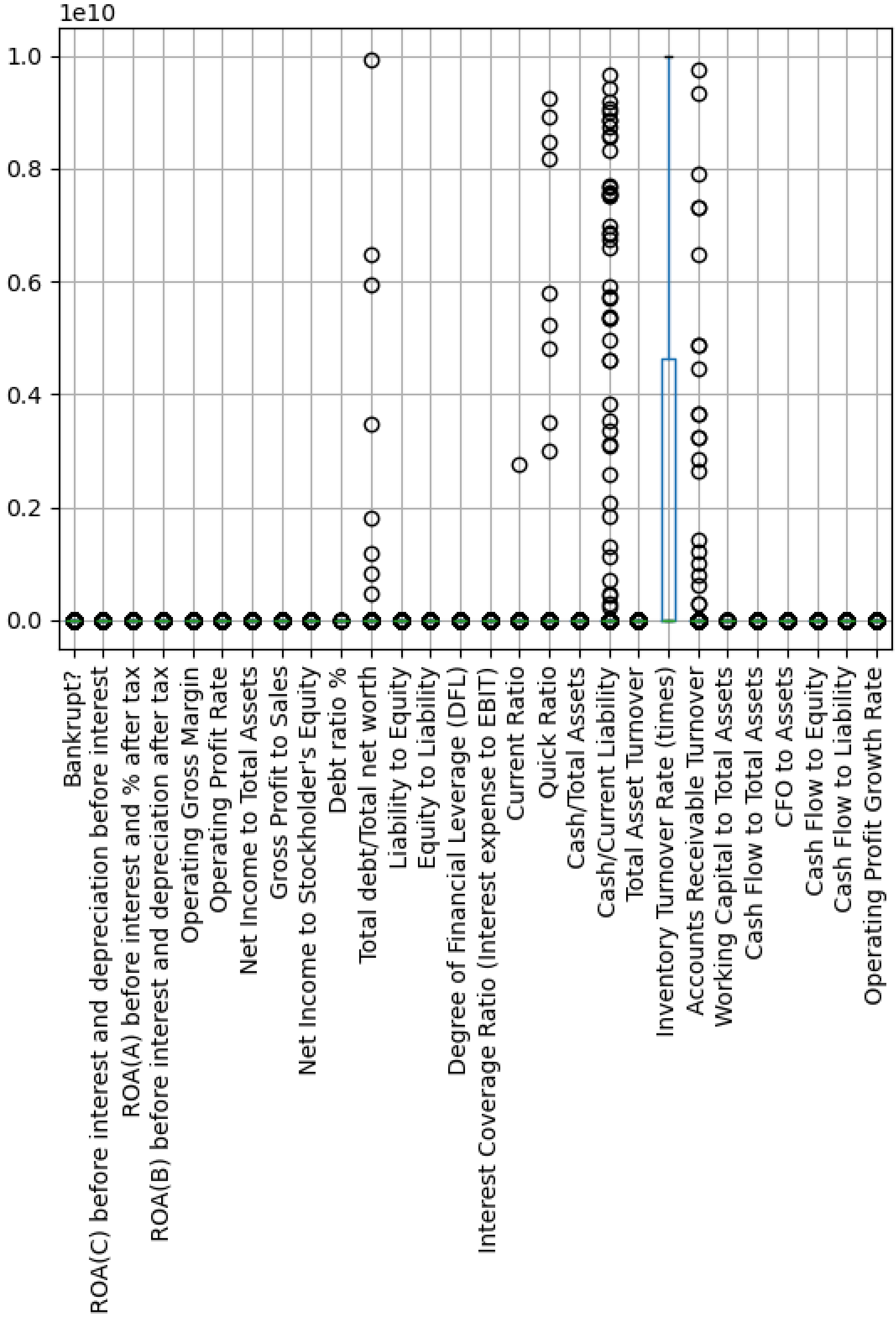
In [16]:

```
features = df[columns]
```

Rechecking the Outliers on the new features

In [17]:

```
features.boxplot()
plt.xticks(rotation = 90)
plt.show()
```



Balancing the outliers by using the Interquartile range

In [18]:
```
def balancing_outliers(dataset_name: pd.DataFrame) -> pd.DataFrame:
```

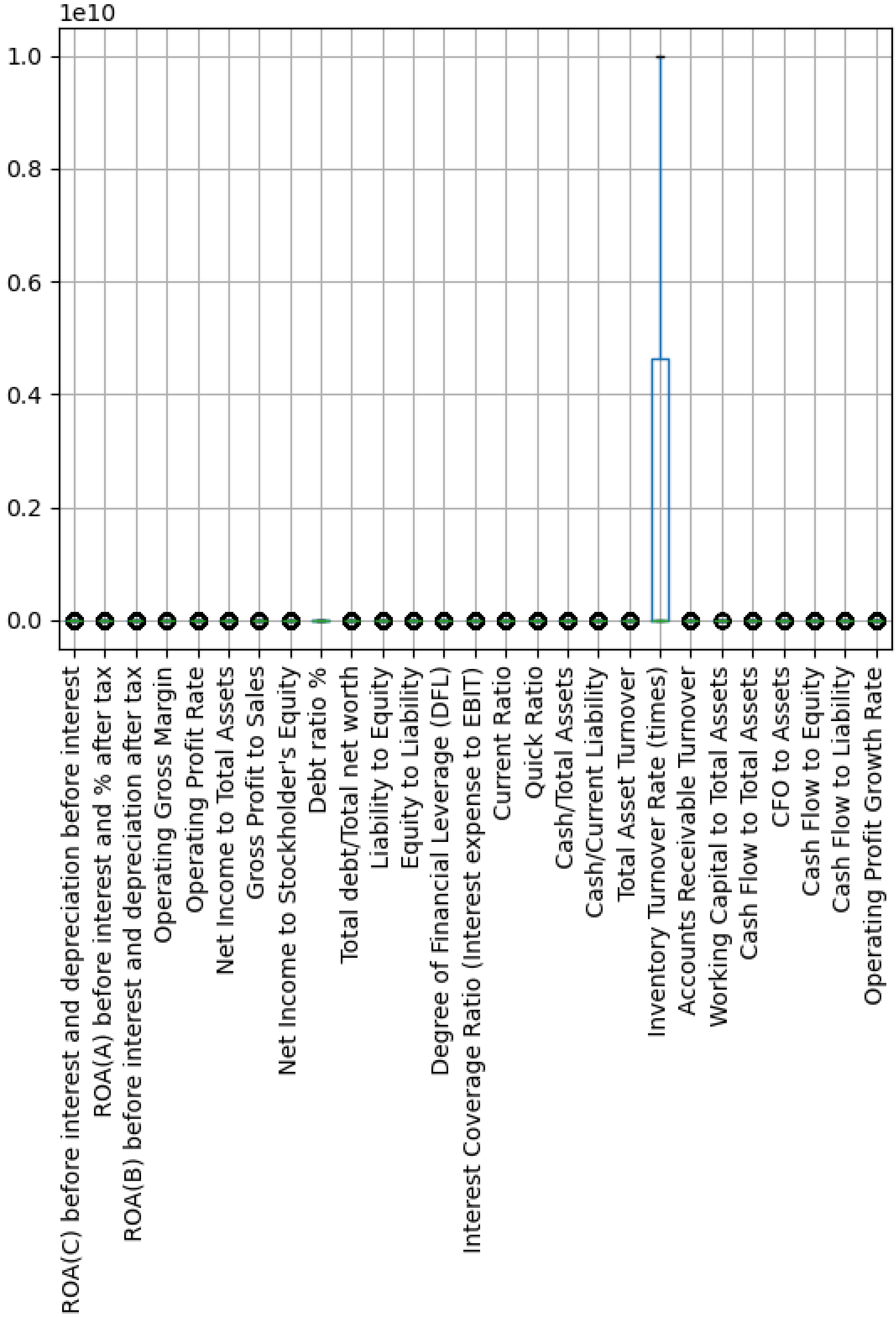
```python
    numeric_columns = dataset_name.select_dtypes(include=["int", "float"]).col
    for col in numeric_columns:
        Q1 = dataset_name[col].quantile(0.25)
        Q3 = dataset_name[col].quantile(0.75)
        IQR = Q3 - Q1
        lower_wisker = Q1 - 1.5 * IQR
        upper_wisker = Q3 + 1.5 * IQR
        median_value = dataset_name[col].median()
        dataset_name.loc[dataset_name[col] < lower_wisker, col] = median_value
        dataset_name.loc[dataset_name[col] > upper_wisker, col] = median_value

    return dataset_name
```

The feature 'Bankrupt' does not have any outliers and this feature is important to classify which companies are bankrupt or not

In [19]:
```python
new_features = balancing_outliers(features.drop('Bankrupt?',axis = 1))
```

In [20]:
```python
new_features.boxplot()
plt.xticks(rotation = 90)
plt.show()
```



In [21]:
```
def scale_data(dataset: pd.DataFrame) -> pd.DataFrame:
    numeric_columns = dataset.select_dtypes(include=["int", "float"]).columns
    scaler = StandardScaler()
    dataset[numeric_columns] = scaler.fit_transform(dataset[numeric_columns])
    return dataset
```

In [22]:

```
new_features = scale_data(new_features)
```

checking the correlation of the features

In [26]:

```
new_features.corr()
```

Out[26]:

	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	Operating Profit Rate	Inc to As
ROA(C) before interest and depreciation before interest	1.000000	0.830925	0.923608	0.437662	0.620554	0.80
ROA(A) before interest and % after tax	0.830925	1.000000	0.861958	0.407159	0.600069	0.92
ROA(B) before interest and depreciation after tax	0.923608	0.861958	1.000000	0.443507	0.617897	0.82
Operating Gross Margin	0.437662	0.407159	0.443507	1.000000	0.572383	0.42
Operating Profit Rate	0.620554	0.600069	0.617897	0.572383	1.000000	0.60
Net Income to Total Assets	0.804662	0.920570	0.826485	0.427971	0.604602	1.00
Gross Profit to Sales	0.437661	0.407160	0.443508	1.000000	0.572385	0.42
Net Income to Stockholder's Equity	0.748745	0.823677	0.760543	0.376591	0.563469	0.84
Debt ratio %	-0.208109	-0.192567	-0.211727	-0.346285	-0.218616	-0.24
Total debt/Total net worth	-0.175576	-0.165058	-0.178569	-0.298618	-0.191032	-0.21
Liability to Equity	-0.172485	-0.162538	-0.175339	-0.297395	-0.189259	-0.21
Equity to Liability	0.210032	0.185702	0.214735	0.293921	0.214284	0.22
Degree of Financial Leverage (DFL)	0.197718	0.200918	0.197378	0.063195	0.154192	0.16
Interest	0.153161	0.148404	0.153356	0.032635	0.106155	0.11

	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	Operating Profit Rate	Inc to As
Coverage Ratio (Interest expense to EBIT)						
Current Ratio	0.236354	0.244152	0.239866	0.286844	0.249250	0.27
Quick Ratio	0.279061	0.265303	0.278221	0.271377	0.233829	0.29
Cash/Total Assets	0.217873	0.199194	0.215751	0.168713	0.139968	0.20
Cash/Current Liability	0.225766	0.195852	0.224749	0.205911	0.179630	0.21
Total Asset Turnover	0.239500	0.259798	0.229835	-0.077495	0.066643	0.25
Inventory Turnover Rate (times)	-0.059558	-0.055902	-0.052836	0.110973	0.012983	-0.05
Accounts Receivable Turnover	0.078443	0.072052	0.086111	-0.031371	0.012276	0.06
Working Capital to Total Assets	0.236914	0.278025	0.236546	0.308600	0.259928	0.30
Cash Flow to Total Assets	0.136362	0.125378	0.135931	0.072503	0.089919	0.11
CFO to Assets	0.412085	0.311182	0.395789	0.305473	0.329373	0.34
Cash Flow to Equity	0.131220	0.123164	0.134714	0.069129	0.091833	0.11
Cash Flow to Liability	0.113599	0.114845	0.114118	0.053942	0.072807	0.10
Operating Profit Growth Rate	0.272439	0.270565	0.278916	0.184931	0.277938	0.26

27 rows × 27 columns

spliting the Data into Traing and testing data

In [27]:
```
from sklearn.model_selection  import train_test_split
```

In [28]:
```
X =  new_features
```

In [29]:
```
y = features["Bankrupt?"]
```

In [30]:
```
x_train,x_test,y_train,y_test = train_test_split(X,y,random_state = 42 , test_
```

Training the Classification models

Logistic Regression

In [31]:
```
LR = LogisticRegression()
```

In [32]:
```
y_train.value_counts()
```

Out[32]:
```
Bankrupt?
0    5286
1     169
Name: count, dtype: int64
```

In [33]:
```
y_test.value_counts()
```

Out[33]:
```
Bankrupt?
0    1313
1      51
Name: count, dtype: int64
```

For solving the bias we used the SMOTE function to balance the data

In [34]:
```
from imblearn.over_sampling import SMOTE
```

In [35]:
```
sm = SMOTE(random_state = 42)
```

In [36]:
```
x_res,y_res = sm.fit_resample(X,y)
```

In [37]:
```
y_res.value_counts()
```

Out[37]:
```
Bankrupt?
1    6599
0    6599
Name: count, dtype: int64
```

In [38]:
```
LR.fit(x_res,y_res)
```

Out[38]:
```
▾ LogisticRegression
LogisticRegression()
```

In [39]:
```
y_pred = LR.predict(x_test)
```

In [40]:
```
confusion_matrix(y_test,y_pred)
```

Out[40]:
```
array([[1077,  236],
       [   3,   48]], dtype=int64)
```

In [41]:
```
accuracy_score(y_test,y_pred)
```

Out[41]:
```
0.8247800586510264
```

In [42]:
```
y_test.value_counts()
```

Out[42]:
```
Bankrupt?
0    1313
1      51
Name: count, dtype: int64
```

In [43]:
```
pd.Series(y_pred).value_counts()
```

Out[43]:
```
0    1080
1     284
Name: count, dtype: int64
```

In [44]:
```
f1_score(y_test,y_pred)
```

Out[44]:
```
0.2865671641791045
```

In [45]:
```
recall_score(y_test,y_pred)
```

Out[45]:
```
0.9411764705882353
```

KNN Classifier

In [46]:
```
KNN = KNeighborsClassifier(n_neighbors=2, n_jobs = -1)
```

In [47]:
```
KNN.fit(x_res,y_res)
```

Out[47]:
```
KNeighborsClassifier

KNeighborsClassifier(n_jobs=-1, n_neighbors=2)
```

In [48]:
```
y_prediction = KNN.predict(x_test)
```

In [49]:
```
pd.Series(y_prediction).value_counts()
```

Out[49]:
```
0    1313
1      51
Name: count, dtype: int64
```

In [50]:
```
confusion_matrix(y_test,y_prediction)
```

Out[50]:
```
array([[1313,    0],
       [   0,   51]], dtype=int64)
```

In [51]:
```
accuracy_score(y_test,y_prediction)
```

Out[51]:
```
1.0
```

In [52]:
```
f1_score(y_test,y_prediction)
```

Out[52]:
```
1.0
```

Now we used the cross validation for testing the model via providing the multiple input and checking the accuracy of the model

In [53]:
```
from sklearn.model_selection import cross_val_score
scores = cross_val_score(KNN, x_res, y_res, cv=5, scoring='accuracy')
print(scores, scores.mean())
```

```
[0.94242424 0.93977273 0.97575758 0.9806745  0.98294809] 0.9643154259533571
```

In [69]:
```
from sklearn.metrics import accuracy_score
train_pred = KNN.predict(x_res)
test_pred = KNN.predict(x_test)

print("Train Accuracy:", accuracy_score(y_res, train_pred))
print("Test Accuracy:", accuracy_score(y_test, test_pred))
```

```
Train Accuracy: 0.9385512956508562
Test Accuracy: 0.9758064516129032
```

Decision Tree Classifier

In [70]:
```
from sklearn.tree import DecisionTreeClassifier
```

In [71]:
```
DTC = DecisionTreeClassifier(criterion='entropy',max_depth = 17, class_weight
```

In [72]:
```
DTC.fit(x_res,y_res)
```

Out[72]:
```
DecisionTreeClassifier

DecisionTreeClassifier(class_weight='balanced', criterion='entropy',
                       max_depth=17, random_state=42)
```

In [73]:
```
y_pred_DTC = DTC.predict(x_test)
```

In [74]:
```
pd.Series(y_pred_DTC).value_counts()
```

Out[74]:
```
0    1300
1      64
Name: count, dtype: int64
```

In [75]:
```
accuracy_score(y_test,y_pred_DTC)
```

Out[75]:
```
0.9904692082111437
```

In [76]:
```
confusion_matrix(y_test,y_pred_DTC)
```

Out[76]:
```
array([[1300,   13],
       [   0,   51]], dtype=int64)
```

In [77]:
```
print(classification_report(y_test,y_pred_DTC))
```

```
              precision    recall  f1-score   support

           0       1.00      0.99      1.00      1313
           1       0.80      1.00      0.89        51

    accuracy                           0.99      1364
   macro avg       0.90      1.00      0.94      1364
weighted avg       0.99      0.99      0.99      1364
```

In [78]:
```
f1_score(y_test,y_pred_DTC)
```

Out[78]:
```
0.8869565217391304
```

Random Forest Classifier

In [79]:
```
RFC = RandomForestClassifier(n_estimators = 10, criterion='entropy',max_depth
```

In [80]:
```
RFC.fit(x_res,y_res)
```

Out[80]:
```
RandomForestClassifier

RandomForestClassifier(class_weight='balanced', criterion='entropy',
                       max_depth=17, n_estimators=10, random_state=4
2)
```

In [81]:
```
y_pred_RFC = RFC.predict(x_test)
```

In [82]:
```
print(classification_report(y_test,y_pred_RFC))
```

```
              precision    recall  f1-score   support

           0       1.00      0.99      1.00      1313
           1       0.82      1.00      0.90        51

    accuracy                           0.99      1364
   macro avg       0.91      1.00      0.95      1364
weighted avg       0.99      0.99      0.99      1364
```

In [83]:
```
accuracy_score(y_test,y_pred_RFC)
```

Out[83]: 0.9919354838709677

In [84]:
```
f1_score(y_test,y_pred_RFC)
```

Out[84]: 0.9026548672566371

Conclusion:

- After testing all the models I choosed the KNN model because it was more accurate than other algorithm
- For KNN accuracy score was 1 and f1 score was also close to 1 because of these conditions we choose this model